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Assessing Drought Vulnerability of the Alberta: A Deep Learning Approach for Hydro-climatological Analysis †

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Abstract: This study investigates the vulnerability of Alberta province in Canada to extreme weather events, particularly drought, which has historically caused significant financial losses. Accurate simulating techniques are crucial for obtaining reliable results to identify trends and patterns in Alberta climatology. In this study, 4 monthly synoptic station data spanning 35 years (1979 to 2014) using Long Short-Term Memory (LSTM) to analyze patterns of precipitation. Additionally, the Standardized Precipitation Index (SPI) was used to identify drought severity at different time scales SPI (3, 6, 12). The results demonstrate that drought occurrences have been observed in the Southern part of Alberta, with rising tendencies in larger areas such as Calgary agricultural areas are prone to severe drought.

Keywords: Drought; Precipitation patterns; Standardized Precipitation Index (SPI); Long Short-Term Memory (LSTM)

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1. Introduction

The changing climate is anticipated to lead to more severe drought events and their consequential impacts on both society and the environment [1, 2]. Drought occurrences are not limited to specific geographical regions, being widespread across the world and posing challenges in their accurate quantification [3]. Extensive research has investigated the effects of climate change on water discharge patterns and unveiled the possibility of increased severity of drought events in numerous regions, such as Europe, central North America, Central America, Mexico, northeastern Brazil, and southern Africa [4]. According to [5] there has been a substantial increase in the extent of global regions prone to chronic draughts

The Standard Precipitation Index (SPI) stands as a widely utilized drought index, considered one of the most popular and accepted ones, originally developed by [6]. The SPI holds several advantages over other drought indices, including consistent spatial interpretation and reduced computational complexity, making it well-suited for prediction and risk analysis [7]. Also Developing an accurate climate model is challenging due to its nonlinear nature [8]. One prominent technique utilized for learning long-term dependencies especially when dealing with time series data, is Long-Short-Term-Memory (LSTM), which was introduced by [9] and has demonstrated superior capabilities compared to Recurrent Neural Networks (RNN). [10]

The main objective of this study is to simulate and find Alberta's climate pattern by deep learnings LSTM method and diagnose the drought vulnerability of Alberta by using SPI (3, 6, 12) with monthly precipitation data from four gauging stations in the study area which is depict in figure 1. To find out the performances of the utilized method, the Root

Mean Square Error (RMSE), as well as the Coefficient of Determination (DC), are used as performance indicators.

2. Methods and Materials

2.1. Study area and data set

Alberta is a Canadian province situated in the southern region, covering an area of 661,000 square kilometers. Figure 1 shows the agricultural areas in the southwestern corner, confined by coordinates 49°N in the south, 110°W in the east, 120°W in the west, and 57°N in the north, spanning approximately 257,848 square kilometers. Agricultural regions in Alberta experience a steppe climate with continental influences. During the hottest days of the year, temperatures can reach up to 30 degrees Celsius or even higher. The region receives an average annual precipitation of approximately 425 millimeters. Additionally, observational data from four stations located within the regions of the province will be employed, and these data are available on the website www.acis.alberta.ca.

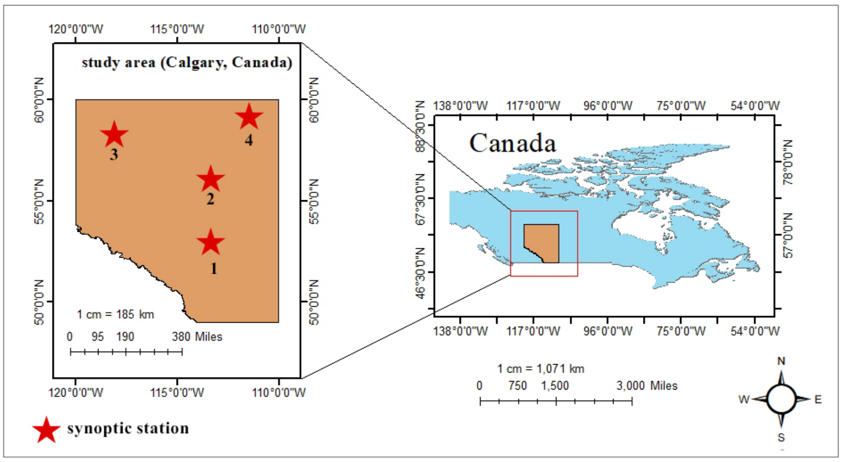

Fig. 1. The location of the study area and synoptic stations employed in the study.

2.2. Standard Precipitation Index (SPI)

SPI is a prominent drought monitoring indicator adopted by the World Meteorological Organization [11]. The SPI is a probabilistic measure that relies exclusively on precipitation data and was introduced by [5] to evaluate precipitation deficits in a manner distinctively linked to probability. The SPI is calculated across various accumulation timeframes, typically relying on monthly precipitation data, denoted as SPI-n, where 'n' signifies the number of months over which the accumulation occurs. This calculation can be likened to a moving average, where each month's value is correlated with preceding months, determined by the chosen accumulation timeframe. Negative SPI values indicate drier conditions than what is considered typical for the given timeframe and location, while positive SPI values denote wetter conditions compared to the expected norm for that specific timeframe and location.

The SPI is defined as:

$$SPI_i = \frac{X_i - \bar{X}}{Sd} \quad (1)$$

Where 'Xi' represents the precipitation value for a specific period 'i. 'X¯' denotes the mean precipitation in the historical series for the same period 'i,' while 'Sd' represents the standard deviation of the mean precipitation in that period.

2.3. Long Short-Term Memory

The LSTM network, a specialized type of Recurrent Neural Network (RNN), has been demonstrated to be stable and effective in modeling long-range dependencies [12] The LSTM networks are a type of recurrent neural network with memory blocks containing a cell state, input gate, forget gate and output gate. The cell state serves as memory, while the gates control information flow. The input gate manages new input, the forget gate determines what to forget from the previous state, and the output gate decides how to use memory for the output. LSTMs excel at learning from sequential data. For detailed mathematics, refer to [9]

2.4. evaluation criteria

In assessing the efficacy of the employed methodologies within this investigation, two evaluation criteria, namely root mean square error (RMSE) and the coefficient of determination (referred to as DC or Nash-Sutcliffe), were utilized:

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{N} (R_i - Z_i)^2}{N}} \tag{2}$$

$$\mathrm{DC} = 1 - \frac{\sum_{i=1}^{N} (Z_i - R_i)^2}{\sum_{i=1}^{N} (Z_i - \bar{Z})^2} \tag{3}$$

Where R_i signifies the estimated value, Z_i represents the target value, $\bar{Z}$ stands for the average value of the target observations, and N denotes the size of the sample. The RMSE maintains the same dimension as the observations, whereas the DC is unitless and falls within the range of (-∞, 1]. A higher DC value approaching 1 indicates a greater degree of accuracy in the regression analysis.

3. Results

3.1. Standard Precipitation Index (SPI)

This study aims to monitor the drought using the SPI index in Alberta, Canada. In this way, the input data were collected from Alberta's 4 synoptic stations for the period spanning from 1979 to 2014. Moreover, an LSTM-based statistical downscaling model was used to simulate and assess the suitability of this method for prediction purposes. Since the input data contains missing values, the missing data was filled by the seasonal pattern method, then, the SPI values were calculated at the temporal time scales of 3, 6, and 12 months. The seasonal pattern method first identified the seasonal pattern of observation data, which refers to repeating patterns or trends that occur at regular intervals. Then, the observation data is decomposed into its constituent components. After that, the method imputed missing values in the seasonal component of the data. In the second step, the SPI values were calculated at the time scales of 1,3,6 and 12 months in different regions of Alberta.

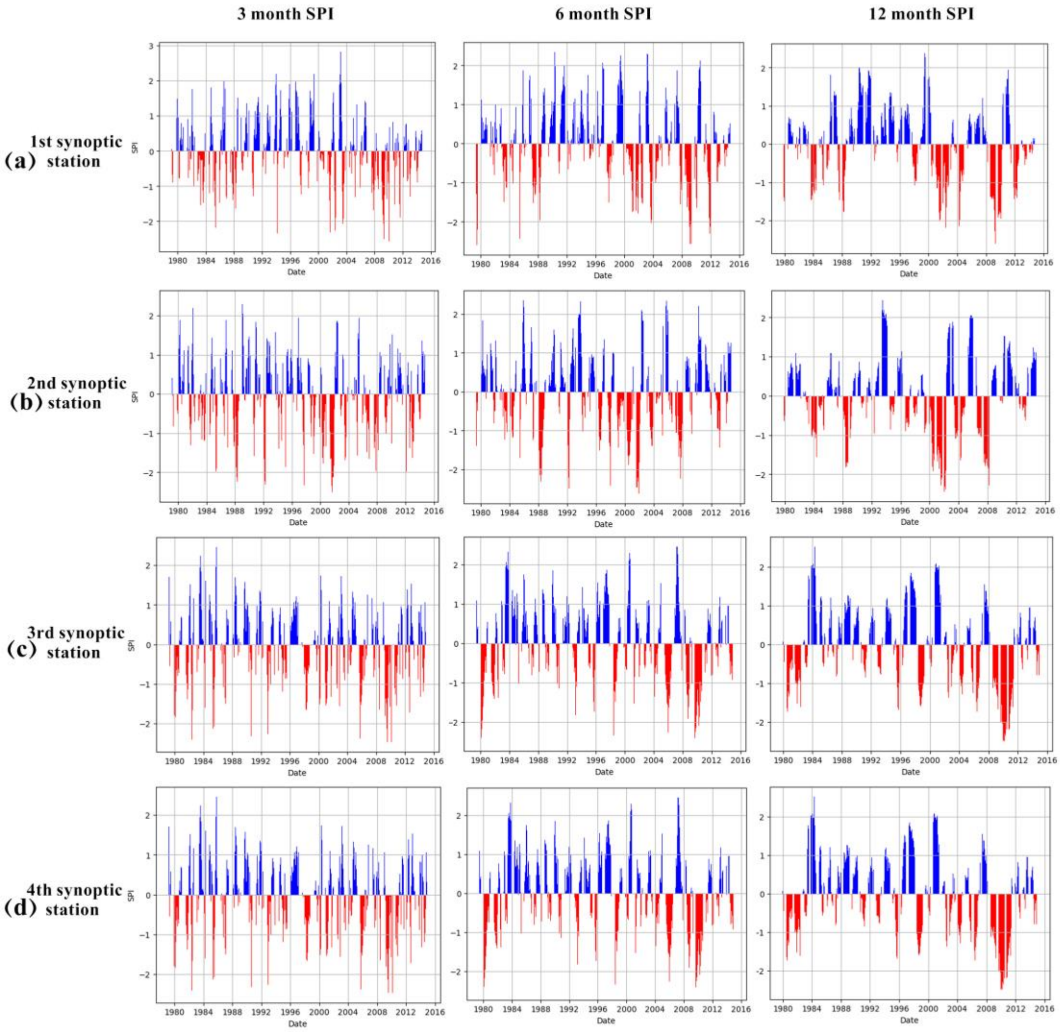

Figure 2. The SPI 3, 6, and 12 indices for 4 synoptic stations of Alberta province which illustrated by (a) to (d) in Figure .

According to the information provided in Figure 2, it is apparent that the indices for all stations displayed significant fluctuations when observed over shorter periods. However, these fluctuations tended to decrease as the analysis focused on longer time scales. In the context of a 12-month drought period, the first station, as depicted in Figure 2 (a), experienced its most pronounced drought conditions during the middle and end portions of the statistical period, specifically spanning from 2000 to 2004 and from 2008 to 2010, covering a duration of eight years. Furthermore, according to figure 2 (b) at the second station, based on the 12-month drought period, the most drought occurred in the middle and the end of the reference period (i.e., 1983-1985, 1988-1989, 2000-2003 and 2007-2008) by the 11 years And at the third station Figure 3 (C), the drought occurred longer than the first and second stations by 15 years. The drought in this station occurred in the first 5 years, middle and the last decade of the statistical period. Finally, in Figure 2 (d) the longest drought period happened by 18 years at the fourth stationSimilar to the third station, drought events transpired during the initial, middle, and final years of the statistical period. The findings from the SPI analysis reveal that the most severe drought occurrences took place at the first and second stations, three times each, and at the third and fourth stations, two times each. Considering severe drought, all stations experienced the same drought event 8 times during the statistical period and concluded that the fourth station had the most intense number of drought events and longest periods among others.

3.2. Statistical downscaling

The simulation procedure was conducted utilizing an LSTM network, as depicted in Figure 3 with the primary objective of evaluating the suitability of this network for the task at hand.

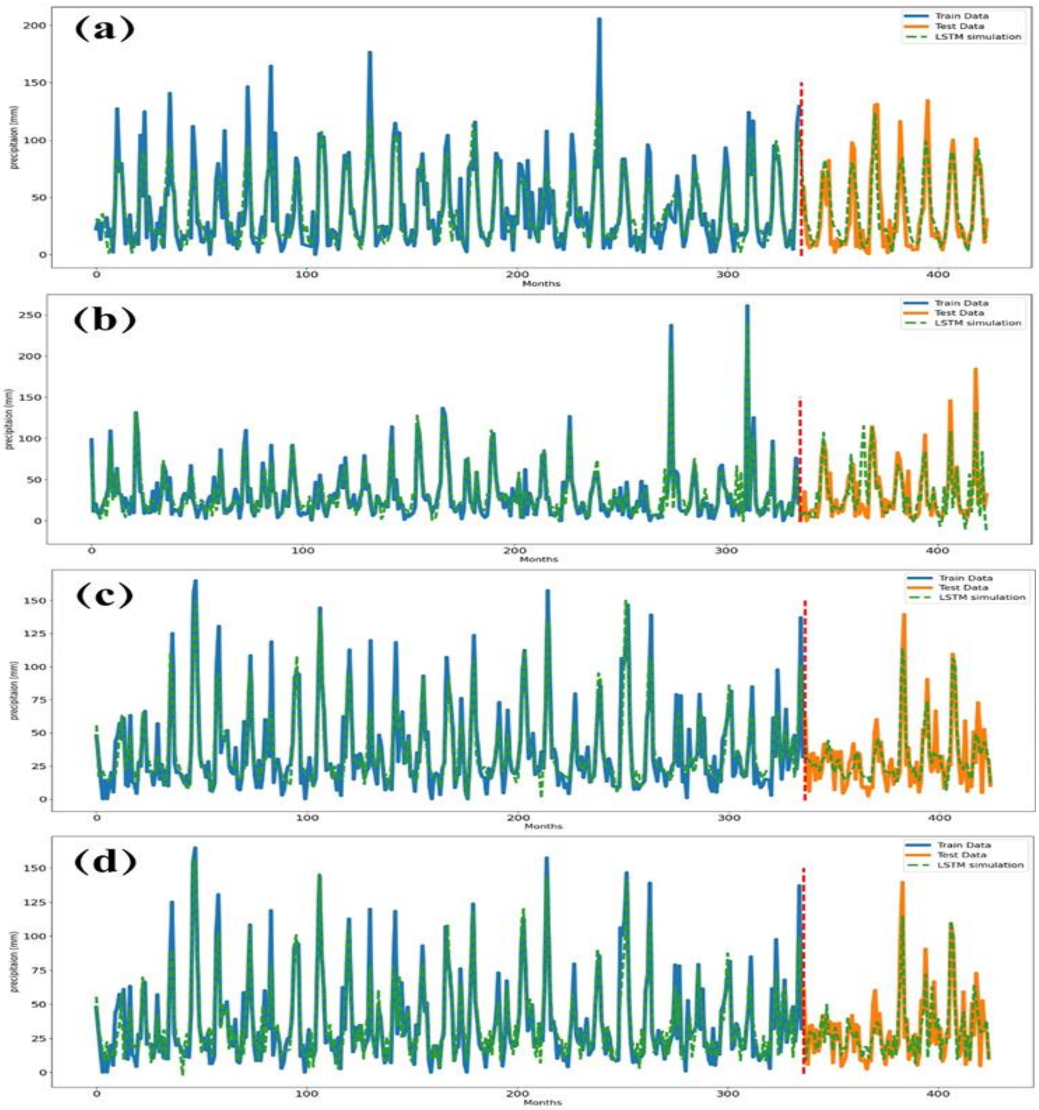

Figure 3. The simulated LSTM precipitation model of Alberta province from 4 synoptic stations which depict the stations (a) to (d) with an 80-20 split sampling approach for model training and validation.

Table 200. epochs, the utilization of a hyperbolic tangent activation function, a batch size of 16, incorporation of six hidden layers, and assessment using RMSE and DC, evaluation metrics. The dataset was partitioned into two subsets: 80% for training and 20% for testing purposes. The outcomes of the simulation procedure are tabulated in Table 1.

Table 1. The training and validation accuracy of the LSTM model.

stations	**Evaluating Criteria**	**train**	**validation**
Station 1	DC	0.71	0.69
	RMSE (mm)	15.61	18.91
Station 2	DC	0.81	0.78

	RMSE (mm)	13.54	14.95
Station 3	DC	0.79	0.74
	RMSE (mm)	13.90	15.41
station 4	DC	0.68	0.58
	RMSE (mm)	18.38	19.44

4. conclusion

Drought, a significant and frequently recurring natural disaster, has detrimental effects on human life. This study aimed to investigate the temporal patterns of drought events spanning short to long durations in an area. The research utilized the SPI-3, SPI-6, and SPI-12 indices and applied deep-learning LSTM models to simulate Alberta, Canada's climate. Data from four synoptic weather stations within the study area (1979 to 2014) were used, with an 80-20 split sampling approach for model training and validation. The findings demonstrate the feasibility of employing the LSTM models technique for investigating drought occurrences in Alberta's climate conditions. Additionally, the study noted that as the SPI magnitude increases, There is a noticeable increase in both the intensity and duration of drought incidents, especially within the southern region of Alberta.

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Data Availability Statement: The data is available upon request

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