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Prediction and Validation of Rainfall Classes for Vaigai River Catchment using El Nino

Mahadevan Palanichamy, Ramaswamy Sankaralingam Narayanasamy

Abstract: ***Extraordinary weather patterns are being observed globally during the past 30 years due to climate change resulting in variations in temperature and rainfall. Studies on long-term trend pattern of temperature and rainfall since 1980 distinctly shows a rise in mean temperature and declining rainfall trend. Due to change of climate at global level change, forecasting of rainfall with the conventional statistical analysis could not predict satisfactory results. Among the available processes, the El Niño Southern Oscillation (ENSO) cycle is considered efficient. Statistical analysis was carried out in this study so as to investigate the implication of rainfall data in seven rain gauge stations located in Vaigai River Catchment through the period from 1959 to 2016. ENSO Cycle was used also to predict rainfall for Vaigai River catchment of the Tamil Nadu State, India. Quadratic discrimination analysis (QDA) and Neural Network models are used to identify the class of rainfall classes with reference to ENSO cycle. The patterns recognized on the study area offer constructive information to administrators of water resource management, to implement the same for agriculture, water supply and power generation.***

Index Terms: ***Climate change, statistical analysis, trend pattern, Vaigai river catchment, water resources management.***

I. INTRODUCTION

Climate change and Global warming are being reported as the threats to society during the recent years in many ways such as flood, cyclones, and droughts causing destruction of the economy. Extraordinary weather patterns are being observed globally during the past 30 years due to climate change resulting in variations in temperature and rainfall. Studies on long-term trend pattern of temperature and rainfall since 1980 distinctly shows a rise in mean temperature and declining rainfall trend. Forecasting of rainfall with the conventional statistical analysis could not predict satisfactory results due to the changes in climate at global level, which has altered the characteristics of extreme rainfall events. It has been established that, any forecast of rainfall can be successful if we consider climatic tele-connections, most importantly the El Niño–Southern Oscillation (ENSO) and Southern Oscillation Index (SOI).

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***** Correspondence Author

Mahadevan Palanichamy*, Department of Civil Engineering, Environmental and Construction Technology, Kalasalingam Academy of Research and Education, Anand Nagar, Krishnankoil - 626126, Tamil Nadu, India.

Ramaswamy Sankaralingam Narayanasamy, Department of Civil Engineering, Anjalai Ammal Mahalingam Engineering College, Kovilvenni, Thiruvarur District - 614403, Tamil Nadu, India.

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Forecasting of rainfall, its quantity i.e. average, or abnormal, possibility of flood or drought, its class, etc will be useful for the officials managing water resources in terms of decision-making.

Tamil Nadu state, situated in the southern end of Indian sub-continent, collects the largest portion of its rainfall during October through December (North East Monsoon). The agricultural activities and economic status of farmers mainly depend on North East Monsoon (NEM). The major challenge faced by the water resources management professional today is allocating the available water for domestic purposes and irrigation, considering the demand. Due to spatial and temporal uncertainty of rainfall, the estimation of water that may be available through rainfall and run-off is a great task. Understanding the patterns and trends of rainfall is extremely vital for arriving at the quantity of water that may be available for distribution in stages throughout the year. Water resources management practice leads to take the choice of operating the multipurpose reservoir systems due to the impact of varying rainfall, runoff and storage quantity.

Bothale and Katpatal [1] have conducted studies using the Oceanic Niño Index (ONI) on rainfall trends in Godavari basin of India for Pranhita catchment.

Annarita Mariotti [2] has conducted studies on climatic variations in south-western parts of central Asia (SWCA) using ENSO. The results suggest that ENSO significantly affects the precipitation in South West Central Area Region (SWCA).

Hafez [3] conducted studies on climatic tele-connection between the Oceanic Nino Index (ONI), temperature of air at surface, its variability and rate of precipitation, etc., for Saudi Arabia (KSA) during 1950 to 2015. They opined that weather parameters, temperature and precipitation rates are controlled by Oceanic Nino index (ONI) mostly in the autumn and winter seasons.

Abbot and Marohasy [4] correlated climate indices of SOI, PDO and Nino 3.4 in association with the historical rainfall and temperature data by applying ANN to forecast rainfall, for Queensland, Australia. They have developed prototype neural network for rainfall prediction and inferred that it can improve the synthesis of knowledge and the actual seasonal forecast. Also, the prototype neural network has the ability to consider large numbers of climate indices and other inputs simultaneously to find solutions independently of assumed relationships.

Badr *et al*. [5] conducted studies on forecasting summer rainfall anomalies employing ANNs in the Sahel region of Africa. They inferred that, the predicted rainfall results were promising and added that there are no previous studies which documented the prediction of Sahelian rainfall.

Roy SS [6] conducted studies on the impact of ENSO on rainfall during winter for India from 1925 to 1998 and suggested that this study is helpful for forecasting of winter precipitation. Studies made by Yadav *et al*. [7] found that the inter annual variability of North West India Winter Precipitation is influenced by Arctic Oscillation / North Atlantic Oscillation (AO/NAO) and El Nino – Southern Oscillation (ENSO) phenomena. T. De Silva M *et al.* [8] have made an attempt to forecast the rainfall of Mahaweli and Kelani River basins of Sri Lanka. Cao *et al.* [9] investigated the rainy-season precipitation in China based on the influence of five El Nino-Southern Oscillations indices.

Chandimala and Zubair [10] have done an investigation on predicting stream flow for various seasons for Kelani River of Sri Lanka using correlation analysis. The investigation with ENSO from October to December revealed that rainfall has a better relationship than stream flow.

Surendran *et al*. [11] stated that the variation of rainfall during monsoon (summer) in India is linked to El Niño-Southern oscillation (ENSO) and also the oscillations in Indian Ocean at Equatorial region.

Singhrattna *et al*. [12] conducted studies to develop a method to forecast rainfall in Thailand statistically due to monsoon in summer and established a significant relationship with ENSO.

Based on the above literature surveys, it is evident that the prediction of rainfall is characterized with the usage of Multivariate ENSO Index (MEI), Southern Oscillation Index (SOI) and ENSO as Sea Surface Temperature (SST). Hence, in this study an attempt has been made to model the effect of ENSO cycle on extreme rainfall events of Vaigai River Catchment area.

There are thirty-four river basins in Tamil Nadu State, India. For hydrological studies, they are grouped into seventeen river basins. The Vaigai River basin is one among them and it lies between the geographic co-ordinates Latitude *9° 33'–10° 27' N* and Longitude *77° 10'–79° 10' E* and covers an area of *7031 sq.km*. The entire basin is located in Theni, Dindigul, Madurai, Sivaganga and Ramanathapuram Districts. The basin is located in between Cauvery and Kottakaraiyar basins in the North, Gundar basin in the South, Western Ghats in the West and Bay of Bengal in the East. The mean annual rainfall of the basin varies from *517 mm* to *1813 mm*. The annual rainfall of around *2000 mm* is reported on the hilly terrains and uplands of Vaigai basin near Periyar Lake and moderately uniform rainfall (ranges from *800 mm* to *900 mm*) has been reported in plains. Around Vaigai Dam, low rainfall (less than *700 mm*) has been recorded. The rainfall decreases as the river reaches its tail end. 46 percentage of the total annual rainfall is received from the North East Monsoon Season (highest amount of rainfall) while 33 percentage of the average annual rainfall is received from the South-West monsoon. The mean annual rainfall of the basin is *882 mm*.

Vaigai river basin lies in a sub-tropical, semi-arid climatic zone. The rainfall pattern of the basin is of tropical monsoon in nature and the impact of winter monsoon is central over the basin. Based on hydro-meteorological characteristics of the basin, monsoon seasons in a year is divided into two periods as the Monsoon period (spanning from June to December) and Non-monsoon period (spanning from January to May) respectively.

The monsoon period is sub- divided into South West Monsoon (SWM) / Monsoon season (4 months spanning from June to September) and North East Monsoon (NEM) / Post monsoon season (3 months spanning from October to December) correspondingly, the non-monsoon period is further sub-divided into Winter season (2 months spanning from January & February) and Summer / Pre-monsoon season (3 months spanning from March to May).

This study investigates the rainfall data from 1959 to 2016 and forecasting in seven rain gauge stations located in Vaigai River Catchment through the period with ENSO Cycle. The temperature on the surface of sea, its monthly anomaly (based on 1981–2010 mean) over NINO3, NINO 3.4 and NINO4 (*17° E-120° W, 5° S-5° N*) region is being used as SST index. The present study also predicts rainfall for Vaigai River catchment of the Tamil Nadu State, India.

II. Data and Study Area Description

A. Rainfall data

Monthly rainfall data of seven identified rain gauge stations (Berijam, Bodynayakkanur, Gudalur, Periyakulam, Uthamapalayam, Vaigai Dam and Veerapandi) on the boundary of Vaigai basin catchment for the period of 1959–2016 were collected from the data sets of India Meteorological Department (IMD) and from the State surface and ground water division of PWD, Tamil Nadu State.

B. ENSO Indices

The ENSO cycle is characterized by Sea Surface Temperature (SST), Southern Oscillation Index (SOI), and Multivariate ENSO Index (MEI). The temperature on the surface of sea, its monthly anomaly (based on 1981–2010 mean) over NINO 3, NINO 3.4 and NINO 4 (*17° E - 120° W, 5° S - 5° N*) region is used as SST index and MEI monthly data for the period from (1959 – 2016). The difference in air pressure between Tahiti and Darwin on surface is represented as Southern Oscillation Index (SOI) in this study. The Multivariate ENSO Index (MEI) comprises of the data obtained from atmospheric variables such as (i) pressure at sea-level, (ii) zonal component of wind at surface, (iii) its meridional component, (iv) temperature at surface of sea, (v) temperature of air at surface of sea, and (vi) total cloudiness in the atmosphere.

III. Methodology

The 58 years data on rainfall during 1959 to 2016 of all the seven identified rain gauge stations were taken up for the analysis. The monthly rainfall data sets are converted into four rainfall season data sets such as; 1. Summer i.e. Pre-monsoon, 2. South West Monsoon season, 3. North East Monsoon season and 4. Winter Season. The step by step procedure for statistical analysis, model studies and rainfall prediction is given in ***Fig. 1*** in the form of flow chart.

The rainfall anomalies An_i are determined by reducing the seasonal mean rainfall (time series) $P(avr)_i$ from the observation rainfall data P_i of the particular month (1) and the standardized anomalies SAn_i are determined (2) by dividing the rainfall anomalies by the standard deviation (time series) SD_i.

$$An_i = (P_i - P(avr)_i) \tag{1}$$

$$SAn_i = \frac{(P_i - P(avr)_i)}{SD_i} \tag{2}$$

When the seasonal variations do exist in the data sets, then the standardized rainfall anomalies are necessarily to be determined. The standardized anomalies are also referred as normalized anomalies. The determined standardized rainfall anomalies are classified into three classes such as; dry, average and wet as reported in ***Table 1***.

Table 1. Classification of rainfall anomaly

Class	Range
Dry	$SAn_i < -0.5$
Average	$-0.5 < = SAn_i < 0.5$
Wet	$0.5 < = SAn_i$

By employing statistical thresholds, the extreme seasonal precipitation is defined in different ways. Here *0.5* is used as a threshold value for defining three classes, by which we can see the distribution of data in an evenly distributed manner. The analyses of the rainfall data sets are done in seasons and so the values of the climate indices are represented by averaging for the seasons. For instance, for the Post monsoon season, Multivariate ENSO Index (MEI) value is the average of October, November and December (OND) monthly values; for the Monsoon season, SOI is the average of June, July, August and September (JJAS) monthly values.

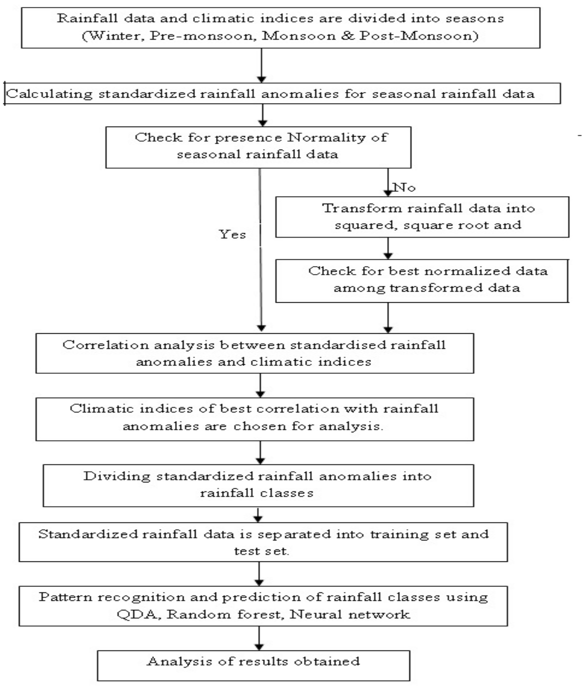

Figure 1. Methodology

Here in, the Shapiro-Wilk tests are carried out to check the presence of normality in seasonal rainfall data sets. Correlation analysis can be performed when the data sets between climate indices and rainfall anomalies are distributed normally, This is done for the identification and selection of the best correlation climate indice. If the seasonal rainfall data sets are not falling in line of normality, it means the transformation of rainfall data into normally distributed data sets. (by taking *log (e)*, square or square root functions). Among the transformed data, the best normalized data is taken up for further analysis. In order to classify the output into three types of rainfall classes, seasonal values of Nino 3, Nino 3.4 and MEI were taken up as the predictors. *75%* of the standardized rainfall data were taken up as training set while the remaining *25%* is considered to carry out model analysis. The statistical analyses are carried out by using the following R studio packages, random forest, caret, rlang, Matrix, tree, openxlsx, tibble, reprtree, MASS, klar, Metrics, neural net for studies. Quadratic discrimination analysis (QDA) and Neural Network (NN) models are used to recognize the patterns of rainfall classes with reference to ENSO cycle and SOI indices. In order to predict the rainfall classes either as drought or not drought, Random decision forest model is used.

A. *Quadratic discriminate analysis (QDA)*

The determined standardized rainfall classes have more than two classes (dry, average and wet). Linear Discriminate Analysis (LDA) and Quadratic Discriminate Analysis (QDA) are the techniques frequently used for the logistic regression classification (traditionally limited to two classes as Yes or No type). For performing analysis using LDA and or QDA, it is specified that required the number of predictor variables (p) must be less than the size of sample (n). LDA & QDA on data sets where $n \geq (5p)$, is normally considered as a thump rule. In our case the predictor variable considered is three and the sample size considered is *58*. The training set is very large, hence QDA is preferred than LDA (preferred when few training observations are available).

It is assumed that the observations made from each of the classes form a Gaussian distribution. Using Bayes theorem, QDA can be formulated mathematically. π_k represents the probability of the randomly chosen observation obtained from the k^{th} class having function of density represented as $f_k(x)$. Then, as per Bayes theorem,

$$P_r(Y = k \mid X = x) = -\frac{\pi_k f_k(x)}{\sum_{l=1}^{K} \pi_l f_l(x)} \tag{3}$$

The posterior probability $P_r(Y = k \mid X = x)$ in equation (3), indicates that observation $X = x$ belongs to the k^{th} class. Equation (4) represents the mathematical form of density function, the multivariate Gaussian distribution for p predictors for every class k.

$$f_k(x) = \left(-\frac{1}{(2\pi)^{p/2} (\Sigma_k)^{1/2}} \exp\left(-\frac{1}{2}(x - \mu_k)^T \Sigma_k^{-1}(x - \mu_k)\right)\right) \tag{4}$$

$$\mu_k = -\frac{1}{N_k} \sum_{i:y_i=k} x_i \tag{5}$$

$$\Sigma_k = -\frac{1}{(N_k - 1)} \sum_{i:y_i=k} (x - \mu_k)^T (x - \mu_k) \tag{6}$$

Gaussian density function is substituted in equation (4) for the k^{th} class. The quadratic discriminate function is derived by taking the logarithmic values, as given in (7). For class $k(\pi_k)$, prior probabilities are calculated by taking the frequency of data points of class k in the training data, as in (8). If we consider N number of points totally in the training observations, then N_k represents the number of observations corresponding to the k^{th} class.

$$\delta_k(x) = -\frac{1}{2}(x - \mu_k)^T \Sigma_k^{-1}(x - \mu_k) + \log \pi_k \tag{7}$$

$$\pi_k = \frac{N_k}{N} \tag{8}$$

Mean, Covariance and Prior Probability values are inserted into the discriminate function $\delta_k(x)$ together with the other state variables, as in equation (5). Considering the largest value of the function, its corresponding class is selected. $k_p.(p+1)/2$ represents the number of parameters that we are going to estimate for the QDA model under consideration comprising k (number of) classes and p (number of) predictors.

B. Neural network

Neural network represents a processing system for information. It can be compared similar to nervous system of human being. It is made up of neurons (information processing units), which are interconnected, similar to the human nervous system. It is a mathematical model, driven by data, used to solve problems such as prediction and discrimination. It consists of many layers; each layer contains nodes for data operations similar to a cell body. The first layer of the neural network receives the raw input, the subsequent layers process the data, which are named as hidden layers and the last layer produces the output.

Important stages for building an optimal artificial neural network model are (i) classification of important input variables and (ii) optimization of the network structure. As described, the best input variables were determined by examining cross-correlations between the standardized rainfall anomaly and the climate indices represented by ENSO. The number of input variables is equal to the number of input nodes. The hidden layer was considered as one; with a learning rate of *0.01*, a node in the hidden layer is determined using trial and error method. For the hidden layer, hyperbolic tangent sigmoid activation function is adopted. 2 to 10 number of hidden nodes was changed for the trial networks.

If the initial weight be chosen randomly at the start of the training process, then a diverse artificial neural network model is formed for each training process, which yields variation in its performance. Therefore, the ANN model generation process repeated to choose the model which can predict optimally based on the average accuracy. The cross-validation procedure has also been used to evaluate the model performances. Usage of this method is to select the best model structure and to prevent over fitting of the particular data set. To avoid overtraining, a premature stopping system has also been followed with sustained examination of the errors in both the training set and validation set during the training process. Subsequent to the selection of the optimum number of hidden nodes (3 numbers), the neural network model has been trained with the cumulative training and validation data sets, then the trained model was finally tested using the unobserved data set to evaluate the model performance.

C. Random forest

For high-dimensional data, Random Forest is considered to be the excellent ensemble classifiers. Random forests are a mixture of tree analysts such that each tree depends on the values of a random vector sampled separately and with the same distribution for all trees in the forest. The simplification error will converge into a boundary when the number of trees in the forest becomes outsized. The error of forest tree classifiers depends on the power of the individual trees in the forest and the association between them. A diverse subset of the training data is selected with replacement and to train each tree. The balance of training data is used to estimate the error and variable of importance. Class assignment is made by the number of votes from all the trees and for regression; the average of the results is used.

Decision trees are a popular method for various machine learning tasks. Trees that are mature very deep tend to learn extremely uneven patterns: they over fit their training sets, i.e. have low biases, but very high variance.

IV. RESULTS AND DISCUSSION

A. *Observations from the monthly rainfall box plots*

The seasonal and spatial variation in rainfall patterns are pointed out using the monthly rainfall box plots of seven rain gauge stations in Vaigai basin catchment area over the period from 1959 to 2016.The following observations were made based on the monthly rainfall box plots of this region (***Fig. 2***).

1. The largest fraction of total rainfall in all the rain gauge stations of the Vaigai basin catchment occurs during the post monsoon (NEM) seasons (approximately *50%* of the total rainfall) ***(Fig. 2a-g)***.
2. The rain gauge stations located (six stations) in the Vaigai basin catchment receives more amount of rainfall in summer seasons (compared with other parts of the country) than the monsoon (SWM) seasons. In view of the fact, that the rain gauge stations located in the Vaigai basin catchment (Suriliyar water shed) is under rain shadow regions and lies in lowered side of the Western Ghats, because of the reasons summer rainfall is high here. The box plot analysis also confirms that all the six stations selected (except Berijam) for the study receives more amount of rainfall in summer seasons next to post monsoon season (approximately *25%* of the total rainfall) ***(Fig. 2b-g)***.
3. The observation from the box plot of Berijam station located on the Palani foot hills receive the highest amount rainfall (approximately *35%* of the total rainfall) during the monsoon seasons (SWM) as like that of other parts of the country ***(Fig. 2a)***.
4. All the stations located in Vaigai basin catchment receive a little amount of rainfall (approximately *2%*) during winter seasons ***(Fig. 2a-g)***.
5. For monsoon season (SWM), all the six stations receive a moderate amount of rainfall (approximately 23% of the total rainfall) (**Fig. 2b-g**).
6. The month of October is generally wettest period of a year across all the rain gauge stations located in this region ***(Fig. 2a-g)***.

The Post monsoon (NEM) and Pre-monsoon (Summer) is the important seasons in the catchment area (Bodynayakkanur, Periyakulam, Uthamapalayam, Vaigaidam, Veerapandi) delivering approximately 80% of annual rainfall ***(Fig. 2b, 2d, 2e, 2f, 2g)***. The Rain gauge station located in Gudalur receives approximately 64% of annual rainfall during the Post monsoon and Monsoon seasons in the catchment. The Berijam receives approximately *75%* of annual rainfall during the Post monsoon (NEM) and Monsoon (SWM) season.

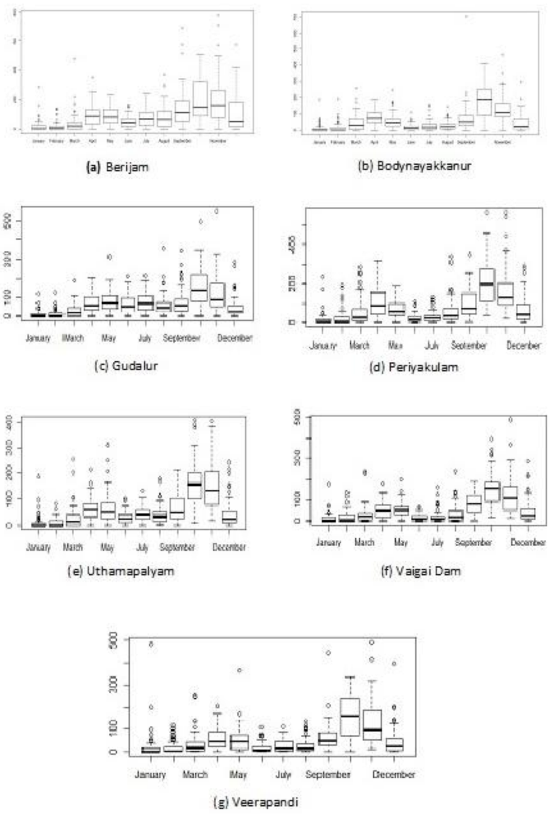

Figure 2. Box plots of rainfall data for stations in Vaigai river basin

B. Observation from the Shapiro-Wilk's normality test

The Shapiro-Wilk test is a way to discover the normality of rainfall distribution. The null hypothesis for this test is that the data are normally distributed.

If the *p-value* is greater than *0.05*, then the null hypothesis is not rejected. The *W* value is the test statistics; small values of *W* indicate that the sample is not normally distributed (rejection of the null hypothesis if the population is normally distributed and the values are under a certain threshold).

The Vaigai Dam Post-monsoon season normality test results are given in ***Fig. 3***, as an example to decide upon the best normalized data among the transformed data to do correlation analysis.

Data: *x1* (represents rainfall anomalies)
W = 0.93671, p-value = 0.004665
Data: *x2* (represents log of rainfall anomalies)
W = 0.90547, p-value = 0.0002675
Data: *x3* (represents log10 (rainfall anomalies))
W = 0.90547, p-value = 0.0002675
Data: *x4* (represents (rainfall anomalies)^2)
W = 0.80498, p-value = 2.576e-07
Data: *x5* (represents square root of rainfall anomalies)
W = 0.96069, p-value = 0.05761
Data: *x6* (represents exponential of rainfall data)
W = 0.11266, p-value < 2.2e-16
Data: *x7* (represents exponential of rainfall anomalies)
W = 0.11266, p-value < 2.2e-16

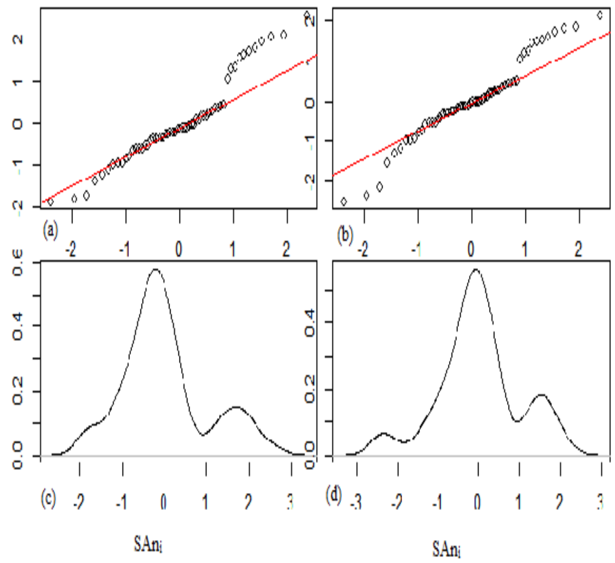

Figure 3. Pre-monsoon Vaigai Dam standardized data plot (a) Original form qqplot, (b) Square root form qqplot, (c) Original form density plot, (d) Square root form density plot.

From the standardised data plots ***(Fig. 3)*** and the Shapiro-Wilk's test results for Post-monsoon season of Vaigai Dam station give a conclusion that the square root transformed data are closer to being normally distributed than the other transformed data results. Based on the observations from Vaigai dam Post monsoon season rainfall anomaly distribution plot ***(Fig. 4)***, portions of the data are moderately squarely distributed into three categories (about *30%*, *58%* and *30%*) for a normal distribution. Hence it is reckoned to consider this as a reasonable choice for the correlation analysis.

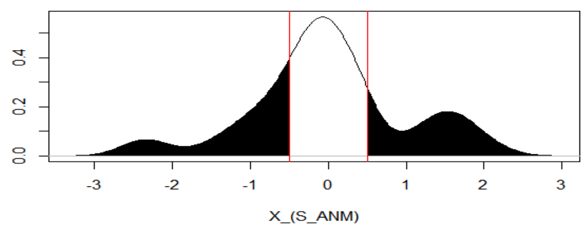

Figure 4. Rainfall anomaly distribution for Post-monsoon season of Vaigai- Dam

C. Correlation Analysis with climatic indices

The correlation study has been done to choose the climatic indices, based on the correlations between rainfall anomalies and multiple climate indices. The index such as MEI, Nino 3.4 and Nino 3 has been selected based on the high correlations as given in ***Table 2***. The ENSO cycle is represented by MEI, SOI, NINO3.4, NINO3, and NINO4 indices. Correlation analysis indicates that MEI, Nino 3.4 and Nino 3 has a higher correlation with rainfall anomalies than the other ENSO indices, hence classification was done with only MEI, Nino 3.4 and Nino 3.

The correlation coefficients between rainfall anomalies and MEI, Nino 3.4 and Nino 3 are negative for the winter, Pre-monsoon, and Monsoon seasons and positive for the Post monsoon season.

Rainfall anomaly correlations to the Nino 3.4 and Nino 3 are not stronger than the correlations to the MEI. However, there are strong correlations for the anomalies of major monsoons to the rain gauge stations in the basin and Nino 3.4, Nino 3 values. For example, rain gauge stations in Vaigai catchment (Berijam and Bodynayakkanur) have a high correlation coefficient between Post monsoon rainfall anomalies and Nino 3.4, Nino 3. Whereas the rain gauge stations (Gudalur, Periyakulam, Uthamapalayam and Vaigai Dam) have high correlation coefficient between winter rainfall anomalies and Veerapandi rain gauge station have high correlation coefficient between Monsoon rainfall anomalies. The Quadratic Discriminate Analysis, Neural Network and Random forest decision classification models were applied to determine the relationship between standardized rainfall anomaly classes (dry, average, wet) and MEI, Nino 3.4, Nino 3 Values ***(Fig. 5.1 – 5.7)***. From the analysis of classification models, the precision of model results were high for the leading monsoon rainfall seasons of the individual rain gauge stations of the Vaigai basin catchment area as seen in ***Table 4*** to ***Table 6***.

The random forest model analysis with ensemble model approach resulted in a comparatively lower out-of bag error rate for the dominant monsoons of rainfall anomaly classification as given in ***Table 9***. All the six stations located in Vaigai river catchment basin (except Bodynayakkanur station which has lower out-of-bag error rate in winter season) have shown the lower random forest error rate for the Pre-monsoon and Post monsoon seasons. Similarly, the neural network model analysis resulted in a comparatively lower sum of square error (SSE) for the dominant monsoons of rainfall anomaly classification and represented in ***Table 8***. All the stations in Vaigai river basin catchment shows lower error rate for all the three dominant monsoon seasons and the precision rate is also higher rate. The Quadratic Discriminate Analysis (QDA) model for the dry and wet class prediction have a higher accuracy rate between *67% - 100%* for all the seven rain gauge stations located in the Vaigai river basin catchment (***Table 7***). The Out-of-bag (OOB) error rate for the random forest two class models varies from *22% - 50%* and the sum of square error (SSE) rate for the Neural network two class models varies from *1.06 – 8.21*. This shows superior proficiency in determining rainfall classes of major monsoons seasons of the rain gauge stations in the basin as given in ***Table 9***.

The finding from the correlation study shows many powerful correlations between the rainfall anomalies and climate indices as seen in ***Table 2*** and ***Table 3***. The high correlation rates between MEI and rainfall anomalies can be noticed compared with other ENSO indices (**Table 2**). Apart from that, the rainfall in Post-monsoon season is very important for the stations located in the Vaigai river basin catchment area and it is the important source of water for the reservoir and for agricultural activity (Table 3). The correlation coefficients between Post monsoon rainfall at Berijam is positive and strong, *0.23* for MEI ($p<0.05$), *0.27* for Nino 3.4 ($p=0.05$) and *0.30* for Nino 3 ($p<0.05$). Since the strength of the correlation is not a noteworthy one based on the highly significance of p value less than *0.01* level, it leads to search the usefulness of classification methods.

D. Classification model observations

The classification results of three noteworthy rain gauge stations have been taken up for the presentation based on the earlier study conducted on the basin by this author using trend detection tools such as Mann Kendall trend test, Spearman rho test , Kendal tau test, Sen's estimator and change point detections methods [13] The earlier studies on the Veerapandi rainfall station showed a significant increasing trend during pre-monsoon season, the Periyakulam station has shown a significant increasing trend during post monsoon season and Vaigai dam station has shown a significant decreasing trend during the Monsoon season. The finding has a relevance to compare it with the results of the classification models conducted to confirm the classification category of rainfall anomaly with the influence of the climatic indices (ENSO) in this region.

The seasonal rainfall class prediction can be the useful information to the water resources managers of this region in reservoir operation planning for hydro power, agricultural operations and drinking water requirements of the city. The electricity, agricultural activity and drinking water requirements of this Vaigai river basin is heavily dependent on the three main seasons (Post-monsoon, Pre-monsoon and Monsoon) which receives its bulk of the rainfall in its fold. Hence it is taken up for the analysis by comparing the results of the classification models and earlier trend analysis done by this author to give a conclusion regarding the climatic impact of the region.

The classification models QDA, Neural Network and Random forest successfully identified the Pre-monsoon season of Veerapandi station pattern with the overall accuracy of *100%* (4 out of 4 occurrences), *75%* (3 out of 4 occurrences) and *75%* (3 out of 4 occurrences) respectively. The results suggest that it may be the possible reason to confirm that the season is anomalously wet. Again, classification using two classes "dry" and not dry" cases using QDA, ANN and Random forest model correctly classifies with the *100%* of anomalously "not dry" case, with the *90%* of anomalously "not dry" cases (the minimal SSE error value of 5.52) and with the *100%* of anomalously "not dry" case (With OOB error rate of *34.09%*) respectively.

The model analysis also done on the Periyakulam station during the Post monsoon season shows a pattern with the overall accuracy of *60%* (3 out of 5 occurrences) in QDA, *75%* (3 out of 4 occurrences) in ANN. The results also suggest that it may be the possible reason to confirm that the season is anomalously wet.

Table 2. Correlation of rainfall anomalies with climatic indices in rainfall stations of Vaigai river catchment

Rainfall Season	BERIJAM					BODYNAYAKKANUR				
	MEI	SOI	Nino34	Nino3	Nino4	MEI	SOI	Nino34	Nino3	Nino4
Winter	-0.226	0.220	-0.186	-0.190	-0.157	-0.158	0.088	-0.157	-0.181	-0.143
Pre-monsoon	-0.167	0.185	-0.151	-0.134	-0.210	-0.187	0.152	-0.165	-0.205	-0.129
Monsoon	-0.017	0.075	0.110	0.131	0.056	-0.135	0.169	-0.219	-0.195	-0.141
Post-monsoon	0.232	-0.251	0.266	0.295	0.213	0.186	-0.088	0.258	0.270	0.177
Rainfall Season	GUDALUR					PERIYAKULAM				
	MEI	SOI	Nino34	Nino3	Nino4	MEI	SOI	Nino34	Nino3	Nino4
Winter	-0.163	0.124	-0.223	-0.265	-0.160	-0.190	0.131	-0.179	-0.219	-0.135
Pre-monsoon	-0.039	-0.0155	-0.061	-0.096	-0.109	-0.082	0.008	-0.083	-0.131	0.027
Monsoon	0.002	0.064	-0.140	-0.095	-0.1788	0.021	0.035	-0.141	-0.082	-0.114
Post-monsoon	0.138	-0.183	0.104	0.087	0.146	0.096	-0.039	0.093	0.059	0.183
Rainfall Season	UTHAMAPALAYAM					VAIGAIDAM				
	MEI	SOI	Nino34	Nino3	Nino4	MEI	SOI	Nino34	Nino3	Nino4
Winter	-0.187	0.136	-0.195	-0.244	-0.126	-0.210	0.159	-0.183	-0.228	-0.174
Pre-monsoon	-0.166	0.133	-0.124	-0.182	-0.056	-0.037	0.014	-0.050	-0.101	-0.016
Monsoon	-0.171	0.188	-0.133	-0.168	-0.138	-0.114	0.133	-0.256	-0.230	-0.271
Post-monsoon	0.101	-0.146	0.125	0.095	0.165	0.139	-0.116	0.121	0.142	0.078
Rainfall Season	VEERAPANDI									
	MEI	SOI	Nino34	Nino3	Nino4					
Winter	-0.066	0.070	-0.026	-0.076	0.037					
Pre-monsoon	-0.017	0.007	-0.021	-0.041	0.012					
Monsoon	0.310	-0.126	0.187	0.223	0.164					
Post-monsoon	0.070	0.030	0.068	0.049	0.097					

Table 3. Correlation of rainfall anomalies with MEI, Nino 3.4 and Nino 3 climatic indices in rainfall stations of Vaigai river catchment.
(High Correlation values are highlighted)

Rainfall Season	BERIJAM			BODYNAYAKKANUR		
	MEI	Nino34	Nino3	MEI	Nino34	Nino3
Winter	**-0.226**	**-0.186**	**-0.190**	-0.158	-0.157	**-0.181**
Pre-monsoon	-0.167	-0.151	-0.134	**-0.187**	-0.165	**-0.205**
Monsoon	-0.017	0.110	0.131	-0.135	**-0.219**	**-0.195**
Post-monsoon	**0.232**	**0.266**	**0.295**	**0.186**	**0.258**	**0.270**
Rainfall Season	GUDALUR			PERIYAKULAM		
	MEI	Nino34	Nino3	MEI	Nino34	Nino3
Winter	-0.163	**-0.223**	**-0.265**	**-0.190**	**-0.179**	**-0.219**
Pre-monsoon	-0.039	-0.061	-0.096	-0.082	-0.083	-0.131
Monsoon	0.002	-0.140	-0.095	0.021	-0.141	-0.082
Post-monsoon	0.138	0.104	0.087	0.096	0.093	0.059
Rainfall Season	UTHAMAPALAYAM			VAIGAIDAM		
	MEI	Nino34	Nino3	MEI	Nino34	Nino3
Winter	**-0.187**	**-0.195**	**-0.244**	**-0.210**	**-0.183**	**-0.228**
Pre-monsoon	-0.166	-0.124	**-0.182**	-0.037	-0.050	-0.101
Monsoon	**-0.171**	-0.133	-0.168	-0.114	**-0.256**	**-0.230**
Post-monsoon	0.101	0.125	0.095	0.139	0.121	0.142
Rainfall Season	VEERAPANDI					
	MEI	Nino34	Nino3			
Winter	-0.066	-0.026	-0.076			
Pre-monsoon	-0.017	-0.021	-0.041			
Monsoon	**0.310**	**0.187**	**0.223**			
Post-monsoon	0.070	0.068	0.049			

Table 4. QDA results of rainfall stations in Vaigai river catchment for dry, average & wet rainfall classes (Highlighted values indicate the forecasting probability of either dry or wet anomaly class)

Rainfall Season	BERIJAM			BODYNAYAKKANUR		
	Dry	Average	Wet	Dry	Average	Wet
Winter	**4/6**	1/4	**2/3**	1/6	2/3	**3/4**
Pre-monsoon	0/2	7/8	1/3	2/6	1/5	**2/2**
Monsoon	1/3	5/6	2/4	2/4	4/6	1/3
Post-monsoon	**2/3**	6/7	0/3	**4/6**	1/1	**4/6**
Rainfall Season	GUDALUR			PERIYAKULAM		
	Dry	Average	Wet	Dry	Average	Wet
Winter	**4/4**	2/5	2/4	1/4	5/6	**2/3**
Pre-monsoon	1/6	2/3	2/4	1/3	3/6	**3/4**
Monsoon	2/4	4/5	2/4	1/3	4/6	2/4
Post-monsoon	**3/5**	3/4	0/4	2/4	4/4	**3/5**
Rainfall Season	UTHAMAPALAYAM			VAIGAIDAM		
	Dry	Average	Wet	Dry	Average	Wet
Winter	**4/6**	4/6	1/2	**4/4**	1/5	**4/5**
Pre-monsoon	2/5	2/4	**4/5**	1/4	6/6	1/4
Monsoon	**4/6**	4/5	1/3	**4/6**	2/4	1/4
Post-monsoon	**4/6**	3/4	0/4	2/8	4/4	0/2
Rainfall Season	VEERAPANDI					
	Dry	Average	Wet			
Winter	3/6	2/5	**2/3**			
Pre-monsoon	1/4	3/6	**4/4**			
Monsoon	**2/3**	4/6	**2/5**			
Post-monsoon	2/5	5/6	**2/3**			

Table 5. Neural network results of rainfall stations in Vaigai river catchment for dry, average & wet rainfall classes (Highlighted values indicate the forecasting probability of either dry or wet anomaly class)

Rainfall Season	BERIJAM			BODYNAYAKKANUR		
	Dry	Average	Wet	Dry	Average	Wet
Winter	**3/5**	3/4	1/4	**3/5**	3/5	2/4
Pre-monsoon	0/3	6/7	**2/3**	**4/5**	1/4	**4/4**
Monsoon	1/3	5/6	2/4	1/4	4/6	**3/3**
Post-monsoon	1/3	6/7	2/4	2/4	4/5	**3/4**
Rainfall Season	GUDALUR			PERIYAKULAM		
	Dry	Average	Wet	Dry	Average	Wet
Winter	**3/5**	2/4	**3/4**	**4/5**	1/4	2/4
Pre-monsoon	**3/4**	5/6	2/4	1/3	4/6	2/4
Monsoon	2/4	3/5	2/4	2/4	4/6	1/4
Post-monsoon	**2/3**	6/6	2/4	2/4	2/5	**3/4**
Rainfall Season	UTHAMAPALAYAM			VAIGAIDAM		
	Dry	Average	Wet	Dry	Average	Wet
Winter	**5/5**	1/5	2/4	2/5	2/4	**3/4**
Pre-monsoon	2/5	4/4	1/5	**3/4**	5/6	0/4
Monsoon	2/4	5/6	1/4	**3/4**	2/5	**3/5**
Post-monsoon	2/4	4/6	**3/3**	1/3	5/7	1/3
Rainfall Season	VEERAPANDI					
	Dry	Average	Wet			
Winter	**4/5**	1/4	**3/4**			
Pre-monsoon	0/4	5/6	**3/4**			
Monsoon	2/5	5/5	1/4			
Post-monsoon	2/4	4/5	2/4			

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Table 6. Random forest results of rainfall stations in Vaigai river catchment for dry, average & wet rainfall classes. (Highlighted values indicate the forecasting probability of either dry or wet anomaly class)

Rainfall Season	BERIJAM			BODYNAYAKKANUR		
	Dry	Average	Wet	Dry	Average	Wet
Winter	1/5	3/4	**4/4**	1/5	4/5	**3/4**
Pre-monsoon	0/3	7/7	0/3	**3/5**	2/4	2/4
Monsoon	1/3	4/6	1/4	1/4	4/6	**2/3**
Post-monsoon	**2/3**	6/7	1/4	2/4	4/5	2/4
Rainfall Season	**GUDALUR**			**PERIYAKULAM**		
	Dry	**Average**	**Wet**	**Dry**	**Average**	**Wet**
Winter	**5/5**	1/4	**3/4**	2/5	2/4	**3/4**
Pre-monsoon	1/4	4/6	**3/4**	0/3	5/6	**3/4**
Monsoon	2/4	2/5	**4/4**	2/4	5/6	1/4
Post-monsoon	**2/3**	6/6	1/4	2/4	5/5	1/4
Rainfall Season	**UTHAMAPALAYAM**			**VAIGAIDAM**		
	Dry	**Average**	**Wet**	**Dry**	**Average**	**Wet**
Winter	2/5	5/5	2/4	**4/5**	3/4	**3/4**
Pre-monsoon	**3/5**	2/4	**3/5**	2/4	3/5	1/4
Monsoon	2/4	5/6	1/4	2/4	1/5	**3/5**
Post-monsoon	4/4	4/6	0/3	0/3	6/7	2/3
Rainfall Season	**VEERAPANDI**					
	Dry	**Average**	**Wet**			
Winter	**3/5**	1/4	**3/4**			
Pre-monsoon	2/4	4/6	**3/4**			
Monsoon	2/5	4/5	2/4			
Post-monsoon	**3/4**	3/5	2/4			

Table 7. QDA of rainfall stations in Vaigai river catchment for dry, not dry rainfall classes

Rainfall Season	BERIJAM		BODYNAYAKKANUR	
	Dry	Not Dry	Dry	Not Dry
Winter	1/5	8/8	1/5	8/9
Pre-monsoon	0/1	12/12	0/3	10/11
Monsoon	1/6	7/7	1/5	9/9
Post-monsoon	1/4	7/9	4/5	9/9
Rainfall Season	**GUDALUR**		**PERIYAKULAM**	
	Dry	**Not Dry**	**Dry**	**Not Dry**
Winter	1/5	8/8	0/5	9/9
Pre-monsoon	1/4	9/9	0/6	7/8
Monsoon	2/4	9/9	0/3	11/11
Post-monsoon	1/3	10/10	0/3	10/11
Rainfall Season	**UTHAMAPALAYAM**		**VAIGAIDAM**	
	Dry	**Not Dry**	**Dry**	**Not Dry**
Winter	3/5	9/9	3/5	9/9
Pre-monsoon	2/5	8/9	0/4	10/10
Monsoon	1/5	8/9	3/6	7/8
Post-monsoon	1/4	9/10	0/3	9/11
Rainfall Season	**VEERAPANDI**			
	Dry	**Not Dry**		
Winter	0/5	7/8		
Pre-monsoon	1/5	8/8		
Monsoon	3/7	4/6		
Post-monsoon	1/4	9/9		

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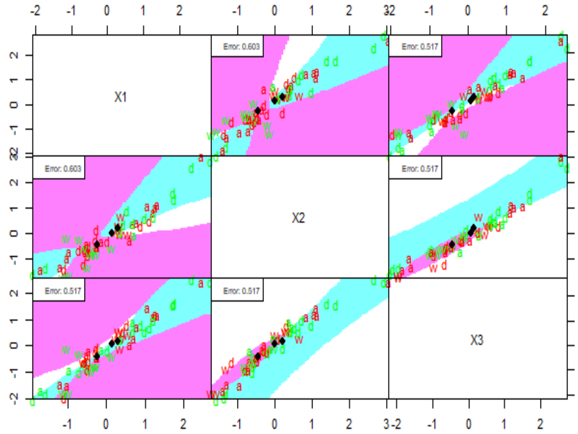
Table 8. Neural Network results of rainfall stations in Vaigai river catchment for dry & not dry rainfall classes

Rainfall Season	BERIJAM			BODYNAYAKKANUR		
	Dry	Not Dry	SSE	Dry	Not Dry	SSE
Winter	4/5	5/8	7.6	1/5	8/9	5.72
Pre-monsoon	0/3	10/11	6	4/5	5/9	3.01
Monsoon	0/3	9/10	5.43	2/4	9/10	4.92
Post-monsoon	1/3	10/11	**1.63**	3/4	6/10	**1.06**
Rainfall Season	**GUDALUR**			**PERIYAKULAM**		
	Dry	**Not Dry**	**SSE**	**Dry**	**Not Dry**	**SSE**
Winter	1/5	7/8	7.26	3/5	8/9	7.23
Pre-monsoon	1/4	9/10	4.06	2/3	9/10	6.04
Monsoon	1/4	9/10	**4.03**	1/4	9/10	**5.13**
Post-monsoon	0/3	10/10	5.64	1/4	10/10	6.38
Rainfall Season	**UTHAMAPALAYAM**			**VAIGAIDAM**		
	Dry	**Not Dry**	**SSE**	**Dry**	**Not Dry**	**SSE**
Winter	4/5	8/9	6.63	3/5	8/9	5.77
Pre-monsoon	2/5	8/9	8.21	2/4	8/10	2.41
Monsoon	0/4	10/10	6.81	3/4	7/10	3.62
Post-monsoon	1/4	9/10	**5.25**	1/3	8/10	**2.03**
Rainfall Season	**VEERAPANDI**					
	Dry	**Not Dry**	**SSE**			
Winter	3/5	7/8	7.13			
Pre-monsoon	2/4	9/10	**5.52**			
Monsoon	2/5	8/9	5.58			
Post-monsoon	2/4	9/10	5.77			

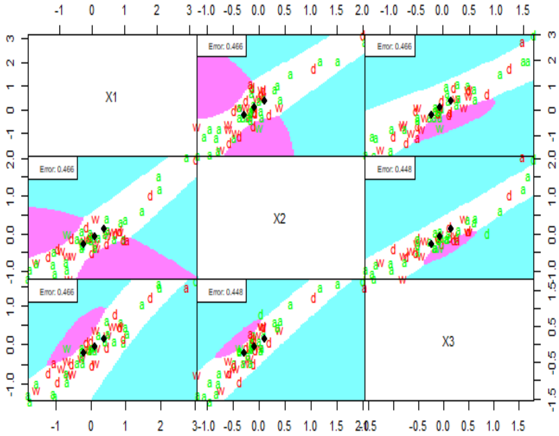
Table 9. Random forest results of rainfall stations in Vaigai river catchment for dry & not dry rainfall classes

Rainfall Season	BERIJAM			BODYNAYAKKANUR		
	Dry	Not Dry	OOB	Dry	Not Dry	OOB
Winter	0/5	7/8	42.20%	1/5	7/9	**27.27%**
Pre-monsoon	0/4	9/9	24.44%	1/6	8/8	31.82%
Monsoon	0/4	8/9	33%	2/7	6/7	36.36%
Post-monsoon	1/2	10/11	**22.22%**	0/3	9/9	36.36%
Rainfall Season	**GUDALUR**			**PERIYAKULAM**		
	Dry	**Not Dry**	**OOB**	**Dry**	**Not Dry**	**OOB**
Winter	2/5	7/8	40.00%	4/5	7/9	40.91%
Pre-monsoon	0/4	10/10	34.09%	0/3	8/10	**26.67%**
Monsoon	0/4	10/10	34.09%	2/4	9/10	36.36%
Post-monsoon	1/3	10/10	**31.11%**	1/4	9/10	47.73%
Rainfall Season	**UTHAMAPALAYAM**			**VAIGAIDAM**		
	Dry	**Not Dry**	**OOB**	**Dry**	**Not Dry**	**OOB**
Winter	2/5	8/9	38.64%	3/5	7/9	40.91%
Pre-monsoon	1/5	9/9	52.27%	1/4	9/10	31.82%
Monsoon	1/4	8/10	36.36%	1/4	9/10	43%
Post-monsoon	1/4	10/10	**34.09%**	3/4	8/10	**26.67%**
Rainfall Season	**VEERAPANDI**					
	Dry	**Not Dry**	**OOB**			
Winter	2/5	8/8	31.11%			
Pre-monsoon	0/4	10/10	34.09%			
Monsoon	1/5	9/9	50%			
Post-monsoon	2/4	9/10	**29.55%**			

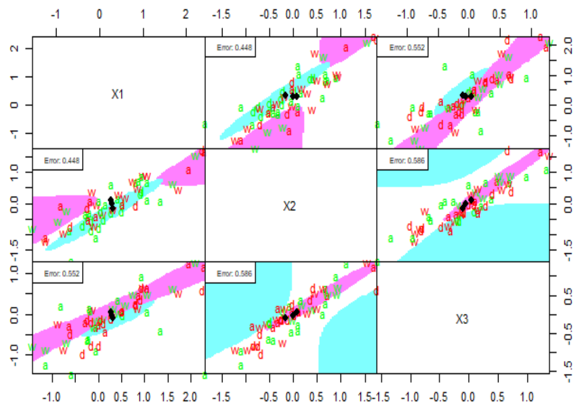
Figure 5. Quadratic discriminative analysis (QDA) for identifying the relationship between three rainfall classes (dry, wet and average) and MEI, NINO3 and NINO34 of different rainfall stations on Vaigai river basin. Where, X1 = MEI, X2 = NINO3, X3 = NINO34. And a, w, d are correct fitted values & a, w, d are wrong values.



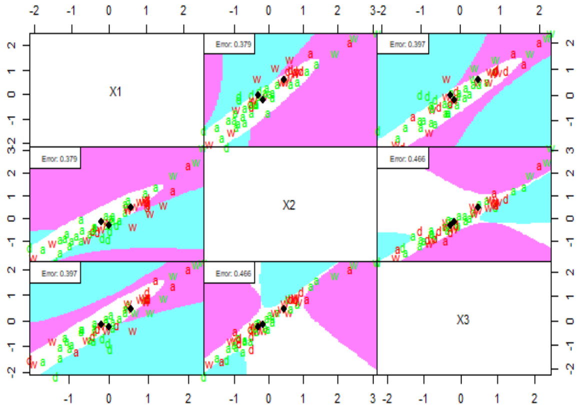
(a) Winter



(b) Pre-monsoon

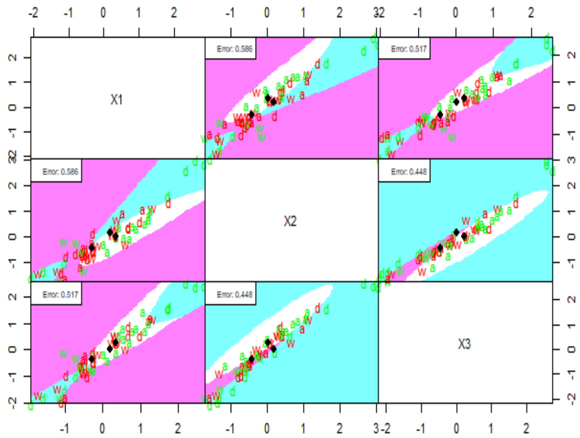


(c) Monsoon

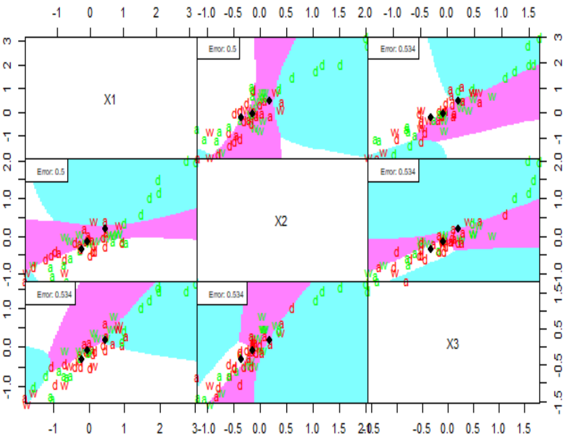


(d) Post-monsoon

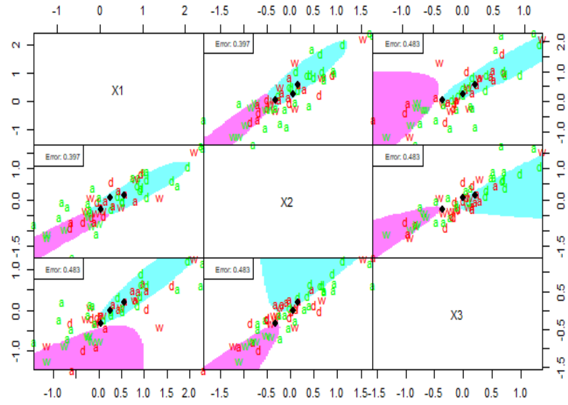
Figure 5.1. QDA of Berijam station under rainfall seasons Dry class average class Wet class



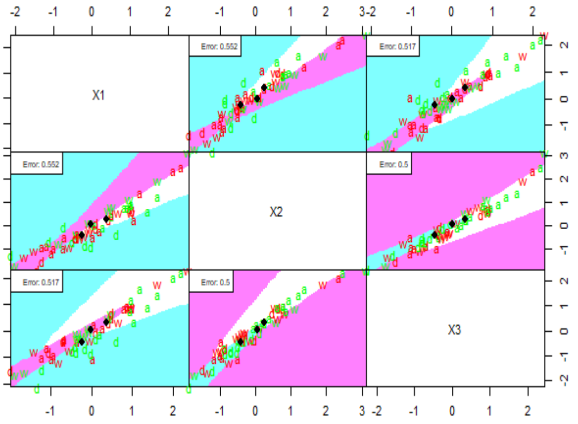
(a) Winter



(b) Pre-monsoon

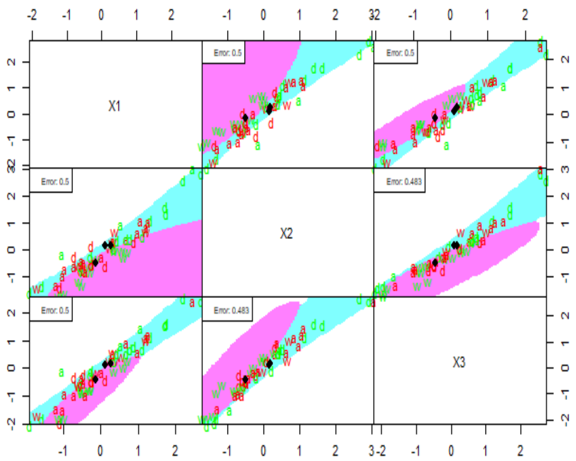


(c) Monsoon

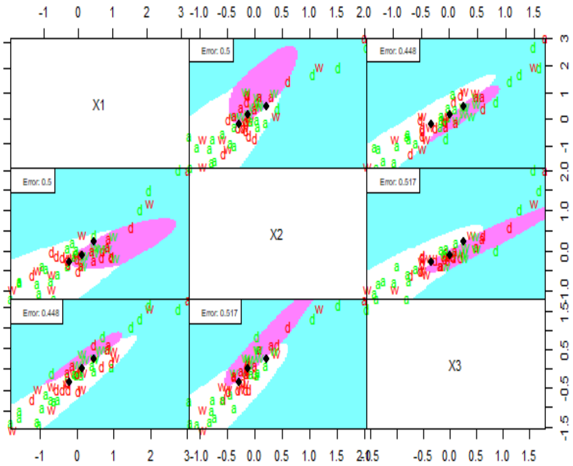


(d) Post-monsoon

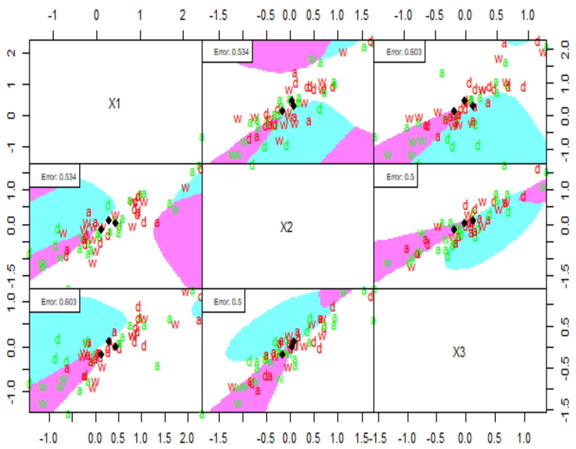
Figure 5.2. QDA of Bodynayakkanur station under rainfall seasons ☐ Dry class ☐ average class ☐ Wet class



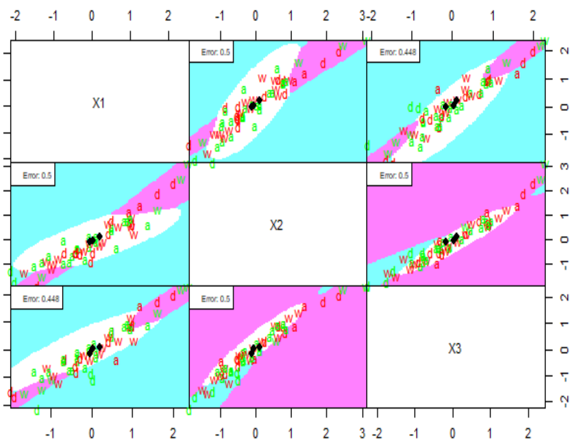
(a) Winter



(b) Pre-monsoon

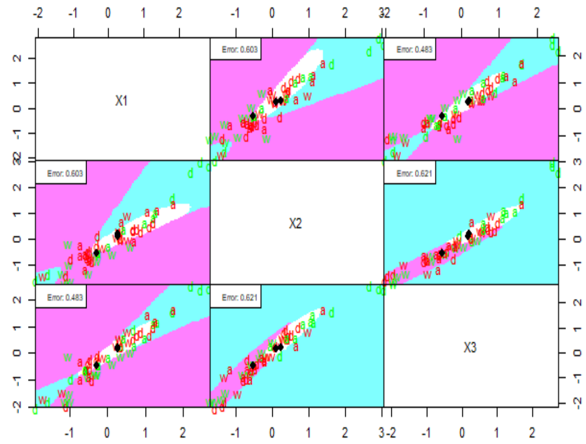


(c) Monsoon

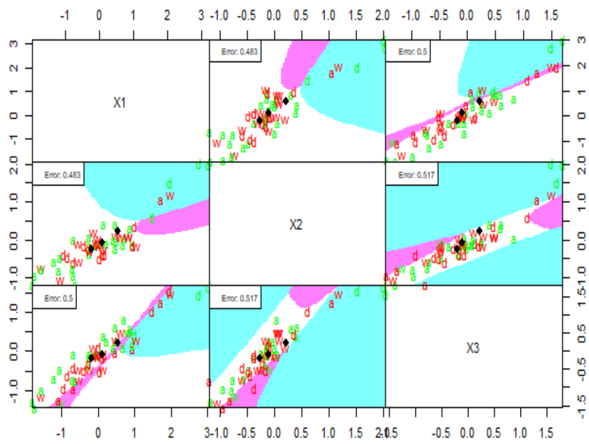


(d) Post-monsoon

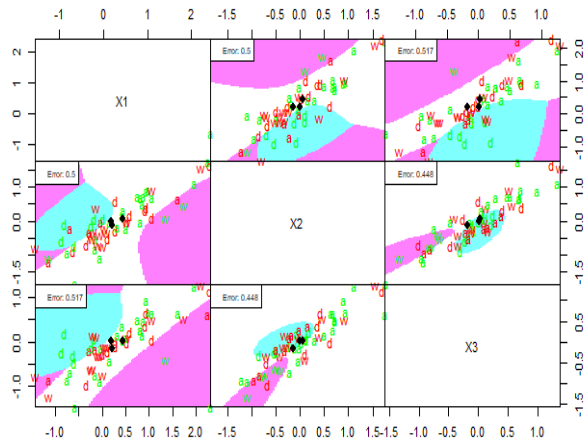
Figure 5.3. QDA of Gudalur station under rainfall seasons ☐ Dry class ☐ average class ☐ Wet class



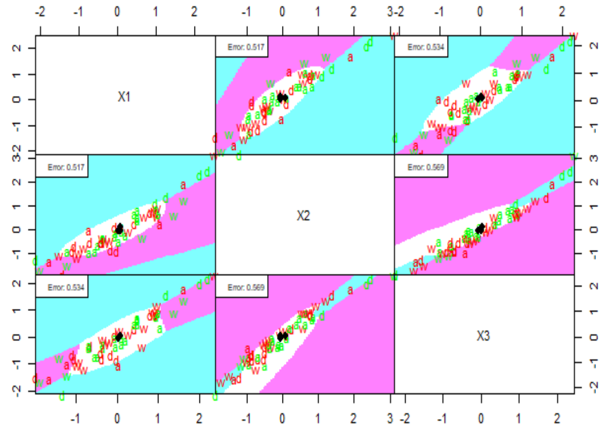
(a) Winter



(b) Pre-monsoon

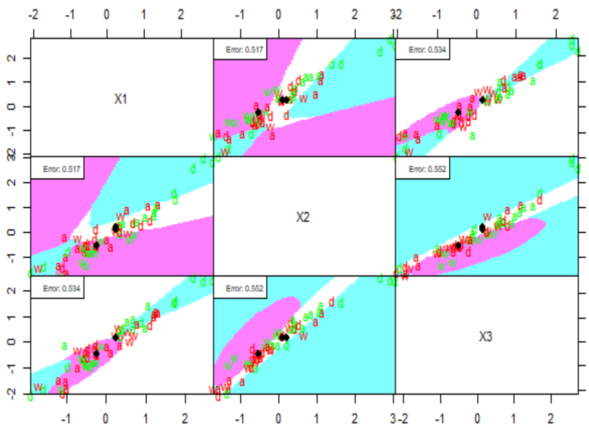


(c) Monsoon

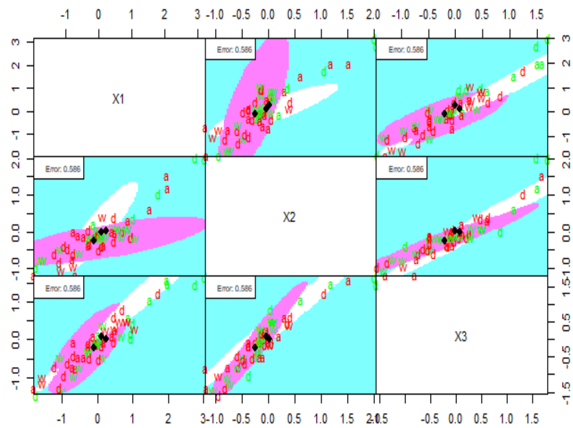


(d) Post-monsoon

Figure 5.4. QDA of Periyakulam station under rainfall seasons Dry class average class Wet class



(a) Winter



(b) Pre-monsoon

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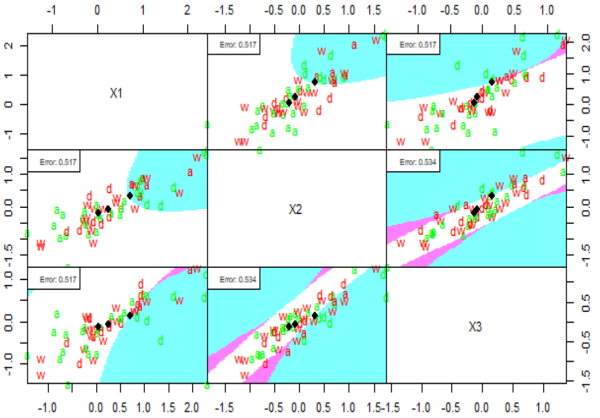
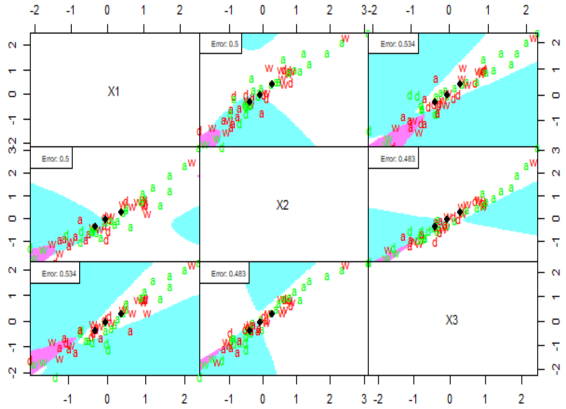
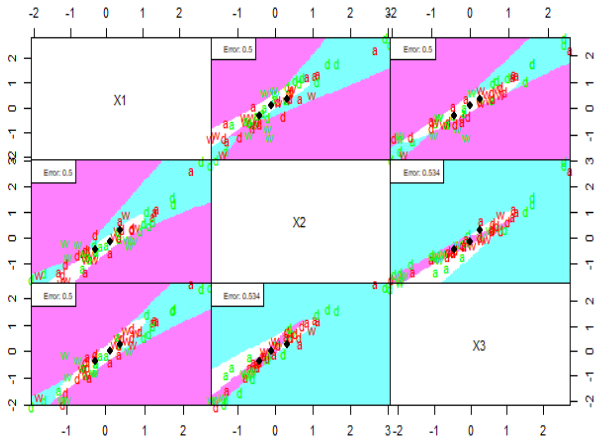


(c) Monsoon

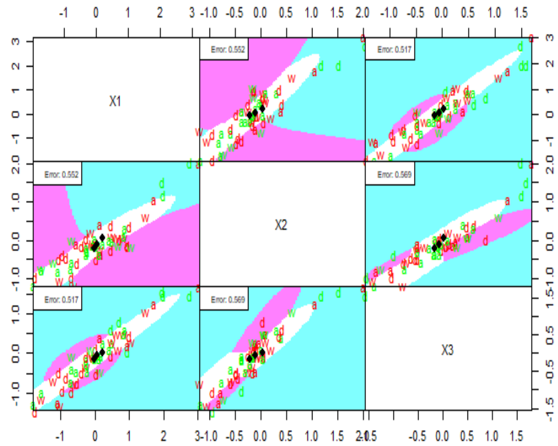


(d) Post-monsoon

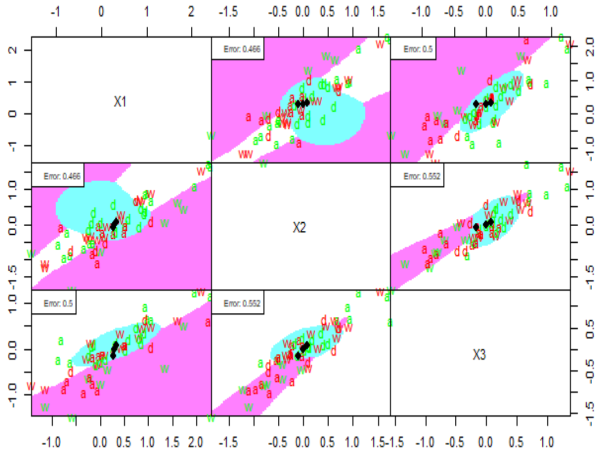
Figure 5.5. QDA of Uthamapalayam station under rainfall seasons Dry class average class Wet class



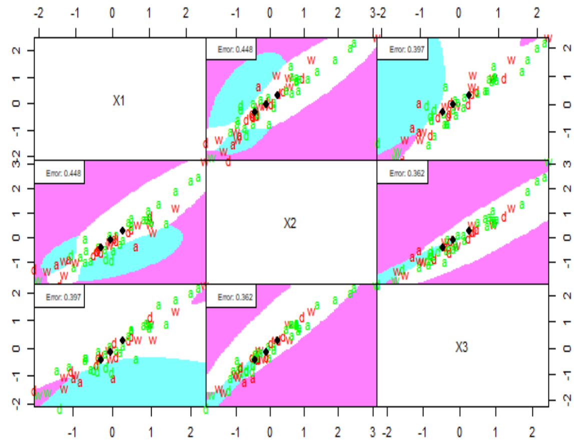
(a) Winter



(b) Pre-monsoon

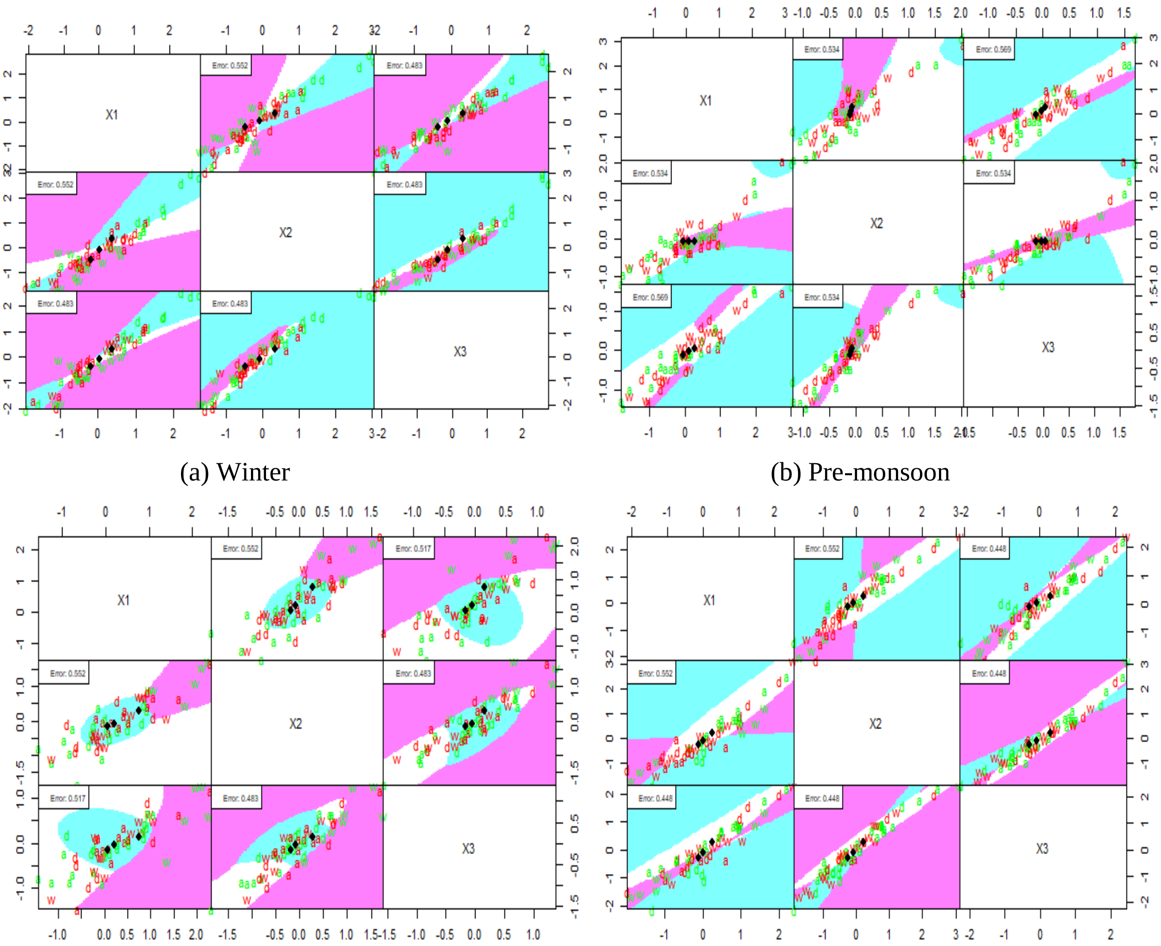


(c) Monsoon



(d) Post-monsoon

Figure 5.6. QDA of Vaigai Dam station under rainfall seasons Dry class average class Wet class



(a) Winter (b) Pre-monsoon

(c) Monsoon (d) Post-monsoon

Figure 5.7. QDA of Veerapandi station under rainfall seasons Dry class average class Wet class

The two-class classification model is also conducted on the same station to identify "dry" and "not dry" cases using the QDA, ANN and Random forest model on Periyakulam station.

The results correctly predicted as "not dry" with the *90%* of anomalously "not dry case, with the *100%* anomalously "not dry" case (SSE error rate of *6.38*) and with the *90%* of anomalously "not dry" case (with the OOB error rate of *47.73%*) respectively. Similarly, for the Vaigai Dam station the model has been applied during the Monsoon season, the results show a pattern with the overall accuracy of *67%* (4 out of 6 occurrences) in QDA, *75%* (3 out of 4 occurrences) in ANN. The results also suggest that it may be the possible reason to confirm that the season is anomalously dry. The two-class classification model is also conducted on the same station to identify "dry" and "not dry" cases using the QDA, ANN and Random forest model. The results also correctly predicted as "dry" with the *75%* of anomalously "dry "case (with SSE error rate of *3.62*) in ANN model.

V. CONCLUSION

The Rainfall data and climatic indices are divided into seasons, standardized rainfall anomalies for seasonal rainfall data have been computed using Climatic Indices (ENSO and SOI) tele-connections with Vaigai river basin catchment. Pattern recognition and prediction of rainfall classes were done using QDA, Random forest, Neural Network. The relationships identified between tele-connection indices and river basin rainfall anomalies agree with the research findings. Prediction of seasonal rainfall classes from ENSO and SOI indices provide useful information for planning towards domestic water supply, irrigation requirements, hydropower generation, *etc.*, for water resources managers in Vaigai river basin.

APPENDIX

ENSO Indices availability

The Climate index data are available in the following web links publicly and references are given as under, (accessed from the respective web links on 22nd April, 2019).

http://www.esrl.noaa.gov/psd/gcos_wgsp/Timeseries/Data/nino3.long.anom.data;

http://www.esrl.noaa.gov/psd/gcos_wgsp/Timeseries/Data/nino34.long.anom.data;

http://www.esrl.noaa.gov/psd/gcos_wgsp/Timeseries/Data/nino4.long.anom.data;

http://www.esrl.noaa.gov/psd/enso/mei.old/table.html

http://www.bom.gov.au/climate/current/soihtm1.shtml.

Retrieval Number: B2078078219/19©BEIESP
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Journal Website: www.ijrte.org

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AUTHORS PROFILE

Mahadevan Palanichamy received his bachelors in Civil Engineering in the year 1990 from P.S.N.A.College of Engineering and Technology, Madurai Kamaraj University, Madurai, Post Graduate Diploma in 1991 from Indian Institute of Ecology and Environment, New Delhi, Master of Business Administration in 1998 from Madurai Kamaraj University, Madurai and Master of Science (By Research) from Anna University, Chennai in the year 2009. He is currently working towards his PhD degree at Kalasalingam Academy of Research and Education (a deemed to be University), Krishnankoil, India. He is a Life member of Indian Society for Technical Education since 1993, Associate Member and also obtained Chartered Engineer Certification in the Institution of Engineers (India), Fellow in Institution of Valuers and Member in International Association of Hydrological Sciences. He has about 26 years of teaching experience and 2 years of industrial experience. His research interest is on Solid Waste Management Planning and Water Resources Management.

Dr. S.N. Ramaswamy is working as Professor in Civil Engineering at Anjalai Ammal Mahalingam Engineering College, TamilNadu. He obtained his B.E. degree in Civil Engineering from Thiagarajar College of Engineering, Madurai and M.E. degree in Structural Engineering from Annamalai University, Chidambaram. He was awarded Ph.D degree from Kalasalingam University, Tamil Nadu. His area of specialization is Explosion resident Structures for Fireworks and match works Industries. He has published more than 30 research papers in Journals and Conferences including 4 SCI Indexed, 6 Scopus Indexed International Journals. He was awarded Summer Research Fellowship in Indian Academy of Sciences during 2009. He is a member of professional bodies such as ASCE, ICI and ISTE. He has also obtained Chartered Engineer Certification and Member of Institution of Engineers (India).