Machine Learning Based Temperature Analysis

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Abstract--- 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 temperature events for the pre-monsoon season have been studied using daily data on maximum and minimum temperatures over 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 temperatures 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 temperature. To attain this aforementioned aim of research work, the temperature 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.

Keywords --- ARIMA, ANN, climate change, KSPCB, machine learning, temperature.

I. INTRODUCTION

Many studies have reported that the global as well as hemispheric mean surface air temperatures have significantly increased in the last century and pronounced warming has occurred in the last three decades [1]. Authors have examined trends in surface temperature over India for the period 1901–2003 and reported that the annual mean, maximum as well as minimum temperatures have significantly increased by 0.2◦C per decade respectively during the last three decades, in a marked acceleration of the warming trend compared to the trends over the past century (1901–2003) [2]. However, manifestation of such changes on shorter timescale has been recognized to be one of the most crucial factors in terms of socio-economic impacts. Extremes in the temperature are characterized by daily temperature levels exceeding tolerable limits, and changes in their frequency, duration and amplitude are of great interest in impact assessment [3]. For example, heat wave conditions are usually associated with fatal conditions, leading to sudden spurt in mortality. In May–June 2003, an unprecedented heat wave occurred in India, claiming an estimated 1600 lives (report on heat wave conditions in Andhra Pradesh, India 2004) [4]. During the last two decades, more attention has been given to study the extremes in daily temperatures and their variability due to their adverse socio-economic impacts [5]. However, studies of trends in temperature extremes and intra-seasonal variability of daily temperatures over various regions of the globe are still limited [6].

In India, pre-monsoon is the warmest season of the year, also referred to as the hot-weather season, and anomalously high daily temperatures during this season severely affect human health and comfort. Identification of long-term changes in such conditions and their spatial extents is of critical importance to the development of appropriate risk management strategies [7]. In view of this, the present paper examines the trends in the frequency of occurrence of temperature extremes in maximum and minimum temperatures and day-to-day fluctuations (intra-seasonal variability) of daily temperatures during the pre-monsoon season [8].

This research focuses on temperature analysis and future temperature predictions from 2020 till 2030.

II. LITERATURE REVIEW

The daily maximum and minimum temperatures data of 121 stations well distributed over the country (figure 1) have been used in the present study, covering the period 1970–2005 [9]. The basic sources of these data are the Indian Daily Weather Reports (IDWRs) and National Data Center of the India Meteorological Department (IMD) [10]. In the present study, adequate care has been taken regarding the homogeneity of the data. The possible in-homogeneities in the data were first assessed by visual examination of the plots of the annual mean maximum and minimum temperature series at each station. Very few stations showed strong discontinuities in the series, and were promptly deleted from further analysis [11]. The RH test is also used to examine the homogeneity of the data, however, inhomogeneity was not found in any station. Further quality control measures were also taken up to identify errors in data archival processes, such as keying or printing errors [12]. The following procedures were followed to identify errors/outliers in the data series:

• Both maximum and minimum temperature is considered to be missing if daily maximum temperature is reported less than daily minimum temperature [13]. Whether the value can be really treated as an outlier or not was then determined by examining the weather situation on that day, and if there is no supporting evidence to the anomaly, it is treated as missing value [14].

• All the daily temperature values for individual stations/months that differ from their corresponding long-term means by more than four times their standard deviation were listed [15].

In the daily temperature datasets, the proportion of missing values (actually missing in the datasets as well as outliers treated as missing) at individual stations ranges from 0 to 5% during the period 1970–2005 [16]. These missing values in the datasets have been filled by using appropriate methods as indicated below:

• If the daily temperatures were nearly uniform for 3 to 4 days before and after a given day with missing temperature data, the weather situation on that missing date is also normal, and then the missing value was filled by the arithmetic average of the temperatures on the preceding and the following days of the missing date [17].

• Other missing daily temperature values have been objectively interpolated by using an inverse squared distance weighted average algorithm [18].

III. RESEARCH METHODOLOGY

3.1 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].

3.2 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

$$\Delta^D y_t = c + \phi_1 \Delta^D y_{t-1} + \dots + \phi_p \Delta^D y_{t-p} + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \dots + \theta_q \varepsilon_{t-q} \quad [1]$$

Where,

$\Delta^D y_t$ denotes a Dth differenced time series, and ε_t is an uncorrelated innovation process with mean zero.

In lag operator notation, $L^i y_t = y_{t-i}$. You can write the ARIMA (p,D,q) model as

$$\phi^*(L) y_t = \phi(L)(1-L)^D y_t = c + \theta(L)\varepsilon_t. \quad [2]$$

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 $\phi(L) = (1 - \phi_1 L - \dots - \phi_p L^p)$ is a stable degree p AR lag operator polynomial (with all roots lying outside the unit circle). Similarly, $\theta(L) = (1 + \theta_1 L + \dots + \theta_q L^q)$ 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

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converting the high frequency variables to the lowest variable frequency. Thus potentially important data 'richness' may be lost in causal models.

IV. 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.

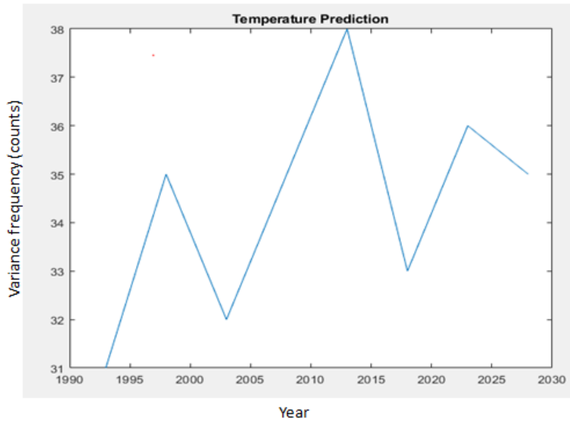

Figure 1 Temperature prediction

The average prediction in temperature seems to be observed. The logical algorithm has been developed that constitutes an occurrence of the predictions in temperature that seems to be improved to an extent in year 2023-2030.

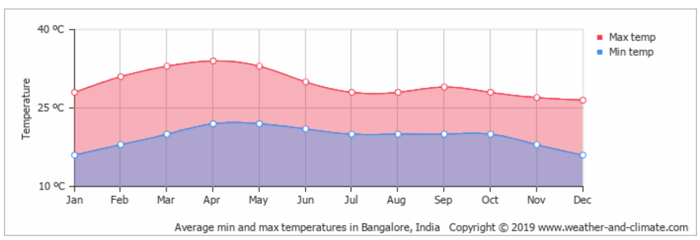

Figure 2 Temperature graph

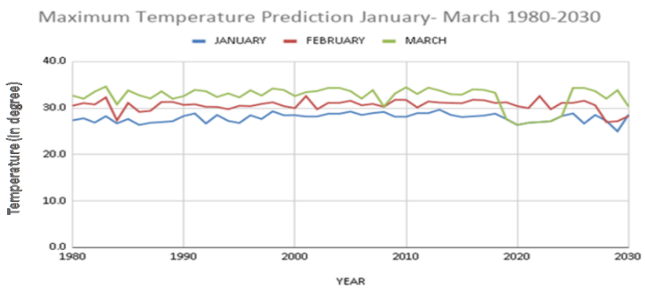

Figure 3 Maximum Temperature Analysis January - March 1980-2030

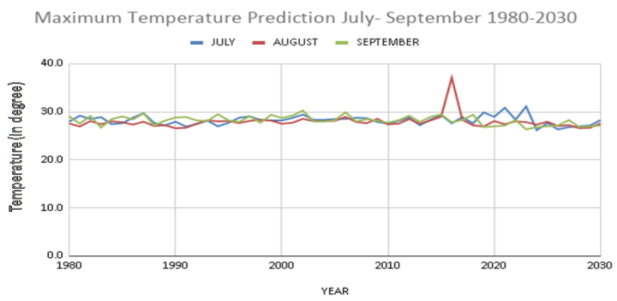

Figure 5 Maximum Temperature Analyses from July-September 1980-2030

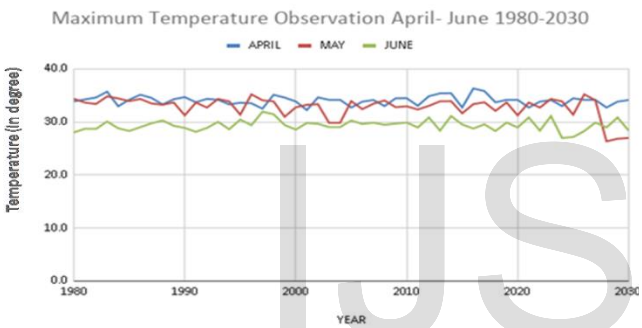

Figure 4 Maximum Temperature Analysis April - June 1980-2030

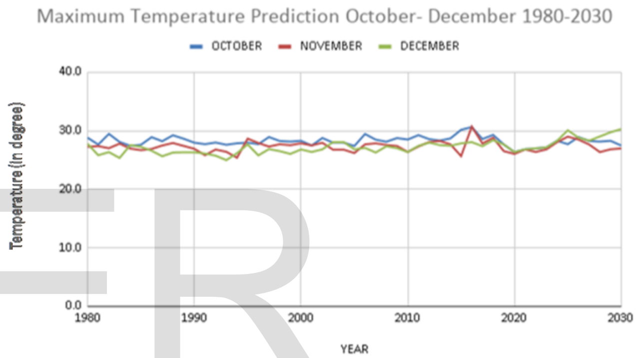

Figure 6 Maximum Temperature Analyses from October - December 1980-2030

	JAN	FEB	MAR	APR	MAY	JUNE	JULY	AUG	SEP	OCT	NOV	DEC
1980	27.4	30.5	32.7	33.9	34.4	28	28	27.6	29.1	28.8	27.3	27.8
1981	27.8	31.1	32	34.3	33.7	28.7	29.2	27	27.6	27.6	27.4	25.8
1982	26.9	30.8	33.5	34.6	33.4	28.7	28.5	28.1	29.1	29.5	27	26.4
1983	28.2	32.3	34.6	35.7	34.8	30.1	28.9	27.4	26.7	28.1	27.8	25.4
1984	26.7	27.3	30.8	33	34.4	28.8	27.4	28	28.5	27.4	27	27.6
1985	27.7	31.1	33.8	34.2	33.9	28.3	27.6	27.9	29.1	27.6	26.7	27.3
1986	26.4	29.2	32.8	35.1	34.3	29	28.8	27.3	28.4	28.9	26.9	26.6
1987	26.8	29.4	32	34.5	33.5	29.8	29.7	28	29.7	28.2	27.5	25.7

1988	27	31.3	33.6	33.3	33.2	30.3	27.7	27.1	27.2	29.2	27.9	26.3
1989	27.2	31.3	32	34.3	33.7	29.3	27.2	27.2	28.2	28.6	27.4	26.3
1990	28.3	30.7	32.6	34.7	31.3	28.9	28	26.6	28.8	28	26.9	26.3
1992	26.7	30.3	33.6	34.4	32.7	28.9	27.5	27.6	28.2	28	26.8	25.8
1993	28.5	30.3	32.4	34.2	34.3	30	28.2	28.2	28.1	27.6	26.4	25
1994	28.5	30.3	32.4	34.2	34.3	30	28.2	28.2	28.1	27.6	26.4	25
1995	28.2	32.3	34.6	35.7	34.8	30.1	28.9	27.4	26.7	28.1	27.8	25.4
1996	26.7	27.3	30.8	33	34.4	28.8	27.4	28	28.5	27.4	27	27.6
1997	27.7	31.1	33.8	34.2	33.9	28.3	27.6	27.9	29.1	27.6	26.7	27.3
1998	26.4	29.2	32.8	35.1	34.3	29	28.8	27.3	28.4	28.9	26.9	26.6
1999	26.8	29.4	32	34.5	33.5	29.8	29.7	28	29.7	28.2	27.5	25.7
2000	27	31.3	33.6	33.3	33.2	30.3	27.7	27.1	27.2	29.2	27.9	26.3
2001	26.4	29.2	32.8	35.1	34.3	29	28.8	27.3	28.4	28.9	26.9	26.6
2002	26.8	29.4	32	34.5	33.5	29.8	29.7	28	29.7	28.2	27.5	25.7
2003	27	31.3	33.6	33.3	33.2	30.3	27.7	27.1	27.2	29.2	27.9	26.3
2004	27.2	31.3	32	34.3	33.7	29.3	27.2	27.2	28.2	28.6	27.4	26.3
2005	28.3	30.7	32.6	34.7	31.3	28.9	28	26.6	28.8	28	26.9	26.3
2006	26.7	30.3	33.6	34.4	32.7	28.9	27.5	27.6	28.2	28	26.8	25.8
2007	26.4	29.2	32.8	35.1	34.3	29	28.8	27.3	28.4	28.9	26.9	26.6
2008	26.8	29.4	32	34.5	33.5	29.8	29.7	28	29.7	28.2	27.5	25.7
2009	27	31.3	33.6	33.3	33.2	30.3	27.7	27.1	27.2	29.2	27.9	26.3
2010	27.2	31.3	32	34.3	33.7	29.3	27.2	27.2	28.2	28.6	27.4	26.3
2011	28.3	30.7	32.6	34.7	31.3	28.9	28	26.6	28.8	28	26.9	26.3
2012	26.7	30.3	33.6	34.4	32.7	28.9	27.5	27.6	28.2	28	26.8	25.8
2013	26.4	29.2	32.8	35.1	34.3	29	28.8	27.3	28.4	28.9	26.9	26.6
2014	26.8	29.4	32	34.5	33.5	29.8	29.7	28	29.7	28.2	27.5	25.7
2015	27	31.3	33.6	33.3	33.2	30.3	27.7	27.1	27.2	29.2	27.9	26.3

2016	27.2	31.3	32	34.3	33.7	29.3	27.2	27.2	28.2	28.6	27.4	26.3
2017	28.3	30.7	32.6	34.7	31.3	28.9	28	26.6	28.8	28	26.9	26.3
2018	26.7	30.3	33.6	34.4	32.7	28.9	27.5	27.6	28.2	28	26.8	25.8
2019	26.4	29.2	32.8	35.1	34.3	29	28.8	27.3	28.4	28.9	26.9	26.6
2020	26.8	29.4	32	34.5	33.5	29.8	29.7	28	29.7	28.2	27.5	25.7
2021	27	31.3	33.6	33.3	33.2	30.3	27.7	27.1	27.2	29.2	27.9	26.3
2022	27.2	31.3	32	34.3	33.7	29.3	27.2	27.2	28.2	28.6	27.4	26.3
2023	28.3	30.7	32.6	34.7	31.3	28.9	28	26.6	28.8	28	26.9	26.3
2024	26.7	30.3	33.6	34.4	32.7	28.9	27.5	27.6	28.2	28	26.8	25.8
2025	26.4	29.2	32.8	35.1	34.3	29	28.8	27.3	28.4	28.9	26.9	26.6
2026	26.8	29.4	32	34.5	33.5	29.8	29.7	28	29.7	28.2	27.5	25.7
2027	27	31.3	33.6	33.3	33.2	30.3	27.7	27.1	27.2	29.2	27.9	26.3
2028	28.2	32.3	34.6	35.7	34.8	30.1	28.9	27.4	26.7	28.1	27.8	25.4
2029	28.3	30.7	32.6	34.7	31.3	28.9	28	26.6	28.8	28	26.9	26.3
2030	27.7	31.1	33.8	34.2	33.9	28.3	27.6	27.9	29.1	27.6	26.7	27.3

Table 1 Maximum Temperature Analysis and Predicted Data January - December 1980-2030

Here months denoted with the spreads of blue as January, red as February and green for March. Now, the minimum temperature prediction in these months starts from 1980 to 2030.

	JAN	**FEB**	**MAR**	**APR**	**MAY**	**JUNE**	**JULY**	**AUG**	**SEP**	**OCT**	**NOV**	**DEC**
1980	**14.7**	**16.7**	**19.4**	**22**	**21.9**	**20.3**	**19.9**	**19.3**	**19.6**	**19.2**	**17.9**	**16.4**
1981	**16.1**	**16.6**	**19.7**	**22**	**21.5**	**20.1**	**19.9**	**19.4**	**19.8**	**19.9**	**17.3**	**15.5**
1982	**14.8**	**17.2**	**20.3**	**22.2**	**22**	**20.1**	**19.6**	**19.6**	**19.3**	**19.6**	**18.4**	**15.6**
1983	**14.8**	**19**	**21.1**	**22.7**	**22**	**20.6**	**20.2**	**20**	**19.6**	**19.2**	**16.3**	**17.2**
1984	**16.8**	**17.7**	**18.7**	**21.4**	**22.1**	**19.6**	**19.5**	**19.2**	**19.2**	**19**	**17.4**	**15.3**
1985	**16.5**	**17.6**	**19.7**	**22.1**	**21.7**	**19.9**	**19.2**	**19.6**	**19.6**	**18.5**	**16.5**	**16.3**
1986	**15.6**	**17.1**	**20.1**	**22.2**	**21.4**	**20.2**	**19.7**	**19.5**	**19.6**	**19.4**	**17.6**	**16.8**
1987	**15.7**	**15.9**	**18.7**	**21.6**	**22**	**20.6**	**20.1**	**20**	**20.4**	**20.1**	**18.3**	**17.2**

1988	**15.2**	**18**	**20.8**	**21.5**	**21.8**	**20.4**	**20.1**	**20**	**19.7**	**19**	**17**	**16**
1989	**15.2**	**15.5**	**19.1**	**21.8**	**21.5**	**19.8**	**19.9**	**19.4**	**19.6**	**19.5**	**17.1**	**16.4**
1990	**14.5**	**17.2**	**20.9**	**22.6**	**21.4**	**20.1**	**19.4**	**19.7**	**20**	**19.6**	**18.1**	**16.2**
1991	**16.4**	**17.4**	**20.8**	**21.8**	**22.1**	**20.7**	**19.5**	**19.2**	**19.8**	**19.4**	**17.7**	**15.7**
1992	**14.8**	**19**	**21.1**	**22.7**	**22**	**20.6**	**20.2**	**20**	**19.6**	**19.2**	**16.3**	**17.2**
1993	**16.8**	**17.7**	**18.7**	**21.4**	**22.1**	**19.6**	**19.5**	**19.2**	**19.2**	**19**	**17.4**	**15.3**
1994	**16.5**	**17.6**	**19.7**	**22.1**	**21.7**	**19.9**	**19.2**	**19.6**	**19.6**	**18.5**	**16.5**	**16.3**
1995	**15.6**	**17.1**	**20.1**	**22.2**	**21.4**	**20.2**	**19.7**	**19.5**	**19.6**	**19.4**	**17.6**	**16.8**
1996	**15.7**	**15.9**	**18.7**	**21.6**	**22**	**20.6**	**20.1**	**20**	**20.4**	**20.1**	**18.3**	**17.2**
1997	**15.2**	**18**	**20.8**	**21.5**	**21.8**	**20.4**	**20.1**	**20**	**19.7**	**19**	**17**	**16**
1998	**15.2**	**15.5**	**19.1**	**21.8**	**21.5**	**19.8**	**19.9**	**19.4**	**19.6**	**19.5**	**17.1**	**16.4**
1999	**15.7**	**15.9**	**18.7**	**21.6**	**22**	**20.6**	**20.1**	**20**	**20.4**	**20.1**	**18.3**	**17.2**
2000	**15.2**	**18**	**20.8**	**21.5**	**21.8**	**20.4**	**20.1**	**20**	**19.7**	**19**	**17**	**16**
2001	**15.2**	**15.5**	**19.1**	**21.8**	**21.5**	**19.8**	**19.9**	**19.4**	**19.6**	**19.5**	**17.1**	**16.4**
2002	**14.5**	**17.2**	**20.9**	**22.6**	**21.4**	**20.1**	**19.4**	**19.7**	**20**	**19.6**	**18.1**	**16.2**
2003	**16.4**	**17.4**	**20.8**	**21.8**	**22.1**	**20.7**	**19.5**	**19.2**	**19.8**	**19.4**	**17.7**	**15.7**
2004	**14.8**	**19**	**21.1**	**22.7**	**22**	**20.6**	**20.2**	**20**	**19.6**	**19.2**	**16.3**	**17.2**
2005	**16.8**	**17.7**	**18.7**	**21.4**	**22.1**	**19.6**	**19.5**	**19.2**	**19.2**	**19**	**17.4**	**15.3**
2006	**16.5**	**17.6**	**19.7**	**22.1**	**21.7**	**19.9**	**19.2**	**19.6**	**19.6**	**18.5**	**16.5**	**16.3**
2007	**15.6**	**17.1**	**20.1**	**22.2**	**21.4**	**20.2**	**19.7**	**19.5**	**19.6**	**19.4**	**17.6**	**16.8**
2008	**15.6**	**17.1**	**20.1**	**22.2**	**21.4**	**20.2**	**19.7**	**19.5**	**19.6**	**19.4**	**17.6**	**16.8**
2009	**15.7**	**15.9**	**18.7**	**21.6**	**22**	**20.6**	**20.1**	**20**	**20.4**	**20.1**	**18.3**	**17.2**
2010	**15.2**	**18**	**20.8**	**21.5**	**21.8**	**20.4**	**20.1**	**20**	**19.7**	**19**	**17**	**16**
2011	**15.2**	**15.5**	**19.1**	**21.8**	**21.5**	**19.8**	**19.9**	**19.4**	**19.6**	**19.5**	**17.1**	**16.4**
2012	**14.5**	**17.2**	**20.9**	**22.6**	**21.4**	**20.1**	**19.4**	**19.7**	**20**	**19.6**	**18.1**	**16.2**
2013	**16.4**	**17.4**	**20.8**	**21.8**	**22.1**	**20.7**	**19.5**	**19.2**	**19.8**	**19.4**	**17.7**	**15.7**
2014	**14.8**	**19**	**21.1**	**22.7**	**22**	**20.6**	**20.2**	**20**	**19.6**	**19.2**	**16.3**	**17.2**

2015	**16.8**	**17.7**	**18.7**	**21.4**	**22.1**	**19.6**	**19.5**	**19.2**	**19.2**	**19**	**17.4**	**15.3**
2016	**16.5**	**17.6**	**19.7**	**22.1**	**21.7**	**19.9**	**19.2**	**19.6**	**19.6**	**18.5**	**16.5**	**16.3**
2017	**15.6**	**17.1**	**20.1**	**22.2**	**21.4**	**20.2**	**19.7**	**19.5**	**19.6**	**19.4**	**17.6**	**16.8**
2018	**15.7**	**15.9**	**18.7**	**21.6**	**22**	**20.6**	**20.1**	**20**	**20.4**	**20.1**	**18.3**	**17.2**
2019	**15.2**	**18**	**20.8**	**21.5**	**21.8**	**20.4**	**20.1**	**20**	**19.7**	**19**	**17**	**16**
2020	**15.2**	**15.5**	**19.1**	**21.8**	**21.5**	**19.8**	**19.9**	**19.4**	**19.6**	**19.5**	**17.1**	**16.4**
2021	**15.7**	**15.9**	**18.7**	**21.6**	**22**	**20.6**	**20.1**	**20**	**20.4**	**20.1**	**18.3**	**17.2**
2022	**15.2**	**18**	**20.8**	**21.5**	**21.8**	**20.4**	**20.1**	**20**	**19.7**	**19**	**17**	**16**
2023	**15.2**	**15.5**	**19.1**	**21.8**	**21.5**	**19.8**	**19.9**	**19.4**	**19.6**	**19.5**	**17.1**	**16.4**
2024	**14.5**	**17.2**	**20.9**	**22.6**	**21.4**	**20.1**	**19.4**	**19.7**	**20**	**19.6**	**18.1**	**16.2**
2025	**15.2**	**15.5**	**19.1**	**21.8**	**21.5**	**19.8**	**19.9**	**19.4**	**19.6**	**19.5**	**17.1**	**16.4**
2026	**14.5**	**17.2**	**20.9**	**22.6**	**21.4**	**20.1**	**19.4**	**19.7**	**20**	**19.6**	**18.1**	**16.2**
2027	**15.2**	**15.5**	**19.1**	**21.8**	**21.5**	**19.8**	**19.9**	**19.4**	**19.6**	**19.5**	**17.1**	**16.4**
2028	**14.5**	**17.2**	**20.9**	**22.6**	**21.4**	**20.1**	**19.4**	**19.7**	**20**	**19.6**	**18.1**	**16.2**
2029	**16.4**	**17.4**	**20.8**	**21.8**	**22.1**	**20.7**	**19.5**	**19.2**	**19.8**	**19.4**	**17.7**	**15.7**
2030	**14.8**	**19**	**21.1**	**22.7**	**22**	**20.6**	**20.2**	**20**	**19.6**	**19.2**	**16.3**	**17.2**

Table 2 Minimum Temperature Analysis January - December 1980-2030

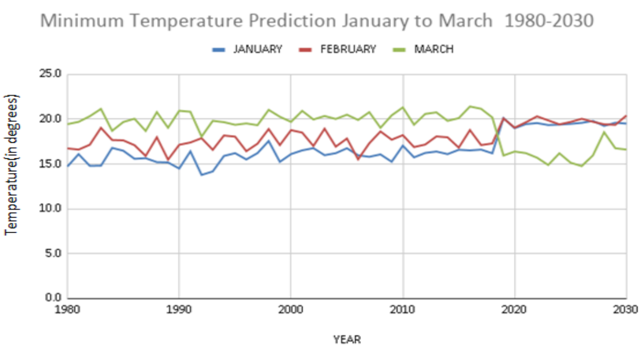

Figure 7 Minimum Temperature Analyses January- March 1980-2030

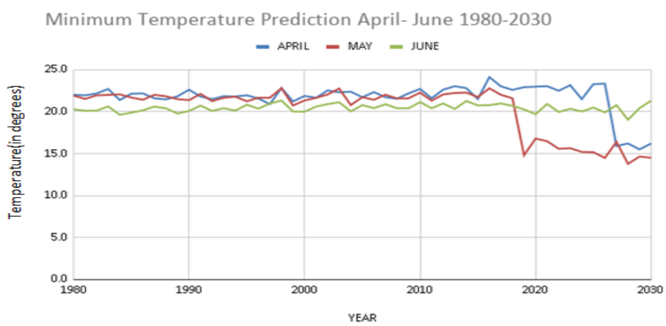

Figure 8 Minimum Temperature Analysis April- June 1980-2030

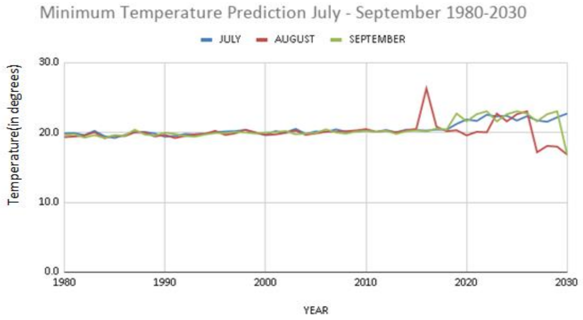

Figure 9 Minimum Temperature Analysis July - September 1980-2030

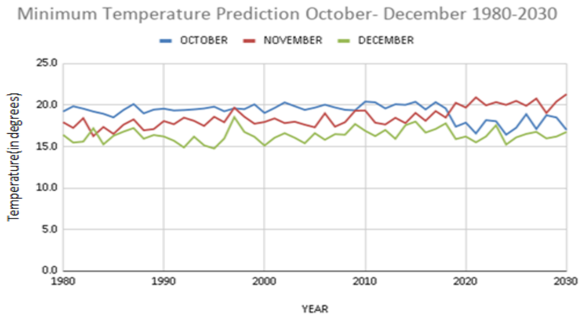

Figure 10 Minimum Temperature Analysis October - December 1980-2030

All the above mentioned discussions are the predictions of temperature. The maximum and minimum temperature 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.

V. CONCLUSION

This current research work mainly focused on effect of temperature. The temperature 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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