Impact of Climate Change on Food Supply Chain

Submitted in partial fulfillment
for the award of degree in

MASTER OF SCIENCE
IN
STATISTICS (2020-2022)

By

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to the

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DECLARATION

I declare that the project report entitled ***"Impact of Climate Change on Food Supply Chain"*** has been written by me and submitted to the Department of Statistics, Babasaheb Bhimrao Ambedkar University, Lucknow in partial fulfillment for the degree of Master of Science in Statistics under the supervision of Dr. Amit Kumar Misra. The book and various sources used in making this project are mentioned at the end.

I also declare that the work has not been submitted or presented previously in any form to any university or any other institutional body or to another examination committee.

Date: ....

SUBMITTED BY :

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A Central University | Established in 1996 | 'A' Grade by NAAC 2015

CERTIFICATE

This is to certify that this dissertation for the project work entitled *"Impact of Climate Change on Food Supply Chain "* has been prepared and submitted by **Mr. Ayush Mishra** towards partial fullfillment for the degree of **Master of Science (Statistics), Course code: MS 406** in Babasaheb Bhimrao Ambedkar University, Vidya Vihar, Raebareli Road, Lucknow-226025. The matter embodied in this project is a genuine work to the best of knowledge and has not been submitted before neither to this university nor any institutional body.

Date: ....

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Supervisor & Assistant Professor
Department of Statistics
BBAU, Lucknow.

Prof. Surinder Kumar
Head
Department of Statistics
BBAU, Lucknow.

ACKNOWLEDGEMENTS

The success and final outcome of this project required a lot of guidance and assistance from many people and I am extremely privileged to have got this all along the completion of our project. All that I have done is only due to such supervision and assistance, and I would not forget to thank them.

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Last but not the least, I would like to thank our family and friends for their constant source of inspiration.

Submitted by:

Ayush Mishra


IMPACT OF CLIMATE CHANGE ON
FOOD SUPPLY CHAIN

Contents

Chapter 1

Climate Change

1.1 Introduction to Climate Change

Climate change is a intermittent alteration of Earth's climate brought about due to the changes within the environment as well as the intuitive between the atmosphere and different other geographical, chemical, natural and geographical factors inside the Earth's system. Climate alter can make weather patterns less unsurprising. These unforeseen weather designs can make it difficult to preserve and develop crops, making agriculture-dependent nations like India vulnerable. It is additionally causing harming climate events like more visit and seriously hurricanes, floods, tornados, flooding etc. Due to the rising temperature caused by climate change, the ice within the polar locales is dissolving at an accelerated rate, causing ocean levels to rise. This is often harming the coastlines due to the increased flooding and disintegration.

1.1.1 Causes of Climate Change

Human activities are to blame for the current rapid climate change, which is jeopardizing humanity's exceptional survival. The most significant driver of warming is the emanation of greenhouse gases, the majority of which are carbon dioxide (CO_2) and methane. The primary source of these outflows is the use of fossil fuels (coal, oil, and natural gas) for energy generation, with additional contributions from horticulture, deforestation, and manufacturing. Climate feedbacks, such as the loss of sunlight-reflecting snow and ice cover, expanded water vapor and changes in arrival and sea carbon sinks, hasten or slow temperature rise. Temperature rise on arrival is roughly twice the global average increment, causing extension to be abandoned and more frequent warm waves to occur.

1.2 The Intergovernmental Panel on Climate Change (IPCC)

The Intergovernmental Panel on Climate Change (IPCC) is the United Nations body for assessing the science related to climate change. Created in 1988 by the World Meteorological Organization (WMO) and the United Nations Environment Programme (UNEP), the objective of the IPCC is to provide scientific informations to the governments at all levels that they can use to develop climate policies. IPCC reports also play an important role in international climate change negotiations. The IPCC is a group of governments that are members of the United Nations or the World Meteorological Organization. The IPCC now has 195 members. The IPCC's work is supported by thousands of people from all over the world. Experts share their knowledge as IPCC authors to assess the thousands of scientific papers published each year in order to provide a comprehensive summary of what is known about the causes of climate change, its impacts, and future risks, as well as how adaptation and mitigation can reduce those risks. To ensure an objective and complete assessment, an open and transparent review by experts and governments from around the world is an essential part of the IPCC process.

1.3 IPCC Assesment of Indian Agriculture

Indian agriculture is adversely impacted by the vicissitudes of climate change, the sector also is a significant contributor to greenhouse gas (GHG) emissions. Around 54.6 per cent of GHG emissions were due to enteric fermentation, followed by 17.5 per cent from rice cultivation, 19.1 per cent from fertiliser applied to agricultural soils, 6.7 per cent from manure management, and 2.2 per cent due to field burning of agricultural residues. Therefore, effective mitigation measures and appropriate adaptation technologies must be taken to reduce GHG emissions from the agriculture sector.

Agricultural Production: Increasing temperatures are affecting agricultural productivity in higher latitudes, raising yields of some crops (maize, cotton, wheat, sugar beets) while yields of others (maize, wheat, barley) are declining in lower-latitude regions.

Nutritional Quality: Increased atmospheric CO_2 levels can reduce the nutritional quality of crops.

Livestock Production: In Future, climate change could affect livestock production. An increase in desertification and heatwaves could have a direct impact on animal morbidity, mortality and distress that in turn could adversely affect the food security.

Higher Prices: Report states that cereal prices could increase by 1-29% by 2050 as a result of climate change, leading to higher food prices and increased risk of food insecurity and hunger.

1.4 Remedies to Climate Change

- **Maintain the use of fossil fuels:** Coal, oil, and gas are examples of fossil fuels, and the more of them extracted and burned, the worse climate change will become. All countries must transition their economies away from fossil fuels.
- **Invest in renewable energy:** Changing our main energy sources to clean and renewable energy is the best way to stop using fossil fuels. These include technologies like solar, wind, wave, tidal and geothermal power.
- **Strenthen the Policies:** Changing our primary policies towards energy sources to clean and renewable energy which is the most effective way to phase out the use of fossil fuels. Solar, wind, wave, tidal, and geothermal power are examples of such technologies.
- Reduce people's consumption because transportation, clothing, food, and other lifestyle choices all have an impact on the environment.
- **Reduce use of plastic:** Because it does not degrade quickly in nature, a lot of it is burned, which contributes to emissions.

Chapter 2

Weather Forecasting

2.1 Visualisation of weather parameters

The climate change pattern across the words has marked a severe impact on the food supply chain of the world. These have been caused by many natural factors, including changes in the sun, emissions from volcanoes, variations in Earth's orbit and levels of carbon dioxide CO_2. Global climate change has typically occurred very slowly, over thousands or millions of years.
We here forecasting a weather parameter such as annual temperature rise, annual sea level rise, annual rainfall, annual Carbon dioxide emission. With the help of previous data, we forecast to study a future pattern of weather parameters.

Annual Temperature

The annual temperature increment is one of the most important weather parameters to study the climate change impact. We have taken dataset from 1901 to 2017 from the official website data.gov.in and based on that dataset, we have forecasted our data up to 2050. This figure shows that the annual icrement in temperature of india from 1901 and we have seen clearly from 1901 to 2017 it seems to be straight line that means the increment in temperatures approximately 1 degree celcius occurred over the century and value of R^2=0.7248 this shows that 72% of the variance of the dependent variable being studied is explained by the variance of the independent variable.

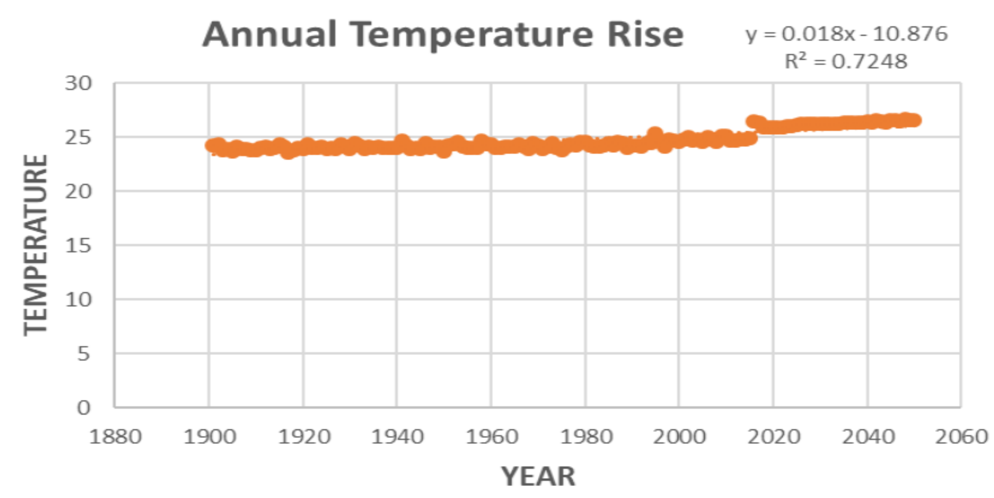


Figure: Annual temperature rise of India

Annual Sea level Rise

The sea level rise is a important concern in terms of climate change , this rise may harm the local residence and agricultral practices of coastal areas. Based on past dataset related to sea level rise ,We have forecasted our dataset up to 2050 to analyse the pattern in upcoming future. In this figure we have seen that the sea level rise of India from 1901 shows upward trend approximately 12 inches level increment up to 2050 and the value of R^2=0.9848 this shows 98% of the variance of the dependent variable being studied is explained by the variance of the independent variable.

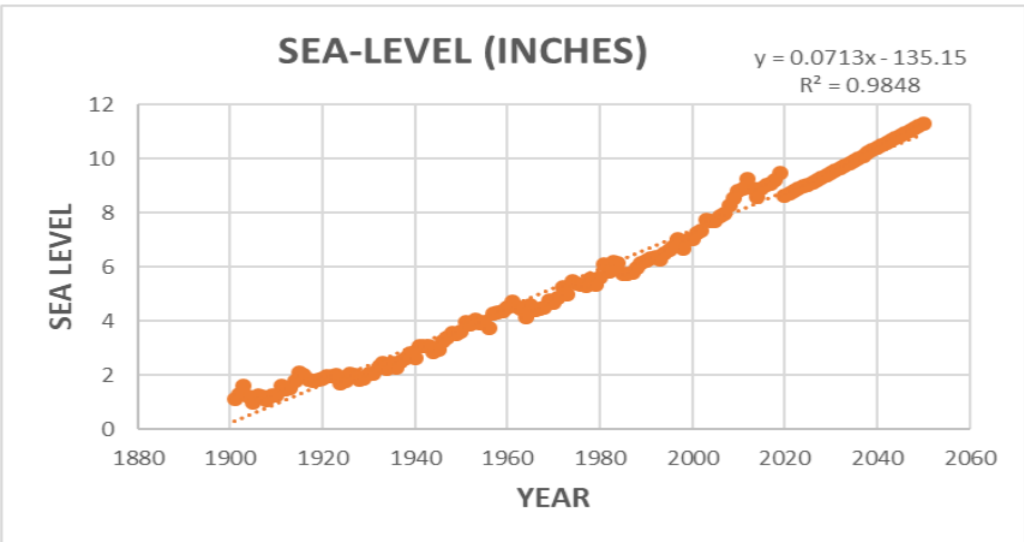


Figure: Annual sea level rise of India

Annual Rainfall

The annual rainfall is very uneven in space and time and there is large variation in actual rainfall due to various topological factors like distance from a sea and height from ground etc. Due to large variation in rainfall pattern the forecasted data is also variated by time. We have forecasted our dataset up to 2050 to analyse the pattern in upcoming future. This figure annual rainfall of India shows that rainfall is random fluctuations in nature. R^2=0.0821 this indicates that the 8% of the variance of the dependent variable being studied is explained by the variance of the independent variable.

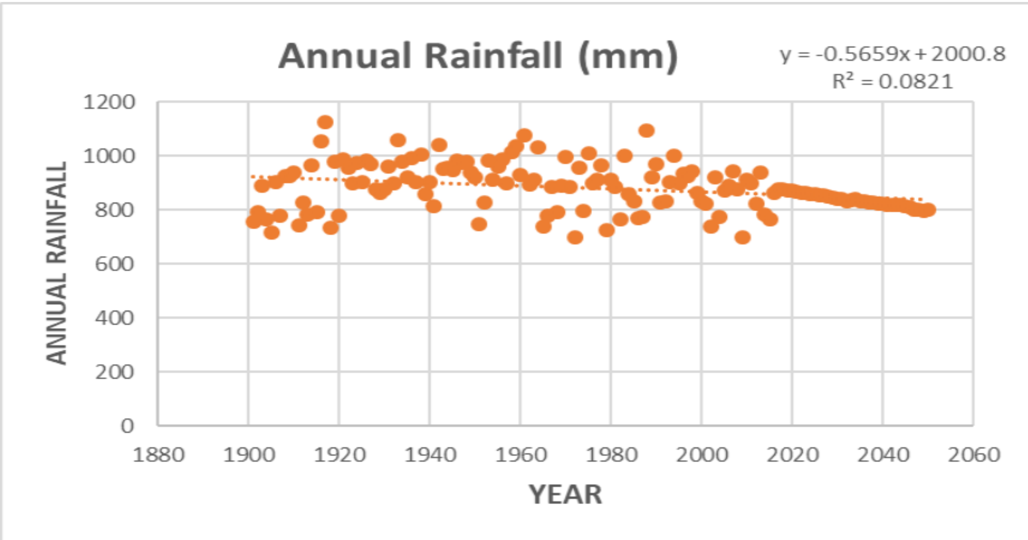


Figure: Annual rainfall of India

Annual Carbon Dioxide Emission

The greenhouse gas emissions from human activities strengthen the greenhouse effect, causing climate change. Most of the carbon dioxide emitted from burning fossil fuels, coal, oil, and natural gas. We have forecasted a dataset up to 2050 based on past emission dataset. This figure shows that annual carbon dioxide emission of India rises exponentially and R^2=0.9799 this means that the 97% of the variance of the dependent variable being studied is explained by the variance of the independent variable.

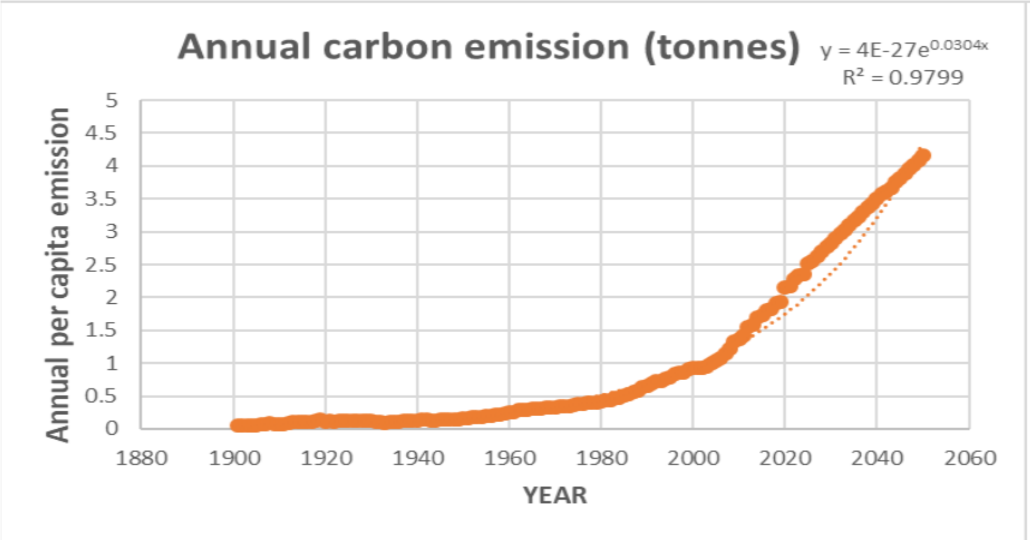


Figure: Annual carbon dioxide emission of India

Chapter 3

Forecasting of Major Crops Production

India is the second largest producer of wheat and rice in the world's major food staples. India is currently the world's second largest producer of several dry fruits, agriculture-based textile raw materials, roots and tuber crops and pulses.
Agriculture is a very important sector of the Indian economy. It is because it provides employment to roughly half of India's workforce and contributes to 17% of India's GDP. Since independence a lot of changes have been observed in the production.
We consider a three main crops like wheat, rice and pulses.
Based on the agriculture production dataset from 2001 to 2017 , We have forecasted crop production up to 2050. The following forecasting technique are used:

Linear Forecasting
Linear regression is a statistical tool that can be used to predict future values based on past values. It is frequently used as a quantitative method to determine the underlying trend and when prices have become overextended. A linear regression trendline plots a straight line through prices using the least squares method to minimize the distances between the prices and the resulting trendline. For each data point, this linear regression indicator plots the trendline value.

Exponential Smoothing
Simple exponential smoothing is a prediction that is based on a weighted sum of previous data, with the model explicitly using an exponentially decreasing weight for previous observations. This strategy is good for projecting data

that doesn't have a trend or a seasonal pattern.

3.1 Wheat Production

The agricultural practices is necessary for livelihood, Wheat is the major production crop of nation and majority of population consumes this. Wheat is the main cereal crop in India. The total area under the crop is about 29.8 million hectares in the country. Wheat can be grown in tropical, sub-tropical and temperate zones. The best wheat are produced in cool and moist weather area under the optimum temperature 20-25 degree celcius.
Based on the agriculture production dataset from 2001 to 2017, We have forecasted wheat crop production up to 2050. This figure shows that the production of wheat in India increases from 2001 to 2050 and the R^2=0.9945 that means 99% of the variance of the dependent variable being studied is explained by the variance of the independent variable.

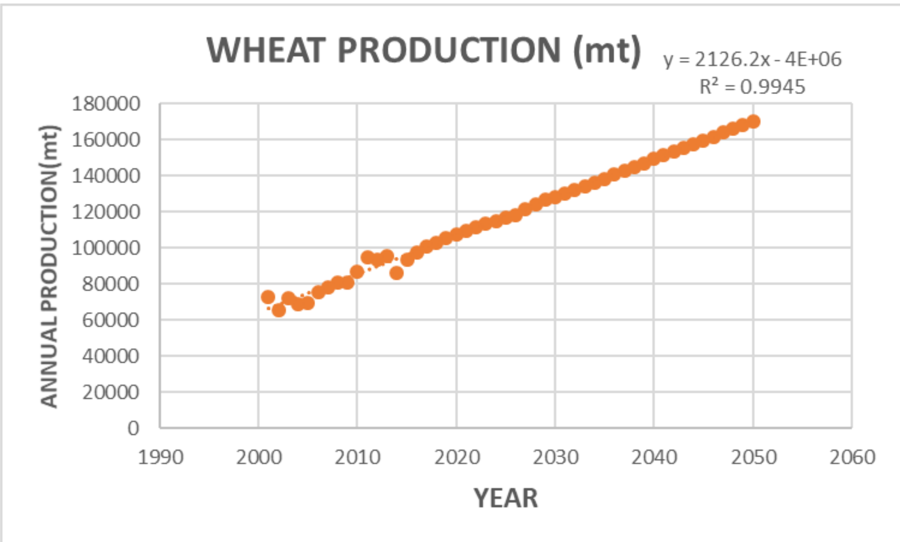


Figure: Wheat production of India

3.2 Rice Production

Rice is India's most important food crop, accounting for roughly one-fourth of all farmed land and feeding almost half of the country's population. This is a significant staple food for those living in the country's eastern and southern regions, particularly in places with more than 150 cm of annual rainfall. Rice is farmed in India under a variety of altitude and climatic conditions.

Rice requires a hot, humid climate to thrive. The average temperature necessary for a successful crop ranges from 21 to 37 degrees celsius, while rice's composition and characteristics vary greatly depending on variety and environmental conditions.
Based on the agriculture production dataset from 2001 to 2017, We have forecasted rice crop production of India up to 2050. This figure shows that the rice production in India increases from 2001 to 2050 and the R^2=0.9316 that means 93% of the variance of the dependent variable being studied is explained by the variance of the independent variable.

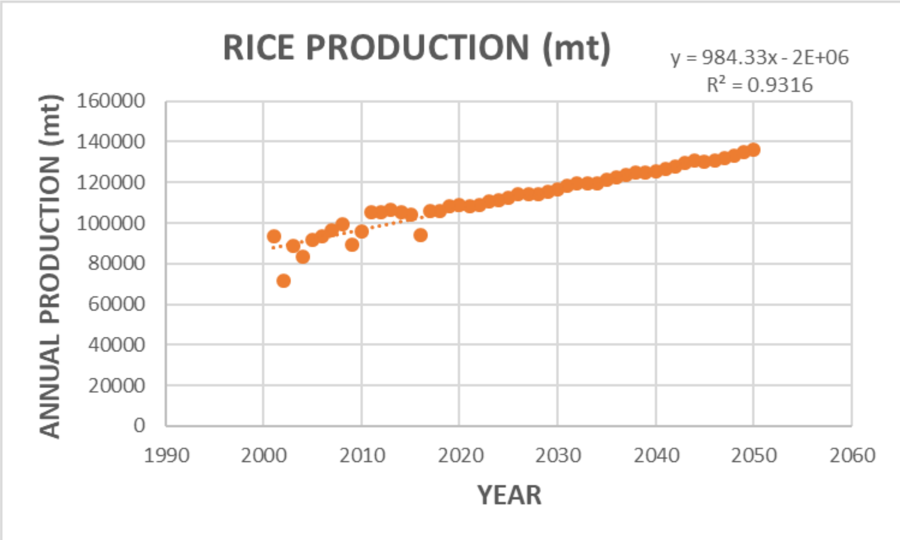


Figure:Rice production of India

3.3 Pulses Production

The states of India that produce pulses provide a substantial contribution to the country's total output. India is a major producer of pulses around the world. Pulse crops are grown during the agricultural year's Kharif, Rabi, and Zaid seasons. Rabi crops require a mild cold temperature during the sowing time, a cold climate during vegetative to pod growth, and a warm climate during mature harvesting. Kharif pulse crops, meanwhile, require a warm temperature throughout their whole life cycle, from seeding to harvesting. Summer pulses prefer to live in warm climates. To produce seed, seed must go through several stages, including germination, seedling, vegetative, flowering, fruit setting, pod development, and grain maturity harvesting.
Based on the agriculture production dataset from 2001 to 2017, We have forecasted crop production of India up to 2050. This figure shows that pulses

production in India steadily increasing from 2001 to 2050 and the R^2=0.6562 that means 65% of the variance of the dependent variable being studied is explained by the variance of the independent variable.

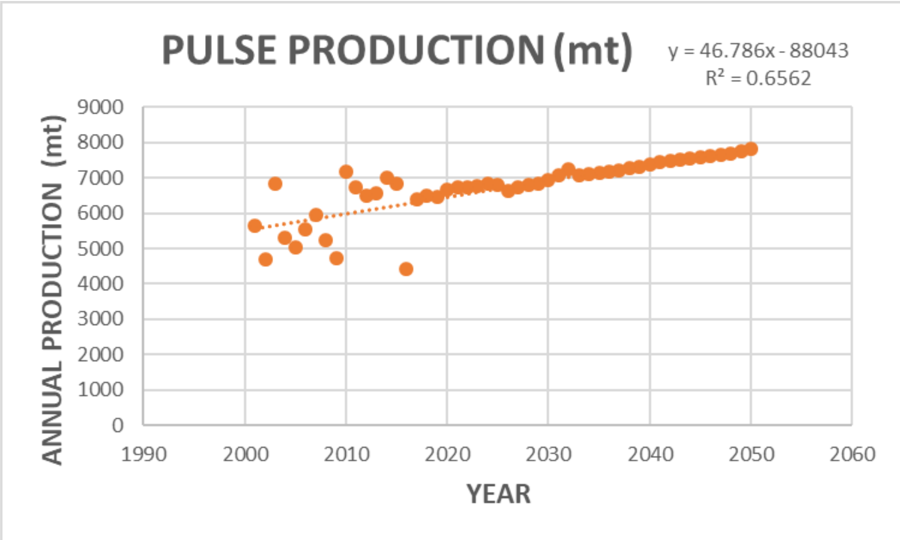


Figure: Pulses production in India

Chapter 4

Analysis of Food Chain under the Effect of Climate Change by R Programming

The climate change can make weather parameter less predictable, this unforeseen weather patterns can make it difficult to maintain agricultural practices stable. Higher temperatures eventually reduce yields of desirable crops while encouraging weed and pest proliferation. Changes in precipitation patterns increase the likelihood of short-run crop failures and long-run production declines. Agriculture is facing droughts, flooding, sea level elevations, natural disasters and health hazards for population. All of these exponents lead to crop failure that creates famines and food inflation which also effects the financial status of nation.
To achieve the aim of this project we have tried to study the impact of four weather parameters annual temperature rise, annual sea level rise, annual rainfall, annual Carbon dioxide emission on three major crops wheat, rice and pulses. To study the effect we have applied the Multiple Linear Regression model, In this technique we have consider a wheat, rice and pulse production as a dependent (explained) variable and annual temperature rise, annual sea level rise, annual rainfall and annual Carbon dioxide emission as a independent (explanatory) variable.

4.1 DefinItion and Concept used in Analysis

4.1.1 Multiple Linear Regression Model

Multiple linear regression is used to estimate the relationship between two or more independent variables and one dependent variable. We can use multiple linear regression when we want to know:

- How strong is the relationship between two or more independent variables and one dependent variable (e.g. how rainfall, temperature, and amount of fertilizer added affect crop growth).

- The value of the dependent variable at a certain value of the independent variables (e.g. the expected yield of a crop at certain levels of rainfall, temperature, and fertilizer addition).

4.1.2 Assumptions of Multiple Linear Regression

Multiple linear regression makes all of the same assumptions as simple linear regression:

- **Homogeneity of variance (homoscedasticity)**: The size of the error in our prediction doesn't change significantly across the values of the independent variable.
- **Independence of observations**: The observations in the dataset were collected using statistically valid methods, and there are no hidden relationships among variables.

  In multiple linear regression, it is possible that some of the independent variables are actually correlated with each other, so it is important to check these before developing the regression model. If two independent variables are too highly correlated ($r^2 \geq 0.6$), then only one of them should be used in the regression model.
- **Normality**: The data follows a normal distribution.
- **Linearity**: The line of best fit through the data points is a straight line, rather than a curve or some sort of grouping factor.

The formula for a multiple linear regression is:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + ... + \epsilon \tag{4.1}$$

4.1.3 Multiple linear regression formula

y = the predicted value of the dependent variable
β_0 = the y -intercept (value of y when all other parameters are set to 0).
$\beta_1 x_1$= the regression coefficient (β_1) of the first independent variable (x_1) (the effect that increasing the value of the independent variable has on the predicted y value).
do the same for however many independent variables you are testing
$\beta_n x_n$ = the regression coefficient of the last independent variable
ϵ = model error (a.k.a. how much variation there is in our estimate of y).
To find the best-fit line for each independent variable, multiple linear regression calculates three things:

- The regression coefficients that lead to the smallest overall model error.

- The t-statistic of the overall model.

- The associated p-value (how likely it is that the t-statistic would have occurred by chance if the null hypothesis of no relationship between the independent and dependent variables was true).

Then calculates the t-statistic and p-value for each regression coefficient in the model.

4.1.4 Coefficient of Determination (R^2)

The coefficient of determination is a statistical measure in a regression model that determines the proportion of variance in the dependent variable that can be explained by the independent variable.

$$R^2 = 1 - \mathrm{RSS}/\mathrm{TSS} \tag{4.2}$$

R^2 : Coefficient of determination.
RSS : Residual sum of square
TSS : Total sum of square

Adjusted R^2

It measures the proportion of variation explained by only those independent variables that really help in explaining the dependent variable. It penalizes you for adding independent variable that do not help in predicting the dependent variable.
In this we have adjusted degree of freedom i.e this is called as Adjusted R^2.
Adjusted R^2 should be used to compare models with different numbers of independent variables.
Adjusted R^2 should be used while selecting important predictors (independent variables) for the regression model.

4.1.5 Correlation Coefficient

Correlation Coefficient measures a linear relationship between two variables. Let x and y be two variables then the formula of pearson correlation coefficient (r) is :

$$r = \frac{Cov(x,y)}{\sqrt{var(x)var(y)}} \tag{4.3}$$

4.1.6 p-Value

The p-value is a probability, calculated from a statistical test, that describes how likely you have found a particular set of observations when the null hypothesis were true.
p-values are used in hypothesis testing to decide whether to reject the null hypothesis. The smaller the p-value, the more likely you are to reject the null hypothesis.

4.2 Analysis on Wheat Production

Wheat is the major production crop of nation and majority of population consumes this. Wheat is the main cereal crop in India. The total area under the crop is about 29.8 million hectares in the country. Wheat can be grown in tropical, sub-tropical and temperate zones.
We have taken dataset on wheat production of India from 2001 to 2017. Based on this dataset we have forecasted up to 2050 and then Multiple Linear Regression model technique is used to study the climate change impact on production.

Impact of climate change on Wheat Production

```
mr=read.csv("C:/Users/dell/Desktop/MRM.csv")
mr

##    Year     RICE    WHEAT   PULSES ANNUAL.TEMP SEA.LEVEL ANNUAL.RAINFALL
## 1  2001  93340.0  72766.0 5635.000       24.73  7.271654           821.9
## 2  2002  71820.0  65761.0 4702.000       25.00  7.366142           737.3
## 3  2003  88526.0  72156.0 6831.000       24.72  7.728346           919.5
## 4  2004  83132.0  68637.0 5314.000       24.74  7.712598           774.2
## 5  2005  91793.0  69355.0 5046.000       24.58  7.716535           874.3
## 6  2006  93355.0  75807.0 5550.000       25.06  7.885827           889.3
## 7  2007  96693.0  78570.0 5937.000       24.77  7.960630           943.0
## 8  2008  99172.0  80679.0 5240.000       24.61  8.303150           877.7
## 9  2009  89083.0  80804.0 4720.000       25.11  8.531496           698.2
## 10 2010  95970.0  86874.0 7159.000       25.13  8.834646           911.1
## 11 2011 105301.0  94882.0 6733.000       24.67  8.897638           901.3
## 12 2012 105241.0  93506.0 6486.000       24.69  9.244094           823.9
## 13 2013 106646.0  95850.0 6555.000       24.82  8.913386           937.2
## 14 2014 105482.0  86527.0 7013.000       24.73  8.579437           781.7
## 15 2015 104320.0  93500.0 6840.000       24.91  8.925435           764.9
## 16 2016  93880.0  97862.9 4410.000       26.45  9.036237           864.4
## 17 2017 105791.8 101007.3 6407.325       26.29  9.087686           879.3
## 18 2018 105796.2 103139.0 6500.131       25.90  9.221200           876.2
## 19 2019 108175.5 105867.5 6456.881       25.86  9.479331           873.5
## 20 2020 108880.0 107868.6 6677.215       24.88  8.634556           872.5
## 21 2021 108196.2 109455.9 6734.435       24.90  8.716495           868.9
## 22 2022 108633.1 111410.7 6731.680       24.92  8.801680           864.0
## 23 2023 110553.8 113372.7 6761.625       24.93  8.892993           862.7
## 24 2024 111532.2 115261.0 6827.565       24.94  8.976937           858.6
## 25 2025 112421.7 116739.1 6784.824       24.95  9.056299           857.6
## 26 2026 113926.1 118609.5 6613.708       24.97  9.140599           856.6
## 27 2027 113958.3 121422.0 6714.044       24.98  9.223398           855.9
## 28 2028 114466.7 124083.8 6789.195       24.99  9.303459           850.2
## 29 2029 115538.5 127037.3 6846.557       25.00  9.386762           846.3
## 30 2030 116807.6 128462.2 6921.031       25.01  9.469328           840.9
## 31 2031 118517.8 130238.7 7075.534       25.03  9.559182           840.2
## 32 2032 119573.2 132196.4 7245.013       25.04  9.645706           834.6
## 33 2033 119353.9 134260.2 7086.472       25.06  9.733481           836.5
## 34 2034 119750.5 136328.3 7117.020       25.07  9.827420           840.9
## 35 2035 121217.2 138500.5 7152.146       25.09  9.929995           833.2
## 36 2036 122440.9 140705.7 7174.145       25.11 10.030941           833.0
## 37 2037 123746.8 142880.7 7217.312       25.12 10.126817           826.2
## 38 2038 125001.0 145059.3 7267.430       25.13 10.220390           826.1
## 39 2039 124908.3 147237.4 7317.593       25.14 10.315302           825.1
## 40 2040 125365.1 149396.8 7371.395       25.16 10.411232           822.0
## 41 2041 126628.1 151457.7 7434.638       25.18 10.509288           821.5
## 42 2042 127855.9 153437.8 7493.686       25.19 10.605447           818.5
```

```
## 43 2043 129354.2 155462.9 7525.583        25.21 10.702381            818.6
## 44 2044 130525.8 157544.2 7558.505        25.23 10.787418            818.3
## 45 2045 130362.8 159762.2 7590.642        25.25 10.873250            813.9
## 46 2046 130792.5 161930.7 7620.184        25.26 10.967102            808.6
## 47 2047 132157.8 164070.8 7649.682        25.28 11.057460            803.6
## 48 2048 133398.3 166193.1 7692.250        25.30 11.139018            802.5
## 49 2049 134794.2 168304.7 7756.528        25.32 11.219889            798.4
## 50 2050 136001.6 170402.0 7801.913        25.33 11.304697            802.7
##    ANNUAL.CO2.EMISSION
## 1             0.923300
## 2             0.935700
## 3             0.953300
## 4             0.996300
## 5             1.033400
## 6             1.080900
## 7             1.147900
## 8             1.218300
## 9             1.324400
## 10            1.359400
## 11            1.423800
## 12            1.551300
## 13            1.590300
## 14            1.687100
## 15            1.731500
## 16            1.798600
## 17            1.818100
## 18            1.922000
## 19            1.933646
## 20            2.150840
## 21            2.163359
## 22            2.289027
## 23            2.339593
## 24            2.353786
## 25            2.512614
## 26            2.557280
## 27            2.628982
## 28            2.698730
## 29            2.767054
## 30            2.833279
## 31            2.902288
## 32            2.970579
## 33            3.035796
## 34            3.103410
## 35            3.170061
## 36            3.236712
## 37            3.304817
## 38            3.372217
## 39            3.439672
## 40            3.506785
## 41            3.573602
```

```
## 42                3.617333
## 43                3.672791
## 44                3.754563
## 45                3.820660
## 46                3.888025
## 47                3.953976
## 48                4.020212
## 49                4.087727
## 50                4.155011
```

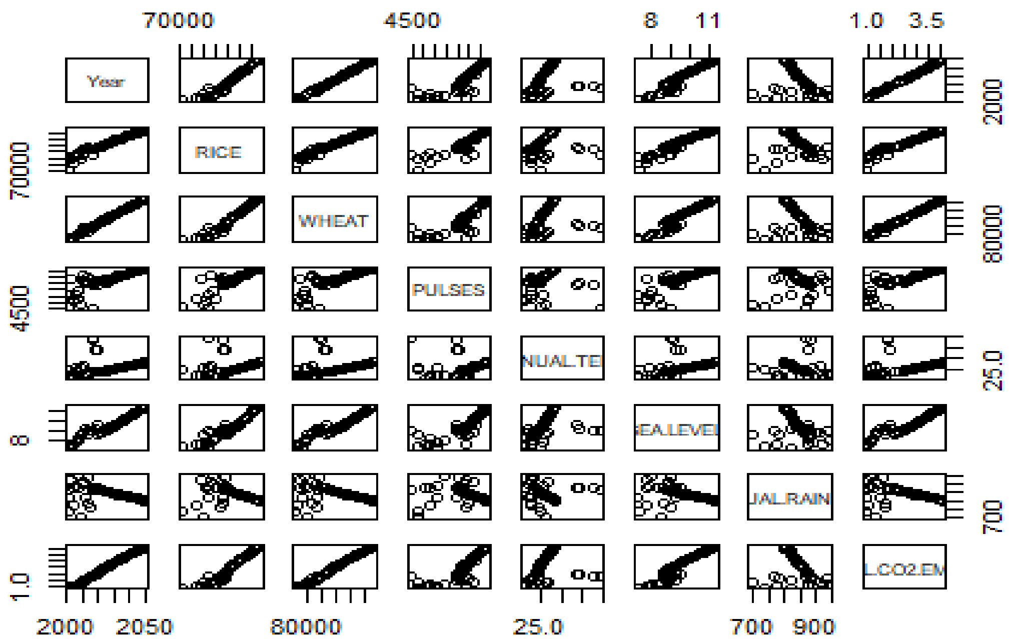
```
colnames(mr)
```

```
## [1] "Year"                 "RICE"                 "WHEAT"
## [4] "PULSES"               "ANNUAL.TEMP"          "SEA.LEVEL"
## [7] "ANNUAL.RAINFALL"      "ANNUAL.CO2.EMISSION"
```

```
#matrix of scatter plot
pairs(mr[,1:8])
cor(mr,method="pearson")
```

```
##                           Year       RICE      WHEAT      PULSES
ANNUAL.TEMP
## Year                 1.0000000  0.9651707  0.9972352  0.81008455
0.28958562
## RICE                 0.9651707  1.0000000  0.9712176  0.87426129
0.20829165
## WHEAT                0.9972352  0.9712176  1.0000000  0.82147115
0.29010710
## PULSES               0.8100846  0.8742613  0.8214711  1.00000000
0.03235588
## ANNUAL.TEMP          0.2895856  0.2082917  0.2901071  0.03235588
1.00000000
## SEA.LEVEL            0.9636380  0.9457205  0.9660819  0.79822535
0.37868301
## ANNUAL.RAINFALL     -0.2876585 -0.1485439 -0.2546646 -0.02275595 -
0.02641675
## ANNUAL.CO2.EMISSION  0.9991003  0.9623197  0.9966014  0.80912746
0.27274905
##                      SEA.LEVEL ANNUAL.RAINFALL ANNUAL.CO2.EMISSION
## Year                 0.9636380     -0.28765855           0.9991003
## RICE                 0.9457205     -0.14854391           0.9623197
## WHEAT                0.9660819     -0.25466455           0.9966014
## PULSES               0.7982254     -0.02275595           0.8091275
## ANNUAL.TEMP          0.3786830     -0.02641675           0.2727491
## SEA.LEVEL            1.0000000     -0.27132627           0.9549497
## ANNUAL.RAINFALL     -0.2713263      1.00000000          -0.2978011
## ANNUAL.CO2.EMISSION  0.9549497     -0.29780113           1.0000000
```

```
#check significance of correlation
#install.packages("Hmisc")
library(Hmisc)
```




```r
rcorr(as.matrix(mr))
```

```
##                          Year  RICE WHEAT  PULSES ANNUAL.TEMP SEA.LEVEL
## Year                     1.00  0.97  1.00    0.81        0.29      0.96
## RICE                     0.97  1.00  0.97    0.87        0.21      0.95
## WHEAT                    1.00  0.97  1.00    0.82        0.29      0.97
## PULSES                   0.81  0.87  0.82    1.00        0.03      0.80
## ANNUAL.TEMP              0.29  0.21  0.29    0.03        1.00      0.38
## SEA.LEVEL                0.96  0.95  0.97    0.80        0.38      1.00
## ANNUAL.RAINFALL         -0.29 -0.15 -0.25   -0.02       -0.03     -0.27
## ANNUAL.CO2.EMISSION      1.00  0.96  1.00    0.81        0.27      0.95
##                         ANNUAL.RAINFALL ANNUAL.CO2.EMISSION
## Year                              -0.29                1.00
## RICE                              -0.15                0.96
## WHEAT                             -0.25                1.00
## PULSES                            -0.02                0.81
## ANNUAL.TEMP                       -0.03                0.27
## SEA.LEVEL                         -0.27                0.95
## ANNUAL.RAINFALL                    1.00               -0.30
## ANNUAL.CO2.EMISSION               -0.30                1.00
##
## n= 50
##
##
## P
##                         Year   RICE   WHEAT  PULSES ANNUAL.TEMP SEA.LEVEL
## Year                           0.0000 0.0000 0.0000 0.0414      0.0000
```

```
## RICE                   0.0000        0.0000 0.0000 0.1466      0.0000
## WHEAT                  0.0000 0.0000        0.0000 0.0410      0.0000
## PULSES                 0.0000 0.0000 0.0000        0.8235      0.0000
## ANNUAL.TEMP            0.0414 0.1466 0.0410 0.8235              0.0067
## SEA.LEVEL              0.0000 0.0000 0.0000 0.0000 0.0067
## ANNUAL.RAINFALL        0.0428 0.3032 0.0743 0.8754 0.8555      0.0567
## ANNUAL.CO2.EMISSION 0.0000 0.0000 0.0000 0.0000 0.0553      0.0000
##                        ANNUAL.RAINFALL ANNUAL.CO2.EMISSION
## Year                   0.0428          0.0000
## RICE                   0.3032          0.0000
## WHEAT                  0.0743          0.0000
## PULSES                 0.8754          0.0000
## ANNUAL.TEMP            0.8555          0.0553
## SEA.LEVEL              0.0567          0.0000
## ANNUAL.RAINFALL                        0.0357
## ANNUAL.CO2.EMISSION 0.0357
```

```
#fitting multiple regression
mlrm=lm(WHEAT~ANNUAL.TEMP+SEA.LEVEL+ANNUAL.RAINFALL+ANNUAL.CO2.EMISSION ,
data = mr)
mlrm
```

```
##
## Call:
## lm(formula = WHEAT ~ ANNUAL.TEMP + SEA.LEVEL + ANNUAL.RAINFALL +
##     ANNUAL.CO2.EMISSION, data = mr)
##
## Coefficients:
##         (Intercept)          ANNUAL.TEMP            SEA.LEVEL
##            -8878.84              -292.70              4721.29
##     ANNUAL.RAINFALL  ANNUAL.CO2.EMISSION
##               29.76             26290.15
```

```
summary(mlrm)
```

```
##
## Call:
## lm(formula = WHEAT ~ ANNUAL.TEMP + SEA.LEVEL + ANNUAL.RAINFALL +
##     ANNUAL.CO2.EMISSION, data = mr)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -5480.0  -509.0   -32.9   390.4  5817.5
##
## Coefficients:
##                      Estimate Std. Error t value Pr(>|t|)
## (Intercept)         -8878.839  17333.657  -0.512    0.611
## ANNUAL.TEMP          -292.695    743.203  -0.394    0.696
## SEA.LEVEL            4721.291    834.611   5.657 1.01e-06 ***
## ANNUAL.RAINFALL        29.761      5.455   5.456 1.99e-06 ***
## ANNUAL.CO2.EMISSION 26290.155    847.540  31.019  < 2e-16 ***
```

```
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 1676 on 45 degrees of freedom
## Multiple R-squared:  0.9973, Adjusted R-squared:  0.9971
## F-statistic:  4202 on 4 and 45 DF,  p-value: < 2.2e-16
```

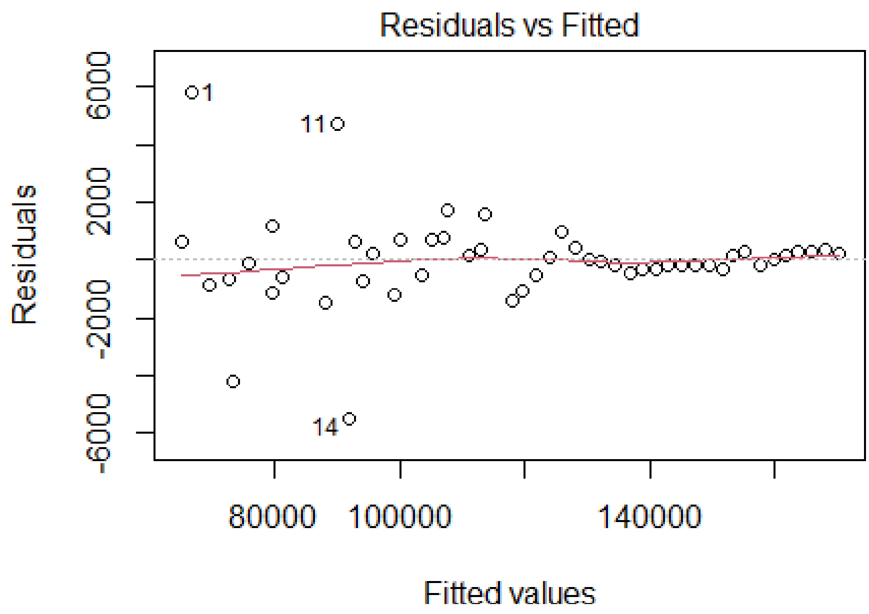
```
#confidence interval of regression coefficient
confint(mlrm ,level=0.95)
```

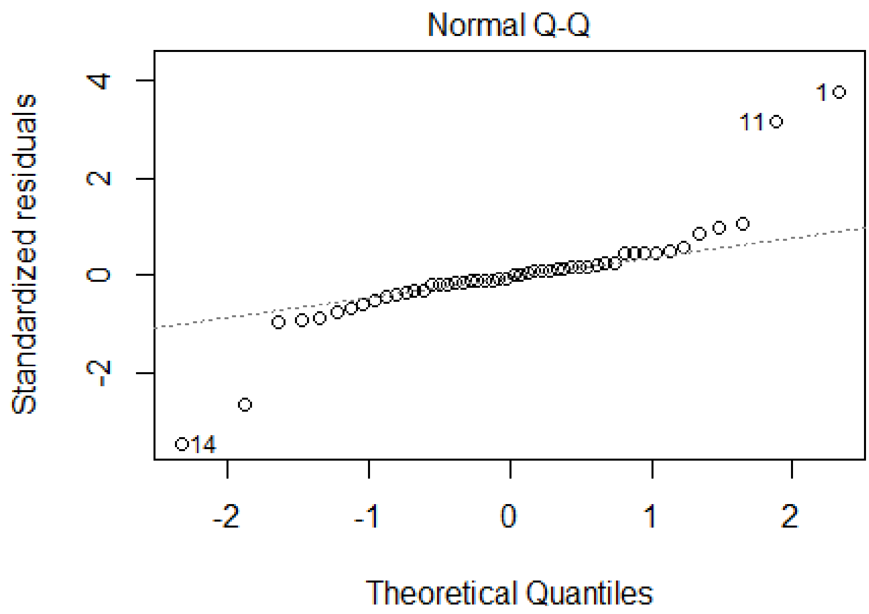
```
##                             2.5 %      97.5 %
## (Intercept)         -43790.61555 26032.93840
## ANNUAL.TEMP          -1789.58367  1204.19314
## SEA.LEVEL             3040.29882  6402.28412
## ANNUAL.RAINFALL         18.77489    40.74677
## ANNUAL.CO2.EMISSION  24583.12139 27997.18837
```

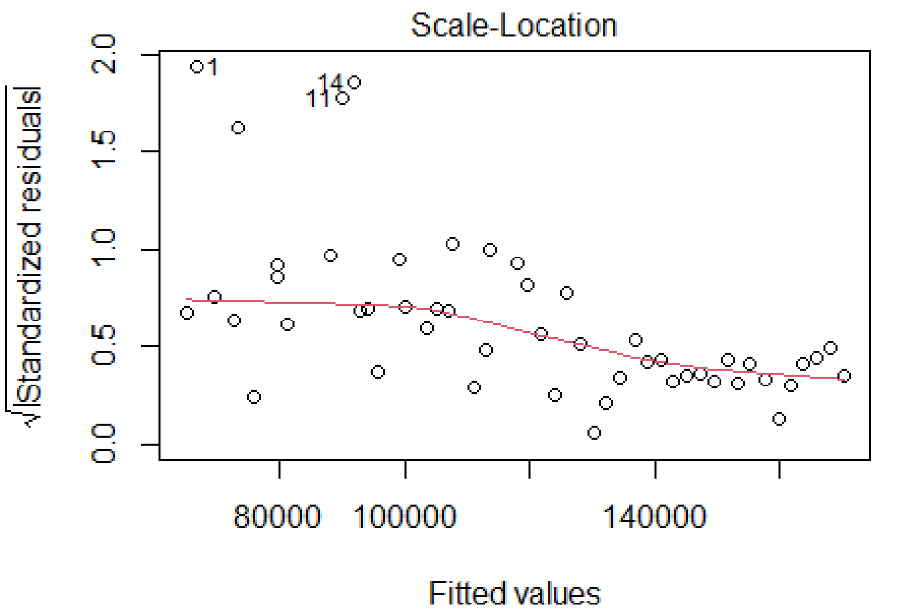
```
#predict for some value
newdata=data.frame(ANNUAL.TEMP=26,SEA.LEVEL=10,ANNUAL.RAINFALL=800,ANNUAL.CO2
.EMISSION=3)
predict(mlrm,newdata)
```

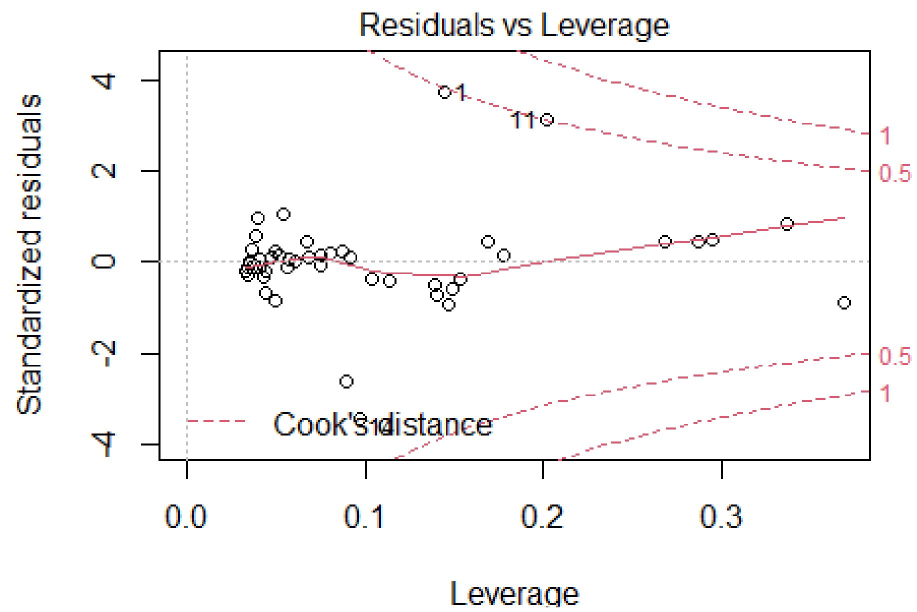
```
##        1
## 133403.1
```

PLOTS OF ANALYSIS






Scale-Location
√|Standardized residuals|
0.0
0.5
1.0
1.5
2.0
1
14
11
80000
100000
140000
Fitted values


Residuals vs Leverage
Standardized residuals
-4
-2
0
2
4
1
11
Cook's distance
0.0
0.1
0.2
0.3
Leverage
1
0.5
0.5
1

4.2.1 Result and Conclusion

Based on the dataset firstly we have calculated correlation coefficient between the weather parameters and production parameters. The matrix of scatter plot shows the relation between all variables. Through this we have an idea of relationship between study and explanatory variable. Here we have clearly seen that sea level and annual carbon dioxide emission have very strongly correlated with wheat production. Then we have computed correlation coefficient table and the respective p value of parameters.
H_0 : There is no correlation between variables.
When we compare the p value of wheat and weather parameters with the significant value i.e There is strong correlation between wheat production and sea level rise, annual rainfall and annual CO_2 emission.
When we are fitting Multiple linear Regression in our model, it explains the actual effect of weather parameter on wheat production.
H_0 : There is no significant effect of weather parameter into wheat production.
When we compare the p value of wheat and weather parameters with the significant value. Then the following inferences are given below:

- We infer that there is no strong significant effect between wheat and annual temperature.
- We infer that there is strong significant effect between wheat and sea Level rise.
- We infer that there is strong significant effect between wheat and annual rainfall.
- We infer that there is strong significant effect between wheat and annual CO_2 emission.

Testing of significance of model Fitting
The Multiple R-Squared : 0.993 and Adjusted R-Squared : 0.9971 with 45 degrees of freedom. F-Statistic : 4202 with 4 and 45 degree of freedom.
H_0: The model is not good fitted .
The p-value is : 2.2e-16 which is much less than significant value 0.05, So the null hypothesis is rejected.
This infer that our model is good fitted and effect of climate parameters on production is significant.

4.2.2 Description of Plots

In our study we have plotted four plots to analyse the impact of climate parameters.

- **Residuals vs Fitted value plot:** The Residual plot explains the difference between the observed value and fitted value of study variable. In this plot we have seen that most of the values lies on 0, this shows that data is homoscedastic and linearly related.

- **Normal Q-Q plot:** This plot describes the normality of the dataset. If the data is normally distributed the points in a Q-Q plot will lie on a straight diagonal line.
  In our dataset the majority of the values lies diagonally and some of the values are outlier. So we infer that 95% of dataset are normally distributed.

- **Scale-Location plot:** This plot displays the fitted values of a regression model along the x-axis and the square root of the standardized residuals along the y-axis.
  A horizontal red line shows the homoscedasticity in model. Here the plot shows that the explanatory variables are heteroscedastic.

- **Residuals vs Leverage plot:** This plot is a type of diagnostic plot that allows us to identify influential observations in a regression model. If any point in this plot falls outside of Cook's distance (the red dashed lines) then it is considered to be an influential observation.
  In our plot all points lies between the Cook's distance i.e the regression model does not have any influential observation.

4.3 Analysis on Rice Production

We have taken dataset on Rice production of India from 2001 to 2017. Based on this dataset we have forecasted up to 2050 and then Multiple Linear Regression model technique is used to study the climate change impact on production.

Impact of Climate change on Rice Production

```
mr=read.csv("C:/Users/dell/Desktop/MRM.csv")
mr

##    Year     RICE    WHEAT   PULSES ANNUAL.TEMP SEA.LEVEL ANNUAL.RAINFALL
## 1  2001  93340.0  72766.0 5635.000       24.73  7.271654           821.9
## 2  2002  71820.0  65761.0 4702.000       25.00  7.366142           737.3
## 3  2003  88526.0  72156.0 6831.000       24.72  7.728346           919.5
## 4  2004  83132.0  68637.0 5314.000       24.74  7.712598           774.2
## 5  2005  91793.0  69355.0 5046.000       24.58  7.716535           874.3
## 6  2006  93355.0  75807.0 5550.000       25.06  7.885827           889.3
## 7  2007  96693.0  78570.0 5937.000       24.77  7.960630           943.0
## 8  2008  99172.0  80679.0 5240.000       24.61  8.303150           877.7
## 9  2009  89083.0  80804.0 4720.000       25.11  8.531496           698.2
## 10 2010  95970.0  86874.0 7159.000       25.13  8.834646           911.1
## 11 2011 105301.0  94882.0 6733.000       24.67  8.897638           901.3
## 12 2012 105241.0  93506.0 6486.000       24.69  9.244094           823.9
## 13 2013 106646.0  95850.0 6555.000       24.82  8.913386           937.2
## 14 2014 105482.0  86527.0 7013.000       24.73  8.579437           781.7
## 15 2015 104320.0  93500.0 6840.000       24.91  8.925435           764.9
## 16 2016  93880.0  97862.9 4410.000       26.45  9.036237           864.4
## 17 2017 105791.8 101007.3 6407.325       26.29  9.087686           879.3
## 18 2018 105796.2 103139.0 6500.131       25.90  9.221200           876.2
## 19 2019 108175.5 105867.5 6456.881       25.86  9.479331           873.5
## 20 2020 108880.0 107868.6 6677.215       24.88  8.634556           872.5
## 21 2021 108196.2 109455.9 6734.435       24.90  8.716495           868.9
## 22 2022 108633.1 111410.7 6731.680       24.92  8.801680           864.0
## 23 2023 110553.8 113372.7 6761.625       24.93  8.892993           862.7
## 24 2024 111532.2 115261.0 6827.565       24.94  8.976937           858.6
## 25 2025 112421.7 116739.1 6784.824       24.95  9.056299           857.6
## 26 2026 113926.1 118609.5 6613.708       24.97  9.140599           856.6
## 27 2027 113958.3 121422.0 6714.044       24.98  9.223398           855.9
## 28 2028 114466.7 124083.8 6789.195       24.99  9.303459           850.2
## 29 2029 115538.5 127037.3 6846.557       25.00  9.386762           846.3
## 30 2030 116807.6 128462.2 6921.031       25.01  9.469328           840.9
## 31 2031 118517.8 130238.7 7075.534       25.03  9.559182           840.2
## 32 2032 119573.2 132196.4 7245.013       25.04  9.645706           834.6
## 33 2033 119353.9 134260.2 7086.472       25.06  9.733481           836.5
## 34 2034 119750.5 136328.3 7117.020       25.07  9.827420           840.9
## 35 2035 121217.2 138500.5 7152.146       25.09  9.929995           833.2
## 36 2036 122440.9 140705.7 7174.145       25.11 10.030941           833.0
## 37 2037 123746.8 142880.7 7217.312       25.12 10.126817           826.2
## 38 2038 125001.0 145059.3 7267.430       25.13 10.220390           826.1
## 39 2039 124908.3 147237.4 7317.593       25.14 10.315302           825.1
## 40 2040 125365.1 149396.8 7371.395       25.16 10.411232           822.0
## 41 2041 126628.1 151457.7 7434.638       25.18 10.509288           821.5
## 42 2042 127855.9 153437.8 7493.686       25.19 10.605447           818.5
```

```
## 43 2043 129354.2 155462.9 7525.583       25.21 10.702381             818.6
## 44 2044 130525.8 157544.2 7558.505       25.23 10.787418             818.3
## 45 2045 130362.8 159762.2 7590.642       25.25 10.873250             813.9
## 46 2046 130792.5 161930.7 7620.184       25.26 10.967102             808.6
## 47 2047 132157.8 164070.8 7649.682       25.28 11.057460             803.6
## 48 2048 133398.3 166193.1 7692.250       25.30 11.139018             802.5
## 49 2049 134794.2 168304.7 7756.528       25.32 11.219889             798.4
## 50 2050 136001.6 170402.0 7801.913       25.33 11.304697             802.7
##    ANNUAL.CO2.EMISSION
## 1             0.923300
## 2             0.935700
## 3             0.953300
## 4             0.996300
## 5             1.033400
## 6             1.080900
## 7             1.147900
## 8             1.218300
## 9             1.324400
## 10            1.359400
## 11            1.423800
## 12            1.551300
## 13            1.590300
## 14            1.687100
## 15            1.731500
## 16            1.798600
## 17            1.818100
## 18            1.922000
## 19            1.933646
## 20            2.150840
## 21            2.163359
## 22            2.289027
## 23            2.339593
## 24            2.353786
## 25            2.512614
## 26            2.557280
## 27            2.628982
## 28            2.698730
## 29            2.767054
## 30            2.833279
## 31            2.902288
## 32            2.970579
## 33            3.035796
## 34            3.103410
## 35            3.170061
## 36            3.236712
## 37            3.304817
## 38            3.372217
## 39            3.439672
## 40            3.506785
## 41            3.573602
```

```
## 42           3.617333
## 43           3.672791
## 44           3.754563
## 45           3.820660
## 46           3.888025
## 47           3.953976
## 48           4.020212
## 49           4.087727
## 50           4.155011
```

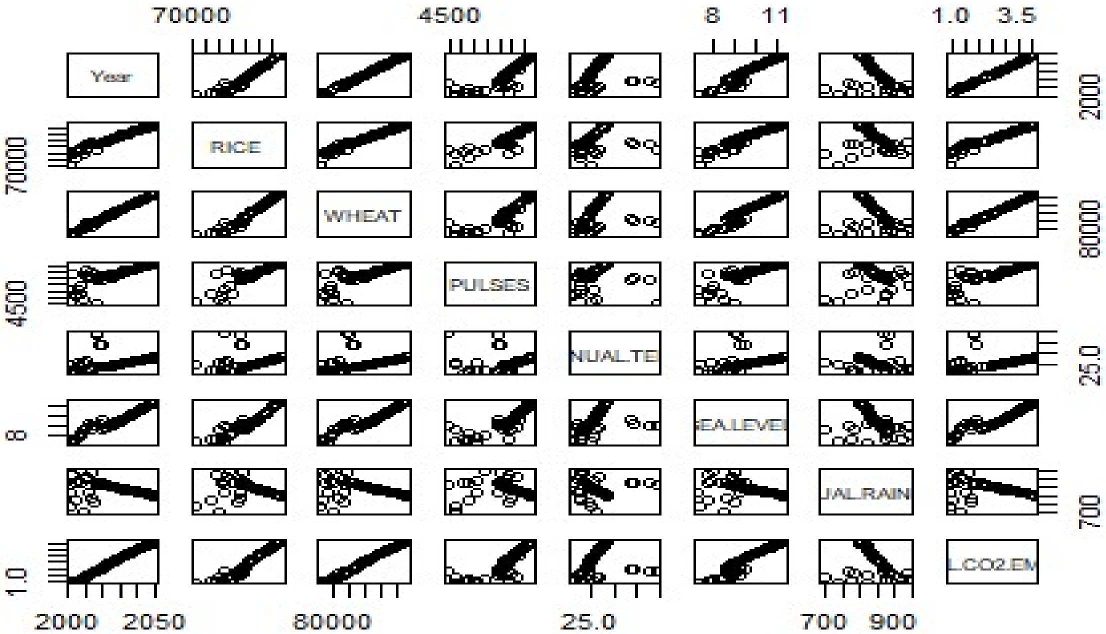
```r
colnames(mr)
```

```
## [1] "Year"                 "RICE"                 "WHEAT"
## [4] "PULSES"               "ANNUAL.TEMP"          "SEA.LEVEL"
## [7] "ANNUAL.RAINFALL"      "ANNUAL.CO2.EMISSION"
```

```r
#matrix of scatter plot
pairs(mr[,1:8])
cor(mr,method="pearson")
```

```
##                           Year       RICE      WHEAT      PULSES
ANNUAL.TEMP
## Year                 1.0000000  0.9651707  0.9972352  0.81008455
0.28958562
## RICE                 0.9651707  1.0000000  0.9712176  0.87426129
0.20829165
## WHEAT                0.9972352  0.9712176  1.0000000  0.82147115
0.29010710
## PULSES               0.8100846  0.8742613  0.8214711  1.00000000
0.03235588
## ANNUAL.TEMP          0.2895856  0.2082917  0.2901071  0.03235588
1.00000000
## SEA.LEVEL            0.9636380  0.9457205  0.9660819  0.79822535
0.37868301
## ANNUAL.RAINFALL     -0.2876585 -0.1485439 -0.2546646 -0.02275595 -
0.02641675
## ANNUAL.CO2.EMISSION  0.9991003  0.9623197  0.9966014  0.80912746
0.27274905
##                      SEA.LEVEL ANNUAL.RAINFALL ANNUAL.CO2.EMISSION
## Year                 0.9636380     -0.28765855           0.9991003
## RICE                 0.9457205     -0.14854391           0.9623197
## WHEAT                0.9660819     -0.25466455           0.9966014
## PULSES               0.7982254     -0.02275595           0.8091275
## ANNUAL.TEMP          0.3786830     -0.02641675           0.2727491
## SEA.LEVEL            1.0000000     -0.27132627           0.9549497
## ANNUAL.RAINFALL     -0.2713263      1.00000000          -0.2978011
## ANNUAL.CO2.EMISSION  0.9549497     -0.29780113           1.0000000
```

```r
#check significance of correlation
#install.packages("Hmisc")
library(Hmisc)
```




```r
rcorr(as.matrix(mr))

##                       Year  RICE WHEAT PULSES ANNUAL.TEMP SEA.LEVEL
## Year                  1.00  0.97  1.00   0.81        0.29      0.96
## RICE                  0.97  1.00  0.97   0.87        0.21      0.95
## WHEAT                 1.00  0.97  1.00   0.82        0.29      0.97
## PULSES                0.81  0.87  0.82   1.00        0.03      0.80
## ANNUAL.TEMP           0.29  0.21  0.29   0.03        1.00      0.38
## SEA.LEVEL             0.96  0.95  0.97   0.80        0.38      1.00
## ANNUAL.RAINFALL      -0.29 -0.15 -0.25  -0.02       -0.03     -0.27
## ANNUAL.CO2.EMISSION  1.00  0.96  1.00   0.81        0.27      0.95
##                      ANNUAL.RAINFALL ANNUAL.CO2.EMISSION
## Year                           -0.29                1.00
## RICE                           -0.15                0.96
## WHEAT                          -0.25                1.00
## PULSES                         -0.02                0.81
## ANNUAL.TEMP                    -0.03                0.27
## SEA.LEVEL                      -0.27                0.95
## ANNUAL.RAINFALL                 1.00               -0.30
## ANNUAL.CO2.EMISSION            -0.30                1.00
##
## n= 50
##
##
## P
##                      Year   RICE   WHEAT  PULSES ANNUAL.TEMP SEA.LEVEL
## Year                        0.0000 0.0000 0.0000 0.0414      0.0000
```

```
## RICE                 0.0000        0.0000 0.0000 0.1466      0.0000
## WHEAT                0.0000 0.0000        0.0000 0.0410      0.0000
## PULSES               0.0000 0.0000 0.0000        0.8235      0.0000
## ANNUAL.TEMP          0.0414 0.1466 0.0410 0.8235             0.0067
## SEA.LEVEL            0.0000 0.0000 0.0000 0.0000 0.0067
## ANNUAL.RAINFALL      0.0428 0.3032 0.0743 0.8754 0.8555      0.0567
## ANNUAL.CO2.EMISSION 0.0000 0.0000 0.0000 0.0000 0.0553      0.0000
##                      ANNUAL.RAINFALL ANNUAL.CO2.EMISSION
## Year                 0.0428          0.0000
## RICE                 0.3032          0.0000
## WHEAT                0.0743          0.0000
## PULSES               0.8754          0.0000
## ANNUAL.TEMP          0.8555          0.0553
## SEA.LEVEL            0.0567          0.0000
## ANNUAL.RAINFALL                      0.0357
## ANNUAL.CO2.EMISSION 0.0357

#fitting multiple regression
mlrm=lm(RICE~ANNUAL.TEMP+SEA.LEVEL+ANNUAL.RAINFALL+ANNUAL.CO2.EMISSION , data
= mr)

mlrm

##
## Call:
## lm(formula = RICE ~ ANNUAL.TEMP + SEA.LEVEL + ANNUAL.RAINFALL +
##     ANNUAL.CO2.EMISSION, data = mr)
##
## Coefficients:
##         (Intercept)          ANNUAL.TEMP            SEA.LEVEL
##           116050.43             -5042.10              6281.00
##     ANNUAL.RAINFALL  ANNUAL.CO2.EMISSION
##               49.22              9002.66

summary(mlrm)

##
## Call:
## lm(formula = RICE ~ ANNUAL.TEMP + SEA.LEVEL + ANNUAL.RAINFALL +
##     ANNUAL.CO2.EMISSION, data = mr)
##
## Residuals:
##     Min      1Q  Median      3Q     Max
## -9158.4  -899.4  -146.0   870.7  7541.3
##
## Coefficients:
##                       Estimate Std. Error t value Pr(>|t|)
## (Intercept)         116050.431  29632.233   3.916 0.000302 ***
## ANNUAL.TEMP          -5042.103   1270.521  -3.969 0.000257 ***
## SEA.LEVEL             6280.999   1426.784   4.402 6.53e-05 ***
## ANNUAL.RAINFALL         49.220      9.325   5.279 3.62e-06 ***
```

```
## ANNUAL.CO2.EMISSION   9002.655   1448.887   6.213 1.50e-07 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 2865 on 45 degrees of freedom
## Multiple R-squared:  0.9659, Adjusted R-squared:  0.9629
## F-statistic: 318.6 on 4 and 45 DF,  p-value: < 2.2e-16
```

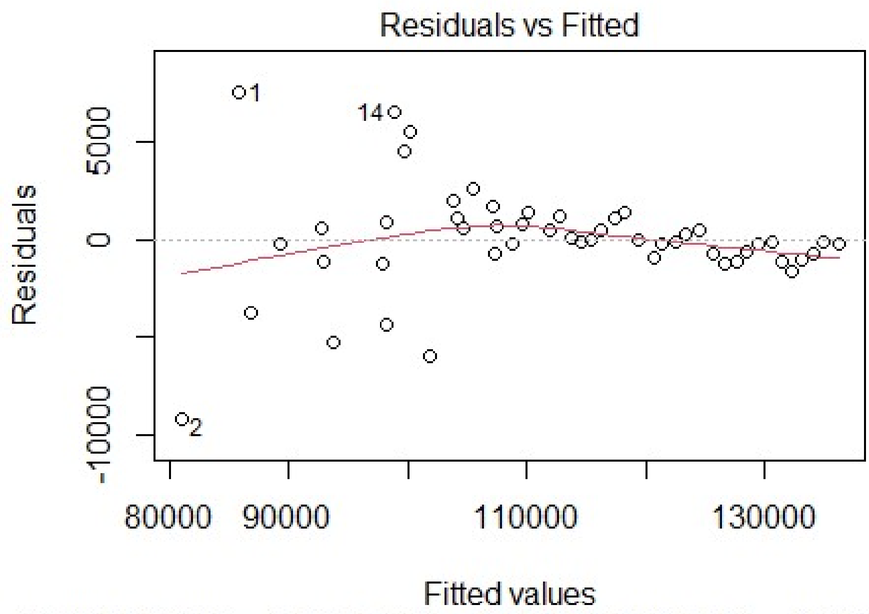
```
# model is RICE= 116050.43 + -5042.10( ANNUAL.TEMP )+ 6281.00 (SEA.LEVEL)+
49.22 ( ANNUAL.RAINFALL)+ 9002.66 (ANNUAL.CO2.EMISSION )

#confidence interval of regression coefficient
confint(mlrm ,level=0.95)
```

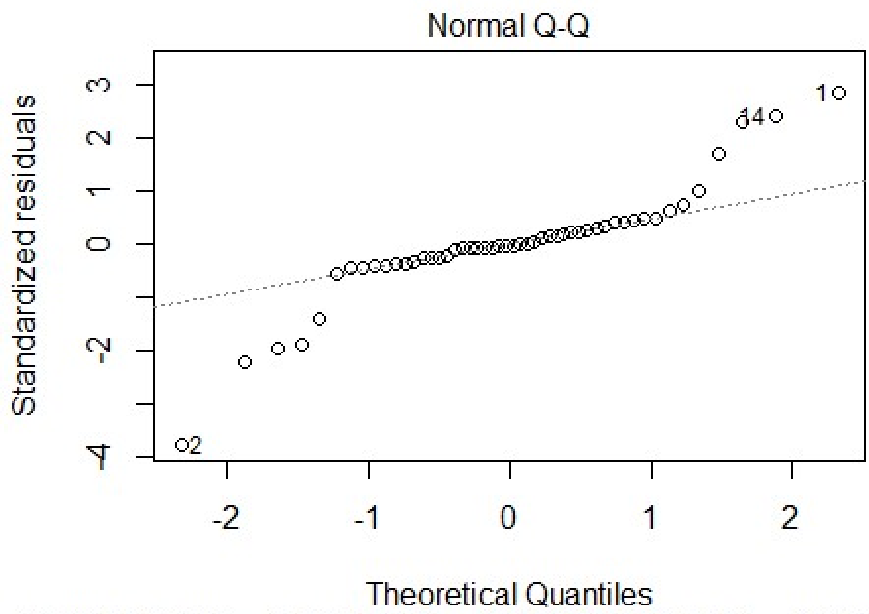
```
##                            2.5 %       97.5 %
## (Intercept)         56368.05028 175732.81177
## ANNUAL.TEMP         -7601.06412  -2483.14281
## SEA.LEVEL            3407.30830   9154.68939
## ANNUAL.RAINFALL        30.43947     68.00084
## ANNUAL.CO2.EMISSION  6084.44756  11920.86332
```

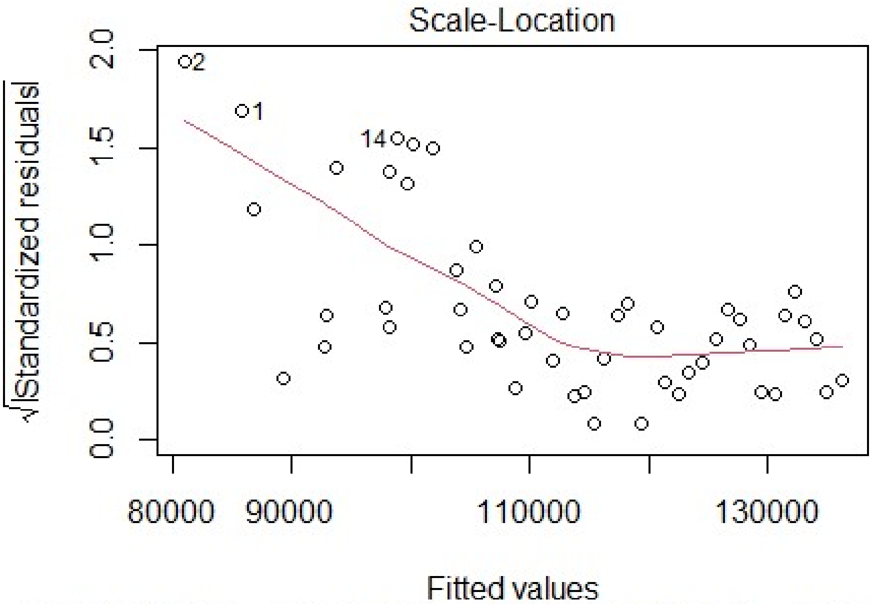
```
#predict for some value
newdata=data.frame(ANNUAL.TEMP=26,SEA.LEVEL=10,ANNUAL.RAINFALL=800,ANNUAL.CO2
.EMISSION=3)
predict(mlrm,newdata)
```

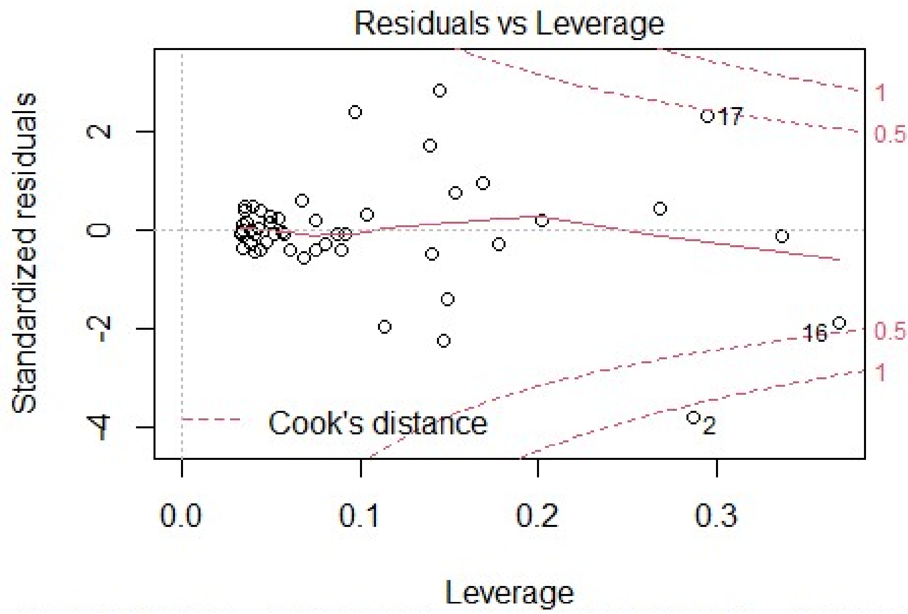
```
##        1
## 114149.8
```

Plots Analysis






Scale-Location
√|Standardized residuals|
2.0
1.5
1.0
0.5
0.0
80000
90000
110000
130000
Fitted values
2
1
14


Residuals vs Leverage
Standardized residuals
2
0
-2
-4
0.0
0.1
0.2
0.3
Leverage
Cook's distance
17
16
2
1
0.5
0.5
1

4.3.1 Result and Conclusion

Based on the dataset firstly we have calculated correlation coefficient between the weather parameters and production parameters. The matrix of scatter plot shows the relation between all variables. Through this we have an idea of relationship between study and explanatory variable. Here we have clearly seen that sea level and annual carbon dioxide emission have very strongly correlated with rice production. Then we have computed correlation coefficient table and the respective p-value of parameters.
H_0 : There is no correlation between variables.
When we compare the p value of rice and weather parameters with the significant value then we have found that there is strong correlation between rice production and sea level rise as well as annual CO_2 emission.
When we are fitting Multiple linear Regression in our model, it explains the actual effect of weather parameter on rice production.
H_0 : There is no significant effect of weather parameter into rice production.
When we compare the p-value of rice and weather parameters with the significant value. Then the following inferences are given below:

- We infer that there is strong significant effect between rice and annual temperature.
- We infer that there is strong significant effect between rice and sea Level rise.
- We infer that there is strong significant effect between rice and annual Rainfall.
- We infer that there is strong significant effect between rice and annual CO_2 emission.

Then we have found that the annual temperature, sea Level rise, annual rainfall and annual CO_2 emission has significant effect on the rice production.
Testing of significance of model Fitting
The Multiple R-Squared : 0.9659 and Adjusted R-Squared : 0.9629 with 45 degrees of freedom.
H_0: The model is not good fitted .
The p-value is : 2.2e-16 which is much less than significant value 0.05, So the null hypothesis is rejected.
This infer that our model is good fitted and effect of climate parameters on production has significant effect.

4.3.2 Description of Plots

In our study we have plotted four plots to analyse the impact of climate parameters.

- **Residuals vs Fitted value plot:** The Residual plot explains the difference between the observed value and fitted value of study variable. In this plot we have seen that most of the values lies on 0, this shows that data is homoscedastic and linearly related.

- **Normal Q-Q plot:** This plot describes the normality of the dataset.If the data is normally distributed the points in a Q-Q plot will lie on a straight diagonal line.
  In our dataset the many of the values lies diagonally and some of the values are outlier. So we infer that approx 90% of dataset are normally distributed.

- **Scale-Location plot:** This plot displays the fitted values of a regression model along the x-axis and the square root of the standardized residuals along the y-axis.
  A horizontal red line shows the homoscedasticity in model. Here the plot shows that the explanatory variables are heteroscedastic.

- **Residuals vs Leverage plot:** This plot is a type of diagnostic plot that allows us to identify influential observations in a regression model.If any point in this plot falls outside of Cook's distance (the red dashed lines) then it is considered to be an influential observation.
  In our plot one points lies outside the Cook's distance i.e the regreesion model does have influential observation.

4.4 Analysis on Pulse Production

We have taken dataset on Pulse production of India from 2001 to 2017. Based on this dataset we have forecasted up to 2050 and then Multiple Linear Regression model technique is used to study the climate change impact on production.

Impact of Climate Change on Pulse Production

```
mr=read.csv("C:/Users/dell/Desktop/MRM.csv")
mr

##    Year     RICE    WHEAT   PULSES ANNUAL.TEMP SEA.LEVEL ANNUAL.RAINFALL
## 1  2001  93340.0  72766.0 5635.000       24.73  7.271654           821.9
## 2  2002  71820.0  65761.0 4702.000       25.00  7.366142           737.3
## 3  2003  88526.0  72156.0 6831.000       24.72  7.728346           919.5
## 4  2004  83132.0  68637.0 5314.000       24.74  7.712598           774.2
## 5  2005  91793.0  69355.0 5046.000       24.58  7.716535           874.3
## 6  2006  93355.0  75807.0 5550.000       25.06  7.885827           889.3
## 7  2007  96693.0  78570.0 5937.000       24.77  7.960630           943.0
## 8  2008  99172.0  80679.0 5240.000       24.61  8.303150           877.7
## 9  2009  89083.0  80804.0 4720.000       25.11  8.531496           698.2
## 10 2010  95970.0  86874.0 7159.000       25.13  8.834646           911.1
## 11 2011 105301.0  94882.0 6733.000       24.67  8.897638           901.3
## 12 2012 105241.0  93506.0 6486.000       24.69  9.244094           823.9
## 13 2013 106646.0  95850.0 6555.000       24.82  8.913386           937.2
## 14 2014 105482.0  86527.0 7013.000       24.73  8.579437           781.7
## 15 2015 104320.0  93500.0 6840.000       24.91  8.925435           764.9
## 16 2016  93880.0  97862.9 4410.000       26.45  9.036237           864.4
## 17 2017 105791.8 101007.3 6407.325       26.29  9.087686           879.3
## 18 2018 105796.2 103139.0 6500.131       25.90  9.221200           876.2
## 19 2019 108175.5 105867.5 6456.881       25.86  9.479331           873.5
## 20 2020 108880.0 107868.6 6677.215       24.88  8.634556           872.5
## 21 2021 108196.2 109455.9 6734.435       24.90  8.716495           868.9
## 22 2022 108633.1 111410.7 6731.680       24.92  8.801680           864.0
## 23 2023 110553.8 113372.7 6761.625       24.93  8.892993           862.7
## 24 2024 111532.2 115261.0 6827.565       24.94  8.976937           858.6
## 25 2025 112421.7 116739.1 6784.824       24.95  9.056299           857.6
## 26 2026 113926.1 118609.5 6613.708       24.97  9.140599           856.6
## 27 2027 113958.3 121422.0 6714.044       24.98  9.223398           855.9
## 28 2028 114466.7 124083.8 6789.195       24.99  9.303459           850.2
## 29 2029 115538.5 127037.3 6846.557       25.00  9.386762           846.3
## 30 2030 116807.6 128462.2 6921.031       25.01  9.469328           840.9
## 31 2031 118517.8 130238.7 7075.534       25.03  9.559182           840.2
## 32 2032 119573.2 132196.4 7245.013       25.04  9.645706           834.6
## 33 2033 119353.9 134260.2 7086.472       25.06  9.733481           836.5
## 34 2034 119750.5 136328.3 7117.020       25.07  9.827420           840.9
## 35 2035 121217.2 138500.5 7152.146       25.09  9.929995           833.2
## 36 2036 122440.9 140705.7 7174.145       25.11 10.030941           833.0
## 37 2037 123746.8 142880.7 7217.312       25.12 10.126817           826.2
## 38 2038 125001.0 145059.3 7267.430       25.13 10.220390           826.1
## 39 2039 124908.3 147237.4 7317.593       25.14 10.315302           825.1
## 40 2040 125365.1 149396.8 7371.395       25.16 10.411232           822.0
## 41 2041 126628.1 151457.7 7434.638       25.18 10.509288           821.5
## 42 2042 127855.9 153437.8 7493.686       25.19 10.605447           818.5
```

```
## 43 2043 129354.2 155462.9 7525.583       25.21 10.702381            818.6
## 44 2044 130525.8 157544.2 7558.505       25.23 10.787418            818.3
## 45 2045 130362.8 159762.2 7590.642       25.25 10.873250            813.9
## 46 2046 130792.5 161930.7 7620.184       25.26 10.967102            808.6
## 47 2047 132157.8 164070.8 7649.682       25.28 11.057460            803.6
## 48 2048 133398.3 166193.1 7692.250       25.30 11.139018            802.5
## 49 2049 134794.2 168304.7 7756.528       25.32 11.219889            798.4
## 50 2050 136001.6 170402.0 7801.913       25.33 11.304697            802.7
##    ANNUAL.CO2.EMISSION
## 1             0.923300
## 2             0.935700
## 3             0.953300
## 4             0.996300
## 5             1.033400
## 6             1.080900
## 7             1.147900
## 8             1.218300
## 9             1.324400
## 10            1.359400
## 11            1.423800
## 12            1.551300
## 13            1.590300
## 14            1.687100
## 15            1.731500
## 16            1.798600
## 17            1.818100
## 18            1.922000
## 19            1.933646
## 20            2.150840
## 21            2.163359
## 22            2.289027
## 23            2.339593
## 24            2.353786
## 25            2.512614
## 26            2.557280
## 27            2.628982
## 28            2.698730
## 29            2.767054
## 30            2.833279
## 31            2.902288
## 32            2.970579
## 33            3.035796
## 34            3.103410
## 35            3.170061
## 36            3.236712
## 37            3.304817
## 38            3.372217
## 39            3.439672
## 40            3.506785
## 41            3.573602
```

```
## 42           3.617333
## 43           3.672791
## 44           3.754563
## 45           3.820660
## 46           3.888025
## 47           3.953976
## 48           4.020212
## 49           4.087727
## 50           4.155011
```

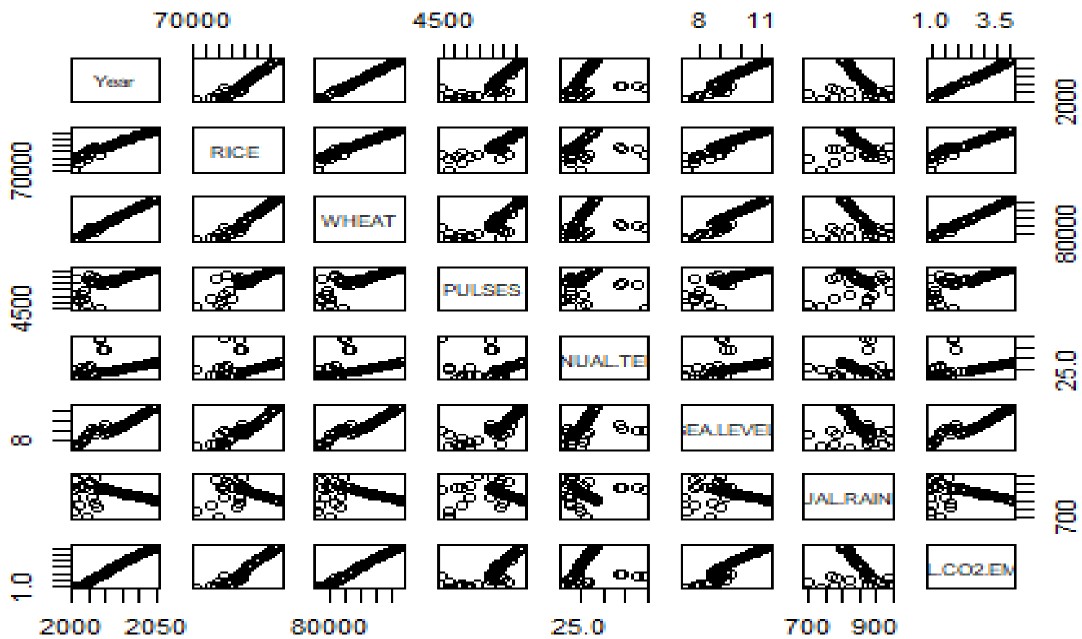
```
colnames(mr)
```

```
## [1] "Year"                 "RICE"                 "WHEAT"
## [4] "PULSES"               "ANNUAL.TEMP"          "SEA.LEVEL"
## [7] "ANNUAL.RAINFALL"      "ANNUAL.CO2.EMISSION"
```

```
#matrix of scatter plot
pairs(mr[,1:8])
cor(mr,method="pearson")
```

```
##                           Year       RICE      WHEAT      PULSES
ANNUAL.TEMP
## Year                 1.0000000  0.9651707  0.9972352  0.81008455
0.28958562
## RICE                 0.9651707  1.0000000  0.9712176  0.87426129
0.20829165
## WHEAT                0.9972352  0.9712176  1.0000000  0.82147115
0.29010710
## PULSES               0.8100846  0.8742613  0.8214711  1.00000000
0.03235588
## ANNUAL.TEMP          0.2895856  0.2082917  0.2901071  0.03235588
1.00000000
## SEA.LEVEL            0.9636380  0.9457205  0.9660819  0.79822535
0.37868301
## ANNUAL.RAINFALL     -0.2876585 -0.1485439 -0.2546646 -0.02275595 -
0.02641675
## ANNUAL.CO2.EMISSION  0.9991003  0.9623197  0.9966014  0.80912746
0.27274905
##                      SEA.LEVEL ANNUAL.RAINFALL ANNUAL.CO2.EMISSION
## Year                 0.9636380     -0.28765855           0.9991003
## RICE                 0.9457205     -0.14854391           0.9623197
## WHEAT                0.9660819     -0.25466455           0.9966014
## PULSES               0.7982254     -0.02275595           0.8091275
## ANNUAL.TEMP          0.3786830     -0.02641675           0.2727491
## SEA.LEVEL            1.0000000     -0.27132627           0.9549497
## ANNUAL.RAINFALL     -0.2713263      1.00000000          -0.2978011
## ANNUAL.CO2.EMISSION  0.9549497     -0.29780113           1.0000000
```

```
#check significance of correlation
#install.packages("Hmisc")
library(Hmisc)
```




```r
rcorr(as.matrix(mr))
```

```
##                        Year  RICE WHEAT PULSES ANNUAL.TEMP SEA.LEVEL
## Year                   1.00  0.97  1.00   0.81        0.29      0.96
## RICE                   0.97  1.00  0.97   0.87        0.21      0.95
## WHEAT                  1.00  0.97  1.00   0.82        0.29      0.97
## PULSES                 0.81  0.87  0.82   1.00        0.03      0.80
## ANNUAL.TEMP            0.29  0.21  0.29   0.03        1.00      0.38
## SEA.LEVEL              0.96  0.95  0.97   0.80        0.38      1.00
## ANNUAL.RAINFALL       -0.29 -0.15 -0.25  -0.02       -0.03     -0.27
## ANNUAL.CO2.EMISSION    1.00  0.96  1.00   0.81        0.27      0.95
##                       ANNUAL.RAINFALL ANNUAL.CO2.EMISSION
## Year                            -0.29                1.00
## RICE                            -0.15                0.96
## WHEAT                           -0.25                1.00
## PULSES                          -0.02                0.81
## ANNUAL.TEMP                     -0.03                0.27
## SEA.LEVEL                       -0.27                0.95
## ANNUAL.RAINFALL                  1.00               -0.30
## ANNUAL.CO2.EMISSION             -0.30                1.00
##
## n= 50
##
##
## P
##                       Year   RICE   WHEAT  PULSES ANNUAL.TEMP SEA.LEVEL
## Year                         0.0000 0.0000 0.0000 0.0414      0.0000
```

```
## RICE                 0.0000        0.0000 0.0000 0.1466      0.0000
## WHEAT                0.0000 0.0000        0.0000 0.0410      0.0000
## PULSES               0.0000 0.0000 0.0000        0.8235      0.0000
## ANNUAL.TEMP          0.0414 0.1466 0.0410 0.8235             0.0067
## SEA.LEVEL            0.0000 0.0000 0.0000 0.0000 0.0067
## ANNUAL.RAINFALL      0.0428 0.3032 0.0743 0.8754 0.8555      0.0567
## ANNUAL.CO2.EMISSION 0.0000 0.0000 0.0000 0.0000 0.0553      0.0000
##                      ANNUAL.RAINFALL ANNUAL.CO2.EMISSION
## Year                 0.0428          0.0000
## RICE                 0.3032          0.0000
## WHEAT                0.0743          0.0000
## PULSES               0.8754          0.0000
## ANNUAL.TEMP          0.8555          0.0553
## SEA.LEVEL            0.0567          0.0000
## ANNUAL.RAINFALL                      0.0357
## ANNUAL.CO2.EMISSION 0.0357

#fitting multiple regression
mlrm=lm(PULSES~ANNUAL.TEMP+SEA.LEVEL+ANNUAL.RAINFALL+ANNUAL.CO2.EMISSION ,
data = mr)

mlrm

##
## Call:
## lm(formula = PULSES ~ ANNUAL.TEMP + SEA.LEVEL + ANNUAL.RAINFALL +
##     ANNUAL.CO2.EMISSION, data = mr)
##
## Coefficients:
##         (Intercept)          ANNUAL.TEMP            SEA.LEVEL
##           14661.722             -691.274              522.419
##     ANNUAL.RAINFALL  ANNUAL.CO2.EMISSION
##               4.535              279.366

summary(mlrm)

##
## Call:
## lm(formula = PULSES ~ ANNUAL.TEMP + SEA.LEVEL + ANNUAL.RAINFALL +
##     ANNUAL.CO2.EMISSION, data = mr)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -1110.40   -63.43   -39.06   136.20   948.41
##
## Coefficients:
##                       Estimate Std. Error t value Pr(>|t|)
## (Intercept)          14661.722   4236.177   3.461 0.001190 **
## ANNUAL.TEMP           -691.274    181.632  -3.806 0.000424 ***
## SEA.LEVEL              522.419    203.971   2.561 0.013852 *
## ANNUAL.RAINFALL          4.535      1.333   3.402 0.001415 **
```

```
## ANNUAL.CO2.EMISSION   279.366    207.131   1.349 0.184169
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 409.6 on 45 degrees of freedom
## Multiple R-squared:  0.7826, Adjusted R-squared:  0.7633
## F-statistic:  40.5 on 4 and 45 DF,  p-value: 2.275e-14
```

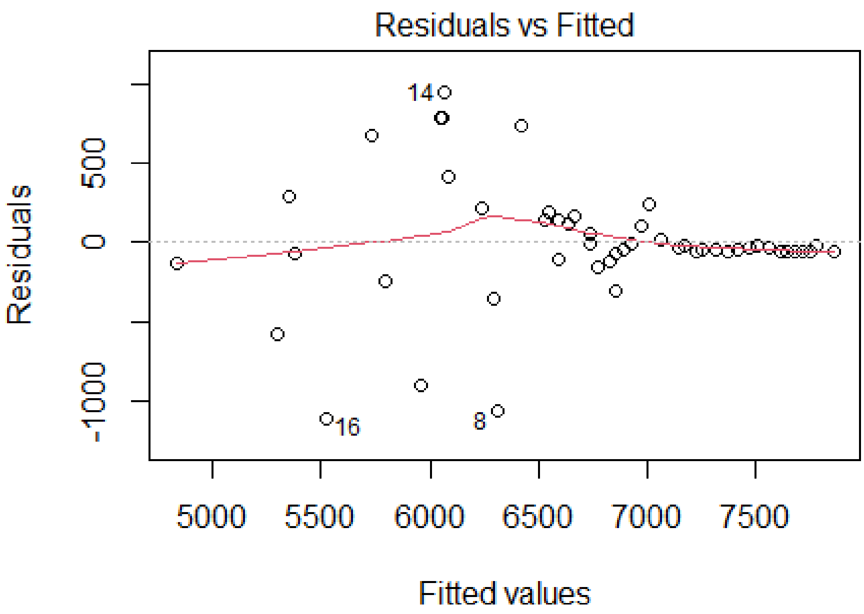
```
#confidence interval of regression coefficient
confint(mlrm ,level=0.95)
```

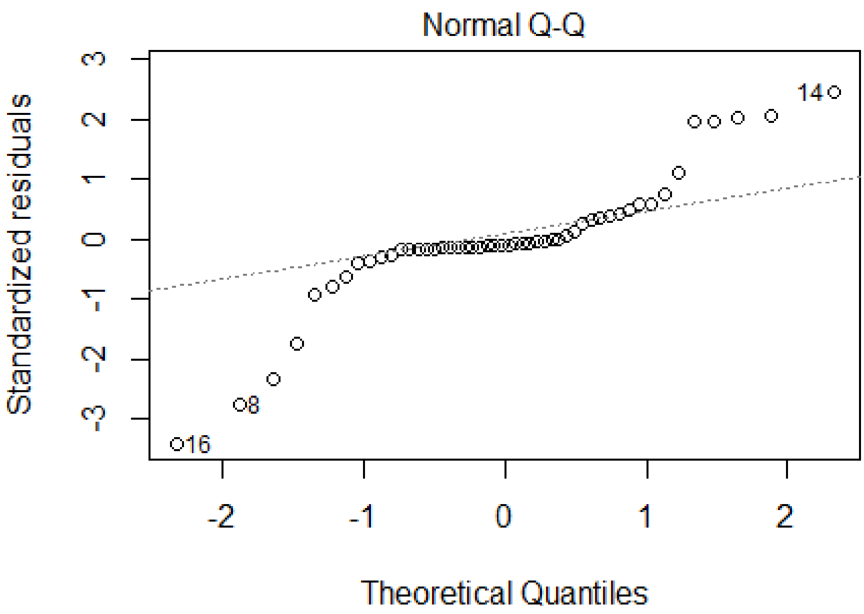
```
##                            2.5 %      97.5 %
## (Intercept)          6129.622298 23193.82091
## ANNUAL.TEMP         -1057.099163  -325.44918
## SEA.LEVEL             111.600397   933.23696
## ANNUAL.RAINFALL         1.849755     7.21947
## ANNUAL.CO2.EMISSION  -137.816826   696.54799
```

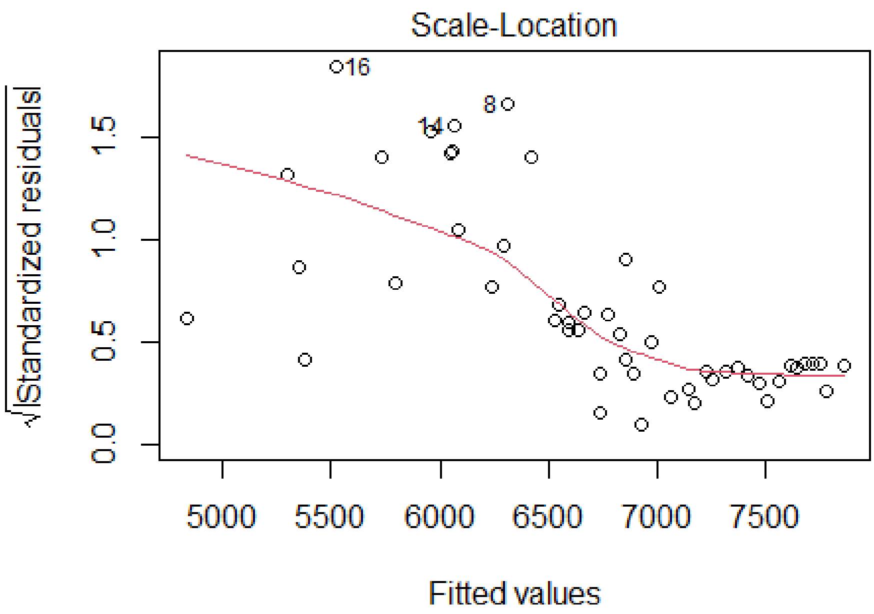
```
#predict for some value
newdata=data.frame(ANNUAL.TEMP=26,SEA.LEVEL=10,ANNUAL.RAINFALL=800,ANNUAL.CO2
.EMISSION=3)
predict(mlrm,newdata)
```

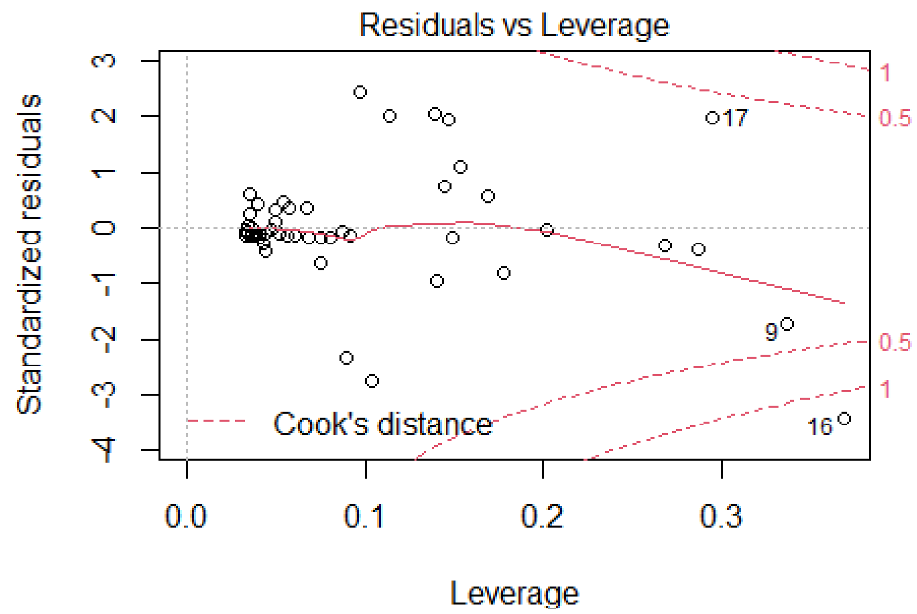
```
##        1
## 6378.567
```

PLOTS OF ANALYSIS






Scale-Location
√|Standardized residuals|
0.0
0.5
1.0
1.5
5000
5500
6000
6500
7000
7500
Fitted values
16
8
14


Residuals vs Leverage
Standardized residuals
3
2
1
0
-1
-2
-3
-4
0.0
0.1
0.2
0.3
Leverage
Cook's distance
17
9
16
1
0.5
0.5
1

4.4.1 Result and Conclusion

Based on the dataset firstly we have calculated correlation coefficient between the weather parameters and production parameters. The matrix of scatter plot shows the relation between all variables. Through this we have an idea of relationship between study and explanatory variable.
Here we have clearly seen that sea level rise and annual carbon dioxide emission have strongly correlated with pulse production. Then we have computed correlation coefficient table and the respective p-value of parameters.
H_0 : There is no correlation between variables.
When we compare the p-value of pulse and weather parameters with the significant value i.e there is high correlation between pulse production and sea level rise as well as annual CO_2 emission.
When we are fitting Multiple linear Regression in our model, it explains the actual effect of weather parameter on pulse production.
H_0 : There is no significant effect of weather parameter into pulse production.
When we compare the p-value of fitted model for pulse production and weather parameters with the significant value. Then the following inferences are given below:

- We infer that there is strong significant effect between pulse and annual temperature.
- We infer that there is strong significant effect between pulse and sea Level rise.
- We infer that there is strong significant effect between pulse and annual rainfall.
- We infer that there is no strong significant effect between pulse and annual CO_2 emission.

Then we have found that the annual temperature, sea Level rise and annual rainfall has significant effect on pulse production.
Testing of significance of model Fitting
The Multiple R-Squared : 0.7826 and Adjusted R-Squared : 0.7633 with 45 degrees of freedom. The F-statistic : 318.6 on 4 and 45 degree of freedom.
H_0: The model is not good fitted .
The p-value is : 2.275e-14 which is much less than the significant value 0.05, hence the null hypothesis is rejected.
This infer that our model is good fitted and effect of climate parameters on

production is significant.

4.4.2 Description of Plots

In our study we have plotted four plots to analyse the impact of climate parameters.

- **Residuals vs Fitted value plot:** The Residual plot explains the difference between the observed value and fitted value of study variable. In this plot we have seen that only half of the values lies on 0, this shows that data is homoscedastic and linearly related.

- **Normal Q-Q plot:** This plot describes the normality of the dataset. If the data is normally distributed the points in a Q-Q plot will lie on a straight diagonal line.
  In our dataset the many of the values lies diagonally and some of the values are outlier .So we infer that approx 90% of dataset are normally distributed.

- **Scale-Location plot:** This plot displays the fitted values of a regression model along the x-axis and the square root of the standardized residuals along the y-axis.
  A horizontal red line shows the homoscedasticity in model. Here the plot shows that the explanatory variables are heteroscedastic.

- **Residuals vs Leverage plot:** This plot is a type of diagnostic plot that allows us to identify influential observations in a regression model.If any point in this plot falls outside of Cook's distance (the red dashed lines) then it is considered to be an influential observation.
  In our plot one points lies outside the Cook's distance i.e the regreesion model does have influential observation.

4.5 CONCLUSION

The India is the second most populated country in the world, the food consumption requirement is very high to fulfill the human being requirement. India is an Agriculture Dominated Counry. Wheat and Rice is the main cereal crop of India and the second largest producer in the world. The majority of population consumes these cereals in a meal and “Right to Food ”is a fundamental right that means government are entitled to provide a good and adequate food to all citizens.
As the pre industrial period the climatic behaviour was very convenient for agricultural practices but in post industrial period the major production level has deteriorating because of unnecessary changes in climate pattern. As we have seen in our study that major climatic parameters like Annual temperature rise, annual sea level rise, annual rainfall, annual carbon dioxide emission has impacted severely on major crops.
“The IPCC mention in his report the remedies of climate change for India, the excessive heat means temperature rise deteriorete the ground water level and reduces the production gradually :IPCC ”
India is a third largest producer of Green House gases the carbon emission is the big challenge because due to global warming various climatic phenomena gets changed and this will consecutively effect the agricultral practices.

REFERENCES

1. For learning R-Programming, we refer course "Introduction to R-programming" by Shalabh sir on NPTEL and various tutorials on Youtube.
2. The defination and theoretical concepts has been taken from various books and internet.
3. The dataset used in Section 4.2 of Chapter 4 has been taken from: https://data.gov.in
4. The dataset used in Section 4.3 of Chapter 4 has been taken from: https://data.gov.in
5. The dataset used in Section 4.4 of Chapter 4 has been taken from: https://data.gov.in
6. The definition and reports has been taken from IPCC report. https://unfccc.int/