International Journal of Applied Research 2015; 1(13): 142-155


**ISSN Print:** 2394-7500
**ISSN Online:** 2394-5869
**Impact Factor:** 5.2
IJAR 2015; 1(13): 142-155
www.allresearchjournal.com
Received: 12-10-2015
Accepted: 14-11-2015

**Banavath Ranga Naik**
Department of Civil,
M. Tech Student, SVU College of Engineering, Tirupathi, 517502, India.

**T. Hema Latha**
Asst. Proffesor,
Department of Civil,
SVU College of Engineering, Tirupathi, 517502, India.

**C. Mahesh Babu**
Department of Civil,
M. Tech Student,
SVU College of Engineering, Tirupathi, 517502, India.

**Correspondence**
**Banavath Ranga Naik**
Department of Civil,
M. Tech Student,
SVU College of Engineering, Tirupathi, 517502, India.

# Command area development by using FAO Cropwat 8.0 model and impact of climate change on crop water requirement-a case study on Araniar reservoir basin (Pichatur dam)

**Banavath Ranga Naik, T Hema Latha, C Mahesh Babu**

**Abstract**
Calculation of irrigation requirements are very important for design the irrigation projects. The irrigation requirements are not adopting scientifically in India. In the present study, the amount of Crop Water Requirement (CWR) for different crops grown in the Araniar Reservoir Basin Command area was calculated by using the FAO CROPWAT model. CROPWAT is a “crop-soil-climate” phenomena will facilitate the estimate of the crop evapotranspiration and irrigation schedule, and agricultural water requirements with different cropping patterns for irrigation planning. Estimation of Reference evapotranspiration and CWR are the very important in application such as irrigation design, irrigation scheduling, water resources management, hydrology and cropping system modelling. The model works on the climatic data as inputs such as minimum and maximum temperature, relative humidity, wind speed, sunshine hours, rainfall, soil parameters and crop details. The CWR was determined in this study for the cropping pattern of the year 2013-14. The results obtained as the CWR requires for the Kharif season as 23.49 MCM (Million Cubic Meter) to irrigate 2226.7 ha and for Rabi Season which is about 8.07 MCM to irrigate 1416 ha in the study area as per 2013 and 2014 cropping pattern system. The past climatic and rainfall data were predicted by using the Artificial Neural Network (ANN) Feed Forward Back Propagation function and IBM-SPSS Statistical model to obtain the future CWR in the study area by making an assumption that there is no change in the cropping pattern system and the future CWR was determined from the years 2015 to 2024.

**Keywords:** Crop Water Requirements, Cropwat, Irrigation Project, ANN Feed Forward Back Propagation, IBM-SPSS Statistical models, Data prediction, Future CWR.

## 1. Introduction
Construction of irrigation projects has been taken up on a massive scale in Andhra Pradesh, India. In the history of irrigation development, there is no precedence in the state and this activity is going to boost the irrigation sector in a significant manner, benefiting irrigated agriculture throughout the state. Twenty six major and medium irrigation projects are taken up for execution. Out of these, eight projects are programmed to be completed within a two year span and remaining eighteen projects within five years. The Araniar Reservoir scheme is also one of such medium projects in the state.

Irrigation is an artificial application of water to the soil usually for assisting the growth of crops. In crop production, irrigation is mainly used to replace the missing rainfall during the periods of deficit. The command areas of Pichatur and Nagalapuram mandals of Chittor district of Andhra Pradesh, India are constantly subjected to drought and are in urgent need of water for meeting their irrigation requirements. There is an urgent need for the provision of wholesome drinking water for the villages presented in the Pichatur Mandal of Chittor district of Andhra Pradesh. The only source of water to the people of this area is the Araniar River, which forms the southern boundary of the district. There are several public representations to Government of Andhra Pradesh for taking up a scheme on supply of water from foreshore of Araniar Reservoir to irrigate the lands of Pichatur and part of Nagalapuram mandals. Accordingly the State Government has taken up detailed investigation of the Araniar Reservoir in irrigate command area of 2226.7 ha (5500 acres in the Kharif season) and 1417 ha (3497 acres in the Rabi season) for raising I.D (Irrigated Dry) crops.

Proposed cropping pattern based on soil suitability & meteorological factors, by the Govt. of Andhra Pradesh under the Araniar Basin for the year 2014 is 518 ha (1279.46 acres) of Sugarcane, 273.4 ha of Cotton, 217.8 ha of Rice, 208 ha of Sunflower, 126.8 ha of the Onion, 144.6 ha of Groundnut, 151 ha of Mango and 172 ha of other crops like Wheat, Chillies, Brinjal, Tomato, Fruits, Beans totalling to 2226.7 ha (5500 acres) in the Kharif Season (July-Oct) only.

Similarly proposed cropping pattern based on soil suitability and meteorological factors by Govt. of Andhra Pradesh under Araniar Basin for the year 2013-14 Rabi season(Oct-Mar) is 449.18 ha (1109.5 acres) of Ground nut, 283.4 ha (700 acres) of Rice, 148.78 ha (367.49 acres) of Sunflower, 99.19 ha (245 acres) of Chillies, 80 ha (197.6 acres) of Cotton, 105.3 ha (260.4 acres) of Banana and 241.15 ha (596 acres) of other crops like Wheat, Tomato, Brinjal, Grapes, Water melon, Onion, Beans totalling of 1416 ha (3497 acres) in the Rabi season.

Crop water demand is calculated as the product of the estimated reference evapotranspiration ($ET_{0)}$ and the crop factor ($K_c$).

CROPWAT for Windows is a decision support system developed by the Land and Water Development Division of FAO, Italy with the assistance of the Institute of Irrigation and Development Studies of Southampton, UK and National Water Research Centre, Egypt. The model carries out calculations for reference evapotranspiration, crop water requirements and irrigation requirements in order to develop irrigation schedules under various management conditions and schemes of water supply. It allows the development of recommendations for improved irrigation practices and for the planning of irrigation schedules and the assessment of production under rain fed conditions or deficit irrigation (Adriana and. Cuculeanu (1999) [1]. CROPWAT for Windows uses the FAO (1992) [13] Penman-Monteith method for calculation of reference crop evapotranspiration. The development of irrigation schedules and evaluation of rain fed and irrigation practices are based on a daily soil-moisture balance, using various options for water supply and irrigation management conditions. Scheme of water supply is calculated according to the cropping pattern provided in the program. (Smith *et al*., 1992) [13].

Artificial Neural Network (ANN) is a massively parallel – disturbed information processing system that has certain performance characteristics resembling biological neural networks of the human brain (Haykin, 1994) [2]. ANNs are developed as generalization of mathematical models of human cognition or neural biology. Their development is based on following rules

- Information processing occurs at many single elements called nodes, also referred as units, cells or neurons.
- Signals are passed between nodes through connection links.
- Each connection links has an associated weight that represents its connection strength.
- Each node typically applies a transformation called an activation function to its net input to determine its output signal.

A neural network is characterized by its architecture that represents the pattern of connection between nodes, its method of determining the connection weights, and the activation function. ANNs can also be categorized based on the direction of the information flow and processing. In a feed forward network, the nodes are generally arranged in layers starting from the first input layer and ending at the final output layer. There can be several hidden layers, with each layer having one or more nodes. Information passes from the input to the output side. The nodes in one layer are connected to those in the next, but not to those in the same layer. Thus, the output of a node in a layer is only a dependent on its inputs it receives from previous layers and corresponding weights. On the other hand, in a recurrent ANN, information flows through the nodes in both directions, from the input to the output side and vice-versa. This is generally achieved by recycling previous network outputs as current inputs, thus allowing for feedback.

In most networks, the input layer receives the input variables that influence the output and provides information to the network. The output layer consists of values predicted by the network and thus represents model output. The number of hidden layers and the number of nodes in each hidden layer are usually determined by trial and error procedure. The nodes with in the neighbouring layers of the network are connected by links. A synaptic weight is assigned to each link to represent the relative connection strength of the two nodes at both ends in predicting the input-output relationship. The activation functions commonly used are linear, Log-Sigmoid and Tan – Sigmoid.

The back propagation algorithm involves two steps. The first step is forward pass, in which the effect of the input is passed forward through the network to reach the output layer. After the error is computed, a second step starts backward through the network. The errors at the output layer are propagated back toward the input layer with the weights being modified based on momentum factor and learning rate. The momentum factor speeds up training and prevents oscillations in the weights. The learning rate is used to increase the chance of avoiding the training process being trapped in local minima instead of global minima.

The performance of a trained ANN is evaluated by subjecting it to new patterns. The performance of the network is determined by computing the percentage error between predicted and desired values. In addition, plotting the model output versus desired response is also used to assess the performance of ANN. The training and validation processes are repeated several times for finding optimal network to ensure satisfactory results.

IBM SPSS Forecasting is the SPSS time series model. A time series is a set of observations obtained by measuring a single variable regularly over time. Time series forecasting is the use of a model to predict future events based on known past events.

A crucial feature of the IBM SPSS Forecasting module is the Expert Modeller. Rather than defining the parameters and settings of time series models manually, the Expert Modeller automatically identifies and estimates the best-fitting ARIMA or exponential smoothing model for one or more dependent variable series. Although users can specify a custom ARIMA or exponential smoothing model manually, Expert Modeller eliminates a great deal of the trial and error associated with doing so.

A further aspect of the Forecasting module is the Apply Time Series Models procedure which applies an existing time series model to the active data set. This allows you to obtain forecasts for series for which new or revised data are available, without rebuilding your models.

In this present study, In order to know the monthly demand of water for the development of Araniar Reservoir Basin command area, CROPWAT 8.0 software is applied. The present study is useful to assess the feasibility of the multipurpose projects and to evolve the optimal operation policy for proper utilization of resources.

The objectives of this study are determination of Reference Evapotranspiration (ETo) by using Penman-Monteith method through the help of CROPWAT model using climatic data of Pichatur Station, the probability of exceedance functions on rainfall data to obtain the dry year condition for optimal development of irrigation projects, determination crop water requirements by using a CROPWAT model for the present scenario (2014 Kharif and Rabi season), prediction of climatic data by using ANN-Back Propagation Feed Forward Function to determine the future CWR, prediction of climatic data by using IBM-SPSS model to obtain future CWR, validating models for the predicted data and estimation of future crop water requirements, i.e., from 2015-2024 by making an assumption that there is no change in the irrigated area (2013-14 cropping pattern is constant).

## 2. Study Area and Climate

### 2.1 Location

The Araniar River originates near Karvetinagar forest in Andhra Pradesh, flows through Thiruvallur District of Tamil Nadu in the eastern direction and falls into Bay of Bengal. It is an ephemeral river and the flood in the river is sporadic. The river basin lies between latitudes 13$^{0}$15’12” and 13$^{0}$32’00”N and, longitudes 79$^{0}$24’40” and 80$^{0}$20’54”E partly in Thiruvallur District, Tamil Nadu and partly in Chittoor District, Andhra Pradesh. The location map of the study area is shown in fig.

The river flows over a length of 65.2 km from its origin in Andhra Pradesh upto Surutapalli anicut and, and over a length of 66.4km in Tamil Nadu amounting to a total length of 131.6km with a catchment area of 1281.3 sq. km. Surutapalli anicut and Pichatur dam in Andhra Pradesh and A.N. Kuppam and Lakshmipuram anicuts in Tamil Nadu are located along the river course. The drainage of basin is bounded by Bay of Bengal in the east, Chittoor District in the west, Swarnamukhi river basin in the north and Kosasthalaiyar river basin in the south.

The basin has an elevation of 3m above mean sea level at the coastal area in the eastern side, rises gently westwards to 1040m high in the upper reaches at Narayanavanam forest in the northwest region and, 565m high at Karvetinagar forest in the West. The surface layers of the basin include sandy, loamy sand, sandy clay loam, clay loam and sandy clay soils. Geologically the study area consists of hard rock formation such as epidote-hornblende gneiss and hornblende-biotite gneiss in the western part and grey brown to black sandy clay formation (sedimentary) in the eastern part.

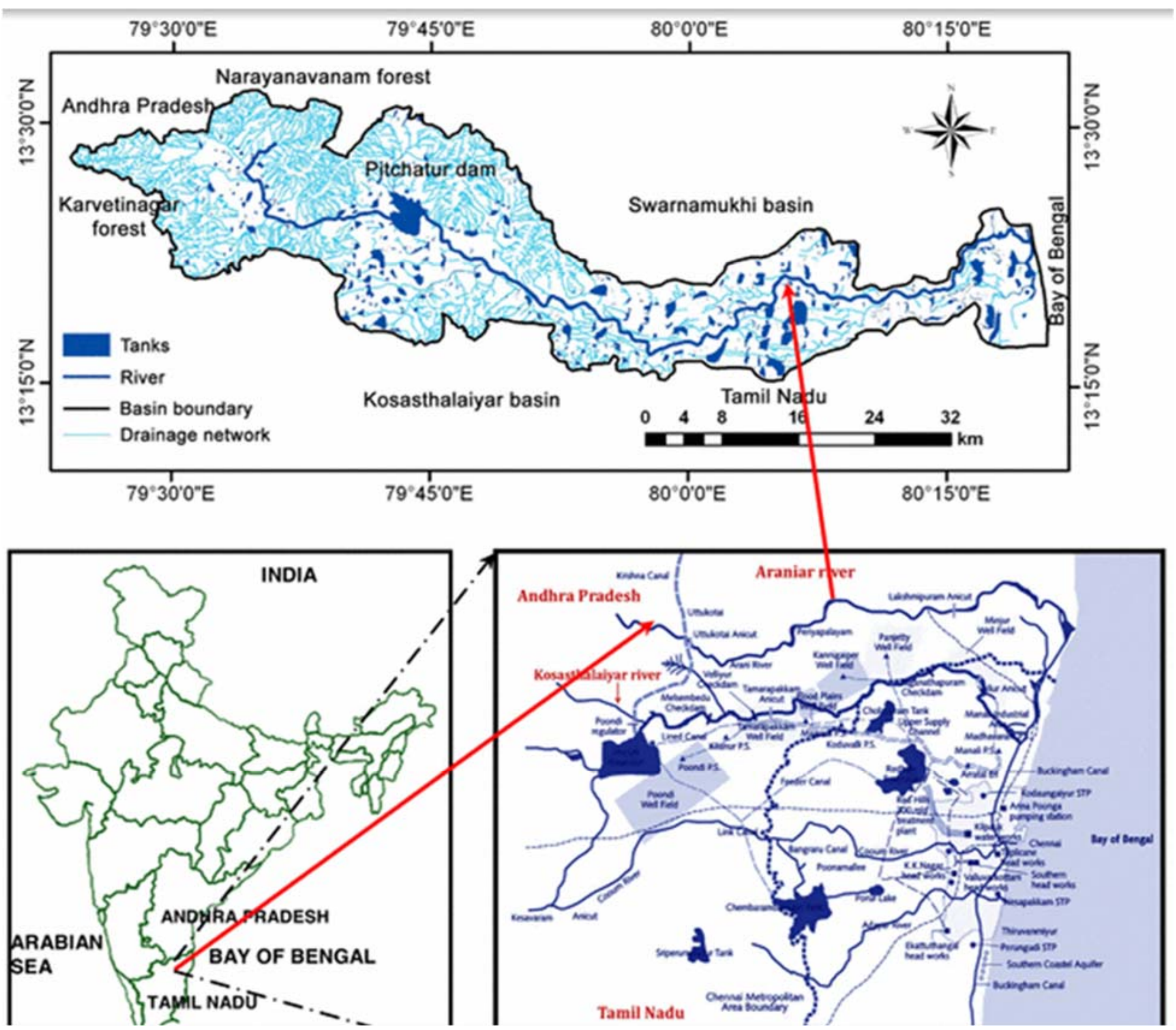



**Fig 1:** Location Map of the Study Area

### 2.2 Data Collection and Climate

The data required for the model inputs are collected from the Chief Planning Office (CPO) of Chittoor district of Andhra Pradesh. To get more accuracy and effective development of irrigation project more data to be required. In the present study the climatic data collected about 30 years (1985-2014). The average annual rainfall for the period 1985-2014 was 1198 mm. The maximum and minimum temperatures of the study area vary between 30 $^0$C to 44 $^0$C and 17 $^0$C to 28 $^0$C respectively with mean monthly relative humidity ranging between 43% and 73%.

## 3. Methodology and Materials Used

### 3.1 Cropwat Model Description

Several versions of CROPWAT have been released. CROPWAT 8.0 is an update of earlier versions, which were based on the Modified Penman method, and is based on the sole recommended FAO Penman-Monteith method of estimating $ET_o$. The programme uses monthly climatic data (temperature, relative humidity, wind speed, sunshine hours, and rainfall) for the calculation of reference evapotranspiration.

It has also four different methods to calculate effective rainfall but to be able to do this it requires dependable rainfall as input. Through the input of crop data (growth stages, $K_c$ factors, root zone depth and allowable soil moisture depletion factor), the programme calculates the crop water requirements on a decade (10-day) basis.

CWR depend on climatic conditions, crop area and type, soil type, growing seasons and crop production frequencies (FAO, 2009; George *et al*., 2000) [7]. CROPWAT is a collection of modules following the Penman–Monteith method that integrates several models necessary to predict CWR, irrigation water management and crop scheduling (Smith, 1991) [6]. It follows the FAO approved Penman–Monteith method to predict reference evapotranspiration ($ET_o$), crop evapotranspiration ($ET_c$) and irrigation water management (FAO, 1998; Smith, 1991) [8]. It is to be noted that $ET_c$ represents the amount of water that crop losses due to evapotranspiration while CWR represent the amount of water to be supplied (Mhashu, 2007) [9]. CWR were estimated for each crop and then added through the irrigation scheme planning to predict the total water requirements. The first step in the CROPWAT software is to predict $ET_c$ on a 10 day basis (e.g., time step = 10 days) as:

$$ET_c = ET_o * K_c$$

Where,

$ET_c$ = actual evapotranspiration by the crop (mm/ day),
$ET_o$ = reference evapotranspiration (mm/day),
$K_c$ = crop coefficient at a specific growth stage.

$K_c$ depends on the type of crop (e.g., height of crop, resistance of canopy, albedo), soil and climatic parameters, such as, soil surface, evaporation and wind speed and direction (FAO, 1998; Smith and Kivumbi, 2006) [3].

The Penman–Monteith method has been recommended by the Food and Agriculture Organization (FAO) for its appropriate combinations of relevant climatic parameters for predicting $ET_o$ (FAO 1998; Smith and Kivumbi, 2006; Mhashu, 2007) [4].

### 3.1.2 Calculation of Reference Evapotranspiration (Eto):

As explained above, the FAO Penman-Monteith method is now the sole recommended method for determining reference crop evapotranspiration ($ET_o$). This method overcomes the values that are more consistent with actual crop water use data in all regions and climates.

The Penman-Monteith Equation is given by the following equation (FAO, 1998a) [5].

$$ET_0 = \frac{0.408\ \Delta^1 (R^1n\text{-}G) + \Upsilon^1 (900/T+273)\ u_2 (e^1_s - e^1_a)}{\Delta^1 + \Upsilon^1 (1 + 0.34\ u_2)}$$

Where

ET = Reference evapotranspiration (mm/day)
Rn= Net radiation at the crop surface (MJ/m$^2$ /day
G = Soil heat flux density (MJ/m$^2$ per day)
T = Mean daily air temperature at 2 m height (°C)
$u_2$ = Wind speed at 2 m height (m/sec)
$e_s$ = Saturation vapour pressure (kPa
$e_a$ = Actual vapour pressure (kPa)
$e_s$-$e_a$ = Saturation vapour pressure deficit (kPa)

### 3.1.3 Rainfall Data

The rainfall contributes greater/lesser extent in satisfying crop water requirement, depending on the location. During monsoon in tropical & some semi-tropical regions, a great part of the crop's water needs are covered by rainfall, while during the dry season, the major supply of water should come from irrigation. It is difficult to predict the contribution of rainfall and contribution of irrigated water as rainfall varies greatly from season to season.

Statistical analysis of long term rainfall record is required to estimate the rainfall deficit for irrigation water requirement. Rainfall used by the crop varies from year to year, due to surface runoff and deep percolation below the root zone.

To determine the portion of the rainfall which effectively contributes to cover crop water requirement, 30 average annual series of monthly rainfall records are processed, by taking weighted average from 2 rain gauge stations namely Pichatur and Nagalapuram, to represent average climatic conditions of Araniar Basin command area. Average rainfall of 30 series records of Araniar Basin command area is *1215mm*.

The amount of dependable rainfall corresponding to 80% probability of exceedance represent a dry year, commonly used for design of the irrigation system capacity. The dependable rain fall corresponding to 20%, 50% and 80% probability of exceedance indicates wet, normal and dry years respectively. The rainfall in normal years is nearly equal to the average rainfall (1215mm).

The rainfall data of dry year is used for the designing of irrigation system capacity. Processed rainfall data for dry, wet and normal can be obtained by computing and plotting probabilities from the rainfall records. The various steps involved are:

i. Yearly rainfall data for 30 years are tabulated
ii. Data is arranged in descending order of magnitude.
iii. Plotting position is tabulated as

$$F_a = 100 * \frac{m}{(N+1)}$$

Where: N = number of records
m = rank number
Fa = plotting position

iv. Values are plotted on log normal scale to obtain logarithmic regression equation.
v. Year values at 20%, 50% and 80% probabilities are calculated as wet ($P_{20}$) = 1431mm, normal ($P_{50}$) = 1102mm and dry ($P_{80}$) = 911mm.
vi. Monthly values of dry year are determined according to the relationship

$$P_{idry} = P_{iav} * [\frac{P_{dry}}{P_{av}}]$$

Where
$P_{iav}$= average monthly rainfall for month i
$P_{idry}$=monthly rainfall dry year for month i
$P_{av}$=average yearly rainfall
$P_{dry}$=yearly rainfall at 80% probability of exceedance

### 3.1.4 Effective Rain Fall

In order to account for the losses due to runoff or percolation, effective rain fall is calculated by empirical method. Dependable rain empirical formula according to Food and Agriculture Organization of United Nations/Water Resources Development Management Service (FAO/AGLW) is

Effective rain fall, Pe = 0.6 * P -10 for rain fall <= 70 mm.
Effective rain fall, Pe = 0.8* P - 24 for rain fall >= 70 mm.

### 3.1.5 Cropping Details

The CROPWAT 8.0 software allows unto maximum of 30 crops data. It has some predefined crops and one can modify or edit the properties of the crop which are inbuilt and can define new crops also which are not present in the software.

The crop properties include name of the crop, first planting date, first harvesting, crop factors, rooting depth, yield response factors, percentage of total area planted and others are collected from regional research agricultural centre, Tirupati, Andhra Pradesh.

## 3.2 Artificial Neural Network (Ann)

### 3.2.1 Pre-Processing of Data

Prior to the training of the network, the input or output dataset was normalized using simple formula of mathematics. The dataset was scaled to range between 0 and 1. The normalized input/output dataset was then partitioned into two subsets consisting training dataset 75% and the test dataset 25%.

The data normalization is done with the formula given below:

$$\text{Normalized}_{\text{data}} = \frac{X_i - X_{MIN}}{X_{MAX} - X_{MIN}}$$

Where Xi = data in a column,
Xmax = maximum data in the column,
Xmin = minimum data value in the column.

### 3.2.2 The Model Building Process and Sequential Steps

(i) Selection of the input and output for the supervised Back propagation learning
(ii) Selection of the activation function
(iii) Training and testing of the model
(iv) Testing the goodness of fit of the model

The Back propagation Algorithm (BP) and the method of steepest descent opened up the application of Multi layered ANN for many problems of practical interest (Sahai *et al*., 2000, 2003; Kamarthi and Pittner, 1999; Sejnowski and Rosenberg, 1987; Widrow and Lehr, 1990) [10]. A multi layered ANN contains three basic types of layers: input layer, hidden layer and output layer. Basically, the Back propagation learning involves propagation of error backwards from the output layers to the hidden layers in order to determine the update for the weights leading to the units in the hidden layer.

From the whole dataset, the input and the desired output matrices are generated. The input data are separated into training and test data set. The training set consists of 75% of the whole data and the remaining 25% constitutes the test set. The input matrix contains twelve columns that correspond to the average monthly temperature, relative humidity, wind speed and sun shine hours over the study period and pertains to the months of January to December. The ANN model generated here is a single-hidden-layer model, and the hidden layer contains 2 nodes. After running the model up to 1000 epochs, the results are validated for the test set.

In the present study, we have 30 years observed climatic and rainfall data of the study area. Among the 30 years data, 75% data given as training and the remaining 25% data given as validation data (sample). In the training dataset values which is divided into input and target data sets. By using the Feed Forward Back propagation function the input and target data were trained. In the present studies for the prediction of any climatic data the feed forward back propagation is the best suitable function. In the training function tan sigmoidal was used. Mean Square Error function was considered for the performance function.

The training data given as input layer and target layer. Here a combination of target and input layers were arranges their hidden layers and weights would prepare. The number of layers used in this practice is 3 i.e., input layer, hidden layer, and output layer. Only 2 neurons were used.

### 3.3 IBM-SPSS Forecasting

IBM SPSS Forecasting is the SPSS time series model. A time series is a set of observations obtained by measuring a single variable regularly over time. Time series forecasting is the use of a model to predict future events based on known past events.

A crucial feature of the IBM SPSS Forecasting module is the Expert Modeller. Rather than defining the parameters and settings of time series models manually, the Expert Modeller automatically identifies and estimates the best-fitting ARIMA or exponential smoothing model for one or more dependent variable series. Although users can specify a custom ARIMA or exponential smoothing model manually, Expert Modeller eliminates a great deal of the trial and error associated with doing so.

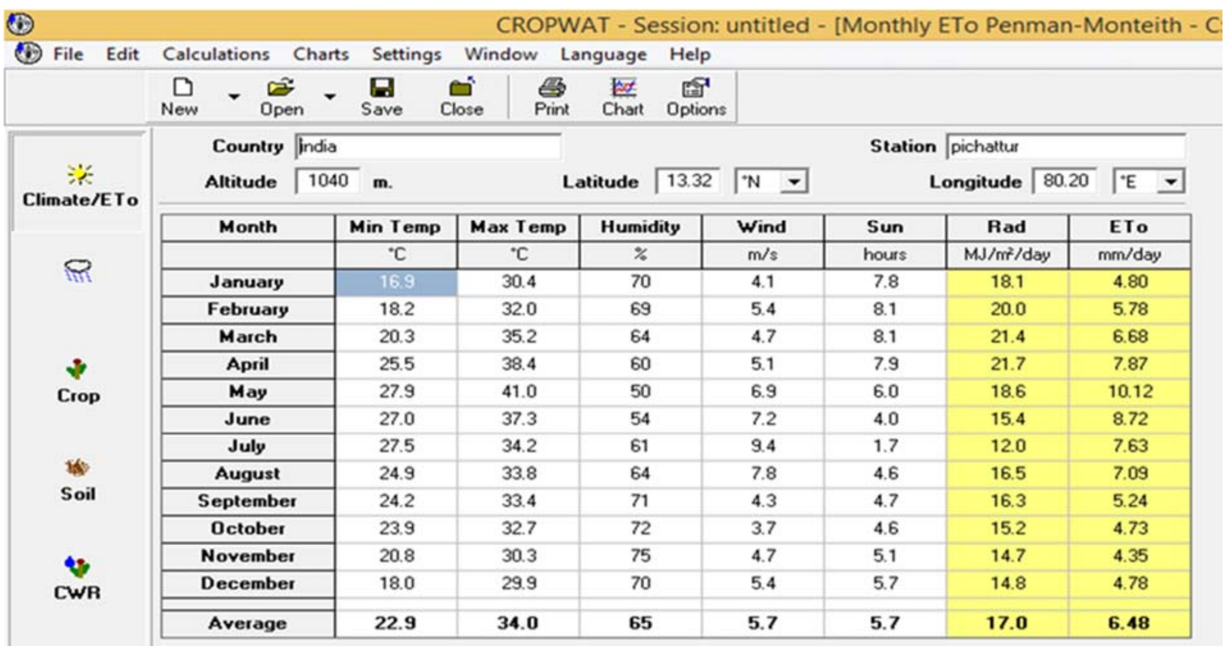
A further aspect of the Forecasting module is the Apply Time Series Models procedure which applies an existing time series model to the active data set. This allows you to obtain forecasts for series for which new or revised data are available, without rebuilding your models.

In this model the past data sets from 2005 to 2014 was used for prediction. And these predicted values are compared with the observed data, i.e. from 2005 to 2014. Then the coefficient of regression ($R^2$) was determined. Hence, these predictions give a good fit for the analysis.

## 4. Results

### 4.1 Reference Evapotranspiration

The reference evapotranspiration of Pichatur station are calculated by using Penman-Monteith method and it is shown in the following figures. It is observed that from the above figures the reference evapotranspiration (Eto) was the high in the month of May i.e.,10mm/day and which is due to high temperature (average high temperature for the month May is 41 ºC) and minimum humidity (50% of average for the month of May). And also the minimum ETo was in the month of November (4.35mm/day). The annual average reference evapotranspiration (ETo) of the Kharif season is 6.48mm/day.




| Month | Min Temp | Max Temp | Humidity | Wind | Sun | Rad | ETo |
|---|---|---|---|---|---|---|---|
| | °C | °C | % | m/s | hours | MJ/m²/day | mm/day |
| January | 16.9 | 30.4 | 70 | 4.1 | 7.8 | 18.1 | 4.80 |
| February | 18.2 | 32.0 | 69 | 5.4 | 8.1 | 20.0 | 5.78 |
| March | 20.3 | 35.2 | 64 | 4.7 | 8.1 | 21.4 | 6.68 |
| April | 25.5 | 38.4 | 60 | 5.1 | 7.9 | 21.7 | 7.87 |
| May | 27.9 | 41.0 | 50 | 6.9 | 6.0 | 18.6 | 10.12 |
| June | 27.0 | 37.3 | 54 | 7.2 | 4.0 | 15.4 | 8.72 |
| July | 27.5 | 34.2 | 61 | 9.4 | 1.7 | 12.0 | 7.63 |
| August | 24.9 | 33.8 | 64 | 7.8 | 4.6 | 16.5 | 7.09 |
| September | 24.2 | 33.4 | 71 | 4.3 | 4.7 | 16.3 | 5.24 |
| October | 23.9 | 32.7 | 72 | 3.7 | 4.6 | 15.2 | 4.73 |
| November | 20.8 | 30.3 | 75 | 4.7 | 5.1 | 14.7 | 4.35 |
| December | 18.0 | 29.9 | 70 | 5.4 | 5.7 | 14.8 | 4.78 |
| Average | 22.9 | 34.0 | 65 | 5.7 | 5.7 | 17.0 | 6.48 |

**Fig 2:** Determination of Reference Evapotranspiration (Eto)

### 4.2 Consumptive Irrigation Requirement (Cir)

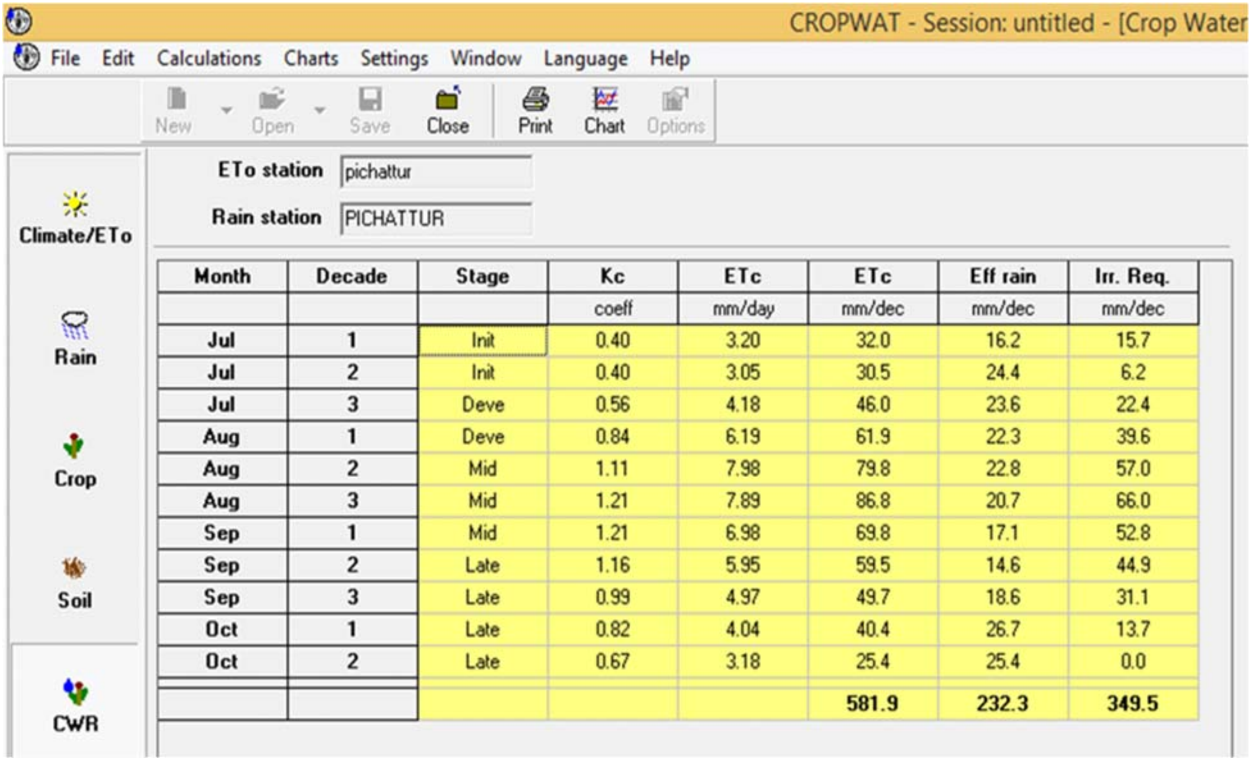
It is defined as the amount of irrigation water that is required to meet the evapotranspiration needs of a crop during its full growth. However, if during the growth period of a crop, rain occurs, a part of it will be retained by the soil in the root zone and the some will be available to meet a part of the evapotranspiration requirements of the crop and hence the quantity of irrigation water required to be applied will be correspondingly reduced.

Thus, if $ET_c$ or $Cu$ is the evapotranspiration or consumptive use of water for a crop and Re is the effective rainfall during the growth period of the crop then

$$CIR = ET_c - Re \text{ (or } Cu - Re)$$

### 4.3 Crop Water Requirement for Araniar Reservoir Basin Command Area

Calculation of Crop water requirement can be carried out by calling up successively the appropriate climate and rainfall data sets, together with the crop files and corresponding planting dates. Crop water requirements of different crops of Araniar Reservoir Basin are shown in the following figure.

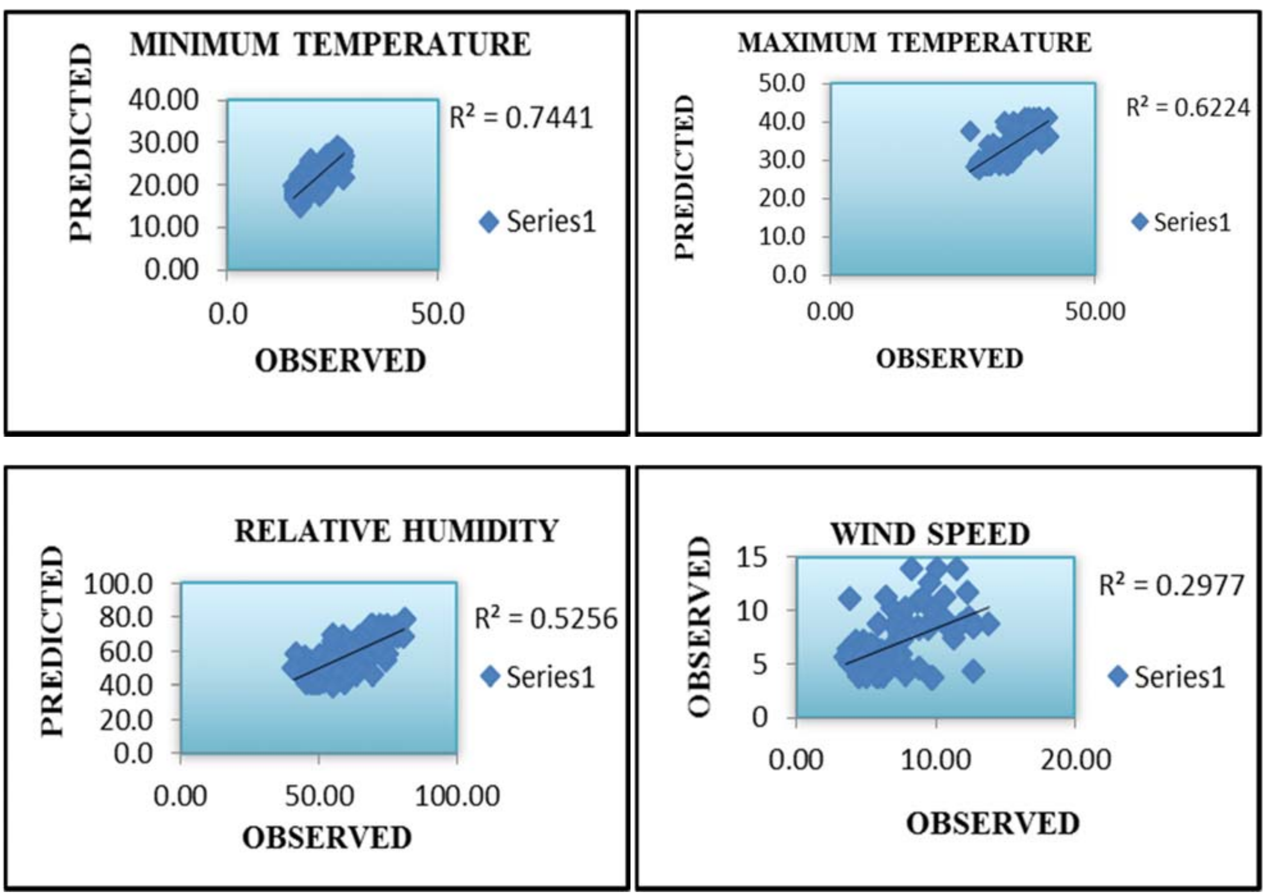



| Month | Decade | Stage | Kc | ETc | ETc | Eff rain | Irr. Req. |
|---|---|---|---|---|---|---|---|
| | | | coeff | mm/day | mm/dec | mm/dec | mm/dec |
| Jul | 1 | Init | 0.40 | 3.20 | 32.0 | 16.2 | 15.7 |
| Jul | 2 | Init | 0.40 | 3.05 | 30.5 | 24.4 | 6.2 |
| Jul | 3 | Deve | 0.56 | 4.18 | 46.0 | 23.6 | 22.4 |
| Aug | 1 | Deve | 0.84 | 6.19 | 61.9 | 22.3 | 39.6 |
| Aug | 2 | Mid | 1.11 | 7.98 | 79.8 | 22.8 | 57.0 |
| Aug | 3 | Mid | 1.21 | 7.89 | 86.8 | 20.7 | 66.0 |
| Sep | 1 | Mid | 1.21 | 6.98 | 69.8 | 17.1 | 52.8 |
| Sep | 2 | Late | 1.16 | 5.95 | 59.5 | 14.6 | 44.9 |
| Sep | 3 | Late | 0.99 | 4.97 | 49.7 | 18.6 | 31.1 |
| Oct | 1 | Late | 0.82 | 4.04 | 40.4 | 26.7 | 13.7 |
| Oct | 2 | Late | 0.67 | 3.18 | 25.4 | 25.4 | 0.0 |
| | | | | | 581.9 | 232.3 | 349.5 |

**Fig 3:** CWR of Groundnut for Kharif Season

Similarly the different crops (Kharif season) such as sugar cane, rice, sunflower, wheat, onion, chillies, brinjal, tomato, beans, mango, cotton, and water melon were calculated and are shown in the following table.

### 4.4 Results from Ann



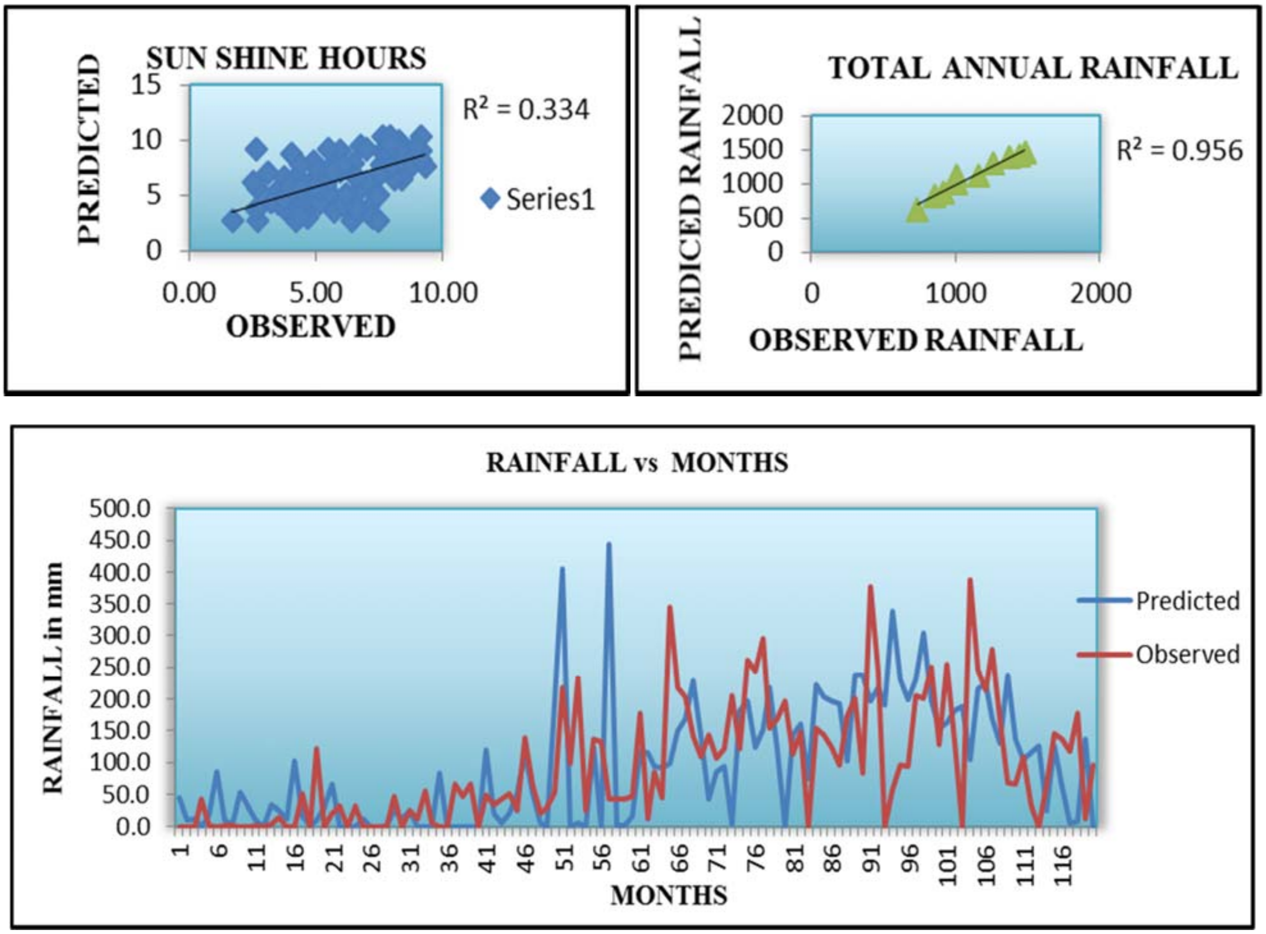
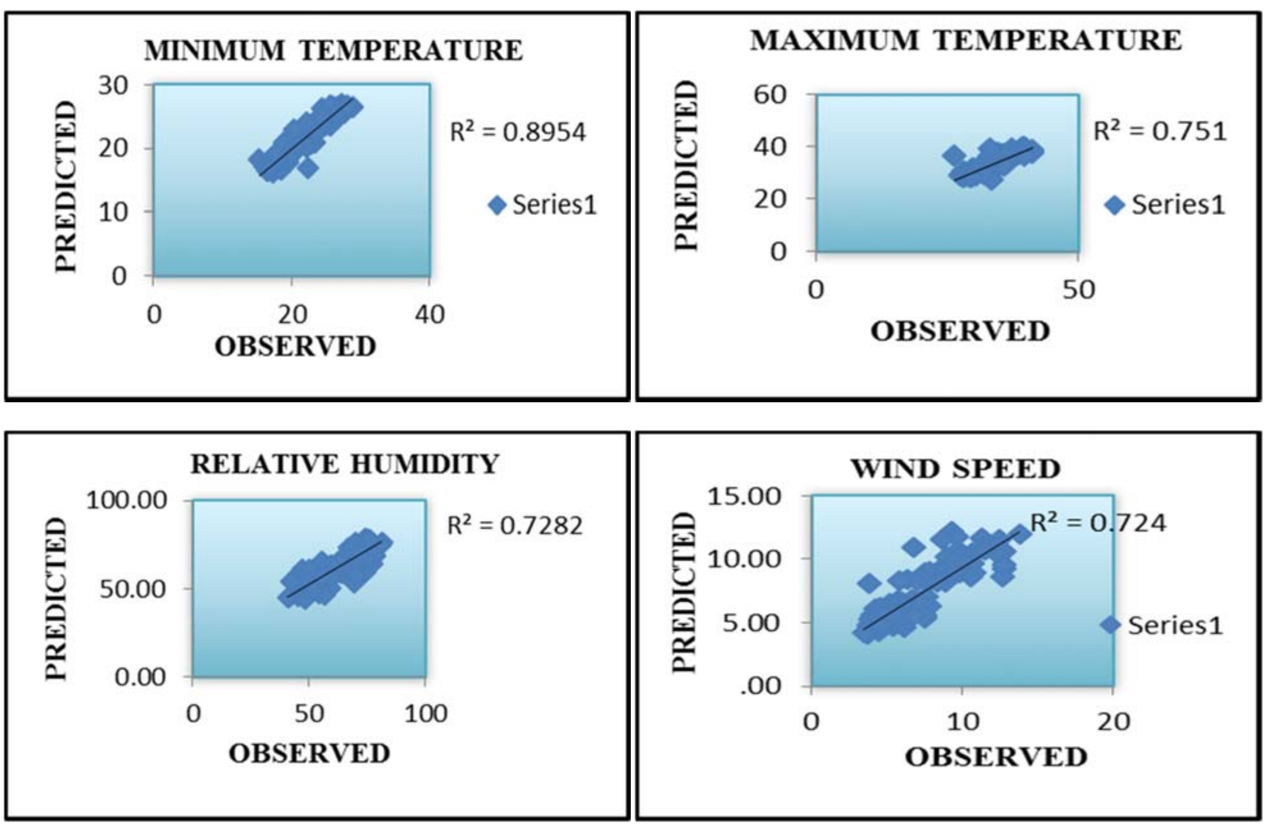



**Fig 4:** Results of Predicted Climatic Parameters Ann

### 4.5 Results from IBM-SPSS Forecasting



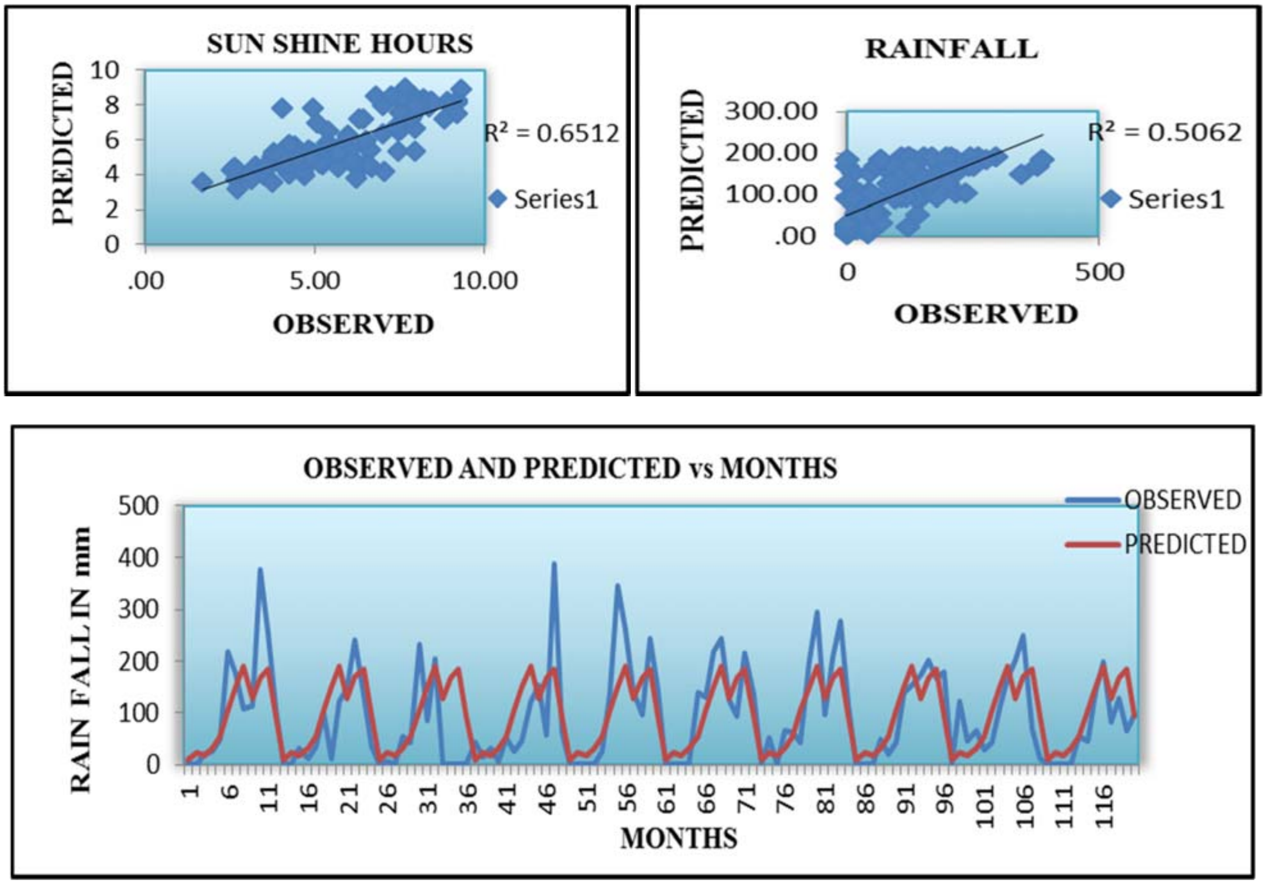



**Fig 5:** Forecasted of Climatic Parameters from IBM-SPSS Statistics

From the above two models we can observe that the regression co-efficient ($R^2$) is better for the IBM-SPSS model results. Hence these outputs were considered for the calculations of future crop water requirements of the Pichatur reservoir basin command area.

**Table 1:** Regression Coefficients ($R^2$) of Two Models

| S No | Parametre | | Regression Co-Efficient ($R^2$) | | Regression Co-Efficient ($R^2$) |
|---|---|---|---|---|---|
| 1 | Minimum Temperature | Ann Feed Forward Back Propagation Model | 0.74 | IBM-SPSS Model (Statistical Model) | 0.89 |
| 2 | Maximum Temperature | | 0.62 | | 0.75 |
| 3 | Relative Humidity | | 0.52 | | 0.72 |
| 4 | Wind speed | | 0.29 | | 0.72 |
| 5 | Sun Shine Hours | | 0.33 | | 0.65 |
| 6 | Rainfall | | 0.95 | | 0.50 |

From the above table it is clear that the regression coefficients ($R^2$) is more for all the parameters like minimum and maximum temperature, relative humidity, wind speed and sun shine hours from the IBM-SPSS model outputs than the ANN model.

In case of rainfall data the $R^2$ was more from the ANN model than the IBM-SPSS model. This rainfall data was considered for the other studies.

Graph 1 and graph 2 showing the result of total CWR from the plating to harvesting and the CWR was high for mango (2340), sugarcane (2319) and least for wheat (319mm) and sorghum (264mm). From the table 5, we can observe that the monthly requirement of CWR for different crops are shown and the maximum CWR was required in the months of august and September (1950.6 mm and 1927.8 mm of water) for the all crops grown in the Kharif season and which is minimum in the months of January, February, March, April, May and December because the is only few crops were irrigated like sugarcane, mango, and partly rice and cotton. The monthly requirements of CWR in the Kharif season is 2.85MCM in the September and 2.77MCM in the month of June and minimum CWR is 1.24 MCM in the month of July and 1.41MCM in February.

The CWR required for banana is the maximum in the Rabi season and the cotton, grapes and rice crops also need more water for their good productivity. Beans, water melon, brinjal and chillies require less water than the other crops.

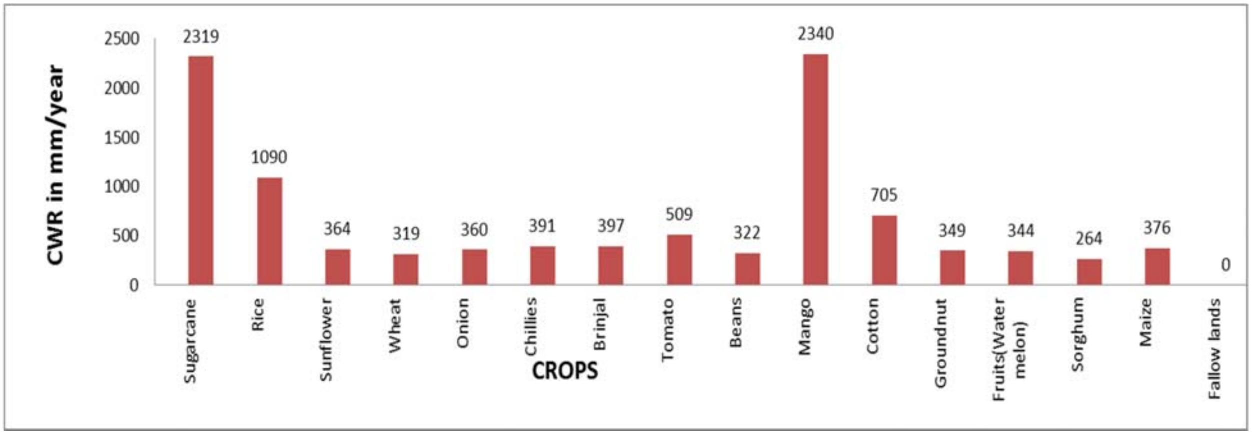
The CWR required maximum in the January month(1.49MCM) and minimum in the month of November (0.097MCM) and the maximum CWR required for the rice (2.37MCM) and minimum for the beans (0.059) and for Brinjal (0.09MCM) in the Rabi season.

**Table 2:** Monthly CWR Calculations for Kharif Season (Mm of Water)

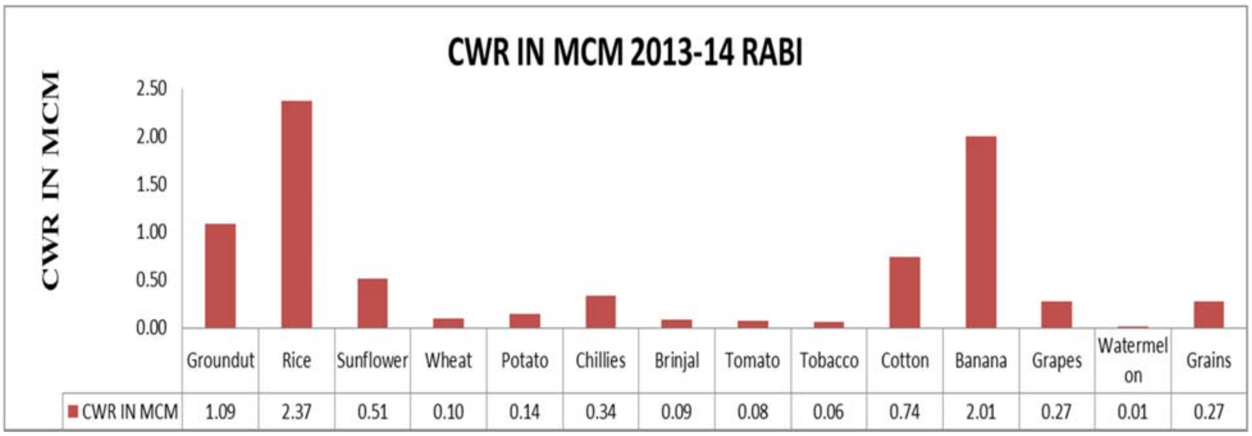
| S. No | Crop | Area Irrigated (Ha) | Monthly Cropwater Requirement(Mm/Month) | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | July | Aug | Sept | Oct | Nov | Dec | Jan | Feb | Mar | Apr | May | June | Mm/Year | MCM/Year |
| 1 | Sugarcane | 518 | 31.2 | 77 | 130 | 117 | 178 | 196 | 200.4 | 215.3 | 278.6 | 295.8 | 344.4 | 254.7 | 2319 | 12.014 |
| 2 | Rice | 217.8 | 200.5 | 201 | 150 | 73 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 466.2 | 1090 | 2.374 |
| 3 | Sunflower | 208 | 22.9 | 121 | 138 | 68 | 14 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 364 | 0.756 |
| 4 | Wheat | 107 | 8.9 | 104 | 137 | 56 | 12 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 319 | 0.341 |
| 5 | Onion | 126.8 | 44.1 | 160 | 139 | 16 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 360 | 0.456 |
| 6 | Chilly | 71.2 | 78.8 | 113 | 120 | 71 | 8 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 391 | 0.278 |
| 7 | Brinjal | 29.3 | 66.7 | 169 | 139 | 22 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 397 | 0.116 |
| 8 | Tomato | 44 | 78.8 | 115 | 133 | 90 | 92 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 509 | 0.224 |
| 9 | Beans | 22 | 64.8 | 148 | 109 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 322 | 0.071 |
| 10 | Mango | 151 | 150.2 | 130 | 93 | 63 | 144 | 176 | 186 | 199.9 | 258.8 | 287.1 | 360.6 | 291.6 | 2340 | 3.533 |
| 11 | Cotton | 273.4 | 19.4 | 71 | 126 | 97 | 157 | 150 | 85.6 | 0 | 0 | 0 | 0 | 0 | 705 | 1.929 |
| 12 | Groundnut | 144.6 | 44.3 | 163 | 129 | 14 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 349 | 0.505 |
| 13 | Fruits (Watermelon) | 35 | 57.5 | 119 | 120 | 48 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 344 | 0.121 |
| 14 | Sorghum | 113 | 18.1 | 106.4 | 115.3 | 23.9 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 264 | 0.298 |
| 15 | Maize | 126 | 22.4 | 152.6 | 149.7 | 47.7 | 3.3 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 376 | 0.473 |
| 16 | Fallow lands | 39.6 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.000 |
| | Total in mm | 2226.7 | 908.6 | 1950.6 | 1927.8 | 805.5 | 608.7 | 521.9 | 472 | 415.2 | 537.4 | 582.9 | 705 | 1012.5 | 6723 | 23.490 |

**Table 3:** Monthly CWR Calculations for Rabi Season (Mm of Water)

| S. No | Cropwater Requirements For Different Crops Under Araniar Reservoir Basin (Rabi 2013-14) | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Crop | Area Irrigated (Ha) | Monthly Cropwater Requirement(Mm/Month) | | | | | | | | | | Total CWR | | | |
| | | | Oct | Nov | Dec | Jan | Feb | Mar | Apr | May | June | July | Aug | Sept | Mm/ Year | MCM/Year |
| 1 | Groundnut | 404.18 | 0 | 61.8 | 142 | 66.2 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 270 | 1.09 |
| 2 | Rice | 283.4 | 86.5 | 86.9 | 151.6 | 153.8 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 357.5 | 836.3 | 2.37 |
| 3 | Sunflower | 148.785 | 0 | 37.8 | 145.9 | 144.7 | 16.6 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 345 | 0.51 |
| 4 | Wheat | 29.61 | 0 | 32.6 | 144.3 | 132 | 14.2 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 323.1 | 0.10 |
| 5 | Potato | 23.52 | 25.5 | 24.5 | 116 | 165.9 | 178.7 | 95.4 | 0 | 0 | 0 | 0 | 0 | 0 | 606 | 0.14 |
| 6 | Chilly | 99.19 | 12 | 33.4 | 130.3 | 153.4 | 10.5 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 339.6 | 0.34 |
| 7 | Brinjal | 29.4 | 8.6 | 64.9 | 141.1 | 76.2 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 290.8 | 0.09 |
| 8 | Tomato | 15.8 | 12 | 36.4 | 145.4 | 173.2 | 121.2 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 488.2 | 0.08 |
| 9 | Tobacco | 22.4 | 0 | 61.6 | 143.9 | 55.9 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 261.4 | 0.06 |
| 10 | Cotton | 80 | 0 | 16.1 | 144.5 | 187 | 197.1 | 221.5 | 159 | 0 | 0 | 0 | 0 | 0 | 924.7 | 0.74 |
| 11 | Banana | 105.35 | 4.8 | 0.1 | 47.6 | 85.7 | 116.7 | 180.4 | 241 | 360.1 | 335.4 | 306.6 | 226.1 | 0 | 1904.3 | 2.01 |
| 12 | Grapes | 20.04 | 0 | 0 | 17.5 | 41.4 | 47.7 | 101.6 | 189 | 264.3 | 213.3 | 202.6 | 182.1 | 103.3 | 1363 | 0.27 |
| 13 | Watermelon | 4 | 4.8 | 36.6 | 129.5 | 127 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 297.9 | 0.01 |
| 14 | Grains | 45 | 0 | 14.6 | 152.9 | 210.5 | 176.4 | 49.7 | 0 | 0 | 0 | 0 | 0 | 0 | 604.1 | 0.27 |
| 15 | Fallow lands | 106.316 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Total | | 1416 | 154.2 | 507.3 | 1752.5 | 1772 | 879.1 | 648.6 | 589 | 624.4 | 548.7 | 509.2 | 408.2 | 460.8 | 8854.4 | 8.07 |




**Graph 1:** The Total Requirement of Water for the Kharif Season




**Graph 2:** The Total Requirement of Water for the Rabi Season

### 4.6 Forecasted Crop Water Requirements

The predicted climatic and rainfall data was used to forecast the future crop water requirements of Pichatur basin command area by using the Cropwat model (2015-2024). The results were shown in the following tables as Kharif and Rabi seasons.

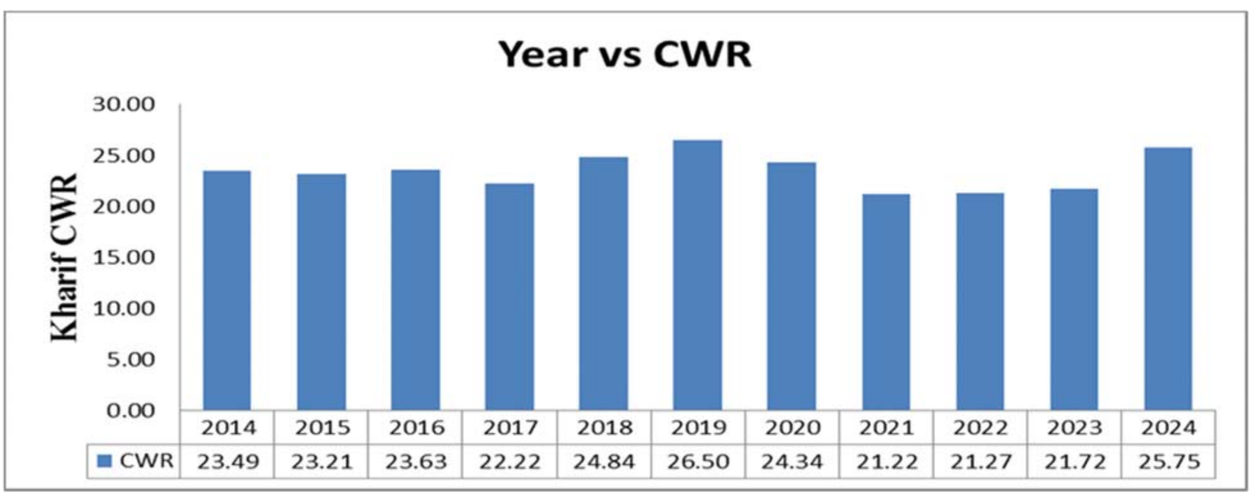



**Fig 6:** Yearly Crop Water Requirements for Kharif Season

The above picture shows that the yearly crop water requirements for the study area and which is depends on the particular year climatic and rainfall data. The CWR was 23.49 MCM in the base year (2014) and the remaining forecasted CWR were shown. The CWR was very high in the year 26.50 MCM and least in the year 2022 (21.22 MCM). The variation of the CWR is due to change in climatic parameters like temperature, relative humidity, wind speed and rainfall.

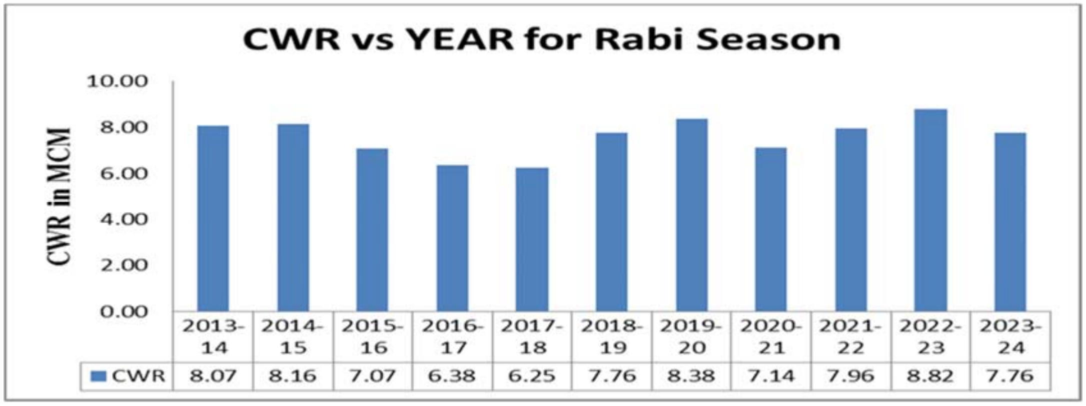



**Fig 7:** Yearly CWR for Rabi Season

## 5 Validation Models

Watershed models are powerful tools for simulating the effect of watershed processes and management on soil and water resources. However, no comprehensive guidance is available to facilitate model evaluation in terms of the accuracy of simulated data compared to measured flow and constituent values.

The following models were taken for the validations:

1. Nash-Sutcliffe Efficiency model
2. RSM (root mean square error of the observations standard deviation ratio) Model.
3. Statistical errors
4. Coefficient of determination ($R^2$)

The model evaluation performance ratings were established for each recommended statistic. In general, model simulation can be judged as satisfactory if NSE > 0.50 and RSR < 0.70.

**Nash-Sutcliffe Efficiency (NSE):** The Nash-Sutcliffe efficiency (NSE) is a normalized statistic that determines the relative magnitude of the residual variance compared to the measured data variance (Nash and Sutcliffe, 1970) [11]. NSE indicates how well the plot of observed versus simulated data fits the line. NSE is computed as shown in equation.

$$NSE=1-\left[\frac{\sum_{i=1}^{n}(y_i^{obs}-y_i^{sim})^2}{\sum_{i=1}^{n}(y_i^{obs}-y^{mean})^2}\right]$$

Where Yi obs is the ith observation for the constituent being evaluated, Yi sim is the ith simulated value for the constituent being evaluated, Y mean is the mean of observed data for the constituent being evaluated, and *n* is the total number of observations.

### 2. RMSE-Observations Standard Deviation Ratio (RSR)

RMSE is one of the commonly used error index statistics (Chu and Shirmohammadi, 2004; Singh *et al.*, 2004; Vasquez-Amabile and Engel, 2005) [12]. RSR is calculated as the ratio of the RMSE and standard deviation of measured data, as shown in equation.

$$RSR=\frac{RMSE}{STDEVobs}=\frac{\sqrt{\sum_{i=1}^{n}(y_i^{obs}-y_i^{sim})^2}}{\sqrt{\sum_{i=1}^{n}(y_i^{obs}-y^{mean})^2}}$$

### 3. Statistical Errors

Statistical errors such as Mean Square Error (MSE), Root Mean Square Error (RMSE) are determined by using the following equations

$$1.\ MSE=\sum_{i=1}^{n}\{\frac{y_{obs}-y_{sim}}{n}\}^2$$

$$2.\ RMSE=\sqrt{\frac{1}{n}\{\sum_{i=0}^{n}[\frac{y_{obs}-y_{sim}}{y_{obs}}]^2\}}$$

Where $y_{obs}$= observed past data
$y_{sim}$= simulated or predicted data
n= total number of observed data

**Table 4:** Statistical Parameters Results

| S. No | Parametre | MSE | RMSE |
|---|---|---|---|
| 1 | Min Temperature | 0.0117 | 0.054 |
| 2 | Max Temperature | 0.025 | 0.062 |
| 3 | Relative Humidity | 0.021 | 0.087 |
| 4 | Wind Speed | 0.013 | 0.202 |
| 5 | Sunshine Hours | 0.009 | 0.024 |

### 5.1 Validation Model Results

Nash-Sutcliffe Efficiency (NSE) model values between 0.0 to 1.0 are generally viewed as acceptable levels of performance. Whereas RSR model values are less than or equal to 0.70 are good performers (≤0. 70).

**Table 5:** Validation Model Results

| S. No | Parameter | NSE Model | | RSR Model | | ($R^{2)}$ | |
|---|---|---|---|---|---|---|---|
| | | Calibration | Validation | Calibration | Validation | Calibration | Validation |
| 1 | Minimum Temperature | 0.87 (very good) | 1.00 (very good) | 0.34 (very good) | 0.40 (very good) | 0.89 (very good) | 1.00 (very good) |
| 2. | Maximum Temperature | 0.73 (very good) | 0.78 (very good) | 0.51 (good) | 0.56 (good) | 0.75 (good) | 1.00 (very good) |
| 3 | Relative Humidity | 0.41 (good) | 0.69 (good) | 0.58 (good) | 0.56 (good) | 0.72 (good) | 1.00 (very good) |
| 4 | Wind Speed | 0.26 (good) | 0.69 (good) | 0.73 (good) | 0.56 (good) | 0.72 (good) | 1.00 (very good) |
| 5 | Sunshine Hours | 0.49 (good) | 0.69 (good) | 0.50 (good) | 0.56 (good) | 0.65 (good) | 1.00 (very good) |
| 6 | Rainfall | 0.50 (good) | 0.69 (good) | 0.49 (good) | 0.56 (good) | 0.50m (good) | 1.00 (very good) |

From the above validation model values we can conclude that NSE model is valid for only minimum temperature and maximum temperature (very good condition) and the other parameters like relative humidity, wind speed, sunshine hours and rainfall are best suitable validation of RSR model (good condition). All the regression values ($R^2$) are satisfactory.

## 6. Summary and Discussions

- Estimating amount of water requirements for crop in particular area is necessary for agricultural production management, in arid and semi-arid, and in seasonal water scarcity conditions. It is possible to reduce water consumption for crop production depending on the varieties that has short growth period and tolerant to the salinity and drought while retaining the qualitative and quantitative level of yield.
- This study was based in computer model with general data for various crops properties, local climate and local soil characteristics.
- The model proved useful in identifying inconsistencies in the design and possible shortcomings or errors in the data records. Therefore, the model may be a powerful tool for helping researchers analyse results and draw conclusions. Use of models will help achieve a more-uniform recording of data and allow meaningful comparisons of findings in different studies and countries.
- The study provides a basis for the timing of irrigations required under the given agro-climatic conditions and the system capacity and in the preparation of project operation plans for the optimal use of water both from seasonal incident rainfall as well as project water.
- During the actual implementation of schedules ever, these results will be quite helpful, if the climatic data on short term and medium term basis could be forecast.
- Monthly demand of water for crop water requirement was estimated as 2.68 MCM, 2.63 MCM, 3.40 MCM, 3.63 MCM, 4.27MCM, 3.97 MCM, 3.39 MCM, 2.27MCM, 2.83MCM, 0.66 MCM, 2.61 MCM, 1.86MCM in January to December in the Kharif season to irrigate 2226.7 ha for the cropping pattern 2014 in the study area.
- Similarly the monthly demand of crop water requirement for Rabi season was estimated as 1.49MCM, 0.34 MCM, 0.86 MCM, 0.41 MCM, 0.43 MCM, 0.39 MCM, 0.34 MCM, 0.35 MCM, 0.18 MCM, 0.30 MCM, 0.09 MCM, 0.69MCM in the months January to December to irrigate 1416 ha in the study area.
- The model CROPWAT 8.0 can appropriately estimate the yield reduction caused by water stress and climatic impacts, which makes this model as a best tool for irrigation planning and management.
- Artificial Neural Network (ANN) tool with feed forward back propagation function in MATLAB has been implemented to predict the average monthly climatic parameters such as minimum temperature, maximum temperature, relative humidity, wind speed, sunshine hours and rainfall. After 1000 epochs, the network has been found to produce a forecast with some error. The average annual rainfall prediction gives less error than the other climatic parameters.
- IBM-SPSS Statistical tool is a user friendly and that can be forecasts the data with the time series expert modeller. All the climatic data were forecasted and the results are fewer errors than the ANN predicted results. Hence IBM-SPSS tool results were adopted to found out the future crop water requirements.
- Results and analysis conclude the effect of climate change on crop water requirement of Kharif and Rabi crops. There are both rise and fall in crop water requirement has been seen in this study with comparing the base cropping pattern period (2013-14).
- It has been concluded from the results and analysis that in future years (2019 in Kharif, 2022-23 in Rabi) crop water requirement will increase in the study area and the reason for this may be due to increase in maximum and minimum temperature and decreasing relative humidity in those future years.
- The results of this study will be useful for policy makers and planners of water resources for future planning projects and suggest water saving techniques to satisfy increasing crop water requirement.

## 7. References


1. Kavitha Rani B. Rainfall Prediction with TLBO Optimized ANN, Journal of Scientific and Industrial Research. 2014; 73:643-647.
2. Chowdhury S, Al-Zahrani M. Characterizing water resources and the trends of sector wise water consumptions in Saudi Arabia. J King Saud Univ Eng Sci. 2013b. http://dx.doi.org/10.1016/j.jksues.2013.02.002.
3. Moraisi DN. Model Evaluation Guidelines for Systematic Quqntification of Accuracy in Watershed Simulations. American Society of Agriculture and Biological Engineers ISSN 0001-2351, 2007.
4. Doorembos J, Pruitt WO. Crop water requirements. FAO Irrigation and Drainage Paper Rome, Italy, 1977.
5. Dr. Falguni Parekh, Kevin Pramodchandra Prajapati (2013). Climate Change Impacts on Crop Water Requirement for Sukhi Reservoir Project. Ijirset, 2009; 2:9.
6. Dr. Modi PN. A text book of Irrigation Water resources and water power engineering, publisher: Standard Book House.
7. FAO (Food and Agriculture Organization). CROPWAT Software, Food and Agriculture Organization, Land and Water Division; Available at: 2009. http://www.fao.org/nr/water/ infores_databases_cropwat.html,
8. Fao Climwat for Cropwat, a climatic database for irrigation planning and management by M. Smith. FAO Irrigation and Drainage, 1993, 49.
9. FAO. Guidelines for predicting crop water requirements by J Doorenbos & W.O. Pruitt. FAO Irrigation and Drainage. 1977, 24.
10. Hsu M.K. Structural Equation Modeling with IBM SPSS Amos. IBM Business Analytics, 2010.
11. S.S De. Artificial Neural Network Based Prediction of Maximum and Minimum Temperature in the Summer Monsoon Months over India, Applird Physics Research 2009; 1:2.
12. Smith BA, Hoogenboom G, McClendon RW. Artificial neural networks for automated year-round temperature

prediction. Computers and Electronics in Agriculture 2009; 68(1):52-61.
13. Smith M. Cropwat: A computer program for irrigation planning and management. FAO Irrigation and Drainage, 1992, 46.
14. Andriana & Cuculeana (1999) FAO Irrigation Water Requirements guidelines paper. [1]
15. Haykin, 1994 A Predictive approach by the Artificial Neural Network feed forward back propagation function on the temperatures. [2]
16. George, B. ., Shende, S. ., & Raghuwanshi, N. (2000). Development and testing of an irrigation scheduling model. Agricultural Water Management, 46(2), 121–136. [3]
17. Smith, M. (1991). FAO Methodologies on Crop Water Use and Crop Water Productivity. Water, 18, 1–18.[4]
18. FAO 1993. CLIMWAT for CROPWAT, a climatic database for irrigation planning and management by M. Smith. FAO Irrigation and Drainage Paper No. 49. Rome. [5]
19. Mhashu, S.V., 2007. Yield response to water function and simulation of deficit irrigation scheduling of sugarcane at estate in Zimbabwe using CROPWAT 8.0 and CLIMWAT 2.0, Master thesis, Universita degli Studi di Firenze Facolta di Agraria (University of Florence, Faculty of Agriculture). [6]
20. Kassam, A., & Smith, M. (2001). FAO Methodologies on Crop Water Use and Crop Water Productivity. Water, 18, 1–18. [7]
21. FAO. 1998. Yield response to water by J. Doorenbos & A. Kassam, Kiruvi, and Mhashu,. FAO Irrigation and Drainage Paper No. 33. Rome. [8]
22. FAO. 1998. Crop evapotranspiration by R. Allen, LA. Pereira, D. Raes & M. Smith. FAO Irrigation and Drainage Paper No. 56. FAO. [9]
23. Sahai (2004) Validating models on the statistical observations. [10]
24. Nash (2001) Validation Models on the water shed parameters for the simulated data and the observed data base. [11]
25. Chu, M. K. (2010). Structural Equation Modeling with IBM SPSS Amos. IBM Business Analytics. [12]