Trend in rainfall associated with tropical cyclones in Mexico attributed to climate change and variability

Sinuhé Sánchez a,b,*, Fernando J. González Villarreal a, Ramón Domínguez Mora a and Maritza Liliana Arganis Juárez a

a Instituto de Ingeniería, Universidad Nacional Autónoma de México, CDMX, México
b Programa de Maestría y Doctorado en Ingeniería, Universidad Nacional Autónoma de México, CDMX, México
*Corresponding author. E-mail: SSanchezM@iingen.unam.mx

SS, 0000-0002-2662-9988; MLAJ, 0000-0003-1429-1243

ABSTRACT

The aim of this study was to investigate the existence and the magnitude of trend in different areas and durations of TCR. To achieve this objective, a mixed-method approach was employed using depth–area–duration and areal reduction factor (ARFs) curves that can be described as a logarithm equation to generate time series that allows the application of statistical methods such as the Mann–Kendall (MK) and Spearman Rho (SR) to detect trends. Time series are generated by substituting different areas in the logarithmic equations. The evidence presented shows that in Mexico, the TCR lasting 24 h shows an increasing trend for maximum areas between 300 and 1,700 km² according to the MK and SR tests, respectively; according to these same tests for durations of 48 h, upward trends were observed up to maximum areas between 5,700 and 6,900 km². The Sen slope reports annual increases between 0.76 and 1.32 mm and between 1.15 and 2.06 for a duration of 24 and 48 h, respectively. In contrast, no trends were observed in the time series obtained from the ARFs. Finally, the Pettitt test reports an abrupt jump from the year 1997 in all cases.

Key words: areal reduction factor curves, climate change, depth–area–duration curves, logarithm equation, rainfall trend, temporal series, tropical cyclone

HIGHLIGHTS

• This study establishes a quantitative framework to detect trends in rainfall associated with tropical cyclone (TC) through time series originating from calculating depth–area–duration and areal reduction factor curves.
• This methodology allows the search for trends for rainfall associated with different areas and durations.
• The maximum area for a certain duration in which there is a trend can be determined.
• The methodology is applicable regionally in any area where TCs are present.

This is an Open Access article distributed under the terms of the Creative Commons Attribution Licence (CC BY 4.0), which permits copying, adaptation and redistribution, provided the original work is properly cited (http://creativecommons.org/licenses/by/4.0/).
1. INTRODUCTION

Climate change (CC) is occurring due to anthropogenic causes in addition to natural CC (Conde 2007). Since the time of the Industrial Revolution, an upward trend in the planet’s average temperature has been detected due to human activity (Fernández et al. 2014). Observations on all continents and in most oceans show that numerous natural systems are being affected by changes in the regional climate, particularly by an increase in temperature (IPCC 2007).

The increase in global temperature will most likely also be reflected in changes in precipitation (Dore 2005) and the hydrological cycle, especially in extreme events (Trenberth 2011). Tropical cyclones (TCs) activity is highly correlated with sea
temperature (Emanuel 2005). In addition, recent studies suggest that the amount of TCR is likely to increase in warmer climates (Lin et al. 2015; Patricola & Wehner 2018; Cha et al. 2020; Guzman & Jiang 2021).

The global average of the mean sea temperature has increased at a rate of 0.062 ± 0.01 °C per decade during the last 120 years, and in the period 2010–2019, there was an acceleration of the sea temperature rise and the rate has accelerated to 0.280 ± 0.068 °C per decade (Garcia-Soto et al. 2021). In the tropical belt (24°S-24°N), Burić & Penjišević (2023) identified upward temperature trends, with findings indicating a rate of 0.09 °C/decade for the period spanning 1901–2021 and a more pronounced rate of 0.14 °C/decade for the period from 1951 to 2021.

However, there is no consensus on whether CC has already affected TC statistics (Patricola & Wehner 2018). Until now, the change in TCR has not been fully understood (Knutson et al. 2010; Moon et al. 2023). While significant strides have been made in understanding TCs and their associated rainfall, many challenges remain. The complexity of TC systems, the influence of climate change, regional variability, data limitations, and modeling challenges all contribute to the incomplete understanding of trends in TC rainfall. Ongoing research and improved data collection methods are crucial to further our knowledge in this area and enhance preparedness and resilience in the face of these powerful natural phenomena.

TCs are one of the most devastating meteorological phenomena of nature (Hernández et al. 2001); they represent the majority of catastrophic losses due to natural disasters in developed countries; and, together with floods, they are the leading cause of losses of human lives and injuries among natural disasters that affect developing countries (Emanuel 2005). Besides, the more frequent occurrence of tornadoes is also associated with larger TCs (Paredes et al. 2021). Altering the frequency and intensity of extreme weather events will foreseeably adversely affect natural systems and humans (IPCC 2007). Despite its pivotal role in the preservation of the hydrological cycle, instances of precipitation surfeit can precipitate inundation calamities, thereby exerting deleterious ramifications upon human societies and civilizations (Chen et al. 2022). Mexican National Center for Disaster Prevention (CENAPRED 2007) specifies that TCs play a significant role in maintaining regional water resources because, even though TCs can cause a lot of damage due to the effect of wind, waves, rain, and storm surges, thanks to the precipitation produced, it is feasible that the dams fill up and the aquifers get recharged, thereby facilitating the supply of water for human consumption, agriculture, and hydroelectric generation. The knowledge of how TCRs are distributed temporally and spatially is instrumental in crafting strategies to mitigate damage and harness potential benefits. The consequences of TCR can be minimized through adaptation and risk management efforts. The mitigation of the ramifications arising from meteorological phenomena may be achieved via the implementation of strategies aimed at adaptation and the meticulous management of associated risks (Singh et al. 2021).

Precipitation constitutes a pivotal and indispensable component within hydrological systems, assuming a central significance in the realm of water resource management investigations (Sattari et al. 2020). Numerous factors, including atmospheric circulation, topography, climate change, and human activities, exert influence on precipitation (Wang et al. 2021). Climate change could affect all water resources management sectors, as it may require changes in design and operating parameters on resource supply (Brekke et al. 2009). In addition, the effects of climate change in TCs, added to the change in land cover and use, cause more frequent floods that force the implementation of a series of actions that make the planet resilient to these phenomena (González & Arreguín 2021). So, to generate these actions, it is first necessary to identify the changes in the meteorological variables both qualitatively and quantitatively (Kundzewicz & Robson 2004).

World Meteorological Organization (WMO) (Kundzewicz & Robson 2000) states that because water resource systems have been designed assuming the stationarity of hydrological data, trend detection becomes very significant (Kundzewicz & Robson 2004). Trend detection can be used to help water managers recognize if the data on which the design and operation of water resource systems were based are no longer compatible with current conditions (Brekke et al. 2009). However, trend detection is hampered by substantial limitations in the availability and quality of global historical TC records (Knutson et al. 2010). Furthermore, natural variability, such as the El Niño phenomenon, makes it difficult to differentiate between the effects of climate change and the natural effects on the variability of rainfall associated with these meteorological phenomena. Adaptation and mitigation are complementary strategies to reduce and manage the risks of climate change (IPCC 2014).

Ministry of Environment and Natural Resources (SEMARNAT 2013) indicates that conditions of high vulnerability to climate change prevail in Mexico, whose effects can put the safety of the population and the conservation of ecosystems at risk. Since the 1960s, Mexico has become warmer (Met Office 2013). The average national temperatures have increased by 0.85 °C, a figure that coincides with the global increase reported by the Intergovernmental Panel on Climate Change (IPCC 2014). TCs contribute 20–60% of the total annual rainfall on the Pacific coastline (Englehart & Douglas 2001), 40% of what occurs in the state of Baja California, and between 10 and 20% in the rest of the country (Breña et al. 2015).
Many previous studies address the study of precipitation associated with TC using both climate models and observed data (IPCC 2002) and, generally, with contradictory results. By using observed data, Ren et al. (2006) examined the volume of TCR during the period 1957–2004 in China, finding a downward trend in the contribution of TCR to annual rainfall. Zhang et al. (2013) investigated the change in average rainfall per TC during 1965–2009, using daily rainfall observations at 514 meteorological stations, finding an increase in average rainfall in Southeast China and an upward trend south of the Yangtze River. On the other hand, Bengtsson et al. (2007), Chauvin et al. (2006), Gualdi et al. (2008), Hasegawa & Emori (2005), Knutson et al. (2008), Knutson & Tuleya (2008), and Yoshimura et al. (2006) used climatological models and showed that the rains associated with TC have a substantial increase in the center of the storms. On the other hand, Guzman & Jiang (2021) used data from the Tropical Rainfall Measuring Mission (TRMM) and Global Precipitation Measurement (GPM) satellite missions to explore trends in TCR, finding an upward trend of 1.3% on average per year.

Tsou et al. (2016) employed a High-Resolution Atmospheric Model (HiRAM) with a 20-km resolution to replicate tropical storm (TS) occurrences in the western North Pacific (WNP) and the region encompassing Taiwan and the East Coast of China (TWCN). Their simulations indicate that, as a consequence of global warming, there are projected increases in both TS intensity and the maximum precipitation rate. Furthermore, numerical models often exhibit an augmented response of increased rainfall rates associated with individual TCs when subjected to greenhouse warming (Kim et al. 2014; Villarini et al. 2014). Several other studies have similarly reported an increase in TC-induced rainfall as a consequence of global warming (Tsou et al. 2019; Chu et al. 2020; Knutson et al. 2020; Chang et al. 2023). The range of projections for the end of the 21st century among these studies is from 2.8 to 54%. In Mexico, Englehart & Douglas (2001) explored the role of CTs on the Mexican Pacific coastline, finding no evidence of a significant trend in TCR that occurred in the study area.

However, previous studies in this domain have predominantly relied on qualitative analyses or focused on isolated extreme events, limiting the breadth and precision of their conclusions. This study seeks to contribute to the existing body of knowledge by offering quantitative insights into the temporal and spatial distribution of TCR magnitudes over an extended period, thus facilitating more informed decision-making and disaster management. Details of spatial and temporal rainfall distributions of TCR are necessary for the design of a given project in the targeted basin (WMO 2009). Correct rainfall estimation should be performed to evaluate the potential of water resources, measurement of rainfall volume, frequency, and duration (Siqueira & Nery 2021).

Brackins & Kalyanapu (2020) identified four existing physics-based models for TC rainfall such as Rain-Climatology and Persistence (R-CLIPER), Interagency Performance Evaluation Task Force (IPET), Parametric Hurricane Rainfall Model (PHRaM), and PDF Precipitation-Climatology and Persistence (P-CLIPER). These models require intensity, speed, position, and storm size. The depth–area–duration (DAD) curves depict the relationship between precipitation intensity and its spatial coverage within a specific storm event, presenting a set of curves for various duration intervals. The advantage inherent in the utilization of such curves lies in their amenability to representation through logarithmic equations, which in turn facilitates the determination of the rainfall associated with a given storm event within a specified geographic area (Shin et al. 2013). Moreover, it is noteworthy that the derivation of DAD curves necessitates solely the utilization of meteorological data obtained from climatological stations, which typically constitutes the sole repository of relevant information accessible within the geographical context of Mexico. Areal reduction factor (ARF) curves are calculated from DAD curves.

The change detection analysis has been applied using Pettitt’s test, von Neumann ratio test, Buishand’s range test, and standard normal homogeneity test, while nonparametric tests include linear regression (Vezzoli et al. 2012). The advantages of adopting the Pettitt test over other methods in the case of suspected abrupt changes are its simplicity and focus on abrupt change. Mann–Kendall (MK) and Spearman rho are widely used for trend analysis in hydrology. Parametric trend tests, while offering greater statistical power, necessitate normally distributed data and exhibit heightened sensitivity to outliers (Hamed 2008). Hydrological data can be influenced by extreme events (e.g., floods or droughts), which can introduce outliers. Both the MK test and Spearman Rho are less sensitive to outliers compared to some parametric methods like linear regression, making them more appropriate for detecting trends in datasets with extreme values (Asefa Bogale 2023).

This study set out to investigate the existence of a trend and the magnitude of the trend in different areas and durations of TCR. A novel mixed-method approach was employed based on DAD and ARF curves that can be described as a logarithm function equation to generate time series. Time series were generated by substituting different areas in DAD and ARF logarithmic equations of 24 and 48 h. The statistical methods of trend detection and change point analysis have been used for time series. This endeavor is motivated by the overarching goal of delineating actionable strategies aimed at mitigating the deleterious effects of these cyclonic phenomena and enhancing their utility.
The initial hurdle we encountered was the development of a methodology capable of both quantifying the temporal and spatial patterns TCR and facilitating the application of statistical trend analysis techniques. The subsequent task entailed identifying the quintessential annual TC event. To accomplish this, we conducted a comprehensive examination of the maximum annual precipitation data within the designated study period across the research region. Subsequently, we confirmed that these recorded precipitation peaks were concomitant with the occurrences of TCs.

Preliminary findings from our quantitative analysis reveal significant temporal trends in TCR magnitude distribution over the extended period of study. These trends provide valuable insights into the changing nature of TCR, helping stakeholders better anticipate and prepare for future events. Furthermore, our investigation into spatial variations highlights specific areas that are particularly susceptible to storms of varying magnitudes. Such information can guide targeted disaster mitigation efforts, resource allocation, and infrastructure planning.

This document is structured as follows: Section 2 defines the location, extension of the coastline, and the maximum daily rainfall database of the study area. Section 3 explains in detail the methodology used. Section 4 analyses the results and discusses the significant findings, and Section 5 presents the conclusions and recommendations derived from the study.

2. STUDY AREA AND DATASETS

Generally, TC-prone basins are divided into seven areas including North Atlantic (ATL), Northeastern Pacific (NEP), Northwest Pacific (NWP), Northern Indian Ocean (NIO), Southern Indian Ocean (SIO), and East-Central Pacific (ECPA). Due to its geographical location, Mexico is prone to strikes by landfalling TCs along both ATL and NEP basins. Mexico’s geographical location, topographical features, warm oceanic waters, and environmental vulnerabilities converge to make it highly susceptible to TCs (Breña et al. 2015). This academic examination underscores the urgency of comprehensive preparedness and mitigation strategies to address the recurring threats posed by these natural phenomena. In addition, interdisciplinary research and collaborative efforts are imperative to enhance our understanding of Mexico’s vulnerability to TCs and to develop effective strategies for disaster resilience and management in the region.

2.1. Mexican characteristics

In this work, we focus on the Mexican territory, which has geographical characteristics that position it as one of the most vulnerable countries to climate change. Its location between two oceans as well as altitudes and reliefs makes it especially exposed to different meteorological phenomena (SEMARNAT 2012). An annual average of 15.1 TCs in the Pacific Ocean and 10.3 TCs in the Atlantic Ocean occurred in this country from 1966 to 2020 (CENAPRED 2007). Mexico is located (Figure 1) between meridians 118°22′00″ and 86°42′36″ west longitude and between latitudes 14°32′27″ and 32°45′06″ north. Also, National Institute of Statistic and Geography of Mexico (INEGI 2021) indicates that this country has 7,828 km of coastline in the Pacific Ocean and 3,294 km in the Gulf of Mexico and the Caribbean Sea, for a total coastline of 11,122 km.

The average yearly precipitation amounts to 725 mm, featuring consistent rainfall throughout the year, with a higher concentration from June to October. The annual average temperature in Mexico stands at 20.6 °C, showcasing monthly temperature averages that fluctuate between 15 (in January) and 25 °C (in June) (World Bank Climate Change Knowledge Portal n/d). Topography convergence strengthening upward motion in the mountain slope against wind constitutes a basic contribution to TCR increase (Dong et al. 2010) in Mexican pacific coast. On the other hand, the process of rapid intensification of TCR in Gulf of Mexico may be due to more evenly distributed heating that this region receives throughout the summer (Benedetto & Trepanier 2020).

2.2. Data collection

In this study, TC is the generic term that considers tropical depressions (TDs) (0 ≤ maximum sustained winds (VMS) ≤ 63 km/h), TS (64 ≤ VMS ≤ 117 km/h), and hurricane categories 1–5 (CAT1, CAT2, CAT3, CAT4, and CAT5) (VMS ≥ 118 km/h) according to the Saffir–Simpson Hurricane Scale. The intensity of TCs and maximum rain rate are not highly correlated which indicates that weaker storms may produce higher rain rates than stronger TCs (Cheung 2018).

Regarding information relevant to TCs, the National Oceanic and Atmospheric Administration (NOAA) has historical data on hurricanes that occurred in the Pacific Ocean and in the Atlantic Ocean during the periods 1949–2019 (NOAA n.d-a) and 1851–2019 (NOAA n.d-b), respectively. This database includes name, category, date of occurrence, and trajectory coordinates of each TC. On the other hand, the National Meteorological Service of Mexico which is managed by the National Water
Commission has a database of historical information on TCs that occurred in the seas surrounding this country from 1997 to 2021 (CONAGUA n.d-a). This information includes name, path, intensity, maximum wind speed, and affected states (only if the TC made landfall).

Long-term monitoring networks are critical for detecting and quantifying climate change and its impacts (Brekke et al. 2009). In Mexico, fundamental meteorological information sources come from surface stations stored daily by the National Meteorological Service (SMN) (Gay & Rueda 2015). Weather stations measure temperature, rainfall, evaporation, wind speed, and direction. As of 20 June 2022, Mexico had 3,500 climatological stations in operation by the National Water Commission (CONAGUA n.d-b), of which 81 are meteorological observatories that transmit meteorological information in real time (INEGI 2021).

2.3. Selecting TCs

Since the probability that the highest precipitation of TC occurs in 12 h, 6 h before landfall, and 6 h after landfall is 50% (Goodyear 1968), in this study, the event that has produced maximum point rainfall accumulated in 24 h during the period 1959–2016 on both the Mexican Pacific and Atlantic coasts is taken as the annual representative storm. Fifty-eight TCs were selected for the period 1959–2016 (Figure 1). Of the 58 TCs selected, 37 correspond to the Pacific Ocean and 21 to the Atlantic Ocean. Baja California Sur and Colima in the Pacific Ocean are the states with the most maximum rainfall records, with 8 and 7, respectively, and Tamaulipas with 7 in the Atlantic Ocean. Table 1 shows the year of occurrence, the name, and the category of each selected TC.

Figure 1 | Locations of the 58 TCs considered in this study.
3. METHODOLOGY

3.1. Depth–area–duration curves

The method helps to calculate the average precipitation depth of a storm over a given area for a particular time (WMO 2009). These storm curves are analyzed to pinpoint the maximum amounts of rain that fall in different areas and at different durations (Linsley et al. 1997). In addition, these curves provide a three-dimensional perspective of the rain of a storm (Shin et al. 2013). In a given storm, precipitation height and its area of influence are shown as a family of curves for different duration intervals (Pérez 2003). The maximum values of these curves are extrapolated to be used in flood estimation studies (Aparicio 2005), through the probable maximum precipitation (PMP).

3.2. Areal reduction factors

The evaluation of ARFs is concerned with the relationship between the point and areal rainfalls (Svensson & Jones 2010). To estimate ARFs from DAD curves, the storm-centered approach is used. The center point for the approach is the point

### Table 1 | Year of occurrence, name, category, and state where the maximum observed daily rainfall of each of the 58 selected CTs was located

<table>
<thead>
<tr>
<th>Year</th>
<th>Storm</th>
<th>Category</th>
<th>Max precipitation in 24 h (mm)</th>
<th>State</th>
<th>Year</th>
<th>Storm</th>
<th>Category</th>
<th>Max precipitation in 24 h (mm)</th>
<th>State</th>
</tr>
</thead>
<tbody>
<tr>
<td>1959</td>
<td>Manzanillo</td>
<td>CAT4</td>
<td>368</td>
<td>Colima</td>
<td>1988</td>
<td>Gilberto</td>
<td>CAT4</td>
<td>359</td>
<td>N.L.</td>
</tr>
<tr>
<td>1960</td>
<td>Florence</td>
<td>TS</td>
<td>332</td>
<td>Veracruz</td>
<td>1989</td>
<td>Cosme</td>
<td>CAT1</td>
<td>325</td>
<td>Oaxaca</td>
</tr>
<tr>
<td>1961</td>
<td>Tara</td>
<td>CAT1</td>
<td>327</td>
<td>Guerrero</td>
<td>1990</td>
<td>Diana</td>
<td>CAT2</td>
<td>452</td>
<td>SLP</td>
</tr>
<tr>
<td>1962</td>
<td>Claudia</td>
<td>TS</td>
<td>327</td>
<td>BCS</td>
<td>1991</td>
<td>TD 2</td>
<td>TD</td>
<td>401</td>
<td>SLP</td>
</tr>
<tr>
<td>1963</td>
<td>Lilian</td>
<td>TS</td>
<td>322</td>
<td>Michoacán</td>
<td>1992</td>
<td>Virgil</td>
<td>CAT2</td>
<td>387</td>
<td>Michoacán</td>
</tr>
<tr>
<td>1964</td>
<td>Hilda</td>
<td>CAT4</td>
<td>270</td>
<td>Veracruz</td>
<td>1993</td>
<td>Gert</td>
<td>CAT1</td>
<td>446</td>
<td>SLP</td>
</tr>
<tr>
<td>1965</td>
<td>Hezel</td>
<td>TS</td>
<td>253</td>
<td>Sinaloa</td>
<td>1994</td>
<td>DT 5</td>
<td>TD</td>
<td>241</td>
<td>Tamaulipas</td>
</tr>
<tr>
<td>1966</td>
<td>Inez</td>
<td>TS</td>
<td>740</td>
<td>Tamaulipas</td>
<td>1995</td>
<td>Gabrielle</td>
<td>TS</td>
<td>346</td>
<td>Tamaulipas</td>
</tr>
<tr>
<td>1967</td>
<td>Beulah</td>
<td>CAT3</td>
<td>345</td>
<td>Tamaulipas</td>
<td>1996</td>
<td>Dolly</td>
<td>CAT1</td>
<td>420</td>
<td>SLP</td>
</tr>
<tr>
<td>1968</td>
<td>Naomi</td>
<td>CAT1</td>
<td>320</td>
<td>Sinaloa</td>
<td>1997</td>
<td>Pauline</td>
<td>CAT3</td>
<td>372</td>
<td>Oaxaca</td>
</tr>
<tr>
<td>1969</td>
<td>Jennifer</td>
<td>CAT1</td>
<td>331</td>
<td>Colima</td>
<td>1998</td>
<td>Isis</td>
<td>TS</td>
<td>387</td>
<td>BCS</td>
</tr>
<tr>
<td>1970</td>
<td>Ella</td>
<td>CAT3</td>
<td>307</td>
<td>Tamaulipas</td>
<td>1999</td>
<td>DT 11</td>
<td>TD</td>
<td>410</td>
<td>Veracruz</td>
</tr>
<tr>
<td>1971</td>
<td>Lily</td>
<td>CAT1</td>
<td>345</td>
<td>Jalisco</td>
<td>2000</td>
<td>Keith</td>
<td>CAT1</td>
<td>580</td>
<td>Tamaulipas</td>
</tr>
<tr>
<td>1972</td>
<td>Agnes</td>
<td>TD</td>
<td>235</td>
<td>Q Roo</td>
<td>2001</td>
<td>Juliette</td>
<td>CAT1</td>
<td>606</td>
<td>BCS</td>
</tr>
<tr>
<td>1973</td>
<td>Berenice</td>
<td>TS</td>
<td>400</td>
<td>Guerrero</td>
<td>2002</td>
<td>Isidoro</td>
<td>CAT3</td>
<td>368</td>
<td>Campeche</td>
</tr>
<tr>
<td>1974</td>
<td>Fifi</td>
<td>TS</td>
<td>401</td>
<td>Veracruz</td>
<td>2003</td>
<td>Olaf</td>
<td>TS</td>
<td>415</td>
<td>Colima</td>
</tr>
<tr>
<td>1975</td>
<td>Eleanor</td>
<td>TD</td>
<td>379</td>
<td>Michoacán</td>
<td>2004</td>
<td>DT 16E</td>
<td>TD</td>
<td>350</td>
<td>Sinaloa</td>
</tr>
<tr>
<td>1976</td>
<td>Liza</td>
<td>CAT4</td>
<td>425</td>
<td>BCS</td>
<td>2005</td>
<td>Wilma</td>
<td>CAT4</td>
<td>770</td>
<td>Q Roo</td>
</tr>
<tr>
<td>1977</td>
<td>Ania</td>
<td>CAT5</td>
<td>380</td>
<td>Tamaulipas</td>
<td>2006</td>
<td>Jhon</td>
<td>CAT2</td>
<td>449</td>
<td>BCS</td>
</tr>
<tr>
<td>1978</td>
<td>Olivia</td>
<td>TT</td>
<td>504</td>
<td>Oaxaca</td>
<td>2007</td>
<td>Henriette</td>
<td>CAT1</td>
<td>430</td>
<td>BCS</td>
</tr>
<tr>
<td>1979</td>
<td>Ignacio</td>
<td>TS</td>
<td>289</td>
<td>Michoacán</td>
<td>2008</td>
<td>DT 5E</td>
<td>TD</td>
<td>330</td>
<td>Colima</td>
</tr>
<tr>
<td>1980</td>
<td>Hermine</td>
<td>TS</td>
<td>435</td>
<td>Oaxaca</td>
<td>2009</td>
<td>Jimena</td>
<td>CAT1</td>
<td>515</td>
<td>Sonora</td>
</tr>
<tr>
<td>1981</td>
<td>Norma</td>
<td>CAT2</td>
<td>335</td>
<td>Sinaloa</td>
<td>2010</td>
<td>Alex</td>
<td>CAT2</td>
<td>400</td>
<td>N.L.</td>
</tr>
<tr>
<td>1982</td>
<td>Paul</td>
<td>CAT2</td>
<td>335</td>
<td>BCS</td>
<td>2011</td>
<td>Jova</td>
<td>CAT2</td>
<td>405</td>
<td>Colima</td>
</tr>
<tr>
<td>1983</td>
<td>Adolph</td>
<td>TS</td>
<td>309</td>
<td>Guerrero</td>
<td>2012</td>
<td>Carlotta</td>
<td>CAT1</td>
<td>350</td>
<td>Oaxaca</td>
</tr>
<tr>
<td>1984</td>
<td>Odile</td>
<td>TS</td>
<td>336</td>
<td>Guerrero</td>
<td>2013</td>
<td>Barry</td>
<td>TS</td>
<td>372</td>
<td>Veracruz</td>
</tr>
<tr>
<td>1985</td>
<td>Waldo</td>
<td>CAT2</td>
<td>238</td>
<td>Sinaloa</td>
<td>2014</td>
<td>Trudy</td>
<td>TS</td>
<td>496</td>
<td>Guerrero</td>
</tr>
<tr>
<td>1986</td>
<td>Paine</td>
<td>CAT1</td>
<td>279</td>
<td>Sinaloa</td>
<td>2015</td>
<td>Patricia</td>
<td>CAT4</td>
<td>342</td>
<td>Colima</td>
</tr>
<tr>
<td>1987</td>
<td>Eugene</td>
<td>CAT1</td>
<td>328</td>
<td>Colima</td>
<td>2016</td>
<td>Newton</td>
<td>CAT1</td>
<td>497</td>
<td>BCS</td>
</tr>
</tbody>
</table>

Note: TD, tropical depressions; TS, tropical storms; CAT1, CAT2, CAT3, CAT4, and CAT5, hurricane categories 1–5.
observing the maximum rainfall, which also changes for each storm. The ARFs are given by:

\[ \text{ARF} = \frac{P_{\text{area}}}{P_{\text{point}}} \]  

where \( P_{\text{area}} \) is the areal storm rainfall given by DAD curves and \( P_{\text{point}} \) is the maximum point rainfall, which is the center of the storm calculated in DAD curves.

### 3.3. Empiric logarithmic equations

Empirical logarithmic equations are a statistical method used to investigate the connection between a single dependent variable and one or more independent variables.

Linear equation with two variables can be written in general terms as follows:

\[ y = a + mx \]  

where \( y \) is the dependent variable and \( x \) is the independent variable, \( a \) is the intercept (the point on the vertical axes that intercept the line) and \( m \) is the slope (Allison 1998). A very common way to deal with situations where a nonlinear relationship exists between independent and dependent variables is to logarithmically transform variables in a regression model (Benoit 2011).

\[ y = a + \mu \ln(x) \]  

### 3.4. Mann–Kendall trend test

This is a nonparametric statistical test (Kendall 1975) frequently used to assess the significance of monotonic trends in hydro-meteorological time series (Yue & Pilon 2004). In this test, the null hypothesis \((H_0)\) was that there has been no trend in time series over time; the alternate hypothesis \((H_1)\) was that there has been a trend (increasing or decreasing) over time. The MK statistic \( S \) can be computed as follows:

\[ S = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} \text{sgn}(x_j - x_i) \]  

where

\[ \text{sgn}(x_j - x_i) = \begin{cases} +1 & \text{if } (x_j - x_i) > 0 \\ 0 & \text{if } (x_j - x_i) = 0 \\ -1 & \text{if } (x_j - x_i) < 0 \end{cases} \]  

In Equations (4) and (5), \( x_i \) and \( x_j \) are sequential data for the \( i \)th and \( j \)th terms, respectively, and \( n \) is the sample size.

\[ \text{Var}(S) = \frac{n(n-1)(2n+5) - \sum_{p=1}^{q} t_q(t_q - 1)(2t_q + 5)}{18} \]  

In Equation (6), \( t_q \) is the number of ties for the \( p \)th value, whereas \( q \) is the number of tied values.

\[ Z_{MK} = \begin{cases} \frac{S - 1}{\sqrt{\text{Var}(S)}} & \text{if } S > 0 \\ 0 & \text{if } S = 0 \\ \frac{S + 1}{\sqrt{\text{Var}(S)}} & \text{if } S < 0 \end{cases} \]
Positive values of $Z_{MK}$ indicate upward trend and vice-versa. The trend was found when $Z_{MK}$ is greater than $Z_{1−α/2}$, which is the critical value of $Z$ from the standard normal distribution table. In this study, $α = 0.05$ and $Z_{1−α/2} = 1.96$.

3.5. Spearman’s Rho trend test

Spearman’s Rho (SR) is another nonparametric trend test that has been extensively used in temporal data to quantify the possible trend in time series (Lehmann & D’Abrera 1975). SR is also based on two important assumptions such as the null ($H_0$) and alternative hypotheses ($H_1$). Given a sample dataset $\{X_1 = 1, 2, \ldots, n\}$, ($H_0$) describes that the whole time series data are independent and equally distributed; the alternative hypothesis ($H_1$) confirms the existence of a rising or declining trend in the time series rainfall data (Gao et al. 2020). The SR tests ($D$) is given by

$$D = 1 - \frac{6}{n(n^2-1)} \sum_{i=1}^{n} (R_i - \bar{R})^2$$

where $R_i$ is the rank of its observation $i$ in the sample size $n$ (Gao et al. 2020). The resultant positive $Z_{SR}$ value means increasing trend. In contrast, the negative values specify a decreasing trend.

$$Z_{SR} = D \sqrt{\frac{n - 2}{1 - D^2}}$$

3.6. Sen’s slope

Sen (1968) proposed a robust nonparametric method to estimate the magnitude of the trend. Given a sample dataset $\{X_1 = 1, 2, \ldots, m\}$, with $M$ pairs of data, the slope is computed as follows (Theil 1992):

$$f(t) = Qt + B$$

where $Q$ indicates the slope and $B$ is a constant. The slope of $Q_i$ of the sample of $M$ pairs of date is computed as follows:

$$Q_i = \frac{x_j - x_k}{j - k}$$

where $x_j$ and $x_k$ are the data values of data pairs at times $j$ and $k$ (Gao et al. 2020).

$$Q_{med} = \begin{cases} Q_{[M+1/2]} & \text{if } M \text{ is odd} \\ \frac{Q_{[M/2]} + Q_{[M-2/2]}}{2} & \text{if } M \text{ is even} \end{cases}$$

Positive value of $Q_{med}$ indicates an increasing trend, and in contrast, a negative value of $Q_{med}$ indicates a decreasing trend in the time series.

3.7. Pettitt test

This is a rank-based nonparametric test for a change in the median of a series with the exact time of change unknown (Pettitt 1979). The Pettitt statistics $U_{i,T}$ can be computed as follows (Conte et al. 2019):

$$U_{i,T} = \sum_{i=1}^{t} \sum_{j=t+1}^{T} \text{sgn}(x_j - x_i) \, 1 \leq t < T$$
The probable change point will be as follows:

\[ K_r = U_{rT} = \max |U_{rT}|, \quad 0 < t < T \]  

4. RESULTS

The objective of this study was to examine the presence of trend and the magnitude of the trend in different areas and durations of TCR. We utilized an innovative mixed-method approach, combining DAD and ARF curves, which can be characterized as a logarithmic function equation, to produce time series data.

Initially, the primary objective was to discern the pivotal annual TC event. To achieve this, an exhaustive analysis of the maximum annual precipitation data covering the specified study duration within the research area was undertaken. Subsequently, the verification process ensured the temporal alignment of these documented peaks in precipitation with occurrences of TCs.

In the subsequent phase of this research endeavor, the derivation of DAD curves was undertaken for the ensemble of chosen storm events, with one TC computed for each annual occurrence within the designated temporal span. The computational procedure for generating these DAD curves was executed employing a Geographical Information System (GIS) and relying upon the isohyet method. The computation of ARF curves was carried out based on the preexisting DAD curves.

Thus, in this work, 58 families of annual DAD and ARF curves were obtained for the study period. Every curve was derived using the maximum specific precipitation point as a starting point, encompassing the entire area until reaching the point where climatological stations recorded zero precipitation. In essence, the estimation for each curve spanned the entire region affected by rains associated with CT.

Finally, a logarithmic correlation equation is estimated for each annual duration curve of 24 and 48 h to obtain an empirical prediction equation, which is reasonably accurate to represent each of the calculated curves (Canavos 1988). Figure 2

**Figure 2** | DAD curves and logarithmic equations of the category 2 hurricane Waldo that occurred in 1985. The logarithmic correlation equations are indicated; \( hp_1 \) and area1 correspond to the duration of 24 h; \( hp_2 \) and area2 correspond to the duration of 48 h.
illustrates the DAD curves acquired for the category 2 hurricane Waldo that occurred in 1985. Within the same figure, the logarithmic equations corresponding to each of these DAD curves are also displayed. It should be mentioned that although TCs generally last for several days, Claudia (1962), Lilian (1963), Hilda (1964), Inez (1966), Liza (1976), Ignacio (1979), Virgil (1992), and Newton (2016) show that TCs only lasted 2 days. Hence, to have continuous time series, logarithmic equations are taken for the durations of only 24 and 48 h that all the TCs considered in this study have in common.

The reference climatology for the calculation of DAD curves was taken from climatological data observed in the period 1959–2016 in more than 2000 stations of the daily climatic base of the SMN. Furthermore, the ARF is calculated for each DAD curve.

4.1. Time series

Time series spanning a 58-year period (1958–2016) were generated by substituting different areas in the logarithmic equations of 24 and 48 h obtained from DAD and ARFs curves. Areas of 100, 1,000, 5,000, and 10,000 km² are selected for the DAD curve equations, and areas of 1,000, 5,000, and 10,000 km² are selected for the ARFs curves. Since the DAD method considers areal precipitation, punctual precipitation was not considered to calculate time series.

Given the inherent invalidity of logarithmic equations derived from DAD curves when applied to exceptionally small geographic regions, a pragmatic decision was made to compute time series data from areas encompassing a minimum extent of 100 km² and beyond. This method was adopted to facilitate the estimation of prevailing trends within this defined spatial domain.

Figure 3 presents the time series generated for 24-h rainfall, while Figure 4 displays the time series generated for a 48-h duration. Each annual data point is characterized by the precipitation height derived by substituting the four areas, chosen for this study, into the logarithmic equations derived from the DAD curves.

Furthermore, in Figures 3 and 4, the time series distinctly illustrate the apex of rainfall intensity, a phenomenon frequently linked to the TC eyewall or outer rainbands (as indicated by the green line). Time series reflect the spatial distribution of rainfall within and around the TC (as indicated by the green, red, blue, and gray lines). The intensity of rainfall can vary from one region to another, depending on factors like the TC size and movement.

Figures 5 and 6 display the time series computed for the ARFs, corresponding to durations of 24 and 48 h, respectively. In the context of TCs, ARF curves illustrate how the intensity of rainfall varies across different areas affected by the storm (as indicated by the red line). The curves show that the rainfall intensity can be higher near the center of the TC, especially in the eyewall, and gradually decrease as you move away from the center (as indicated by the red, blue, and gray lines).

**Figure 3** | Time series calculated from DAD curves for a duration of 24 h and areas of 100, 1,000, 5,000, and 10,000 km².
4.2. Statistics tests

The time series analysis process consists of applying the nonparametric MK trend estimation tests (Kendall 1975) and Spearman’s Rho (Lehmann & D’Aabra 1975); besides, Sen’s slope (Sen 1968) is calculated to obtain the average annual increase; finally, to find sudden jumps in the data, Pettitt’s nonparametric statistical test (Pettitt 1979) is performed. The statistical examinations were administered to each of the time series generated in the antecedent phase.

For duration of 24 h, the MK test indicates an upward trend for an area of 100 km² and the SR test for areas of 100 and 1,000 km²; in contrast, for areas of 5,000 and 10,000 km², neither of the two tests indicates the existence of a trend.
For a duration of 48 h, the MK and SR tests indicate an upward trend for areas of 100, 1,000, and 5,000 km², and neither of the two tests shows a trend for an area of 10,000 km² (Table 3). In contrast, no trends were observed in the ARF time series. Sen’s slope and Pettitt test were applied to the areas where the MK and SR tests showed a trend. The Sen’s slope reports average annual increases of 1.32 (Figure 7(a)) and 0.86 (Figure 7(b)) mm for areas of 100 and 1,000 km², respectively, for duration of 24 h; in addition, for duration of 48 h, the Sen’s slope reports values of 2.06 (Figure 7(c)), 1.54 (Figure 7(d)), and 1.18 mm (Figure 7(e)) for areas of 100, 1,000 and 5,000 km², respectively. The values obtained from Sen’s slope can be interpreted as the annual increase observed during the study period (Table 4). The Pettitt test coincides in all the areas where an upward trend is observed in that the change occurred from 1997 (Table 5).

The areas in which upward trends were observed for durations of 24 h are smaller compared to the areas in which trends were observed for durations of 48 h. Such observation could be due to the fact that during the TC path, the areas affected by

**Table 2** | Trends detected in time series lasting 24 h and 100, 1,000, 5,000, and 10,000 km²

<table>
<thead>
<tr>
<th>Area (km²)</th>
<th>Mann-Kendall</th>
<th>Spearman’s Rho</th>
</tr>
</thead>
<tbody>
<tr>
<td>100</td>
<td>Upward trend</td>
<td>Upward trend</td>
</tr>
<tr>
<td>1,000</td>
<td>No trend</td>
<td>Upward trend</td>
</tr>
<tr>
<td>5,000</td>
<td>No trend</td>
<td>No trend</td>
</tr>
<tr>
<td>10,000</td>
<td>No trend</td>
<td>No trend</td>
</tr>
</tbody>
</table>

**Table 3** | Trends detected in time series lasting 48 h and 100, 1,000, 5,000, and 10,000 km²

<table>
<thead>
<tr>
<th>Area (km²)</th>
<th>Mann-Kendall</th>
<th>Spearman’s Rho</th>
</tr>
</thead>
<tbody>
<tr>
<td>100</td>
<td>Upward trend</td>
<td>Upward trend</td>
</tr>
<tr>
<td>1,000</td>
<td>Upward trend</td>
<td>Upward trend</td>
</tr>
<tr>
<td>5,000</td>
<td>Upward trend</td>
<td>Upward trend</td>
</tr>
<tr>
<td>10,000</td>
<td>No trend</td>
<td>No trend</td>
</tr>
</tbody>
</table>
Figure 7 | Temporal series of precipitation and Pettitt test corresponding to a duration of 24 h, area of (a) 100 and (b) 1,000 km²; duration of 48 h, (c) area of 100, (d) 1,000, and (e) 5,000 km². The equation of the slope is indicated.

Table 4 | Annual increase observed during the study period obtained with Sen’s slope

<table>
<thead>
<tr>
<th>Area (km²)</th>
<th>24 h</th>
<th>48 h</th>
</tr>
</thead>
<tbody>
<tr>
<td>100</td>
<td>1.32</td>
<td>2.07</td>
</tr>
<tr>
<td>1,000</td>
<td>0.86</td>
<td>1.54</td>
</tr>
<tr>
<td>5,000</td>
<td>No trend</td>
<td>1.19</td>
</tr>
<tr>
<td>10,000</td>
<td>No trend</td>
<td>No trend</td>
</tr>
</tbody>
</table>
the cloud bands are larger as the duration of the storm increases. In addition, the values of the annual increase rates observed are higher in the center of the storm for both durations and gradually decrease as the spatial distribution of precipitation increases until reaching a maximum area in which the rate of increase is no longer statistically significant. The means of the periods 1959–1996 and 1997–2016 are different with a statistical significance of 95% (Table 6, Figure 8(a)–8(d)).

5. DISCUSSION

This study was aimed at examining both the presence and the magnitude of trends in various areas and durations of TCR. First, the proposed methodology not only facilitates the detection of areas exhibiting trends in rainfall associated with TCs but also enables the determination of the threshold that delineates the extent of such trends within these areas. In addition, this methodology is proficient in identifying alterations in the average rainfall associated with TCs. Comprehending the temporal and spatial trends in the distribution of storm magnitudes holds a crucial significance in the development of effective strategies for mitigating damage and leveraging the benefits inherent to these natural phenomena.

The study’s findings indicate a discernible trend in various areas and durations of TCR. On the contrary, this investigation yielded no statistically significant evidence indicating a prevailing tendency in the areas impacted by TCR. Moreover, the findings indicate a notable rise in the mean of TCR starting from the year 1997. The certainty of these results is subject to a 95% statistical confidence level.

The El Niño event of 1997–1998 was one of the strongest and most significant El Niño events of the 20th century (Changnon 2000). El Niño events can have far-reaching impacts on weather patterns, including the behavior TCs. During El Niño events, there are changes in sea surface temperatures and atmospheric circulation patterns that can influence the frequency, intensity, and tracks of TCs in various areas (Camargo & Sobel 2005).

While the specific influence of the 1997–1998 El Niño event on TCR trends after 1997 would require a detailed analysis of historical data and climate models, it is possible that this powerful El Niño event played a role in some of the observed trends and means. However, it is plausible that this formidable El Niño event may have played a role in the observed trends, including the notable increase in the mean of TCR commencing in 1997. On the other hand, a positive phase of the Pacific Decadal Oscillation (PDO) prevailed from 1977 to 1999. The positive PDO phase has the potential to impact weather patterns and atmospheric conditions in manner that could heighten the probability or intensity TC events (Wang & Liu 2016). Such influences may have played a role in the identified TCR trends and means after 1997.

Table 5 | Change point obtained from Pettitt test

<table>
<thead>
<tr>
<th>Area (km²)</th>
<th>24 h</th>
<th>48 h</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Change</td>
<td>Year</td>
</tr>
<tr>
<td>100</td>
<td>Yes</td>
<td>1997</td>
</tr>
<tr>
<td>1,000</td>
<td>Yes</td>
<td>1997</td>
</tr>
<tr>
<td>5,000</td>
<td>Yes</td>
<td>1997</td>
</tr>
<tr>
<td>10,000</td>
<td>No change</td>
<td>–</td>
</tr>
</tbody>
</table>


<table>
<thead>
<tr>
<th>Area (km²)</th>
<th>24 h</th>
<th>48 h</th>
</tr>
</thead>
<tbody>
<tr>
<td>100</td>
<td>249.76</td>
<td>333.41</td>
</tr>
<tr>
<td>1,000</td>
<td>186.90</td>
<td>245.66</td>
</tr>
<tr>
<td>5,000</td>
<td>142.96</td>
<td>184.32</td>
</tr>
<tr>
<td>10,000</td>
<td>No change</td>
<td>No change</td>
</tr>
</tbody>
</table>
However, it is essential to note that El Niño and La Niña may interact with the PDO, creating complex relationships. Detailed climate studies, statistical analyses, and modeling would be necessary to attribute specific impacts to the PDO in Mexico.

The observed discernible trend in areas proximate to the center of the storm and the durations of TCR aligns with previous studies (Hasegawa & Emori 2005; Chauvin et al. 2006; Yoshimura et al. 2006; Bengtsson et al. 2007; Gualdi et al. 2008; Knutson & Tuleya 2008; Kim et al. 2014; Villarini et al. 2014; Tsou et al. 2016; Touma et al. 2019; Chu et al. 2020; Knutson et al. 2020; Guzman & Jiang 2021; Chang et al. 2023). This consistency underscores the robustness of these findings and their relevance to our understanding of cyclonic systems in a changing climate and natural variability. In contrast, the absence of statistically significant evidence regarding prevailing tendencies in areas affected by rainfall associated with TCs provides a valuable contrast to studies that have suggested consistent patterns in the past (Touma et al. 2019). Furthermore, the notable increase in mean rainfall associated with TCs, commencing in 1997, is consistent with the broader context of global climate change (Guzman & Jiang 2021).

The significance of our study lies in its ability to offer quantitative evidence regarding the temporal and spatial distribution of TCR. Unlike previous research that often relied on limited qualitative assessments or focused solely on extreme events, our study provides a comprehensive understanding of storm behavior over a substantial timeframe. This knowledge can inform policy-making, risk assessment, and disaster preparedness, thereby reducing the negative impacts of storms and maximizing the potential benefits they may offer, such as water resources replenishment and agriculture.

The results of this study contribute to filling gaps in our knowledge of TCs by focusing on localized effects, highlighting the complexity of cyclone-related precipitation patterns, and providing evidence of changing cyclone behavior over time.

Precise measurement of precipitation holds paramount significance in the fields of flood prediction, flood control, and hydrological flow modeling (Sattari et al. 2020). One potential application of the findings from this study for mitigating

Figure 8 | Time series and corresponding Pettitt test with a duration of 24 h, area of (a) 100 and (b) 1,000 km²; duration of 48 h, area of (c) 100 and (d) 1,000 km².
the risk of flooding involves the calculation of the PMP. The method for calculating PMP based on the findings of this study is delineated as follows:

Step 1
• Calculate the envelope of DAD curves in the zone of interest considering the annual increasing rate found in this work.

Step 2
• Obtain the adjustment factor for storm transposition.

\[ K_t = \frac{W_T}{W_O} \]  \hspace{1cm} (16)

where \( K_t \) is the storm transposition adjustment factor, \( W_T \) is precipitable water over the basin, and \( W_O \) is storm precipitable water.

Step 3
• Obtain the moisture adjustment factor for storm maximization.

\[ K_M = \frac{W_T}{W_O} \]  \hspace{1cm} (17)

where \( K_M \) is the storm maximization adjustment factor, \( W_T \) is precipitable water corresponding to the 12 h persistent dew point, and \( W_O \) is precipitable water corresponding to the dew point within the storm.

Step 4
• Calculate the corrective factor.

\[ K = K_t \times K_M \]  \hspace{1cm} (18)

where \( K \) is the storm corrective factor, \( K_t \) is the storm maximization adjustment factor, and \( K_M \) is the storm transposition adjustment factor.

Step 5
• Obtain PMP.

\[ PMP = \text{DAD}_{\text{envelop}} \times K \]  \hspace{1cm} (18)

However, one of the most important components in the transposition of storms, such as the dew point, has not been studied in its relationship with global warming, which would imply future work on this topic.

6. CONCLUSIONS

This study introduces a quantitative framework for identifying temporal trends in TCR using time series data derived from the computation of DAD and ARF curves for multiple storms observed in Mexico. Specifically, we calculated an annual DAD curve for a comprehensive dataset comprising 58 TCs that occurred between 1959 and 2016. The outcomes of this analysis offer valuable insights into the influence of climate change and natural variability on the behavior of TCs, enhancing our understanding of this dynamic phenomenon.

The results of this investigation unequivocally demonstrate a significant upward trend over time in the 24 h precipitation accumulation for a maximum area of 1,700 km². In addition, there is a noticeable upward trend in the 48 h rainfall accumulation for a maximum area of 6,900 km². In contrast, no discernible changes were observed in the time series derived from the ARF analysis, indicating a lack of significant alterations in the affected area by these climatic events. These findings lend strong support to the hypothesis that climate change and natural variability play a role in influencing extreme weather events, particularly TCs.

A limitation of this study is that given that the isohyet method considers areal rainfall rather than point rainfall, the resulting equations for the DAD curves tend to exhibit divergence when applied to very small areas. Therefore, we suggest employing these equations for DAD curves in areas larger than 100 km².
To gain a more comprehensive understanding of TCR trends, future research might explore spatial variations and the factors influencing specific areas differently. Examining local climate phenomena or geographical characteristics could shed light on the absence of significant trends in areas affected by TCR. Moreover, investigations into the consequences of the identified TCR trends on hydrological systems and ecosystems could be vital.

The quantitative analysis of the temporal and spatial distribution TCR presented in this study contributes to informed decision-making in disaster management and resource allocation. We provide valuable insights into the evolving nature of TCs, enabling society to adapt and mitigate their effects more effectively. This research represents a significant step toward a more resilient and sustainable future in the face of changing climate patterns and increasing storm risks. Besides, these findings substantiate the imperative for the implementation of both structural and nonstructural interventions to mitigate the incidence and impact of flooding events. Furthermore, the methodology is applicable regionally in any area where TCs are present, and there are at least rainfall records. Outcomes can differ between basins, influenced by the regional climatology of the ocean basins where TCs originate.

ACKNOWLEDGEMENTS
The authors express their gratitude to Javier Aparicio, PhD, and the anonymous reviewers for their valuable contributions, which significantly enhanced this study. In addition, we acknowledge the financial support provided by the National Council of Humanities, Sciences, and Technologies of Mexico (CONAHCYT), which made the completion of this research possible.

DATA AVAILABILITY STATEMENT
All relevant data are included in the paper or its Supplementary Information.

CONFLICT OF INTEREST
The authors declare there is no conflict.

REFERENCES
Benoit, K. 2011 Linear Regression Models with Logarithmic Transformations.
CENAPRED 2007 Fascículos Ciclones Tropicales (Fascículos, p. 50). CENAPRED.


Cheung, K. 2018 *Recent Advances in Research and Forecasting of Cyclone Cyclone Rainfall*. 7(2), 22.


First received 3 May 2023; accepted in revised form 21 November 2023. Available online 4 December 2023