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Comparative Reliability Analysis of CHIRPS and Gauge-based Precipitation Measurements over the Zarqa River Basin

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Abstract

This study highlights the growing need for reliable and consistent precipitation data to support sustainable water resource management by evaluating the Climate Hazards Group Infrared Precipitation with Station dataset (CHIRPS) as a potential alternative to ground-based observations. The study objectives were to analyze the trends of precipitation indices using CHIRPS and observed data (station data) and to compare the correlations between station data and CHIRPS.

Trend analyses of extreme precipitation indices were conducted using observed data from 18 meteorological stations. A total of 12 annual climate indices were extracted from daily rainfall records (1985-2012) using the CLIMPACT software. Furthermore, a trend analysis was performed for the period 1998–2023 using CHIRPS data, and the results were compared with observations from five stations with available records for the same period. In addition, long-term trends spanning 1992–2023 were evaluated using CHIRPS data exclusively.

The CHIRPS data showed moderate agreement with station observations at the monthly and annual scales, with mean PCCs of 0.65 and 0.69, respectivelybut demonstrated clear limitations in capturing long-term trends. It identified only three significant trends (P< 0.05) at CDD, CWD, and R10mm, with values of 1, -0.05, and -0.132, respectively (20% of those detected by stations), none of which aligned with station records. For 1998–2023, CHIRPS detected three downward and four upward trends, the strongest trend shown in the PRCTOT indicator with values 1.92, 2.99, and 7.497 (28 % of those detected by stations), and the third part of the study, conducted over CHIRPS data (1998-2023) only, showed 3 downward trends and 11 upward trends. These results indicate that CHIRPS requires bias correction before reliable use and underscore the importance of expanding the rainfall monitoring network.

Keywords: *CHIRPS dataset; Climate variability; Data validation; Hydrological monitoring; Rainfall indices; Trend analysis.*

1. Introduction

Climate change remains one of the most pressing global challenges, affecting both environmental systems and socio-economic stability (Abu-Afifeh et al., 2023; Teweldebrihan and Dinka, 2024; Al-Afeshat et al., 2025; Hroub et al., 2025; Obeidat et al., 2025a, 2025b). Variability in precipitation and temperature—key indicators of climate change—has become a significant focus of hydrological studies (Suharyanto et al., 2023). These fluctuations have particularly severe consequences in arid and semi-arid regions, where fragile ecosystems are highly vulnerable to drought and water scarcity (Al-Addous et al., 2023; Dede et al., 2023). As global temperatures rise, evaporation rates increase, intensifying drought in some regions and amplifying rainfall in others. These dynamics complicate water management, especially in water-scarce areas (Kundzewicz et al., 2007). The Intergovernmental Panel on Climate Change (IPCC) highlights that changing rainfall patterns, rising temperatures, and more frequent extreme weather events are disrupting global water availability and distribution (Trenberth, 2011). For example, surface runoff in northwest China has increased due to altered rainfall patterns and glacier melt (Chen et al., 2020). In Africa, studies suggest that drought severity is projected to worsen (Masih et al., 2014; Justus Reymond and Sudalaimuthu, 2023). In the Middle East and North Africa (MENA), temperatures are expected to increase by up to 4 °C, accompanied by a decline in rainfall by the 'Century's end (Lelieveld et al., 2016). Regionally, Iraq has experienced declining spring and winter rainfall, with increasing summer rainfall and rising temperatures (Salman et al., 2017). Drought trends in the Gaza Strip between 1974 and 2016 varied spatially, with some areas severely affected during 1990, 2010, and 2014 (Ajjur and Riffi, 2020). Egypt recorded rising minimum temperatures and more hot days, though rainfall patterns remained relatively stable (Hamed et al., 2023).

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In Syria, rainfall slightly increased in autumn but declined significantly in winter between 1991 and 2009 (Zeleňáková et al., 2022). In Jordan, rainfall data from 58 stations (1970–2013) showed a decreasing trend at 38 stations at an average rate of 1.2 mm/year (Rahman et al., 2015). Droughts have become more frequent and severe (Al-Qinna et al., 2011). Alsalal et al. (2024) projected a 23 % decrease in precipitation in the Mujib Basin and a 1.4–6.4°C increase in temperature by the end of the Century. In the Zarqa River Basin (ZRB)—a key water source in Jordan—declining rainfall (Al-Houri, 2014) and shortened rainy seasons (Shatanawi et al., 2022) have been reported. Due to the limited distribution of meteorological stations in arid areas like the ZRB, alternative datasets such as the Climate Hazards Group Infrared Precipitation with Station (CHIRPS) are increasingly used to fill spatial gaps (Shen et al., 2020). However, CHIRPS must be evaluated before it is used in climate analysis. In Brazil, CHIRPS failed to capture rainfall trends in semi-arid zones, although its performance improved in wet seasons (Cavalcante et al., 2020; Hasibuan et al., 2025; Paredes-Trejo et al., 2017). In Colombia, CHIRPS performed better in highland areas (Ocampo-Marulanda et al., 2022). In Cyprus, rainfall was slightly overestimated but showed acceptable correlation (Katsanos et al., 2016). In India, CHIRPS reliably captured monthly rainfall variability (Prakash, 2019), and in Jordan, it has been deemed useful for filling data gaps (El-Mahroug et al., 2025; Alsalal et al., 2023). Furthermore, an investigation by Al Shamayleh et al. (2024) on rainfall in Mujib showed that a moderate correlation between CHIRPS and gauge data at the annual and monthly scale; however, an in-depth trend analysis for 11 extreme precipitation indices showed that CHIRPS captured the variability and produced the same trends as the observed data. The use of the mentioned indices significantly enhances the robustness of the climate trend analysis by providing a more detailed and comprehensive view of precipitation variability. This approach allows for the detection of subtle shifts in rainfall intensity and frequency, which are critical for understanding the impacts of climate change on water resources. Previous research indicated that there are still knowledge gaps in climate change research in Jordan, especially in major basins such as the ZRB, which still require trend analysis for major precipitation variables. Additionally, there is a need to validate alternative climatic data, such as CHRPS, to improve the spatial representation of precipitation in the ZRB, as well as to compensate for missing data. Thus, the study aims to analyze precipitation index trends using CHIRPS and observed (gauge station) data, and to compare correlations between the observed (gauge station) and CHIRPS data. This study was carried out at the ZRB, Jordan, during 2013-2023.

2. Materials and Methods

2.1 Study area description

The study area is located in the north-central part of Jordan (Fig. 1) and covers 3567 km². The Zarqa River Basin is the second major tributary to of the Jordan River and lies between longitudes 35° to 37° East and latitudes 31° to 33° North. The basin hosts parts of several major cities, Amman, Zarqa, and Jerash, and serves as a key area for urban expansion. It is considered one of the most vital basins in Jordan for agricultural, social, and economic importance (Al-Abed and Al-Sharif, 2007).

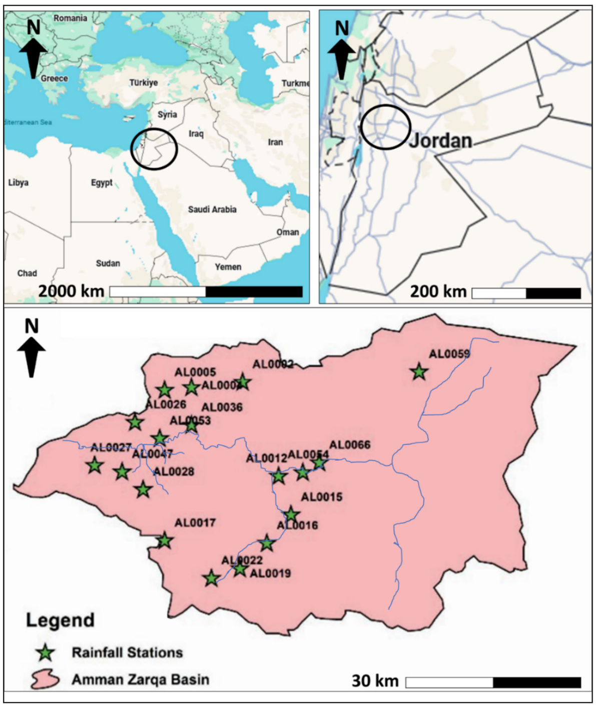

Figure 1. Geographical location of the study area along with rainfall stations in the Zarqa River Basin in Jordan

The ZRB is characterized by a semi-arid to arid Mediterranean climate. Summers are warm and dry, while winters are cool and wet, with occasional snowstorms and moderate frost events. The average summer temperature is 35°C, and the average winter temperature is 5 °C. Precipitation varies spatially, ranging from about 500 mm/y in the western half to 150 mm/y in the eastern half. Most of the rainfall occurs between November and April (MWI, 2020).

2.2 Methodological process overview

The research methodology flow of the study, illustrated in Fig. 2, comprised three main steps. First, observed meteorological data and CHIRPS satellite-based precipitation data were collected using the RStudio programming language (RStudio, 2024.08.0 Build 463©2009-2025 Posit Software, Public Benefit Corporation (PBC). Second, the CLIMPACT software was used to evaluate climate indices and analyze their trends for both observed and CHIRPS datasets. Finally, the results were analyzed, and the trends derived from both data sources were compared. Each step is briefly discussed in the following sections.

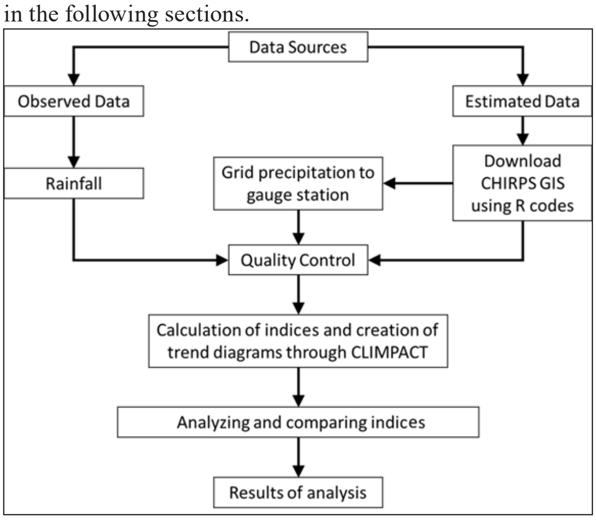

Figure 2. The study methodology flowchart

2.3 Data sources and quality control procedures

Observed daily precipitation data for 18 stations with different lengths of historical record were obtained from the Ministry of Water and Irrigation (MWI) (Table 1).

Table 1. Metadata for the selected meteorological stations used in Part One of the analysis. Stations annotated with an asterisk (*) were also used in Part Two of the analysis for the period 1998–2023.

Station		Location			Base year (start-end)	time period (years)
Name	Symbol	Latitude	Longitude	Altitude		
Amman Airport	AL0019*	31.97489	35.9878	790	1985-2012	28
King Talal Dam	AL0053*	32.19398	35.8316	218	1985-2012	28
Um El-Jumal	AL0059*	32.30221	36.3441	620	1985-2012	28
Burma	AL0026*	32.22127	35.7830	600	1985-2012	28
Rumimin	AL0028*	32.10847	35.7982	675	1985-2012	28
Kitta	AL0005	32.27509	35.8417	665	1985-2012	28
Sweilih	AL0017	32.32588	36.0916	1000	1985-2012	28
Amman Hussein College	AL0022	31.95899	35.9316	834	1985-2012	28
Subeihi	AL0027	32.14946	35.7031	500	1985-2012	28
Sihan	AL0047	32.13842	35.7570	495	1985-2012	28
Midwar	AL0002	32.28774	35.9957	760	1985-2012	28
Jarash	AL0004	32.27932	35.8948	585	1985-2012	28
Sukhna	AL0012	32.1294	36.0654	500	1985-2012	28
Zarqa	AL0015	32.06440	36.0891	610	1985-2012	28
Russifa	AL0016	32.34484	36.2087	655	1985-2012	28
Hashimiya	AL0054	32.13546	36.1131	550	1985-2012	28
Khirebit EsSamra	AL0066	32.12920	36.1925	540	1986-2012	27
Prince Feisal Nursery	AL0036	32.21620	35.8943	600	1985-2012	28

** only CHIRPS*

The study used version 2 of the open-source worldwide database CHIRPS 2.0, developed by the Climate Hazards Group at the University of California to provide precipitation data from 50° South to 50° North. CHIRPS data uses satellite- estimated precipitation blended with station data. Furthermore, the accuracy of the rainfall estimates is enhanced by using climatological models are used for bias correction. Overall, CHIRPS rainfall time series are produced at a high spatial resolution of the 0.05o (Funk et al., 2015). The data was downloaded using the library (CHIRPS) in RStudio. The longitude and latitude coordinates were entered in the R script for each station, then the daily CHIRPS data corresponding to the historical record of the selected stations (Table 1) was extracted from a spatial resolution of 0.05° using the point-to-pixel approach, which compares the observed rainfall to the grid-cell estimates that correspond to the coordinates of the selected stations. This is a widely used approach that eliminates the errors and uncertainties introduced by the interpolation process (Baez Villanueva et al., 2018; Wu et al., 2019). All selected stations are more than 5.5 meters apart, except for stations AL0047 and AL0028, so the same data extracted for both stations and thus CLIMPACT gave the same trend.

2.4 Trend and correlation analysis

CLIMPACT software, accessed online at CLIMPACT-sci.org, was used to analyse daily rainfall, maximum, and minimum temperature data, generating 71 climate indices relevant to the water and agriculture sectors. This study focused specifically on extreme precipitation indices (Table 2), which are critical for addressing climate risk, water scarcity, and food security (Alexander and Herold, 2013).

Table 2. Extreme precipitation indices

Indicator name and unit (Index)	Definition
Consecutive dry days (CDD)	Number of maximum consecutive days with rainfall record (RR) < 1 mm
Consecutive wet days (CWD)	Number of maximum consecutive days with RR > 1mm
Simple daily intensity index (SDII) millimeters per day (mm/day)	Annual Total RR divided by the number of wet days (when RR ≥ 1mm
Number of heavy precipitation days (R10mm)	Number of days when RR ≥ 10 mm
Number of very heavy precipitation days (R20mm)	Number of days when RR ≥ 20 mm
Very wet days (R95p) (mm)	Annual sum daily of RR > 95th %
Extremely wet days (R99p) (mm)	Annual sum daily of RR > 99th percentile
Contribution from very wet days (R95PTOT) (%)	Fraction of total wet-day rainfall that comes from very wet days
Contribution from extremely wet days (R99PTOT) (%)	Fraction of total wet-day rainfall that comes from extremely wet days
Max 1day precipitation amount (RX1day) (mm)	Maximum of total RR in 1 day
Max 5day precipitation amount (RX5day) (mm)	Maximum of total RR in 5 day
Annual total wet-day precipitation (PRCPTOT) (mm)	Annual total RR in wet days (when RR ≥ 1 mm)

The p-value criterion was applied to assess trend significance. A p-value less than 0.05 was considered statistically significant, while values above 0.05 were deemed non-significant (Mentaschi et al., 2013). For both observed station data and CHIRPS datasets, analyses were conducted at monthly and annual scales. In this study, the Pearson Correlation Coefficient (PCC) was used to assess the agreement between CHIRPS and station data, as it is a widely accepted and commonly applied metric in similar precipitation validation studies to evaluate the strength and direction of linear relationships. PCC values range from -1 to 1, where 1 indicates a perfect positive correlation, and -1 indicates a perfect negative correlation. The PCC was used to assess the reliability of CHIRPS in estimating monthly and yearly rainfall amounts and precipitation indices. The PCC is illustrated in Eq. 1 (Mentaschi et al., 2013):

$$PCC = \frac{\sum(P_{MWI} - \bar{P}_{MWI})(P_{CHIRPS} - \bar{P}_{CHIRPS})}{\sqrt{\sum(P_{MWI} - \bar{P}_{MWI})^2 \sum(P_{CHIRPS} - \bar{P}_{CHIRPS})^2}} \quad (1)$$

Where, P_{MWI} is the value of the precipitation according to the MWI, $\bar{P}_{MWI}$ is the mean of the values of the precipitation according to the MWI, P_{CHIRPS} is the value of the precipitation according to the CHIRPS and $\bar{P}_{CHIRPS}$ is the mean precipitation value according to CHIRPS.

The study was divided into three parts. The first part examined trends and compared station data with CHIRPS data for the period 1985–2012. The second part conducted the same comparison for a different period (1998–2023), focusing only on five stations identified in Table 1. The third part analyzed trends in CHIRPS data for the period 1992–2023.

3. Results and Discussion

3.1 Monthly and yearly precipitation assessment

The PCC for the annual precipitation between the station and CHIRPS datasets (Fig. 3) showed weak to moderate positive correlations (mean PCC = 0.70), although the PCC values were moderate to strong, with values greater than 0.5 (maximum PCC of 0.81), which were mainly observed in the eastern part of the basin. However, the PCC values for annual rainfall do not indicate a strong resemblance between the station and CHIRPS datasets, as evidenced by the low PCC values for all indices. Paredes-Trejo et al. (2017) and Du et al. (2024) noted that the sparse network of rainfall stations may contribute to weak correlation between CHIRPS and station data due to the lack of ground observations and CHIRPS's heavy reliance on satellite data. A study in Wadi Wala, Jordan found moderate correlation between annual station and CHIRPS data but performed poorly with extreme indices, indicating the need for further bias correction and validation of CHIRPS data in regions with limited station data (Al Shamayleh et al., 2024).

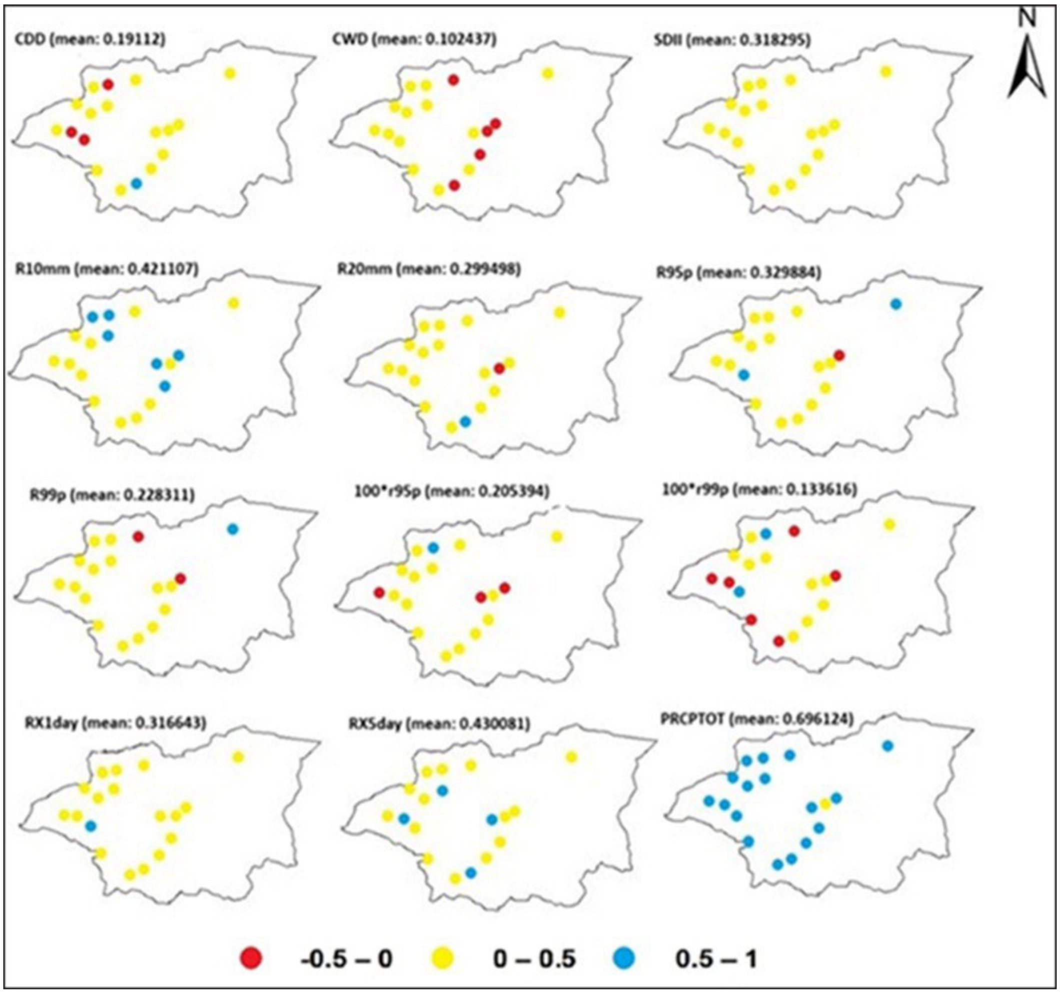

Figure 3. Spatial distribution of Pearson's linear yearly correlation coefficient of extreme precipitation indices, as measured by CHIRPS and station observations (1985-2012)

The PCC values for monthly rainfall between the stations and CHIRPS datasets (Fig. 4) indicated weak to moderate correlations with a mean value of 0.65 and a maximum value of 0.94 observed at station AL0005 for the November, In fact, November and December had the highest correlation coefficients, 0.83 and 0.78, respectively, compared to May and October, which had 0.29 and 0.53, respectively. In general, the highest PCC values were observed from November to April.

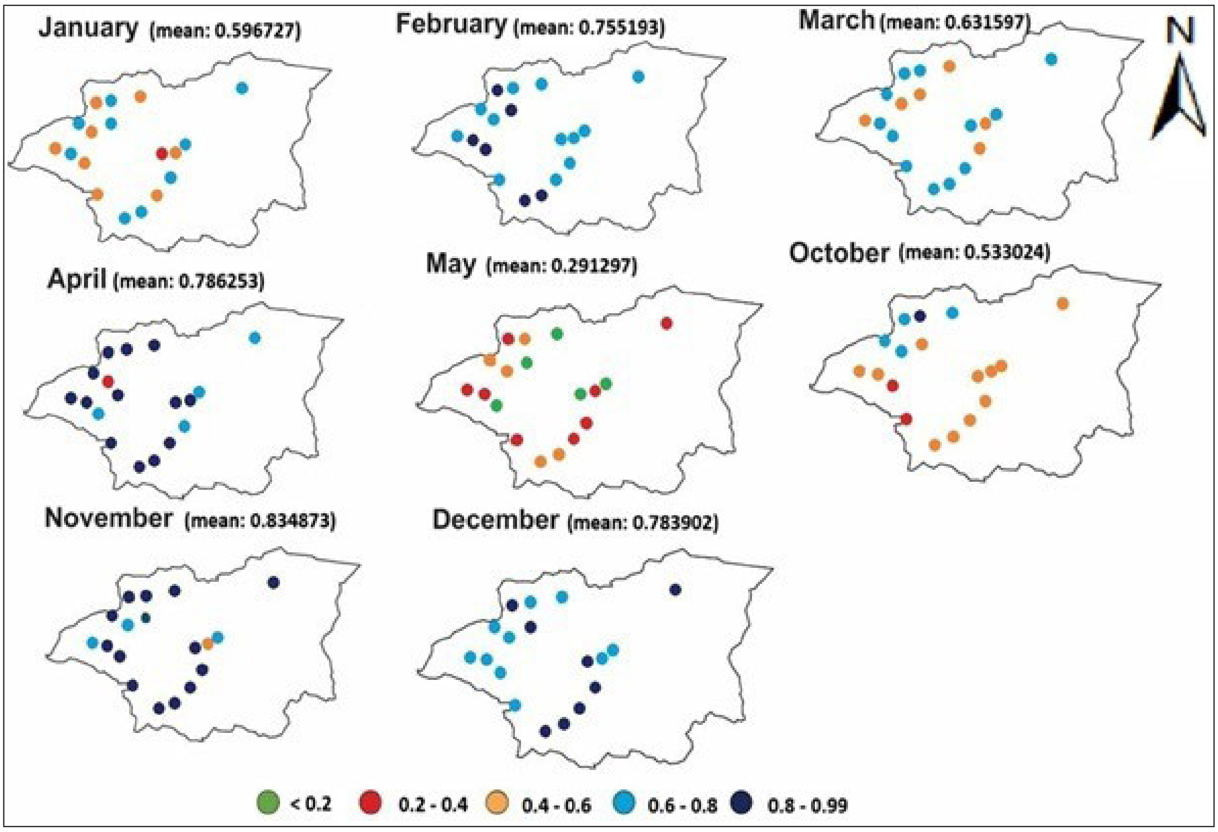

Figure 4. Spatial distribution of Pearson's linear correlation coefficient for monthly precipitation between CHIRPS and station observations (1985-2012)

These results are partially consistent with those of Al Shamayleh et al. (2024), who found that May had the lowest average correlation coefficient (0.24) among all months in the Wala Basin, Jordan. Also, they are consistent with the findings of Saeidizand et al., who showed that the CHIRPS data are reasonably correlated with the observed data during the spring months. The AL0026 station, located in the northeast of ZRB, had the highest average monthly correlation of 0.74, while AL0066 had the lowest average PCC. The AL0066, station demonstrated negative PCC values for May. It has been reported that CHIRPS performance depends on climate conditions and geographic location (Alejo et al., 2024, Du et al., 2024). In fact, during the winter months, CHIRPS may provide better rainfall estimates due to the prevalence of dense clouds, which allow sufficient time for the sensors to detect them, whereas detection opportunity is smaller due to the rapid disappearance of clouds (Mianabadi et al., 2022). The AL0004, AL0005, AL0019, AL0022 and AL0026 stations, which are about 100 meters (m) higher than other stations, demonstrated reasonable agreement between the stations and the CHIRPS dataset, where the average PCC values ranged from 0.71 to 0.73, in contrast to the other stations, where the PCC values were below 0.70. Several research studies found that CHIRPS performed slightly better in high-altitude stations. Gebrechorkos et al. (2018) reported similar findings. Research in Saudi Arabia found that CHIRPS data performed better at altitudes between 500 and 750 m than at altitudes of 0 to 500 m (Helmi and Abdelhamed, 2022). The reason CHIRPS underperforms in low-altitude regions may be due to localized convective rainfall, combined with a sparse network of rainfall stations that does not provide enough information for CHIRPS to capture rainfall patterns (Funk et al., 2015). The lack of correlation between CHIRPS and station data sets was also observed in several other studies. Previous research has suggested that CHIRPS dataset is not suitable as a source of precipitation data in the dry and semi-arid regions (Paredes Trejo et al., 2017). Cavalcante et al. (2020) indicated that that CHIRPS data underestimated rainiest events. However, the CHIRPS data may be suitable for detecting main drought events (Das et al., 2022).

3.2 Observed and CHIRPS trends in rainfall indices

All 12 selected indices, except for CDD, determined station data (Fig. 5) and CHIRPS data (Fig. 6), showed a clear distinction between the western and eastern parts of the basin due to the higher precipitation in the western part, where the recorded mean annual rainfall values were greater than 260 mm. In contrast, below-average annual rainfall was observed in the station located in the eastern part.

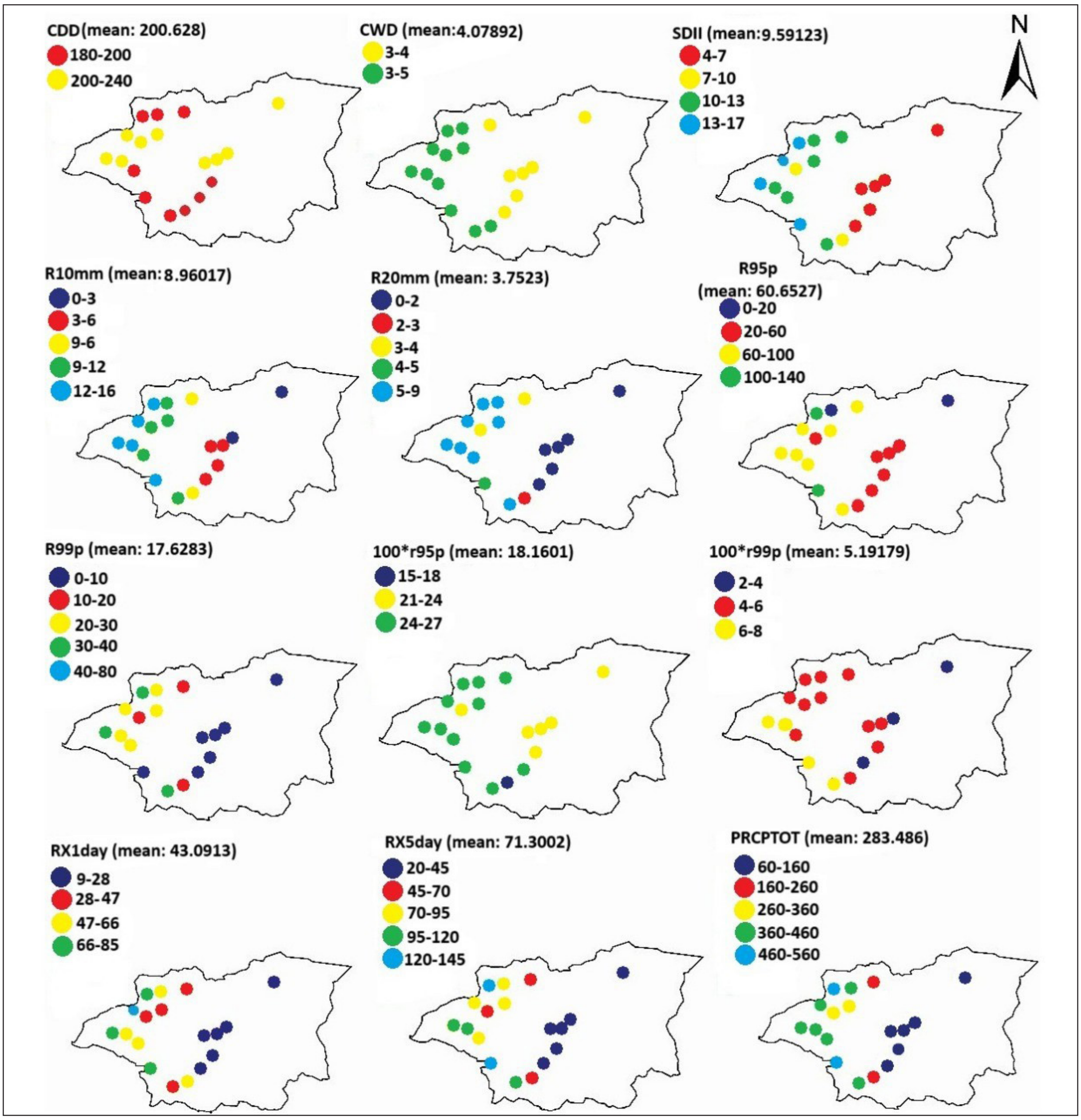

Figure 5. Extreme precipitation indices, measured by stations (1985-2012)

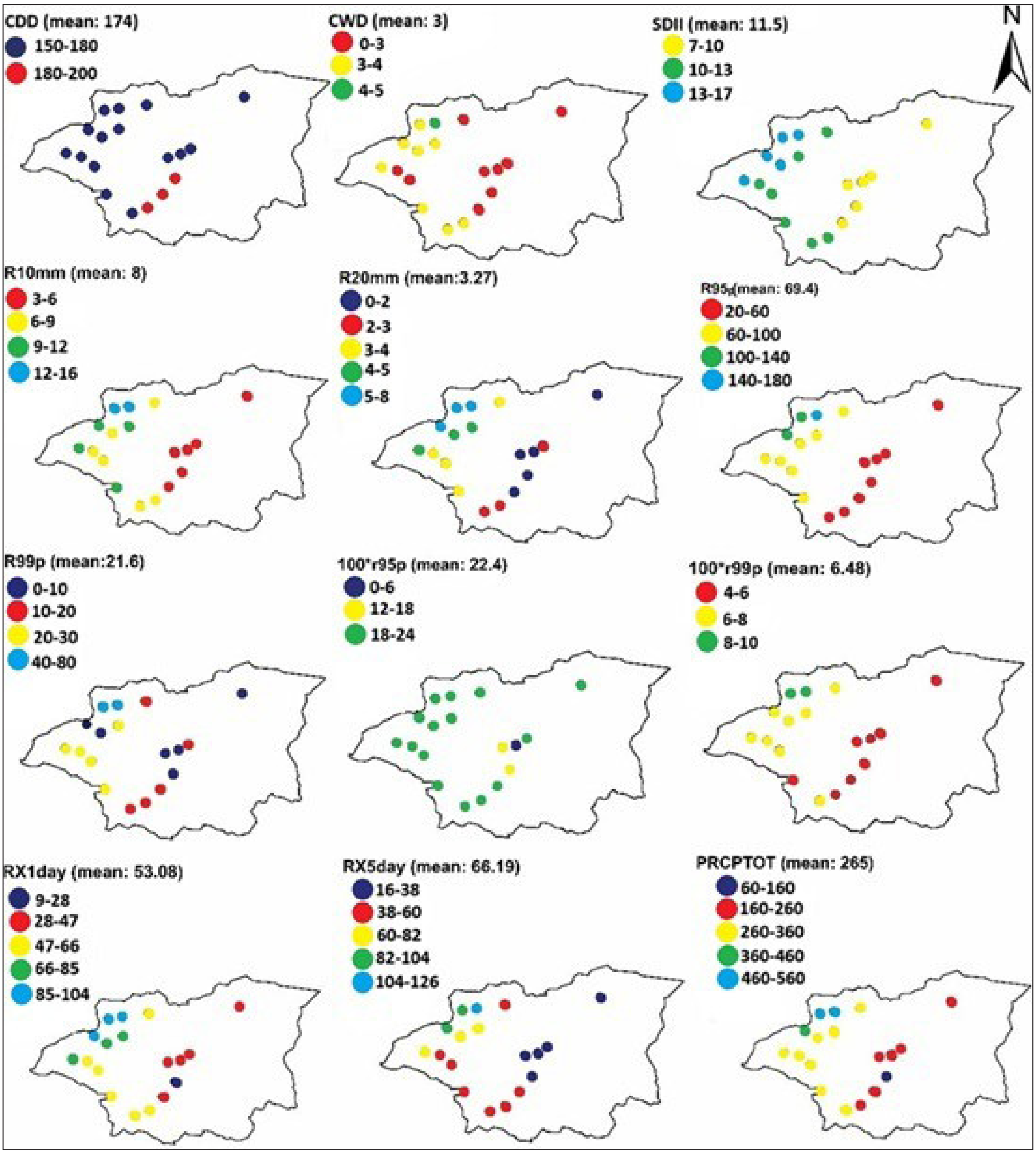

Figure 6. Extreme precipitation indices, measured by CHIRPS (1985-2012)

The results of the trend analysis obtained for observed rainfall data from 18 meteorological stations in the ZRB from 1985-2012 (Fig. 7) can be classified into three groups. The first group includes the results from stations AL0066, and AL0002, which display statistically significant (p-values < 0.05) increasing or decreasing trends across more than one index. The second group contains the results from four stations (AL0015, AL0019, AL0028, and AL0047), which show a statistically significant trend in only one indicator, which may differ across stations. As for the third group, it contains the remaining the stations that did not show any statistically significant trend, although some stations showed a high-value trend, whether upward or downward. The CWD, SDII, R20mm, R95p, RX1day, RX5day, and PRCPTOT indicators showed significant trends at AL0002. These indicators, except for CWD, trended upward, as indicated by positive slope values ranging from 0.111 for R20mm to 4.713 for PRCPTOT. Also, CWD, SDII, and R10mm trended upward, as indicated by slope values between 0.067 and 0.125 at AL0066. CWD also showed a weak downward trend at AL0019, AL0028, AL0047, and AL0015, indicated by slope values ranging from –0.044 to –0.062.

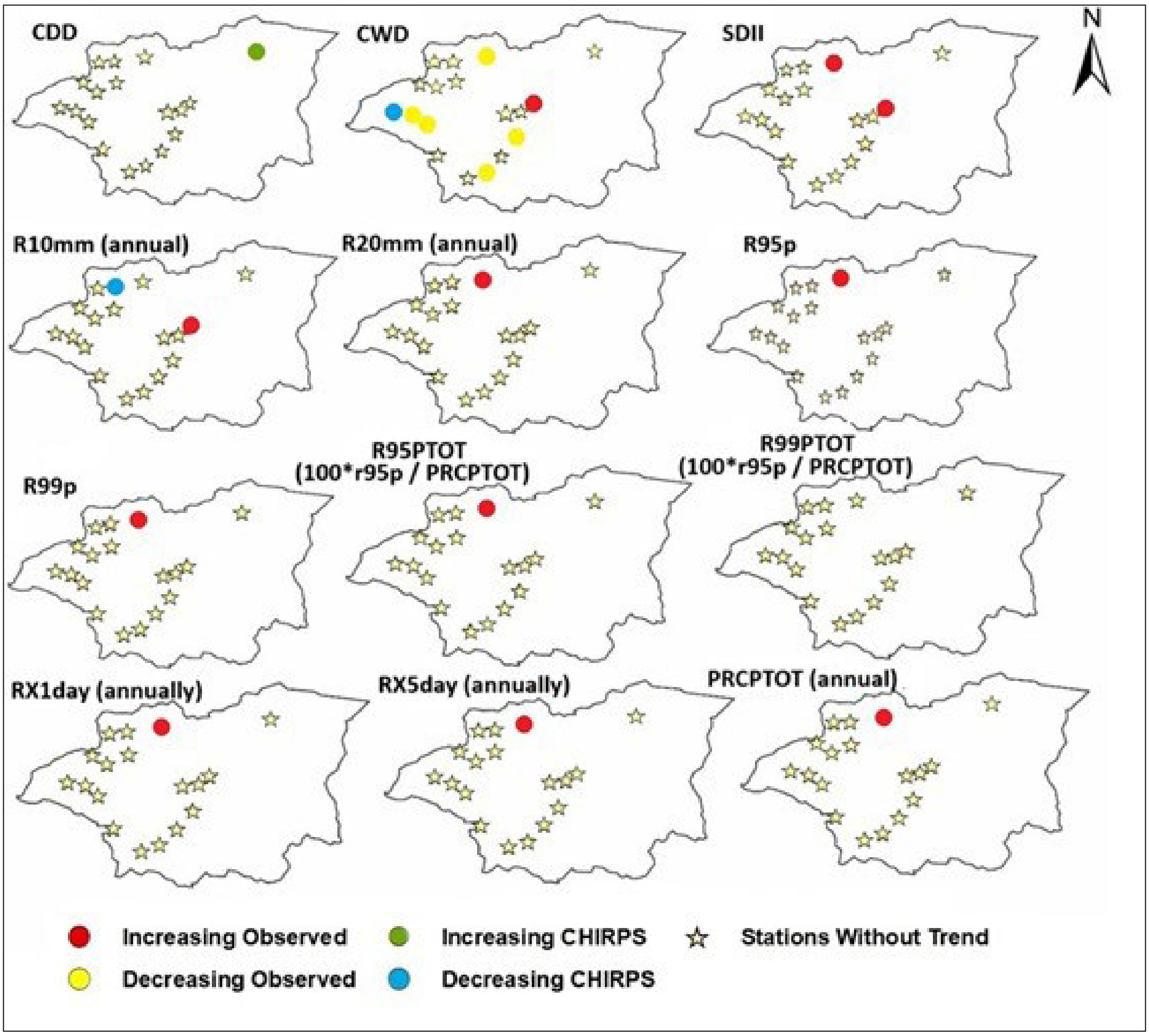

Figure 7. The significant trends for each of the precipitation indices (1985-2012)

Overall, there were 15 significant trends, or about 6 % of the total number of possible trends, which is about the same or less than the percentages obtained in similar studies (Cavalcante et al., 2020; Mubialiwo et al., 2023). Although such sporadic trends should be interpreted with caution, they can nevertheless reveal critical insights relevant to water resources management. For example, Mubialiwo et al. (2023) reported that rainfall is less frequent over the Mpologoma catchment in Uganda, East Africa, but with higher intensity. In this study, one significant and strong PRCPTOT trend (Station AL0002) points to the onset of climate change, characterized by increasing annual rainfall in the northwest part of the ZRB. This PRCPTOT trend is linked to other indices, such as increasing SDII and decreasing CWD. Increasing SDII and decreasing CWD values were also detected in the Wala basin in Jordan (Al-Shamayleh et al., 2024). The CHIRPS data sets for the same period 1985-2012 replicated the same distinction between the eastern and western parts of the watershed. However, it did not generate the same trend as the station data (Fig. 8). It produced only 3 significant trends produced by CHIRPS, or 1.2% of the total number of significant trends produced from the station data. Furthermore, none of the trends were similar to the two datasets. In fact, CHIRPS data showed a significant downward trend at AL0026 and AL0004 for the CWD and R10mm indices, recording values of -0.05 and -0.132, respectively (Tables 3 and 4), in addition to the upward trend shown in the CDD indicator, which showed a value of 1 at AL0059 station. (Tables 5 and 6). These discrepancies in trend analysis between CHIRPS and station data reaffirm the underlying shortcomings of CHIRPS data in arid regions, specifically the lack of sufficient ground rainfall data. This leads to heavy reliance on satellite data, which in turn suffers from inaccuracies due to the small window of opportunity for cloud detection (Mianabadi et al., 2022; Funk et al., 2015).

Table 3. Annual trend of extreme CHIRPS precipitation indices (AL0002, AL0004, AL0005, AL0047, AL0012, AL0015, AL0016, AL0017 and AL0019) (*: Significant at P < 0.05; NT: No trend)

Index	AL0002	AL0004	AL0005	AL0047	AL0012	AL0015	AL0016	AL0017	AL0019
CDD	−0.189	0.028	−0.025	−0.143	0.5	0.552	0.294	−0.174	1
CWD	NT	NT	NT	NT	NT	NT	NT	NT	NT
SDII	−0.046	0.063	0.103	0.06	−0.025	−0.014	0.021	−0.025	−0.048
R10mm	NT	−0.132*	−0.1	NT	NT	NT	−0.071	NT	−0.071
R20mm	NT	NT	NT	NT	NT	NT	NT	−0.05	NT
R95p	NT	NT	NT	0.571	NT	NT	NT	NT	NT
R99p	NT	NT	NT	NT	NT	NT	NT	NT	NT
R95PTOT	NT	0.109	NT	0.417	NT	NT	NT	0.007	NT
R99PTOT	NT	NT	NT	NT	NT	NT	NT	NT	NT
RX1day	−0.256	0.279	0.26	0.237	−0.089	0.008	0.292	−0.111	−0.155
RX5day	−0.641	−0.735	−0.383	−0.002	−0.309	−0.055	−0.022	−0.323	−0.344
PRCPTOT	−1.095	−1.584	−1.419	−0.753	−0.674	−0.671	−0.533	−1.274	−1.535

Table 4. Annual trend of extreme CHIRPS precipitation indices (AL0026, AL0022, AL0027, AL0028, AL0036, AL0053, AL0054, AL0059 and AL0066) (*: Significant at P < 0.05; NT: No trend)

Index	AL0022	AL0026	AL0027	AL0028	AL0036	AL0066	AL0054	AL0059	AL0053
CDD	0.775	0.5	0.092	−0.143	0.257	0.812	0.303	1*	0.155
CWD	NT	−0.05*	NT	NT	NT	NT	NT	NT	NT
SDII	−0.044	0.161	0.089	0.06	0.001	−0.06	−0.047	−0.029	0.07
R10mm	−0.077	−0.118	−0.087	NT	NT	NT	NT	NT	NT
R20mm	NT	0.02	NT	NT	NT	NT	NT	NT	NT
R95p	−0.076	3.441	0.311	0.571	NT	−0.552	NT	−0.143	NT
R99p	NT	NT	NT	NT	NT	NT	NT	NT	NT
R95PTOT	NT	0.893	0.532	0.417	0.02	−0.497	NT	NT	NT
R99PTOT	NT	NT	NT	NT	NT	NT	NT	NT	NT
RX1day	−0.128	0.185	0.272	0.237	0.275	−0.404	−0.1	−0.193	0.141
RX5day	−0.153	−0.055	−0.195	−0.002	−0.454	−0.55	−0.187	0.127	−0.172
PRCPTOT	−1.795	−1.691	−1.043	−0.753	−1.344	−0.857	−0.137	−0.402	−0.945

Table 5. Annual trend of extreme station precipitation indices (AL0002, AL0004, AL0005, AL0047, AL0012, AL0015, AL0016, AL0017 and AL0019) (*: Significant at P < 0.05; NT: No trend)

Index	AL0002	AL0004	AL0005	AL0047	AL0012	AL0015	AL0016	AL0017	AL0019
CDD	0.513	0.475	0.45	0.106	0.655	0.523	0.4	0.388	0.674
CWD	−0.071*	NT	NT	−0.062*	−0.044	−0.054*	NT	NT	−0.045*
SDII	0.288*	0.064	0.009	0.153	0.053	−0.008	0.024	0.072	−0.014
R10mm	0.156	NT	NT	−0.044	NT	NT	NT	−0.186	NT
R20mm	0.111*	0.048	−0.054	NT	NT	NT	NT	−0.093	NT
R95p	3.072*	0.535	0.542	1.462	NT	NT	NT	NT	NT
R99p	NT	NT	NT	NT	NT	NT	NT	NT	NT
R95PTOT	1.056*	0.28	0.333	0.522	NT	NT	NT	0.033	NT
R99PTOT	NT	NT	NT	NT	NT	NT	NT	NT	NT
RX1day	1.667*	0.46	0.394	0.757	0.161	0.008	0.17	0.343	0.032
RX5day	1.448*	0.533	0.278	0.414	0.342	−0.16	−0.021	−0.634	0.224
PRCPTOT	4.713*	1.321	−1.07	−1.163	−0.033	−1.032	−0.736	−3.398	−0.816

Table 6. Annual trend of extreme station precipitation indices (AL0026, AL0022, AL0027, AL0028, AL0036, AL0053, AL0054, AL0059 and AL0066) (*: Significant at P < 0.05; NT: No trend)

Index	AL0026	AL0022	AL0027	AL0028	AL0036	AL0053	AL0054	AL0059	AL0066
CDD	−0.321	0.293	0.05	0.793	0.265	0.864	1.183	−0.23	1
CWD	NT	−0.044	−0.053	−0.044*	NT	NT	NT	NT	0.091*
SDII	−0.021	0.053	0.147	0.127	−0.064	0.026	0.027	−0.031	0.067*
R10mm	0.129	NT	0.1	−0.061	−0.111	−0.091	NT	NT	0.125*
R20mm	NT	NT	0.062	NT	−0.063	NT	NT	NT	NT
R95p	0.049	0.333	2.243	0.149	NT	−0.5	NT	NT	0.25
R99p	NT	NT	NT	NT	NT	NT	NT	NT	NT
R95PTOT	0.336	0.244	0.194	0.151	NT	0.168	NT	NT	0.017
R99PTOT	NT	NT	NT	NT	NT	NT	NT	NT	NT
RX1day	0.149	0.667	1.096	0.491	−0.269	−0.211	0.107	−0.221	0.25
RX5day	0.731	0.252	1.156	0.635	−0.812	0.043	0.183	−0.085	0.669
PRCPTOT	1.637	−0.478	3.919	−0.981	−3.981	−2.415	−1.01	−0.833	1.533

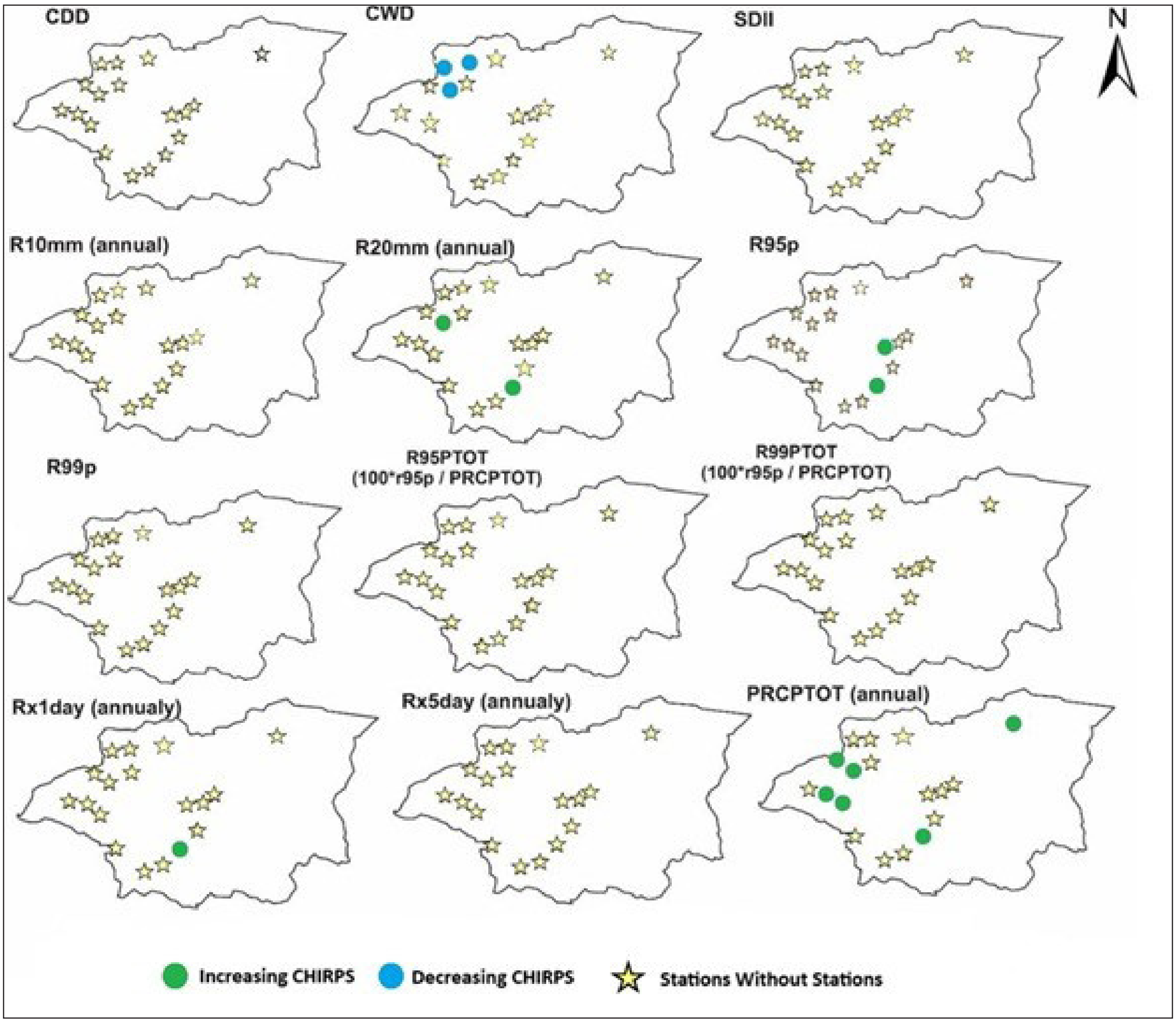

Figure 8. The significant trends for each of the precipitation indices (1992-2023 CHIRPS)

Furthermore, the results of the trend analysis obtained for CHIRPS rainfall data from 1992 to 2023 (Fig 8) from 18 stations showed a strong upward trend for PRCPTOT indicators at stations AL0059, AL0053, AL0026, AL0028, AL0047 and AL0016 as indicated by slope values of 1.707, 2.909, 5.366, 2.691, 2.691, 2691 and 1.709, respectively. Significant trends for R95p were found at AL0012 and AL0016 with slope values of 1.136 and 1.244, respectively. The remaining trends are weak downward for CWD, as indicated by slope values ranging from -0.041 to -0.034 at AL0053, AL004, and AL005, respectively. Also, a weak upward trend for R20, with slope values of 0.091 and 0.04 at AL0053 and AL0016, respectively.

In addition, rainfall trends were analyzed at five stations with available records spanning 1998 to 2023 (Fig 9).

Significant trends detected for R20mm: weak upward slope of 0.067 at AL0019 and strong downward slope of -35.809 for PRCPTOT at AL0059. On the other hand, the results for the same five stations were analyzed using CHIRPS data, and differences were revealed. Contrary to the trend in the observed rainfall data, an upward trend in PRCPTOT was observed at station AL0059 with a slope value of 1.92. Also, upward trends appeared in the same indicator PRCPTOT at stations AL0026 and AL0028, with values of 7.947 and 2.993 respectively. Also AL0053 showed a slight upward trend in the R20mm indicator with a value of 0.1.

Three stations showed a downward trend in the CDD indicator with values between 1 and 1.5 for AL0019, AL0028 and AL0059. Thus, the total number of trends in the results of CHIRPS data is 7 significant trends while the total number of trends in the observed data results is only 2 significant trends.

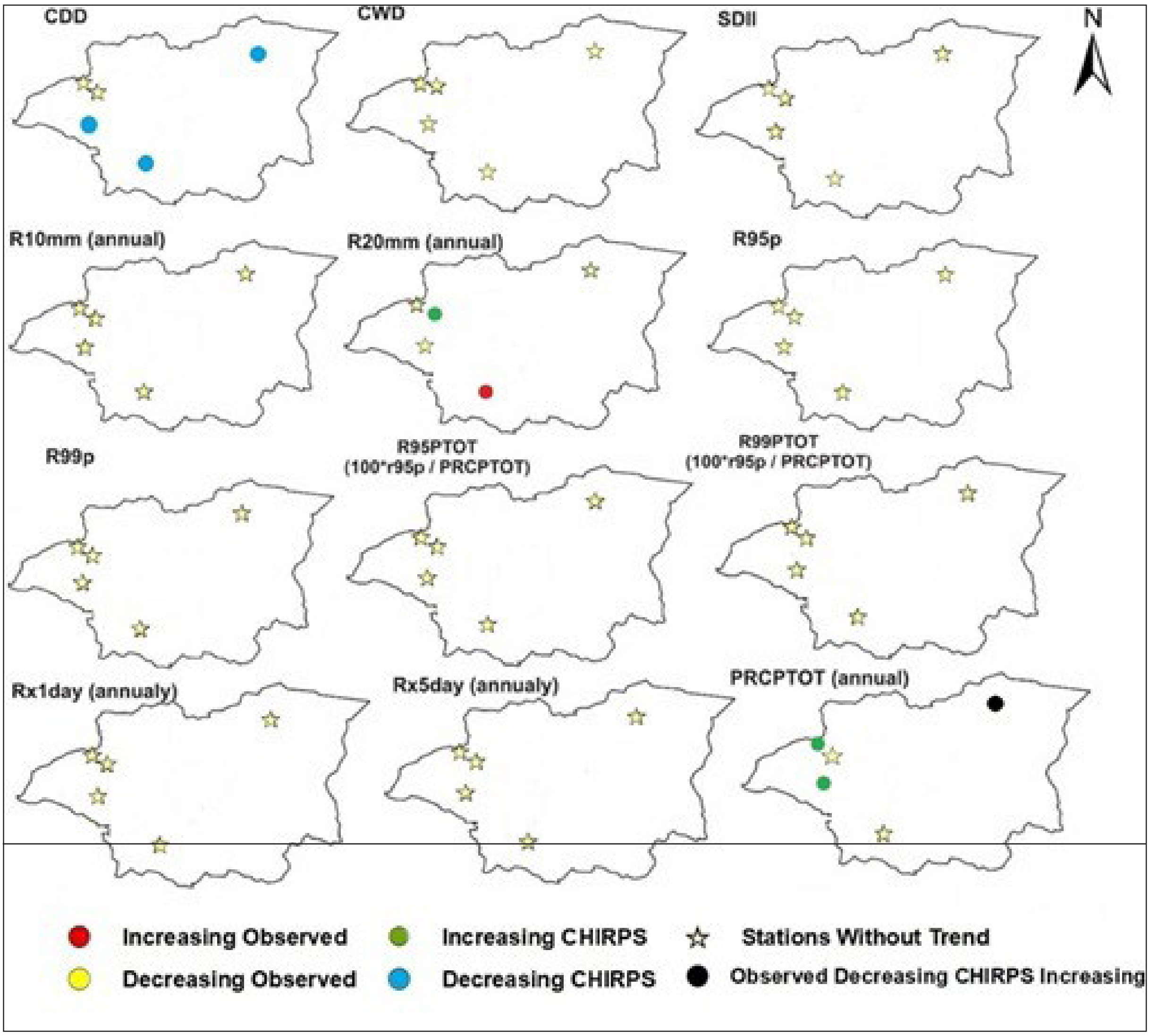

Figure 9. The significant trends for each of the precipitation indices (1998-2023 for both observed and CHIRPS data groups)

3.3 Implications for water resources management

The weak monthly and annual correlations between station and CHIRPS, and discrepancies in trend identification between the two datasets, pose serious challenges for using CHIRPS data in hydrological and water resources assessments, such as runoff modelling and frequency analysis. This is particularly true in low-altitude areas during autumn or late spring months, as observed in annual and monthly precipitation (Du et al., 2024). However, CHIRPS's better performance in high-altitude areas and during winter months offers potential for assessing rainfall patterns and making informed decisions on land and water resource sustainability and seasonal water allocation (Al-Shamayleh et al., 2024). Nonetheless, CHIRPS should always be used with caution due to divergent trends in extreme rainfall indices between the stations and the CHIRPS data. For example, the mismatch in rainfall trends between CHIRPS and station data underscores the need to strengthen the existing network of rainfall stations, especially in lower-altitude areas of the ZRB, to better monitor rainfall patterns and enhance the bias correction and validation of CHIRPS data.

Mismatches between CHIRPS and station trends, combined with delayed or missed flood warnings and spatial bias in low-altitude zones, reduce the accuracy of extreme rainfall detection. These discrepancies lead to errors in rainfall peak timing, resulting in underestimation or overestimation of flood forecasts and distorted hydrographs, thereby compromising timely warnings and emergency preparedness. Similarly, inaccuracies in trend detection hinder the correct identification of drought onset and recovery. The weak performance of CHIRPS during transitional seasons (spring and autumn) obscures intermediate drought phases, yielding ineffective mitigation policies and poor water allocation strategies. Moreover, these discrepancies complicate calibration and validation of runoff simulation models. Input uncertainty and divergence in extreme rainfall indices can skew runoff volumes and timing, since such models are susceptible to precipitation accuracy.

4. Conclusion

This study, conducted in three parts, assessed precipitation trends over 27, 25, and 31 years in Jordan's Zarqa River Basin (ZRB) using ground station and CHIRPS data. The analysis examined variability, CHIRPS reliability, and implications for water resource management and climate adaptation. Results show that CHIRPS performs relatively well in high-elevation areas and during the wet season (November–April), but underperforms in arid, low-elevation zones and dry months. Correlation analysis indicated weak to moderate agreement with ground data at monthly and annual scales, with mean PCCs of 0.65 and 0.69, respectively.

Trend analysis revealed distinct differences between datasets: station data (1985–2012) showed 15 significant trends, mostly upward in the northwest and downward in the east, while CHIRPS detected only three, including mismatches and additional signals. In the 1998–2023 period, station data showed one strong downward and one upward trend, while CHIRPS alone identified three downward and 11 upward trends. These findings highlight both the potential and the limitations of CHIRPS for long-term climate trend detection in complex terrains. In arid regions, limited opportunities to detect clouds, reinforcing the need for calibration and validation.

For practical application, CHIRPS should be used only after bias correction and integration with validated ground-station data. Policymakers and practitioners should expand and modernize rainfall monitoring networks, particularly in low-altitude zones, to improve calibration and strengthen climate datasets. A hybrid data approach will enhance hydrological modelling, support resilient infrastructure design, and strengthen climate adaptation planning. Accurate precipitation data are especially critical for dam development and operation, which play a central role in water security, groundwater recharge management, and sustainable harvesting projects. Strengthening monitoring systems and adopting integrated datasets will ensure more reliable water resource planning and climate-resilient strategies across the ZRB.

Author Contributions

N.H. Alnizami played a central role in the study, contributing to the conceptualization and methodology design. M. Rahbeh oversaw project administration, provided supervision, and prepared the original draft. M.M. Zoubi was instrumental in the investigation, performing the formal analysis and drafting the manuscript. Q.Y. Abu-Afifeh contributed by managing data curation. T.A. Qutishat was responsible for the visualization aspects. M.R. AlHalaigah contributed by providing resources. H. Al-Jawaldeh was responsible for the software aspects. B. Al Qarallah handled manuscript editing.

Conflict Of Interest

The authors declare that there is no conflict of interest regarding the publication of this manuscript.

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