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Machine Learning Based Rainfall Analysis

Namratha V,
Civil Engineering Department,
UVCE, JB Campus,
Bangalore University, India.

Usha N Murthy,
Professor and Head, Civil Engineering Department,
UVCE, JB Campus,
Bangalore University, India.

ABSTRACT

Rainfall exhibits unique characteristics of high volatility and chaotic patterns that do not exist in other time series data. This work's main impact is to show the benefit machine learning algorithms, and more broadly intelligent systems have over the current state-of-the-art techniques for rainfall prediction within rainfall derivatives. This research apply the predictive performance of the current state-of-the-art of ARIMA modeling based ANN. Extreme climate and weather events are progressively being renowned as key aspects of climate change. Pre-monsoon season (March–May) is the hottest part of the year over almost the entire South Asian region, in which hot weather extremes including heat waves are recurring natural hazards having serious societal impacts, particularly on human health. In the present paper, recent trends in extreme rainfall events for the pre-monsoon season have been studied using daily data on a well-distributed network. In general, the frequency of occurrence of hot days and hot nights showed widespread increasing trend, while that of cold days and cold nights has shown widespread decreasing trend. However, the results generally indicate that the daily maximum and minimum rainfall are becoming less variable within the season. Climate change is a problem of global proportion, requiring equally global responses. Yet climate change is a fundamental urban issue. This current research work mainly focuses on effect of changes in rainfall. To attain this aforementioned aim of research work, the rainfall data is obtained from Karnataka pollution control board (KSPCB) from 1980 to 2019. Advanced machine learning techniques such as ARIMA model and ANN are incorporated in this research and the temperature prediction is made till 2030. MATLAB is the forecasting software used for predicting the meteorological data till 2025.The version used in this research is MATLAB 2014b and this work is compatible with MATLAB 2013a and above versions.

INDEX TERMS ARIMA, ANN, climate change, KSPCB, machine learning, rainfall.

1. INTRODUCTION

Rainfall is a crucial phenomenon within a climate system, whose chaotic nature has a direct influence on water resource planning, agriculture and biological systems. Within finance, the level of rainfall over a period of time is vital for estimating the value of a financial security. Over recent years, scientists' abilities in understanding and predicting rainfall have increased, due to numerous models developed for increasing the accuracy of rainfall prediction [1]. Subsequently, such efforts in new techniques can lead to the correct predictions of rainfall amounts for weather derivatives. Rainfall derivatives share similar principles with weather derivatives and other regular derivatives. They are defined as contracts between two or more parties, where the value of a contract is dependent upon the underlying financial asset [2]. Hence, in the case of weather derivatives, the underlying asset is a weather type, such as rainfall. One significant difference between common derivatives and weather derivatives is that the underlying asset that governs the price of the contract is not tradable. Therefore, many existing methods in the literature for other derivatives become unsuitable for the prediction of weather derivatives. Rainfall derivatives are a new method for reducing the financial risk posed by adverse or uncertain weather circumstances [3]. These contracts are aimed towards individuals whose business is directly or indirectly affected by rainfall. For example, farmers whose crops are their main source of income, requiring a certain range of rainfall over a period of time to maximise their income [4]. Moreover, rainfall derivatives are a better alternative than insurance, because it can be difficult to prove that the rainfall has had an impact unless it is destructive, such as severe floods or drought. Therefore, rainfall derivatives offer a simple solution to resolving the problems of financial protection against un-favourable rainfall. Similar contracts exist for other weather variables, such as temperature and wind. The pricing of rainfall derivatives consists of two problems. The first problem is the prediction of accumulated rainfall over a specified period [5]. The second problem is developing a pricing framework2 . The latter has its own unique problematic features, as rainfall derivatives constitute an incomplete market3 . This paper focuses on the first aspect of predicting the level of rainfall. Note it is important to have a model that can accurately predict the level of rainfall before pricing derivatives, because the contracts are priced on the predicted accumulated rainfall over a period of time. Hence, we want to reduce issues of mispricing. Prediction in rainfall derivatives poses many obstacles, both in research and in financial practice [6]. There is a light amount of literature researched in rainfall derivatives, because the concept is fairly new, as well as rainfall can be very difficult to accurately measure. In financial practice, investors also share the same kind of difficulties, deterring the trading of rainfall derivatives in financial markets. Therefore, our broad goal is to develop a methodology for accurate rainfall prediction, which should decrease the observed risk from investors [7]. This research focuses on rainfall analysis and future rainfall predictions from 2020 till 2030.

II. LITERATURE REVIEW

Markov-chain extended with rainfall prediction (MCRP) is the most commonly and successfully used rainfall prediction method. MCRP is broken down into two stages. The first stage is to produce an occurrence pathway using a Markovchain (i.e. a sequence of rainy or dry days). The second stage is to generate a random rainfall amount (from a distribution) for every rainy day in the sequence. MCRP is a popular approach having the key advantages of providing a simplistic and lightweight algorithm for the problem of daily rainfall prediction [8]. However, one of its key disadvantages is that MCRP is heavily reliant on past information being reflective of the future, by taking the past average to be the major contribution to future rainfall. MCRP relies on a stochastic process to simulate future rainfall pathways, but it produces a large number of potential pathways that are not necessarily reflective of future events [9]. Thus, producing weak predictive models as the annual deviations and short term behaviour in rainfall are not explicitly captured. Moreover, the model needs to be tuned for each city as each exhibits unique statistical properties and a general “one-size-fits-all” model cannot be applied. The disadvantage is that MCRP does not produce a general model that can be applied to all cities. Meaning that with new information (e.g. updated weather information or different data sets), more emphasis is required on calibrating a new model [10]. Therefore, it is computationally inefficient by the continuous need to specify a new model for each day. Without updating the model, MCRP will never change the output, as there is no consideration of recent rainfall behavior [11]. The above disadvantages inspired the use of machine learning methods to provide more accurate predictions, where the dynamics and behaviour in rainfall can be captured, favouring prediction over the need for simulation [12]. A key advantage is that the structure and patterns of the data are explored, creating a sophisticated model to represent the problem [13]. However, a potential drawback of machine learning methods is that they must be tuned, which can be very computationally expensive and hard to find an optimum model set-up if an algorithm has many parameters [14]. Thus, leading to problems of model mis-specification, can be overcome through a rigorous tuning procedure [15]. The use of machine learning algorithms allows for a more robust model set-up, capable of representing a range of different climates and providing new predictions on the availability of new information. Thus, machine learning methods are computationally more efficient compared to MCRP since the need for constant calibration can be relaxed. Typical applications within machine learning revolve around short term predictions (e.g. rainfall-runoff models up to a few hours or monthly amounts. For daily predictions, used a feed-forward back-propagation neural network for daily rainfall prediction in Sri Lanka, which was inspired by the chain-dependent approach from statistics [17]. Kisi & Shiri (2011) applied Genetic Programming (GP) to daily rainfall data, but the GP performed poorly by itself, although when assisted by wavelets the predictive accuracy did improve. In the context of rainfall derivatives there exists a few applications of GP (Cramer et al., 2015, 2016a,b), which showed that GP statistically outperformed MCRP. One issue within daily rainfall prediction using machine learning methods is the challenges that exist with trying to fit the time series of rainfall [16]. The unique characteristic of a highly discontinuous and irregular pattern exhibited by daily rainfall makes the problem very hard for fitting the time series of rainfall. A machine learning method must cope with irregular and randomly occurring spikes, indicating rainfall on a given day, where each day has little connection to the previous day. Cramer et al. (2015) notes the issues for this particular type of time series and suggests accumulating rainfall to allow GP to cope with the issues of discontinuity and chaotic nature of daily rainfall, whilst maintaining the consistency of the end goal of pricing rainfall derivatives. More precisely, Cramer et al. (2015) suggested the use of a sliding window accumulation method in order to predict accumulated rainfall amounts on a daily basis. By accumulating daily rainfall data, the problem of rainfall prediction aligns with the goal of pricing, as the cost of a contract is based on the accumulated level of rainfall over a period of time [18].

III. STUDY AREA

In this paper, we have taken a daily rainfall series of rainy season and a monthly rainfall series of the Bangalore city. The rainfall data are taken from nearby weather stations, A rainfall forecasting method uses machine learning models. Our objective is to analyze the rainfall across Bangalore city from 1989 till 2019 and to predict the future rainfall from 2020 till 2030.

IV. RESEARCH METHODOLOGY

4.1 Source of Data Collection

Data collection is a preliminary work in the research projects. The idea of the work has been extracted from the Karnataka State Pollution Control Board (KSPCB) and Indian Meteorological department. The research focuses on the changes that are happening around the environment. The change of Agricultural and forest lands into urban areas by constructing commercial spaces and other activities [19]. The idea of the research is to focus on the in depth idea through which the awareness been created to save our environment for the upcoming generations.

In data collection, the work has been considered from 1980-2019 for the predictions of the future data and analysis. The data have been expanded with the better ideas to generate different manipulations that cause various other impacts in the environment [20].

4.2 ARIMA model in MATLAB

The time series analysis and modeling represent important process and are very often demanded in various areas of life. The reason is simple because in most cases it is needed to predict future values of time series. The answer to why predict future values is quite clear. Almost everybody wants to know something about the future progress, about the future opportunities. In some fields it may be also the main content to predict future values.

The proposed methodology or steps in which the implementation is done will be explained in detail in this section. The source of data and both hardware and software used are examined in this chapter.

The learning operation is performed in the database source as well as database reference. Here the predictive modeling is deployed with various algorithms like ARIMA Time series modeling; Artificial Neural networks (ANN) and so on.

Since the previous few decades, ANN a voluminous development within the application field of ANN has unfolded new avenues to the forecasting task involving environment connected development. French et al. (1992), took a pioneering work in applying ANN for rain forecasting, that used a neural network to forecast two-dimensional rainfall, 1h prior to.

Their ANN model used present rainfall information, generated by a mathematical rainfall simulation model, as an input data. This work is, however, restricted in a very range of aspects. For instance, there's a trade-off between the interactions and also the training time, that couldn't be simply balanced. The amount of hidden layers and hidden nodes appear short, compared with the amount of input and output nodes, to reserve the upper order relationship required for adequately abstracting the method. Still, it's been thought-about because the 1st contribution to ANN's application and established a brand new trend in understanding and evaluating the roles of ANN in investigating complicated geophysical processes.

A series that you can model as a stationary ARMA (p, q) process after being differenced D times is denoted by ARIMA (p, D, q). The form of the ARIMA (p, D, q) model in Econometrics Toolbox™ is

$\Delta Dyt=c+\phi 1\Delta Dyt-1+\ldots+\phi p\Delta Dyt-p+\varepsilon t+\theta 1\varepsilon t-1+\ldots+\theta q\varepsilon t-q$ [1]

Where,

ΔDyt denotes a Dth differenced time series, and εt is an uncorrelated innovation process with mean zero.

In lag operator notation, $Liyt=yt-i$. You can write the ARIMA (p,D,q) model as

$\phi*(L)yt=\phi(L)(1-L)Dyt=c+\theta(L)\varepsilon t$. [2]

Here,

$\phi*(L)$ is an unstable AR operator polynomial with exactly D unit roots. You can factor this polynomial as $\phi(L)(1-L)D$, where $\phi(L)=(1-\phi 1L-\ldots-\phi pLp)$ is a stable degree p AR lag operator polynomial (with all roots lying outside the unit circle). Similarly, $\theta(L)=(1+\theta 1L+\ldots+\theta qLq)$ is an invertible degree q MA lag operator polynomial (with all roots lying outside the unit circle).

The signs of the coefficients in the AR lag operator polynomial, $\phi(L)$, are opposite to the right side of Equation 1. Specifying and interpreting AR coefficients in Econometrics Toolbox uses the form in Equation 1.

ARIMA Model Specifications

This example shows how to use the shorthand arima (p,D,q) syntax to specify the default ARIMA(p, D, q) model,

$\Delta^D y_t=c+\phi_1\Delta^D y_{t-1}+\ldots+\phi_p\Delta^D y_{t-p}+\varepsilon_t+\theta_1\varepsilon_{t-1}+\ldots+\theta_q\varepsilon_{t-q}$,

Where,

$\Delta^D y_t$ is a D^{th} differenced time series.

This model can be modified in condensed form using lag operator notation:

$\phi(L)(1-L)^D y_t=c+\theta(L)\varepsilon_t$.

By default, all parameters in the created model object have unknown values, and the innovation

Specify the default ARIMA(1,1,1) model:

```
model = arima(1,1,1)
model =
  arima with properties:
    Description: "ARIMA(1,1,1) Model (Gaussian Distribution)"
    Distribution: Name = "Gaussian"
```

P: 2
D: 1
Q: 1
Constant: NaN
AR: {NaN} at lag [1]
SAR: {}
MA: {NaN} at lag [1]
SMA: {}
Seasonality: 0
Beta: [1×0]
Variance: NaN

The output shows that the created model object, model, has NaN values for all model parameters: the constant term, the AR and MA coefficients, and the variance. You can modify the created model using dot notation, or input it (along with data) to estimate. The property P has value 2 ($p + D$).

This is the number of pre-sample observations needed to initialize the AR model. It may seem unusual to apply univariate techniques commonly used in business and economic modeling to global temperature data, but there are some persuasive arguments for doing so. Although the strengths and limitations of causal relative to non-causal modeling are well known, it may be useful to restate this debate in the context of modeling climate change. The data requirements for univariate ARIMA modeling are usually less onerous than those for other techniques such as causal modeling, and this is particularly true in the case of climate change.
Causal models of climate change often include a large number of explanatory variables to reflect the complexity of the causal relationships. A model of global temperature change, for example, might include (at least) variables for natural phenomena such as the El Nino Southern Oscillation and volcanic and solar activity, and variables for human influence such as greenhouse gas and aerosol concentrations, as well as changes in stratospheric and tropospheric ozone.

Given that global temperature changes are the product of gradually evolving processes, it is desirable to calibrate these causal models on data that go as far back in time as possible. But observations for some of the causal variables may not be reliable, and may not even be available for period's further back in time. Additionally, mixing variables observed at high frequencies (monthly, daily) with others observed only at low frequencies (annual) will generally require converting the high frequency variables to the lowest variable frequency. Thus potentially important data 'richness' may be lost in causal models.

V. Results

The tool which is used for the development of the ARIMA model is MATLAB.
As per the analysis made with Time series algorithm known as ARIMA modeling with the existing data from 1988 to 2018 for both LULC analysis. LULC analysis has observed the following observations that the vegetation area in hectares has been reduced drastically and the built up area have been started increasing with consistent support. This leads to various environmental impacts like global warming.

The correlation analysis of meteorological factors, including precipitation anomaly percentage, precipitation, maximum and minimum temperatures, average relative humidity, potentially affecting the AQI was carried out monthly and seasonal basis from the year 1980 to 2018. The weather changes have higher correlation with meteorological factors. The table presents the Air Quality Index data obtained from Karnataka State Pollution Control Board (KSPCB).

Based on the predictions made from ARIMA modeling the following predictions are made. Based on the average predictions as per the model the observed values are determined as follows. The average prediction of rainfall seems to be observed. The logical algorithm has been developed that constitutes an occurrence of the predictions in rainfall that seems to be improved to an extent in year 2023-2030.

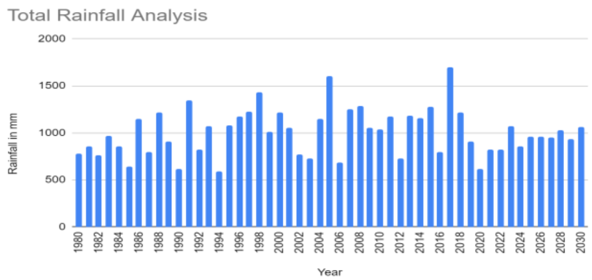

Figure 1 Total Rainfall Analyses in mm from 1980 to 2030

YEAR	JAN	FEB	MAR	APR	MAY	JUNE	JULY	AUG	SEPT	OCT	NOV	DEC
1980	0	0	10.9	7.2	151.7	41.8	112.7	114.5	213	78	51.6	Trace
1981	1.5	Trace	101.2	9.6	119.4	16.9	154.1	123.8	204	86.6	16.9	21.7
1982	0	0	1.1	16.1	100.2	144.1	46.9	81	206.5	139.4	23.9	1.2
1983	0	0	0	0.2	106.5	218.4	64.2	178.5	275.8	53.7	2.9	69.8
1984	0.7	33.4	91.7	42.7	60.2	25.3	146	45	243.6	144.8	10.7	10.9
1985	2.8	0	20.7	10	78.6	81.4	72.9	67.8	139.8	70.9	97.3	3
1986	18.6	17.2	Trace	8.4	85.4	131.7	65.3	97.5	516.6	102.6	87.9	14.7
1987	0	0	25.3	57.6	84.2	84.2	53.7	157.8	102.7	144.4	35.1	53.6
1988	0	Trace	29.2	71.4	108.9	25.9	243.8	242	425	10	35.4	30
1989	0	0	2	6.2	88.9	47.9	208.9	67	235.5	238.6	6.6	3.5
1990	1.2	Trace	3.4	32.2	146.9	57.2	36.6	109	98.6	91	26.2	10.8
1991	0.3	0	Trace	43.3	194.4	209.4	72.5	119.4	227.7	303	180.5	Trace
1992	Trace	0	0	7.6	91	178.1	93.8	104.6	154.8	159.8	36.2	0.4
1993	0	0	29.5	38.8	100.9	140.3	92.9	127.6	263.5	164.9	27.3	82.7
1994	Trace	0.2	0	11	78.5	38.7	107.5	58.6	80.6	180.6	25.6	5.9
1995	18.5	0	16.5	33.8	147.7	95.6	107.7	237.1	251.6	155.1	13.1	0
1996	0	0	0	90.8	117.6	228.2	51	302.9	275.8	83.8	1.4	21.8
1997	5.4	0	26.7	65.2	77	78.8	25.6	161.7	277	328.5	164.4	19.5
1998	0	Trace	0.1	95	110.3	60.7	257.7	387.1	235.3	215.4	49.6	20.6
1999	0	15.7	Trace	74.9	200.6	75.7	114.4	94.7	164.2	192.4	64.8	16.6
2000	0	57.7	Trace	76.2	56.6	91.8	115.9	276.7	208.8	310	8.9	15.1
2001	0.6	0	2.2	323.8	60.2	27.4	112.1	85.1	248.6	155.9	35	7.6
2002	Trace	0.7	Trace	8.8	183.5	180.9	36.8	45.5	94.8	173.9	38	4.8

2003	Trace	1.8	3.3	84.1	1.3	86	96.2	139.2	77.2	207.7	27.4	2.6
2004	5	1.6	1.2	51.3	207.9	70	285.3	74.6	268.7	153.3	26.2	0
2005	0.6	7.7	11.2	80.3	150.1	108	163	229.3	181	605.6	60.9	9.1
2006	0.5	0	88.6	37.3	164.2	157	46.3	51.1	45.3	50.2	41.5	0.3
2007	Trace	0	0	134.5	120.2	47.7	216.6	224	271.4	156.2	35.8	42
2008	0	19.5	59.8	12.2	84.8	117	283.4	309.8	140	193.7	65.5	0.9
2009	0.2	0	18.9	49.7	151.8	204.6	18.2	152.4	345.8	25.4	64.8	26.1
2010	0.3	Trace	5.9	101.7	108.2	105.2	100.3	137.6	190.3	141.3	145.3	3.3
2011	0	44.1	0.2	217.1	150.5	57.7	92.8	278.2	111.1	170	49.9	7.2
2012	0.4	0	0.7	13.4	143.6	7.2	66.7	189.1	68.4	83.2	125	26.9
2013	0	2.9	0.6	23.3	151	177.1	139.7	94.3	352.6	100.2	143.7	0.3
2014	0	0.2	4.7	15	74.6	172	100.9	102.4	319	343.8	25.7	1
2015	9	0	37.7	226.5	178.4	85.3	94.1	110	189.8	47	296.4	5.1
2016	5.2	0	19.9	25.3	140.6	191.3	209.4	82.8	33.2	11.5	1.5	74.9
2017	0.2	0	47.8	30.4	241.9	25.1	59	351.8	513.8	385.7	20.6	19.7
2018	18.6	17.2	Trace	8.4	85.4	131.7	65.3	97.5	516.6	102.6	87.9	14.7
2019	0	0	25.3	57.6	84.2	84.2	53.7	157.8	102.7	144.4	35.1	53.6
2020	0	16.5	29.2	71.4	108.9	25.9	243.8	242	425	10	35.4	30
2021	0	0	2	6.2	88.9	47.9	208.9	67	235.5	238.6	6.6	3.5
2022	0	19.5	59.8	12.2	84.8	117	283.4	309.8	140	193.7	65.5	0.9
2023	0.2	0	18.9	49.7	151.8	204.6	18.2	152.4	345.8	25.4	64.8	26.1
2024	0.3	17.2	5.9	101.7	108.2	105.2	100.3	137.6	190.3	141.3	145.3	3.3
2025	0.6	7.7	11.2	80.3	150.1	108	163	229.3	181	605.6	60.9	9.1
2026	0	19.5	59.8	12.2	84.8	117	283.4	309.8	140	193.7	65.5	0.9
2027	2.8	0	20.7	10	78.6	81.4	72.9	67.8	139.8	70.9	97.3	3
2028	18.6	17.2	22.5	8.4	85.4	131.7	65.3	97.5	516.6	102.6	87.9	14.7
2029	0	19.5	59.8	12.2	84.8	117	283.4	309.8	140	193.7	65.5	0.9
2030	0.2	0	18.9	49.7	151.8	204.6	18.2	152.4	345.8	25.4	64.8	26.1

Table 1 Rainfall prediction Analysis from January to December 1980 -2030

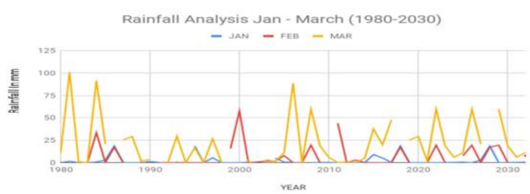

Figure 2 Rainfall Prediction Analyses from January - March 1980-2030

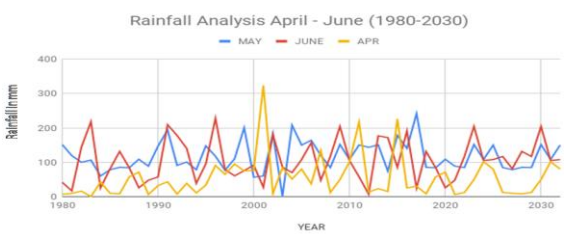

Figure 3 Rainfall Prediction Analyses from April - June 1980-2030

Figure 4 Rainfall Prediction Analyses from July - September 1980-2030

Figure 5 Rainfall Prediction Analyses from October - December 1980-2030

All the above mentioned discussions are the predictions of rainfall. The rainfall prediction for all of the months in the corresponding range of years has been mentioned. The prediction of rainfall in the upcoming years has been discussed. Some of the years have abrupt changes in different months.

VI. Conclusion

This current research work mainly focused on effect of rainfall. The rainfall prediction graph is exhibited for past years from 1989 to 2019. With the aid of ARIMA modeling, future temperature prediction is done till 2030 and the values are presented. Bangalore is a rapidly growing city that has undergone a profound social and economic transformation in the last two decades, associated with the rise of the information technology (IT) industry. This has had a strong impact on the urban fabric, for example by developing new communication infrastructures and the building of new developments on the edge of the city to serve the needs of a rapidly emerging industry and middle-class population. The climatic change occurs due to urbanization, deforestation, etc.

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