# GROUNDWATER LEVEL FORECASTING USING RADIAL BASIS FUNCTION AND GENERALIZED REGRESSION NEURAL NETWORKS

Thesis

Submitted in partial fulfillment of the requirements for the degree of

DOCTOR OF PHILOSOPHY

By

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# D E C L A R A T I O N

*by the Ph.D. Research Scholar*

I hereby *declare* that the Research Thesis entitled **"Groundwater Level Forecasting using Radial Basis Function and Generalized Regression Neural Networks"** Which is being submitted to the **National Institute of Technology Karnataka, Surathkal** in partial fulfillment of the requirements for the award of the Degree of **Doctor of Philosophy** in **Civil Engineering** is a *bonafide report of the research work carried out by me*. The material contained in this Research Thesis has not been submitted to any University or Institution for the award of any degree.


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Date: 20 - 07 - 2012

# C E R T I F I C A T E

This is to *certify* that the Research Thesis entitled **"Groundwater Level Forecasting using Radial Basis Function and Generalized Regression Neural Networks"** submitted by **Sreenivasulu D** (Register Number: **090706AM09F02**) as the record of the research work carried out by *him, is accepted as the Research Thesis submission* in partial fulfillment of the requirements for the award of degree of **Doctor of Philosophy**.

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**DEDICATED**

**TO MY BELOVED**

**PARENTS AND TEACHERS**

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## ABSTRACT

Forecasting of groundwater levels is very much useful for efficient planning in integrated management of groundwater and surface water resources in a basin. Accurate and reliable groundwater level forecasting models can help ensuring the sustainable use of a watershed's aquifer for both urban and rural water supply. The present work investigates the potential of two Neural networks, such as Radial Basis Function Neural Networks (RBFNN) and Generalized Regression Neural Networks (GRNN) in comparison to regular ANN models like Feed Forward Back Propagation (FFBP) and Non-Linear Regression Model (NARX) for modeling in Ground water level (GWL) forecasting in a coastal aquifer at western Ghats of India. Total 24 wells (both shallow and deep) located within the study area (microwatershed of Pavanje river basin) were selected covering around 40sqkm. Here, two different dataset such as weekly Time series GWL and Meteorological variables those recorded during the study period (2004-2011) were used in the analysis. Various performance indices such as Root Mean Squared Error (RMSE), Coefficient of Correlation (CC) and Coefficient of Efficiency (CE) were used as evaluation criteria to assess the performance of the developed models.

At the first stage, the potential and applicability of RBF for forecasting groundwater level are investigated. Weekly time series groundwater level data upto four lagged data has been used as various input scenario where predicted output are one and two week leadtime GWL. The analysis has been carried out separately for three representative open wells. For all the three well stations, higher accuracy and consistent forecasting performance for RBF network model was obtained compared to FFBP network model.

After confirming the suitability of RBF in GWL forecasting and with better accuracy over FFBP, the work has been extended further to consolidate the applicability of RBF in multistep leadtime forecasting upto six week ahead. In this study, six representative wells are covered for development of RBF models for six different input combinations using lagged time series data. Outputs are the predicted GWL upto six week. RBF models are developed for every well station and results are compared with Non linear regression model (NARX). It has been observed that for all

the six well station, the higher and consistent forecasting performance by RBF network model in multi step week lead which consolidates the forecasting capability of RBF. The NARX model result shows poor performance.

In the third stage, to examine the potential and applicability of GRNN in GWL forecasting, various GRNN models has been developed by considering the advantage of S-summation and D-summation layers for different input combinations using time series data. Weekly time series groundwater level data upto four lagged data has been used as inputs where predicted outputs are one week leadtime GWL. The analysis has been carried out separately for three representative open wells. GRNN models were developed for every well and best model results were compared with best RBF and FFBP with LM training algorithm models. The RBF and GRNN models are almost performed similarly in GWL forecasting with higher accuracy in all the representative well station. The poor performance of FFBP-LM model is also satisfactory but found inferior than both GRNN and RBF.

After confirming the potential and applicability of GRNN and RBF in time series GWL forecasting with similar capability, the robustness, adaptability and flexibility characteristics of these two techniques are further investigated for suitability with cause and effect relationship. Here various meteorological parameters are used as causable variable and the GWL is used as output effect .Only GRNN models are developed in the present study as RBF was found with similar predicting performance in previous studies. Five various input combinations are used to obtain best results as one step leadtime output for three representative wells. In this case also, GRNN model is predicting groundwater level with higher accuracy and with satisfactory results. The GRNN model performance is compared to general ANN (FFBP) model and found outperforming FFBP performance.

The result of the study indicates the potential and suitability of RBFNN and GRNN modeling in GWL forecasting for multistep leadtime data. The performance of RBFNN and GRNN were found almost equally good. Although accuracy of forecasted GWL generally decreases with the increase of leadtime, the GWL forecast were obtained within acceptable accuracy for both the models.

**Keywords:** Coastal regions, Dakshina Kannada, Groundwater level, ANN, RBF, GRNN, NARX, FFBP.

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## NOMENCLATURE

| Symbol | Description |
|---|---|
| ANN | Artificial Neural Network |
| NN | Neural  Network |
| FFBP | Feed-forward back Propogation |
| LM | Levenberg-Marquartz |
| MLP | Multilayer Perception |
| RBFNN | Radial Basis Function Neural Network |
| GRNN | Generalized Regression Neural Network |
| SOM | Self Organized Map |
| RNN | Recurrent Neural Network |
| RMSE | Root Mean Square Error |
| CC | Coefficient of Correlation |
| CE | Coefficient of Efficiency |
| MAPE | Mean Absolute Error |
| MSE | Mean Square Error |
| SW | Shallow well |
| DW | Deep well |
| GWL | Groundwater level |
| D.K. | Dakshina Kannada |

# CHAPTER - 1

# INTRODUCTION

## 1.1. Introduction

Groundwater level is an indicator of groundwater availability, groundwater flow, and the physical characteristics of an aquifer or groundwater system. Groundwater level forecasting plays a vital role in designing, planning, development, operation and management of groundwater resource in a sustainable manner. For many years, hydrologists have attempted to understand the dynamics/complete behavior of groundwater level (GWL) fluctuations. In coastal regions, owing to non-uniform temporal and spatial distributions of groundwater and the presence of high fluctuations and steep channels all over the catchment, the groundwater system appears to be complex.

The groundwater level mainly depends on the rate and duration of rainfall, geological formation, the antecedent soil moisture conditions, and type of soil. Records of water level fluctuation in wells are worth the cost and trouble of collecting only if they are used as a basis for hydrologic interpretations. Although water level records have been vital to the reaching of conclusions regarding the occurrence and development of groundwater in specific areas, many such records still await interpretation. Similarly, a wealth of climatologic and other hydrologic data is in need of analysis (Korkmaz, 1988).

Prediction of region specific water table fluctuation is one of the basic necessities for formulations of appropriate design and taking scientific measures to ensure sustainable groundwater management. Dependable forecasts of groundwater level are essential for many aspects such as water resources projects, irrigation, industrial and domestic purposes. Thus accurate and reliable forecasting GWL are always a benchmark problem for hydrologists and water resources engineers (Lin and Chen 2005).

To date, a wide variety of models have been developed and successfully applied in water resources engineering both in surface water and groundwater hydrology, in particular groundwater level forecasting. These models can be categorized into empirical time series model and physical descriptive model. Physical models and statistical regression models have been developed in the past to simulate water table variations in different areas. However, all of these models need extensive inputs/information/observations to perform for the effective modeling. The physically based model requires an explicit relationship between the input and output parameters. But, the presence of errors or uncertainties in the observations will result in errors or deviations in the model output (Shirmohammadi et al., 2006). The physical based model requires enormous data which is costly and time consuming and hence difficult to adopt in developing countries like India (Nayak et al. 2006). On the other hand, the major disadvantage of empirical approach is that they are not adequate for forecasting when the dynamic behavior of hydrologic system changes with time (Bierkens, 1998). Also, the relationship between, rainfall, stream flow, evapotranspiration and the groundwater level are likely to be non-linear as very few nonlinear empirical models have been reported for shallow water table modeling (Bierkens, 1998; Knotters and Bierkens, 2000; Scanlon et al, 2002).

Accurate groundwater level forecasting is required in long-term and short-term for better water management strategy. However, classical regression methods are unable to model this nonlinear complex system. A major concern in forecasting the groundwater table in existing traditional methods are the difficulty in assessing the uncertainty associated with any given estimate and inaccuracies arises from several sources, spatial and temporal variability in process and parameter values, measurement errors and the validity of assumption upon which different methods are based.

Use of ANN technique has been increased for the past few decades in groundwater hydrology for the purpose of forecasting, modelling, estimation of aquifer parameter, aquifer contamination and many more problems. A lot of successful applications have shown that ANN Provides powerful determine tool for time series modelling (Zahang et al., 1998; Nag and Mitra, 2002). Comparisons were made between traditional methods and ANN on time series forecasting (Hamid and Zahid, 2004). The supports for ANN in time series analysis are the capability of non-linear modelling in real world complex phenomena. Also, ANN is non parametric methods and prior knowledge is not mandatory. All these features make ANN attractive for time series modelling and forecasting.

In general, ANN is provided as either substitutive or complementary option to traditional computational schemes of statistical regression, time series, and pattern matching and numerical methods. Some of the merits of this approach are that it does not require the complex nature of the underlying process under considering to be explicitly described in mathematical form. Several researchers were utilized various types of neural networks to forecast groundwater level fluctuations to improve the performance of models and their reliability.

## 1.2. Problem background

In the coastal region of Karnataka (India), more than 20% of geographical area falls under Laterite formations with low groundwater development status. Average groundwater development of the state has been assessed to 20%, which is far below the national average groundwater development. The state as a whole has a huge balance of groundwater resources with a wide scope of its development. But due to presence of Laterite formations and many associated problems with complex hydrological system, it has not been exploited to the desirable levels.

In the last few years, with reference to total monitoring wells, majority of wells showed depletion in water table depth during pre-monsoon or dry season. This leads to the associated problem of lowering deep well depth and drying of open dug wells in these areas, which also indicated the decreasing trend of groundwater table over a period of time. The possible reason may be increase of draft due to population growth, low groundwater recharge etc. As the water demand increases day by day, it may be difficult to check the draft of groundwater resources in the near future which may a major threat to the stakeholder (GEC, 1997). Fortunately, there is scope to enhance the recharge rate to the aquifer by suitable means due to the heavy rainfall occurred in the study area during monsoon. Hence, it is necessary to quantify the current rate of recharge, monitor the change in water table depth before any interference towards groundwater development. Keeping in this view, this study was carried out in a microwatershed of Pavanji watershed, Karnataka, India.

Efficient planning of a reliable water supply project, especially during dry season requires accurate acceptable predictions of water table depth fluctuations. The prediction of groundwater level in a well, based on continuous monitoring of selected of nearby wells is of immense importance in the management of groundwater resources (Coulibaly et al 2001). In this real world situation with uncertainty and errors attached with limited observed records, physical or conceptual model may not be feasible or perform poorly. Therefore, the data driven modeling such as Artificial Neural Network (ANN) may be an alternate viable option as it will model the data rather than the physical process.

Most of the works in ANN are related to FeedForward error Back Propagation (FFBP) algorithm. However, the major difficulties in FFBP are slow convergence, often trapped in local minimum and suffer in extrapolation (Chen et al., 2010). An alternate network algorithm, Radial Basis Function (RBF) can be used to reduce the limitations of FFBP, a fast method for designing nonlinear feed forward networks. Powell (1987) introduced RBF in solving the real multivariate interpolation problem. Radial Basis Function (RBF) is a powerful technique for interpolation in multidimensional space. RBF networks have been used for engineering applications due to their advantages over traditional multilayer perceptrons, such as faster convergence, smaller extrapolation errors, and higher reliability (Moradkhani et al., 2004).

RBF Neural Networks was increasingly used for prediction purposes as an efficient alternative to traditional methods (Lin and Chen 2005; Krishna et al 2008). RBF networks have the advantage of not suffering from local minima in the same way as Multi-Layer Perceptrons. This is because the only parameters that are adjusted in the learning process are the linear mapping from hidden layer to output layer. The architecture and training algorithms for radial basis function networks (RBF) are very simple and clear. Generally RBF neurons are not identical and require global computations to determine their parameters.

Also, Generalized Regression Neural Network (GRNN) is a class of neural networks widely used for the continuous function mapping. An important advantage of the GRNN is that training is very fast and adding new data is almost free. GRNN belongs to the well known nonparametric kernel regression models (Hardle 1989, Fan and Gijbels 1997). The GRNN model has a solid mathematical background to support confidence estimates. The GRNN architecture subsumes the RBF method. The major difference between GRNN and RBF neural networks is the methodology adopted for determination of weights. Instead of training weights, the GRNN assigns the target value directly to the weights, from the training set associated with input training vector and a component of its corresponding output vector (Kisi, 2006).

GRNN looks much like the common feedforward Backpropagation (FFBP) training but operation is fundamentally different. GRNN is based on non-linear regression theory for function approximation. The GRNN can be viewed as the normalized RBF network where there is a unit centre at every training case. The network architecture is of highly parallel structure and follows single pass learning. The algorithm provides smooth transitions from one observed value to another even with sparse data in multidimensional measurement space. The algorithm adopted in the GRNN can be also used for any regression problem where an assumption of linearity is not justified. GRNN can be termed as universal approximator for smooth functions and is capable of solving any smooth function approximation problem (Disorntetiwat, 2001).

Usually, FFBP performance is observed as very sensitive to randomly assigned initial weights which may lead to long computational time for convergence. On the other hand, this problem was not appears in GRNN simulations (Cigizoglu, 2005). Also, the GRNN is not linked up to iterative training procedure as required by FFBP

(Specht, 1991). The problem of trapped in local minima was not appears in GRNN as was critical in FFBP. Due to the reasons mentioned above, GRNN was preferred instead of FFBP.

It is observed that sufficient lengths of water table depth measurements are usually unavailable in developing countries (Coulibaly et al, 2001). Such countries typically have very few observable wells and lack long time period time series data due to budget limitations and policy (Affandi et al 2007). This is the driving element in developing model that is capable of forecasting GWL using limited data.

The current study aims to examine potential and applicability of RBF and GRNN models in this situation for predicting GWL using time series data. Also, we investigate the effect of meteorological parameters which includes temperature, relative humidity, rainfall, evaporation, land use/cover on groundwater level fluctuations. Further, we explore the applicability of this network for groundwater level forecasting in multistep lead-time upto six week ahead. Finally, we investigated the suitability of network for the site specific groundwater level prediction with acceptable and improved accuracy.

## 1.3. Scope of the Present Study

The scope of the present study is to evaluate the application of various Artificial Neural Networks algorithms such as RBF and GRNN for groundwater level forecasting at site specific catchment (microwatershed) using historical groundwater level data and meteorological data.

The present research work focused on the suitability of RBF and GRNN techniques in groundwater hydrology and insufficient data situation for groundwater level forecasting. It is expected that this research work will be helpful for proper planning, operation, development and management of groundwater resources in a sustainable manner.

## 1.4. Research Objectives

In the present research, an attempt has been made to examine the applicability and capability of different ANN networks for groundwater level forecasting. Therefore, based on literature review, considering groundwater related problems in coastal region (Dakshina Kannada) and the availability and limitations of database/data sets, the research objectives are framed. In this context, the specific objectives for the present study are identified as follows.

### 1.4.1. Main Objective

The main objective of this research is to investigate the utility of Artificial Neural Networks (ANNs) algorithms like RBF and GRNN for short term forecasting of groundwater level fluctuations forecasting. Short term is defined as weekly time steps up to a time horizon of one week ahead. This research work explores the capabilities of RBF and GRNN compares the performance of this tool to conventional approaches used to forecast groundwater level at one, two, three, four, five and six weeks in advance.

### 1.4.2. Specific Objectives

- Development of RBF and GRNN model for groundwater level forecasting using time series data
- To assess the performance of model for higher lead-time forecasting and multiple input scenario
- To assess the suitability of GRNN model using meteorological variables groundwater level forecasting
- Selection of best network for site specific groundwater level prediction in coastal region.

## 1.5. Conceptual basis for the study

The conceptual basis for the study is shown in Figure.1.6.From the Figure 1.1 it is to understand how the forecasting groundwater level has been carried out in a systematic manner using time series data and cause effect and variables and then by adopting the various neural networks to select the best model for the site specific problem.

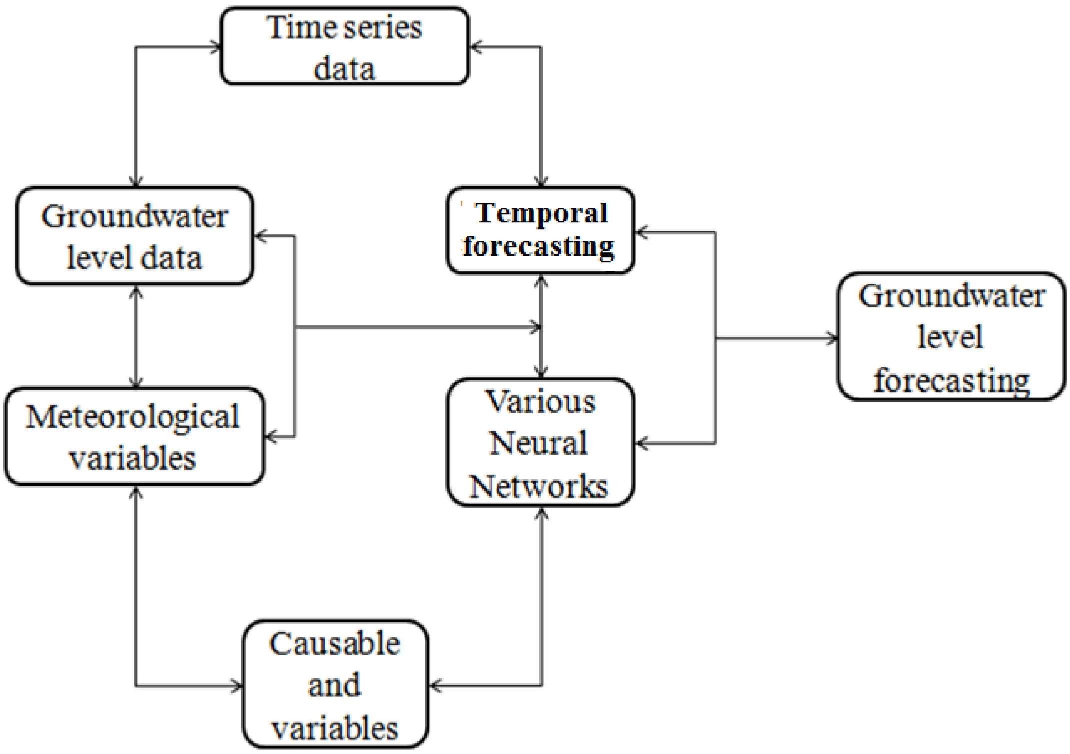



Figure 1.1 Conceptual basis of the present study

## 1.6. Organization of the Thesis

This thesis comprises of five chapters as follows.

**Chapter 1 Introduction** Presents the relevant information pertaining to groundwater water related problems, and further deals with the problem identification, research objectives, assumptions and limitations of research, overview of the conceptual basis for the research,

**Chapter 2 Literature Review** Discusses the groundwater level fluctuations, conventional methods of forecasting and thereby explains the effects of meteorological parameters on groundwater level, ANN application in groundwater related problems so far.

**Chapter 3 Materials and Methodology** Describes the study area and its significance, different datasets used and explains the methodology adopted in order to achieve the research objectives. This includes the essential background information, a description of the structure and terminology of various ANN models such as RBF, GRNN, NARX and FFBP.

**Chapter 4 Results and Discussion** Describes the method of evaluation and goes on to present the analysis of the results obtained from the developed models and network performance for different input configuration.

**Chapter 5 Summary and Conclusions** presents summary of research work carried out, contribution and conclusions. Further, the limitations of the research work and scope for future work are included towards the end.

# CHAPTER – 2

# LITERATURE REVIEW

## 2.1 Introduction

The present chapter focuses on a review of research carried out in the past involving the time series analysis, effect of meteorological parameters and suitability of Artificial Neural Networks algorithms for groundwater level fluctuations in catchment groundwater modeling.

It is presently attempted to make the literature review on the applications of ANN in groundwater engineering particularly in the following four categories.

1. Assessment of groundwater level in coastal regions
2. ANN applications for groundwater level forecast
3. Cause and effect relationship on groundwater level fluctuations
4. Suitability of neural network modeling in multistep lead time forecasting using few data and insufficient information

## 2.2 Causes of groundwater level changes

Groundwater level is a dynamic flow system, it travels into and thorough aquifers from areas of higher elevation to lower level. Groundwater level changes occur due to several reasons, both natural and anthropogenic activities. In general, groundwater level changes are broadly classified into two categories. They are short-term and long-term groundwater level changes. Short-term changes can observe only when the water level measurements are collected at several times in a day/week. Long term changes can be observed only after several years. A groundwater level fluctuation occurs due to changes in the volume of water stored in the aquifer, changes in atmospheric pressure and changes caused by aquifer deformation. Aquifer storage is due to addition/extraction of water from a particular well by natural or man induced activities. Aquifer storage is mainly depends on the porosity of the soil. Groundwater levels in major aquifers are declined due to pumping for water supply and usage of tree plantation. Aquifer deformation are generally occurs due to earth tide or earthquakes. The tidal effect on the groundwater is known as earth tides which are directly related to gravitational effects of the sun and moon. This type of issues is common in coastal area. When the precipitation is high, there will be significant changes in water level during wet period, because evaporation and plan usage rates are low. Usually unconfined aquifers are quite sensitive and respond quickly to changes in rainfall than that of confined aquifer.

## 2.3 ANN Applications in groundwater hydrology

In recent decades, considerable interest has been raised for various ANN algorithms over their practical applications, because the neural networks can automatically develop a forecasting model through a simple process of the historic data. Such a training process enables the neural system to capture the complex and non-linear relationships that are not easily analyzed by conventional methods (Lin and Chen 2004). ANN were first developed in 1940s/around more than 60 years ago. Since then, it has been widely used on pattern/speech recognition and image/signal processing in the field of science and technology (Widrow and Lehr, 1992). The application of ANN in hydrology started in the early 1990s (ASCE, 2000a; 2000b). In the late 1990, ANN modeling began to be used in the simulation of water table fluctuations at different locations (Yang et al, 1997; Yang et al, 2000; Coulibaly et al. 2001; and Affandi et al., 2007). These/the above studies indicate that ANN modeling is a convenient tool for predicting water table fluctuation, especially in areas where the aquifer system and its detailed information is not available or where the available records are relatively short. ANN can solve a variety of groundwater related problems where conventional methods have limitations. However, use of ANN technology is on the increase interest in groundwater hydrology for the purpose of forecasting, modeling, measuring contamination and its remedies and estimation of aquifer parameters and many more. Hence, ANN is considered as a promising tool in groundwater resources when sufficient data are available and even with limited data records too.

## 2.4 Motivation to Artificial Neural Networks (ANN)

Artificial neural networks are powerful tools that can learn to solve problems in a way similar to the human brain. An artificial neuron is a computational model inspired in the natural neurons. The natural neurons receive signals through *synapses* located on the dendrites or membrane of the neuron. When the signals received are strong enough (surpass a certain *threshold*), the neuron is *activated* and emits a signal though the *axon*. This signal might be sent to another synapse, and might activate other neurons. The complexity of real neurons is highly abstracted when modeling with artificial neurons. These basically consist of *inputs* (like synapses), which are multiplied by *weights* (strength of the respective signals), and then computed by a mathematical function which determines the *activation* of the neuron. Another function (which may be the identity) computes the *output* of the artificial neuron (sometimes in dependence of a certain *threshold*). ANNs combine artificial neurons in order to process information. The schematic biological neuron and artificial neuron are shown in Figure 2.1 and Figure 2.2. Figure 2.2 shows the structure of the simple ANN. It is a combination of many single neurons.

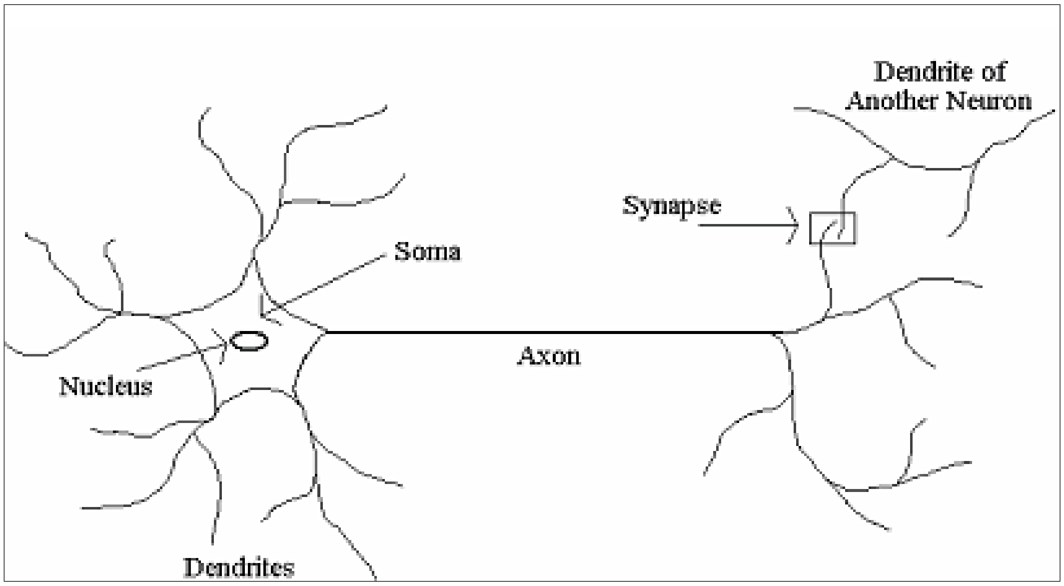



**Figure 2.1 Schematic diagram of a biological neuron**

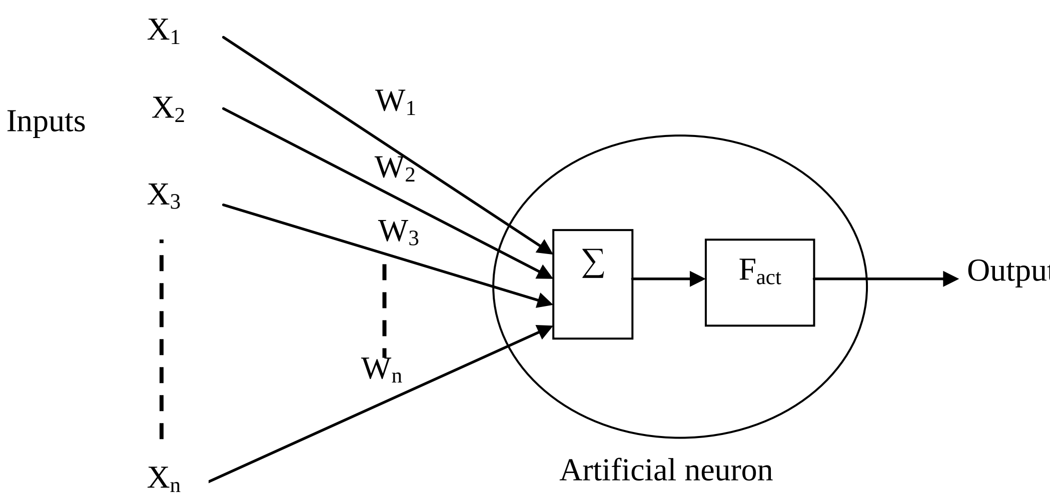



**Figure 2.2 Schematic diagram of a simple artificial neuron**

Where $X_1$, $X_2$ …$X_n$ are the inputs, $W_1$, $W_2$, ….$W_n$ are the weights, $F_{act}$ is the activation function.

In general, the higher a weight of an artificial neuron is, the stronger the input which is multiplied by it will be. The weights can also be negative, then the signal is inhibited by the negative weight. Computation of the neuron varies based on the weights. Outputs of artificial neuron for specific inputs can be obtained by adjusting the weights. When the neuron are less then it is easy to adjust the weights, but when size of neurons increases from hundreds to thousands, then it quite complicated to find all the necessary weights by hand. However, in order to obtain the desired output from the network, researchers are explored several algorithms which will adjust the weights of ANN. This process of adjusting the weights is known as learning or training. ANNs gather knowledge by detecting the patterns and relationships in data and learn (or: are trained) through experience.

The number of types of ANNs and their uses is increasing day by day. Different ANN are having different topology, the learning algorithms, etc. ANN such as backpropagation algorithm (Rumelhart and McClelland, 1986) is widely used for learning the appropriate weights as it is one of the most common models used in ANNs, and many others are based on it. Since the function of ANNs is to process the information, they are used mainly in fields related with it. There are a wide variety of ANNs that are used to model real neural networks, such as behavior and control of machines. Also, there are ANNs applications which are used in both Science (Medicine) and Technology (Engineering) purposes, such as pattern recognition, forecasting, data compression, signal processing and many more in multi disciplinary fields.

## 2.5. Classification of Artificial Neural Networks (ANN)

Artificial Neural Networks are sub branch of artificial intelligence. Broadly ANN are classified into two categories. They are feed-forward neural networks and recurrent/feed-back neural networks. Various types neural networks and their classification are shown in Figure 2.3 and are discussed in briefly. The back propogation (BP) is most commonly and widely used for several groundwater related problems such as prediction, groundwater pollution, water quality analysis, aquifer parameter estimations etc.

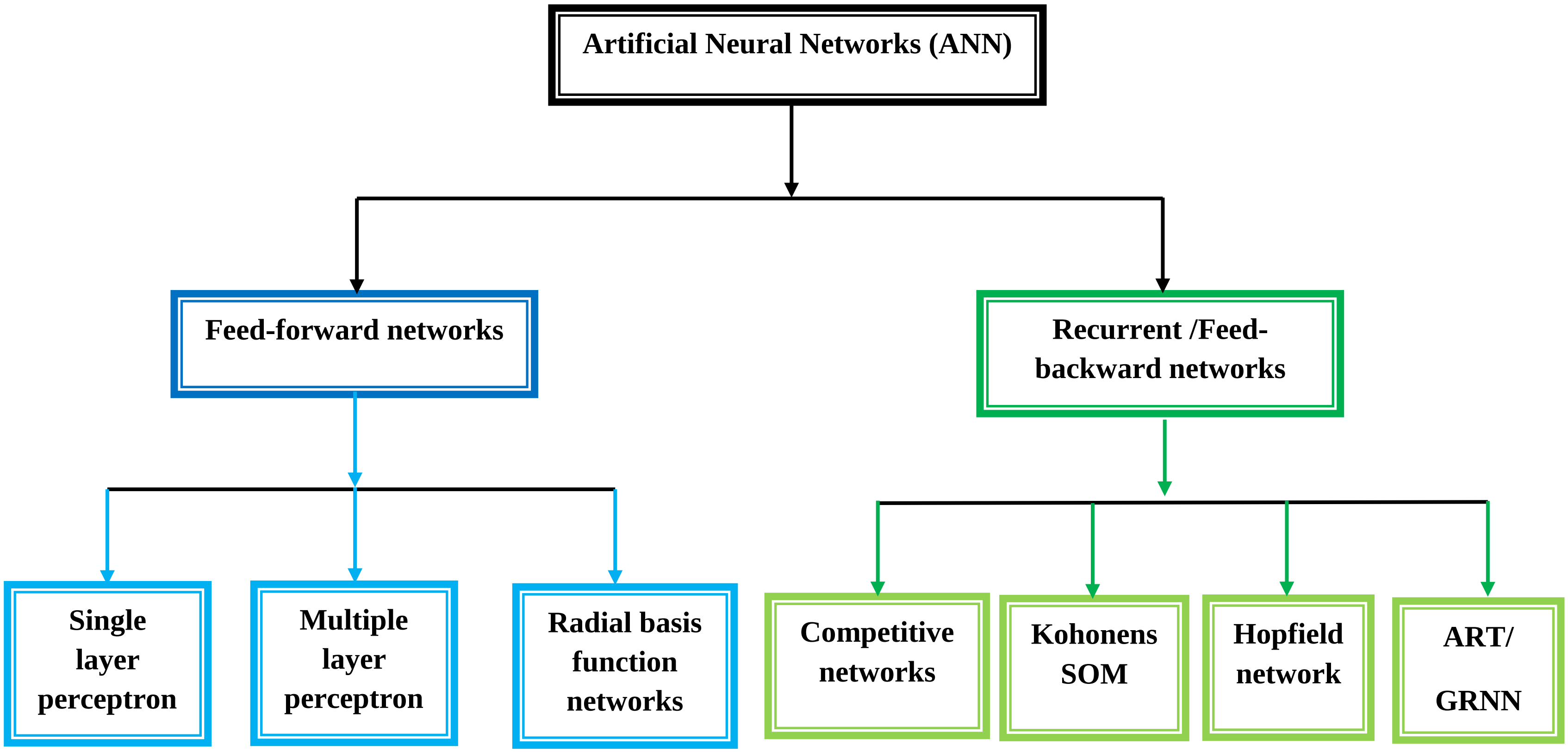



**Figure 2.3 Types of Artificial Neural Networks and their classification**

## 2.6 Selected ANN Applications for Groundwater Level Forecasting

A perceived strength of ANN is the capability for representing complex, nonlinear relationships as well as being able to model interaction effects. This capability is expected to be beneficial for forecasting since the relationship between the input variables and the resulting output (groundwater level) is typically quite complex. To explore the ability and capability of Artificial Neural Networks as an advance tool to use in the groundwater hydrology, in this direction a detailed literature survey has been carried out. The specific issues addressed in this research include the applicability of various algorithms of ANNs for forecasting groundwater levels for better accuracy, multistep lead times, limited data and their influencing variables; seasonal analysis of groundwater level, effect of meteorological parameters; the approaches that are best used for identifying the appropriate structure of the ANN for groundwater level in catchment groundwater modeling.

Coulibaly et al. (2001) assessed the performance of three types of functionality different ANN models for prediction of GWL fluctuations using hydro-meteorological data such as past groundwater level, rainfall, river stage and temperature. The ANN model performance was found satisfactory.

Sudheer et al. (2002) described the selection procedure of cross correlation, auto correlation and partial auto correlation for identifying an appropriate input vector/parameter which has a significant influence on the predicted output. Their proposed algorithm is simple and easy to use and also, helps to find the relationship between the input and output time series/variables. However, the best input variable can improve the performance of the model and variable that does not have any significant effect on the performance of the model can be trimmed off, through that computational time, number of models can be reduced and avoid the long trial and error procedure.

Kerh et al. (2003) carried out settlement estimation due to the effect of groundwater drawdown using FFBP along main red line sections of Kaoh siyung mass rapid transit, Taiwan. They used onsite boring test data such as void ratio, groundwater drawdown depth, unit weight of soil as input parameters. The applicability and capability of BPNN model demonstrated in their study.

Coppala et al. (2003) investigated the potential of ANN to complex groundwater management problems. Various ANN model developed with hydrologic and climatic data for geo-hydrologic environment problems. They found that ANN substantially outperformed a well calibrated numerical problem model. They demonstrated that ANN techniques can solve many varieties of problems and overcome limitations of traditional physically based flow models.

Anctil et al. (2004) examined the effect of data length using multiple-layer perceptions (MLP) and conceptual model. 1, 3, 5, 9, and 15year time sub-series created from a 24year training set, shifting by a 1-year sliding window to forecast 1-day ahead stream flow predictions. Based on their results, it is revealed that the MLP stream flow mapping was efficient as long as wet weather data were available during training. Increases in the length of data the results may consistent due to longer series of data which contains valuable information and gives clear information of hydrological behavior of a particular variable. However, it is plausible that a large number of internal parameters may allow better use of longer calibration series, but this was not verified in their study.

Lallahem at al. (2005) evaluated the feasibility of Artificial Neural Network for estimating groundwater level in unconfined aquifer of Northern France. They concentrated on the most influential parameters which has impact on groundwater level in fissured chalky media. In addition to this they also focused on the effect of temporal and spatial information with the help of variety of piezometer readings using current and past data sets. Moreover, they focused to simulate the groundwater level in a selected piezometer.

Daliakopoulos et al. (2005) examined the performance of different neural networks in groundwater level forecasting at Messara valley in Greece. Where over-exploitation of groundwater is takes for long period. They have compared seven different type of architecture training algorithms performance and found that standard feedforward neural network trained with LM algorithm provides better results upto eighteen months forecasting.

Almedeij and Alsruwaih (2006) investigated the periodic pattern of groundwater level fluctuation in residential areas of Kuwait. Monthly water level data for six monitoring wells are used in the study to examine relationship with monthly temperature and evaporation. A time series model that regards the influence of detected periodicity is developed for water level data for providing forecast of groundwater level change.

Nayak et al. (2006) investigated the potential of Artificial Neural Network for forecasting groundwater level in an unconfined coastal aquifer at central Godavari delta region in India. Monthly averages of rainfall, canal releases and groundwater level are used as input for three observation wells to on spatial scale predict groundwater level. Cross correlation analysis was employed to find the significant relationship among the three wells and their influencing parameters. They studied the influencing factors for groundwater level at three different wells namely Munganda, Cheyyeru and Kattunga located in different places.

Affandi and Watanabe (2007a) had investigated groundwater level fluctuation under two different scenarios and compared with three different techniques, such as Adaptive Neuro-Fuzzy Inference System (ANFIS), Levenberg-Marquardt (LM) and Radial Basis Function (RBF). They found insignificance difference in performance among these three algorithms in groundwater level fluctuation forecasting.

Panda et al. (2007) investigates the response of groundwater levels to extreme weather events to understand the forcing mechanisms of droughts in consumption with anthropogenic pressure. They have analyzed pre and post monsoon groundwater level records of 1002 monitoring stations during the period 1994-2003. They found that the decline of groundwater level is due to deficient rainfall during dry years, high temperature and anthropogenic pressure with low rate of recharge in wet years.

Joorabchai et al. (2007) adopted artificial neural networks to simulate groundwater level fluctuations at east coast of Australia using back propogation algorithm. The data used in the study are water table, tide elevation, beach slope and hydraulic conductivity. They found that ANN model is very useful for prediction of groundwater level where variation in tide elevation appears the major influencial parameters in coastal aquifers.

Affandi et al. (2007b) examines and compares the capability of ANN with different BP algorithms for estimating groundwater level fluctuations, where Matlab was used to develop programme 5 daily measurements of groundwater level fluctuations data in an observation well. The input to the model uses six time lag groundwater level fluctuation data with 10 hidden neurons gave optimum result. It was found that LM algorithm delivered better results than RBF using relatively few data sample and they concluded the usefulness of this study in developing countries where lack of long-period time series data with few observation wells exists.

Jyothiprakash and Sahara (2008) used sophisticated ANN model to capture the pattern and predicting groundwater level time series. They have used groundwater level data at sriramsajar project reservoir, Andhra Pradesh, India using back-propogation algorithm with hyperbolic tangent activation function. The output predicted groundwater levels are found within accepted accuracy.

Yang et al. (2009) used BP ANN for prediction of groundwater level in the arid and semi arid areas of western Jalin province of China using monthly average groundwater level data from 1986-2011. They have suggested that BPNN model is reliable for modelling groundwater level for forecasting purpose in their study area.

Diemssie et al. (2009) developed a frame work to handle systematic error in physically based groundwater flow model that uses error correcting data driven models in a complimentary fashion in terms of bias prediction; uncertainty range the complimentary work has shown substantial work over the MODFLOW pattern. This integrated flow model significantly reduces the prediction errors and local bais.

Benerjee et al. (2009) used feed-forward neural network model to forecast groundwater level for various scenarios of stress on aquifer in hard rock aquifer system of Kurmaphally watershed in Andhra Pradesh, India. The application of ANN has successfully demonstrated for different scenario allowing modelling of complex dependencies.

Ma et al. (2009) combined back propagation neural network with differential evolution developed predicting model of groundwater level in Zhang jiakoe area of china. The model performed better than GA-BP.

Sreekanth et al. (2009) have developed ANN models to prediction of groundwater level using Feed Forward Neural Network–Levenberg Marquartd algorithm to improve the accuracy and reliability of groundwater level forecasting model using weather parameters.

Ghose et al. (2010) studied the effect of meteorological parameters such as precipitation, temperature and relative humidity on groundwater level. They compared the performance of RBF and FFBP for forecasting groundwater level. They concluded that ANN techniques are becoming popular because there is less need for internal aquifer system modeling. As where the detailed aquifer system information is not available to run a descriptive model, and even with limited data also the ANN technique will gives better results.

Chen et al. (2010) proposed a SOM-RBFN model (combined theory of self-organizing map and radial basis function network) to forecast groundwater level at southern Taiwan, in order to overcome the position of radial basis centers. They observed that too much information/data is unable to improve the generalization ability of the multisite model due to more noises to the networks and undermines the performance of the network. Though SOM-RBFN multisite model can forecast more precisely than the single site model, but still there is question how to choose and how much data is required to get the accurate and reliability result. However, their research is confined to prediction of groundwater level in vertical plane only.

Weesakul et al. (2010) used simple Genetic Algorithm (GA) and ANN as alternative tool for monitoring and forecasting groundwater level fluctuations using 12 years data on monthly basis at Bangkok area and its vicinity. In total, 43 monitoring wells are identified and grouped into three categories based on the correlation (low <0.9, medium, 0.9 to 0.92 and high >0.95). GA is used to divide the area into sub-regions within the watershed. Based on their results they observed that ANN has a better performance for all cases with accuracy of 9% to 26% relative error. However, they also noticed that excessive pumping rate of groundwater in Bangkok results in land subsidence problem and saltwater intrusion problem arises in shallow aquifers which are adjacent to the coast.

Sethi et al. (2010) have investigated influencing and controlling factors on the groundwater table in a specific geomorphorlogic Munijhara microwatershed in Nayagarh block of Orissa, India. Monthly rainfall, groundwater level and potential evapotranspiration (PET) data for a period of 2005-2008 are used as inputs to develop ANN models. Forecasting groundwater level has been carried out for different geological formations. Their results showed that the prediction accuracy in flood plain and upland plain areas were comparatively better than that of granite zone. They also observed that the FFBP performance is equally good even with limited data.

Mohanty et al. (2010) used the three different ANN algorithms such as gradient descent with momentum and adaptive learning rate back propogation (GDX) algorithm, Levenberg Marquartz (LM) algorithm and Bayesian regularization (BR) algorithm to predict the groundwater level at Bayalish Mouza near Kathajodi RIvwe basin of Orissa, India where BR performance was better.

Ghadampour and Rakshandehroo (2010) used FFBP to forecast groundwater depth. The data sets of an observation well in Union County New Jersey, was used in the study as 80 days of the domain. It was found that more accurate measure of daily data was the reason for better forecast.

Trichkas et al. (2010) used ANN to predict hydraulic head at a well location using advert aquifer in Texas, which is a unique groundwater system and one of most profile artesian in aquifer in the well. Hydrologic parameters like rainfall and temperature and as well as pumping rate nearby wells were used as input. The results show that there is a need for exact knowledge for pumping in karstic aquifer with suggesting ANN was preferable.

Mayilvaganan and Naidu (2011) compared two computational intelligent techniques such as ANN and Fuzzy Logic (FL) in groundwater level prediction of kulingapuram watershed of Tamilnadu, India. The ANN model was developed using sigmodial activation function and back propogation algorithm, where inputs are monthly rainfall and groundwater level. They found that ANN performed significantly better than FL with Gaussian membership function.

Aflatooni and Mardaneh (2011) studied the effect of temperature and rainfall on groundwater level fluctuations using time series data and cross-correlation analysis at Maharloo basin located in south west of Iran. Moreover, they observed when the air temperature increases the water table declines with a delay time and after departure of the rain, the water table increases with a delayed time interval.

Sreekanth et al. (2011) made a comparison between FFBP trained with Levenberg-Marquartz algorithm and adaptive neuro fuzzy inference systems (ANFIS) for forecasting groundwater level in a Maheshwaram watershed, Andhra Pradesh, India and found that ANN models slightly more accurate on an average than that of ANFIS.

Schilling and Zhang (2012) have studied the temporal scaling of groundwater level fluctuations near a stream using spectral analysis to identify the potential of surface water and groundwater interaction in riparian zone of Walnut Creek in Jasper County, Iowa. Hourly groundwater level data for a period of July 2005 to March 2008, stream discharge at 15 minute interval for a period of 1996-2005 and daily precipitation data of the same period were used. In general, spectral analysis is used to study the temporal variations of hydrologic process. However, in their study area the groundwater levels respond quickly to precipitation recharge. They assessed the hydrologic and geomorphic factors that have scaling variations. Moreover, this type of studies is useful where long-term monitoring or intensive sampling may not be practical or possible.

Here, it was observed that most of the researchers made an attempt/tried to improve accuracy of their developed models by adopting different networks. However, it was noticed that very few researches have used GRNN and RBF networks in groundwater hydrology. Hence, in this study, RBF and GRNN networks are used to forecast groundwater level using time series data for different input scenario and multiple lead time forecast. In addition to this, an attempt has been made on the effect of meteorological parameters on groundwater level forecasting model.

## 2.7 Outcome of Literature Review

Based on the literature review on ANN applications in groundwater hydrology it is observed that some of the grey area appears as mentioned below

- Few research works were carried out on groundwater level forecasting other than FFBP. So, there is wide scope to explore the different ANN networks for groundwater level forecasting

- Multiple lead time forecasting is not tried so far which affects long-term planning.

- There is no data integrated approach for Groundwater level forecasting (combination with time series and causable and variable)

- Poorly understood or partly understood of groundwater system and their complex hydro-geological process need to study in detail manner.

- A major concern for several researchers experienced in different application of ANN is, the lack of quality and quantity of the required data, detailed information of the system or problem and data size of effective domain in time series.

To address above limitations, an attempt has been made to improve the forecasting accuracy of groundwater level using various Artificial Neural Network algorithms for various input scenarios.

## 2.8 Closure of the study

Considering the above aspects, an attempt was made to develop an ANN based model for forecasting groundwater level fluctuations in a specific geologic situation and test its potential in predicting groundwater table depth with limited time series groundwater level data at temporal scale. Also, stress is given for Forecasting accuracy as it is one of the important factors involved in selected a forecasting method. Hence, research directed at improving upon the effective time series models using ANN are.

- The applicability of two neural networks such as GRNN and RBF are investigated and predicting performances are evaluated in GWL forecasting
- Selection of best model both in time series and cause and effect variables in GWL forecasting
- Assessment of model accuracy for multi-step lead time GWL forecasting

# CHAPTER - 3

# MATERIALS AND METHODOLOGY

## 3.1 Introduction

The present work aims to forecast the groundwater level at temporal scale using various Neural Networks in a microwatershed of coastal aquifer in Dakshina Kannada, southwest coast of India using weekly time series data. Also, an investigation has been carried out on the influence of meteorological parameters on groundwater level fluctuations. In this chapter the proposed methodology is to investigate the potential, capability and applicability of various Neural Networks such as Feedforward Backpropogarion (FFBP), Non-Linear Auto Regressive with Exogenous inputs neural network (NARX), Radial Basis Function (RBF), Generalized Regression Neural Network (GRNN) for groundwater level forecasting are discussed in detailed manner. A comparative study was made among different ANN networks. Performance evaluation of various developed models was examined based on performance indices and the selection of best ANN model. Finally a suitable ANN technique is suggested for site specific problem in the current study area.

Time series analysis is useful to understand the complete behavior of groundwater level in a particular catchment. Since it yields the long-term trends of water table fluctuations, and thus it can aid one in arriving at effective and meaningful policy decisions and also to take scientific measures for the development of groundwater resources.

### 3.2. Study Area

The study area selected for the present research is the micro-watershed that comes under the sub basin of Pavanje river catchment at west coastal aquifer of India. It is situated approximately 3km from the Arabian Sea which extends over an area of approximately 40 sqkm as shown in the Figure 3.1. The study area is located between 13°00′00″ to 13°02′30″ North Latitude and 74°47′00″ to 74°50′00″ East Longitude. It receives 80% of total annual rainfall during the southwest monsoons and remaining 20% rainfall during non monsoon period where annual average is 4200mm. In the study area, Lateritic soil covers most parts of the region and is fairly common in the area occupied by the Deccan traps and some Archaean Gneisses.

Laterite gravelly soil mainly consists of coarse grained soil and hence is porous and highly permeable. The geological formation of the study area consists of 3 layers. The laterite deposits vary in thickness from 3 m to 15 m. usually first layer or top layer of soils is ferruginous in character and is hard and dark brown in color. The thickness of this layer is ranges from 0.5 m to 1.5 m. Second layer is of aluminum in characteristic consists of fines in the form of silt and clay and finally thick layer of fine silt and clay bed is present below this layer which is underlined by impervious Granitic Gneiss. Hence, the study area may be classified as rich lateritic soil zone (Udayakumar G 2008). The hydraulic conductivity is in the range of $10^{-4}$ to $10^{-5}$ cm/sec. The specific yield is in the range of 0.08% to 4.94% (Hareshendra 1991). The average recharge coefficient is 7% with infiltration rate 0.9 cm/hr to 27.5 cm/hr (GEC 1997).

Precipitation is the principal source for groundwater recharge in coastal region. In spite of receiving heavy rainfall during monsoon season in the microwatershed, but still the study area experiences acute shortage of drinking water during summer season (March to May). The water shortage problem is due to the non-availability of surface water retaining structures as it is not feasible considering the soil behavior. The soil is highly pervious and porous in nature. The infiltration rate is high and shallow wells shows very quick response to rainfall event and the water table rise immediately and subsequently drastically water level goes down within short period of time. In spite of dry up of shallow wells during the summer, shallow wells are more preferable than that of deep wells because deep wells are prone to salt water intrusion.

Altogether 24 open wells, (shallow wells which are less than 9.0m depth from ground surface and deep wells which are more than 9.0m from ground surface) were selected for the entire micro-watershed to make comprehensive analysis of groundwater level fluctuation. In the current study, shallow and deep wells were analyzed separately. Groundwater level varies from well to well both spatially and temporally. The main intension of selecting these different shallow and deep wells is to understand the behavior of groundwater level due to nearby streams, and various type of landuse/cover. The locations of 24 open wells in the study area are shown in Figure 3.1.

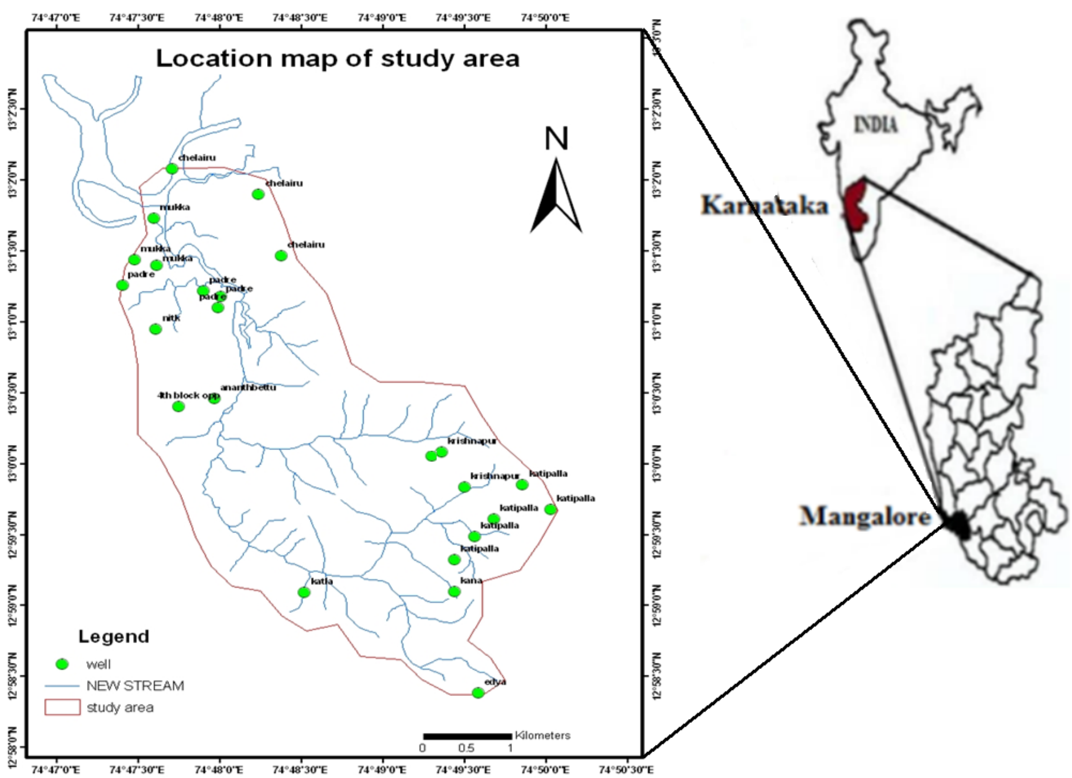



**Figure 3.1 Index map of Study area and location of 24 observation wells**

### 3.2.1. Temperature

Temperature is one of major factor which has direct influence on groundwater level in the open wells of any catchment. The average max and min temperature during the study period are shown Figure 3.2. From the Figure.3.2 it appears that April and May are the hottest months. The December and January are the cooler months. Average maximum temperature is 32$^{o}$C and average minimum temperature is 22$^{o}$C.

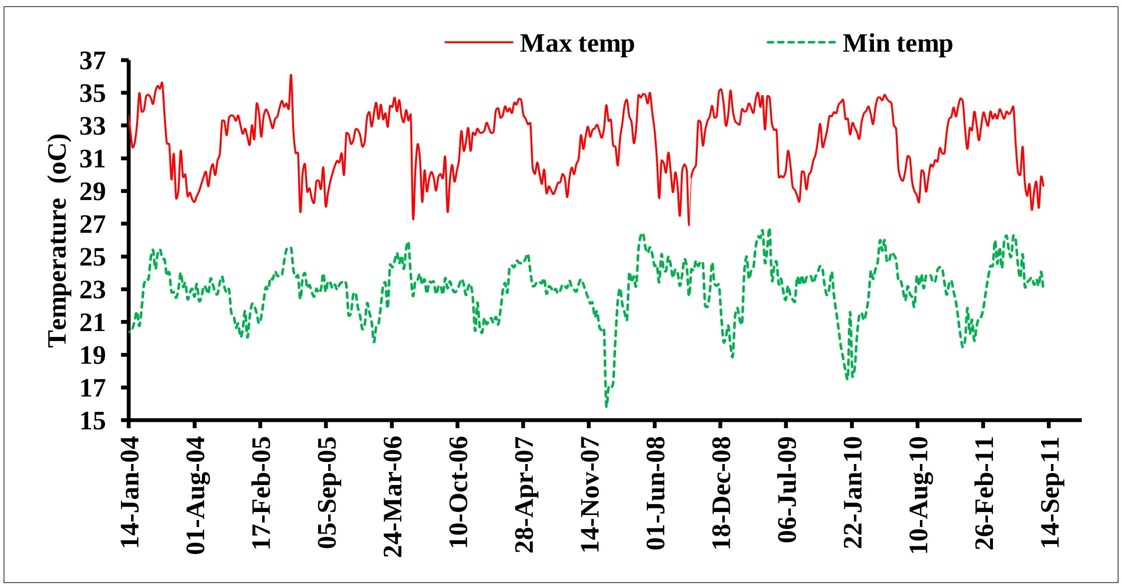



**Figure.3.2 Weekly variations in the temperature (2004-2011)**

### 3.2.2. Rainfall

The south-west monsoon is the principal rainy season during which the state receives 80% if its rainfall. Rainfall in the winter season (January to February) is less than one percent of the annual total, in the hot weather season (March to May) about 7% and in the post-monsoon season about 12%. Figure 3.3 shows weekly hydrograph and hyetograph variations during study period. It is observed that due to the presence of lateritic formations in the study area, most of the wells show a similar variations/pattern irrespective of the depth of wells. In general, the well hydrograph clearly indicates that the high groundwater level corresponds to period of high rainfall and low groundwater level corresponds to period of low rainfall.

South-west monsoon normally sets in over the extreme southern parts of the state by about 1$^{st}$ of June and covers the entire state by about 10$^{th}$ of June. The rainy months July and August account individually to about 30% and 18% of annual rainfall.

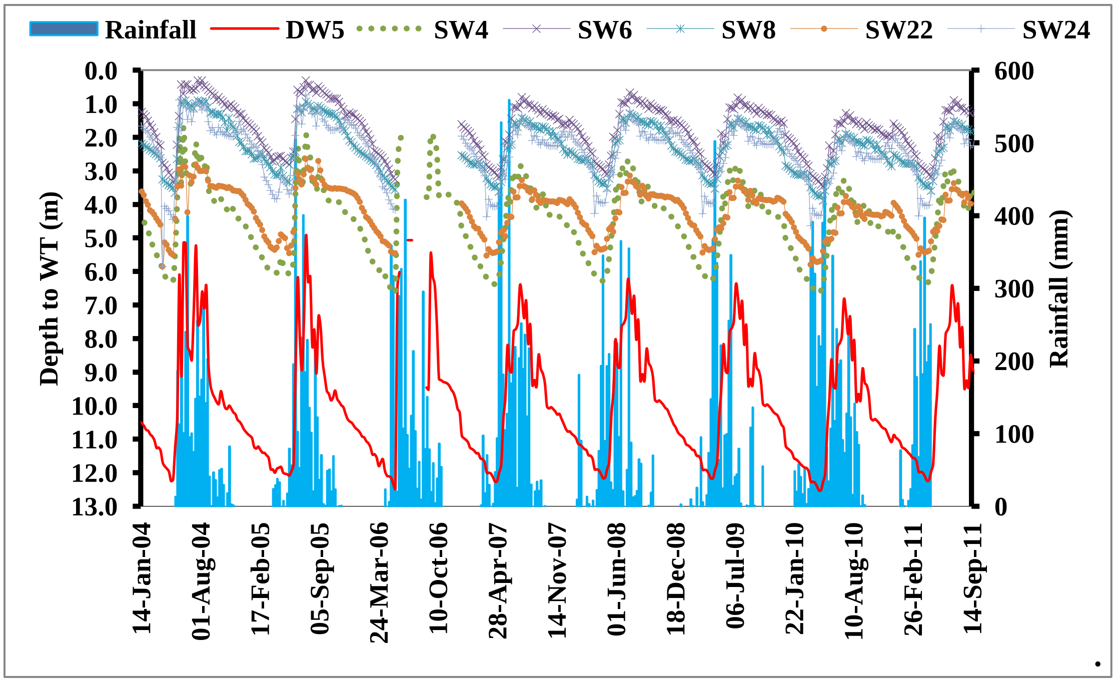



**Figure 3.3 Weekly hydrograph and hyetograph (2004-2011)**

### 3.2.3. Evaporation

Evaporation is having direct impact on the groundwater levels which further lower the groundwater level. Weekly evaporation variations during the study period are shown in Figure 3.4.

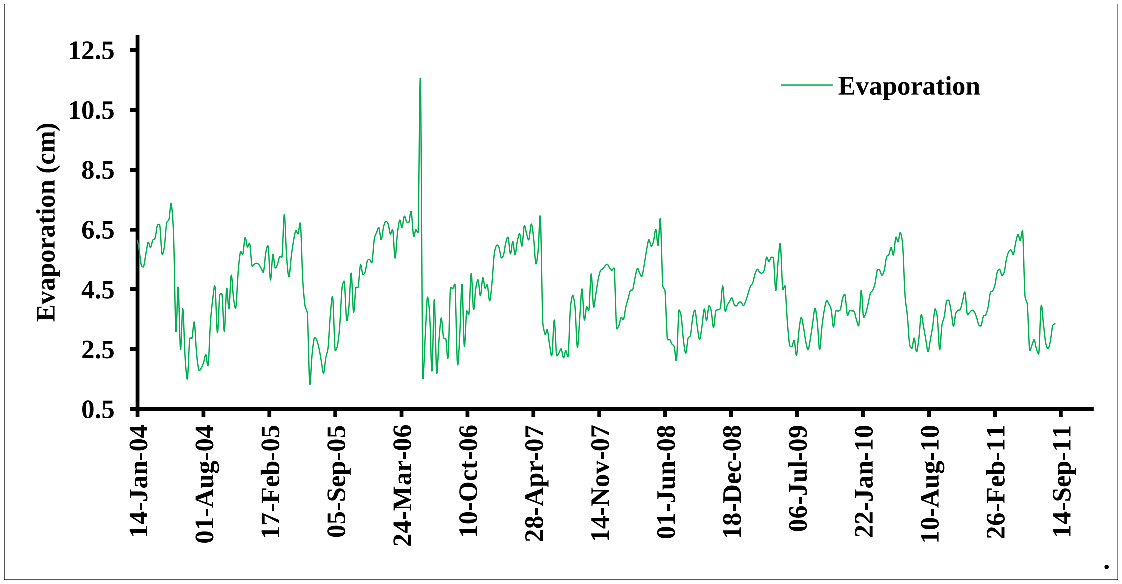



**Figure 3.4 Weekly evaporation (2004-2011)**

### 3.2.4. Relative humidity

The relative humidity or aridity of a region is another factor that influences the abundance of groundwater. Normally in humid region, water in the top soil layer is slowly evaporates into the atmosphere where as in the case of deserts it quickly into the atmosphere. Figure 3.5 shows the relative humidity pattern of the study area.

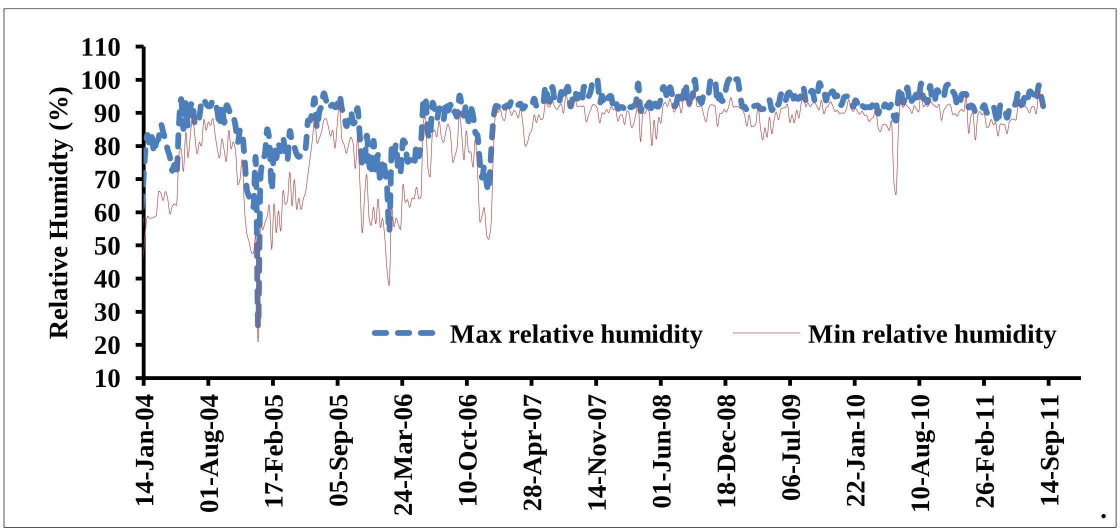



**Figure 3.5 Weekly relative humidity (2004-2011)**

Also, the study area has representatives of all types of variations in topography-high mountains, plateaus, residual hills and coastal plains. It consists mainly of plateau which has higher elevation of 600 to 900 metres above mean sea level. The entire landscape is undulating, broken up by mountains and deep ravines.

The study area is dominated by various types of mixed forests and varies land cover such as Temperate Broadleaved, Subtropical Evergreen, Moist Deciduous, Dry Deciduous, Degraded Forest, Irrigated Agriculture, Rainfed Agriculture, Intensive Agriculture, Water Body, Fallow/Arable, Cloud/Shadow, Plantation Orchard, Alpine Meadow and Grassland as various Land use classes with a rapid increase in built area.

### 3.3 Data Collection and Field Observations

In order to improve the performance of any model, the model requires sufficient amount of input data. In this type/such of situation, it is often difficult to obtain reliable forecasts of future groundwater level events due, in part, to the lack of accurate data for the required model inputs. The remote location and complex hydraulic relationships of many of the sites contribute to a poor quality of groundwater level monitoring. The advance tool such as ANN has been found to be effective and more efficient in situations where noisy data attached with shorter length of observed data.

Two different types of datasets are considered in the current research. They are historical time series groundwater level data and meteorological parameters. The obtained two different types of dataset and their basic characteristic pertaining to the present study and its relevant information are discussed. The details of data used and their purposes in the current work are presented in Table.3.1.

Table.3.1 Details of available data and their purpose (Data Division)

| Sl. No | Data Type | Years (s) | Data Source | Purpose/Usage of data |
|---|---|---|---|---|
| 01 | Weekly groundwater level (m) | 2004-2011 | *AMD and Field visit | Development of RBF , GRNN , FFBP, NARX models for Short-term GWL forecasting |
| 02 | Precipitation(mm)<br>Evaporation (mm)<br>Relative humidity (%)<br>Temperature ($^{o}$C) | 2004-2011 | *IMD Dept of AMD, NITK<br>**IMD, Panambur station | Development of GRNN and FFBP model to investigate the Effect of meteorological parameters on GWL forecasting |

**AMD= Applied Mechanics and Hydraulics department, udayakumar 2008; **= IMD= India Meteorological Department, Panambur*

In the present study, weekly groundwater level data were obtained by monitoring the 24 open wells at different locations. Monitoring of groundwater level was carried out for a period of eight years (2004-2011). As shown in Figure 3.6, the wells are non-uniformly distributed at space as study interest is on GWL trend due to land use/cover. The nearest well (padre) is approximately 1 km and the farthest well is approximately 8 km (katipalla) away from seashore. (Appendix-1) Plate. 1 shows well location and number for shallow and deep wells. The primary analysis has been carried out using weekly groundwater level time series data. The selection of monitoring of open wells was based on their geological formations and various type of land use/cover. The details of wells are presented in Table. 3.2. These open wells were located in different places like Padre, Mukka, Munchuru, Mulky, Udaynagar, Krishnapura, Katipalla, Ganeshpura, Eddya, Kanna, Chelairu, Thadambailu, Madhya and NITK. These wells are private wells and used for domestic purposes only.

Figure 3.6 illustrates twenty four open wells and their location within microwatershed. Table.3.1 presents the well inventory details of all open wells in the study area. The second set of data i.e. meteorological parameters such as rainfall, temperature, evaporation, relative humidity, wind speed, and wind direction on daily basis are obtained from nearby Indian Meteorological Station (IMD) Panambur station, Karnataka, for the period of 2004 to 2011. The secondary work has been carried out to see the Influence of meteorological variables on groundwater level in the study area. The measured groundwater level with respect to ground surface is converted into mean sea level (MSL) using Differential Geographical positioning system (DGPS) survey in the study area. The Latitude and Longitude of the well points are indentified and details of location of wells are presented in Table.3.2

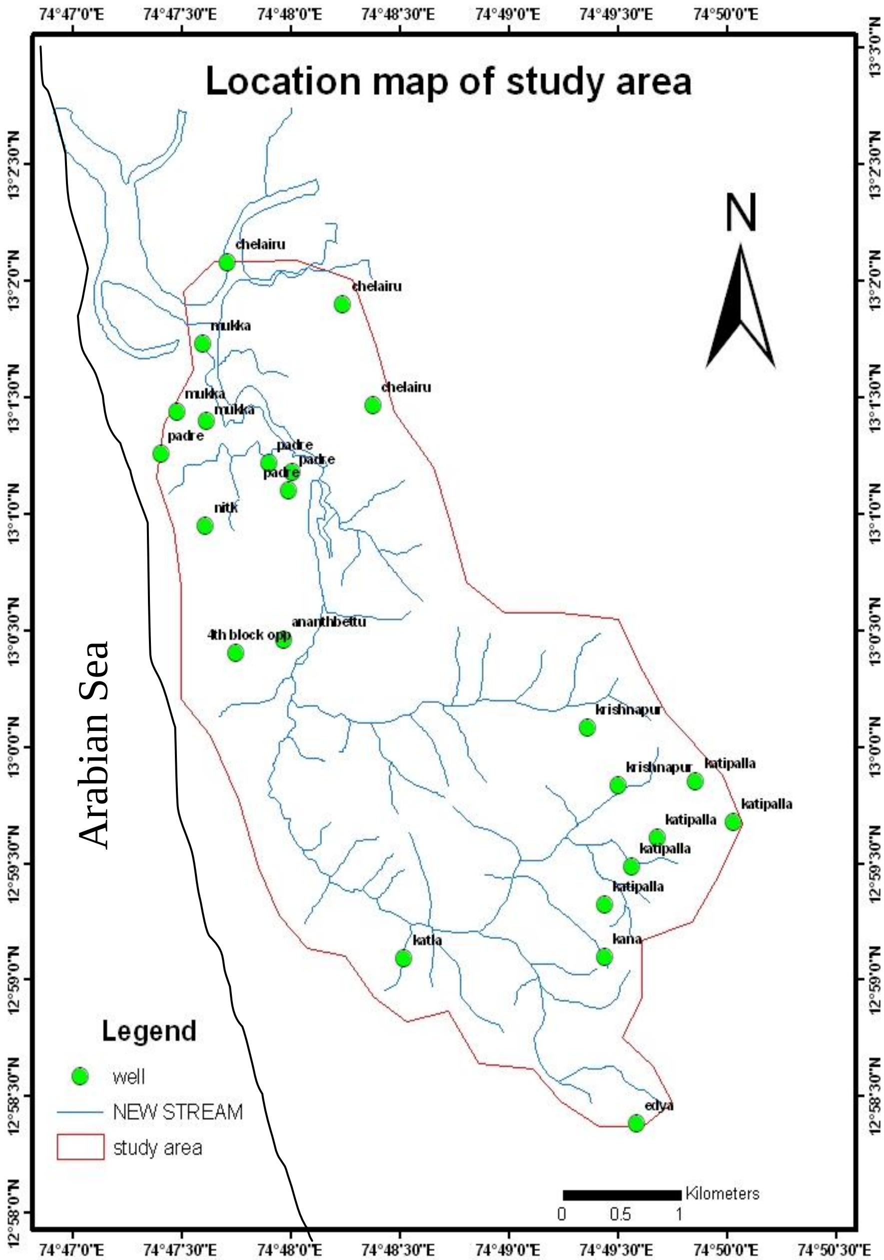



**Figure 3.6 Location of monitoring open wells in the study area**

Table 3.2 Well information (Well inventory data showing the details of open wells in the study area)

| Sl. No | Well number | Location of the well | Diameter of well (m) | Total depth of well (m) | Elevation (m) | Well Bottom Elevation in m (MSL) | Latitude | Longitude | Location/Land use/Land cover changes |
|---|---|---|---|---|---|---|---|---|---|
| 1 | DW1 | NITK | 5.00 | 9.20 | 8.08 | -1.113 | 13$^o$00'24" | 74$^o$47'44" | Built up area (low lying area) |
| 2 | SW2 | Padre | 1.80 | 9.35 | 10.04 | 0.697 | 13$^o$01'06" | 74$^o$47'59" | Thick vegetation (semi forest low lying area) |
| 3 | DW3 | Padre | 2.12 | 9.40 | 6.16 | -3.240 | 13$^o$01'15" | 74$^o$47'56" | Paddy fields (low lying area) |
| 4 | SW4 | Padre | 2.40 | 7.54 | 8.13 | 0.068 | 13$^o$01'10" | 74$^o$47'56" | Paddy fields (low lying area) |
| 5 | DW5 | Padre | 2.40 | 15.50 | 11.18 | -2.220 | 13$^o$01'13" | 74$^o$47'53" | Paddy fields (low lying area) |
| 6 | SW6 | Mukka | 2.00 | 4.30 | 4.43 | 0.105 | 13$^o$01'24" | 74$^o$47'36" | Thick vegetation, Close to stream (low lying area) |
| 7 | DW7 | Mukka | 2.60 | 11.60 | 13.40 | 1.808 | 13$^o$01'26" | 74$^o$47'28" | Thick vegetation (low lying area), Close to stream |
| 8 | SW8 | Mukka | 2.00 | 4.95 | 4.83 | -0.117 | 13$^o$01'43" | 74$^o$47'35" | Close to stream (low lying area) |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| 9 | DW11 | Chelairu | 2.40 | 14.80 | 27.42 | 12.625 | 13°01'27" | 74°48'22" | Close to bore wells Built up area (up land) |
| 10 | DW9 | Chelairu | 2.40 | 9.73 | 13.61 | 3.880 | 13°01'56" | 74°47'51" | Close to bore wells Built up area (up land) |
| 11 | DW10 | Chelairu | 2.40 | 9.35 | 8.95 | -0.399 | 13°01'54" | 74°48'14" | Close to bore wells Built up area (up land) |
| 12 | SW13 | Krishnapur | 2.75 | 8.71 | 24.76 | 16.050 | 13°00'05" | 74°49'21" | Built up area (mid land) |
| 13 | SW12 | Krishnapur | 2.75 | 9.51 | 26.09 | 16.587 | 12°59'52" | 74°49'30" | Built up area (mid land) |
| 14 | DW14 | Katipalla | 3.10 | 9.80 | 28.39 | 18.592 | 12°59'51" | 74°49'51" | Thick vegetation, Close to stream (low lying area) |
| 15 | SW15 | Katipalla | 2.20 | 7.90 | 22.49 | 14.595 | 12°59'36" | 74°49'40" | Thick vegetation Close to stream (low lying area) |
| 16 | DW16 | Katipalla | 1.34 | 12.94 | 30.73 | 17.795 | 12°59'19" | 74°49'26" | Thick vegetation Close to stream (low lying area) |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| 17 | DW17 | Katipalla | 2.66 | 9.60 | 27.09 | 17.493 | 12°59'29" | 74°49'34" | Thick vegetation Close to stream (low lying area) |
| 18 | SW18 | Katipalla | 2.65 | 8.50 | 38.02 | 29.529 | 12°59'39" | 74°49'55" | Thick vegetation Close to stream (low lying area) |
| 19 | SW19 | Kana | 2.33 | 9.00 | 25.02 | 16.022 | 12°59'06" | 74°49'26" | Built up area (mid land), Well with R.C.C rings |
| 20 | DW21 | Edya | 2.40 | 15.18 | 24.99 | 9.810 | 12°59'06" | 74°48'31" | Built up area (mid land), Deep wells with RCC rings |
| 21 | DW20 | Katla | 2.68 | 15.7 | 24.84 | 9.142 | 12°59'05" | 74°48'31" | Sparse vegetation Nearby to stream |
| 22 | SW22 | Munchuru | 2.40 | 7.48 | 9.30 | 0.748 | 13°00'27" | 74°47'57" | Build up area (up land) |
| 23 | DW23 | NITK | 5.78 | 11.02 | 11.20 | 0.186 | 13°00'56" | 74°47'36" | Thick forest Low lying area |
| 24 | SW24 | Munchuru | 2.40 | 5.80 | 6.50 | 0.70 | 13°00'26" | 74°47'47" | Build up area (up land) |

### 3.4 Measurement of groundwater level

Water table depth is the vertical distance from ground surface to the water table. Monitoring of open wells were carried out with the help of water level meter named dipper-T (graded tape) which gives both light and sound signals when it touches the initial level of water in the open well, with an accuracy of ± 2mm. The ground water level was recorded when the water level is in almost in stable condition such that water table fluctuation errors and recording time can be minimised. Water Level Meters are portable hand operated meters, sturdy, easy to use and read accurately to 1/100 ft. or each millimetre as shown Figure 3.7.


**Figure 3.7 Groundwater level measuring instrument-Dipper-T**

### 3.5 Types of open wells

The open wells are categorized into two types for the purpose of analysis based on their topographical location and overall depth of open wells. The first type of wells located in the topographic low area is considered as shallow wells. The depths of these wells are in the range of 4m to 9m from the ground surface. The slope of the terrain is mild. These wells show a quick response to the sudden variation in the rainfall compared to those wells in the topographic high region. Altogether 10 wells have been identified as shallow wells

The second type of wells located in topographic high areas with steep slopes is generally deep wells. Majority of these wells dry up later part of summer months. The depths of these wells are in the range of 9m to 17m. These wells respond relatively slow with the variation in rainfall. 14 wells are identified as deep wells.

### 3.6 Classification and selection of representative monitoring wells

Classification of monitoring was selected based on the type of land use/cover as shown in Appendix - 1 (Plate 2 to 5). Lateritic block rings well and well with RCC rings are shown in Appendix - 1 (Plate 2). Wells with Lateritic block rings and well with RCC rings were studied in the study area. It is observed that the water level is retains longer time in wells which is constructed with lateritic blocks than that of wells with RCC rings. Wells located in the different fields are shown in Appendix - 1 (Plate 3). It is clear that effect of watering to the crop has direct influence on the water table. Few wells are located in built up area as shown in Appendix - 1 (Plate 4). It is observed in these type of well water is declines gradually after monsoon season. Shallow wells and deep wells are shown in Appendix - 1 (Plate 5). It is observed the water table in the shallow wells rose as the rainfall continues for the longer time and vice versa. However, these shallows well dried up during summer season. In the case of deep well atleast few meters of water table is available when compared to shallow wells. Moreover, deep are more prone to saltwater intrusion in coastal areas. Classification of monitoring wells based on different type of land use/cover and the details of well no are presented in Table.3.3.

Table 3.3 Classification of monitoring wells based on different type of land use/cover

| **Station name/ representative well** | **Well no** | **Land use/cover type** |
|---|---|---|
| Padre | SW2, DW3, SW4, DW5 | Within paddy fields, (semi forest, low lying area) |
| Mukka | SW6,DW7,SW8 | Sparse vegetative cover, Close to stream |
| Chelairu | DW9, DW10, DW11, | Built up area<br>Close to bore wells |
| Katipalla | DW14, SW15 DW16, DW17, SW18 | Sparse vegetative cover Close to stream |
| Krishnapura | SW12, SW13 | Built up area, mid land |
| Kana | SW19 | Built up area<br>Well with R.C.C rings |
| Edya | DW21 | Deep wells with RCC rings,<br>Sparse vegetation<br>Nearby to stream |
| Katla | DW20 | Deep wells, Build up area, Sparse vegetation, Nearby to stream |
| Munchuru | DW22, SW24 | Build up area, away from stream |
| NITK | DW1, DW23 | Thick forest and low lying area |

### 3.7 Data Division/Pattern/Compilation

For the present work, weekly time series groundwater level data were used for a span of almost eight years (March 2004 up to Dec 2011). Groundwater level data were obtained by monitoring the open wells at different locations as mentioned in earlier section. The initial 70% of total available data were used for training (calibration) of the models as a first part and the remaining 30% of total data were used for testing (validation) of the models as a second part. The training data set has been selected in such a way that it includes both wet and dry periods along with transition period (from wet to dry and dry to wet). The water year starts from first week of June to next year May. The MATLAB 9.2 version is used for the analysis.

### 3.8 Overview of Research Methodology Adopted

The overview of research methodology adopted in the study are shown in Figure 3.8.

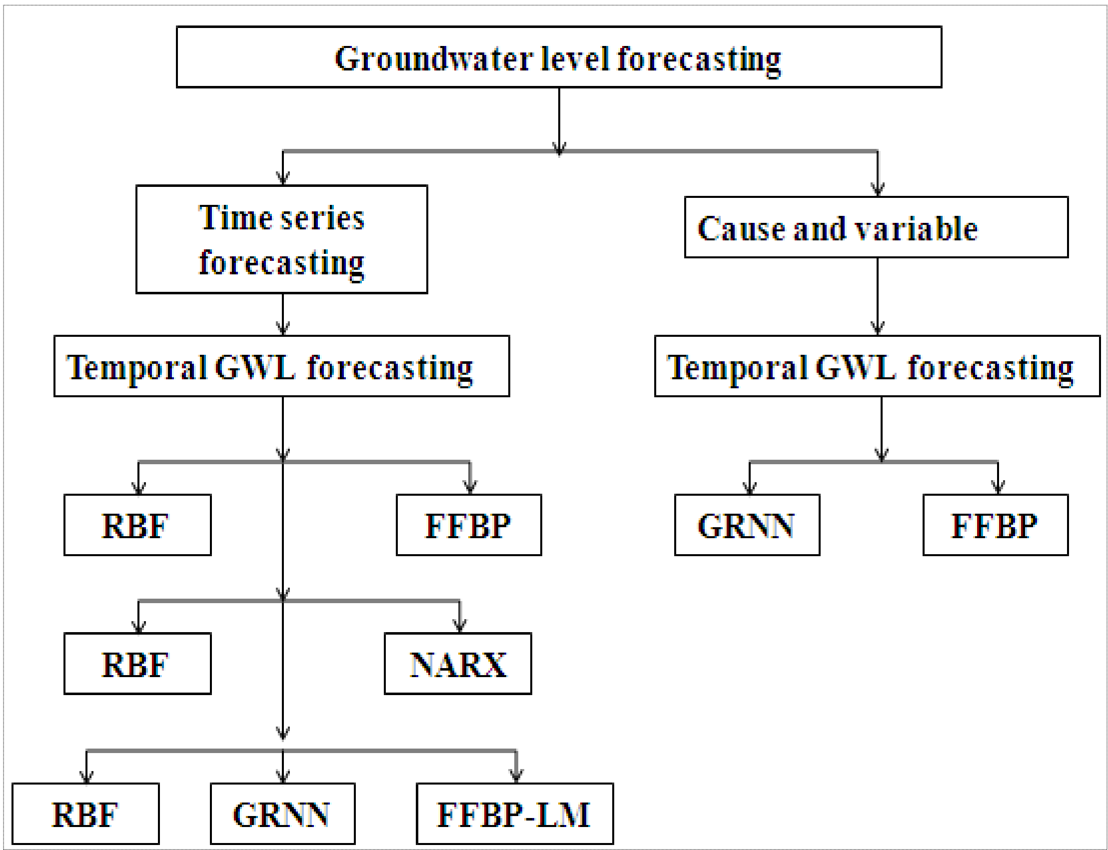



**Figure 3.8 Flow chart of research methodology**

### 3.8.1 Feed-forward back propagation-Levenberg-Marquardt (FFBP-LM)

Here, the Feedforward Backpropagation (FFBP) neural network was trained using Levenberg-Marquardt (LM) technique because it is more powerful and faster than the conventional gradient descent technique (Hagan and Menhaj; 1994; Kisi, 2007). The LM algorithm was designed to approach second order training speed without having to compute the Hessian matrix (More, 1977). The Levenberg-Marquardt method is a standard technique used to solve nonlinear least squares problems. Nonlinear least squares problems arise when the function is not linear in the parameters. Nonlinear least squares methods involve an iterative improvement to parameter values in order to reduce the sum of the squares of the errors between the function and the measured data points. It has become a standard technique for nonlinear least-squares problems and can be thought of as a combination of two minimization methods steepest gradient descent and the Gauss-Newton method. The Levenberg-Marquardt curve-fitting method is actually a combination of two minimization methods: the gradient descent method and the Gauss-Newton method. The performance function will always be reduced at each iteration of the algorithm. The application of LM to neural network training is described in Hagan and Menhaj (1994). Schematic diagram of feedforward neural network are shown in Figure 3.9.

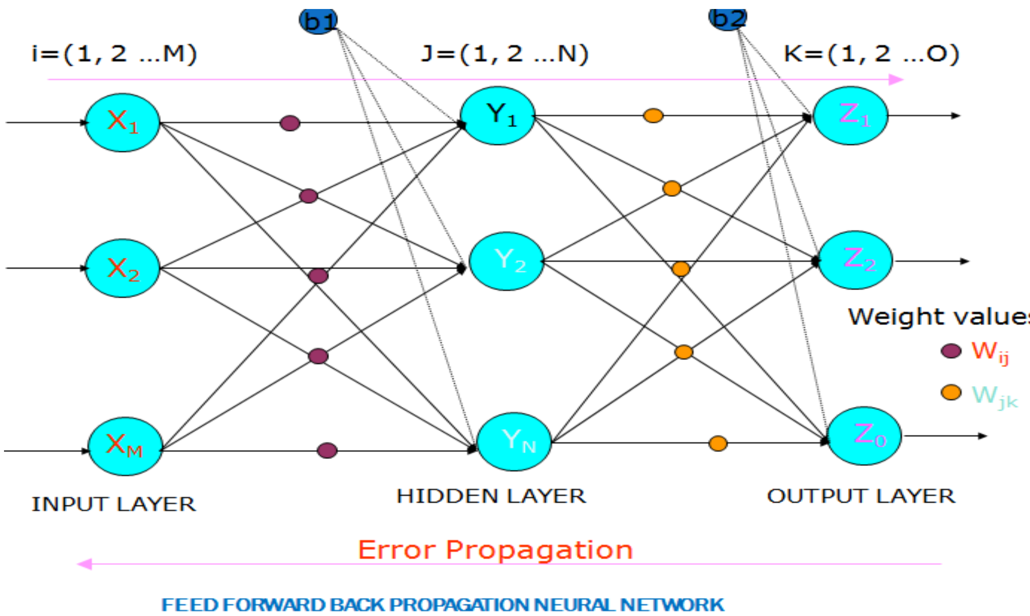



**Figure 3.9 schematic diagram of feedforward neural network**

The Feedforward back propogation algorithm (FFBP) has widely used in hydrology because of its simplicity, robustness and the advent of error back propagating. Basically this algorithm consists of two phases. In the forward pass the input signals propagate from the network input to the output. In the backward or reverse pass, the calculated error signals propagate backward through the network, where these are used to adjust the weights. Because of this reason several researchers have tried with back propogation for forecasting purposes. FFBP can be found in detail manner (Haykin 1999).

### 3.8.2 Radial Basis Function (RBF)

A radial basis function (RBF) is a special type of neural network that utilizes the radial basis function as its activation function. RBF networks becoming very popular and used for function approximation, curve fitting, time series prediction, control and classification problems (Park and Sanderg. 1991). The basic architecture of a three layered RBF neural network is shown in Figure 3.10. A RBFNN is composed of three layers similar to Feedforward BackPropagation (FFBP) namely input layer, hidden layer or radial basis layer and output layer or linear layer (Affandi, 2007). Here, Input to hidden layer of an RBF is nonlinear, whereas the hidden to output layer is linear. Each layer is consists of large number of simple and highly interconnected artificial neurons. The argument of the activation function of each hidden unit in a RBFNN computes the Euclidean distance between the input vector and the center of hidden unit in the network (Chen, 2010; Ghose et al., 2010). The architecture and training algorithms for radial basis function networks (RBF) are simple and clear.

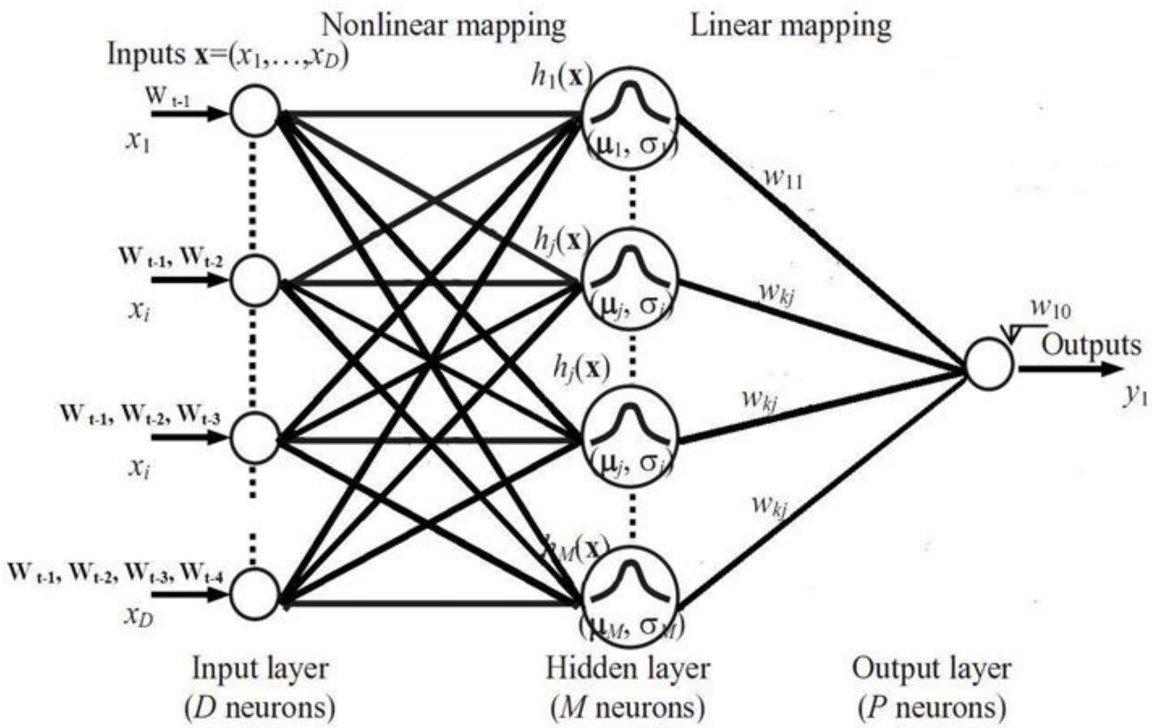



**Figure 3.10 Basic architecture of RBFNN**

The input data Z is a P-dimensional vector, Z=(z1 , z2 , ... ,$z_P$)$^T$. In the structure of RBFN, the input layer serves only as input distributor to the hidden layer. The dimensionality of hidden units is the same as that of the input data. The response from the j$^{th}$ hidden unit for the i$^{th}$ input data $z_i$ has the following form:

$$\emptyset i(Zj) = \emptyset(\|Zj - ci)\| \quad j = 1, 2, 3, \dots m \dots\dots\dots\dots\dots\dots\dots Eq\ (1)$$

Where ‖ ‖ denotes the Euclidean norm $c_j$ is the center of the j$^{th}$ unit in the hidden layer, ∅ () is the activation function, and m is the number of hidden units. In the structure of RBFN, the activation function of hidden units is symmetric in the input space, and the output of each hidden unit depends only on the Euclidean distance between the input vector and the center of the hidden unit. There are various types of functions can be used such as Gaussian, multiquadratic, inverse multiquadratic and Cauchy. Among these functions Gaussian, G, is the most popular and widely used in RBF networks. (ASCE Task Committee 2000; Govindaraju and

Rao 2000; Lin and Chen 2005) In the present research work, a Gaussian basis function was used for the hidden units given as $Z_j$ for j=1, 2, 3,…..J,

$$\text{Where } \emptyset(Z) = \exp\left[\frac{\|Z-c\|2}{2\sigma j2}\right] \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots Eq(2)$$

Where $\sigma_j$ is width of the network and can be calculated by Eq (3)

$$\sigma j = \frac{d max}{\sqrt{2Nh}} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots. Eq(3)$$

Where $d_{max}$ is the maximum distance between the centers of hidden units

The activity of the $r^{th}$ unit in the output layer can be obtained from Eq (4)

$$\hat{y}r = wo + \sum_{q=1}^{Nh} wqr\emptyset(Z) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots. Eq(4)$$

where r = 1,2,3,0………..$N_{R,}$ $\emptyset(z)$ is the response of the qth hidden unit resulting from all input data, $w_{qr}$ is the connection weight between the $q^{th}$ hidden unit and the $r^{th}$ output unit, $w_o$ is the bias term, and $N_R$ is the number of output units. In the present study, least square method is used to estimate the weight after fixing the centers and width of hidden units as discussed by Lin and Chen (2005); Chen et al., (2010). For RBFNN, the critical parameter for optimal performance is the setting of radial basis spread. Usually, the larger spread value is resulting smoother function approximation. For too large spread, many neurons will be required to fit a fast changing function. Also, for small spread, the network will not be generalized. In this study, a set of trial and error of spread valued has been worked out to obtain optimal result for best network.

### 3.8.3 Generalized Regression Neural Network (GRNN)

General regression neural networks are fast, simple and clear models. They are based on a well elaborated mathematical background - multivariate kernel regression methods, which have long successful statistical history. The resultant GRNN model is simpler, more accurate and faster compared to the work in FFBP (Caputo et.al, 2009). GRNN is a one-pass learning algorithm with a highly parallel structure. Even with sparse data in a multidimensional measurement space, the GRNN algorithm provides smooth transitions from one observed value to another (Specht, 1991).

The principal advantages of GRNN are fast learning and convergence to the optimal regression surface as the number of samples becomes very large. GRNN is particularly advantageous with sparse data in a real time environment, because the regression surface is instantly defined everywhere, even with just one sample (Specht.D, 1991). Since GRNN always estimates using a nonlinearly weighted average of the given samples, the estimates are always within the observed range of the dependent variable. GRNN can be treated as a normalised radial basis function network in which there is a hidden unit centered at every training case. By definition, the regression of a dependent variable Y on an independent X estimates the most probable value of Y with a minimised root mean squared error. GRNN is a method for estimating the joint probability density function of X and Y, given only training set. Because the probability density function is derived from the data with no pre conceptions about its form, the system is perfectly general (Wang et al, 2009). The success of the GRNN depends on the selection of the appropriate smoothing factors (Wasserman, 1993).

In the literature, the fundamentals of the GRNN can be obtained from Specht, (1991); Schioler and Hartmann (1992); Tsoukalas and Uhrig, (1997). A diagrammatic of the GRNN is depicted in Figure.3.11.

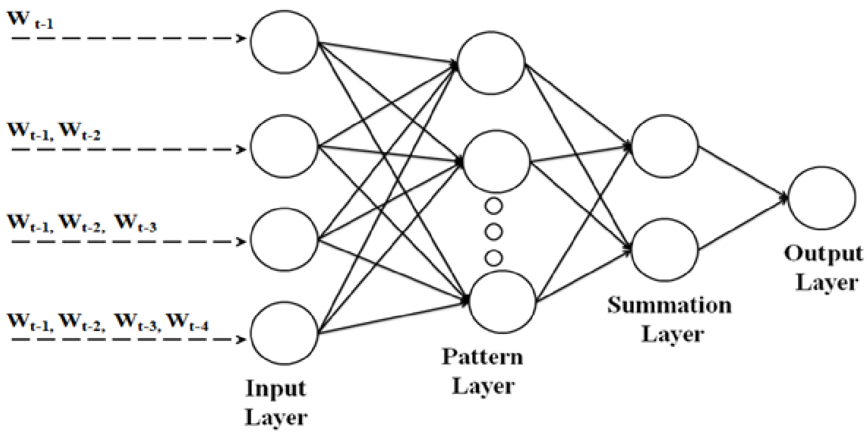



**Figure 3.11 General Structure of a General regression neural network**

A general regression neural network (GRNN) does not require an iterative training procedure. It can approximate any arbitrary function between input and output vectors, drawing the function estimate directly from the training data. Furthermore, it is consistent; that is, as the training set size becomes large, the estimation error approaches zero, with only mild restrictions on the function. The GRNN is used for estimation of continuous variables, as in standard regression techniques. General regression neural network (GRNN) is a memory-based network that provides estimates of continuous variables and converges to the underlying (linear or nonlinear) regression surface (Specht,1991).

The GRNN architecture was selected in this study is due to the fast learning and convergence to the optimal regression surface. In general, GRNN is a method for estimation f(x, y) using only a training set. In GRNN, the probability density function is derived from the training data with no pre conceptions about its form makes the system perfectly general. Even there is no problem if the functions are composed of multiple disjoint non-Gaussian regions in any number of dimensions, as well as those of simpler distributions (Wasserman, 1993).

The generalization of the GRNN is controlled by the use of smoothing factor, σ. Higher the smoothing factors close to 1 will straighten the path of the prediction line.

On the other hand, low smoothing factor such as approaching 0 creates dot to dot map. High smoothing factor increases the network's ability to generalize as well as may degrade the error of prediction. In the similar way, low smoothing factor usually degrades the network's ability to generalize but make predictions at all (Kisi, 2006). Hence, a range of smoothing factors and procedure for finalizing smoothing factors are checked in this study for optimal smoothing factor for various input scenarios.

The GRNN is consists of four layers namely Input layer, pattern layer, summation layer, and output layer as shown in the Figure 3.11. All the four layers are connected each other only in forward direction. The input layer I is fully connected to the pattern layer. In the pattern layer, each unit symbolizes a training pattern and it output measures the distance of the input from the stored pattern. This pattern layer is connected to the summation layer and also the pattern layer is linked to the two neurons in the summation layer namely S-summation neuron S(x) and D-summation neuron D(x). The summation neuron calculates the sum of the weighted output in the pattern layer. D-summation neuron calculates the un-weighted output in the pattern layer and is represented by $y_{i;}$ the target output value reciprocal to the $i^{th}$ input pattern. The linkage weight for D-summation considered as one. Finally the summation layer is connected to the output layer. The output layer divides the output of each S-summation neuron by the output of each D-summation neuron, supplying the predicted value to an unknown input vector ŷ

$$D(S,T,t) = \sum_{j=1}^{p} \left( \frac{x_j - x_{ij}}{\sigma_j} \right)^2 \ldots\ldots\ldots\ldots\ldots\ldots. Distance\ Value \ldots\ldots\ldots\ldots\ldots\ldots\ldots Eq(5)$$

$$\hat{y}(x) = \frac{\sum_{j=1}^{p} exp\left(-D(S,T,t)\right)}{\sum_{j=1}^{p} exp\left(-D(S,T,t)\right)} = \frac{N(x)}{D(x)} \ldots\ldots\ldots.. Predicted\ Function \ldots\ldots\ldots Eq(6)$$

### 3.8.4 Data Standardization/Preprocessing

In the present work, the data are normalized between 0.1 and 0.9 to ensure that each input is represented in the network training as wells as different kinds of input quantities are normalized in the same scale. Normalization of data with certain uniform range is necessary because to prevent larger numbers from overriding smaller ones, and to prevent premature saturation of hidden nodes, which impedes the learning process (Jiang et al., 2008). This is suitable when the actual input data take large values. There is no single standard procedure for normalization method for inputs and outputs. Before modeling it is suggested that the data can be normalized slightly offset values such as 0.1 and 0.9 (Basheer and Hajmeer, 2000; Ghose et al., 2010). After modeling, the final forecast results were then back transformed by reversing calculation using equation (7). The normalization of data is as follows

$$Y = 0.1 + 0.8\left[\frac{(X - X_{min})}{(X_{max} - X_{min})}\right] \dots \dots \dots \dots \dots \dots \dots \dots \dots \dots .. Eq\,(7)$$

Where X is the actual value, $X_{max}$ is the maximum value, $X_{min}$ is the minimum value of X and Y is the normalized value corresponding to X

### 3.8.5 Nonlinear Autoregressive with Exogenous Variable (NARX)

One of the most convenient model forms for prediction purposes is the nonlinear autoregressive model with exogenous variables (NARX) (Leontaritis and Billings, 1985a, b). NARX is a general formulation where the current output value is made dependent on the past values of the input and output signals through a suitable nonlinear static function. NARX models (Leontaritis and Billings, 1985a) are the non-linear generalization of the well-known ARX models, which constitute a standard tool in linear black-box model identification.

A NARX models is formulated as a discrete time input/output recursive Eq 8 such as,

Y(t) =f(y(t-1),…..y(t-ny), u(t-1),…..u (t-nu)) ………………..………………..Eq (8)

Where u(t), y(t) is the model input and output, ny, nu are the respective maximum lags, generally assumed Gaussian and white.

### 3.8.6 Model Evaluation Criteria

Root Mean Squared Error (RMSE) indicates the discrepancy between the observed and calculated values. It is used by researchers in order to evaluate the effectiveness of each network in its ability to make precise predictions. The lower the RMSE, the more accurate is the prediction. The best fit between observed and calculated values, which is unlikely to occur, would have and RMSE as 0. On the other hand, Coefficient of Efficiency (C.E) is used to check the model performance above average or below the observed data. Higher CE value (approaching one) reveals better predicting ability. In this study, following performance indices are used. The correlation coefficient (Cc) is a commonly used statistic and provides information on the strength of linear relationship between the observed and the computed values. General procedure for the development of a model using RBF and GRNN are shown in Figure 3.12 and Figure 3.13.

1. **Coefficient of Efficiency**,

$$CE = 1 - \frac{\sum (X-Y)^2}{\sum x^2} \quad \text{.....Eq (9)}$$

2**. Root Mean Square Error**,

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N} (X - Y)^2}{N}} \quad \text{Eq (10)}$$

3. **Correlation Coefficient**

$$\boldsymbol{Cc} = \frac{\boldsymbol{n}\sum \boldsymbol{XY} - (\sum \boldsymbol{X})(\sum \boldsymbol{Y})}{\sqrt{\boldsymbol{n}(\sum \boldsymbol{X^2}) - (\sum \boldsymbol{Y^2})}\sqrt{\boldsymbol{n}(\sum \boldsymbol{Y^2}) - \sum (\boldsymbol{Y})^2}} \quad \text{..Eq (11)}$$

Where, X=observed values, Y=predicted values, N = total number of values and x = $\boldsymbol{X\text{-}X_{mean}}$.

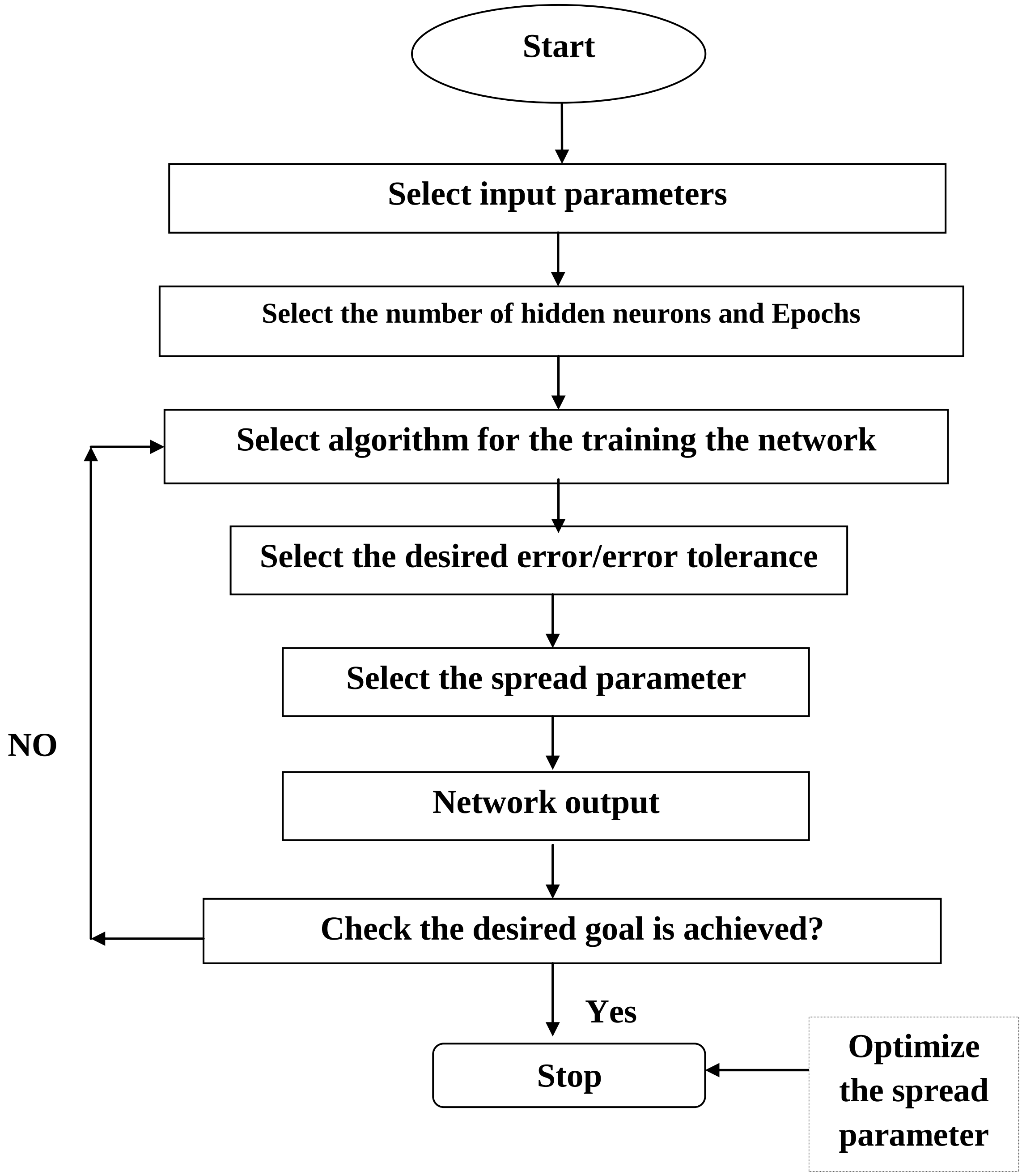



**Figure 3.12 Flow chart for the development of RBF model**

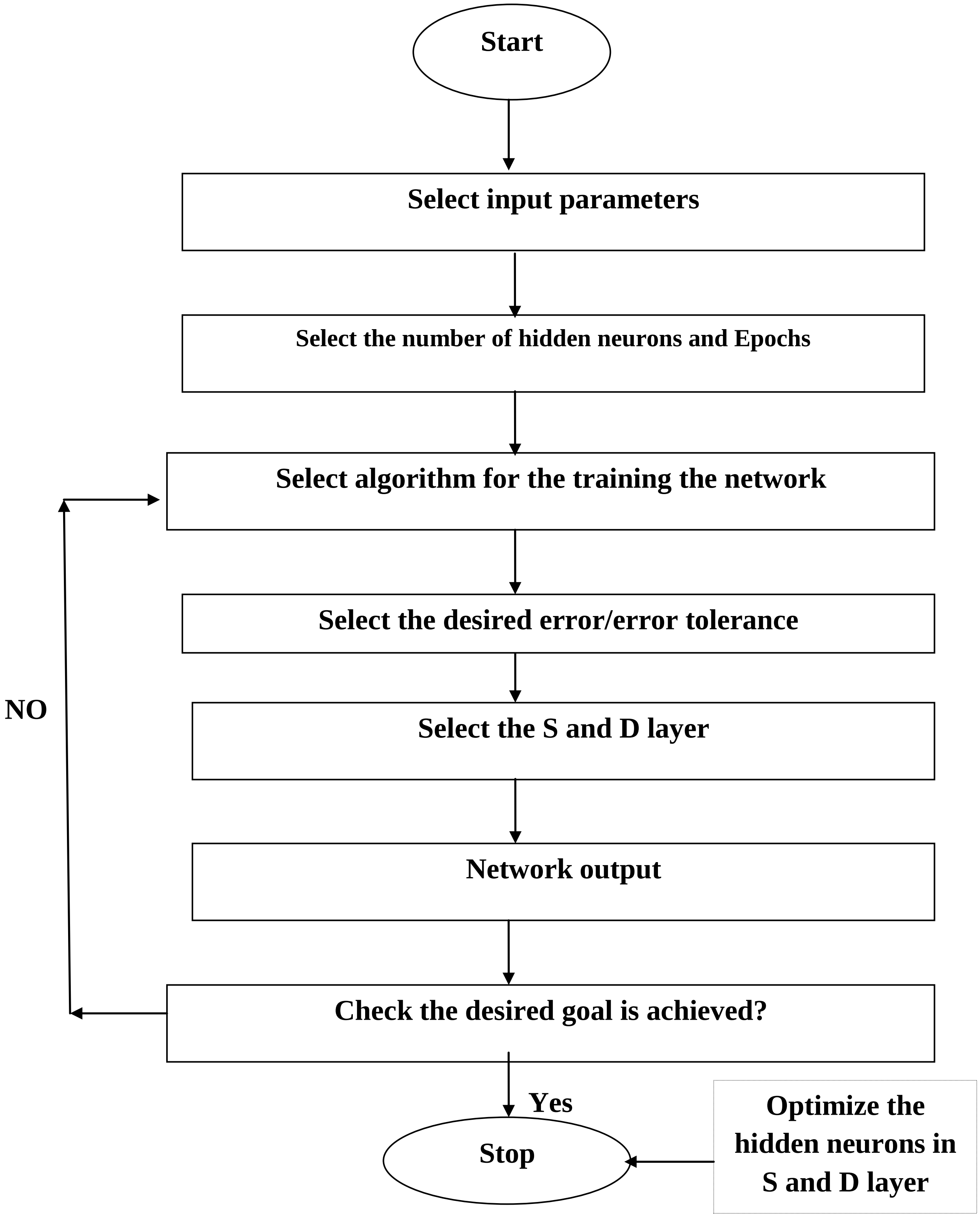



**Figure 3.13 Flow chart for the development of GRNN model**

# CHAPTER – 4

# RESULTS AND DISCUSSIONS

## 4.1. Introduction

In the present chapter the results are discussed based on the various models developed for groundwater level forecasting at southwest coast of Dakshina Kannada, India. Weekly time series groundwater level data for a period of eight years (2004-2011) has been used for groundwater level forecasting. Groundwater level forecasting has been carried out using different Artificial Neural Networks (ANN) such as RBF, GRNN are adopted in the study and their performance are compared with FFBP, NARX.

This chapter consists of four different themes and are discussed under different sections such as

1. Development of RBF model for GWL forecasting using time series
2. Performance evaluation of RBF model for more forecasting horizon using time series
3. Development of GRNN models for GWL forecasting using time series
4. Applicability of GRNN model in Cause and effect relationship

## 4.2. Development of RBF model for GWL forecasting using time series

### 4.2.1. Introduction

In this first work, the potential and applicability of Radial Basis Function (RBF) was investigated for forecasting groundwater level. The main objective of the present study is to forecast the weekly groundwater level forecasting for different lead times and also evaluate the performances of RBF and FFBP. Various models were developed for two time-step lead time forecasting. Weekly time series groundwater level data has been used as input and the analysis has been carried out separately for three open wells located at different land use and land cover. The effectiveness of the developed models and its capability to make more accurate predictions was assessed based on Root mean square error (RMSE) and correlation coefficient (Cc).

### 4.2.2. Selection of representative open wells

The selections of monitoring of three representative open wells were based on their geological formations and various land use and land cover. The details of three wells are presented in Table 4.1. The model input and output structure of the groundwater level forecasting are presented in Table.4.2

Table.4.1 Description of observation wells

| Well No | Location | Diameter (m) | Depth (m) | Remarks |
|---|---|---|---|---|
| SW4 | Padre | 2.40 | 7.54 | Within paddy fields<br>Low lying area |
| SW6 | Mukka | 2.00 | 4.33 | Close to stream<br>sparse vegetation |
| SW24 | Munchuru | 2.40 | 5.80 | Built up area<br>away from first order stream<br>in Munchuru. |

### 4.2.3. Selection of Inputs for model development

The determination of significant input variables is one of major steps in the process of model development. Normally, all the potential input variables may not be uniformly influential since some may be correlated, noisy or have no significant relationship with output variable being modeled Maier and Dandy, 2000. Usually, some priori knowledge is used to specify the initial set of inputs (e.g. Thirumalaiah and Deo, 2000). However, it depends on expert’s knowledge and hence it is very subjective and case dependent. Again, cross-correlation is often used as analytical techniques when the input-output mapping not fully understood (e.g. Sajikumar and Thandaveswara, 1999, Sudheer et al. 2002). Here also, a major difficulty associated in using cross correlation is that it is capable of detecting only linear dependences between two variables. In case of non-linear dependence between input and output, cross-correlation may not be effective and possibility exists in omission of influencing inputs. (Maier and Dandy, 1997) preferred a combination of a priori knowledge and analytical approaches for determining appropriate inputs and lags of inputs. Various input scenarios has been tried to obtain the optimal results for forecasting groundwater level using water level with various lag period are presented in Table 4.2.

For RBF models, proper spread values and optimal number of hidden nodes were determined by trial and error method as there are no specific guidelines available to assign this value. Here, number of trials has been carried out to optimize the best network within a range of 1 to 5. The optimal spread constant was found as 4 which was used for various input scenarios along with other internal parameters in the RBF network structure. The FFBP models has been developed using same input scenarios by altering the hidden neurons keeping learning rate and momentum coefficient are kept constant..

Table.4.2 Model Input and Output structure of the groundwater level forecasting

| Sl. No | Input structure | Output | Output | Output |
|---|---|---|---|---|
| Model (s) | GWL time series data | SW4 | SW6 | SW24 |
| Model 1 | $w_{(t-1)}$ | $w_{(t)}$, $W_{t+1}$ | $w_{(t)}$, $W_{t+1}$, | $w_{(t)}$, $W_{t+1}$ |
| Model 2 | $w_{(t-1)}$ and $w_{(t-2)}$, | $w_{(t)}$, , $W_{t+1}$ | $w_{(t)}$, , $W_{t+1}$ | $w_{(t)}$, , $W_{t+1}$ |
| Model 3 | $w_{(t-1}$, $w_{(t-2}$ and $w_{t-3)}$, | $w_{(t)}$, , $W_{t+1}$ | $w_{(t)}$, , $W_{t+1}$ | $w_{(t)}$, , $W_{t+1}$ |
| Model 4 | $w_{(t-1)}$, $w_{(t-2)}$, $w_{(t-3)}$ and $w_{(t-4)}$ | $w_{(t)}$, , $W_{t+1}$ | $w_{(t)}$, , $W_{t+1}$ | $w_{(t)}$, , $W_{t+1}$ |

*Wt-1, Wt-2, Wt-3 and Wt-4 represent one, two, three and four previous weekly groundwater level and Wt, Wt,+1 are one and two time step lead time*

### 4.2.4. Results and Discussions

All the training and testing results are presented in the Table.4.3. From the Table 4.3, it appears clearly that RBF forecasting performance was better than FFBP considering RMSE and Cc. As the leadtime increases, the FFBP performances decreases drastically compared to RBF. The correlation coefficient for RBF are very much satisfactory both in training and in testing. The RBF network seems to learned the groundwater level fluctuations behavior very effectively than FFBP and forecasting accuracy has been improved significantly due to the use of Gaussian function with optimized spread parameters. FFBP performance also with acceptable accuracy for 2$^{nd}$ week ahead, it is better than RBF for SW$ and SW24 in testing considering Cc.

Table.4.3 Model Performance during training and testing for FFBP and RBF

| Well No | Lead time (weeks) | Training | | | | Testing | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | RMSE (m) | | Cc | | RMSE (m) | | Cc | |
| | | RBF | FFBP | RBF | FFBP | RBF | FFBP | RBF | FFBP |
| SW4 | 1 week ahead | 0.66 | 1.56 | 0.93 | 0.62 | 0.79 | 1.31 | 0.92 | 0.83 |
| | 2 week ahead | 1.06 | 5.06 | 0.82 | 0.54 | 1.14 | 4.26 | 0.84 | 0.87 |
| SW6 | 1 week ahead | 0.18 | 0.38 | 0.97 | 0.92 | 0.19 | 0.34 | 0.94 | 0.87 |
| | 2 week ahead | 0.30 | 1.46 | 0.93 | 0.83 | 0.27 | 1.60 | 0.88 | 0.86 |
| SW24 | 1 week ahead | 0.27 | 1.04 | 0.95 | 0.87 | 0.30 | 1.01 | 0.85 | 0.82 |
| | 2 week ahead | 0.41 | 1.06 | 0.90 | 0.70 | 0.39 | 0.82 | 0.70 | 0.84 |

Figure. 4.1 shows the RBF model performance graphically and scatter plots between observed and predicted value one week lead time for **SW4**. The RBF model captures the pattern during the dry season but significant shifting during wet season. The scatter plots are more or less linearly placed representing unbiasness and systematic error in the RBF model as shown in Figure.4.2. The RBF model performed similarly for SW6 also as model partially capture the trend during wet season as shown in Figure.4.3. The scatter plot for SW6 station looks to be within accepted accuracy of the RBF model performance as shown in Figure.4.4. Figure.4.5 shows the RBF model performance for SW24. Here, the RBF model very closely follows the observed groundwater level with insignificant shifting during wet season. The scatter plot for SW24 shown in Figure.4.6 where, points are very densely placed. As the week progresses, the RBF model output closely followed the observed pattern of GWL both during low level and high level.

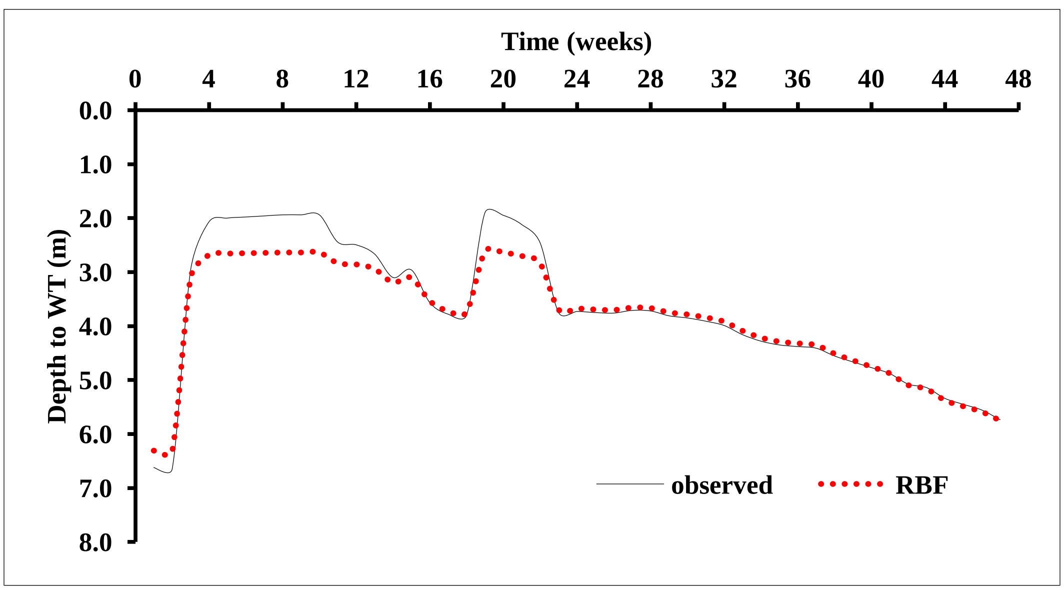



Figure.4.1. Time series plot for SW4 during testing for one week time step ahead

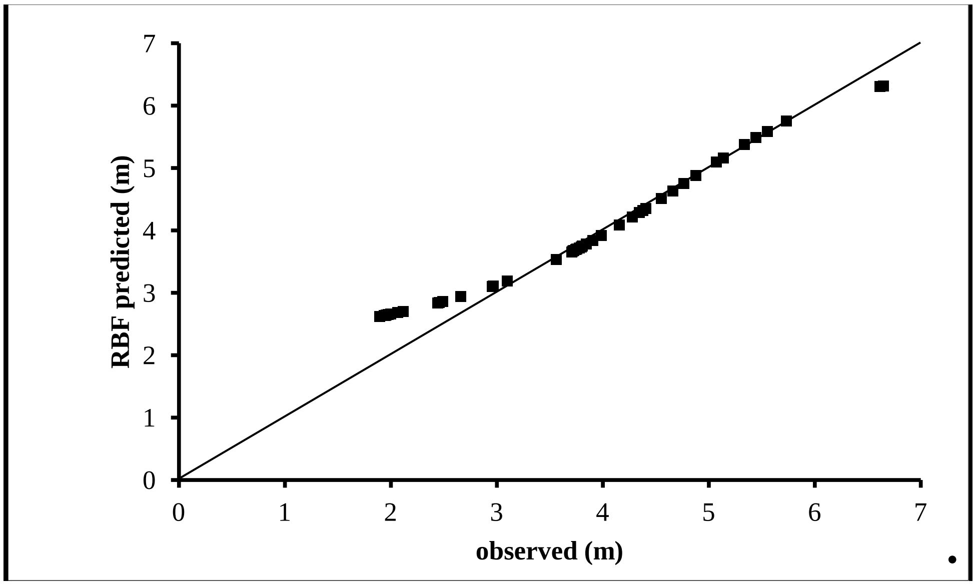



Figure.4.2. Scatter plot for SW4 during testing for one week time step ahead

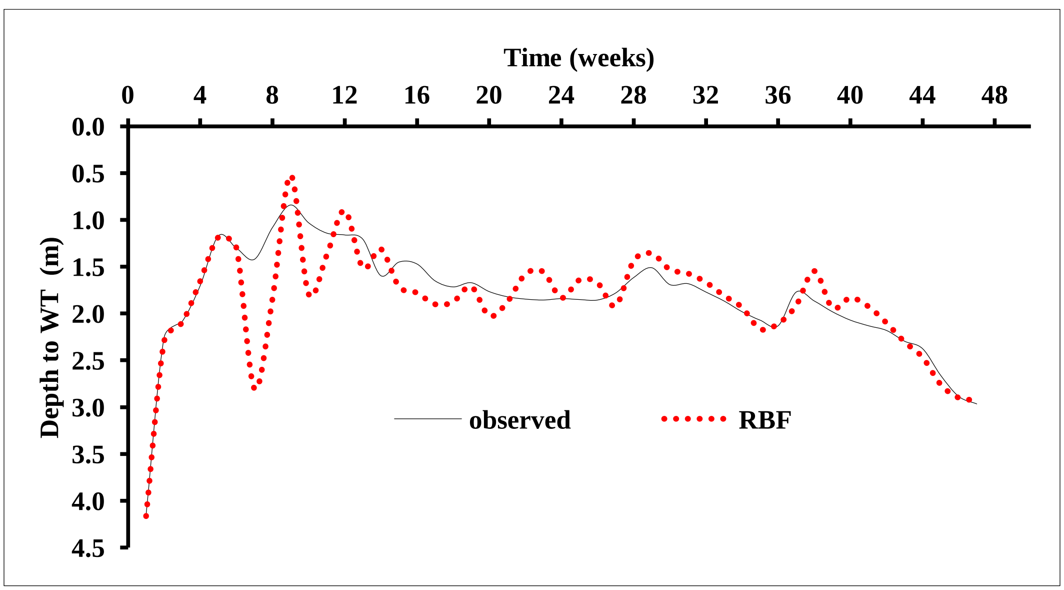



Figure.4.3 Time series plot for SW6 during testing for one week time step ahead

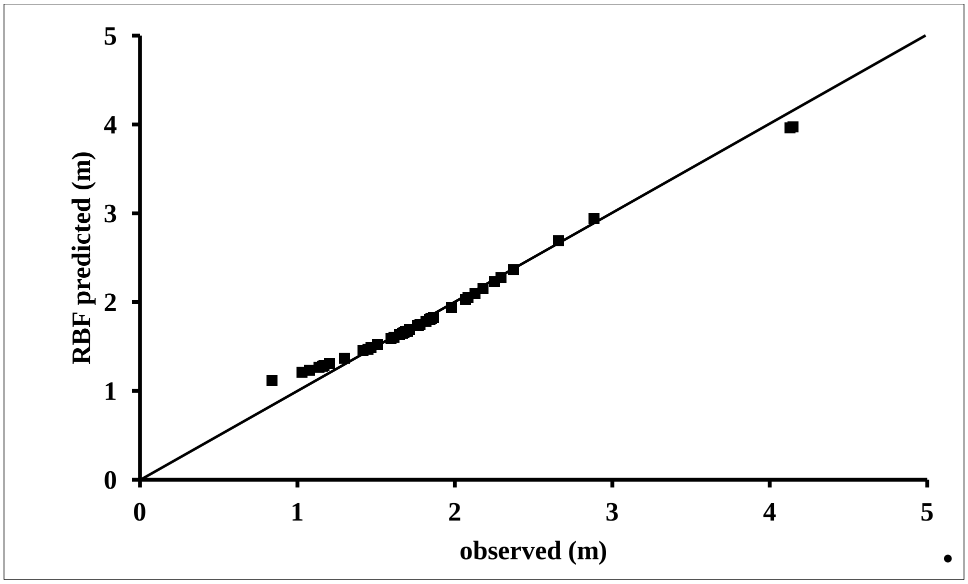



Figure.4.4 Time series plot for SW6 during testing for one week time step ahead

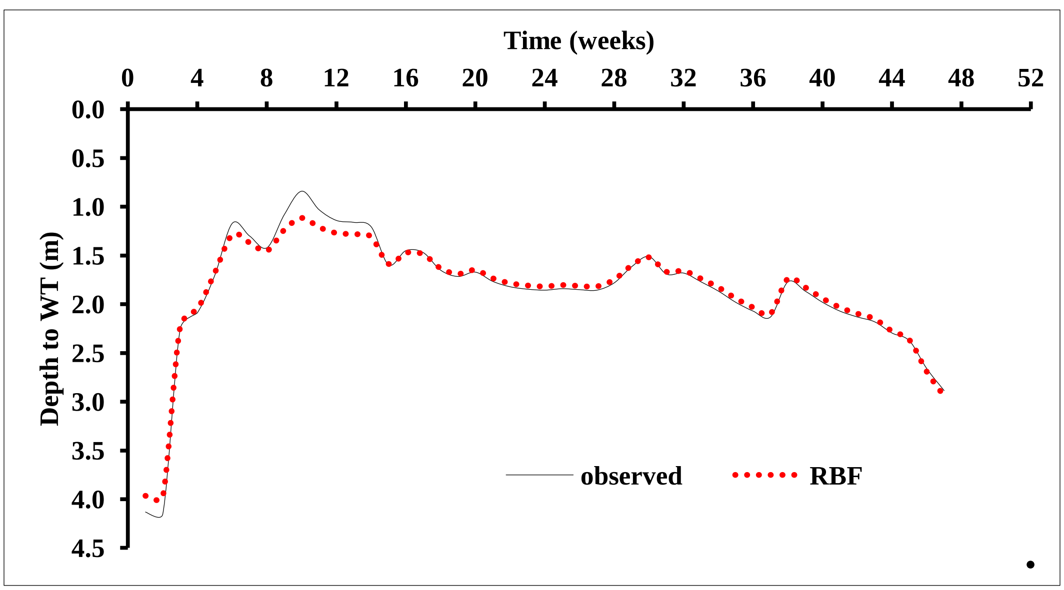



Figure.4.5. Time series plot for SW24 during testing for one week time step ahead

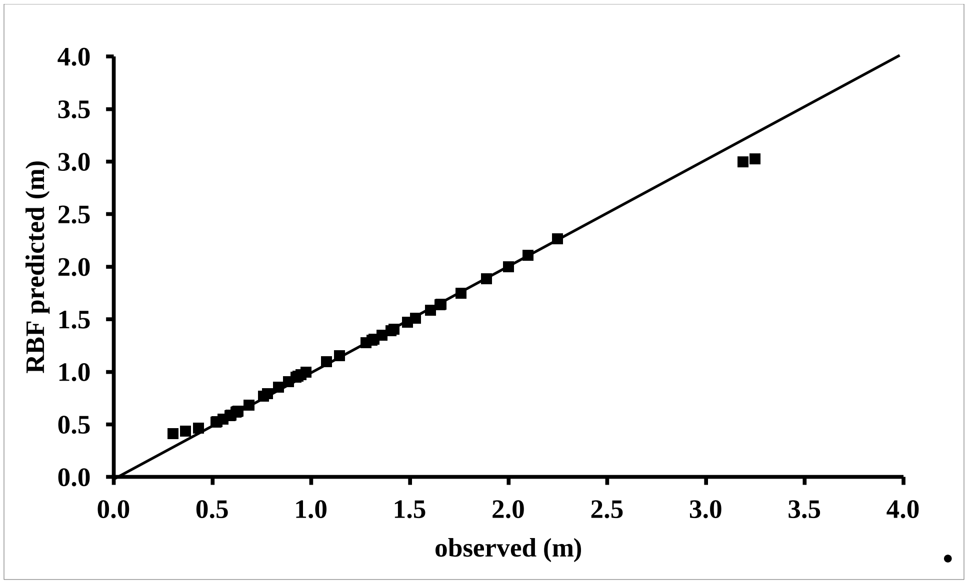



Figure.4.6. Scatter plot for SW24 during testing for one week time step ahead

### 4.2.5. Summary

In the present work, the potential and applicability of RBF in groundwater level forecasting has been investigated and found satisfactory performance. To assess the forecasting accuracy of RBF model results were compared with general FFBP model. All the three well stations are different statistical characteristics which are well understood by RBF model as revealed by the analysis. It has been observed that for all the three open wells, the higher and consistent performance for RBF network for one week lead time and decaying performance for FFBP network model. The obtained results show that the RBFNN performed better compared to FFBP models considering two performance indices such as Root mean squared error (RMSE) and Correlation coefficient (Cc). The model results clearly reveals that RBF network have the potential in forecasting ground water level efficiently for multistep lead time can be used as an effective tool for weekly groundwater level forecasting.

### 4.3. Performance evaluation of RBF model for more forecasting horizon using time series

After confirming the suitability of RBF in GWL forecasting and with better accuracy over FFBP, the work has been extended further to consolidate the applicability of RBF in multistep leadtime forecasting upto six week ahead. In this study, in addition to the earlier work the additional three representative wells are selected for the analysis. The time series GWL data are used for development of RBF models for six different input combinations using lagged time series data. Outputs are the predicted GWL upto six week. The optimized spread parameter (obtained in first study) 4 is used for development of RBF model by varying hidden neurons in a similar manner to earlier study. The details of six representative open wells are presented in Table 4.4. All these six wells are private wells and used for drinking and domestic purposes only. To compare the predicting performance of RBF models in multistep lead time, another regression model such as NARX also developed in the study.

Table.4.4 Description of observation wells under current study

| Well No | Location | Well Diameter (m) | Total Depth (m) | Remarks |
|---|---|---|---|---|
| DW5 | Padre | 2.40 | 15.50 | Within Paddy Fields, |
| SW4 | Padre | 2.40 | 7.54 | Within Paddy Fields, |
| SW6 | Mukka | 2.00 | 4.33 | Close to stream |
| SW8 | Mukka | 2.00 | 4.95 | Close to stream |
| SW22 | Munchuru | 2.40 | 7.48 | Built up area and away from stream |
| SW24 | Munchuru | 2.40 | 5.80 | Built up area and away from stream |

The available data is divided into two sets, for training calibration and testing or validation. The training data set has been selected in such a way that it includes both wet and dry periods along with transition period (from wet to dry and dry to wet) so as to provide satisfactory learning to the network. The water year starts from first week of June to next year May with almost negligible rainy period from November to next May month. Therefore, testing data are kept in time series from June onwards to evaluate the model performance in critical time periods (both wet and dry). The statistical parameters such as minimum value and maximum value, mean and standard deviation for both training and testing data sets are computed and presented in Table 4.5. For DW5, groundwater level fluctuation is very high and standard deviation also reveals the sparsely location of data points. Also, it is appears that for SW4, water level fluctuation and standard deviation are moderate compared to DW5. One of the reason is that both the DW5 and SW4 are located in paddy fields and there may be water logging conditions during wet period. For the remaining wells groundwater level fluctuations are minimal with lower standard deviation value as data points are closed spaced.

Table.4.5 Statistical analysis of observed data (gwl) for all the six open wells

| **Well No** | **Training** | | | | **Testing** | | | |
|---|---|---|---|---|---|---|---|---|
| | Min (m) | Max (m) | Mean (m) | St.dv | Min (m) | Max (m) | Mean (m) | St.dv |
| DW5 | 4.93 | 12.25 | 9.99 | 1.87 | 5.07 | 12.48 | 8.83 | 2.17 |
| SW4 | 1.70 | 6.52 | 4.48 | 1.24 | 1.90 | 6.65 | 3.70 | 1.29 |
| SW6 | 0.30 | 3.33 | 1.50 | 0.88 | 0.30 | 3.25 | 1.22 | 0.65 |
| SW8 | 0.90 | 3.65 | 2.05 | 0.84 | 0.91 | 3.56 | 1.83 | 0.68 |
| SW22 | 2.64 | 5.50 | 3.98 | 0.82 | 2.77 | 5.45 | 3.72 | 0.58 |
| SW24 | 0.73 | 4.45 | 2.19 | 0.96 | 0.84 | 4.15 | 1.85 | 0.63 |

### 4.3.1. Selection of Inputs for Multiple input scenario

For development of both RBF and NARX models, various input scenarios has been tried to obtain the optimal results for forecasting groundwater level using water level with various lag period are presented in Table 4.6. The optimal input scenarios were found for 4 input combinations for all the wells.

Table.4.6 Description of Model Inputs and outputs

| Model Inputs | Outputs |
|---|---|
| Wt-1, | Wt, Wt+1, Wt+2, Wt+3,Wt+4, Wt+5, |
| Wt-1, Wt-2 | Wt, Wt+1, Wt+2, Wt+3,Wt+4, Wt+5, |
| Wt-1, Wt-2, Wt-3 | Wt, Wt+1, Wt+2, Wt+3,Wt+4, Wt+5, |
| Wt-1, Wt-2, Wt-3, Wt-4 | Wt, Wt+1, Wt+2, Wt+3,Wt+4, Wt+5, |
| Wt-1, Wt-2, Wt-3, Wt-4, Wt-5, | Wt, Wt+1, Wt+2, Wt+3,Wt+4, Wt+5, |
| Wt-1, Wt-2, Wt-3, Wt-4, Wt-5, Wt-6 | Wt, Wt+1, Wt+2, Wt+3,Wt+4, Wt+5, |

*Note: Wt-1, Wt-2, Wt-3, Wt-4, Wt-5, Wt-6 are the lag time groundwater level,*

*Wt, Wt+1, Wt+2, Wt+3,Wt+4, Wt+5, are forecasted groundwater level from one week to six week ahead*

### 4.3.2. Results and discussion

The best results which are obtained for 4input combinations are presented in Table 4.7 and Table 4.8, Table 4.9, Table 4.10, Table 4.11 and Table 4.12 for all the six wells. In general, for all the wells, RBF model performance is better than NARX model considering the performances indices RMSE and Cc. Also, RBF was better during various lead time forecasting than NARX. These results indicate that potential of RBFNN in forecasting groundwater level from one week lead time to six week lead time. However, for water management in the aquifer, one week lead time forecasting may be sufficient, but for efficient planning of conjunctive use, higher lead time forecasting of groundwater table are required. The performances of RBF and NARX models has been analyzed and discussed based on lead time and location of well in the following section.

**DW5 and SW 4**

The consistent performance of RBF model was reflected both in training and as well as in testing. For the DW5, the RMSE of RBF is very small such as 0.02m considering one week leadtime as appears in the Table 4.7 which can be accepted as very much satisfactory. Similarly, correlation coefficient remains consistent in training and as well as in testing which is very close to1for RBF model as presented in Table 4.7.On the other hand, the RMSE of NARX are very high such as 0.098m and 1.22m during training and testing respectively for one week lead time (Table 4.7). Even upto sixth week leadtime also, RBF is consistent in terms of Correlation coefficient both in training and testing which is 0.99. The NARX model performance was inconsistent for various leadtime with a variation of correlation coefficient from 0.84 to 0.79 in testing. It is also noticeable that the performance of NARX model is fluctuating from training to testing considering both correlation coefficient and RMSE indices as presented in Table 4.7. Figure. 4.7 shows the performance of RBF and NARX for one to six week lead time. Also, scatter plots between observed between predicting groundwater levels are shown in Figure. 4.7

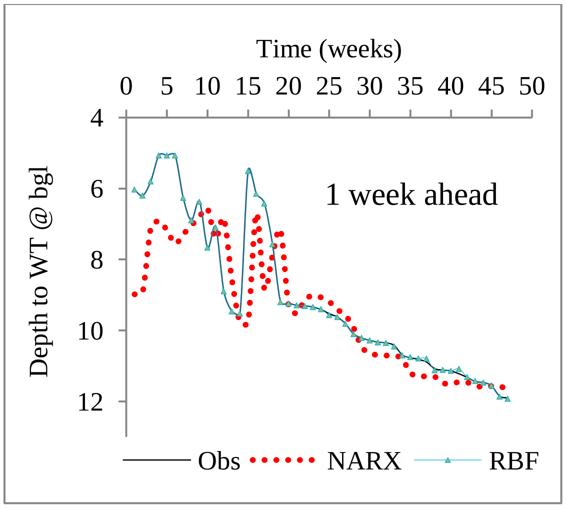
For SW4, which is also located in the similar land use and land cover, the trend of RBF model results are appeared in a similar fashion as presented in Table 4.8. Here also, RMSE is very small for one week lead time such as 0.07m for RBF model and also Cc is very much close to 1. The NARX model performance was poor and constantly declining for both training and testing. Figure.4.8 shows the model performance of RBF and NARX during testing for one to six week lead time. Also, scatter plots between RBF and observed values for SW4 during testing are shown in Figure.4.8. RBF is in close agreement with observed value during rainy season (wet period) as well as non monsoon season (dry period). But NARX is deviating from the observed value during wet period (0 week to 20 week). Similar trend is observed upto six week lead time (Figure.4.8). From the scatter plot of Figure.4.8, it appears that RBF model is unbiased and only little systematic error is observed for all the lead time.

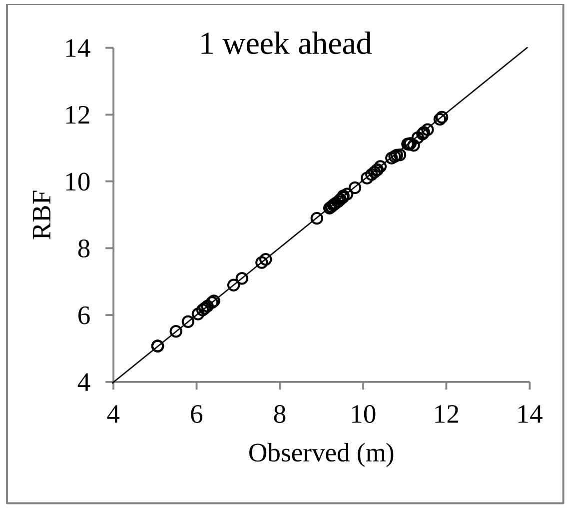
Table.4.7 Comparison of model performance for DW5

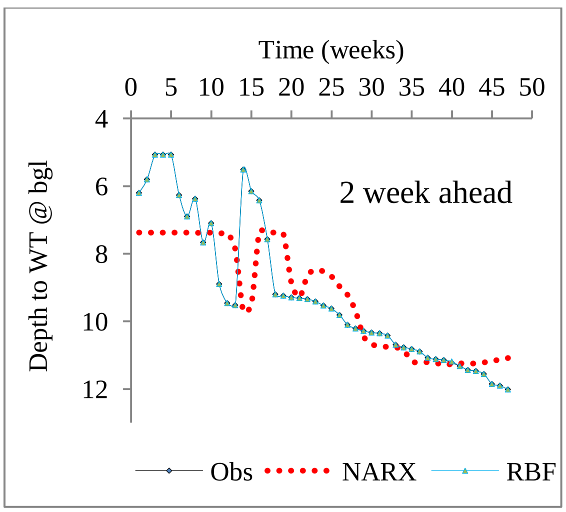
| **Lead Time (week)** | **Training** | | | | **Testing** | | | |
|---|---|---|---|---|---|---|---|---|
| | **RMSE (m)** | | **Cc** | | **RMSE (m)** | | **Cc** | |
| | **RBF** | **NARX** | **RBF** | **NARX** | **RBF** | **NARX** | **RBF** | **NARX** |
| 1 | 0.02 | 0.98 | 0.99 | 0.86 | 0.02 | 1.22 | 0.99 | 0.84 |
| 2 | 0.00 | 1.25 | 0.99 | 0.76 | 0.00 | 1.27 | 0.99 | 0.80 |
| 3 | 0.02 | 1.10 | 0.99 | 0.82 | 0.02 | 1.13 | 0.99 | 0.84 |
| 4 | 0.04 | 1.12 | 0.99 | 0.82 | 0.04 | 1.12 | 0.99 | 0.84 |
| 5 | 0.02 | 1.26 | 0.99 | 0.78 | 0.01 | 1.15 | 0.99 | 0.85 |
| 6 | 0.03 | 1.34 | 0.99 | 0.76 | 0.03 | 1.23 | 0.99 | 0.79 |

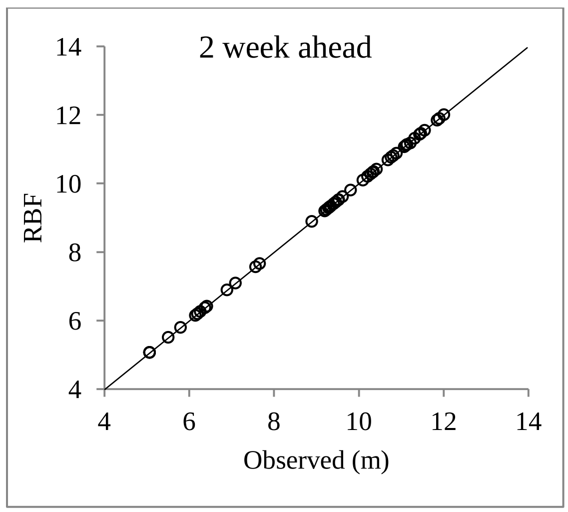
Table.4.8 Comparison of model performance for SW4

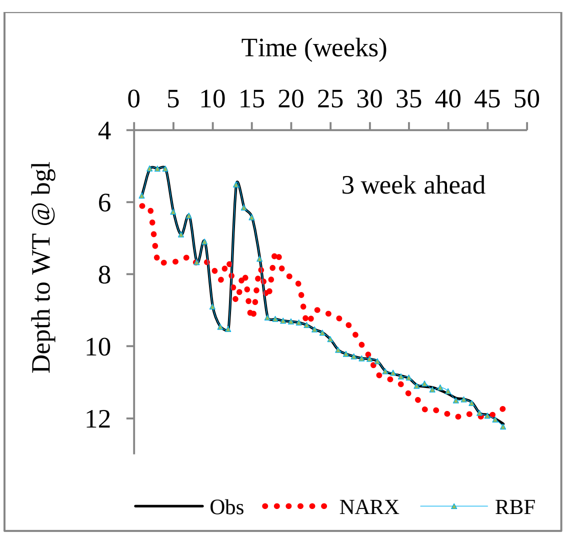
| **Lead Time (week)** | **Training** | | | | **Testing** | | | |
|---|---|---|---|---|---|---|---|---|
| | **RMSE (m)** | | **Cc** | | **RMSE (m)** | | **Cc** | |
| | **RBF** | **NARX** | **RBF** | **NARX** | **RBF** | **NARX** | **RBF** | **NARX** |
| 1 | 0.00 | 0.46 | 0.99 | 0.92 | 0.08 | 0.58 | 0.99 | 0.89 |
| 2 | 0.03 | 0.53 | 0.99 | 0.90 | 0.02 | 0.60 | 0.99 | 0.88 |
| 3 | 0.10 | 0.68 | 0.99 | 0.85 | 0.09 | 0.69 | 0.99 | 0.86 |
| 4 | 0.12 | 0.65 | 0.99 | 0.85 | 0.11 | 0.56 | 0.99 | 0.90 |
| 5 | 0.08 | 0.74 | 0.99 | 0.82 | 0.06 | 0.55 | 0.99 | 0.91 |
| 6 | 0.12 | 0.75 | 0.99 | 0.81 | 0.11 | 0.90 | 0.99 | 0.76 |

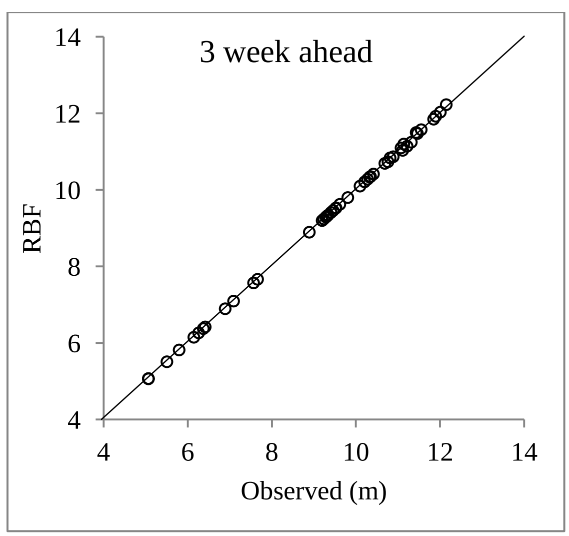

Time (weeks)
0 5 10 15 20 25 30 35 40 45 50
4 6 8 10 12
Depth to WT @ bgl
1 week ahead
Obs NARX RBF


1 week ahead
14 12 10 8 6 4
RBF
4 6 8 10 12 14
Observed (m)


Time (weeks)
0 5 10 15 20 25 30 35 40 45 50
4 6 8 10 12
Depth to WT @ bgl
2 week ahead
Obs NARX RBF


2 week ahead
14 12 10 8 6 4
RBF
4 6 8 10 12 14
Observed (m)


Time (weeks)
0 5 10 15 20 25 30 35 40 45 50
4 6 8 10 12
Depth to WT @ bgl
3 week ahead
Obs NARX RBF


3 week ahead
14 12 10 8 6 4
RBF
4 6 8 10 12 14
Observed (m)

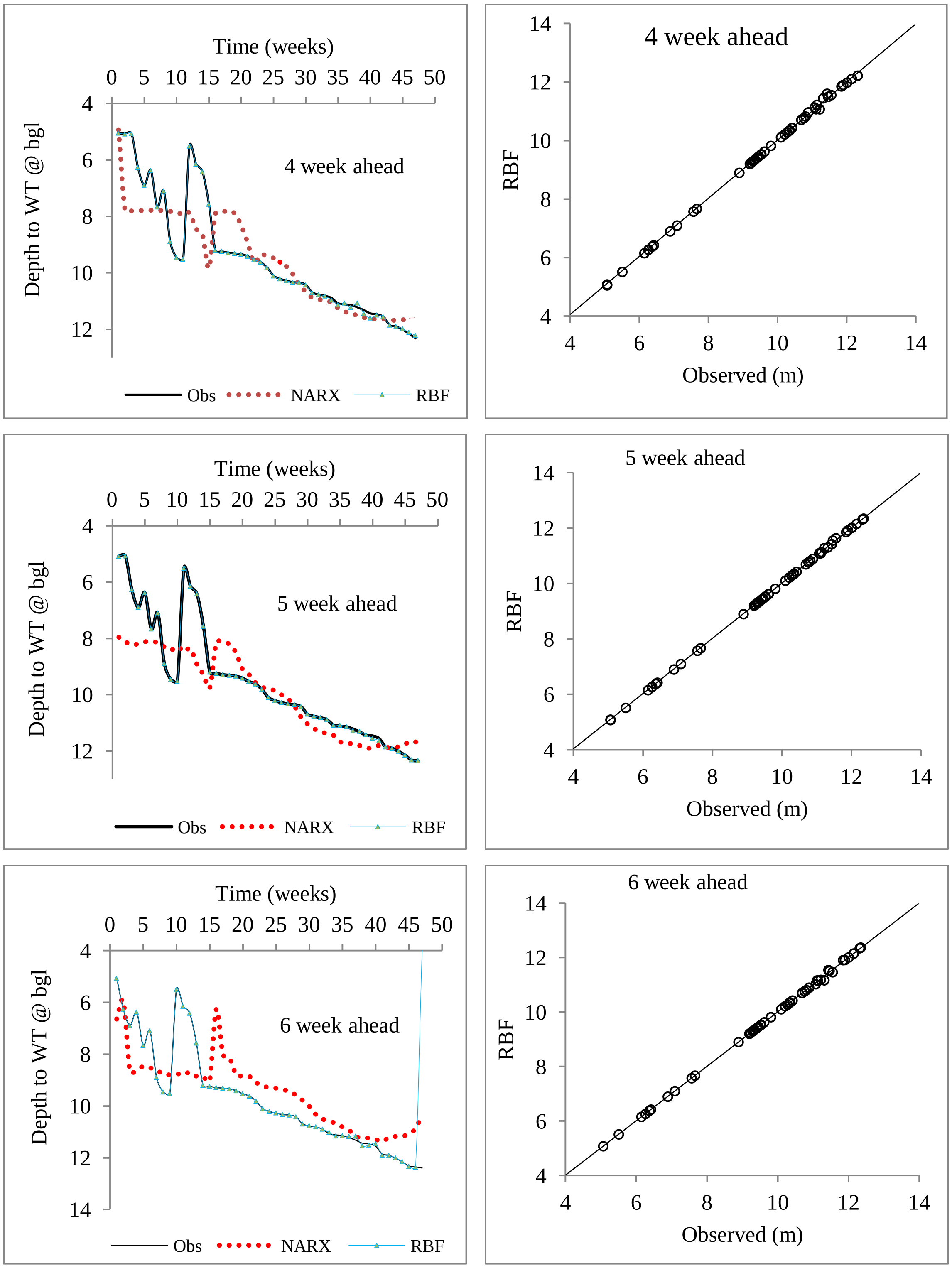
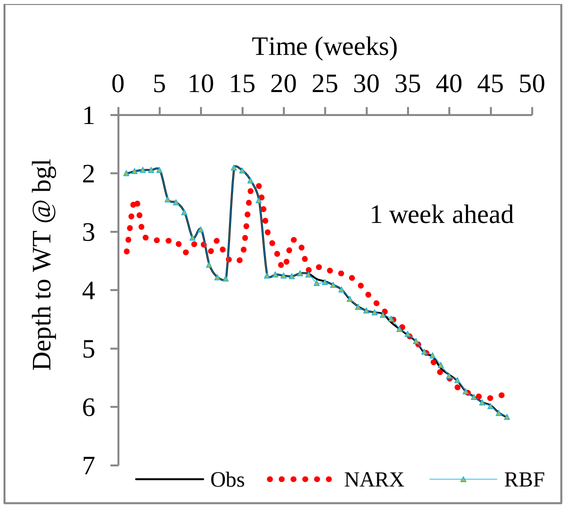
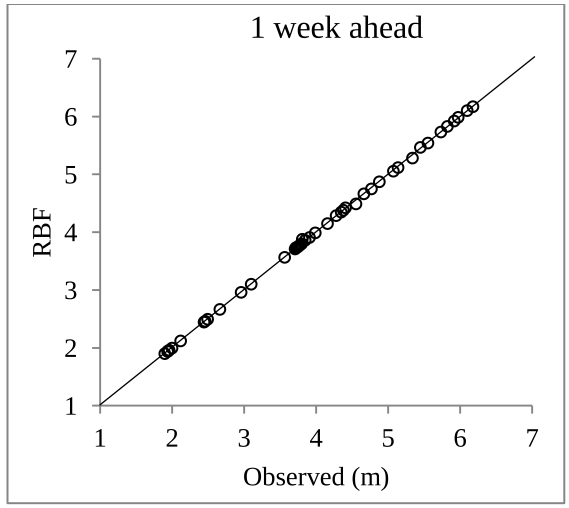
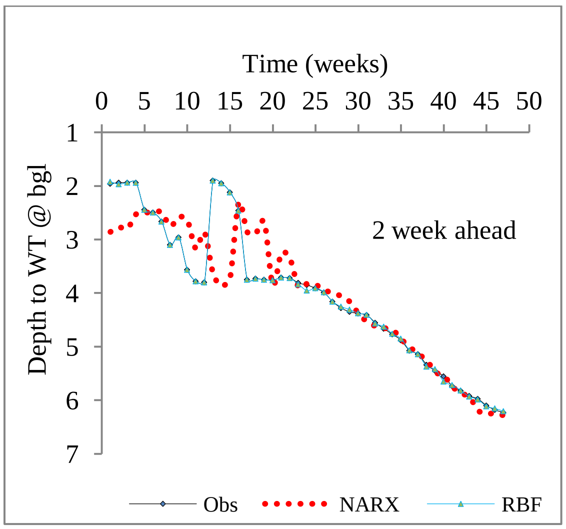
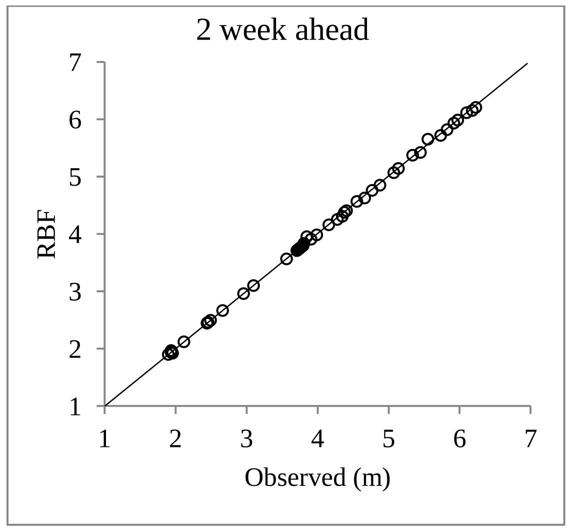


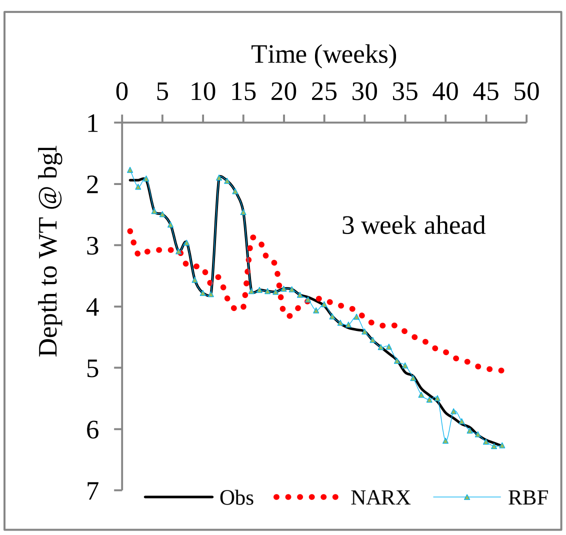

Figure.4.7. Fourth Input scenario for multiple lead time forecasting for DW5

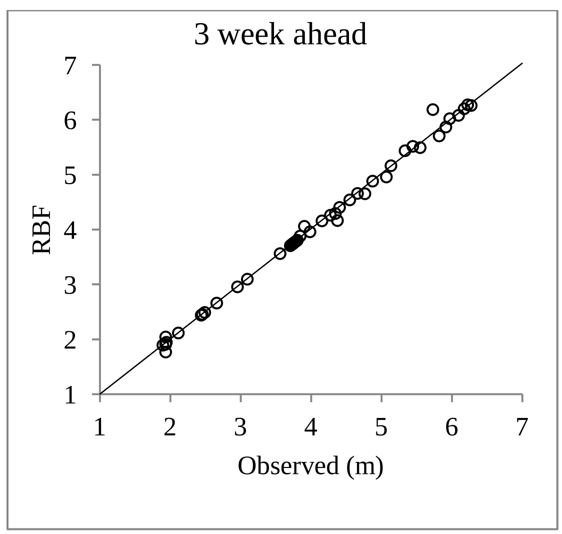

Time (weeks)
0 5 10 15 20 25 30 35 40 45 50
1 2 3 4 5 6 7
Depth to WT @ bgl
1 week ahead
Obs NARX RBF


1 week ahead
7 6 5 4 3 2 1
RBF
1 2 3 4 5 6 7
Observed (m)


Time (weeks)
0 5 10 15 20 25 30 35 40 45 50
1 2 3 4 5 6 7
Depth to WT @ bgl
2 week ahead
Obs NARX RBF


2 week ahead
7 6 5 4 3 2 1
RBF
1 2 3 4 5 6 7
Observed (m)


Time (weeks)
0 5 10 15 20 25 30 35 40 45 50
1 2 3 4 5 6 7
Depth to WT @ bgl
3 week ahead
Obs NARX RBF


3 week ahead
7 6 5 4 3 2 1
RBF
1 2 3 4 5 6 7
Observed (m)

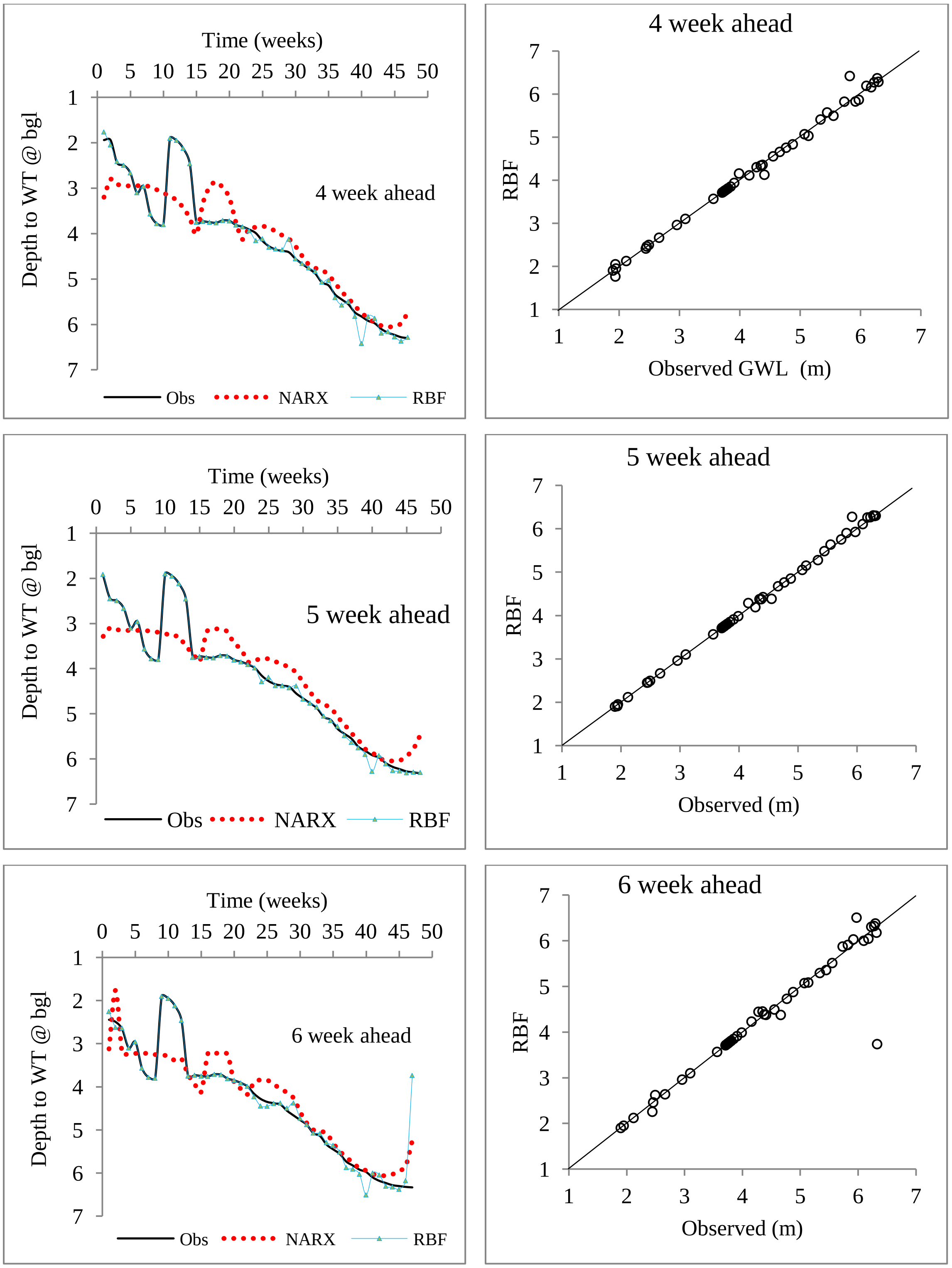



Figure.4.8. Fourth Input scenario for multiple lead time forecasting for SW4

**SW6 and SW8**

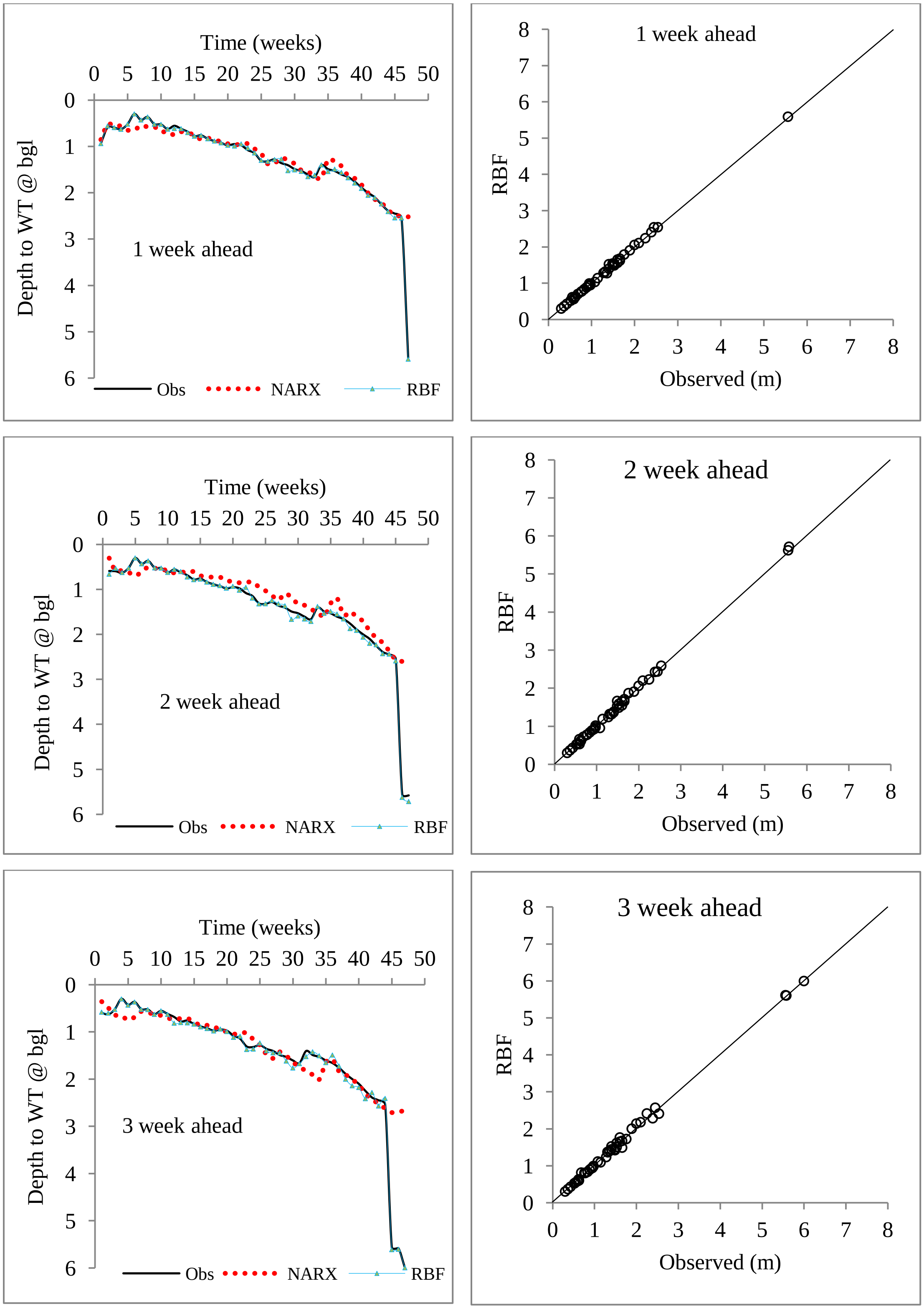
The model results for SW6 and SW8, located close to stream and surrounded by sparse vegetation are presented in Table 4.9. In case of SW6, for one week lead time, correlation coefficient for RBF model is 0.99 both in training and testing whereas correlation coefficient of NARX carrying lower value and shows poor testing performance compared to training performance. The RMSE for RBF model changes almost linearly for higher lead time during training. Figure.4.9 shows model performance of RBF with scatter plots during testing from one week to six week lead time. For **SW8**, the RMSE for RBF is also very low such as 0.025m whereas NARX is carrying higher RMSE such as 0.13m during testing for one week lead time. The correlation coefficients for RBF are remaining almost same for all the lead time confirms the strong linear relationship between the observed value and RBF model value. The model performance of **SW8** with scatter plot is shown in Figure. 4.10 during testing upto four week lead time. From the Figure.4.10, it is observed that RBF is closely following the observed value during wet period and both NARX and RBF performing similarly during dry period (beyond 20week). The groundwater level fluctuation for SW8 is almost gradual and the scatter plots between the RBF and observed value shows the consistent and unbiased performance. Here, the data variation is very small as well as standard deviation which clearly represents closely spaced data set both in training and testing data set. RBF is performing well here because there is no scope for extrapolation.

Table.4.9 Comparison of model performance for **SW6**

| Lead Time (week) | Training | | | | Testing | | | |
|---|---|---|---|---|---|---|---|---|
| | RMSE (m) | | Cc | | RMSE (m) | | Cc | |
| | RBF | NARX | RBF | NARX | RBF | NARX | RBF | NARX |
| 1 | 0.03 | 0.21 | 0.99 | 0.97 | 0.03 | 0.45 | 0.99 | 0.87 |
| 2 | 0.05 | 0.24 | 0.99 | 0.96 | 0.05 | 0.64 | 0.99 | 0.88 |
| 3 | 0.07 | 0.31 | 0.99 | 0.93 | 0.07 | 0.78 | 0.99 | 0.83 |
| 4 | 0.09 | 0.34 | 0.99 | 0.91 | 0.08 | 0.94 | 0.99 | 0.83 |
| 5 | 0.10 | 0.41 | 0.99 | 0.87 | 0.07 | 1.15 | 0.98 | 0.80 |
| 6 | 0.10 | 0.35 | 0.99 | 0.90 | 0.07 | 1.18 | 0.98 | 0.83 |

Table.4.10 Comparison of model performance for **SW8**

| Lead Time (week) | Training | | | | Testing | | | |
|---|---|---|---|---|---|---|---|---|
| | RMSE (m) | | Cc | | RMSE (m) | | Cc | |
| | RBF | NARX | RBF | NARX | RBF | NARX | RBF | NARX |
| 1 | 0.03 | 0.22 | 0.99 | 0.96 | 0.02 | 0.13 | 0.99 | 0.97 |
| 2 | 0.05 | 0.25 | 0.99 | 0.94 | 0.03 | 0.14 | 0.99 | 0.97 |
| 3 | 0.07 | 0.26 | 0.99 | 0.94 | 0.03 | 0.18 | 0.99 | 0.96 |
| 4 | 0.10 | 0.28 | 0.99 | 0.93 | 0.06 | 0.22 | 0.95 | 0.95 |
| 5 | 0.07 | 0.37 | 0.95 | 0.89 | 0.05 | 0.20 | 0.97 | 0.96 |
| 6 | 0.09 | 0.62 | 0.93 | 0.64 | 0.06 | 0.30 | 0.96 | 0.92 |


Time (weeks)
Depth to WT @ bgl
1 week ahead
Obs NARX RBF
RBF
Observed (m)
1 week ahead
Time (weeks)
Depth to WT @ bgl
2 week ahead
Obs NARX RBF
RBF
Observed (m)
2 week ahead
Time (weeks)
Depth to WT @ bgl
3 week ahead
Obs NARX RBF
RBF
Observed (m)
3 week ahead

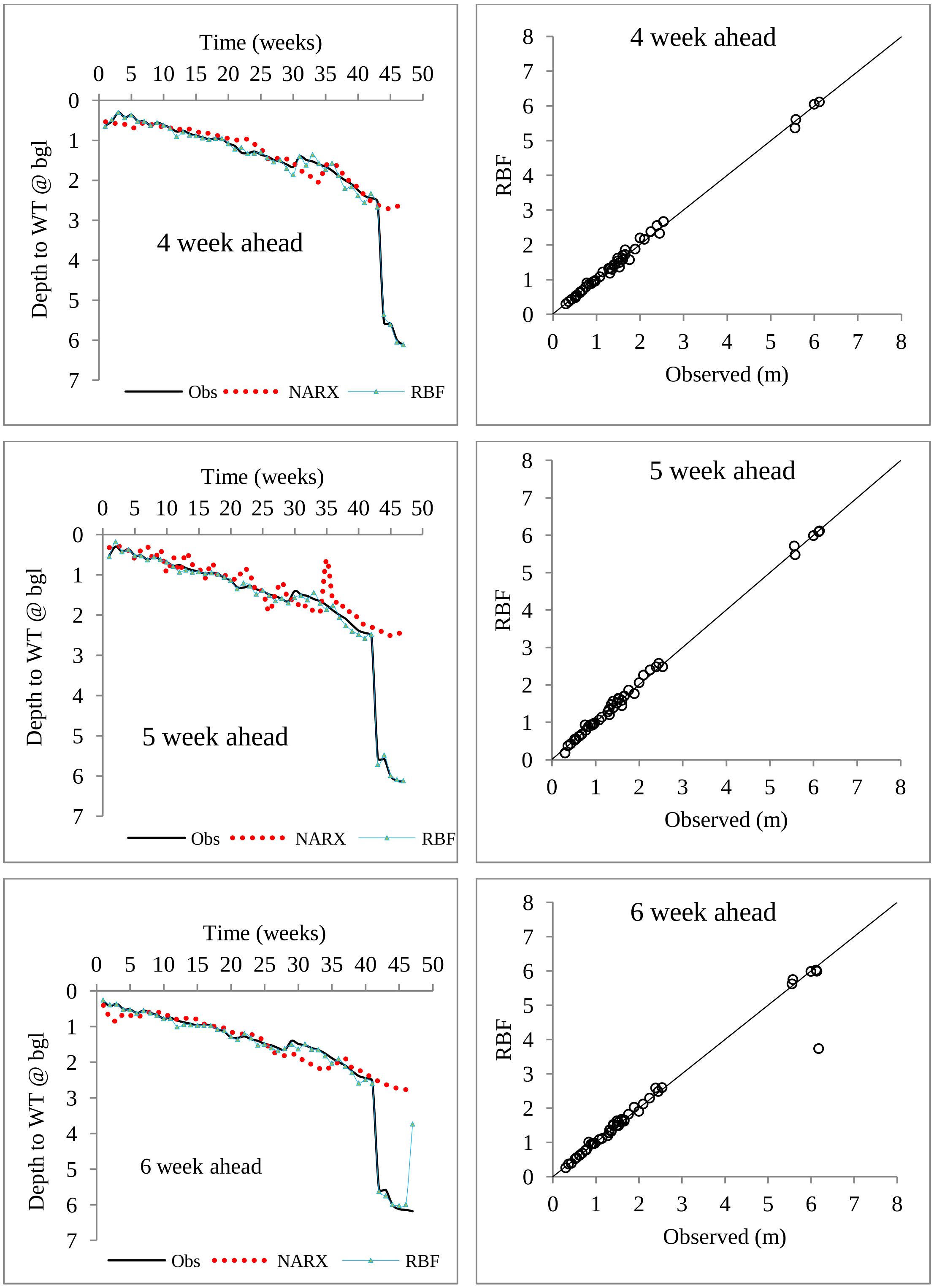
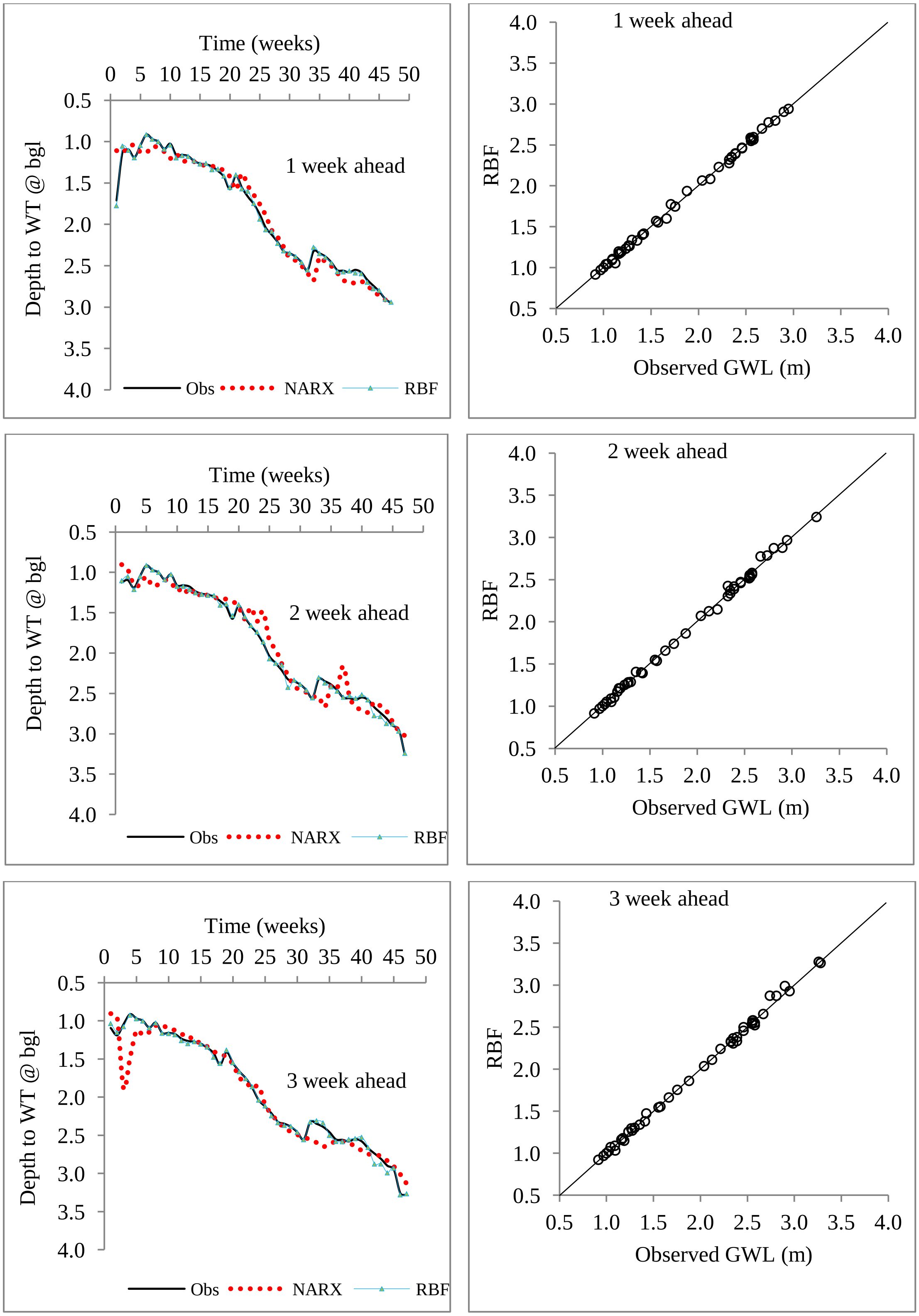



Figure.4.9. Fourth Input scenario for multiple lead time forecasting for **SW6**


Time (weeks)
0 5 10 15 20 25 30 35 40 45 50
0.5 1.0 1.5 2.0 2.5 3.0 3.5 4.0
Depth to WT @ bgl
1 week ahead
Obs NARX RBF
4.0 3.5 3.0 2.5 2.0 1.5 1.0 0.5
RBF
1 week ahead
0.5 1.0 1.5 2.0 2.5 3.0 3.5 4.0
Observed GWL (m)
Time (weeks)
0 5 10 15 20 25 30 35 40 45 50
0.5 1.0 1.5 2.0 2.5 3.0 3.5 4.0
Depth to WT @ bgl
2 week ahead
Obs NARX RBF
4.0 3.5 3.0 2.5 2.0 1.5 1.0 0.5
RBF
2 week ahead
0.5 1.0 1.5 2.0 2.5 3.0 3.5 4.0
Observed GWL (m)
Time (weeks)
0 5 10 15 20 25 30 35 40 45 50
0.5 1.0 1.5 2.0 2.5 3.0 3.5 4.0
Depth to WT @ bgl
3 week ahead
Obs NARX RBF
4.0 3.5 3.0 2.5 2.0 1.5 1.0 0.5
RBF
3 week ahead
0.5 1.0 1.5 2.0 2.5 3.0 3.5 4.0
Observed GWL (m)

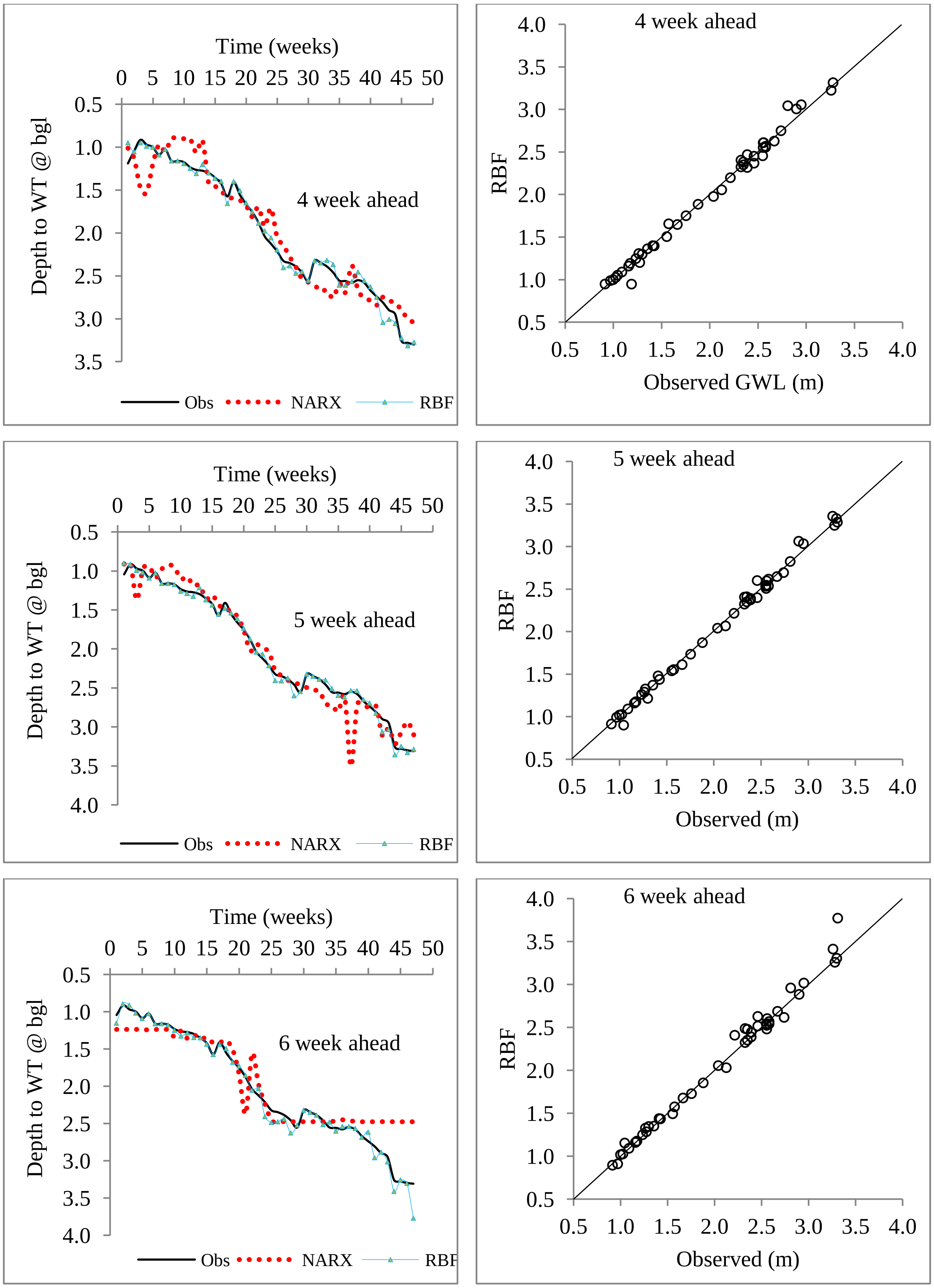



Figure.4.10. Fourth Input scenario for multiple lead time forecasting for **SW8**

**SW22 and SW24**

The Model results for **SW22** and **SW24** are presented in Table 4.11 and Table 4.12. For **SW22**, RMSE for RBF is very small such as 0.02m for one week leadtime upto 0.06m for sixth week lead time with linear gradual variation during testing. The RMSE for NARX Model changes from 0.23m to 0.54m during testing.

Table.4.11 Comparison of model performance for **SW22**

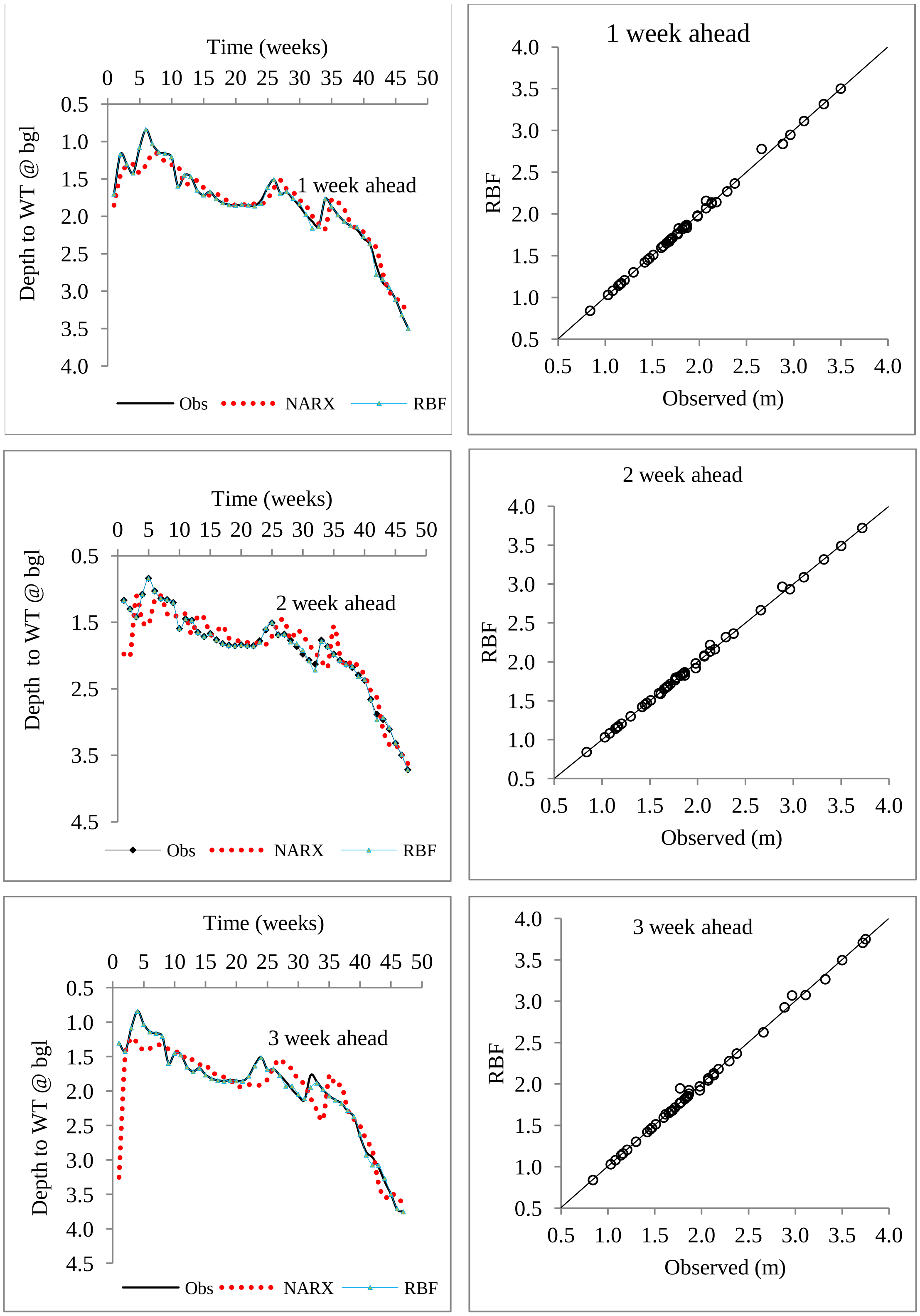
| Lead Time (week) | Training | | | | Testing | | | |
|---|---|---|---|---|---|---|---|---|
| | RMSE (m) | | Cc | | RMSE (m) | | Cc | |
| | RBF | NARX | RBF | NARX | RBF | NARX | RBF | NARX |
| 1 | 0.01 | 0.24 | 0.99 | 0.95 | 0.02 | 0.23 | 0.99 | 0.93 |
| 2 | 0.02 | 0.32 | 0.99 | 0.91 | 0.03 | 0.24 | 0.99 | 0.92 |
| 3 | 0.02 | 0.32 | 0.99 | 0.91 | 0.03 | 0.22 | 0.99 | 0.94 |
| 4 | 0.04 | 0.33 | 0.98 | 0.90 | 0.03 | 0.32 | 0.98 | 0.89 |
| 5 | 0.06 | 0.48 | 0.97 | 0.79 | 0.04 | 0.38 | 0.97 | 0.84 |
| 6 | 0.08 | 0.56 | 0.94 | 0.71 | 0.06 | 0.54 | 0.97 | 0.68 |

Table.4.12 Comparison of model performance for **SW24**

| Lead Time (week) | Training | | | | Testing | | | |
|---|---|---|---|---|---|---|---|---|
| | RMSE (m) | | Cc | | RMSE (m) | | Cc | |
| | RBF | NARX | RBF | NARX | RBF | NARX | RBF | NARX |
| 1 | 0.02 | 0.32 | 0.99 | 0.93 | 0.02 | 0.15 | 0.99 | 0.96 |
| 2 | 0.03 | 0.47 | 0.99 | 0.85 | 0.02 | 0.26 | 0.99 | 0.90 |
| 3 | 0.04 | 0.42 | 0.98 | 0.87 | 0.03 | 0.35 | 0.98 | 0.86 |
| 4 | 0.06 | 0.45 | 0.98 | 0.85 | 0.04 | 0.24 | 0.97 | 0.94 |
| 5 | 0.06 | 0.45 | 0.97 | 0.85 | 0.05 | 0.32 | 0.97 | 0.90 |
| 6 | 0.08 | 0.51 | 0.95 | 0.80 | 0.06 | 0.31 | 0.97 | 0.91 |

The correlation coefficient for RBF model is consistent such as 0.99 whereas NARX model correlation changes from 0.93 to 0.68 during testing. Similar trend is also observed in **SW24** for both the models.

Figure. 4.11 shows the model performance graphically and scatter plots between observed and predicted value upto fourth week lead time for **SW22**. The scatter plots are linearly placed representing unbiasness and systematic error in the RBF model. The wet period as well as dry period weekly behavior of observed groundwater level almost accurately followed by RBF model with a little variation from lower leadtime to higher leadtime as shown in Figure.4.11. The NARX model performing well during lower lead time but deviating sharply during higher lead time. similar pattern observed in Figure.4.12 for SW24. Since, both the **SW22** and **SW24** are located in built up area and also away from stream shows the gradual fluctuations of water level which was captured fully by RBF model may be due to smaller variation of water level data as well as low standard deviation of the training and as well as testing data set. Also, there may not be significant influence from rain during wet as the recharge rate may be very slow and might be taking longer duration to join well. This phenomenon may be further explored.


Time (weeks)
Depth to WT @ bgl
1 week ahead
Obs
NARX
RBF
1 week ahead
RBF
Observed (m)
Time (weeks)
Depth to WT @ bgl
2 week ahead
Obs
NARX
RBF
2 week ahead
RBF
Observed (m)
Time (weeks)
Depth to WT @ bgl
3 week ahead
Obs
NARX
RBF
3 week ahead
RBF
Observed (m)

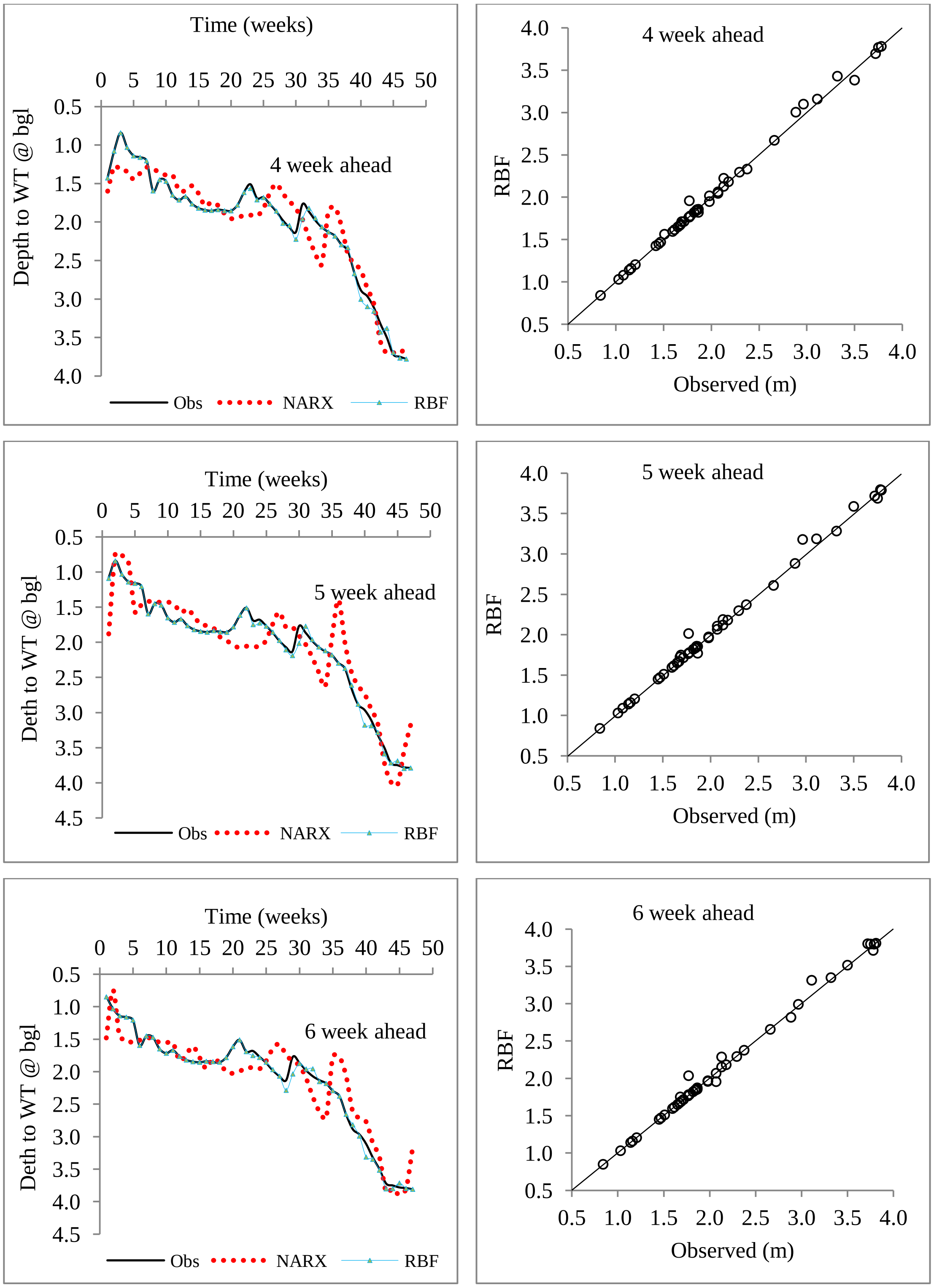
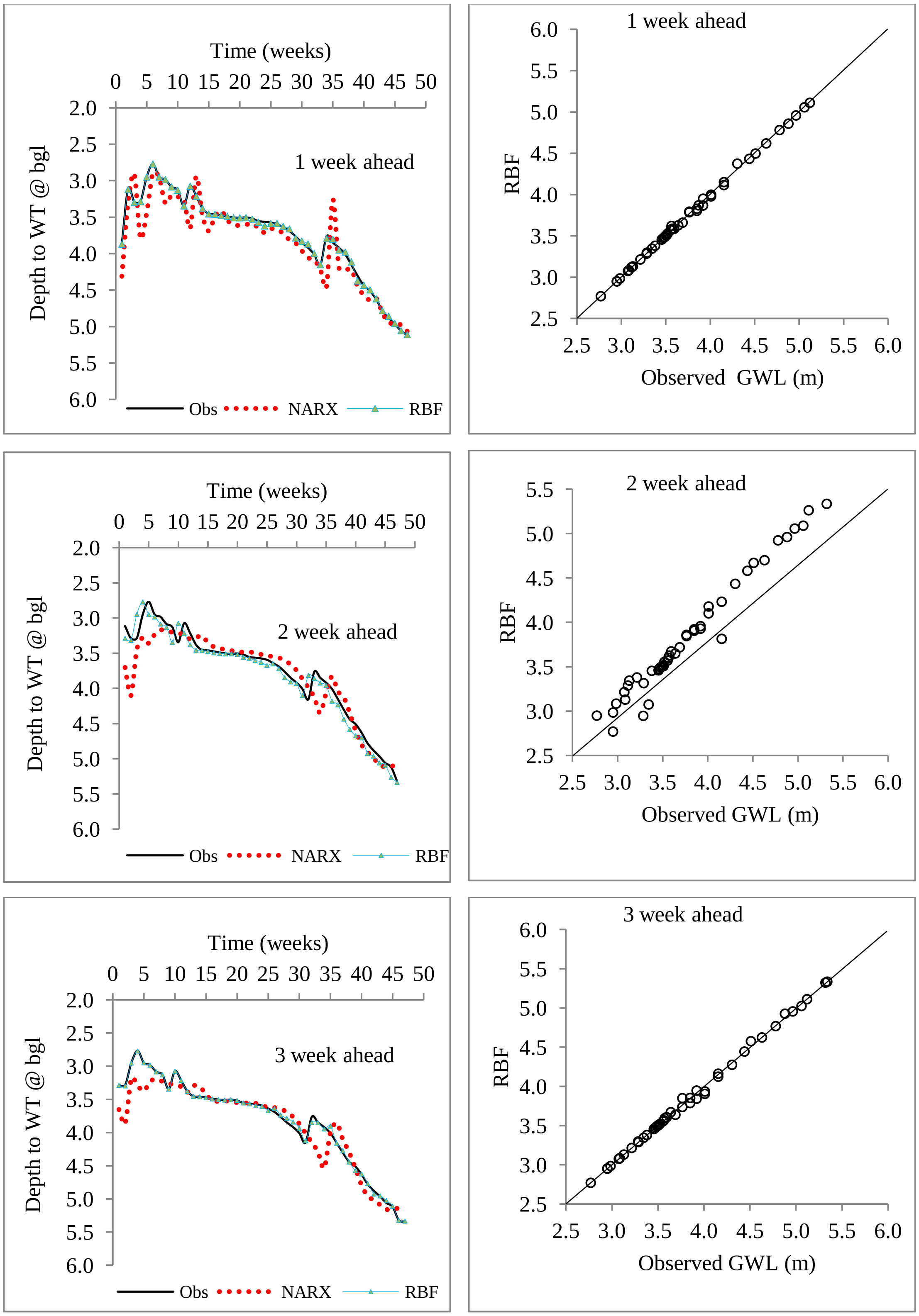



Figure.4.11. Fourth Input scenario for multiple lead time forecasting for **SW24**


Time (weeks)
0 5 10 15 20 25 30 35 40 45 50
2.0 2.5 3.0 3.5 4.0 4.5 5.0 5.5 6.0
Depth to WT @ bgl
1 week ahead
Obs NARX RBF
RBF
6.0 5.5 5.0 4.5 4.0 3.5 3.0 2.5
1 week ahead
2.5 3.0 3.5 4.0 4.5 5.0 5.5 6.0
Observed GWL (m)
Time (weeks)
0 5 10 15 20 25 30 35 40 45 50
2.0 2.5 3.0 3.5 4.0 4.5 5.0 5.5 6.0
Depth to WT @ bgl
2 week ahead
Obs NARX RBF
RBF
5.5 5.0 4.5 4.0 3.5 3.0 2.5
2 week ahead
2.5 3.0 3.5 4.0 4.5 5.0 5.5 6.0
Observed GWL (m)
Time (weeks)
0 5 10 15 20 25 30 35 40 45 50
2.0 2.5 3.0 3.5 4.0 4.5 5.0 5.5 6.0
Depth to WT @ bgl
3 week ahead
Obs NARX RBF
RBF
6.0 5.5 5.0 4.5 4.0 3.5 3.0 2.5
3 week ahead
2.5 3.0 3.5 4.0 4.5 5.0 5.5 6.0
Observed GWL (m)

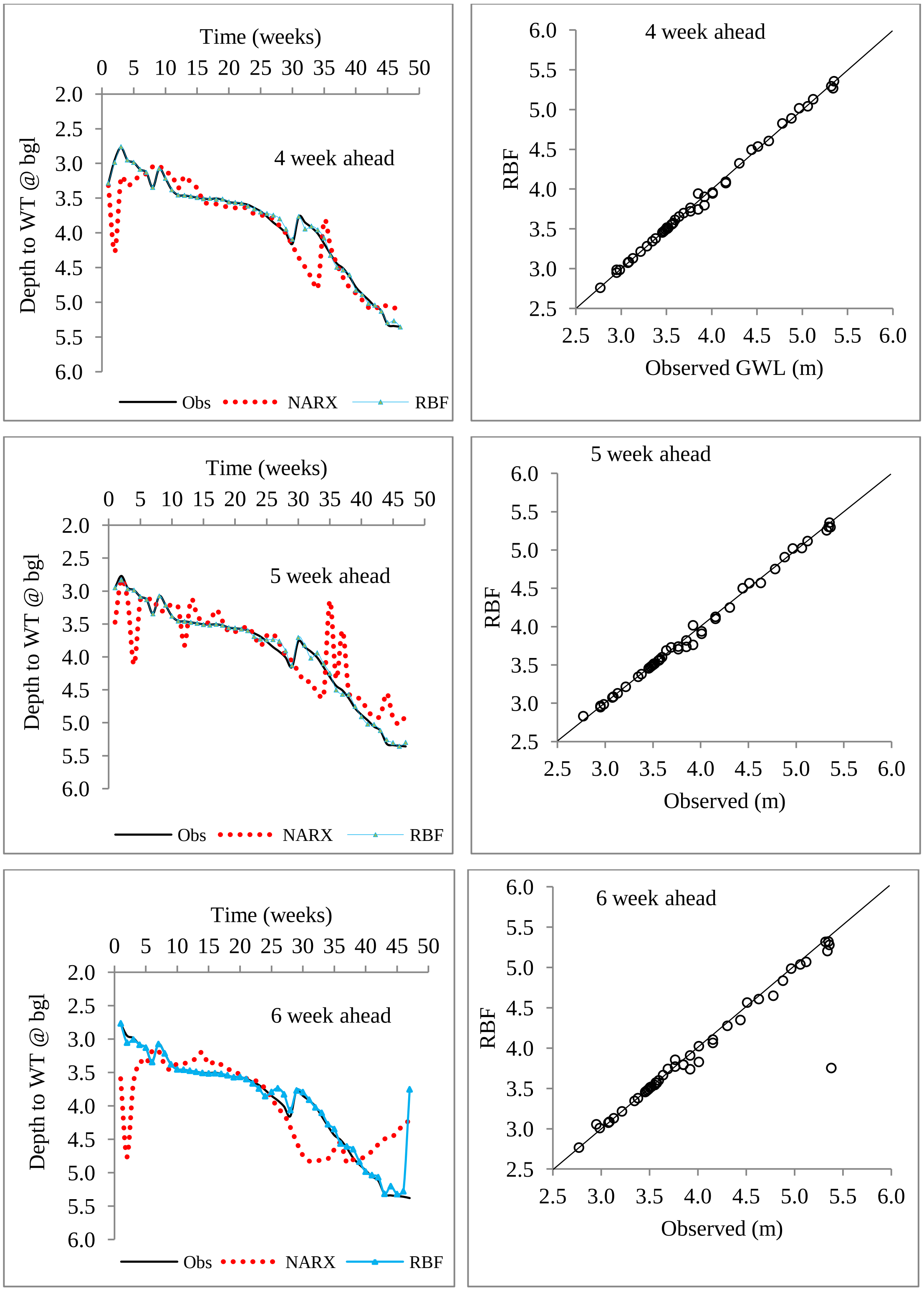



Figure.4.12. Fourth Input scenario for multiple lead time forecasting for **SW22**

### 4.3.3. Summary:

In the second work, RBFNN model has been developed for various spread parameters and the optimum structure is selected for six representative wells. Further, the model performance has been evaluated for mutli lead time forecasting from one week to six week lead time. It has been observed that for all the six wells, the higher and consistent performance for RBF network upto six week lead time and decaying performance for NARX network model. The advantage and robustness of RBFNN model has been checked and results are found quite satisfactory over the NARX model.

## 4.4. Development of GRNN models for GWL forecasting using time series

### 4.4.1. Introduction

The focus of the current research paper is to investigate the potential of another recurrent networks such as GRNN networks to (1) Forecast the groundwater level using different input combinations of weekly time series groundwater level data, (2) Compare the performance of GRNN models to RBF and Levenberg Marquartz algorithm and (3) To select the best model among the various developed models.

### 4.4.2. Selection of representative open wells

The details of three representative open wells used in the study are presented in Table.4.13.

Table.4.13 Details of observation wells for the current study

| Well No | Type of well | Location | Diameter (m) | Depth (m) | Remarks |
|---|---|---|---|---|---|
| SW4 | Shallow well | Padre | 2.40 | 7.54 | Within Paddy Fields |
| SW6 | Shallow well | Mukka | 2.00 | 4.30 | Close to stream |
| SW22 | Shallow well | Munchuru | 2.40 | 7.48 | Built up area |

### 4.4.3. Model development

### 4.4.4. Input structure

Input selection was based on the statistical properties such as cross correlation has been adopted for the time series groundwater level (Coulibaly et al., 2000; Sudheer et al., 2002; Nayak et al., 2006). Considering the persistence in time series data, the correlation coefficients between the input data and output data are calculated and presented in Table 4.14. In general, among all the three wells, one week lag time showing the higher correlation and four week lag time shows the lower correlation in all the three wells. The performance of the model usually depends on the input combinations. Based on the autocorrelation between input and output variables the different model input structures were studied and are presented in Table 4.15.

Table. 4.14 Cross correlation of the whole data set for three representative wells

| Well No | $W_{(t)}$ | $W_{(t-1)}$ | $W_{(w-2t)}$ | $W_{(t-3)}$ | $W_{(t-4)}$ |
|---|---|---|---|---|---|
| **SW4** | $W_{(t)}$ | 1.00 | 0.80 | 0.69 | 0.59 |
| **SW6** | $W_{(t)}$ | 0.95 | 0.88 | 0.81 | 0.71 |
| **SW22** | $W_{(t)}$ | 0.93 | 0.84 | 0.76 | 0.65 |

Table. 4.15 Model Input and Output structure of the groundwater level forecasting

| Model | | SW4 | SW6 | SW22 |
|---|---|---|---|---|
| Sl. No | Input structure | Output | | |
| Model 1 | $w_{(t-1)}$ | $w_{(t)}$ | $w_{(t)}$ | $w_{(t)}$ |
| Model 2 | $w_{(t-1)}$ and $w_{(t-2),}$ | $w_{(t)}$ | $w_{(t)}$ | $w_{(t)}$ |
| Model 3 | $w_{(t-1}$, $w_{(t-2}$ and $w_{t-3)}$, | $w_{(t)}$ | $w_{(t)}$ | $w_{(t)}$ |
| Model 4 | $w_{(t-1)}$, $w_{(t-2),}$ $w_{(t-3)}$ and $w_{(t-4)}$ | $w_{(t)}$ | $w_{(t)}$ | $w_{(t)}$ |

*Wt-1, Wt-2, Wt-3 and Wt-4 represent one, two, three and four previous weekly groundwater level*

Table.4.16 Statistical parameters for observed groundwater level data

| **Parameters** | **SW4** | | | **SW6** | | | **SW22** | | |
|---|---|---|---|---|---|---|---|---|---|
| | Train. data | Test data | Total data | Train. data | Test data | Total data | Train. data | Test. data | Total data |
| Max (m) | 6.42 | 6.65 | 6.65 | 3.65 | 3.56 | 3.65 | 5.50 | 5.45 | 5.50 |
| Min (m) | 1.70 | 1.90 | 1.70 | 0.90 | 0.92 | 0.90 | 2.64 | 2.77 | 2.64 |
| St dv (m) | 1.23 | 1.32 | 1.30 | 0.84 | 0.71 | 0.81 | 0.82 | 0.61 | 0.77 |
| Skewness | -0.13 | 0.41 | -0.02 | 0.17 | 0.68 | 0.32 | 0.43 | 1.35 | 0.66 |
| Mean (m) | 4.46 | 3.68 | 4.23 | 2.05 | 1.84 | 1.98 | 3.97 | 3.71 | 3.89 |

The statistical parameters such as minimum value and maximum value mean and standard deviation both for training and testing data sets are computed and presented in Table. 4.16 For **SW4**, groundwater level fluctuation is very high and standard deviation also reveals the sparsely location of data points. Also, it is appears that for **SW6**, water level fluctuation and standard deviation are moderate compared to **SW4**. The **SW4** is located in paddy fields and there may be water logging conditions during wet period. For the **SW22**, groundwater level fluctuations are minimal with lower standard deviation value as data points are closed spaced.

### 4.4.5. Results and Discussion

In GRNN model development, for each input combination, the optimal smoothing factor for the model was determined according to the mean square error criteria. Various smoothing factor value for each combination were tried from 0.5 to 1.0 and the best smoothing factor was found as 1.0. In general, the smoothing values are increasing in parallel to the number of inputs but not necessarily for all the scenarios as observed here.

Similarly for RBF models, proper spread values and optimal number of hidden nodes were determined by trial and error method as there are no specific guidelines available to assign this value. Here, number of trials has been carried out to optimize the best network within a range of 1 to 5. The optimal spread constant was found as 4 which was used for various input scenarios along with other internal parameters in the RBF network structure. The FFBP with Levenberg-Marquadart training algorithm were adopted for best performance trying various numbers of hidden nodes for various input scenarios. The training and testing results of all the models developed for different input scenarios for all the **SW4**, **SW6** and **SW22** are presented in Table 4.17, Table 4.18 and Table 4.19 sequentially. The proposed GRNN and RBF model results were compared with FFBP trained with LM models. All the models were tested for one week lead time and best model results are presented.

Table.4.17 Training and testing results for different inputs scenario (**SW4)**

| **Comparison** | **Input (s)** | **Hidden Neuron** | **Training** | | **Testing** | |
|---|---|---|---|---|---|---|
| | | | **RMSE** | **CE** | **RMSE** | **CE** |
| LM | 1 | 05 | 0.28 | 0.92 | 0.64 | 0.77 |
| | 2 | 20 | 0.38 | 0.90 | 0.67 | 0.75 |
| | 3 | 19 | 0.43 | 0.90 | 0.69 | 0.75 |
| | 4 | 17 | 0.46 | 0.88 | 0.76 | 0.64 |
| RBF | 1 | 03 | 0.18 | 0.94 | 0.20 | 0.92 |
| | 2 | 18 | 0.32 | 0.93 | 0.42 | 0.90 |
| | 3 | 20 | 0.34 | 0.92 | 0.44 | 0.85 |
| | 4 | 07 | 0.42 | 0.88 | 0.52 | 0.81 |
| GRNN | 1 | 17 | 0.14 | 0.98 | 0.18 | 0.91 |
| | 2 | 07 | 0.20 | 0.96 | 0.28 | 0.93 |
| | 3 | 09 | 0.24 | 0.93 | 0.35 | 0.88 |
| | 4 | 10 | 0.25 | 0.93 | 0.38 | 0.87 |

**SW4**

For the **SW4** data analysis, it can be seen from Table 4.17, GRNN model performance in groundwater level forecasting was found to be similar or better than RBF for the entire input scenario in terms of coefficient of Efficiency (CE) and root mean square error (RMSE) criteria. The FFBP (LM) was placed at the bottom rank with inferior performance as compared to GRNN and RBF.

Here, CE is used instead as in earlier few cases Cc is giving contradictory results to RMSE. The C.E. was revealing higher forecasting performance as close agreement with observed level for GRNN model such as ranges from 0.94 to 0.91 during testing for different input scenarios as presented in Table 4.17 (**SW4**).The GRNN model performance was observed to be almost similar or slightly better compared to RBF performance considering C.E. and RMSE. The C.E ranges from 0.97 to 0.87 for GRNN which can also be treated as acceptable accuracy.

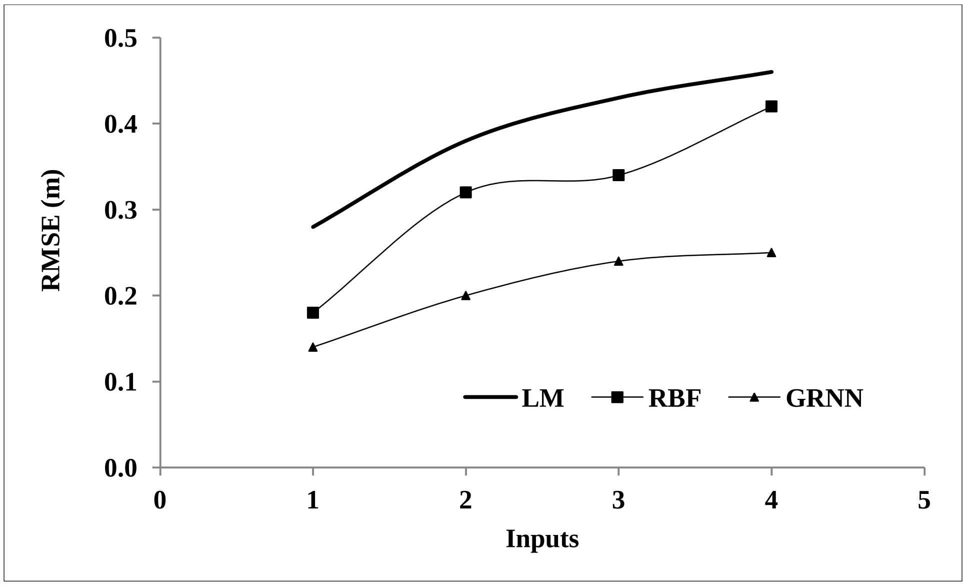



Figure.4.13. RMSE vs. Input combinations for **SW4** during training

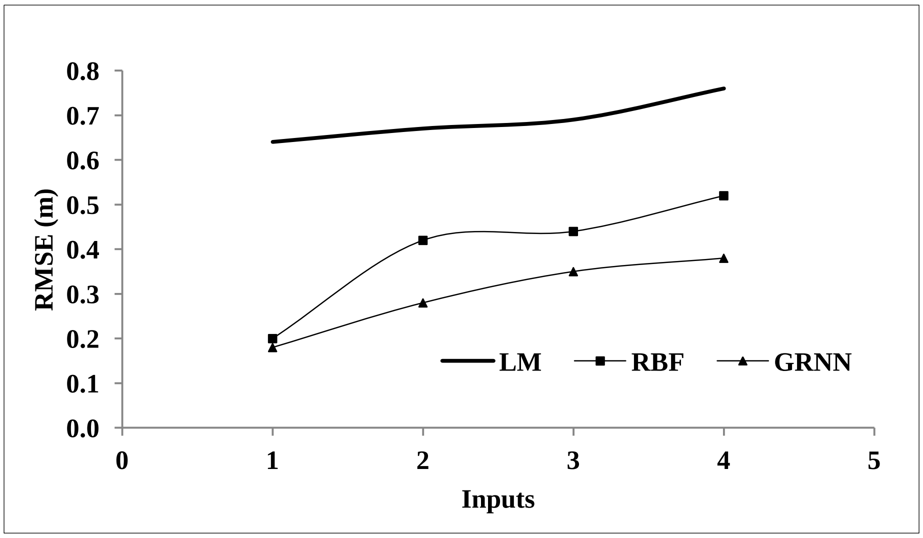



Figure.4.14. RMSE vs. Input combinations for **SW4** in shown during testing

The variations of RMSE in different input scenario for all the models during training and testing for **SW4** are shown in Figure.4.13 and Figure.4.14 respectively. Considering the various input combinations, it was observed that the performance of GRNN was either similar or better (Lower RMSE) than RBF networks both during training and testing. The LM was placed at bottom rank with higher RMSE.

Also, to focus more on the predicting capability of the developed model, RBF and GRNN were evaluated during crucial stage of ground water level such as wet, dry and normal periods as LM was kept out of the discussion. Hence, Time series plot for both RBF and GRNN were presented in Figure.4.15 during testing to visualize the model behavior during different time periods. In testing, GRNN was closely followed the observed pattern during rainy season as well as non-rainy season than that of RBF model. Similarly, Figure.4.16 shows the closed scatter points for GRNN depicting higher predicting ability. RBF was sparsely placed with $45^0$ line as shown in Figure.4.17 indicating inferior performance compared to GRNN.

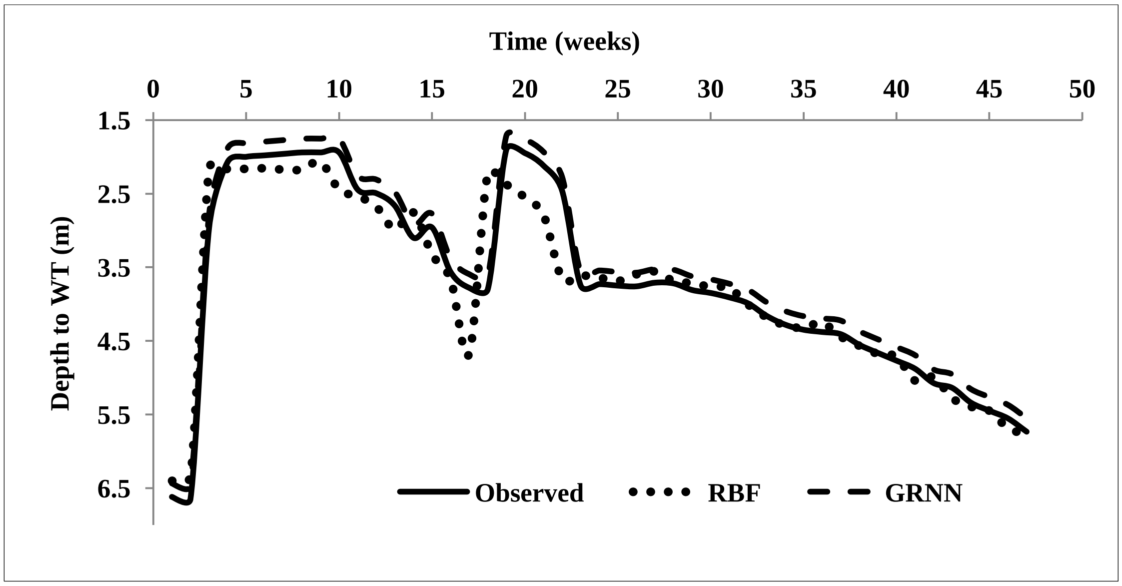



Figure.4.15. Time series plot of GRNN and RBF for **SW4** in testing

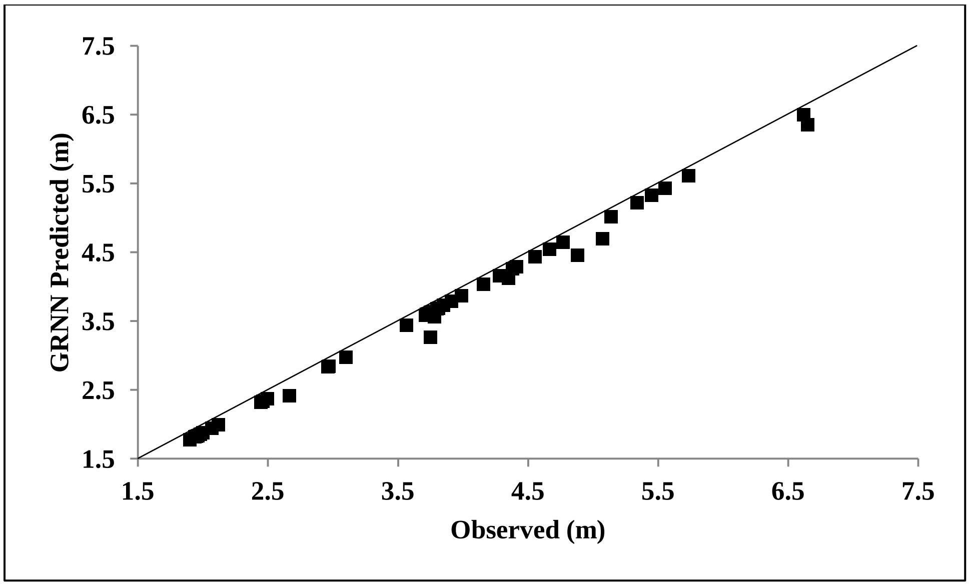



Figure.4.16. Scatter plots of GRNN for testing at **SW4**

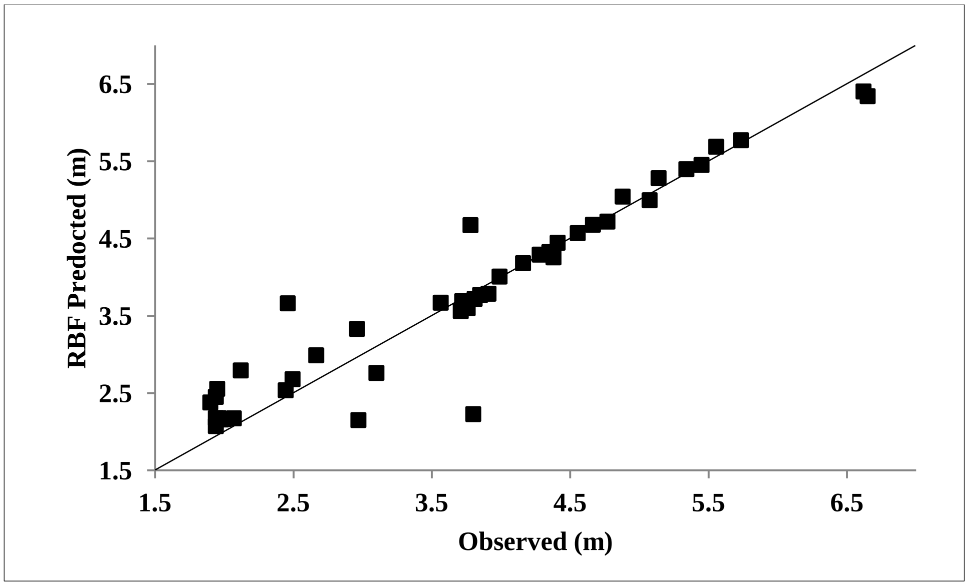



Figure.4.17. Scatter plots of RBF for testing at **SW4**

Based on above results for **SW4**, GRNN is well ahead of RBF and LM for groundwater level prediction accuracy both during frequent and non-frequent ground water fluctuations along with transition stage period because of optimal learning with smoothing factor in spite of water level variation is very high and standard deviation is also significantly large.

**SW6 and SW22**

Similarly for **SW6** the different input scenarios and their results were presented in Table 4.18. The statistical behavior of **SW6**and **SW22** are almost similar but drastically different from **SW4**. It was observed that the model performances for **SW6** were also shown similar trend of results like **SW4** during training and testing. The network structure of GRNN showing higher C.E ranges from 0.93 to 0.98 during training stage (Table.4.18). Also, during testing phase, C.E of GRNN provided the best performance as ranges from 0.87 to 0.93. RBF was placed second to GRNN considering C.E. The performance of RBF can also be classified as under acceptable accuracy. Here, LM suffers in both training and testing with lower C.E such as 0.43 to 0.89.

Table.4.18 Training and testing Results for different inputs scenario **(SW6)**

| **Comparison** | **Input (s)** | **Hidden Neuron** | **Training** | | **Testing** | |
|---|---|---|---|---|---|---|
| | | | **RMSE** | **CE** | **RMSE** | **CE** |
| LM | 1 | 28 | 0.21 | 0.81 | 0.37 | 0.65 |
| | 2 | 25 | 0.18 | 0.85 | 0.22 | 0.89 |
| | 3 | 21 | 0.43 | 0.73 | 0.43 | 0.54 |
| | 4 | 30 | 0.44 | 0.72 | 0.48 | 0.43 |
| RBF | 1 | 05 | 0.14 | 0.96 | 0.26 | 0.92 |
| | 2 | 11 | 0.22 | 0.87 | 0.56 | 0.82 |
| | 3 | 07 | 0.25 | 0.86 | 0.63 | 0.80 |
| | 4 | 11 | 0.27 | 0.82 | 0.69 | 0.74 |
| GRNN | 1 | 20 | 0.14 | 0.95 | 0.25 | 0.94 |
| | 2 | 10 | 0.11 | 0.98 | 0.16 | 0.98 |
| | 3 | 06 | 0.18 | 0.93 | 0.41 | 0.88 |
| | 4 | 13 | 0.19 | 0.93 | 0.45 | 0.87 |

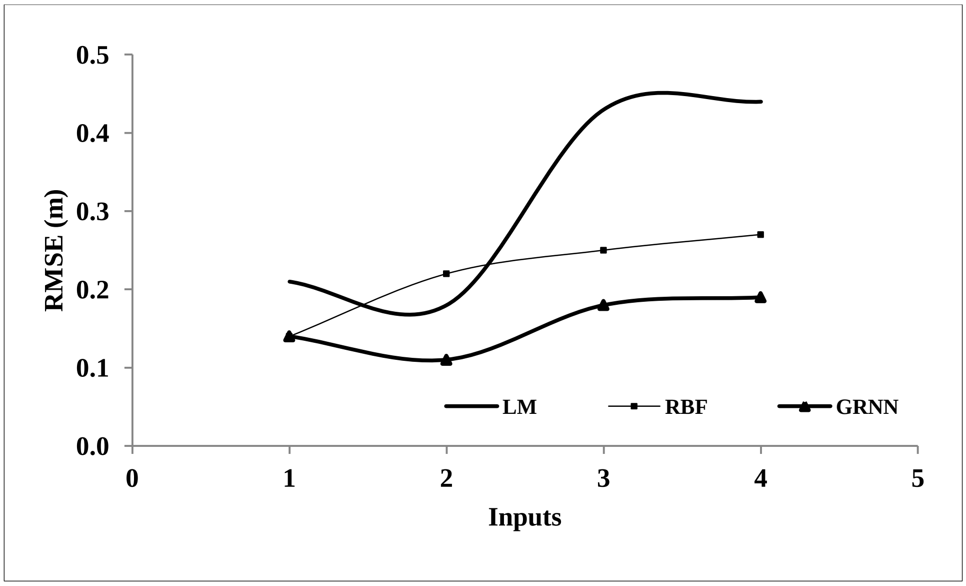



Figure.4.18. RMSE vs. Input combinations for **SW6** during training

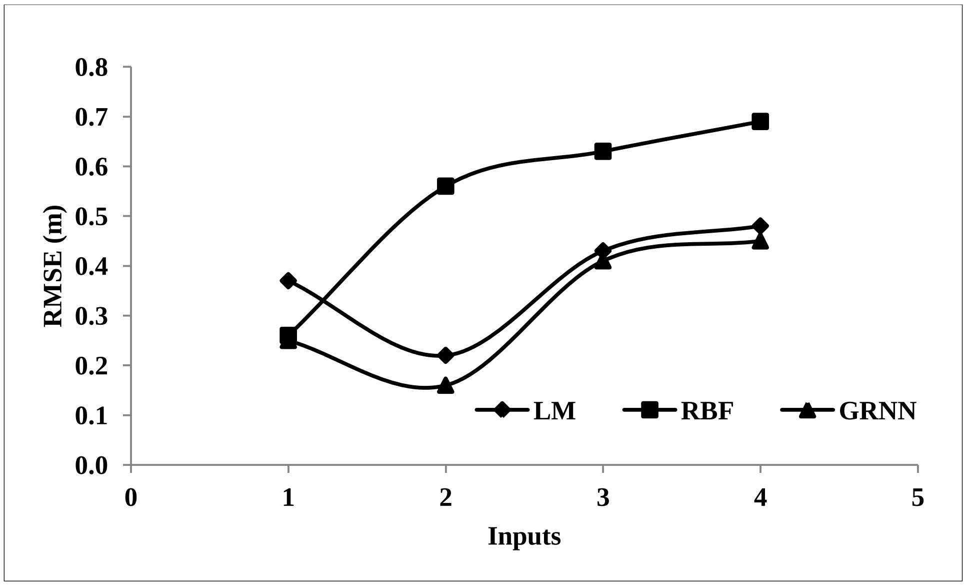



Figure.4.19. RMSE vs. Input combinations for **SW6** during testing

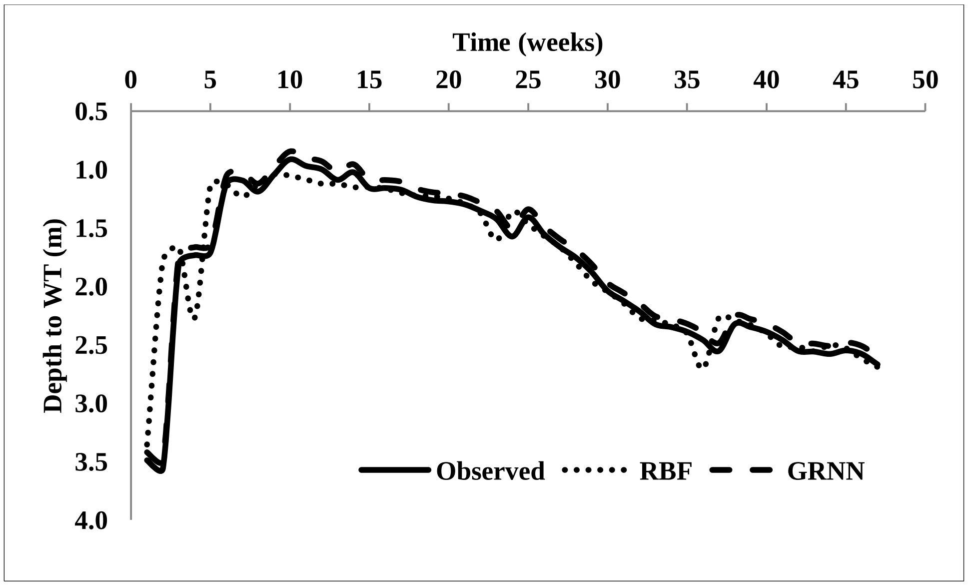



Figure.4.20. Time series plot of GRNN and RBF for **SW6** in testing

The variations of RMSE in different input scenario for all the models were shown in Figure.4.18 in training and Figure.4.19 during testing for **SW6**. GRNN was attached with minimum RMSE for every input combinations compared to RBF and LM. Again, Time series plot shown in Figure.4.20 reinforced the superiority of GRNN over RBF models during testing. Figure4.21 shows the closely spaced scatters of computed and observed ground water level for GRNN. The RBF model results were sparsely placed as shown in scatter plot as depicted in Figure.4.22 during the testing phase.

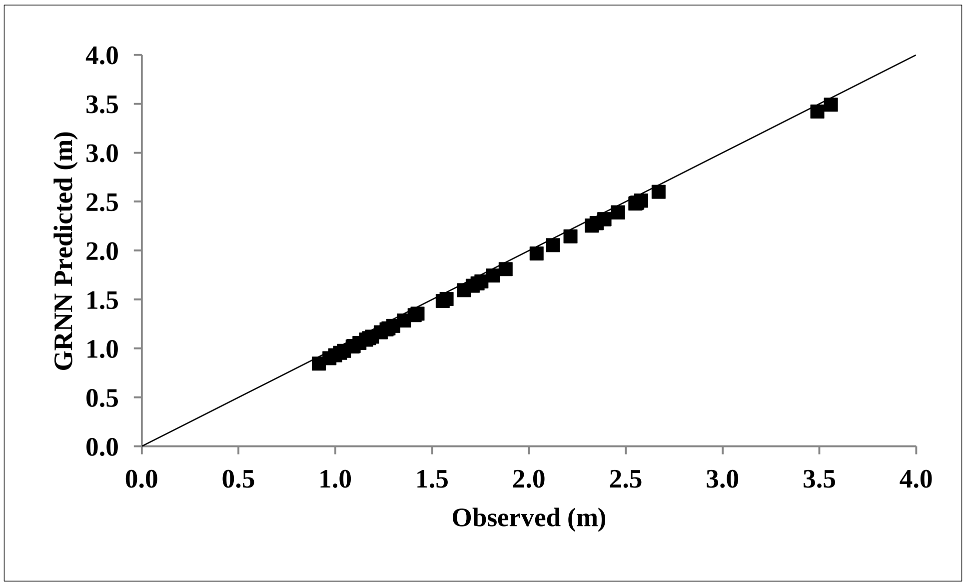



Figure.4.21. Scatter plots of GRNN for testing at **SW6**

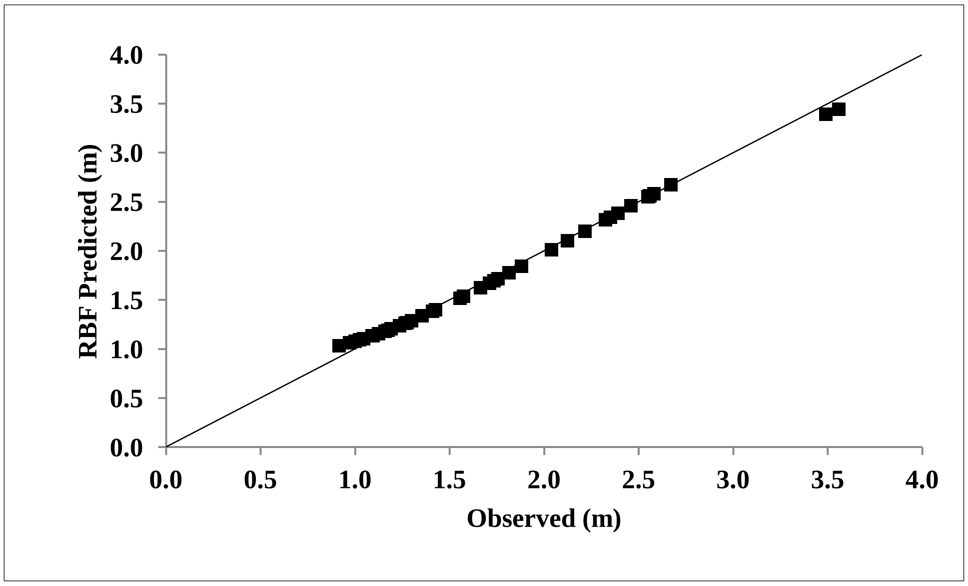



Figure.4.22. Scatter plots of RBF for testing at **SW6**

Finally, SW22 results are tabulated in Table. 4.19 for different input combinations. However, the GRNN model has improved performance than that of LM and RBF for all the three different wells. The performing trend of GRNN was found to be in similar fashion to earlier results. The deviation between GRNN and RBF was not too much significant in terms of performance indices such as C.E and RMSE. The variations of RMSE in different input scenario for all the models are shown in Figure.4.23 for training and Figure.4.24 during testing for **SW22**. Time series plot for both the GRNN and RBF were shown in Figure.4.25 to visualize the deviation with observed ground water level during testing for SW22. Here also, close agreement of GRNN with observed ground water level were clearly established the consistency and robust performance. Scatter plots were shown in Figure.4.26 for GRNN and Figure.4.27 for RBF which showed the clear higher performance by GRNN for SW22 during testing.

Table.4.19 Training and testing results for different inputs scenario **(SW22)**

| **Comparison** | **Input (s)** | **Hidden Neuron** | **Training** | | **Testing** | |
|---|---|---|---|---|---|---|
| | | | **RMSE** | **CE** | **RMSE** | **CE** |
| LM | 1 | 19 | 0.45 | 0.69 | 0.51 | 0.66 |
| | 2 | 10 | 0.30 | 0.86 | 0.39 | 0.82 |
| | 3 | 06 | 0.42 | 0.73 | 0.52 | 0.68 |
| | 4 | 06 | 0.50 | 0.65 | 0.55 | 0.62 |
| RBF | 1 | 20 | 0.41 | 0.74 | 0.48 | 0.71 |
| | 2 | 18 | 0.14 | 0.96 | 0.17 | 0.91 |
| | 3 | 11 | 0.19 | 0.94 | 0.28 | 0.89 |
| | 4 | 14 | 0.23 | 0.91 | 0.32 | 0.86 |
| GRNN | 1 | 20 | 0.44 | 0.76 | 0.52 | 0.68 |
| | 2 | 05 | 0.10 | 0.96 | 0.15 | 0.92 |
| | 3 | 17 | 0.31 | 0.85 | 0.41 | 0.78 |
| | 4 | 19 | 0.38 | 0.78 | 0.43 | 0.74 |

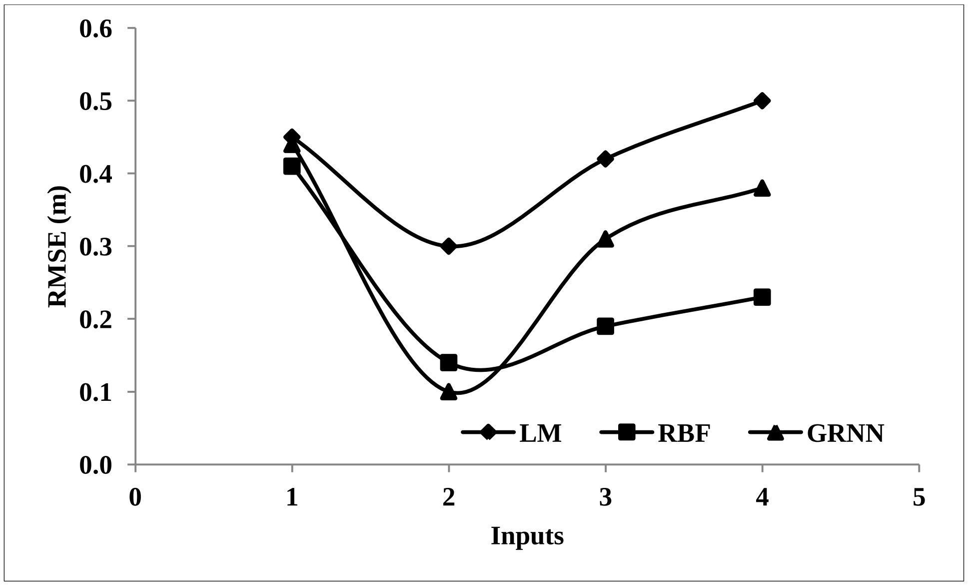



Figure.4.23 RMSE vs. Input combinations for **SW22** during training

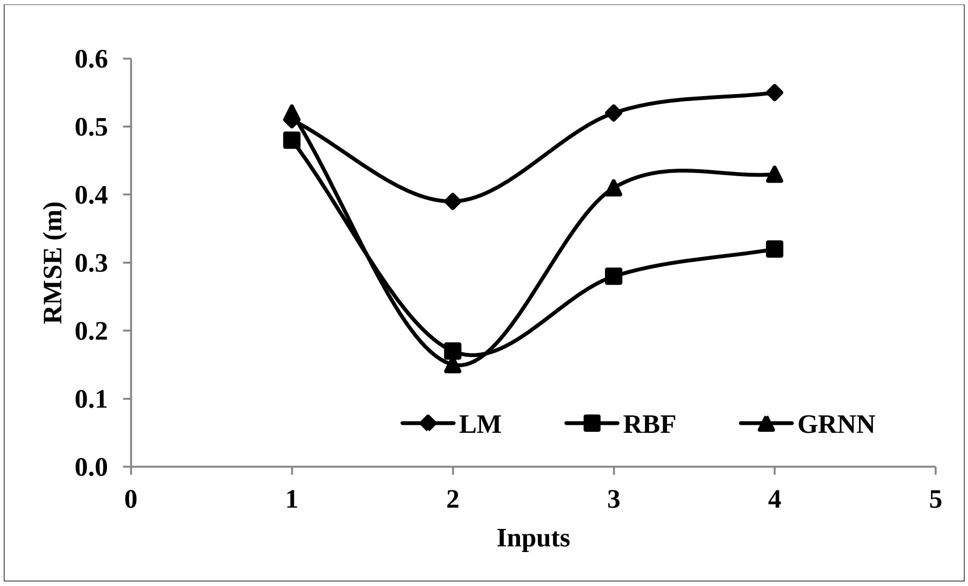



Figure.4.24 RMSE vs. Input combinations for **SW22** during testing

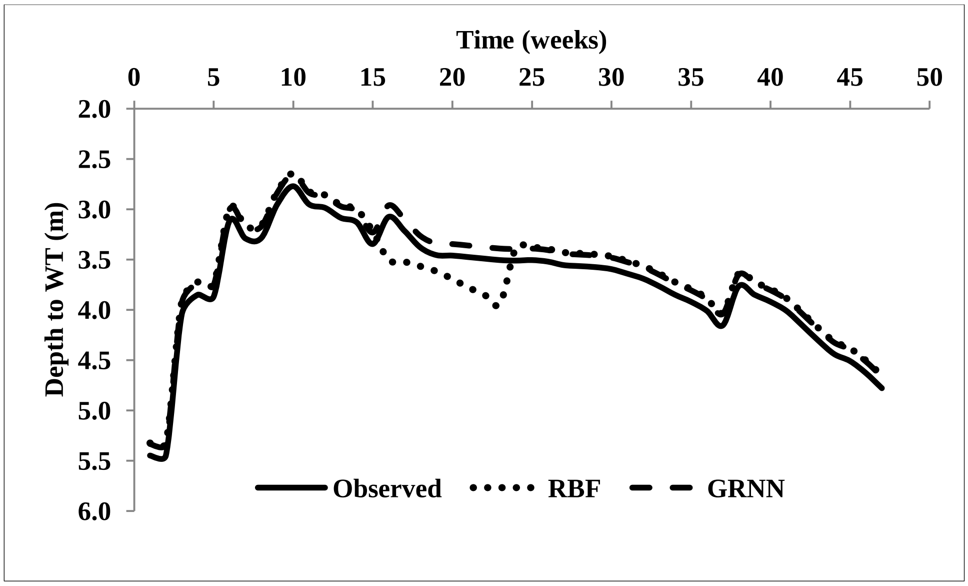



Figure.4.25 Time series plot of GRNN and RBF for **SW22** in testing

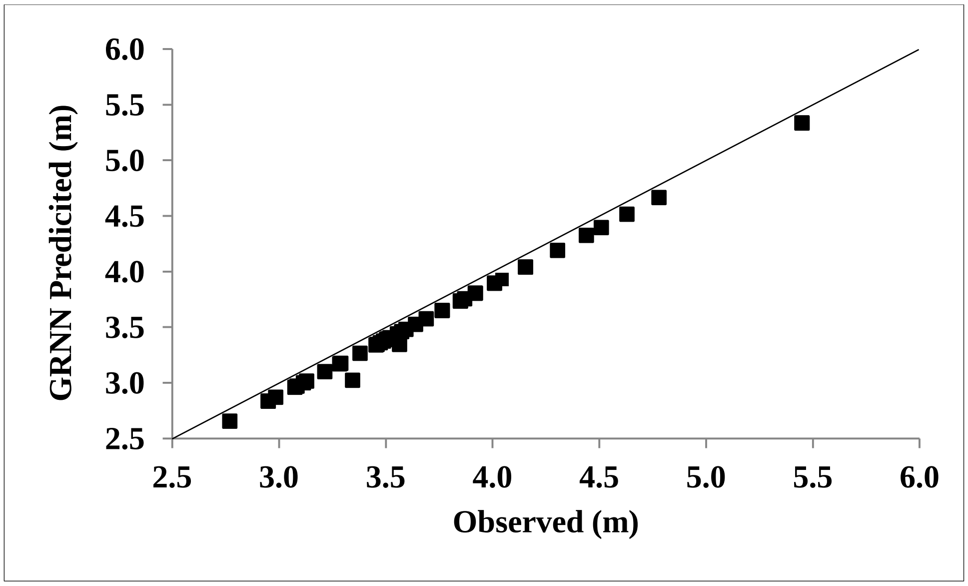



Figure.4.26. Scatter plots of GRNN for testing at **SW22**

Analyzing the results tabulated above, the GRNN was found to be front runner for the current study of ground water level forecasting for one week leadtime. The RBF was placed second to GRNN with very insignificant deviations.

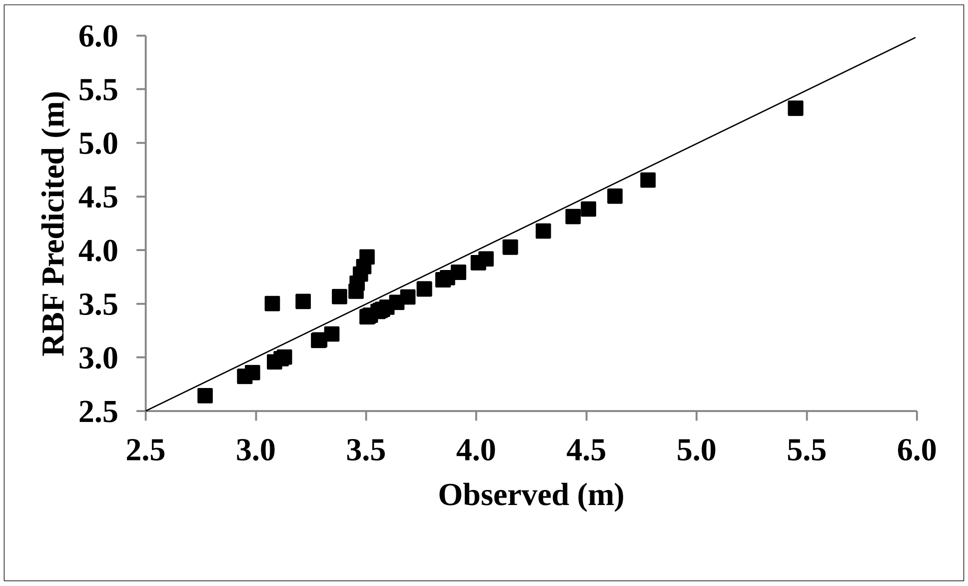



Figure.4.27. Scatter plots of RBF for testing at **SW22**

Both the model provides higher accuracy considering C.E and RMSE. In the **SW4**, where nonlinearity was observed to be higher than other wells, GRNN model performance was found to be highly satisfactory. The inferior performance of LM algorithm may be due to the nature of non-linearities associated with hidden nodes.

### 4.4.6 Summary

The non-linearities in LM is implemented by a fixed function such as sigmoid. On the other hand, The RBF bases its non-linearities on the data in the training set. Once all the basis functions in the hidden layer have been found, the network only needs to learn at the output layer in a linear summation fashion. Also, by varying smoothing parameters ,GRNN model might be capturing fully the nonlinear trends of the ground water levels during training which extracts large scale structure that results higher accuracy than other models. The improved performance of model clearly shows that the GRNN can be used as an effective predictive tool for forecasting purposes.

## 4.5. Applicability of GRNN model in Cause and effect relationship

### 4.5.1. Introduction

After confirming the potential and applicability of GRNN and RBF in time series GWL forecasting with similar capability, the robustness, adaptability and flexibility characteristics of these two techniques are further examined with cause and effect relationship. Here various meteorological parameters are used as causable variable and the GWL is used as output effect. Only GRNN models are developed in the present study. In the fourth work, the effect of meteorological parameters such as temperature, relative humidity, evaporation and rainfall on groundwater level fluctuation has been investigated for Dakshina Kannada coastal aquifer at southwest coast of India. Five various input combinations are used to obtain best results as one step leadtime output for three representative wells.

### 4.5.2. Data used

For the analysis of groundwater level three different representative open wells were selected based on different land use and land cover (LU/LC). Weekly time series meteorological parameters such as rainfall (P), evaporation (E) and temperature ($T_{max}$) were as model inputs. Further to examine the influence of meteorological parameters on groundwater level, the meteorological data (rainfall, temperature evaporation, sunshine hours and relative humidity) are procured from the Indian meteorological Department (IMD), Panambur. The gathered data from the field and IMD are prepared as a set of database. These data are divided into two parts as per the requirement of ANN (training and testing); the first data set consists of 70% of the total database as training (calibration) and second includes 30% of total data for the testing of the model. Details of open wells and site specifications are presented in Table.4.20 the statistical properties of the time series of IMD data for training and testing data set are presented in Table.4.21.

Table.4.20 Description of selective open wells and their details

| Well No | Well Type | Location | Diameter (m) | Depth (m) | Remarks |
|---|---|---|---|---|---|
| **SW4** | Shallow well | Padre | 2.4 | 7.54 | Paddy Fields |
| **SW6** | Shallow well | Mukka | 2.0 | 4.33 | Close to stream |
| **SW22** | Shallow well | Munchuru | 2.4 | 7.48 | Built up Area |

Table 4.21 Data statistics during training and testing

| **Statistics** | **Rainfall P (mm)** | **$T_{max}$ ($^0C$)** | **$T_{min}$ ($^0C$)** | **Evaporation E (mm)** |
|---|---|---|---|---|
| Training | | | | |
| Max | 505.0 | 36.0 | 25.5 | 7.3 |
| Min | 0.0 | 27.7 | 19.7 | 1.3 |
| Avg | 71.4 | 31.9 | 22.9 | 4.7 |
| St. dv | 102.0 | 2.0 | 1.3 | 1.5 |
| Skewness | 1.9 | -0.2 | -0.2 | -0.3 |
| Testing | | | | |
| Max | 422.0 | 34.1 | 25.8 | 11.4 |
| Min | 0.0 | 27.3 | 20.3 | 1.6 |
| Avg | 120.0 | 31.5 | 22.7 | 4.5 |
| St. dv | 122.8 | 1.8 | 1.2 | 1.7 |
| Skewness | 1.1 | -0.4 | -0.1 | 1.1 |

### 4.5.3. Model Development

In the present study, auto correlation was used to reduce more number of input combinations and to minimize computation time. Performance of the model can be improved by selecting the proper input combination. The auto correlation between the different input and output variables are presented in Table.4.22. From the Table 4.22 it is observed that relative humidity is showing very poor correlation with groundwater level data. Though the relative humidity seems to be influencing factor but this parameter can be neglected while developing models for groundwater level fluctuations. Based on auto-correlation different input combinations for GRNN models are developed and are presented in Table.4.23 where results are compared to FFBP.

Table 4.22 Auto correlation for different input parameters

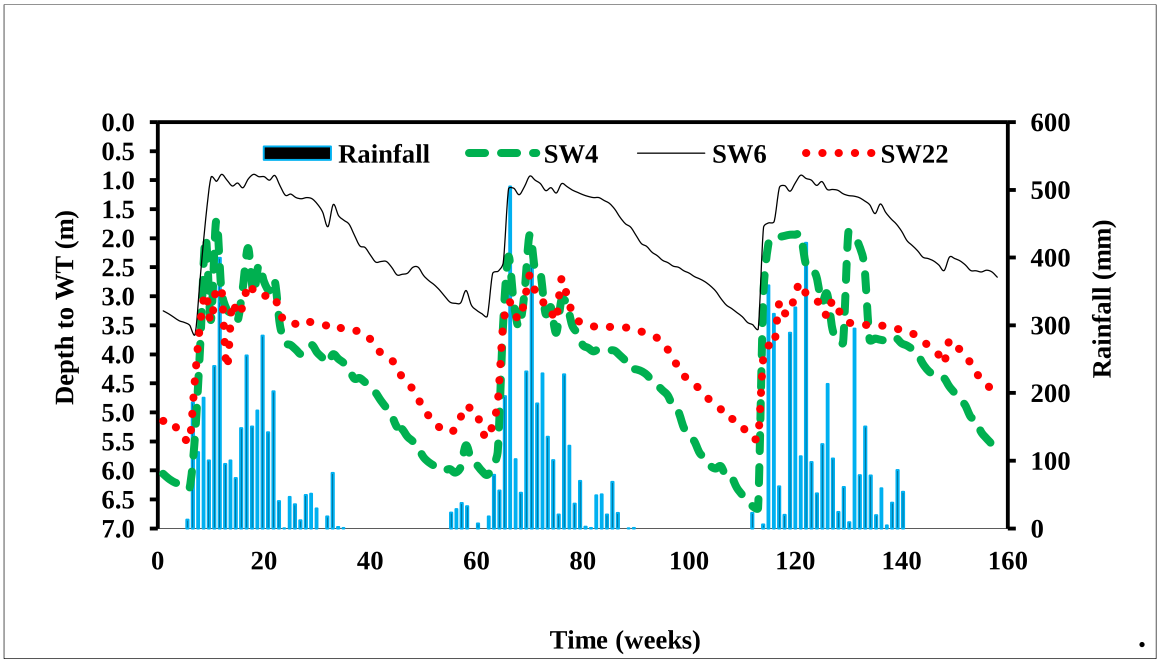
| Well No | Rainfall | $T_{max}$ | $T_{min}$ | Evapo | gwl |
|---|---|---|---|---|---|
| **SW4** | -0.65 | 0.82 | 0.21 | 0.80 | gwl |
| **SW6** | -0.46 | 0.82 | 0.19 | 0.78 | gwl |
| **SW22** | -0.49 | 0.77 | 0.38 | 0.72 | gwl |

Table.4.23 Description of model input and output

| Sl. No. | Input (s) | Output (s) |
|---|---|---|
| 1 | P+T | gwl |
| 2 | E | gwl |
| 3 | P+E | gwl |
| 4 | T+E | gwl |
| 5 | P+T+E | gwl |

### 4.5.4 Effect of Rainfall on Groundwater Level Fluctuations

The well hydrograph and hyetograph for three different wells are shown in Figure.4.28. The study area receives heavy rainfall during rainy season. From the Figure.4.28 it is clear that groundwater level is showing a very quick response to rainfall events in the monsoon season due to characteristics of lateritic soil properties such as highly porous and pervious in nature and the geological formations. As we can see in three different wells groundwater level is rising almost nearer to the ground surface during monsoon period. There is gradual decline in groundwater level during non monsoon season, though groundwater level usage only meant for domestic purpose (not for industrial and commercial). This happens only there is an additional factors which influences the groundwater levels.




Figureure.4.28. well hydrograph and hyetograph for three wells

### 4.5.5 Results and Discussion

The performances of developed models were evaluated using performance indices such as root mean square error (RMSE) and coefficient of efficiency (CE) shown in Table.4.24, Table.4.25. and Table.4.26. The obtained results showed closed relationship between rainfall event and groundwater level during monsoon. It was also, observed that the temperature and evaporation had significant effect on groundwater level fluctuations in non-monsoon season. The obtained GRNN results were compared with that of FFBP. A better agreement was observed between the actual and modeled groundwater levels for GRNN than that of FFBP.

Table.4.24 Comparative performance of various GRNN and FFBP models during training and testing at **SW4**

| SW4 | Performance Indices | Training | | | | Testing | | | |
|---|---|---|---|---|---|---|---|---|---|
| Model no | | RMSE (m) | | CE | | RMSE (m) | | CE | |
| | Inputs | GRNN | FFBP | GRNN | FFBP | GRNN | FFBP | GRNN | FFBP |
| 1 | T+E | 0.24 | 0.28 | 0.96 | 0.94 | 0.41 | 0.46 | 0.95 | 0.94 |
| 2 | E | 0.310 | 0.35 | 0.93 | 0.92 | 0.51 | 0.72 | 0.93 | 0.86 |
| 3 | P+T+E | 0.36 | 0.41 | 0.91 | 0.89 | 0.59 | 0.68 | 0.91 | 0.88 |
| 4 | P+T | 0.40 | 0.49 | 0.89 | 0.83 | 0.72 | 0.82 | 0.86 | 0.82 |
| 5 | P+E | 0.45 | 0.52 | 0.86 | 0.82 | 0.74 | 0.82 | 0.86 | 0.82 |

*Where T= Temperature (Max), E=Evaporation, P=Rainfall*

Table.4.25 Comparative performance of various GRNN and FFBP models during training and testing at **SW6**

| SW6 | Performance Indices | Training | | | | Testing | | | |
|---|---|---|---|---|---|---|---|---|---|
| Model no | | RMSE (m) | | CE | | RMSE (m) | | CE | |
| | Inputs | GRNN | FFBP | GRNN | FFBP | GRNN | FFBP | GRNN | FFBP |
| 1 | T+E | 0.12 | 0.16 | 0.98 | 0.96 | 0.30 | 0.41 | 0.97 | 0.95 |
| 2 | E | 0.14 | 0.18 | 0.97 | 0.95 | 0.36 | 0.46 | 0.96 | 0.94 |
| 3 | P+T+E | 0.20 | 0.23 | 0.94 | 0.92 | 0.50 | 0.52 | 0.93 | 0.93 |
| 4 | P+T | 0.22 | 0.28 | 0.93 | 0.88 | 0.56 | 0.67 | 0.92 | 0.88 |
| 5 | P+E | 0.24 | 0.35 | 0.91 | 0.82 | 0.59 | 0.84 | 0.91 | 0.82 |

*Where T= Temperature (Max), E=Evaporation, P=Rainfall*

Table.4.26 Comparative performance of various GRNN and FFBP models during training and testing at **SW22**

| SW22 | Performance Indices | Training | | | | Testing | | | |
|---|---|---|---|---|---|---|---|---|---|
| Model no | | RMSE (m) | | CE | | RMSE (m) | | CE | |
| | Inputs | GRNN | FFBP | GRNN | FFBP | GRNN | FFBP | GRNN | FFBP |
| 1 | T+E | 0.11 | 0.13 | 0.98 | 0.97 | 0.30 | 0.41 | 0.97 | 0.95 |
| 2 | E | 0.16 | 0.16 | 0.96 | 0.96 | 0.41 | 0.48 | 0.95 | 0.94 |
| 3 | P+T+E | 0.20 | 0.22 | 0.93 | 0.92 | 0.52 | 0.58 | 0.93 | 0.91 |
| 4 | P+T | 0.23 | 0.25 | 0.92 | 0.90 | 0.58 | 0.63 | 0.91 | 0.89 |
| 5 | P+E | 0.29 | 0.35 | 0.87 | 0.81 | 0.74 | 0.87 | 0.86 | 0.80 |

*Where T= Temperature (Max), E=Evaporation, P=Rainfall*

The model performance evaluations showed GRNN statistically superior to that of the FFBP regardless of the input configurations. Therefore, FFBP showed poor performance due to slower convergence, trapping with local minima and requires more computational time.

### 4.5.6. Summary

The obtained results showed closed relationship between rainfall event and groundwater level during monsoon. It was also, observed that the temperature and evaporation had significant effect on groundwater level fluctuations in non-monsoon season. The obtained GRNN results were compared with that of FFBP. A better agreement was observed between the actual and modeled groundwater levels for GRNN than that of FFBP. From the study, GRNN can be applied successfully for forecasting groundwater level due to its accuracy and reliable results.

# CHAPTER – 5

# SUMMARY AND CONCLUSION

The present study explores the potential and suitability of RBF and GRNN algorithms in both time series forecasting and cause and effect of southwest coastal aquifer (D.K.), Karnataka, India. This chapter summarizes the initiatives that have been taken in order to achieve the objectives of the study. Finally, some suggestion for future work has also been included at the end of the chapter.

## 5.1 Summary of work

The current study, the following tasks has been carried out at different stages-

The weekly groundwater levels for total 24 number of open wells fairly distributed in the micro-watershed have been collected for a period of 8 years (2004-2011). Analysis were carried out for selective representative open wells based on land use/land cover to ascertain the variation in responses of recharge, discharge, natural drainage, atmospheric pressure, salt water intrusion, etc. Here, First 70% of observed data are used for model calibration and remaining 30% data are used for validation. A huge number of RBF and GRNN models are obtained on the basis of combining number of inputs, number of outputs, number of hidden neurons, spread parameters and smoothing parameters.

In this study, Root Mean Squared Error (RMSE), Correlation Coefficient (CC) and Coefficient of Efficiency (CE) are used to evaluate the forecasting performance accuracy of developed models.

### 1. Development of RBF model

At the first stage, the potential and applicability of RBF for forecasting groundwater level are investigated. Weekly time series groundwater level data upto four lagged data has been used as input where predicted output are one and two week leadtime GWL. The analysis has been carried out separately for three representative open wells. Number of neurons in the hidden layer used from 1 to 10, to optimize the results keeping learning rate and momentum coefficient constant in all the training. The numbers of iteration are kept fixed at 40000.All the data are normalized between 0.1 to 0.9, using TANSIG as activation function. Also, to optimize the best output, 5 different spread parameters are used in the range of 1to 5.Total 400(4x5x10x2) RBF models were developed for every well and best model results were compared with best FFBP models. It has been observed that for all the three open wells, the higher and consistent performance for RBF network for one week lead time and decaying performance for FFBP network model. The obtained results show that the RBFNN performed better compared to FFBP models.

**2. Performance evaluation of RBF model for more  forecasting horizon**

After confirming the suitability of RBF in GWL forecasting and with better accuracy over FFBP, the work has been extended further to consolidate the applicability of RBF in multistep leadtime forecasting upto six week ahead.

In this study, six representative wells are covered for development of RBF models for six different input combinations using lagged time series data. Output are the predicted GWL upto six week. The optimized spread parameter (obtained in first study) 4 is used for development of RBF model by varying hidden neurons in a similar manner to earlier study. Total 360 (6x1x10x6) RBF models are developed for every well and results are compared with Non linear regression model (NARX). It has been observed that for all the six wells, the higher and consistent performance for RBF network upto fourth week lead time and decaying performance for NARX network model.

**3. Development of GRNN models**

In the third stage, to examine the potential and applicability of GRNN in GWL forecasting, GRNN models has been developed by considering the advantage of S-summation and D-summation layers for different input combinations using time series data. Weekly time series groundwater level data upto four lagged data has been used as input where predicted outputs are one week leadtime GWL. The analysis has been carried out separately for three representative open wells. Number of neurons in the hidden layer used from 1 to 20 to optimize the results keeping learning rate and momentum coefficient constant in all the training. The number of iteration is kept fixed at 40000.All the data are normalized in between 0.1 to 0.9 using TANSIG as activation function. Also, to optimize the best output, smoothing factor from 0.5 to 1 are used and the 1is selected as optimized value. Total 400(4x5x20x1) GRNN models were developed for every well and best model results were compared with best RBF and FFBP with LM training algorithm models. The RBF and GRNN models are almost performed similarly in ground water level forecasting in all the representative wells with the poor performance of FFBP-LM. The GRNN has little edge over RBF.

**4. Potential of GRNN model in Cause and effect relationship**

After confirming the potential and applicability of GRNN and RBF in time series GWL forecasting with similar capability, the robustness, adaptability and flexibility characteristics of these two techniques are further examined with cause and effect relationship. Here various meteorological parameters are used as causable variable and the GWL is used as output effect. Only GRNN models are developed in the present study as RBF was found with similar predicting performance in previous studies. Five various input combinations are used to obtain best results as one step leadtime output for three representative wells. Total 100(5x20x1) GRNN models are developed using constant smoothing parameter as 1. The model performance is compared with FFBP. Here, also GRNN model is predicting groundwater level with higher accuracy and with satisfactory results compared to FFBP.

## 5.2 Conclusions

- Highly accurate GWL forecasting models such as RBFNN and GRNN that are developed in this study can be an useful tool in sustainable groundwater extraction and optimized management in a watershed.
- The study examines the effectiveness of RBF and GRNN model as alternative tools for forecasting purposes in multistep leadtime. This study provides a guide in design of ANN for forecasting time series and cause and effect, we used groundwater level time series and meteorological data to illustrate this process.

- In general, the model results clearly reveals that RBF network and GRNN have the potential in forecasting groundwater level efficiently for multistep lead time can be used as an effective tool for weekly groundwater level forecasting. However, there is a need to study in comprehensive manner to assess the long term tendency of groundwater level in the study area in order to take scientific measure for planning and designing purposes.
- It can be concluded that RBF and GRNN are almost performed equally in ground water level forecasting in all the wells. The GRNN has little edge over RBF. As the statistical characteristics of the GWL vary from well to well, it is difficult to recommend single algorithm suitability for the best forecasting method considering performance accuracy. Although the forecasting accuracy in both RBF and GRNN are very high, further study will be required for computational time requirement, flexibility, limited data, limited input variables and simplicity to user for concrete conclusion.

## 5.3 Contribution

Following are the contributions from this study:

- ANN modeling found suitable for site specific GWL forecasting
- RBF and GRNN algorithm found suitable for time series forecasting of GWL compared to other model considered
- The limitations of FFBP has been eliminated by using RBF and GRNN
- Higher forecasting accuracy has been obtained through using RBF and GRNN
- The spread constant in RBF and smoothing parameter in GRNN plays vital role for improvement of model performance

## 5.4 Limitations

- The RBFNN and GRNN model are predicting satisfactorily upto certain multiple leadtime. If the prediction period is too long, no model can perform with acceptable accuracy.

- Other factors which are not included but supposed to be influential such as vadose zone characteristics, seepage, infiltration, pressure, evapotranspiration, temperature, soil characteristics, and hydraulic conductivity in the network inputs could explain the poor relationship between the persistence and future water level. Also, Human factors to land use may be more influential on the water level fluctuations during dry season.

## 5.5 Scope for future work

- The use of these techniques may be adopted in GWL forecasting for other watersheds in different geographical and geomorphological regions with monthly, yearly forecasting.
- Further, to optimize the internal parameters of the networks and to enhance the forecasting accuracy in real field situation of developing countries, integration of other techniques like Fuzzy Logic, Genetic programming, Wavelet transformation may be tried.

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# APPENDIX - 1








**Plate: 1 Location of different wells and their identification number**


**Plate: 2 Wells with Lateritic block ring and well with RCC rings**


**Plate: 3 Wells located in the fields**


**Plate: 4 Location of wells in built up area**


**Plate: 5 Location of shallow wells and deep wells**

## LIST OF PUBLICATIONS BASED ON PHD RESEARCH WORK

Papers published in Refereed International Journals

1. **Sreenivasulu D** and Paresh Chandra Deka (2011). "A Comparative Study on RBF and NARX Based Methods for Forecasting of Groundwater Level." *International Journal of Earth Sciences and Engineering*, 4(4), 743-756.
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