



UNIVERSITI MALAYA

WQD7001 Principle of Data Science

Session 2023/2024: Semester 1

Group 5

Title: Predictive Analysis for Precipitation in Kuala Lumpur

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1.0 Project Background

Climate change poses significant challenges globally, impacting various facets of our environment and necessitating innovative solutions. One critical aspect that demands attention is the accurate prediction of rainfall, especially in regions prone to weather extremes. In this context, Kuala Lumpur, which is a densely populated urban center, emerges as a pivotal location for the focus of this project. Given its tropical climate and susceptibility to heavy rainfall, the city serves as a crucial case study for enhancing our understanding and predictive capabilities.

As we witness the intensification of climate change, the need for precise and timely rainfall predictions becomes even more urgent to effectively address the challenges that may arise. The urban landscape of Kuala Lumpur faces challenges related to heavy rainfall, including flash floods and infrastructure strain. Accurate rainfall prediction plays a crucial role in disaster preparedness and response, enabling authorities to implement timely measures to safeguard public safety and mitigate the impact on critical infrastructure.

In light of these considerations, this project aims to contribute to the advancement of rainfall prediction methodologies in Kuala Lumpur. This study also aims to empower stakeholders across various sectors, from environmental conservation to urban planning, with insights that foster resilience in the face of changing weather patterns.

2.0 Problem Statement

Traditional methods of rainfall prediction often fall short in providing accurate and timely information, especially in the context of Kuala Lumpur, Malaysia. The region's unique climate dynamics, influenced by factors such as monsoons and localized weather patterns, contribute to the complexity of predicting precipitation events. Inaccurate forecasts can have far-reaching consequences, affecting both businesses and the general public, necessitating a more sophisticated approach to predictive analysis.

The increased frequency and intensity of extreme weather events, driven by climate change, pose risks to various sectors and communities. Sudden and heavy rainfall can lead to floods, resulting in property damage, disruptions to transportation networks, and financial losses. These adverse impacts extend beyond businesses to impact the daily lives of residents, emphasizing the need for a predictive analysis framework for rainfall in Kuala Lumpur to implement adaptive strategies and enhance resilience.

In response to these challenges, the project aims to enhance rainfall prediction methodologies through advanced predictive analytics tailored to the specific characteristics of Kuala Lumpur's climate. By leveraging data-driven approaches, the goal is to provide timely and accurate information not only to businesses but also to the public.

Through this predictive analysis on precipitation, the project seeks to contribute to minimizing the adverse and disruptive effects caused by changes in weather patterns and climate in Kuala Lumpur. The project aims to foster a more resilient and prepared community in the face of unpredictable rainfall patterns.

3.0 Project Objectives

Below are the objectives identified for the project:

1. To Identify the Optimal Machine Learning Model for Rainfall Prediction in Kuala Lumpur.
2. To evaluate and compare the performance of selected machine learning algorithms in predicting rainfall in Kuala Lumpur.
3. To evaluate various metrics to determine the most suitable evaluation criteria for assessing the performance of the machine learning model in the context of rainfall prediction in Kuala Lumpur.

4.0 Project Scope / Domain

The project resides within the domain of environmental studies, with a primary focus on developing rainfall forecasting methodologies using machine learning techniques. Specifically, the scope of this study is confined and tailored explicitly to the characteristics of Kuala Lumpur's climate.

The primary goal is to develop machine learning models specifically designed for the unique characteristics of Kuala Lumpur's climate. This model seeks to outperform existing forecasting methods, providing a more accurate and dependable tool for predicting rainfall patterns in Kuala Lumpur. By concentrating on Kuala Lumpur, this project aims to tackle the challenges in the local weather patterns. Advanced analytics and machine learning techniques will be employed to gain comprehensive understanding of Kuala Lumpur's climate and rainfall patterns.

5.0 Literature Study

Table 1.1 below includes six research articles published in recent years, which are deemed as valuable resources for our model development and the formulation of project objectives. A thorough review has been conducted, summarizing the work and key findings of each article.

No.	Authors	Title	Summary of work and key findings
1.	Sulaiman, N. A. F., Shaharudin, S. M., Ismail, S., Zainuddin, N. H., Tan, M. L., & Jalil, Y. A. (2022)	Predictive Modelling of Statistical Downscaling Based on Hybrid Machine Learning Model for Daily Rainfall in East-Coast Peninsular Malaysia	<ul style="list-style-type: none">• This study focuses on Kelantan and Terengganu states in Peninsular Malaysia, which are situated on the east coast. The study incorporates 10 strategically selected rainfall observation stations across the chosen region.• Through Principal Component Analysis (PCA), the study effectively reduced the high-dimensional dataset to six principal components, capturing over 70% of the total variance. The careful selection of predictors based on PCA loadings ensured that the most influential factors were retained for further analysis. This approach streamlined the dataset and also facilitated the identification of factors significantly influencing rainfall patterns in east-coast Peninsular Malaysia.• This study evaluated various machine learning models for statistical downscaling, with Support Vector Classification (SVC) and Support Vector Regression (SVR) demonstrating solid performance. However, the hybrid model of Support Vector Classification and Relevant Vector Machine (SVC-RVM) emerged as the most robust approach. This model not only outperformed

			<p>others in terms of accuracy, misclassification error, and support vectors but also excelled in forecasting daily rainfall. The SVC-RVM hybrid model showcased a superior ability to predict rainfall patterns accurately for the next two years, making it a recommended choice for statistical downscaling in the context of climate change impact assessment.</p>
2.	<p>Barrera-Animas, A. Y., Oyedele, L. O., Bilal, M., Akinosho, T. D., Delgado, J. M. D., & Akanbi, L. A. (2022)</p>	<p>Rainfall prediction: A comparative analysis of modern machine learning algorithms for time-series forecasting</p>	<ul style="list-style-type: none"> • This study compared XGBoost, AutoML ensemble, and LSTM-based models for hourly rainfall prediction in major UK cities. • The AutoML ensemble, combining Gradient Boosting, Linear Support Vector, and Extra-trees Regressors, outperformed XGBoost, with Cardiff showing the best overall performance. LSTM and Stacked-LSTM models consistently demonstrated superior predictive abilities compared to traditional machine learning approaches. • This study suggested that model complexity played a crucial role in performance, as evidenced by the poor performance of a 10-layer Stacked-LSTM model compared to shallower networks. This study also emphasized the need for careful architecture selection and hyperparameter tuning.
3.	<p>Liyew, C. M., & Melese, H. A. (2021)</p>	<p>Machine learning techniques to predict daily rainfall amount</p>	<ul style="list-style-type: none"> • This study focuses on predicting daily rainfall intensity in Bahir Dar City, Ethiopia, utilizing machine learning algorithms. Environmental features collected from a

			<p>meteorological station were analyzed for their relevance in rainfall prediction.</p> <ul style="list-style-type: none"> • This study stands out for its meticulous analysis of environmental features' relevance through Pearson correlation. This approach ensures that only significant variables are utilized for predicting daily rainfall, enhancing the accuracy of the models. Relevant features, determined through Pearson correlation, were used as inputs for three machine learning models: Multiple Linear Regression (MLR), Random Forest (RF), and XGBoost. • This study suggested that XGBoost was found to be the most suitable algorithm for daily rainfall prediction, with the highest prediction accuracy.
4.	Mohammed, M., Kolapalli, R., Golla, N., & Maturi, S. S. (2020)	Prediction Of Rainfall Using Machine Learning Techniques	<ul style="list-style-type: none"> • This study focuses on offering non-experts easy access to the techniques, approaches utilized in the sector of precipitation prediction, especially in rainfall prediction as well as provide a comparative study among the various machine learning techniques which can be used to predict rainfall. • This study uses and compare three different regression analysis technique (Multiple Linear Regression (MLR), Support Vector Regression (SVR) and Lasso Regression) to predict rainfall from year 1901 to 2015 for each state in India. • This study concludes that Support Vector Regression (SVR) is a more valuable and adaptable strategy to be used. As SVR able

			to provide the least errors in rainfall prediction compared to the other two methods.
5.	Adaryani, F. R., Jamshid Mousavi, S., & Jafari, F. (2022)	Short-term rainfall forecasting using machine learning-based approaches of PSO-SVR, LSTM and CNN	<ul style="list-style-type: none"> • This study focuses on short-term (5 minutes and 15 minutes ahead) rainfall prediction of Niyavaran station of Tehran, capital of Iran from 1974 to 2014 using three different machine and deep learning-based (PSO Support Vector Regression (PSO-SVR), Long-Short Term Memory (LSTM) and Convolutional Neural Network (CNN)) model. • This study indicates that PSO-SVR and LSTM approaches performed almost the same and better than CNN. Classification of the events will be able to improve the forecast models accuracy. • This study concludes that each models have its own strengths and weaknesses. In terms of short-term rainfall prediction, PSO-SVR and LSTM will be a better choice. However, which model is more suitable to be used still need to based on what are the outcome researchers want.
6.	Ridwan, W. M., Sapitang, M., Aziz, A., Kushiar, K. F., Ahmed, A. N., & El-Shafie, A. (2020)	Rainfall forecasting model using machine learning methods: Case study Terengganu, Malaysia	<ul style="list-style-type: none"> • This study uses several machine learning models (Bayesian Linear Regression (BLR), Boosted Decision Tree Regression (BDTR), Decision Forest Regression (DFR) and Neural Network Regression (NNR)) and methods (Forecasting Rainfall Using Autocorrelation Function (ACF) and Forecasting Rainfall Using Projected Error)

			<p>to predict the rainfall data in 10 stations covering the Tasik Kenyir, Terengganu.</p> <ul style="list-style-type: none"> • This study uses the Thiessen Polygon method to calculate the proximity area around the point with other points. It also can help to calculate station rainfall weight and average rainfall based on each station. • This study concludes that the results presented that for ACF gets better with cross-validation with BDTR and tuning its parameter. Also, the more input included to the model, the more accurate the model can perform.
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Table 1: Summary for reviewed journal articles

6.0 Description of Methodology

6.1 Obtain

In the initial phase of our methodology, the meteorological data essential for rainfall prediction in Kuala Lumpur was acquired from the online weather data provider, Visual Crossing. This platform offers comprehensive and high-quality weather datasets, including information on precipitation, temperature, maximum and minimum temperature, temperature feeling, maximum and minimum temperature feeling, dew, humidity, precipitation coverage, cloud coverage, visibility, solar radiation, solar energy, un index and precipitation description. The decision to utilize Visual Crossing was guided by the platform's reliability, extensive coverage, and the availability of historical weather data specific to the Kuala Lumpur region. The dataset obtained from Visual Crossing encompasses a temporal scope that spans 1000 days, from 1st February 2021 to 28th October 2023 and consists of 1000 observations and 33 variables.

6.2 Scrub

From the original dataset, our initial step is removing redundant or irrelevant variables, such as name and datetime. After removing those variables, there are some categorical variables existing in our dataset. Before analyzing those variables, we transform them from characters into factors. After that, we proceed to examine the relationship between our dependent variable and independent variables to help us to identify those variables

that are having insignificant relationship with the dependent variable and to remove them. In the last part of data scrubbing, we used to define missing value, outlier and duplicate value from datasets. In this part, we retained all existing data without removing any missing values or duplicates, as none were identified during our thorough examination. We do not remove outliers from our dataset. The rationale behind this decision is rooted in the belief that outliers, rather than being anomalies to be discarded from analysis, can hold valuable information in our study. In the context of rainfall prediction, extreme weather events or unusual patterns might be precisely what we need to capture and investigate, in order to build more robust and reliable models.

6.3 Explore

6.3.1 *Basic Exploration*

Dataset after scrubbing consists of 1000 observations and 16 variables. First round of basic data exploration was performed before data scrubbing to define the data that need to be cleanse. The exploration process involves function including `names()`, `class()`, `dim()`, `str()`, `summary()`, `head()` and `tail()` to see the overall data frame pattern. Dataset is found consisting of categorical and numerical variables. Therefore, we transformed the categorical variables into correct structure using `as.factor()` function.

6.3.2 *Univariate Analysis*

After selecting the variables that are significant to dependent variable, we proceed to perform univariate analysis for each of the variable to see their pattern and distribution. We used boxplot and histogram for numerical variable to identify trend and pattern. For categorical variable, we created bar chart using `ggplot()` to visualize the pattern.

As numerical variables, we observed that several variables such as `tempmax`, `tempmin`, `temp`, `feelslikemax`, `feelslike`, `dew`, `humidity`, `precip`, `precipcover`, `visibility`, `solarradiation` and `solarevergy` have outliers shown in the boxplot (refer to appendix) while `cloudcover` did not exhibit outliers. Based on histogram, `tempmax`, `temp`, `feelslikemax`, `dew`, `humidity`, `solarradiation` and `solarenergy`

skewed to left. Conversely, tempmin, feelslikemin, feelslike, precip, precipcover, cloudcover and visibility shown rightward skeweness.

As category variables, the highest frequency of description is partly cloudy throughout the day (346) followed by partly cloudy throughout the day with rain (183). The lowest frequency is partly cloudy throughout the day with a chance of rain throughout the day (7). Next, the highest frequency of uvindex is 9 (315) followed by 8 (184) while the lowest frequency is 1 (3) (refer to appendix).

6.3.3 **Bivariate Analysis**

Correlation matrix was utilized to examine the relationship between dependent variable (precipitation) and independent variables. We also use scatter plots to represent the relationship between dependent variable and numerical independent variables. ANOVA test was used to determine the relationship between categorical variables and dependent variable. The correlation matrix below shows the correlation between every variable.

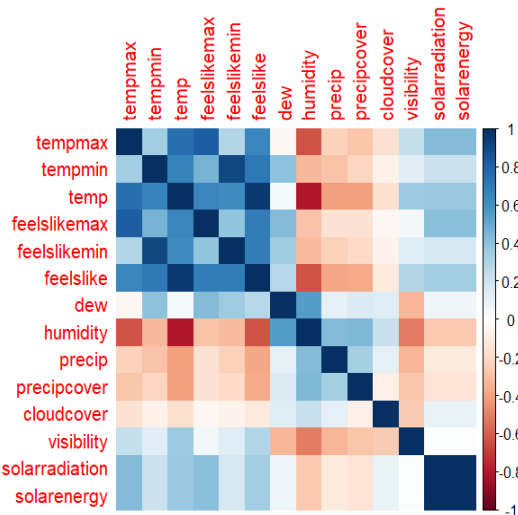


Figure 1: Correlation matrix

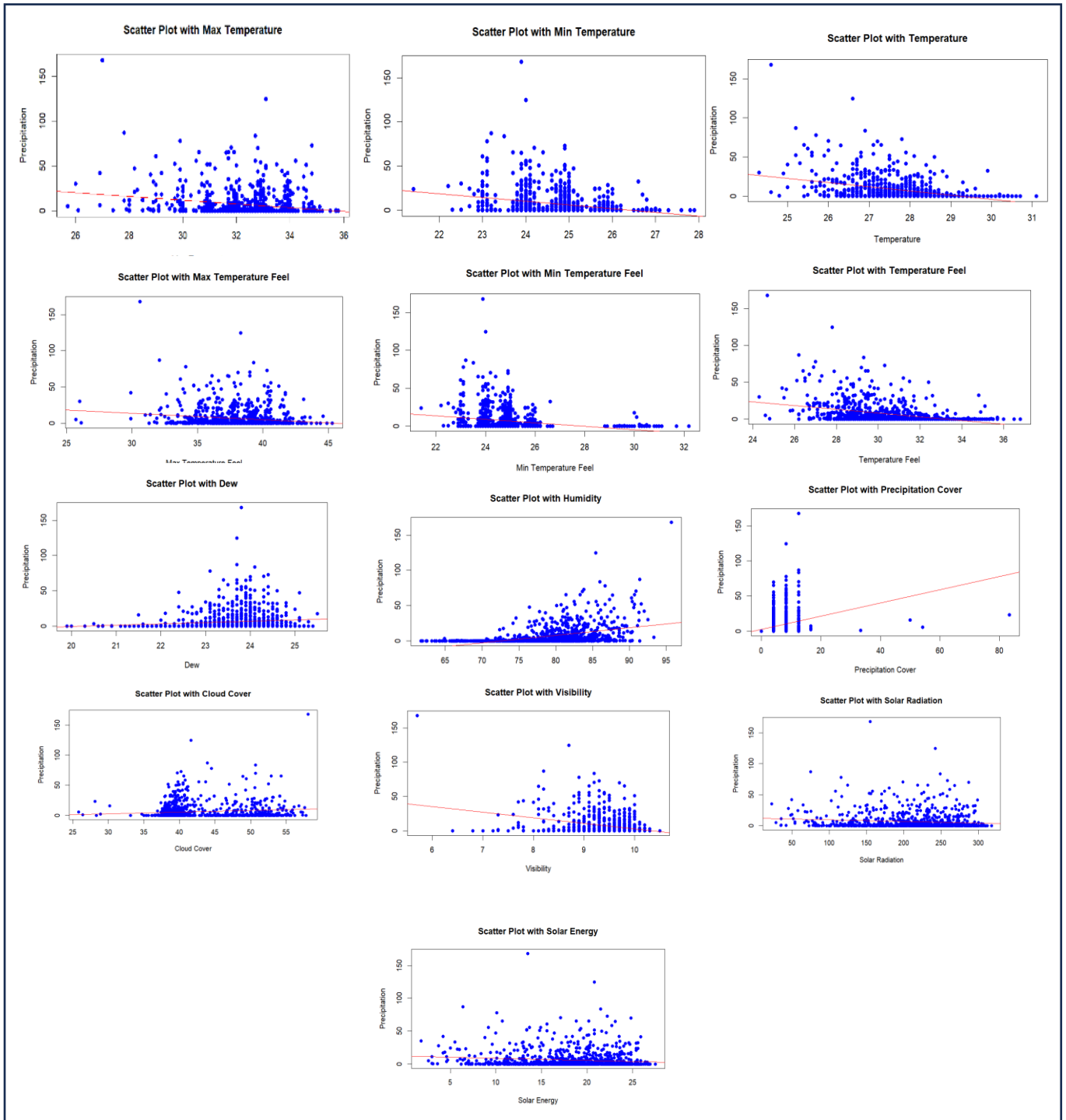


Figure 2: Scatter Plots for Independent Variables against Precipitation

According to the scatter plots, maximum temperature, minimum temperature, temperature, maximum temperature feel, minimum temperature feel, temperature feel, visibility, solar radiation, and solar energy show negative correlation with the precipitation. Dew, humidity, precipitation cover, and cloud cover are having positive correlation with precipitation.

	Df	Sum Sq	Mean Sq	F value	Pr(>F)	
description	8	39139	4892	30.606	<2e-16	***
uvindex	9	825	92	0.573	0.820	
description:uvindex	51	7079	139	0.868	0.732	
Residuals	931	148822	160			

Signif. codes:	0	'***'	0.001	'**'	0.01	'*' 0.05 '.' 0.1 ' ' 1

Figure 3: ANOVA test for categorical variables against precipitation

H_0 : All group means are equal.

H_1 : At least one group mean is different

From the ANOVA test result, we conclude that there is a significant difference in mean weight loss between description and precipitation since the p-value is less than 0.05. The main effects of uvindex and the interaction effect between description and uvindex are not statistically significant because its p-value is larger than 0.05. Therefore, we reject the null hypothesis and conclude that at least one group having a significant difference on mean.

6.3.4 **Multivariate Analysis**

We examine the relationship between multiple independent variables and the dependent variable using multiple linear regression and ANOVA test. After that, we show the distribution of the model residuals using histograms.

Analysis of Variance Table						
Response: precip						
	Df	Sum Sq	Mean Sq	F value	Pr(>F)	
description	8	39139	4892.4	37.0930	< 2.2e-16	***
uvindex	9	825	91.6	0.6948	0.7140506	
tempmax	1	1228	1227.9	9.3094	0.0023419	**
tempmin	1	4485	4484.9	34.0034	7.490e-09	***
temp	1	5891	5890.6	44.6615	3.946e-11	***
feelslikemax	1	577	577.1	4.3756	0.0367174	*
feelslikemin	1	1364	1363.8	10.3399	0.0013450	**
feelslike	1	117	116.9	0.8861	0.3467760	
dew	1	1795	1795.3	13.6115	0.0002373	***
humidity	1	9948	9948.1	75.4242	< 2.2e-16	***
precipcover	1	7	6.6	0.0501	0.8229131	
cloudcover	1	475	475.4	3.6043	0.0579260	.
visibility	1	1245	1244.6	9.4359	0.0021871	**
solarrradiation	1	834	833.6	6.3203	0.0120976	*
solarenergy	1	130	130.2	0.9871	0.3207109	
Residuals	969	127807	131.9			

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1						

Figure 4: ANOVA test Result for Multiple Linear Regression

H_0 : All group means are equal.

H_1 : At least one group mean is different

The histogram above skewed to the right, and we cannot conclude the normality with enough confidence. Thus, we plot the residues on the normal Q-Q plot. From the normal Q-Q plot, we can observe that most residuals lie in a straight line which indicates that it follows a normal distribution.

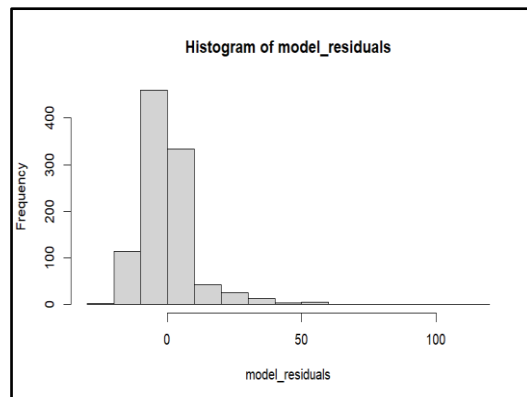


Figure 6: Histogram of Model Residuals

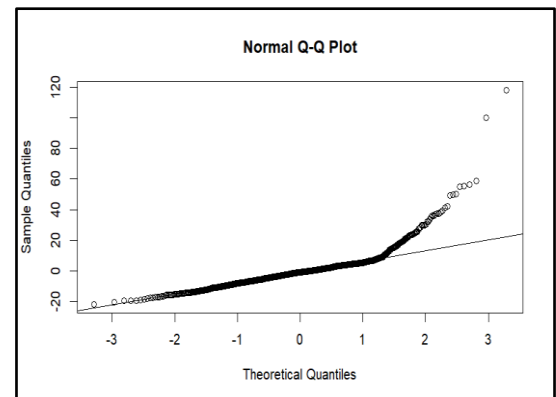


Figure 6: Normal Q-Q Plot

7.0 Ethical Consideration

Below are some of the ethical considerations need to be taken into account for this project:

1. Transparency in Data Processing will be prioritized by maintaining transparency in data processing steps, clearly documenting and communicating the methods used for data cleaning, imputation, and feature engineering.
2. Equitable Representation in Model Training will be highlighted to ensure equitable representation of diverse meteorological conditions within Kuala Lumpur during the training phase of the machine learning model. Prevention of over-reliance on specific weather patterns shall be considered to hinder biased predictions produced, especially in cases of extreme events.

8.0 Impact of the Project to the Society

The implementation of accurate rainfall predictions in Kuala Lumpur using advanced machine learning models would benefit various sectors, significantly enhancing the region's resilience and sustainability.

Firstly, in the agricultural sector, precise forecasts empower farmers with invaluable information for optimal crop planning and irrigation management. Aside from improved agricultural productivity, it also minimizes resource wastage and provides a more sustainable approach to farming amidst climate-induced uncertainties.

Additionally, the project facilitates more effective water resource management, enabling local authorities to plan and allocate resources based on anticipated rainfall patterns. This contributes to sustainable water usage for both urban and agricultural needs, addressing critical water scarcity challenges.

Timely and accurate rainfall predictions also play a vital role in flood risk mitigation, and rainfall would be one of the crucial indicators in implementing preventive measures and reducing the impact of floods.

The project also contributes towards urban planning and infrastructure design, where reliable forecasts inform the development of resilient systems, including drainage and flood control. Moreover, an improved forecasting would be beneficial in developing an efficient disaster response plan and may potentially reduce economic costs associated with emergency services, such as flood evacuation services.

Beyond these practical benefits, the project fosters community empowerment and resilience by providing accurate weather information. People can make informed decisions, take proactive measures, and be well-prepared for climate-related challenges.

Most importantly, the project aligns with global efforts toward climate action, addressing a critical aspect of climate change adaptation. Accurate rainfall prediction supports local and national climate resilience strategies, contributing to broader initiatives aimed at mitigating the impact of climate change. Furthermore, businesses may also take advantage from this project outcome, especially those reliant on weather conditions. Industries such as tourism, construction, and logistics can optimize operations based on reliable weather forecasts and make data-driven decisions.

In summary, the implementation of accurate rainfall predictions in Kuala Lumpur is capable of offering a transformative approach that positively impacts agriculture, water management, disaster resilience, urban planning, climate action and business decision-making.

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Appendix

Rainfall

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2023-12-09

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0.1 Get data

#Data Exploration

```
names(Rainfall)
```

```
## [1] "name"           "datetime"       "tempmax"        "tempmin"
## [5] "temp"           "feelslikemax"   "feelslikemin"   "feelslike"
## [9] "dew"            "humidity"       "precip"         "precipprob"
## [13] "precipcover"    "preciptype"     "snow"           "snowdepth"
## [17] "windgust"       "windspeed"      "winddir"        "sealevelpressure"
## [21] "cloudcover"     "visibility"      "solarradiation"  "solarenergy"
## [25] "uvindex"        "severerisk"     "sunrise"        "sunset"
## [29] "moonphase"     "conditions"     "description"     "icon"
## [33] "stations"
```

```
class(Rainfall)
```

```
## [1] "data.frame"
```

```
str(Rainfall)
```

```
## 'data.frame':   1000 obs. of  33 variables:
## $ name          : chr  "Kuala Lumpur,Malaysia" "Kuala Lumpur,Malaysia" "Kuala Lumpur,Malaysia" "K
## $ datetime      : chr  "2021-02-01" "2021-02-02" "2021-02-03" "2021-02-04" ...
## $ tempmax       : num  33.1 34 33.8 33.1 33.9 34.1 34.8 33.8 32.9 32.9 ...
## $ tempmin       : num  24.1 25.8 24.9 24.1 22.9 24.1 24.9 25 24.9 24.8 ...
```

```
## $ temp      : num  27.5 28.8 28 28.3 27.9 28.5 28.6 27.7 28.6 28.4 ...
## $ feelslikemax : num  36.2 37.3 38.6 36.3 36 38.2 40.4 39 39.1 37.2 ...
## $ feelslikemin : num  24.1 25.8 24.9 24.1 22.9 24.1 24.9 25 24.9 24.8 ...
## $ feelslike   : num  28.8 31.3 30.5 29.7 29.3 30.7 31 29.6 31.8 31.6 ...
## $ dew         : num  22.4 22.2 23.2 21.7 20.6 22.5 22.9 23.4 23.8 24 ...
## $ humidity    : num  76.4 69.1 76.5 69.5 66.5 72.2 72.8 78.6 76.8 77.9 ...
## $ precip      : num  47.739 0 0.707 0 0 ...
## $ precipprob  : int   100 0 100 0 0 100 0 100 0 100 ...
## $ precipcover : num  4.17 0 4.17 0 0 ...
## $ preciptype  : chr   "rain" "" "rain" "" ...
## $ snow        : int   NA NA NA NA NA NA NA NA NA NA ...
## $ snowdepth   : int   NA NA NA NA NA NA NA NA NA NA ...
## $ windgust     : num  NA NA NA NA NA NA NA NA NA NA ...
## $ windspeed   : num  19 12.5 15.7 8.7 14.3 14.6 17.7 15.7 17.3 13.9 ...
## $ winddir     : num  67.3 5.7 294 40.5 307.2 ...
## $ sealevelpressure: num  1012 1012 1011 1011 1011 ...
## $ cloudcover   : num  41.2 37.9 39.6 37.3 37.2 38.6 37.6 40.1 38.2 34.7 ...
## $ visibility   : num  9.5 10.2 10 9.5 10.2 10.1 9.9 9.9 9.5 9.7 ...
## $ solarradiation : num  258 264 266 293 298 ...
## $ solarenergy  : num  22.1 22.7 22.9 25.2 25.6 24.9 25.8 23.9 24 19.3 ...
## $ uvindex      : int   9 9 9 10 10 10 10 10 10 7 ...
## $ severerisk   : int   NA NA NA NA NA NA NA NA NA NA ...
## $ sunrise      : chr   "2021-02-01T07:27:12" "2021-02-02T07:27:16" "2021-02-03T07:27:19" "2021-02-04T07:27:23"
## $ sunset       : chr   "2021-02-01T19:26:28" "2021-02-02T19:26:39" "2021-02-03T19:26:50" "2021-02-04T19:27:01"
## $ moonphase    : num  0.62 0.66 0.69 0.73 0.75 0.8 0.83 0.87 0.91 0.94 ...
## $ conditions   : chr   "Rain, Partially cloudy" "Partially cloudy" "Rain, Partially cloudy" "Partly cloudy"
## $ description  : chr   "Partly cloudy throughout the day with early morning rain." "Partly cloudy"
## $ icon         : chr   "rain" "partly-cloudy-day" "rain" "partly-cloudy-day" ...
## $ stations     : chr   "48647099999,48650099999,WMSA,WMKK" "48647099999,48650099999,WMSA,WMKK" "48647099999,48650099999,WMSA,WMKK" "48647099999,48650099999,WMSA,WMKK"
```

```
dim(Rainfall)
```

```
## [1] 1000 33
```

```
summary(Rainfall)
```

```
##      name      datetime      tempmax      tempmin
## Length:1000    Length:1000    Min.      :25.70    Min.      :21.4
## Class :character Class :character 1st Qu.:31.90    1st Qu.:24.1
## Mode  :character Mode  :character Median :32.90    Median :24.9
##                                     Mean  :32.59    Mean   :24.9
##                                     3rd Qu.:33.80    3rd Qu.:25.7
##                                     Max.   :35.80    Max.   :27.9
##
##      temp      feelslikemax      feelslikemin      feelslike
## Min.      :24.30    Min.      :25.70    Min.      :21.40    Min.      :24.30
## 1st Qu.:27.30    1st Qu.:36.80    1st Qu.:24.10    1st Qu.:29.30
## Median :28.00    Median :38.10    Median :24.90    Median :30.60
## Mean   :28.01    Mean   :38.14    Mean   :25.07    Mean   :30.72
## 3rd Qu.:28.80    3rd Qu.:39.60    3rd Qu.:25.70    3rd Qu.:32.00
## Max.   :31.10    Max.   :45.30    Max.   :32.20    Max.   :36.80
##
##      dew      humidity      precip      precipprob
```

```

## Min. :19.90 Min. :61.70 Min. : 0.0000 Min. : 0.0
## 1st Qu.:23.20 1st Qu.:74.70 1st Qu.: 0.0000 1st Qu.: 0.0
## Median :23.70 Median :78.60 Median : 0.5535 Median :100.0
## Mean :23.62 Mean :78.47 Mean : 6.5294 Mean : 65.4
## 3rd Qu.:24.10 3rd Qu.:82.20 3rd Qu.: 6.1513 3rd Qu.:100.0
## Max. :25.50 Max. :95.70 Max. :168.0730 Max. :100.0
##
## precipcover preciptype snow snowdepth
## Min. : 0.000 Length:1000 Min. :0 Min. :0
## 1st Qu.: 0.000 Class :character 1st Qu.:0 1st Qu.:0
## Median : 4.170 Mode :character Median :0 Median :0
## Mean : 4.134 Mean :0 Mean :0
## 3rd Qu.: 4.170 3rd Qu.:0 3rd Qu.:0
## Max. :83.330 Max. :0 Max. :0
## NA's :343 NA's :343
## windgust windspeed winddir sealevelpressure
## Min. : 3.20 Min. : 5.40 Min. : 3.1 Min. :1006
## 1st Qu.: 8.70 1st Qu.:13.50 1st Qu.:171.3 1st Qu.:1009
## Median :11.20 Median :15.50 Median :263.3 Median :1010
## Mean :15.06 Mean :15.69 Mean :237.3 Mean :1010
## 3rd Qu.:15.10 3rd Qu.:17.50 3rd Qu.:305.6 3rd Qu.:1010
## Max. :59.40 Max. :38.00 Max. :358.8 Max. :1015
## NA's :310 NA's :1
## cloudcover visibility solarradiation solarenergy
## Min. :25.8 Min. : 5.70 Min. : 22.6 Min. : 1.80
## 1st Qu.:38.2 1st Qu.: 9.30 1st Qu.:178.1 1st Qu.:15.40
## Median :39.8 Median : 9.70 Median :225.4 Median :19.40
## Mean :42.5 Mean : 9.57 Mean :214.0 Mean :18.47
## 3rd Qu.:47.4 3rd Qu.:10.00 3rd Qu.:256.8 3rd Qu.:22.20
## Max. :58.1 Max. :10.50 Max. :317.8 Max. :27.50
##
## uvindex severerisk sunrise sunset
## Min. : 1.000 Min. :10.0 Length:1000 Length:1000
## 1st Qu.: 7.000 1st Qu.:30.0 Class :character Class :character
## Median : 8.000 Median :30.0 Mode :character Mode :character
## Mean : 7.887 Mean :37.6
## 3rd Qu.: 9.000 3rd Qu.:60.0
## Max. :10.000 Max. :75.0
## NA's :343
## moonphase conditions description icon
## Min. :0.0000 Length:1000 Length:1000 Length:1000
## 1st Qu.:0.2500 Class :character Class :character Class :character
## Median :0.4800 Mode :character Mode :character Mode :character
## Mean :0.4839
## 3rd Qu.:0.7500
## Max. :0.9800
##
## stations
## Length:1000
## Class :character
## Mode :character
##
##
##

```

##

head(Rainfall)

```
##           name      datetime tempmax tempmin temp feelslikemax
## 1 Kuala Lumpur,Malaysia 2021-02-01    33.1    24.1 27.5        36.2
## 2 Kuala Lumpur,Malaysia 2021-02-02    34.0    25.8 28.8        37.3
## 3 Kuala Lumpur,Malaysia 2021-02-03    33.8    24.9 28.0        38.6
## 4 Kuala Lumpur,Malaysia 2021-02-04    33.1    24.1 28.3        36.3
## 5 Kuala Lumpur,Malaysia 2021-02-05    33.9    22.9 27.9        36.0
## 6 Kuala Lumpur,Malaysia 2021-02-06    34.1    24.1 28.5        38.2
##  feelslikemin feelslike  dew humidity precip precipprob precipcover precipdtype
## 1         24.1        28.8 22.4    76.4 47.739         100         4.17      rain
## 2         25.8        31.3 22.2    69.1  0.000          0         0.00
## 3         24.9        30.5 23.2    76.5  0.707         100         4.17      rain
## 4         24.1        29.7 21.7    69.5  0.000          0         0.00
## 5         22.9        29.3 20.6    66.5  0.000          0         0.00
## 6         24.1        30.7 22.5    72.2  0.354         100         4.17      rain
##  snow snowdepth windgust windspeed winddir sealevelpressure cloudcover
## 1    NA         NA      NA      19.0    67.3         1011.6        41.2
## 2    NA         NA      NA      12.5     5.7         1011.6        37.9
## 3    NA         NA      NA      15.7   294.0         1011.1        39.6
## 4    NA         NA      NA       8.7    40.5         1011.2        37.3
## 5    NA         NA      NA      14.3   307.2         1010.9        37.2
## 6    NA         NA      NA      14.6   111.2         1009.8        38.6
##  visibility solarradiation solarenergy uvindex severerisk      sunrise
## 1         9.5          257.9      22.1     9      NA 2021-02-01T07:27:12
## 2        10.2          263.6      22.7     9      NA 2021-02-02T07:27:16
## 3        10.0          266.3      22.9     9      NA 2021-02-03T07:27:19
## 4         9.5          293.2      25.2    10      NA 2021-02-04T07:27:21
## 5        10.2          297.8      25.6    10      NA 2021-02-05T07:27:22
## 6        10.1          288.5      24.9    10      NA 2021-02-06T07:27:23
##           sunset moonphase      conditions
## 1 2021-02-01T19:26:28    0.62 Rain, Partially cloudy
## 2 2021-02-02T19:26:39    0.66      Partially cloudy
## 3 2021-02-03T19:26:50    0.69 Rain, Partially cloudy
## 4 2021-02-04T19:27:00    0.73      Partially cloudy
## 5 2021-02-05T19:27:09    0.75      Partially cloudy
## 6 2021-02-06T19:27:18    0.80 Rain, Partially cloudy
##           description      icon
## 1 Partly cloudy throughout the day with early morning rain.      rain
## 2           Partly cloudy throughout the day. partly-cloudy-day
## 3 Partly cloudy throughout the day with late afternoon rain.      rain
## 4           Partly cloudy throughout the day. partly-cloudy-day
## 5           Partly cloudy throughout the day. partly-cloudy-day
## 6 Partly cloudy throughout the day with late afternoon rain.      rain
##           stations
## 1 48647099999,48650099999,WMSA,WMKK
## 2 48647099999,48650099999,WMSA,WMKK
## 3 48647099999,48650099999,WMSA,WMKK
## 4 48647099999,48650099999,WMSA,WMKK
## 5 48647099999,48650099999,WMSA,WMKK
## 6 48647099999,48650099999,WMSA,WMKK
```

```
tail(Rainfall)
```

```
##              name      datetime tempmax tempmin temp feelslikemax
## 995 Kuala Lumpur,Malaysia 2023-10-23      33.7      24.0 27.0          39.4
## 996 Kuala Lumpur,Malaysia 2023-10-24      31.9      24.8 26.5          37.5
## 997 Kuala Lumpur,Malaysia 2023-10-25      32.6      24.8 27.5          38.6
## 998 Kuala Lumpur,Malaysia 2023-10-26      33.0      24.8 26.7          39.3
## 999 Kuala Lumpur,Malaysia 2023-10-27      33.1      25.0 27.4          40.3
## 1000 Kuala Lumpur,Malaysia 2023-10-28      33.4      25.0 26.8          39.8
##      feelslikemin feelslike  dew humidity precip precipprob precipcover
## 995          24.0      28.8 23.3      82.0  4.884          100          4.17
## 996          24.8      27.6 23.9      86.3 23.056          100          8.33
## 997          24.8      29.6 24.0      82.3  2.232          100          4.17
## 998          24.8      28.0 24.3      87.5 16.000          100         50.00
## 999          25.0      29.2 24.0      83.3  5.700          100         54.17
## 1000         25.0      28.4 24.1      86.4 23.500          100         83.33
##      preciptype snow snowdepth windgust windspeed winddir sealevelpressure
## 995          rain    0          0       7.6      19.9   310.6          1012.0
## 996          rain    0          0       9.0      16.6   311.5          1011.9
## 997          rain    0          0       8.3      19.6   308.3          1012.3
## 998          rain    0          0       8.3      17.1   255.2          1011.7
## 999          rain    0          0      11.9      18.5   302.1          1010.8
## 1000         rain    0          0      38.9      18.1    77.3          1010.6
##      cloudcover visibility solarradiation solarenergy uvindex severerisk
## 995          50.0          9.4          256.0          22.2      10          60
## 996          48.0          9.3          234.2          20.1      10          30
## 997          52.7          9.6          276.7          24.0      10          30
## 998          30.2          9.4          276.1          23.7       9          30
## 999          25.8          7.8          221.9          19.2      10          30
## 1000         28.1          7.3          230.3          19.9       9          30
##      sunrise      sunset moonphase      conditions
## 995 2023-10-23T06:56:44 2023-10-23T18:58:30      0.30 Rain, Partially cloudy
## 996 2023-10-24T06:56:40 2023-10-24T18:58:17      0.33 Rain, Partially cloudy
## 997 2023-10-25T06:56:37 2023-10-25T18:58:05      0.37 Rain, Partially cloudy
## 998 2023-10-26T06:56:34 2023-10-26T18:57:53      0.40 Rain, Partially cloudy
## 999 2023-10-27T06:56:33 2023-10-27T18:57:43      0.44 Rain, Partially cloudy
## 1000 2023-10-28T06:56:32 2023-10-28T18:57:33      0.48 Rain, Partially cloudy
##      description
## 995      Partly cloudy throughout the day with early morning rain.
## 996      Partly cloudy throughout the day with rain.
## 997      Partly cloudy throughout the day with morning rain.
## 998      Partly cloudy throughout the day with rain.
## 999 Partly cloudy throughout the day with a chance of rain throughout the day.
## 1000 Partly cloudy throughout the day with a chance of rain throughout the day.
##      icon      stations
## 995 rain 48647099999,48650099999,WMSA,WMKK
## 996 rain 48647099999,48650099999,WMSA,WMKK
## 997 rain 48647099999,48650099999,WMSA,WMKK
## 998 rain 48647099999,48650099999,WMSA,WMKK
## 999 rain      WMSA,WMKK
## 1000 rain      WMSA,WMKK
```

```
#First Variable Drop
```

```
Rainfall <- subset(Rainfall,
  select = -c(name,datetime,precipprob,preciptype,snow,
    snowdepth,sunrise,sunset,conditions,stations))
str(Rainfall)
```

```
## 'data.frame':    1000 obs. of  23 variables:
## $ tempmax      : num  33.1 34 33.8 33.1 33.9 34.1 34.8 33.8 32.9 32.9 ...
## $ tempmin      : num  24.1 25.8 24.9 24.1 22.9 24.1 24.9 25 24.9 24.8 ...
## $ temp         : num  27.5 28.8 28 28.3 27.9 28.5 28.6 27.7 28.6 28.4 ...
## $ feelslikemax : num  36.2 37.3 38.6 36.3 36 38.2 40.4 39 39.1 37.2 ...
## $ feelslikemin : num  24.1 25.8 24.9 24.1 22.9 24.1 24.9 25 24.9 24.8 ...
## $ feelslike    : num  28.8 31.3 30.5 29.7 29.3 30.7 31 29.6 31.8 31.6 ...
## $ dew          : num  22.4 22.2 23.2 21.7 20.6 22.5 22.9 23.4 23.8 24 ...
## $ humidity     : num  76.4 69.1 76.5 69.5 66.5 72.2 72.8 78.6 76.8 77.9 ...
## $ precip       : num  47.739 0 0.707 0 0 ...
## $ precipcover  : num  4.17 0 4.17 0 0 ...
## $ windgust     : num  NA NA NA NA NA NA NA NA NA NA NA ...
## $ windspeed    : num  19 12.5 15.7 8.7 14.3 14.6 17.7 15.7 17.3 13.9 ...
## $ winddir      : num  67.3 5.7 294 40.5 307.2 ...
## $ sealevelpressure: num  1012 1012 1011 1011 1011 ...
## $ cloudcover   : num  41.2 37.9 39.6 37.3 37.2 38.6 37.6 40.1 38.2 34.7 ...
## $ visibility   : num  9.5 10.2 10 9.5 10.2 10.1 9.9 9.9 9.5 9.7 ...
## $ solarradiation : num  258 264 266 293 298 ...
## $ solarenergy  : num  22.1 22.7 22.9 25.2 25.6 24.9 25.8 23.9 24 19.3 ...
## $ uvindex      : int  9 9 9 10 10 10 10 10 10 7 ...
## $ severerisk   : int  NA NA NA NA NA NA NA NA NA NA NA ...
## $ moonphase    : num  0.62 0.66 0.69 0.73 0.75 0.8 0.83 0.87 0.91 0.94 ...
## $ description  : chr  "Partly cloudy throughout the day with early morning rain." "Partly cloudy
## $ icon         : chr  "rain" "partly-cloudy-day" "rain" "partly-cloudy-day" ...
```

#Transform categorical variable

```
Rainfall$description<-as.factor(Rainfall$description)
Rainfall$icon<-as.factor(Rainfall$icon)
Rainfall$uvindex<-as.factor(Rainfall$uvindex)
```

##Checking relationship between cat var with dependent var

```
corr<-aov(precip ~ description * uvindex * icon, data=Rainfall)
summary(corr)
```

```
##              Df Sum Sq Mean Sq F value Pr(>F)
## description    8  39139    4892  30.606 <2e-16 ***
## uvindex         9    825      92   0.573  0.820
## description:uvindex 51   7079     139   0.868  0.732
## Residuals      931 148822     160
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

#correlation matric


```
Rainfall_sub <- subset(Rainfall, select = -c(description,icon,uvindex))
library(corrplot)
```

```
## Warning: package 'corrplot' was built under R version 4.3.2
```

```
## corrplot 0.92 loaded
```

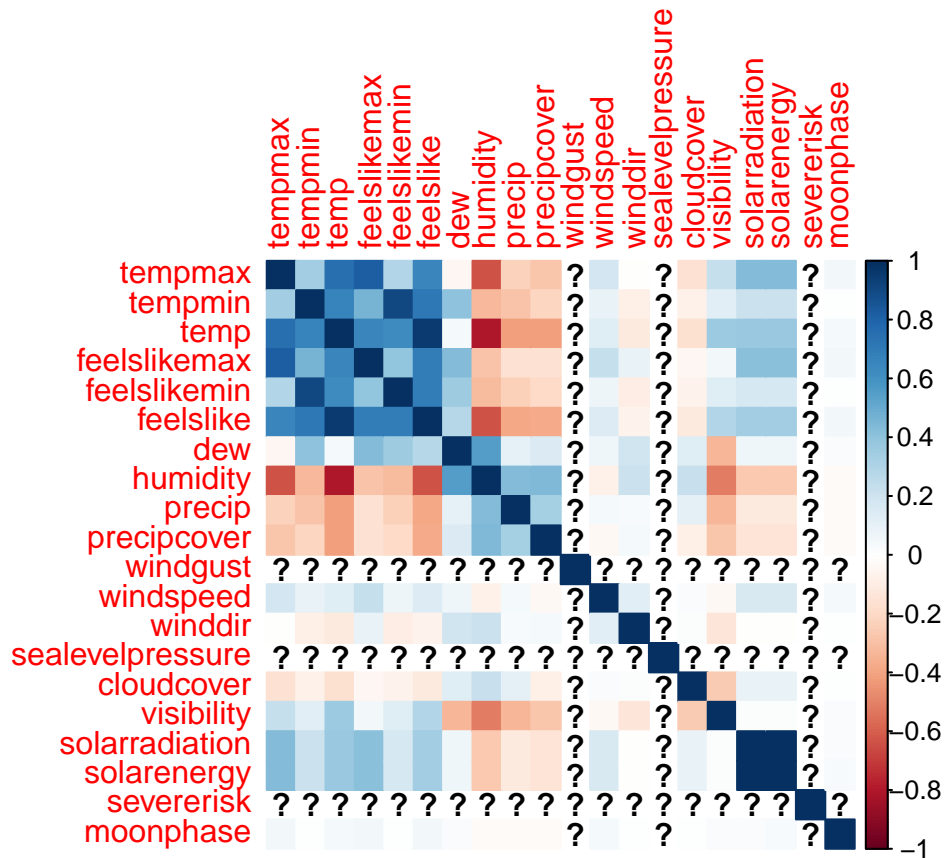
```
cr_Rainfall <- cor(Rainfall_sub)
cr_Rainfall
```

```
##           tempmax      tempmin      temp feelslikemax
## tempmax      1.000000000  0.346286275  0.75697724  0.82183941
## tempmin      0.346286275  1.000000000  0.66498921  0.46399103
## temp         0.756977238  0.664989209  1.00000000  0.65925566
## feelslikemax 0.821839415  0.463991031  0.65925566  1.00000000
## feelslikemin 0.298867339  0.909092422  0.62148532  0.39844155
## feelslike     0.655585169  0.716528872  0.95234958  0.69867355
## dew          -0.049046346  0.409861903  0.04211583  0.43098257
## humidity     -0.635125753 -0.323443217 -0.80675532 -0.28192083
## precip       -0.228235231 -0.287535073 -0.41880522 -0.15148459
## precipcover  -0.276169757 -0.216538872 -0.41953149 -0.15795598
## windgust      NA          NA          NA          NA
## windspeed     0.185626044  0.098122898  0.13824272  0.23592413
## winddir       -0.007335355 -0.083734130 -0.11818292  0.09684709
## sealevelpressure NA          NA          NA          NA
## cloudcover    -0.151926306 -0.073853416 -0.16376114 -0.04422532
## visibility     0.232677360  0.125655224  0.36044288  0.05390195
## solarradiation 0.438493948  0.214263651  0.37407025  0.41577111
## solarenergy    0.439040783  0.215774508  0.37602754  0.41571567
## severerisk     NA          NA          NA          NA
## moonphase     0.051458584  0.005763154  0.04652635  0.05795330
##           feelslikemin  feelslike      dew      humidity      precip
## tempmax      0.298867339  0.65558517 -0.04904635 -0.63512575 -0.22823523
## tempmin      0.909092422  0.71652887  0.40986190 -0.32344322 -0.28753507
## temp         0.621485317  0.95234958  0.04211583 -0.80675532 -0.41880522
## feelslikemax 0.398441552  0.69867355  0.43098257 -0.28192083 -0.15148459
## feelslikemin 1.000000000  0.69017903  0.35123283 -0.31942190 -0.23785457
## feelslike     0.690179031  1.00000000  0.28192648 -0.63424905 -0.38041634
## dew          0.351232826  0.28192648  1.00000000  0.55043979  0.10831756
## humidity     -0.319421901 -0.63424905  0.55043979  1.00000000  0.43586047
## precip       -0.237854565 -0.38041634  0.10831756  0.43586047  1.00000000
## precipcover  -0.199202915 -0.37050155  0.15098855  0.44660758  0.33492667
## windgust      NA          NA          NA          NA          NA
## windspeed     0.077500198  0.14584869  0.06417030 -0.07411025  0.04802204
## winddir       -0.096307935 -0.06845136  0.19146693  0.21375965  0.03359117
## sealevelpressure NA          NA          NA          NA          NA
## cloudcover    -0.069321499 -0.11543448  0.13981211  0.22175313  0.11285197
## visibility     0.139598477  0.29322085 -0.33233999 -0.51885448 -0.33523942
## solarradiation 0.174907437  0.34224519  0.06210029 -0.26352374 -0.11037574
## solarenergy    0.176218568  0.34407816  0.06136088 -0.26574257 -0.11273581
## severerisk     NA          NA          NA          NA          NA
## moonphase     0.005589589  0.05162397  0.02387654 -0.02616104 -0.02378210
```

##	precipcover	windgust	windspeed	winddir
## tempmax	-0.27616976	NA	0.18562604	-0.0073353552
## tempmin	-0.21653887	NA	0.09812290	-0.0837341302
## temp	-0.41953149	NA	0.13824272	-0.1181829186
## feelslikemax	-0.15795598	NA	0.23592413	0.0968470926
## feelslikemin	-0.19920292	NA	0.07750020	-0.0963079346
## feelslike	-0.37050155	NA	0.14584869	-0.0684513597
## dew	0.15098855	NA	0.06417030	0.1914669252
## humidity	0.44660758	NA	-0.07411025	0.2137596532
## precip	0.33492667	NA	0.04802204	0.0335911681
## precipcover	1.00000000	NA	-0.03990282	0.0413750578
## windgust	NA	1	NA	NA
## windspeed	-0.03990282	NA	1.00000000	0.1295410134
## winddir	0.04137506	NA	0.12954101	1.0000000000
## sealevelpressure	NA	NA	NA	NA
## cloudcover	-0.08821699	NA	0.02145366	0.0135095683
## visibility	-0.27099911	NA	-0.03972945	-0.1313638011
## solarradiation	-0.14227183	NA	0.16195969	-0.0016971329
## solarenergy	-0.14449900	NA	0.16106639	-0.0026558909
## severerisk	NA	NA	NA	NA
## moonphase	-0.02746689	NA	0.04953837	0.0004913426
##	sealevelpressure	cloudcover	visibility	solarradiation
## tempmax	NA	-0.151926306	0.23267736	0.438493948
## tempmin	NA	-0.073853416	0.12565522	0.214263651
## temp	NA	-0.163761137	0.36044288	0.374070249
## feelslikemax	NA	-0.044225324	0.05390195	0.415771111
## feelslikemin	NA	-0.069321499	0.13959848	0.174907437
## feelslike	NA	-0.115434483	0.29322085	0.342245187
## dew	NA	0.139812114	-0.33233999	0.062100290
## humidity	NA	0.221753131	-0.51885448	-0.263523736
## precip	NA	0.112851966	-0.33523942	-0.110375742
## precipcover	NA	-0.088216993	-0.27099911	-0.142271826
## windgust	NA	NA	NA	NA
## windspeed	NA	0.021453660	-0.03972945	0.161959688
## winddir	NA	0.013509568	-0.13136380	-0.001697133
## sealevelpressure	1	NA	NA	NA
## cloudcover	NA	1.000000000	-0.25781629	0.093954154
## visibility	NA	-0.257816286	1.00000000	0.018634019
## solarradiation	NA	0.093954154	0.01863402	1.000000000
## solarenergy	NA	0.094312815	0.01947126	0.999699051
## severerisk	NA	NA	NA	NA
## moonphase	NA	0.004187397	0.02269174	0.029699572
##	solarenergy	severerisk	moonphase	
## tempmax	0.439040783	NA	0.0514585839	
## tempmin	0.215774508	NA	0.0057631535	
## temp	0.376027537	NA	0.0465263499	
## feelslikemax	0.415715671	NA	0.0579533047	
## feelslikemin	0.176218568	NA	0.0055895892	
## feelslike	0.344078164	NA	0.0516239725	
## dew	0.061360875	NA	0.0238765359	
## humidity	-0.265742572	NA	-0.0261610447	
## precip	-0.112735807	NA	-0.0237821045	
## precipcover	-0.144499000	NA	-0.0274668863	
## windgust	NA	NA	NA	

```
## windspeed      0.161066392      NA  0.0495383667
## winddir        -0.002655891      NA  0.0004913426
## sealevelpressure      NA      NA      NA
## cloudcover      0.094312815      NA  0.0041873973
## visibility      0.019471256      NA  0.0226917435
## solarradiation    0.999699051      NA  0.0296995721
## solarenergy      1.000000000      NA  0.0313434266
## severerisk       NA      1      NA
## moonphase       0.031343427      NA  1.0000000000
```

```
corrplot(cr_Rainfall,method="color")
```



0.2 Second Variable Drop

```
Rainfall <- subset(Rainfall,
  select = -c(windgust, windspeed, winddir, sealevelpressure,
    moonphase, severerisk, icon))
```

0.3 Check missing value

```
sum(is.na(Rainfall))
```

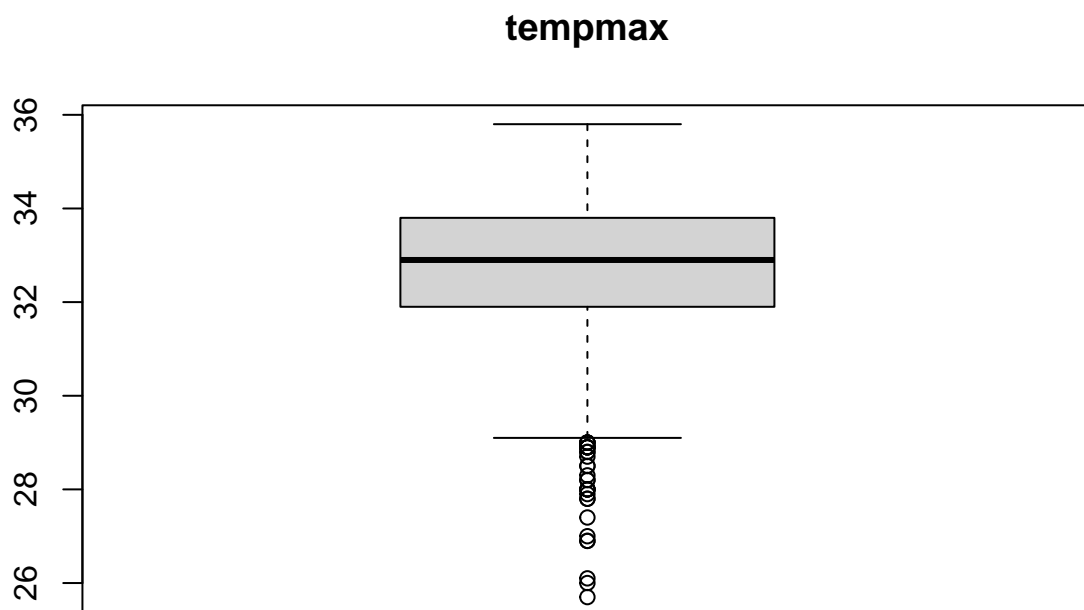
```
## [1] 0
```

```
colSums(is.na(Rainfall))
```

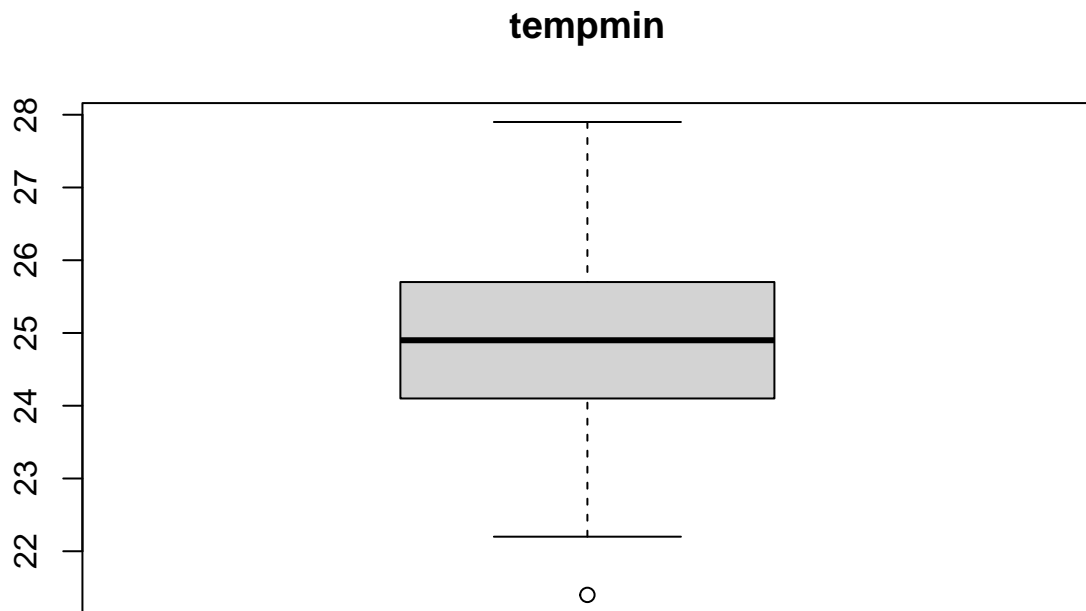
```
##      tempmax      tempmin      temp  feelslikemax  feelslikemin  
##          0          0          0          0          0  
##    feelslike      dew    humidity    precip    precipcover  
##          0          0          0          0          0  
##  cloudcover  visibility solarradiation  solarenergy    uvindex  
##          0          0          0          0          0  
## description  
##          0
```

0.4 Check outliers

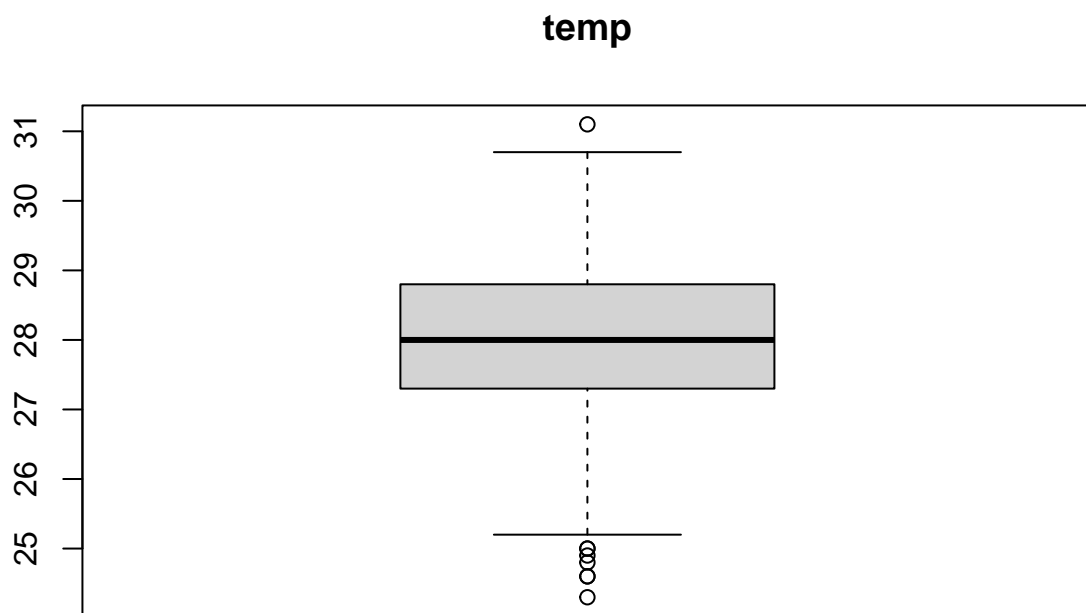
```
boxplot(Rainfall$tempmax)  
title("tempmax")
```



```
boxplot(Rainfall$tempmin)  
title("tempmin")
```

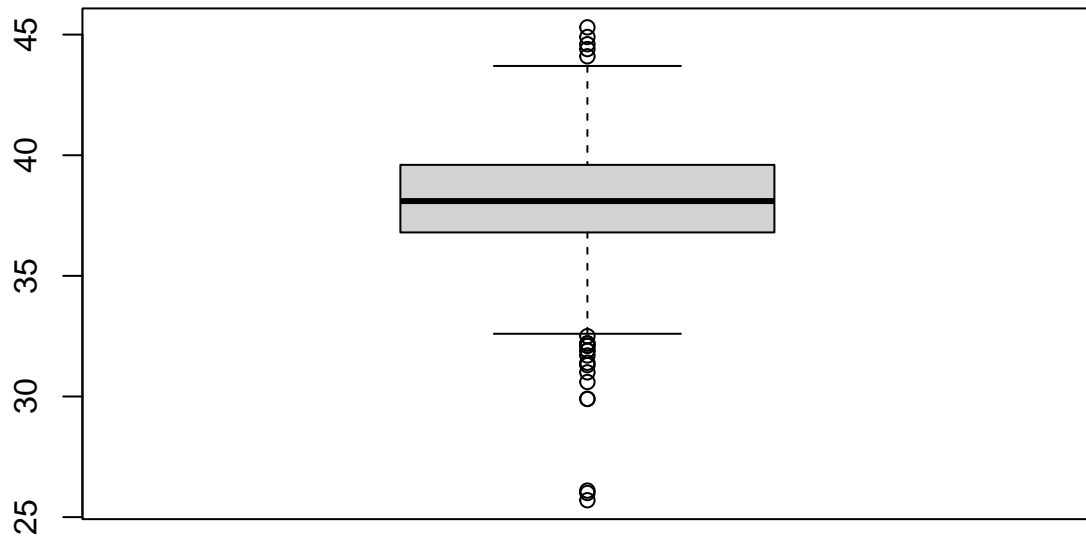


```
boxplot(Rainfall$temp)  
title("temp")
```



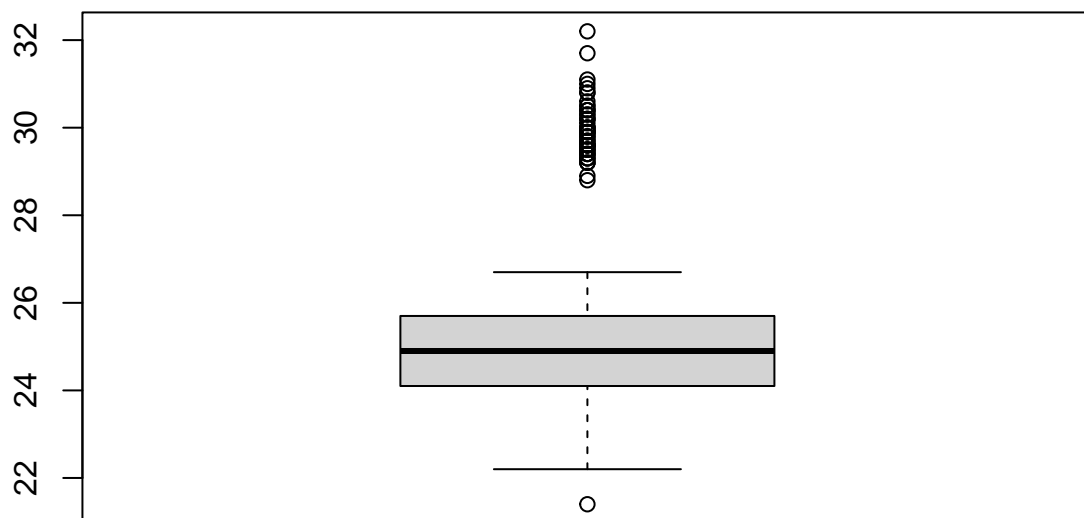
```
boxplot(Rainfall$feelslikemax)  
title("feelslikemax")
```

feelslikemax

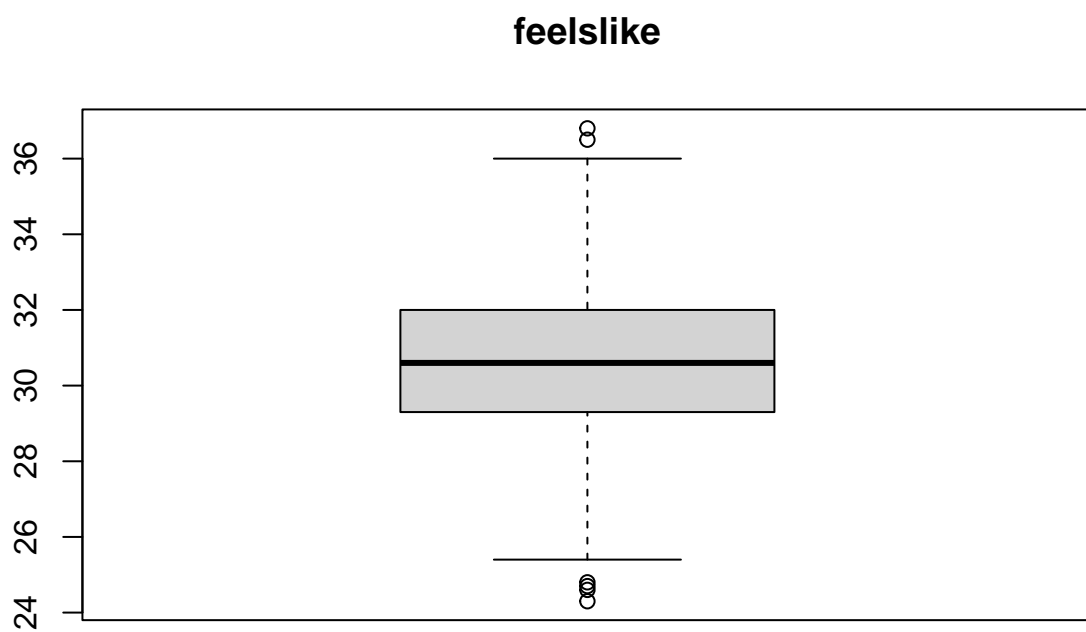


```
boxplot(Rainfall$feelslikemin)  
title("feelslikemin")
```

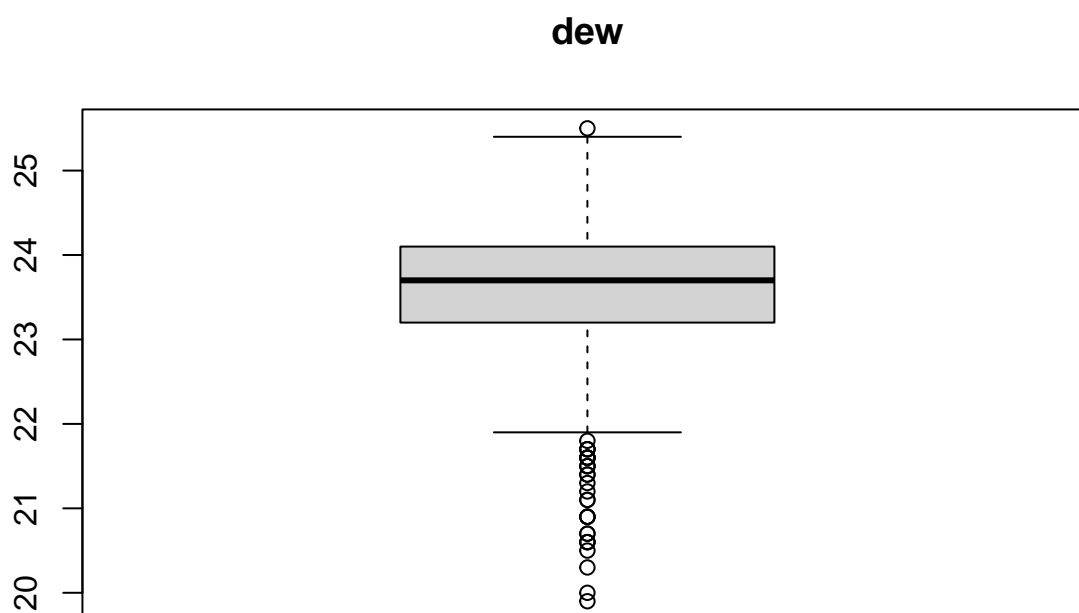
feelslikemin



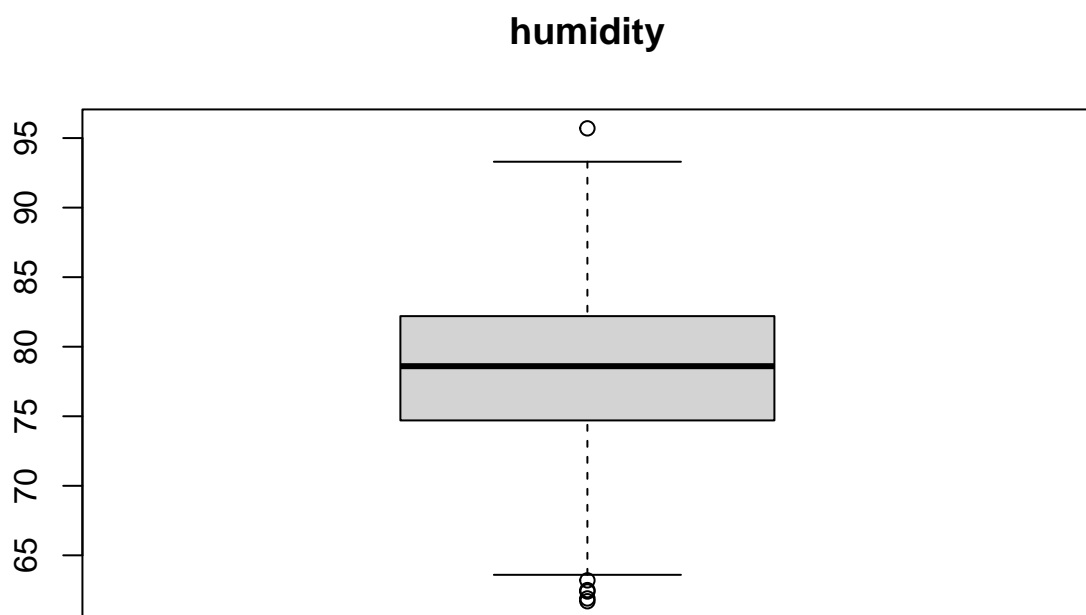
```
boxplot(Rainfall$feelslike)
title("feelslike")
```

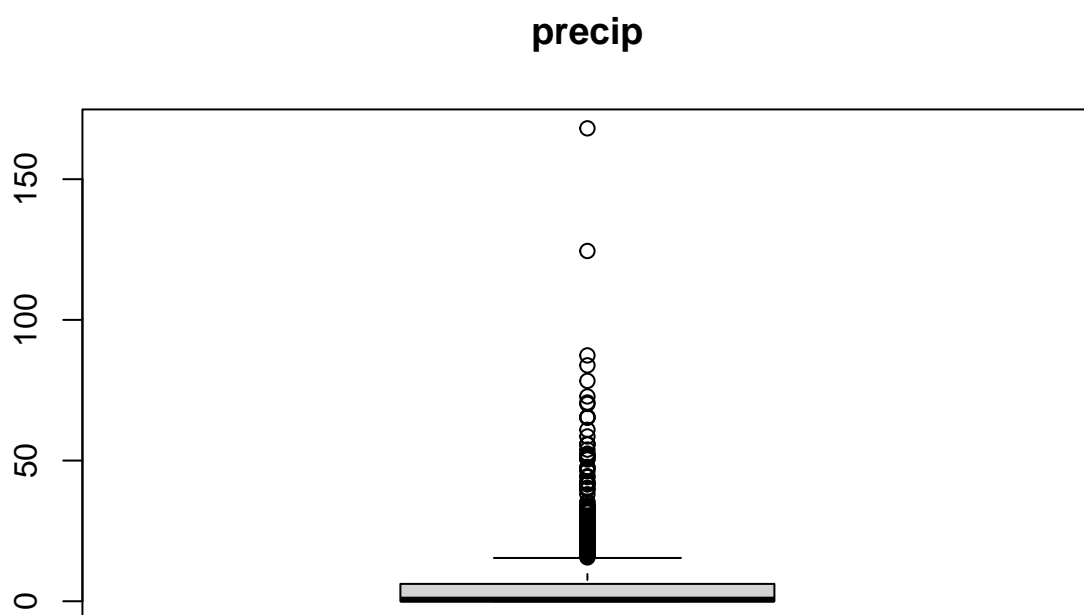
```
boxplot(Rainfall$dew)  
title("dew")
```



```
boxplot(Rainfall$humidity)
title("humidity")
```

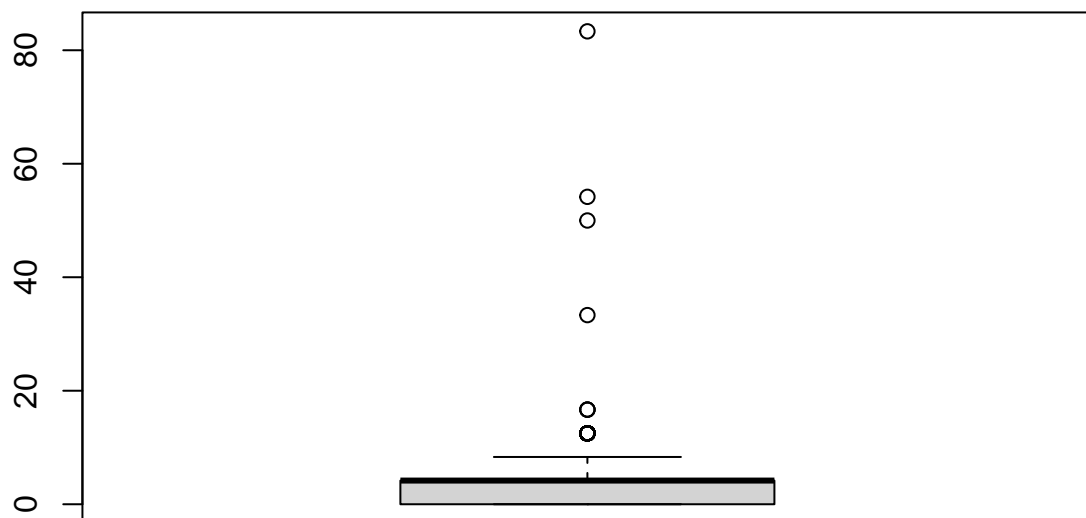


```
boxplot(Rainfall$precip)  
title("precip")
```



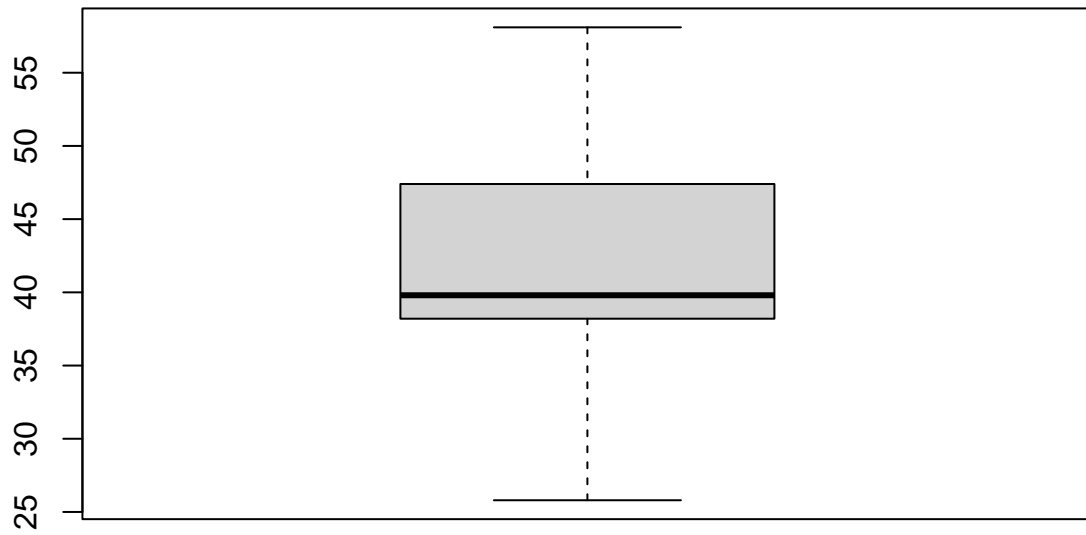
```
boxplot(Rainfall$precipcover)  
title("precipcover")
```

precipcover

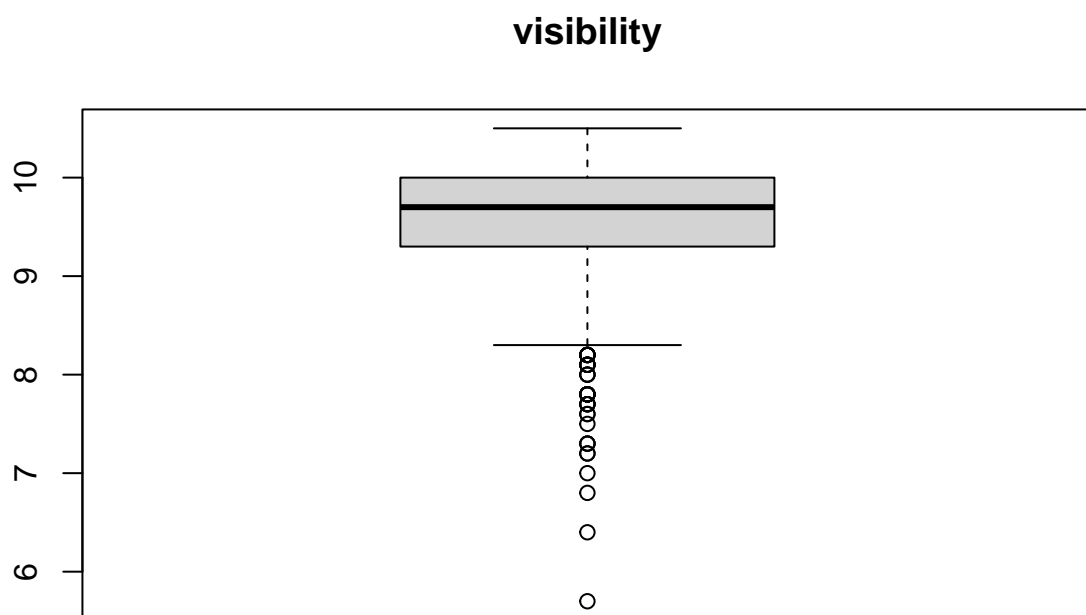


```
boxplot(Rainfall$cloudcover)  
title("cloudcover")
```

cloudcover

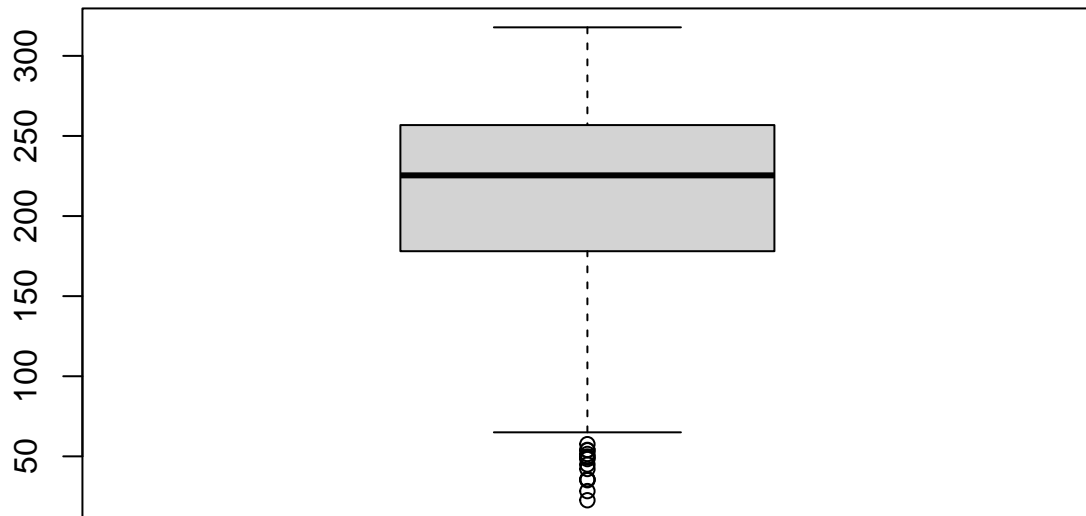


```
boxplot(Rainfall$visibility)
title("visibility")
```

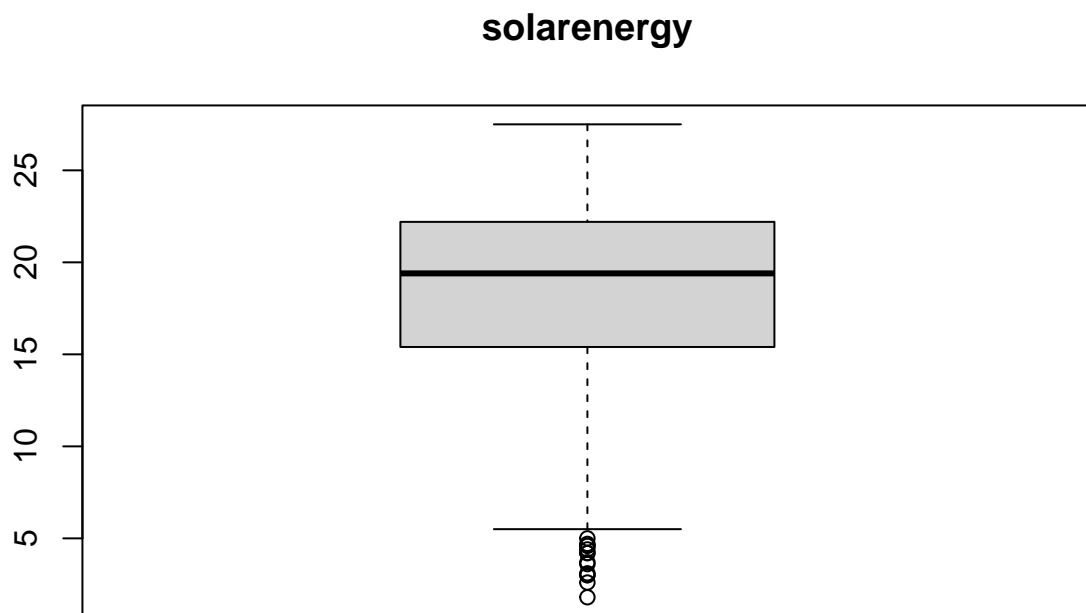


```
boxplot(Rainfall$solarradiation)  
title("solarradiation")
```

solarradiation



```
boxplot(Rainfall$solarenergy)  
title("solarenergy")
```

```
##Check duplication
```

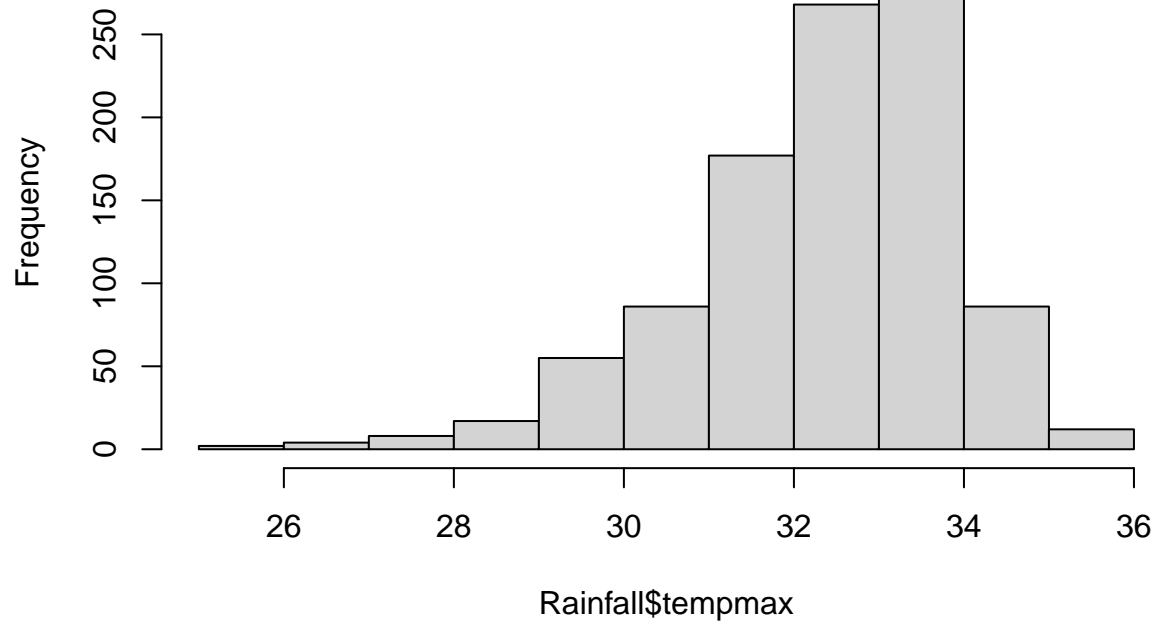
```
sum(duplicated(Rainfall))
```

```
## [1] 0
```

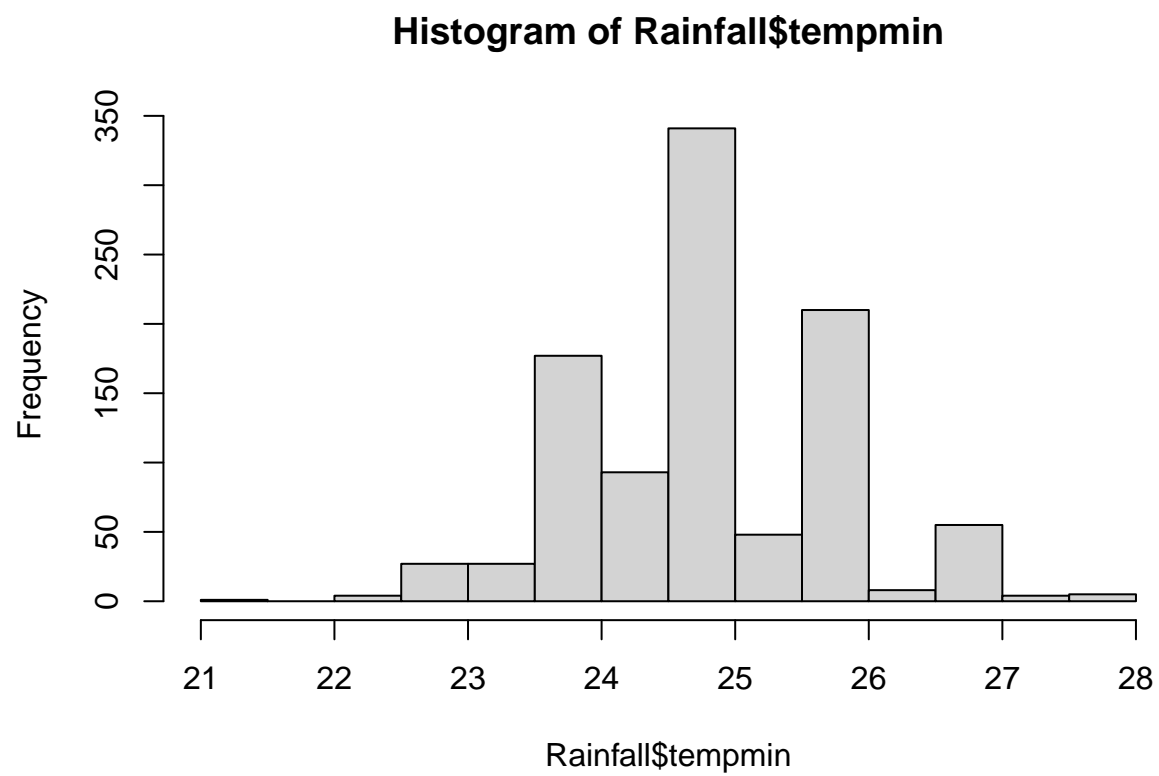
```
#skewness
```

```
hist(Rainfall$tempmax)
```

Histogram of Rainfall\$tempmax

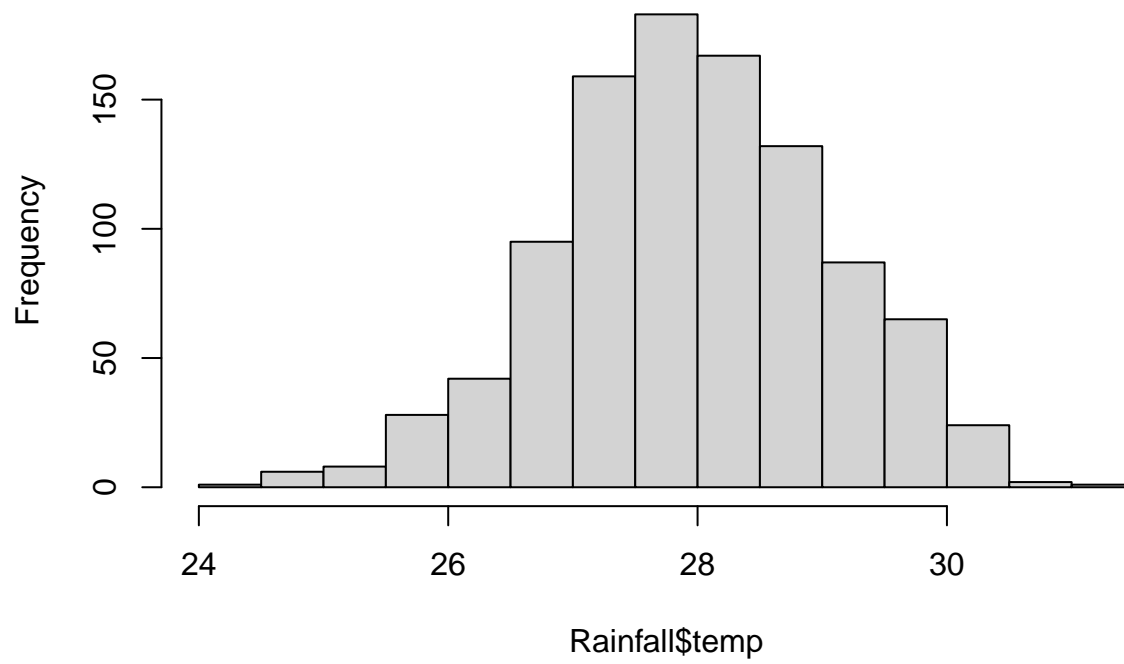


```
hist(Rainfall$tempmin)
```



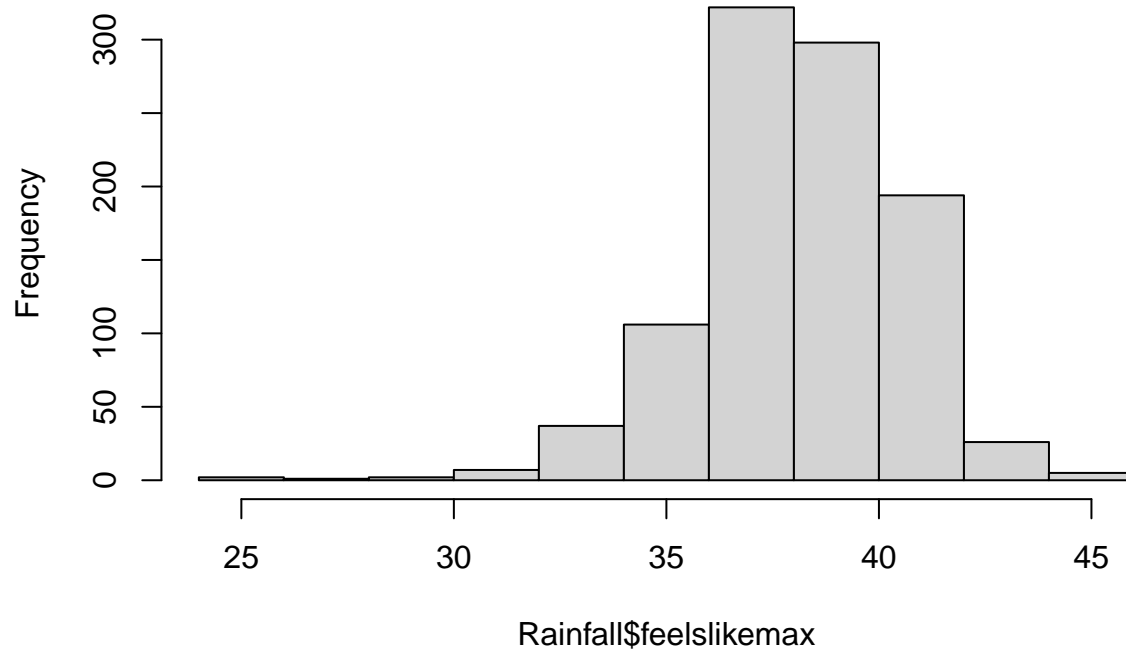
```
hist(Rainfall$temp)
```

Histogram of Rainfall\$temp



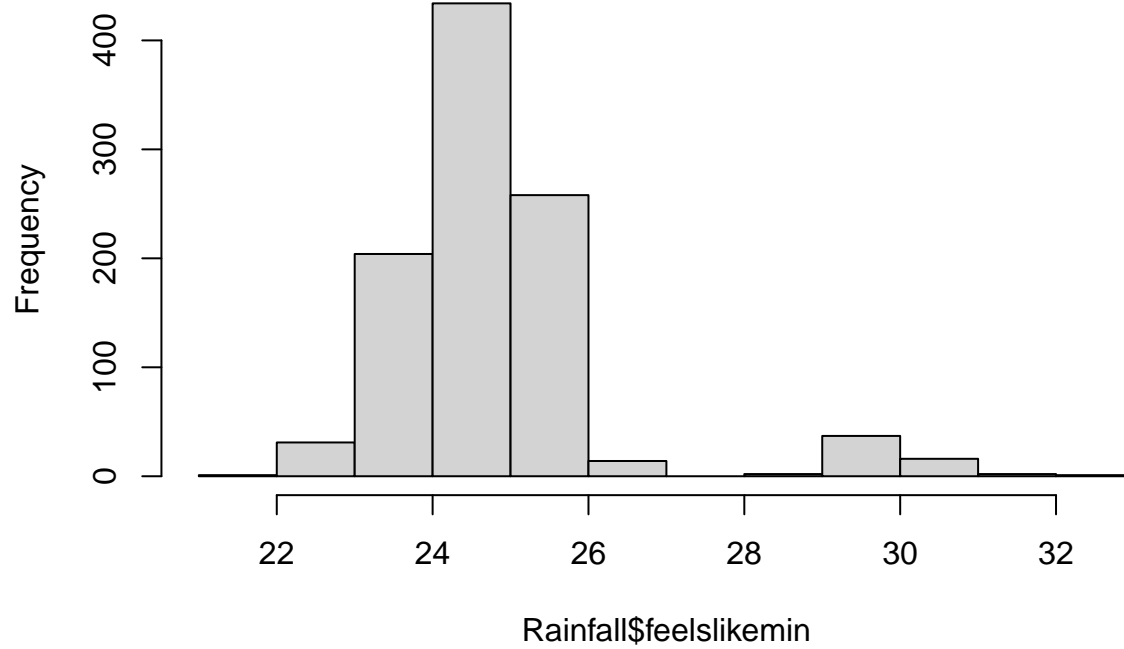
```
hist(Rainfall$feelslikemax)
```

Histogram of Rainfall\$feelslikemax

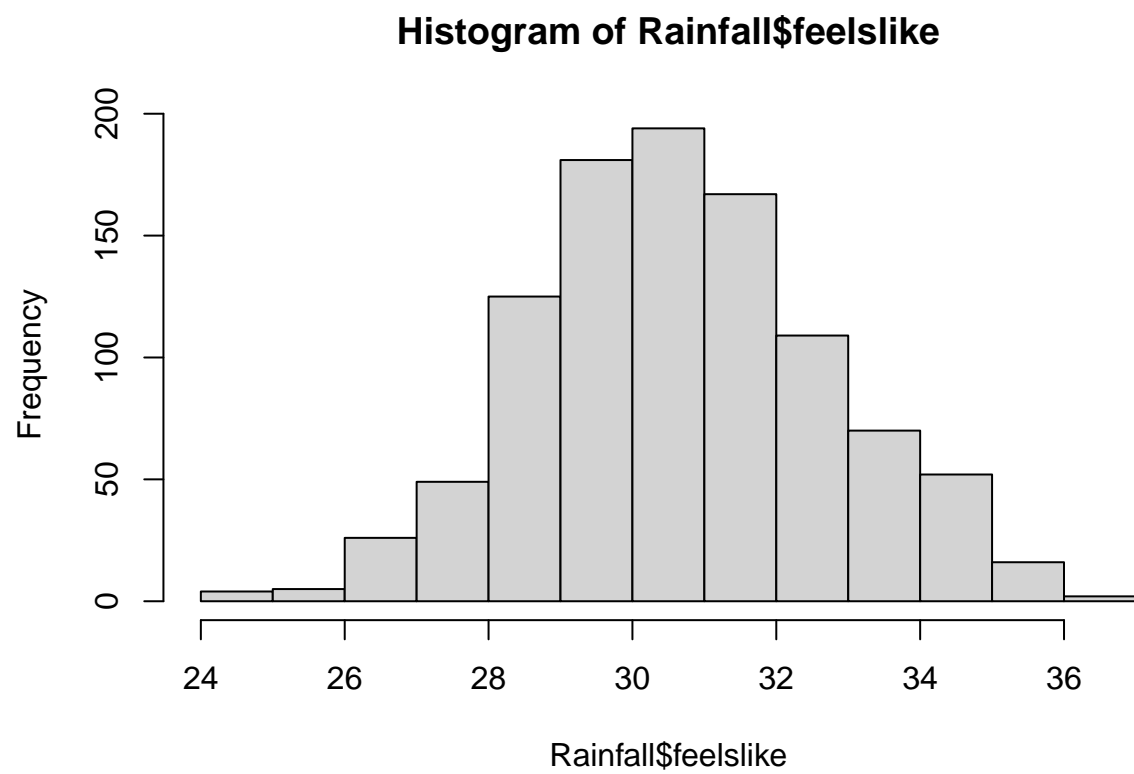


```
hist(Rainfall$feelslikemin)
```

Histogram of Rainfall\$feelslikemin

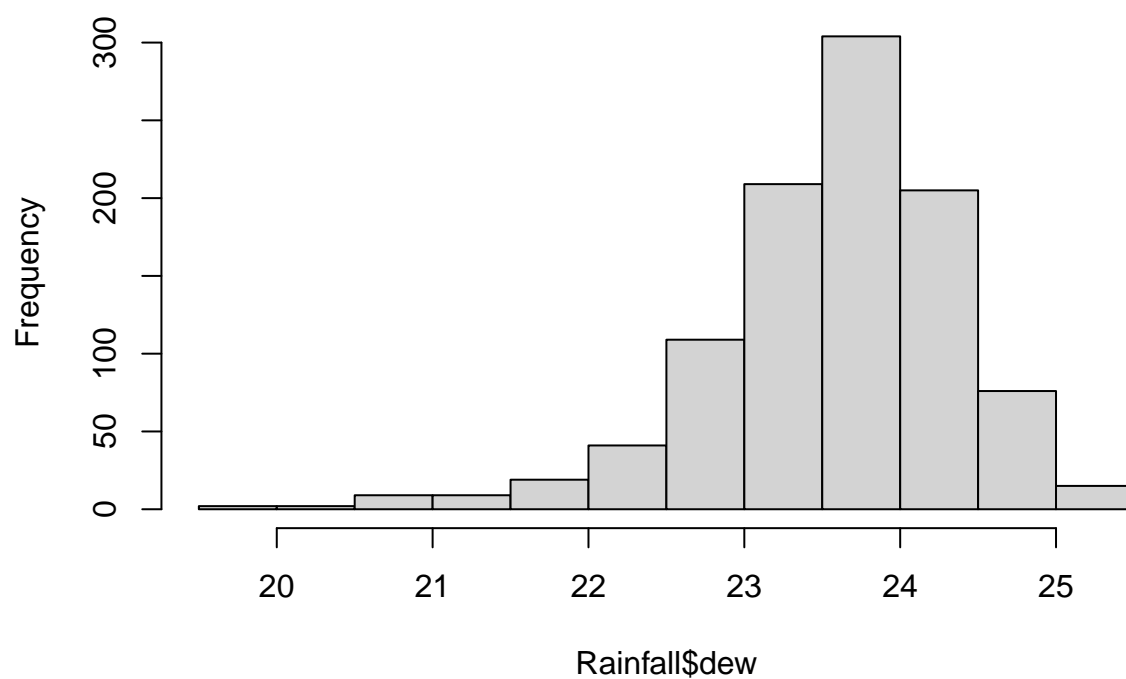


```
hist(Rainfall$feelslike)
```



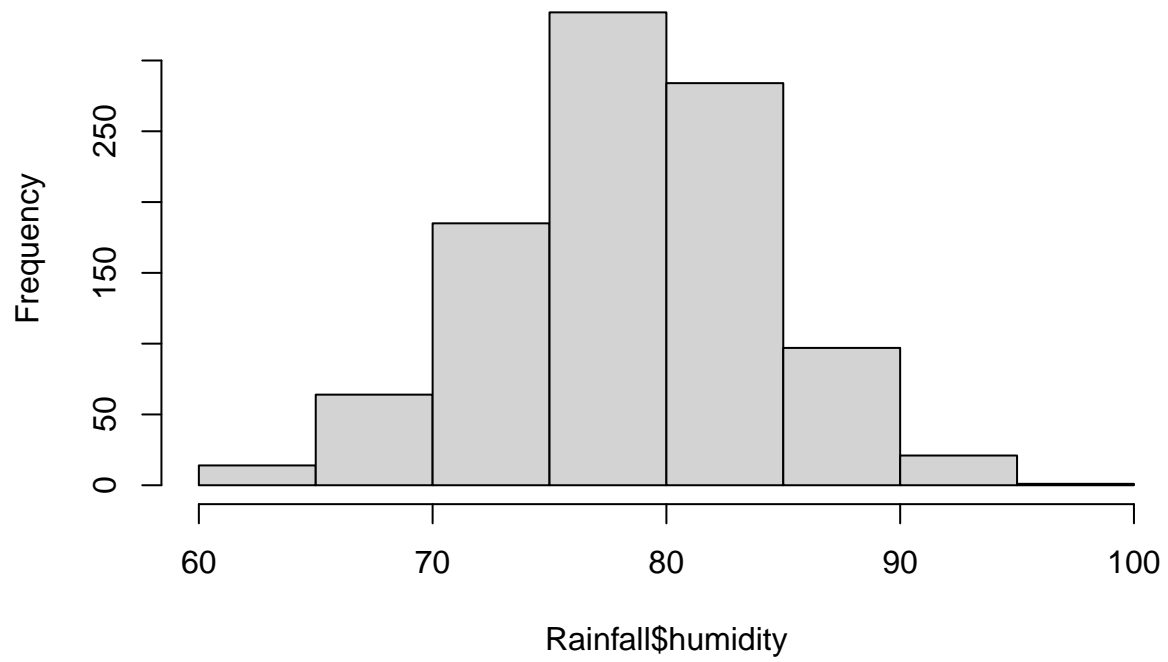
```
hist(Rainfall$dew)
```

Histogram of Rainfall\$dew



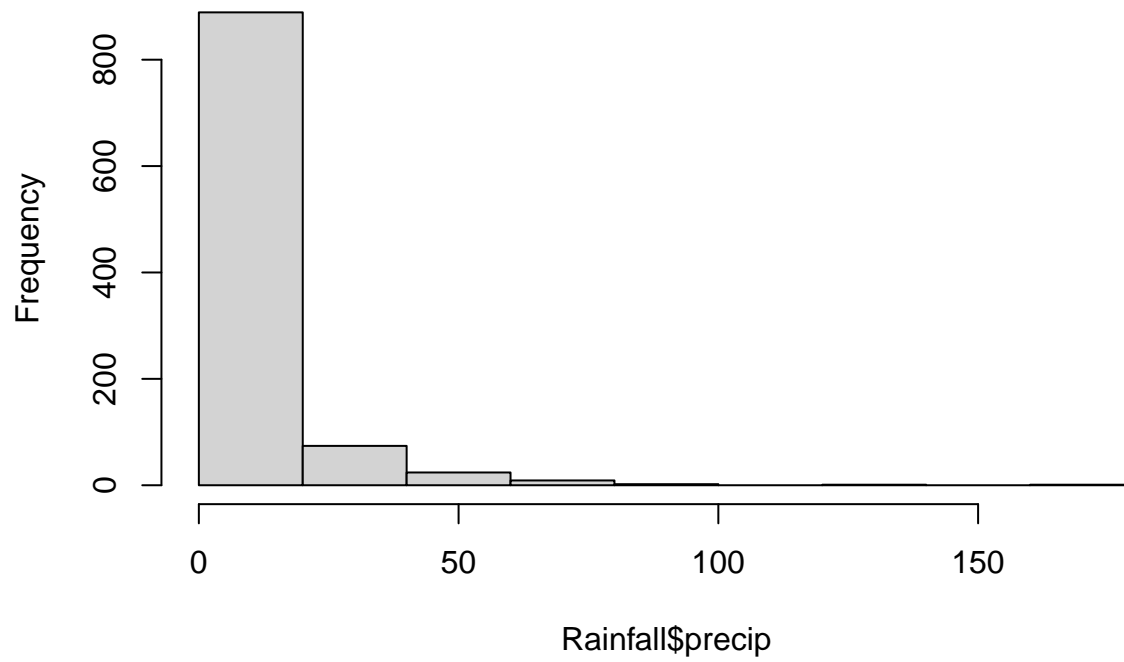
```
hist(Rainfall$dew)
```


Histogram of Rainfall\$humidity



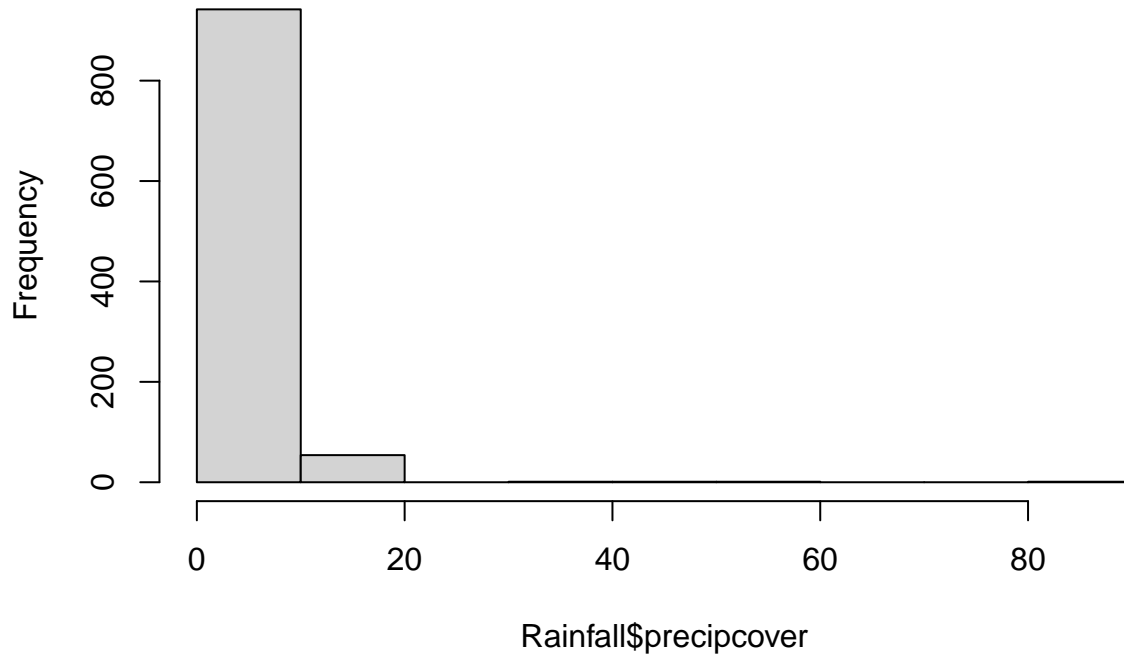
```
hist(Rainfall$precip)
```

Histogram of Rainfall\$precip



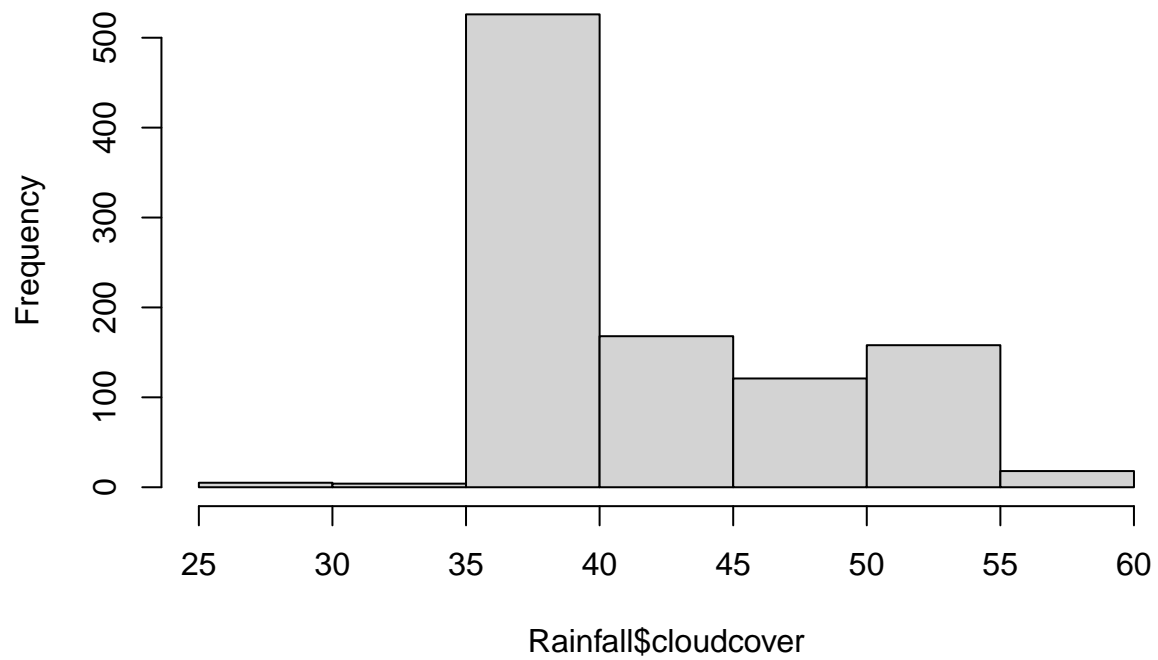
```
hist(Rainfall$precipcover)
```

Histogram of Rainfall\$precipcover



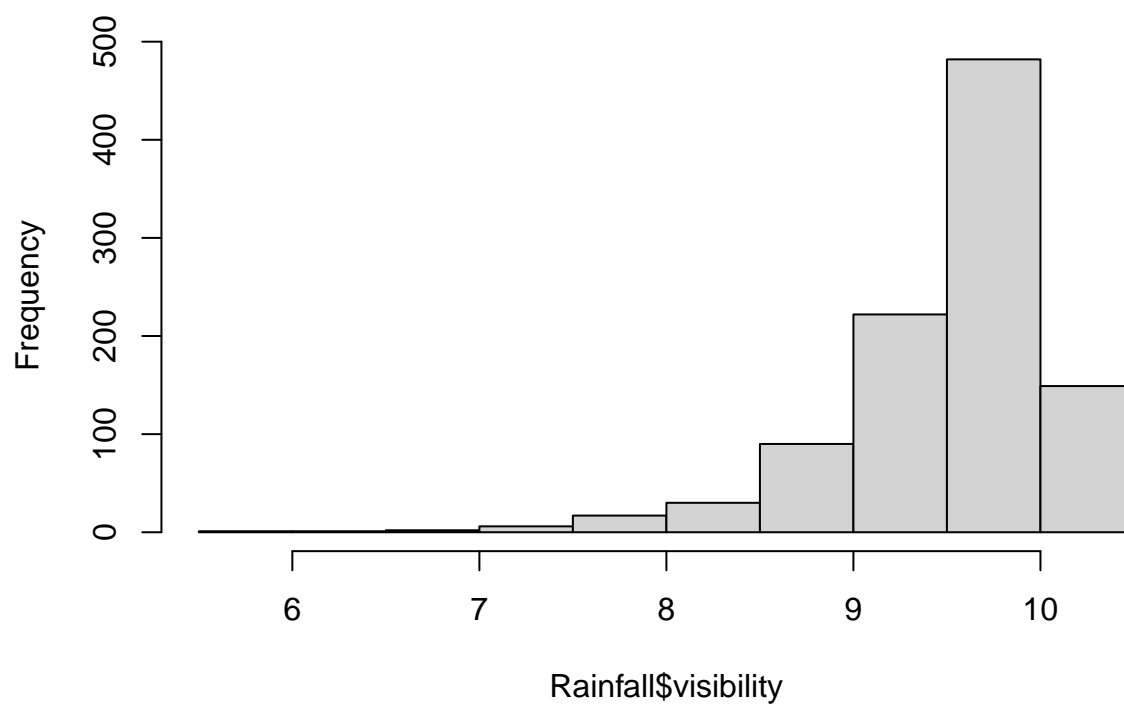
```
hist(Rainfall$cloudcover)
```

Histogram of Rainfall\$cloudcover



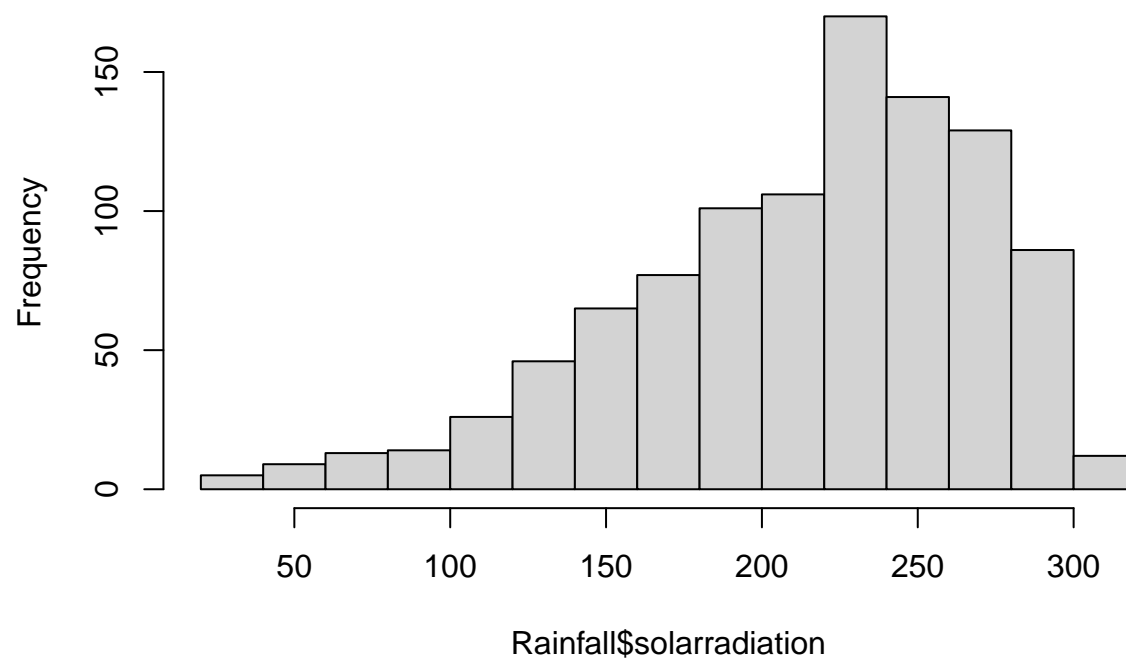
```
hist(Rainfall$visibility)
```

Histogram of Rainfall\$visibility



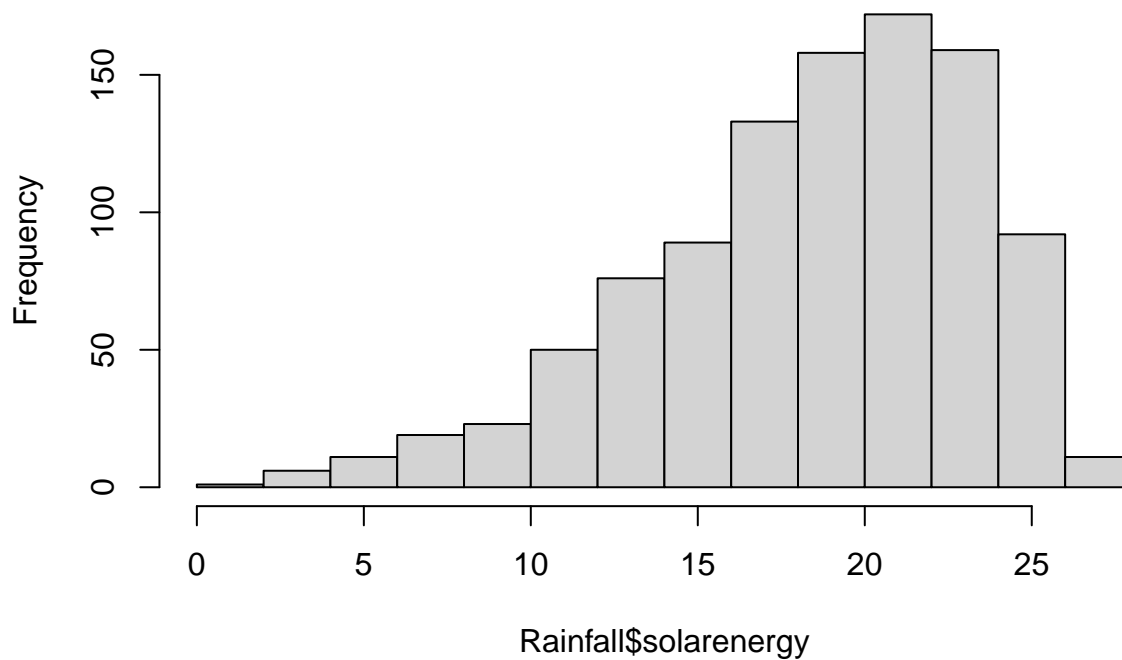
```
hist(Rainfall$solarradiation)
```

Histogram of Rainfall\$solarradiation



```
hist(Rainfall$solarenergy)
```

Histogram of Rainfall\$solarenergy



```
#skewness test
```

```
install.packages("moments")
```

```
## Installing package into 'C:/Users/XIN WEI/AppData/Local/R/win-library/4.3'  
## (as 'lib' is unspecified)
```

```
## package 'moments' successfully unpacked and MD5 sums checked  
##
```

```
## The downloaded binary packages are in  
## C:\Users\XIN WEI\AppData\Local\Temp\RtmpSK8f2W\downloaded_packages
```

```
library(moments)  
skewness(Rainfall$tempmax, na.rm=TRUE)
```

```
## [1] -0.9449293
```

```
skewness(Rainfall$tempmin, na.rm=TRUE)
```

```
## [1] 0.1149611
```

```
skewness(Rainfall$temp, na.rm=TRUE)
```

```
## [1] -0.1375686
```

```
skewness(Rainfall$feelslikemax,na.rm=TRUE)
```

```
## [1] -0.6173491
```

```
skewness(Rainfall$feelslikemin,na.rm=TRUE)
```

```
## [1] 1.993798
```

```
skewness(Rainfall$feelslike,na.rm=TRUE)
```

```
## [1] 0.1003294
```

```
skewness(Rainfall$dew,na.rm=TRUE)
```

```
## [1] -1.008102
```

```
skewness(Rainfall$humidity,na.rm=TRUE)
```

```
## [1] -0.1757896
```

```
skewness(Rainfall$precip,na.rm=TRUE)
```

```
## [1] 4.22407
```

```
skewness(Rainfall$precipcover,na.rm=TRUE)
```

```
## [1] 6.209487
```

```
skewness(Rainfall$cloudcover,na.rm=TRUE)
```

```
## [1] 0.8282789
```

```
skewness(Rainfall$visibility,na.rm=TRUE)
```

```
## [1] -1.892846
```

```
skewness(Rainfall$solarradiation,na.rm=TRUE)
```

```
## [1] -0.7626326
```

```
skewness(Rainfall$solarenergy,na.rm=TRUE)
```

```
## [1] -0.7636563
```

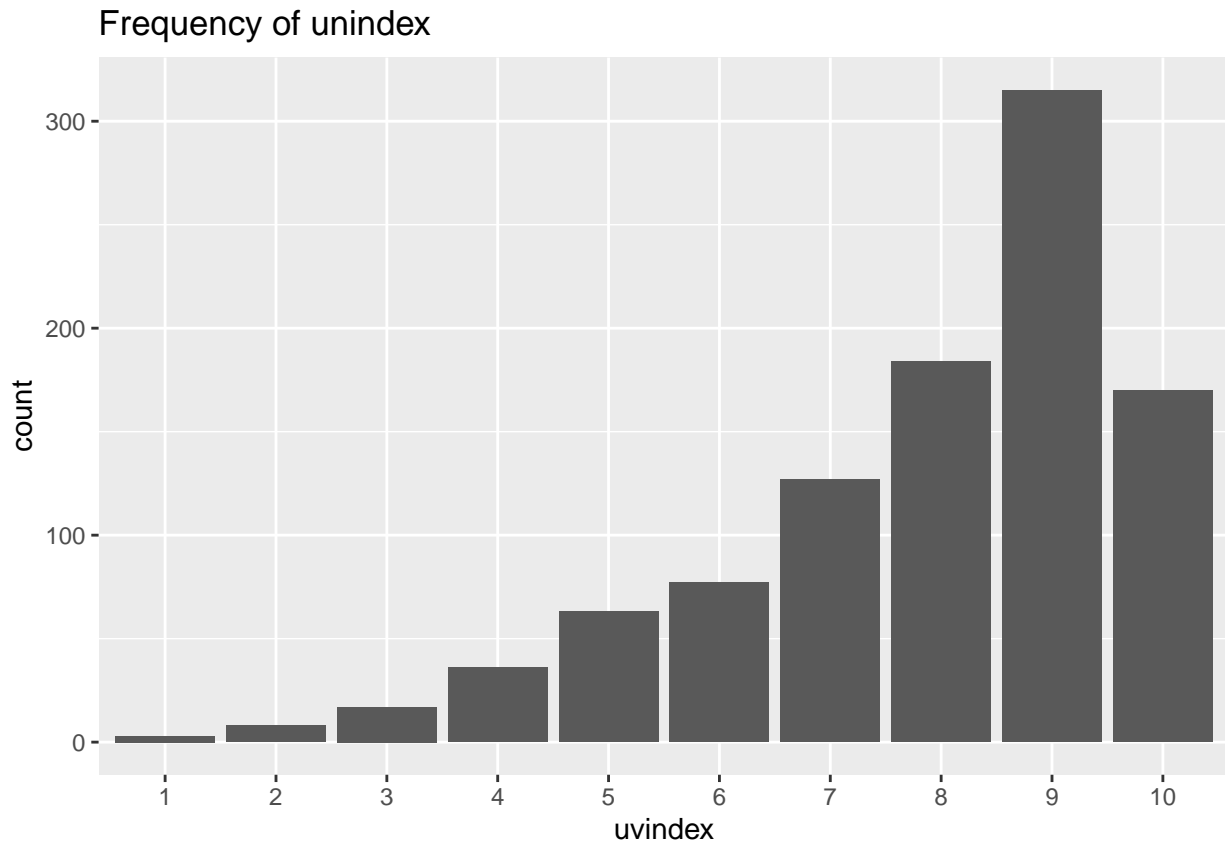
```
#Categorical variable
```



```
library(ggplot2)
```

```
## Warning: package 'ggplot2' was built under R version 4.3.2
```

```
uvi<-ggplot(Rainfall,aes(x=uvindex))+geom_bar()
uvi + ggtitle("Frequency of unindex")
```



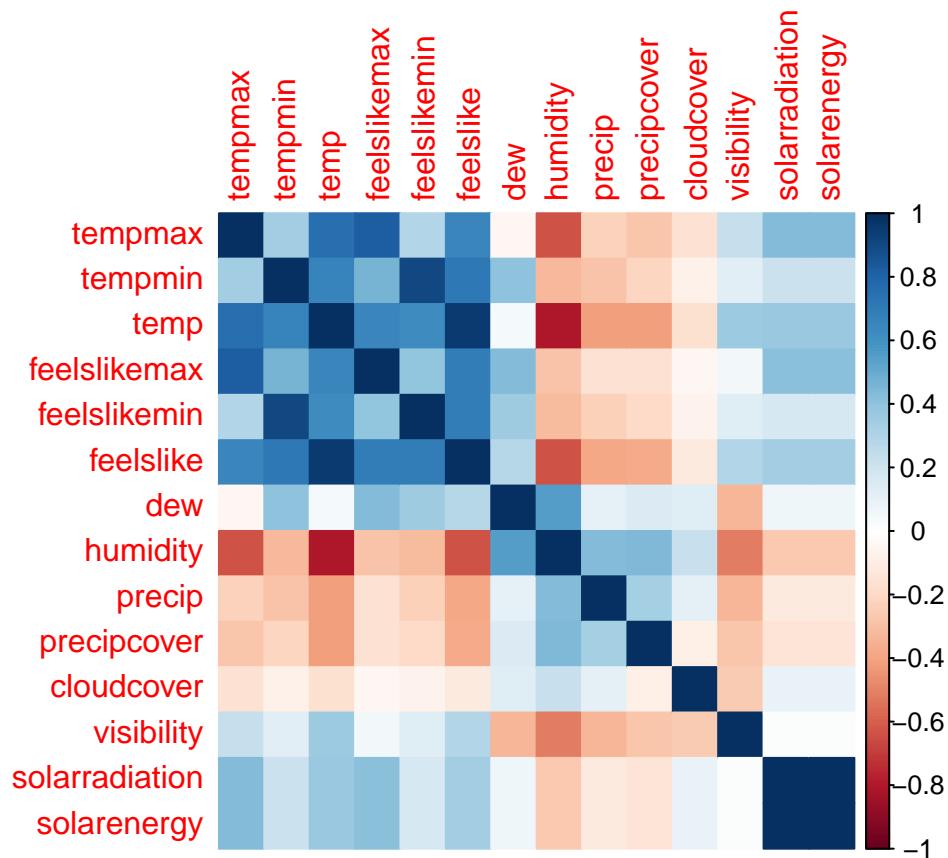
```
#correlation
```

```
Rainfall_sub <- subset(Rainfall, select = -c(description, uvindex))
cr_Rainfall <- cor(Rainfall_sub)
cr_Rainfall
```

```
##          tempmax    tempmin      temp feelslikemax feelslikemin
## tempmax      1.00000000  0.34628627  0.75697724   0.82183941   0.2988673
## tempmin      0.34628627  1.00000000  0.66498921   0.46399103   0.9090924
## temp         0.75697724  0.66498921  1.00000000   0.65925566   0.6214853
## feelslikemax 0.82183941  0.46399103  0.65925566   1.00000000   0.3984416
## feelslikemin 0.29886734  0.90909242  0.62148532   0.39844155   1.0000000
## feelslike    0.65558517  0.71652887  0.95234958   0.69867355   0.6901790
## dew          -0.04904635  0.40986190  0.04211583   0.43098257   0.3512328
## humidity     -0.63512575 -0.32344322 -0.80675532  -0.28192083  -0.3194219
## precip       -0.22823523 -0.28753507 -0.41880522  -0.15148459  -0.2378546
## precipcover  -0.27616976 -0.21653887 -0.41953149  -0.15795598  -0.1992029
```

```
## cloudcover      -0.15192631 -0.07385342 -0.16376114 -0.04422532 -0.0693215
## visibility      0.23267736  0.12565522  0.36044288  0.05390195  0.1395985
## solarradiation  0.43849395  0.21426365  0.37407025  0.41577111  0.1749074
## solarenergy     0.43904078  0.21577451  0.37602754  0.41571567  0.1762186
##                feelslike      dew      humidity      precip precipcover
## tempmax         0.6555852 -0.04904635 -0.6351258 -0.2282352 -0.27616976
## tempmin         0.7165289  0.40986190 -0.3234432 -0.2875351 -0.21653887
## temp            0.9523496  0.04211583 -0.8067553 -0.4188052 -0.41953149
## feelslikemax    0.6986736  0.43098257 -0.2819208 -0.1514846 -0.15795598
## feelslikemin    0.6901790  0.35123283 -0.3194219 -0.2378546 -0.19920292
## feelslike       1.0000000  0.28192648 -0.6342491 -0.3804163 -0.37050155
## dew             0.2819265  1.00000000  0.5504398  0.1083176  0.15098855
## humidity        -0.6342491  0.55043979  1.0000000  0.4358605  0.44660758
## precip          -0.3804163  0.10831756  0.4358605  1.0000000  0.33492667
## precipcover     -0.3705015  0.15098855  0.4466076  0.3349267  1.00000000
## cloudcover      -0.1154345  0.13981211  0.2217531  0.1128520 -0.08821699
## visibility      0.2932208 -0.33233999 -0.5188545 -0.3352394 -0.27099911
## solarradiation  0.3422452  0.06210029 -0.2635237 -0.1103757 -0.14227183
## solarenergy     0.3440782  0.06136088 -0.2657426 -0.1127358 -0.14449900
##                cloudcover visibility solarradiation solarenergy
## tempmax         -0.15192631  0.23267736      0.43849395  0.43904078
## tempmin         -0.07385342  0.12565522      0.21426365  0.21577451
## temp            -0.16376114  0.36044288      0.37407025  0.37602754
## feelslikemax    -0.04422532  0.05390195      0.41577111  0.41571567
## feelslikemin    -0.06932150  0.13959848      0.17490744  0.17621857
## feelslike       -0.11543448  0.29322085      0.34224519  0.34407816
## dew             0.13981211 -0.33233999      0.06210029  0.06136088
## humidity        0.22175313 -0.51885448     -0.26352374 -0.26574257
## precip          0.11285197 -0.33523942     -0.11037574 -0.11273581
## precipcover     -0.08821699 -0.27099911     -0.14227183 -0.14449900
## cloudcover      1.00000000 -0.25781629      0.09395415  0.09431281
## visibility      -0.25781629  1.00000000      0.01863402  0.01947126
## solarradiation  0.09395415  0.01863402      1.00000000  0.99969905
## solarenergy     0.09431281  0.01947126      0.99969905  1.00000000
```

```
corrplot(cr_Rainfall,method="color")
```



0.5 Bivariate Analysis

```
library(tidycomm)
```

```
## Warning: package 'tidycomm' was built under R version 4.3.2
```

```
correlate(Rainfall)
```

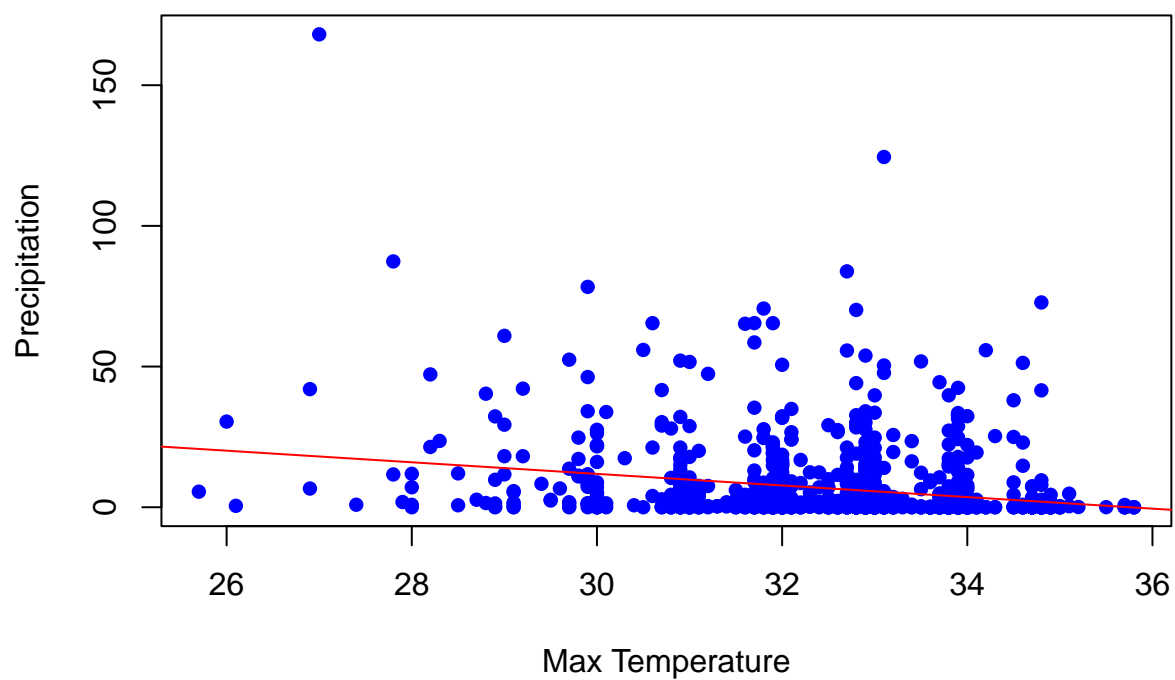
```
## # A tibble: 91 x 5
##   x      y      r    df      p
##   <chr> <chr>   <dbl> <int>   <dbl>
## 1 tempmax tempmin 0.346   998 1.51e- 29
## 2 tempmax temp    0.757   998 1.26e-186
## 3 tempmax feelslikemax 0.822   998 4.33e-246
## 4 tempmax feelslikemin 0.299   998 4.42e- 22
## 5 tempmax feelslike 0.656   998 7.01e-124
## 6 tempmax dew    -0.0490 998 1.21e- 1
## 7 tempmax humidity -0.635   998 4.68e-114
## 8 tempmax precip  -0.228   998 2.77e- 13
## 9 tempmax precipcover -0.276   998 5.79e- 19
## 10 tempmax cloudcover -0.152   998 1.39e- 6
## # i 81 more rows
```

```
correlate(Rainfall)%>%
  to_correlation_matrix()
```

```
## # A tibble: 14 x 15
##   r      tempmax tempmin    temp feelslikemax feelslikemin feelslike    dew
##   <chr>      <dbl>  <dbl>    <dbl>      <dbl>      <dbl>      <dbl>  <dbl>
## 1 tempmax      1      0.346  0.757      0.822      0.299      0.656 -0.0490
## 2 tempmin    0.346      1      0.665      0.464      0.909      0.717  0.410
## 3 temp      0.757      0.665      1      0.659      0.621      0.952  0.0421
## 4 feelslik~ 0.822      0.464  0.659      1      0.398      0.699  0.431
## 5 feelslik~ 0.299      0.909  0.621      0.398      1      0.690  0.351
## 6 feelslike 0.656      0.717  0.952      0.699      0.690      1      0.282
## 7 dew     -0.0490  0.410  0.0421      0.431      0.351      0.282  1
## 8 humidity -0.635 -0.323 -0.807      -0.282     -0.319     -0.634  0.550
## 9 precip   -0.228 -0.288 -0.419      -0.151     -0.238     -0.380  0.108
##10 precipco~ -0.276 -0.217 -0.420      -0.158     -0.199     -0.371  0.151
##11 cloudcov~ -0.152 -0.0739 -0.164     -0.0442    -0.0693    -0.115  0.140
##12 visibili~ 0.233  0.126  0.360      0.0539      0.140      0.293 -0.332
##13 solarrad~ 0.438  0.214  0.374      0.416      0.175      0.342  0.0621
##14 solarene~ 0.439  0.216  0.376      0.416      0.176      0.344  0.0614
## # i 7 more variables: humidity <dbl>, precip <dbl>, precipcover <dbl>,
## #   cloudcover <dbl>, visibility <dbl>, solarradiation <dbl>, solarenergy <dbl>
```

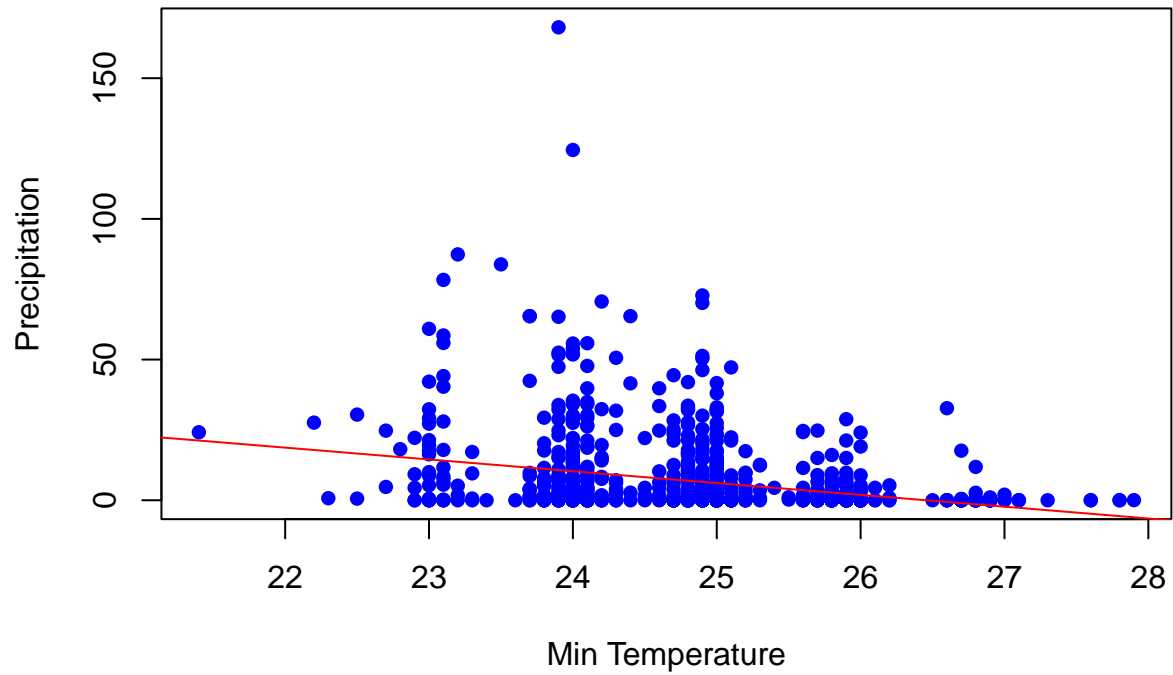
```
plot(Rainfall$tempmax, Rainfall$precip,
     main="Scatter Plot with Max Temperature", xlab="Max Temperature",
     ylab="Precipitation", col="blue", pch=16)
abline(lm(Rainfall$precip ~ Rainfall$tempmax), col="red")
```

Scatter Plot with Max Temperature



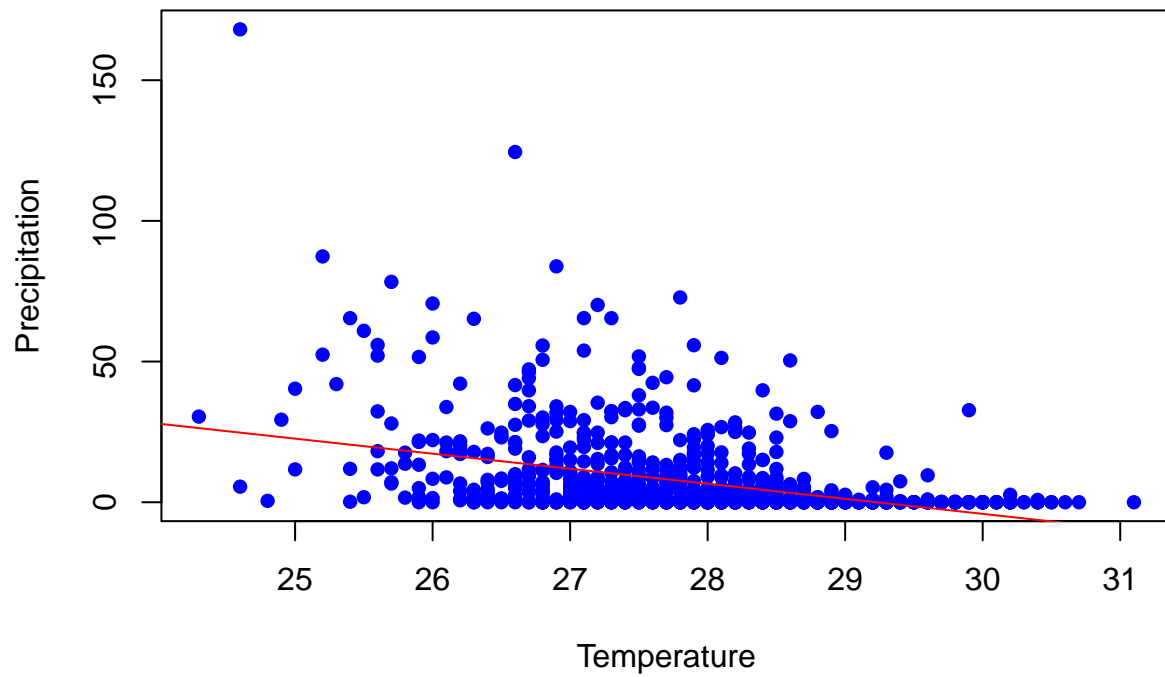
```
plot(Rainfall$tempmin, Rainfall$precip,  
     main="Scatter Plot with Min Temperature", xlab="Min Temperature",  
     ylab="Precipitation", col="blue", pch=16)  
abline(lm(Rainfall$precip ~ Rainfall$tempmin), col="red")
```

Scatter Plot with Min Temperature



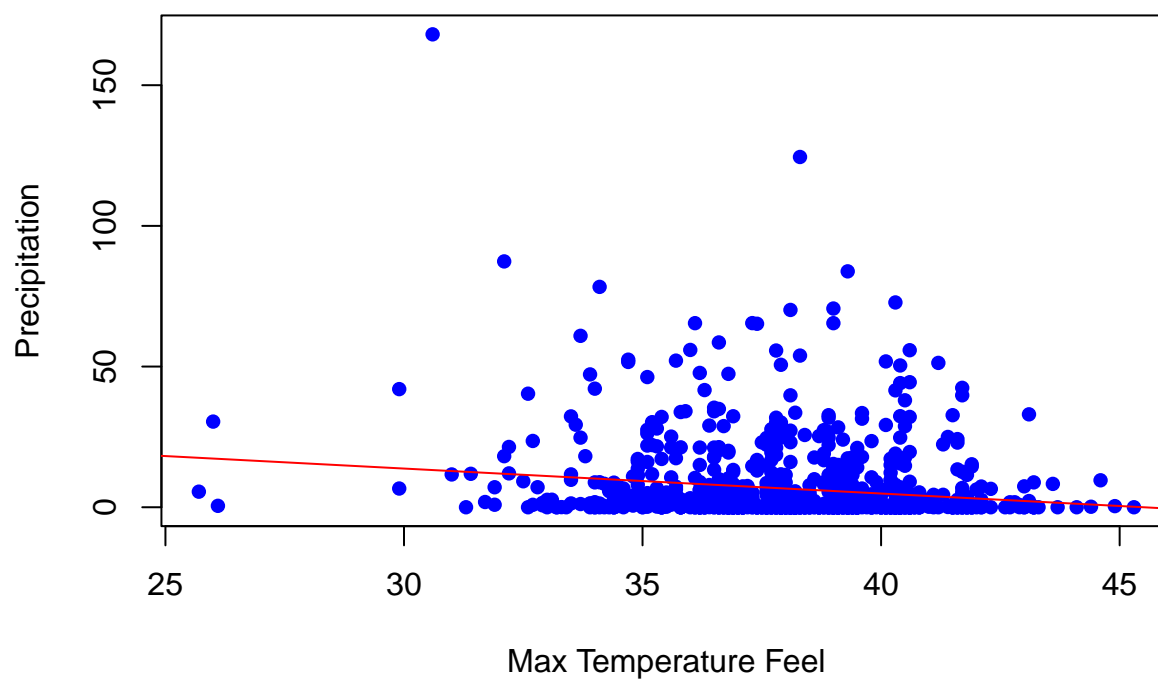
```
plot(Rainfall$temp, Rainfall$precip,  
     main="Scatter Plot with Temperature", xlab="Temperature",  
     ylab="Precipitation", col="blue", pch=16)  
abline(lm(Rainfall$precip ~ Rainfall$temp), col="red")
```

Scatter Plot with Temperature



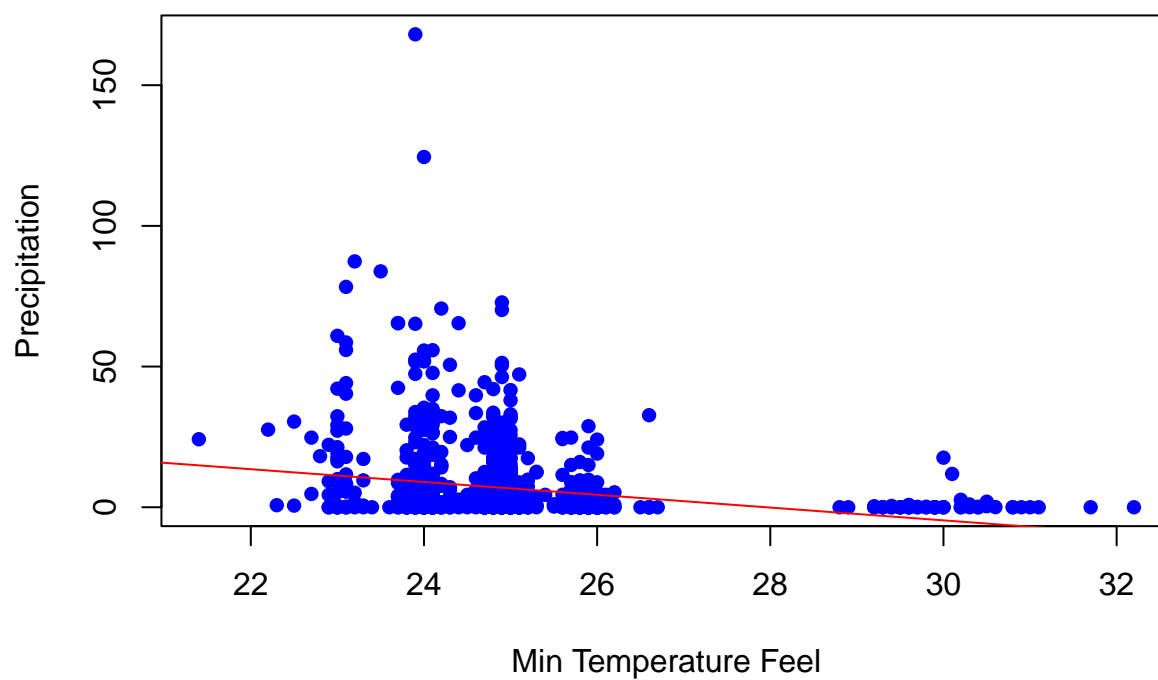
```
plot(Rainfall$feelslikemax, Rainfall$precip,  
     main="Scatter Plot with Max Temperature Feel", xlab="Max Temperature Feel",  
     ylab="Precipitation", col="blue", pch=16)  
abline(lm(Rainfall$precip ~ Rainfall$feelslikemax), col="red")
```

Scatter Plot with Max Temperature Feel



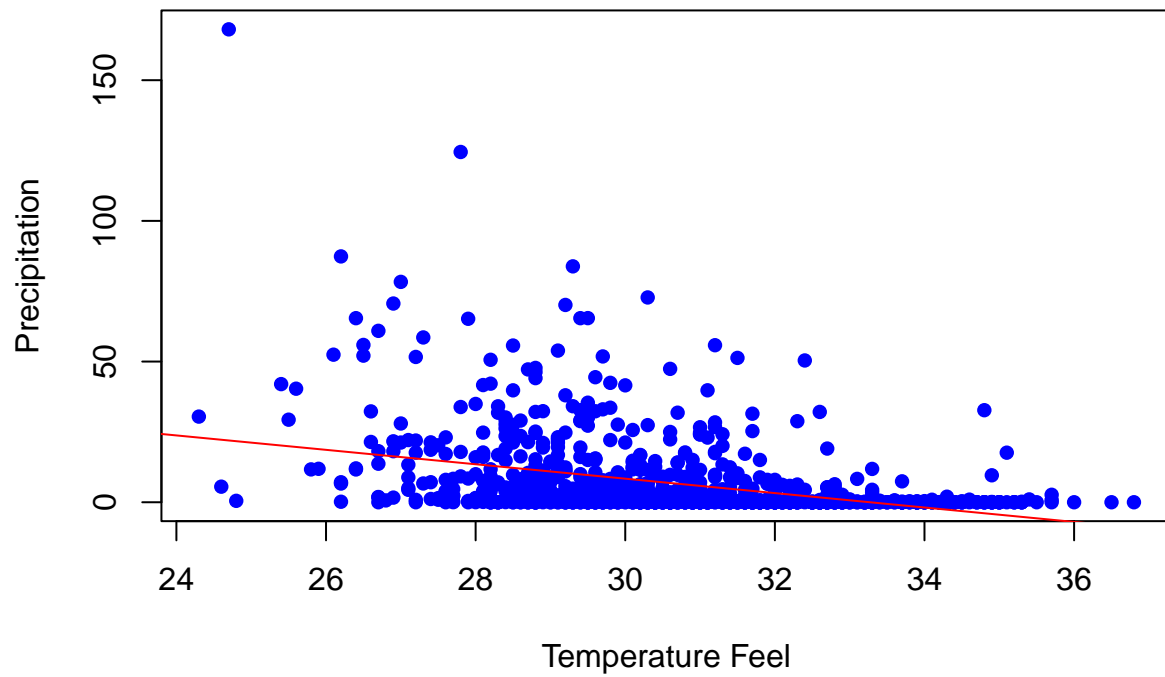
```
plot(Rainfall$feelslikemin, Rainfall$precip,  
     main="Scatter Plot with Min Temperature Feel", xlab="Min Temperature Feel",  
     ylab="Precipitation", col="blue", pch=16)  
abline(lm(Rainfall$precip ~ Rainfall$feelslikemin), col="red")
```


Scatter Plot with Min Temperature Feel



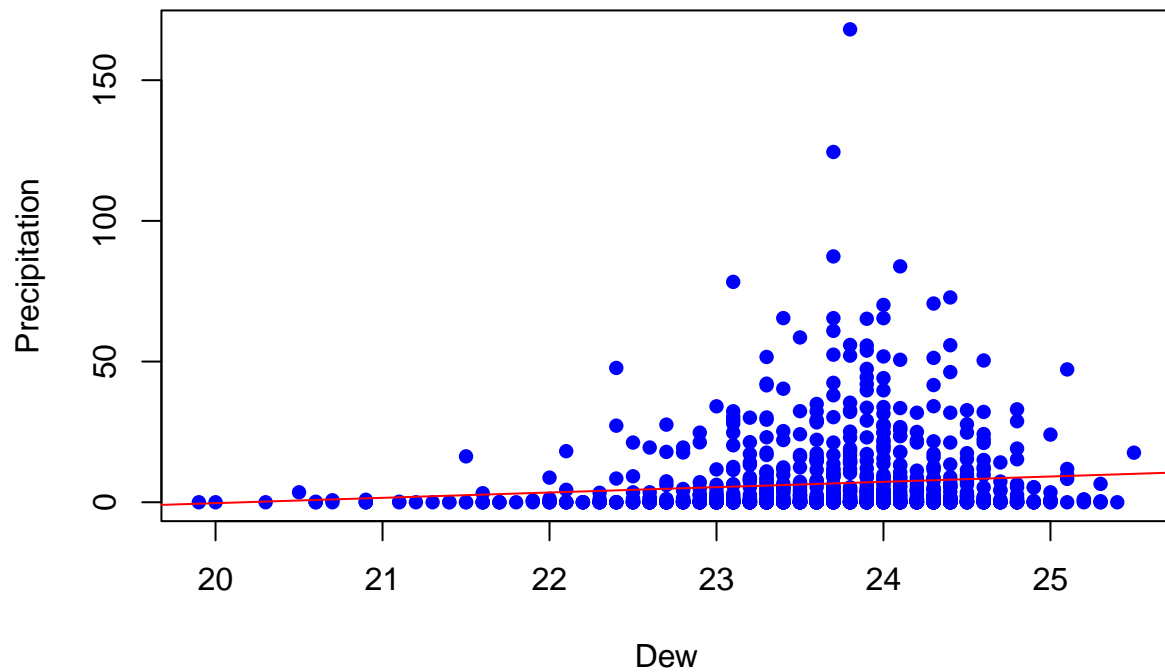
```
plot(Rainfall$feelslike, Rainfall$precip,  
     main="Scatter Plot with Temperature Feel", xlab="Temperature Feel",  
     ylab="Precipitation", col="blue", pch=16)  
abline(lm(Rainfall$precip ~ Rainfall$feelslike), col="red")
```

Scatter Plot with Temperature Feel



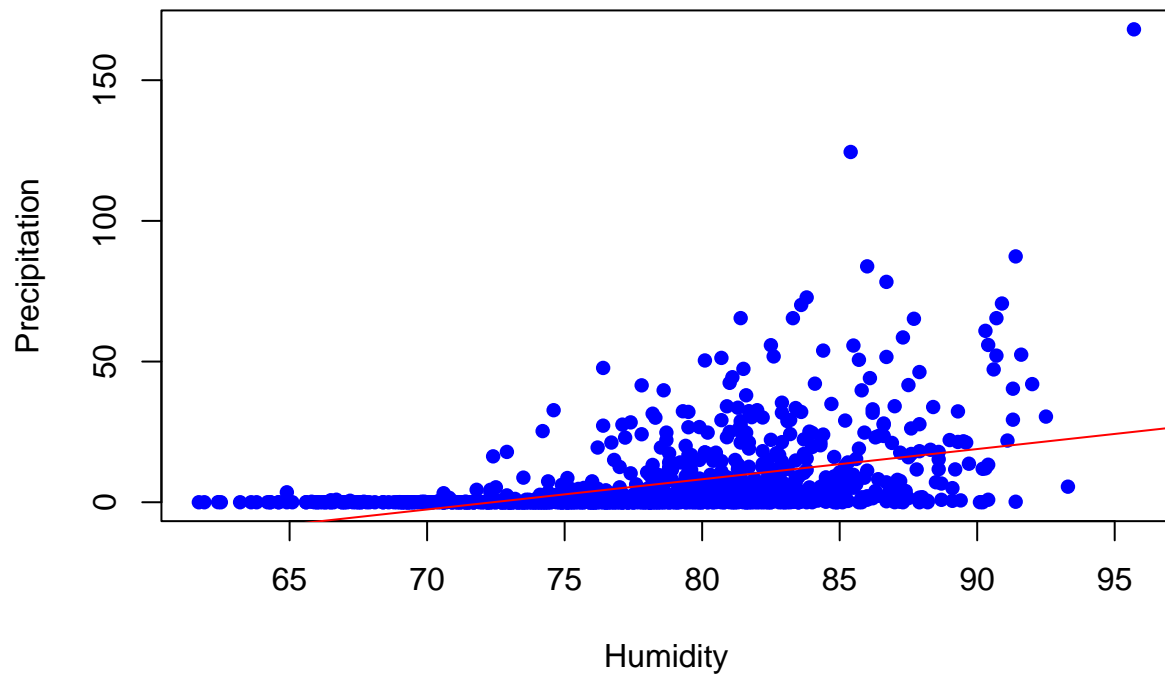
```
plot(Rainfall$dew, Rainfall$precip,  
     main="Scatter Plot with Dew", xlab="Dew",  
     ylab="Precipitation", col="blue", pch=16)  
abline(lm(Rainfall$precip ~ Rainfall$dew), col="red")
```

Scatter Plot with Dew



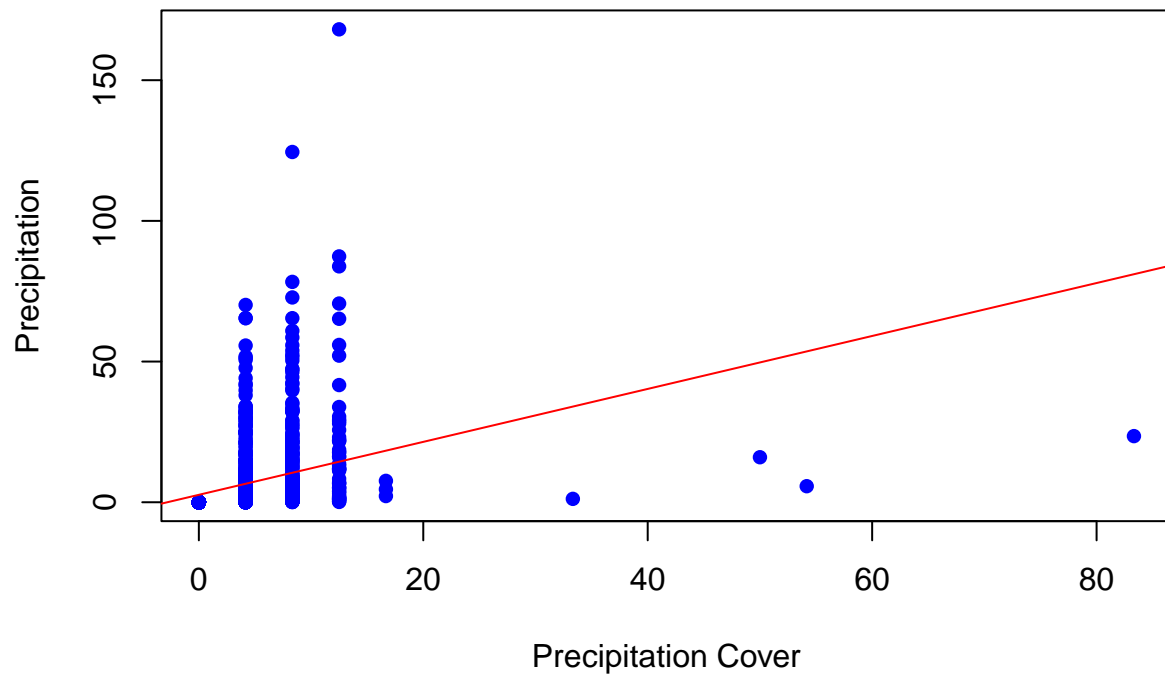
```
plot(Rainfall$humidity, Rainfall$precip,  
     main="Scatter Plot with Humidity", xlab="Humidity",  
     ylab="Precipitation", col="blue", pch=16)  
abline(lm(Rainfall$precip ~ Rainfall$humidity), col="red")
```

Scatter Plot with Humidity



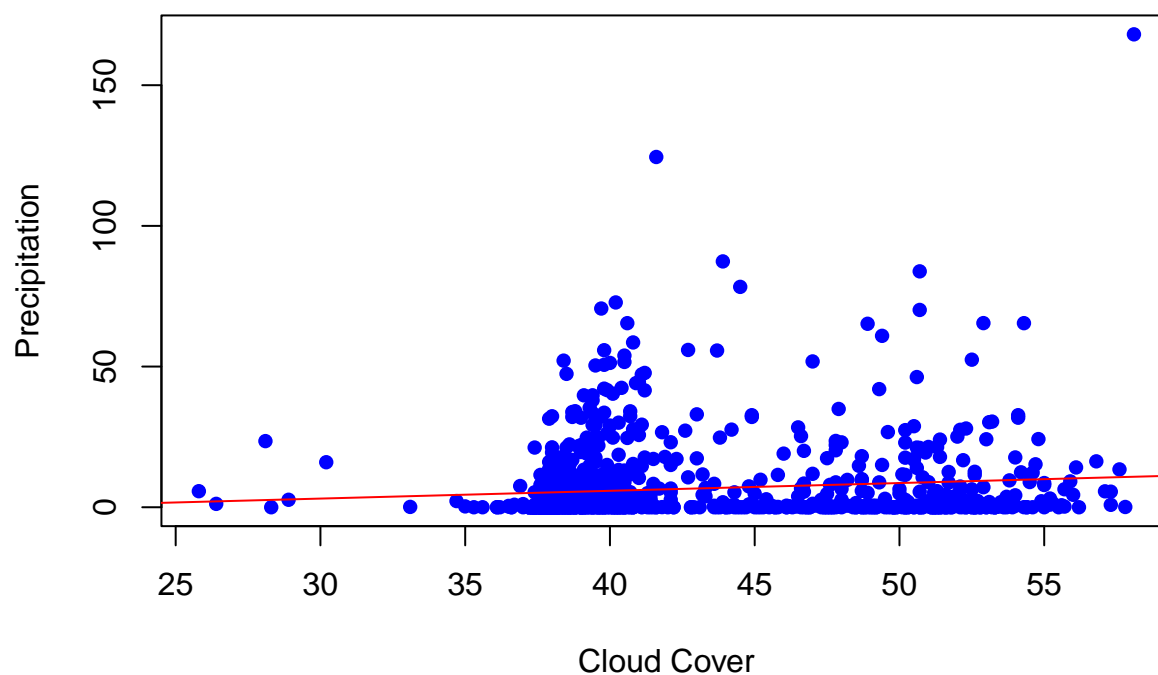
```
plot(Rainfall$precipcover, Rainfall$precip,  
     main="Scatter Plot with Precipitation Cover", xlab="Precipitation Cover",  
     ylab="Precipitation", col="blue", pch=16)  
abline(lm(Rainfall$precip ~ Rainfall$precipcover), col="red")
```

Scatter Plot with Precipitation Cover



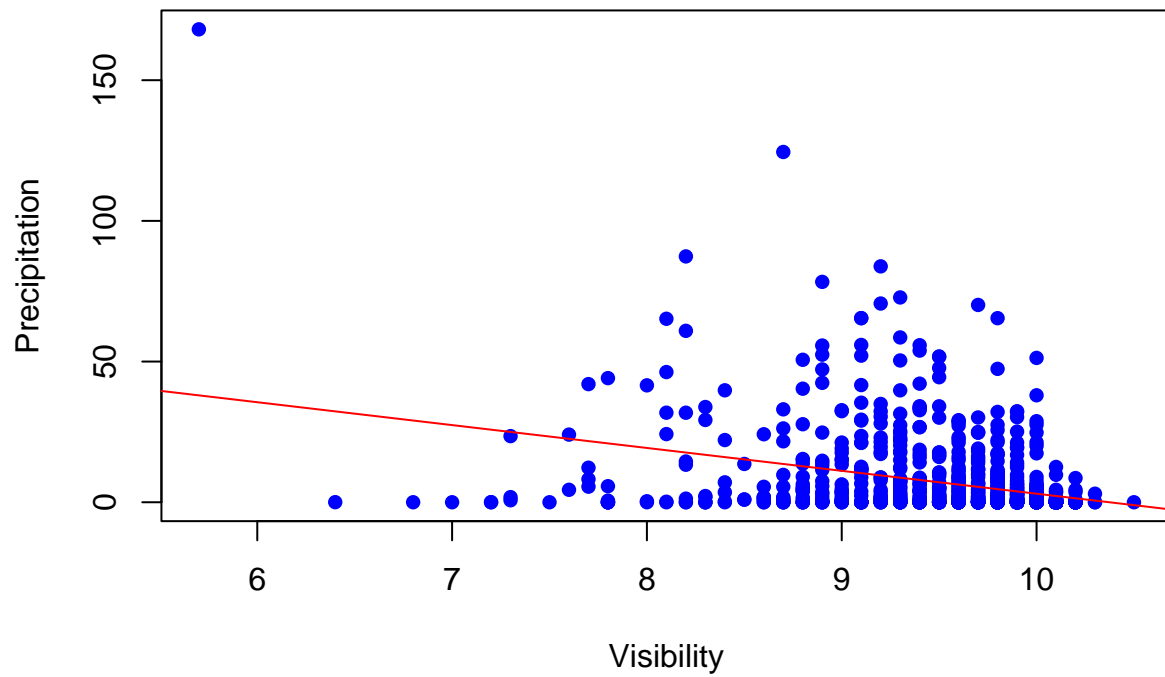
```
plot(Rainfall$cloudcover, Rainfall$precip,  
     main="Scatter Plot with Cloud Cover", xlab="Cloud Cover",  
     ylab="Precipitation", col="blue", pch=16)  
abline(lm(Rainfall$precip ~ Rainfall$cloudcover), col="red")
```

Scatter Plot with Cloud Cover



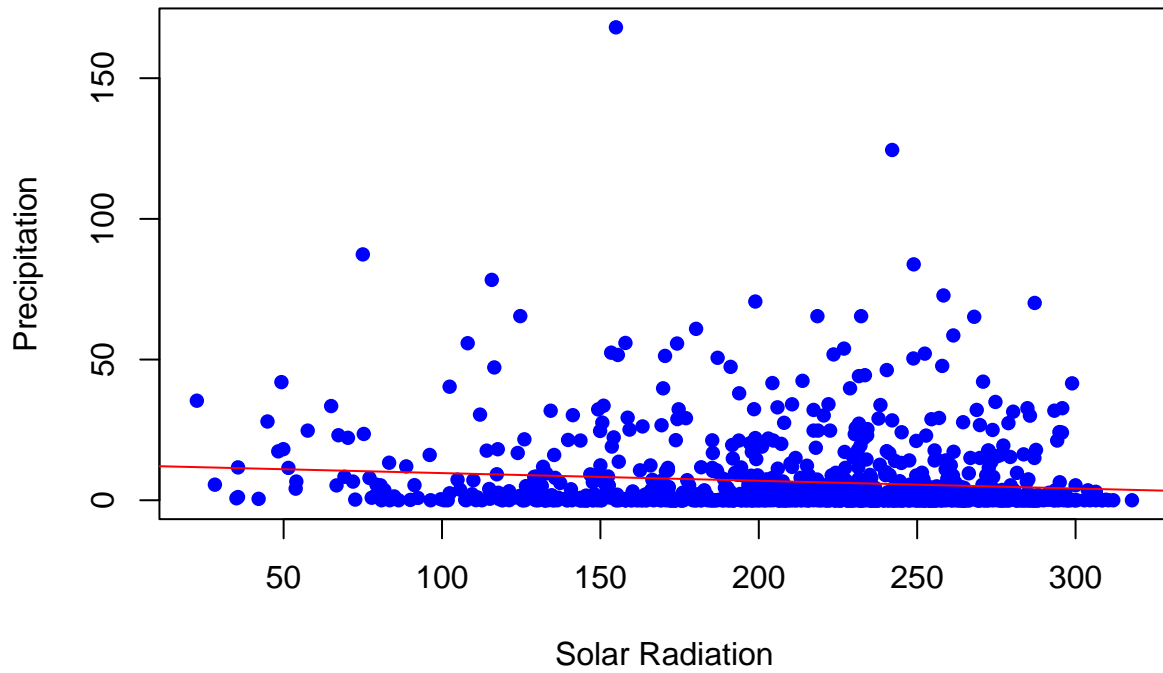
```
plot(Rainfall$visibility, Rainfall$precip,  
     main="Scatter Plot with Visibility", xlab="Visibility",  
     ylab="Precipitation", col="blue", pch=16)  
abline(lm(Rainfall$precip ~ Rainfall$visibility), col="red")
```

Scatter Plot with Visibility



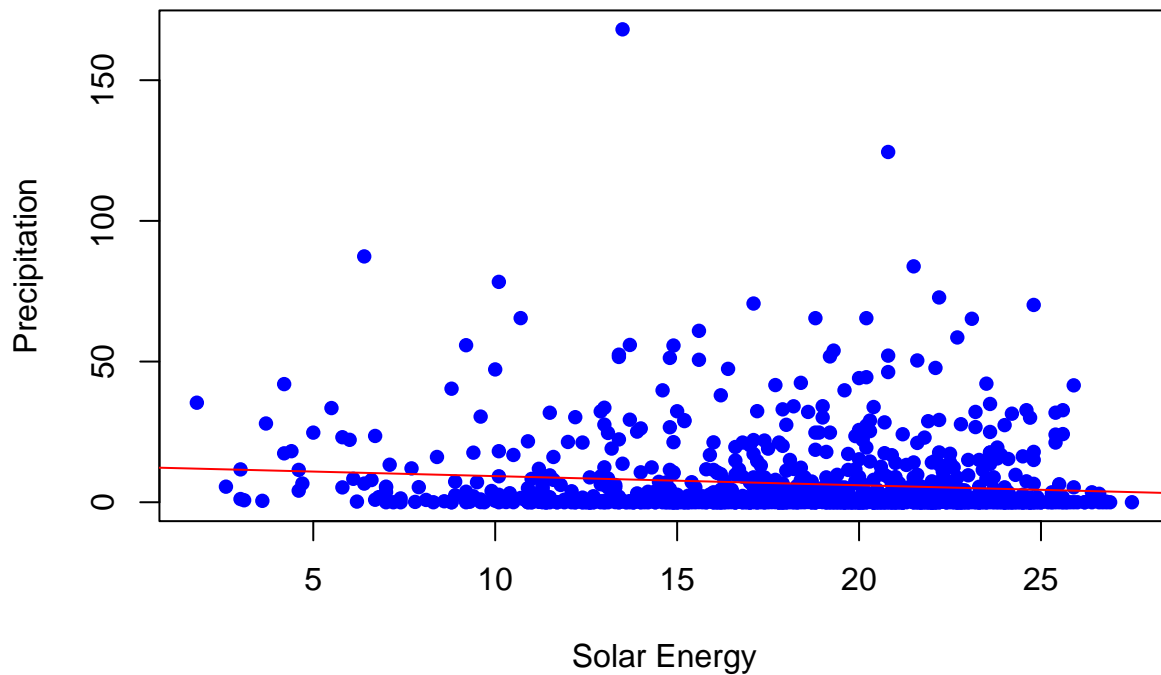
```
plot(Rainfall$solarradiation, Rainfall$precip,
     main="Scatter Plot with Solar Radiation", xlab="Solar Radiation",
     ylab="Precipitation", col="blue", pch=16)
abline(lm(Rainfall$precip ~ Rainfall$solarradiation), col="red")
```

Scatter Plot with Solar Radiation



```
plot(Rainfall$solarenergy, Rainfall$precip,  
     main="Scatter Plot with Solar Energy", xlab="Solar Energy",  
     ylab="Precipitation", col="blue", pch=16)  
abline(lm(Rainfall$precip ~ Rainfall$solarenergy), col="red")
```


Scatter Plot with Solar Energy



```
corr<-aov(precip ~ description * uvindex, data=Rainfall)
summary(corr)
```

```
##              Df Sum Sq Mean Sq F value Pr(>F)
## description      8  39139    4892  30.606 <2e-16 ***
## uvindex          9    825      92   0.573  0.820
## description:uvindex 51   7079     139   0.868  0.732
## Residuals      931 148822     160
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

0.6 Multivariate Analysis

Multiple Linear Regression

```
Precipitation <- lm(precip ~ description + uvindex + tempmax + tempmin +
  temp + feelslikemax + feelslikemin + feelslike + dew + humidity +
  precipcover + cloudcover + visibility + solarradiation + solarenergy,
  data = Rainfall)
anova(Precipitation)
```

```
## Analysis of Variance Table
##
## Response: precip
```

```
##           Df Sum Sq Mean Sq F value    Pr(>F)
## description      8  39139   4892.4  37.0930 < 2.2e-16 ***
## uvindex          9    825    91.6   0.6948  0.7140506
## tempmax          1   1228   1227.9   9.3094  0.0023419 **
## tempmin          1   4485   4484.9  34.0034  7.490e-09 ***
## temp             1   5891   5890.6  44.6615  3.946e-11 ***
## feelslikemax     1    577    577.1   4.3756  0.0367174 *
## feelslikemin     1   1364   1363.8  10.3399  0.0013450 **
## feelslike        1    117    116.9   0.8861  0.3467760
## dew              1   1795   1795.3  13.6115  0.0002373 ***
## humidity         1   9948   9948.1  75.4242 < 2.2e-16 ***
## precipcover      1     7     6.6   0.0501  0.8229131
## cloudcover       1    475   475.4   3.6043  0.0579260 .
## visibility       1   1245   1244.6   9.4359  0.0021871 **
## solarradiation   1    834   833.6   6.3203  0.0120976 *
## solarenergy      1    130   130.2   0.9871  0.3207109
## Residuals       969 127807   131.9
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
summary(Precipitation)
```

```
##
## Call:
## lm(formula = precip ~ description + uvindex + tempmax + tempmin +
##      temp + feelslikemax + feelslikemin + feelslike + dew + humidity +
##      precipcover + cloudcover + visibility + solarradiation +
##      solarenergy, data = Rainfall)
##
## Residuals:
##      Min       1Q   Median       3Q      Max
## -22.221  -6.111  -1.080   3.443  118.419
##
## Coefficients:
##                                     Estimate
## (Intercept)                        -5.343e+02
## descriptionPartly cloudy throughout the day with afternoon rain.      -1.733e+00
## descriptionPartly cloudy throughout the day with early morning rain.    -4.493e+00
## descriptionPartly cloudy throughout the day with late afternoon rain.     1.162e-01
## descriptionPartly cloudy throughout the day with morning rain.           -1.002e-01
## descriptionPartly cloudy throughout the day with rain clearing later.      2.096e+00
## descriptionPartly cloudy throughout the day with rain in the morning and afternoon. 1.756e+00
## descriptionPartly cloudy throughout the day with rain.                    4.739e+00
## descriptionPartly cloudy throughout the day.                             -4.368e+00
## uvindex2                          -3.139e+00
## uvindex3                           4.767e-01
## uvindex4                         -1.701e+00
## uvindex5                         -2.016e+00
## uvindex6                         -2.708e+00
## uvindex7                         -5.896e+00
## uvindex8                         -6.986e+00
## uvindex9                         -8.733e+00
## uvindex10                        -8.659e+00
## tempmax                           7.294e-01
```

## tempmin	-1.468e+00
## temp	2.218e+01
## feelslikemax	-7.237e-03
## feelslikemin	9.085e-01
## feelslike	3.861e+00
## dew	-3.351e+01
## humidity	7.671e+00
## precipcover	1.542e-02
## cloudcover	1.130e-01
## visibility	-2.489e+00
## solarradiation	3.021e-01
## solarenergy	-3.081e+00
##	Std. Error
## (Intercept)	9.840e+01
## descriptionPartly cloudy throughout the day with afternoon rain.	5.758e+00
## descriptionPartly cloudy throughout the day with early morning rain.	5.659e+00
## descriptionPartly cloudy throughout the day with late afternoon rain.	5.576e+00
## descriptionPartly cloudy throughout the day with morning rain.	5.591e+00
## descriptionPartly cloudy throughout the day with rain clearing later.	5.647e+00
## descriptionPartly cloudy throughout the day with rain in the morning and afternoon.	6.043e+00
## descriptionPartly cloudy throughout the day with rain.	5.174e+00
## descriptionPartly cloudy throughout the day.	5.912e+00
## uvindex2	7.918e+00
## uvindex3	7.393e+00
## uvindex4	7.128e+00
## uvindex5	7.105e+00
## uvindex6	7.166e+00
## uvindex7	7.192e+00
## uvindex8	7.290e+00
## uvindex9	7.431e+00
## uvindex10	7.590e+00
## tempmax	8.323e-01
## tempmin	1.195e+00
## temp	4.333e+00
## feelslikemax	5.061e-01
## feelslikemin	6.701e-01
## feelslike	1.291e+00
## dew	5.015e+00
## humidity	1.060e+00
## precipcover	1.324e-01
## cloudcover	7.472e-02
## visibility	8.085e-01
## solarradiation	2.681e-01
## solarenergy	3.101e+00
##	t value
## (Intercept)	-5.430
## descriptionPartly cloudy throughout the day with afternoon rain.	-0.301
## descriptionPartly cloudy throughout the day with early morning rain.	-0.794
## descriptionPartly cloudy throughout the day with late afternoon rain.	0.021
## descriptionPartly cloudy throughout the day with morning rain.	-0.018
## descriptionPartly cloudy throughout the day with rain clearing later.	0.371
## descriptionPartly cloudy throughout the day with rain in the morning and afternoon.	0.291
## descriptionPartly cloudy throughout the day with rain.	0.916
## descriptionPartly cloudy throughout the day.	-0.739

## uvindex2	-0.396
## uvindex3	0.064
## uvindex4	-0.239
## uvindex5	-0.284
## uvindex6	-0.378
## uvindex7	-0.820
## uvindex8	-0.958
## uvindex9	-1.175
## uvindex10	-1.141
## tempmax	0.876
## tempmin	-1.229
## temp	5.118
## feelslikemax	-0.014
## feelslikemin	1.356
## feelslike	2.990
## dew	-6.683
## humidity	7.239
## precipcover	0.116
## cloudcover	1.513
## visibility	-3.079
## solarradiation	1.127
## solarenergy	-0.994
##	Pr(> t)
## (Intercept)	7.13e-08
## descriptionPartly cloudy throughout the day with afternoon rain.	0.76348
## descriptionPartly cloudy throughout the day with early morning rain.	0.42736
## descriptionPartly cloudy throughout the day with late afternoon rain.	0.98338
## descriptionPartly cloudy throughout the day with morning rain.	0.98570
## descriptionPartly cloudy throughout the day with rain clearing later.	0.71062
## descriptionPartly cloudy throughout the day with rain in the morning and afternoon.	0.77140
## descriptionPartly cloudy throughout the day with rain.	0.35993
## descriptionPartly cloudy throughout the day.	0.46022
## uvindex2	0.69187
## uvindex3	0.94860
## uvindex4	0.81139
## uvindex5	0.77667
## uvindex6	0.70555
## uvindex7	0.41252
## uvindex8	0.33813
## uvindex9	0.24016
## uvindex10	0.25420
## tempmax	0.38106
## tempmin	0.21950
## temp	3.73e-07
## feelslikemax	0.98859
## feelslikemin	0.17550
## feelslike	0.00286
## dew	3.95e-11
## humidity	9.20e-13
## precipcover	0.90731
## cloudcover	0.13061
## visibility	0.00214
## solarradiation	0.26003
## solarenergy	0.32071

```

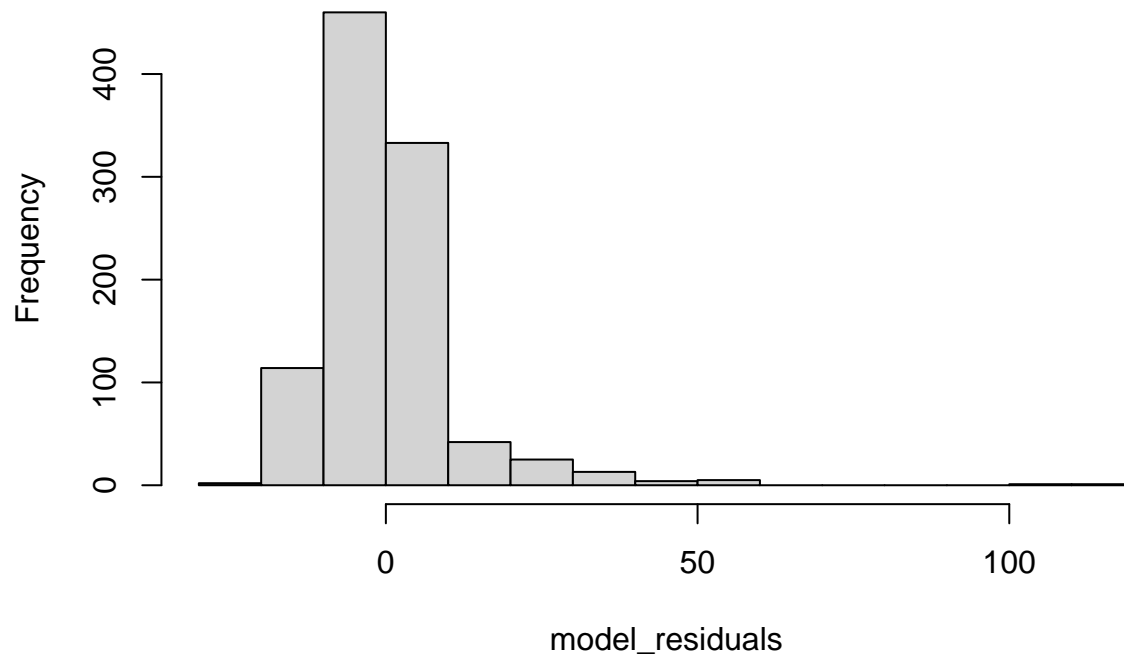
##
## (Intercept) ***
## descriptionPartly cloudy throughout the day with afternoon rain.
## descriptionPartly cloudy throughout the day with early morning rain.
## descriptionPartly cloudy throughout the day with late afternoon rain.
## descriptionPartly cloudy throughout the day with morning rain.
## descriptionPartly cloudy throughout the day with rain clearing later.
## descriptionPartly cloudy throughout the day with rain in the morning and afternoon.
## descriptionPartly cloudy throughout the day with rain.
## descriptionPartly cloudy throughout the day.
## uvindex2
## uvindex3
## uvindex4
## uvindex5
## uvindex6
## uvindex7
## uvindex8
## uvindex9
## uvindex10
## tempmax
## tempmin
## temp ***
## feelslikemax
## feelslikemin
## feelslike **
## dew ***
## humidity ***
## precipcover
## cloudcover
## visibility **
## solarradiation
## solarenergy
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Residual standard error: 11.48 on 969 degrees of freedom
## Multiple R-squared:  0.3475, Adjusted R-squared:  0.3273
## F-statistic: 17.2 on 30 and 969 DF, p-value: < 2.2e-16

# Get the model residuals
model_residuals = Precipitation$residuals

# Plot the result
hist(model_residuals)

```

Histogram of model_residuals



```
# Plot the residuals  
qqnorm(model_residuals)  
# Plot the Q-Q line  
qqline(model_residuals)
```

Normal Q-Q Plot

