# CHAPTER 4
# METHODOLOGY

## 4.1 GENERAL

This chapter covers the detailed outline of the procedure and methodology to calculate different meteorological drought indices, hydrological drought indices and agricultural drought indices. Also, Trend analysis test techniques for development of drought forecasting are discussed.

## 4.2 METEOROLOGICAL DROUGHT INDICES

Droughts are serious extreme events that have adverse effects on the physical environment and water resource systems in both developed and developing countries. Consequently, there is need for adequate measures for responding to and mitigating various impacts arising from drought occurrence.

Meteorological drought is usually defined on the basis of the degree of dryness (in comparison to some "normal" or average amount) and the duration of the dry period. Definitions of meteorological drought must be considered as specific to a region since the atmospheric conditions that result in deficiencies of precipitation are highly variable from region to region.

In the current assessment study, different meteorological drought indices like percent normal (PN), Percentage of departure from mean (PD), Deciles index (DI), Standardized Precipitation Index (SPI), Reconnaissance Drought index (RDI), Standardised Potential Evapotranspiration Index (SPEI), China Z index (CZI), Modified China Index (MCZI) and the Z-Score were used for estimating drought severity. All the aforesaid indices work using precipitation, potential Evapotranspiration and temperature data. Detailed description of the drought indices used in this study are presented hereunder.

### 4.2.1 Percent of Normal (PN)

This index is computed by dividing the actual precipitation by the "normal" precipitation (typically considered to be a 30-year mean) and multiplying by 100. This index can be calculated for a variety of time scales.PN is typically expressed in percentages given by (Willeke et al. 1994) for drought assessment. The PN classification is shown in below Table 4.1. The equation for this index is:

$$PN = \frac{P}{P_{30}} \times 100$$

Values of the index less than 100 means drought conditions exist.

Table 4.1: Percent of Normal Classification

| PNI (%) | Drought Classes |
|---------|-----------------|
| ≥110 | Moderately Wet |
| 80 to 110 | Near Normal |
| 55 to 80 | Moderately Drought |
| 40 to 55 | Severely Drought |
| ≤40 | Extremely Drought |

### 4.2.2 Percentage of Departure from Mean (PD)

**Percentage of Departure from Mean (Annual)**

This indices clearly indicates the departure of any precipitation events from its mean. If the departure of annual rainfall from normal (%) is 0 or above then there is no drought, 0 to -25 mild drought,-26 to -50 moderate droughts,-50 or more it's a severe drought situation. This index is estimated using the following equation.

$$P_d = \left[ \frac{P_i - \overline{P}}{\overline{p}} \right] \times 100$$

Here, Pd is the percentage departure; Pi is the rainfall at any time and $\overline{p}$ is the mean rainfall.  The PD classification is shown in below Table 4.2.

Table 4.2: Percentage Departure from Mean Classification

| Percentage Departure from Normal | Intensity of Drought |
|----------------------------------|----------------------|
| > 0.0 | No Drought |
| 0 to -25 | Mild Drought |
| -25 to -50 | Moderate Drought |
| > -50 | Severe Drought |

Source: Indian Meteorological Department (IMD), Pune

**Percentage of Departure from Mean (Seasonal)**

About 85% of the annual rainfall is received from southwest monsoon that occurs during June to September. In order to compute the deficiency of seasonal rainfall, the seasonal rainfall analysis has been carried out. Normal rainfall of the monsoon season was calculated as the arithmetic average of rainfall during June to September, over the basin. India Meteorological Department defined seasonal drought as the period with the seasonal rainfall deficiency more than 25% from its normal value.

### 4.2.3 Rainfall Anomaly Index (RAI)

Rainfall anomaly index calculates the annual rainfall variability. It is used for the purpose of assessing the degree of droughts and their management. This technique incorporates the rainfall measurements for a given area during a particular time period. The rainfall data were arranged in descending order of intensity in which higher rainfall values are ranked first and the lowest rainfall values are ranked last.

Further the average value of the ten highest rainfall measurements comprising the maximal average of ten extrema and the ten lowest rainfall measurement comprising the minimal average of ten extrema was computed for the period under consideration. These values represent the positive and negative anomalies respectively based on average rainfall values of ten extrema.

RAI is calculated for positive anomalies and negative anomalies as given in below equation.

$$\text{RAI} = +3 \left[ \frac{\text{RF} - \text{M}_{\text{RF}}}{\text{M}_{\text{H}10} - \text{M}_{\text{RF}}} \right]$$

$$\text{RAI} = -3 \left[ \frac{\text{RF} - \text{M}_{\text{RF}}}{\text{M}_{\text{L}10} - \text{M}_{\text{RF}}} \right]$$

In above equations RAI is the annual Rainfall anomaly index, RF represent total rainfall obtained during a particular year whereas MRF constitute the mean rainfall recorded during the study period. The mean value of the 10 highest and 10 lowest rainfall values is given by $\text{MH}_{10}$ and $\text{ML}_{10}$ respectively. Classification of drought according to the value of the rainfall anomaly index is given by (Van Rooy, 1965) is shown in below Table 4.3.

Table 4.3: Rainfall Anomaly Index Classification

| Range | Classification |
|---|---|
| ≥ 3.00 | Extremely wet |
| 2.00 to 2.99 | Very wet |
| 1.00 to 1.99 | Moderately wet |
| 0.50 to 0.99 | Slightly wet |
| 0.49 to −0.49 | Near normal |
| −0.50 to −0.99 | Slightly dry |
| −1.00 to −1.99 | Moderately dry |
| −2.00 to −2.99 | Very dry |
| ≤ −3.00 | Extremely dry |

### 4.2.4  Precipitation Deciles (DI)

One of the simplest meteorological drought indices is the method of Deciles which was introduced by Gibbs and Maher (1967). In this method monthly precipitation totals from a long-term record are first ranked from highest to lowest to construct a cumulative frequency distribution.

The drought ends when:

(i)     The precipitation measured during the past month already places the 3-month total in or above the fourth decile, or

(ii)    The precipitation total for the past three months is in or above the eighth decile. The advantage of the method of deciles is its computational ease, but its simplicity can lead to conceptual difficulties.

The distribution is then split into 10 parts (deciles). The first decile is the precipitation value not exceeded by the lowest 10% of all precipitation values in a record; the second is between the lowest 10 and 20%, etc. Any precipitation value (e.g. from the current or past month) can be compared with and interpreted in terms of these deciles. The deciles are grouped into five classes as presented in Table 4.4. Also, formula for drought calculation is:

$$P_i = \frac{i}{n+1} \times 100$$

Table 4.4: Decile Classification

| Range | Percent | Classification |
|---|---|---|
| Decile 1-2 | 20% lower | Much Below Normal |
| Decile 3-4 | 20% Following | Below Normal |
| Decile 5-6 | 20% medium | Near Normal |
| Decile 7-8 | 20% following | Above Normal |
| Decile 8-9 | 20% more high | Much Above Normal |

### 4.2.5  Standardized Precipitation Index (SPI)

The Standardized Precipitation Index (SPI) was developed by McKee et al (1993). The SPI is based only on precipitation. The SPI assigns a single numeric value to the precipitation, which can be compared across regions and time scales with markedly different climates.

There are a number of indices to quantify drought using meteorological data; however, the SPI is most widely used index. SPI can be computed at different time scales and hence can quantify water deficit so different duration.SPI was designed to demonstrate that it is possible to simultaneously go through wet conditions on one or

more time scales and dry conditions at another time scale. The calculation of the index needs only precipitation record. It is calculated by considering the precipitation anomaly with regard to the average value for a given time scale, separated by its standard deviation.

The precipitation is not a normal distribution, at least for timescales less than one year. Therefore, the variable is adjusted so that the SPI is a Gaussian distribution with zero mean and unit variance. The SPI classification is shown in below Table 4.5 which is given by McKee et al (1993).

$$SPI = \frac{x_i - x}{\sigma}$$

Where, X: the mean annual rainfall, $X_i$: the annual rainfall at any year and σ: the standard variation.

Table 4.5: SPI Classification

| SPI Values | Classification |
|---|---|
| 2.0 + | Extremely wet |
| 1.5 to 1.99 | Very wet |
| 1.0 to 1.49 | Moderate wet |
| -0.99 to +0.99 | Near normal |
| -1.0 to -1.49 | Moderate dry |
| -1.5 to -1.99 | Severe dry |
| -2.0 to less | Extreme dry |

### 4.2.6  Reconnaissance Drought Index (RDI)

A new reconnaissance drought identification and assessment index was first presented by Tsakiris (2004) while a more comprehensive description was presented in Tsakiris et al. (2005).

The index, which is referred to as the Reconnaissance Drought Index (RDI) calculated by the following equations. For illustrative purposes the yearly expressions are presented first. The first expression, the initial value ($\alpha_0$), is presented in an aggregated form using a monthly time step and may be calculated for each month of the hydrological year or a complete year. The $\alpha_0$ is usually calculated for the year i in an annual basis as follows:

$$\alpha_0^{(i)} = \frac{\sum_{j=1}^{12} P_{ij}}{\sum_{j=1}^{12} PET_{ij}} \quad i = 1 \text{ to N, and } j = 1 \text{ to } 12$$

Pij and PETij are the precipitation and potential evapotranspiration of the month j of the year i.

A second expression, the Normalized RDI, (RDIn) is computed using the following equation for each year, in which it is evident that the parameter $\bar{a}_0$ is the arithmetic mean of $a_0$ values calculated for the N years of data.

$$RDI_n^{(i)} = \frac{a_0^{(i)}}{\bar{a}_0} - 1$$

The third expression, the Standardized RDI (RDIst), is computed following similar procedure to the one that is used for the calculation of the SPI. The expression for the Standardized RDI is:

$$RDI_{st}^{(i)} = \frac{y^{(i)} - \bar{y}}{\widehat{a_y}}$$

Where, $y^{(i)}$ is the $\ln(a_0^{(i)})$, $\bar{y}$ is its arithmetic mean and $\widehat{a_y}$ is its standard deviation.

In case the gamma distribution is applied, the RDIst can be calculated by fitting the gamma probability density function (pdf) to the given frequency distribution of αk (Tsakiris et al. 2008; Tigkas 2008).

For short reference periods (e.g. monthly or 3-months) which may include zero values for the cumulative precipitation of the period, the RDIst can be calculated based on a composite cumulative distribution function including the probability of zero precipitation and the gamma cumulative probability. Positive values of RDIst indicate wet periods, while negative values indicate dry periods compared with the normal conditions of the area. The RDI classification is shown in below Table 4.6.

Table 4.6: RDI Classification

| RDI Values | Classification |
|---|---|
| 2.00 or more | Extremely wet |
| 1.5 to 1.99 | Severely wet |
| 1.00 to 1.49 | Moderately wet |
| 0 to 0.99 | Normal Conditions-wet |
| 0 to -0.99 | Normal Conditions-dry |
| -1 to -1.49 | Moderate drought |
| -1.5 to -1.99 | Severe drought |
| -2 or less | Extreme drought |

### 4.2.7  Standardized Precipitation Evapotranspiration Index (SPEI)

The standardized precipitation evapotranspiration index (SPEI) index was developed by Vicente-Serrano et al. (2010). It is calculated in the same way as that of SPI, but

instead of using the time series of precipitation, it uses the monthly difference between precipitation and potential evapotranspiration (PET).

The SPEI is another meteorological drought index that considers the variability of both precipitation and temperature to predict drought conditions in a region. The first step to calculate the SPEI is the estimation of monthly potential evapotranspiration (PET). Then, the water balance equation is used to calculate the monthly deficit (Di).

$$D_i = P_i - PET_i$$

Where, Pi is the total precipitation value at the month i. Finally, the changed in deficit values are standardized and fitted to a log-logistic distribution function. The SPEI value at the month i is the standardized values of the exceeding probability (p) of a given Di and is calculated by Eq.

$$SPEI_i = W_i - \frac{2.515517 + 0.802853W_i + 0.010328W_i^2}{1 + 1.432788W_i + 0.189269W_i^2 + 0.001308W_i^3}$$

While for P≤0.5, $W_i = \sqrt{-2\ln p}$ while, if P>0.5, $W_i = \sqrt{-2\ln(1-p)}$ and the sign of the resultant SPEI is reversed for P > 0.5

In this study, SPEI package developed by Beguería and Vicente-Serrano (2013) available in R is used and fitted the data to the log-logistic distribution. It is worthy to mention that the log-logistic model was suggested by Vicente-Serrano et al. (2010) in the original SPEI methodology. The SPEI classification is shown in below Table 4.7.

Table 4.7: SPEI Classification

| Range | Classification |
|---|---|
| ≤ -2.00 | Extreme dry |
| -1.50 to -1.99 | Severe dry |
| -1.00 to -1.49 | Moderate dry |
| +0.99 to -0.99 | Near normal |
| +1.00 to +1.49 | Moderate wet |
| +1.50 to +1.99 | Very wet |
| ≥ 2.00 | Extreme wet |

### 4.2.8 China-Z Index (CZI) and Modified CZI (MCZI)

**China-Z index (CZI)**

The National Climate Center of China developed the CZI in 1995 as an alternative to the SPI. Wu et al. (2001) stated that China Z Index is based on the Wilson–Hilferty

cube– root transformation. In CZI, it is supposed that rainfall data fit the Pearson Type III distribution.

The calculation of the Z-index was based on the assumption that the precipitation data obey the Pearson III distribution, is then normalized via the following normalization formula CZI equation can be written as:

The CZI is calculated as:

$$CZI_{ij} = \frac{6}{C_{si}}\left(\frac{C_{si}}{2} * \varphi_{ij} + 1\right)^{\left(\frac{1}{3}\right)} - \frac{6}{C_{si}} + \frac{C_{si}}{6}$$

Where, i is the time scale of interest and j is the current month; $CZI_{ij}$ means the CZI's amount of the current month (j) for period i; $C_{si}$ is the coefficient of skewness; and $\varphi_{ij}$ is the standardized variation. Furthermore, the MCZI can also be calculated using the formula above but substituting the median precipitation for mean precipitation.

**Modified CZI (MCZI)**

In Modified China Z Index, mean rainfall has been changed to Median precipitation as done for the calculation of the CZI (Wu et al., 2001).CZI and MCZI drought severity classes are also presented in below Table 4.8.

Table 4.8: CZI and MCZI values Classification

| Range | Classification |
|---|---|
| ≤ -2.00 | Extreme dry |
| -1.50 to -1.99 | Severe dry |
| -1.00 to -1.49 | Moderate dry |
| +0.99 to -0.99 | Near normal |
| +1.00 to +1.49 | Moderate wet |
| +1.50 to +1.99 | Very wet |
| ≥ 2.00 | Extreme wet |

### 4.2.9 Z-Score Index (ZSI)

The ZSI measures moisture or dryness abnormality and reflects the departure of moisture conditions of a particular month from normal moisture conditions. Similar to SPI, ZSI is simple to calculate as it is computed by subtracting the mean precipitation value from the target rainfall value and then dividing the difference by the standard deviation. However, ZSI does not require adjusting data to be fitted into frequency distributions. This index is calculated as follows (Javed et al. 2021):

$$Z \, score = \frac{P_i - \overline{P}}{S}$$

Where, S is the standard deviation, $\bar{P}$ is the mean monthly precipitation and Pi is precipitation in a specific month. The more the value of this index, the more severe the drought. Table 4.9 presents various classes for the ZSI index.

Table 4.9: Z-Score index Classification

| Range | Classification |
|---|---|
| -0.25 to 0.25 | No drought |
| -0.52 to -0.25 | Slight drought |
| -0.84 to -0.52 | Moderate drought |
| -1.25 to -0.84 | Severe drought |
| < -1.25 | Extreme drought |

## 4.3  CLIMATIC DROUGHT INDEXES

The characterization of the drought periods by climatic indexes has been using De Mortone Aridity Index (IdM); Seleaninov Hydrothermic Index (his); and Donciu Climate Index (IcD). The correlation established between the assured rainfall (A %) for years and climatic indexes provide the polynomial expression, statistically very significant. It has quantified very significant correlation between annual rainfall assurance (A %) and climatic indexes using logarithmic expression which is shown in Table 4.10.

Table 4.10: Correlation between Annual Rainfall and the Climatic Indexes

| Climatic index | Symbol | Mathematical function |
|---|---|---|
| Mortone aridity index | IdM | IdM = − 7.3566 lnA + 58.037 |
| Seleaninov hydrotheremic index | His | IhS = − 0.4006 lnA + 3.1001 |
| Donciu climate index | IcD | IcD = − 24.269 lnA + 191.17 |

The average rainfall of all years has been determined first then percentage of rainfall for every years of average rainfall has been determined. Deducting percentage value from 150 the annual rainfall assurance has been found. By putting the value of A in each climatic index equation the value of each climatic index has been determined. By comparing the value of climatic indexes with the Table 4.11 the yearly drought analysis has been performed.

Table 4.11: Climatic Index Classification

| Classification | IdM | His | IcD |
|---|---|---|---|
| Excessive Rainy | >40 | >2.0 | >110 |
| Very Rainy | 33-40 | 1.6-2.0 | 100-110 |
| Rainy | 29-33 | 1.4-1.6 | 95-100 |
| Medium | 25-29 | 1.3-1.4 | 80-95 |
| Droughty | 24-25 | 1.1-1.3 | 70-80 |

| Very Droughty | 23-24 | 1.0-1.1 | 65-70 |
| Excessive Droughty | <23 | <1.0 | <65 |

### 4.3.1 Climate Change Related Precipitation Indices

### a) Precipitation Concentration Index (PCI)

The PCI, proposed as an indicator of rainfall concentration and rainfall erosivity can be calculated The PCI is estimated on Annual and Seasonal basis. Precipitation Concentration Index is analyzed at annual and seasonal scale to identify the pattern of rainfall in the study area for the period of 1901-2002.

$$PCI_{Annual} = \frac{\sum_{i=1}^{12} P_i^2}{(\sum_{i=1}^{12} P_i)^2} * 100$$

Where Pi is the monthly precipitation in month i.

The precipitation concentration index was also calculated on a seasonal scale for winter (December-January-February), Spring (March-April-May) Sumer(June-July-August), Autumn (September-October-November), and on supra-seasonal scales for wet (October to March) and dry (April to September) seasons according to following equations.

$$PCI_{Seasonal} = \frac{\sum_{i=1}^{3} P_i^2}{(\sum_{i=1}^{3} P_i)^2} * 25$$

$$PCI_{Supra\ Seasonal} = \frac{\sum_{i=1}^{6} P_i^2}{(\sum_{i=1}^{6} P_i)^2} * 50$$

Oliver (1980) suggested that PCI values of less than 10 represent a uniform precipitation distribution (i.e., low precipitation concentration); PCI values from 11 to 15 denote a moderate precipitation concentration; values from 16 to 20 denote irregular distribution and values above 20 represent a strong irregularity (i.e., high precipitation concentration) of precipitation distribution. The Classification of PCI is given in below Table 4.12

Table 4.12: Precipitation Concentration Index Classification

| PCI value | Distribution of precipitation |
| --- | --- |
| PCI < 10 | Uniform precipitation distribution |
| 11 - 15 | Moderate precipitation concentration |
| 16 - 20 | Irregular distribution |
| PCI > 20 | Strongly irregular distribution |

**b) Modified Fournier Index (MFI)**

The Modified Fournier Index (MFI) were calculated on an annual basis for each station, according to the following equation:

$$MFI = \frac{\sum_{i=1}^{12} P_i^2}{P_t}$$

With Pi being the monthly precipitation at month i, and Pt the annual precipitation. MFI Arnoldus (1980) value less than 60 indicates very low erosion capacity of rainfall; 60 to 90 indicates low, 90-120 indicates moderate, 120-160 indicates high and value greater than 160 indicates very high erosion capacity of rainfall. Classification given in below Table 4.13

Table 4.13: Modified Fournier index Classification

| MFI | Erosivity class |
|---|---|
| 0-60 | Very low |
| 60-90 | Low |
| 90-120 | Moderate |
| 120-160 | Severe |
| >160 | Very severe |

## 4.4   ARIDITY INDEXES

Increased aridity due to climate change is a growing environmental problem of the agricultural land. It is essential to assess and monitor aridity to combat the probable land degradation and drought desertification. Identification of arid and semi-arid regions on climatic basis using different well known aridity models viz., UNESCO Aridity index, Erinc Aridity index, Thornthwaite Precipitation Effectiveness index, Thornthwaite Moisture index and De Martonne Aridity index are used.

### 4.4.1   UNESCO Aridity Index

The UNESCO (1979) proposed a method for aridity mapping from the ratio of precipitation (P) to potential evapotranspiration ($ET_o$), i.e.

$$AI = \frac{P}{ET_o}$$

Where, AI is the aridity index; P is the precipitation (mm); $ET_O$ is the potential evapotranspiration by penmen's formula (mm). Five climatic zones namely, hyper arid, arid, semi-arid, dry sub humid and humid are proposed by UNESCO Aridity index as shown in Table 4.14

Table 4.14: UNESCO Aridity Index Classification

| AI Values | Climate Class |
|-----------|---------------|
| ≤0.03 | Hyper Arid |
| 0.03-0.2 | Arid |
| 0.2-0.5 | Semi-Arid |
| 0.5-0.65 | Dry Sub Humid |
| >0.65 | Humid |

The UNESCO Index is attractive in that it is very simple conceptually as well as operationally. It is totally based on the two main parameters that define aridity. Warm arid region have low precipitation and high evapotranspiration rate therefore they have low value of aridity index. For hyper arid region, the value will less than equal to 0.03 while for humid region its will be greater than 0.65.

### 4.4.2   Erinc Aridity Index

Erinc (1996) calculated aridity index by taking the ratio of total annual rainfall (P) to the annual mean maximum temperature (Tmax) as shown;

$$I_m = \frac{P}{T_{max}}$$

Where, $I_m$ is the aridity index; P is the annual total precipitation (mm); $T_{max}$ is the mean annual maximum temperature (°C).  Six climatic classes namely, hyper arid, arid, semi-arid, dry sub humid, humid and very humid are proposed by Erinc Aridity index as shown in Table 4.15

Table 4.15: Erinc Aridity Index Classification

| Im Values | Climate Class |
|-----------|---------------|
| <8 | Hyper Arid |
| 8-15 | Arid |
| 15-23 | Semi-arid |
| 23-40 | Dry sub humid |
| 40-55 | Humid |
| >55 | Very Humid |

### 4.4.3   Thornthwaite's Precipitation Effectiveness Index

Thornthwaite (1931) classified the climatic region into different classes based on the precipitation effectiveness index (PE), which is computed from the monthly values of precipitation and temperature. The index is given as;

$$PE_{Index} = \sum_{1}^{n=12} 115(P/(T-10))^{10/9}$$

Where, P is the Monthly precipitation in inches; T is the mean temperature in °F; and n = months=12. The classification of the climatic regions based on Thornthwaite's Precipitation Effectiveness into six groups namely, arid, semi-arid, dry sub humid, humid and very humid given in Table 4.16

Table 4.16: Thornthwaite's Precipitation Effectiveness Index Classification

| PE Values | Climate Class |
|---|---|
| <16 | Arid |
| 16-31 | Semi-arid |
| 32-63 | Dry sub humid |
| 64-99 | Wet sub humid |
| 100-127 | Humid |
| ≥128 | Very Humid |

### 4.4.4 Thornthwaite's Moisture Index

Thornthwaite's Moisture index is defined using the mean annual rainfall and mean annual potential evapotranspiration.

$$I_m = \frac{(R - ET_o)}{ET_o} \times 100$$

Where, Im is moisture index in percentage; R is the mean annual rainfall in mm; and $ETo$ is the mean annual Potential Evapotranspiration in mm. The negative and positive values of Im respectively refer to dry and wet zones. Reddy & Reddy (1973) defined the moisture limits for broad climatic zones into eight groups namely, Hyper arid, arid, dry semi-arid, wet semi-arid, dry sub-humid, wet sub-humid, humid and very humid as shown in Table 4.17

Table 4.17: Thornthwaite Moisture Index Classification

| Moisture Index (Im, %) | Climate Class |
|---|---|
| <-90 | Hyper Arid |
| -90 to -80 | Arid |
| -79 to -56 | Dry Semi-Arid |
| -55 to -26 | Wet semi-arid |
| -25 to 0 | Dry sub humid |
| 1 to 20 | Wet sub humid |
| 21 to 50 | Humid |
| >50 | Very humid |

### 4.4.5   De Martonne's Aridity Index

De Martonne's (1926) proposed a method for calculating aridity index (AI) of an area using the following equation;

$$AI = [P/(T + 10) + 12p/(t + 10)]/2$$

Where, P is the mean annual precipitation in mm; T is the mean annual temperature in °C; p the precipitation of the driest month in mm; and t the mean temperature of the driest month in °C.

According to the AI values, De Martonne classified the climate into six groups namely, arid, semi-arid, dry sub humid, humid and very humid. De Martonne classification of aridity index is shown in Table 4.18.

Table 4.18: De Martonne's Aridity Index Classification

| Range | Classification |
|-------|----------------|
| ≤5 | Arid |
| 5-12 | Semi-arid |
| 12-20 | Dry Sub humid |
| 20-30 | Wet Sub humid |
| 30-60 | Humid |
| ≥60 | Very Humid |

**DROUGHT FREQUENCY**

Drought frequency was also calculated to assess relative vulnerability of regions to various intensity of drought using the formula

$$\text{Drought Proneness} = \frac{\text{Number of droughts under each category}}{\text{Total number of droughts}} \times 100$$

## 4.5   HYDROLOGICAL DROUGHT INDICES

Hydrological drought may be the result of long term meteorological droughts that results in the drying up of reservoirs, lakes, streams, rivers and a decline in groundwater levels.

Hydrological drought refers to deficiencies in surface and subsurface water supplies. It is measured as stream flow, and as lake, reservoir and groundwater levels. There is usually a delay between the lack of rain and less measurable water in streams, lakes and reservoirs. When rainfall decreases or rainfall deficit takes place over an

extended time period, the shortage will be reflected by the reduced surface water and reduced groundwater.

### 4.5.1 Normalized Difference Water Index (NDWI)

Based on the fact that water has strongest absorption while vegetation has strongest reflectivity at near infra-red, McFeeters S.K. (1996) proposed the method of NDWI to highlight water body. NDWI proved to work well in separating water body. The classification of NDWI index is shown in below Table 4.19.The following equation was used to calculate:

$$NDWI = \frac{(NIR - SWIR)}{(NIR + SWIR)}$$

Table 4.19: NDWI Classification

| Range | Classification |
|---|---|
| < 0.00 | Very Low |
| 0.00 to 0.15 | Low Moisture |
| 0.15 to 0.30 | Moderate Moisture |
| 0.30 to 0.45 | High Moisture |
| > 0.45 | Very High Moisture |

### 4.5.2 Water Ratio Index (WRI)

Due to dominating spectral reflectance of water in green (Band 2) and red (Band 3) bands as compared to Near Infra-red (Band 4) and Medium Infrared (Band 5). The value of the WRI for water bodies is greater than 1. The classification of WRI (Shen and Li 2010) index is shown in below Table 4.20.WRI is defined as below equation:

$$WRI = \frac{GREEN + RED}{NIR + MIR}$$

Table 4.20: WRI Classification

| Range | Classification |
|---|---|
| <0.00 | Extreme Dry |
| 0.00 to 0.40 | Moderate Dry |
| 0.40 to 0.60 | Medium Dry |
| 0.60 to 0.80 | Moderate Water |
| > 0.80 | High Water |

### 4.5.3  Modified Normalized Difference Water Index (MNDWI)

It was proposed that the Normalized Difference Water Index (NDWI) would delineate open water features, which is expressed as follows: Due to the limitations of NDWI, Xu (2006) proposed MNDWI which was found to be efficient in distinguishing water and urban areas.

$$MNDWI = \frac{(GREEN - SWIR)}{(GREEN + SWIR)}$$

Where, GREEN is a green band such as Landsat 8 data band 3, and SWIR is a near Shortwave Infrared (SWIR) band such as Landsat 8 data band 6. This index maximizes reflectance of water by using green light wavelengths and minimizes low reflectance of SWIR by water features. Therefore, water features are enhanced with positive values and vegetation and soil are presented as zero or negative values.

### 4.5.4  Normalized Difference Salinity Index (NDSI)

Soil salinity can be sensed directly from multi-temporal (satellite imagery) data through salinity behaviours that are noticeable at the soil surface. Salinity indices developed in the study associated with soil salinity mapping were observed for Landsat images in which two bands namely, red and near-infrared are used majorly for salinity indices. As a result, the variation between red or near-infrared can provide detailed information about the salt-affected area from an image. Below equation NDSI is as follows:

$$NDSI = \frac{RED - NIR}{RED + NIR}$$

## 4.6   AGRICULTURAL DROUGHT INDICES

Agriculture is a very crucial sector for the well existence of the socio-economic situations. Drought is a potential threat with a destructive damage to agricultural production. The necessity of a drought index specialized for agriculture led to development of various indices with explicit characteristics for Agricultural drought assessment.

The various remotely sensed data serves as input for the various methods, which are used for the identification, monitoring and assessment of the drought. It is facilitated by several satellite based indices like (NDVI, SAVI, VCI, LST, TCI, VHI,) in Visible, Near Infrared and Thermal Infrared and Microwave regions, to target and analyze the concerned areas.

### 4.6.1  Normalized Difference Vegetation Index (NDVI)

NDVI is a widely used slope based vegetation index using red and near infrared band. It is one of the most widely used vegetation indexes. Furthermore, the measurement scale has the desirable property of ranging from -1 to 1, with 0 representing the approximate value of no vegetation, and negative values non-vegetated surfaces. The following equation was used to calculate:

$$NDVI = \frac{(NIR - RED)}{(NIR + RED)}$$

Where, NIR is the reflectance in Near Infrared band, Red is the reflectance in Red band The NDVI Ranges between (-1 to +1) with positive values for vegetation and negative values for non-vegetative areas. Classification is given in Table 4.21

Table 4.21: NDVI Classification

| Range | Classification |
|---|---|
| < 0 | Extreme Dry |
| 0.0 to 0.2 | Severe Dry |
| 0..2 to 0.4 | Moderate Dry |
| 0.4 to 0.6 | Moderate Wet |
| > 0.6 | Extreme Wet |

**NDVI Deviation**

In Deviation NDVI, the NDVI data set is used by comparing the deviation of the current satellite observation from the historical average within a certain time period, or window of interest. It is calculated as:

$$Dev\ NDVI = \ NDVI_I - NDVI_{mean}$$

Where, $NDVI_i$ = month's NDVI, $NDVI_{Mean}$ = the monthly mean NDVI over considered time period. Negative values of Dev NDVI indicate below normal vegetation conditions that suggest drought situation (Berhan et al. 2011).

### 4.6.2  Soil Adjusted Vegetation Index (SAVI)

The SAVI index was developed as a modification of the NDVI. The SAVI is used to correct the influence of soil brightness. For calculation of SAVI (Qi et al.1994) below equation is used

$$SAVI = \frac{(NIR - RED)}{(NIR + RED + L)} * (1 + L)$$

Where, NIR is the near Infrared band, RED is the red band, and L is the soil brightness correction factor. Generally, L=0.5 works well in most situations and it is the default value used for calculation. For Classification the range for highly vegetation is >0.60, moderate vegetation ranges from 0.30 to 0.60, slight dense 0.00 to 0.30 and no vegetation < 0.00.

### 4.6.3   Vegetation Condition Index (VCI)

This algorithm was developed by Kogan (1995) to discriminate overall differences in ecosystem productivity, by separating short-term weather component from long-term ecological component. VCI was developed as a normalisation of NDVI, by scaling NDVI values from 0 – 1 using their relative minimum and maximum values for that composite period and location.

$$VCI = \frac{NDVI_I - NDVI_{min}}{NDVI_{max} - NDVI_{min}}$$

Where, NDVIi is the actual annual NDVI for that composite period, NDVImin and NDVImax are the relative multi-year minimum and maximum values. VCI values range from 0 – 1, with low values representing stressed vegetation conditions, middle values representing fair vegetation conditions and high values representing optimal vegetation conditions.

VCI value is being measured in percentage ranging from 1 to 100. The resulted images of Vegetation Condition Index (VCI) were classified Table 4.22 on the basis of drought severity classification proposed by Kogan (1995).

Table 4.22: VCI Classification

| VCI Range | Drought Classes |
|---|---|
| < 10 | Extreme Drought |
| 10 – 20 | Severe Drought |
| 20 – 30 | Moderate Drought |
| 30 – 40 | Light Drought |
| > 40 | No Drought |

### 4.6.4   Land Surface Temperature (LST)

i.      **Top of Atmosphere (TOA) Radiance:**

Using the radiance rescaling factor, Thermal Infra-Red Digital Numbers can be converted to TOA spectral radiance.

$$L\gamma = ML * Qcal + AL$$

Where,

| | | |
|---|---|---|
| Lγ | = | TOA spectral radiance (Watts/ (m$^2$ * sr * µm)) |
| ML | = | Radiance multiplicative Band (No.) |
| AL | = | Radiance Add Band (No.) |
| Qcal | = | Quantized and calibrated standard product pixel values (DN) |

## ii. Top of Atmosphere (TOA) Brightness Temperature:

Spectral radiance data can be converted to top of atmosphere brightness temperature using the thermal constant Values in Meta data file.

$$BT = \frac{K2}{\ln\left(\frac{k1}{L\gamma} + 1\right)} - 272.15$$

Where,

| | | |
|---|---|---|
| BT | = | Top of atmosphere brightness temperature (°C) |
| Lλ | = | TOA spectral radiance (Watts/ (m$^2$ * sr * µm)) |
| K1 | = | K1 Constant Band (No.) |
| K2 | = | K2 Constant Band (No.) |

## iii. Normalized Differential Vegetation Index (NDVI):

The Normalized Differential Vegetation Index (NDVI) is a standardized vegetation index which Calculated using Near Infra-red (Band 5) and Red (Band 4) bands.

$$NDVI = \frac{NIR - RED}{NIR + RED}$$

Where,

| | | |
|---|---|---|
| RED | = | DN values from the RED band |
| NIR | = | DN values from Near-Infrared band |

## iv. Land Surface Emissivity (LSE):

Land surface emissivity (LSE) is the average emissivity of an element of the surface of the Earth calculated from NDVI values.

$$PV = \left(\frac{NDVI - NDVI_{min}}{NDVI_{max} + NDVI_{min}}\right)^2$$

Where,

| | | |
|---|---|---|
| PV | = | Proportion of Vegetation |
| NDVI | = | DN values from NDVI Image |

NDVI min     =     Minimum DN values from NDVI Image
NDVI max     =     Maximum DN values from NDVI Image

$$E = 0.004 * PV + 0.986$$

Where,
E      =     Land Surface Emissivity
PV     =     Proportion of Vegetation

### v.     Land Surface Temperature (LST):

The Land Surface Temperature (LST) is the radioactive temperature which calculated using Top of atmosphere brightness temperature, Wavelength of emitted radiance, Land Surface Emissivity.

$$LST = BT((1 + (W * BT/14380) * LN(E)))$$

Where,
BT     =     Top of atmosphere brightness temperature (°C)
W      =     Wavelength of emitted radiance
E      =     Land Surface Emissivity

Table 4.23: LST Classification

| LST Range | Classification |
|---|---|
| 0 to 15 | Low Temperature |
| 15 to 25 | Medium Temperature |
| 25 to 35 | Average Temperature |
| 35 to 45 | High Temperature |
| 45 to 55 | Very High Temperature |

### 4.6.5  Temperature Condition Index (TCI)

This is an LST derived algorithm developed by Kogan (1995) to determine temperature related vegetation stress and excessive wetness related stress. This algorithm is similar to VCI, it is a normalisation of LST, scaled from $0 - 1$ with conditions estimated relative to their minimum and maximum temperature values for that time period.

$$TCI = \frac{LST_{max} - LST_i}{LST_{max} - LST_{min}}$$

Where, LSTmax and LSTmin are the absolute multi-year maximum and minimum LST values for that time series, respectively, while LSTi is the actual annual LST for

that composite time-period. It is significant to note that this index was developed as an inverse ratio to VCI. Therefore, TCI values ranging from 0 − 1 indicate changes from unfavourable conditions (high temperature) to most optimal conditions closer to one (low temperatures). The Classification of TCI is given in below Table 4.24

Table 4.24: TCI Classification

| TCI Range | Drought Classes |
|-----------|-----------------|
| 0 to 20 | Extreme Drought |
| 20 to 40 | Severe Drought |
| 40 to 60 | Moderate Drought |
| 60 to 80 | Low Drought |
| 80 to 100 | No Drought |

### 4.6.6   Vegetation Health Index (VHI)

Kogan (2001) developed another index called as "Vegetation Health index" (VHI) from the joint information of VCI and TCI. The TCI teams up along with VCI to forms VHI as a substitute index characterizing vegetation health. The VHI is defined as:

$$VHI = a * VCI + (1 - a) * TCI$$

Where, "a" is the coefficient determining the contribution of the two indices. The value for VHI less than 40 represents presence of vegetation stress and greater than 60 favors good condition for vegetation. The VHI Classification is given in below Table 4.25

Table 4.25: VHI Classification

| VHI Range | Drought Classes |
|-----------|-----------------|
| < 10 | Extreme Drought |
| 10 to 20 | Severe Drought |
| 20 to 30 | Moderate Drought |
| 30 to 40 | Light Drought |
| > 40 | No Drought |

## 4.7   TREND ANALYSIS TEST

Generally parametric (distribution-dependent) or non-parametric (distribution-free) statistical tests can be used to decide whether there is a statistically significant trend. A test is said to be parametric if the change evaluated by the test can be specified in terms of one or more parameters. Linear regression is an example of a parametric test. Parametric testing procedures are widely used in classical statistics. In parametric testing, it is necessary to assume an underlying distribution for the data

(often the normal distribution), and to make assumptions that data observations are independent of one another.

A long-term change analysis was performed in this study using a linear approach. A straight line was adjusted to each pixel location in the time-series data by using the least squares linear regression method. The linear regression line can be computed as follows:

$$y = a + bx$$

The extracted regression line was then used to estimate the slope, where x (time) and y (drought indices) the explanatory variable and dependent variable, respectively, are while "a" & "b" are the intercept and slope, respectively. The slope indicates the temporal change of the studied variable at the pixel level. A positive slope indicates an increasing trend, while a negative slope indicates a decreasing trend.

### 4.7.1   Mann Kendall Test

Mann Kendall test is a statistical test widely used for the analysis of trend in climatologic and in hydrologic time series. There are two advantages of using this test.

First, it is a non-parametric test and does not require the data to be normally distributed.

Second, the test has low sensitivity to abrupt breaks due to inhomogeneous time series. Any data reported as non-detects are included by assigning them a common value that is smaller than the smallest measured value in the data set. According to this test, the null hypothesis $H_0$ assumes that there is no trend (the data is independent and randomly ordered) and this is tested against the alternative hypothesis $H_1$, which assumes that there is a trend.

The computational procedure for the Mann Kendall test considers the time series of n data points and Ti and Tj as two subsets of data where i = 1,2,3,…, n-1 and j = i+1, i+2, i+3, …, n. The data values are evaluated as an ordered time series.

Each data value is compared with all subsequent data values. If a data value from a later time period is higher than a data value from an earlier time period, the statistic S is incremented by 1.

On the other hand, if the data value from a later time period is lower than a data value sampled earlier, S is decremented by 1. The net result of all such increments and decrements yields the final value of S

The Mann-Kendall S Statistic is computed as follows:

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} \text{sign}(Tj - Ti)$$

$$\text{sign}(Tj - Ti) = \begin{cases} +1 \text{ if } Tj - Ti > 0 \\ 0 \quad \text{if } Tj - Ti = 0 \\ -1 \text{ if } Tj - Ti < 0 \end{cases}$$

Where, Tj and Ti are the annual maximum daily values in years j and i, j > i, respectively.

If n < 10, the value of |S| is compared directly to the theoretical distribution of S derived by Mann and Kendall. The two tailed test is used. At certain probability level H0 is rejected in favor of H1 if the absolute value of S equals or exceeds a specified value Sα/2, where Sα/2 is the smallest S which has the probability less than α/2 to appear in case of no trend. A positive (negative) value of S indicates an upward (downward) trend. For n ≥ 10, the statistic S is approximately normally distributed with the mean and variance as follows:

$$E(S) = 0$$

The variance ($\sigma^2$) for the S-statistic is defined by:

$$\sigma^2 = \frac{n(n-1)(2n+5) - \sum t_i(i)(i-1)(2i+5)}{18}$$

In which $t_i$ denotes the number of ties to extent i. The summation term in the numerator is used only if the data series contains tied values. The standard test statistic Zs is calculated as follows:

$$Z_s = \begin{cases} \dfrac{s-1}{\sigma} & \text{for } S > 0 \\ 0 & \text{for } S = 0 \\ \dfrac{s+1}{\sigma} & \text{for } S < 0 \end{cases}$$

The test statistic Zs is used a measure of significance of trend. In fact, this test statistic is used to test the null hypothesis, H0. If |Zs| is greater than Zα/2, where α represents the chosen significance level (e.g.: 5% with $Z_{0.025} = 1.96$) then the null hypothesis is invalid implying that the trend is significant.

### 4.7.2   Sen's Slope Estimator Test

**Sen's Slope Estimator Test:** The magnitude of trend is predicted by the Sen's estimator. Here, the slope (Ti) of all data pair is computed as (sen, 1968)

$$T_i = \frac{x_j - x_k}{j - k}$$

Where, $x_j$ and $x_k$ are considered as data values at time j and k (j>k) correspondingly. The median of these N values of Ti is represented as Sen's estimator of slope which is given as:

$$Q_i = \begin{cases} T_{\frac{N+1}{2}}, & N \ is \ odd \\ T_{\frac{N}{2}} + T_{\frac{N+2}{2}}, & N \ is \ even \end{cases}$$

Sen's estimator is computed as Qmed = T (N+1)/2 if N appears odd, and it is considered as Qmed = [T$_{N/2}$ + T $_{(N+2)/2}$]/2 if N appears even. At the end, Qmed is computed by a two sided test at 100(1-α) % confidence interval and then a true slope can be obtained by the non-parametric test. Positive value of Qi indicates an upward or increasing trend and a negative value of Qi gives a downward or decreasing trend in the time series.

## 4.8   DROUGHT FORCASTING MODELS

Soft computing techniques, including FL and ANFIS models, were used in the present study to assess and monitor drought. The most important step in developing a satisfactory estimation model is the selection of proper input variables, since these variables determine the model structure and affect the accuracy of the model. Selection of proper input variables is done using the correlation coefficient between the variables.

### 4.8.1   Fuzzy Logic (FL)

Drought forecasting plays an important role in the mitigation of impacts of drought on water resources systems. Fuzzy logic system concept was introduced by Zadeh in the year 1965. A fuzzy set has a membership function that admits a degree of membership in the set from complete exclusion (0) to absolute inclusion (1). The membership represents a certain degree of belonging of the object in the fuzzy set.

Fuzzification of Input and output variables using convenient linguistics subsets such as low, medium, high, etc. IF-Then rules constructed based on expert knowledge and available information to combine the linguistic inputs subsets to the output fuzzy sets using the logical operator such as "and". The implication part of fuzzy system is defined as the shape of the consequent based on the premise (antecedent) part. Finally, having a crisp value, the resulted fuzzy set is defuzzify using the appropriate defuzzification method such as centroid.

Meteorological drought indices (SPI and RDI), accurate and reliable estimation of drought is very important. The proposed Fuzzy model uses SPI and RDI as input and drought severity class as output. Though there are several different approaches for expressing the membership function in a Fuzzy Logic, the unique evaluation of membership function is still one of the main subjects of debate in the application of this technique. The triangular-shaped membership functions have been used in the present study to express the degree of membership in a Fuzzy Logic model. These types of membership functions are simple to implement in terms of mathematical manipulations and are also adequate for practical purposes.

The steps in designing a simple Fuzzy Logic model as follows:

- Identify the variables (inputs and outputs) of the system, partition the set of each variable into a number of fuzzy subsets assigning each subset a linguistic label.
- Determine a membership function of each fuzzy subset.
- Assign the fuzzy relationships between the input fuzzy subsets on the one hand and the output fuzzy subsets on the other hand, thus forming the rule-base.
- Fuzzify the inputs to the fuzzy model.
- Use fuzzy approximate reasoning to infer the output contributed from each rule.
- Aggregate the fuzzy outputs recommended by each rule and finally apply defuzzification to form crisp output.

Different components of the FL controller structure, including the inputs, fuzzifier units, databases, rule bases, fuzzy inference engines, defuzzifier units, and outputs. The algorithm first defines the linguistic variables and terms. For instance, if the variable to be measured is temperature, it is necessary to set a range of degrees to translate the measurement in fuzzy terms [0, 1]. Membership functions must be constructed as they are essential in the fuzzification and defuzzification processes.

In other words, the membership function is used to transform the non-fuzzy input values to fuzzy linguistic terms and vice versa. Moreover, fuzzy rules are constructed to control the output variable, where the fuzzy rule is a simple IF-THEN rule with a condition and consequence. After constructing fuzzy membership functions and rules, the inference engine combines them to derive the fuzzy output. The defuzzification process produces a quantitative outcome based on the membership function, creates a lookup Table to evaluate each input to its associated output, and converts the output data in nonfuzzy values.

### 4.8.2 Adaptive Neuro-Fuzzy Inference System (ANFIS)

Adaptive Neuro Fuzzy Inference system (ANFIS) is the famous hybrid approach for modeling the complex non-linear systems, which combines the features of both fuzzy and neural network. The ANFIS having a learning algorithm which composed of least square and back propagation method called hybrid learning algorithm.

There is no systematic procedure to define the membership functional parameters in fuzzy logic. The basic problem in fuzzy system includes, defining the membership function and fuzzy rules is eliminated by using ANFIS. Adaptive neuro fuzzy inference system has a greater potential to capture the advantage of both neural network and fuzzy logic in a single frame work. ANFIS structure is shown in below Figure 4.1
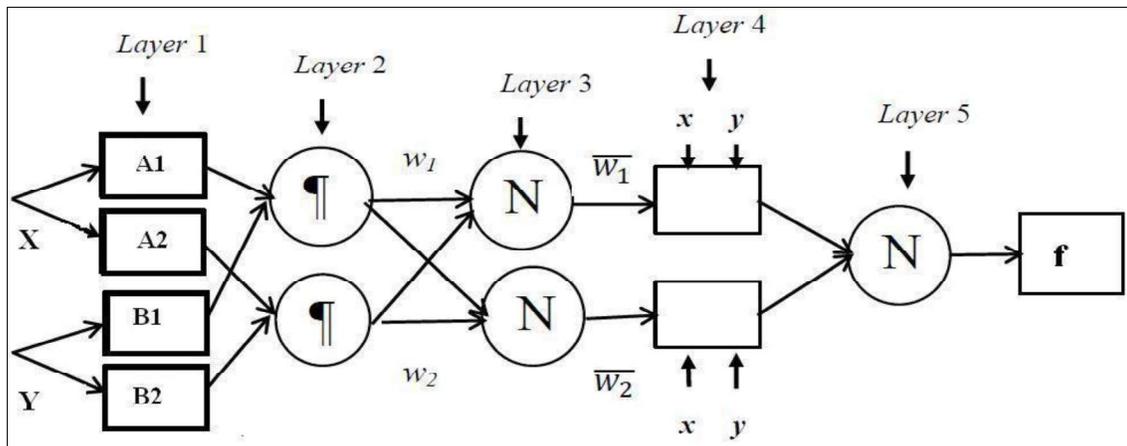


Figure 4.1: ANFIS structure used for the analysis

The ANFIS is a neuro-fuzzy system, which uses a feed-forward network to search for fuzzy decision rules that perform well on a given task. Using a given input/output data set, ANFIS creates a fuzzy inference system whose membership function parameters are adjusted using a back-propagation algorithm alone or combination of a back-propagation algorithm with a least mean squares method (hybrid learning).

ANFIS provides a method for the fuzzy modeling procedure to learn information from the data set, followed by creation of the membership function parameters that best performs the given task Antonio, (1997) and Mitra and Hayashi (2000). The ANFIS can simulate and analyze the mapping relation between the input and output data through a learning algorithm to optimize the parameters of a given Fuzzy Inference System (FIS).

The criterion chosen for development of the ANFIS model based on the selection of the following:

- Membership Function Type
- Number of Membership Functions
- Learning Algorithm
- Epoch Size
- Data Size

The model was developed using the following procedures at the ANFIS Graphical User Interface:

- Obtaining training data
- Data sizing
- Data partitioning
- Loading the data sets

### 4.8.3 Evaluation of the Performance of the Models

The performances of the developed models were compared using statistical evaluation performance indices, namely the coefficient of correlation (r), coefficient of determination ($R^2$), Root Mean-squared error (RMSE) and Maximum Absolute Error (MAE) is the most commonly used measure of success of numeric estimation. The values of these performance indices were computed from the observed and predicted values of the dependent variable. They were calculated for both the training and validation data sets. Table 4.26 shows different Performance Evaluation Parameters.

Table 4.26: Performance Evaluation Parameters

| | |
|---|---|
| **Correlation coefficient (r)** | $$\dfrac{\sum_{i=1}^{n}(y(i)-\bar{y})(\hat{y}(i)-\tilde{y})}{\sqrt{\sum_{i=1}^{n}(y(i)-\bar{y})^2 \sum_{i=1}^{n}(\hat{y}(i)-\tilde{y})^2}}$$ |
| **Coefficient of determination ($R^2$)** | $$\left(\dfrac{\sum_{i=1}^{n}(y(i)-\bar{y})(\hat{y}(i)-\tilde{y})}{\sqrt{\sum_{i=1}^{n}(y(i)-\bar{y})^2 \sum_{i=1}^{n}(\hat{y}(i)-\tilde{y})^2}}\right)^2$$ |
| **Root Mean Square Error (RMSE)** | $$\sqrt{\frac{1}{n}\left(\sum_{i=1}^{n}(x-y)^2\right)}$$ |
| **Maximum Absolute Error (MAE)** | $\max(\lvert x-y\rvert)$ |

Where,
x = observed data values. y = estimated (computed) data values.