DROUGHT TRENDS IN A COASTAL REGION WITH COMPLEX TOPOGRAPHY IN NORTHERN COLOMBIA

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ABSTRACT
This research focused on analysing drought trends in a geographically diverse coastal region in northern Colombia (10°76′–11°14″N, 72°85′–72°71′W) from 1982 to 2022, using a rigorous methodology. We used the Standardised Precipitation Index (SPI) to study the variability of meteorological drought monthly and annually. Our analysis incorporated precipitation data from the ERA5-Land dataset and monthly precipitation records from four weather stations in the study area. It allowed us to refine the accuracy of the drought index by accounting for bias. The SPI index was calculated considering the 12-month total precipitation accumulation period. Our findings revealed two significant characteristics of estimated surface precipitation in the region: higher precipitation levels were observed between August and November compared to the months from December to April, and a bimodal pattern was identified showing peaks in May and October. Analysis based on the SPI index identified medium and long-term drought trends, with several extreme drought events occurring between 1997–1998 and 2014–2016.
Keywords: meteorological droughts, SPI, ERA5-Land global reanalysis.

1 INTRODUCTION
The increase in extreme weather events, such as heavy rains, storms, floods, droughts, and heat waves, is attributed to human-induced climate change resulting from various human activities. Droughts are extensively studied climatological occurrences due to their significantly severe socioeconomic and environmental impacts compared to other natural disasters [1]. Droughts result in annual economic losses between US$6 billion and US$8 billion, significantly surpassing other natural disasters [2]. The UN World Food Programme has reported that drought events in Africa have resulted in approximately 13 million people facing food insecurity [3]. Drought events can have a detrimental impact on the environment as they increase the likelihood of forest fires, which can destroy flora and fauna and disrupt ecosystems.

The frequency and intensity of drought tend to be more severe in numerous tropical regions, including Central Africa, Southeast Asia, Australia, and various countries in South America [4]–[7]. In recent years, Colombia has faced multiple droughts, significantly impacting agricultural production. The economy, heavily reliant on agriculture, has suffered as a result. La Guajira department, in particular, is susceptible to droughts due to its location and socioeconomic circumstances. Over the past few decades, the region has endured several droughts, leading to socioeconomic and environmental consequences.

One of the most concerning environmental impacts in the La Guajira department is the diminishing water sources, which significantly affect rural and urban communities. The decrease in river water supply for urban populations is primarily due to droughts. Over recent years, the flow of the Tapia River has decreased significantly because of low rainfall during the summer season [8]. Water shortages in the La Guajira department affect the food security of rural populations, leading to significant crop losses and directly impacting over 63,000 people [9], [10]. Indigenous communities, with 90% of their population residing in

www.witpress.com, ISSN 1743-3541 (on-line)
doi:10.2495/SDP240501

municipalities classified as very high water vulnerability areas, are particularly affected by this issue [11], [12]. In light of ongoing climate change and heightened human activities, it is imperative to comprehend the evolving nature of droughts across different spatial and temporal scales. Thus, this study aims to calculate the droughts within northern Colombia’s topographically intricate coastal region during the last decades.

2 MATERIALS AND METHODS

This study was conducted in the Department of La Guajira, located in northern Colombia in the Caribbean Region (Fig. 1). The geographic coordinates of the area are approximately between 10°00' and 12°30' N and 71°15' and 73°00' W (Fig. 1). La Guajira experiences a predominantly arid and semi-arid climate with high temperatures and trade winds contributing to the arid conditions. Due to its location and proximity to the Caribbean Sea, the diverse topography in the Department also plays a role in modifying the climate. To the west, the Sierra Nevada de Santa Marta mountain system and to the east, the Perijá mountain range, both part of the Andes Mountains, contribute to the varying humidity levels. Higher humidity levels are recorded in areas adjacent to the Sierra Nevada de Santa Marta and the Serrania de Perijá. In contrast, humidity and precipitation levels decrease in the extensive plains in the northern part of the Department. The drought index was determined using data from ERA5-Land, a reanalysis dataset that offers a consistent view of changes in terrestrial variables over several decades with improved resolution compared to ERA5. The data is available hourly and can be downloaded in a regular 0.1° × 0.1° latitude/longitude grid via the Climate Data Store (CDS) catalogue (https://cds.climate.copernicus.eu/#!/home) [13].

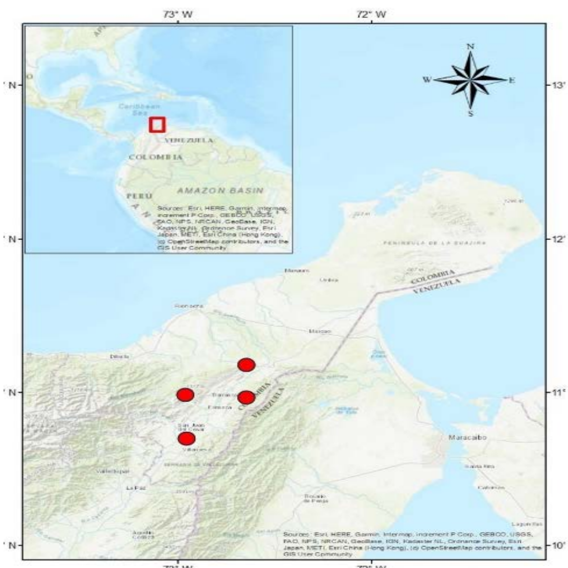

Figure 1: Study domain: coastal region with complex topography in northern Colombia. Red circles represent the locations of the rain gauges used in this study.

We assessed the accuracy of ERA5-Land datasets in depicting rainfall by comparing the recorded rainfall estimates from four rain gauges (Fig. 1). We calculated the mean square error (MSE), BIAS, correlation coefficient (r), normalised root mean square error (NRMSE), and Nash–Sutcliffe efficiency (NSE). To address any bias in the precipitation data estimated by the ERA5-Land dataset, we applied quantile mapping (QM) for adjustment. This method involves aligning the distribution of the estimated variables with the observed distribution through a quantile-based transformation.

The procedure begins with the calculation of empirical quantiles for the distributions of the ERA5-Land data ($Q_m(p)$) and the data recorded by rain gauges $Q_r(p)$, where p represents the specific percentile. Quantiles are obtained as the inverse function of the empirical cumulative distribution function, described by eqns (1) and (2):

$$Q_m(p) = F_m^{-1}\,(p) \tag{1}$$

$$Q_r(p) = F_r^{-1}\,(p) \tag{2}$$

where F_m^{-1} and F_r^{-1} are the inverse functions of the empirical cumulative distributions for the ERA5-Land dataset and the observational data, respectively.

Subsequently, a transfer function is constructed to establish a relationship between the quantiles of the ERA5-Land data and those of the rain gauge data. This transfer function allows for adjusting the ERA5-Land estimates using eqn (3) [14]:

$$X_{adj} = Q_m^{-1}\,(F_m(X)) \tag{3}$$

where X is the precipitation value estimated by the model, F_m is the empirical cumulative distribution function of the ERA5-Land data, and Q_m^{-1} is the quantile function of the observed data.

This transformation ensures that the quantiles of the ERA5-Land data align with the observed quantiles, thereby improving the correspondence between the estimated distributions and the empirical observations. Finally, the adjustment is validated by comparing the adjusted distributions with the observational distributions, ensuring an accurate representation of the modelled data relative to the actual data [15]. The bias correction through quantile mapping was conducted using R version 4.4.1, and the $qmap$ statistical package facilitated the quantile transformation [16].

It is important to note that droughts were assessed using the Standardised Precipitation Index (SPI). This index helped evaluate the variations and patterns of precipitation over different time periods. The study specifically used two SPI calculations: SPI-6, which considered precipitation over six months and provided insights into medium-term droughts, and SPI-12, which considered precipitation over twelve months and helped identify and analyse long-term hydrological droughts [17]. To calculate the SPI, a Gamma distribution adjustment must be made (see eqn (4)). Then, the Cumulative Distribution Function (CDF) is calculated (eqn (5)), and finally, the transformation to a Standard Normal Distribution is performed (eqn (6)).

$$f(x;\alpha,\beta) = \frac{x^{\alpha-1}e^{-x/\beta}}{\beta^{\alpha}\Gamma(\alpha)} \tag{4}$$

where x represents the cumulative precipitation, α is the shape parameter, β is the scale parameter, and $\Gamma(\alpha)$ is the gamma function.

$$F(x) = \frac{1}{\Gamma(\alpha)} \int_0^x t^{\alpha-1} e^{-t/\beta} dt \tag{5}$$

$$SPI = \phi^{-1} F(x) \tag{6}$$

where ϕ^{-1} is the inverse function of the CDF of the standard normal distribution.

3 RESULTS AND DISCUSSION

3.1 ERA5-Land precipitation dataset performance

In order to verify the accuracy of ERA5 ground data in predicting precipitation in the mountainous areas of the Guajira department, we compared it with data from surface weather stations in the same regions. Table 1 presents BIAS, NRMSE, *r*, NSE, and MAE values. Overall, ERA-Land accurately predicted monthly precipitation variations with acceptable BIAS values. The study found that ERA5-Land tends to underestimate monthly precipitation in the study area, especially in areas below 500 m of altitude. However, in higher altitude areas (>500 m), ERA5-Land shows a slight overestimation of monthly precipitation. These results are based on data from four rainfall gauges. The average values of NRMSE and MAE were 1.04 and 51.82 mm, respectively. The higher NRMSE value indicates that ERA5-Land may have limited accuracy in replicating rainfall compared to actual observations. The moderate linear relationship (average *r* of 0.56) between ERA5-Land data and observed data suggests that the dataset can capture general trends, but caution is advised when using it for drought indicators.

Table 1: Statistical performance of monthly rainfall estimates provided by ERA-Land regarding four rainfall events in the study area.

Rain gauge ID	BIAS	NRMSE	*R*	NSE	MAE (mm)
Saba_1	−0.07	0.77	0.68	0.37	44.39
Cana_1	−0.32	0.93	0.51	0.04	62.10
LaGl_3	0.12	1.20	0.51	0.02	42.42
LasLom4	0.04	1.28	0.52	0.05	58.38

In Fig. 2, most of the data points are concentrated around the $y = x$ line, indicating that ERA5-Land effectively captures the overall trends in monthly precipitation. However, there is notable variability in the precision of the estimates, as evidenced by the significant scatter around this line. The trend line slope fitted to the scatter plot data is less than 1, with a coefficient close to 0.84. This suggests that ERA5-Land can estimate more than 80% of the observed variability.

The analysis reveals a significant observation: NRMSE values are notably higher in higher altitude areas than in other regions. An analogous study in the Andean region of South America, utilising similar precipitation datasets, reported an NRMSE of 0.85, indicating significant errors smaller than those in our analysis, emphasising that regions with intricate topography cannot replicate precipitation data [18]. Moreover, on a global scale, research indicates that precipitation reanalysis products exhibit higher errors in areas with complex topography. For instance, the Global Precipitation Measurement (GPM) reported lower

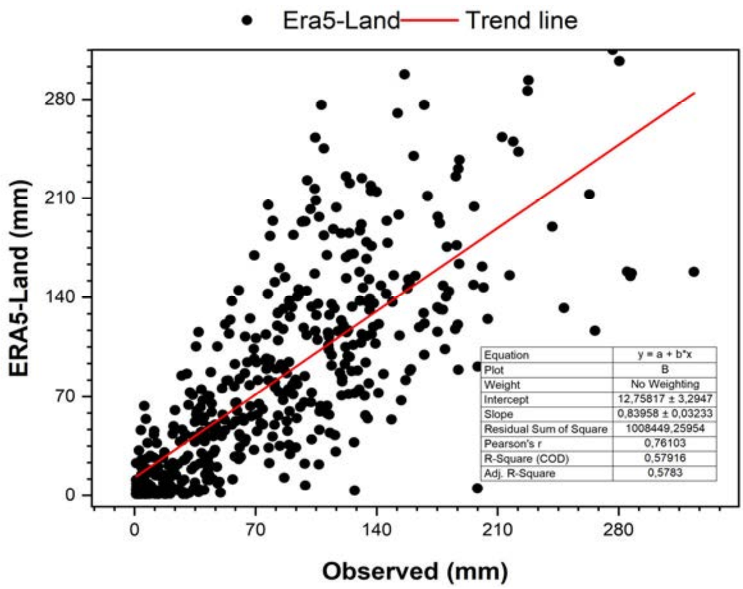

Figure 2: Scatter plots of observed vs. estimated monthly rainfall data by ERA5-Land.

NRMSE in flat areas than in mountainous regions [19]. These findings substantiate our observation that altitude and terrain complexity harm the accuracy of ERA5-Land.

3.2 Monthly and annual rainfall patterns

The heatmap in Fig. 3 illustrates the monthly precipitation (mm/month) in four rain gauges located in a coastal region with complex topography in northern Colombia. In the first half of the year, the highest precipitation levels were observed in April, with an average of up to 198 mm recorded in May. Conversely, from August to October, the highest rainfall levels were recorded during the second half of the year, with values surpassing 90 mm (reaching up to 230 mm). From December to March, there was a notable decrease in rainfall, making these months relatively dry. The region's rainfall pattern has two distinct phases: a dry spell from December to March and the highest rainfall in October and November [20]. Lower wind speeds during this time, as the trade winds wane, likely influence this pattern [21]. The intertropical convergence zone (ITCZ) movement directly across the study area from September to November causes this effect. As a result, the trade winds merge with the ITCZ and struggle to reach the region due to their reduced force, insufficient to disperse the clouds when the winds are blowing [22]. This is in line with research conducted by Beltrán, which suggests that the weakening of the trade winds and the shift of the ITCZ impact humidity transport, leading to irregular rainfall in northern Colombia [23].

The average annual precipitation in the study area is 946 mm. In 2010, the highest recorded precipitation levels in the study area reached 1742 mm annually. In contrast, the mean annual precipitation in 2016 was 424 mm. The area's precipitation decline is associated with the El Niño phenomenon. According to Arias et al. [22] and Beltrán and Díaz [23], the reduced precipitation levels during 2001–2003 are connected to the warm phase of ENSO. ENSO events result in emergencies related to food security, water scarcity, and forest fires.

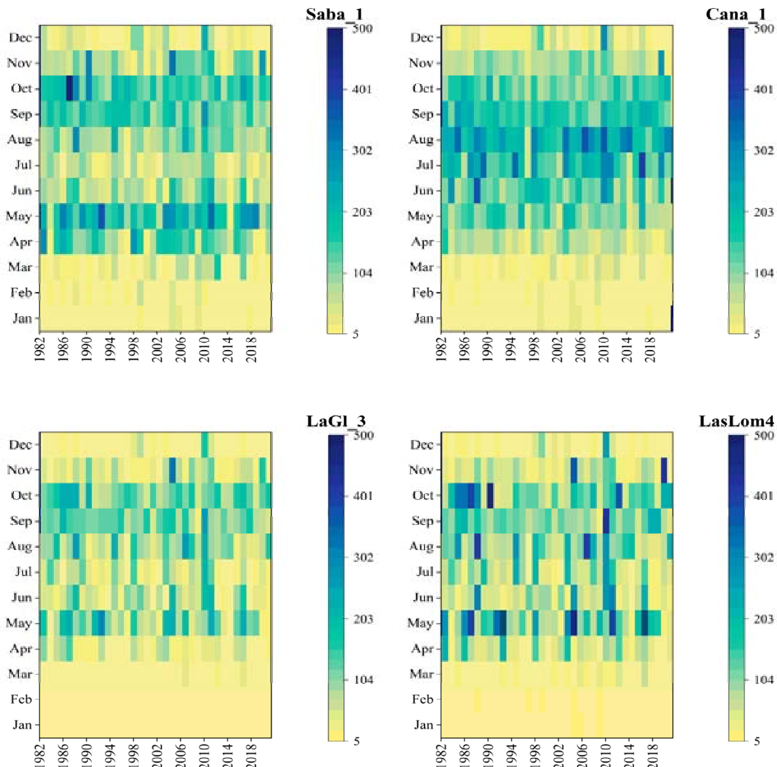

Figure 3: Heatmap of monthly precipitation (mm/month) in four rain gauges in a coastal region with complex topography in northern Colombia.

3.3 SPI index

Fig. 4 illustrates the SPI variations for the study area from 1982 to 2022. An SPI value below −1 indicates a significant drought event. Medium-term drought trends are discernible, with multiple extreme drought events occurring between 1997 and 1998 and 2014 and 2016. Long-term drought trends are evidenced by the SPI 12-month values, depicting prolonged periods of annual water deficit. The notably dry periods of 2014–2017 and 2020–2021 substantially impacted water resource availability. Analysis of SPI-6 values reveals 38 moderate, 16 severe, and 15 extreme drought events.

3.4 Drought management: Comparing strategies and implications for La Guajira

The findings of this study have significant implications for local communities in La Guajira and public policy formulation. The comprehensive analysis of drought data over the study period (1982–2022) using the ERA5-Land dataset has identified critical trends and patterns to enhance preparedness for future drought events. Previous research has demonstrated that adopting resilient agricultural practices, such as using drought-resistant crops and optimising planting schedules, can significantly increase agricultural productivity and sustainability in

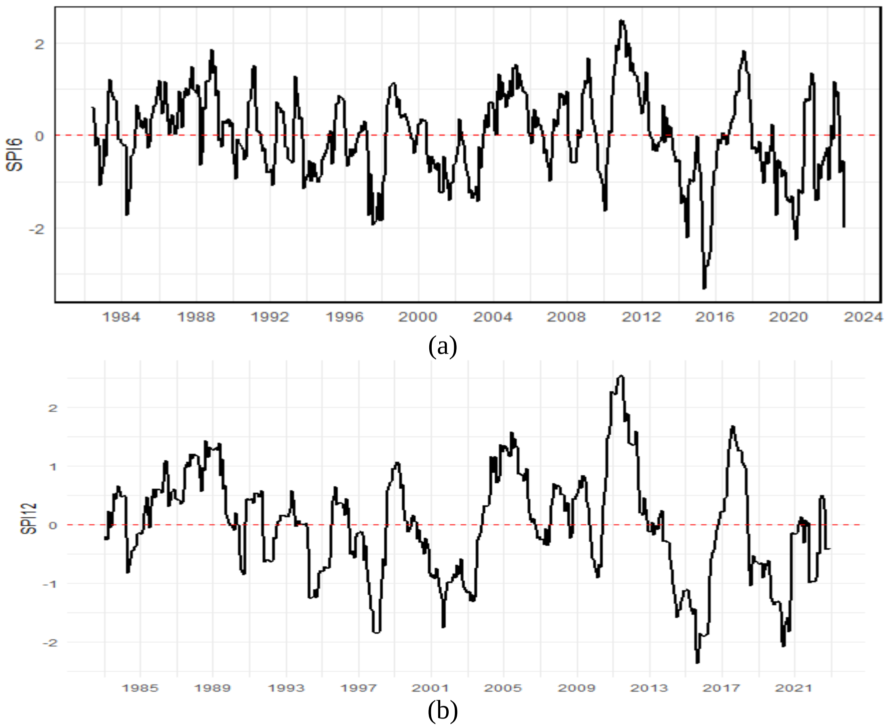

Figure 4: Variations of SPI-6 (a) and SPI-12 (b) in the study area from 1982 to 2022.

water-stressed regions [24]. Furthermore, implementing advanced irrigation technologies has been identified as a critical strategy to optimise water use and enhance agricultural resilience to climate variability [25]. Research in other arid regions, such as the Sahel in Africa, reveals that during the 2000–2020 period, intense droughts reduced annual precipitation by up to 20%–30% compared to previous years [26]. Similarly, in the southwestern United States, the frequency of winter droughts more than tripled, affecting 41%–65% of the years compared to 7%–14% in previous decades [27]. In the Sahel, adopting drought-adapted crops and improvements in water storage infrastructure have effectively mitigated food insecurity and health problems related to water scarcity, reducing food insecurity by approximately 25% and water-related diseases by 15% [28]. Similarly, in the southwestern United States, implementing efficient irrigation technologies and water management based on historical climate data has improved water use efficiency by 20% and increased agricultural resilience by 18% [29].

The findings of this research highlight the need for robust public policies for sustainable water resource management in La Guajira. Planning and implementing water storage infrastructure, such as reservoirs and wells, as well as promoting rainwater harvesting systems, are recommended strategies to ensure a reliable water supply during droughts [30]. Additionally, regulating water use based on historical data and climate projections can facilitate more sustainable management and reduce the risk of shortages [31]. Integrating these practices and research from regions with similar climate challenges will enhance La Guajira’s capacity to address climate variability and promote equitable and sustainable water resource management.

4 CONCLUSION

The ERA5-Land was found to underestimate precipitation by as much as −0.7 mm and performs relatively well in regions with medium altitudes, with a slight bias. The NRMSE suggests that its accuracy of precipitation predictions is limited. In addition, it presents an acceptable average accuracy level in terms of MAE. It presents a moderate ability to replicate general precipitation trends, as indicated by the *r* of 0.56. The analysis of July monthly precipitation reveals a systematic overestimation by ERA5-Land compared to weather station observations. The behaviour of annual precipitation reveals a systematic tendency for the estimated values to underestimate precipitation in different years of the period studied. Although the ERA captures the annual variability well, the constant overestimation suggests the need for adjustments in its parameterisation. With continued improvements and rigorous calibration, it is possible to increase the accuracy and reliability of the ERA5-Land for future water resource management and agricultural planning applications. The use of SPI allowed the identification and characterisation of drought events at different time scales, providing a comprehensive view of drought conditions in the region. It is recommended that additional adjustment and validation methods be explored to improve the estimates. This study reveals that ongoing droughts significantly affect local communities, especially the Wayuu, worsening food insecurity and health problems. Effective policies should prioritise adopting drought-resistant crops, optimising irrigation practices, and investing in water storage solutions. By utilising data-driven strategies and implementing sustainable practices, La Guajira can strengthen its resilience and enhance preparedness for future droughts, thereby improving community well-being and regional stability.

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