Systemic Analytics

www.sa-journal.org

Research Expansion Alliance

J. Syst. Anal. Vol. 4, No. 1 (2026) 27–38.

Paper Type: Original Article

Fuzzy Regression Model to Assess the Rainfall Variability Trend in Kalahandi, Odisha: Leveraging 100 Years of Data for Trend Robustness and Predictive Accuracy

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Received: 17 May 2025 *Revised: 12 July 2025* *Accepted: 05 August 2025*	Mohanta, K. K., & Mohanta, J. (2026). Fuzzy regression model to assess the rainfall variability trend in Kalahandi, Odisha: Leveraging 100 years of data for trend robustness and predictive accuracy. *Systemic Analytics*, *4*(1), 27-38.

Abstract

Linear regression analysis is one of the most common statistical methods used to investigate trends in rainfall over time. However, conventional regression models usually require datasets that have been completely and accurately determined for trend analysis with rainfall, the datasets often include monthly or annual averages which can result in uncertainty in trend analysis. In order to incorporate this uncertainty, fuzzy set theory represents the ambiguity from the analyzed datasets. The fuzzy regression models consider both input and output variables to be Triangular fuzzy numbers. This study proposes a fuzzy regression approach that describes the relationships between precipitation and time in a context of excessive variability in rainfall which creates challenges for the sustainable management of water resources. Kalahandi district in Odisha has been acknowledged as one of the impoverished districts in the KBK Region. The utilization of the fuzzy regression model in addressing trend variability or trends in rainfall in Kalahandi, Odisha is a comprehensive investigation of historical rainfall records related to trends and variability of rainfall in Kalahandi, especially the region's severe effects associated with climate change; it is of utmost importance to understand how rainfall variability trends have changed over time for local agrariens or agriculture workers and policy-makers to recognize changes in rainfall patterns and develop adapted agriculture plans and manage water resources in a variable climate. The data collection process included 100 years of fuzzy rainfall data (1923-2023) which helps to frame current rainfall variability trends in Kalahandi. From this study, it has been shown that Kalahandi is experiencing climate change or other environmental factors that are leading to a substantial increase in rainfall variability. The study methodologically establishes fuzzy regression as an alternate approach to provide a more accurate predictive model for uncertain rainfall.

Keywords: Fuzzy regression model, Rainfall variability, Trend analysis, Predictive analysis, KBK region.

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https://doi.org/10.31181/sa41202668

1|Introduction

The Kalahandi district of Odisha, India, has long been recognized as a climate-vulnerable region due to its reliance on rain-fed agriculture and susceptibility to erratic monsoon patterns [1]. Over the past century, shifts in global climate dynamics—marked by rising temperatures and altered precipitation regimes—have exacerbated hydrological uncertainties in semi-arid regions like Kalahandi [2]. Recent projections indicate a 4–16% increase in rainfall over Odisha by mid-century, coupled with an extended rainy season. While such changes may superficially suggest improved water availability, the inherent variability of monsoon systems poses significant risks to agricultural productivity and water resource management. Traditional statistical methods, such as linear regression and Mann–Kendall trend tests, have been widely employed to analyze climatic trends. However, these approaches often struggle to account for the non-stationarity and uncertainty embedded in long-term rainfall datasets, particularly in regions with pronounced climatic extremes. For instance, linear models may oversimplify nonlinear relationships between climatic drivers and rainfall anomalies, while deterministic frameworks fail to quantify epistemic uncertainties arising from sparse or noisy historical data. This limitation is critical in Kalahandi, where monsoon rainfall directly influences crop yields and socioeconomic stability.

However, in real world-world application of data concerning inputs and/or outputs often has the qualities of being unquantifiable, inconsistent, muddled, and inaccessible when necessary information is absent. The rainfall data used for the analysis does not provide precise values, nor are these values accruate, thus results can be uncertain. This situation can be overcome by using uncertain theory since uncertain theory can be able to mathematically embody the uncertainty encompassed in the sources of data. In 1965 Zadeh [3] was the first to introduce the fuzzy set (FS) as refinement and development of traditional set theory, hence the fuzzy set theory provides a sound framework for the mathematical representation of phenomena that encompasses degrees of imprecision, uncertainty, or ambiguity. This theory can be utilized across fields including; engineering, math, economics, and computer science and etc [4, 5, 6, 7, 8, 9].

To address these challenges, this study proposes a fuzzy regression model tailored for analyzing century-scale rainfall trends (1923–2023) in Kalahandi. Fuzzy logic, with its capacity to model imprecise systems through membership functions and rule-based inference, offers a robust alternative for capturing the vagueness inherent in climatic datasets. By integrating fuzzy sets with regression analysis, our framework quantifies both magnitude and directionality of rainfall trends while systematically evaluating uncertainty—a methodological advance over conventional approaches like ARIMA or multiple linear regression.

The choice of Kalahandi as a case study is strategic because the district epitomizes the interplay between climatic variability and agrarian vulnerability in eastern India. Monsoon rainfall here accounts for over 80% of annual precipitation, yet its spatiotemporal distribution remains highly unpredictable. Prolonged dry spells interspersed with intense rainfall events have destabilized staple crop production, threatening food security for millions. A rigorous analysis of century-long trends is thus imperative to inform adaptive strategies, from irrigation scheduling to drought-resilient crop selection.

By leveraging a 100-year uncertain rainfall datasets, this work aims to:

1. Identify long-term trends in annual and seasonal rainfall, contextualizing findings against global climate change projections
2. Quantify uncertainties in trend detection through fuzzy regression parameters, addressing gaps in deterministic models
3. Assess linkages between rainfall variability and historical crop yield patterns, bridging climatology and agricultural planning

The sections of this manuscript are divided as follows: Section 2 provides an extensive review of the literature on method-focused trend analysis using weather data. Section 3 discusses the features of the study area and states the approach proposed for the analysis of rainfall trends. Section 4 presents the case study rainfall analysis of Kalahandi district, Odisha, by fuzzy regression where the rainfall data is expressed as a triangular fuzzy number to reflect uncertainty. Section 5 summarizes the manuscript by discussing the limitations encountered and considerations for future research.

2|Litereture Review

Rainfall trend analysis is crucial for understanding climate change impacts, water resource management, and agricultural planning [10, 11, 12]. Regression analysis, a widely used statistical technique, plays a significant role in identifying and quantifying these trends. This literature review explores the application of regression methods in rainfall trend analysis, highlighting various approaches, findings, and limitations. Regression analysis is employed to establish a functional relationship between rainfall and time, allowing for the detection of increasing or decreasing trends. The most common approach is linear regression, where a straight line is fitted to the rainfall data over time [13, 14]. The slope of the regression line indicates the rate of change in rainfall per unit of time.

A study by Alahacoon et al. (2018) combined rainfall trend analysis with flood maps derived from satellite data to arrive at holistic spatio-temporal patterns of floods in Sri Lanka [15]. The study used Asian Precipitation-Highly Resolved Observational Data Integration towards Evaluation of Water Resources (APHRODITE) gridded rainfall data. The time series rainfall data explains increasing trend in the extreme rainfall indices with similar observation derived from satellite imagery. The results demonstrate the feasibility of using multi-sensor flood mapping approaches, which will aid Disaster Management Center (DMC) and other multi-lateral agencies involved in managing rapid response operations and preparing mitigation measures. Rathnayake (2019) compared statistical methods to graphical methods in rainfall trend analysis for two tropical catchments in Sri Lanka [16]. Results reveal that, in general, both trend analysis techniques produce comparable results in identifying rainfall trends for different time steps including annual, seasonal, and monthly rainfalls.

Sharma et al. (2018) conducted a trend analysis of historical rainfall data in Agra district, Uttar Pradesh, using parametric and non-parametric models [17]. It was found that some of the months are showing rising trend whereas others showing falling trend of rainfall. Similar types of results were found when annual and seasonal rainfall and rainy days series were tested for their trend. In most cases trends were found no significant at 5% significance level except monthly rainfall of May and August months and also for monsoon season rainfall and rainy days. Saini et al. (2020) analyzed the rainfall trend of the West Coast Plain and Hill Agro-Climatic Region of India for 117 years (1901-2017) [18]. Results indicate that significant trends are observed in January, July, August, September as well Winter season. Among all trends, January and July showed decreasing trend. August months with combined 30% rainfall, show an increasing high magnitude whereas winter season shows comparatively low magnitudes. Adarsh and Reddy (2015) analyzed long-term trends of rainfall in four subdivisions of southern India using linear regression, nonparametric Mann-Kendall (MK) test and Sen's slope estimator methods [19]. Trend analysis of annual rainfall time series shows an increasing trend in three subdivisions – Tamil Nadu, NI Karnataka and Telangana, and a decreasing trend in Kerala subdivision. ALAM and Majumder (2022) focused on the altering historical rainfall data analysis and its variability in Kolkata, India [20]. The MK test shows an upward trend in annual rainfall between 1901 and 2020. Bora et al. (2022) analysed the variability and trends in annual as well as seasonal rainfall in the seven states of North East India for the period 1901-2020, using non-parametric tests like MannKendall, trend-free pre-whitening MannKendall, modified MannKendall (MMK), as well as using the innovative trend analysis (ITA) [21]. The study revealed the variabilities in annual and seasonal rainfall in these seven states. Rehan Khan et al. (2024) presents a comprehensive analysis of rainfall and temperature trends in the Periyar River Basin, using historical climate data spanning several decades [22]. Rainfall analysis revealed substantial inter-annual and intra-seasonal variability in the basin. Enocak and Emek (2019) researched the trend analysis of total monthly and annual rainfalls in the East Anatolia Region [23]. As to assessed monthly total rainfalls trend analysis, it is observed that in the summer months generally rainfalls are increasing direction tendency, in the winter months it is decreasing direction tendency. Ng et al. (2020) conducted a trend analysis using the Mann-Kendall test and Sen's slope estimator in the Kelantan River Basin, Malaysia [24]. The results showed that both increasing and decreasing trends were detected and indicated a northern region Basin an increasing trend, whilst southwest had a decreasing trend. Kruger and Nxumalo (2017) updated the analysis historical rainfall trends in South Africa from 1921-2015 [25]. In general, results show an increase most southern interior Africa, with indications of decreases in far northern and north-eastern parts. Khalil (2023) investigated the monthly, seasonal, and annual rainfall variability in the Mae Klong River Basin in Thailand using the Mann-Kendall (MK) test, Sen's slope method, Spearman's Rho (SR) test, and the innovative trend analysis (ITA) method [26]. For the entire basin, trend analysis found increasing rainfall on both seasonal and annual scales by all the tests. Chemutai Koskei Ednah et al. (2018) assessed actual rainfall trends and variability in Baringo County [27]. Annual rainfall in LM5 and IL6 showed decreasing trends while in LH2, it showed an increasing trend. Monir et al. (2023) analyzed spatiotemporal variations in rainfall for the period 1980-2020 over Bangladesh at seasonal and monthly scales using MAKESENS, the Pettitt test, and innovative trend analysis [28]. The Mann-Kendall trend test reveals that 77% of stations are declining, and 23% have a rising trend in the monthly rainfall. Ogunbode et al. (2022) conducted a thirty-year (1989-2018) rainfall data analysis for Iwo in Osun State, southwestern Nigeria to determine the trend pattern of rainfall [29]. The results showed that while five months showed negative trend indicating declining rainfall over the period, seven months revealed a positive trend implying increasing rainfall over the period for those months. Farhangi et al. (2016) selected 10 subbasins in western Iran and analyzed average monthly and annual rainfall time series to investigate trends [30]. Analysis of mentioned time series of control stations reveals that 51% of time series have decreasing trends, while 49% experience increasing trends. Alemu and Bawoke (2019) investigated the spatial temporal trends of Amhara region using series data [31]. Trend analysis showed an overall increase in annual and seasonal rainfall (except winter) during the period.

Rainfall patterns can be influenced by non-climatic factors, such as land use changes and urbanization [32]. It is important to consider these factors when interpreting rainfall trends. The choice of appropriate statistical and graphical methods is crucial for accurate trend analysis [16]. Different methods may yield different results, and it is important to select methods that are appropriate for the specific dataset and research question. The accuracy of rainfall trend analysis depends on the availability and quality of rainfall data [33]. Long-term, reliable data is essential for identifying meaningful trends. Rainfall patterns can vary significantly across different regions [27]. Trend analysis should account for spatial variability to provide a comprehensive understanding of rainfall patterns. The temporal resolution of rainfall data can affect the accuracy of trend estimation [34]. Using rainfall data with coarse time-resolution can lead to significant errors in trend analysis.

3|Study Area and Methodology

3.1|Study Area

Kalahandi is in one of 30 eastern Odisha districts, located in the west of Odisha, India. Kalahandi district of Odisha is one of the backward districts of KBK Region. Geographically, Kalahandi can be found between latitude 19° 3' N and latitude 21° 5' N and longitude 82° 20' E and longitude 83° 47' E, as shown in Figure 1. Balangir and Nuapada are to the north, Rayagada is south, Koraput and Nabarangpur are to the west and Kandhamal is to the east. Based on its geography Kalahandi has forests, hills, and plains. Its climate is tropical with hot summers and monsoonal rains. The prominent river Indravati supplies water to farmers for irrigating their fields. In Kalahandi, the total population was approximately 1.57 million in 2011, based only on the people who identify mainly as tribes of which the main tribes are Kondha and Soura. In terms of language, most people speak Odia, though there are also dialects of the tribespeople that are also spoken. The economy in Kalahandi is primarily agrarian, with paddy being the main crop. In addition, Kalahandi has a small number of non-timber forest products local and some small-scale industries to support local livelihoods. Historically, despite placing natural endowments, Kalahandi has been known for droughts and food insecurity, and that has become significant to the interest of policymakers and/or researchers. Kalahandi district has been chosen as the study area shown in Figure 1 because it has a complicated socio-economic structure, abundant natural resources, and developmental hurdles that make it a sophisticated place to study rural-ality in a tribal dominated region.

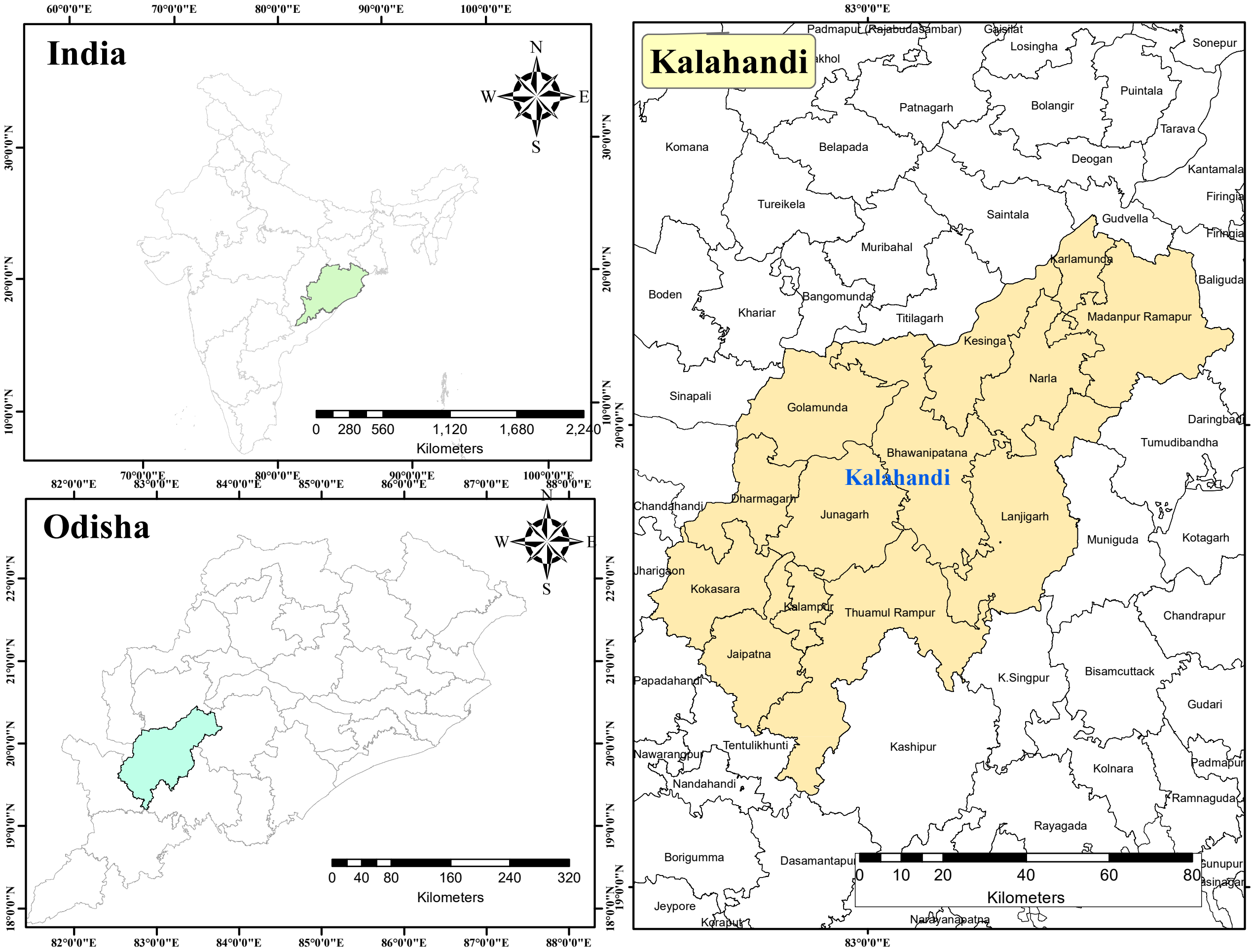

FIGURE 1. Study area for rainfall analysis

3.2|Methodology

Preliminaries

This subsection provides an overview of fundamental concepts such as fuzzy sets, triangular fuzzy numbers (TFNs), and their arithmetic operations.

Definition 1 (Fuzzy set [3]). *The fuzzy set (FS) $\hat{A}$ in Ω is defined as*

$$\hat{A} = \{\langle x, \mu_A \rangle : x \in \Omega\}, \tag{1}$$

where the function $\mu_A : \Omega \to [0,1]$ is the membership grade.

Definition 2. [35] *The triangular fuzzy number (TFN) is denoted by $\widehat{A} = \langle a^L, a^M, a^U \rangle$, the membership degrees of $x \in \mathbb{R}$ is defined as follows*

$$\mu_A(x) = \begin{cases} \dfrac{x - a^L}{a^M - a^U}, & a^L \leq x \leq a^M \\ \dfrac{a^U - x}{a^U - a^M}, & a^M \leq x \leq a^U \\ 0, & otherwise \end{cases} \tag{2}$$

Definition 3 (Arithmetic properties [35]). *Let $\widehat{A} = \langle a^L, a^M, a^U \rangle$ and $\widehat{B} = \langle b^L, b^M, b^U \rangle$ are two triangular fuzzy number, such that*

(i) $\widehat{A} \oplus \widehat{B} = \langle a^L + b^L, a^M + b^M, a^U + b^U \rangle$

(ii) $\widehat{A} \ominus \widehat{B} = \langle a^L - b^U, a^M - b^M, a^U + b^L \rangle$

(iii) $\widehat{A} \otimes \widehat{B} = \langle a^L b^L, a^M b^M, a^U b^U \rangle$

(iv) $\frac{\widehat{A}}{\widehat{B}} = \langle \frac{a^L}{b^U}, \frac{a^M}{b^M}, \frac{a^U}{b^L} \rangle$

(v) $\lambda \widehat{A} = \begin{cases} \langle \lambda a^L, \lambda a^M, \lambda a^U \rangle; & \textit{if } \lambda \geq 0 \\ \langle \lambda a^U, \lambda a^M, \lambda a^L \rangle; & \textit{if } \lambda \leq 0 \end{cases}$

Definition 4 (Expected Value of TFN)**.** *The expected value for a TFN* $\widehat{A} = \langle a^L, a^M, a^U \rangle$ *is defined by*

$$EV(\widehat{A}) = \frac{a^L + 2a^M + a^U}{4} \tag{3}$$

Fuzzy Regression

Regression analysis is a complex statistical technique used to model and examine the relationship between a dependent variable, often referred to as the outcome or response variable, and one or more independent variables, which can also be referred to as predictors or features. The primary purposes of regression analysis are to predict the dependent variable based upon the values of the independent variable, or to show the effect of changing any one independent variable on the dependent variable. The linear regression model is the most commonly used statistical technique, as it offers a simple but powerful way to describe and quantify relationships between one or more variables. By describing these relationships with a linear equation, it allows users to predict future outcomes, identify trends, and make data-driven decisions in fields as diverse as economics, engineering, medicine, and the social sciences. Because of its simplicity to use and interpret, and its role as a basic building block for more complex models, it is one of the most important tools in academia and industry. The traditional simple linear regression model is expressed as

$$Y = \beta_0 + \beta_1 X \tag{4}$$

where Y is the dependent variable, X is the independent variable, β_0 is the intercept, and β_1 is the slope of the regression line. The aim is to estimate the coefficients β_0 and β_1 such that the sum of squared residuals

$$\sum_{i=1}^{n} (Y_i - \beta_0 - \beta_1 X_i)^2 \tag{5}$$

is minimized. This is the classical least squares approach, which assumes that all data points (X_i, Y_i) are precisely known (i.e., crisp values).

However, in many real-life situations, data is uncertain or imprecise and is better represented using fuzzy numbers. To handle such uncertainty, the regression model is extended to a fuzzy regression framework. Fuzzy regression models have become a powerful tool for contending with uncertainty and imprecision in data analysis, which takes conventional regression processes and allows for fuzzy inputs and outputs. Tanaka et al. (1989) [36] were the first to introduce fuzzy linear regression using linear programming methods, while Diamond (1988) [37] introduced a least squares method for estimating fuzzy parameters. Advancements included possibilistic regression [38] and nonlinear fuzzy regression models [39, 40], facilitating broader analysis involving more complex relationships. Recent developments included machine learning-based approaches with fuzzy support vector regression [40] and adaptive neuro-fuzzy inference systems [41], which improve prediction and flexibility. Applications in fuzzy regression are aplenty, including economics [42], engineering [43] and any healthcare related research to the extent there is imprecise data. Despite improvements, there still exist some challenges in scalability, interpretability and the ability to conduct online applications. In this work, we consider the input data in the form of triangular fuzzy numbers (TFNs), denoted as

$$\widehat{X}_i = (X_i^L, X_i^M, X_i^U), \quad \widehat{Y}_i = (Y_i^L, Y_i^M, Y_i^U), \tag{6}$$

where X_i^L, X_i^M, and X_i^U are the lower, middle (most likely), and upper values of the fuzzy input, respectively. Similarly, Y_i^L, Y_i^M, and Y_i^U are the respective components of the fuzzy output.

$$\widehat{Y}_i = \widehat{\beta_0} + \widehat{\beta_1}\widehat{X}_i, \; i = 1, 2, \cdots, n. \tag{7}$$

The independent variable is defined by $\widehat{X} = (\widehat{X}_i)$ and the dependent variable is defined by $\widehat{Y} = (\widehat{Y}_i)$ The fuzzy regression model assumes the same linear form for each component of the TFN, resulting in three separate regression models:

$$Y^L = \beta_0^L + \beta_1^L X^L, \tag{8}$$

$$Y^M = \beta_0^M + \beta_1^M X^M, \tag{9}$$

$$Y^U = \beta_0^U + \beta_1^U X^U, \tag{10}$$

Each model is fitted using the least squares method independently, i.e., by minimizing

$$\sum_{i=1}^{n}(Y_i^L - \beta_0^L - \beta_1^L X_i^L)^2, \tag{11}$$

$$\sum_{i=1}^{n}(Y_i^M - \beta_0^M - \beta_1^M X_i^M)^2, \tag{12}$$

$$\sum_{i=1}^{n}(Y_i^U - \beta_0^U - \beta_1^U X_i^U)^2. \tag{13}$$

The solution to each of these is obtained using matrix operations:

$$\widehat{\boldsymbol{\beta}} = (\widehat{A}^T\widehat{A})^{-1}\widehat{A}^T\widehat{Y}, \tag{14}$$

where $\widehat{\boldsymbol{\beta}} = \begin{bmatrix} \widehat{\beta_0} \\ \widehat{\beta_1} \end{bmatrix}_{2\times 1}$ is the coefficient matrix, $\widehat{A} = [\widehat{1} \quad \widehat{X}]_{n\times 2} = \begin{bmatrix} 1 & \widehat{X_1} \\ 1 & \widehat{X_2} \\ \vdots & \vdots \\ 1 & \widehat{X_n} \end{bmatrix}$ is the design matrix formed using the respective component (lower, middle, or upper) of the TFNs, and $\widehat{Y} = \begin{bmatrix} \widehat{Y_1} \\ \widehat{Y_2} \\ \vdots \\ \widehat{Y_n} \end{bmatrix}_{n\times 1}$ is the corresponding output vector.

Once the regression coefficients are estimated that is $\widehat{\boldsymbol{\beta}^*} = \begin{bmatrix} \widehat{\beta_0}^* \\ \widehat{\beta_1}^* \end{bmatrix}_{2\times 1}$, the predicted output for a new fuzzy input $\widehat{X}_{\text{new}} = (X_{\text{new}}^L, X_{\text{new}}^M, X_{\text{new}}^U)$ is computed as another triangular fuzzy number:

$$\widehat{Y}_{\text{new}} = (Y_{\text{new}}^L, Y_{\text{new}}^M, Y_{\text{new}}^U),$$

where

$$Y_{\text{new}}^L = \beta_0^{L^*} + \beta_1^{L^*} X_{\text{new}}^L, \quad Y_{\text{new}}^M = \beta_0^{M^*} + \beta_1^{M^*} X_{\text{new}}^M, \quad Y_{\text{new}}^U = \beta_0^{U^*} + \beta_1^{U^*} X_{\text{new}}^U.$$

This formulation provides a predictive model that reflects the trend and imprecision of the input–output relationship while capturing the inherent uncertainty in the data.

If one of the input or output is considered as not fuzzy in nature, which converted equivalent triangular fuzzy by considering the three components (lower, middle, or upper) are equal to the observed crisp value.

4|Case Study

4.1|Data Collection

The Table 1 provides a statistical overview of historical monthly rainfall data covering 100 years (1923 - 2023) collected from official government data in Odisha, India (https://indiawris.gov.in/wris/#/timeseriesdata), and presented at 5-year intervals. The data demonstrates large interannual variability, with total annual rainfall occurring from 1023.7mm (1988) to 1932.41 mm (2003), with average monthly totals varying from 85.31 mm (1988) to 161.03 mm (2003). You can see some extreme monthly values with maximum monthly precipitation reaching 816.83 mm (1978), presumably associated with cyclone development, and multiple years had minimum monthly totals in a month of zero, reflecting a number of dry months occurring during the year. The wettest year was 2003 (1932.41 mm total, 161.03 mm average monthly total), and the driest year was 1988 (1023.7 mm total, 85.31 mm average monthly total). Such patterns underline that Odisha has a monsoon climate system, whereby it experiences high variability in the occurrence and amount of rainfall, resulting in weeks of very wet conditions followed by long periods of no precipitation. The data also provide a useful overview of long-term climatic patterns that may inform consideration of water resource management, agricultural forecasting, and infrastructure priorities for the part of India at risk of both flooding and drought. Both the extreme moisture totals observed in particular months of the year alongside repeated zero months in the month suggest the need for adaptive strategies to climatic variability stresses and possible future climate change impacts on this region's water security and ecosystem stability.

Table 1. Statistical description of the rainfall data

Year	Total Rainfall (mm)	Average Monthly Rainfall	Max Monthly Rainfall	Min Monthly Rainfall
1923	1058.35	88.19583333	419.21	0
1928	1420.36	118.3633333	526.7	0
1933	1721.03	143.4191667	477.96	2.03
1938	1410.01	117.5008333	258.02	0
1943	1488.03	124.0025	412.71	0
1948	1376.35	114.6958333	395.62	0
1953	1355.17	112.9308333	529.75	0
1958	1924.59	160.3825	556.69	0
1963	1147.06	95.58833333	331.39	0
1968	1089.02	90.75166667	288.45	1.66
1973	1447.95	120.6625	592.41	0.02
1978	1741.91	145.1591667	816.83	4.46
1983	1219.42	101.6183333	313.28	0
1988	1023.7	85.30833333	251.14	0
1993	1276.31	106.3591667	412.39	0
1998	1088.53	90.71083333	338.81	0
2003	1932.41	161.0341667	660.75	0.17
2008	1862.12	155.1766667	688.6	0
2013	1523.21	126.9341667	377.94	0
2018	1826.19	152.1825	675.58	0
2023	1482.99	123.5825	463.52	0

4.2|Results and Discussions

The study of past 100 years rainfall variability trends in Kalahandi, Odisha shows significant climatic changes that are affecting agricultural practices. Local farmers have shared information on the dramatic changes in temperature and rainfall patterns experienced locally, with nearly 100% of respondents noticed it had changed over the last 40 years. In this study, fuzzy linear regression analysis was applied to model the historical rainfall data of Kalahandi district from the year 1923 to 2023. Each annual rainfall data point was expressed as a triangular fuzzy number. The fuzzy linear regression model was constructed by separately solving the least squares estimates for the lower, middle, and upper bounds, give in equation. The estimated fuzzy regression coefficients were found to be

$$\widehat{\boldsymbol{\beta}^*} = \langle \beta_L, \beta_M, \beta_U \rangle = \begin{bmatrix} \widehat{\beta_0}^* \\ \widehat{\beta_1}^* \end{bmatrix}_{2\times 1} = \begin{bmatrix} \langle \beta_{0L}, \beta_{0M}, \beta_{0U} \rangle \\ \langle \beta_{1L}, \beta_{1M}, \beta_{1U} \rangle \end{bmatrix}_{2\times 1}$$

where β_0 represents the intercept and β_1 represents the slope for each bound of the fuzzy rainfall data. $\beta_L = [\beta_{0L},\, \beta_{1L}]^T = [-11.9284, 0.0137]^T$, $\beta_M = [\beta_{0M},\, \beta_{1M}]^T = [-119.2840, 0.1371]$, and $\beta_U = [\beta_{0U},\, \beta_{1U}]^T = [-550.6927, 0.5117]$. The fuzzy regression model for predicting the future rainfall pattern can be obtained by solving the given equations.

$$Y^L_{\text{new}} = -11.9284 + 0.0137 X_{\text{new}} \tag{15}$$

$$Y^M_{\text{new}} = -119.2840 + 0.01371 X_{\text{new}} \tag{16}$$

$$Y^U_{\text{new}} = -550.6927 + 0.5117 X_{\text{new}} \tag{17}$$

The fuzzy regression model developed was applied to predict annual amounts of rainfall from 2024 to 2040, the results are displayed in Table 2. The predictions were made in the form of a lower bound (Rainfall_L), most likely value (Rainfall_M), and an upper bound (Rainfall_U), which provides the uncertainty range encompassing extreme estimates of rainfall. The expected value of rainfall was also calculated using Equation (3), which can be viewed as a defuzzified single-point estimate for each year. The results demonstrate a steady increase in predicted amounts of rainfall over the years, shown by a definitive rising trend across the fuzzy bounds and expected values. The expected value rainfall especially is indicative of this increasing trend, as it increases from 204.275 mm in 2024, to 207.495 mm in 2040. The lower bound (Rainfall L) remained constant (approximately 15.8 – 16.04 mm), indicating very little variability across the driest scenarios. The upper bound (Rainfall_U) on the other hand, demonstrated more increasing trend with the Rainfall_U value increasing from 484.9 mm in 2024, to 493.18 mm in 2040. The increase for Rainfall_U also reflects greater uncertainty associated with extreme rainfall events.

Table 2. Predicting rainfall upto year 2040

Year	Rainfall_L (mm)	Rainfall_M (mm)	Rainfall_U (mm)	Expected Value (mm)
2024	15.82	158.19	484.9	204.275
2026	15.85	158.46	486.01	204.695
2028	15.87	158.74	487.04	205.0975
2030	15.9	159.01	488.06	205.495
2032	15.93	159.29	489.08	205.8975
2034	15.96	159.56	490.11	206.2975
2036	15.98	159.83	491.13	206.6925
2038	16.01	160.11	492.15	207.095
2040	16.04	160.38	493.18	207.495

The trend lines for lower, middle, and upper bounds of the fuzzy rainfall were generated and plotted in Figure 2. The results show the following observations:

1. The middle value trend (Rainfall_M) exhibited a gradual increase over the decades, indicating a possible overall rise in average rainfall.
2. The lower bound trend (Rainfall_L) showed a slower rate of increase compared to the middle trend, reflecting the lower range of variability.
3. The upper bound trend (Rainfall_U) displayed significant variability and steeper increases, particularly influenced by years of extreme rainfall.

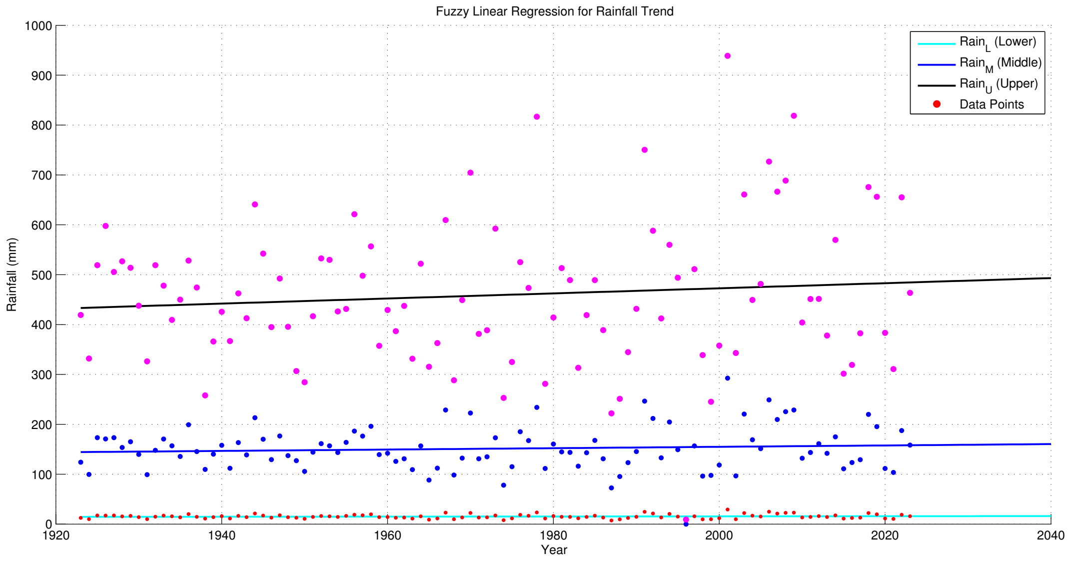

FIGURE 2. Rainfall Trend analysis using fuzzy regression model

The fuzzy regression model utilizes fuzziness (variability and uncertainty) very well, making it appropriate for predicting long-run rainfall, where the predictor variables may have imprecise data. The expected values trend upwards suggesting that the projected changes in precipitation due to climate change, as projected in the future climates rainfall, demonstrates that there are trends towards more precipitation in some locations. The stable lower bound suggests that we may not increase drought conditions significantly and the increase of the upper bound suggests that we are relatively more likely to see more extreme rainfall amounts.

5|Conclusion

The uncertain nature of the data highlights the unpredictability and variability of precipitation, which is extremely important for hydrological planning and agricultural activities in the region. The fuzzy regression model supplied greater flexibility of use and a more realistic basis for predicting rainfall than conventional precise methods. The fuzzy precipitation range for the 2040 year will help planners and decision-makers develop better possible options to address uncertainties in precipitation predictions. The large variability in the lower and upper limits in some periods indicates years of significant uncertainty and highlights the need for proper water management practices in Kalahandi.

This show that the fuzzy regression model allows for both deterministic, by showing the expected values and probabilistic by showing that the fuzzy bounds are used, guidance for policy makers when they contemplate risk-to-benefit analysis and for water resource planning. Future research to validate the forecasts could be compared to the observed data and then expanding the model to use climatic variables beyond relative humidity and temperature would further improve the forecasts.

Author Contribution

KK Mohanta: conceptualization, methodology, writing and editing. J Mohanta: writing, editing, data collectionh, software, and editing. All authors have read and agreed to the published version of the manuscript.

Funding

The authors declare that no external funding for the research presented in this paper.

Data Availability

All data supporting the reported findings in this research paper are provided within the manuscript.

Conflicts of Interest

The authors declare that there is no conflict of interest concerning the reported research findings.

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