DOI: 10.24850/j-tyca-2026-05-06

Articles

Methodological projection of droughts in Bravo-Conchos, Mexico, using combined techniques

Proyección metodológica de sequías en Bravo-Conchos, México, con técnicas combinadas

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Abstract

Water scarcity is a critical issue exacerbated by population growth, climate change, and increasing water demand. The Bravo-Conchos hydrological region, located along the U.S.-Mexico border, faces severe drought conditions that threaten water availability and economic stability. This research applied a hybrid approach, combining the Svanidze method for synthetic data generation with traditional drought analysis to project future drought scenarios. The methodology includes assessing water stress using the Falkenmark Index, analyzing climate projections with CMIP5 models, and characterizing multiyear droughts. Results indicate a projected decrease in precipitation and rising temperatures, intensifying drought frequency and severity. The region should adapt to an average precipitation of approximately 243.35 mm, which is 78.82 % of the historical mean precipitation, considering future droughts and climate fluctuations. Findings highlight the urgent need for adaptive water management policies, cross-border cooperation, and infrastructure improvements to mitigate climate change impacts. This research also provides accessible and cost-effective tools for decision-making, supporting public policies and sustainable water resource management in data-scarce regions.

Keywords: drought, arid zones, water resources management, water balance, Svanidze method, Falkenmark index, CMIP5 models, water supply, river basins, mathematical models, climate change, bilateral relations, transboundary waters, Mexico.

Resumen

La escasez de agua es un problema crítico, agravado por el crecimiento poblacional, el cambio climático y la creciente demanda de agua. La región hidrológica Bravo-Conchos, ubicada a lo largo de la frontera entre EUA y México, enfrenta severas condiciones de sequía que amenazan la disponibilidad de agua y la estabilidad económica. En esta investigación se aplicó un enfoque híbrido, que combinó el método Svanidze para la generación de datos sintéticos y el análisis tradicional de sequías para proyectar escenarios futuros de esta situación meteorológica. La metodología incluye la evaluación del estrés hídrico mediante el índice Falkenmark, el análisis de proyecciones climáticas con modelos CMIP5 y la caracterización de sequías plurianuales. Los resultados indican una disminución proyectada de la precipitación y un aumento de las temperaturas, lo que intensifica la frecuencia y severidad de las sequías. Se encontró que la región debe adaptarse a una precipitación promedio de aproximadamente 243.35 mm, lo que representa el 78.82 % de la precipitación media histórica, considerando futuras sequías y fluctuaciones climáticas. Los hallazgos resaltan la urgente necesidad de políticas adaptativas de gestión del agua, cooperación transfronteriza y mejoras de infraestructura para mitigar los impactos del cambio climático. Esta investigación también proporciona herramientas de fácil acceso para la toma de decisiones, apoyando las políticas públicas y la gestión sostenible de los recursos hídricos en regiones con escasez de datos.

Palabras clave: sequía, zona árida, gestión de los recursos hídricos, equilibrio hídrico, método Svanidze, índice de Falkenmark, modelos CMIP5, abastecimiento de agua, cuenca fluvial, modelo matemático, cambio climático, relaciones bilaterales, aguas transfronterizas, México.

Received: 21/04/2025

Accepted: 09/12/2025

Available ahead of print: 03/02/2026

Version of record: 01/09/2026

Introduction

Owing to population growth and the expansion of the agricultural, energy, and industrial sectors, water demand has increased tenfold, leading to water shortages in many parts of the world almost every year. Other factors; such as climate change and water supply pollution, further exacerbated water scarcity (Mishra & Singh, 2010). The environmental impact of droughts is evident, however, but their surprisingly high economic costs are often overlooked. Between 1980 and 2003, droughts (and associated heatwaves) accounted for 10 out of 58 climate-related disasters in the United States, each costing over a billion dollars (Cook *et al.*, 2007).

Recent droughts have been influenced by the tropical Atlantic Sea surface temperatures and Asian monsoons. Additionally, recent warming has increased atmospheric moisture demand and likely altered atmospheric circulation patterns, both of which contribute to drought conditions. Climate models project increasing aridity in the 21st century across most of Africa, the southern Europe, the Middle East, the Americas, Australia, and Southeast Asia. While the United States has avoided prolonged droughts over the past 50 years due to natural climate variations, persistent droughts could emerge in the next 20 to 50 years.

Future drought predictions will depend on the ability of climate models to accurately forecast sea surface temperatures (Dai, 2011).

Following the Paris Agreement, countries committed to "keeping the global average temperature increase well below 2 °C above pre-industrial levels and pursuing efforts to limit the increase to 1.5 °C", recognizing that this would significantly reduce climate change risks and impacts. The assessment of 1.5 and 2 °C warming should not rely solely on direct model outputs but also on the scientific understanding of physically plausible climate responses to anthropogenic warming. Existing research suggests that rising global temperatures are likely to be associated with changes in circulation systems, nonlinear mechanisms, and possible disruptions in the climate system, which could lead to complex local changes. Therefore, more local research is needed to analyze climate change mechanisms in different regions (James *et al*., 2017).

Since droughts have been identified as a consequence of climate change, monitoring and predicting them is crucial for assessing risks and making timely decisions to mitigate their negative effects. Early drought warnings, including information on intensity, duration, and spatial extent, are essential for developing proactive strategies to manage drought impacts. Given the increasing frequency, intensity, and duration of dry periods worldwide, it is important to develop forecasting tools to anticipate future hydrological conditions (Villazón-Bustillos *et al*., 2015).

Droughts with similar characteristics (e.g., magnitude and duration) can spread differently across regions depending on basin characteristics, leading to varying socioeconomic impacts. Improving our understanding of drought propagation mechanisms and their climatic, hydrological, and social controls can help water resource managers design more effective drought mitigation strategies for their respective regions (Apurv *et al*., 2017).

Recent studies have used advanced deep learning models, such as convolutional neural networks and transformers, to integrate temporal and spatial climate data, improving short-term drought prediction accuracy (up to 12 months) (Marusov *et al*., 2024). However, these studies are limited to short-term forecasts and do not provide a comprehensive outlook on future drought evolution, particularly when considering climate change projections.

The generation of synthetic time series is crucial in hydrology for extending historical records and enhancing the accuracy of models predicting extreme events such as floods and droughts.

Autoregressive Moving Average (ARMA) and Autoregressive Integrated Moving Average (ARIMA) models are widely used in hydrology for generating synthetic time series that extend beyond historical records. These models are particularly valued for their ability to capture the autocorrelation structure of hydrological data, making them suitable for modeling and forecasting various hydrological processes. The primary advantage of ARMA and ARIMA models lies in their simplicity and effectiveness in handling stationary time series, where the mean and variance are constant over time (Ledolter, 1976). ARIMA models are adept at transforming non-stationary series into stationary ones by differencing, thus enabling more accurate predictions (Wang *et al*., 2014). However, these models also have notable limitations. They require a large amount of historical data to build reliable models, and their performance can degrade with increasing forecast horizons due to the accumulation of prediction errors (Liu *et al*., 2024). Additionally, ARIMA models may struggle with capturing complex nonlinear relationships and multiple seasonalities present in hydrological data, which can limit their applicability in certain contexts (Chetverikov *et al*., 2021). Despite these challenges, ARMA and ARIMA models remain valuable tools in hydrological modeling, particularly for short-term forecasts and scenarios where computational simplicity is desired.

Among the more advanced methods for generating synthetic time series are GANs and long memory models. Dodig *et al*. (2024) propose a framework for predicting water quality time series using synthetic data generated by GANs and deep learning models, improving prediction accuracy. This approach captures nonlinear dynamics and complex interdependencies in hydrological data, offering greater precision in forecasts.

Nguyen and Chen (2022) developed a stochastic rainfall generator to create continuous rainfall time series with high temporal resolution, using Monte Carlo simulation and modified Huff curves, applied in the Yilan River basin in Taiwan. This method generates synthetic data that preserve the statistical characteristics of observed time series, essential for accurate hydrological modeling.

Karimanzira (2024) utilizes GANs to generate synthetic extreme flood events, enhancing the accuracy of probabilistic forecasting models by incorporating hydrological principles into the GAN model. This approach allows for better representation of extreme events, crucial for risk management and mitigation planning.

The Svanidze method, also known as the fragment method, is highly valued for its simplicity and effectiveness. This method allows for the creation of synthetic records of periodic time series that are longer than the historical record, preserving essential statistical characteristics such as mean, standard deviation, and skewness (Svanidze, 1980). One of the main advantages of the Svanidze method is its ability to maintain the correlation structure and higher-order properties of the original series, which is crucial for hydrological applications such as modeling extreme flood and drought events (Svanidze, 1980). Additionally, its implementation is relatively straightforward compared to more complex methods such as Generative Adversarial Networks (GANs) or long memory models, facilitating its use in preliminary studies or situations with limited computational resources (Dodig *et al*., 2024).

However, a notable disadvantage of the Svanidze method is its potential inability to adequately capture the nonlinear dynamics present in hydrological time series, which could limit its accuracy in certain contexts (Svanidze, 1980) In comparison, methods such as GANs offer greater capacity to model these complexities, albeit at the cost of increased complexity and computational requirements (Dodig *et al*., 2024). In summary, the Svanidze method is a valuable tool for its balance between simplicity and accuracy, making it particularly useful in studies requiring rapid and efficient generation of synthetic series.

The objective of this study is to assess the impacts of climate change on the frequency, duration, and intensity of droughts in the Bravo-Conchos Hydrological Region, Mexico. To achieve this, a hybrid approach is applied that combines the generation of synthetic precipitation series using the Svanidze method with traditional drought analysis techniques. The study integrates climate projections under RCP 4.5 and RCP 8.5 scenarios, along with water stress estimation via the Falkenmark Index, to produce technical information that supports the design of adaptive public policies and water management strategies. This methodology aims to provide accessible, cost-effective, and reliable tools to support decision-making in water resource management and public policy design, ensuring preparedness for current and future climate challenges.

In regions like northern Mexico, characterized by mountainous terrain and limited meteorological infrastructure, the lack of historical data prevents the application of sophisticated methods like deep neural networks. In this context, the Svanidze method (Svanidze, 1980; Arganis *et al*, 2023) has been chosen for its simplicity, low computational cost, and ability to produce interpretable results. These features make it a valuable tool in data-scarce environments.

For this study, the Svanidze method is particularly suitable as it generates synthetic time series based on historical patterns, which are then used in meteorological drought analysis to project future events. This approach is not only effective and cost-efficient but also facilitates decision-making in public policy implementation without requiring complex computational systems. The proposed hybrid approach combines synthetic data generation via the Svanidze method with traditional meteorological drought analysis methods, yielding more robust and reliable projections.

This methodology lays the foundation for developing predictive systems that support water resource management in vulnerable regions. Furthermore, this approach is accessible, fast, and useful for generating future climate information without relying on advanced technological tools. It is recommended to extend this method to incorporate additional climate variables, such as temperature and humidity, and to explore its application in different regions worldwide, also evaluating climate change impacts on extreme drought recurrence.

The structure of this study is organized as follows: first, the introduction is presented. This is followed by the methodology section, where the equations and methods utilized are described in detail. Subsequently, the results section is outlined, leading into the discussion, which includes brief suggestions. Finally, the study concludes with a synthesis of the principal findings.

Methodology

This study followed a structured methodology. First, water availability across Mexico was assessed. The analysis was conducted based on hydrological regions, as these provide multiple societal benefits derived from a wide range of ecosystem goods and services. Additionally, working at the regional level recognizes the importance of proper water management in any social development process, considering a region as a set of basins and a management unit integrating environmental, economic, and social aspects (Conagua, 2013a).

The Bravo-Conchos hydrological region (Figure 1) has a diverse economy, with agriculture as a key sector. Crops rely on water from the Conchos River for irrigation. In 2017, Chihuahua accounted for 64.7 % of the region's agricultural production, followed by Tamaulipas, Coahuila, and Nuevo León. Livestock farming is also a significant activity (Hernández-Romero & Patiño-Gómez, 2017).

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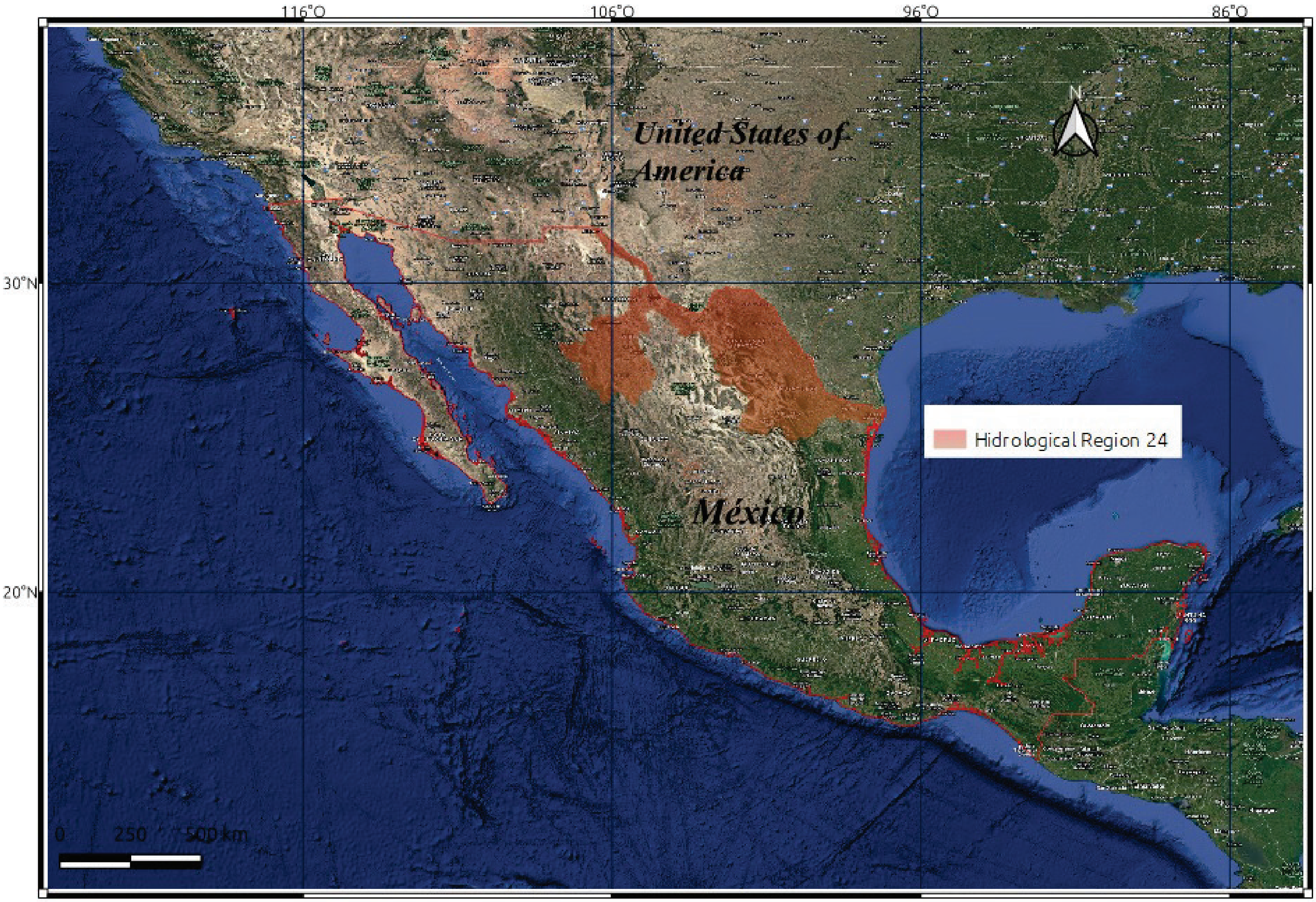

Figure 1. Location of Hydrological Region 24 "Bravo-Conchos".

Additionally, the region has a strong industrial base, particularly in the manufacturing of machinery, transportation equipment, and electronics, with major industrial hubs in Monterrey and Chihuahua. The automotive and steel industries are also prominent in Nuevo León and Coahuila.

Tecnología y ciencias del agua, ISSN 2007-2422, 17(5), 272-310. DOI: 10.24850/j-tyca-2026-05-06

However, water scarcity —exacerbated by climate change and high-water demand under the 1944 U.S.-Mexico Water Treaty— has led to more frequent and intense droughts, impacting water availability for agriculture, industry, and human consumption. This situation threatens regional economic stability, particularly in irrigation-dependent areas (Semarnat, 2021).

Assessment of water availability

Water availability was evaluated using the Falkenmark Index (Equation (1)), also known as the Water Stress Indicator, one of the most common tools for assessing regional water availability. Developed by Swedish hydrologist Malin Falkenmark, this index calculates the amount of renewable freshwater available per person per year in a specific region:

$$Falkenmark\ Index = \frac{Annual\ Renewable\ Water\ Resources\left[\frac{m^3}{year}\right]}{Population\ (people)} \quad (1)$$

For the calculation of the key input "Annual Renewable Water Resources" (ARWR), the annual volume of natural runoff in the Bravo-Conchos Hydrological Region was obtained from official records of the National Water Commission of Mexico (Conagua, 2013b). This value corresponds to the multi-year average of natural runoff, derived from hydrometric station data. The ARWR was then divided by the total population of the region, according to official demographic data from the National Institute of Statistics and Geography (INEGI, 2020), to obtain per capita renewable water availability. This approach ensures that the index reflects both hydrological supply and demographic demand, in line with the methodology proposed by Falkenmark.

This index classifies water availability into the following categories:

- **Water abundance**: More than 1 700 m³/person/year.
- **Water stress**: Between 1 000 and 1 700 m³/person/year. In this range, difficulties in meeting water demand begin to appear, especially during dry periods.
- **Water scarcity**: Less than 1 000 m³/person/year. In this range, available water is insufficient to meet population needs, potentially leading to conflicts and water crises.
- **Extreme water scarcity**: Less than 500 m³/person/year. This critical level is often associated with severe social, economic, and environmental problems.

Once it was determined that the Bravo-Conchos hydrological region (Region 24) is experiencing water stress—covering parts of Chihuahua, Coahuila, Nuevo León, and Tamaulipas and bordering the United States—the second step was to analyze climate change trends in the region.

Climate change analysis

The climate change study was conducted in 2020 using data from CMIP-5 (Coupled Model Intercomparison Project Phase 5), which can be updated using CMIP-6 to assess possible future climate variations in the region. This was since this work began early in the pandemic.

Projections for temperature and precipitation were obtained for the future periods 2039, 2045-2069, and 2075-2099, using the CNRMCM5, GFDL-CM3, HADGEM2-ES, and MPI-ESM-LR climate models. These models were analyzed under Representative Concentration Pathways (RCPs) 4.5 and 8.5. They were selected based on their strong performance in representing observed regional climate patterns and are commonly used for impact studies in Mexico (Conde & López, 2016).

The projected climate data were compared with the historical average annual rainfall recorded in the region, derived from a study of 150 meteorological stations with 60 years of records. Additionally, population projections for 2050 were incorporated.

To facilitate future public policy planning, the climate change study was conducted using open-access tools, such as QGIS and WorldClim, which provide future climate projections and models in raster format, enabling numerical analysis.

Multi-year drought characterization

The third step involved characterizing multi-year droughts, following approaches used by Escalante-Sandoval and Nuñez-Garcia (2017), by analyzing and describing drought events over several years using the following sequence:

1. **Drought-threshold**: The annual average precipitation at the studied weather station.

2. **Anomaly**: The difference between each year’s recorded precipitation and the drought-threshold.

3. **Periodicity**: The number of years between the start of one drought and the next.

4. **Duration**: The consecutive years with negative anomalies.

5. **Severity**: The sum of all anomalies within a drought period, representing the total rainfall deficit.

6. **Intensity**: The severity divided by the drought duration.

7. **Intensity percentage**: The ratio of intensity to the drought -threshold.

8. **Rainfall available**: The sum of intensity and the drought -threshold.

9. **Exceedance probability and return period**: Calculated using the fitting function for the rainfall series.

The goal of this analysis was to provide interpretable data to facilitate decision-making in critical drought situations.

Synthetic data generation using the Svanidze method

The fourth step involved generating synthetic annual rainfall data up to 2050 using the Svanidze method (Svanidze, 1980). This technique generates synthetic time series, extending historical records of water flow, precipitation volumes, and other hydrological parameters, enabling a more robust analysis of extreme events and climate patterns.

The method preserves the statistical properties of the original series (Arganis *et al.*, 2023), such as mean, standard deviation, and cross-correlations, ensuring accuracy in hydrological analysis (Domínguez-Mora *et al.*, 2005).

The methodology consists of the following steps:

1. **Data selection**: A historical hydrological time series (e.g., river flows or precipitation volumes) is chosen, ideally spanning at least 30 years to capture seasonal variations and extreme events.

2. **Statistical analysis**: Basic statistics such as mean, standard deviation, and autocorrelation are computed to ensure synthetic samples retain the original data's properties.

3. **White noise generation**: A random number generator produces a white noise series with a mean of zero and a standard deviation of one, introducing variability.

4. **White noise filtering**: A low-pass filter is applied to replicate the original series' characteristics, adjusting autocorrelation properties.

5. **Statistical parameter adjustment**: The filtered series is scaled and shifted to match the mean and standard deviation of the original dataset.

6. **Model validation**: The synthetic series is compared with the original series to ensure similarity. If significant discrepancies exist, model parameters are adjusted and reprocessed.

7. **Synthetic sample generation**: Once validated, multiple synthetic samples are generated for further analysis, such as extreme event evaluation or hydraulic infrastructure design.

This methodology enables the generation of synthetic data that faithfully replicates the characteristics of the original time series, making it a valuable tool for hydrological studies and water resource management. By applying the multi-year drought analysis described in the third section to these synthetic series, it is possible to assess the potential impacts of future drought scenarios. Once synthetic drought events are generated using the Svanidze method, their results are compared with historical records to validate their accuracy.

To strengthen the analysis of extreme drought events within the synthetic series, the inverse Gumbel distribution was applied (Equation (2)). This statistical approach enables the estimation of precipitation values associated with specific cumulative probabilities:

$$x = \left[\frac{1}{a}\right] * \left[-\ln\left(\ln\left(\frac{1}{F(x)}\right)\right)\right] + \beta \qquad (2)$$

Where:

x = Estimated precipitation value.

$F(x)$ = Cumulative probability of occurrence.

α = Scale parameter.

β = Location parameter.

This formulation was integrated with the synthetic series generated using the Svanidze method to simulate drought scenarios projected for the year 2050 in the Bravo-Conchos hydrological region. By combining both methods, the study enhances its ability to assess future water scarcity risks under changing climate conditions, supporting long-term planning and resource management strategies.

This study analyzes the increasing frequency and severity of droughts and their impacts on agriculture due to declining water availability. Understanding these trends is crucial for developing mitigation strategies through effective water management policies.

Groundwater recharge plays a key role in water resource resilience. As a prolonged process dependent on natural recharge conditions, it can significantly extend the recovery time of water resources in regions affected by severe droughts (Soto, 2024). However, the adoption of sustainable water management practices and ecosystem restoration policies can enhance recharge rates, thereby accelerating the recovery of affected communities and ecosystems (FAO, 2025).

Results

The analysis began with the identification of climatological stations in Hydrological Region 24 (Bravo–Conchos). Of the 150 registered stations (CLICOM, 2020), most had fragmented or incomplete data, with short continuous records and long gaps of up to 20 years. Due to these limitations, only 10 stations were selected for detailed analysis based on two criteria: relative data continuity and the presence of non-stationary trends, which may reflect climate variability and change. Missing values were reconstructed using the Inverse Distance Weighting (IDW) method (Shepard, 1968), a common geostatistical technique. Descriptive statistics—mean, standard deviation, maximum, minimum, and range—were calculated for each station (Table 1). These results form the empirical foundation for the drought analysis, which incorporates the Falkenmark Index to assess water stress based on population distribution and regional water availability.

Table 1. Statistical characteristics of the analyzed precipitation series.

Station	Mean	Standard Deviation	Maximum	Minimum	Range
5003	218.95	144.31	471.00	6.00	465.00
5005	315.86	186.92	889.50	5.50	884.00
5013	225.50	95.01	441.10	62.90	378.20
5016	331.50	139.58	601.00	22.50	578.50
5022	361.39	270.61	1303.80	19.50	1284.30
5030	309.77	146.68	675.40	6.00	669.40
8081	316.85	114.03	526.66	65.50	461.16
8185	335.39	190.63	899.10	66.84	832.26
8254	227.16	113.39	495.50	38.00	457.50
8270	285.30	132.97	552.20	16.30	535.90

The average annual precipitation calculated from 10 stations was 292.77 mm. To verify the official value of mean natural runoff (Annual Renewable Water Resources, ARWR) of 5 590 hm³/year reported by (Conagua, 2021) for Hydrological Region 24, the annual precipitation volume was estimated by multiplying this average by the regional area (229 740 km²), resulting in 67.26 billion m³/year. Applying a runoff coefficient of 0.0831 yielded a runoff volume of 5.59 billion m³/year, which matches the official value and validates its hydrological representativeness. According to the Falkenmark Index, with a population of 14.7 million in 2020, per capita water availability is 380 m³/year, indicating extreme scarcity (<500 m³/person/year). The region is 99.7 % urban, with projected population growth from 10.98 million in 2010 to 19.56 million by 2030, concentrated in metropolitan areas (84 %). In

2011, total water demand was 11 881 hm³, with 60 % allocated to consumptive use. Table 2 summarizes the values used and distinguishes between precipitation volume (P×A) as an upper bound and ARWR as the basis for index calculation.

Table 2. ARWR and precipitation volume in Falkenmark Index Evaluation for Water-Stressed Regions.

HR	**Area (km²)**	**Population per HR**	**Hp (mm/year)**	**P×A (m³/person/year)**	**FI (ARWR/person/year)**	**FI Category (ARWR)**
7	6 911	442 304	71.43	1 116	1 116	Stress (1 000–1 700)
20	39 936	2 555 904	81.32	1 271	1 271	Stress (1 000–1 700)
24	229 740	14 700 000	35.6	556	380	Extreme (< 500)

Notes:

P×A = Precipitation (m) × area (m²) ÷ population; represents a theoretical upper bound, not ARWR.

FI (ARWR/person/year) uses official ARWR values: HR 24 = 5 590 000 000 m³/year; for HR 7 and HR 20, reported values match P×A from the source dataset.

FI thresholds: > 1 700 (abundance); 1 000–1 700 (stress); 500-1 000 (scarcity); < 500 (extreme scarcity).

A climate change analysis for the Bravo-Conchos hydrological region, conducted in the present study, revealed significant changes projected for the next 30 years. The baseline climate, calculated from the 1950–2000 period using historical climate records, showed an annual monthly average precipitation of 36 mm, a maximum temperature of 27 °C, and a minimum temperature of 14 °C (Ramírez-Abundis, 2024).

Comparing Representative Concentration Pathways (RCP) 4.5 and 8.5, climate projections for the year 2050 were obtained from four climate models: GFDL-CM3, CNRM-CM5, HADGEM2-ES, and MPI-ESM-LR.

The GFDL-CM3 model projected the most unfavorable scenario in terms of precipitation. Under RCP 4.5, rainfall is expected to decrease by 6 % compared to the baseline, while under RCP 8.5, the decline is projected to reach 22 %, posing a significant threat to the region's water resources (Table 3).

Table 3. Projected climate variables for 2050 to Bravo-Conchos (Region 24).

Model	RCP 4.5 Rainfall (mm)	RCP 8.5 Rainfall (mm)	RCP 4.5 Tmax (°C)	RCP 8.5 Tmax (°C)	RCP 4.5 Tmin (°C)	RCP 8.5 Tmin (°C)
CNRMCM5	34.99	32.17	29.08	29.78	14.00	14.59
GFDL-CM3	33.53	27.90	30.81	31.88	14.58	15.43
HADGEM2-ES	31.58	34.26	30.27	30.96	14.73	15.57
MPI-ESM-LR	33.24	29.86	29.01	29.98	14.14	15.10

This decrease in precipitation is concerning, especially considering that Mexico must deliver a portion of water to the United States every five years (Conagua, 2021). It is urgent that the government, public and private industry, and the general population recognize the evidence of climate change and act to implement appropriate water management policies and urban planning.

Additionally, an increase in average temperature is projected for the region: a rise of 14 % under RCP 4.5 and an increase of 18 % under RCP 8.5, which would negatively affect evapotranspiration and hinder aquifer recharge, endangering water availability in the region. The minimum temperature would also experience an increase under these scenarios, further exacerbating the situation. It is important to highlight that GFDL-CM3 is particularly detailed in its interaction between atmosphere and oceans, which could explain the projected reduction in future rains. In comparison, the CNRM-CM5 model has a stronger focus on the water cycle and aerosols, while the HadGEM2-ES model focuses on large-scale climate dynamics. The MPI-ESM-LR model stands out for its resolution and simulation of complex climatic processes, but with a different focus on the carbon cycle and global temperature changes.

The results for characterizing multi-year droughts, after studying ten climatological stations with rainfall records from 1974 to 2013 and strategically located in hydrological region 24 Bravo-Conchos, show that drought occurs on average every 4.63 years with an average duration of 2.33 years and severity of -155.65 mm, equivalent to an intensity of -68.69 mm/year, amounting to -23.46 % less than its threshold, and whose available deficit sheet would be 224.07 mm with an exceedance probability of 0.55 and a return period of 3.71 years (Figure 2). The obtained values have dispersion compared to expected values, so considering the standard deviation (Escalante-Sandoval & Reyes-Chávez, 2013), the values characterizing drought in the most unfavorable environment in hydrological region 24 Bravo-Conchos would be those where drought occurs on average every 6.31 years with an average duration of 4.07 years and severity of -275.05 mm, equivalent to an intensity of -105.74 mm/year, amounting to -36.12 % less than its drought-threshold, and whose available deficit sheet would be 187.02 mm with an exceedance probability of 0.16 and a return period of 6.07 years, as shown in Table 4.

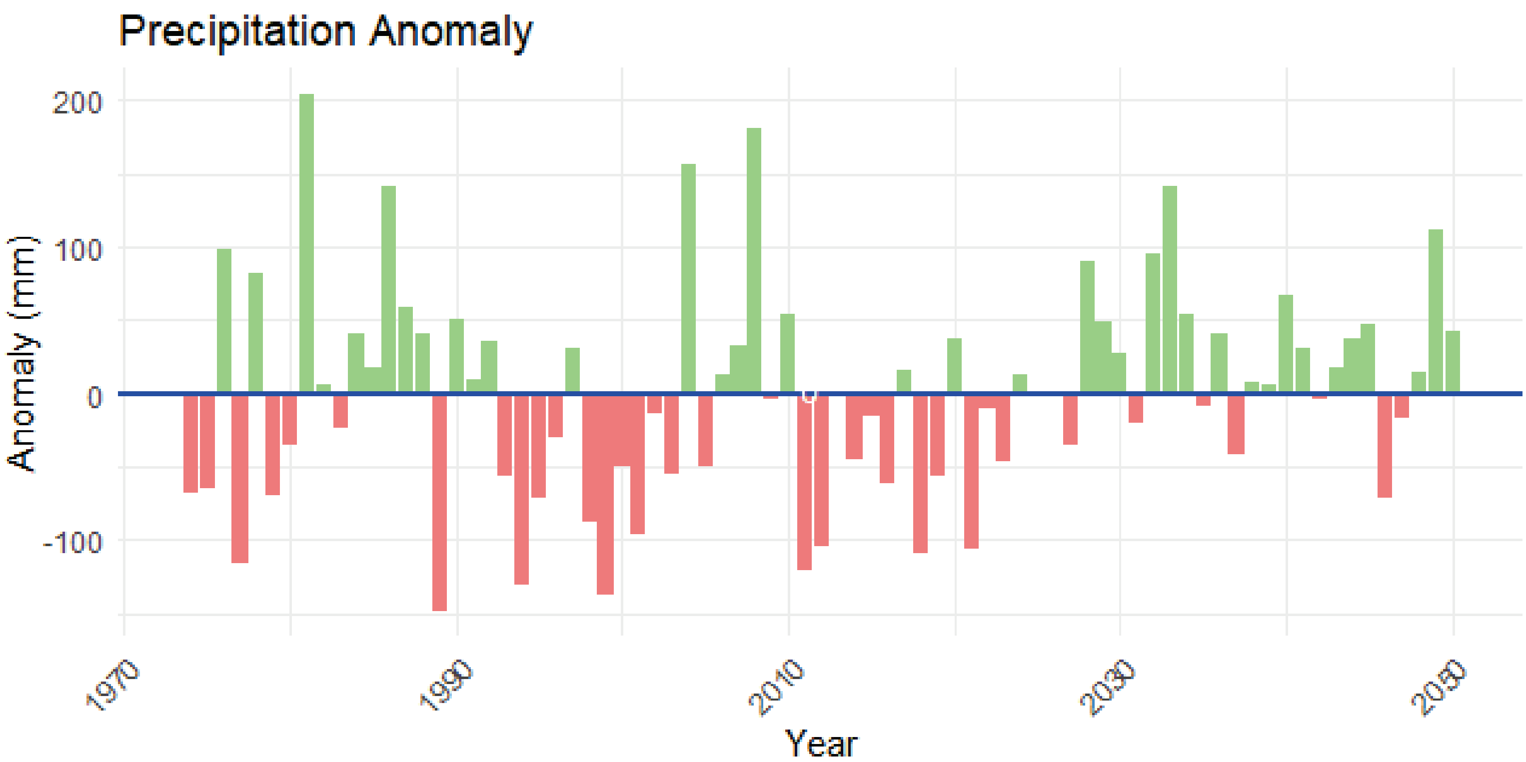

Figure 2. Annual accumulated rainfall of the original series and the synthetic series projected to 2050, showing duration, severity, and possible drought period.

Table 4. Drought frequency and severity estimates for the Bravo-Conchos (Region-24).

Statistic	Mean	Worst-case Scenario
Drought recurrence	5 years	6 years
Average duration	2 years	4 years
Severity (mm)	-155.65	-275.05
Intensity (mm/year)	-68.69	-105.74
Rainfall deficit (%)	-23.46 %	-36.12 %
Available rainfall (mm)	224.07	187.02
Exceedance probability	0.55	0.16
Return period (years)	4	6

Based on these findings, it is recommended that regional water management plans consider an adjusted annual rainfall estimate of 187.02 mm rather than the current average of 292.77 mm—equivalent to 63.87 % of the mean annual precipitation.

Using the Svanidze method, synthetic rainfall projections for the Bravo-Conchos Hydrological Region, as shown in Table 5, indicate an expected annual accumulated rainfall of 308.72 mm over the next 25 years — a 5 % increase compared to the historical average. The trend is to remain the same, as shown in Figure 3.

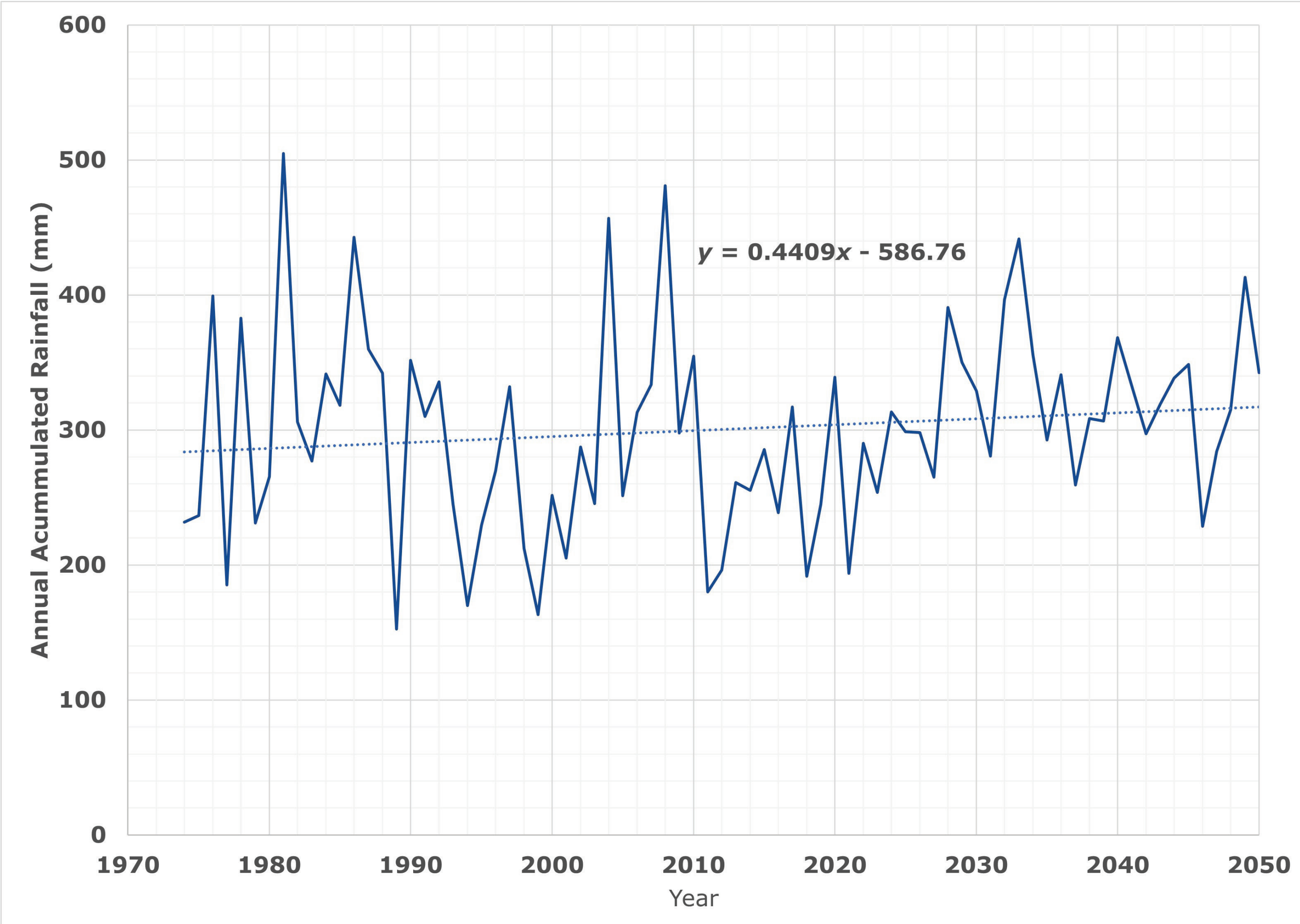

Figure 3. Trend of recorded annual accumulated rainfall with annual accumulated rainfall predicted using the Svanidze method.

Tecnología y ciencias del agua, ISSN 2007-2422,
17(5), 272-310. DOI: 10.24850/j-tyca-2026-05-06

Table 5. Projected synthetic annual rainfall using the Svanidze method (2014-2050).

Year	Rainfall (mm)
2014	255.35
2015	285.43
2016	238.82
2017	316.91
2018	191.72
2019	244.84
2020	338.90
2021	193.90
2022	290.13
2023	253.73
2024	313.37
2025	298.68
2026	297.9
2027	264.95
2028	390.78
2029	349.92
2030	328.84
2031	280.75
2032	396.53
2033	441.48
2034	355.47
2035	292.63
2036	340.99

Year	Rainfall (mm)
2037	259.10
2038	308.32
2039	306.55
2040	368.35
2041	331.88
2042	297.15
2043	318.94
2044	338.38
2045	348.62
2046	228.60
2047	284.10
2048	314.79
2049	413.02
2050	342.52

By applying the study of droughts to the synthetic series, it was found that on average, in the hydrological region 24 Bravo-Conchos, a drought would occur every 3.67 years with an average duration of 2.11 years and a severity of -88.1 mm, equivalent to an intensity of -38.77 mm/year. This amount represents -12.56 % less than its threshold, and the available deficit sheet would be 269.95 mm, with an exceedance probability of 0.55 and a return period of 3.55 years.

The obtained values have dispersion compared to expected values, so considering the standard deviation (Escalante-Sandoval & Reyes-Chávez, 2013), the values characterizing drought in the most unfavorable environment in the hydrological region 24 Bravo-Conchos for the coming years would be those where drought occurs on average every 4.78 years with an average duration of 3.04 years and a severity of -157.79 mm, equivalent to an intensity of -65.37 mm/year. This amount represents -21.17 % less than its threshold, and the available deficit sheet would be 243.35 mm, with an exceedance probability of 0.22 and a return period of 4.55 years as shown in Table 6.

Table 6. Projected drought characteristics using synthetic data.

Statistic	**Mean**	**Worst-case scenario**
Drought recurrence	4 years	5 years
Average duration	2 years	3 years
Severity (mm)	-88.1	-157.79
Intensity (mm/year)	-38.77	-65.37
Rainfall deficit (%)	-12.56 %	-21.17 %
Available rainfall (mm)	269.95	243.35
Exceedance probability	0.55	0.22
Return period (years)	4 years	5 years

For regional planning purposes, it is recommended that projections based on synthetic data using the modified Svanidze method assume an adjusted annual rainfall of 243.35 mm instead of 308.72 mm, which equates to 78.82 % of the historical mean precipitation.

This study highlights the need for urgent adaptation measures to mitigate the effects of increasing drought frequency and severity due to climate change. Water management strategies and ecosystem restoration policies should be prioritized to ensure the region’s long-term water security.

Discussion

The Bravo-Conchos Hydrological Region (Region 24) faces critical water scarcity, with per capita availability at merely 380 m³/year, classifying it as extremely scarce under the Falkenmark Index (Liu *et al*., 2017; Conagua, 2013b). Despite an annual runoff of 5 590 hm³, the region's low precipitation (36 mm/year) and pronounced aridity render it highly vulnerable to hydrological stress, exacerbated by rapid urban population growth and climate change (López-García *et al*., 2017). International obligations under the 1944 U.S.-Mexico Water Treaty further strain resources, requiring Mexico to deliver 432 million m³/year to the United States (IBWC, 2022), intensifying pressure on agricultural and urban sectors. Strategic binational cooperation, including aquifer recharge, irrigation efficiency, and adaptive allocation, is essential to balance treaty compliance with regional water security.

Climate projections indicate a 22 % reduction in precipitation and up to 18% temperature increase by 2050 under RCP 8.5 (Estrada *et al*., n.d.), threatening aquifer recharge and increasing evapotranspiration. Multi-year drought analysis reveals recurrence every 4.63 years, with an average duration of 2.33 years and a severity deficit of 24 % (Ortiz-Gómez *et al*., 2018). Synthetic series via the Svanidze method suggest stable mean precipitation but heightened drought frequency and intensity. These findings align with Escalante-Sandoval and Reyes-Chávez (2013), confirming drought as a principal threat to water security in northern Mexico.

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Interannual climate variability, particularly ENSO, significantly modulates regional precipitation. El Niño events reduce rainfall via weakened thermal gradients and intensified Caribbean jets, while La Niña may enhance precipitation (Dobler-Morales & Bocco, 2021). Incorporating ENSO dynamics into hydrological models is vital for improving predictive capacity and designing adaptive water management strategies. Planning should consider an adjusted average precipitation of 243.35 mm, representing 78.82 % of the historical mean, necessitating enhanced water use efficiency, storage, and climate-resilient infrastructure.

Comparative analyses with urban regions such as Cape Town and Chennai (Enqvist & Ziervogel, 2019; Jain *et al*., 2021) underscore the compounded impact of demographic pressure and limited renewable water resources, even in non-arid climates. These parallels reinforce the urgency of integrating population dynamics into hydrological planning. The convergence of reduced rainfall, rising temperatures, and international commitments demands comprehensive, multi-scale water governance to ensure long-term sustainability in the Bravo-Conchos region.

Implications of the results

The findings of this study on water availability and climate change in the Bravo-Conchos Hydrological Region suggest that the region will face significant challenges in water management soon. The projected reduction in precipitation and increase in temperatures could further exacerbate water stress in an already water-deficient region.

The precipitation decline under RCP 8.5 could pose a serious threat to surface water resources, affecting urban populations, agriculture, and

Tecnología y ciencias del agua, ISSN 2007-2422, 17(5), 272-310. DOI: 10.24850/j-tyca-2026-05-06

key economic sectors. This highlights the urgent need for adaptation policies, including water management strategies and climate-resilient infrastructure, considering long-term climate projections.

Study limitations

Implications and limitations

The projected decline in precipitation and rise in temperature under RCP 8.5 scenarios pose a substantial threat to water availability in the Bravo-Conchos Hydrological Region, intensifying existing stress on urban, agricultural, and ecological systems. These findings underscore the urgency of implementing adaptive water management policies and climate-resilient infrastructure. However, limitations persist due to the use of CMIP5 models lacking CMIP6 updates, low spatial resolution of global climate models, uncertainties in long-term socioeconomic projections, and limited historical climate data, which collectively constrain the precision of regional assessments.

Future research directions

Future studies should integrate CMIP6 datasets to enhance climate projection accuracy and employ high-resolution models to better capture local variability. Establishing transboundary monitoring systems will be essential for coordinated water governance, particularly under treaty obligations. Additionally, comparative analyses of drought adaptation strategies in regions such as Texas may offer valuable insights for policy development in northern Mexico.

Model evaluation considerations

Due to manuscript length constraints, explicit calibration and validation metrics such as NSE or RMSE were not included. However, the study does not aim to assess the predictive performance of the Svanidze method, but rather to characterize evolving climatic patterns in the Bravo-Conchos region through a triangulated approach. This includes non-homogeneity and trend tests on meteorological stations, climate projections using CMIP5 models under RCP 4.5 and 8.5 scenarios, and synthetic drought modeling via the Svanidze method. Together, these components provide a robust framework for understanding future drought and water stress scenarios, even in data-scarce environments. Future research will incorporate precision metrics like NSE to evaluate the performance of stochastic models. This will enhance the reliability of projections and support more informed decision-making in the face of climate change.

Conclusions

This study reveals a concerning outlook for the Bravo-Conchos Hydrological Region, as climate change threatens to worsen water scarcity in an already water-stressed region.

The projected decline in precipitation and rise in temperatures require urgent adaptation measures, including efficient water management and urban planning strategies. Future research should integrate CMIP6 climate models to enhance projection accuracy. Finally, cross-border collaboration with the United States, particularly with Texas, is crucial for joint water resource management and addressing climate change challenges effectively.

Acknowledgements

I would like to express my gratitude to the National Autonomous University of Mexico (UNAM) for its support in conducting this research. I also acknowledge the financial assistance provided by SECIHTI during my research stay. Furthermore, I am deeply grateful to Dr. Lelys Bravo de Guenis for her support in facilitating my scholar research at the University of Illinois at Urbana-Champaign.

Funding

This research was conducted as part of the doctoral program in engineering at the National Autonomous University of Mexico (UNAM). The work was supported by a national graduate fellowship awarded by the then-National Council for Science and Technology (Conacyt) during the lead author's doctoral studies.

Conflict of interest statement

The authors declare that there are no conflicts of interest related to the research, authorship, or publication of this article.

Statement on the use of Artificial Intelligence (AI)

No artificial intelligence tools were used in the preparation, analysis, interpretation of results, or writing of this article.

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