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Drought Analysis and Forecasting in Odisha using Machine Learning Techniques

Neena Uthaman[1], Saroj Kumar Das[2], Kaibalya Pattnaik[2], S.Dhanasekar[2*]
[1]Arab Open University, Oman
School of Advanced Sciences, Vellore Institute of Technology, Chennai
neena.u@aou.edu.om sarojkumar.dash@vit.ac.in dhanasekar.sundaram@vit.ac.in

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Abstract: Drought is a natural phenomenon that damages agricultural land severely. The severity of drought must be reduced to decrease its impact on agricultural productivity. The study of drought was carried out for the state Odisha which experienced drought 8 times during the last 20 years due to failure of monsoon. Analysis for the data was explored by explorative analysis.The drought forecasting was carried out using machine learning techniques like the Auto-regressive model (AR), Long Short-Term Memory (LSTM), and Auto-regressive Integrated Moving Average (ARIMA) using daily rainfall data collected for 28 years (1993-2020). Further using this data each district was categorised into four different categories namely Flood (FL), No Drought (ND), Moderate Drought (MD), and Severe Drought (SD). To classify the districts after forecasting, classification models were used like Support Vector Classifier (SVC) and Naïve Bayes. The results of the forecasting model as well as the classification model were compared. It becomes important to forecast drought for proper planning and management of the water resource system to decrease the damage due to such calamities. This study is valuable for the government, farmers, and other stakeholders to understand the pattern and reason behind the severity of drought to take relevant precautionary measures and improve decisions and facilities to tackle such natural calamities.

Keywords: Drought, Long Short-Term Memory (LSTM), Auto-regressive model (AR), Auto-regressive Integrated Moving Average (ARIMA) and Support Vector Classifier (SVC), Naïve Bayes

1. Introduction

Drought is a type of natural calamity that occurs due to a shortage of water supply, whether it is due to precipitation below average, low surface water, or groundwater. Drought can be long-term and lasts for months and years or it can be short-term that lasts even for 15 days. Droughts are divided into three categories: Meteorological droughts, Hydrological droughts, and Agricultural droughts. Meteorological droughts are based on the precipitation or the degree of dryness. It is considered as region-specific as the precipitation that depends on the atmospheric condition varies from region to region. Whereas hydrological droughts are based on the water supply like groundwater table decline, stream flow, and reservoir. Agricultural droughts are related to both meteorological and hydrological droughts to the agricultural impact.

Drought has a great impact on agricultural production, which further brings down the economy of that area. As drought causes water and food shortages, it has a direct impact on the affected population's health, increasing the risk of acute and chronic illness, as well as mortality. Diseases like anaemia (iron deficiency disease) are seen in drought-affected areas due to malnutrition as the availability of food decreases in such areas. Even there’s a risk of infectious diseases like diarrhoea, pneumonia due to displacement, acute malnutrition and lack of water and sanitation. People also suffer from Mental health and psychological social stress. Drought may trigger wildfires and dust storms, lowering air quality and increasing the risk of lung disorders such as asthma as well as heart disease.

Every year, drought affects 55 million people throughout the world. It poses a significant threat to crops and cattle across the world. Drought raises the risk of infections, shortages of fuel, and mass migration. Water scarcity affects 40 per cent of the world's population and an estimated 700 million people are at risk of displacing by drought by 2030.
Due to rising temperatures, water evaporates more quickly making dry regions drier and wet regions wetter, so it increases the risk of droughts in dry areas and floods in wet areas. Most of the disasters that have been recorded in the past 10 years are from floods, droughts, heat waves and severe storms. Numerous investigators have demonstrated that anthropogenic influence produces major changes in the trends and variability of climate indicators [32]. According to their research, the countries in southern Asia are the most susceptible to the current global warming, and the effects of major hazard occurrences like droughts pose a growing threat to India. Thus, Odisha, which is situated on India's eastern coast, is susceptible to frequent extreme weather occurrences like cyclones, floods, and droughts [33,34]. Odisha was the most vulnerable state in India in terms of climate extremes, as demonstrated by [35] From 1951 to 2010, the state experienced 35 years of floods, 22 years of droughts, and 8 years of cyclones. Consequently, it is necessary and relevant to develop studies and monitoring in this agroeconomic state, such as those of [36], [37],[38] , [39] and [40].

Odisha has 61,80,000 hectares of cultivated land out of 1,55,707 square kilometres of geographical area. Natural disasters like drought, flood, and storms have significantly impacted the state's economy over the ages. For 41 years in the last 50 years, the state has been plagued by natural disasters, for 19 years, it has been hit by drought. Droughts cause a severe decline in agricultural productivity, thus reducing a farmer's revenue. Even rural job options, such as agricultural labour, rural craftsmen, and small rural companies, are substantially impacted. Drought in Odisha generally occurs during the month of June to October that is during the Kharif season and greatly affects the paddy crops. Districts like Bolangir, Rayagada, Kalahandi, Malkangiri, Nuapada, Sonepur, Nabarangpur and Koraput which include 47 blocks are drought-prone districts in Odisha.

2. Objectives

Antenesh BELAYNEH and Jan ADAMOWSKI investigated machine learning techniques in the Awash River Basin of Ethiopia in 2013, like Artificial neural network, coupled wavelet, and Support Vector Regressor in which the input data was pre-processed using wavelet analysis for forecasting short-term drought. To illustrate drought in the river basin, they employed the Standard Precipitation Index as a drought index. The study found that coupled wavelet neural networks are a superior model to forecast drought in the Awash River Basin than the other two machine learning approaches[1].

Other machine learning models for drought forecasting, such as Self-Adaptive Scalable Extreme Machine (SADEELM), Online Sequential Polar Machine (OSELM), and Extreme Machine Learning (ELM) were compared using Sea Surface Temperature Anomaly (SSTA) as input variables in the Nino4 and NinoW zones. The main objective of the project was to predict drought using drought indices like the Precipitation Standardized Evaporation Index (SPEI) and the Standardized

Precipitation Index (SPI). Using RMSE and CORR as statistical indices to quantify accuracy, this study found that the self-adaptive evolutionary extreme learning machine model outperformed the other two models [2]

The possibility of deep learning models for drought assessment as well as machine learning approaches were looked into in [3]. They employed soil moisture, air temperature, wind speed, surface pressure, geopotential height, and relative humidity as major hydrometeorological antecedents for the investigation. They used a deep learning method which is based on a one-way agglomeration neural network to capture the fundamental relationship between hydrometeorological factors and precipitation.

In 2019, Amandeep Kaur and Sandeep K. Sod developed a novel method for assessing drought. They developed a system for drought evaluation and prediction that incorporates Dimensionality Reduction for determining drought severity levels using Artificial Neural Networks (ANN) that were optimised with Genetic Algorithm (ANN-GA), and Deep Neural Networks (DNN). Drought conditions were predicted using Support Vector Regression (SVR) for several climatic blocks and time periods. Drought conditions were predicted using support vector regression (SVR) for several climatic blocks and time periods. The paper's findings demonstrate that Deep Neural Networks (DNN) performed with 95.36 per cent accuracy [4].

The drought prediction model was established for Pakistan for the first time, utilising the Standardised Precipitation Evapotranspiration Index as a drought index, for two crop seasons - Rabi and Kharif. They employed Recursive feature elimination (RFE) as a feature selection strategy for finding sets of predictors and created a prediction model utilising three machine learning techniques Artificial Neural Network, Support Vector Regressor and K-Nearest Neighbour. The paper concludes that the SVM-based model outperformed the ANN and KNN models [5].

The Sea Surface Temperature (SST) was used as a primary predictor in the development of a drought prediction model in 2021. They constructed three models that are ASFP-SVR, ASFP-ELM, and ASFP-RF employing the Antecedent SST Fluctuating Pattern and machine learning techniques like Support Vector Regressor, Extreme Learning Machine, and Random Forest. The Orange, Pearl, Colorado, and Danube River Basins were studied. As a drought index, the Standardised Precipitation Evapotranspiration Index (SPEI) was utilised. ASFP-ELM outperformed the other two models, according to the findings [6]

Multilayer Perceptron (MLP), Adaptive neuro-fuzzy interface system (ANFIS), Support Vector Machine (SVM), and Radial Basis function Neural Network were used to forecast drought in Iran in 2020. (RBFNN). MLP, ANFIS, RBFNN and SVM were also trained using the Nomadic People Algorithm (NPA). These models were used to anticipate the Standardised Precipitation Index for the next three months (3-months SPI). The results reveal that the ANFIS-NPA model was better than RBFNN-NPA, SVM-NPA and MPL-NPA models, as well as demonstrating that hybrid models outperform solo models [7]

For agricultural drought prediction in 2019, an enhanced support vector regression model was applied. They employed the Boosted Support Vector Regression (BS-SVR) model and the Fuzzy Support Vector Regression (F-SVR) model as upgraded SVR models, using the Standardise Precipitation

Evapotranspiration Index (SPEI) as a drought index. The paper's main goal was to reduce drought in the Langat River Basin's downstream end. Model accuracy was determined using MBE, MAE, R-Square and RMSE and it was determined that the F-SVR model is more accurate than the BS-SVR model [8].

Drought analysis and estimation for the period 1980-2019 were carried out in 2021 utilising the Standardised Precipitation Evapotranspiration Index as a drought index, with the Tibetan Plateau, China as a case study. Random Forest, Long Term Short Memory (LSTM), Convolutional Neural Network and Extreme Gradient Boost were the machine learning approaches investigated (XGB). In this work, seven scenarios were investigated, each of which was based on a mix of diverse climatic conditions. The findings reveal that the XGB Model was used as an input, which included precipitation, wind speed, lowest temperature, maximum temperature, average temperature, and relative humidity[9].

Many studies have been conducted to anticipate and forecast drought conditions in different parts of the world [11, 12, 13,19,20], but comparatively few have looked at the larger picture of overall drought vulnerability. Only a few studies have examined drought prediction in particular states [14, 15]. Various factors influencing the drought was analysed in [16,17] . Assessing drought risk is essential for efficient livelihood management given this sensitivity and the region's dense population and heavy reliance on agriculture. Notably, research by [17, 18,13] produced drought risk maps by applying the Analytical Hierarchical Process (AHP), with positive results.

A wide variety of metrics have been used over time to analyze drought conditions, with regional variations in their applicability. Several techniques, such as temperature, rainfall, vegetation index, and soil moisture, have been applied to simulate drought conditions in different regions of the world [21, 22]. Measurement methods vary as well since the nature of drought varies depending on local climate conditions [23]. There are two types of connections that drought parameters can show: linear and nonlinear [24, 25]. Drought frequency and intensity have been effectively proved by the probability density functions (PDFs) of drought indices [26,27,28].

A combination of topographical, meteorological, and socioeconomic variables make Odisha vulnerable to drought [29]. The climate is primarily tropical, with irregular and seasonal monsoons that provide an uneven dispersion of rainfall throughout the area. Due to the state's undulating topography and low soil moisture retention, dry spells make water scarcity worse [30]. The region's vulnerability is further increased by high evaporation rates, excessive groundwater resource use, and insufficient water management techniques [30, 31].

Deep learning algorithms were looked into for drought prediction [10]. Taking lagged values of Standardise Streamflow Index (SSI) as input, long-term drought was predicted. This approach was carried out using Support Vector Regressor (SVR) and Multilayer Perceptron (MLP).

3. Methods

In this paper, the methodology comprises four stages. In the first stage data collection was done. The second stage consists of data pre-processing. In the third stage, the forecasting model was implemented using the Long short-term Memory model (LSTM), the Auto-regressive model (AR) and the Auto-regressive Integrated Moving Average model (ARIMA). In the fourth stage classification of the forecasted precipitation was done using Naïve Bayes and Support Vector Classifier (SVC).

3.1 Data Collection

The dataset was collected from the official website of the special relief organisation, Government of Odisha. This organisation was created for relief and rescue operations during various natural calamities. The data collection and analysis was done on Windows 10 (64-bit), and Microsoft Excel (2016 version) was used for consolidating and grouping the data. Python (3.8.8 version) was used for forecasting and performing classification algorithms.

The dataset contains daily rainfall that was recorded from the year 1998 to 2021 for all the blocks under all 30 districts in Odisha. There are 30 districts in Odisha namely – Angul, Balangir, Bargarh, Dhenkanal, Rayagada, Koraput, Debagarh, Kendujhar, Sambalpur, Subarnapur Sundargarh, Bhadrak, Cuttack, Jagatsinghpur, Kendrapara, Khordha Mayurbhanj, Puri, Boudh, Gajapati, Ganjam, Kalahandi, Nuapada, Jajpur, Kandhamal, Malkangiri, Nabrangpur, Balasore, Nayagarh, Jharsuguda and there are 315 blocks that comes under these 30 districts.

3.2 Pre Processing of Data

The raw data that consists of the daily rainfall data for each block of Odisha was aggregated to district-wise. Instead of considering the whole dataset only 28 years of data was considered because before 1993 there were only 13 districts in Odisha namely – Keonjhar, Bolangir, Cuttack, Dhenkanal, Kalahandi, Koraput, Mayurbhanj, Phulbani, Puri, Balasore, Sambalpur, Ganjam, and Sundargarh. But from 1993 these 13 districts were further divided into 30 districts. After getting it aggregated average rainfall and standard deviation for 28 years were calculated for each district.

Here simple statistical measures like Average and standard deviation were used for the classification of different districts into different drought severity. Using the average and standard deviation of 28 years of rainfall (where standard deviation was calculated for 28 years of yearly rainfall record) each district was categorised into four different categories according to the severity level namely Severe Drought (SD), Moderate Drought (MD), No Drought (ND) and Flood (FL). The categorisation was done in such a way that –

- If the average rainfall for a particular district for a given year falls below the difference in average rainfall of 28 years and 0.5 times its standard deviation, then it comes under Severe Drought (SD) situation.
- If the average rainfall for a particular district for a given year falls in between its average rainfall of 28 years and the difference of average rainfall of 28 years and 0.5 times its standard deviation, then it comes under a Moderate Drought (MD) situation.
- If the average rainfall for a particular district for a given year falls in between its average rainfall of 28 years and the sum of the average rainfall of 28 years and 0.5 times its standard deviation, then it comes under the No Drought (ND) situation.
- If the average rainfall for a particular district for a given year falls above the sum average rainfall of 28 years and 0.5 times its standard deviation, then it comes under the Flood (FL) situation.

3.3 Forecasting Model

For forecasting three models have been used i.e., the Auto-regressive model (AR), Long Short-Term Memory model (LSTM) and Auto-regressive Integrated Moving Average (ARIMA). For these models, the dataset was split into a train set and a test set in the ratio 90:10.

3.3.1 AR Model

When there is any association between the values in a time series and the values that succeed and precede them, an auto-regressive (AR) model is used to anticipate future behaviour based on previous behaviour. It is a linear regression of the data in the time series against one or more previous values in the same time series, i.e., the value of the outcome variable (Y) at time t is similar to simple linear regression where the predictor variable is directly associated (X). However, the AR model differs from a basic linear regression in that Y is dependent on X and prior Y values.

3.3.2 ARIMA Model

The strength of a dependent variable relative to other variables is used in the autoregressive integrated moving average (ARIMA) model, which is a type of regression analysis. ARIMA forecasts the future by looking at the difference between values in a string rather than the actual values. "AR" stands for Auto Regression, which depicts a converting variable that regresses on its very own lagged, or previous values, "I" stands for Integrated, which depicts the differencing of raw observations in the dataset in order for the time series to become, and "MA" stands for Moving Average, which illustrates how an observation and how the residual error of a moving average model depends when applied to lagged observations.

3.3.3 LSTM Model

LSTM networks are a form of recurrent neural network that learns order dependency in sequence prediction challenges. Because there might be gaps of undetermined duration between critical events in a time series, LSTM networks are optimal for classification and prediction. In simple language, for example, we have a dataset that consists of the temperature for five months say from January to May and we want a prediction to be done for the next 3 months say June, July and August. So, this algorithm will first use the inputs i.e, the temperature of January, February, March, April and May and use it to predict the temperature of June. Then in the next case, it will drop the temperature of January and take the temperature from February, March, April, May and June to predict the temperature of July. Again, in the second case, it will drop the temperature of February and take the temperature from March, April, May, June and July to predict the temperature of August.

3.4 Classification Model

For classifying the severity of drought according to the precipitation forecasted, two forecasting models have been used i.e., Support Vector Classifier and Naive Bayes. Similarly for these models also dataset was split into a train set and a test set in the ratio 90:10.

3.4.1 Naive Bayes Classifier

A Bayesian classifier is a probabilistic classification model. Naive Bayes uses machine learning to distinguish between various objects based on particular attributes. The Bayes theorem is used in this model. The Bayes theorem may be used to calculate the likelihood of A occurring given B, where B is the evidence and A is the hypothesis. The underlying assumption is that all characteristics are independent of one another. These algorithms are commonly used in sentiment analysis, spam filtering, recommendation systems, and other applications since they are quick and simple to construct.

3.4.2 Support Vector Classifier

SVM is a supervised machine learning technique that may be used to solve both regression issues and classification problems. Each data point in this algorithm is plotted in an n-dimensional space, with the value of each characteristic assigned to a specific coordinate. Then classification is carried out by locating the hyper-plane that best distinguishes the classes.

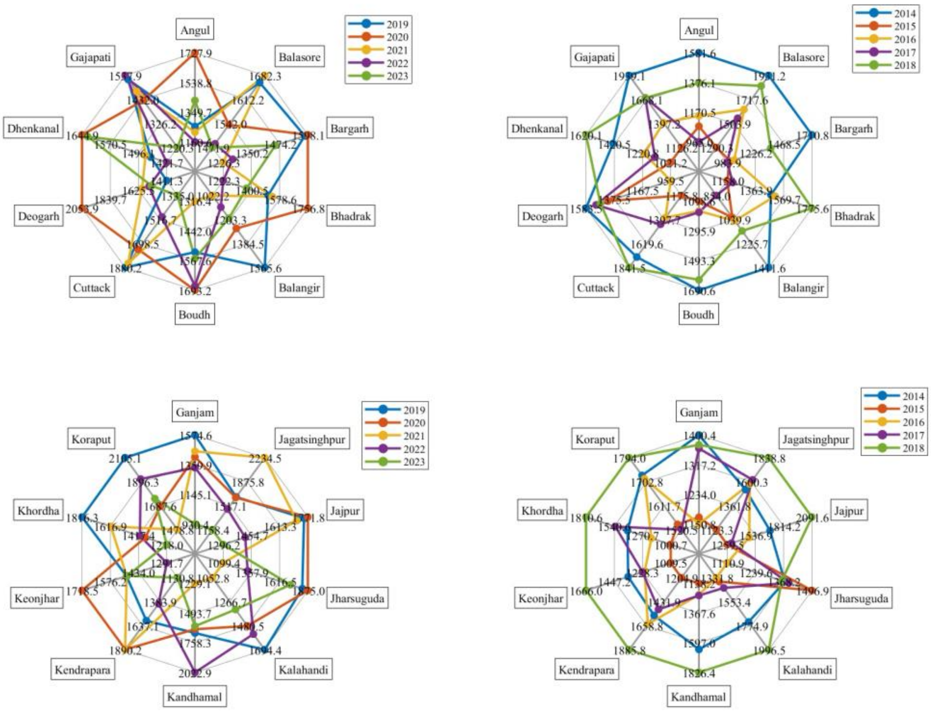
3.5 Accuracy measure

Root Mean Square Error is the standard deviation of the residuals. Residuals are the distance between the regression line and the data points. It is a measure of the uniform distribution of residuals. It shows how closely the data points are grouped around the best-fit line.

The percentage mean absolute error (MAPE) measures the prediction accuracy of the system. It is determined as the difference between the mean absolute percent error for each time period and the actual value divided by the actual value and expressed as a percentage.

4. Analysis

The analysis of the rainfall in Odisha using visualization in MATLAB. The following are the visualiztions of the data



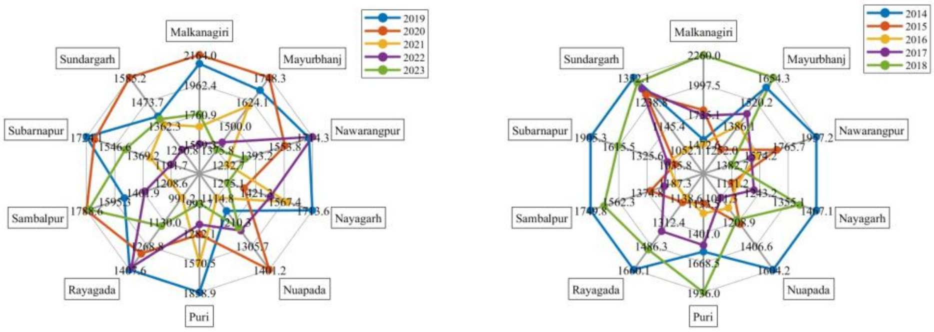


Fig 1 Districtwise Visualiztion of Total Rainfall from 2004-2023

From **Fig 1** District wise analysis rain fall and Drought can be done.

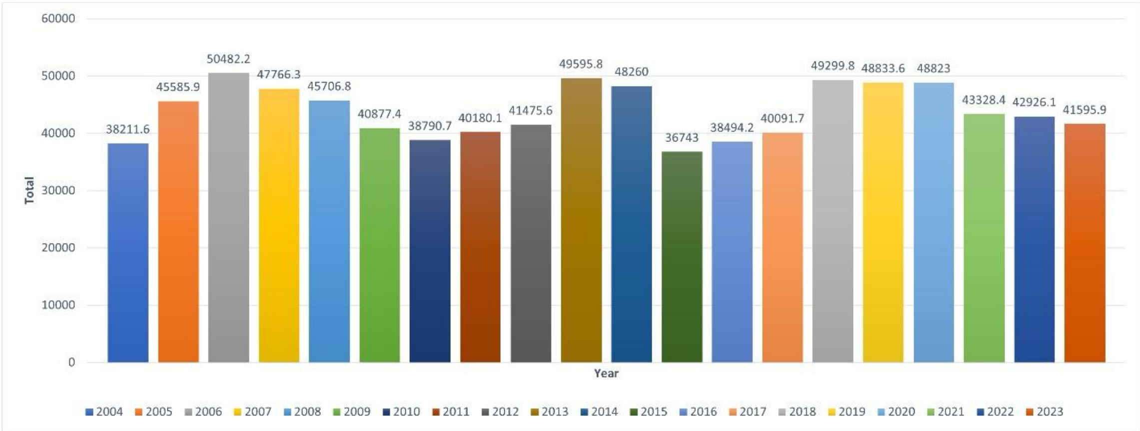


Fig 2Total Rainfall from the year 2004-2023

From the **Fig 2** the years 2005, 2006,2007,2008,20113,2014,2018,2019 2020 had rainfall more than 45,000 mm. It can be considered as flood scenorio. The years 2004,2010,2015,2016 had rainfall below 40,000 mm. It can be considered as drought scenorio.

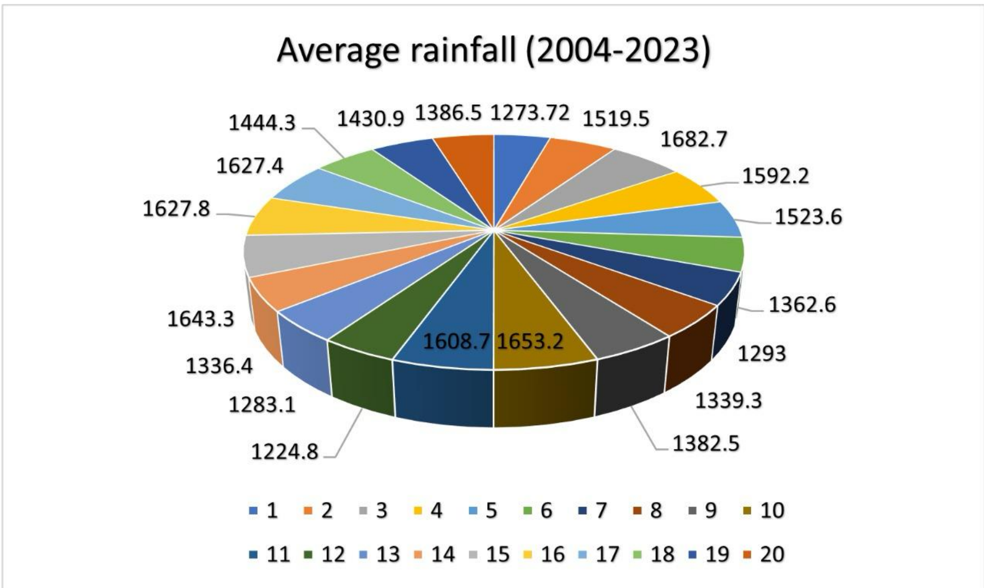


Fig 3 Average Rainfall

From the **Fig 3** the average rainfall was lesser than 1400mm were **2004,2010,2015,2016,2017,2023.** The average rainfall were higher than 1600mm in the years **2006,2007,2013,2014,2018,2019,2020.** This inferes that more reains occurs in consecutive years.

Fig 4 Plot of Total Rain fall from 2004-2023

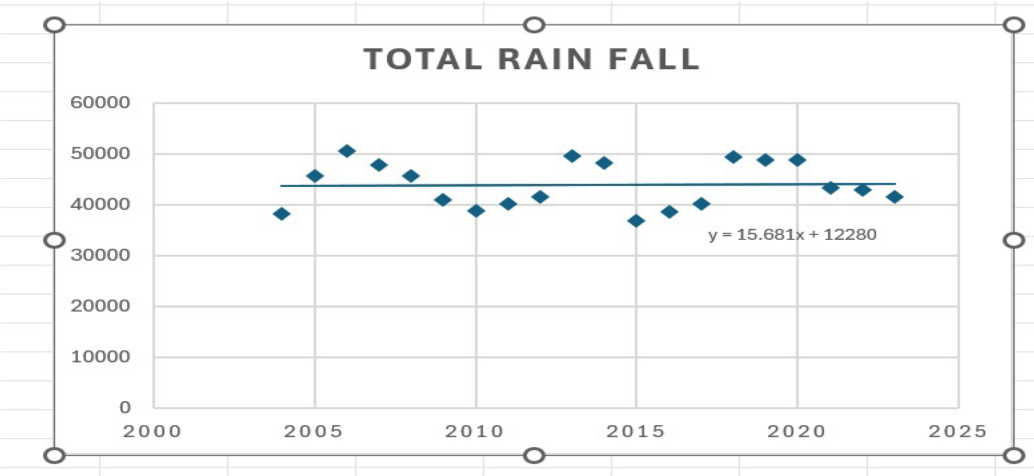


Fig 5 Plot of Linear Trend of Total Rain fall from 2004-2023

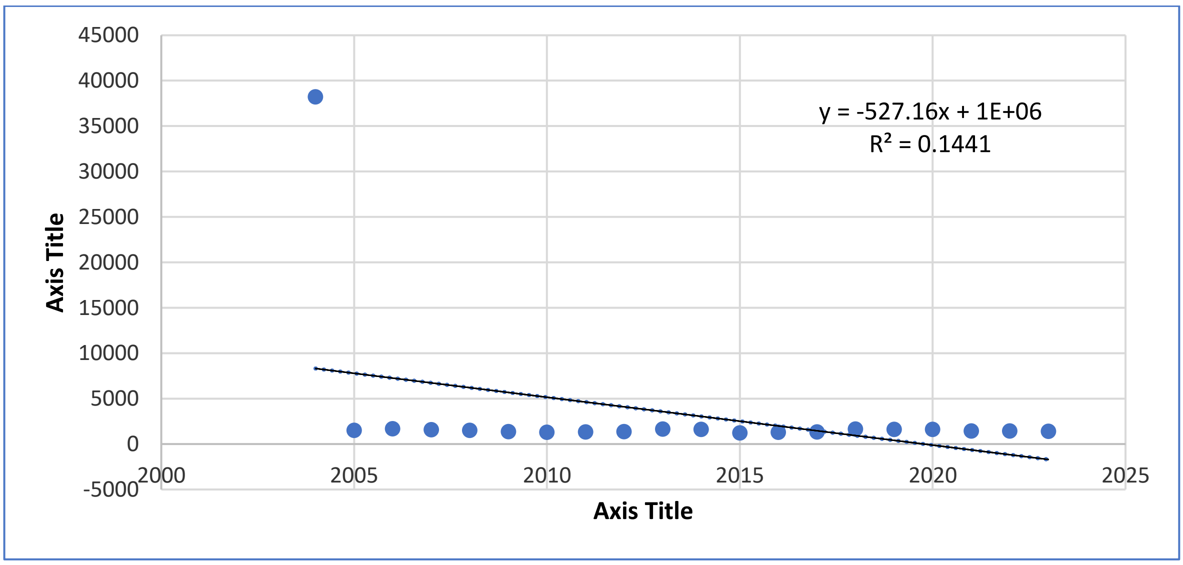


Fig 6 Plot of Average Rain fall from 2004-2023

From the **Fig 4 , Fig 5, Fig 6** it is noticed that there exists a pattern in the rain fall of odisha.

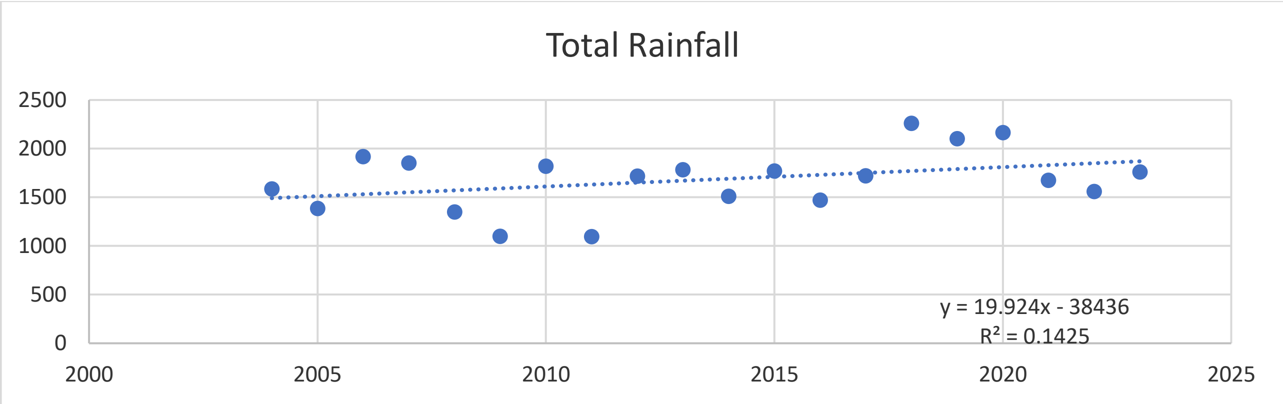
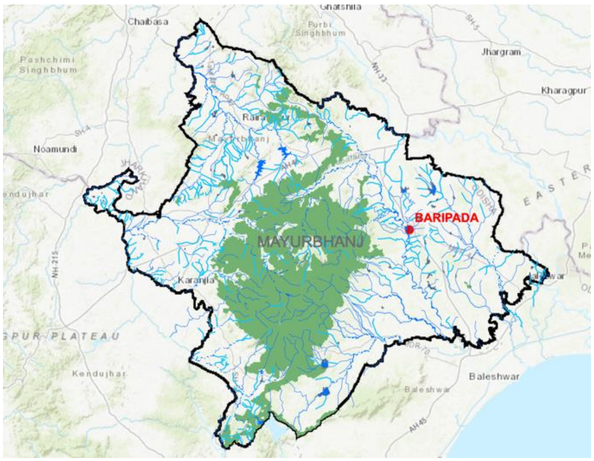


Fig 7 Trend line for the district Malkangiri

In Fig 7 , the average rainfall of Malkangiri distict which is on the bank river Mahanadhi gives the trend as same as overall trend.



*Courtesy National Informatics Centre.

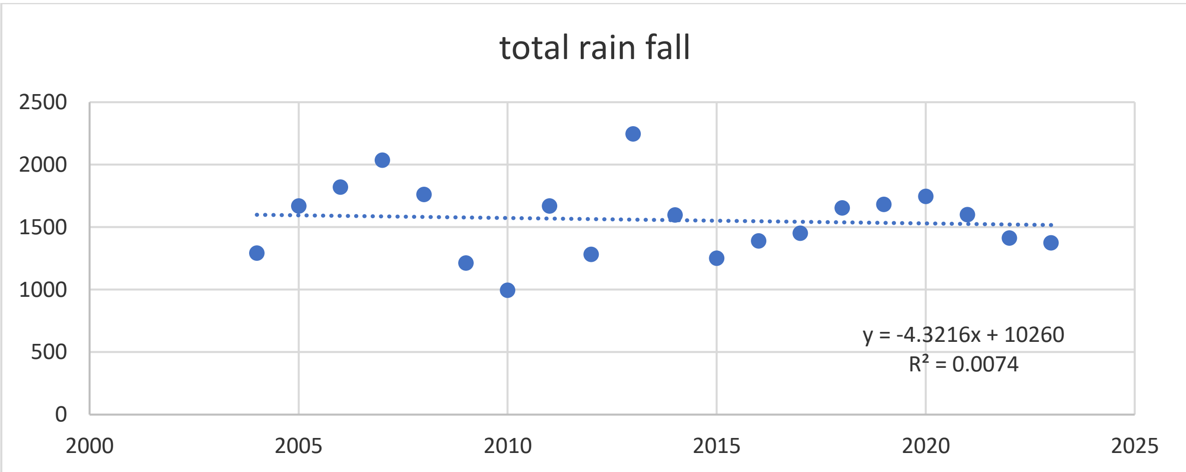
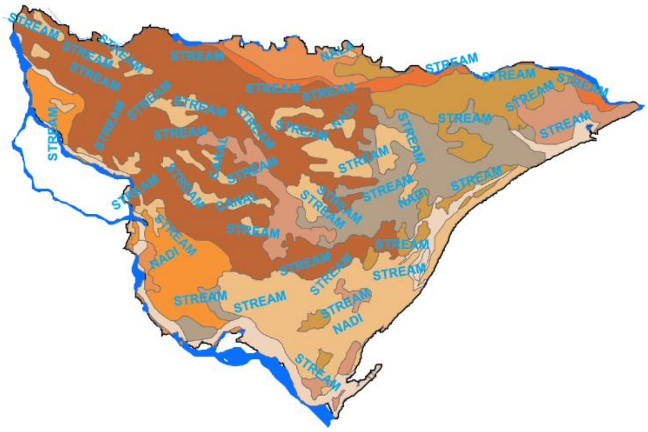


Fig 8(a) Geo Map of Mayurbhanj District 8(b)Trend line for the largest district Mayurbhanj of Odisha.



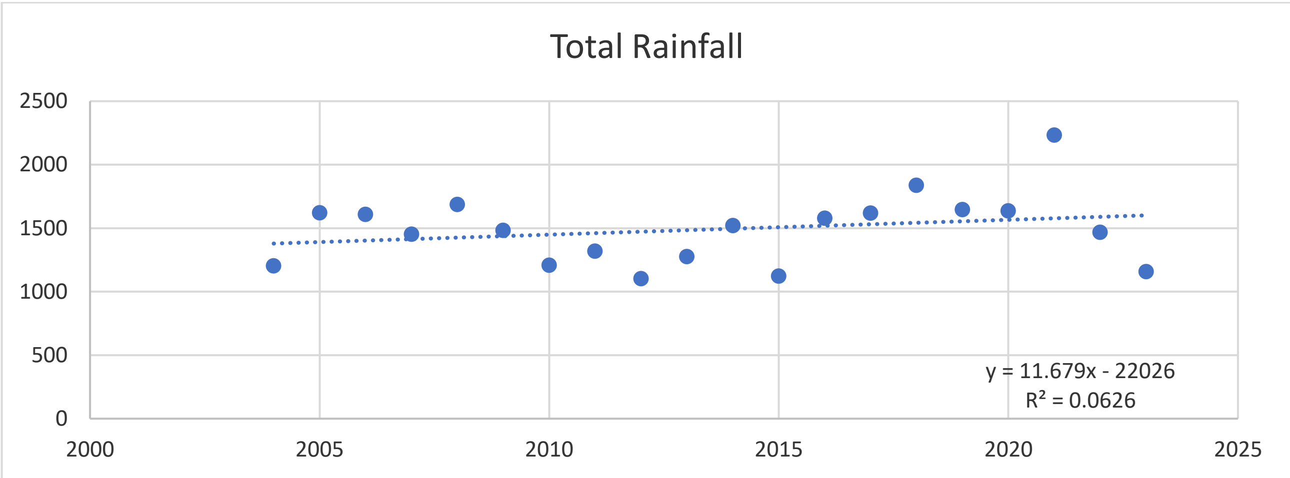


Fig 9(a) Geo Mapof Jagatsinghpur 9(b) Trend line for the smallest district

Jagatsinghpur districtin Odisha

5. Results and discussions

In this paper, the rainfall records of Odisha were used to successfully identify the severity level of drought from the year 1993 to 2021 for all the districts of the State.

5.1 Drought and Flood Scenario

It was found that in 1996 drought was recorded and in 1994 flood situation was recorded in Subarnapur district. The rainfall pattern of both scenarios, where the blue bars show the rainfall recorded in the given month and the red line shows 28 years of average rainfall in Subarnapur district and the Green line shows the average monsoon rainfall recorded in that year was compared. The first half of the 1996 graph shows the moderate drought scenario (1995) and the second half shows the drought scenario (1996). There was a sudden fall in the average monsoon rainfall in the year 1996 and the rainfall that was recorded for each month didn't cross the average rainfall for that year and during monsoon season it was just touching the average monsoon rainfall line.

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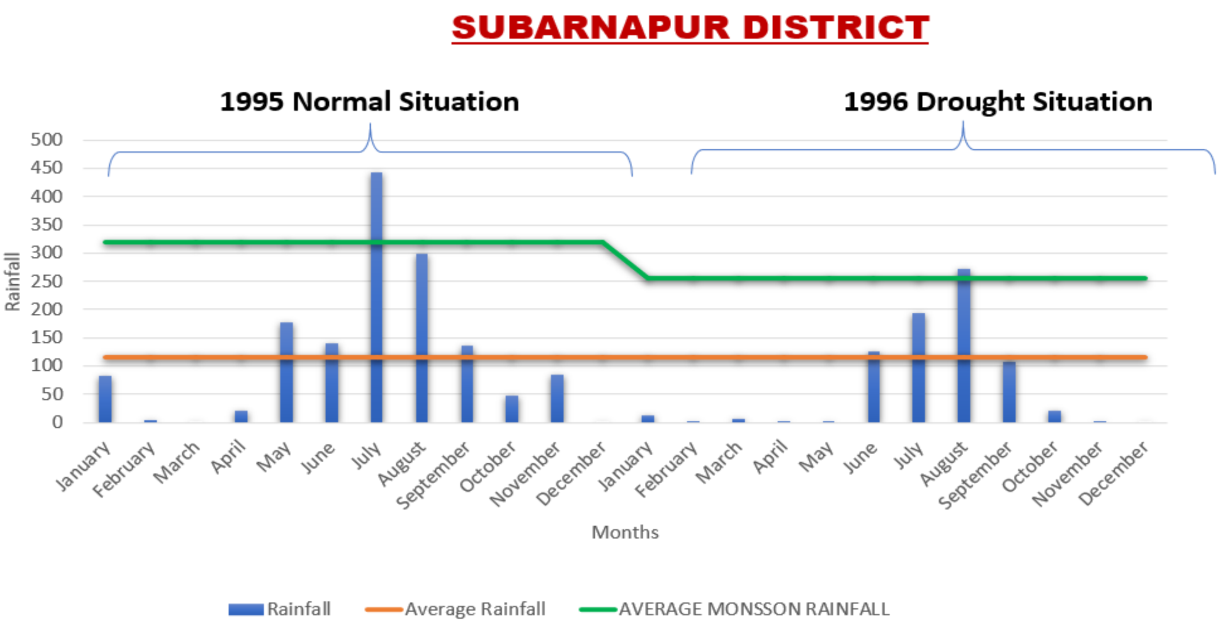

Fig 10 Average Rainfall

Unlike 1996, The first half of 1994 graph shows the no drought scenario (1993) and second half shows a flood scenario (1994). There's a sudden rise in the average monsoon rainfall in the year 1994 and the rainfall that was recorded for each month were much higher than the average monsoon rainfall line.

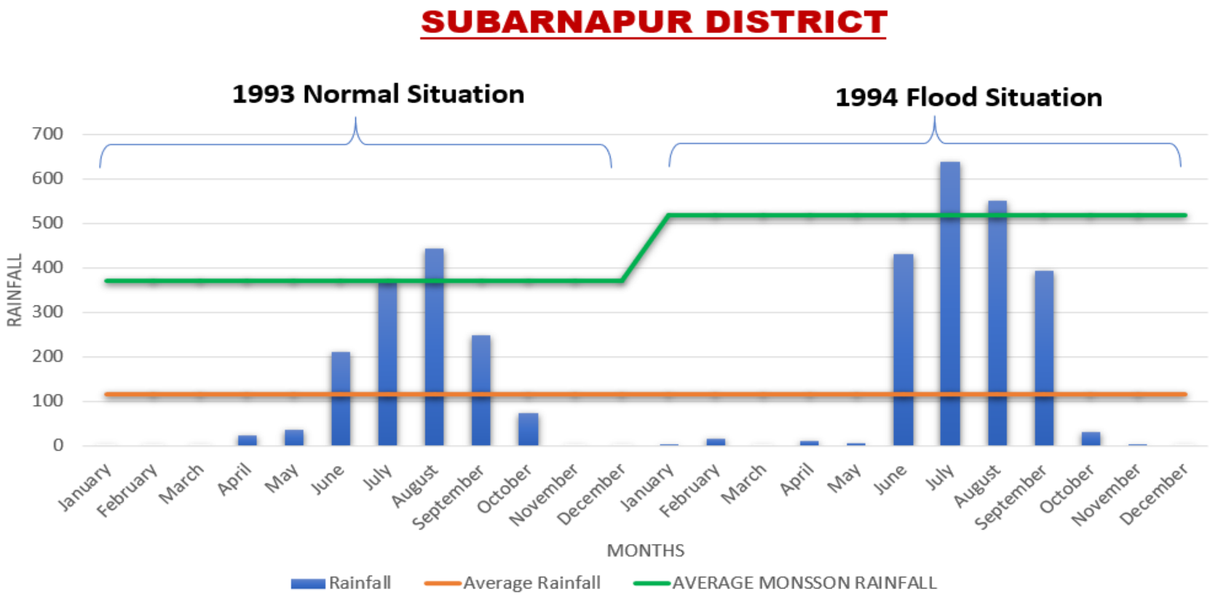

Fig 11 Flood scenario

5.2 Model Accuracy

The accuracy of the forecasting model was determined using RMSE and MAPE. The average RMSE of ARIMA, AR and LSTM is 13.8061, 29.5594 and 25.5067 respectively. The average MAPE of ARIMA, AR and LSTM is 0.0846, 0.1779 and 0.1589 respectively.

For the classification model, F1 Score and Precision Score were used as the accuracy measure. The F1 Score of Naive Bayes and SVM is 0.9393 and 0.8956 respectively. The Precision Scores of Naive Bayes and SVM are 0.9778 and 0.9407 respectively.

6. Conclusions

Comparing the average RMSE and MAPE value for the forecasting model, ARIMA outperforms LSTM and AR in predicting rainfall using the last 28 years of data. For classification, Naive Baye's accuracy is much better than SVM for classifying the predicted rainfall into severity levels.

7. Limitations and future scope

There are some limitations to the model used in this paper. Firstly, precipitation is not the only factor that affects drought. There are various other factors like soil moisture, air temperature, wind speed, surface pressure, Geo-potential height, relative humidity, etc. However, rainfall might be the primary factor that can be considered for drought prediction. Secondly, here only simple statistical measures were used to identify the severity level of drought and classify the districts accordingly. Another issue is that the models used here can have greater accuracy only for predicting one or at most two years of precipitation.

Future scope includes overcoming the above-mentioned limitations and building a more robust model. Real-time drought prediction that includes all the factors affecting drought can be developed, which can be made user-friendly by developing a Mobile Application.

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