PREDICTION OF GROUND WATER LEVEL OF PUNJAB STATE USING ARTIFICIAL NEURAL NETWORK

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Submitted by

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DECLARATION

I hereby declare that this is a bonafide work which is presented in this thesis entitled **"PREDICTION OF GROUND WATER LEVEL OF PUNJAB STATE USING ARTIFICIAL NEURAL NETWORK"**as per the requirements for the award of **Master of Engineering** in **Infrastructural Engineering**, submitted in the Department of Civil Engineering, Thapar Institute of Engineering and Technology (TIET), Patiala. This work is carried out under the guidance of **Dr.Dwarikanath Ratha.** It is declared that this work is original and has not been submitted anywhere else for the award of any other degree or certificate.

Date: 29 July 2022

Harjit Singh

This is to certify that the above declaration made by the student concerned is correct according to the best of my knowledge and belief.

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Harjit Singh

ABSTRACT

Groundwater has always been an essential and reliable resource to supply drinking and agriculture water and is considered dependable for supporting the consumption needs of different users. For groundwater resource management, predicting groundwater level fluctuations with the desired accuracy is very much required. Consequently, there's a need to deploy models capable of efficiently forecasting groundwater levels.

In the past decade or so, artificial neural network has become very known in the field of hydrology and for good reason. ANN model used in this study was ANN-BP, back propagation. The architecture of the ANN model was with two hidden layers with 10 neurons on each hidden layer. The prediction was done using three separate algorithms levenberg-marquardt, Bayesian regularization and scaled conjugate gradient. The best results were given by Bayesian regularization, with the available data the ANN model can predict groundwater up to 6 months for 11 districts; Amritsar, Bathinda, Faridkot, Fazilka, Hoshiarpur, Kapurthala, Ludhiana, Mansa, Moga, Patiala and Sangrur.

Keywords:

Artificial neural networks; Groundwater level forecasting; Aquifer exploitation; Groundwater management; Groundwater hydrology; Amritsar; Bathinda; Faridkot; Fazilka; Hoshiarpur; Kapurthala; Ludhiana; Mansa; Moga; Patiala and Sangrur; Punjab

Contents

Chapter: - 1

INTRODUCTION

1.1 General

Groundwater is one of the significant sources of supply for industrial, domestic, and agricultural purposes. In some areas, such as arid or semi-arid areas, it is the only source of supply, while in some regions, it is chosen because of its ready availability. In recent years, groundwater supplies have been overused, especially in industry and agriculture and this causes the groundwater level to be declined. Accurate prediction of groundwater level is one of the most critical stages in the sustainable yield of groundwater resources. It helps engineers, planners, and water managers to make appropriate decisions to avoid or reduce adverse effects such as loss of pumpage in water wells, aquifer compaction, and surface are subsidence. New data, new data driven techniques such as artificial neural network (ANN) have been accepted as an efficient tool for modeling hydrologic systems and widely used for prediction. During the past decade, the Artificial Neural Network model has become popular in hydrological modeling and forecasting. Humans can do complex tasks like perception, pattern recognition, or reasoning much more efficiently and learn from examples and neural systems of the human brain are to learn from examples and neural systems of the humanbrain are to some extent,fault-tolerant. Research and development in Artificial Neural Networks started with an attempt to model the bio-physiology of the human brain, creating models capable of mimic on a computational level. Neural networks are widely processing potentially effective approach for handling large amounts, of dynamic, nonlinear and noisy data, especially in such situations where the underlying physical relationships are not fully understood. Groundwater has always been an essential and reliable resource to supply drinking and agriculture water and is s considered reliable for supporting consumption the needs of different users. For the groundwater resource management, predictingwater level fluctuations with desired accuracy this is very much required. Consequently, there is a need for developing such models which are very capable of efficiently predicting groundwater levels. In regards, applications of soft computing techniques like Artificial Neural Networks are far more effective. Artificial neural network (ANN) model is a 'black box' model having particular properties which are exceptionally suited to dynamic nonlinear modelling. Several studies demonstrated the capability of ANN in hydrological modeling and forecasting.

1.2 Need for Groundwater Management

The state of Punjab has a number of groundwater-related issues. While a great portion of the Punjab state is experiencing dropping groundwater levels as a result of resource overexploitation, a smaller portion is seeing rising water levels and flooding. There have been examples of groundwater pollution as a result of numerous human activities, as well as a scarcity of safe drinking water in urban areas.Some of the major significance that needs to be addressed are outlined below:

1. Groundwater depletion due to overexploitation
2. Rising water table and waterlogging
3. Saline / Brackish water – use and disposal
4. Flood plains – groundwater development potential
5. Water shortage in urban areas
6. Groundwater development in hilly areas
7. Groundwater pollution

Farmers had traditionally followed maize-wheat or sugarcane-maize-wheat cropping patterns. Nonetheless, they have moved to a Wheat-Rice cropping pattern in the previous four decades, resulting in increased demand for irrigation water.
In 1970, the state had just 1.92 million shallow tube wells, which climbed to 6.00 million in 1980, and now there are more over 14.76 million tube wells in the state as of 2018-19.

Out of 137 blocks in the State, 103 are overexploited critical, 4 are semi-critical, and 25 are safe. The safe category blocks are located throughout the state's foothills, where water levels are high, and in the state's south-western region, where water logging is common and water is not potable.

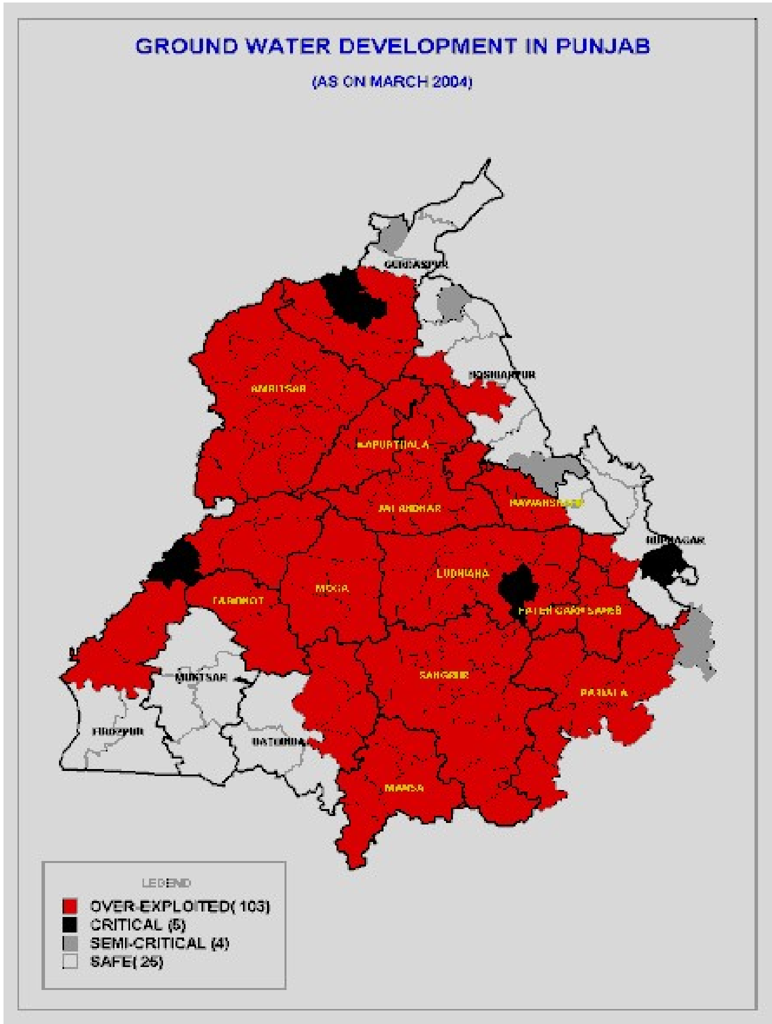


Figure- 1.1 Punjab map showing status of groundwater level (S gupta 2009)

1.3 Causes for Groundwater Fluctuations

The elevation of atmospheric pressure of an aquifer is indicated by a groundwater level, whether it is the water table of an unconfined aquifer or the piezo metric surface of a confined aquifer. Groundwater levels fluctuate due to differences in supply and withdrawal.

Other influences on groundwater levels include:

- Evapotranspiration
- Meteorological
- Urbanization
- Earthquakes
- External loads

1.3.1 Evapotranspiration-Induced Fluctuations: -

Unconfined aquifers with water tables near the ground surface frequently exhibit diurnal fluctuations due to evaporation or transpiration. Both processes cause a discharge of groundwater into the atmosphere. From a practical perspective, it is burdensome to segregate evaporation and transpiration losses from groundwater, therefore, the combined loss, which is referred to as evapotranspiration (or consumptive use) is normally measured.

1.3.2 Meteorological Phenomenon-Induced Fluctuations: -

1)Atmospheric pressure: Wells accessing constrained aquifers experience significant swings as air pressure changes. Changes in atmospheric pressure are directly conveyed to the water table in an unconfined aquifer, both in the aquifer and in a well. (no pressure difference occur)

2)Rainfall: Because of surface and subsurface losses, as well as vertical percolation travel time, rainfall is not a reliable indicator of groundwater recharge.

3)Wind: Wind blowing over the tops of wells causes minor changes in water levels. When a gust of wind passes across the top of a casing, the air pressure inside the well drops rapidly, causing the water level to increase swiftly. The air pressure in the well rises once the gust passes, and the water level lowers.

4)Frost: In areas with significant frost, shallow water tables have been seen to progressively decrease during the winter and increase abruptly in early spring before replenishment from the ground surface can occur. The appearance of a frost layer above the water table is to blame for the oscillations.

1.3.3 Urbanization-induced Effect: -

As a result of decreased recharge and increasing withdrawal, the process of urbanisation frequently produces changes in groundwater levels. The effects of urbanisation on groundwater levels are numerous:

1. Groundwater recharge is reduced as a result of paved surface areas and storm drains.

2. Increased groundwater discharge by pumping wells.

3. Groundwater recharge is reduced as a result of wastewater collected by sanitary sewers being exported.

1.3.4 Earthquakes-induced Fluctuations: -

Earthquakes have a variety of consequences on groundwater, including rapid spikes or declines in well water levels, changes in discharge and the formation of new springs, and mud eruptions.

1.3.5 External Loads-Induced Fluctuations: -

The aquifer is compressed and the hydrostatic pressure is increased when load is applied. As water travels radially away from the spot where the load is applied, the pressure falls and approaches its initial value. As a result, the load is first shared by the restricted water and the aquifer's solid material; but, as the water flows radially outward, an increasing amount of the weight is carried by the aquifer's structure.

1.5 OBJECTIVES

- To find the reasons associated with factors affecting Groundwater levels in Punjab.
- Forecasting the future water tables so that the districts which are under most exploitedgroundwater reserve can be avoided or measures can be taken accordingly.
- The purpose is to develop a new data-based method of highly accurategroundwater level forecasting that can be used to help water managers, engineers and stake-holders manage groundwater in a more effective and sustainable manner.

Chapter: - 2

LITERATURE REVIEW

2.1 INTRODUCTORY COMMENTS

In the previous chapter we discussed about the groundwater source of Punjab and the need for groundwater management for upcoming years. For groundwater management causes for groundwater fluctuations is discussed in order to better groundwater management.

In this chapter literature review will be talked in depth different methods for groundwater forecasting. Different artificial neural network models and different techniques to overcome different problems like when there is less available physical data for forecasting etc. the point of this chapter is to broaden our view for this study and get up to speed of what has been done so far in this area of field and to try and find a better or more efficient approach for this study and learn from previously published papers in this area of expertise.

2.2 LITERATURE SUMMERY

The study conducted by **Lohani and Krishan (**2015); identifies the most reliable and effective neural network architecture for predicting groundwater level in Punjab, India's Amritsar and Gurdaspur districts. The other study done by them shows that the best results can be obtained using a typical feed forward neural network trained with the Levenberg-Marquardt algorithm, it has been observed after enhancing the model accuracy using various types of network designs and training procedures.Designing specific networks for various sites can help estimate groundwater levels accurately, and the ANN approach has been shown to do so in the Punjab, India districts of Faridkot, Ferozepur, Ludhiana, and Patiala.**Riccardo Taormina**(2012); conducted this study, Up to a few time steps in advance, groundwater levels can be predicted and estimated with great success using artificial neural networks.In this study, we show how feed forward neural networks can be used to mimic hourly groundwater levels over extended periods of time in an unconfined coastal aquifer situated in the Lagoon of Venice, Italy.**Fabio and Francesco**(2020);conducted this study, the precise results achieved for the Apulia region point to the potential use of the NARX network for groundwater level forecasting in other regions with problematic groundwater resource management.**Ashish and Anjali** (2020); conducted this study, In this study, an ANN model was used to predict the pre and post monsoon groundwater fluctuation at the Tikri Kalan observation well situated in the West Delhi, India.The architecture of 3-15-1 is found to be generating the best results and can be employed in urban areas for forecasting groundwater fluctuation and managing water resources effectively.**Sanghoon et al.** (2018); conducted this study , change in groundwater level is predicted for a special site where transient natural factors affecting the groundwater level are mixed with very irregular anthropogenic influences.The prediction results showed good performance with root mean square errors of 3–6 cm when the average groundwater level is about 25.59 m, the correlation coefficient is >0.9 and the Nash– Sutcliffe efficiency is >0.75, indicating that the ANN models are well suited for assessing complex groundwater systems.**Ozgur et al.** (2017);conducted this study, the accuracies of three different evolutionary artificial neural network (ANN) approaches, ANN with genetic algorithm (ANN-GA), ANN with particle swarm optimization (ANN-PSO) and ANN with imperialist competitive algorithm (ANN-ICA), were compared in estimating groundwater levels (GWL) based on precipitation, evaporation and previous GWL data.**Samad et al.** (2013); conducted this study, this study investigates the potential of two intelligence models namely, Artificial Neural Network (ANN) and Adaptive Neuro-Fuzzy Inference System (ANFIS) in the forecasting of the groundwater level of Bastam Plain in Iran.Finally, three scenarios were considered to predict the groundwater level in the next 2 years as follows 1- The rainfall recharge and pumping rate of water wells will be constant, 2- The rainfall recharge will be constant, but the pumping rate of water wells will be reduced equal to the water deficit of the aquifer, 3- The pumping rate of water wells will be constant but the rainfall recharge will be reduced 30 %.**Manouchehr et al.** (2013); conducted this study, In this paper, the Artificial Neural Network (ANN) approach is applied for forecasting groundwater level fluctuation in Aghili plain, southwest Iran.**Ioannis N et al.** (2004);conducted this study, a proper design of the architecture of Artificial Neural Network (ANN) models can provide a robust tool in water resources modeling and forecasting.The performance of different neural networks in a groundwater level forecasting is examined in order to identify an optimal ANN architecture that can simulate the decreasing trend of the groundwater level and provide acceptable predictions up to 18 months ahead.**Chang et al.** (2015);conducted this study, two ANN models, one with three input variables (previous groundwater level, temperature and precipitation) and another with two input variables (temperature and precipitation only), were developed to simulate and predict the site-specific suprapermafrost groundwater level on the slope scale.The results indicate that the three input variable ANN model has superior real-time site-specific prediction capability and produces excellent accuracy performance in the simulation and forecasting of the variation in the suprapermafrost groundwater level.However, if there are no field observations of the suprapermafrost groundwater level, the ANN model developed using only the two input variables of the accessible climate data also has good accuracy and high validity in simulating and forecasting the suprapermafrost groundwater level variation to overcome the data limitations and parameter uncertainty.**Sasmita and Madan**(2013); conducted this study, the potential of multiple linear regression (MLR) and artificial neural network (ANN) techniques in predicting transient water levels over a groundwater basin were compared.MLR and ANN modeling was carried out at 17 sites in Japan, considering all significant inputs: rainfall, ambient temperature, river stage, 11 seasonal dummy variables, and influential lags of rainfall, ambient temperature, river stage and groundwater level.Comparison of the goodness-of-fit statistics of the MLR models with those of the ANN models indicated that there is better agreement between the ANN-predicted groundwater levels and the observed groundwater levels at all the sites, compared to the MLR.**Gholam et al** (2012);conducted this study , effective parameters on groundwater level such as 5-month precipitation and groundwater level histories, temperature or evaporation, and runoff were utilized as the input data to forecast groundwater level at the next time step as output of the networks.Different networks forecasted groundwater level in all wells with acceptable root mean square errors of 0.6–12.17 m. Best overall performance was achieved by feed-forward neural network and the second best by Elman neural network.**Ripon et al.** (2020);conducted this study, this study presents implementation of non-linear autoregressive model with exogenous inputs (NARX) of Artificial neural network (ANN), used for groundwater level (GWL) simulation to predict its weekly level up to 52 weeks ahead in selected 14 Permanent Hydrograph Stations (PHSs) in the drought prone Barind Tract in the northwestern part of Bangladesh and is considered to be the first attempt of this type in the country.**Ioannis C. et al.** (2011);conducted this study, ANNs can prove to be very useful because, unlike numerical groundwater models, they are very easy to implement in karstic regions without the need of explicit knowledge of the exact flow conduit geometry and they avoid the creation of extremely complex models in the rare cases when all the necessary information is available.With hydrological parameters like rainfall and temperature, as well as with hydrogeological parameters like pumping rates from nearby wells as input, the ANN applies a black box approach and yields the simulated hydraulic head.That aside, the ANN is still a useful way to simulate karstic aquifers that are difficult to be simulated by numerical groundwater models.**Purna et al.** (2006);conducted this study, this paper reports a research study that investigates the potential of artificial neural network technique in forecasting the groundwater level fluctuations in an unconfined coastal aquifer in India.An input sensitivity analysis suggested that exclusion of antecedent values of the water level time series may not help the model to capture the recharge time for the aquifer and may result in poorer performance of the models.**Thendiyath et al.** (2020);conducted this study, emotional artificial neural network coupled with genetic algorithm (EANN-GA) is one such novel hybrid neural network which has been used in the present study for the forecasting of groundwater levels at three sites (Site H3, Site H4.5, and Site H9) in a coastal aquifer system.This study was conceived to address and investigate the efficiency of the ensemble model (EANN-GA) for forecasting one-month ahead groundwater level and to compare its performance with emotional artificial neural network (EANN), generalized regression neural network (GRNN), and the conventional feedforward neural network (FFNN).Variations in the rainfall, tidal levels, and groundwater levels are selected as inputs for the development of EANN-GA, EANN, GRNN, and FFNN models.Thus, it can be inferred that the EANN-GA model outperforms the developed EANN model, GRNN model, and FFNN model.Superior prediction capability and generalization ability make the EANNGA model a better alternative for predicting groundwater levels.Overall, this study demonstrates the effectiveness of EANN-GA in modeling spatio-temporal fluctuations of groundwater levels.**Vahid et al.** (2008);conducted this study, In the present research the performance of different neural networks for groundwater level forecasting is examined in order to identify an optimal ANN architecture that can simulate the piezometers water levels.**Akram et al.** (2020);conducted this study, In the present study, six meta-heuristic schemes are hybridized with artificial neural network (ANN), adaptive neuro-fuzzy interface system (ANFIS), and support vector machine (SVM), to predict monthly groundwater level (GWL), evaluate uncertainty analysis of predictions and spatial variation analysis.Groundwater level (GWL) data of Ardebil plain (Iran) for a period of 144 months were selected to evaluate the hybrid models.**Esmaeil et al.** (2019);conducted this study,In the first step, the best models for the study region were selected from the general circulation models provided under the Fifth Assessment Report of the United Nations Intergovernmental Panel on Climate Change. The model simulation under the three above-mentioned scenarios and the trend in groundwater decline in the Shabestar Plain for the base and future periods illustrated that the groundwater level dynamics were not related solely to climate parameters and that the impact of anthropogenic factors would be high.**Imam et al.** (2020);conducted this study, the main purpose of the research is to develop a groundwater level forecasting model to monitor the dynamics of land water fluctuations in tropical peatland in order to comply with government regulation No.57 of 2016 on the protection and management of peat ecosystems. Data that is used to build a model of groundwater level forecasting in tropical peatland sourced from Hobo Water Logger measuring device that record water table in 2014.The main results of the research proved that the implementation of a groundwater level forecasting model on the tropical peatlands in Bengkalis using the ANN method approach for the next day (t + 24) has a very strong classification tested using statistical parameters coefficient of correlation (R) and Mean Square Error (MSE) respectively 0.995929 and 0.0003026 so that the model can be applied on tropical peatlands.**Supreetha et al.** (2019);conducted this study, the groundwater level modelling and forecasting have wide application for effective groundwater resources management. The alternative approach for groundwater level forecasting is data-driven models. We developed an innovative hybrid ABC algorithm based on PSO searching mechanism to carry out forecasts of future groundwater levels with the aid of earlier recorded groundwater levels and rainfall.**KAYA et al.** (2018)conducted this study, In this study, groundwater level (GWL) was investigated using artificial neural networks (ANN), M5tree (M5T) approaches in Reyhanlı region in Turkey.**Amandeep et al.** (2018);conducted this study,Precise prediction of groundwater level is important for management of groundwater source.In Artificial neural network also different models were used for forecasting of groundwater level but most accurate predictions was achieved with a standard feed forward neural network trained with the Leven berg-Marquardt algorithm.**Arman et al.** (2022);conducted this study, modeling the groundwater level is the most popular application of machine learning models, and the groundwater level in previous time steps is the most employed input data.The feed-forward artificial neural network is the most employed and accurate model, although the model performance does not exhibit a striking dependence on the model choice, but rather the information content of the input variables.**R. Sarma & S. K. Singh** (2022); conducted this study,prediction models have been widely used to forecast groundwater levels at the regional scale.This study compares the accuracy of five commonly used data-driven models–Holt–Winters' Exponential Smoothing, Seasonal Autoregressive Integrated Moving Average, Multi-Layer Perceptron, Extreme Learning Machine, and Neural Network Autoregression for simulating the declining groundwater levels of three monitoring wells in the National Capital Territory of Delhi in India.MultiLayer Perceptron was used to forecast the groundwater level in the study wells for 2025.**Demirci et al.** (2019);conducted this study,In this study, the groundwater level of Reyhanli region in Turkey was predicted using multi-linear regression (MLR), adaptive neural fuzzy inference system (ANFIS), Radial basis neural network (RBNN), support vector machines with radial basis functions (SVM-RBF) and support vector machines with poly kernels (SVM- PK) methods.Comparisons revealed that the SVM–RBF and SVM-PK models had the most accuracy in the groundwater level prediction.**Mohammad and Amir** (2012);conducted this study,Accurate groundwater level modeling and forecasting contribute to civil projects, land use, cities planning and water resources management.This study investigates the sensitivity of the pre-processing to the wavelet type and decomposition level in WANN model for groundwater level forecasting.

2.3 LITERATURE REVIEW

Lohani and Krishan (2015); conducted this study. This study identifies the most reliable and effective neural network architecture for predicting groundwater level in Punjab, India's Amritsar and Gurdaspur districts. Different types of network designs and training procedures are researched and compared for forecasting the model efficiency and accuracy.A typical feed-forward neural network that has been trained using the Levenberg-Marquardt method has been proven to be capable of making correct predictions. By segmenting the data from the boreholes/observation wells into different groups and creating unique networks, which is validated by the ANN technique, good groundwater level estimation may be achieved. The ANN model's forecasting accuracy is within acceptable bounds. In the Punjab province of India, the Amritsar and Gurdaspur districts have discovered that the ANN approach can predict groundwater level.

Lohani and Krishan (2015); conducted this study,an effective and reliable artificial neural network (ANN) model is presented in this research for predicting groundwater level in south-east

Punjab, India. The best results can be obtained using a typical feed forward neural network trained with the Levenberg-Marquardt algorithm, it has been observed after enhancing the model accuracy using various types of network designs and training procedures.Designing specific networks for various sites can help estimate groundwater levels accurately, and the ANN approach has been shown to do so in the Punjab, India districts of Faridkot, Ferozepur, Ludhiana, and Patiala.

Riccardo et al. (2012); conducted this study,up to a few time steps in advance, groundwater levels can be predicted and estimated with great success using artificial neural networks.In this study, we show how feed forward neural networks can be used to mimic hourly groundwater levels over extended periods of time in an unconfined coastal aquifer situated in the Lagoon of Venice, Italy. Once the model has been initialised using groundwater levels observed at a specific period, the constructed FNN should be able to mimic variations in water level using only the external input variables, which have been identified as rainfall and evapotranspiration. To accomplish this, the models are first trained on a training dataset to make predictions of future groundwater levels one hour in advance utilising data from previously observed groundwater levels and outside inputs.The anticipated groundwater levels and actual external data are iteratively fed back into simulations, which are then produced on another data set. The findings demonstrate that over several months, the created FNN can faithfully reproduce groundwater depths of the shallow aquifer. The study suggests that, provided historical data for the influencing variables is available, thesenetworks can be used as a feasible alternative to physical based models to simulate the responses of the aquifer under possible future scenarios or to reconstruct lengthy periods of missing observations.

Fabio and Francesco(2020); conducted this study,due to occurrences like saltwater intrusion the high demand for water in the Mediterranean region usually causes excessive water resource exploitation. As a result the quality of freshwaters stored in coastal aquifers is deteriorated. The NARX network was employed in this study to forecast the daily variation in groundwater levels for 76 monitored wells situated on the Apulian territory.In order to determine the influence of two input parameters, rainfall and evapotranspiration, as well as the sensitivity to modifications in the training algorithm and input time delay, a preliminary investigation on reference wells was conducted.A thorough regional analysis and in-depth subregional analyses were conducted based on the preliminary analysis's findings, demonstrating the accuracy of the NARX-BR network for predicting groundwater levels in wells situated on various hydrogeological structures. The precise results achieved for the Apulia region point to the potential use of the NARX network for groundwater level forecasting in other regions with problematic groundwater resource management.

Ashish and Anjali (2020); conducted this study,the demand for water resources has increased due to the rapid growth of metropolitan areas brought on by population growth and industrialization. Additionally, the groundwater recharge is being impacted by the shifting land use pattern brought on by urban development.Therefore, accurate groundwater forecasting has become a must for effective groundwater resource development. Artificial neural networks (ANN) are a modelling method that can be applied to complex issues with water resources. ANN is a mathematical model that simulates how nerve cells function. It is capable of recognizing the relationship between the input and output without understanding the physical connection between them. In this study, an ANN model was used to predict the pre and post monsoon groundwater fluctuation at the Tikri Kalan observation well situated in the West Delhi, India. The model comprises of three layers feed forward network trained with Levenberg-Marquardt (LM) algorithm and activated with log sigmoid function. Four different architectural networks are formulated and the optimum one is identified on the performance of statistical indices. The architecture of 3-15-1 is found to be generating the best results and can be employed in urban areas for forecasting groundwater fluctuation and managing water resources effectively.

Sanghoon et al. (2018); conducted this study, change in groundwater level is predicted for a special site where transient natural factors affecting the groundwater level are mixed with very irregular anthropogenic influences. When there is not enough hydrogeological information about the area to be analyzed, an artificial neural network (ANN) is a powerful tool for groundwater level forecasting in highly irregular and uncertain groundwater systems. In this study, groundwater levels were predicted by using ANN models with input variables composed of one natural factor and two anthropogenic factors in Yangpyeong riverside area, South Korea. Complex and irregular change of the groundwater level was monitored due to the operation of a groundwater heat pump system and winter intensive pumping for water curtain cultivation (by which greenhouses are warmed). The prediction results showed good performance with root mean square errors of 3–6 cm when the average groundwater level is about 25.59 m, the correlation coefficient is >0.9 and the Nash– Sutcliffe efficiency is >0.75, indicating that the ANN models are well suited for assessing complex groundwater systems. Along with the prediction, an extraction method was devised to calculate contributions and relative impacts of the input variables in the time-series-based ANN models. As a result, it was proved that the river level dominantly affects the groundwater level fluctuation, and the contributions of each influencing factor were obtained reliably according to spatial distribution and temporal variance. This makes the scheme effective for managing and using groundwater resources with consideration of every crucial influencing factor of the groundwater level fluctuation.

Ozgur et al. (2017);conducted this study, the accuracies of three different evolutionary artificial neural network (ANN) approaches, ANN with genetic algorithm (ANN-GA), ANN with particle swarm optimization (ANN-PSO) and ANN with imperialist competitive algorithm (ANN-ICA), were compared in estimating groundwater levels (GWL) based on precipitation, evaporation and previous GWL data. The input combinations determined using auto-, partial auto- and cross-correlation analyses andtried for eachmodel are: (i) GWLt-1 and GWLt-2; (ii) GWLt-1, GWLt-2 andPt ; (iii) GWLt-1, GWLt-2 andEt ; (iv) GWLt-1, GWLt-2,Pt andEt ; (v) GWLt-1, GWLt-2 andPt-1where GWLt ,Pt and Et indicate the GWL, precipitation and evaporation at time t, individually. The optimal ANNGA, ANN-PSO and ANN-ICA models were obtained by trying various control parameters. The best accuracies of the ANN-GA, ANN-PSO and ANN-ICA models were obtained from input combination (i). The mean square error accuracies of the ANN-GA and ANN-ICA models were increased by 165 and 124% using ANN-PSO model. The results indicated that the ANN-PSO model performed better than the other models in modeling monthly groundwater levels.

Samad et al. (2013), conducted this study, prediction of the groundwater level (GWL) fluctuations is very important in the water resource management. This study investigates the potential of two intelligence models namely, Artificial Neural Network (ANN) and Adaptive Neuro-Fuzzy Inference System (ANFIS) in the forecasting of the groundwater level of Bastam Plain in Iran. For this purpose, 9 years data-sets including hydrological and hydrogeological parameters like rainfall recharge, irrigation returned flow and also pumping rates from water wells were used as input data to predict groundwater level. The results showed that ANN and

ANFIS models can predict GWL accurately. Also, it was found that the ANFIS model (with root-mean-square-error (RMSE) 0.02 m and determination coefficient ($R2$) of 0.96) performed better than the ANN model with RMSE=1.06 m and $R2$ =0.83. Finally, three scenarios were considered to predict the groundwater level in the next 2 years as follows 1- The rainfall recharge and pumping rate of water wells will be constant, 2- The rainfall recharge will be constant, but the pumping rate of water wells will be reduced equal to the water deficit of the aquifer, 3- The pumping rate of water wells will be constant but the rainfall recharge will be reduced 30 %. The prediction with these scenarios showed that the groundwater level has the minimum reduction when the pumping rate of water wells is equal to the water deficit of the aquifer.

Manouchehr et al. (2013); conducted this study, in this paper, the Artificial Neural Network (ANN) approach is applied for forecasting groundwater level fluctuation in Aghili plain, southwest Iran. An optimal design is completed for the two hidden layers with four different algorithms: gradient descent with momentum (GDM), levenberg marquardt (LM), resilient back propagation (RP), and scaled conjugate gradient (SCG). Rain, evaporation, relative humidity, temperature (maximum and minimum), discharge of irrigation canal, and groundwater recharge from the plain boundary were used in input layer while future groundwater level was used as output layer. Before training, the available data were divided into three groups, according to hydrogeological characteristics of different parts of the plain surrounding, each piezometer. Therefore, FFN-LM algorithm has shown best result in the present study for all three hydrogeological groups. At last, to evaluate applied division, a unit network with all data and using LM algorithm was trained. Validation of the network shows that dividing the piezometers into different groups of data and designing distinct networks gives more focus on simulating groundwater level in the plain. The degree of accuracy of the ANN model in prediction is acceptable. Thus, it can be determined that ANN provides a feasible method in predicting groundwater level in Aghili plain.

Ioannis N. et al. (2004); conducted this study, a proper design of the architecture of Artificial Neural Network (ANN) models can provide a robust tool in water resources modeling and forecasting. The performance of different neural networks in a groundwater level forecasting is examined in order to identify an optimal ANN architecture that can simulate the decreasing trend of the groundwater level and provide acceptable predictions up to 18 months ahead. Messara

Valley in Crete (Greece) was chosen as the study area as its groundwater resources have being overexploited during the last fifteen years and the groundwater level has been decreasing steadily. Seven different types of network architectures and training algorithms are investigated and compared in terms of model prediction efficiency and accuracy. The different experiment results show that accurate predictions can be achieved with a standard feedforward neural network trained with the Levenberg–Marquardt algorithm providing the best results for up to 18 months forecasts.

Chang Juan et al. (2015),conducted this study, suprapermafrost groundwater has an important role in the hydrologic cycle of the permafrost region. However, due to the notably harsh environmental conditions, there is little field monitoring data of groundwater systems, which has limited our understanding of permafrost groundwater dynamics. There is still no effective mathematical method and theory to be used for modeling and forecasting the variation in the permafrost groundwater. Two ANN models, one with three input variables (previous groundwater level, temperature and precipitation) and another with two input variables (temperature and precipitation only), were developed to simulate and predict the site-specific suprapermafrost groundwater level on the slope scale. The results indicate that the three input variable ANN model has superior real-time site-specific prediction capability and produces excellent accuracy performance in the simulation and forecasting of the variation in the suprapermafrost groundwater level. However, if there are no field observations of the suprapermafrost groundwater level, the ANN model developed using only the two input variables of the accessible climate data also has good accuracy and high validity in simulating and forecasting the suprapermafrost groundwater level variation to overcome the data limitations and parameter uncertainty. Under scenarios of the temperature increasing by 0.5 or 1.0 C per 10 years, the suprapermafrost groundwater level is predicted to increase by 1.2–1.4% or 2.5–2.6% per year with precipitation increases of 10–20%, respectively. There were spatial variations in the responses of the suprapermafrost groundwater level to climate change on the slope scale. The variation ratio and the amplitude of the suprapermafrost groundwater level downslope are larger than those on the upper slope under climate warming. The obvious vulnerability and spatial variability of the suprapermafrost groundwater to climate change will impose intensive effects on the water cycle and alpine ecosystems in the permafrost region.

Sasmita & Madan (2013); conducted this study, the potential of multiple linear regression (MLR) and artificial neural network (ANN) techniques in predicting transient water levels over a groundwater basin were compared. MLR and ANN modeling was carried out at 17 sites in Japan, considering all significant inputs: rainfall, ambient temperature, river stage, 11 seasonal dummy variables, and influential lags of rainfall, ambient temperature, river stage and groundwater level. Seventeen sitespecific ANN models were developed, using multi-layer feed-forward neural networks trained with LevenbergMarquardt backpropagation algorithms. The performance of the models was evaluated using statistical and graphical indicators. Comparison of the goodness-of-fit statistics of the MLR models with those of the ANN models indicated that there is better agreement between the ANN-predicted groundwater levels and the observed groundwater levels at all the sites, compared to the MLR. This finding was supported by the graphical indicators and the residual analysis. Thus, it is concluded that the ANN technique is superior to the MLR technique in predicting spatio-temporal distribution of groundwater levels in a basin. However, considering the practical advantages of the MLR technique, it is recommended as an alternative and cost-effective groundwater modeling tool.

Gholam (2012); conducted this study, groundwater level forecasting plays an important role in water resources management. Artificial neural network have been used as a robust instrument for this subject. In this paper, four architectures of different neural networks were used for groundwater level prediction in Shiraz Plain and their results were compared by using the statistical measures of mean square error and square of correlation coefficient. Effective parameters on groundwater level such as 5-month precipitation and groundwater level histories, temperature or evaporation, and runoff were utilized as the input data to forecast groundwater level at the next time step as output of the networks. All networks were trained for a ten-year period of data (from 1993 to 2003) and calibrated for an 18-month period (from Apr. 2003 to Sep. 2004). Networks were verified based on groundwater level observations in 29 wells located in the plain for another 18-month period (from Oct. 2004 to Mar. 2006). Results showed that artificial neural networks may be successfully utilized to forecast groundwater levels. Different networks forecasted groundwater level in all wells with acceptable root mean square errors of 0.6–12.17 m. Best overall performance was achieved by feed-forward neural network and the second best by Elman neural network.

Ripon et al. (2020);conducted this study, this study presents implementation of non-linear autoregressive model with exogenous inputs (NARX) of Artificial neural network (ANN), used for groundwater level (GWL) simulation to predict its weekly level up to 52 weeks ahead in selected 14 Permanent Hydrograph Stations (PHSs) in the drought prone Barind Tract in the northwestern part of Bangladesh and is considered to be the first attempt of this type in the country. In this regard, the weekly historical time series climatological data (rainfall, temperature, humidity and evaporation) during 1980–2017 have been used as input variables to forecast GWL. Auto-correlation of GWL time series data to find out the dependent relationship between current GWL to the previous level were carried out and crosscorrelation between GWL and rainfall have been used to find out the effectiveness with time. Here GWL is mostly influenced by rainfall having lagged continuation with corresponding peak (max) and trough (min) of rainfall indicating time delayed response of 11.25–14.0 (avg. 12.73) weeks. Analysis before training of ANN reveals that NARX models are good in prediction. Moreover, rainfall has affected by climatological parameters where rainfall is one of the potential input parameter influencing GWL. In recent years, groundwater withdrawals are higher than the rainwater recharge to aquifer due to continuous expansion of irrigated agriculture in the area. Finally, present study as pioneer approach provides significant contributions for groundwater management in resource planning of Bangladesh.

Ioannis C. et al. (2011);conducted this study, a relatively new method of addressing different hydrological problems is the use of artificial neural networks (ANN). In groundwater management ANNs are usually used to predict the hydraulic head at a well location. ANNs can prove to be very useful because, unlike numerical groundwater models, they are very easy to implement in karstic regions without the need of explicit knowledge of the exact flow conduit geometry and they avoid the creation of extremely complex models in the rare cases when all the necessary information is available. With hydrological parameters like rainfall and temperature, as well as with hydrogeological parameters like pumping rates from nearby wells as input, the ANN applies a black box approach and yields the simulated hydraulic head. During the calibration process the network is trained using a set of available field data and its performance is evaluated with a different set. Available measured data from Edward's aquifer in Texas, USA are used in this work to train and evaluate the proposed ANN. The Edwards Aquifer is a unique groundwater system and one of the most prolific artesian aquifers in the world. The present work focuses on simulation of hydraulic head change at an observation well in the area. The adopted ANN is a classic fully connected multilayer perceptron, with two hidden layers. All input parameters are directly or indirectly connected to the aquatic equilibrium and the ANN is treated as a sophisticated analogue to empirical models of the past. A correlation analysis of the measured data is used to determine the time lag between the current day and the day used for input of the measured rainfall levels. After the calibration process the testing data were used in order to check the ability of the ANN to interpolate or extrapolate in other regions, not used in the training procedure. The results show that there is a need for exact knowledge of pumping from each well in karstic aquifers as it is difficult to simulate the sudden drops and rises, which in this case can be more than 6 ft (approx. 2 m). That aside, the ANN is still a useful way to simulate karstic aquifers that are difficult to be simulated by numerical groundwater models.

PURNA et al. (2006);conducted this study, forecasting the ground water level fluctuations is an important requirement for planning conjunctive use in any basin. This paper reports a research study that investigates the potential of artificial neural network technique in forecasting the groundwater level fluctuations in an unconfined coastal aquifer in India. The most appropriate set of input variables to the model are selected through a combination of domain knowledge and statistical analysis of the available data series. Several ANN models are developed that forecasts the water level of two observation wells. The results suggest that the model predictions are reasonably accurate as evaluated by various statistical indices. An input sensitivity analysis suggested that exclusion of antecedent values of the water level time series may not help the model to capture the recharge time for the aquifer and may result in poorer performance of the models. In general, the results suggest that the ANN models are able to forecast the water levels up to 4 months in advance reasonably well. Such forecasts may be useful in conjunctive use planning of groundwater and surface water in the coastal areas that help maintain the natural water table gradient to protect seawater intrusion or water logging condition.

Thendiyath et al. (2020);conducted this study, advances in the artificial intelligence-based models can act as robust tools for modeling hydrological processes. Neural network architectures coupled with learning algorithms are considered as useful modeling tools for groundwater-level fluctuations. Emotional artificial neural network coupled with genetic algorithm (EANN-GA) is one such novel hybrid neural network which has been used in the present study for the forecasting of groundwater levels at three sites (Site H3, Site H4.5, and Site H9) in a coastal aquifer system. This study was conceived to address and investigate the efficiency of the ensemble model (EANN-GA) for forecasting one-month ahead groundwater level and to compare its performance with emotional artificial neural network (EANN), generalized regression neural network (GRNN), and the conventional feedforward neural network (FFNN). Variations in the rainfall, tidal levels, and groundwater levels are selected as inputs for the development of EANN-GA, EANN, GRNN, and FFNN models. Suitable goodness-of-fit criteria such as Nash–Sutcliffe efficiency (NSE), bias, root mean squared error (RMSE), and graphical indicators are used for assessing the efficiency of the developed models. The improvement in the performance of the EANN-GA model over the developed EANN, GRNN, and FFNN models in terms of NSE is 0.81, 6.02, and 9.56% at Site H3; 4.35, 5.50, and 22.68% at Site H4.5; and 1.05, 7.18, and 21.75% at Site H9. Thus, it can be inferred that the EANN-GA model outperforms the developed EANN model, GRNN model, and FFNN model. Further, this paper examines the predictive capability of extreme events by the EANNGA, EANN, GRNN, and FFNN models. The RMSE values of the EANN-GA model at all peak points are found as 0.27, 0.23, and 0.10 m at sites H3, H4.5, and H9, respectively, and the results indicate superior performance of EANN-GA model. To check the generalization ability of the developed EANN-GA models, they are validated with the data of another site (Site I2) located in the same coastal aquifer. Superior prediction capability and generalization ability make the EANNGA model a better alternative for predicting groundwater levels. Overall, this study demonstrates the effectiveness of EANN-GA in modeling spatio-temporal fluctuations of groundwater levels. It is also concluded that the EANN-GA model yields remarkably better predictions of extreme events, and hence, it could be a promising technique for developing alarm systems for real-world water problems.

Vahid et al. (2008);conducted this study, this paper evaluates the feasibility of using an artificial neural network (ANN) methodology for estimating the groundwater levels in some piezometers placed in an aquifer in north-western Iran. This aquifer is multilayer and has a high groundwater level in urban areas. Spatiotemporal groundwater level simulation in a multilayer aquifer is regarded as difficult in hydrogeology due to the complexity of the different aquifer materials. In the present research the performance of different neural networks for groundwater level forecasting is examined in order to identify an optimal ANN architecture that can simulate the piezometers water levels. Six different types of network architectures and training algorithms are investigated and compared in terms of model prediction efficiency and accuracy. The results of different experiments show that accurate predictions can be achieved with a standard feedforward neural network trained usung the Levenberg–Marquardt algorithm. The structure and spatial regressions of the ANN parameters (weights and biases) are then used for spatiotemporal model presentation. The efficiency of the spatio-temporal ANN (STANN) model is compared with two hybrid neural-geostatistics (NG) and multivariate time series-geostatistics (TSG) models. It is found in this study that the ANNs provide the most accurate predictions in comparison with the other models. Based on the nonlinear intrinsic ANN approach, the developed STANN model gives acceptable results for the Tabriz multilayer aquifer.

Akram et al. (2020);conducted this study, in the present study, six meta-heuristic schemes are hybridized with artificial neural network (ANN), adaptive neuro-fuzzy interface system (ANFIS), and support vector machine (SVM), to predict monthly groundwater level (GWL), evaluate uncertainty analysis of predictions and spatial variation analysis. The six schemes, including grasshopper optimization algorithm (GOA), cat swarm optimization (CSO), weed algorithm (WA), genetic algorithm (GA), krill algorithm (KA), and particle swarm optimization (PSO), were used to hybridize for improving the performance of ANN, SVM, and ANFIS models. Groundwater level (GWL) data of Ardebil plain (Iran) for a period of 144 months were selected to evaluate the hybrid models. The pre-processing technique of principal component analysis (PCA) was applied to reduce input combinations from monthly time series up to 12-month prediction intervals. The results showed that the ANFIS-GOA was superior to the other hybrid models for predicting GWL in the first piezometer (RMSE:1.21, MAE:0.878, NSE:0.93, PBIAS:0.15, R2 :0.93), second piezometer (RMSE:1.22, MAE:0.881, NSE:0.92, PBIAS:0.17, R2 :0.94), and third piezometer (RMSE:1.23, MAE:0.911, NSE:0.91, PBIAS:0.19, R2 :0.94) in the testing stage. The performance of hybrid models with optimization algorithms was far better than that of classical ANN, ANFIS, and SVM models without hybridization. The percent of improvements in the ANFIS-GOA versus standalone ANFIS in piezometer 10 were 14.4%, 3%, 17.8%, and 181% for RMSE, MAE, NSE, and PBIAS in training stage and 40.7%, 55%, 25%, and 132% in testing stage, respectively. The improvements for piezometer 6 in train step were 15%, 4%, 13%, and 208% and in test step were 33%, 44.6%, 16.3%, and 173%, respectively, that clearly confirm the superiority of developed hybridization schemes in GWL modelling. Uncertainty analysis showed that ANFIS-GOA and SVM had, respectively, the best and worst performances among other models. In general, GOA enhanced the accuracy of the ANFIS, ANN, and SVM models.

Esmaeil et al. (2019);conducted this study, in recent decades, increasing global water demand, coupled with the efects of climate change, has led to increased variation in groundwater level depletion. In this work, the efect of climate parameters is investigated with respect to groundwater levels in the Shabestar Plain, Iran. In the frst step, the best models for the study region were selected from the general circulation models provided under the Fifth Assessment Report of the United Nations Intergovernmental Panel on Climate Change. To increase the spatial resolution of the precipitation data, downscaling of the models was performed using the Long Ashton Research Station weather generator for three representative concentration pathway (RCP) scenarios (RCP2.6, RCP4.5, RCP8.5) for the future period 2020–2049. The results of these models illustrated an increase in temperature and a decrease in precipitation for the study region. In the next step, an artifcial neural network (ANN) technique for studying aquifer behavior was used. To increase the efciency of the model, spatial and temporal preprocessing of data was performed using k-means clustering and wavelet transform de-noising, respectively. A fuzzy inference system was also used as a tool for estimating groundwater extraction and reducing uncertainty of illegal extraction. The results of ANN for fve selected observation wells showed correlation coefcients of 0.92, 0.86, 0.76, 0.57 and 0.94 for the simulation. The model simulation under the three above-mentioned scenarios and the trend in groundwater decline in the Shabestar Plain for the base and future periods illustrated that the groundwater level dynamics were not related solely to climate parameters and that the impact of anthropogenic factors would be high.

Imam et al. (2020);conducted this study, one of the key parameters in peat land management is water, which is expressed in the water level of peat land. The water level fluctuations of a peat land are closely related to the decomposition of the peat constituent material, its cover and hydrological conditions. When the water level drops, the peat decomposition increases and will release the carbon into the atmosphere. In addition, the condition of peat will be dry so that the area becomes prone to fire. The main purpose of the research is to develop a groundwater level forecasting model to monitor the dynamics of land water fluctuations in tropical peatland in order to comply with government regulation No. 57 of 2016 on the protection and management of peat ecosystems, especially the necessity to maintain water level at a rate of 40 cm. The method of research approach used is using ANN as one branch of soft computing. The location of research on peatland of PT Meskom Pulau Bengkalis, Riau province. Data that is used to build a model of groundwater level forecasting in tropical peatland sourced from Hobo Water Logger measuring device that record water table in 2014. The main results of the research proved that the implementation of a groundwater level forecasting model on the tropical peatlands in Bengkalis using the ANN method approach for the next day (t + 24) has a very strong classification tested using statistical parameters coefficient of correlation (R) and Mean Square Error (MSE) respectively 0.995929 and 0.0003026 so that the model can be applied on tropical peatlands.

Supreetha et al. (2019);conducted this study,the groundwater level modelling and forecasting have wide application for effective groundwater resources management. The traditional numerical groundwater level forecasting requires various hydrogeological parameters. The alternative approach for groundwater level forecasting is data-driven models. The ANN hybrid models are found to be more effective for predicting ground-water levels at different time domains. Soft computing based model is developed by considering historical groundwater level and rainfall data. We developed an innovative hybrid ABC algorithm based on PSO searching mechanism to carry out forecasts of future groundwater levels with the aid of earlier recorded groundwater levels and rainfall. The evaluation metrics of parameters such as RMSE, Error Variation Regression coefficient, and MAE have been used. The results obtained prove that hybrid soft computing technique is able to forecast the groundwater level over several years effectively. The model predicted trend followed the observed data closely (RMSE = 0.3928, R^2 = 0.90029). The Mean Absolute Error and relative error of predicted results are 0.574 and 2.11% respectively. The ABC-PSO technique has shown promising results in accurate monthly groundwater level prediction vis-à-vis ANN methods.

KAYA et al. (2018);conducted this study, most of the fresh water resources in our world consist of underground water reserves. Estimation of fluctuations of groundwater level (GWL) is very important in the management of water resources. In this study, groundwater level (GWL) was investigated using artificial neural networks (ANN), M5tree (M5T) approaches in Reyhanli region in Turkey. Total 196 data from 2000-2015 taken from 1 observation station belonging to

Reyhanli sub-basin located in Asi basin were used in the study. Using the monthly average precipatation and temperature, the change in GWL is modeled by artificial neural networks (ANN), M5tree (M5T) approaches. The results showed that (ANN) and M5tree (M5T) models were found to be very close to each other.

Amandeep et al. (2018);conducted this study, as groundwater resources are more intensively used, there is increasing demand for monitoring of groundwater systems. Precise prediction of groundwater level is important for management of groundwater source. Out of the various methods available, ANN is a very useful tool for predicting groundwater level. In Artificial neural network also different models were used for forecasting of groundwater level but most accurate predictions was achieved with a standard feed forward neural network trained with the Leven berg-Marquardt algorithm.

Arman et al. (2022);conducted this study, groundwater is a vital source of freshwater, supporting the livelihood of over two billion people worldwide. The quantitative assessment of groundwater resources is critical for sustainable management of this strained resource, particularly as climate warming, population growth, and socioeconomic development further press the water resources. Rapid growth in the availability of a plethora of in-situ and remotely sensed data alongside advancements in data-driven methods and machine learning offer immense opportunities for an improved assessment of groundwater resources at the local to global levels. This systematic review documents the advancements in this field and evaluates the accuracy of various models, following the protocol developed by the Center for Evidence-Based Conservation. A total of 197 original peer-reviewed articles from 2010–2020 and from 28 countries that employ regression machine learning algorithms for groundwater monitoring or prediction are analyzed and their results are aggregated through a meta-analysis. Our analysis points to the capability of machine learning models to monitor/predict different characteristics of groundwater resources effectively and efficiently. Modeling the groundwater level is the most popular application of machine learning models, and the groundwater level in previous time steps is the most employed input data. The feed-forward artificial neural network is the most employed and accurate model, although the model performance does not exhibit a striking dependence on the model choice, but rather the information content of the input variables. Around 10–12 years of data are required to develop an acceptable machine learning model with a monthly temporal resolution. Finally, advances in machine and deep learning algorithms and computational advancements to merge them with physics-based models offer unprecedented opportunities to employ new information, e.g., InSAR data, for increased spatiotemporal resolution and accuracy of groundwater monitoring and prediction.

R. Sarma and S. K. Singh(2022); conducted this study, irregular rainfall patterns and limited freshwater availability have driven humans to increase their dependence on groundwater resources. An essential aspect of efective water resources management is forecasting groundwater levels to ensure that sufcient quantities are available for future generations. Prediction models have been widely used to forecast groundwater levels at the regional scale. This study compares the accuracy of five commonly used data-driven models–Holt–Winters' Exponential Smoothing, Seasonal Autoregressive Integrated Moving Average, Multi-Layer Perceptron, Extreme Learning Machine, and Neural Network Autoregression for simulating the declining groundwater levels of three monitoring wells in the National Capital Territory of Delhi in India. The performance of the selected models was compared using coefcient of determination (R2), Root Mean Squared Error (RMSE) and Mean Absolute Error (MAE). Results indicate that MultiLayer Perceptron had high R2 while ftting the training data and least RMSE and MAE during testing, thus proving to be more accurate in forecasting than the other models. MultiLayer Perceptron was used to forecast the groundwater level in the study wells for 2025. The results showed that the groundwater level will decline further if the current situation continues. Such studies help determine the appropriate model to be used for regions with limited available data. Additionally, predictions made for the future will help policymakers understand which areas need immediate attention in terms of groundwater management.

Demirci et al. (2019); conducted this study,determination of the change in groundwater level in terms of planning and managing resources is important. In this study, the groundwater level of Reyhanli region in Turkey was predicted using multi-linear regression (MLR), adaptive neural fuzzy inference system (ANFIS), Radial basis neural network (RBNN), support vector machines with radial basis functions (SVM-RBF) and support vector machines with poly kernels (SVM-PK) methods. Models were carried out using 192 data of monthly ground water level, monthly total precipitation and monthly average temperature values measured for 16 years between 2000 and 2015. Comparisons revealed that the SVM–RBF and SVM-PK models had the most accuracy in the groundwater level prediction.

Mohammad and Amir (2012);conducted this study, accurate groundwater level modeling and forecasting contribute to civil projects, land use, citys planning and water resources management. Combined Wavelet-Artificial Neural Network (WANN) model has been widely used in recent years to forecast hydrological and hydrogeological phenomena. This study investigates the sensitivity of the pre-processing to the wavelet type and decomposition level in WANN model for groundwater level forecasting. To this end, the monthly groundwater level time series were collected from October 1997 to October 2007 in 26 piezometers of Qorveh aquifer, Iran. Using discrete wavelet transform method and different mother wavelets (Haar, db2, db3 and db4), these time series were decomposed into sub-signals in various resolution levels. Then, these sub-signals entered to the ANN model to reconstruct the original forecasted time series for 6 months ahead. The Root Mean Square Errors (RMSE) and coefficient of determination (R2) statistics were used for evaluating the accuracy of the model. The results showed merits of db2 and db4 wavelets in comparison with Haar and db3 because of similarity between the signal of groundwater level and the functions of mother wavelets. For a better and precise analysis, the forecasted results of the model were compared with the observed data not only in the validation stage but also in the test stage.

Chapter: - 3

METHODOLOGY

3.1 INTRODUCTORY COMMENTS

In the previous chapter we discussed literature review, after reviewing the report by Sushil Gupta, Regional Director "Central Ground Water Board". In this paper it has been shown the depleting groundwater resource in Punjab. For better management of groundwater in Punjab ANN's capability can be used to the fullest. ANN in the past decade or so has become more and more popular.

Studies carried out by Lohani AK, Fabio, Riccardo, Ashish, Sanghoon, Ozgur have demonstrated the application ANN for hydrological forecasting is very effective and the works of Sanghoon, Lohani have demonstrated the prediction of hydrological model when there is not enough hydrological data.

In this chapter we will discuss about the study area, data collection, artificial neural network and its applications, neural network architecture used for prediction, measures of prediction and performance of the neural network model, spatial and contour analysis of groundwater and rainfall data of the study area to get the better understanding of the study area.

3.2 STUDY AREA

Punjab is a state in India that is located in the north-western section of the country 31.1471° N, 75.3412°E. Punjab is located in an inland subtropical region with a continental climate that ranges from semiarid to sub-humid. Summers are scorching. In June, the hottest month, daily temperatures in Ludhiana average over 30s degrees Celsius with a low in the mid-20s C. Daily temperatures in January, the coldest month, typically range from about 7 °C to the upper 10s C. Annual rainfall is highest in the Siwalik Range, with over 45 inches (1,150 mm) possible, and lowest in the southwest, with less than 12 inches (300 mm) possible; statewide average annual precipitation is around 16 inches (400 mm).

The southwest monsoon season lasts from July through September, and this is when the majority of the annual rainfall falls. Winter rains from western cyclones contribute for less than a quarter of total rainfall, falling between December and March. Punjab has a total area of $50{,}362 Km^2$.

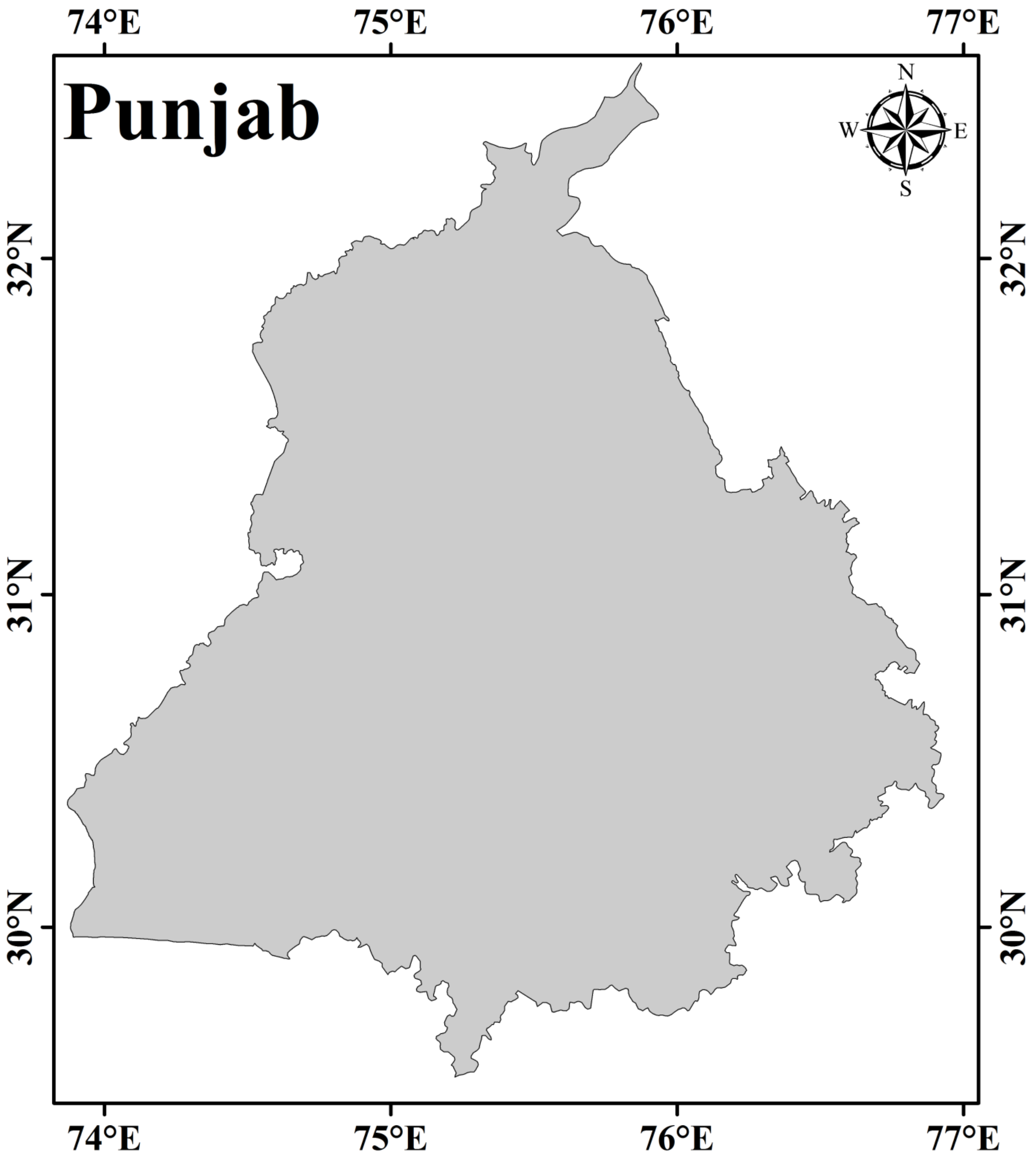


Fig-3.1 Map of Punjab – Showing the area of study

According to “INDIAN METROLOGY DEPARTMENT” there are four seasons shown below are the following: -

- Winter season: - January-February.
- Summer season: - March-May.
- Monsoon season: - June-September.
- Post monsoon season: - October-December.

The data provided to us by “CENTRAL GROUNDWATER BOARD” Ministry of water resources, river development and Ganga rejuvination government of India. The groundwater level data contained 4 quadrants of data per year: MAY, AUG, NOV and JAN. 4 quadrants of data per year for 4 different seasons.

Punjab has 23 districts. Which are classified into four regions mentioned below with their districts: -

- ❖ **MAJHA: -** Amritsar, Gurdaspur, Pathankot and Taran-Taran.
- ❖ **DOABA: -** Hoshiarpur, Jalandhar, Kapurthala, Shaheed Bhagat Singh Nagar.
- ❖ **MALWA: -** Barnala, Bathinda, Ferozepur, Fazilka, Faridkot, Ludhiana, Moga, Malerkotla, Mansa, Sri Muktsar Sahib, Patiala and Sangrur.
- ❖ **PUADH: -** SAS Nagar (Mohali), rupnagar and Fatehgarh Sahib.

Between 2015 and 2019, the five-year annual average rainfall in Punjab was 535.0 mm (53.5 cm). During the five year period from 2006 to 2010, it was 437.6 mm. The monsoon season, which runs from July through September, sees the most rainfall in a year. During these three months, Punjab receives over 70% of its annual rainfall (July, August and September).

3.3 DATA COLLECTION

Our goal, as stated in the introduction, is to create a neural network model that can simulate groundwater variation over long periods of time utilising observed time series of external factors. The model is trained and then validated before being used to identify the system. The model is tested when it has been validated successfully. The better the validation, the better the model's prediction performance, and the better the model's simulation performance.

The simulation of groundwater was done using monthly groundwater level from 1999-2020 and rainfall data from 1999-2018. The groundwater data was provided by **“CENTRAL GROUND WATER BOARD”** Ministry of water resources, river development and Ganga rejuvination government of India. The groundwater level data contained 4 quadrants of data per year: MAY, AUG, NOV and JAN.

The rainfall data was provided by **“INDIA METEOROLOGICAL DEPARTMENT”** Ministry of earth sciences. Rainwater data provided was monthly which was later converted into 4 quadrants of data per year to match with corresponding months of groundwater level: MAY, AUG, NOV and JAN. For converting the rainfall data into 4 separate quadrants rainfall of previous months were added i.e. JAN-APRIL added for MAY quadrant.

Groundwater level data contained 1330 stations all over Punjab and 192 stations were selected and these 192 stations were selected with at least 7 years of data (4 quadrants each year for 7 years / 28 readings). Groundwater data provided is from 1999-2020 with some missing years. Total 16 years of groundwater level data covering complete Punjab was used for the simulation of groundwater level. Rainfall is one of the major inputs for the groundwater level forecasting model, and analogue output and input data from the same period with an equivalent time step were utilised to create the network.

3.4 SPATIAL ANALYSIS

From data capture to interpreting findings, spatial analysis is a process of GIS data interpretation, exploration, and modelling. The obtained data is analysed on a computer using spatial analysis software, and the time it takes varies depending on the number of activities and their complexity. The most basic is visualisation, while a more complete strategy calls for comprehensive analytics and specific tools to develop in-sights that can be used.

Measures distances and shapes, establishes routes and tracks transportations, and establishes relationships between items, events, and places by relating their locations to geographical placements are all examples of spatial analysis.

The flexibility of GIS spatial analysis and modelling is one of its distinguishing features. You can mix and combine as many layers as you want to create different outcomes.

Individual maps and layers' spatial analysis uses geostatistical techniques and two-dimensional processing, including reclassification, thresholding, neighbourhood functions using spatial filters, distance and buffer calculations, 2D spatial transformations, and, most importantly, interpolation.

To emphasise spatial association within a data layer, geo-statistical methods, which apply probabilistic methodologies to geographically connected occurrences, might be used. This idea is predicated on the basis that locations in close proximity ought to have comparable values. The existing data is then utilized to interpolate into regions where there is no data.

3.5 THIESSEN POLYGON

The examination of proximity and neighbourhood relies heavily on Thiessen polygons, often known as Voronoi polygons or Voronoi diagrams. The closest point feature is given space using Thiessen polygons. Every site in the defined area is closer to the point in question than it is to any other location. In ArcMap, Thiessen polygons can be created using the Create Thiessen Polygons tool.

3.6 CONTOUR ANALYSIS

On maps, contour lines are a common means of representing surfaces. A contour is a line that passes through all contiguous points that have the same height (or other) value. The continuous surface of water table elevations for the Punjab area was generated using geographic information system techniques.A line sketched on a map to indicate an imaginary line in a specific level's water table.

The data provided by the water-table levels has been used to create these contours, water-table contours can sometimes be seen on a site investigation or an opencast plan.

Important details on the movement and flow directions of ground water are available from a ground water contour map. There will be an identification of the many water-scarce zones. With the use of research into geographic features and groundwater availability, the groundwater potential zones are established.

3.6 GWL MAPPING

1) Addition of shape file (Punjab).
2) Addition of XY data (GWL data).
3) Conversion sheet data to shape file.
4) Environment set up for analysis.
5) Spatial Analysis (IDW).
6) Contour Analysis.

3.7 RAINFALL MAPPING

1) Addition of shape file (Punjab).
2) Addition of XY data (Rainfall data).
3) Conversion sheet data to shape file.
4) Thiessen polygon area.
5) Spatial analysis (IDW).

3.8 GROUNDWATER AND RAINFALL ANALYSIS

ArcGIS software was used to create maps and conduct data analysis for the analysis of rainfall and groundwater. One of the key techniques for the systematic and controlled development and planning of ground-water resources is groundwater (hydrogeological) mapping. Engineers, planners, and decision-makers use these maps to distribute, develop, and manage groundwater in accordance with a national water policy. Hydrogeological data is displayed on maps using hydrogeological information. The location of aquifers and their topographical, geological, hydrographical, hydrological, and hydrochemical characteristics are displayed on a hydrogeological map. The quick assessment of a specific area is made possible by the presentation of these data as maps. As a result, hydrogeological maps can identify places that require further protection. Groundwater hydrology has a lot of potential applications for remote sensing and geographic information system (GIS) technologies. For handling spatial data and making choices across a wide range of industries, GIS is an excellent tool, including geological and environmental ones. One of the key methods for obtaining data on landforms, lineaments, and other surface features relevant to groundwater is remote sensing. To integrate with various forms of data, such information can be quickly loaded into a GIS system.

Note: - All the maps are created both for spatial analysis and contour maps.

Using ArcGIS the maps created for analysis are following: -

3.8.1 Base Maps: -

1) Groundwater stations map.
2) Rainfall stations map.
3) Thiessen polygon map.
4) Thiessen area with rainfall stations.

3.8.2 Groundwater Analysis Maps: -

3.8.2.1 Maximum and Minimum Maps: -

1) Annual max, annual min.
2) May max, May min.
3) August max, August min.
4) November max, November min.
5) January max, January min.

3.8.2.2 Monthly and Annual Average Maps: -

1) Annual average.
2) May average.
3) August average.
4) November average.
5) January average.

3.8.3 Rainfall Analysis Maps: -

3.8.3.1Monthly and Annual Average Maps: -

1) Annual average.
2) May average.
3) August average.
4) November average.
5) January average.

3.8.3.2Rainfal data graphs with standard deviation: -

1) Annual.
2) May.
3) August.
4) November.
5) January.

3.9 ARTIFICIAL NEURAL NETWORK

The study of hydrology and water resources is seeing an increase in the use of artificial neural networks (ANN), which function similarly to biological neurons. ANN models are data-driven models that are referred to as black-box models in the hydrological environment. ANN models, which have a high processing capacity and can execute future scenarios quickly, can be a useful alternative to mathematical models. The majority of hydrological processes are non-linear. The ability of ANN to model non-linear processes suggests that it should be used to model various hydrological processes in hydrology and water resources. Numerous studies have proposed various ANN architectures to mimic various real-life problems as computational techniques have progressed.

Studies carried out by Lohani AK, Fabio, Riccardo, Ashish, Sanghoon, Ozgur have demonstrated the application ANN for hydrological forecasting is very effective and the works of Sanghoon, Lohani have demonstrated the prediction of hydrological model when there is not enough hydrological data.

In recent years, groundwater supplies have been overused, especially in industry and agriculture and this causes the groundwater level to be declined. Accurate prediction of groundwater level is one of the most critical stages in the sustainable yield of groundwater resources. It helps engineers, planners, and water managers to make appropriate decisions to avoid or reduce adverse effects such as loss of pumpage in water wells, aquifer compaction, and-surface are subsidence. New data, new data driven techniques such as artificial neural network (ANN) have been accepted as an efficient tool for modeling hydrologic systems and widely used for prediction. During the past decade, the Artificial Neural Network model has become popular in hydrological modeling and forecasting.

This project's goal is to create a workable ANN model and evaluate how effectively it predicts changes in groundwater levels in the Punjab districts of AMRITSAR, BATHINDA, FARIDKOT, FAZILKA, HOSHIARPUR, KAPURTHALA, LUDHIANA, MANSA, MOGA, PATIALA, and SANGRUR. This net has input data such as rainfall for the current month and the two months prior to that, groundwater level for the current month and the two months prior to that, and it has one output parameter, which is the anticipated groundwater level with a six month lead period. As input, the ANN-based ground water level prediction algorithm was given the monthly data that was available. When designing networks, the output and input information of analogues were taken from the same time period and had the same amount of step time. For the years 2006 through 2013, data regarding the groundwater level of groundwater samples was made public. The data for the years 1999 to 2018 have been segmented into separate sets in order to facilitate the training and evaluation of the ANN models.

3.10APPLICATION OF NEURAL NETWORK

For developing ANN model generally the data sets are required for the training, validation and testing of the ANN networks. In this study observed rainfall and observed groundwater level were used to train and validate an artificial neural network. Because NN performs best in the range of 0–1, all outputs have indeed been scaled to this value.

An ANN model with a dual hidden layer was trained using the back propagation learning algorithm. In this case, the SCG (Scaled conjugate gradient), Levenberg–Marquardt (LM), BR (Bayesian regularization), and back propagation methods were applied to achieve the goal. MATLAB's Neural Network Toolbox was used to create the neural network model. The optimal number of neurons in the hidden-layer was determined by increasing the neurons one-by-one and testing the model outputs. The input layer's neurons lack a transfer function. Data was transferred using Logistic Sigmoid (logsig) and Purelinear (purelin) transfer functions, respectively.

3.11 MEASURES OF PREDICTION-PERFORMANCE

The finished network was tested using the data that had been successfully trained. In addition, statistical approaches such as RMSE and regression coefficients (R2) between output of the system and net target outputs in train and test groups have evaluated the predicting effectiveness of ANN model results.

3.12 NETWORK ARCHITECTURE

- NODES IN INPUT LAYER: 2
- HIDDEN LAYER: 2
- NODES PER HIDDEN LAYER : 10
- NODES IN OUTPUT LAYER: 1

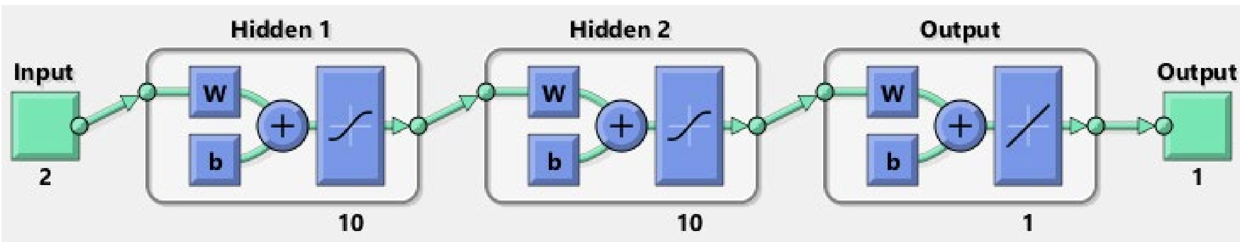


Fig-3.1 Artificial neural network model (Back propagation) used for the forecasting of groundwater level in punjab

Chapter: - 4

RESULTS AND DISCUSSION

4.1 INTRODUCTORY COMMENTS

In the previous chapter we discussed about the study area, data collection and different-different analysis done on the received ground water and rainfall data. The main study was done in artificial neural network to forecast the groundwater in future for better management of groundwater in Punjab as discussed in chapter-1 according to study done by Sushil Gupta, Regional Director, Central Ground Water Board. Groundwater is being over exploited. And ANN has been proven in past few decades to be very reliable and efficient over other methods like mathematical models.

In this chapter results of this study will be shown and explained, and based on those results conclusion of this whole study will drawn to better understand the importance of this study and future potential of the usage of the artificial neural network.

4.2 BASE MAPS OF THE STUDY AREA

These two maps show the rainfall and groundwater stations spread in the study area.

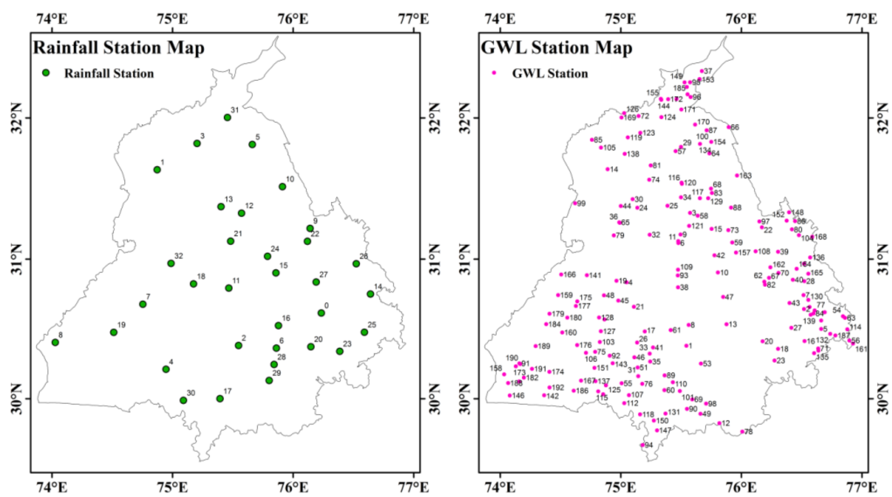


Fig- 4.1 (a) **Fig- 4.1 (b)**

Fig- 4.1(a) shows the rainfall stations and (b) shows the groundwater stations in punjab

4.1.2 THIESSEN AREA OF RAINFALL STATIONS: -

This map shows all the rainfall stations and their respective thiessen area, using Arc GIS. Using this map we can overlap groundwater stations and use the rainfall stations data for the groundwater stations that fall in the respective thiessen area of the rainfall station.

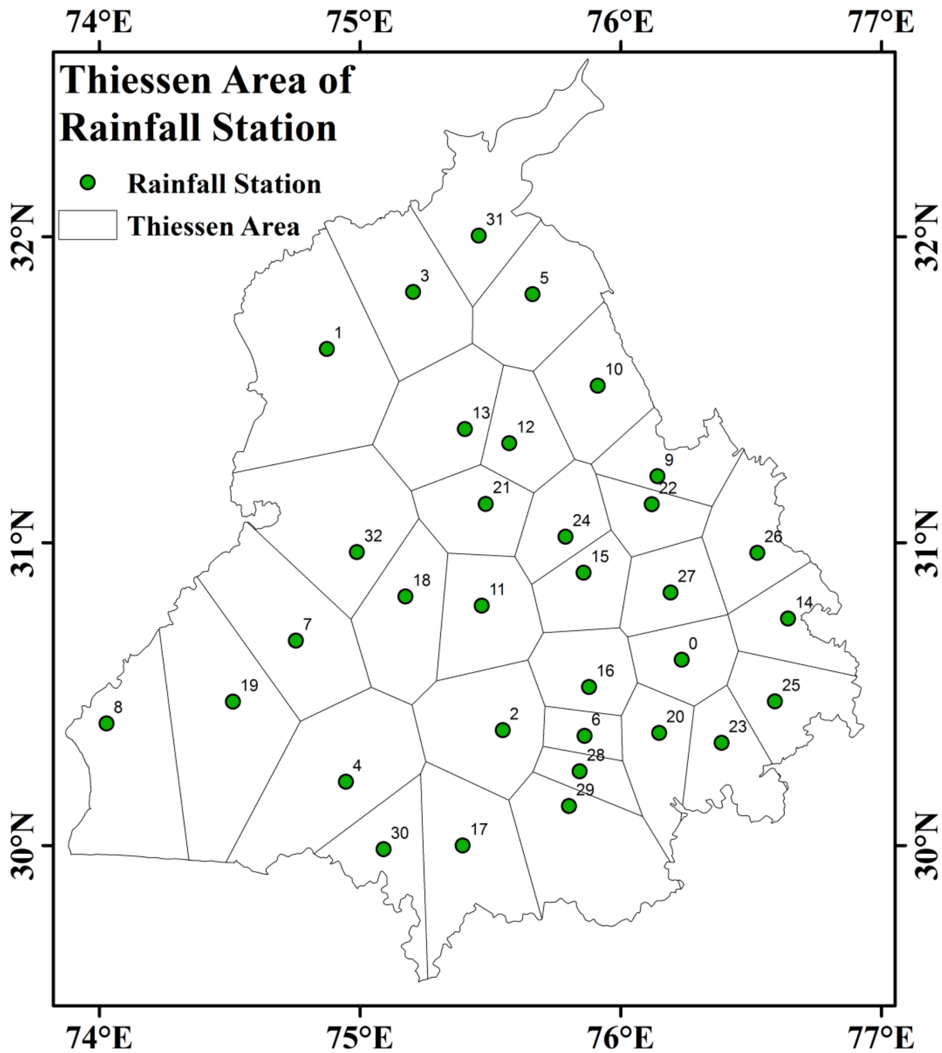


Fig- 4.2 shows the rainfall stations thiessen area

The map shown below portrays all the rainfall and groundwater stations with the respective thiessen polygon area of the rainfall stations. This makes it easier to recognize which rainfall station data will be used for the groundwater stations.

4.1.3 THIESSEN POLYGON MAP: -

All the stations are compiled onto one map to show the respective groundwater stations with rainfall station with thiessen polygon area.

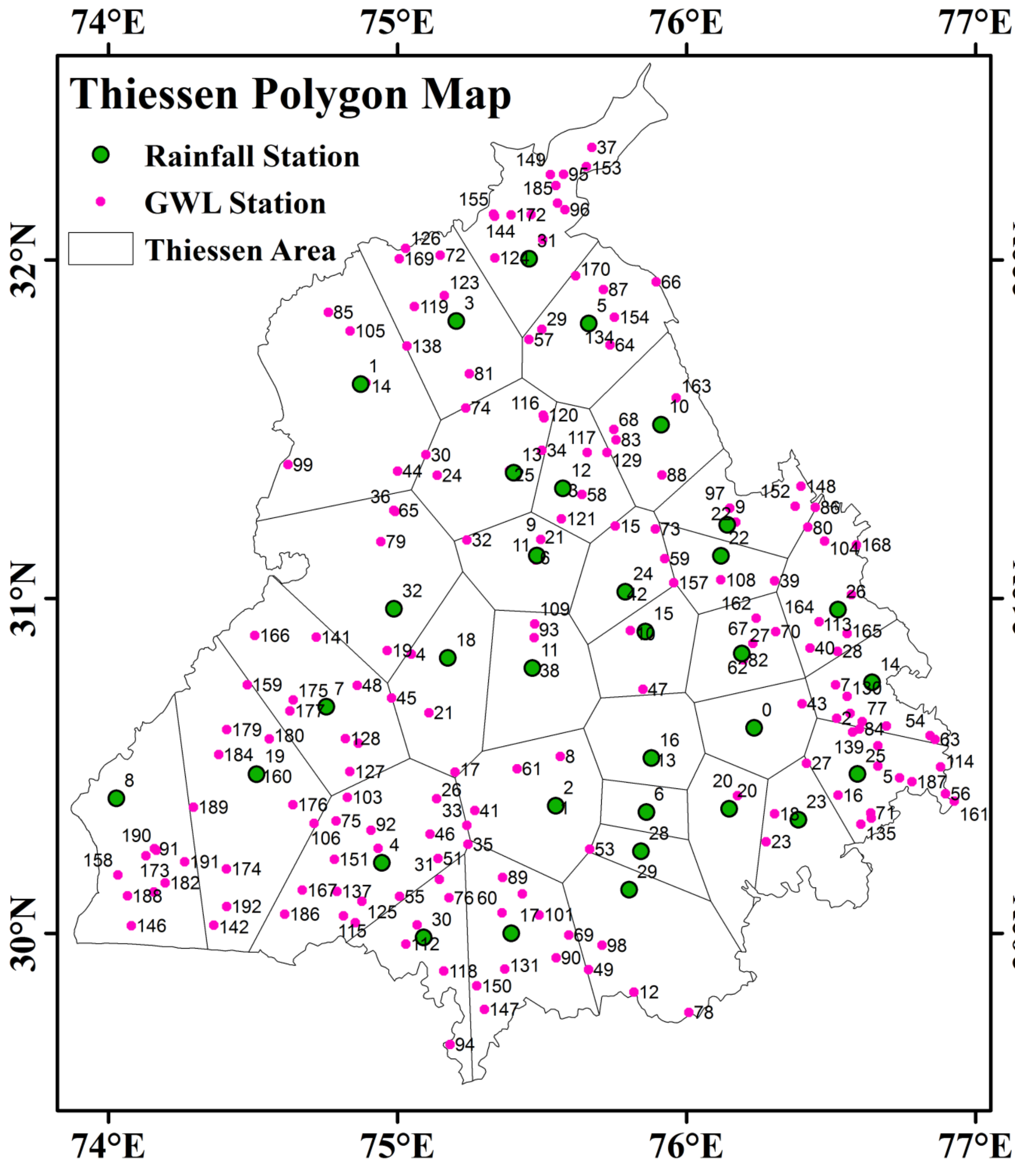
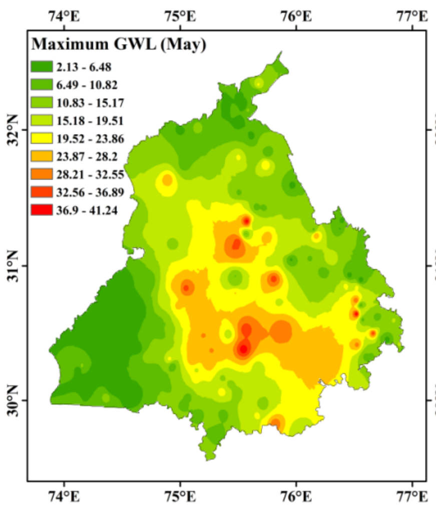


Fig- 4.3 displays all the rainfall and groundwater station spread all over the study area of punjab with thiessen area of rainfall stations

4.2 GROUNDWATER ANALYSIS MAPS: -

Using ArcGIS two different types of groundwater data analysis was done spatial and contour analysis. For spatial and contour analysis maximum and minimum, seasonal and annual average were drawn to show the groundwater level fluctuations over time.

4.2.1 Maximum monthly spatial maps: -



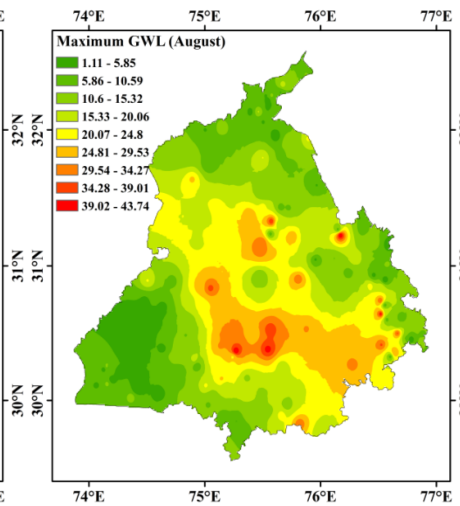
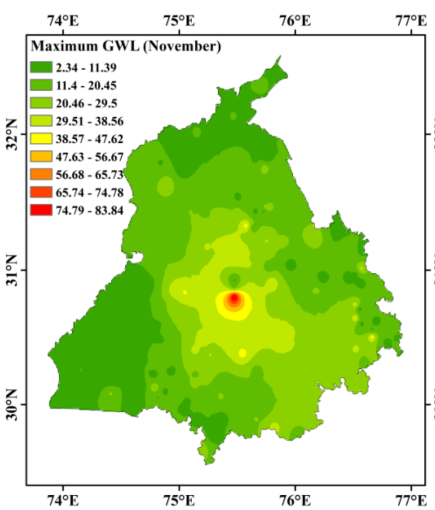


Fig- 4.4 (a) **Fig- 4.4 (b)**



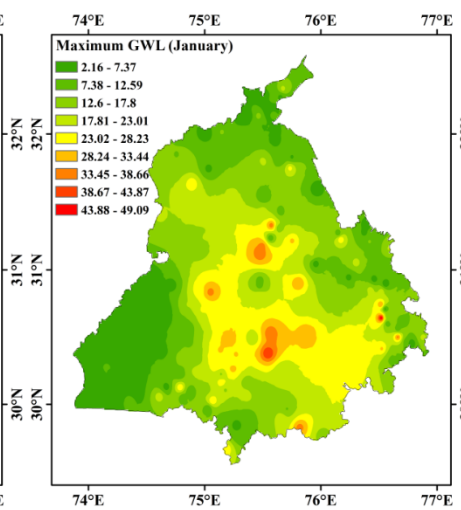
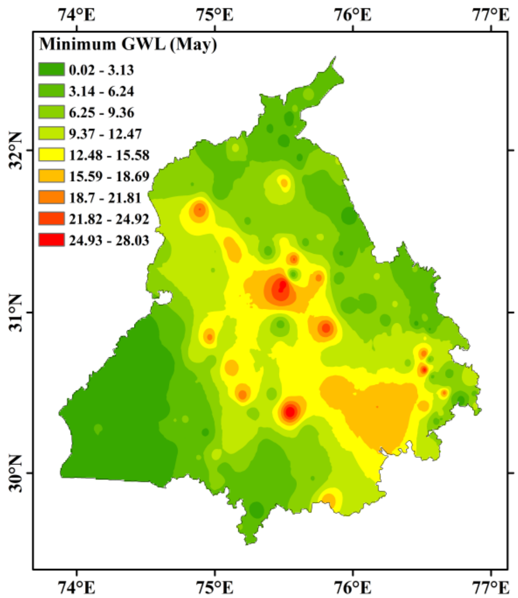


Fig- 4.4 (c) **Fig- 4.4 (d)**

Fig- 4.4 a, b, c & d shows maximum monthly groundwater level in may, aug, nov and jan respectively

4.2.2 Minimum monthly spatial maps: -



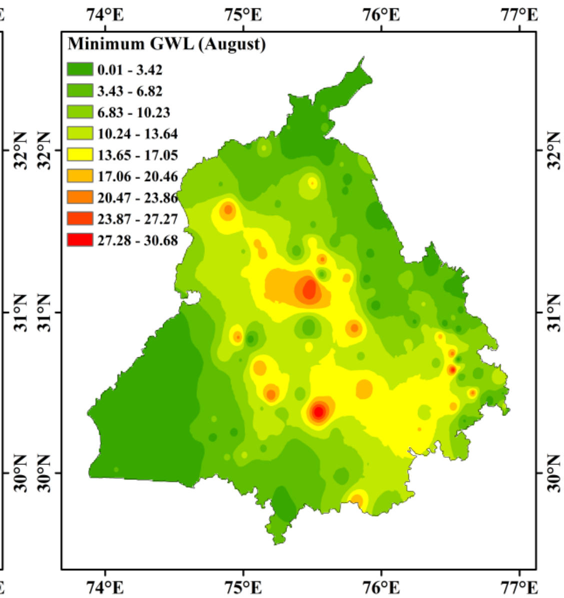
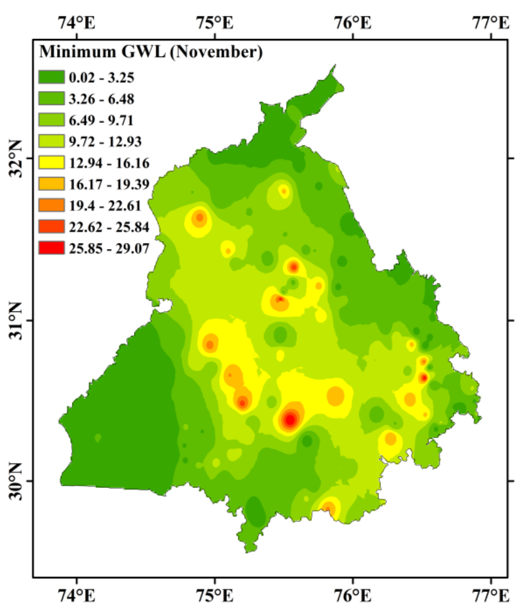


Fig- 4.5(a) **Fig- 4.5 (b)**



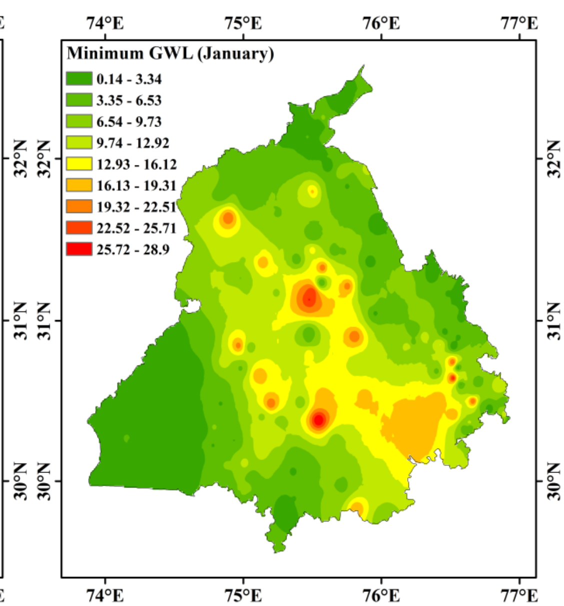


Fig- 4.5(c) **Fig- 4.5 (d)**

Fig- 4.5 a, b, c & d shows monthly minimum groundwater level in may, aug, nov and jan respectively

4.2.3 Maximum and minimum annual spatial maps: -

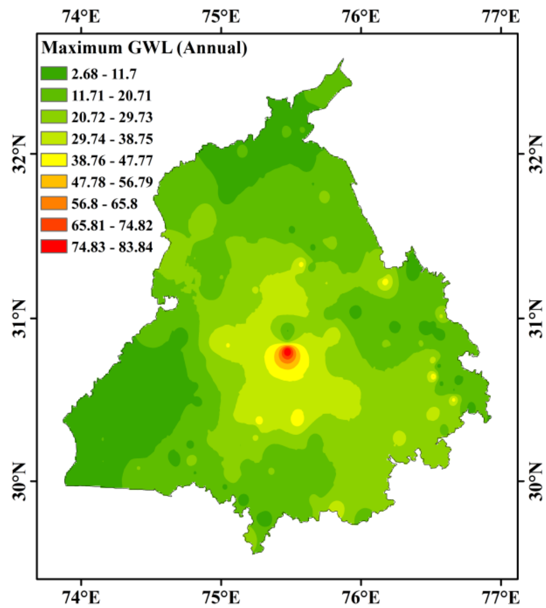


Fig- 4.6 (a)

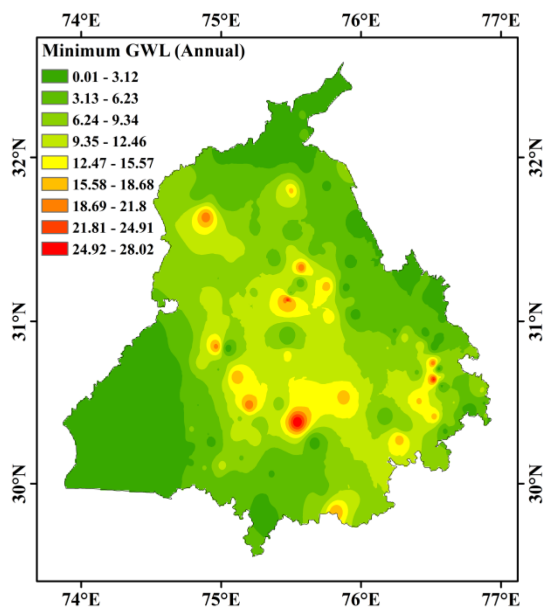


Fig- 4.6 (b)

Fig- 4.6 (a) displays maximum annual groundwater level and (b) minimum annual groundwater level of punjab

4.2.4 Maximum monthly contour maps: -

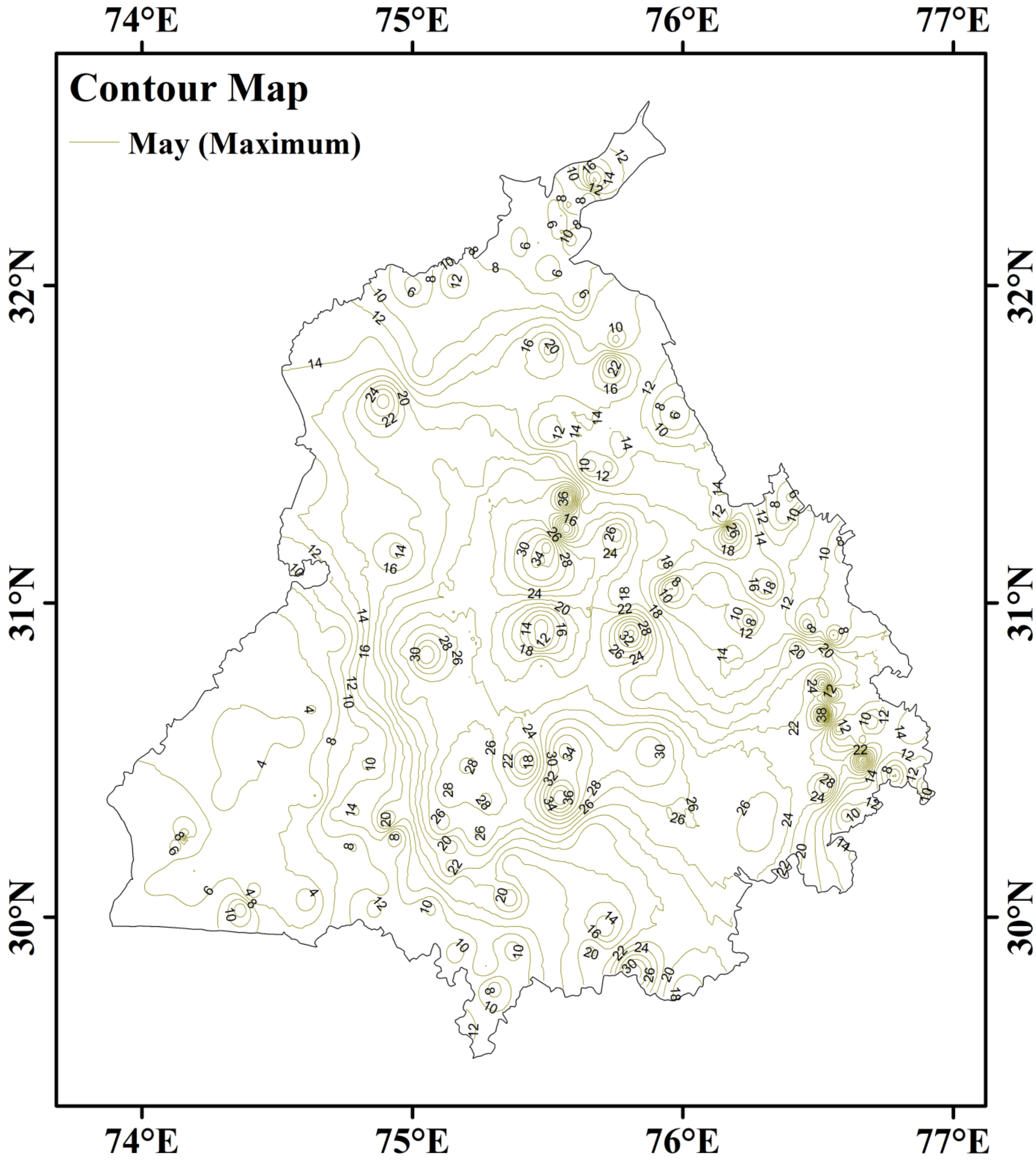


Fig- 4.7 displays maximum groundwater level contours all over punjab in may month

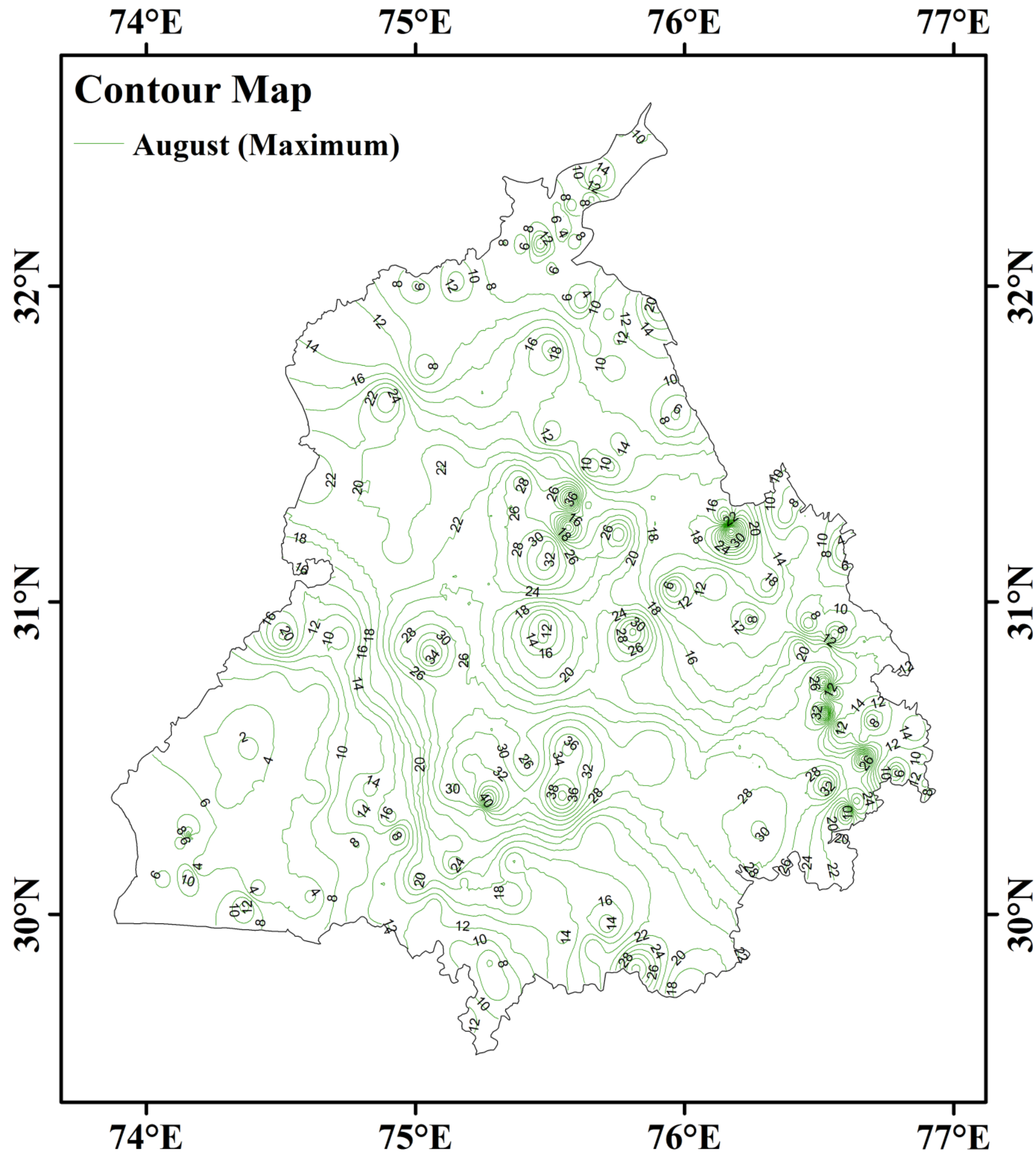


Fig- 4.8 displays maximum groundwater level contours all over punjab in august month

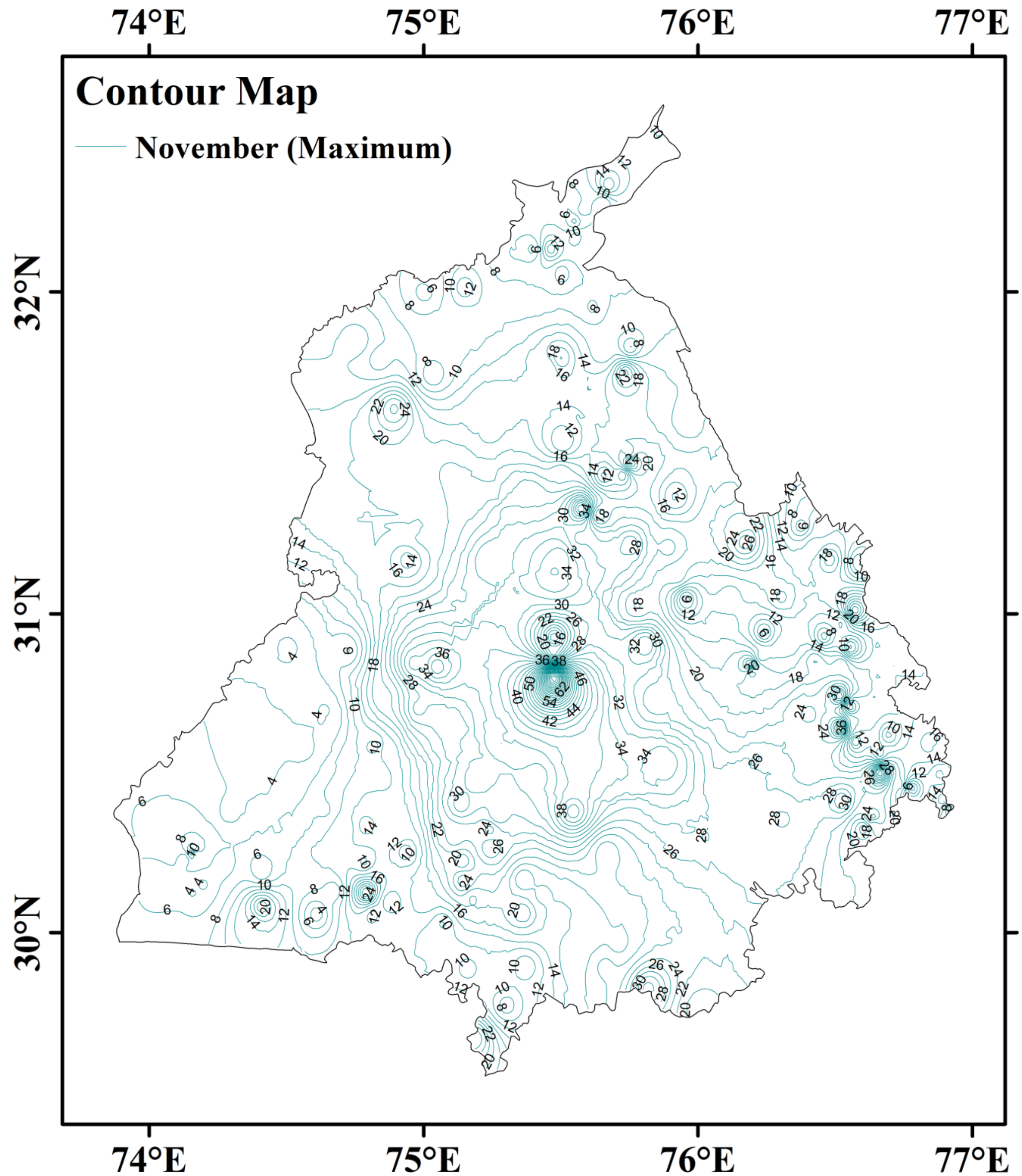


Fig- 4.9 displays maximum groundwater level contours all over punjab in november month

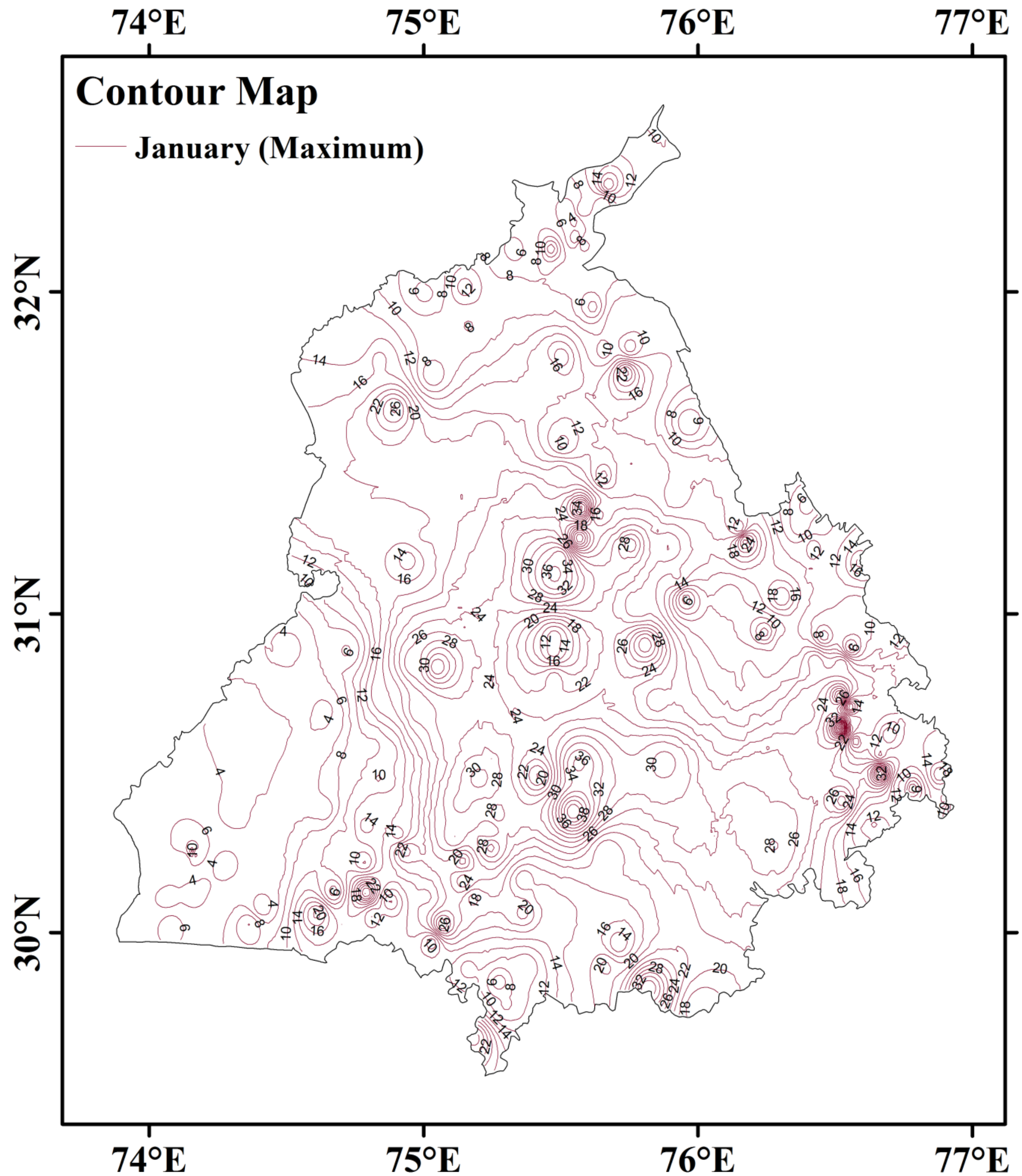


Fig- 4.10 displays maximum groundwater level contours all over punjab in january month

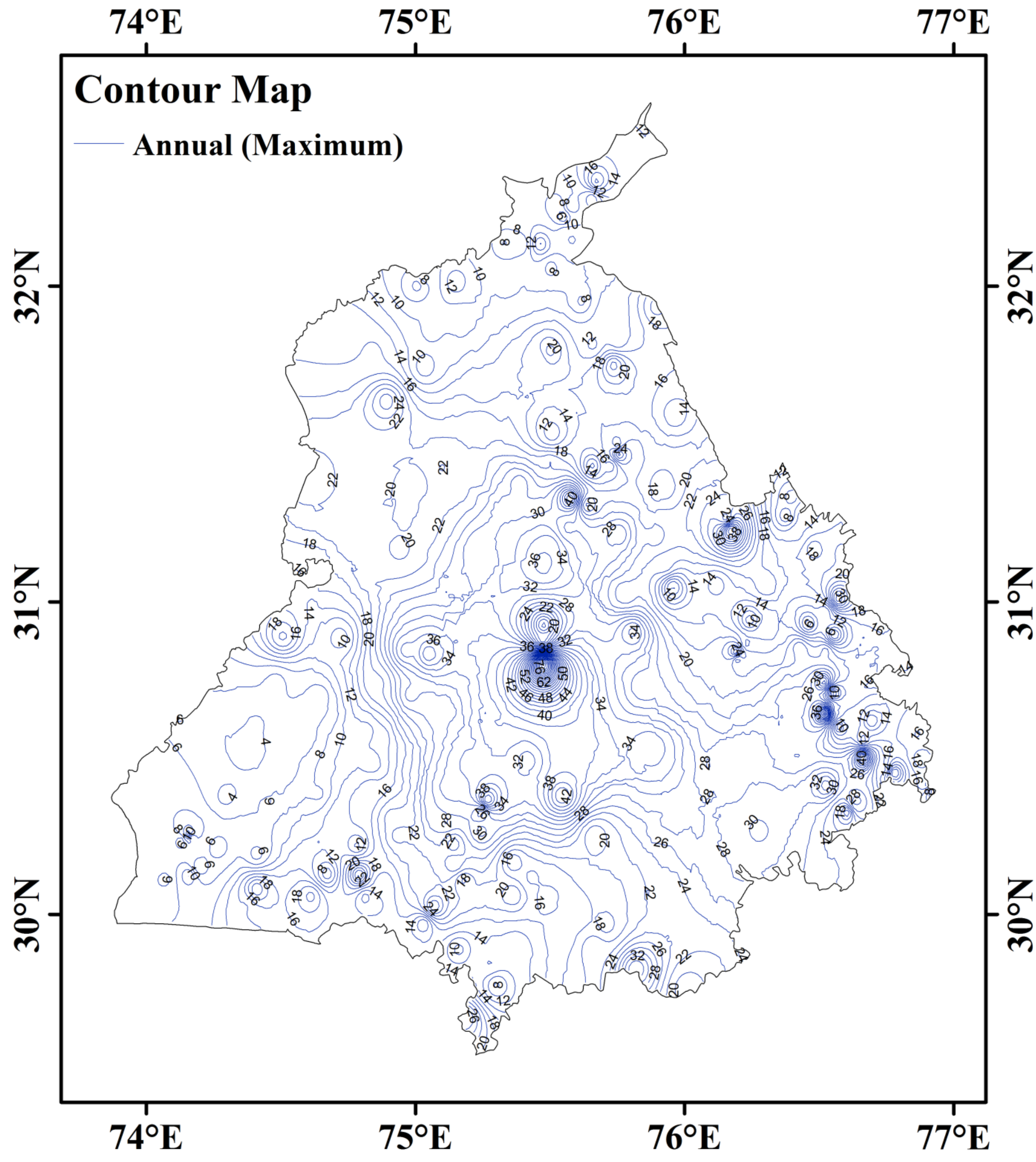


Fig- 4.11 displays maximum annual groundwater level contours

4.2.5 Minimum monthly contour maps: -

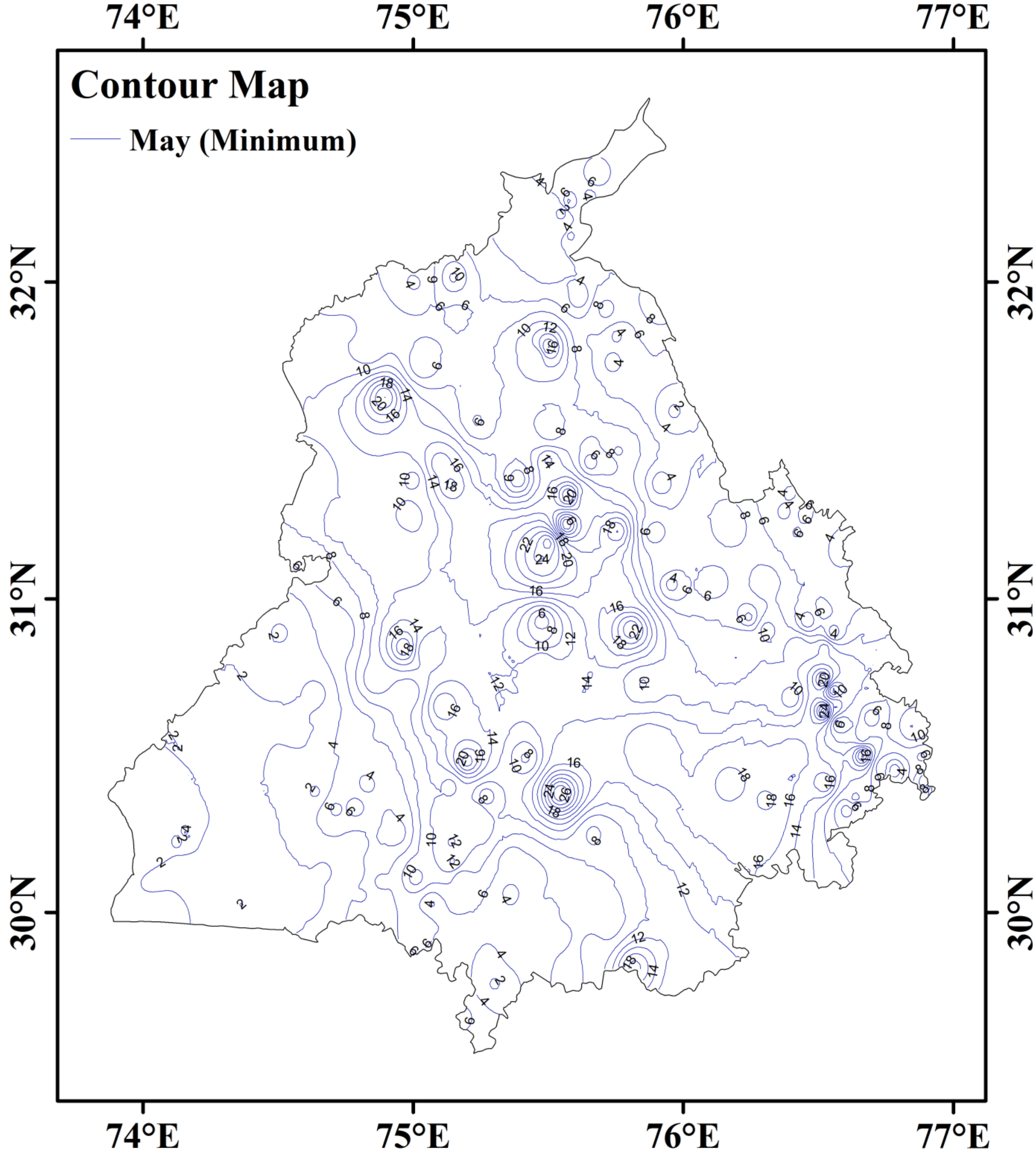


Fig- 4.12 displays minimum groundwater level contours all over punjab in may month

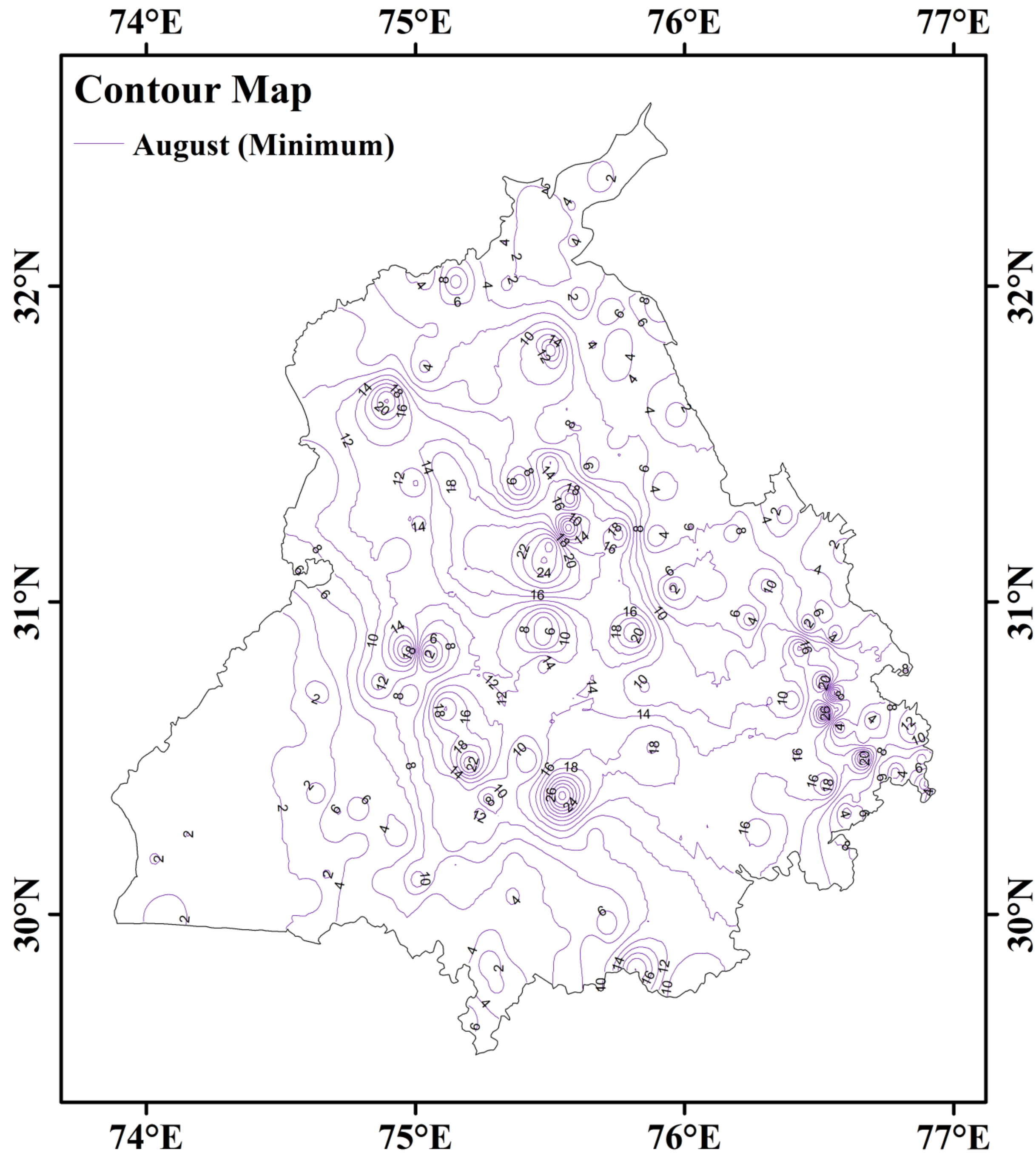


Fig- 4.13 displays minimum groundwater level contours all over Punjab in august month

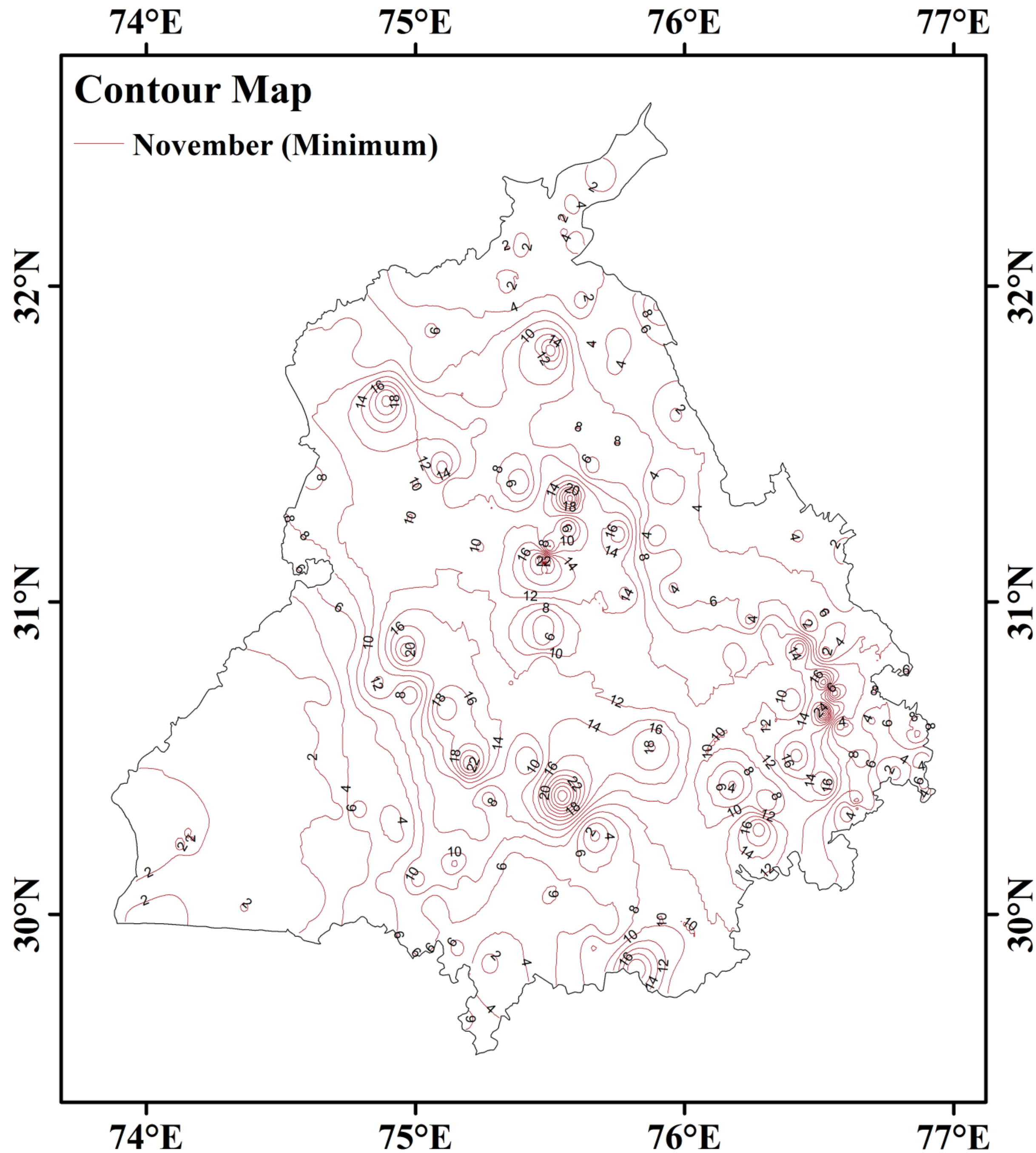


Fig- 4.14 displays minimum groundwater level contours all over Punjab in November month

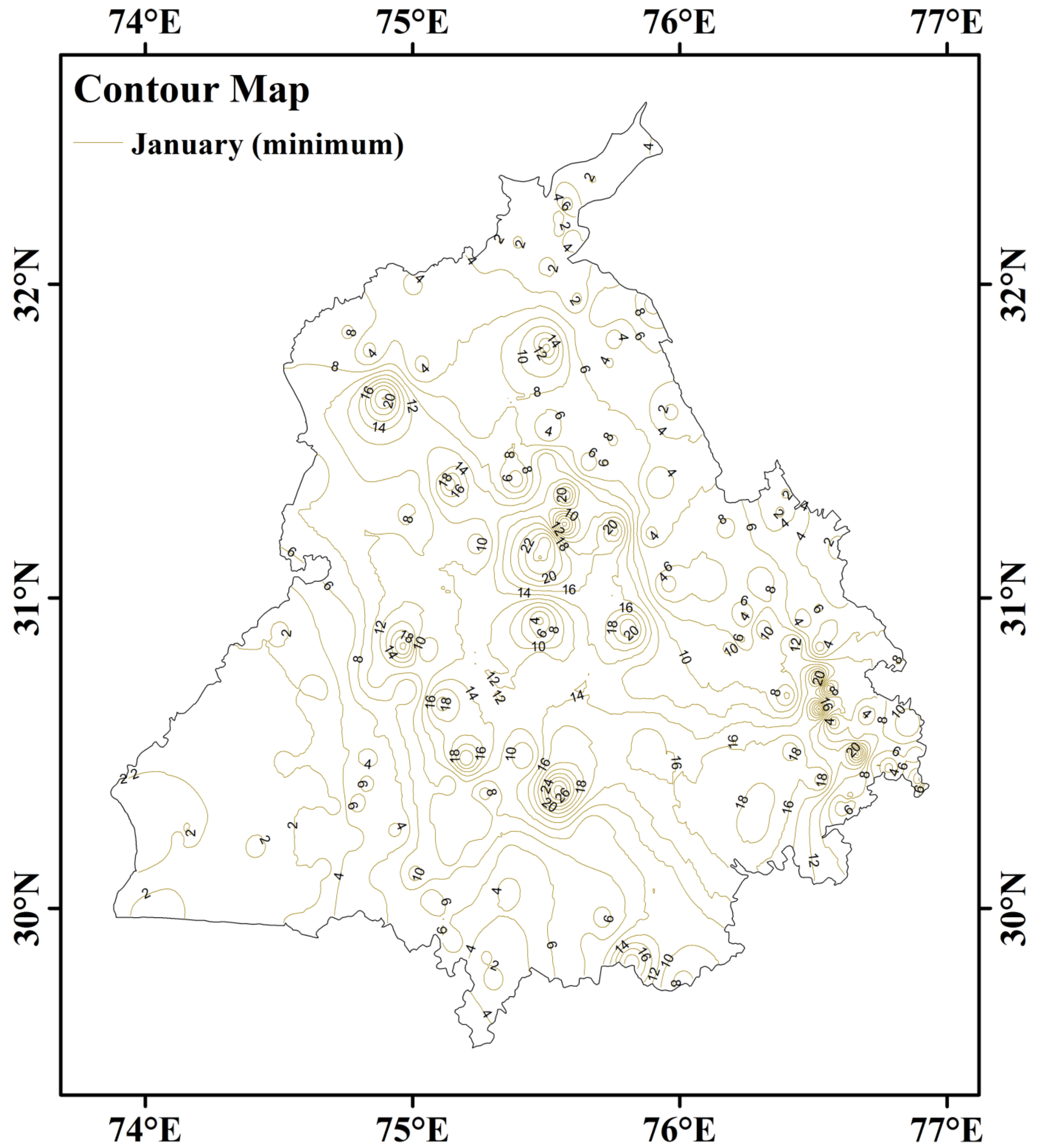


Fig- 4.15 displays minimum groundwater level contours all over Punjab in January month

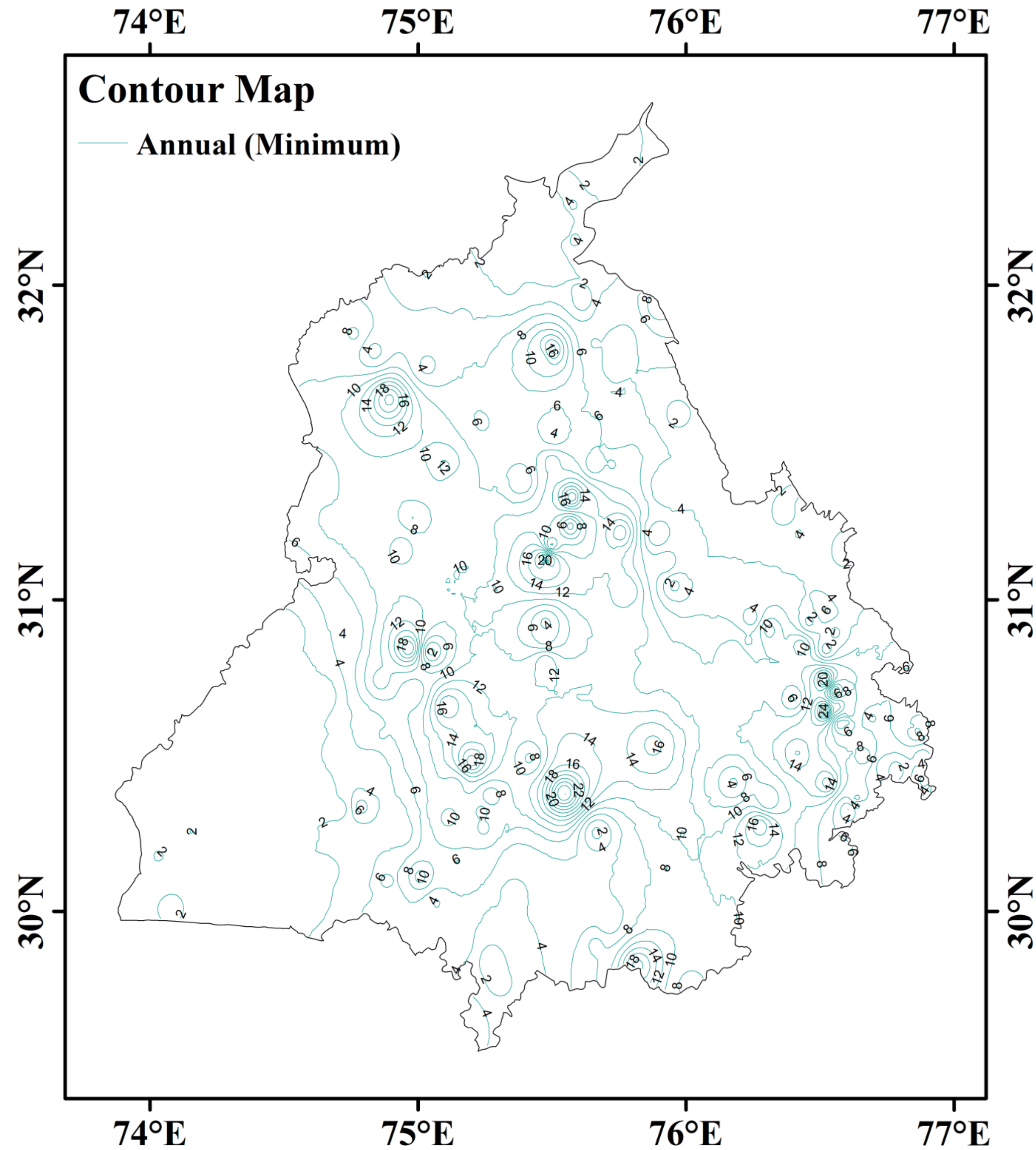
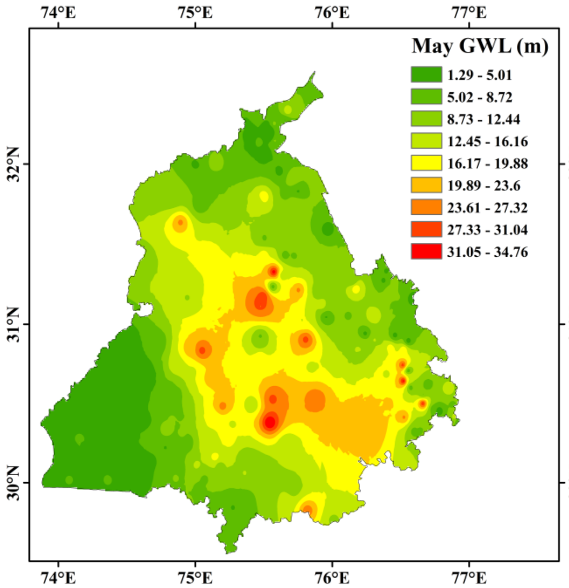


Fig- 4.16 displays minimum annual groundwater level contours

4.2.6 Monthly and annual average spatial maps: -



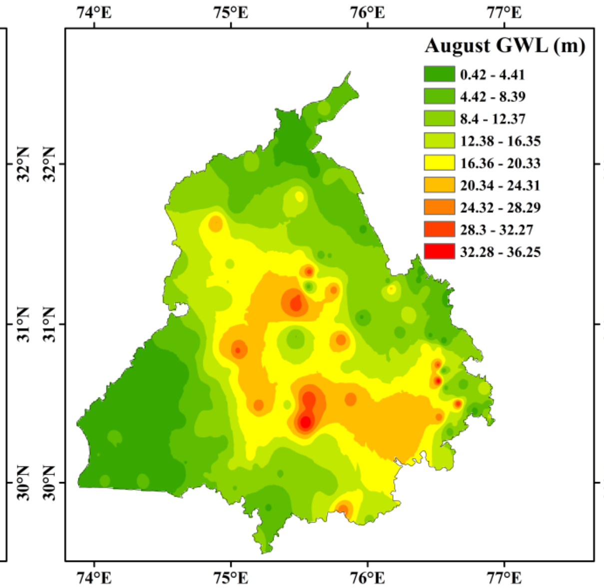
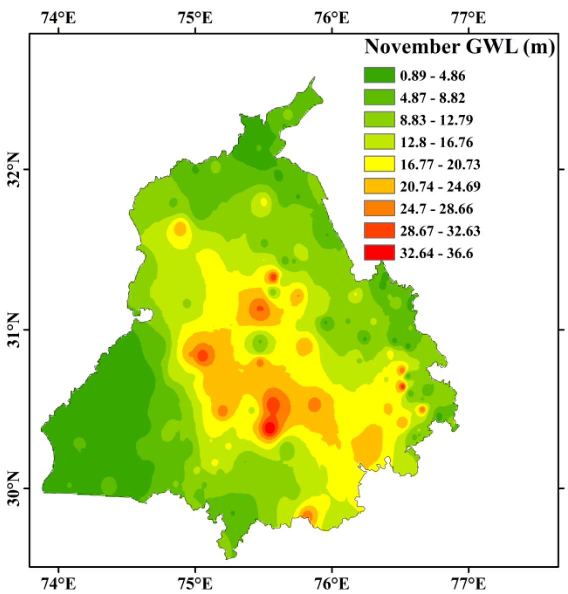


Fig- 4.17(a)Fig- 4.17 (b)



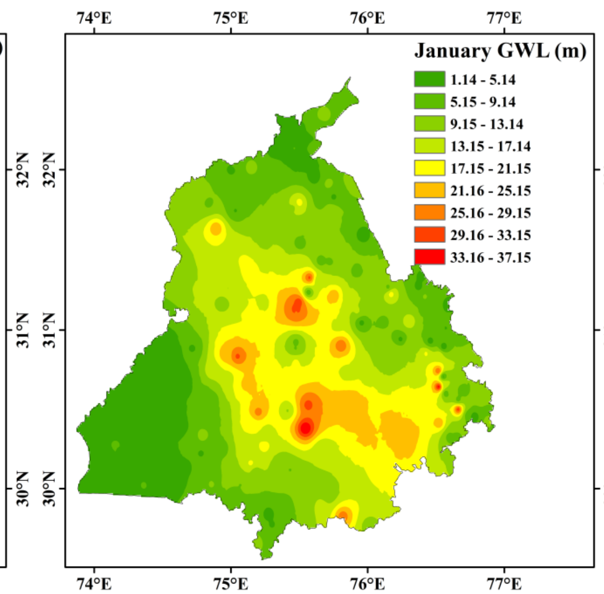


Fig- 4.17 (c)

Fig- 4.17 (d)

Fig- 4.17 a, b, c & d shows monthly average groundwater level in may, aug, nov and jan respectively

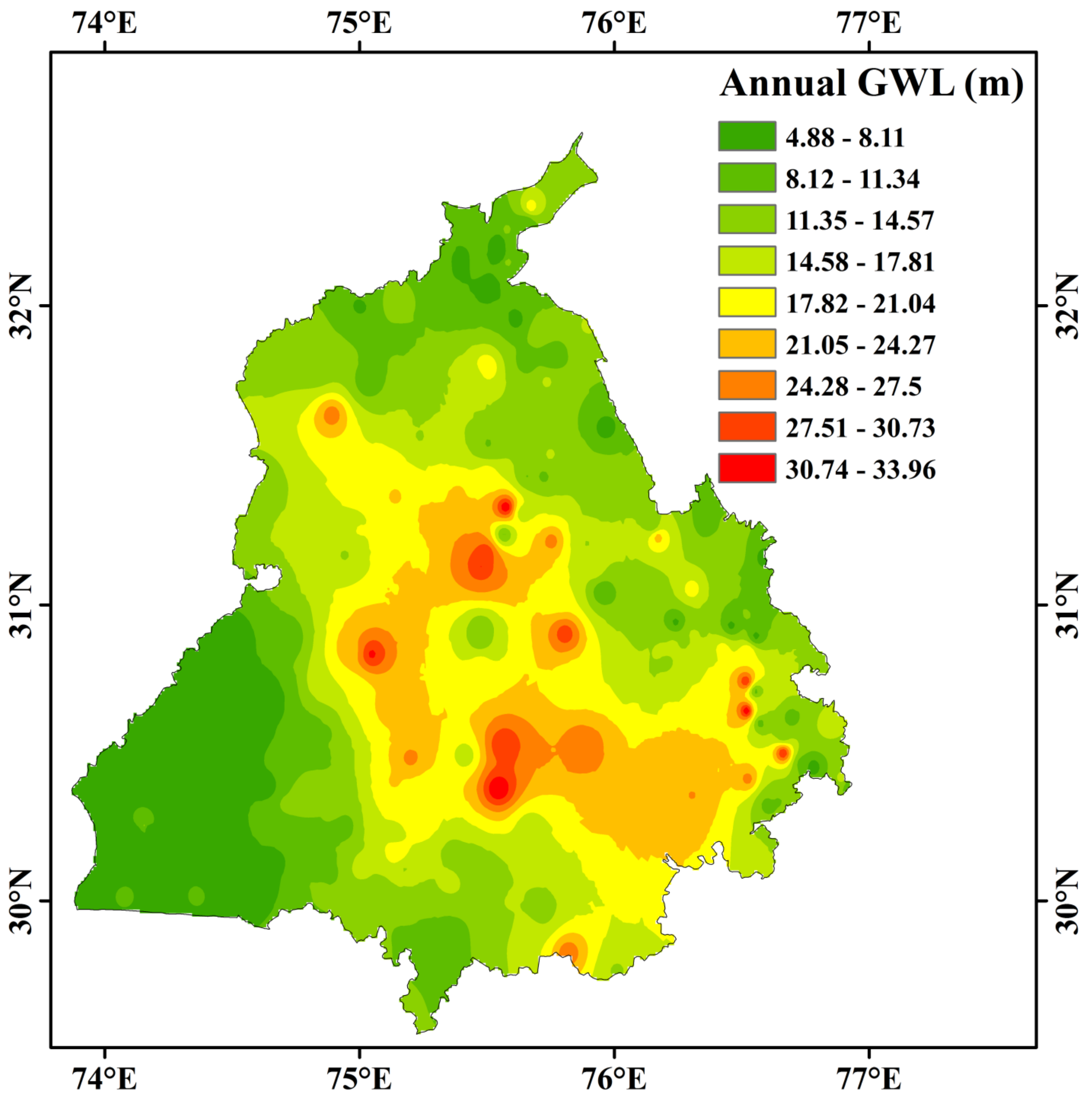


Fig- 4.18 shows the annual average groundwater level of punjab

4.2.7 Monthly and annual average contour maps: -

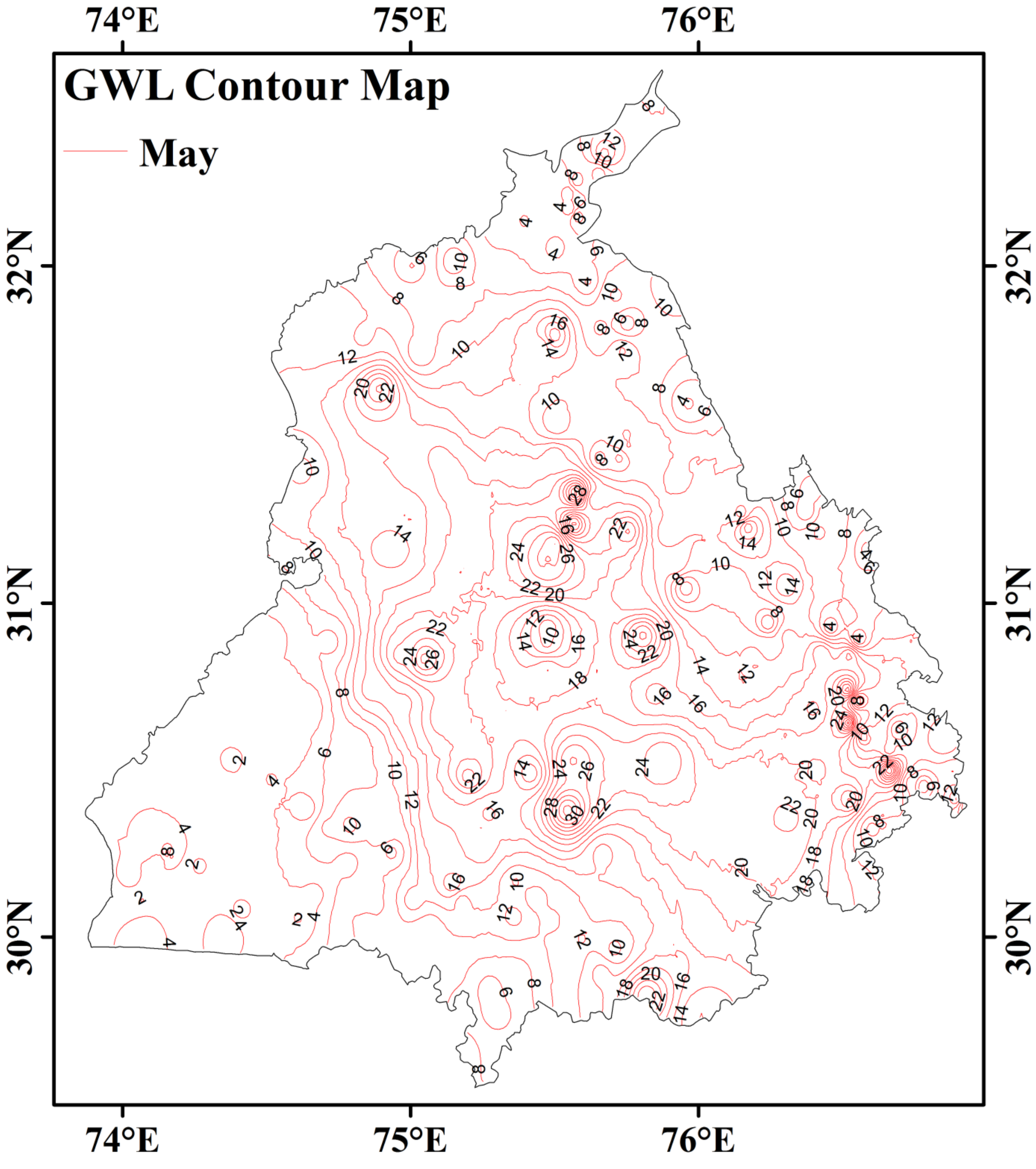


Fig- 4.19 displays the average groundwater level in may

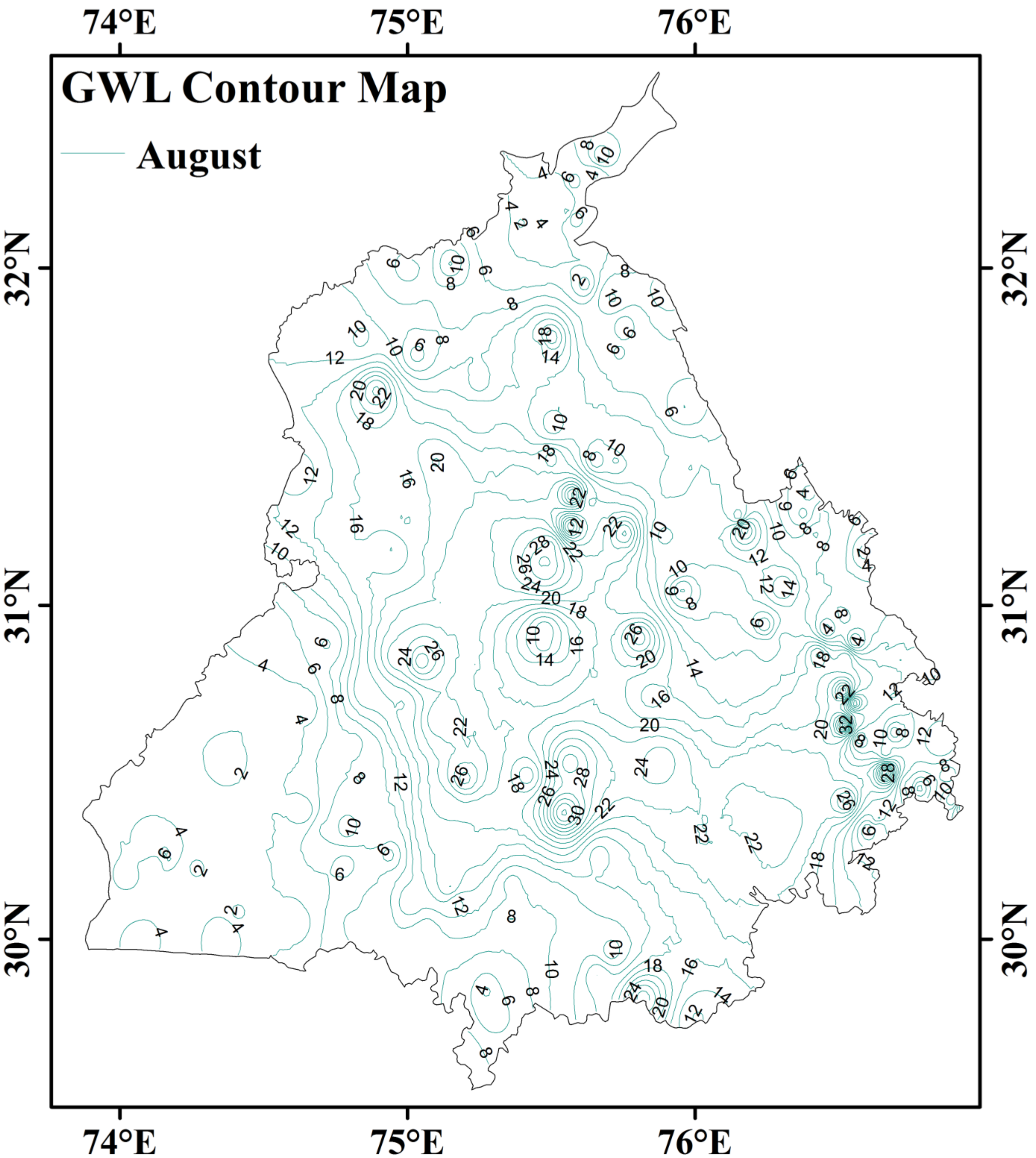


Fig- 4.20 displays the average groundwater level in august

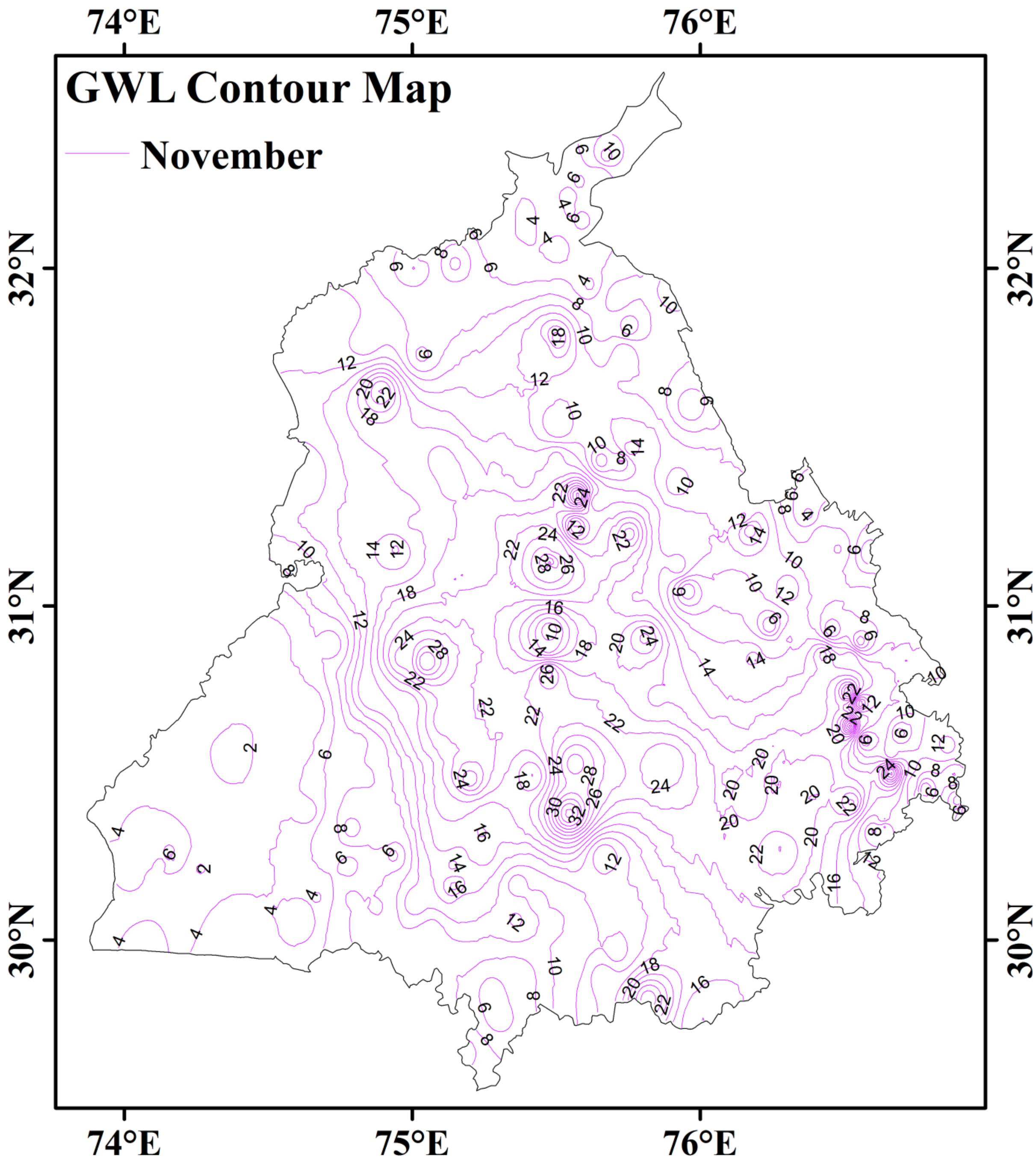


Fig- 4.21 displays the average groundwater level in november

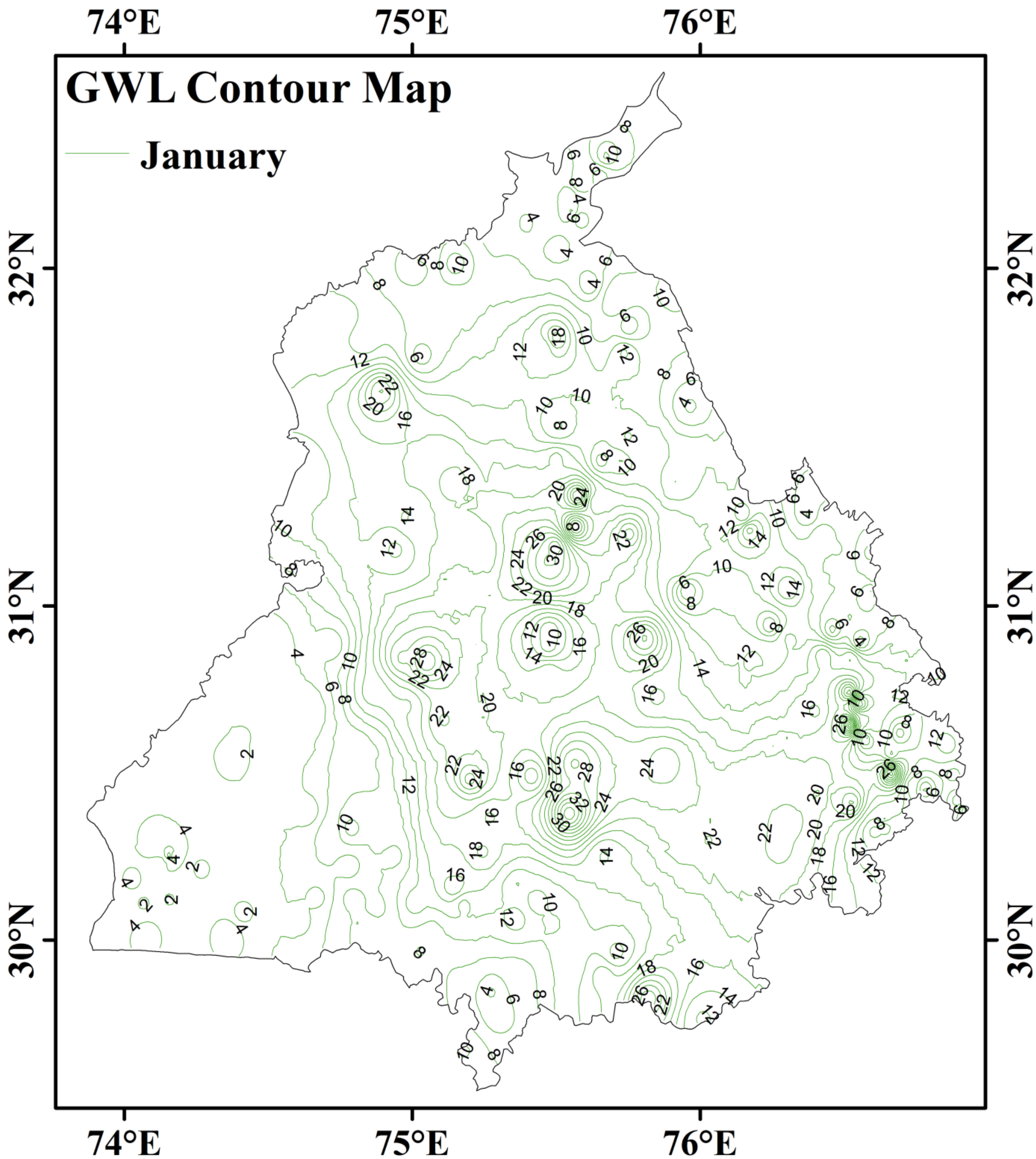


Fig- 4.22 displays the average groundwater level in january

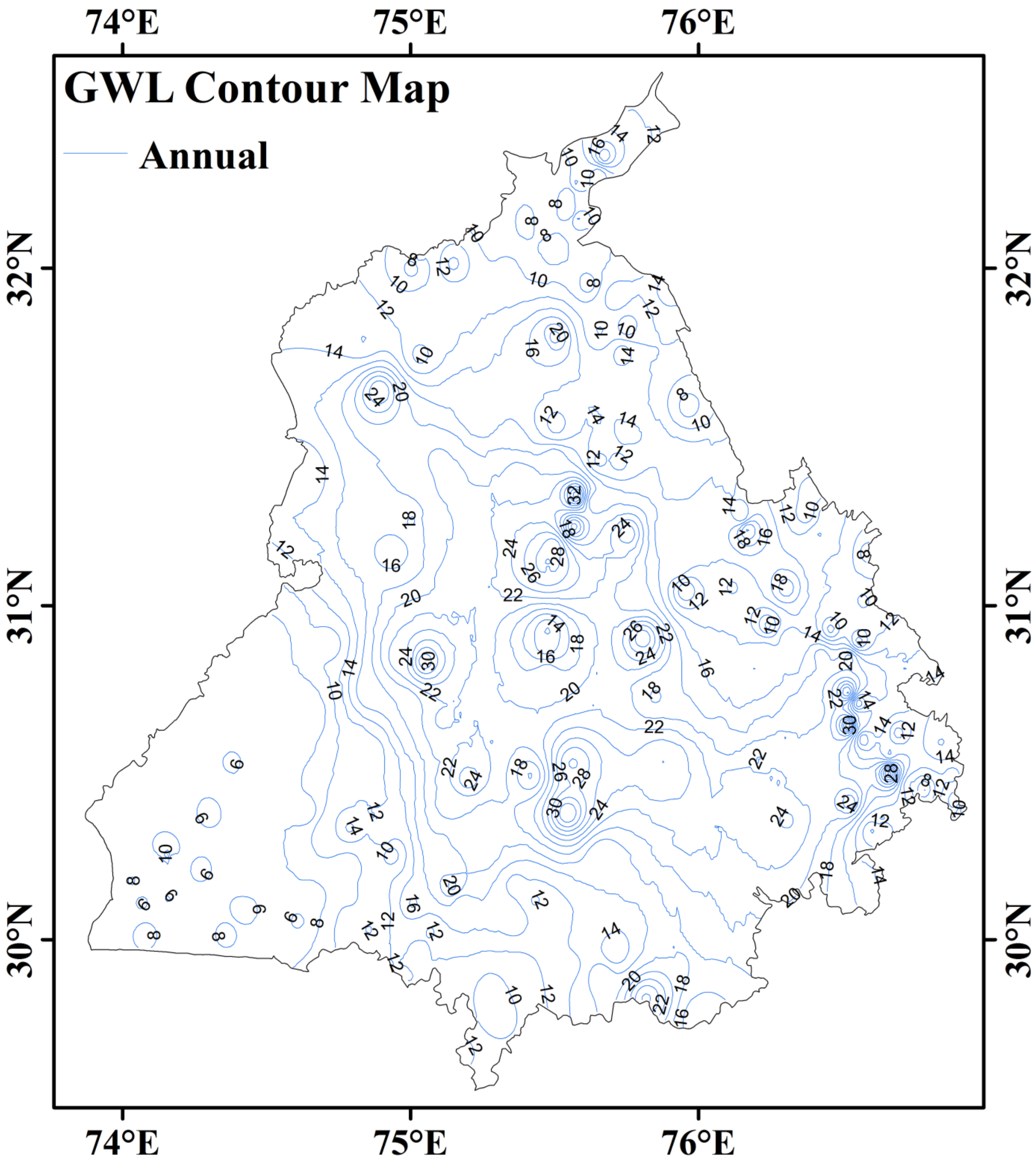
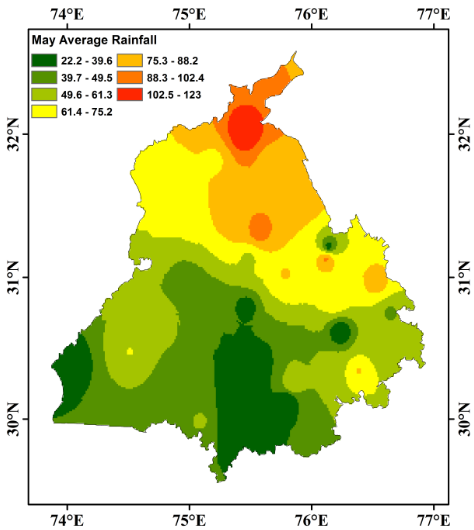


Fig- 4.23 displays the annual average groundwater level of punjab

4.3 RAINFALL ANALYSIS MAPS: -

Using ArcGIS seasonal and annual average maps were drawn using spatial analysis. Also rainfall data graphs were drawn with standard deviation using Microsoft office excel.

4.3.1 Monthly and annual average spatial maps: -



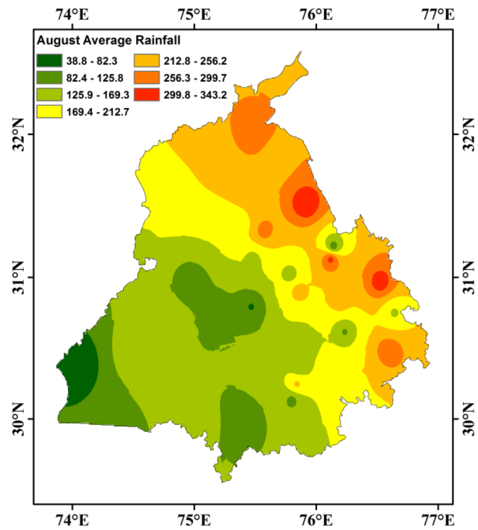
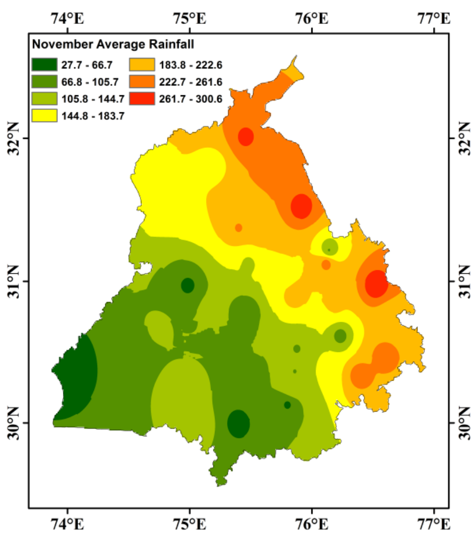


Fig- 4.24 (a)Fig- 4.24 (b)



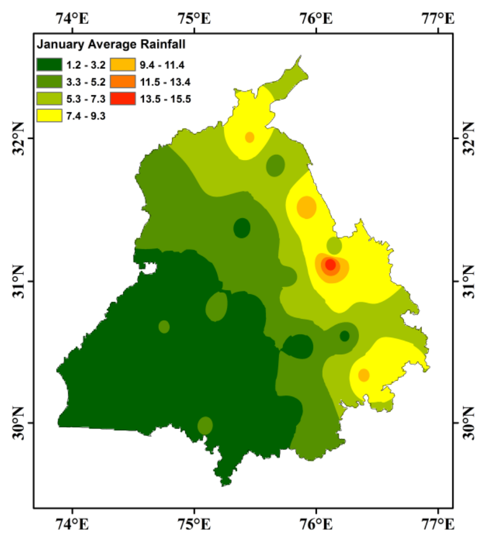


Fig- 4.24 (c) **Fig- 4.24 (d)**

Fig- 4.24 a, b, c & d shows the rainfall data in may, aug, nov and jan respectively

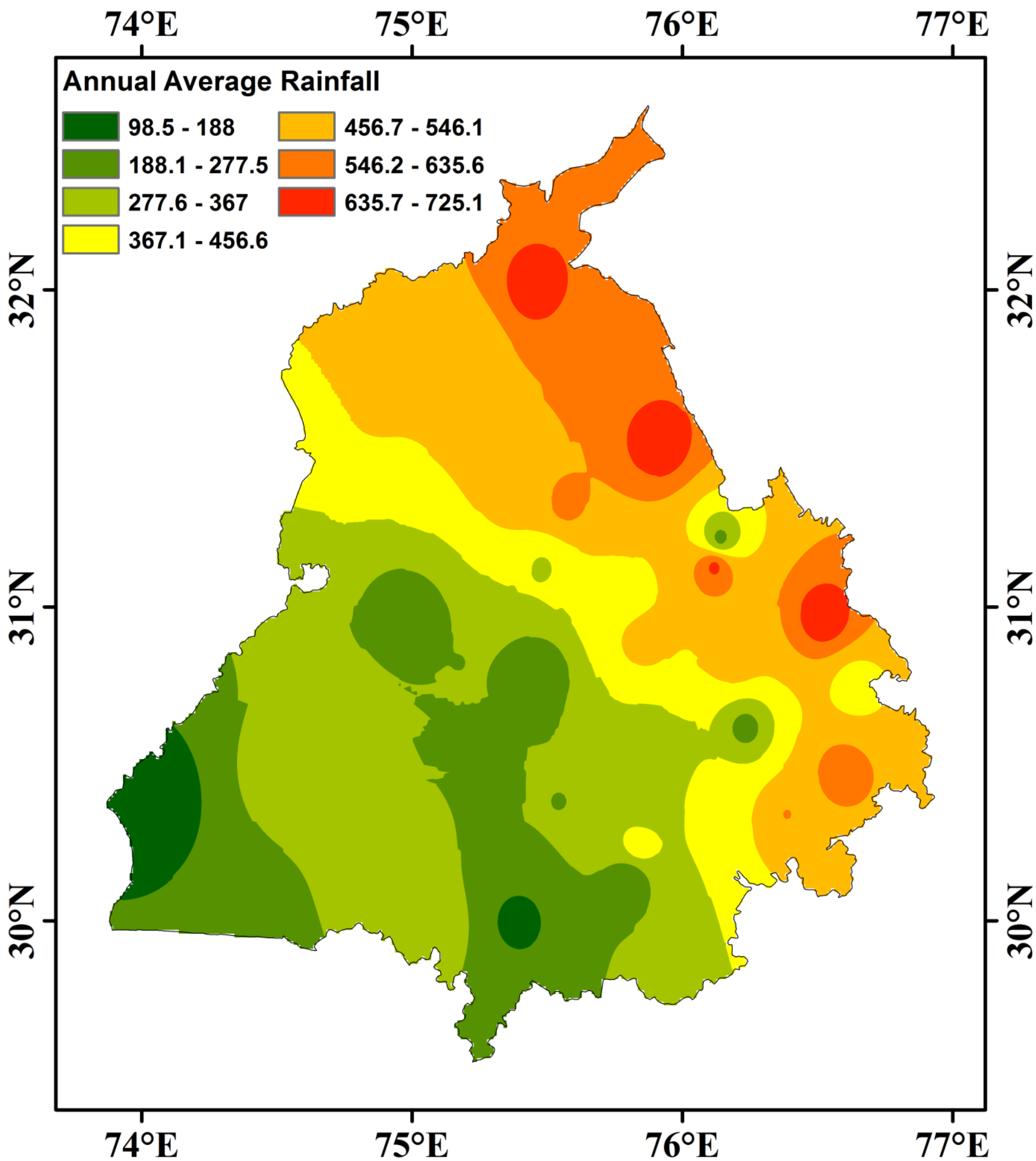


Fig- 4.25 shows the annual rainfall data

4.3.2 Rainfall data graphs with standard deviation: -

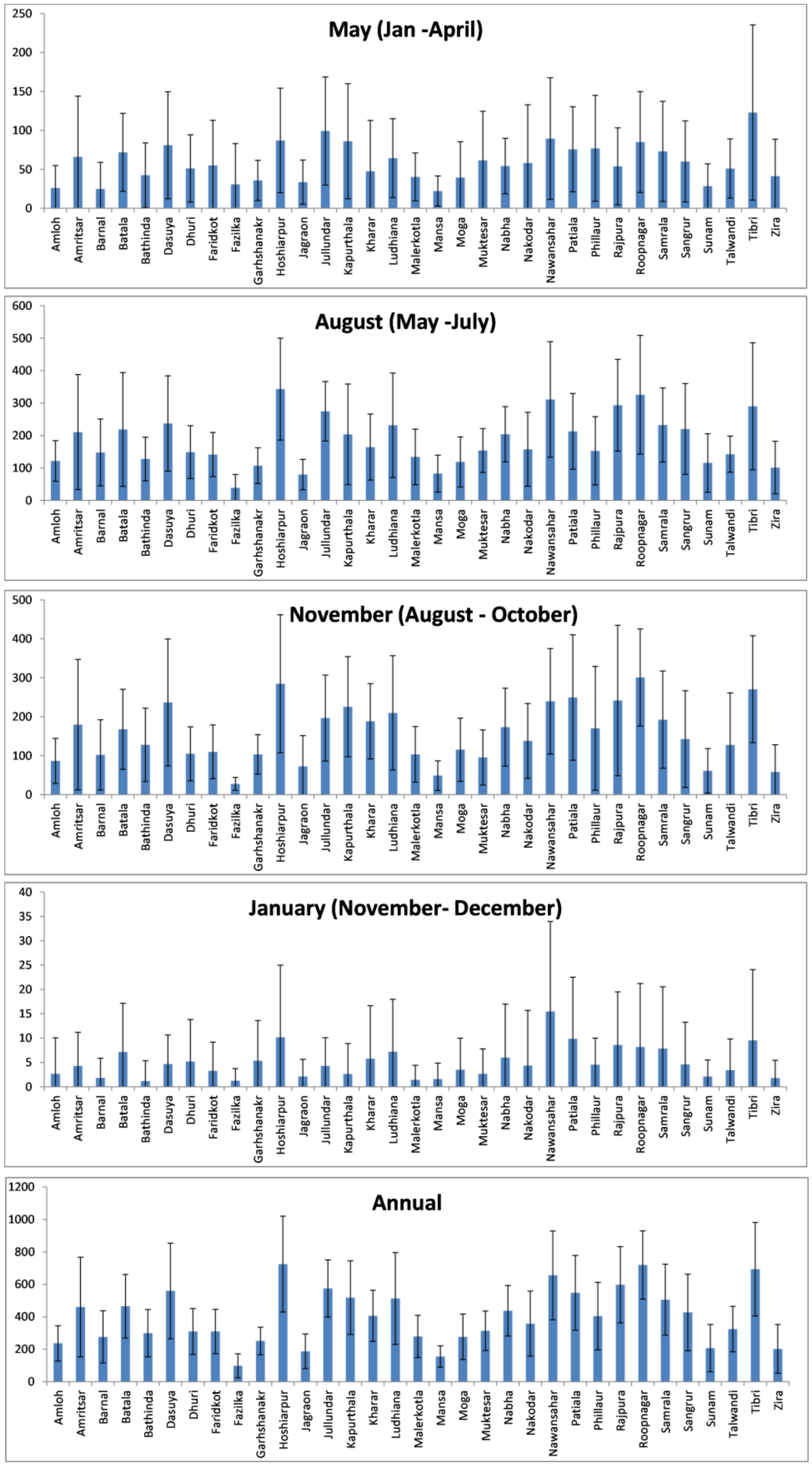


Fig- 4.26 shows the average monthly and annual rainfall data with standard deviation of every rainfall station

4.4 ARTIFICIAL NEURAL NETWORK MODEL RESULTS GRAPHS: -

Using matlab ANN model was designed and optimized to give best results for groundwater level forecasting. The data which was available we were able to forecast groundwater level for upto 6 months. Back propagation method was used in ANN modeling and was able to forecast groundwater level for 11 districts.

Which are as following mentioned below: -

1) Amritsar
2) Bathinda
3) Faridkot
4) Fazilka
5) Hoshiarpur
6) Kapurthala
7) Ludhiana
8) Mansa
9) Moga
10) Patiala
11) Sangrur

And all these districts the artificial neural network was trained in three different algorithms levenberg-marquardt, Bayesian regularization and scaled conjugate gradient algorithms. The results of each district and algorithm have five graphs showing results of the model in each district.

The graphs are as following mentioned below: -

1) Error histogram
2) Performance
3) Plot (Observed and calculated data graph)
4) Regression
5) Train state

4.4.1 Error histogram graph: -

Error histogram is the histogram of the errors between target values and predicted values after training a neural network model in this instance we used back propagation neural network. As these error values indicates how predicted values are differing from the target values hence these can be negative.

Bins are the number of vertical bars you are observing on the graph. And zero error line corresponding to the zero error value on the error axis (i.e. x-axis). In this case zero error point falls under the bin with centre yellow line.

4.4.2 Performance graph: -

The performance graph points out the best results given between minimum mean square error and at any given number of epochs. Where the dotted line denoted by best on graph converges and the train, validation and test line pass close to it or pass through the converging line of best.

An epoch means training the neural network with all the training data for one cycle. In an epoch we use all of the data exactly once. A forward pass and a backward pass together are counted as one pass.

4.4.3 Plot graph: -

This graph shows us the comparative graph of the actual data and the calculated data graph both denoted by different colour. This graph is plotted between water level (groundwater) and time in days (months and years can also be used but to make both plots visible and not overlap we chose days).

4.4.4 Regression graph: -

These graphs give you an idea of how close the output from our model is to the actual target values. Looking at the results, it seems we have a pretty good fit, though it seems to have some outliers. This graph is the mathematical approach to find the relationship between two or more variables is known as regression in AI. Regression is widely used in machine learning to predict the behavior of one variable depending upon the value of another variable.

4.4.5 Train state graph: -

This graph contains three individual graphs but linked at any given epoch. First is gradient graph, plotting gradient values, mu and validation fail. Gradient represent slope of tangent of graph of function. It points to the direction in which there is high rate of increase for the considering function. ‘mu’ is the control parameter for the back-propagation neural network that we modeled and choice of mu directly affects the error convergence. Validation check is used to terminate the learning of neural network. The number of validation check will depend on the number of successive iteration of neural network.

4.5 ARTIFICIAL NEURAL NETWORK RESULTS: -

4.5.1 Amritsar: -

4.5.1.1 Amritsar bayesian regularization: -

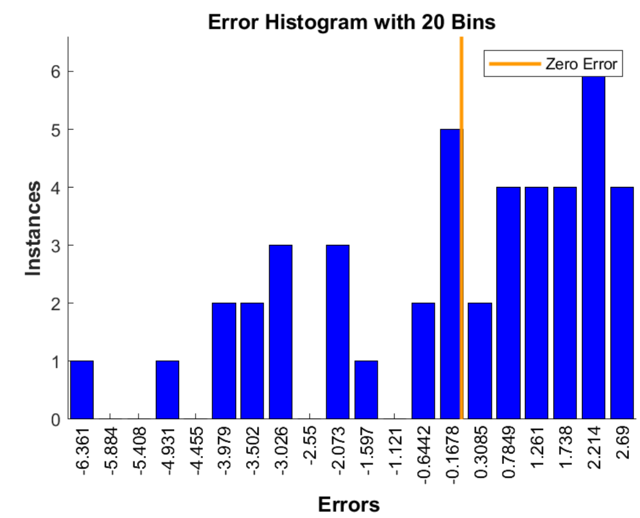


Fig- 4.27 (a)

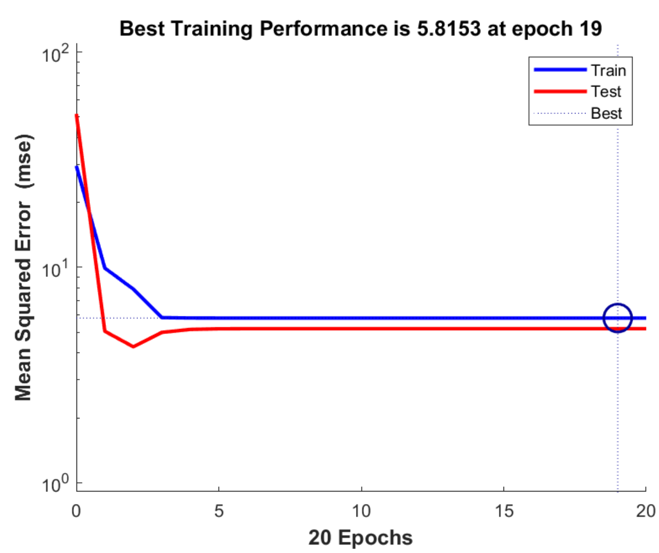


Fig- 4.27 (b)

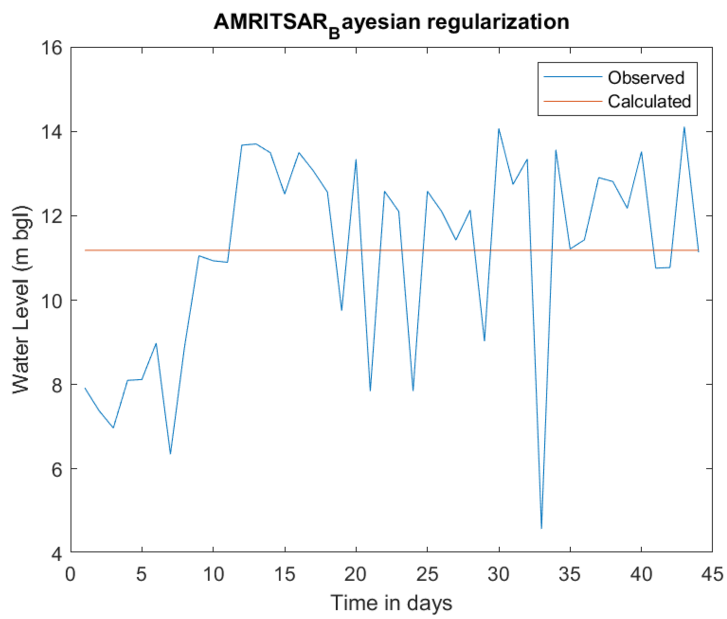
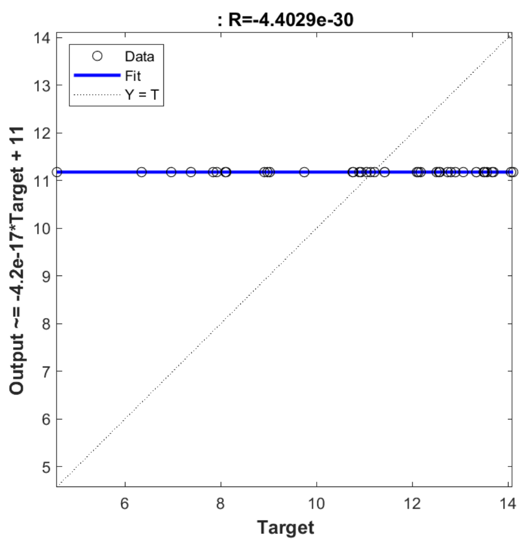


Fig- 4.27 (c)



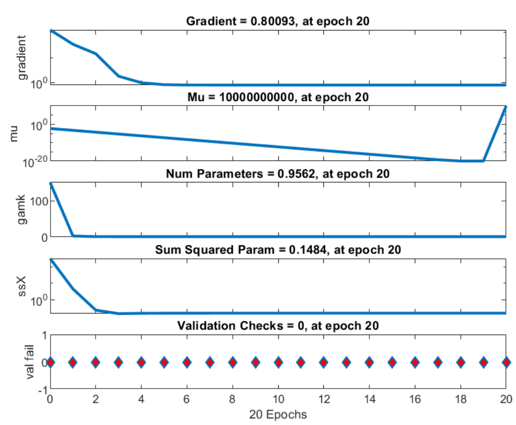


Fig- 4.27 (d)

Fig- 4.27 (e)

Fig- 4.27 a, b, c, d & e display the Error histogram, Performance Plot (Observed and calculated data graph), Regression& Train state graphs respectively

4.5.1.2 Amritsar levenberg-marquardt: -

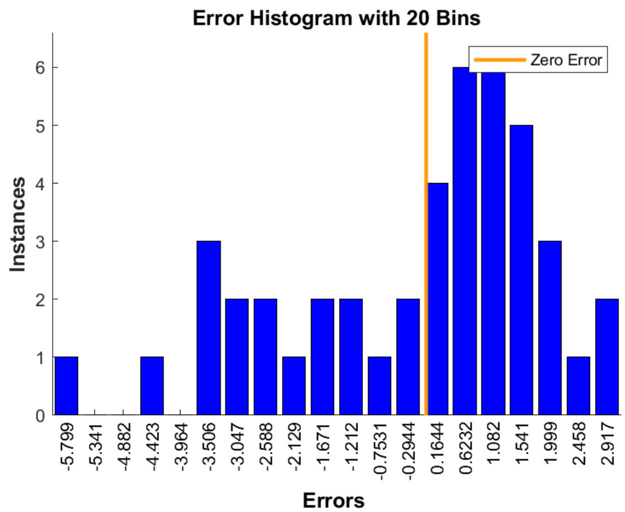


Fig- 4.28 (a)

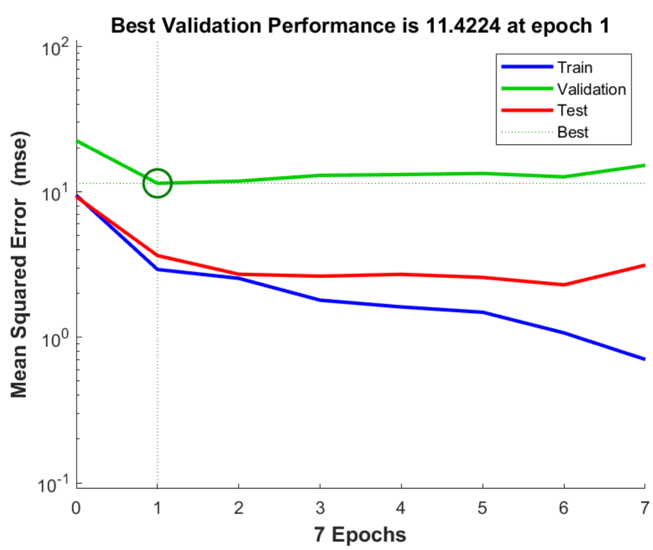


Fig- 4.28 (b)

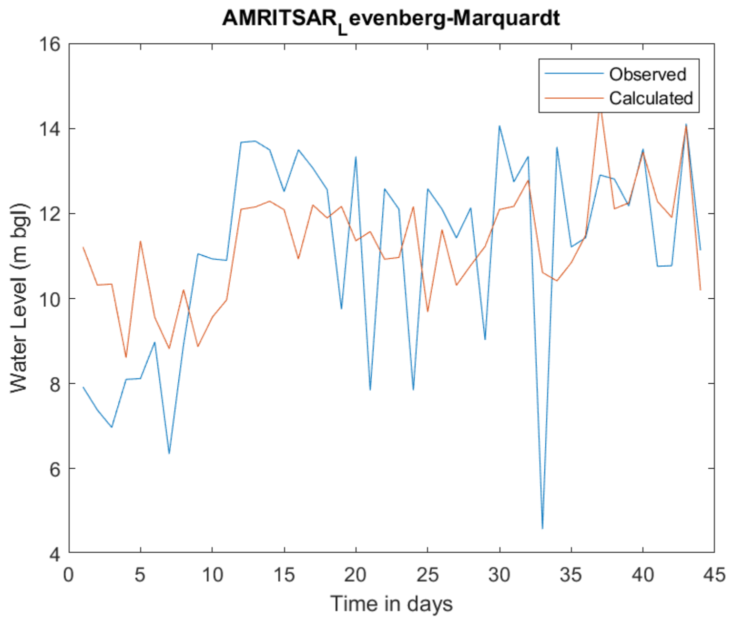
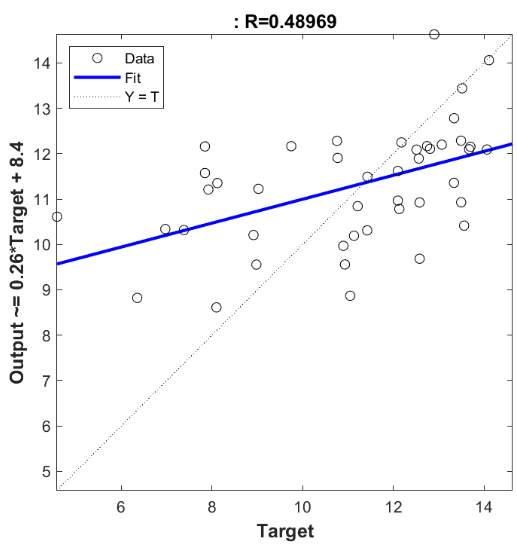


Fig- 4.28 (c)



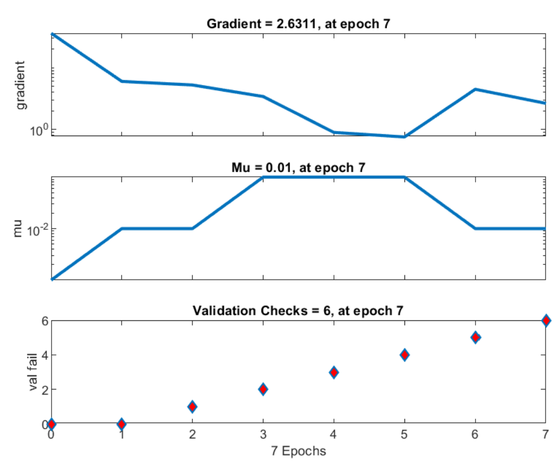


Fig- 4.28 (d) **Fig- 4.28 (e)**

Fig- 4.28 a, b, c, d & e display the Error histogram, Performance Plot (Observed and calculated data graph), Regression& Train state graphs respectively

4.5.1.3 Amritsar scaled conjugate gradient: -

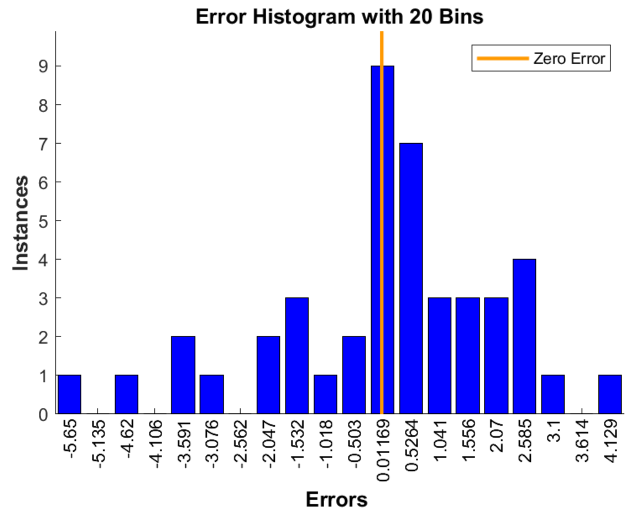


Fig- 4.29 (a)

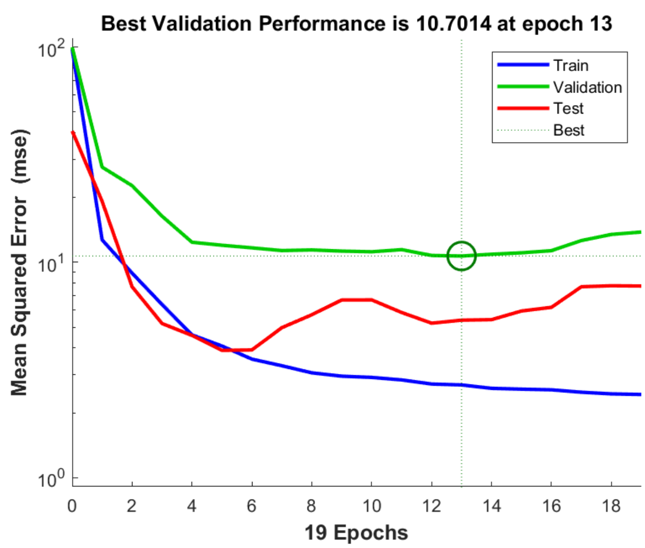


Fig- 4.29 (b)

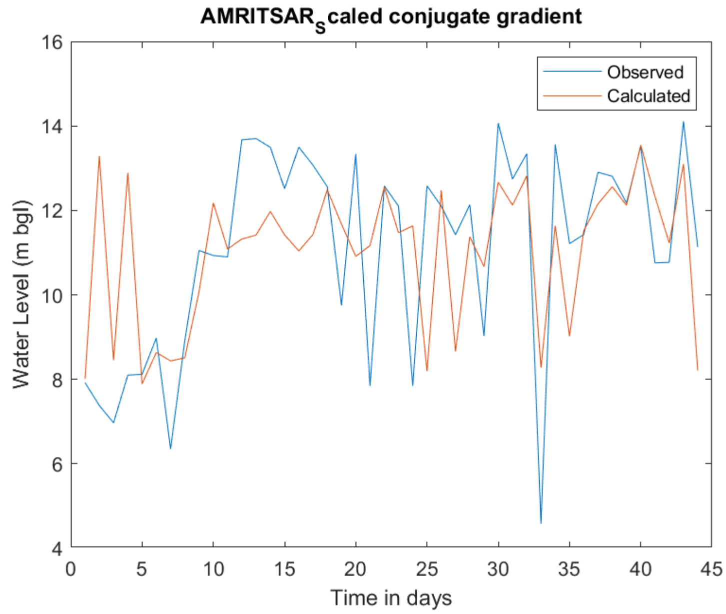
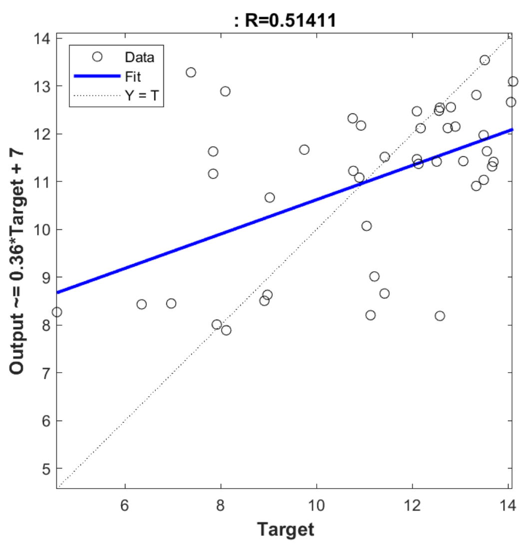


Fig- 4.29 (c)



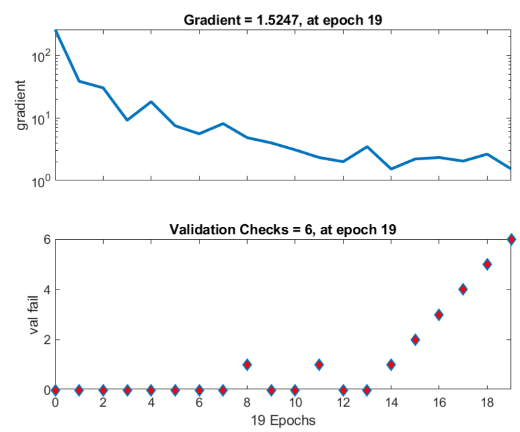


Fig- 4.29 (d) **Fig- 4.29 (e)**

Fig- 4.29 a, b, c, d & e display the Error histogram, Performance Plot (Observed and calculated data graph), Regression& Train state graphs respectively

4.5.2 Bathinda: -

4.5.2.1 Bathinda bayesian regularization: -

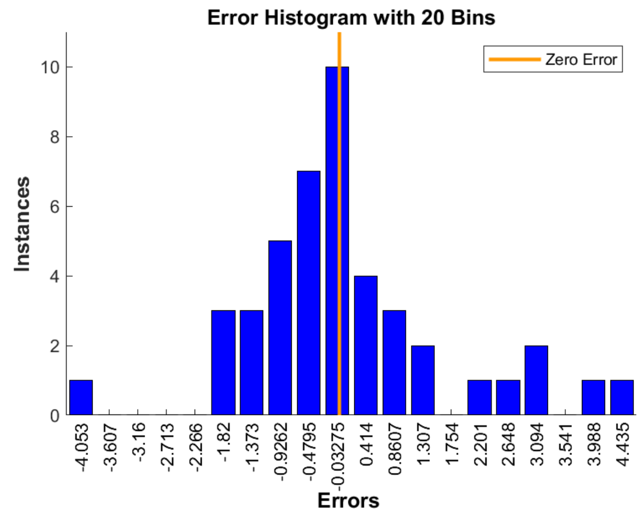


Fig- 4.30(a)

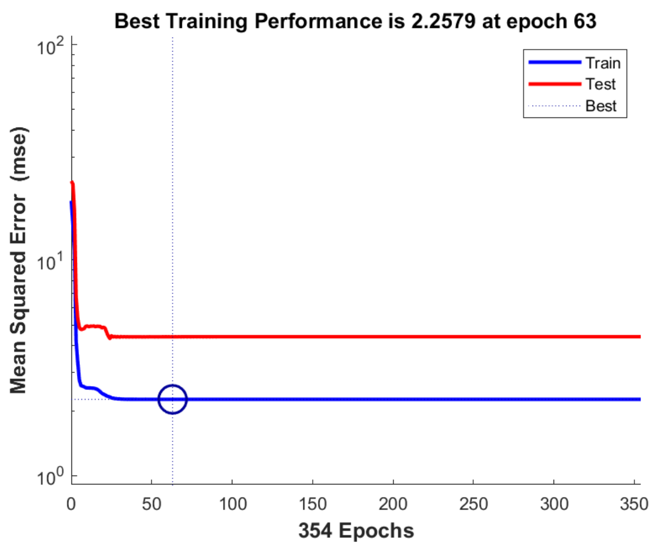


Fig- 4.30(b)

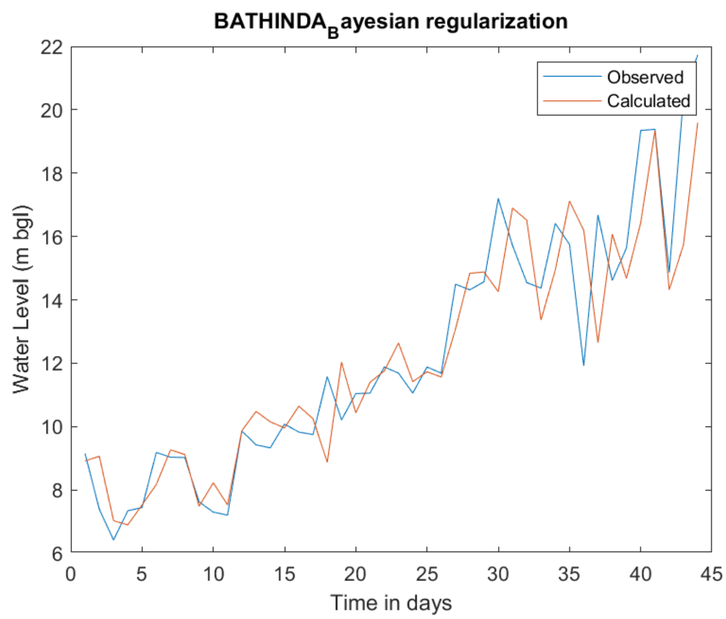
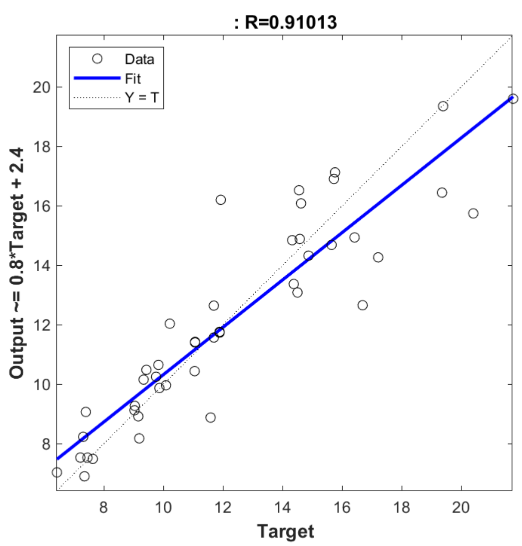


Fig- 4.30(c)



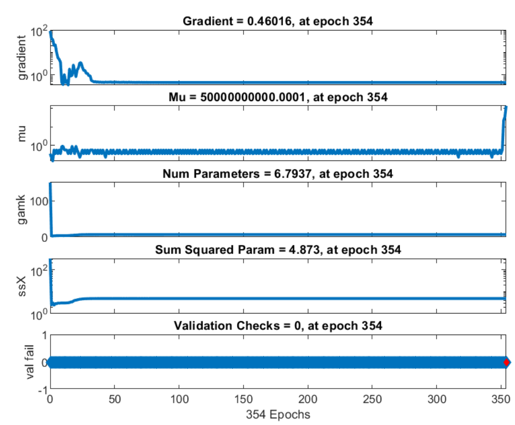


Fig- 4.30(d) **Fig- 4.30(e)**

Fig- 4.30 a, b, c, d & e display the Error histogram, Performance Plot (Observed and calculated data graph), Regression& Train state graphs respectively

4.5.2.2 Bathinda levenberg-marquardt: -

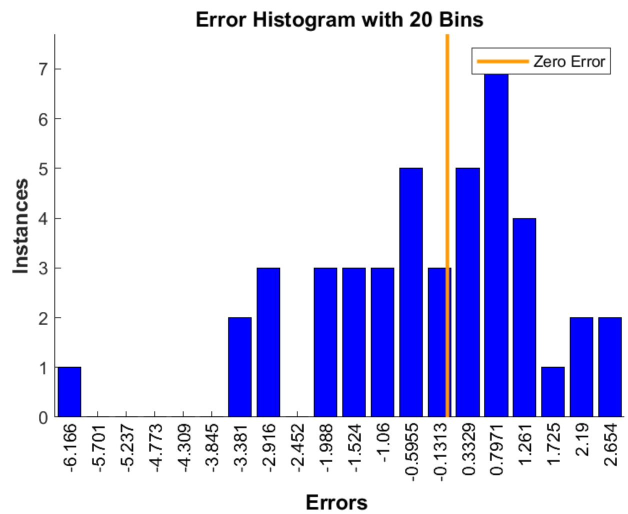


Fig- 4.31(a)

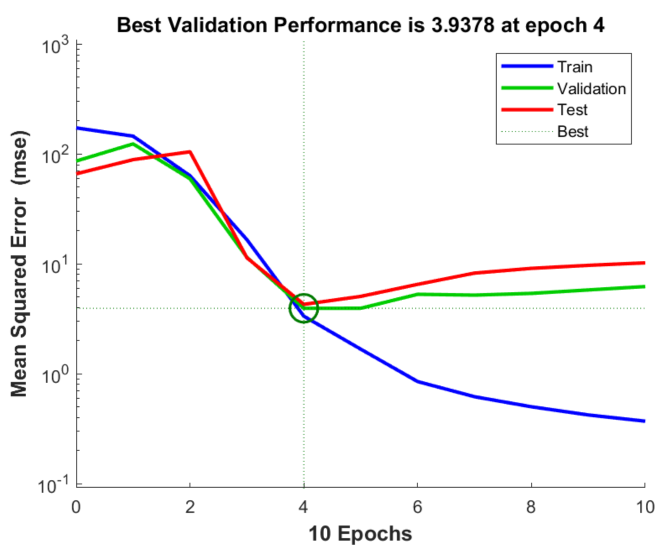


Fig- 4.31(b)

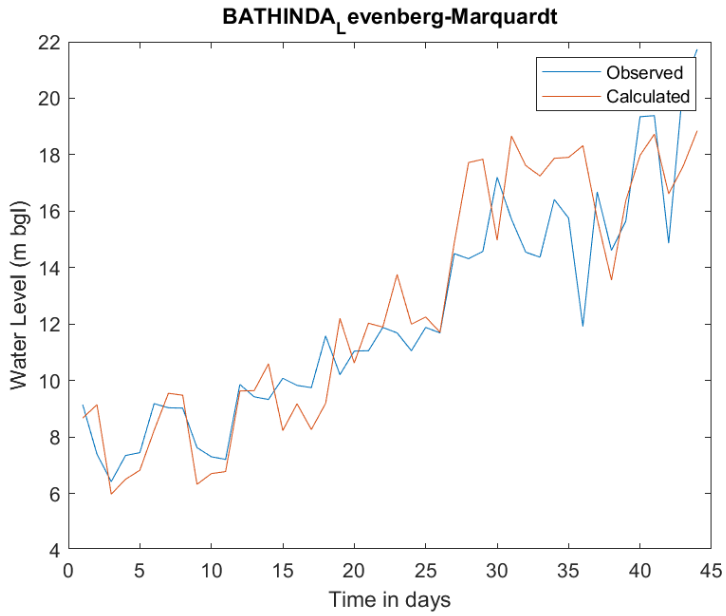
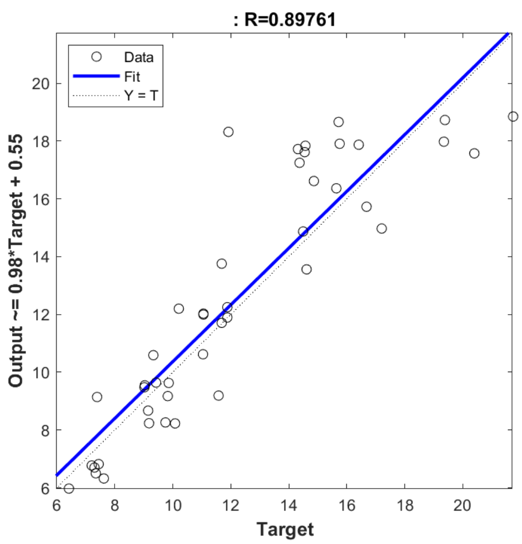


Fig- 4.31(c)



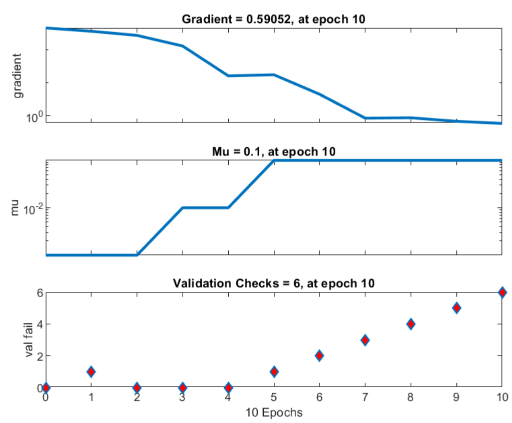


Fig- 4.31(d) **Fig- 4.31(e)**

Fig- 4.31 a, b, c, d & e display the Error histogram, Performance Plot (Observed and calculated data graph), Regression& Train state graphs respectively

4.5.2.3 Bathinda scaled conjugate gradient: -

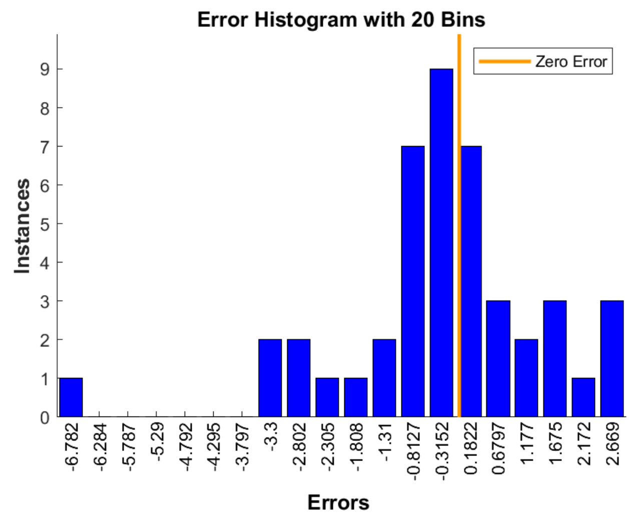


Fig- 4.32(a)

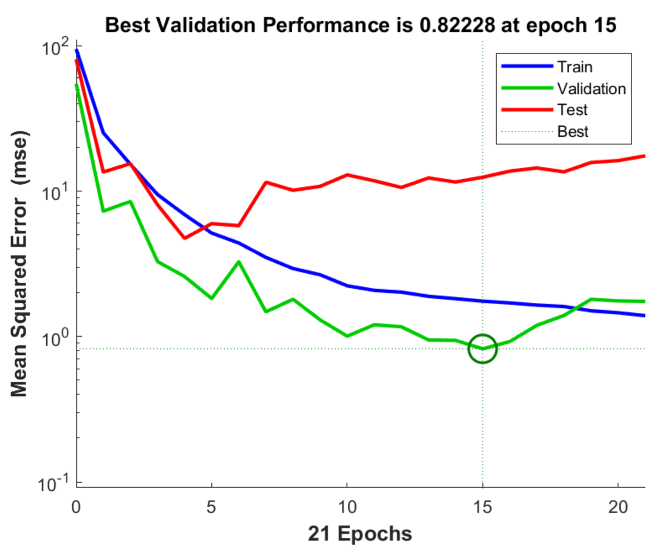


Fig- 4.32(b)

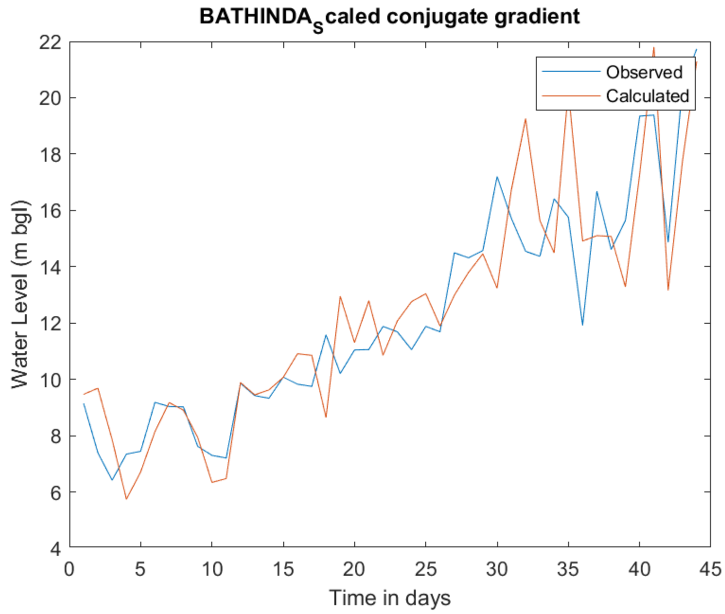
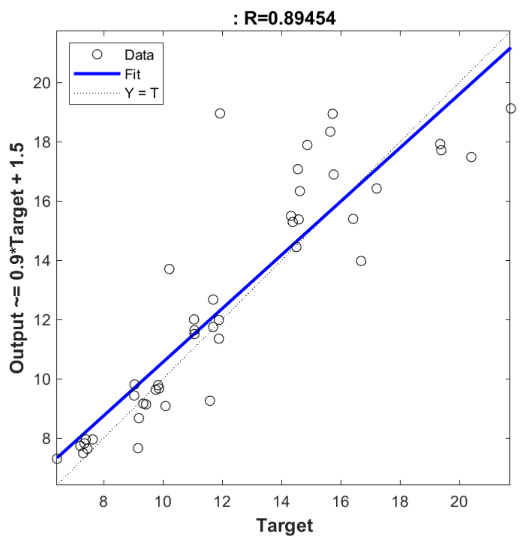


Fig- 4.32(c)



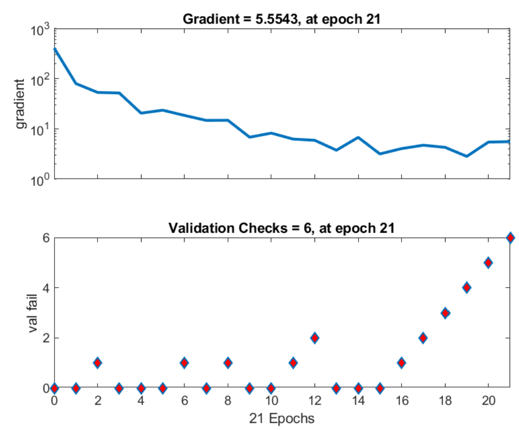


Fig- 4.32(d) **Fig- 4.32(e)**

Fig- 4.32 a, b, c, d & e display the Error histogram, Performance Plot (Observed and calculated data graph), Regression& Train state graphs respectively

4.5.3 Faridkot: -

4.5.3.1 Faridkot bayesian regularization: -

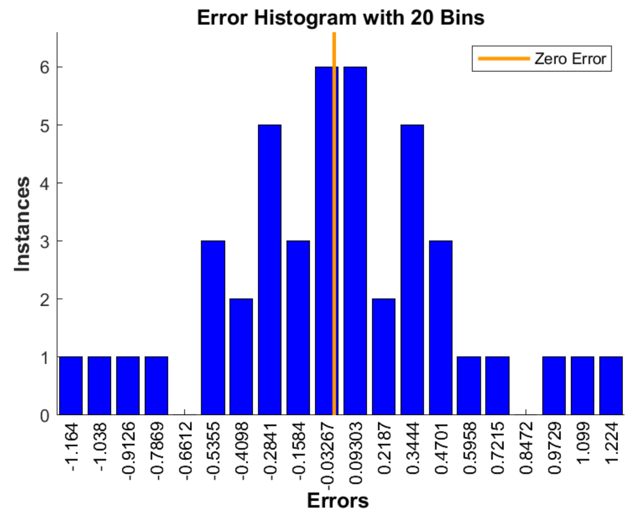


Fig- 4.33(a)

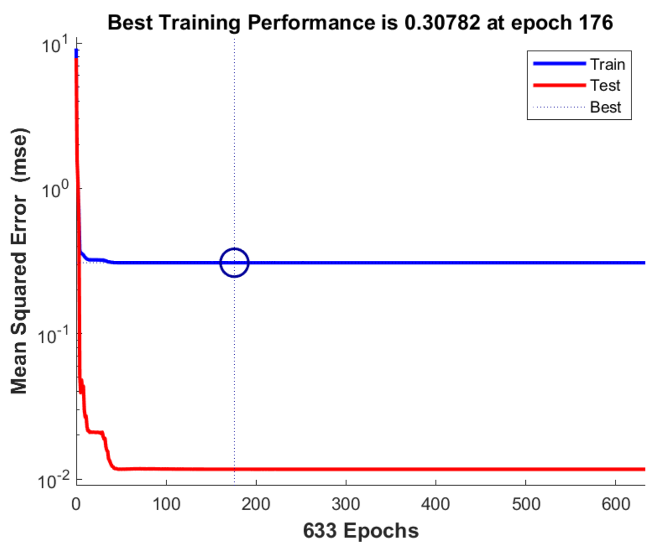


Fig- 4.33(b)

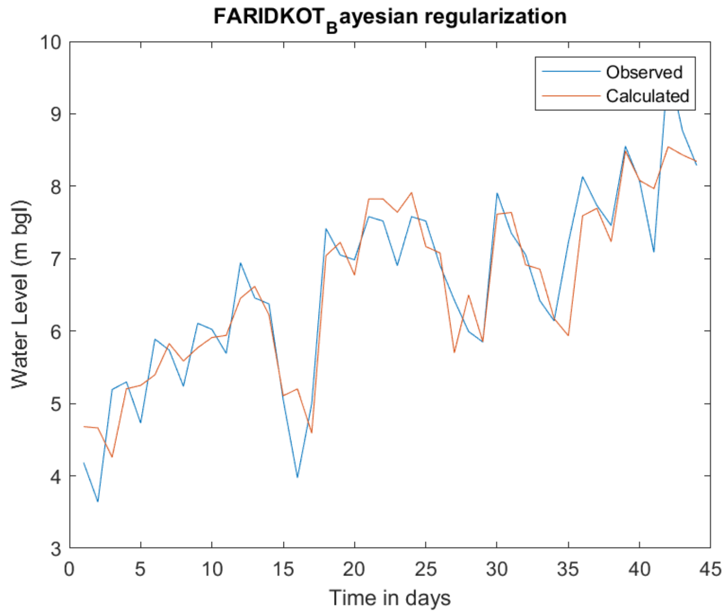
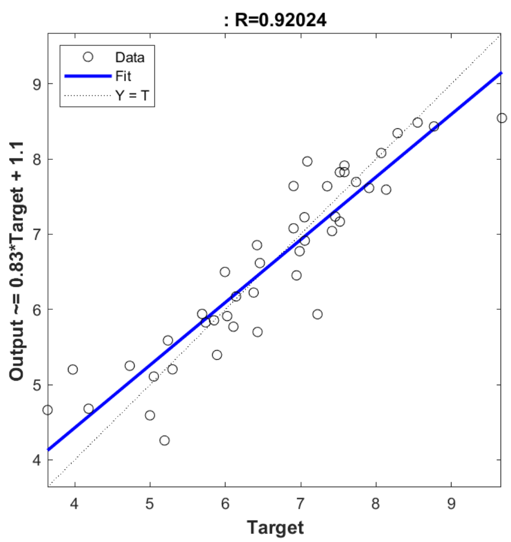


Fig- 4.33(c)



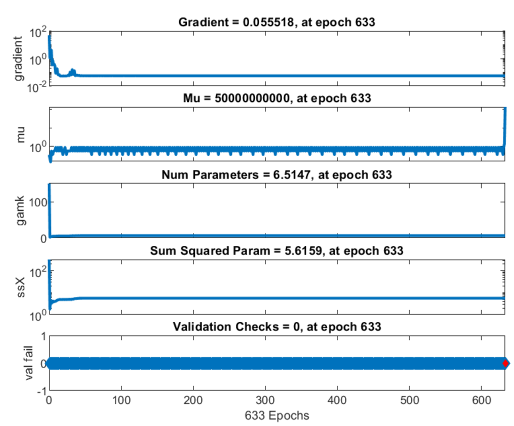


Fig- 4.33(d) **Fig- 4.33(e)**

Fig- 4.33 a, b, c, d & e display the Error histogram, Performance Plot (Observed and calculated data graph), Regression& Train state graphs respectively

4.5.3.2 Faridkot levenberg-marquardt: -

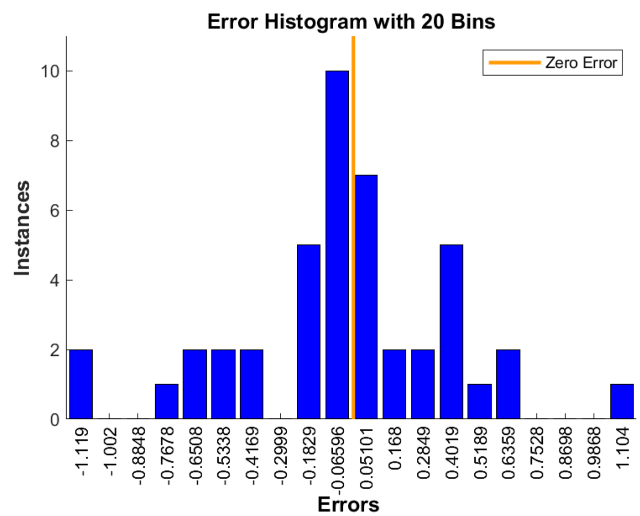


Fig- 4.34(a)

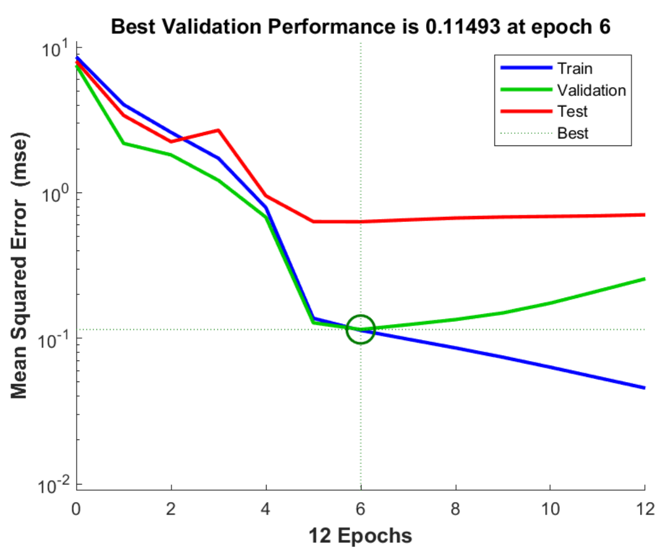


Fig- 4.34(b)

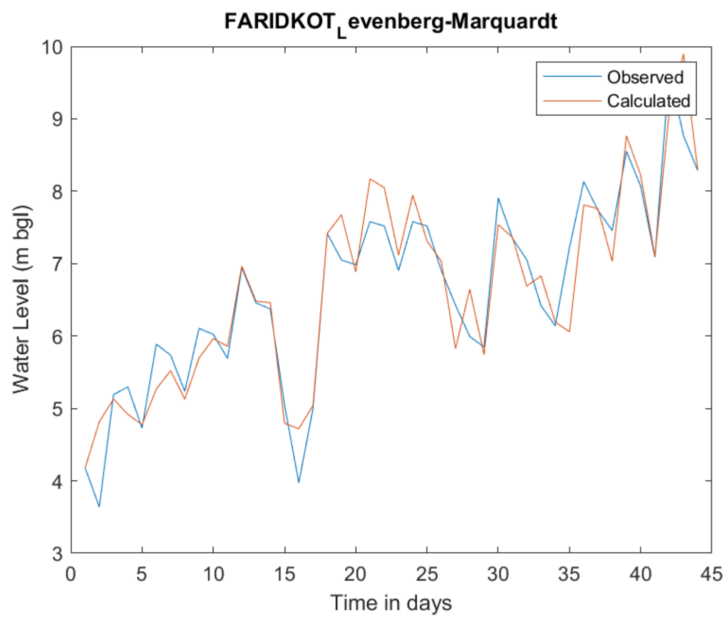
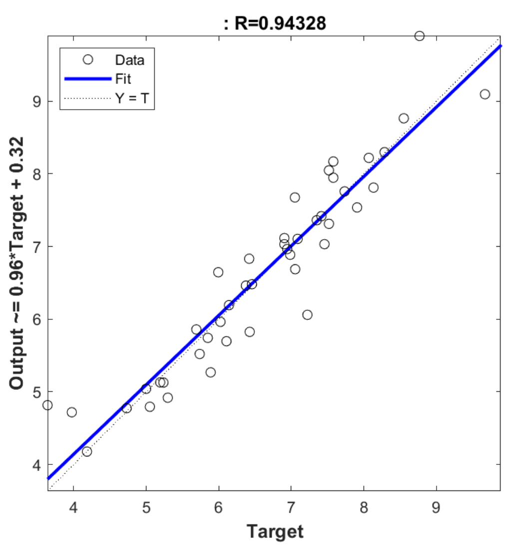


Fig- 4.34(c)



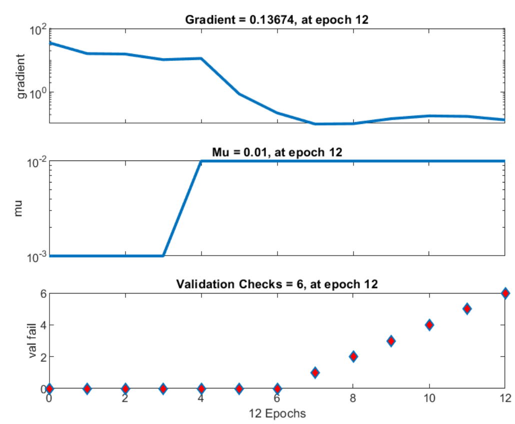


Fig- 4.34(d) **Fig- 4.34(e)**

Fig- 4.34 a, b, c, d & e display the Error histogram, Performance Plot (Observed and calculated data graph), Regression& Train state graphs respectively

4.5.3.3 Faridkot scaled conjugate gradient: -

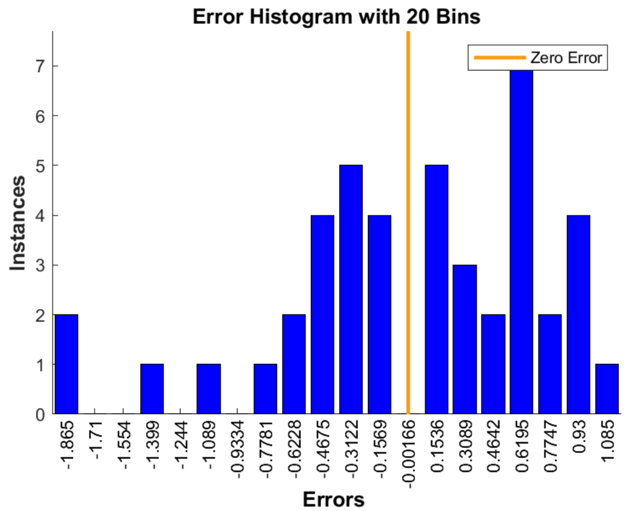


Fig- 4.35(a)

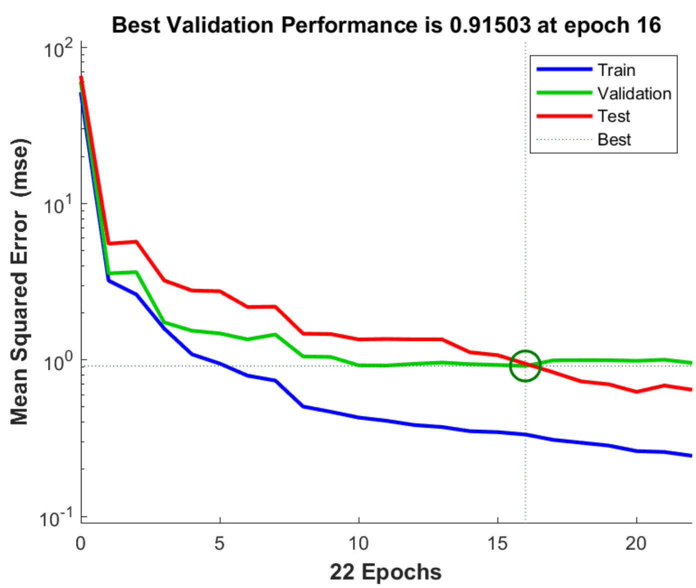


Fig- 4.35(b)

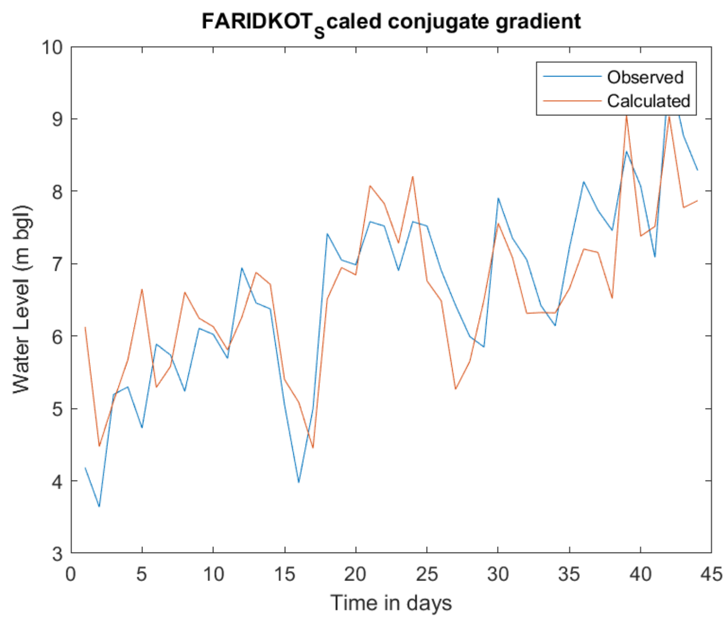
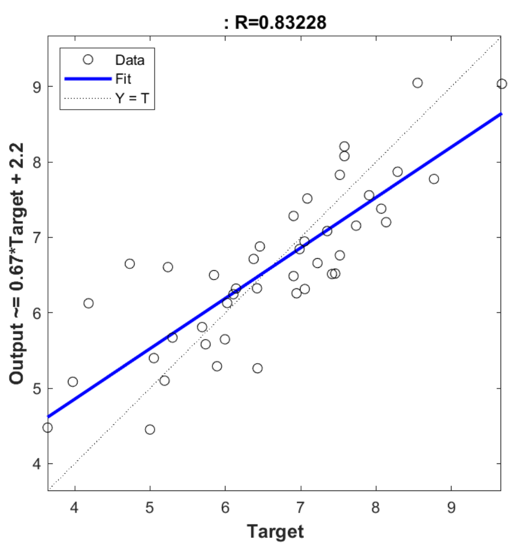


Fig- 4.35(c)



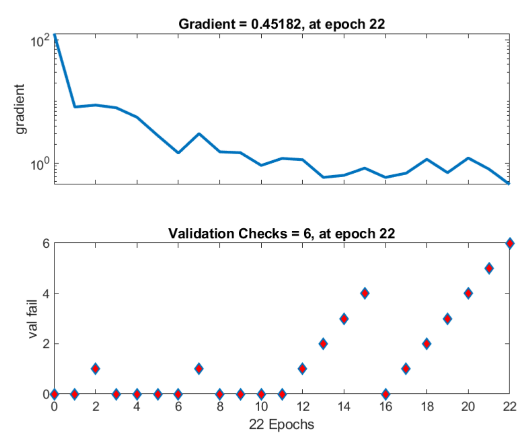


Fig- 4.35(d) **Fig- 4.35(e)**

Fig- 4.35 a, b, c, d & e display the Error histogram, Performance Plot (Observed and calculated data graph), Regression& Train state graphs respectively

4.5.4 Fazilka: -

4.5.4.1 Fazilka bayesian regularization: -

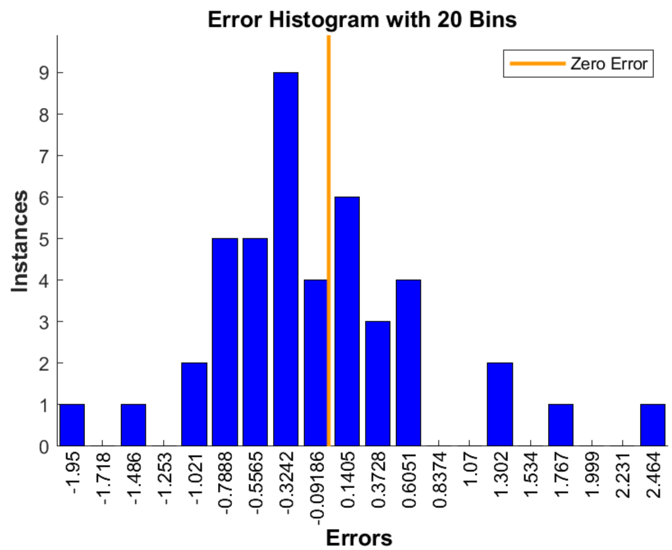


Fig- 4.36(a)

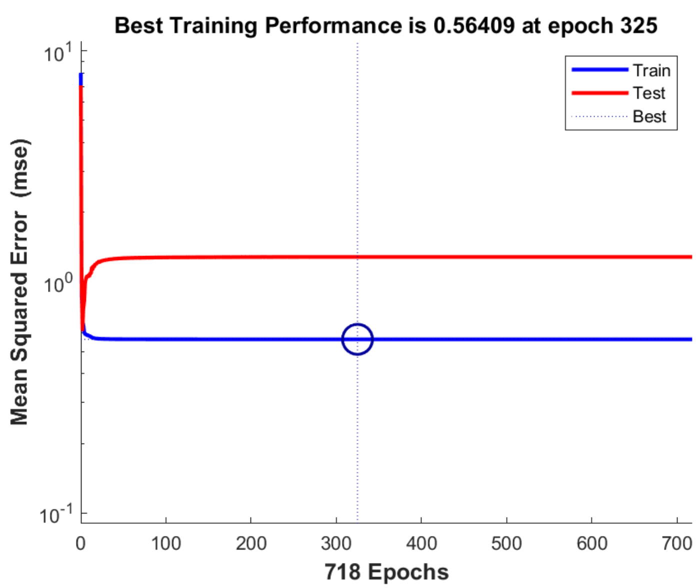


Fig- 4.36(b)

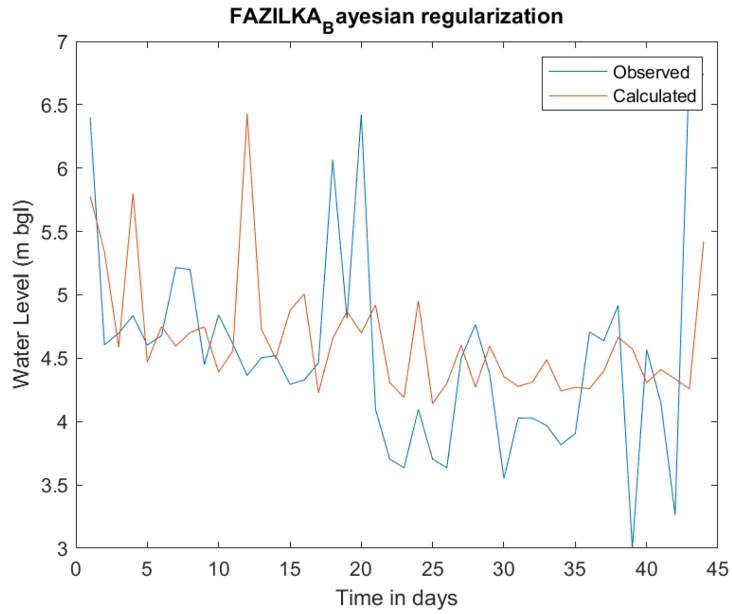
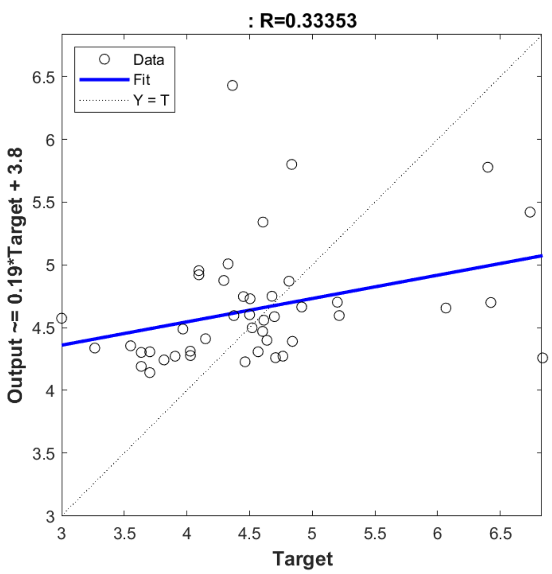


Fig- 4.36(c)



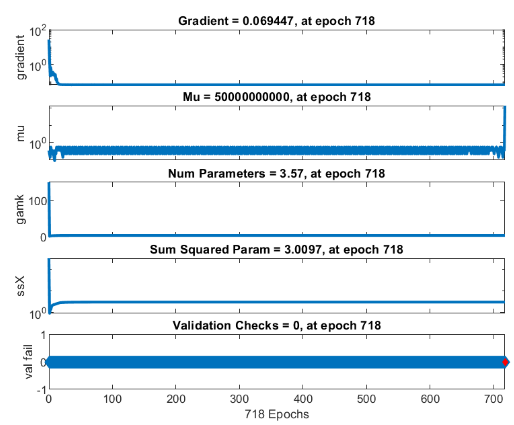


Fig- 4.36(d) **Fig- 4.36(e)**

Fig- 4.36 a, b, c, d & e display the Error histogram, Performance Plot (Observed and calculated data graph), Regression& Train state graphs respectively

4.5.4.2 Fazilka levenberg-marquardt: -

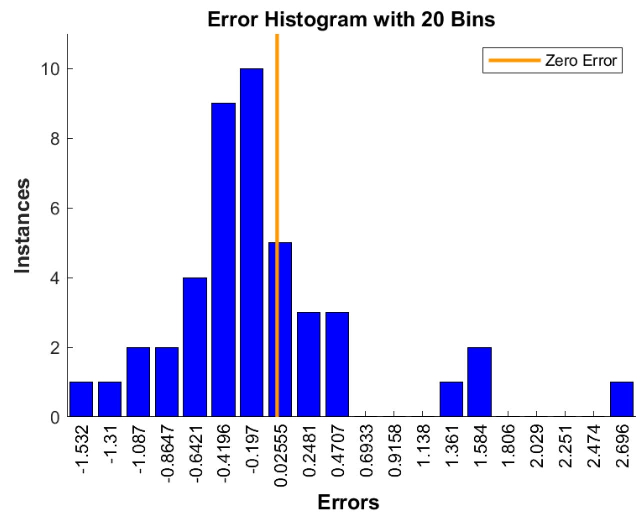


Fig- 4.37(a)

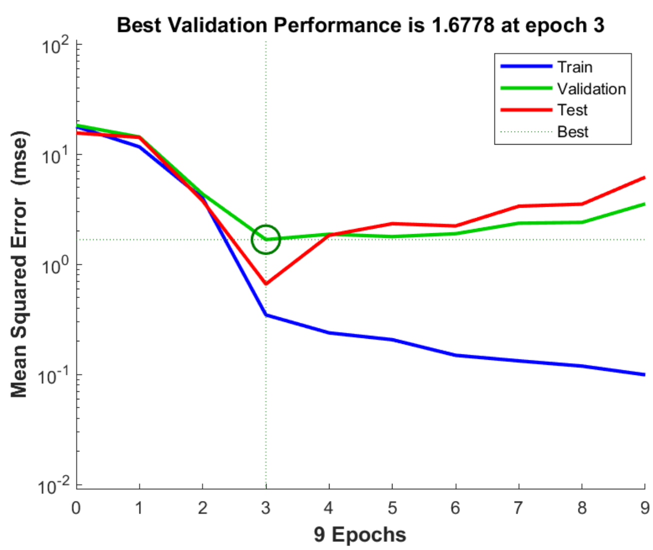


Fig- 4.37(b)

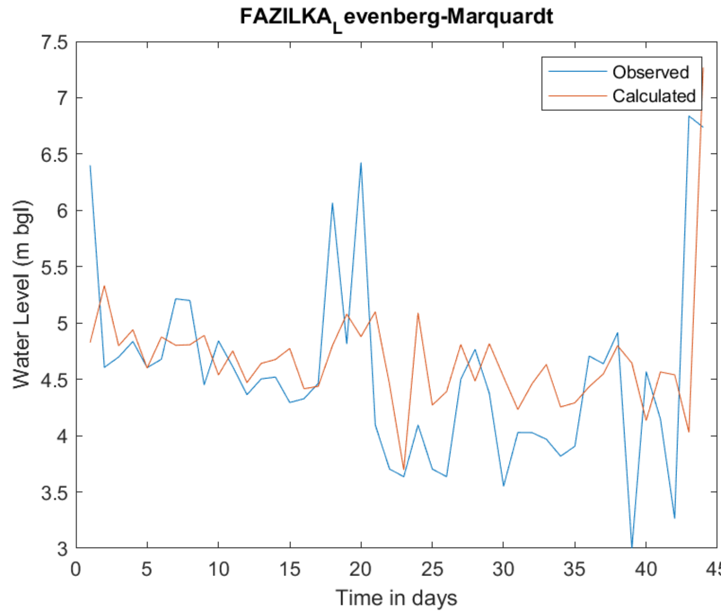
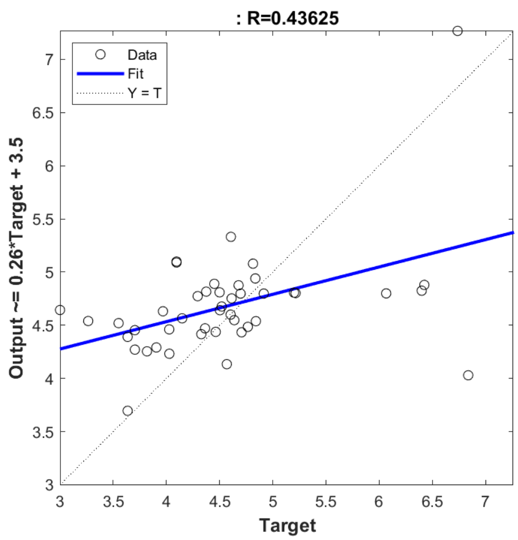


Fig- 4.37(c)



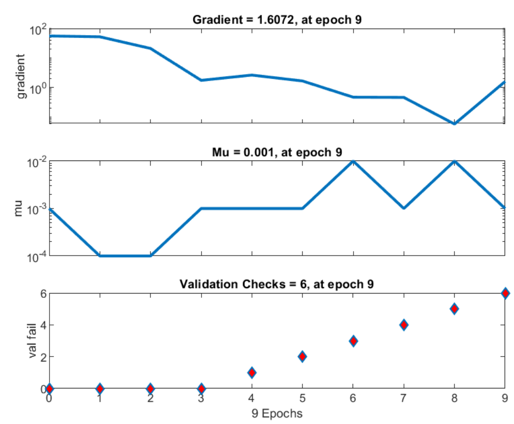


Fig- 4.37(d) Fig- 4.37(e)

Fig- 4.37 a, b, c, d & e display the Error histogram, Performance Plot (Observed and calculated data graph), Regression& Train state graphs respectively

4.5.4.3 Fazilka scaled conjugate gradient: -

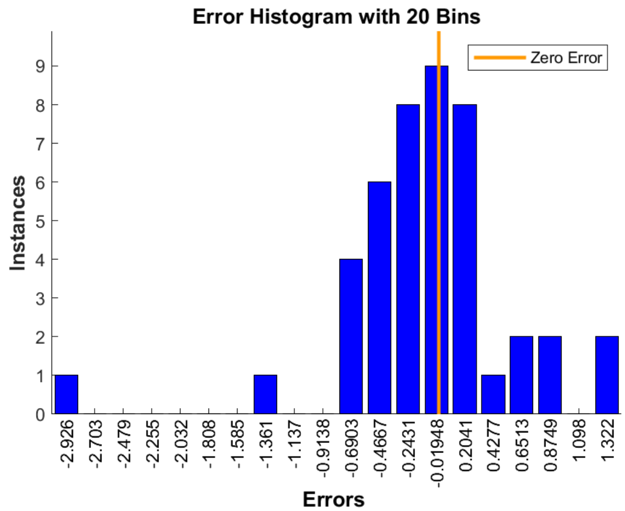


Fig- 4.38(a)

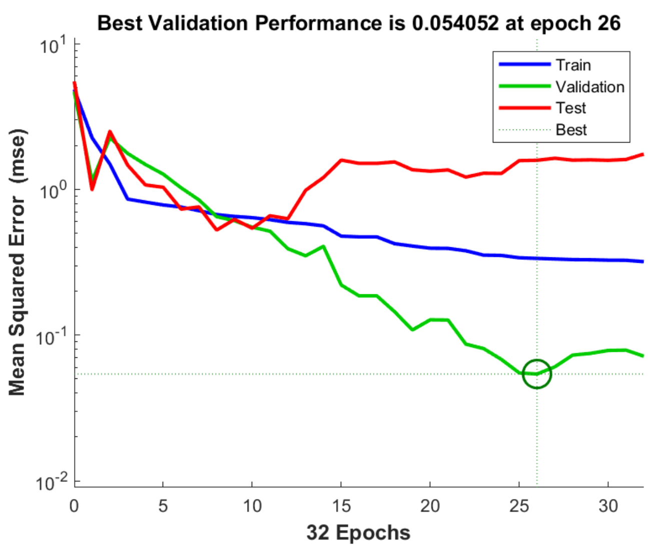


Fig- 4.38(b)

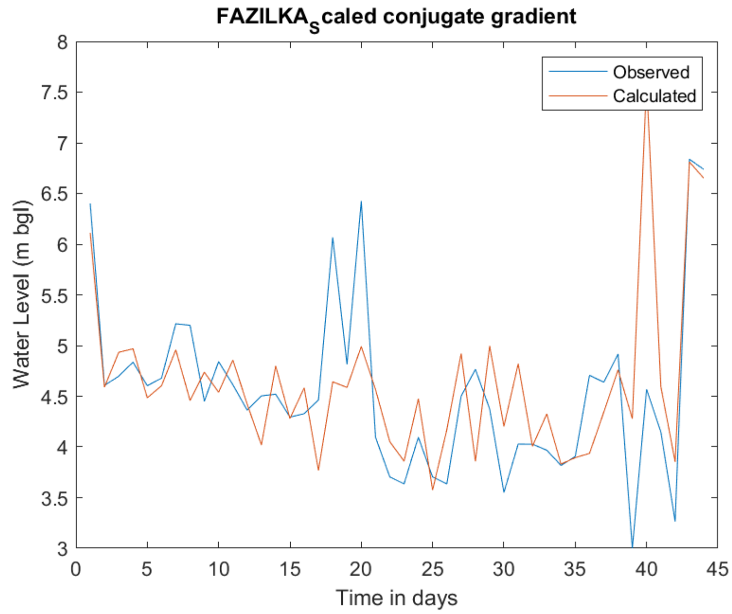
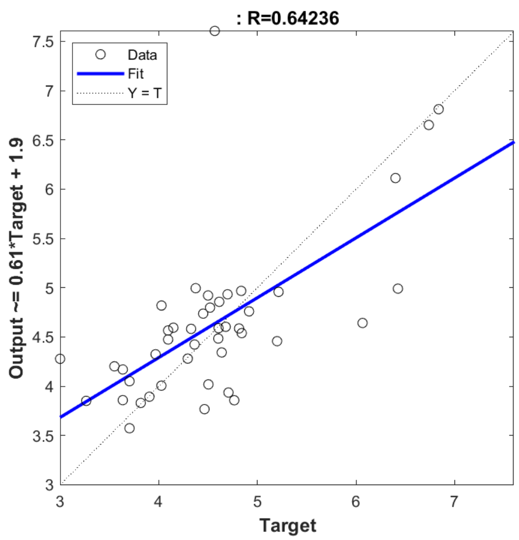


Fig- 4.38(c)



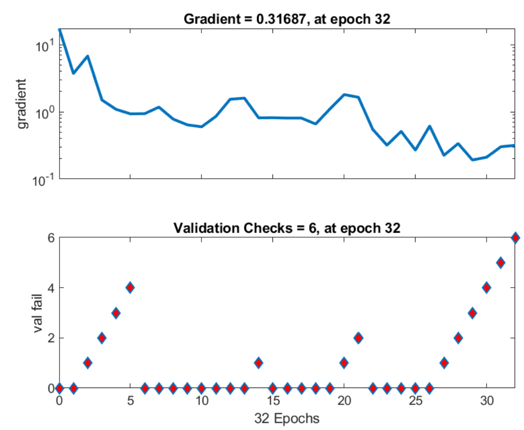


Fig- 4.38(d) **Fig- 4.38(e)**

Fig- 4.38 a, b, c, d & e display the Error histogram, Performance Plot (Observed and calculated data graph), Regression& Train state graphs respectively

4.5.5 Hoshiarpur: -

4.5.5.1 Hoshiarpur bayesian regularization: -

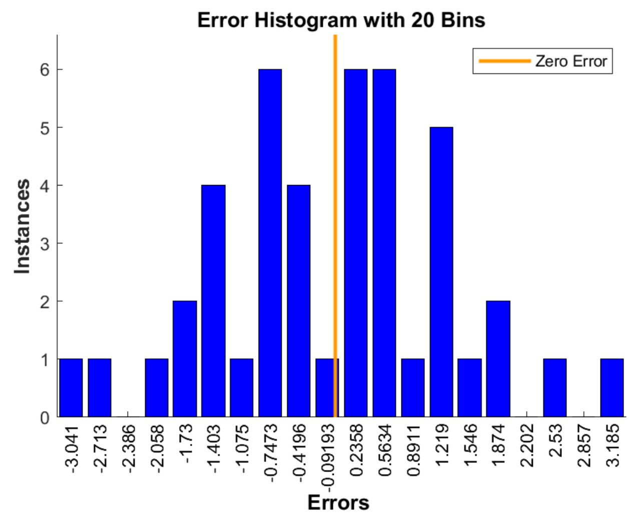


Fig- 4.39(a)

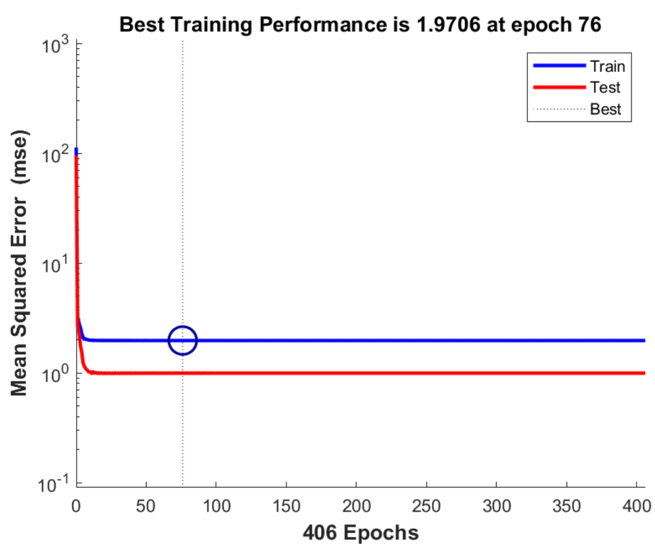


Fig- 4.39(b)

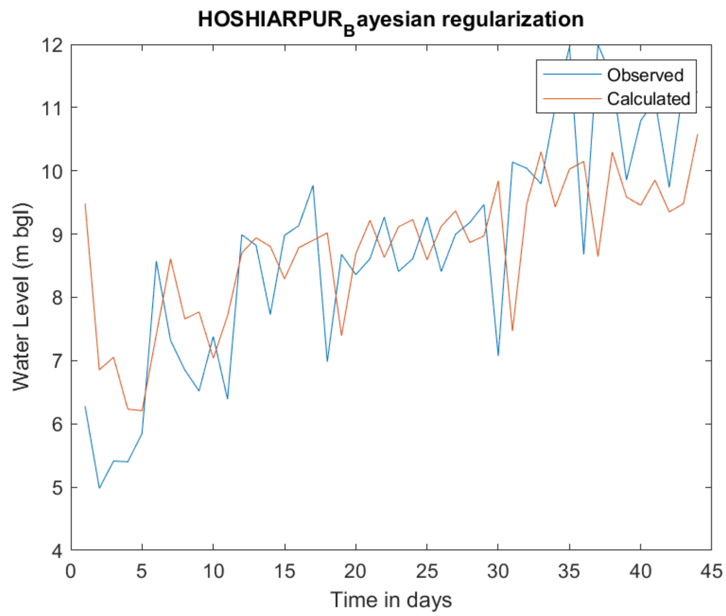
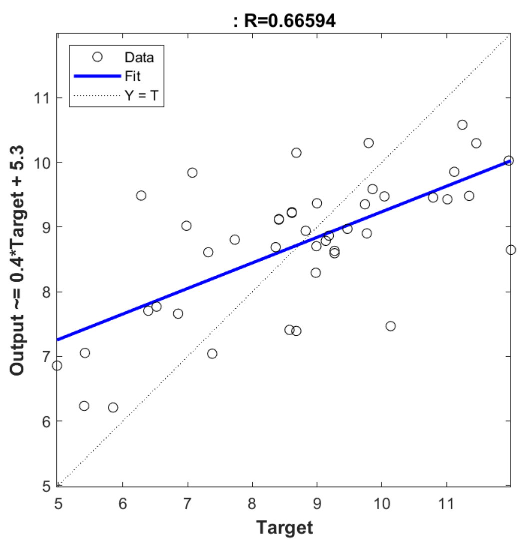


Fig- 4.39(c)



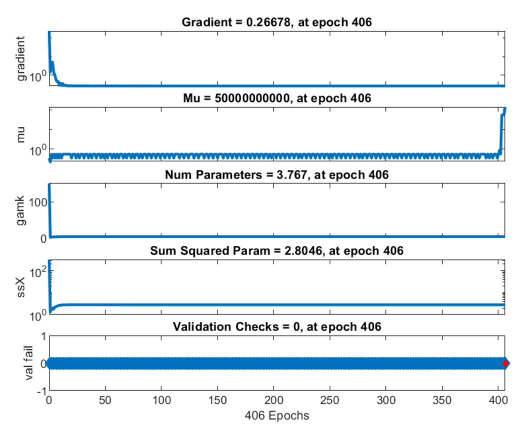


Fig- 4.39(d) Fig- 4.39(e)

Fig- 4.39 a, b, c, d & e display the Error histogram, Performance Plot (Observed and calculated data graph), Regression& Train state graphs respectively

4.5.5.2 Hoshiarpur levenberg-marquardt: -

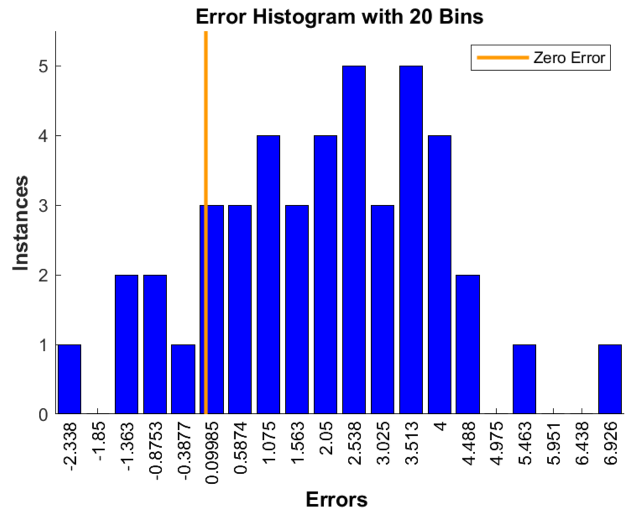


Fig- 4.40(a)

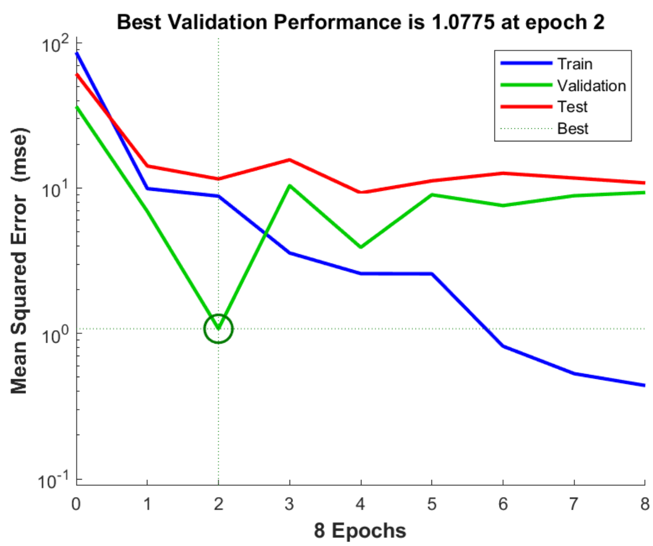


Fig- 4.40(b)

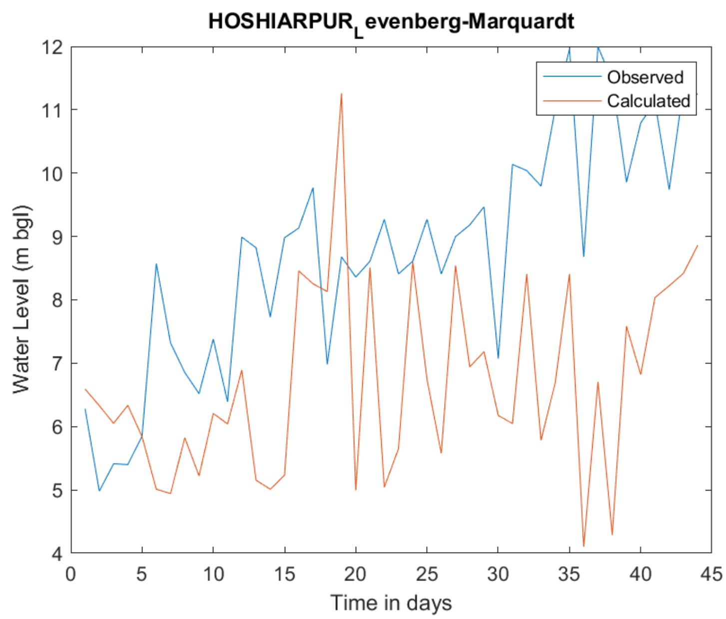
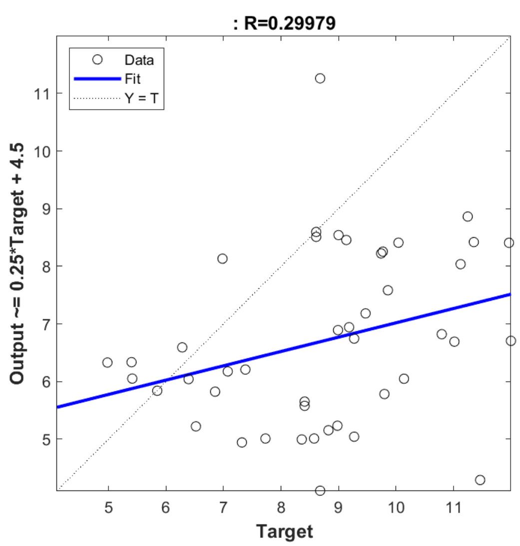


Fig- 4.40(c)



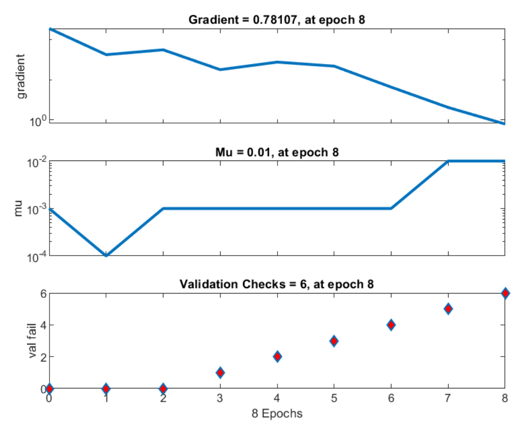


Fig- 4.40(e) **Fig- 4.40(e)**

Fig- 4.40 a, b, c, d & e display the Error histogram, Performance Plot (Observed and calculated data graph), Regression& Train state graphs respectively

4.5.5.3 Hoshiarpur scaled conjugate gradient: -

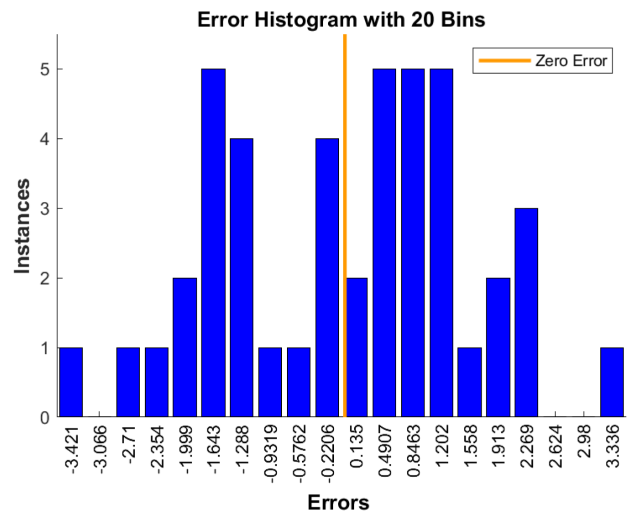


Fig- 4.41(a)

Fig- 4.41(b)

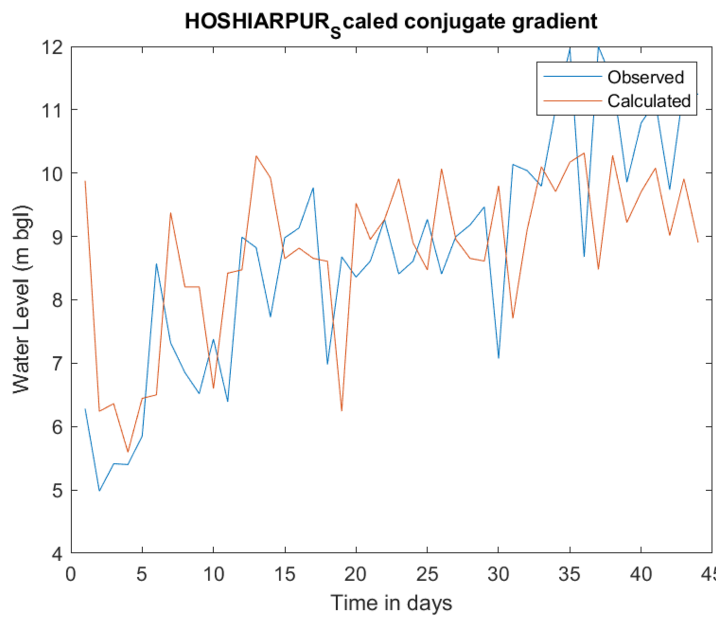
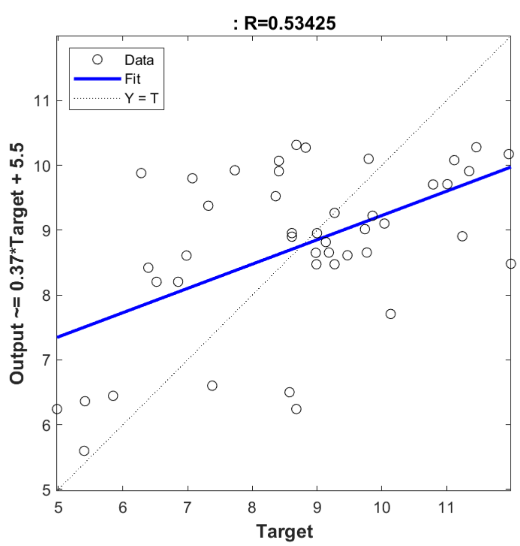


Fig- 4.41(c)



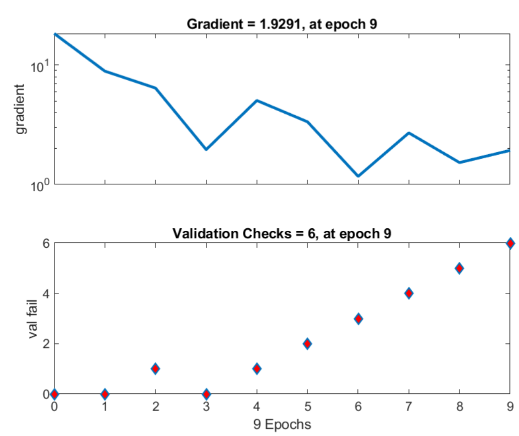


Fig- 4.41(d) **Fig- 4.41(e)**

Fig- 4.41 a, b, c, d & e display the Error histogram, Performance Plot (Observed and calculated data graph), Regression& Train state graphs respectively

4.5.6 Kapurthala: -

4.5.6.1 Kapurthala bayesian regularization: -

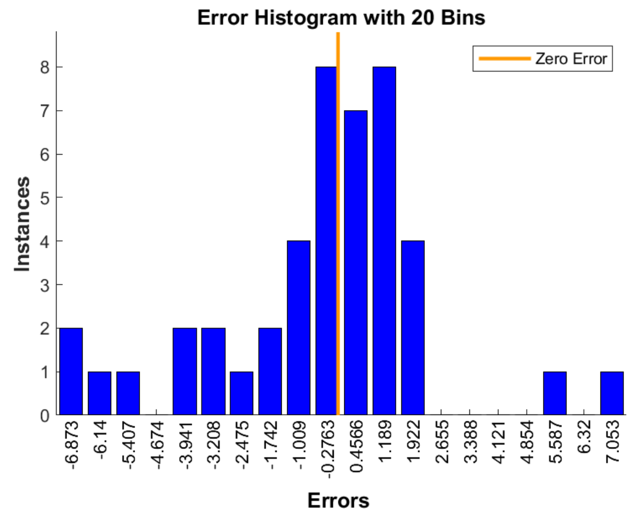


Fig- 4.42(a)

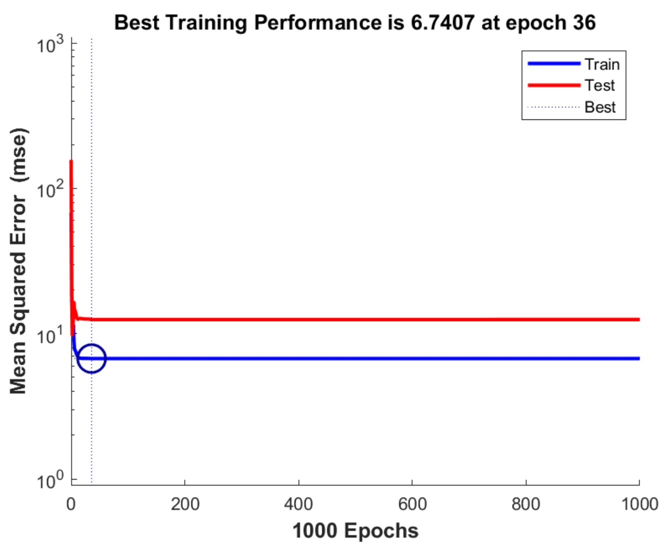


Fig- 4.42(b)

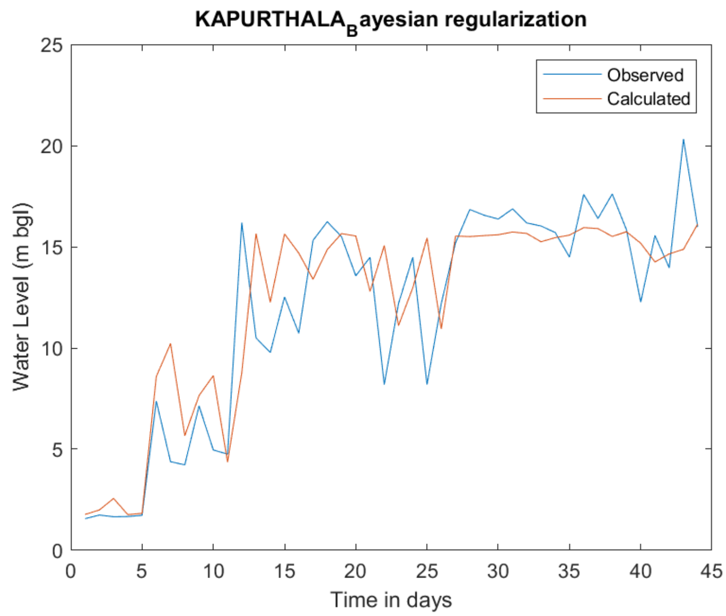
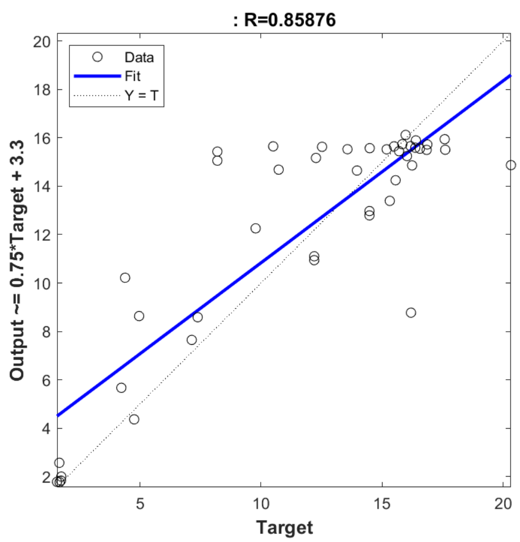


Fig- 4.42(c)



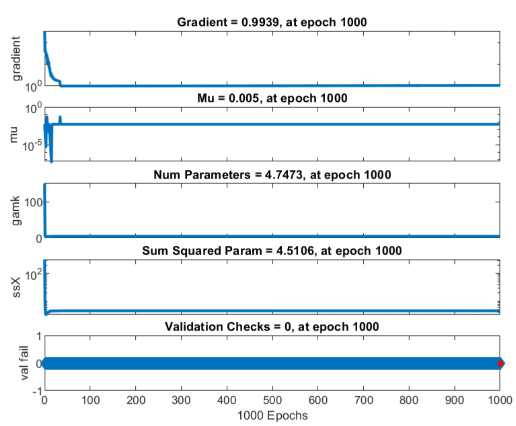


Fig- 4.42(d) **Fig- 4.42(e)**

Fig- 4.42 a, b, c, d & e display the Error histogram, Performance Plot (Observed and calculated data graph), Regression& Train state graphs respectively

4.5.6.2 Kapurthala levenberg-marquardt: -

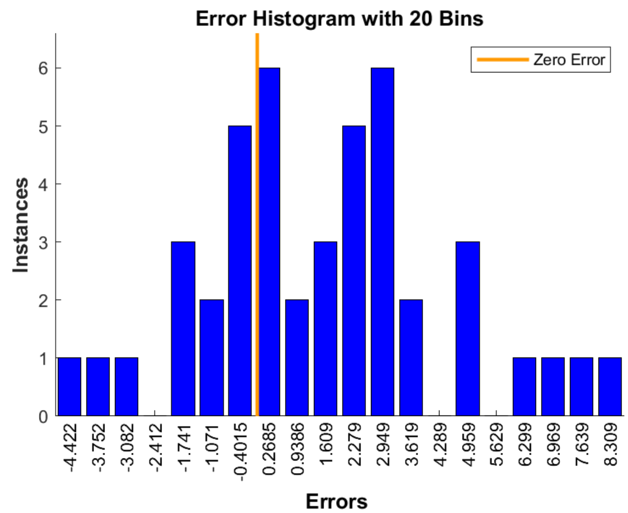


Fig- 4.43(a)

Fig- 4.43(b)

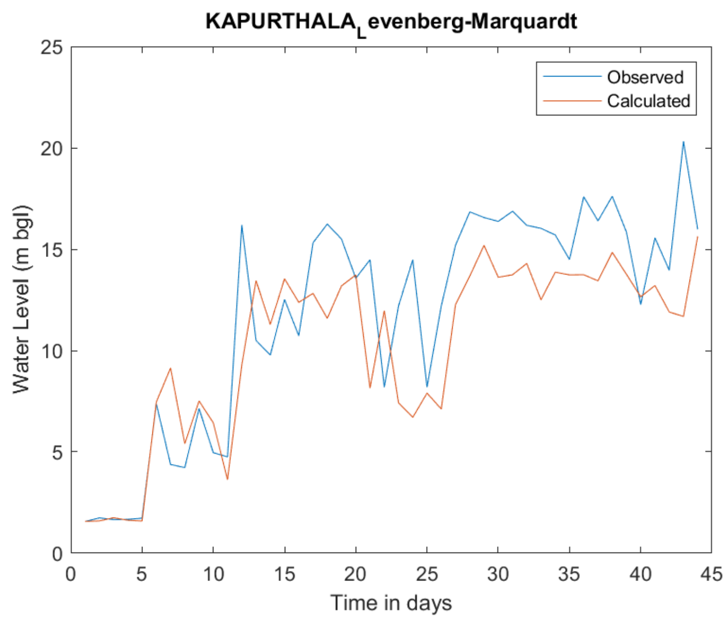
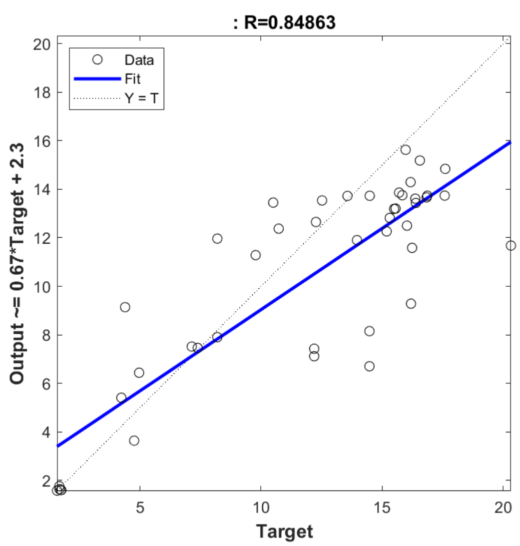


Fig- 4.43(c)



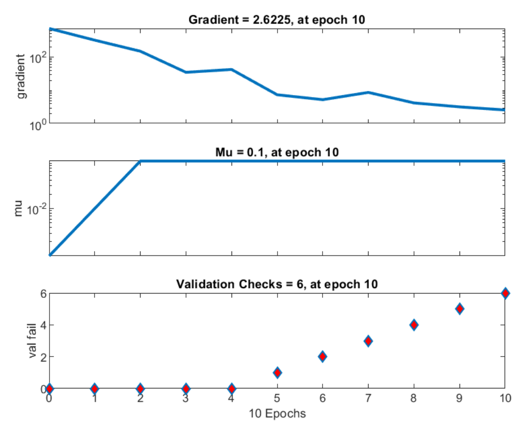


Fig- 4.43(d) **Fig- 4.43(e)**

Fig- 4.43 a, b, c, d & e display the Error histogram, Performance Plot (Observed and calculated data graph), Regression& Train state graphs respectively

4.5.6.3 Kapurthala scaled conjugate gradient: -

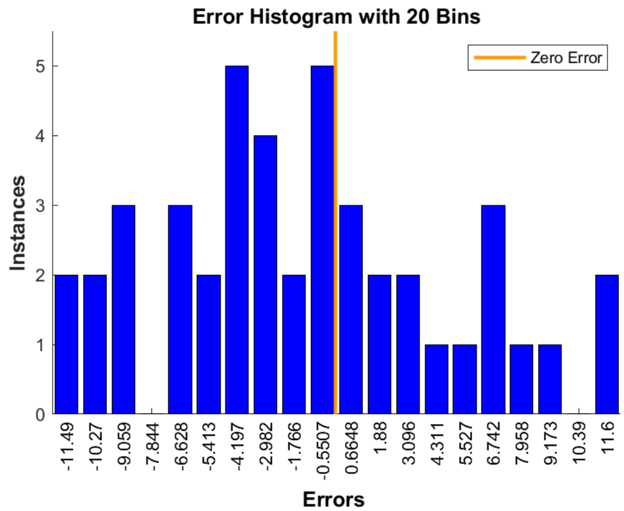


Fig- 4.44(a)

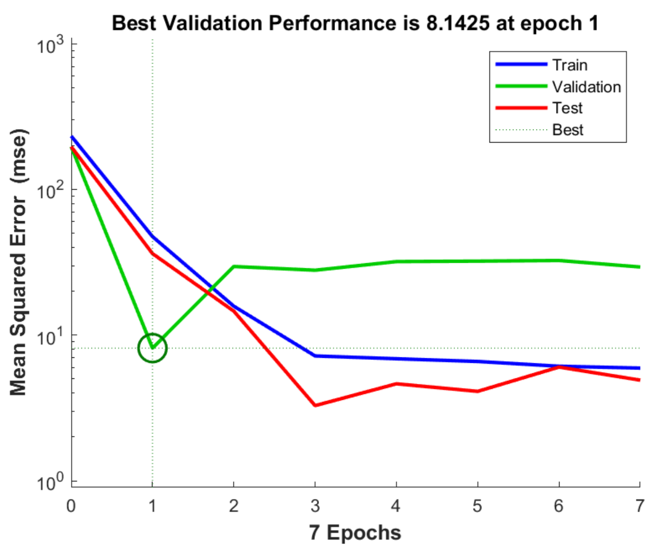


Fig- 4.44(b)

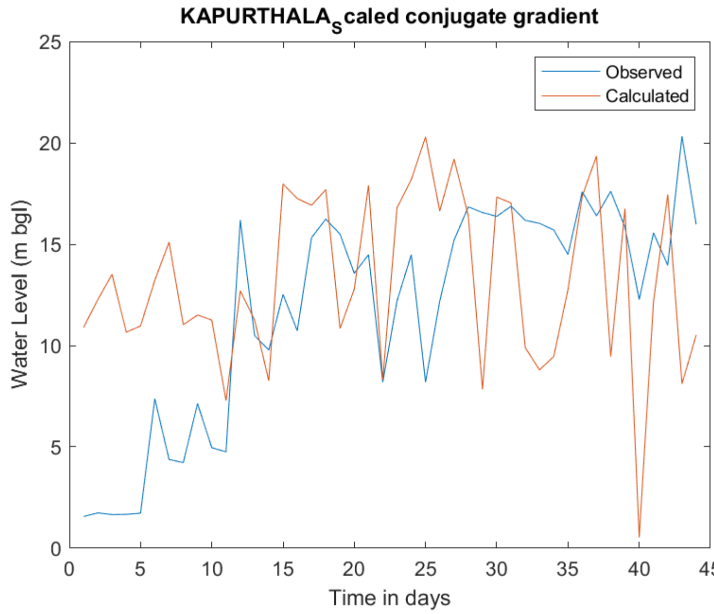
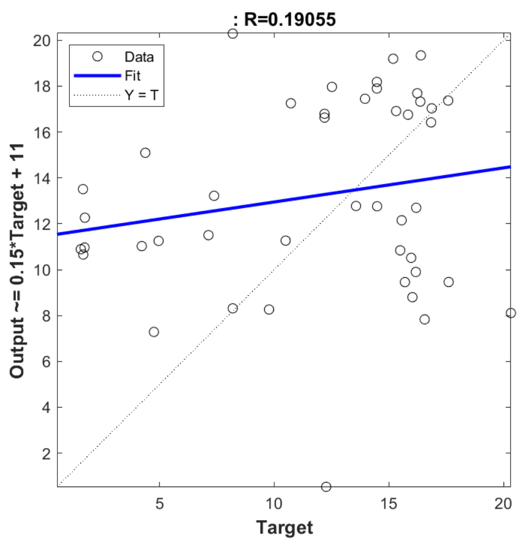


Fig- 4.44(c)



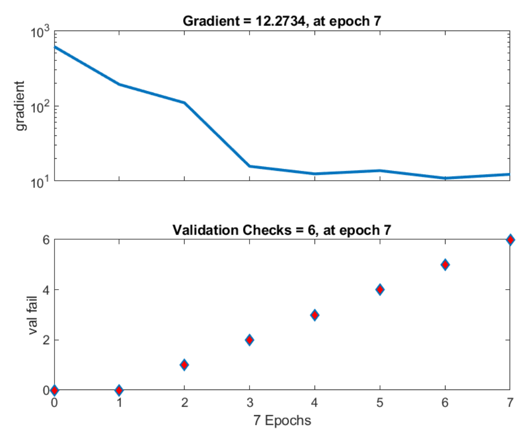


Fig- 4.44(d) **Fig- 4.44(e)**

Fig- 4.44 a, b, c, d & e display the Error histogram, Performance Plot (Observed and calculated data graph), Regression& Train state graphs respectively

4.5.7 Ludhiana: -

4.5.7.1 Ludhiana bayesian regularization: -

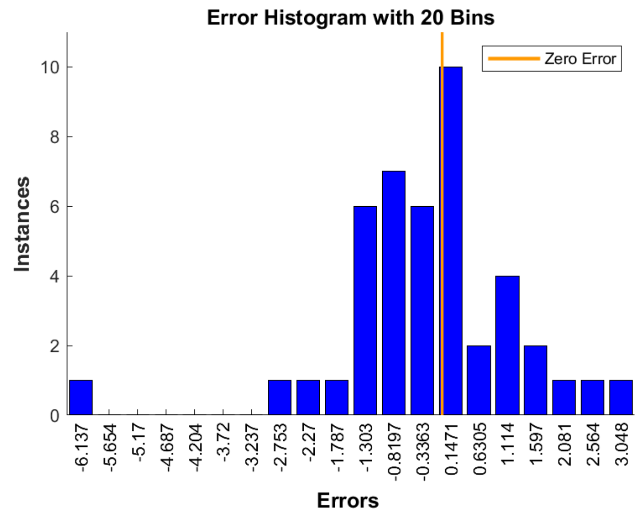


Fig- 4.45(a)

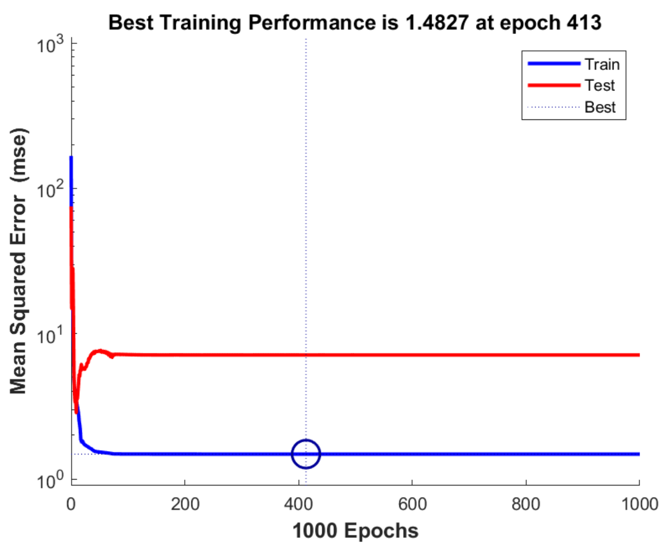


Fig- 4.45(b)

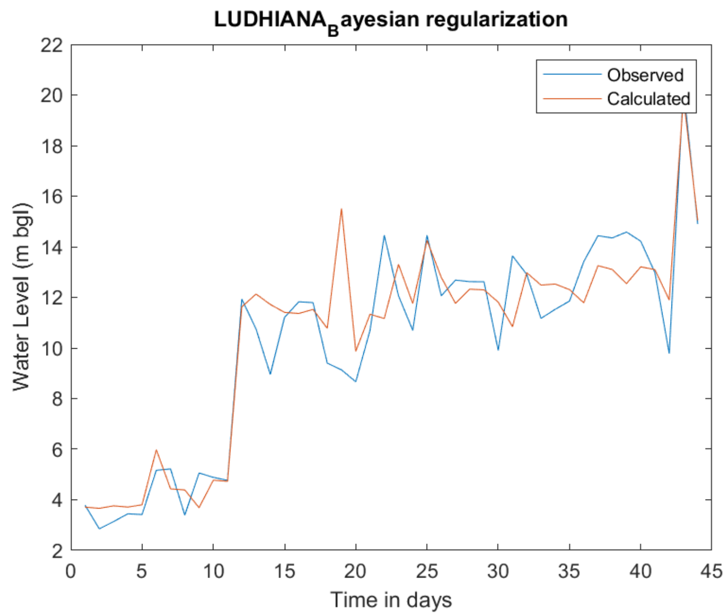
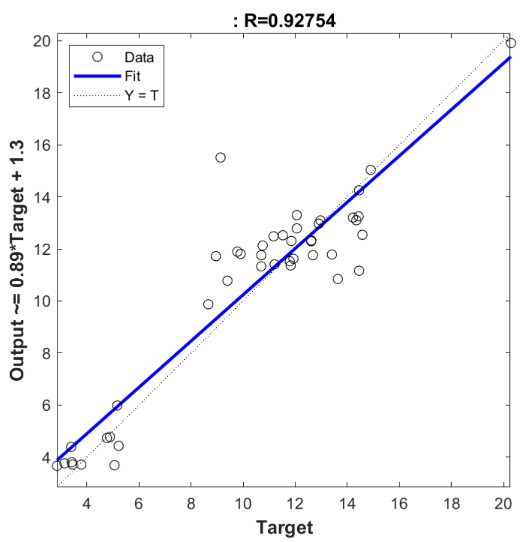


Fig- 4.45(c)



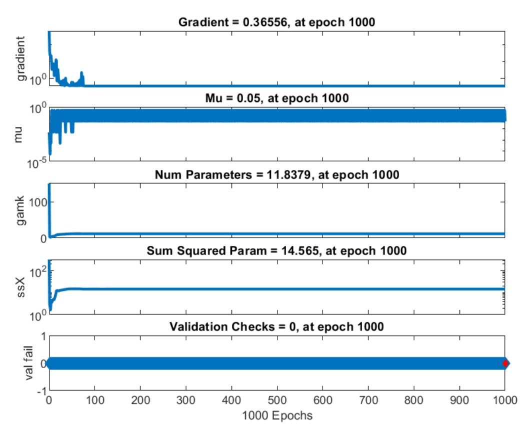


Fig- 4.45(d) **Fig- 4.45(e)**

Fig- 4.45 a, b, c, d & e display the Error histogram, Performance Plot (Observed and calculated data graph), Regression& Train state graphs respectively

4.5.7.2 Ludhiana levenberg-marquardt: -

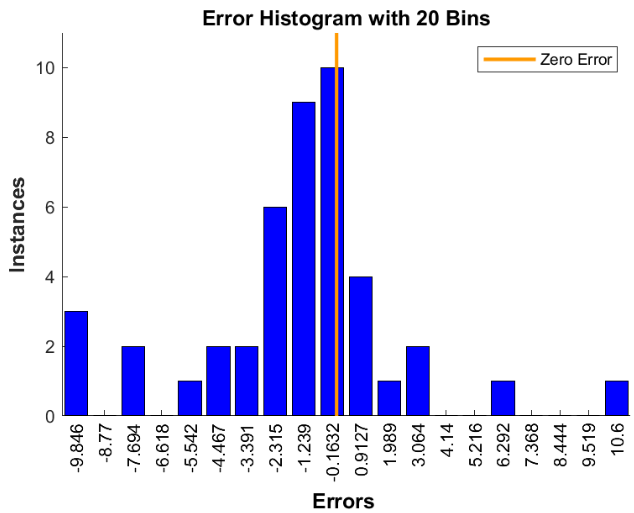


Fig- 4.46(a)

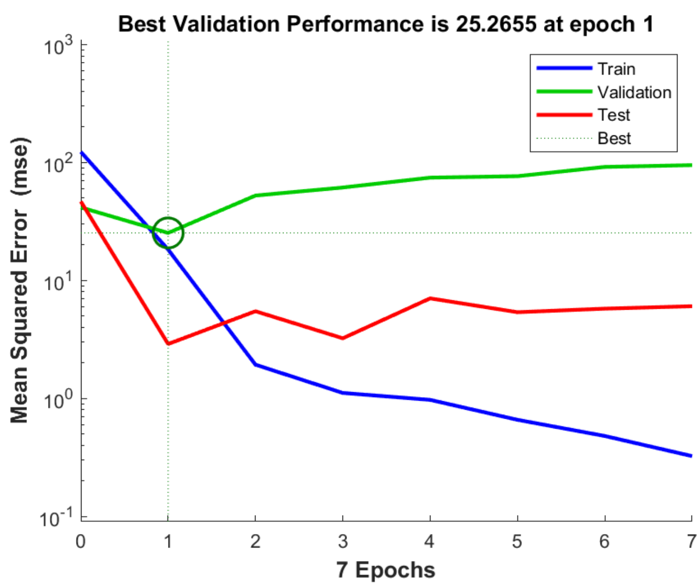


Fig- 4.46(b)

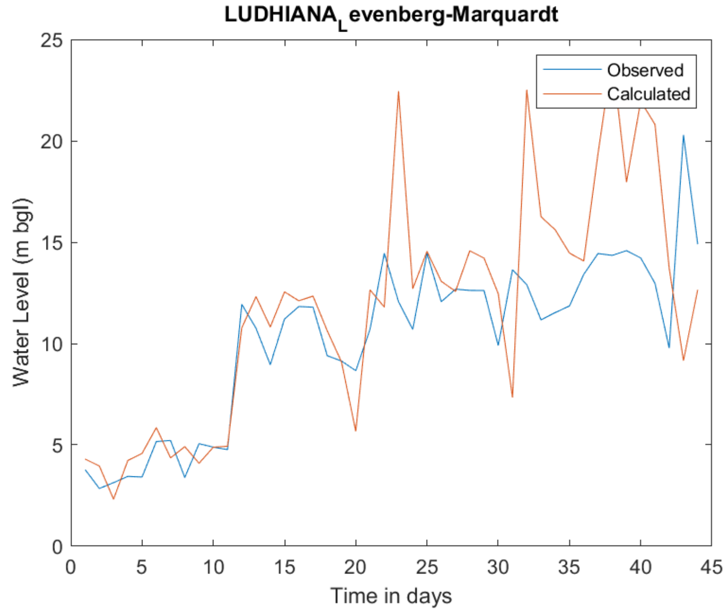
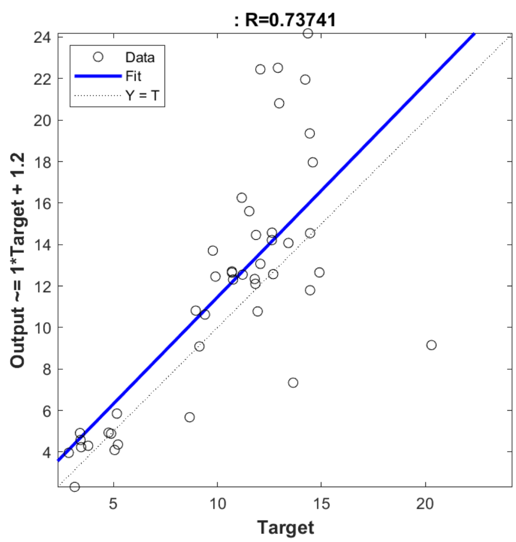


Fig- 4.46(c)



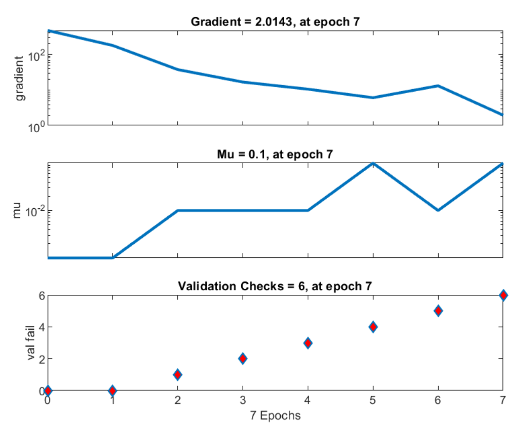


Fig- 4.46(d) **Fig- 4.46(e)**

Fig- 4.46 a, b, c, d & e display the Error histogram, Performance Plot (Observed and calculated data graph), Regression& Train state graphs respectively

4.5.7.3 Ludhiana scaled conjugate gradient: -

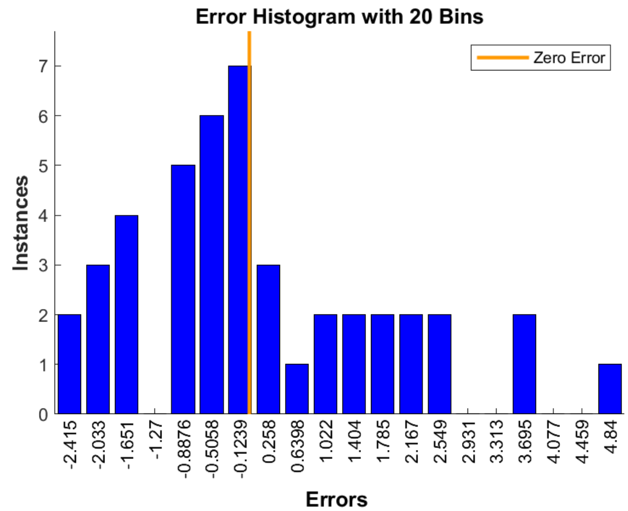


Fig- 4.47(a)

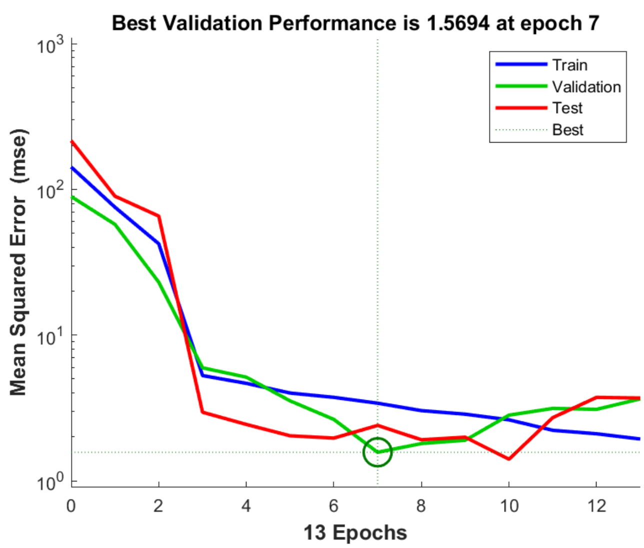


Fig- 4.47(b)

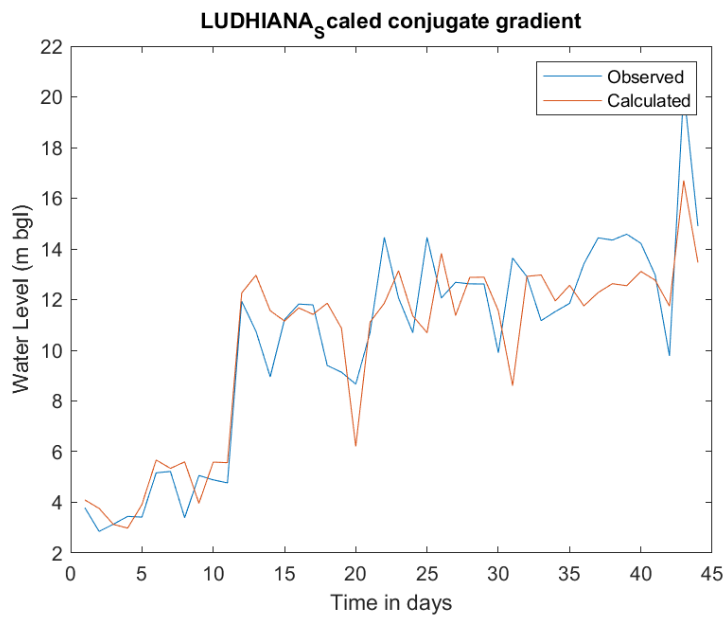
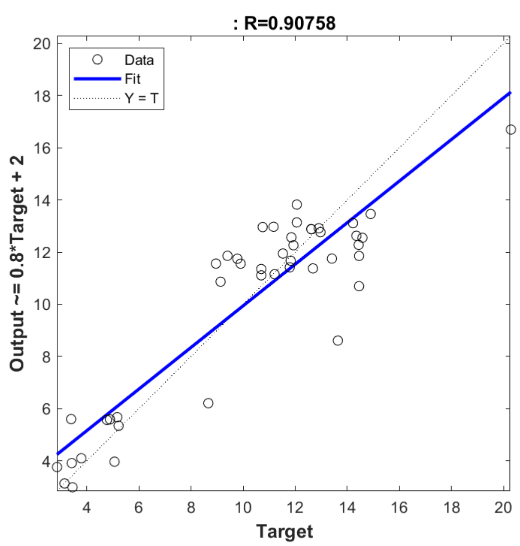


Fig- 4.47(c)



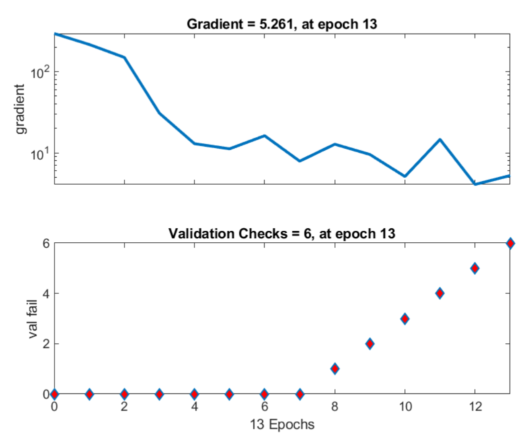


Fig- 4.47(d) **Fig- 4.47(e)**

Fig- 4.47 a, b, c, d & e display the Error histogram, Performance Plot (Observed and calculated data graph), Regression& Train state graphs respectively

4.5.8 Mansa: -

4.5.8.1 Mansa bayesian regularization: -

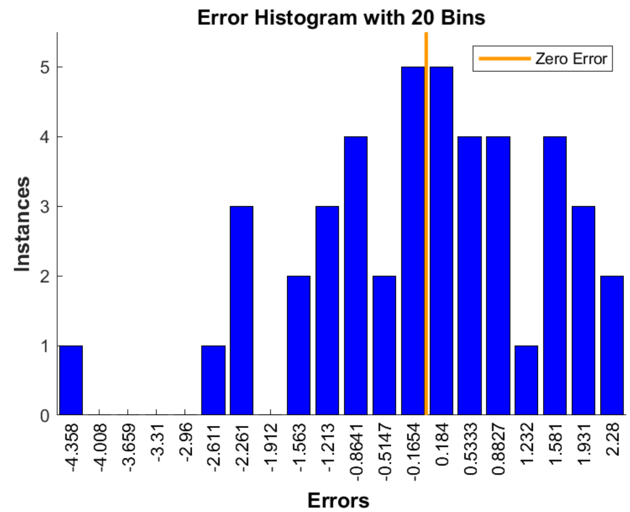


Fig- 4.48(a)

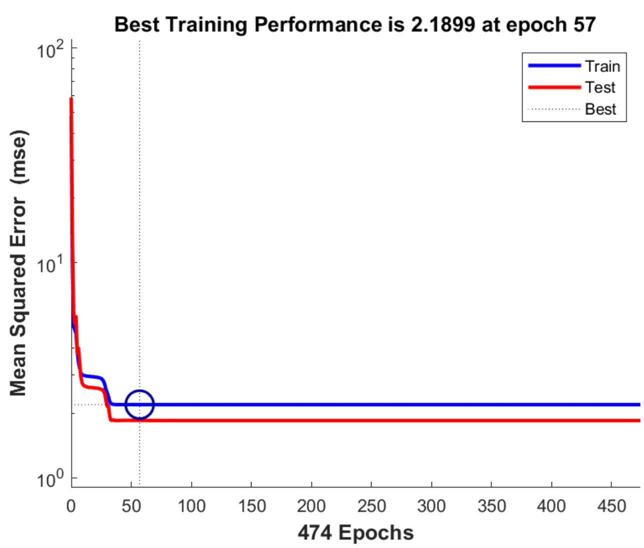


Fig- 4.48(b)

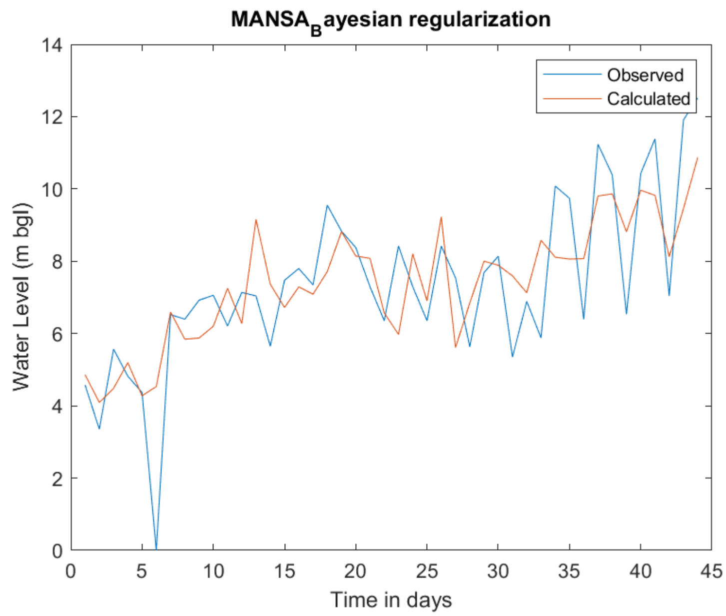
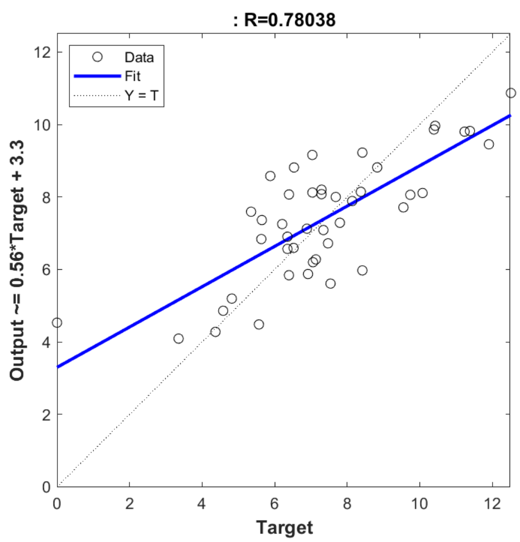


Fig- 4.48(c)



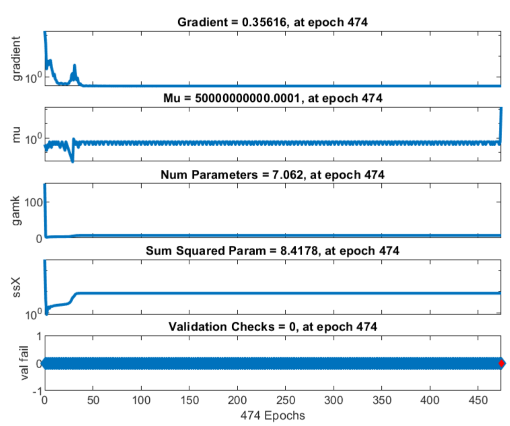


Fig- 4.48(d) **Fig- 4.48(e)**

Fig- 4.48 a, b, c, d & e display the Error histogram, Performance Plot (Observed and calculated data graph), Regression& Train state graphs respectively

4.5.8.2 Mansa levenberg-marquardt: -

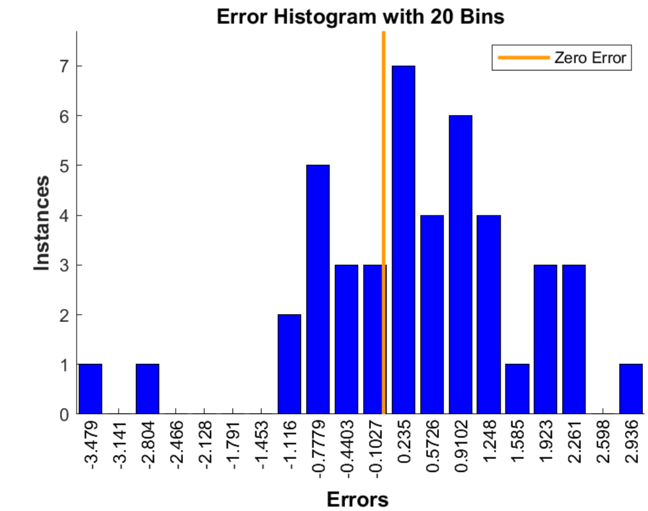


Fig- 4.49(a)

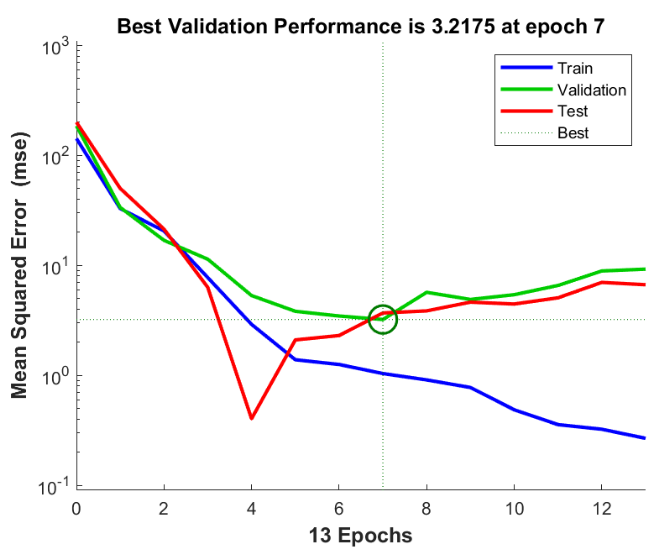


Fig- 4.49(b)

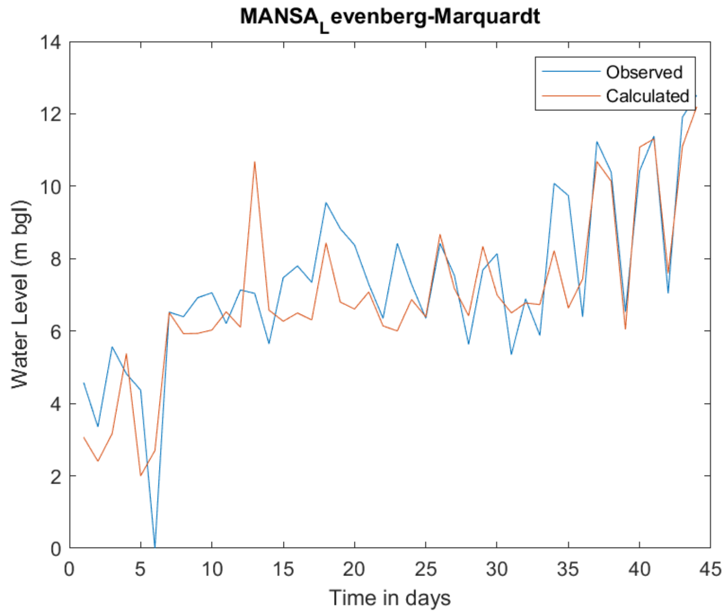
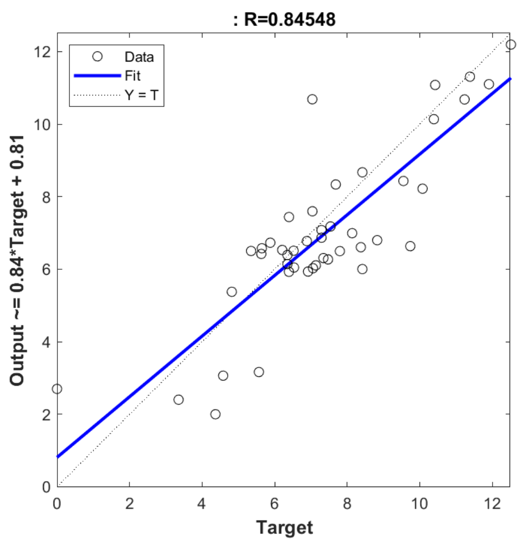


Fig- 4.49(c)



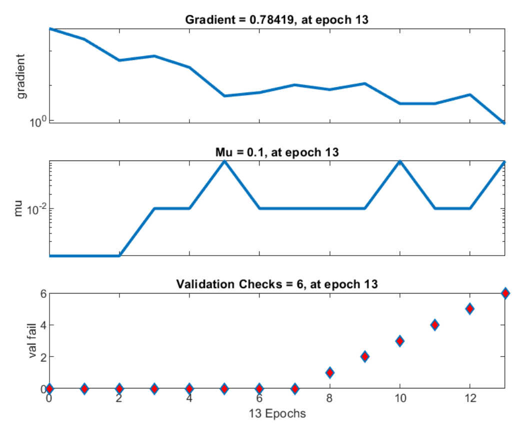


Fig- 4.49(d) **Fig- 4.49(e)**

Fig- 4.49 a, b, c, d & e display the Error histogram, Performance Plot (Observed and calculated data graph), Regression& Train state graphs respectively

4.5.8.3 Mansa scaled conjugate gradient: -

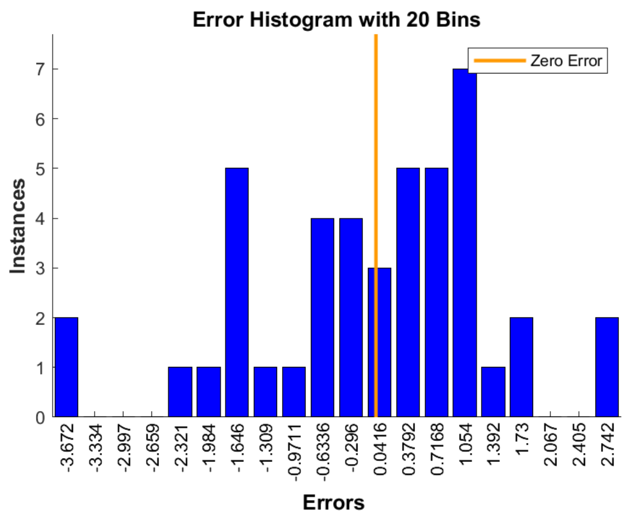


Fig- 4.50(a)

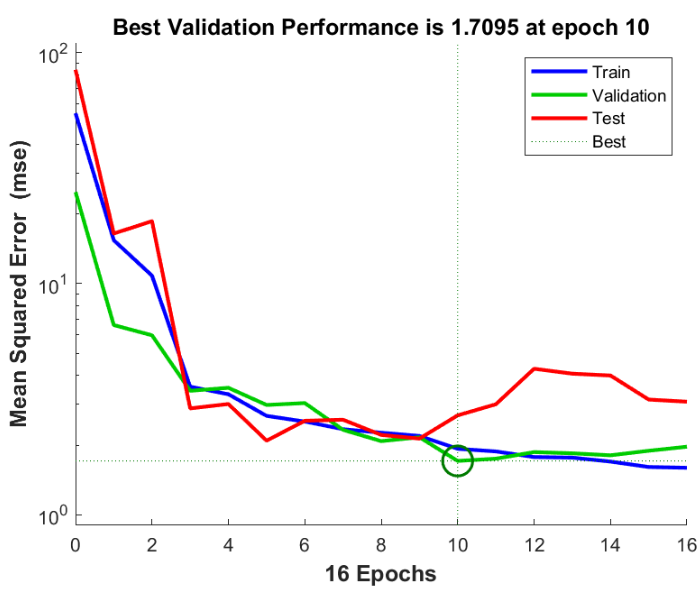


Fig- 4.50(b)

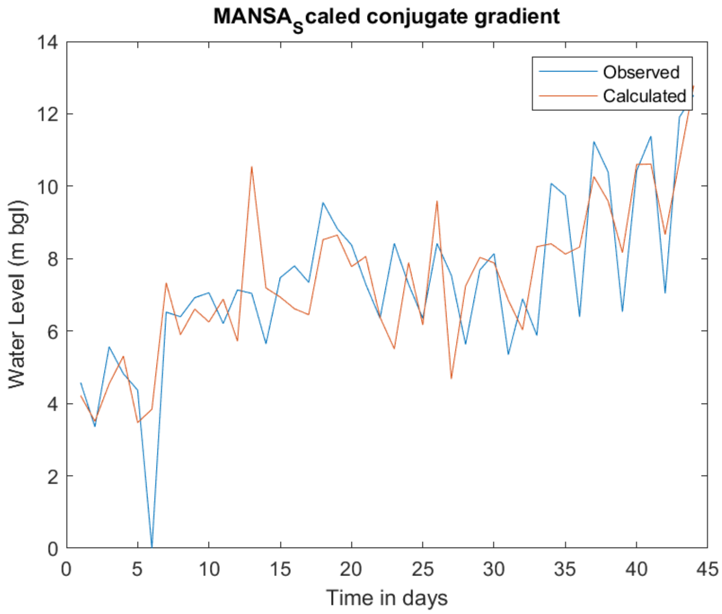
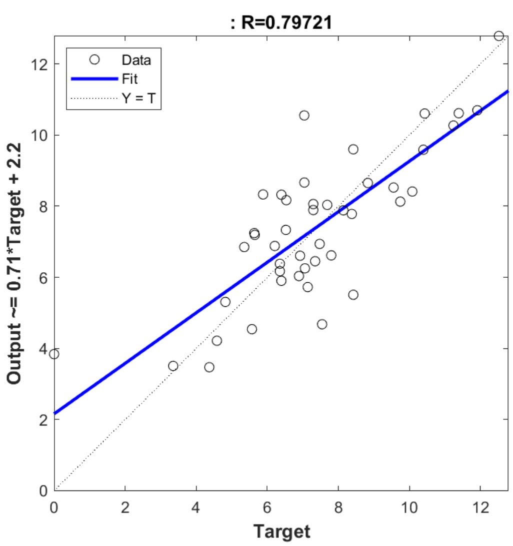


Fig- 4.50(c)



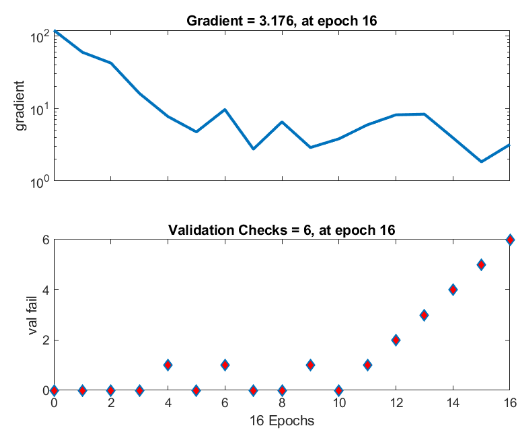


Fig- 4.50(d) **Fig- 4.50(e)**

Fig- 4.50 a, b, c, d & e display the Error histogram, Performance Plot (Observed and calculated data graph), Regression& Train state graphs respectively

4.5.9 Moga: -

4.5.9.1 Moga bayesian regularization: -

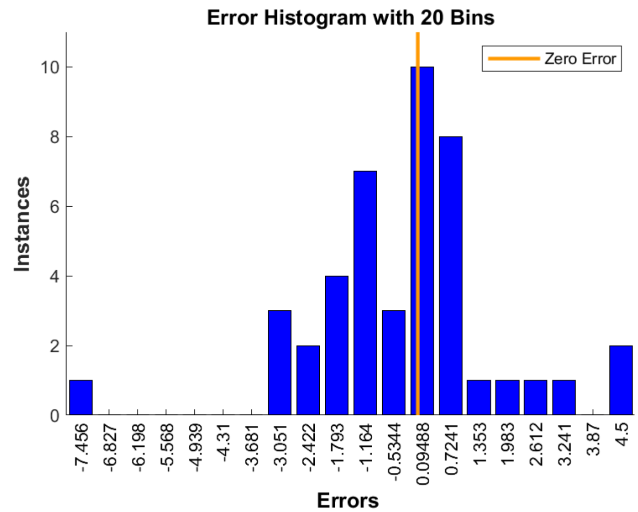


Fig- 4.51(a)

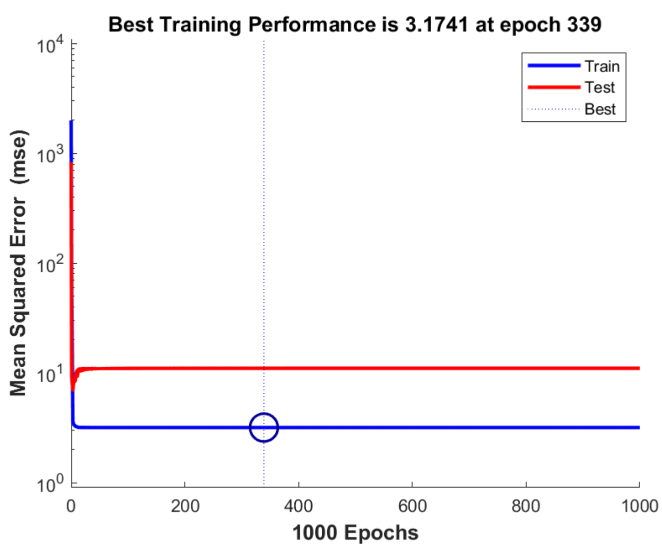


Fig- 4.51(b)

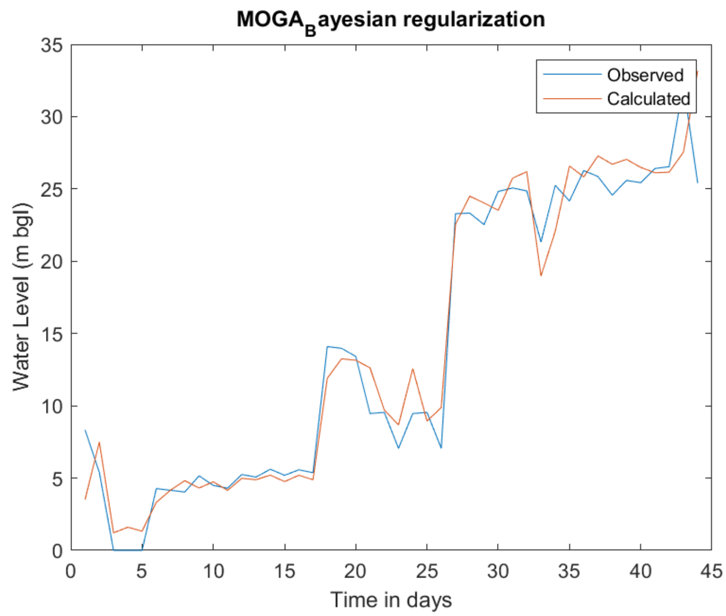
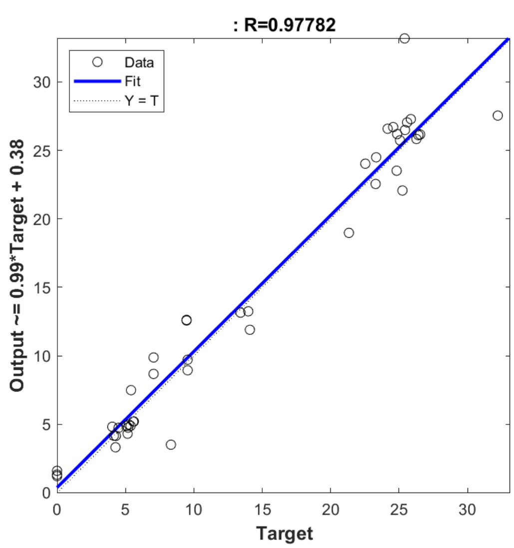


Fig- 4.51(c)



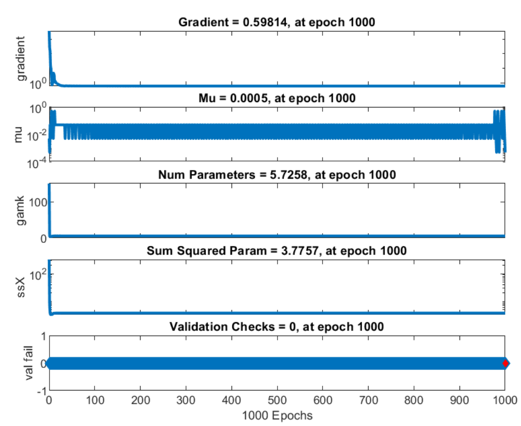


Fig- 4.51(d) Fig- 4.51(e)

Fig- 4.51 a, b, c, d & e display the Error histogram, Performance Plot (Observed and calculated data graph), Regression& Train state graphs respectively

4.5.9.2 Moga levenberg-marquardt: -

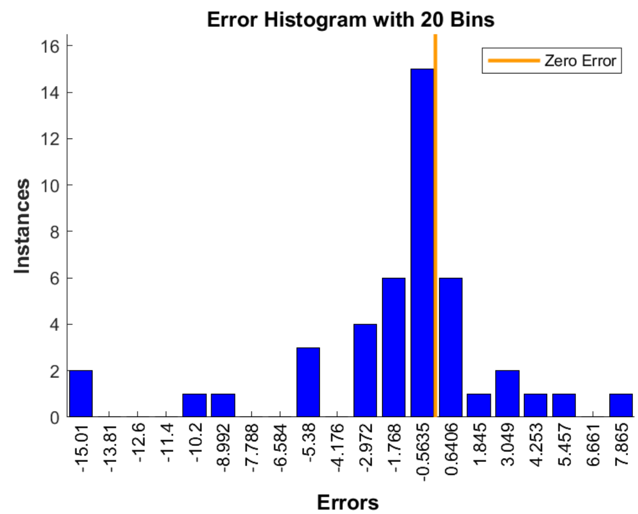


Fig- 4.52(a)

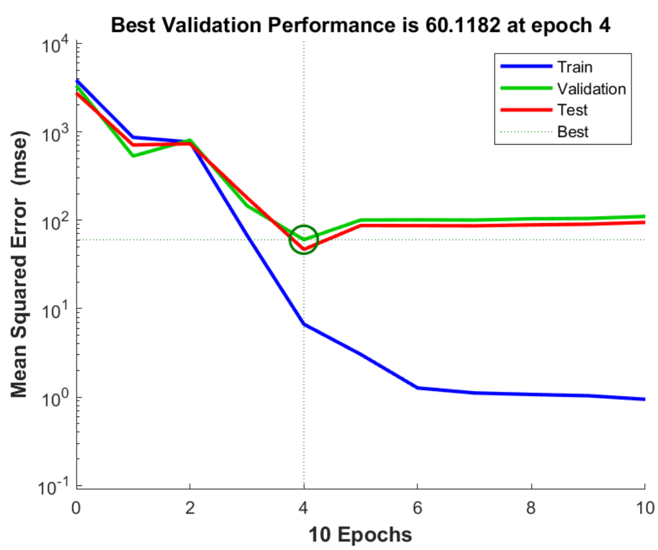


Fig- 4.52(b)

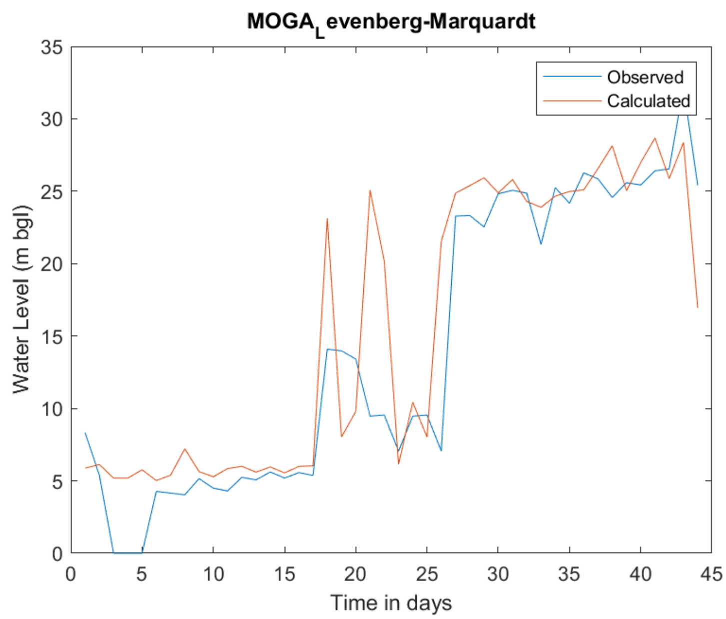
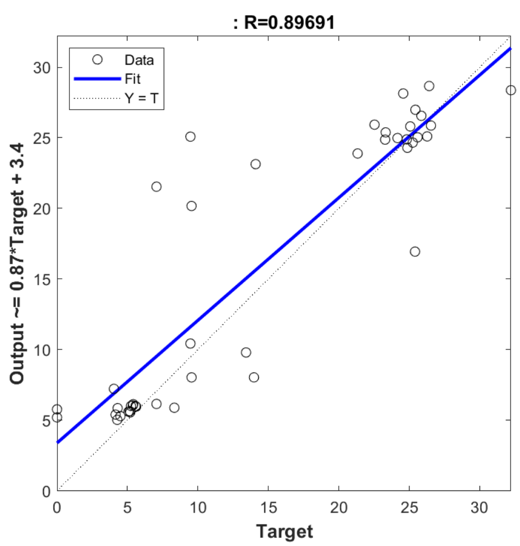


Fig- 4.52(c)



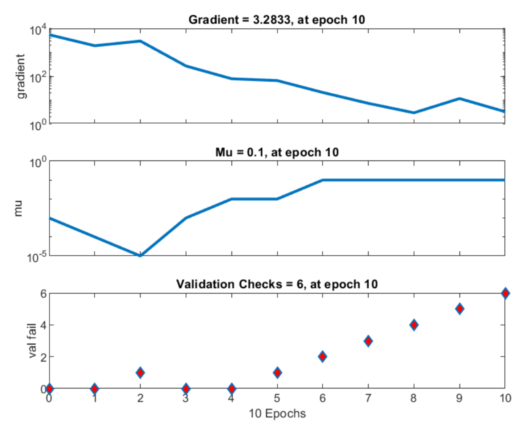


Fig- 4.52(d) Fig- 4.52(e)

Fig- 4.52 a, b, c, d & e display the Error histogram, Performance Plot (Observed and calculated data graph), Regression& Train state graphs respectively

4.5.9.3 Moga scaled conjugate gradient: -

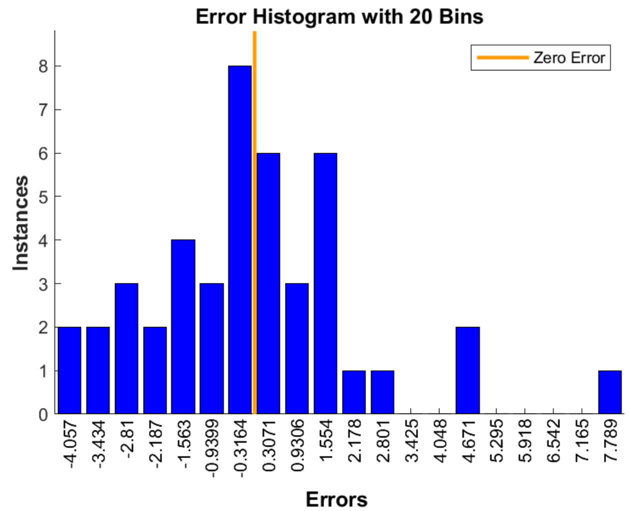


Fig- 4.53(a)

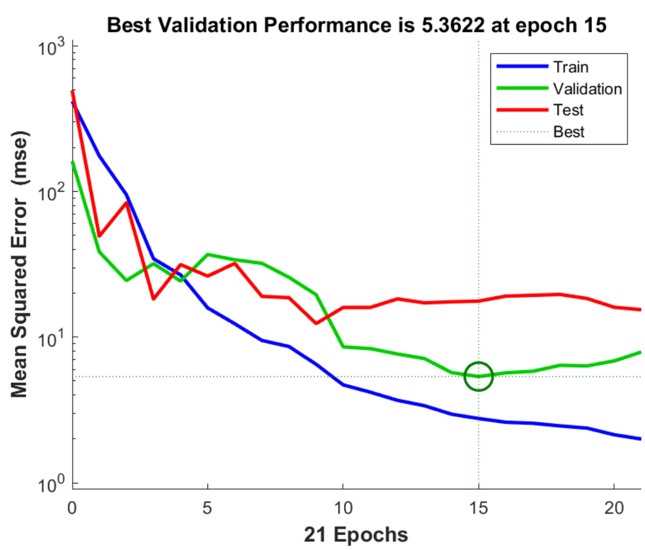


Fig- 4.53(b)

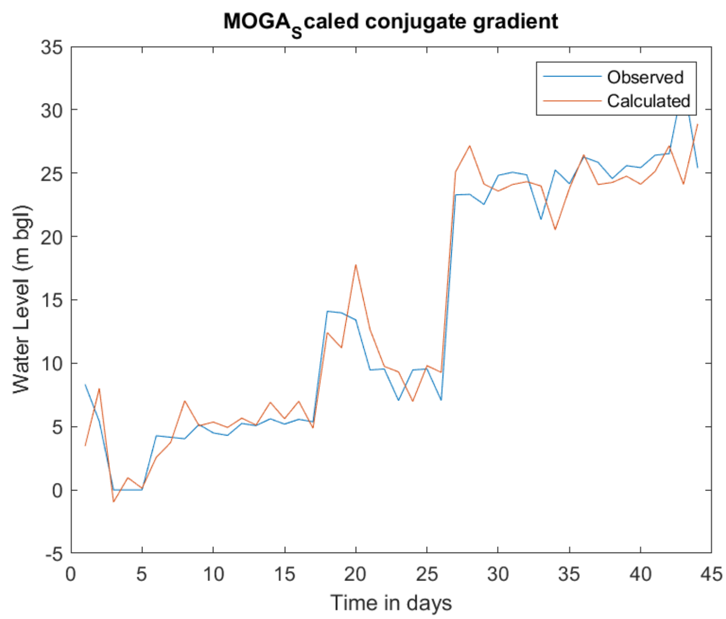
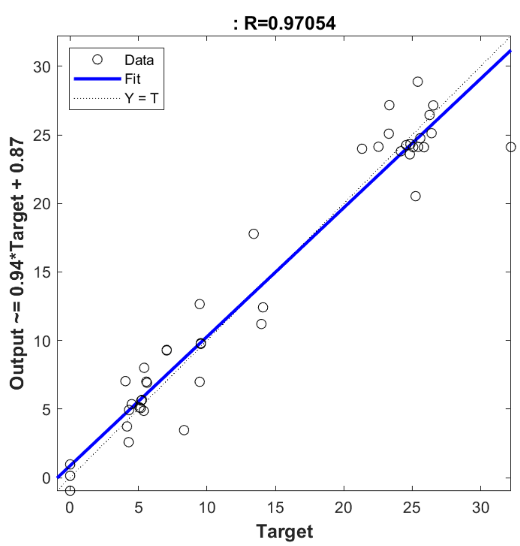


Fig- 4.53(c)



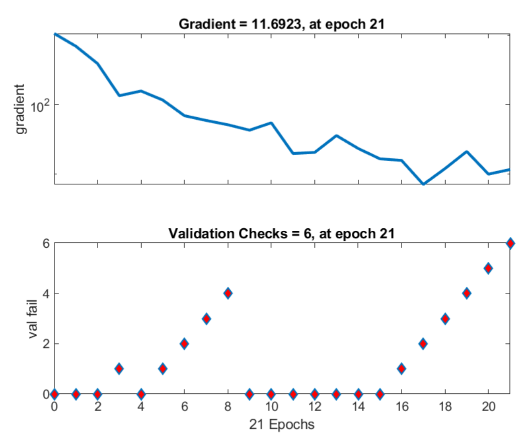


Fig- 4.53(d) **Fig- 4.53(e)**

Fig- 4.53 a, b, c, d & e display the Error histogram, Performance Plot (Observed and calculated data graph), Regression& Train state graphs respectively

4.5.10 Patiala: -

4.5.10.1 Patiala bayesian regularization: -

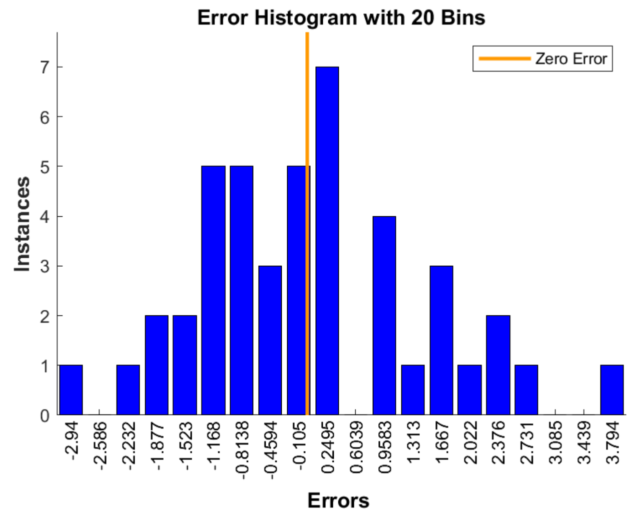
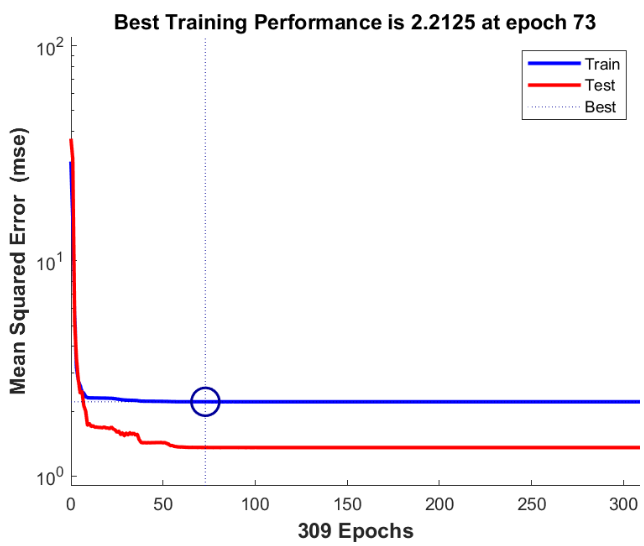


Fig- 4.54(a)



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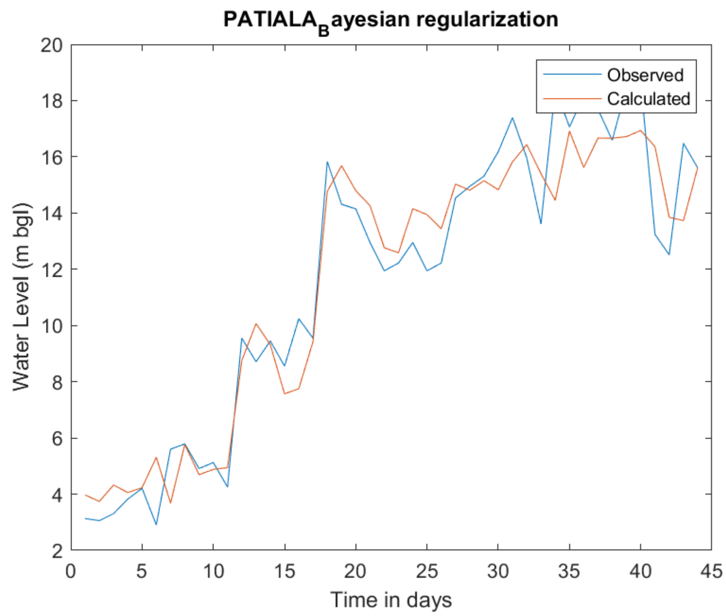
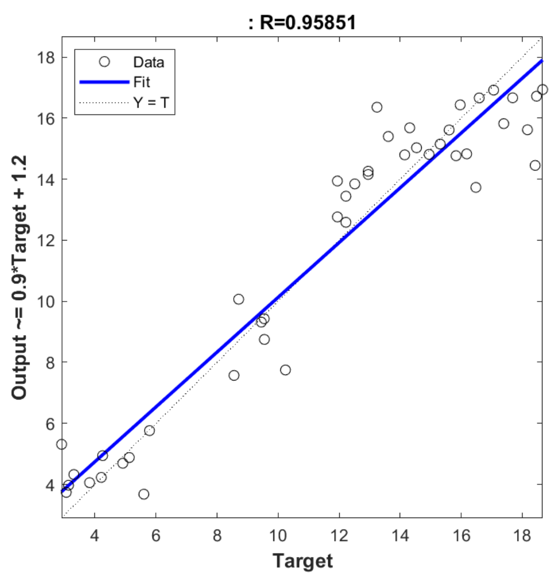


Fig- 4.54(c)



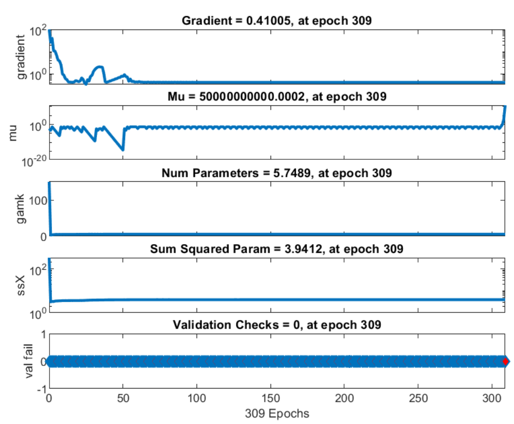


Fig- 4.54(d) **Fig- 4.54(e)**

Fig- 4.54 a, b, c, d & e display the Error histogram, Performance Plot (Observed and calculated data graph), Regression& Train state graphs respectively

4.5.10.2 Patiala levenberg-marquardt: -

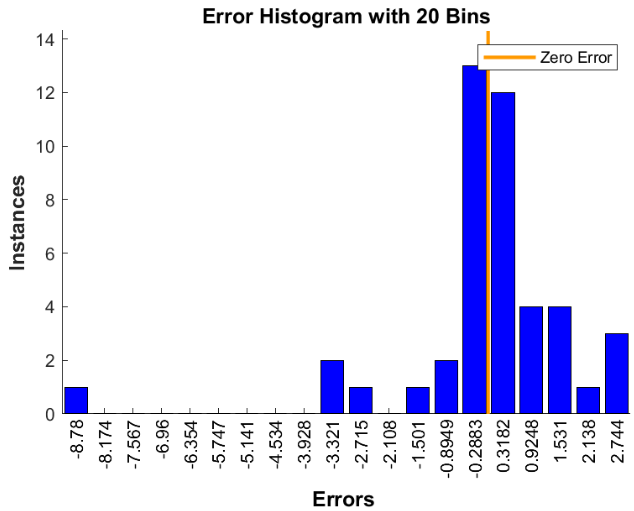


Fig- 4.55(a)

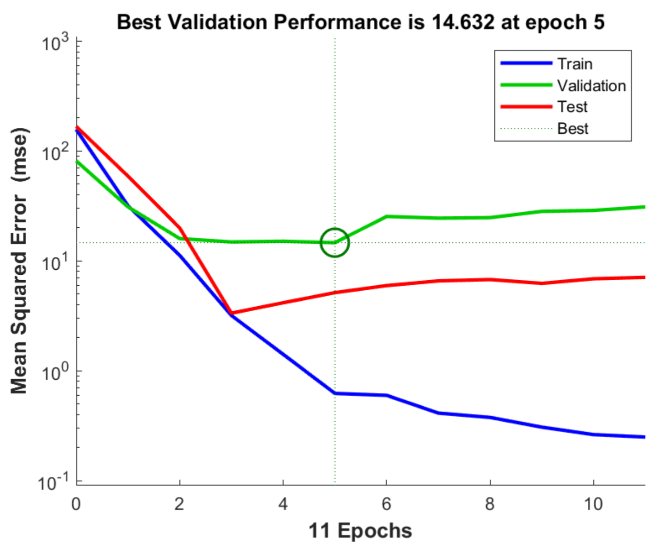


Fig- 4.55(b)

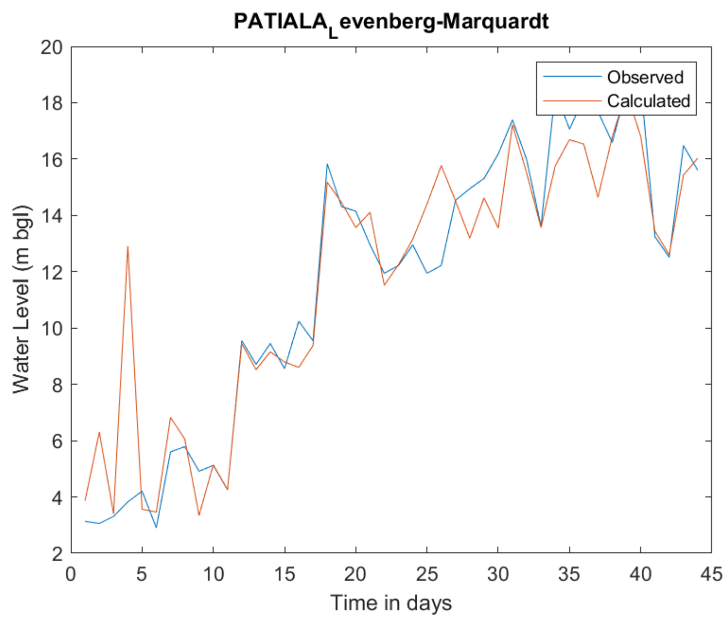
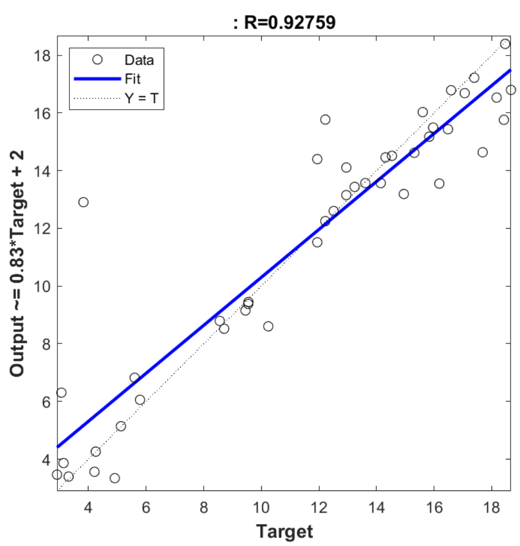


Fig- 4.55(c)



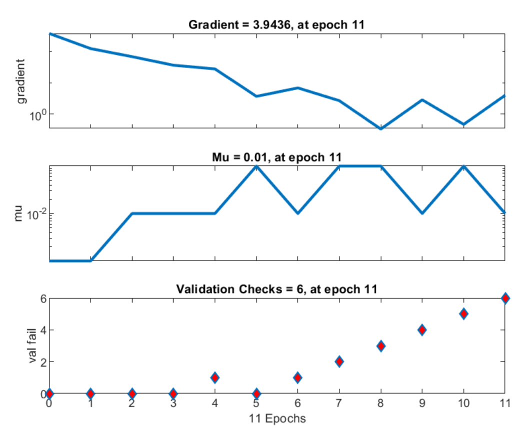


Fig- 4.55(d) **Fig- 4.55(e)**

Fig- 4.55 a, b, c, d & e display the Error histogram, Performance Plot (Observed and calculated data graph), Regression& Train state graphs respectively

4.5.10.3 Patiala scaled conjugate gradient: -

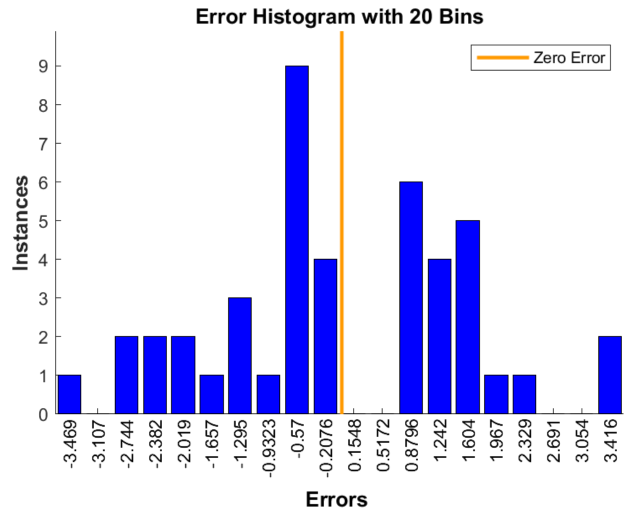


Fig- 4.56(a)

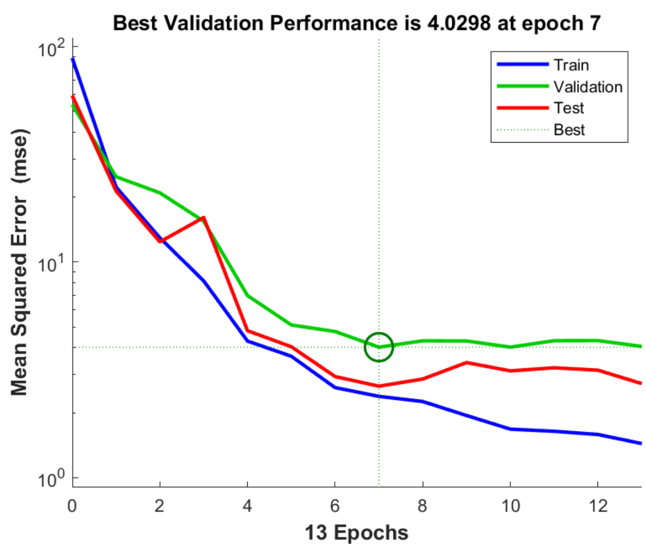


Fig- 4.56(b)

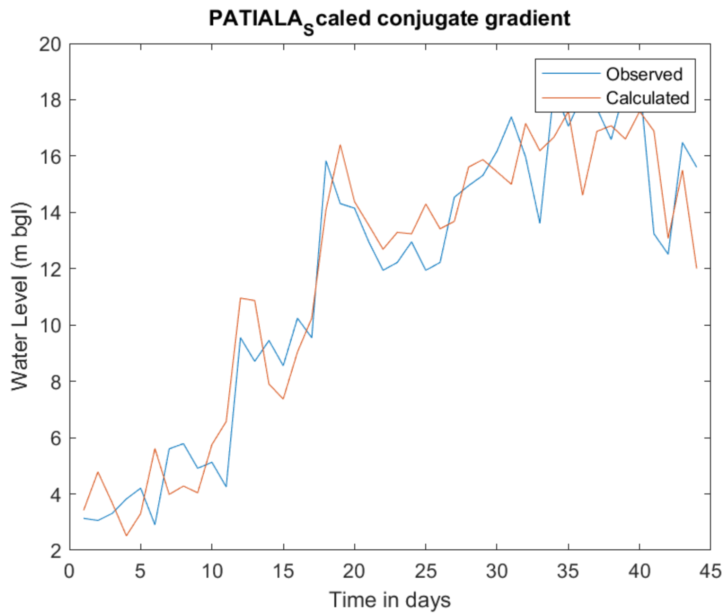
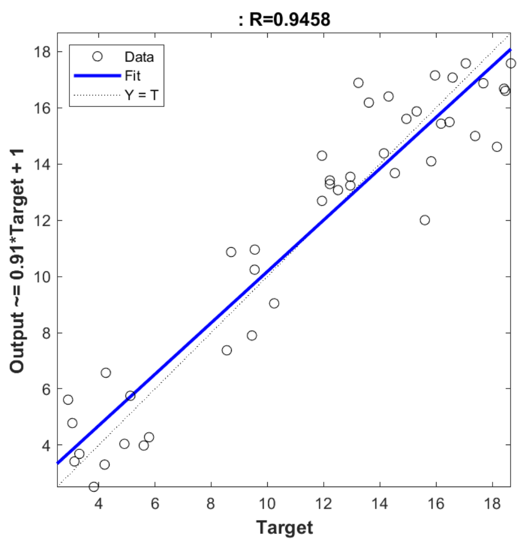


Fig- 4.56(c)



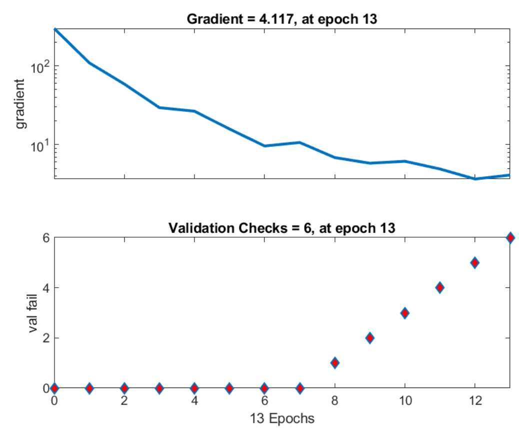


Fig- 4.56(d) **Fig- 4.56(e)**

Fig- 4.56 a, b, c, d & e display the Error histogram, Performance Plot (Observed and calculated data graph), Regression& Train state graphs respectively

4.5.11 Sangrur: -

4.5.11.1 Sangrur bayesian regularization: -

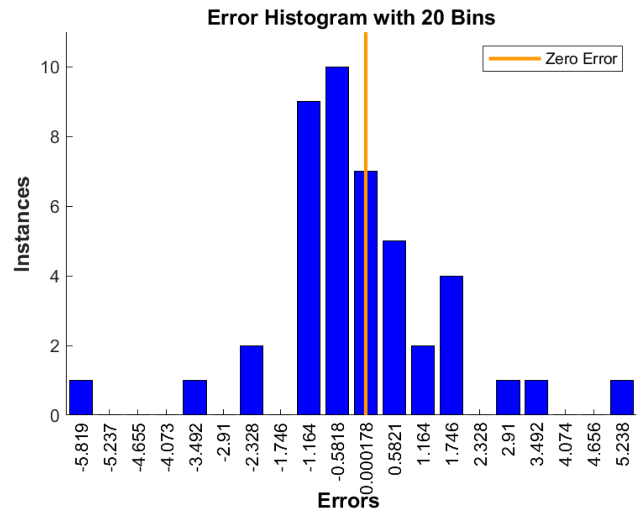


Fig- 4.57(a)

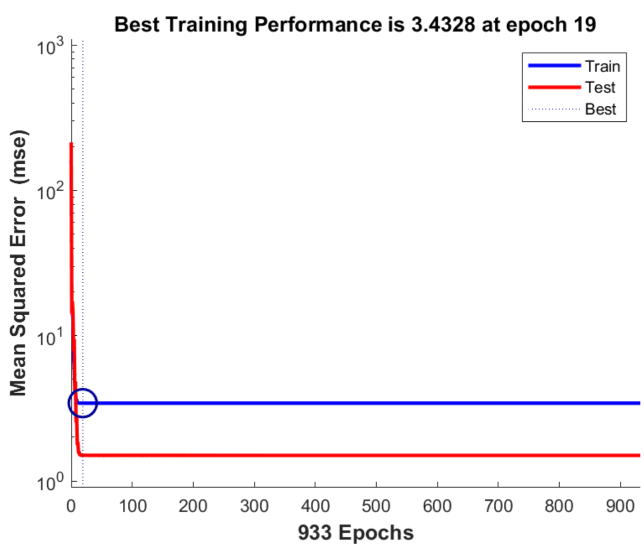


Fig- 4.57(b)

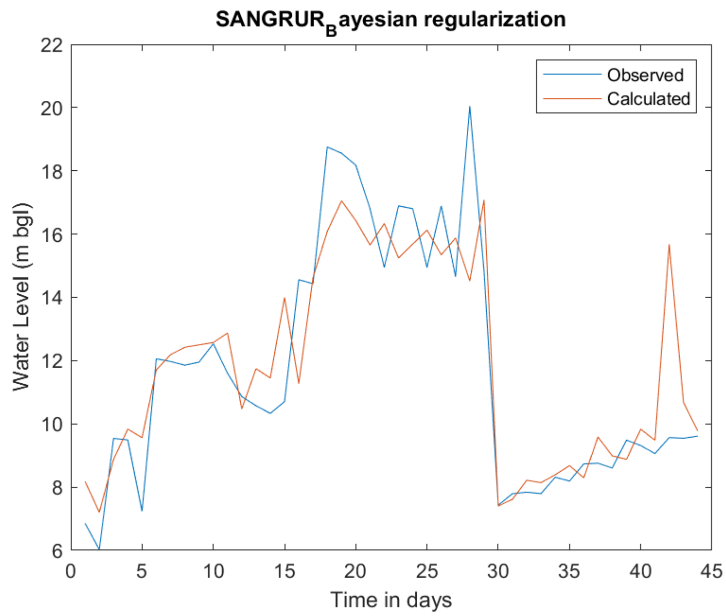
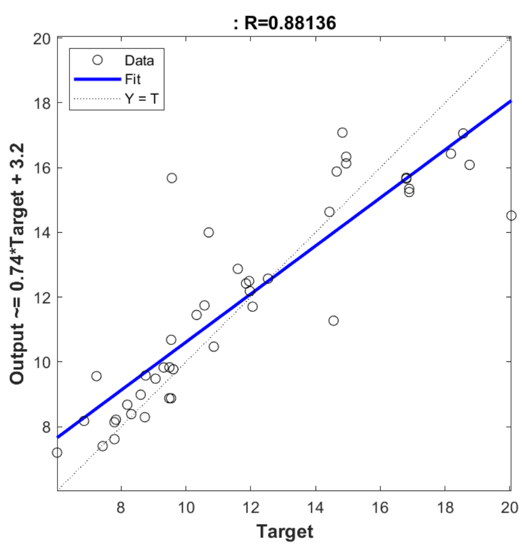


Fig- 4.57(c)



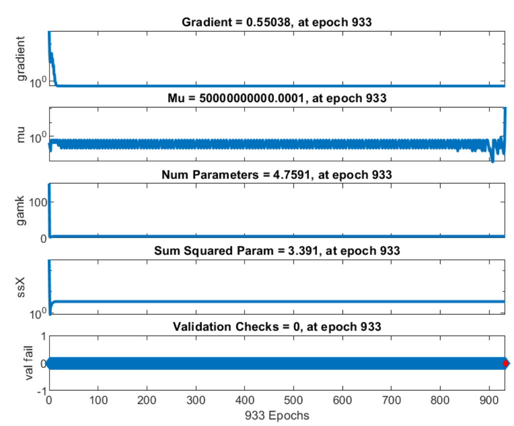


Fig- 4.57(d) Fig- 4.57(e)

Fig- 4.57 a, b, c, d & e display the Error histogram, Performance Plot (Observed and calculated data graph), Regression& Train state graphs respectively

4.5.11.2 Sangrur levenberg-marquardt: -

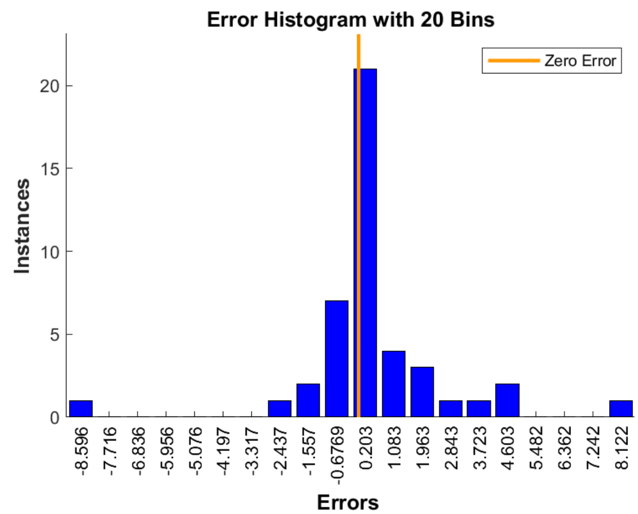


Fig- 4.58(a)

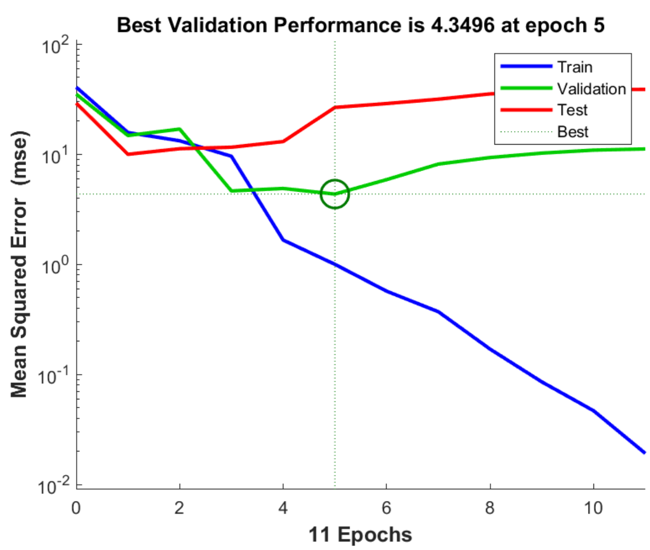


Fig- 4.58(b)

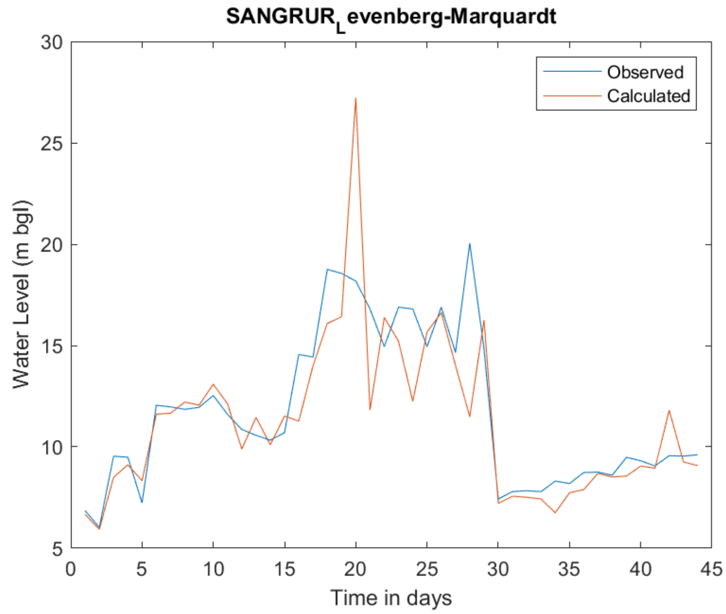


Fig- 4.58(c)

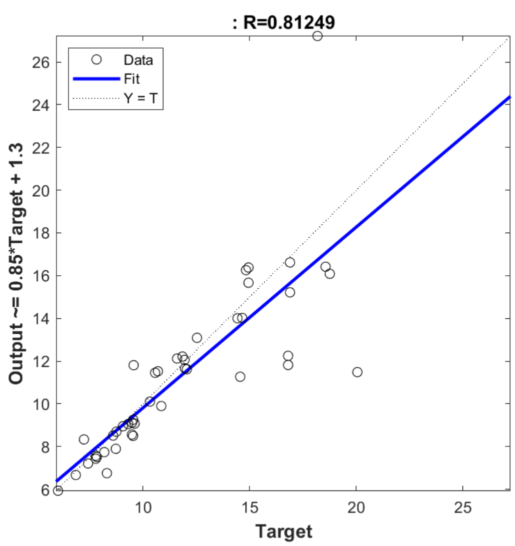


Fig- 4.58(d)

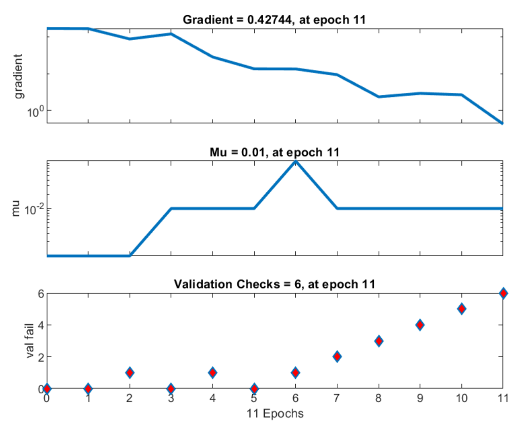


Fig- 4.58(e)

Fig- 4.58 a, b, c, d & e display the Error histogram, Performance Plot (Observed and calculated data graph), Regression& Train state graphs respectively

4.5.11.3 Sangrur scaled conjugate gradient: -

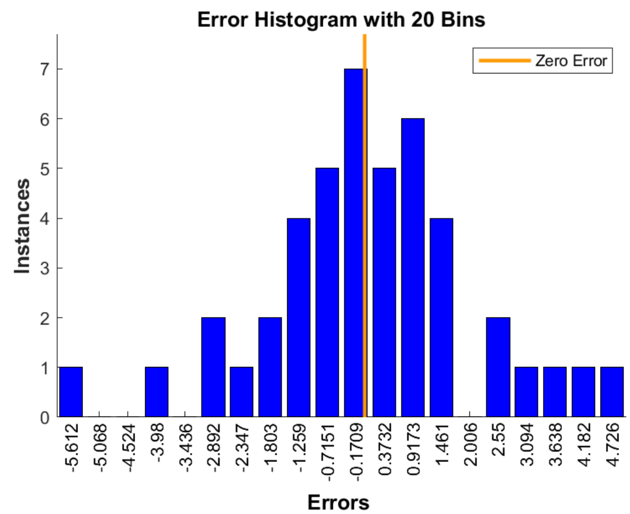


Fig- 4.59(a)

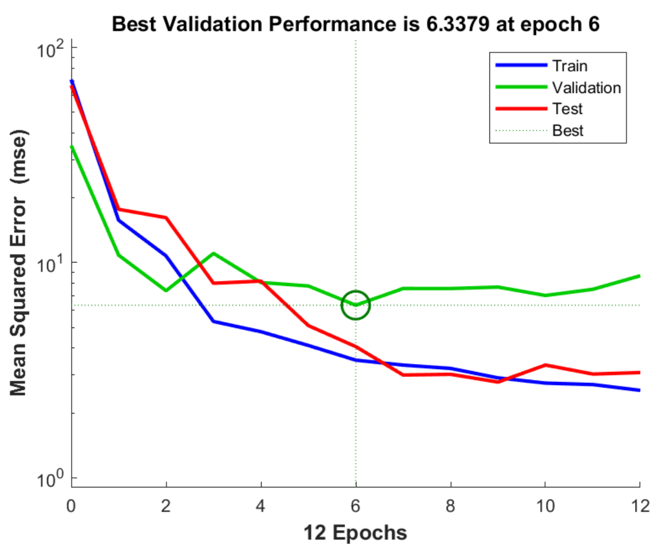


Fig- 4.59(b)

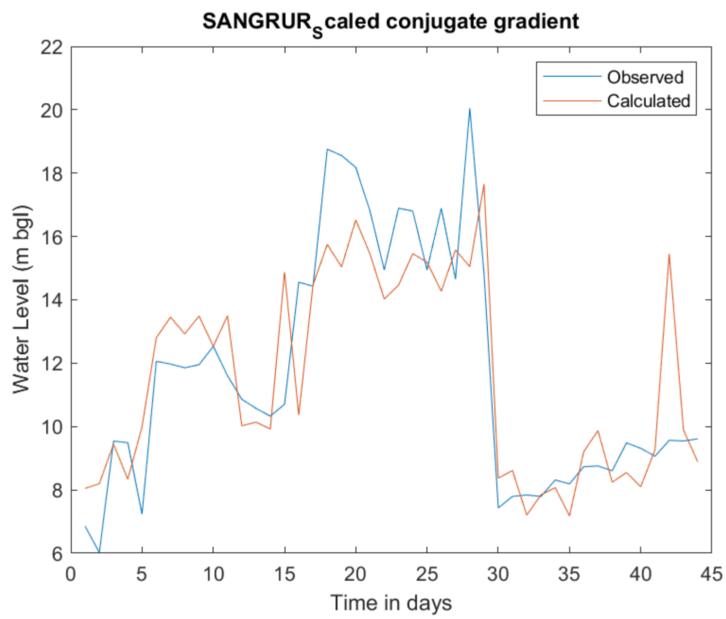
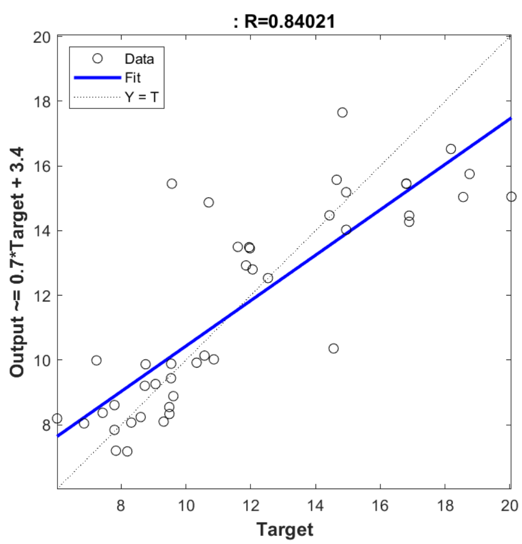


Fig- 4.59(c)



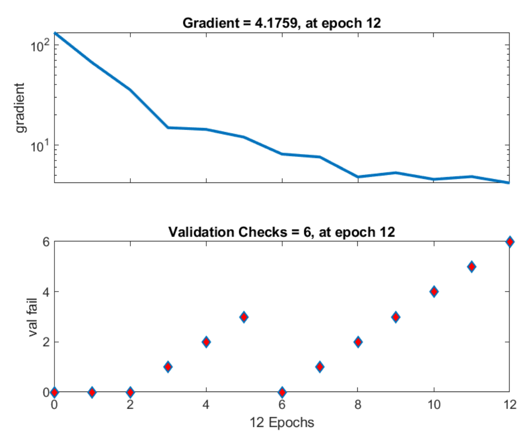


Fig- 4.59(d) **Fig- 4.59(e)**

Fig- 4.59 a, b, c, d & e display the Error histogram, Performance Plot (Observed and calculated data graph), Regression& Train state graphs respectively

4.6 ARTIFICIAL NEURAL NETWORK TESTING AND VALIDTION RESULTS

The constructed neural network models needed to be validated, therefore additional observation data were added to the networks, and the predicted groundwater level was compared with the actual groundwater level of all groundwater samples in the research region. This was done so that the models could be used effectively. According to the presented figures, neural networks are able to provide groundwater level predictions for a period of six months into the future with a degree of accuracy that is reasonable in the majority of the groundwater samples. The capacity of ANN models to anticipate ground water levels was tested using the root-mean-square error (RMSE) and the regression coefficients of the observed and predicted ground water levels from a variety of wells. It can be seen in Table shown below that the value of RMSE can range anywhere from 0.48 to 0.5 metres when being validated. In addition, the coefficient of determination, which was calculated based on the calibration data as well as the validation data, demonstrates that the predicted groundwater tables have reasonably strong correlations.

Station and ANN Techique	RMSE TRAIN	R2 TRAIN	RMSE TEST	R2 TEST
AMRITSAR_Bayesian regularization	2.4065	-0.01469	1.997088182	0.388063
AMRITSAR_Levenberg-Marquardt	2.0769	0.24428	2.3873	0.11103
AMRITSAR_Scaled conjugate gradient	2.1508	0.18951	2.2446	-0.07598
BATHINDA_Bayesian regularization	1.6994	0.80652	1.997088182	0.388063
BATHINDA_Levenberg-Marquardt	2.4648	0.59299	2.6391	0.53464
BATHINDA_Scaled conjugate gradient	2.0984	0.70499	3.414	0.3555
FARIDKOT_Bayesian regularization	0.54146	0.82748	1.997088182	0.388063
FARIDKOT_Levenberg-Marquardt	0.68066	0.72738	1.2418	0.44772
FARIDKOT_Scaled conjugate gradient	0.61169	0.77983	0.94288	0.2055
FAZILKA_Bayesian regularization	0.84049	0.009837	1.997088182	0.388063
FAZILKA_Levenberg-Marquardt	0.65582	0.39715	0.94754	-0.74306
FAZILKA_Scaled conjugate gradient	0.72207	0.26919	1.0168	-0.95108
HOSHIARPUR_Bayesian regularization	1.3327	0.45044	1.997088182	0.388063
HOSHIARPUR_Levenberg-Marquardt	1.7182	0.086481	0.99532	0.67993
HOSHIARPUR_Scaled conjugate gradient	1.2591	0.50947	1.0494	0.34707
KAPURTHALA_Bayesian regularization	2.7542	0.73465	1.997088182	0.388063
KAPURTHALA_Levenberg-Marquardt	2.8125	0.72331	2.7986	0.82048
KAPURTHALA_Scaled conjugate gradient	2.5508	0.7724	2.5199	0.72057
LUDHIANA_Bayesian regularization	1.8394	0.79637	1.997088182	0.388063
LUDHIANA_Levenberg-Marquardt	1.5912	0.84762	1.7799	0.66942

Station and ANN Techique	RMSE TRAIN	R2 TRAIN	RMSE TEST	R2 TEST
LUDHIANA_Scaled conjugate gradient	4.6388	-0.29511	2.8275	0.48981
MANSA_Bayesian regularization	1.7258	0.44812	1.997088182	0.388063
MANSA_Levenberg-Marquardt	2.6989	-0.3497	1.142	0.3011
MANSA_Scaled conjugate gradient	1.7203	0.4516	1.1092	0.62902
MOGA_Bayesian regularization	1.7926	0.96636	1.997088182	0.388063
MOGA_Levenberg-Marquardt	1.5819	0.9738	2.9082	0.89452
MOGA_Scaled conjugate gradient	3.1976	0.89296	2.3513	0.90225
PATIALA_Bayesian regularization	1.4224	0.92027	1.997088182	0.388063
PATIALA_Levenberg-Marquardt	1.1085	0.95157	1.807	0.90278
PATIALA_Scaled conjugate gradient	1.8399	0.86659	2.0023	0.43002
SANGRUR_Bayesian regularization	1.764	0.77411	1.997088182	0.388063
SANGRUR_Levenberg-Marquardt	2.1965	0.64976	2.4779	0.631
SANGRUR_Scaled conjugate gradient	2.1092	0.67704	3.3334	0.23514

Table 1: ANN Type and Station based RMSE and R2 score

Summary Statistics:

- Best RMSE train: 0.54146
- Best R2 train: 0.9738
- Best RMSE test: 8
- Best R2 test: 28
- Best RMSE station: FARIDKOT_Bayesian
- Best RMSE type: Bayesian regularization

	RMSE TRAIN	**R2 TRAIN**	**RMSE TEST**	**R2 TEST**
count	33	33	33	33
mean	1.836469394	0.5570478	1.99708818	0.388063
std	0.857387803	0.3608192	0.67221693	0.388659
min	0.54146	-0.3497	0.94288	-0.95108
25%	1.3327	0.39715	1.7799	0.3555
50%	1.764	0.70499	1.99708818	0.388063
75%	2.1965	0.80652	2.3873	0.62902
max	4.6388	0.9738	3.414	0.90278

Table 2: Result Statistics

Chapter: - 5

CONCLUSION

- All three algorithms levenberg-marquardt, Bayesian regularization and scaled conjugate gradient were used and bayesian regularization algorithm gave the best results.
- Artificial neural network back propagation gave very good and efficient results.
- Other actual world affecting groundwater level data were not available for this study but if they are added over this model results can be made efficient and more reliable (i.e. evapotranspiration).
- Levenberg-marquardt algorithm was faster than other algorithms but was not as efficient like Bayesian regularization algorithm.
- Bayesian regularization algorithm was slow but it also gave the best results than the other two algorithms and Bayesian regularization generalizes well.
- Scaled Conjugate Gradient Back-Propagation algorithm requires more iterations to converge than other algorithms. But, computations in each iteration are significantly less compared to others.
- Given the last 3-month Rainfall data and the last 3-month GWL data, the ANN predict the next 6-month GWL data.

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