INTELLIGENT PREDICTIVE MODELS FOR WATER RESOURCES ENGINEERING

A Thesis submitted in fulfilment of the requirements
for the award of the degree of

Master of Philosophy

by

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September 2008

Declaration

This work has not previously been submitted for a degree or diploma in any university. To the best of my knowledge and belief, the Thesis contains no material previously published or written by another person except where due reference is made in the Thesis itself.

Amirhassan Joorabchi

September 2008

List of Publications

Published paper:

JOORABCHI, A. ZHANG, H and BLUMENSTEIN, M., Application of artificial neural networks in flow discharge prediction for the Fitzroy River, Australia. Journal of Coastal Research, SI 50, pp. 287-291, 2007

Papers in preparation:

JOORABCHI, A. ZHANG, H and BLUMENSTEIN, M., Application of artificial neural networks in groundwater dynamics in coastal aquifer. 10th International Coastal Symposium, 13-18 April 2009. Lisbon, Portugal. (Submitted)

JOORABCHI, A. ZHANG, H and BLUMENSTEIN, M., ANN model validation for prediction of flow in Fitzroy River in an extreme event. (In preparation)

Abstract

Fresh water is considered to be one of the most important resources for humans and the environment. Due to the increase in population and the currently unsustainable usage of this limited resource, more attention is needed in the management of water resources. Advanced computational methods can help in attaining a better understanding of all aspects of water.

Indeed, a better understanding of water resources requires a vast knowledge of a wide variety of fields such as atmospheric science, geology, hydrology, hydraulics and mathematics etc. To assist in this process computing techniques have been widely applied in water resources engineering problems.

An artificial neural network (ANN) has been applied to solve many engineering problems since the 1980s. However, there are still many engineering fields that have the potential to benefit from ANN, such as water resource engineering. In the present research two important applications; time-series prediction and function estimation for water resource engineering are investigated.

Within water engineering the prediction of river discharge is important. The results can be used for many purposes including flooding management, risk assessment and saving lives. New techniques are always being sought to improve the accuracy of predictions. In the first part of this research a neural network model was developed as a tool for time-series prediction to forecast water flow discharge of Fitzroy River near Rockhampton in central Queensland. A feed-forward back-propagation network was selected to predict the daily time-series of the Fitzroy Rivers' discharge at The Gap station, Queensland. The data was derived from the Queensland Department of Natural Resources and Mines. The two developed ANN models are investigated and compared after many trials with a number of inputs, outputs, hidden layers, learning rate and transfer functions. The final model uses the flow data for 15 successive days and then predicts the discharge for the next 4 days. The results show that an accurate prediction was obtained during flood events. The advantage of the ANN model, when

compared to other numerical models, is that it only uses the historical data of the discharge from this particular river. Thus it is free of the need for other data such as rainfall data, topography of the area and stream sections. In addition, after the ANN was trained, a very fast prediction was obtained. Consequently, this model can be used as a real-time tool for flow forecasting in the Fitzroy River. Similar models could be developed, based on the structure of this ANN model, for any river in Australia and in the world.

Another interesting problem in water resource engineering is groundwater dynamics that occur near the coast. Indeed, a knowledge of groundwater dynamics in coastal aquifers is important for understanding sediment transport processes in the swash zone; shoreline stability; the design of coastal structures close to beaches; water quality in closed coastal lakes and lagoons; the operation of dune sewage disposal and domestic water supply. Analytical methods or numerical models have been used to predict this groundwater table fluctuation due to tides, waves and precipitation etc. In the present study ANN is adopted to simulate groundwater table fluctuations. In the study a multilayer feed-forward neural network model has been developed and trained using a back-propagation algorithm. The training data was based on field measurements (KANG *et al.*, 1994a) from five different locations down the east coast of Australia. The data included information on watertable, tide elevation, beach slopes and hydraulic conductivity at each beach. The results from the developed model show that the artificial neural network model is very successful in terms of the prediction of a target that is dependent on a number of variables. Sensitivity analysis was undertaken which confirmed that a variation in tide elevation is the most important parameter to use for simulating groundwater flow in coastal aquifers. In contrast the low number of training data available for hydraulic conductivity and beach slope did not have a significant effect on the prediction of groundwater table fluctuations in this model. Thus, to improve the accuracy of prediction for the developed model, more data should be collected.

Acknowledgments

I would like to thank all those in the Griffith School of Engineering. Special thanks to my supervisors, Dr Hong Zhang and Dr Michael Blumenstein, who devoted their own time to assist me in my studies; it is greatly appreciated.

I am grateful to Professor Bofu Yu, Associate Professor Charles Lemckert and Dr Nick Cartwright for their helpful suggestions. I am also thankful for the support provided by the Griffith University Research Grant (GURG, 2006). The Queensland Department of Natural Resources and Water, and the University of Queensland, are also gratefully acknowledged for their provision of the data.

I would like to thank my wife, Golnoosh for her great assistance, patience and understanding. Last but not least, my appreciation to my parents, Ali and Mehran, for their unlimited love and support during my study.

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1 Introduction

1.1 Importance of water resources in our environment

Our environment is composed of 70% water; however, most of it is saline water (97.5%) with only a small percent freshwater (2.5%). Most of the freshwater on Earth is locked away in ice-caps and glaciers (76%) or is stored far below the ground in aquifers (23.5%). The remaining 0.5 precent consists of freshwater lakes (54%), soil moisture (38%) and the atmosphere (8%).

Currently, the whole world faces environmental challenges such as global warming which is the increase of the average near-surface temperature of the oceans. The temperature increase causes sea level rising; increasing the intensity of weather events and changing the amount and pattern of precipitation.

Australia, known as the world's driest inhabited continent (SMITH, 1998), comprises approximately 5 percent of the world's land area but has less than 1 percent of global river runoff. With the limited amount of available freshwater, the increasing population level and the current climate change conditions there is a need to find a better solution to control, manage and use our valuable resources of freshwater.

In engineering, generally, a variety or combination of the following methods are used to study physical phenomena:

- Physical models: a physical representation of a real system
- Analytical models: a mathematical model that determines the exact solution of the problem
- Numerical models: Numerical models are mathematical models that use some time-stepping procedure to obtain the models behaviour over time, such as the finite difference method, the finite element method and the finite volume method; and

- Artificial intelligence (AI): computational techniques that are developed to enable computers to learn and solve problems from available information including artificial neural networks, statistical learning etc.

Physical modelling is usually very expensive for engineering problems, while an analytical solution is not always available, because of the complexity of the mathematical equations. Analytical models are always limited to very simple cases with some simplified assumptions; numerical models have been increasingly used to solve engineering problems, with the advent of more powerful computers and more user-friendly software. However, both have numerical errors resulting from the imperfections inherent in the methods and the simplified assumptions made by engineers, planners etc.

1.2 Artificial neural network method

An alternative method that is gaining confidence, and is increasingly being used by engineers to solve engineering problems, is artificial intelligence (AI). According to Sage (1990) the aim of artificial intelligence is to develop algorithms that require machines to perform the cognitive tasks that humans are currently better at handling. Indeed, artificial intelligence is very popular because of its ability to solve complex problems, provide accurate results and, in many cases, produce fast computations. Today, AI is used for many applications in different fields such as pattern recognition (CANNESSON *et al.*, 2007), virtual reality (CAVAZZA *et al.*, 2005), image processing (CHIEN *et al.*, 1999), strategic planning (HOLLOWAY, 1983) and robotics (BODEN, 1984).

Artificial neural network (ANN) is amongst the most powerful AI techniques. ANN's strength in problem solving lies in its ability to learn and generalise the knowledge received from its input data. ANN can solve complex problems such as pattern recognition, non-linear modelling classification, association and control (GOVINDARAJU, 2000a).

The technique of artificial neural networks was inspired by biological neural systems and the study of the human brain, beginning in the early 1940s. A simple mathematical model, to explain the function of biological neurons, was developed by MCCULLOCH and PITTS (1943). However, a significant growth in the application of ANN in diverse disciplines occurred following RUMELHART *et al.*'s (1986) development of a sophisticated algorithm; the theoretical framework for ANN.

Recently, artificial neural network models have been applied to various engineering problems, for example: the optimum design of aerospace structural components (BERKE *et al*, 1993), the classification and forecasting of freeway traffic flow stability (FLORIO and MUSSONE, 1996), modelling the strength of high-performance concrete, (YEH, 1998), tidal-level forecasting (TSAI and LEE, 1999), improving wave predictions (MAKARYNSKYY, 2004) and parameter estimation in groundwater (GARCIA and SHIGIDI, 2006).

1.3 ANN applications for water resources engineering problems

Within the engineering field, increasing the accuracy of results is one of the main targets that engineers have always looked for in the tools that they use. The application of new methods is always of interest to engineers, who seek to advance the problem solving. Water is a valuable and important resource for life. For this reason, water has always received special attention during the history of civilization. However, there are many water resource engineering problems that have not been solved or are not yet well understood.

An artificial neural network is a relatively new method for computation and modelling with few examples of ANN being applied to engineering problems, in particular water resources engineering. In this research, two multilayer feed-forward neural networks have been developed and trained by a back-propagation algorithm. These models are applied to two important sources of water: rivers and groundwater. The ANN models are applied, firstly, to predict a time-series (prediction of flow in a river) and, secondly, to estimate a function (groundwater dynamics in coastal aquifers). Although some analytical and numerical models are available to predict these problems, this research focuses on the application of ANN in an attempt to identify the usefulness and accuracy of the ANN for flood prediction and groundwater dynamics in coastal aquifer groundwater.

1.3.1 Flood Prediction

Floods are one of the most important sources of damage for areas close to rivers. Therefore, manmade structures are constructed to protect land, property and lives against the floods. To design appropriate structures it is essential to know the magnitude and variation of flow discharge over time. From such knowledge, flood prediction will enable accurate risk assessments to be made and lives to be saved.

Engineers have already developed many analytical and numerical models to predict the flow motion in rivers, to obtain accounting data for storage and to study the attenuation of flood peaks. However, since existing analytical and numerical models are not perfect, their results inevitably include errors. For this reason many researchers have attempted to improve the quality of numerical model prediction. This study investigates the application of multilayer artificial neural networks to identify their usefulness as an alternative method to analytical to predict flow discharge in one of the most important rivers in Queensland, the Fitzroy River.

1.3.2 Groundwater dynamics in coastal aquifers

The amount, availability and distribution in groundwater is another important problem for engineering and management of water resources in coastal areas. As noted by TURNER *et al*. (1997), the estimation of the water table for groundwater in coastal areas is essential for the management of shoreline stability, the design of structures adjacent to the coast, water quality in closed coastal lakes and lagoons, coastal ecological studies, the operation of dune sewage disposal and domestic water supply.

Some numerical and analytical models, such as NIELSEN'S (1990) and JENG *et al.*'s (2005), are available to help estimate groundwater table fluctuations under the effect of tides or waves, hydraulic conductivity, beach slope and porosity. The successful application of artificial neural networks in solving other engineering problems motivated the current investigation into how accurate the ANN model could predict the fluctuation of groundwater table in coastal aquifers. In this research the data, chosen from measurements along the eastern coast of Australia, were based on the work of KANG *et al.* (1994a). The sensitivity of the model with tide, distance, hydraulic conductivity and beach slope was trialled using the data.

1.4 Significance of this study

Conventional models, including physical deterministic numerical models, are expensive and have many limitations when applied to solving water resource problems. The present research seeks to contribute to the current knowledge using the neural network method by addressing two problems, for which accurate predictions are important for engineers. These problems are the prediction of flow discharge into rivers and the prediction of groundwater table fluctuations in coastal aquifers under the effect of tides. This study has contributed in the following major areas to the existing body of knowledge:

- The flood prediction problem has been addressed through the development of an ANN model to predict flow discharge into the Fitzroy River; one of the most important rivers in Queensland
- The developed neural network model for flood prediction is a significant contribution in terms of an alternative to the current statistical and numerical models resulting from the independency of rainfall data, the boundary conditions, the initial conditions and the topography.
- The current flood prediction model extends and advances the prediction time, formerly 60 hours (BOM, 2005) to 96 hours, using only the history of the rivers' discharge.

- The developed ANN model increases our understanding of groundwater dynamics and the behaviour of groundwater table fluctuations, specifically in coastal aquifers, on the eastern coast of Australia.
- The great adaptivity of the ANN models enabled them to be simply and effectively trained for a new situation or a new event. Thus the model enhanced the capacity and accuracy to find new patterns in both river discharge data and groundwater table fluctuations.
- The trained ANN models provide fast predictions and are able to work as real-time tools for flood warning systems and coastal management.
- Now the current models can be adopted, simply, for any river or coastal aquifer in the world where historical data are available. This is an important practical outcome that will facilitate the predictions of water resource engineers to limit or eliminate damage to people, property and infrastructure.

1.5 Outline of thesis

The background to some of the problems experienced in water resource engineering, modelling methods and, in particular, artificial intelligence methods to solve these problems are presented in Chapter 1.

An introduction to runoff-routing models and an overview of previous work on the hydrodynamics of flow in rivers, the groundwater dynamics in coastal areas and the application of artificial neural networks in engineering are summarised in Chapter 2.

A brief review of artificial neural networks is presented in Chapter 3. The architecture of neurons, the types of networks and their learning methods along with the advantages and disadvantages of artificial neural networks are discussed.

Based on the data provided for the flow discharge into the Fitzroy River, a neural network model was developed to predict the flow discharge up to four days ahead at The Gap station. The results are analysed in Chapter 4.

Chapter 5 outlines the development of an artificial neural network model to predict the watertable in coastal areas, under the effect of tidal forces. Additionally, a sensitivity analysis, undertaken to find the effectiveness of the parameters used in the model, is discussed.

Finally, a summary of the current research, with further suggestions and recommendation for future research, is presented in Chapter 6.

2 Literature review

2.1 Introduction

Many models have been developed to solve water resource engineering problems, with powerful computers and software helping engineers to utilise the more complex of the models and thus to study a variety of domains and parameters.

Previous models used to solve water resource engineering problems have been based on conventional engineering methods. Unfortunately, they have incorporated some simplified assumptions about flood prediction and the groundwater dynamics in coastal aquifers that limit their application. Artificial neural networks have been applied to solving problems in a variety of fields such as science, medicine, business and engineering. However, its application to water resources engineering needs further investigation and study.

This chapter presents an overview of previous research on the hydrodynamics of rivers and the groundwater dynamics in coastal areas. A brief introduction to ANN and its application in engineering follow the overview.

2.2 Flood prediction methods

The need for freshwater resources means that people settle close to rivers or streams. However, while there are the advantages associated with the river the risk of a flood is always of concern. For this reason the ability to predict floods is a primary task of water resource engineering. Further, the prediction of the flow discharge into rivers is important in the hydraulic design of bridges, culvert crossings, dams and hydraulic structures.

Generally, design flood estimations can be classified into two groups: rainfall-based methods and streamflow-based methods.

1. Rainfall-based methods: the most common method used in the prediction of flood when rainfall data are available. These methods include a loss model to compute excess rainfall and a runoff-routing model, or unit hydrograph, to convert rainfall into flood discharge. Empirical methods, event based methods and continuous methods are examples of rainfall-based methods.

2. Streamflow-based methods: used when a long history of stream flow data is available. Flood frequency analysis is the most applied method of streamflow-based methods. The analysis analyses the past stream-gauging data to relate the flood magnitude to the flood frequency. These methods are independent of rainfall data, however, so they can only predict peak flows.

Some runoff-routing models are available to convert the rainfall to runoff and to estimate the flow and water level in a river. One model is RORB (LAURENSON *et al*, 2007), which is used widely in Australia. RORB is a general runoff and streamflow routing program used to calculate flood hydrographs from rainfall and other channel inputs. It subtracts the losses from the rainfall data to produce the rainfall-excess and routes this through the catchment storage to produce runoff hydrographs, at any location. Also, it can be used to design basins and to route floods through channel networks.

Another example of runoff-routing models is URBS (CARROLL, 2004), which is an integrated rainfall-runoff and runoff-routing model suitable for integrated catchment management. URBS model allows users to configure the model to match the characteristics of individual catchments. The model has a catchment discretisation (similar to RORB model) and can split the hydrograph routing into catchment and channel components. The runoff-routing can be used for flood prediction; it is used by the Australian Bureau of Meteorology for a number of catchments in Australia.

The flood wave moving down a river is described as flood routing. Runoff-routing models, such as URBS and RORB, can estimate the magnitude and elevation of the flow in rivers if the rainfall data is available. The information that these hydrological models provide can be used directly in planning a catchment or feeding hydrodynamic models. Indeed, the boundary conditions of the hydrodynamic models often use the output of the runoff-routing models. A hydrodynamic model can determine the motion of the flow in the rivers including discharge, water level and velocity. This can be very helpful, along with the hydrologic model, for flood forecasting. For example, a flood, with a particular annual probability, can be estimated by a runoff-routing model. The result (discharge or water elevation) can be fed into a hydrodynamic model, including hydraulic structures, to simulate the flow motion; finally, to determine the inundation of the areas close to the river and allow a study of the population at risk. Hydrodynamic models are also being used as a base for sediment transport models and water quality models. A number of hydrodynamic models are presented below in brief.

The study of the flow motion in rivers is an important factor in flood predictions. Numerical models have been applied to open channel flows for many years (MOLLS and CHAUDHRY, 1995). Most of the models are based on some simplified assumptions such as depth averaged models and kinematic wave equations.

MCGUIRK and RODI (1978) developed a 2D depth-averaged model to calculate velocity, temperature and concentration using an efficient finite deference procedure. The depth-averaged continuity, momentum, temperature and transport equations were solved. The model has been applied to the problem of a side discharge into an open-channel flow where a recirculation zone develops at downstream of the discharge.

Another 2D depth-averaged numerical model was developed by PONCE and YABUSAKI (1981). It employed a multi-operational procedure in a finite difference method to advance the values of the dependent variables in time. It appears that the proper modelling of the effective stresses is a necessary condition for the resolution of steady, closed-streamline circulation in depth-averaged mathematical models.

A kinematic wave routing, for a diverging-converging surface, was developed by AGIRALIOGLU (1981) using an implicit finite difference method. The model shows that the geometry of a watershed has an important effect on the runoff hydrograph for both equilibrium and partial equilibrium conditions.

Flood levels and flow patterns were studied by VREUGDENHIL and WIJBENGA (1982) by investigating the quasi-steady flow in a river, with flood plains, using 2D hydrodynamic equations. The bottom and lateral friction were identified as having an important influence on the model.

PURI and KUO (1985) employed the penalty function finite element technique to solve the vertically averaged hydrodynamic and turbulence equations for a water body using iso-parametric elements. The results of their simulations indicated that the depth-averaged two-equation k-ε turbulence model yields an excellent agreement with the experimental observations.

The diffusion equation was used by GONWA and KAVVAS (1986) for flood propagation in trapezoidal channels. After numerically testing with a linearised version of the modified diffusion equation they concluded that the assumption of constant values for the parameters of the diffusion approximation yields inadequate flood routing results. Therefore, they suggested that there was a need to consider the non-linear form of the diffusion approximation to Saint-Venant's equations, as an approximate model for flood routing.

TINGSANCHALI and MAHESWARAN'S (1990) model used a hybrid finite difference scheme and an iterative method to solve the governing equations of flow and turbulence transport. Their model computed depth-averaged velocity and bottom shear stress distributions in a rectangular channel near a groyne. They found that, in this region, the bottom shear stress is largely influenced by the 3D effects. Therefore, a 3D correction factor was introduced to greatly improve the computed bottom shear stresses.

A general mathematical model was developed by MOLLS and CHAUDHRY (1995) to solve unsteady, depth-averaged equations. The model used boundary-fitted coordinates and was able to consider both sub-critical and supercritical flows. A positive factor with the model was its general application to hydraulic problems, being tested on flows in a channel with an hydraulic jump, the flow in a channel contraction, the flow near a spur-dike, the flow in a 180° channel bend and a dam-break simulation.

A simplified dynamic form of the momentum equation was derived by KESKIN and AGIRALIOGLU (1997) to solve the Saint-Venant's equations for flood routing in rectangular open channels with constant width. The momentum equation was transformed into a partial differential equation which had two parameters related to the cross-sectional area and the discharge of the channel.

WU *et al*'s (2000) 3D numerical model for calculating flow and sediment transport in open channels calculates the flow by solving the full Reynolds-averaged Navier-Stokes equations with the k –ε turbulence equation. A finite-volume method on an adaptive, non-staggered grid was used. Additionally, special free-surface and roughness treatments were introduced for the open-channel flow. The water levels were determined from a 2D Poisson equation derived from 2D depth-averaged momentum equations.

The fully integrated 3D time dependant, hydrodynamic and sediment transport numerical model ECOMSED (BLUMBERG and MELLOR, 1987) was modified by ADMASS (2005) to simulate hydrodynamics and sediment transport in rivers. It solved the equations of RANS, along with a second order turbulence model in an orthogonal curvilinear σ-coordinate system.

2.3 Groundwater dynamics in coastal aquifer

The effects of tide and wave, with the groundwater table elevation, is less well known in the field of groundwater engineering (TURNER *et al.*, 1997). Many factors affect the watertable along the coast. The most important factor is the diurnal rise and fall of the swash zone. Also, the beach morphology, tidal stage and prevailing wave conditions can affect the elevation of groundwater.

HORN (2006), in his review of the research literature on beach groundwater dynamics, identified questions that need to be answered before the swash zone sediment transport and beach profile evolution. According to his study, models of beach watertable responses to tidal forcing have been successfully validated. However, models of watertable response to waves are less well developed and require verification. A list of the types of groundwater flow models, classified according to the response to tide and wave, are presented in Appendix 1.

The governing equation for 1D unsteady groundwater flow is derived from Darcy's law, and is well explained in many reference books, such as BEAR (1972). NIELSON (1990) investigated the tidal motions of the watertable height, inside a sloping beach, using field measurements and theoretical considerations. However, his study only considered the tidal influence and neglected wave activity. Nevertheless, the observed behaviour of the watertable was analysed, based on the perturbation method, with the nonlinearity in the interior of, and the boundary condition at, the sloping beach face was taken into account.

INOUCHI *et al*. (1990) applied two different models (the freshwater-saltwater interface model and the dispersion model) to analyse the problems of seawater intrusion into confined coastal aquifers under the influence of the tide. The position of the outlet of the confined groundwater into the sea, as well as the variation of the aquifer's thickness, was also investigated.

An analytical solution to the two-dimensional depth-averaged groundwater flow equation for a semi-infinite aquifer subject to oscillating head conditions at the boundaries was undertaken by LI *et al*. (2000a). Their solution described the tidal dynamics of a coastal aquifer that is adjacent to a cross-shore estuary. They studied both the effects of the oceanic and estuarine tides on the aquifer, and verified the analytical prediction of the head fluctuations, with numerical solutions computed, using a standard finite-difference method.

Later, JENG *et al*. (2005) developed a closed-form analytical solution for a two-dimensional unconfined coastal aquifer bounded by a rhythmic coastline. They also considered the effect of the beach slope, a feature that had not been considered in previous two-dimensional approximations. Further, their numerical results demonstrated the coastline shape and beach slopes that have a significant influence on tide-driven coastal groundwater table fluctuations.

Beach groundwater flow, under the influence of tidal forcing, has been studied and reviewed widely. However, recent studies have concentrated on groundwater in the cross-shore direction in sandy beaches (HORN, 2006).

2.4 Artificial Neural Network

The concept of artificial neural network (ANN) has been based on how the human brain works. The history of artificial neural networks began from the work of psychologists MCCULLOCH and PITTS (1943) who tried to model the biological neuron. This primary model (known today as a logic circuit) had two inputs and a single output. Each input had equal weight, while the output was binary. The next neuron model, the perceptron was developed by psychologist ROSENBLATT (1958). In this model the perceptrons, a mathematical representation of the biological neuron, were interconnected with the weights being changed by trials. A later mathematical method for adapting the weights, known as Least Mean Squares (LMS), was developed by WIDROW and HOFF (1960). In this method the learning process, instead of being based on trials, was based on the gradient search method which minimised the error squared. RUMELHART *et al*. (1986) proposed a revolutionary learning method of back-propagation, where the perceptrons are trained in a multi-layer configuration. The error between the simulated output and the desired output adjusts the weights backwards through the network from the output layer to the input layer.

2.4.1 Artificial neuron model

A neuron (Figure 2.1), an information–processing unit of a neural network, consists of three basic elements:

1. Connecting links that are characterised by a weight;
2. A summation operator added to the input signals; and

3. An activation function to limit the amplitude of the output of a neuron.

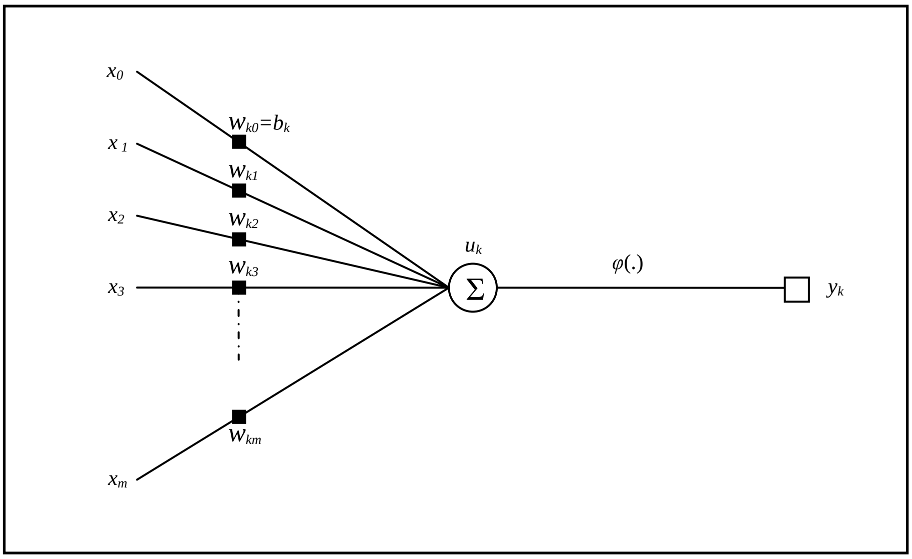


Figure 2.1 Structure of an artificial neural network

In Figure 2.1, b_k is seen to increase or decrease the net input of the activation function. A neuron can be mathematically described as follows:

$$u_k = \sum_{j=1}^{m} w_{kj} x_j \tag{2.1}$$

and

$$y_k = \varphi(u_k + b_k) \tag{2.2}$$

where x_i is the input signal, w_{kj} is the synaptic weight of neuron k, u_k is the linear combiner output, b_k is the bias, $\varphi(.)$ is the activation function, and y_k is the output signal of the neuron.

2.4.2 Activation functions

The activation function (φ) defines the output of a neuron with the linear function (Equation 2.3) being one of the simplest forms of activation functions. The linear transfer function calculates the output of a neuron by returning the value passed to it. Another frequently used activation function, the sigmoid function, has an s-shaped graph and a privilege to consider linear and nonlinear behaviour because of its definition as a strictly increasing function. Examples of sigmoid in the current research are the log-sigmoid function (Equation 2.4) and the hyperbolic tangent sigmoid function (Equation 2.5).

$$\varphi(u) = wx + b \tag{2.3}$$

$$\varphi(u) = \frac{1}{1 + \exp(-au)} \tag{2.4}$$

$$\varphi(u) = \tanh(u) \tag{2.5}$$

where a is the slope parameter of the sigmoid function.

2.4.3 Types of neural networks

Many types of artificial neural networks are available. Each has their own advantages and disadvantages. The following ANN, feed-forward networks, recurrent networks, radial basis function (RBF) networks and support vector machine (SVM) are presented below.

2.4.3.1 Feed-forward networks

The feed-forward network was the first and simplest form of neural networks. Within this network the information passes in one direction only, from the inputs nodes to the hidden layer, and then from the output layer; it does not pass through any cycles and loops. There are two types of feed-forward networks (single-layer feed-forward networks and multi-layer feed-forward networks).

Single-layer feed-forward networks

Single-layer feed-forward networks are the simplest form of a layered network, consisting of an input layer of source nodes and output layer. The computation occurs at the output layer within the input layer not counted as a layer.

Multi-layer feed-forward networks

A multi-layer feed-forward network has one or more hidden layers to extract higher-order statistics. The hidden neurons intervene between the external inputs and the network output.

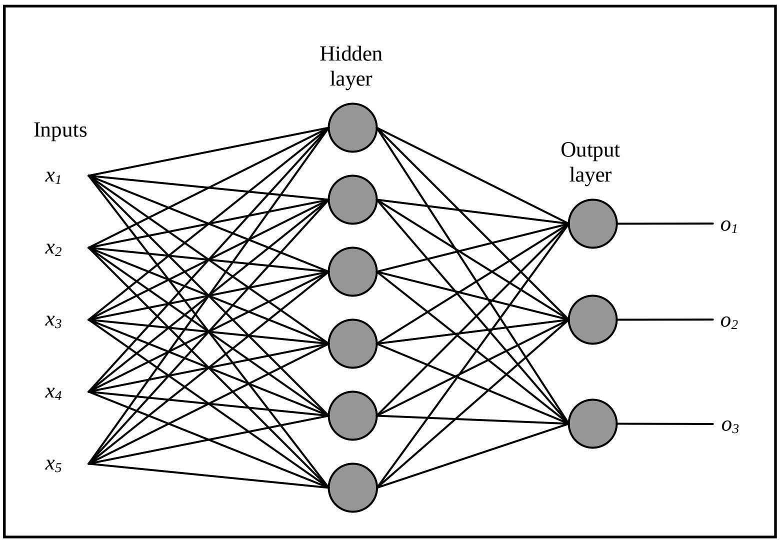


Figure 2.2 Multi-layer neural network

2.4.3.2 Recurrent networks

A recurrent network (HAYKIN, 1999), another tool for temporal classification, has at least one feedback loop which increases the learning capability of the network. However, feed-forward neural networks without recurrent connections are still preferred to use in scientific and industrial applications because the way humans use recurrence in learning language or logical decisions is not completely recognised. On the other hand, training of recurrent neural networks is difficult to manage due to complexity of chaotic behaviour. One example of recurrent network is the Hopfield network. The Hopfield network (HOPFIELD, 1982) is a powerful application for problems that use binary inputs such as pattern recognition.

2.4.3.3 Radial Basis Function (RBF) network

A Radial Basis Function network (HAYKIN, 1999) is another technique for pattern classification, which is an alternative to a back-propagation neural network. RBF uses a linear method for computation and is not iterative. The output from the hidden layer usually passes through a Gaussian function; however, due to the huge number of hidden units the RBF network has a slow computation time.

2.4.3.4 Support Vector Machine

The foundation of the support vector machine (SVM) was developed by VAPNIK (1995), using a formulation that represents the Structural Risk Minimisation (SRM) principle. The SRM is superior to the Empirical Risk Minimisation (EMR) principle employed by ordinary neural networks. The SVM has a greater ability than the ANN to generalise because the SRM minimises an upper bound based on the expected risk while the ERM minimises the error on the training data sets. SVM was originally developed to solve classification problems but later their capabilities have been extended to regression problems (VAPNIK *et al.*, 1997).

2.4.4 Training of an ANN

One of the most important characteristics of a neural network is its learning ability; learning from its environment and improving its performance through the learning process. A learning algorithm is a set of rules to solve a learning problem. To undertake a specific task using neural networks, how connection weights are chosen is very important. This can be done by two ways (supervised and unsupervised learning):

1. Supervised learning: uses both the input and output data for the calculation of an error in the network based on the difference between the calculated output and given output.

2. Unsupervised learning: has the weights adjusted based only on the input data. This algorithm locates clusters in the input data.

2.4.5 ANN optimisation

Some methods, such as cascade-correlation (FAHLMAN and LEBIERE, 1990), are developed to find the optimum hidden units often with an extensive number of inputs and data sets. Increasing the number of hidden layers, and neurons in the hidden layers, prevents the neural network from generating poor results and increases the accuracy of forecasting. However, such calculations need more computation time which can result in over-fitting.

Researchers have studied the number of hidden layer nodes. For example, the relationship between the network size and the number of training samples was investigated by BAUM and HAUSSLER (1989) and WEIGEND *et al.* (1990). CHAKRABORTY (1992) discovered that these methods are not very accurate in the case of a data set with a small number of data. For this reason the upper limit of 2I+1 hidden layer node was proposed by HECHT-NIELSEN (1987) where I is the number of inputs. However, for many practical applications such as with DESILETS *et al.* (1992) the optimum number of hidden layers is less than this.

2.4.6 Advantages and disadvantages of ANN

According to HAYKIN (1999), artificial neural networks have the following benefits:

1. Nonlinearity, to deal with complex physical problems;
2. Input-Output mapping, to employ supervised learning;
3. Adaptivity, to adapt their synaptic weights to changes in the surrounding environment;
4. Evident response, to provide information about the confidence in the decision making;

5. Contextual information, to affect every neuron in the network by the global activities of all other neurons in the network;
6. Fault tolerance, to degrade its performance gracefully under adverse operating conditions;
7. VLSI implementability, to make it fast for the computation of certain tasks;
8. Uniformity of analysis and design, to share theories and learning algorithms in different applications of neural networks and also to build modular networks; and
9. Neurobiological analogy, to inspire from neurobiology new ideas to solve complex problems.

The disadvantages of ANN are that they require a reasonable number or period of data for the training as well as long (or extended) training times that increase with the size of the network. ANN also requires high quality data, input variables with physical meaning.

2.4.7 General applications

Artificial neural networks have been applied to solve real problems since RUMELHART *et al*. (1986) introduced the back-propagation algorithm. Since then much research has been undertaken to solve a wide range of problems from business to engineering.

An improvement was made to the protein's secondary structure prediction by KNELLER *et al*. (1990). They added neural network units to detect periodicities in the input sequence thus increasing the accuracy of the secondary structure prediction.

SCHÖNEBURG (1990) analysed the possibility of predicting stock prices on a short-term, day-to-day basis with neural networks. The study looked at three important German stocks, selected randomly. With a back-propagation network an absolute-value prediction was carried out. The network was able to recognise, on its own, an obvious heuristic and showed behaviour similar to the exponential smoothing algorithm. Consequently, the neural network showed that it could improve, greatly, the prognosis of stock prices (and more generally, the prognosis of semi-chaotic time series) in the future.

PRYBUTOK *et al* (2000) examined the potential of neural networks in predicting daily maximum ozone concentrations. This was important as the development of traditional deterministic models causes difficulties because the photochemical reactions involved in ozone formation are complex. The ANN model was developed and compared with two conventional statistical models (regression and Box–Jenkins ARIMA). The study showed that the neural network model was superior to the regression and Box–Jenkins ARIMA models.

HANEWINKEL *et al*. (2004) applied a three-layered feed-forward neural network with a back-propagation training algorithm, using a momentum term and flat spot elimination, to identify forest stands susceptible to wind damage. The performance of the network and the logistic regression model was measured using the mean squared sensitivity error. The results of the dichotomous model demonstrated that a feed-forward network was able to classify forests susceptible to wind damage better than a logistic regression model, especially when the frequency of the undamaged and damaged forest stands differs significantly.

2.4.8 ANN applications in water resources engineering

As noted previously, artificial neural networks have been used widely to solve many complex engineering problems. In this section previous studies, related to the application of ANN in engineering especially in water resource engineering, are summarised.

FLOOD and KARTAM (1994a, 1994b) published the primary papers on the principles and applications of neural networks in civil engineering. Their work was a brief introduction to the concept, training and generalisation problems, followed by specific approaches to different problems, including mapping problems, modelling dynamic processes, transitory problems and optimisation problems. They concluded that the neural networks offer a powerful means of solving poorly defined problems that have eluded solutions by conventional digital computing techniques. However, the success of the neural networks depends on the quality of the data used for the training, as well as the type and structure of the neural network, and the method of training.

An important reference, provided by the ASCE Task Committee on Application of Artificial Neural Networks in Hydrology (GOVINDARAJU, 2000a), summarises the concept and mathematical aspects of neural networks. Further, the application of neural networks in modelling and in solving hydrologic problems are discussed in GOVINDARAJU'S (2000b) paper including rainfall-runoff modelling, modelling stream-flow, water-quality modelling, groundwater modelling and estimating precipitation. Additionally, an essential component in the proper use of ANN to solve hydrological problems is an understanding of the physical mechanisms involved in the hydrological process as well as knowledge of ANN and their operation.

The example of the neural networks to solve hydrologic problems was the study by IMRIE *et al*. (2000) which predicted river flow. River flow was added to a cascade correction learning architecture. Two case studies were investigated and their results were compared with a standard error back-propagation algorithm. Their results showed the ability for the generalisation to new data and the extrapolation beyond the range of values included in the calibration range.

Three years later, flow and sediment transport in a river system were modelled using an artificial neural network by YITIAN and Gu (2003). They incorporated flow and sediment mass conservation equations into an artificial neural network using an actual river network to design the ANN architecture. A comparison of the predicted and observed data showed that ANN is a powerful tool for the real time prediction of flow and sediment transport in a complex network of rivers. Accordingly, ANN has a great advantage in flow prediction because of the minimum level of data required for the topographical and morphometric information without a significant loss of model accuracy.

DALIAKOPOULOS *et al*. (2005) developed an artificial neural network to forecast groundwater level up to 18 months ahead. Seven types of network architectures and training algorithms were investigated and compared to address the model's prediction efficiency and accuracy. Their results confirm that accurate predictions can be achieved with a standard feed-forward neural network, trained with the Levenberg–Marquardt algorithm, to provide the best results for forecasts up to 18 months.

More recently, DIAMANTOPOULOU *et al.* (2006) applied a three layer cascade correlation Time Delay Artificial Neural Network (TDANN) model to forecast a one-day-ahead daily flow at the Ilarionas station, on the Aliakmon River, in Northern Greece. The results represented a good performance from the TDANN approach for forecasting the daily flow values and demonstrated the models' adequacy and potential for river flow routing.

2.5 Summary

This chapter presents a brief literature review of runoff-routing models, the hydrodynamics of flow in rivers and groundwater dynamics, along with an introduction to the application of ANN. From previous studies it can be seen that artificial neural network methods have an enormous potential for solving many engineering problems. The advantages and disadvantages of each model are also presented in this chapter.

3 Flood prediction

3.1 Introduction

The prediction of river discharge is an important task in water engineering, being used for many purposes, such as river/flooding management and hydraulics structure design. New techniques are always being sought by engineers to improve the accuracy of their predictions. In fact, more accurate and earlier predictions can prevent and reduce damage to properties and save the lives of people and animals, both stock and native.

A powerful method in prediction for any time-series (e.g. time-series of river discharge) is artificial neural networks. In this chapter the occurrences and magnitude of flooding in the Fitzroy River is predicted using ANN.

The Fitzroy River, in central-east Queensland, has a number of dams and weirs that provide fresh water to the city of Rockhampton and its surrounding area. The importance of this scientific study lies in the frequent flood events that occur and the significant loads of sediment and nutrients that are transported through the river.

In the last few years researchers from the Coastal Cooperative Research Centre (Coastal CRC) have carried out a number of projects in the Fitzroy region. KELLY and WONG (1996) studied sediment transport in the Fitzroy River during flood events. A one-dimensional hydrodynamic, sediment transport and biochemistry model was undertaken for the Fitzroy estuary (MARGVELASHVILI *et al.*, 2003 and 2005), using a conceptual model designed by WEBSTER *et al.* (2003). Nutrient dynamics and sediment budgets for an estuary during a flood event were examined by FORD (2006).

The Queensland Department of Natural Resources and Water operates a number of stations along the Fitzroy River to control a number of parameters including stream water level and discharge (NRW, 2006). The Australian Bureau of Meteorology

(BOM) operates a flood warning system for the Fitzroy River and its tributaries based on a rainfall and river height observations network. The bureau predicts the flood heights for the Fitzroy River at Rockhampton when it is expected to be more than 5 metres high. Current predictions are up to 60 hours ahead of the flood (BOM, 2005). For flood forecasting in the Fitzroy River the Bureau currently uses an URBS runoff routing model (CARROLL, 2004) during flood events, on a 3 hour time schedule.

The present research aims to extend the prediction time to 96 hours in advance using only the history of the rivers' discharge. The ANN model is independent of the rainfall data. The developed neural network model can be used as an alternative to conventional statistical and numerical models due to the independency of the rainfall data, the boundary conditions, the initial condition and the topography as well as the reliable results and the real-time prediction of the flow discharge. In general although the training and optimising of a neural network, for a long period of data, is time consuming the simulation of the new data is very fast and can be used for real-time forecasting.

3.2 Description of study area

The Fitzroy catchment, the study area for this project, is one of the largest catchments in Queensland, Australia. The Fitzroy River (Figure 3.1) is one of the main rivers in this catchment and passes the city of Rockhampton. It is about 60 km in length and is fed by five major rivers. They drain the catchment into Keppel Bay with the Fitzroy River mouth being to the east of the northern end of Curtis Island. The Nogoa River rises in the west part of catchment and passes through Emerald and is joined by Theresa Creek. The Comet River drains the south-central part of the Fitzroy catchment with the Comet and the Nogoa Rivers forming the Mackenzie River. The northern area of the Fitzroy catchment is drained by the Connor and Isaac Rivers which join the MacKenzie River upstream of the Tartus Weir. The southern part of the catchment is drained by the Dawson River.

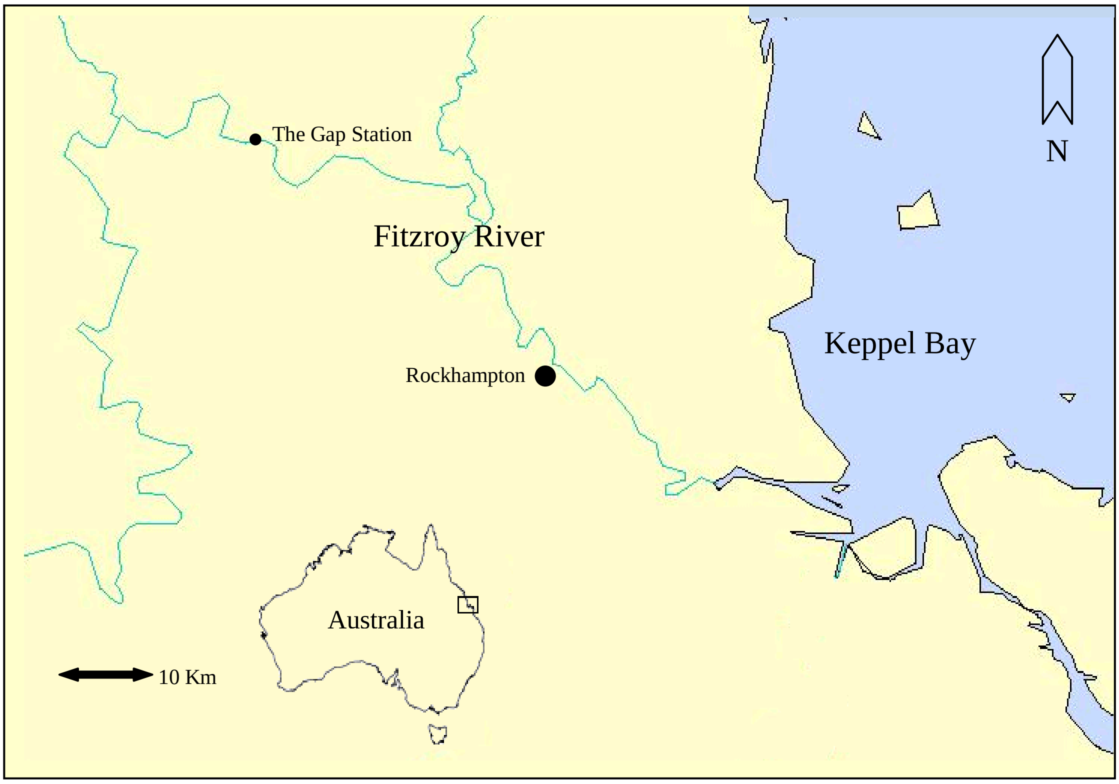


Figure 3.1 The Fitzroy River, Central Queensland, Australia, (ANRA, 2008)

3.3 Flow regime in Fitzroy River

The Fitzroy River discharge has a seasonal and inter-annual flow variation as a result of the rainfall. Figure 3.2 shows the monthly river flow and rainfall at the Gap Station. In January, the river discharge is slightly greater than 415 m^3/s. As a result of maximum rainfall (102 mm), the river discharge reaches its peak of 454 m^3/s in February. Then, from March to August, there is a downward trend in river discharge except in May (163 m^3/s). The Fitzroy River has the least average discharge in August, about 42 times less than the highest discharge in February. It is mainly caused by the very low volume of rain in July (7 mm/month). The river discharge starts to rise in September due to the considerable amount of rain in August. From October to December river discharge increases rapidly from 14 to 139 m^3/s because of increasing rain in these months from 34 to 91 mm. From the recorded discharge it can be concluded that the Fitzroy estuarine is a typical river from those catchments that are dominated by summer floods and winter droughts in the subtropical region of

Australia. Table 3.1 shows the historical flooding events on Rockhampton with the highest floods in January 1918, February 1956 and January 1991.

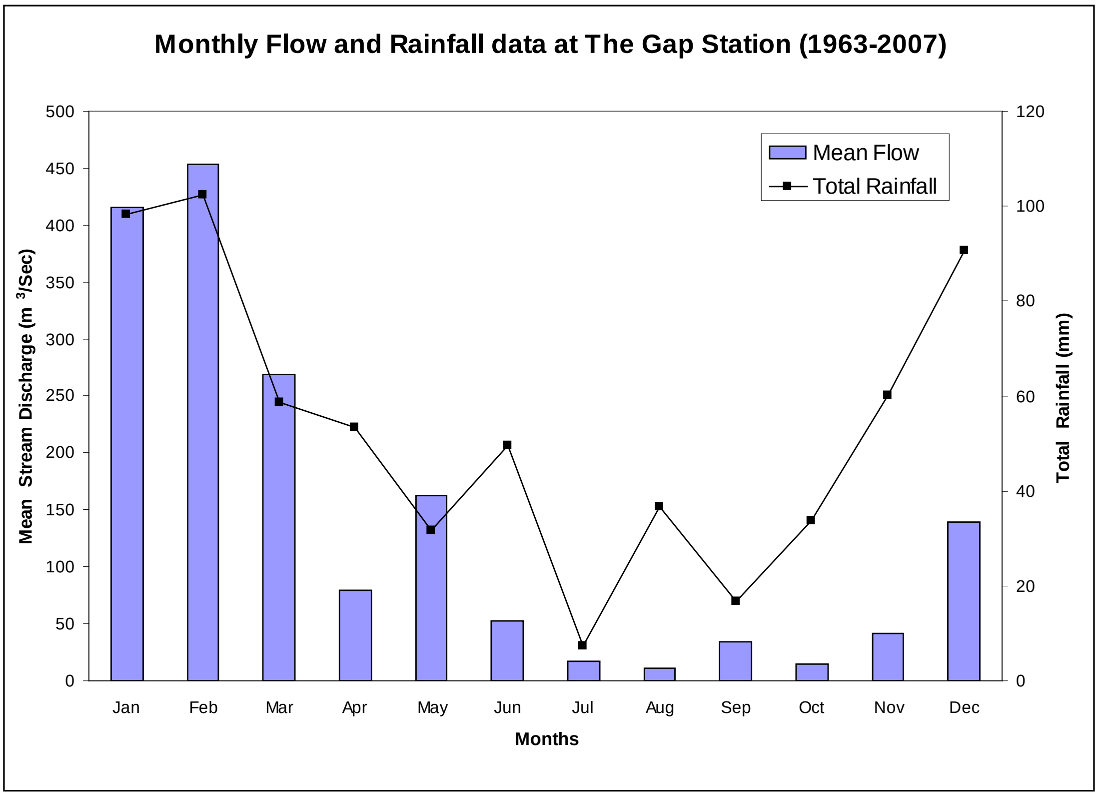


Figure 3.2 Monthly flow and total rainfall at the Gap Station, (NRW, 2008)

Table 3.1 Historical flooding events in Rockhampton (BOM, 2005)

Date	Flood gauge height (m)
Jan-1918	10.11
Feb-1954	9.40
Jan/Feb-1978	8.15
May-1983	8.25
Mar-1988	8.40
Jan-1991	9.30

3.4 ANN model

3.4.1 Description of data

In this study a neural network model was developed to predict the river discharge. It is based on the data of 64 years of daily discharge, measured from 1964 up to the end of

2005 at The Gap station (23° 5' 18" S and 150° 6' 28" E). The largest river discharge in the studied period occurred in 1991 reaching over 14000 m^3/s. Due to the seasonal behaviour of Fitzroy River, discharge is very low in most of the year. Figure 3.3 shows the maximum measured values of the Fitzroy River's flow discharge in each year at The Gap station.

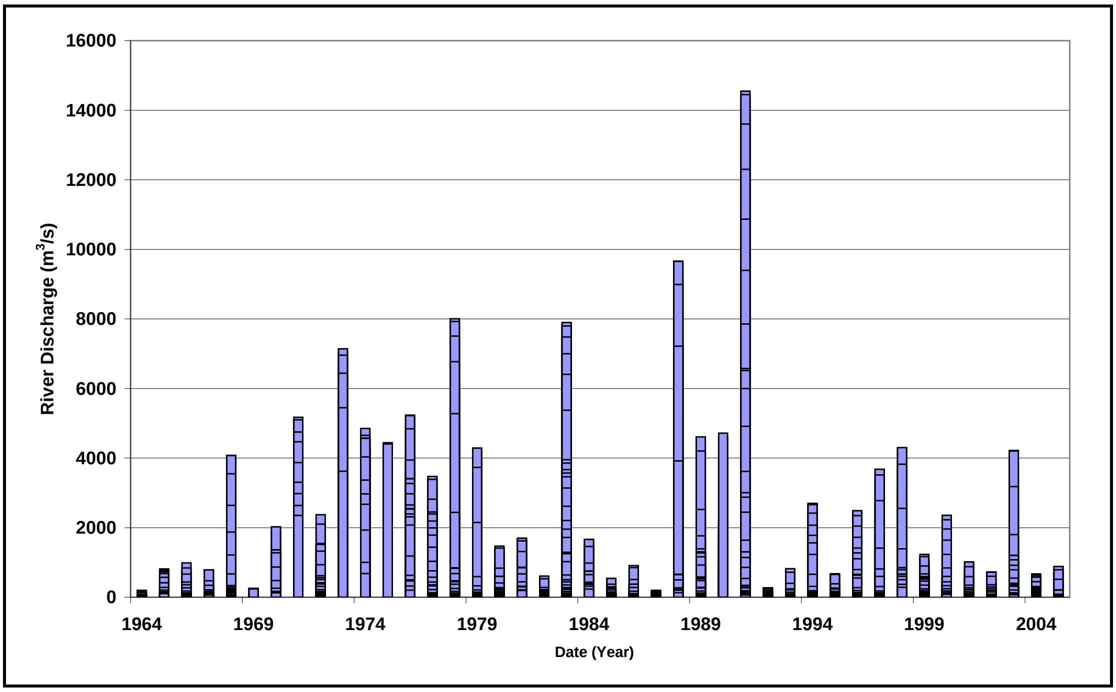


Figure 3.3 Maximum flow discharge happened each year at Fitzroy River (The Gap station) from 1964 to 2006. (Data source: NRW, 2006)

The aim of developing the ANN model was to predict the Fitzroy River discharge in the next four days based on the previous 15 days river discharge data. Because available data were collected daily, the model inputs include 15 successive days, while the outputs include the following 4 days discharge. The example of the time-series of the inputs and outputs are presented in Figure 3.4.

The existing data set consisted of 14960 training pairs, with 15 successive daily river flow discharge values as the input and four outputs, representing the river discharge in the four days. The data were divided into three subsets: training set (60%), validation set (20%) and testing sets (20%). The validation error was monitored during the training process. Such errors on the validation and training set usually decreased during the initial phase of training; as soon as the network began to overfit the data the validation error increased for a number of iterations; the training was then stopped.

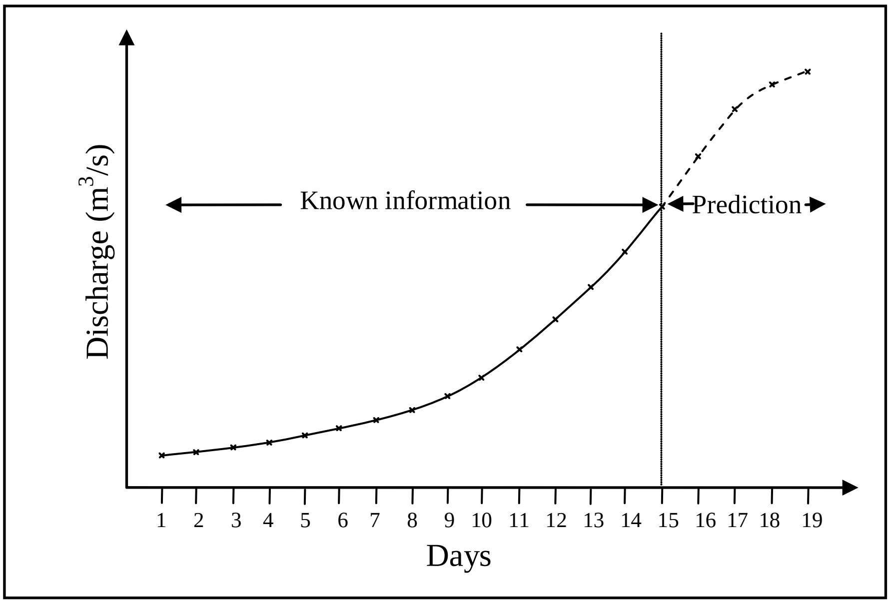


Figure 3.4 Example of input and targets for river discharge

3.4.2 ANN training with the back-propagation algorithm

In this research, the back-propagation algorithm has been used to train the ANN models. In the back-propagation algorithm interconnection weights are adjusted, according to the error convergence technique, to obtain the required output for the given inputs. The interconnection weights are adjusted based on the following equation:

$$\Delta w_{ij}(n) = -\varepsilon \frac{\partial E}{\partial w_{ij}} + \alpha \Delta w_{ij}(n-1) \tag{3.1}$$

where ε and α are the learning rate and the momentum, respectively. Learning rate is training parameter that controls the size of weight and bias changes during learning. $\Delta w_{ij}(n)$ and $\Delta w_{ij}(n-1)$ in equation (3.1) are the increment of weights between nodes i and j for the n-th and (n-1)-th iteration. Figure 3.5 demonstrates the flowchart for back-propagation algorithm.

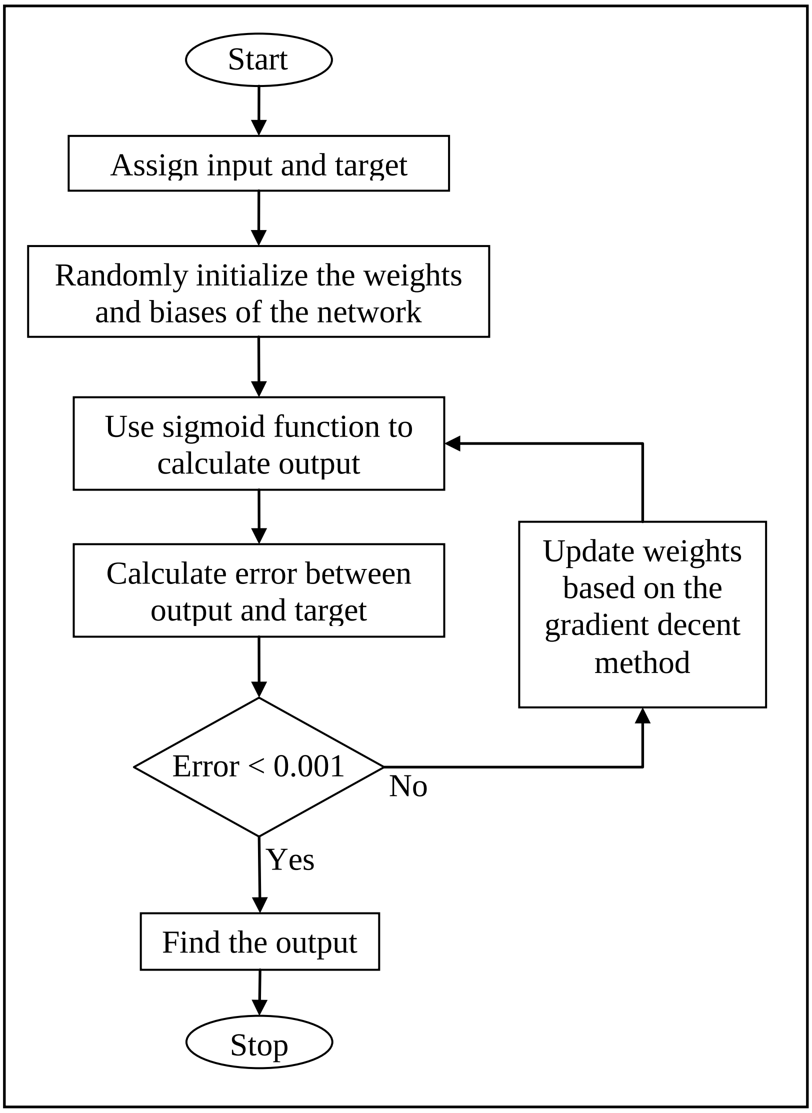


Figure 3.5 Flowchart for back-propagation training

3.4.3 Early stopping for ANN training

A common problem that happens during the training of a neural network is over-fitting. Since the network has memorised the training pattern, it is unable to generalise to new data. While in such a case the error for a training set is very small, the network results enlarge the error for the new data sets. With the early stopping method if an error of the validation data set is increasing in five iterations, then the training will be stopped to avoid over-fitting.

3.4.4 ANN model architecture

Different ANN structures had been investigated to find the optimum ANN model. The optimum neuron number in each hidden layer was also investigated. In the ANN model architecture the input layer includes 15 inputs (successive days); the hidden layers have 10 neurons; and the output layer consists of 4 neurons as shown in Figure (3.6). The input layer receives the inputs from the training data, while the hidden layer and the output layer receives it from the interconnections. The neurons use log-sigmoid (Equation 2.4) and hyperbolic tangent sigmoid (Equation 2.5) transfer functions to produce their outputs. Feed-forward back-propagation algorithm (HAYKIN, 1999) has been used to train the ANN models.

In this model, a supervised learning algorithm was used. The selection of the number of hidden layers and the number of neurons in each layer was one of the most important factors in the development of the neural network. In general, there was no specific rule to estimate the number of neurons for the hidden layers and the optimum topology was obtained by experimental selection. In order to find the best structure for the ANN model many networks with different structures have been developed. These models had one to five hidden layers. The number of neurons in each hidden layer is also very important in the structure of ANN. The low number of neurons in each layer decreases the learning performance. In contrast, a higher number of neurons increases the training time. Therefore, the optimum number of neurons in each layer is essential to build the ANN structure. In the present research, a different number of neurons (3-20 neurons) have been tested to find the best ANN structure. By comparing performance of developed ANN models the optimum number of neurons in each hidden layer was 10 for this particular application. By examining various network structures it was found that ANN models with more than two hidden layers are not superior to ANN models with a single or two hidden layers. Therefore, two ANN models have been chosen to assess the model performance, including one hidden layer (Figure 3.6) and two hidden layers (Figure 3.7) models. The only difference between these two models is the number of hidden layers while their other parameters are the same.

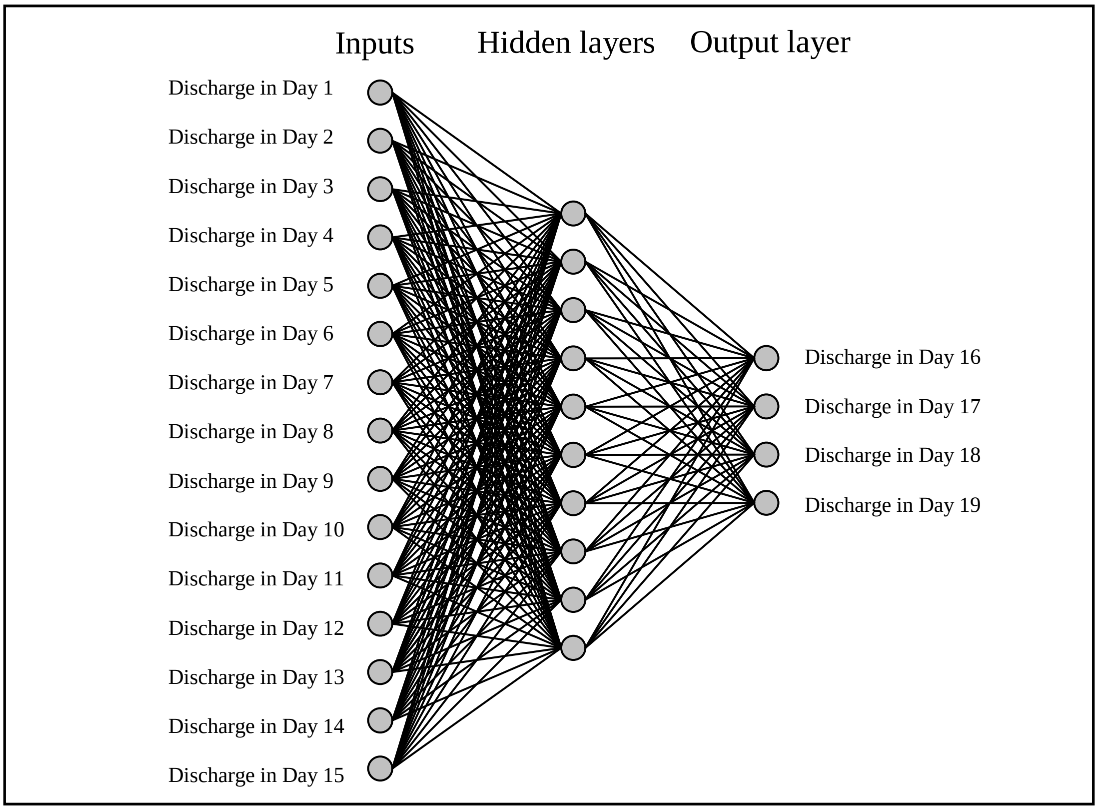


Figure 3.6 Structure of the developed artificial neural networks with 1 hidden layer and 10 neurons in hidden layer.

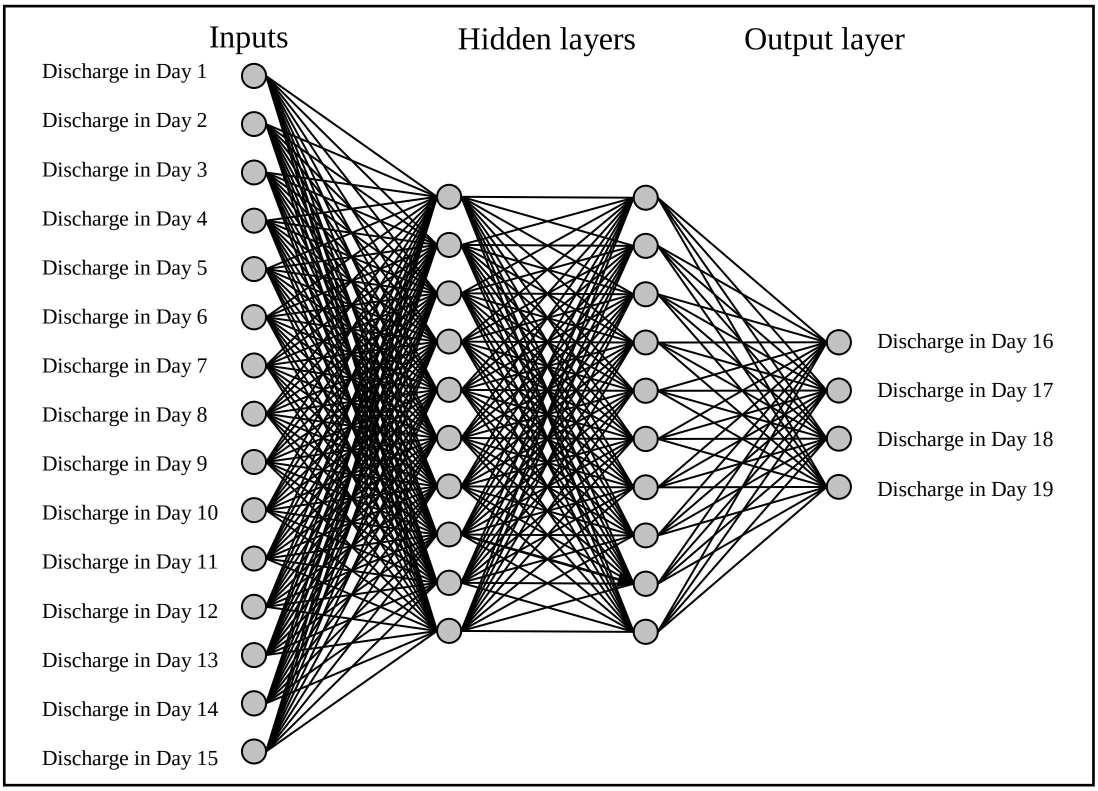


Figure 3.7 Structure of the developed artificial neural networks with 2 hidden layers and 10 neurons in each hidden layer.

The best value of 0.01 was chosen for the learning rate, training parameter that controls the size of weight and bias changes during learning, after trials (Table 3.2). To avoid over-fitting and to improve the generalisation, early stopping method was used in the training of the model.

Table 3.2 Values for ANN model

ANN Parameter	Value
Number of hidden layers	2
Number of iteration to train	28
Learning rate	0.01

3.5 Performance of the ANN model

The performance of the ANN model can be quantified by statistical measures addressing the magnitude of the variables. The model can be validated in terms of root mean square error (*RMSE*), correlation coefficient (*R*) and scatter index (*SI*) as follows:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(y_i - x_i)^2}{N}} \tag{3.2}$$

$$R = \frac{\sum_{i=1}^{N}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{N}(x_i - \bar{x})^2 \sum_{i=1}^{N}(y_i - \bar{y})^2}} \tag{3.3}$$

$$SI = \frac{RMSE}{\bar{x}} \tag{3.4}$$

where x_i is the observed values at the i-th time step, y_i is the simulated values, N is the number of time increments and $\bar{x}$ and $\bar{y}$ are the mean value of observations and simulations, respectively.

3.6 Results and discussions

3.6.1 ANN structure

The performance of the ANN model with different structures is investigated. The performance parameters for ANN with 1 hidden layer and 2 hidden layers are listed in Table 3.3. The model results for ANN with 2 hidden layers have higher *R*, lower *RMSE* and smaller *SI*. Therefore, it provides more accurate prediction results. The difference between the two developed network structures increased with a larger number of flow discharge predictions. The developed neural network with the two hidden layers resulted in 17% more accuracy for the prediction of the flow discharge on the fourth day. Therefore, the multi-layer neural network with the two hidden layers was selected to simulate and forecast the flow discharge time-series.

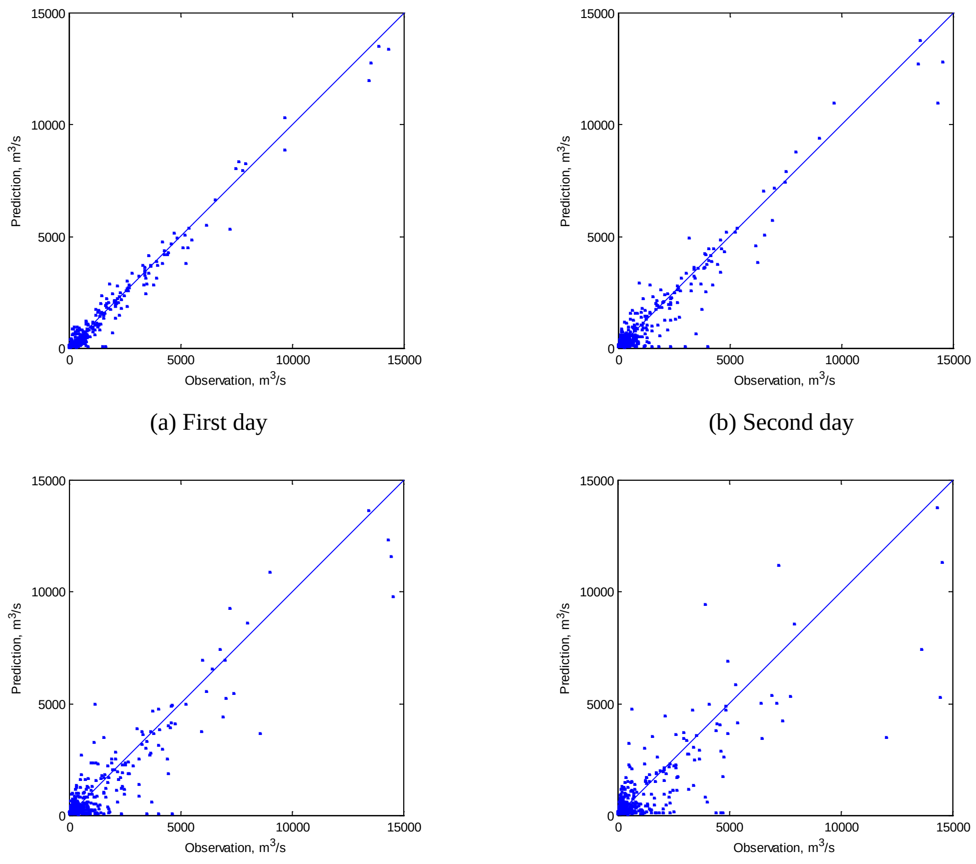
Table 3.3 Verification statistics of Fitzroy River flow discharge for different predicted day.

Network	Days	*R*	*RMSE* (m^3/s)	*SI*
ANN with 1 hidden layer	1	0.97	149	0.94
	2	0.93	253	1.59
	3	0.86	358	2.23
	4	0.68	531	3.28
ANN with 2 hidden layers	1	0.99	139	0.77
	2	0.97	256	1.25
	3	0.93	315	1.76
	4	0.85	442	2.52

3.6.2 Prediction accuracy

When the error for validation data set increased in five iterations the training was stopped by the early stopping method to avoid over-fitting. When short prediction intervals of one to three days were considered the flow discharge, simulated by this network, had a high accuracy rate. Figure 3.8 illustrates the comparison between the measured and the predicted flow discharge with 2992 testing pairs (equal to 20% of the total data) from the first to the fourth day of the prediction. From the results in Figure 3.7 and Table 3.3 it is concluded that the developed ANN model has high accuracy in the first day of prediction (R=0.99). The accuracy drops for the next three following days. The $RMSE$ were equal to 139, 256 and 315 m^3/s for the first to the third day of flow discharge predictions, respectively. The correlation coefficients that indicate the strength of the relationship between the observed and predicted data were higher than 0.9 (maximum scale is 1) for the first three days. The best result was predicted for the first day's prediction with a correlation coefficient equal to 0.99. The scatter indices for the first three days predictions were 0.77, 1.25 and 1.76, respectively. The prediction of the flow discharge was less reliable for the fourth day. However, it had reasonable values of 442 m^3/s, 0.85 and 2.52 for $RMSE$, R and SI, respectively.

As indicated in Figure 3.9, for low discharge, ANN overestimates the discharge in the Fitzroy River about 80-85 m^3/s. This overestimate can be ignored because the target of this model is the prediction of flooding events. For the great discharge of 1000 to 10000 m^3/s the prediction is reasonable. It depends on the history of discharge data the ANN model underestimates or overestimates the discharge. Prediction results were underestimated for the flood greater than 10000 m^3/s. It is because the model suffers from a low number of discharge data greater than 10000 m^3/s in the training, and the developed ANN's weights were not adjust perfectly for extreme flooding events.



(a) First day (b) Second day

(c) Third day (d) Fourth day

Figure 3.8 Comparison between the recorded and predicted river discharge in 4th day.

3.6.3 Extreme event

Figure 3.10 shows the comparison of the simulated and measured river discharges for the entire period from 1964 to 2005. The neural network overestimated the discharge during the dry seasons (Figure 3.9), with a mean value equal to 82 (m^3/s). It appears that the results were due to extreme variation between the flood events and dry season with a maximum value of 15000 (m^3/s). However, the main application of this model is the prediction of a flood and so the neural network is able to predict a flood with a high degree of accuracy (Figure 3.11). This figure indicates the peak flows (floods) are well simulated. There is a potential further study to investigate the application of different learning algorithm as well as the sensitivity of mapping scale to avoid the over-prediction in dry seasons.

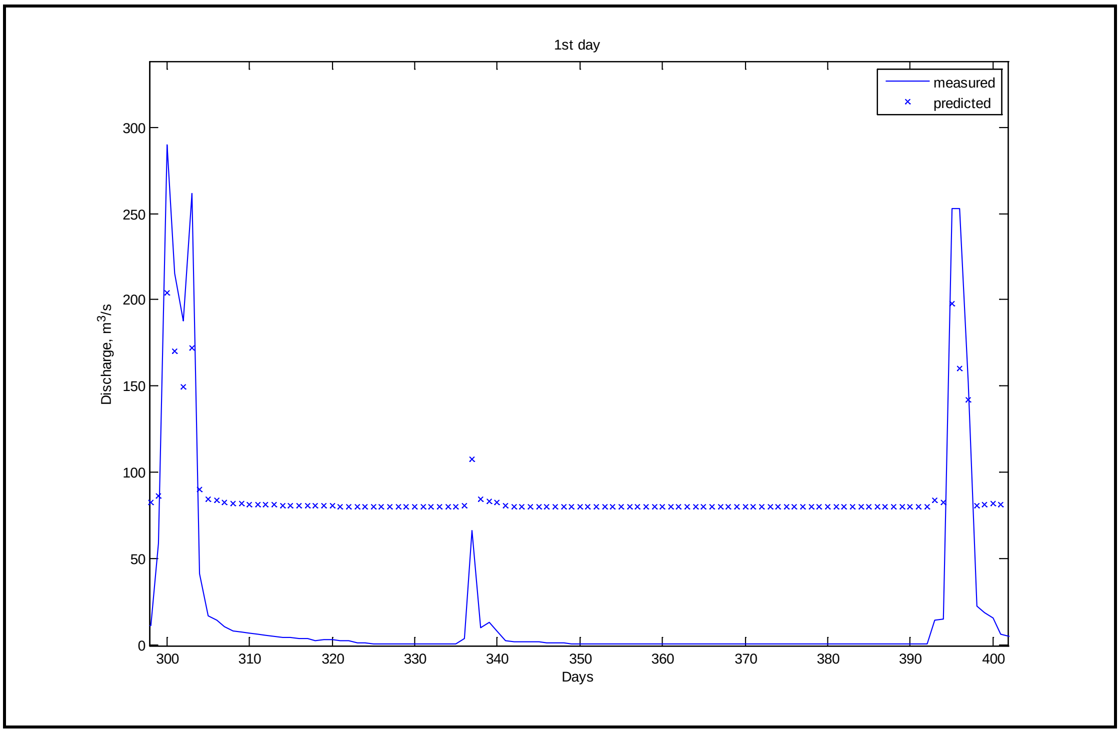


Figure 3.9 Time series of measured and predicted flow discharge in the first day of prediction for low to average discharge values.

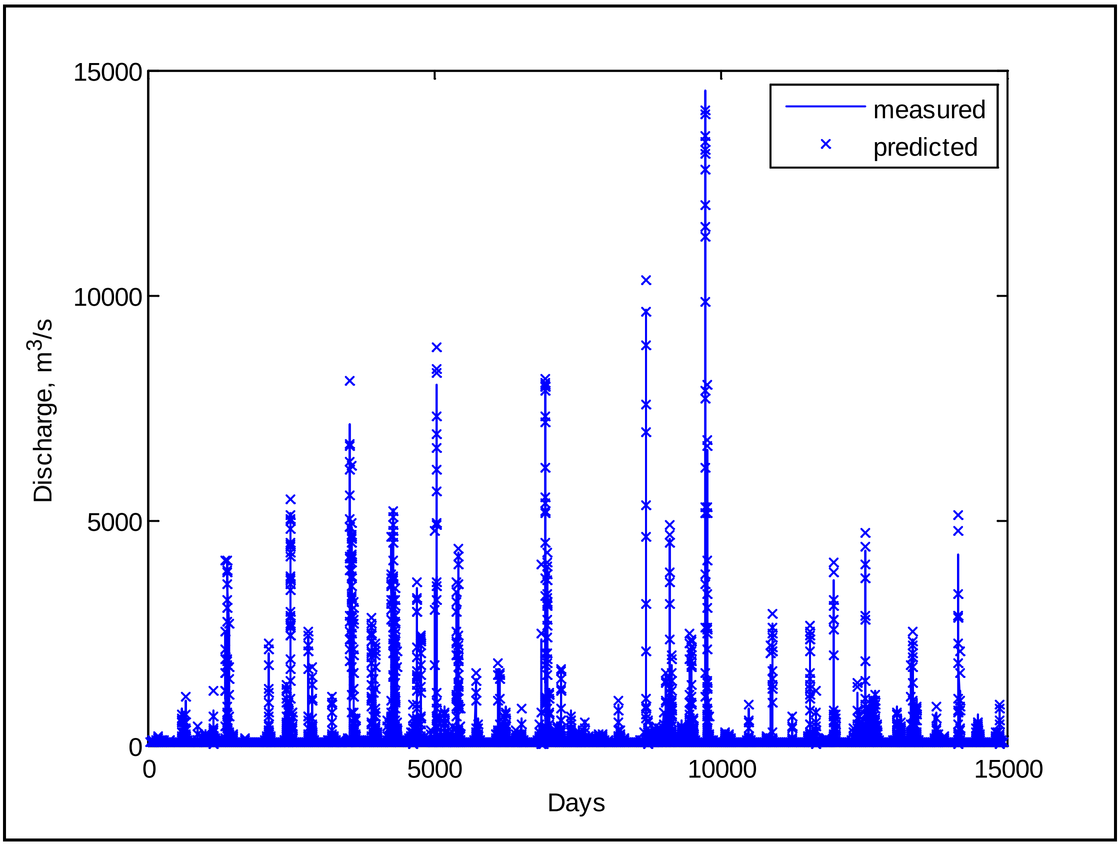


Figure 3.10 Time series of measured and predicted flow discharge starts from 01/05/1964 to 01/11/2005.

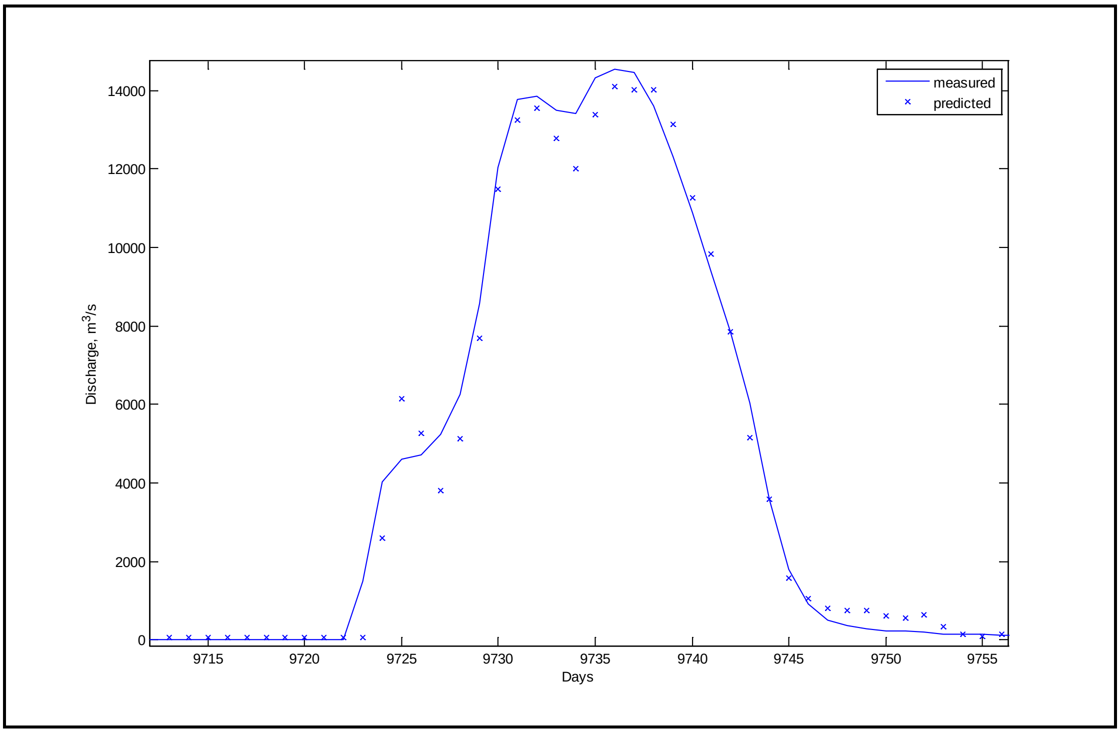


Figure 3.11 Time series of measured and predicted flow discharge in the first day of prediction for high discharge values

3.7 Summary

An artificial neural network model, with a feed-forward back-propagation learning algorithm was developed to predict the daily flow discharge on the Fitzroy River, up to four days ahead, by the learning and recalling process. Two network structures were compared. The network with the two hidden layers had more accurate prediction. Early stopping method was used to prevent the networks from over-fitting. The results show that the neural network provides a high accuracy prediction of flow discharge for the next three days with a reliable prediction for the fourth day. One of the advantages of the presented model, compared to the ordinary deterministic numerical models, is that unlike the conventional models it is not dependent on the rainfall, initial and boundary conditions. However, the reliability of the results depend on the availability of the data quality for the training of the network.

The developed neural network model can accurately predict flood events. However, it over predicts the low flow discharge with an average value of 82 (m^3/s). Further investigation is, therefore, suggested to use other network structures, transfer functions and mapping scales to expand and enhance this model from flood prediction only to drought prediction.

4 Estimation of groundwater table fluctuations in coastal aquifers

4.1 Introduction

The artificial neural network method has often been used in function approximation. This chapter describes how an ANN model was developed to predict the watertable variations in coastal aquifers due to tide elevation.

Within water resource engineering, groundwater flow has been investigated for a long time by both engineers and scientists using many models such as analytical, porous media, viscous fluid, electrical analog, empirical, mass balance and numerical. Understanding the groundwater flow in coastal zones is one of the most challenging and important areas. Additionally, beach watertable fluctuations in coastal aquifers is also important, namely for sediment transport processes in the swash zone, shoreline stability, the design of coastal structures close to beaches, water quality in closed coastal lakes and lagoons, the operation of dune sewage disposal and domestic water supply. Further detailed discussions can be found in TURNER (1995c). As the beach is a boundary for groundwater the study of groundwater dynamics in the inland areas close to this boundary is critical in obtaining a sound understanding of groundwater processes in coastal areas.

The objective of this study was to develop an artificial neural network model that could accurately predict groundwater table fluctuations based on data from five locations along the eastern coast of Australia.

4.1.1 Groundwater Hydraulics

Darcy's law (TURNER *et al.*, 1997) is used in the governing equation for unsteady groundwater flow in an unconfined, homogeneous and isotropic aquifer. The law is valid if the flow is laminar (i.e. Reynolds number is small), which is applicable for sandy beaches, but it may not be valid for gravel beaches (PACKWOOD and PEREGRINE, 1980). By using Darcy's law, specific velocity (v_x) in x direction can be defined as:

$$v_x = -K\frac{\partial h}{\partial x} \tag{4.1}$$

and the continuity equation is

$$\frac{\partial h}{\partial t} = -\frac{1}{n_e}\frac{\partial}{\partial x}(h v_x) \tag{4.2}$$

where h is the elevation of groundwater level above a lower-bounding aquitard, K is the hydraulic conductivity, and n_e is the drainable porosity. By substituting Equation (4.1) into Equation (4.2), there is

$$\frac{\partial h}{\partial t} = \frac{K}{n_e}\frac{\partial}{\partial x}(h\frac{\partial h}{\partial x}) \tag{4.3}$$

According to NIELSON (1990), Equation (4.3) is sufficient to describe shore-normal groundwater flow if the horizontal flow dominates over the vertical flow. When the magnitude of the watertable fluctuations is small in comparison with the depth of the aquifer (d), Equation (4.3) can be linearised as follows:

$$\frac{\partial h}{\partial t} = \frac{Kd}{n_e}\frac{\partial^2 h}{\partial x^2} \tag{4.4}$$

In previous studies, various methods have been used to model the watertable in coastal aquifers including analytical models and numerical models. Every model has its advantages and limitations. Applying new methods have been always considered necessary by engineers. Some of the conventional methods have been briefly introduced as follows.

Finite difference model

The finite difference approximation for the second-order partial derivatives can be used to obtain a finite deference scheme for groundwater table fluctuations (Equation 4.5):

$$h_i^{t+1} = h_i^t + D_i \Delta t \frac{h_{i+1}^t - 2h_i^t + h_{i-1}^t}{\Delta x^2} \tag{4.5}$$

where i indicates location of monitoring wells, t is time-step index, and D equals $\frac{Kd_i}{n}$. Here, n is porosity of soil.

Simple analytical solution

For a highly simplified system (i.e. vertical beach and small tidal amplitude), if

$$h_{tide} = d + A\cos(\omega t), \tag{4.6}$$

the solution is:

$$h(x, t) = d + A\cos(\omega t - kx)e^{-kx} + B(x) \tag{4.7}$$

where k is the wave number, A is the tidal amplitude, ω is the radian frequency of the tide, and B is any flux of water out of the beach caused by rainfall, etc.

Perturbation model

The beach slope acts as a nonlinear filter causing the water to enter the porous medium across the beach face more easily than it leaves. This results in the faster raising and slower lowering of the watertable level in the landward side of the shoreline. The groundwater table fluctuations in a sloping beach can be solved by the perturbation method. NEILSEN (1990) used the perturbation method when considering a sloping beach. The watertable can be expressed in the first (Equation 4.8) and second orders (Equation 4.9):

$$h(x,t) = d + A\cos(\omega t - kx)e^{-kx} + \varepsilon A\left[\frac{1}{2} + \frac{\sqrt{2}}{2}\cos(2\omega t + \frac{\pi}{4} - \sqrt{2}kx)e^{-\sqrt{2}kx}\right] \tag{4.8}$$

$$h(x,t) = d + A\cos(\omega t - kx)e^{-kx} + \varepsilon A\left[\frac{1}{2} + \frac{\sqrt{2}}{2}\cos(2\omega t + \frac{\pi}{4} - \sqrt{2}kx)e^{-\sqrt{2}kx}\right] + \varepsilon^2 A(\frac{1}{4} - \frac{\sqrt{2}}{2})\left[\sin(\omega t - kx)e^{-kx} + \sin(3\omega t - \sqrt{3}kx)e^{-\sqrt{3}kx}\right] \tag{4.9}$$

Assuming β is the beach slope, then the perturbation parameter (ε) can be defined as *kAcot(β)*.

However, it is always difficult to set up numerical models for a specific region due to the complexity of the system and limitation of boundary conditions. ANN can overcome limitation of the abovementioned limitations and enhance the prediction results.

4.2 ANN model for groundwater dynamics

As discussed in Section 4.1, groundwater level estimation models solve equations of underlying physical processes which include the development of analytical or numerical models for groundwater in coastal aquifers. These models are generally complex; therefore artificial neural networks can be used as an alternative to process-based models. ANN models help to make maximum use of the existing data by identifying patterns in the data that can be used to predict the future values of specific variables.

4.2.1 Description of data

The data to feed the network are available from KANG *et al.* (1994a), who monitored five natural beach sites along the coast of south east of Queensland and northern New South Wales (Figure 4.1). These locations were:

1. Kings Beach, Caloundra, Queensland;
2. Eagers Beach, Moreton Island, Queensland;
3. Shelley Beach, Caloundra, Queensland;
4. Brunswick Beach, Brunswick Heads, New South Wales; and
5. Unnamed Beach, North Bribie Island, Queensland

The selected sites have common characteristics in that they were two dimensional (i.e. allowing cross-sectional representation) and were composed of homogeneous sand (KANG et. al, 1994). The data included water levels in monitoring wells, usually at 30, 20 or 15 minute intervals over a 25 hour period. The tide was also monitored with the typical range being 1 to 2 metres. Because of high measured intervals for sea water elevation the wave data could not be distinguished in recorded data. Therefore, tide was assumed to be the dominant force in this model. Position of monitoring wells from coastline is presented in Figure (4.2). Hydraulic conductivity (Table 4.1) was measured *in situ* between the seepage exit point and the run-up limit during low tide. The average beach slope ($\tan\beta$) was also measured and, as indicated in Table 4.1, it was an important cause of nonlinearity in the physical process.

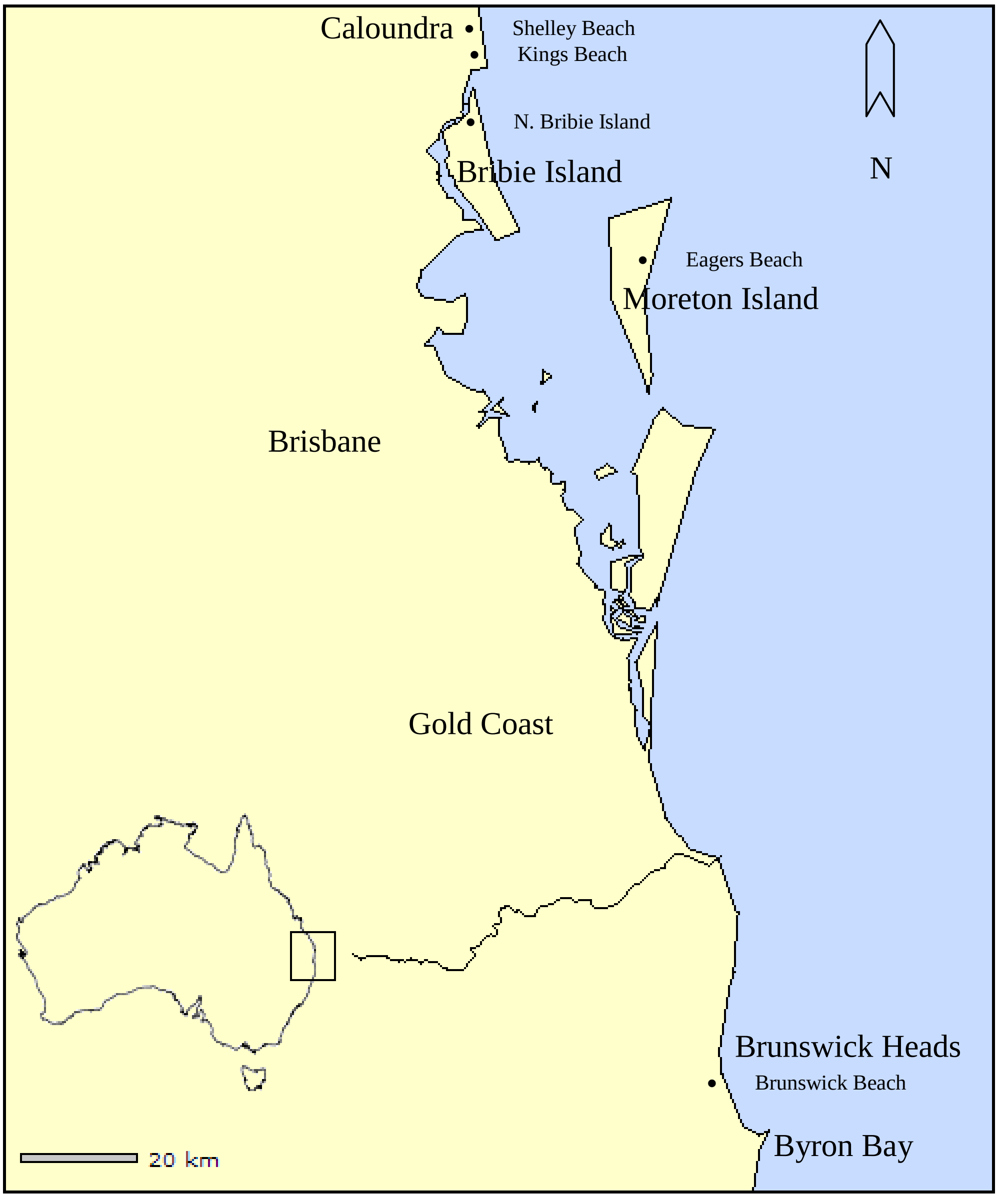


Figure 4.1 Location of watertable monitoring wells. (ANRA, 2008, Adopted from Kang *et al*., 1994a)

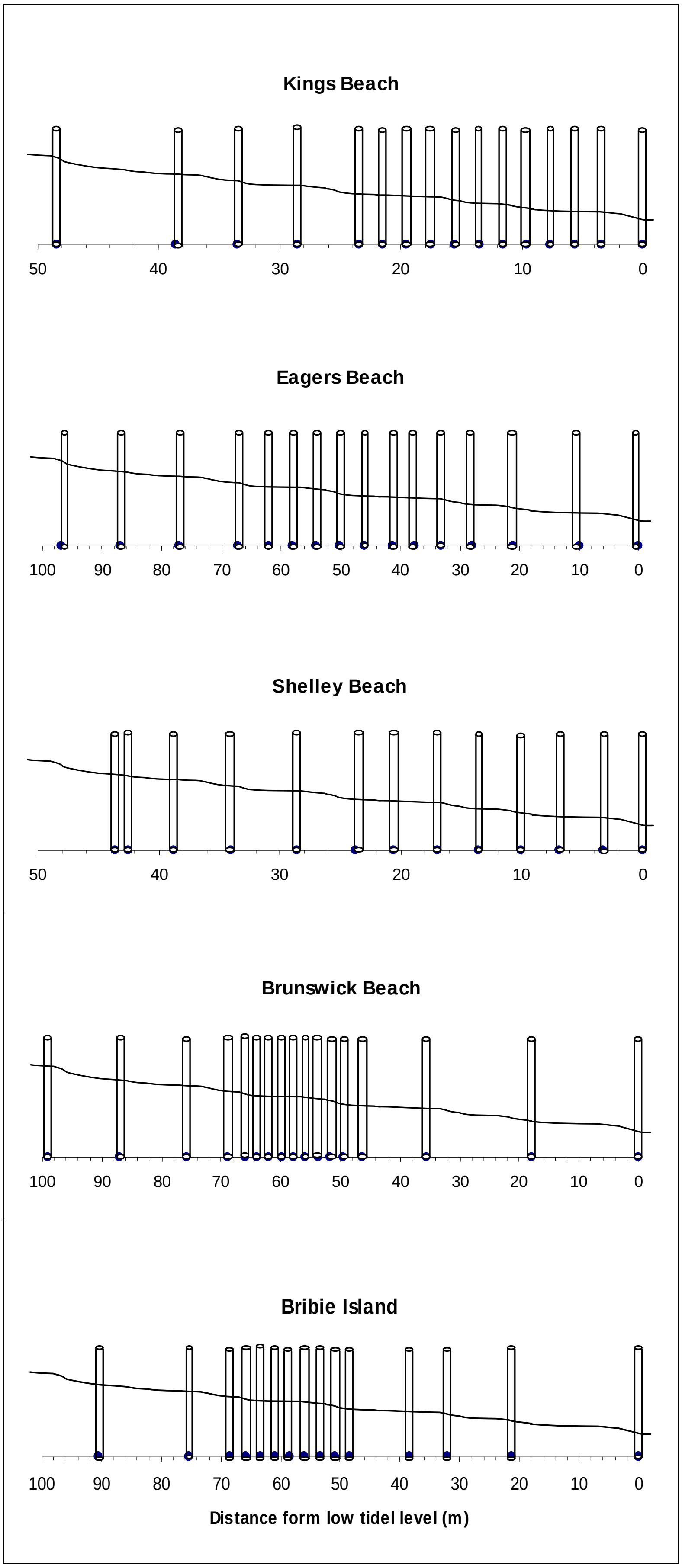


Figure 4.2 Position of monitoring wells

Table 4.1 Summary of beach characteristics (adopted from Kang *et al.* (1994a))

Location	Rain	*tanβ*	*K*(m/s)
Kings Beach, *Caloundra*	No	0.103	3.0×10^{-4}
Eagers Beach, *Moreton Island*	Yes	0.040	3.4×10^{-4}
Shelley Beach *Caloundra*	Yes	0.110	2.4×10^{-3}
Brunswick Beach, *Brunswick Heads*	No	0.037	1.2×10^{-4}
Unnamed Beach, *North Bribie Island*	No	0.030	3.7×10^{-5}

Based on the underlying physics of the groundwater dynamics in coastal aquifer, (Section 4.1.1), the parameters that affect the fluctuations including tide elevation, beach slope (*tanβ*) and hydraulic conductivity (*K*) were selected (KANG *et al*., 1994a). Measurements for the groundwater level were available at the monitoring points from 1991 to 1993 (KANG *et al*., 1994a). The measured values are listed in Appendix 3.

4.2.2 ANN structure

A classic multilayer feed-forward network (Figure 4.3) was developed for this study using MATLAB with the Neural Network Toolbox. The method for dividing the data into training (60%), validation (20%) and testing (20%) was arbitrary, to include all random behaviour of the watertable fluctuations.

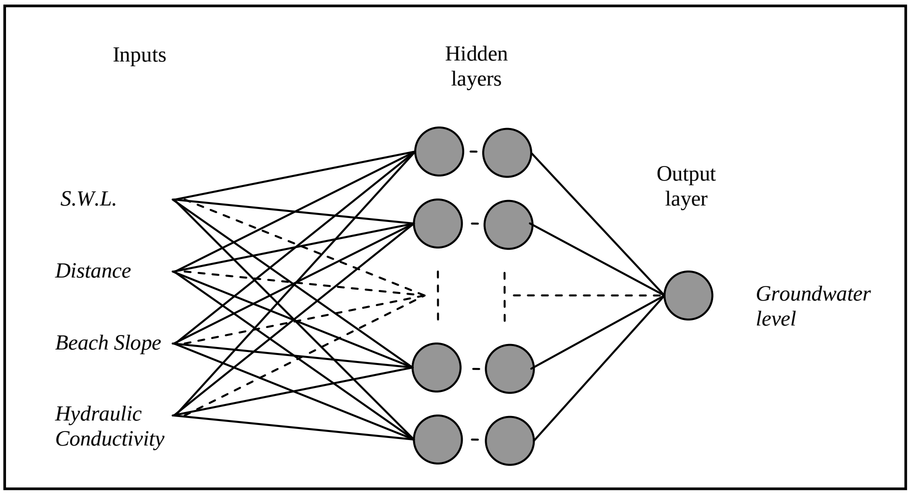


Figure 4.3 Architecture of developed ANN model for prediction of groundwater elevation

Different ANN structures had been investigated to find the optimum ANN model. The ANN models with one and more hidden layers were examined. The optimum neuron number in each hidden layer was also investigated. Performance of the ANN models was measured by *RMSE* and *R* as discussed in Equation (3.2) and (3.4). The model with two hidden layers and 20 and 10 neurons each hidden layers was found to be the best ANN model. The models with higher complexity in the ANN structure did not result better performance. Because it required greater number of data to train these networks.

Log-sigmoid transfer function, Equation (2.4), and linear transfer function, Equation (2.3), for hidden layers and output layers, respectively, were found to have better results in this particular ANN model. The selected network parameters are listed in Table 4.2. The model performance was influenced by the data used for training and testing.

Table 4.2 Network parameters for developed ANN model

ANN Parameter	Value
Number of hidden layers	2
Number of iteration to train	193
Learning rate	0.01

4.3 Results and discussions

The ANN training stopped by early stopping method when the error in validation data set increased in five iterations to avoid over-fitting. In the current research, to quantify the performance of the ANN model, the Root Mean Squired Error (*RMSE)*, the correlation coefficient (*R*) and Scatter Index (*SI*) have been used. The *RMSE* is a commonly used criterion because it has the advantage of penalising large forecasting errors rather than penalising small ones. The *RMSE* can also provide the maximum likelihood estimate of the model parameters in a normally distributed dataset. The results of the ANN model performance are summarised in Table 4.3 in terms of *R*, *RMSE* and *SI* for all locations.

The measured and predicted data are plotted in Figures 4.4 for testing data set in all locations. These figures show a good agreement between prediction and measured watertable.

As indicated in Figure 4.4, the developed model tends to underestimate the watertable in the places closer to coastline with high fluctuation. However, the prediction is very accurate (*R*=1, *RMSE*=0.07 and *SI*=0.1). As it moves further from the coastline, the simulation errors are increasing. The Coefficient of Correlation was more than 0.9 within 20 metres from the coastline. Outside this zone, the prediction accuracy dropped rapidly for Kings Beach. The total *R*, *RMSE* and *SI* for Kings Beach were 0.94, 0.12 and -1.83 respectively. Since the mean watertable of the monitoring wells in Kings Beach were very small, its *SI* (Equation 3.4), values are greater than other beaches. Detailed model performance for Kings Beach is available in Table 4.3.

The ANN model results for Eagers Beach had prediction performance of *R*=0.98, *RMSE*=0.09 and *SI*=0.01. Eagers Beach and Brunswick Beach had the best accuracy among the other beaches. The highest RMSE belonged to Shelley Beach of 0.15.

The ANN model tends to underestimate the maximum watertable in the wells close to coastline except in Bribie Island which predicted watertable is above the recorded watertable.

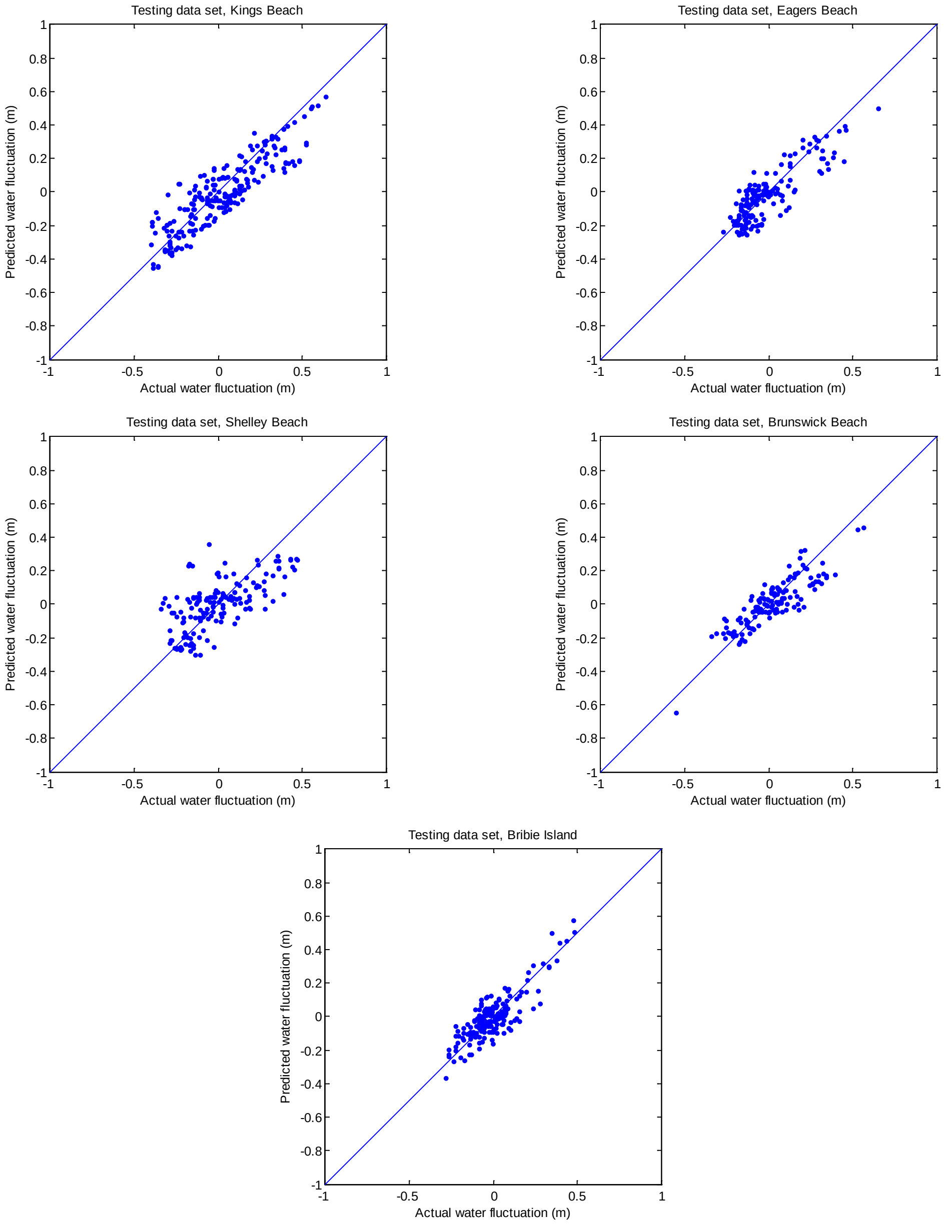


Figure 4.4 The comparison of watertable fluctuation between the ANN model prediction and field measured values.

Table 4.3 Performance of developed ANN model for testing data set

Location	Well No.	17	16	15	14	13	12	11	10	9	8	7	6	5	4	3	2	1	Total testing set
Kings Beach	Distance (m)	-	0	3.4	5.6	7.6	9.6	11.6	13.5	15.5	17.5	19.5	21.5	23.5	28.5	33.5	38.5	48.4	-
	R	-	1.00	0.99	0.98	0.99	0.84	0.83	0.95	0.94	0.98	0.94	0.81	0.72	0.28	0.16	0.04	0.05	0.94
	RMSE	-	0.07	0.04	0.06	0.05	0.11	0.10	0.09	0.13	0.14	0.20	0.24	0.13	0.13	0.09	0.08	0.09	0.12
	SI	-	-0.10	-0.08	-0.17	-0.25	-0.31	-0.42	-3.00	3.25	7.00	1.82	2.18	2.60	2.17	2.25	2.00	4.50	-1.83
Eagers Beach	Distance (m)	-	0	10	20.9	28	33.1	37.6	41.2	45.8	50.1	54.1	58	62	67.1	77.1	87	96.8	-
	R	-	1.00	0.97	0.92	0.92	0.87	0.94	0.95	0.94	0.93	0.91	0.91	0.83	0.52	-0.06	0.17	0.09	0.98
	RMSE	-	0.06	0.11	0.08	0.07	0.06	0.08	0.08	0.08	0.08	0.08	0.11	0.15	0.14	0.13	0.05	0.03	0.09
	SI	-	0.01	0.02	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.02	0.02	0.02	0.01	0	0.01
Shelley Beach	Distance (m)	-	-	-	-	-	0	3.2	6.9	10	13.6	16.9	20.5	23.7	28.6	34	38.7	42.5	-
	R	-	-	-	-	-	1.00	0.28	0.94	0.67	0.80	0.41	0.90	0.87	0.5	0.73	0.21	0.57	0.98
	RMSE	-	-	-	-	-	0.11	0.23	0.05	0.10	0.17	0.14	0.08	0.15	0.19	0.16	0.18	0.10	0.15
	SI	-	-	-	-	-	0.03	0.07	0.01	0.02	0.04	0.03	0.02	0.03	0.03	0.03	0.03	0.02	0.03
Brunswick Beach	Distance (m)	0	18	35.6	46.3	49.5	51.7	53.8	55.8	57.9	59.9	61.9	63.9	65.9	69	75.8	87	99	-
	R	1.00	1.00	0.94	0.97	0.92	0.97	1.00	0.91	1.00	0.95	1.00	0.95	0.83	0.72	0.71	0.80	0.28	0.98
	RMSE	0.12	0.11	0.08	0.06	0.05	0.07	0.07	0.06	0.04	0.05	0.10	0.12	0.09	0.1	0.15	0.08	0.06	0.09
	SI	1.09	-1.38	0.38	0.12	0.08	0.10	0.08	0.07	0.04	0.05	0.09	0.12	0.09	0.09	0.13	0.07	0.06	0.11
Bribie Island	Distance (m)	-	-	0	21.2	32	38.5	48.3	50.9	53.4	55.9	58.4	60.8	63.2	65.7	68.5	75.2	90.4	-
	R	-	-	0.86	0.95	0.99	0.91	0.98	0.47	0.61	0.64	0.57	0.49	0.29	0.28	0.01	-0.29	-0.11	0.91
	RMSE	-	-	0.08	0.10	0.05	0.06	0.05	0.10	0.09	0.08	0.10	0.06	0.08	0.05	0.07	0.05	0.07	0.08
	SI	-	-	0.13	0.12	0.05	0.06	0.05	0.09	0.08	0.07	0.09	0.05	0.07	0.05	0.06	0.05	0.07	0.07

The times-series of measured and predicted watertable fluctuation for Kings Beach are displayed in Figure (4.5) as an example of ANN prediction. In this figure, total testing set represents the total number of testing set in each beach. In general, the wells closer to coastline had the higher prediction accuracy in both the magnitude and the phase. The ANN model tends to overestimate watertable in coastline and underestimate in the high water level. This model also overestimated watertable during watertable rising and it underestimated watertable during watertable falling.

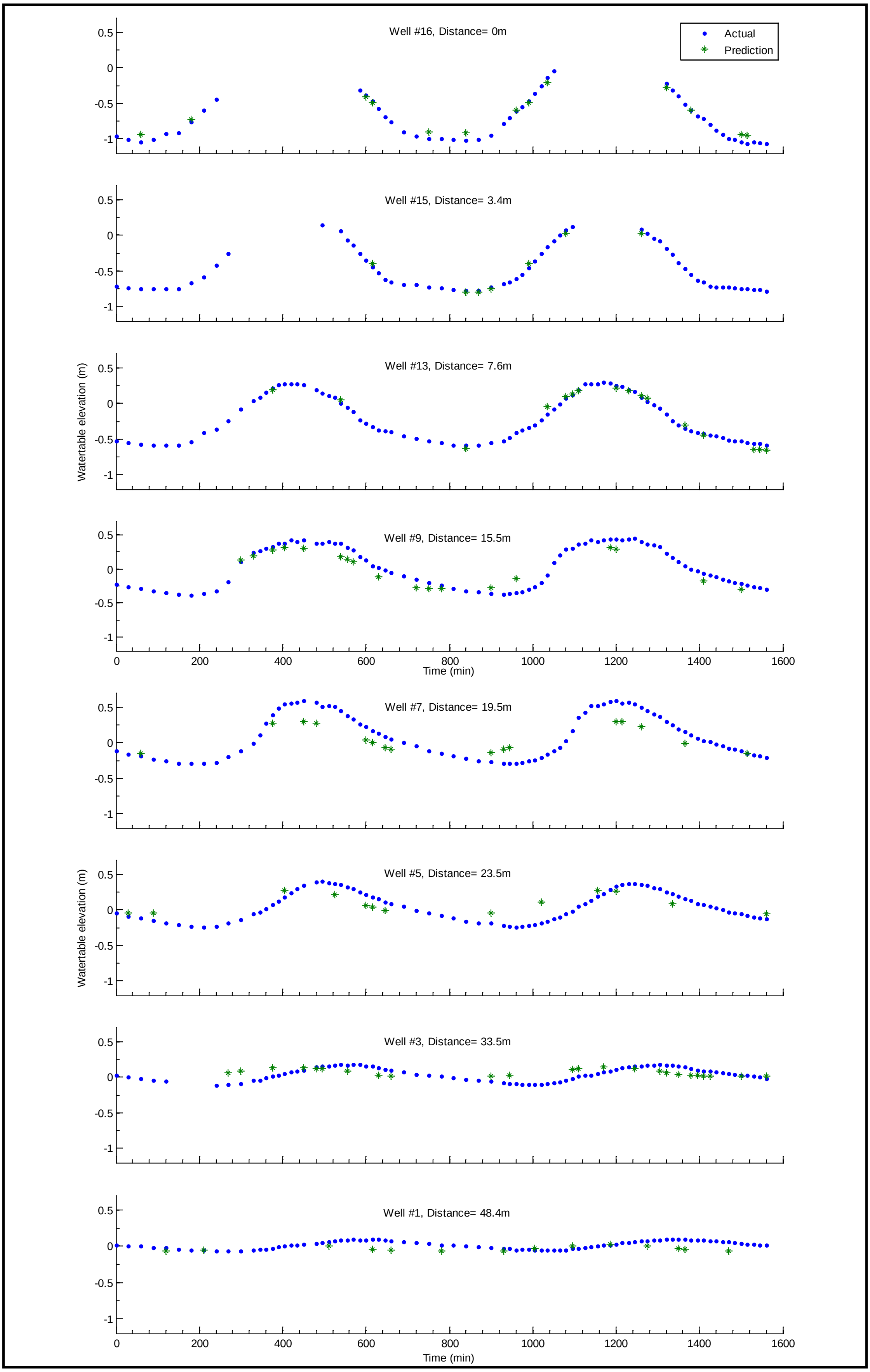


Figure 4.5 Time-series of actual and predicted groundwater table fluctuation for Kings Beach.

4.4 Sensitivity study

In the present study, ANN model depends on the parameters such as tide elevation, distance from the coastline, hydraulic conductivity and beach slope. The sensitivity of each input parameter was examined by removing each input parameter from the data set. Table 4.4 summarises the results of testing data set for the sensitivity analysis in terms of the Correlation Coefficient (*R*), Root Mean Square Error (*RMSE*) and Scatter Index (*SI*).

Table 4.4 Model performance for sensitivity study

Location	Performance Index	Normal Condition	Removed Parameter				
			Tide	Distance	*K*	Beach Slope	K and Beach Slope
Kings Beach	***R***	0.94	0.67	0.68	0.94	0.93	0.90
	RMSE	0.12	0.25	0.25	0.11	0.13	0.15
	SI	-1.83	-3.95	-3.89	-1.76	-1.99	-2.34
Eagers Beach	***R***	0.98	0.94	0.37	0.98	0.99	0.98
	RMSE	0.09	0.18	0.46	0.10	0.08	0.09
	SI	0.01	0.02	0.06	0.01	0.01	0.01
Shelley Beach	***R***	0.98	0.96	0.50	0.98	0.98	0.98
	RMSE	0.15	0.20	0.64	0.15	0.14	0.15
	SI	0.03	0.04	0.13	0.03	0.03	0.03
Brunswick Beach	***R***	0.98	0.86	0.51	0.97	0.96	0.94
	RMSE	0.09	0.21	0.34	0.11	0.11	0.13
	SI	0.11	0.25	0.41	0.13	0.13	0.16
Bribie Island	***R***	0.91	0.62	0.52	0.91	0.89	0.86
	RMSE	0.08	0.14	0.16	0.08	0.10	0.12
	SI	0.07	0.14	0.15	0.08	0.09	0.11

By comparing the results of the sensitivity analysis for Bribie Island, as a good example, it can be concluded that by removing tide data from model inputs, the worst prediction resulted. In this situation *R* dropped from 0.91 to 0.62. In addition, *RMSE* and *SI* increased from 0.08 to 0.14 and 0.07 to 0.14, respectively.

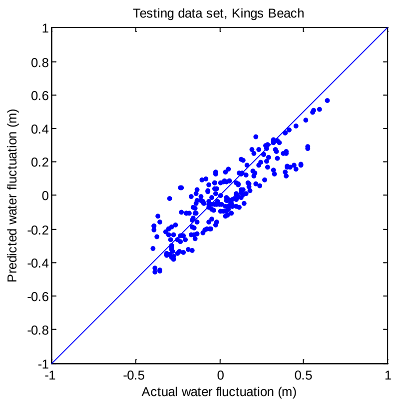
If the distances from coastline have been removed from input then the second inaccurate prediction happened. In this situation *R* dropped from 0.91 to 0.52. Additionally, *RMSE* and *SI* increased from 0.08 to 0.16 and 0.07 to 0.15, respectively.

There was not a significant difference in prediction when the hydraulic conductivity was deleted from inputs. Therefore, hydraulic conductivity can be removed from the ANN model. This is important because less parameter is required for prediction of watertable in coastal aquifers.

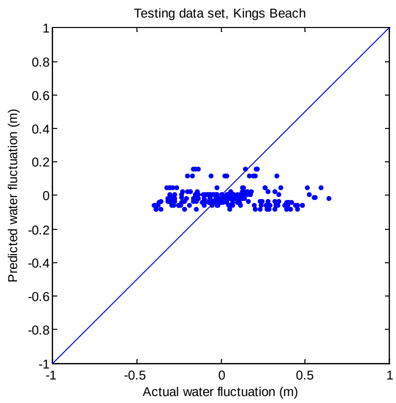
The model result indicated the influence of beach slope on this prediction. In this situation *R* dropped from 0.91 to 0.89. Moreover, *RMSE* and *SI* increased from 0.08 to 0.10 and 0.07 to 0.09, respectively.

In another experiment, by removing both hydraulic conductivity and beach slope, prediction accuracy dropped. In this case, *R* dropped from 0.91 to 0.86. Additionally, *RMSE* and *SI* increased from 0.08 to 0.12 and 0.07 to 0.1, respectively.

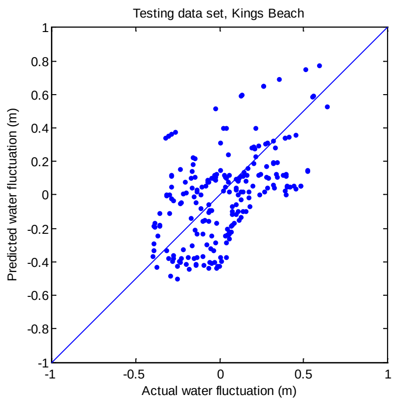
The ANN results for testing the data set at Kings Beach is presented in Figure (4.6). In the normal condition, all parameters are included in the ANN model. It can be seen that the model is sensitive to the tide elevation and the distance from the coastline in Figure 4.6(b) and (c), but it is not sensitive to the hydraulic conductivity (Figure 4.6(d)) and beach slope (Figure 4.6(e)).



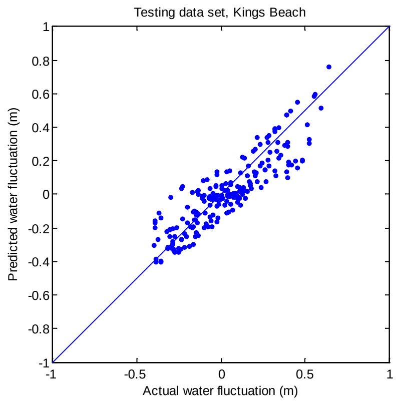
(a) Normal condition



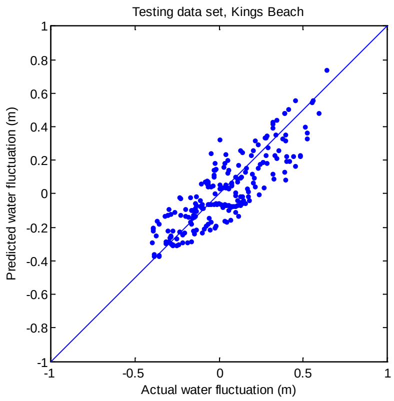
(b) Tide condition is removed



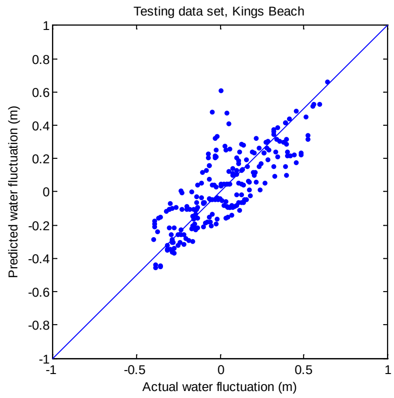
(c) Distance condition is removed



(d) Hydraulic conductivity condition is removed



(e) Beach slope condition is removed



(f) Beach slope condition and hydraulic conductivity is removed

Figure 4.6 The water level comparison between the ANN prediction and measured values for Kings Beach.

4.4.1 Importance of tide

Since measured intervals for sea water elevation were greater than 15 minutes the wave effect could not be distinguished in recorded data. Therefore, tide was assumed to be dominant in this model. If the tide is removed from the input data the ANN cannot correctly simulate the fluctuation. In this situation, the predicted watertable for all time steps at each monitoring point is close to the mean watertable. Examples of four different points selected at Eagers Beach are depicted in Figure (4.7). In this figure, it can be seen that the prediction results are constant for any time step making them similar to the mean watertable (Table 4.5)

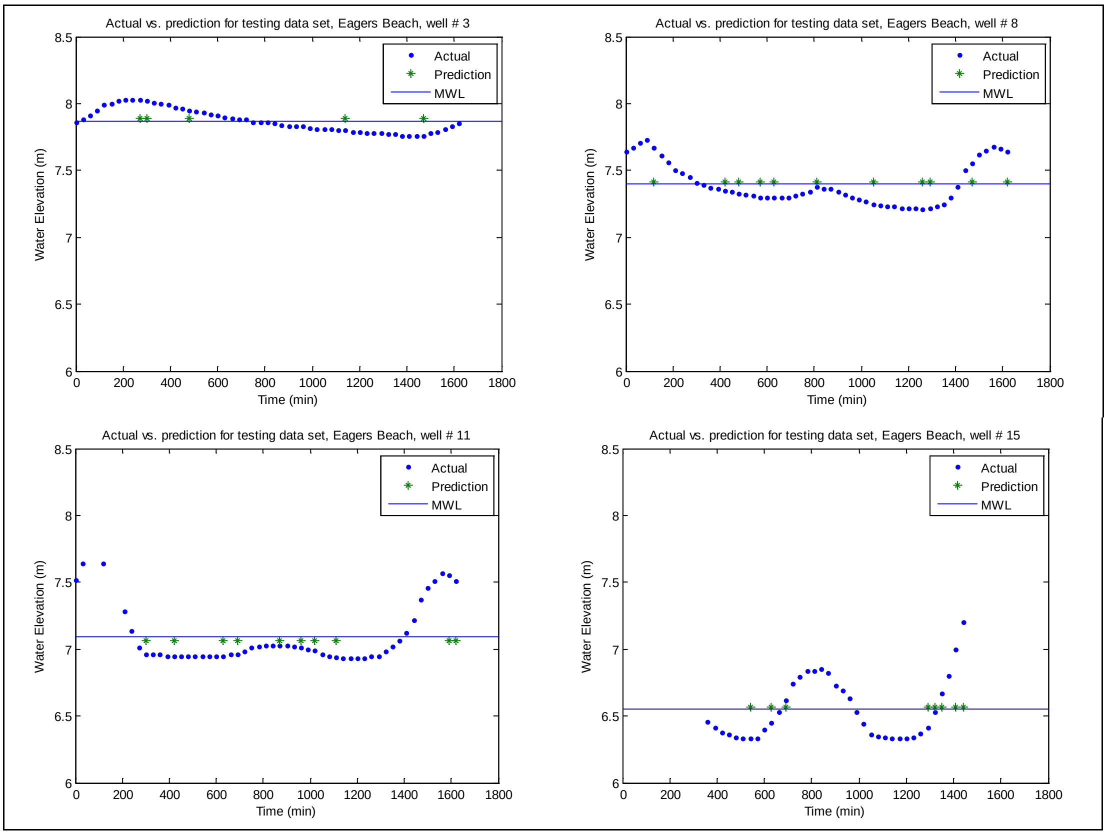


Figure 4.7 The water level comparison between the ANN prediction and measured values for some monitoring points in Eagers Beach without considering effects of tide

Table 4.5 Mean watertable for monitoring wells

	Mean Water Level (m)																	SWL
Well No.	17	16	15	14	13	12	11	10	9	8	7	6	5	4	3	2	1	
Kings Beach	-	-0.73	-0.48	-0.36	-0.20	-0.36	-0.24	-0.03	0.04	0.02	0.11	0.11	0.05	0.06	0.04	0.04	0.02	-0.38
Eagers Beach	-	6.38	6.55	6.75	6.90	6.98	7.09	7.17	7.28	7.40	7.49	7.60	7.68	7.75	7.87	8.00	8.11	6.75
Shelley Beach	-	-	-	-	-	3.46	3.53	3.97	4.24	4.56	4.87	5.10	5.29	5.51	5.64	5.65	5.72	4.05
Brunswick Beach	0.11	-0.08	0.21	0.52	0.62	0.70	0.90	0.83	1.03	0.92	1.12	1.01	1.04	1.08	1.12	1.10	1.03	0.20
Bribie Island	-	-	0.64	0.84	0.97	1.01	1.09	1.17	1.17	1.16	1.13	1.13	1.11	1.11	1.10	1.08	1.04	0.83

4.4.2 Importance of distance from coastline

The effect of the distance from the beach face to the watertable fluctuation was also examined. As presented in Figure (4.8) four wells in Shelley Beach (well no. 4, 7, 9 and 11 with distances equal to 28.6, 16.9, 10 and 3.2 meters, respectively) have been selected. From the ANN model results it is concluded that if the distance is not included the neural network model could only simulate the fluctuation of watertable and the magnitudes that are similar for any point inland.

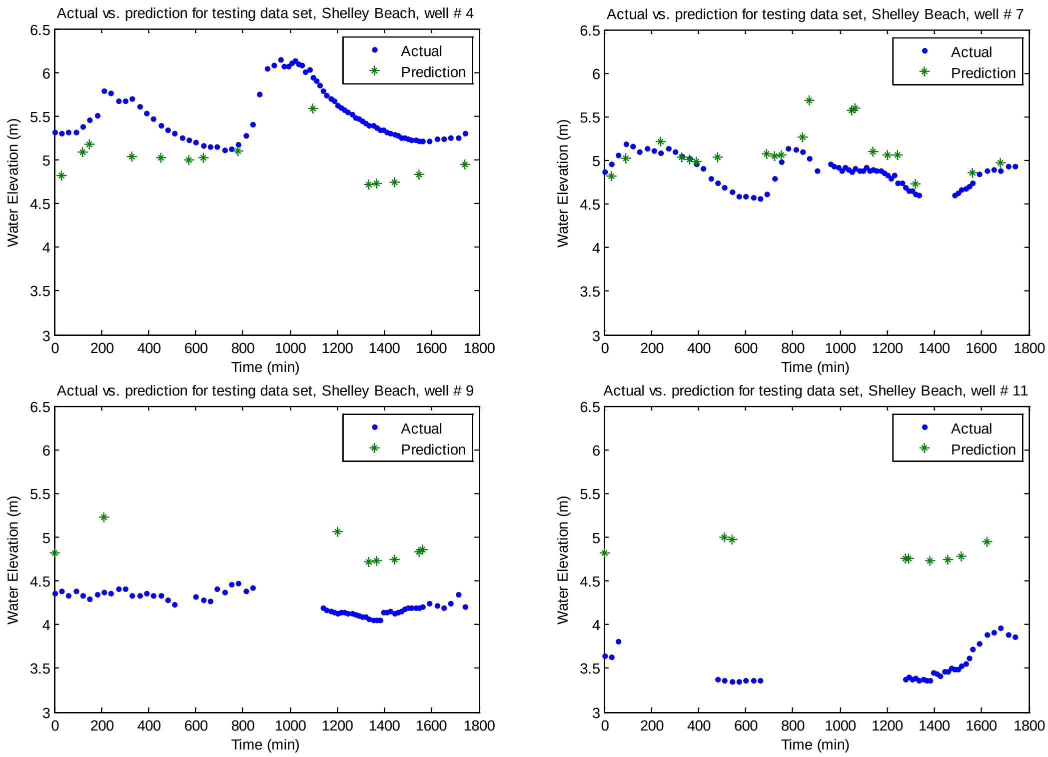


Figure 4.8 The water level comparison between the ANN prediction and measured values for some monitoring points in Shelley Beach without considering effects of distance

4.4.3 Importance of hydraulic conductivity and beach slope

From results, listed in Table 4.4, there is not a significant change in the result when hydraulic conductivity was removed from inputs. Therefore, hydraulic conductivity is not sensitive. By removing beach slope, the performance of prediction decreased by a small magnitude. Effect of beach slope also can be ignored if it is compared with the influence of tide and distance. Therefore, it can be concluded that the hydraulic conductivity (K) of the soil and the beach slope do not have significant effects on the ANN model developed for this study.

In addition to applied parameters, soil porosity is an important factor that affects the dynamics of groundwater table in coastal aquifers. However, due to a lack of this parameter in the measurements (KANG *et al*., 1994a), soil porosity was not included in the modelling. It is reasonable to speculate, however, that an increase in the data for the porosity of soil will increase the accuracy of the prediction.

4.5 Summary

The application of the ANN to predict groundwater table fluctuations in coastal aquifers is described in this chapter. Field monitoring data, from five coastal aquifers on the east coast of Australia, were chosen to train, validate and test the model. The ANN model predicts the watertable within 100 metres from coastline. A sensitivity analysis was undertaken to ascertain the effectiveness of the chosen parameters. The results show that tidal variations and the distance from the shoreline are the most important parameters. In contrast, the developed ANN model was not very sensitive to hydraulic conductivity and beach slope.

5 Conclusion

5.1 Conclusion

Intelligent predictive method for water resource engineering has been investigated. Back-propagation feed-forward ANN models was developed to simulate the flow discharge in the Gap Station in Fitzroy River. The discharge data collected from 1964 to 2005 at the Fitzroy River were used to predict flow discharge up to four days ahead. The following conclusions are postulated for the first part of the study:

1. It has been found that the structure of network is very important in the performance of the developed models. In this research, an ANN model with two hidden layers outperforms a single layer model. Through experimental selection it is also investigated that the ANN model with the higher number of hidden layers and neurons could not result in a better prediction. Indeed, more data and higher computation time are necessary to train a bigger ANN model.
2. Back-propagation algorithm has been used in training procedure and resulted in a high accuracy of predictions. The early stopping method was used in training the model, to avoid over-fitting and to improve the generalisation.
3. The results show an accurate prediction during flood events with R greater than 0.9 in the first three days of prediction and 0.85 in the fourth day.
4. The current model can be adopted, simply, for any river where the measured flow discharges are available. There is a great potential for applying the ANN method in wider areas of water resource engineering.
5. The great advantage of this model, in comparison to rainfall-runoff deterministic models, is that it depends on the historical discharge data at the particular location only, while other models need other physical parameter such as topography, roughness and rainfall, to predict a flood. Thus, if monitoring data for flow discharge are available at a location, the real-time prediction is achievable with the ANN model.

6. The prediction results show that the developed ANN model is accurate for real time flood predictions, which provides sufficient information for flood warning systems in the Fitzroy River.

To simulate the groundwater table fluctuation in coastal aquifers, a back-propagation feed-forward ANN model was also developed for function approximation The data were collected by KANG *et al*. (1994a) which describes the underlying physics of the groundwater dynamics in coastal aquifers. The data included tide level, distance from coastline, hydraulic conductivity and beach slope. The following conclusions can be drawn from the research findings:

1. The ANN model, with two hidden layers, has optimally estimated the watertable in the studied coastal areas.
2. Similar to the flood prediction model, the back-propagation algorithm and the early stopping method have been used in training procedure.
3. A sensitivity analysis helped to identify the effectiveness level of the input for the developed ANN model. It has been found that the tide variation is the most effective parameter to the fluctuation of watertable. Without distance data, the ANN model can only predict the mean watertable for each monitoring point. Hydraulic conductivity and beach slope had no significant influences on the model and can be removed from this model to simplify the ANN model.
4. The ANN can be used as an alternative and effective tool for water resource engineers and coastal managers. This model also can be adopted, simply, for any coast within Australia or overseas, when records of the groundwater table fluctuations are available.

5.2 Recommendations for future research

A flood prediction model can be a valuable tool, for local authorities or state and federal governments, to diminish the loss of life and reduce damage to property for those who live close to rivers during times of flood.

1. It is recommended that these models be enhanced and extended to other rivers in Australia, as a real-time prediction and flood warning tool.

2. Further study to investigate the application of different learning algorithms, as well as the sensitivity of the mapping scale, to avoid over-prediction, is highly recommended. Other network structures (such as recurrent networks and radial basis network) and transfer functions can be investigated to improve the model performance.
3. The investigation of the influence of other parameters such as precipitation and evaporation on the flow discharge is recommended.
4. Additionally, the model should be expanded from just flood prediction to drought prediction. This latter is particularly important with the impact of climate change expected to increase droughts.

Prediction of the beach watertable fluctuations in coastal aquifers is another important problem in water resource engineering, with the applications in such areas like shoreline stability and the design of coastal structures.

1. The author recommended having more data collection from beaches within Australia to improve the results.
2. To help identify the model performance, other artificial intelligence methods can be studied. Support Vector Machine (SVM) is one of the new approaches for data mining (VAPNIK, 1995) and as only a little research has been undertaken in water resource engineering and management so the SVM has a great potential to solve these kinds of problems.
3. In this study, the porosity of the soil was not taken into account in the developed ANN model because of the lack of data. Thus, it is recommended that porosity be a measure for such sites to increase the accuracy of the ANN model.
4. Due to the ANN model success in this research, its application to other water resource engineering problems is recommended.

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7 Appendices

7.1 Appendix 1- Models of beach groundwater

Table 7.1 Models of beach groundwater response to tidal forcing (Source: Horn, 2006)

Author(s)	Type of model	Aim of model	Input parameters	Tests of model
Dominick *et al*. (1971)	Finite difference solution to 1D Boussinesq equation	Tide-induced beach watertable fluctuations	Measured initial watertable elevation, tidal amplitude, K, n	Field data, Galleon Beach, Grand Cayman Island
Harrison *et al*. (1971)	Finite element solution to 1D Boussinesq equation	Tide-induced beach watertable fluctuations	Tidal amplitude, K, n, drainage velocity obtained from watertable elevation in wells	Field data, Virginia Beach, Virginia, USA
Fang *et al*. (1972)	Finite element solution to 2D flow equation	Tide-induced beach watertable fluctuations	Tidal amplitude, K, n, s, drainage velocity obtained from watertable elevation in wells	Field data, Virginia Beach, Virginia, USA
Nielsen (1990)	Analytical solution to 1D Boussinesq equation	Tide-induced beach watertable fluctuations	Beach slope, tidal amplitude, depth of impermeable layer, K, n	Field data, Barrenjoey Beach, Sydney NSW, Australia
Turner, 1993b and 1995b	Analytical solution to Dracos (1963)	Development of seepage face/ movement of exit point	Beach profile, measured tide or tidal constituents, D50, sorting, n	Field data, North Harbour Beach, Mackay, Queensland; Australia; comparison to field data of Nielsen (1990)
Li *et al*. (1996)	Boundary element method solution to 2D flow equation	Groundwater response to beach dewatering	Tidal constituents, beach slope, K, n	Numerical simulations
Li *et al*. (1997b)	Boundary element method solution to 2D flow equation	Tide-induced beach watertable fluctuations	Tidal constituents, beach slope, K, n	Comparison to field data of Nielsen (1990) and Turner (1993a)
Nielsen *et al*. (1997)	Analytical solution to second order Boussinesq equation	Watertable waves in aquifers of intermediate depth	Amplitude and frequency of tidal oscillations, aquifer depth, K, n	Comparison to lab data of Aseervatham (1994) and Kang *et al*. (1994a)
Baird *et al*. (1998)	Finite difference solution to 1D Boussinesq equation	Tide-induced beach watertable fluctuations	Measured tide or tidal amplitude and elevation, measured beach profile, measured initial water levels, deep-water Hrms, deep water L, depth of aquifer, K, s	Field data, Canford Cliffs, Dorset, UK
Raubenheimer *et al*. (1999)	Finite difference solution to 1D Boussinesq equation	Tide-induced beach watertable fluctuations; spring-neap tidal water table fluctuations	Measured tide, measured beach profile, measured initial water levels, depth of aquifer, K, n	Field data, Torrey Pines beach, California, USA
Li *et al*. (2000a)	Analytical solution to Boussinesq equation including vertical flow effects and captillarity	groundwater waves in aquifers of intermediate depth	Amplitude and period of tidal oscillations, aquifer depth, thickness of capillary fringe, K, n	Comparison to solutions of Barry *et al*. (1996), Nielsen *et al*. (1997) and Li *et al*. (1997b) and field data of Kang *et al*. (1994a)
Li *et al*. (2000b)	Analytical solution to linearised 1D Boussinesq equation	Spring-neap tidal water table fluctuations	Tidal constituents, beach slope, K, n	Numerical simulations
Li *et al*. (2002b)	Finite difference solutions to 1D and 2D Boussinesq equations	Spring-neap tidal water table fluctuations	Measured tidal constituents, beach slope, aquifer depth, aquifer transmissivity, K, n	Field data, Tentsmuir beach, Scotland

Table 7.2 Models incorporating wave effects (Source: Horn, 2006)

Author(s)	Type of model	Aim of model	Input parameters	Tests of model
Packwood and Peregrine (1980)	Analytical solution to Laplace equation	Instantaneous bore-driven circulation	Wave amplitude, water depth at bore front, depth of porous bed, K	Numerical simulations
Longuet-Higgins (1983)	Analytical solution to Laplace equation	Beach groundwater circulation in porous bed due to set-up	Pressure gradient, porosity	Laboratory experiments, wave channel, sloping bed, regular waves
Turner (1995a)	Process-based numerical model	Effect of groundwater seepage on swash zone sediment transport	Initial profile, tidal constituents, breaking wave height, wave period, D50, sediment sorting, porosity	Numerical simulations
Kang and Nielsen (1996)	Finite difference solution to 1D Boussinesq equation	Watertable overheight due to wave run-up	Beach slope, tidal amplitude, depth of impermeable layer, infiltration velocity per unit area, K, n	Field data, Kings Beach, Caloundra, Queensland, Australia
Li *et al*. (1997a)	Boundary element method solution to Laplace equation; depth-averaged shallow water equations for run-up	Beach watertable fluctuations due to wave run-up, including capillary effects	Wave or tidal amplitude and period, beach slope, thickness of capillary fringe, K, ne	Comparison of analytical and numerical predictions
Turner and Masselink (1998)	Finite-difference solution to 1D Boussinesq equation; relative sediment transport rate incorporating modified Shields parameter	Swash infiltration–exfiltration and sediment transport	Measured swash depth, simulated vertical and horizontal flow velocities, sediment and fluid density, depth of impermeable layer, friction factor, K, s	Field data, Duck, North Carolina, USA Numerical simulations
Nielsen (1999)	1D Boussinesq equation; depth-integrated salinity equation; diffusivity for steady and oscillatory flow	Watertable fluctuations and salinity in coastal barriers	Vertical flow velocity, salinity of seawater, local instantaneous salinity, density of fresh and salt water, salt water recharge rate due to run-up, depth of impermeable layer	Numerical simulations
Li and Barry (2000)	Boundary element method solution to Laplace equation; depth-averaged shallow water equations for run-up (Li *et al*., 1997a)	Wave-induced beach groundwater flow	Wave height and period, beach slope, depth of aquifer, thickness of capillary fringe, K, n	Numerical simulations; comparison to solution of Packwood and Peregrine (1980)
Butt *et al*. (2001)	Relative sediment transport rate incorporating modified Shields parameter	Effects of infiltration/exfiltration on sediment transport	Measured swash depth and vertical and horizontal flow velocities, sediment and fluid density, friction factor, D50, K, n	Field data, Perranporth, Cornwall, UK Numerical simulations

Li *et al*. (2002a)	Process-based numerical model incorporating: finite-difference solution to shallow water equations; boundary element method solution to Laplace equation (Li *et al*., 1997a); energetics sediment transport model (Bagnold, 1966)	Groundwater effects on swash sediment transport and beach profile change	Wave height, wave period, depth of aquifer, beach slope, D50, watertable elevation; OR measured beach profile, depth of impermeable layer, measured waves, friction factor, K, ku, kb	Field data, Slapton, Devon UK (Horn *et al*., 2003; Horn and Li, 2006) Laboratory data (Ang *et al*., 2004)
Cartwright *et al*. (2002, 2003, in press)	2D application of Mike SHE model	Influence of vertical flow on infiltration distributions	Hydraulic head, hydraulic conductivity	Laboratory data of Cartwright *et al*. (2004b)

7.2 Appendix 2- Artificial neural network model to predict the flow discharge in Fitzroy River

```
close all;
clear all;
clc;
days=15;
predict=4;
load fitz05a
Q=fitz05a;              %discharge
[m,n]=size(Q);

for j=1:n-days-predict+1
    e=j;
    for i=1:days+predict
        pt(i,j)=Q(1,e);
        e=e+1;
    end
end
p=pt(1:days,:);         %inputs
t=pt(days+1:end,:);     %targets

% mapping to default interval [-1,+1]
[pm,ps] = mapminmax(p);
[tm,ts] = mapminmax(t);

% randomly divide data to three part training=60% testing=20%
validation=20%
[trainV,val,test] = dividevec(pm,tm,0.20,0.20);

net = newff(minmax(pm),[10 10
predict],{'logsig','tansig','tansig'},'trainrp'); %neural network
structure
%et.trainParam.show = 10;
net.trainParam.epochs = 800;
%net.trainParam.max_fail = 10;
%net.trainParam.mem_reduc = 2;
[net,tr]=train(net,trainV.P,trainV.T,[],[],val,test);       %training
neural network
am = sim(net,pm);                   % simulate new data
a = mapminmax('reverse',am,ts);
%%%%%%
a1 = a(1,:);
t1 = t(1,:);

a2 = a(2,:);
t2 = t(2,:);

a3 = a(3,:);
t3 = t(3,:);

a4 = a(4,:);
t4 = t(4,:);

x=1:15000;
y=x;
figure;scatter(t1,a1,5,'*');hold on
plot(y);hold off
```

```
xlabel('Observation, m3/s')
ylabel('Prediction, m3/s')
axis square
box on

figure;scatter(t2,a2,5,'*');hold on
plot(y);hold off
xlabel('Observation, m3/s')
ylabel('Prediction, m3/s')
axis square
box on

figure;scatter(t3,a3,5,'*');hold on
plot(y);hold off
xlabel('Observation, m3/s')
ylabel('Prediction, m3/s')
axis square
box on

figure;scatter(t4,a4,5,'*');hold on
plot(y);hold off
xlabel('Observation, m3/s')
ylabel('Prediction, m3/s')
axis square
box on

figure;plot(t1,'b'); hold on
plot(a1,'x'); hold off
xlabel('Days')
ylabel('Discharge, m3/s')
legend('measured','predicted')
box on

figure;plot(a2,'x'); hold on
plot(t2,'g'); hold off

figure;plot(a3,'x'); hold on
plot(t3,'g'); hold off

figure;plot(a4,'x'); hold on
plot(t4,'g'); hold off

e1=t1-a1;
MSE1=mse(e1);       % mean squared error for first day of prediction
RMSE1=sqrt(MSE1);   % root mean squared error

e2=t2-a2;
MSE2=mse(e2);
RMSE2=sqrt(MSE2);

e3=t3-a3;
MSE3=mse(e3);
RMSE3=sqrt(MSE3);

e4=t4-a4;
MSE4=mse(e4);
RMSE4=sqrt(MSE4);

RMSE = [RMSE1 RMSE2 RMSE3 RMSE4]
```

```
R = corrcoef(a1,t1); R1=R(1,2);
R = corrcoef(a2,t2); R2=R(1,2);
R = corrcoef(a3,t3); R3=R(1,2);
R = corrcoef(a4,t4); R4=R(1,2);

R=[R1 R2 R3 R4]

mean_t1=mean(t1);
SI1=RMSE1/mean_t1;

mean_t2=mean(t2);
SI2=RMSE2/mean_t2;

mean_t3=mean(t3);
SI3=RMSE3/mean_t3;

mean_t4=mean(t4);
SI4=RMSE4/mean_t4;

SI=[SI1 SI2 SI3 SI4]

%%%%%
mean_a1=mean(a1);
mean_a2=mean(a2);
mean_a3=mean(a3);
mean_a4=mean(a4);
mean_a=[mean_a1 mean_a2 mean_a3 mean_a4]
mean_t=[mean_t1 mean_t2 mean_t3 mean_t4]
error_a_t=mean_a-mean_t
percent_error=error_a_t./mean_t
t1=t1+0.1;
plot((1:14960),a1(1,:),(1:14960),t1(1,:))
plot(abs(a1(1,:)-t1(1,:))./t1(1,:))
```

7.3 Appendix 3- Watertable levels in wells (Source: Kang *et al., 1994)*

Table 7.3 Watertable levels in wells; Kings Beach, Caloundra, 24-25 Sep. 1991

Kings Beach, Caloundra, 24-25 SEP. 1991																	
Well No	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	SWL
Distance from B.M.	30.16	40.01	45.01	50.03	55.09	57.04	59.02	61.02	63.02	65.02	66.97	68.93	70.91	72.96	75.11	78.55	
Distance from coastline (m)	**48.39**	**38.54**	**33.54**	**28.52**	**23.46**	**21.51**	**19.53**	**17.53**	**15.53**	**13.53**	**11.58**	**9.62**	**7.64**	**5.59**	**3.44**	**0**	
Av. Sand level	1.63	1.74	1.76	1.64	1.36	1.22	0.95	0.62	0.39	0.15	-0.05	-0.27	-0.40	-0.57	-0.75	-1.05	
Time (EST)																	
13:00	0.02	0.03	0.02	0.02	-0.05	-0.08	-0.12	-0.14	-0.22	-0.27	-0.36	-0.48	-0.53	-0.60	-0.71	-0.96	-0.96
13:30	0.00	0.01	0.00	-0.02	-0.09	-0.12	-0.16	-0.18	-0.26	-0.31	-0.38	-0.46	-0.55	-0.63	-0.74	-1.01	-1.01
14:00	0.00	-0.01	-0.02	-0.04	-0.12	-0.16	-0.19	-0.22	-0.29	-0.34	-0.41	-0.49	-0.57	-0.66	-0.75	-1.04	-1.04
14:30	-0.02	-0.02	-0.04	-	-0.15	-0.19	-0.23	-0.26	-0.32	-0.37	-0.43	-0.51	-0.59	-0.66	-0.75	-1.01	-1.01
15:00	-0.02	-	-0.06	-	-0.18	-0.22	-0.26	-0.29	-0.35	-0.39	-0.45	-0.52	-0.58	-0.65	-0.75	-0.93	-0.93
15:30	-0.04	-	-	-	-0.21	-0.24	-0.29	-0.31	-0.37	-0.41	-0.46	-0.51	-0.58	-0.64	-0.75	-0.91	-0.91
16:00	-0.05	-	-	-	-0.23	-0.25	-0.29	-0.33	-0.38	-0.41	-0.45	-0.50	-0.54	-0.58	-0.67	-0.76	-0.76
16:30	-0.05	-	-	-	-0.24	-0.26	-0.29	-0.32	-0.36	-0.38	-0.41	-0.42	-0.41	-0.52	-0.59	-0.60	-0.60
17:00	-0.06	-	-0.11	-0.15	-0.23	-0.25	-0.28	-0.29	-0.32	-0.31	-0.26	-0.25	-0.36	-0.39	-0.42	-0.44	-0.44
17:30	-0.06	-0.08	-0.10	-0.14	-0.19	-0.19	-0.20	-0.20	-0.19	-0.03	-0.06	-0.18	-0.24	-0.26	-0.26	-	-0.26
18:00	-0.06	-0.08	-0.09	-0.11	-0.14	-0.13	-0.12	-0.09	0.10	0.09	-0.03	-	-0.08	-0.07	-	-	-0.08
18:30	-0.05	-0.05	-0.05	-0.05	-0.06	-0.06	-0.01	-	0.24	0.12	-	-	0.04	0.14	-	-	0.04
18:45	-0.04	-0.03	-0.04	-0.03	-0.03	0.00	0.11	-	0.26	0.17	-	-	0.09	0.16	-	-	0.09
19:00	-0.04	-0.03	-0.01	0.00	0.01	0.07	0.27	-	0.30	0.18	-	-	0.15	0.23	-	-	0.15
19:15	-0.03	-0.01	0.01	0.03	0.07	-	0.39	-	0.33	0.24	-	-	0.21	0.25	-	-	0.21
19:30	-0.01	-0.01	0.03	0.06	0.12	-	0.48	-	0.38	0.26	-	-	0.26	0.27	-	-	0.26
19:45	0.00	0.02	0.05	0.08	0.18	-	0.54	-	0.38	0.31	-	-	0.27	0.28	-	-	0.28
20:00	0.01	0.04	0.07	0.11	0.24	-	0.55	-	0.42	0.29	-	-	0.27	-	-	-	0.27
20:15	0.02	0.06	0.09	0.14	0.29	-	0.57	-	0.40	0.30	-	-	0.27	-	-	-	0.27
20:30	0.03	0.07	0.10	0.16	0.34	-	0.59	-	0.42	0.29	-	-	0.26	-	-	-	0.26
21:00	0.04	0.10	0.14	0.21	0.39	-	0.56	-	0.37	0.25	-	-	0.19	-	-	-	0.19
21:15	0.05	0.11	0.15	0.22	0.40	-	0.51	-	0.37	0.24	-	-	0.14	-	0.14	-	0.14
21:30	0.06	0.12	0.16	0.23	0.38	-	0.52	-	0.40	0.25	-	-	0.11	-	-	-	0.11
21:45	0.07	0.13	0.17	0.24	0.37	-	0.51	-	0.37	0.22	-	-	0.09	-	-	-	0.09
22:00	0.08	0.14	0.18	0.25	0.35	-	0.45	-	0.37	0.20	-	-	0.00	-	0.06	-	0.00
22:15	0.08	0.15	0.17	0.24	0.32	-	0.38	-	0.31	0.16	0.10	-	-0.06	-0.07	-0.07	-	-0.07
22:30	0.09	0.15	0.18	0.23	0.29	-	0.33	-	0.28	0.17	0.09	-	-0.11	-0.13	-0.14	-	-0.14
22:45	0.08	0.15	0.18	0.22	0.25	-	0.26	-	0.18	0.15	0.00	-	-0.23	-0.26	-0.26	-0.31	-0.31
23:00	0.08	0.14	0.16	0.19	0.21	-	0.22	-	0.13	0.06	-0.03	-0.08	-0.28	-0.33	-0.35	-0.38	-0.38
23:15	0.09	0.13	0.15	0.17	0.18	-	0.17	-	0.05	-0.03	-0.07	-0.15	-0.33	-0.41	-0.44	-0.47	-0.47
23:30	0.09	0.12	0.13	0.14	0.15	-	0.13	-	0.02	-0.08	-0.13	-0.14	-0.37	-0.49	-0.52	-0.57	-0.57
23:45	0.08	0.11	0.11	0.12	0.11	-	0.08	-	-0.02	-0.12	-0.18	-0.19	-0.38	-0.52	-0.62	-0.69	-0.69
00:00	0.07	0.10	0.10	0.10	0.09	-	0.05	-	-0.05	-0.15	-0.22	-0.21	-0.40	-0.53	-0.66	-0.76	-0.76
00:30	0.06	0.07	0.07	0.07	0.05	-	0.00	-	-0.10	-0.19	-0.26	-0.27	-0.45	-0.55	-0.69	-0.90	-0.90
01:00	0.05	0.06	0.04	0.04	-0.01	-	-0.05	-	-0.15	-0.20	-0.30	-0.35	-0.49	-0.60	-0.69	-0.96	-0.96

01:30	0.04	0.04	0.03	0.01	-0.05	-	-0.11	-	-0.20	-0.27	-0.34	-0.40	-0.52	-0.62	-0.72	-1.00	-1.00
02:00	0.02	0.02	0.01	-0.01	-0.08	-	-0.15	-	-0.24	-0.31	-0.37	-0.47	-0.55	-0.64	-0.74	-1.00	-1.00
02:30	0.01	0.01	-0.01	-0.04	-0.12	-	-0.19	-0.22	-0.29	-0.35	-0.40	-0.50	-0.58	-0.66	-0.76	-1.01	-1.01
03:00	0.00	-0.01	-0.03	-0.07	-0.16	-	-0.22	-0.26	-0.32	-0.38	-0.42	-0.51	-0.59	-0.68	-0.77	-1.02	-1.02
03:30	-0.01	-0.02	-0.05	-0.09	-0.18	-	-0.26	-0.29	-0.34	-0.41	-0.45	-0.53	-0.59	-0.68	-0.77	-1.01	-1.01
04:00	-0.02	-0.04	-0.06	-0.11	-0.18	-	-0.27	-0.31	-0.36	-0.42	-0.45	-0.49	-0.55	-0.63	-0.72	-0.95	-0.95
04:30	-0.03	-0.05	-0.08	-0.13	-0.22	-	-0.29	-0.32	-0.37	-0.42	-0.44	-0.48	-0.52	-0.58	-0.68	-0.78	-0.78
04:45	-0.03	-0.05	-0.09	-0.14	-0.23	-	-0.29	-0.32	-0.36	-0.40	-0.43	-0.46	-0.48	-0.54	-0.65	-0.70	-0.70
05:00	-0.05	-0.06	-0.09	-0.15	-0.24	-	-0.29	-0.32	-0.35	-0.39	-0.41	-0.41	-0.41	-0.51	-0.61	-0.61	-0.61
05:15	-0.04	-0.06	-0.10	-0.15	-0.23	-	-0.28	-0.29	-0.33	-0.36	-0.37	-0.30	-0.37	-0.49	-0.55	-0.55	-0.55
05:30	-0.04	-0.06	-0.10	-0.14	-0.22	-	-0.26	-0.27	-0.30	-0.32	-0.32	-0.23	-0.34	-0.42	-0.46	-0.47	-0.47
05:45	-0.05	-0.07	-0.10	-0.14	-0.21	-	-0.24	-0.24	-0.26	-0.24	-0.17	-0.20	-0.30	-0.34	-0.36	-0.36	-0.36
06:00	-0.05	-0.07	-0.10	-0.13	-0.18	-	-0.21	-0.20	-0.20	-0.05	-0.08	-0.18	-0.23	-0.25	-0.26	-0.25	-0.25
06:15	-0.05	-0.07	-0.09	-0.12	-0.16	-	-0.16	-0.14	-0.09	0.06	-0.05	-0.14	-0.15	-0.14	-0.16	-0.14	-0.14
06:30	-0.05	-0.07	-0.08	-0.10	-0.13	-	-0.12	-0.07	0.09	0.09	0.01	-	-0.08	-0.04	-0.08	-0.05	-0.05
06:45	-0.05	-0.06	-0.07	-0.08	-0.10	-	-0.07	0.02	0.20	0.13	0.07	-	-0.01	-	0.00	-	0.00
07:00	-0.05	-0.05	-0.05	-0.05	-0.06	-0.05	0.02	0.25	0.29	0.18	-	-	0.07	-	0.07	-	0.07
07:15	-0.03	-0.03	-0.02	-0.02	-0.02	0.01	0.17	0.36	0.30	0.21	-	-	0.12	-	0.12	-	0.12
07:30	-0.03	-0.01	0.01	0.01	0.05	0.12	0.35	0.43	0.36	0.26	-	-	0.19	-	-	-	0.19
07:45	-0.02	0.00	0.02	0.03	0.08	0.18	0.42	0.46	0.37	0.28	-	-	0.27	0.27	-	-	0.27
08:00	-0.01	0.01	0.03	0.06	0.13	0.31	0.52	0.48	0.42	0.38	-	-	0.27	0.27	-	-	0.27
08:15	0.00	0.03	0.05	0.09	0.19	0.40	0.52	0.48	0.40	0.33	-	-	0.27	0.27	-	-	0.27
08:30	0.01	0.04	0.07	0.11	0.23	0.45	0.54	0.52	0.43	0.38	-	-	0.29	0.28	-	-	0.28
08:45	0.02	0.06	0.09	0.14	0.28	0.51	0.58	0.54	0.44	0.39	-	-	0.28	0.28	-	-	0.28
09:00	0.03	0.07	0.11	0.17	0.33	0.53	0.59	0.54	0.44	0.35	-	-	0.25	-	-	-	0.25
09:15	0.05	0.09	0.13	0.19	0.35	0.51	0.55	0.53	0.42	0.34	-	-	0.24	-	-	-	0.25
09:30	0.05	0.10	0.14	0.21	0.36	0.52	0.56	0.51	0.44	0.29	-	-	0.19	-	-	-	0.19
09:45	0.06	0.11	0.15	0.22	0.37	0.50	0.54	0.53	0.45	0.30	-	-	0.17	-	-	-	0.17
10:00	0.07	0.12	0.16	0.23	0.35	0.46	0.50	0.50	0.40	0.24	-	-	0.08	-	0.08	-	0.08
10:15	0.07	0.13	0.17	0.23	0.34	0.43	0.45	0.43	0.36	0.21	-	-	0.03	-	0.03	-	0.03
10:30	0.08	0.14	0.17	0.23	0.31	0.37	0.40	0.41	0.35	0.20	-	-	-0.02	-	-0.04	-	-0.04
10:45	0.08	0.14	0.18	0.23	0.29	0.35	0.37	0.38	0.33	0.18	0.10	-	-0.07	-	-0.08	-	-0.08
11:00	0.09	0.14	0.17	0.21	0.25	0.30	0.29	0.27	0.23	0.14	0.05	-	-0.15	-0.17	-0.18	-0.22	-0.22
11:15	0.09	0.14	0.17	0.19	0.23	0.26	0.25	0.23	0.17	0.07	0.01	-	-0.24	-0.27	-0.27	-0.31	-0.31
11:30	0.09	0.14	0.15	0.17	0.19	0.22	0.19	0.17	0.10	0.00	-0.04	-	-0.30	-0.36	-0.38	-0.40	-0.40
11:45	0.09	0.13	0.14	0.15	0.16	0.18	0.15	0.11	0.04	-0.06	-0.09	-	-0.35	-0.44	-0.47	-0.51	-0.51
12:00	0.08	0.12	0.12	0.12	0.13	0.14	0.11	0.07	0.00	-0.10	-0.14	-	-0.38	-0.50	-0.55	-0.60	-0.60
12:15	0.08	0.11	0.10	0.10	0.09	0.11	0.06	0.03	-0.03	-0.13	-0.18	-	-0.41	-0.54	-0.63	-0.68	-0.68
12:30	0.08	0.10	0.09	0.09	0.07	0.08	0.03	0.00	-0.06	-0.16	-0.21	-	-0.42	-0.55	-0.66	-0.71	-0.71
12:45	0.07	0.09	0.08	0.07	0.05	0.05	0.01	-0.03	-0.09	-0.18	-0.25	-	-0.44	-0.56	-0.71	-0.80	-0.80
13:00	0.07	0.08	0.07	0.06	0.02	0.02	-0.02	-0.06	-0.12	-0.20	-0.27	-	-0.46	-0.57	-0.72	-0.88	-0.88
13:15	0.06	0.06	0.06	0.05	0.00	-0.01	-0.05	-0.09	-0.15	-0.23	-0.29	-	-0.48	-0.59	-0.72	-0.94	-0.94
13:30	0.06	0.05	0.05	0.03	-0.03	-0.04	-0.08	-0.12	-0.18	-0.25	-0.32	-	-0.51	-0.61	-0.73	-1.00	-1.00
13:45	0.05	0.05	0.04	0.02	-0.04	-0.06	-0.09	-0.14	-0.20	-0.27	-0.33	-	-0.52	-0.62	-0.74	-1.01	-1.01

14:00	0.04	0.04	0.03	0.00	-0.06	-0.08	-0.12	-0.16	-0.21	-0.28	-0.34	-	-0.53	-0.63	-0.75	-1.04	-1.04
14:15	0.03	0.02	0.02	-0.01	-0.08	-	-0.15	-0.18	-0.24	-0.31	-0.37	-	-0.55	-0.64	-0.75	-1.06	-1.06
14:30	0.03	0.02	0.01	-0.02	-0.10	-	-0.17	-0.20	-0.26	-0.33	-0.38	-	-0.56	-0.65	-0.76	-1.04	-1.04
14:45	0.02	0.01	0.00	-0.03	-0.11	-	-0.18	-0.22	-0.27	-0.35	-0.39	-	-0.56	-0.66	-0.76	-1.05	-1.05
15:00	0.01	0.00	-0.02	-0.05	-0.13	-	-0.21	-0.24	-0.30	-0.37	-0.41	-	-0.59	-0.68	-0.78	-1.06	-1.06
Average	**0.02**	**0.04**	**0.04**	**0.06**	**0.05**	**0.11**	**0.11**	**0.02**	**0.04**	**-0.03**	**-0.24**	**-0.36**	**-0.20**	**-0.36**	**-0.48**	**-0.73**	**-0.38**
Max	0.09	0.15	0.18	0.25	0.40	0.53	0.59	0.54	0.45	0.39	0.10	-0.08	0.29	0.28	0.14	-0.05	0.28
Min	-0.06	-0.08	-0.11	-0.15	-0.24	-0.26	-0.29	-0.33	-0.38	-0.42	-0.46	-0.53	-0.59	-0.68	-0.78	-1.06	-1.06

Table 7.4 Watertable levels in wells; Eagers Beach, Moreton Island, 26-27 Nov. 1991

Eagers Beach, Moreton Island, 26-27 NOV 1991																	
Well No.	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	SWL
Distance from BM	1.10	10.86	20.75	30.75	35.86	39.87	43.79	47.78	52.04	56.61	60.24	64.77	69.83	76.92	87.85	97.85	
Distance from coastline (m)	**96.75**	**86.99**	**77.10**	**67.10**	**61.99**	**57.98**	**54.06**	**50.07**	**45.81**	**41.24**	**37.61**	**33.08**	**28.02**	**20.93**	**10.00**	**0.00**	
Av. Sand level	9.64	8.86	8.59	8.69	8.43	8.02	7.72	7.48	7.25	7.10	6.98	6.85	6.73	6.57	6.32	5.89	
Time (EST)																	
11:00	8.12	7.99	7.86	7.76	7.81	7.97	7.77	7.64	7.54	7.54	7.52	7.53	-	-	-	-	7.53
11:30	8.12	8.00	7.88	7.82	8.03	8.00	7.76	7.67	7.66	7.63	7.64	-	-	-	-	-	7.63
12:00	8.12	8.02	7.91	7.93	8.12	7.99	7.77	7.71	7.73	7.68	-	-	-	-	-	-	7.68
12:30	8.12	8.03	7.95	8.01	8.13	7.99	7.78	7.73	7.67	7.67	-	-	-	-	-	-	7.67
13:00	8.13	8.04	7.99	8.04	8.10	7.97	7.74	7.67	7.62	-	7.64	-	-	-	-	-	7.64
13:30	8.13	8.06	8.00	8.05	8.10	7.98	7.74	7.61	7.53	-	-	-	-	-	-	-	7.53
14:00	8.14	8.07	8.02	8.06	8.04	7.94	7.72	7.56	7.44	-	-	-	-	-	-	-	7.44
14:30	8.15	8.08	8.03	8.03	7.97	7.86	7.65	7.50	7.32	7.26	7.28	-	7.27	-	-	-	7.27
15:00	8.15	8.08	8.03	8.00	7.92	7.78	7.60	7.48	7.27	7.16	7.14	7.08	7.11	-	-	-	7.10
15:30	8.16	8.09	8.03	7.97	7.87	7.71	7.56	7.45	7.27	7.10	7.01	6.90	6.93	-	-	-	6.92
16:00	8.16	8.09	8.02	7.94	7.84	7.68	7.54	7.41	7.24	7.08	6.96	6.87	6.77	-	-	-	6.77
16:30	8.16	8.09	8.01	7.92	7.81	7.65	7.51	7.39	7.22	7.07	6.96	6.83	6.74	6.66	-	6.51	6.51
17:00	8.16	8.09	8.00	7.89	7.78	7.63	7.48	7.37	7.21	7.07	6.96	6.83	6.72	6.60	6.46	6.39	6.39
17:30	8.16	8.08	7.99	7.87	7.75	7.61	7.47	7.36	7.20	7.07	6.95	6.83	6.71	6.59	6.41	6.26	6.26
18:00	8.16	8.07	7.97	7.85	7.73	7.59	7.46	7.35	7.19	7.06	6.95	6.83	6.71	6.60	6.38	6.18	6.18
18:30	8.16	8.06	7.96	7.84	7.72	7.58	7.44	7.34	7.18	7.05	6.95	6.83	6.71	6.60	6.36	6.13	6.13
19:00	8.16	8.06	7.95	7.82	7.70	7.56	7.43	7.33	7.18	7.05	6.95	6.83	6.72	6.60	6.34	6.09	6.09
19:30	8.15	8.06	7.94	7.80	7.68	7.54	7.42	7.32	7.17	7.05	6.95	6.83	6.71	6.60	6.33	6.11	6.11
20:00	8.15	8.05	7.93	7.79	7.66	7.53	7.41	7.31	7.17	7.04	6.95	6.83	6.71	6.60	6.33	6.09	6.09
20:30	8.14	8.04	7.92	7.77	7.65	7.52	7.39	7.30	7.16	7.04	6.95	6.83	6.71	6.62	6.33	6.17	6.17
21:00	8.14	8.03	7.91	7.76	7.64	7.51	7.39	7.30	7.16	7.04	6.95	6.83	6.72	6.63	6.40	6.29	6.29
21:30	8.13	8.02	7.90	7.75	7.62	7.50	7.39	7.30	7.16	7.05	6.95	6.83	6.75	6.65	6.45	6.34	6.34
22:00	8.13	8.02	7.89	7.73	7.61	7.49	7.39	7.30	7.17	7.05	6.96	6.84	6.77	6.67	6.53	6.52	6.52
22:30	8.12	8.01	7.88	7.72	7.60	7.49	7.39	7.30	7.18	7.06	6.96	6.89	6.80	6.72	6.62	6.59	6.59
23:00	8.12	8.01	7.88	7.72	7.60	7.49	7.39	7.31	7.20	7.08	6.98	6.97	6.86	6.80	6.74	6.74	6.74
23:30	8.12	8.00	7.86	7.70	7.59	7.48	7.39	7.33	7.21	7.10	7.01	6.96	6.88	6.83	6.79	6.75	6.75
00:00	8.11	8.00	7.86	7.69	7.58	7.48	7.40	7.34	7.24	7.12	7.02	6.97	6.93	6.89	6.84	-	6.84
00:30	8.11	8.00	7.86	7.69	7.59	7.50	7.43	7.38	7.26	7.12	7.03	6.97	6.91	6.89	6.84	-	6.84
01:00	8.11	7.99	7.85	7.68	7.58	7.48	7.41	7.36	7.26	7.13	7.03	6.95	6.91	6.88	6.85	-	6.85
01:30	8.11	7.99	7.84	7.68	7.57	7.48	7.42	7.36	7.26	7.14	7.03	6.92	6.89	6.84	6.82	6.84	6.84
02:00	8.11	7.99	7.83	7.67	7.57	7.47	7.40	7.34	7.24	7.13	7.03	6.92	6.83	6.79	6.73	6.72	6.72
02:30	8.10	7.98	7.83	7.67	7.57	7.47	7.39	7.32	7.21	7.11	7.02	6.91	6.83	6.74	6.69	6.71	6.70
03:00	8.10	7.98	7.83	7.65	7.55	7.46	7.37	7.30	7.19	7.09	7.01	6.89	6.77	6.70	6.63	6.58	6.58
03:30	8.10	7.98	7.82	7.65	7.54	7.45	7.36	7.28	7.17	7.07	7.00	6.89	6.76	6.62	6.53	6.45	6.45
04:00	8.10	7.97	7.81	7.64	7.53	7.43	7.35	7.27	7.16	7.06	6.99	6.88	6.76	6.61	6.44	6.38	6.38
04:30	8.10	7.97	7.81	7.63	7.52	7.42	7.33	7.25	7.14	7.03	6.96	6.87	6.76	6.59	6.36	6.27	6.27
05:00	8.10	7.96	7.81	7.62	7.52	7.41	7.32	7.24	7.13	7.02	6.95	6.85	6.75	6.59	6.35	6.20	6.20
05:30	8.09	7.96	7.80	7.62	7.51	7.41	7.31	7.23	7.12	7.02	6.94	6.84	6.74	6.59	6.34	6.16	6.16
06:00	8.09	7.96	7.80	7.61	7.50	7.40	7.30	7.23	7.12	7.01	6.93	6.84	6.73	6.59	6.33	6.12	6.12
06:30	8.09	7.96	7.79	7.60	7.49	7.39	7.30	7.22	7.11	7.01	6.93	6.84	6.73	6.59	6.33	6.11	6.11
07:00	8.09	7.96	7.79	7.60	7.49	7.39	7.29	7.22	7.10	7.00	6.93	6.83	6.73	6.59	6.33	6.11	6.11
07:30	8.08	7.95	7.78	7.59	7.48	7.38	7.29	7.22	7.10	7.01	6.93	6.84	6.74	6.59	6.34	6.18	6.18
08:00	8.08	7.95	7.78	7.58	7.48	7.37	7.28	7.21	7.11	7.02	6.95	6.86	6.75	6.60	6.37	6.26	6.26
08:30	8.08	7.95	7.78	7.58	7.47	7.37	7.28	7.22	7.11	7.02	6.95	6.87	6.77	6.59	6.41	6.35	6.35
09:00	8.08	7.94	7.77	7.57	7.47	7.37	7.29	7.23	7.14	7.05	6.98	6.89	6.78	6.66	6.53	6.51	6.51
09:30	8.08	7.94	7.77	7.57	7.47	7.38	7.31	7.25	7.16	7.09	7.02	6.92	6.79	6.71	6.67	6.69	6.68
10:00	8.08	7.94	7.76	7.57	7.47	7.40	7.34	7.30	7.23	7.15	7.06	6.97	6.88	6.88	6.80	6.86	6.80
10:30	8.07	7.93	7.76	7.58	7.49	7.43	7.39	7.38	7.31	7.20	7.12	7.03	7.01	7.03	7.00	-	7.01
11:00	8.07	7.93	7.76	7.59	7.53	7.49	7.61	7.50	7.34	7.25	7.22	7.23	7.22	7.23	7.20	-	7.22
11:30	8.07	7.93	7.76	7.62	7.58	7.58	7.66	7.55	7.40	7.37	7.37	7.37	7.35	7.36	-	-	7.36
12:00	8.06	7.93	7.78	7.66	7.64	7.83	7.75	7.62	7.48	7.47	7.46	7.45	7.44	7.47	-	-	7.47
12:30	8.06	7.93	7.79	7.70	7.73	7.84	7.76	7.65	7.53	7.51	7.51	7.54	7.53	7.54	-	-	7.51
13:00	8.06	7.94	7.81	7.74	7.82	7.95	7.79	7.68	7.58	7.58	7.57	7.58	7.57	-	-	-	7.57
13:30	8.06	7.95	7.83	7.78	7.90	7.94	7.81	7.66	7.55	7.55	7.55	7.53	7.53	-	-	-	7.53
14:00	8.06	7.96	7.85	7.81	7.94	7.91	7.80	7.64	7.51	7.51	7.51	7.52	7.53	-	-	-	7.52
Average	**8.11**	**8.00**	**7.87**	**7.75**	**7.68**	**7.60**	**7.49**	**7.40**	**7.28**	**7.17**	**7.09**	**6.98**	**6.90**	**6.75**	**6.55**	**6.38**	**6.75**
Max	8.16	8.09	8.03	8.06	8.13	8.00	7.81	7.73	7.73	7.68	7.64	7.58	7.57	7.54	7.20	6.86	7.68

Min	8.06	7.93	7.76	7.57	7.47	7.37	7.28	7.21	7.10	7.00	6.93	6.83	6.71	6.59	6.33	6.09	6.09

Table 7.5 Watertable levels in wells; Shelley Beach, Caloundra, 25-26 Nov. 1993

Shelley Beach, Caloundra, 25-26 NOV. 1993														
Well No	Pool	1	2	3	4	5	6	7	8	9	10	11	12	SWL
Distance from B.M.	0.00	1.13	4.85	9.63	15.04	19.92	23.05	26.67	30.02	33.58	36.72	40.37	43.59	
Distance from coastline (m)	**43.59**	**42.46**	**38.74**	**33.96**	**28.55**	**23.67**	**20.54**	**16.92**	**13.57**	**10.01**	**6.87**	**3.22**	**0.00**	
Av. Sand level				6.77	6.34	5.83	5.42	4.98	4.56	4.21	3.86	3.35	3.00	
Time (EST)														
17:00	-	5.69	5.64	5.55	5.32	5.05	4.92	4.87	4.69	4.36	3.87	3.64	-	3.64
17:30	6.29	5.69	5.63	5.53	5.31	5.08	4.99	4.96	4.86	4.38	3.91	3.63	-	3.63
18:00	6.27	5.68	5.61	5.50	5.32	5.14	5.08	5.06	4.84	4.34	3.89	3.81	-	3.81
18:30	6.26	5.66	5.59	5.55	5.32	5.16	5.14	5.19	4.74	4.39	4.06	-	-	4.06
19:00	6.25	5.65	5.57	5.49	5.38	5.43	5.41	5.16	4.58	4.33	4.16	-	-	4.16
19:30	6.24	5.64	5.58	5.52	5.46	5.50	5.37	5.10	-	4.30	-	-	-	4.30
20:00	6.22	5.64	5.58	5.54	5.51	5.58	5.40	5.14	-	4.35	-	-	-	4.35
20:30	6.16	5.67	5.60	5.60	5.79	5.61	5.42	5.11	-	4.37	-	-	-	4.37
21:00	6.11	5.68	5.64	5.65	5.76	5.65	5.50	5.09	-	4.36	-	-	-	4.36
21:30	6.07	5.69	5.66	5.68	5.68	5.54	5.43	5.14	-	4.41	4.14	-	-	4.14
22:00	5.90	5.70	5.67	5.67	5.67	5.61	5.42	5.10	-	4.41	4.21	-	-	4.21
22:30	5.80	5.68	5.67	5.68	5.70	5.51	5.33	5.05	-	4.33	4.08	-	-	4.08
23:00	5.75	5.69	5.66	5.65	5.61	5.42	5.22	5.03	-	4.34	4.04	-	-	4.04
23:30	5.74	5.68	5.65	5.62	5.54	5.34	5.18	4.96	-	4.36	3.99	-	-	3.99
00:00	5.73	5.66	5.63	5.59	5.47	5.24	5.04	4.91	-	4.34	4.05	-	-	4.05
00:30	5.73	5.64	5.60	5.55	5.40	5.14	4.95	4.80	-	4.34	4.06	-	-	4.06
01:00	5.73	-	5.58	5.53	5.35	5.08	4.90	4.75	-	4.28	4.08	3.38	-	4.08
01:30	5.73	-	5.57	5.49	5.30	5.03	4.85	4.69	-	4.23	4.01	3.36	-	4.01
02:00	5.73	-	5.55	5.47	5.26	4.99	4.80	4.64	-	-	3.98	3.35	-	3.98
02:30	5.73	-	5.53	5.44	5.23	4.95	4.76	4.59	-	-	4.01	3.35	-	4.01
03:00	5.72	-	5.50	5.41	5.20	4.91	4.73	4.59	-	4.32	4.07	3.36	-	4.07
03:30	5.72	-	5.49	5.39	5.17	4.89	4.72	4.58	-	4.29	4.07	3.37	-	4.07
04:00	5.72	-	5.48	5.37	5.15	4.88	4.71	4.57	-	4.27	4.06	3.36	-	4.06
04:30	5.71	-	5.47	-	5.15	4.87	4.72	4.62	-	4.41	4.14	-	-	4.14
05:00	5.71	-	-	-	5.11	4.88	4.78	4.80	4.80	4.37	4.11	-	-	4.11
05:30	5.70	-	-	-	5.13	4.97	5.00	4.99	4.95	4.46	4.12	-	-	4.12
06:00	5.70	-	-	-	5.18	5.19	5.26	5.14	4.89	4.47	4.19	-	-	4.19
06:30	5.69	-	-	-	5.28	5.38	5.33	5.13	4.83	4.39	4.21	-	-	4.21
07:00	5.69	-	-	-	5.41	5.56	5.39	5.10	4.86	4.43	-	-	-	4.43
07:30	5.69	-	-	5.47	5.75	5.64	5.33	5.03	4.91	-	-	-	-	5.03
08:00	5.70	-	5.50	5.64	6.05	5.83	5.35	4.89	-	-	-	-	-	4.89
08:30	5.71	-	5.60	5.85	6.08	5.72	5.33	-	-	-	-	-	-	5.33
09:00	5.77	-	5.69	5.96	6.15	5.72	5.34	4.96	-	-	-	-	-	4.96
09:15	-	5.66	5.76	6.00	6.07	5.75	5.40	4.94	-	-	-	-	-	4.94
09:30	5.83	5.68	5.79	6.02	6.07	5.75	5.35	4.92	-	-	-	-	-	4.92
09:45	5.83	5.71	5.82	6.04	6.11	5.76	5.35	4.89	-	-	-	-	-	4.89
10:00	5.92	5.72	5.85	6.06	6.13	5.72	5.33	4.92	-	-	-	-	-	4.92
10:15	5.91	5.75	5.88	6.09	6.10	5.70	5.35	4.90	-	-	-	-	-	4.90
10:30	5.91	5.78	5.89	6.04	6.09	5.63	5.31	4.87	-	-	-	-	-	4.87
10:45	5.91	5.80	5.89	6.02	6.01	5.71	5.35	4.91	-	-	-	-	-	4.91
11:00	5.91	5.81	5.88	5.99	6.03	5.72	5.33	4.89	-	-	-	-	-	4.89
11:15	5.90	5.81	5.88	5.97	5.95	5.65	5.34	4.88	-	-	-	-	-	4.88
11:30	5.90	5.81	5.87	5.94	5.90	5.68	5.38	4.92	4.53	-	-	-	-	4.53
11:45	5.90	5.80	5.86	5.92	5.85	5.61	5.34	4.88	4.54	-	-	-	-	4.54
12:00	5.90	5.79	5.85	5.88	5.79	5.61	5.34	4.90	4.57	4.19	-	-	-	4.19
12:15	5.90	5.80	5.82	5.84	5.74	5.52	5.31	4.89	4.47	4.17	-	-	-	4.17
12:30	5.89	5.80	5.81	5.82	5.70	5.47	5.29	4.88	4.52	4.16	-	-	-	4.16
12:45	5.89	5.79	5.80	5.80	5.67	5.44	5.21	4.86	4.53	4.14	-	-	-	4.14
13:00	5.89	5.78	5.78	5.77	5.63	5.38	5.17	4.83	4.50	4.13	-	-	-	4.13
13:15	5.88	5.78	5.77	5.75	5.60	5.34	5.12	4.79	4.54	4.14	-	-	-	4.14
13:30	5.88	5.77	5.76	5.73	5.58	5.31	5.12	4.83	4.53	4.14	-	-	-	4.14
13:45	5.87	5.76	5.75	5.71	5.55	5.28	5.06	4.75	4.49	4.13	-	-	-	4.13
14:00	5.86	5.76	5.73	5.69	5.52	5.25	5.04	4.74	4.51	4.13	-	-	-	4.13
14:15	5.86	5.75	5.72	5.67	5.49	5.22	5.00	4.69	4.45	4.12	-	3.38	-	3.38
14:30	5.85	5.74	5.71	5.66	5.47	5.19	4.98	4.66	4.41	4.10	3.81	3.40	-	3.40
14:45	5.85	5.73	5.70	5.64	5.45	5.17	4.95	4.65	4.40	4.09	3.76	3.38	3.25	3.25
15:00	5.85	5.72	5.68	5.62	5.42	5.14	4.93	4.62	4.43	4.09	3.78	3.39	3.25	3.25
15:15	5.84	5.72	5.68	5.61	5.40	5.12	4.91	4.60	4.35	4.07	3.78	3.37	3.21	3.21
15:30	5.85	5.71	5.67	5.59	5.39	5.11	4.90	-	4.37	4.05	3.77	3.38	3.19	3.19
15:45	5.84	5.71	5.66	5.58	5.37	5.08	4.87	-	4.33	4.05	3.78	3.37	3.22	3.22
16:00	5.84	5.69	5.65	5.56	5.35	5.06	4.85	-	4.33	4.06	3.78	3.37	3.22	3.22
16:15	5.84	5.69	5.64	5.55	5.34	5.04	4.84	-	4.37	4.14	3.82	3.45	3.24	3.24
16:30	5.83	5.68	5.62	5.53	5.32	5.03	4.83	-	4.44	4.14	3.82	3.44	3.26	3.26

16:45	5.83	5.67	5.61	5.52	5.30	5.02	4.82	-	4.39	4.15	3.83	3.42	3.32	3.32
17:00	5.82	5.66	5.60	5.51	5.29	5.00	4.81	-	4.38	4.13	3.83	3.46	3.32	3.32
17:15	5.82	-	5.59	5.49	5.28	4.99	4.81	-	4.40	4.14	3.83	3.46	3.34	3.34
17:30	5.81	-	5.58	5.48	5.26	4.99	4.81	-	4.41	4.15	3.86	3.51	3.35	3.35
17:45	5.81	-	5.58	5.47	5.25	4.98	4.81	4.60	4.42	4.18	3.87	3.49	3.38	3.38
18:00	5.81	-	5.56	5.46	5.24	4.98	4.82	4.63	4.47	4.20	3.87	3.49	3.43	3.43
18:15	5.80	-	5.55	5.45	5.23	4.98	4.83	4.67	4.52	4.20	3.86	3.53	3.48	3.48
18:30	5.80	-	5.54	5.44	5.23	4.98	4.84	4.68	4.51	4.19	3.88	3.56	3.56	3.56
18:45	5.79	-	5.54	5.44	5.22	4.98	4.85	4.70	4.58	4.20	3.89	3.62	3.66	3.66
19:00	5.79	-	5.53	5.43	5.22	5.00	4.88	4.75	4.59	4.21	3.90	3.72	3.73	3.73
19:30	5.78	-	5.51	5.42	5.22	5.04	4.96	4.84	4.62	4.24	3.98	3.78	3.80	3.80
20:00	5.78	-	5.50	5.40	5.24	5.11	5.10	4.88	4.59	4.22	3.98	3.89	3.91	3.91
20:30	5.76	-	5.49	5.40	5.24	5.13	5.10	4.90	4.58	4.20	4.03	3.91	3.97	3.97
21:00	5.76	-	5.48	5.39	5.25	5.17	5.16	4.89	4.62	4.25	4.04	3.97	-	3.97
21:30	5.76	-	5.47	5.39	5.26	5.22	5.17	4.94	4.61	4.35	4.06	3.89	-	3.89
22:00	5.75	-	5.46	5.39	5.30	5.24	5.20	4.93	4.60	4.21	3.97	3.86	3.92	3.92
Average	**5.85**	**5.72**	**5.65**	**5.64**	**5.51**	**5.29**	**5.10**	**4.87**	**4.56**	**4.24**	**3.97**	**3.53**	**3.46**	**4.05**
Max	6.29	5.81	5.89	6.09	6.15	5.83	5.50	5.19	4.95	4.47	4.21	3.97	3.97	5.33
Min	5.69	5.64	5.46	5.37	5.11	4.87	4.71	4.57	4.33	4.05	3.76	3.35	3.19	3.19

Table 7.6 Watertable levels in wells; Brunswick Beach, Brunswick Heads, 16-17 June 1993

Brunswick Beach, Brunswick Heads, 16-17 JUNE 1993																		
Well No	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	SWL
Distance from B.M.	0.00	12.05	23.23	30.03	33.15	35.07	37.11	39.12	41.15	43.23	45.25	47.34	49.53	52.73	63.38	81.00	99.00	
Distance from coastline (m)	**99.00**	**86.95**	**75.77**	**68.97**	**65.85**	**63.93**	**61.89**	**59.88**	**57.85**	**55.77**	**53.75**	**51.66**	**49.47**	**46.27**	**35.62**	**18.00**	**0.00**	
Av. Sand level	2.93	2.17	1.91	1.60	1.44	1.35	1.26	1.15	1.06	0.95	0.86	0.74	0.65	0.57	0.07	-0.59	-0.98	
Time (EST)																		
14:00	1.00	1.04	0.99	0.94	0.89	0.89	0.85	0.83	0.82	0.80	0.80	0.73	0.69	0.58	0.26	0.17	-	0.17
14:30	1.00	1.03	0.99	0.95	0.93	0.94	0.99	0.96	0.95	0.90	0.86	0.74	0.66	0.58	0.33	0.24	0.19	0.19
15:00	0.99	1.02	0.99	0.98	1.05	1.15	1.16	1.11	1.08	0.99	0.92	0.78	0.73	0.64	0.42	0.39	0.39	0.39
15:30	0.99	1.03	1.02	1.07	1.13	1.14	1.13	1.14	1.05	0.98	0.89	0.78	0.76	0.71	0.51	0.45	0.43	0.43
16:00	0.99	1.03	1.04	1.19	1.26	1.29	1.23	1.15	1.08	1.00	0.91	0.87	0.84	0.75	0.60	0.50	0.49	0.60
16:30	0.99	1.03	1.10	1.35	1.41	1.31	1.23	1.20	1.11	1.10	0.92	0.97	0.97	0.88	0.77	-	-	0.77
17:00	1.00	1.06	1.25	1.48	1.42	1.36	-	1.17	-	1.15	-	0.98	-	-	-	-	-	0.85
17:30	1.01	1.11	1.46	1.47	1.42	1.34	-	1.17	-	1.07	-	0.95	-	0.92	-	-	-	0.92
18:00	1.03	1.17	1.52	1.53	1.44	1.36	1.28	1.20	1.14	1.08	0.99	0.89	-	-	-	-	-	0.89
18:30	1.05	1.21	1.57	1.49	1.38	1.31	-	1.14	-	1.04	-	0.89	-	-	-	-	-	0.89
19:00	1.07	1.25	1.50	1.41	1.43	1.35	-	1.19	-	1.03	-	0.88	0.83	-	-	-	-	0.83
19:30	1.08	1.28	1.45	1.40	1.36	1.33	-	1.17	-	1.01	-	0.82	0.78	0.71	-	-	-	0.71
20:00	1.09	1.28	1.42	1.33	1.30	1.27	-	1.17	-	0.98	-	0.79	0.76	0.71	-	-	-	0.71
20:30	1.09	1.28	1.38	1.31	1.23	1.20	-	1.09	-	0.97	-	0.78	0.79	0.63	0.37	-	-	0.37
21:00	1.10	1.27	1.36	1.27	1.17	1.13	-	1.01	-	0.91	-	0.76	0.67	-	-	-	-	0.30
21:30	1.10	1.26	1.33	1.24	1.15	1.10	-	1.04	-	0.91	-	0.73	0.65	-	0.22	-	-	0.22
22:00	1.10	1.24	1.30	1.21	1.12	1.06	-	0.94	-	0.84	-	0.67	0.62	-	0.16	-	-	0.16
22:30	1.10	1.23	1.27	1.19	1.10	1.04	-	0.92	-	0.81	-	0.68	0.61	-	0.14	-	-	0.14
23:00	1.10	1.22	1.25	1.16	1.08	1.02	-	0.90	-	0.79	-	0.68	0.62	-	0.10	-	-	0.10
23:30	1.09	1.21	1.22	1.13	1.05	1.01	-	0.88	-	0.77	-	0.61	0.55	-	0.09	-	-	0.09
00:00	1.10	1.19	1.20	1.11	1.04	0.99	-	0.87	-	0.75	-	0.62	0.56	0.48	0.10	-	-	0.10
00:30	1.08	1.18	1.18	1.10	1.02	0.97	-	0.86	-	0.74	-	0.60	0.55	0.47	0.10	-	-	0.10
01:00	1.08	1.17	1.16	1.09	1.00	0.97	-	0.85	-	0.74	-	0.60	0.55	0.44	0.10	-	-	0.10
01:30	1.07	1.16	1.14	1.07	0.99	0.96	-	0.85	-	0.74	-	0.62	0.56	0.46	0.10	-	-	0.10
02:00	1.07	1.15	1.12	1.05	0.98	0.94	-	0.84	-	0.73	-	0.63	0.60	0.49	0.10	-	-	0.10
02:30	1.06	1.13	1.11	1.04	0.97	0.94	-	0.83	-	0.74	-	0.65	0.64	0.50	0.15	-	-	0.15
03:00	1.06	1.13	1.10	1.03	0.97	0.93	-	0.86	-	0.79	-	0.74	0.66	0.51	0.19	-	-	0.19
03:30	1.05	1.11	1.08	1.02	0.96	0.93	-	0.86	-	0.79	-	0.77	0.65	0.50	0.22	-	-	0.22
04:00	1.04	1.11	1.07	1.01	0.96	0.94	-	0.89	-	0.84	-	0.74	0.66	0.48	0.29	-	-	0.29
04:30	1.03	1.10	1.06	1.01	0.96	0.94	-	0.90	-	0.86	-	0.73	0.66	0.54	0.31	-	-	0.31
05:00	1.03	1.08	1.05	1.01	0.98	0.98	-	0.95	-	0.92	-	0.75	0.68	0.53	0.35	-	-	0.35
05:30	1.02	1.08	1.05	1.02	0.99	1.01	-	0.98	-	0.92	-	0.77	0.68	0.58	0.38	-	-	0.38
06:00	1.02	1.07	1.05	1.02	1.01	1.03	-	0.97	-	0.93	-	0.76	0.67	0.57	0.38	-	-	0.38
06:30	1.01	1.06	1.04	1.03	1.04	1.07	-	1.00	-	0.92	-	0.73	0.65	0.54	0.32	-	-	0.32
07:00	1.00	1.05	1.04	1.04	1.04	1.07	-	1.00	-	0.92	-	0.73	0.65	0.54	0.32	-	-	0.32
07:30	1.00	1.05	1.03	1.01	0.98	0.97	-	0.90	-	0.82	-	0.70	0.64	0.52	0.23	-	-	0.23
08:00	1.01	1.04	1.02	0.99	0.96	0.94	-	0.86	-	0.78	-	0.69	0.64	0.50	0.18	0.07	-	0.08
08:30	0.99	1.03	1.00	0.97	0.93	0.91	-	0.84	-	0.75	-	0.67	0.62	0.49	0.14	-0.03	-	-0.03
09:00	0.99	1.02	0.99	0.96	0.91	0.89	-	0.80	-	0.71	-	0.59	0.53	0.46	0.08	-0.13	-	-0.13
09:30	0.99	1.02	0.98	0.94	0.90	0.87	-	0.78	-	0.67	-	0.58	0.52	0.45	0.06	-0.19	-	-0.19
10:00	0.98	1.02	0.97	0.93	0.88	0.85	-	0.76	-	0.64	-	0.55	0.46	0.38	0.05	-0.32	-0.38	-0.38
10:30	0.98	1.01	0.96	0.92	0.86	0.84	-	0.75	-	0.63	-	0.55	0.44	0.36	0.03	-0.39	-0.44	-0.44
11:00	0.98	1.00	0.95	0.91	0.85	0.82	-	0.74	-	0.62	-	0.52	0.45	0.35	0.03	-0.39	-	-0.39
11:30	0.97	0.99	0.94	0.89	0.84	0.81	-	0.72	-	0.61	-	0.51	0.43	0.35	0.04	-0.42	-	-0.42
12:00	0.97	0.98	0.93	0.88	0.82	0.79	-	0.71	-	0.60	-	0.49	0.40	0.34	0.04	-0.42	-	-0.42
12:30	0.97	0.98	0.92	0.87	0.81	0.79	-	0.70	-	0.60	-	0.48	0.36	0.33	0.05	-0.37	-	-0.37
13:00	0.96	0.97	0.91	0.86	0.80	0.77	-	0.69	-	0.59	-	0.48	0.42	0.34	0.06	-0.32	-	-0.32
13:30	0.96	0.97	0.90	0.85	0.79	0.76	-	0.68	-	0.59	-	0.49	0.44	0.41	0.07	-0.25	-	-0.25
14:00	0.95	0.96	0.90	0.84	0.79	0.76	-	0.69	-	0.64	-	0.53	0.50	0.39	0.09	-	-	-

															0.10		0.10
14:30	0.95	0.95	0.89	0.83	0.78	0.75	-	0.69	-	0.64	-	0.63	0.64	0.51	0.15	0.05	-	-0.05
15:00	0.95	0.95	0.89	0.82	0.78	0.76	-	0.74	-	0.73	-	0.67	0.63	0.53	0.23	-	-	-
Average	**1.03**	**1.10**	**1.12**	**1.08**	**1.04**	**1.01**	**1.12**	**0.92**	**1.03**	**0.83**	**0.90**	**0.70**	**0.62**	**0.52**	**0.21**	**-0.08**	**0.11**	**0.20**
Max	1.10	1.28	1.57	1.53	1.44	1.36	1.28	1.20	1.14	1.15	0.99	0.98	0.97	0.92	0.77	0.50	0.49	0.92
Min	0.95	0.95	0.89	0.82	0.78	0.75	0.85	0.68	0.82	0.59	0.80	0.48	0.36	0.33	0.03	-0.42	-0.44	-0.44

Table 7.7 Watertable levels in wells; Unnamed Beach, North Bribie Island, 9-10 Nov 1993

Unnamed Beach, North Bribie Island 9-10 NOV 1993																
Well No	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	SWL
Distance from B.M.	-15.20	0.00	6.70	9.47	11.97	14.36	16.81	19.30	21.81	24.35	26.88	36.70	43.19	54.00	75.20	
Distance from coastline (m)	**90.40**	**75.20**	**68.50**	**65.73**	**63.23**	**60.84**	**58.39**	**55.90**	**53.39**	**50.85**	**48.32**	**38.50**	**32.01**	**21.20**	**0.00**	
Av. Sand level			2.81	2.61	2.49	2.36	2.17	1.97	1.82	1.63	1.20	0.94	0.91	0.57	0.40	
Time (EST)																
14:00	-	0.99	0.99	1.01	1.02	1.04	1.06	1.09	1.12	1.23	1.30	1.25	1.25	-	-	1.25
14:20	-	0.99	1.01	1.02	1.04	1.06	1.08	1.11	1.15	1.32	1.31	1.27	1.27	-	-	1.27
14:40	-	1.00	1.03	1.05	1.07	1.09	1.11	1.16	1.24	1.42	1.38	1.35	1.35	-	-	1.35
15:00	-	1.01	1.06	1.08	1.10	1.13	1.17	1.25	1.43	1.54	1.42	1.42	1.40	-	-	1.40
15:20	-	1.04	1.08	1.12	1.14	1.19	1.24	1.37	1.57	1.59	1.46	1.45	1.45	-	-	1.45
15:40	-	1.05	1.10	1.13	1.16	1.21	1.29	1.46	1.61	1.59	1.46	1.45	1.45	-	-	1.45
16:00	-	1.07	1.11	1.15	1.19	1.25	1.34	1.51	1.63	1.60	1.47	1.45	1.45	-	-	1.45
16:20	-	1.08	1.13	1.18	1.22	1.28	1.38	1.55	1.64	1.60	1.48	1.44	1.46	-	-	1.46
16:40	-	1.10	1.15	1.20	1.24	1.31	1.40	1.54	1.62	1.59	1.42	1.42	1.39	-	-	1.39
17:00	-	1.11	1.17	1.21	1.25	1.32	1.39	1.50	1.56	1.54	1.37	1.36	1.36	-	-	1.36
17:20	-	1.12	1.18	1.22	1.26	1.33	1.39	1.48	1.54	1.53	1.37	1.36	1.35	-	-	1.35
17:40	1.05	1.14	1.19	1.23	1.27	1.33	1.39	1.47	1.51	1.52	1.36	1.35	1.33	1.32	-	1.33
18:00	1.05	1.14	1.20	1.24	1.27	1.32	1.37	1.43	1.44	1.39	1.20	1.10	1.09	1.25	-	1.09
18:20	-	1.14	1.19	1.23	1.25	1.28	1.32	1.36	1.35	1.28	1.00	0.97	0.85	1.03	-	0.85
18:40	-	1.14	1.19	1.23	1.24	1.26	1.29	1.33	1.31	1.26	1.02	1.00	0.97	0.97	-	0.75
19:00	1.06	1.15	1.18	1.21	1.22	1.24	1.27	1.29	1.28	1.23	1.04	0.97	0.87	0.92	0.92	0.65
19:20	-	1.15	1.19	1.21	1.21	1.23	1.25	1.26	1.25	1.21	1.06	0.95	0.83	0.84	0.99	0.58
19:40	-	1.15	1.18	1.19	1.20	1.21	1.23	1.24	1.22	1.18	1.04	0.93	0.80	0.76	0.90	0.52
20:00	-	1.14	1.16	1.18	1.18	1.20	1.21	1.22	1.20	1.16	1.02	0.90	0.79	0.70	0.54	0.50
20:20	-	1.14	1.16	1.17	1.17	1.18	1.19	1.20	1.18	1.13	1.00	0.88	0.77	0.65	0.55	0.48
20:40	-	1.13	1.15	1.16	1.16	1.17	1.18	1.17	1.16	1.11	0.99	0.88	0.77	0.63	0.56	0.46
21:00	-	1.13	1.14	1.15	1.15	1.15	1.16	1.16	1.13	1.10	0.97	0.86	0.75	0.60	0.50	0.44
21:20	-	1.12	1.13	1.14	1.14	1.14	1.14	1.14	1.11	1.09	0.95	0.83	0.71	0.56	0.41	0.41
21:40	-	1.12	1.12	1.13	1.13	1.13	1.13	1.13	1.10	1.07	0.94	0.83	0.70	-	0.37	0.37
22:00	-	1.11	1.12	1.13	1.12	1.13	1.12	1.12	1.10	1.06	0.92	0.80	0.68	-	0.34	0.34
22:20	-	1.11	1.11	1.12	1.11	1.12	1.11	1.10	1.08	1.05	0.92	0.80	0.67	-	0.34	0.34
22:40	-	1.10	1.10	1.11	1.10	1.10	1.09	1.08	1.06	1.03	0.92	0.78	0.66	-	0.34	0.34
23:00	-	1.10	1.09	1.10	1.09	1.09	1.08	1.07	1.05	1.01	0.89	0.77	0.65	-	0.36	0.36
23:20	-	1.09	1.09	1.09	1.09	1.08	1.07	1.06	1.03	1.01	0.88	0.77	0.66	-	0.38	0.38
23:40	-	1.09	1.08	1.09	1.08	1.07	1.06	1.05	1.02	1.00	0.88	0.78	0.68	-	0.38	0.38
00:00	-	1.08	1.08	1.08	1.07	1.07	1.06	1.04	1.02	1.00	0.89	0.78	0.68	-	0.44	0.44
00:20	-	1.07	1.07	1.07	1.06	1.06	1.05	1.04	1.01	0.99	0.90	0.81	0.75	0.58	-	0.50
00:40	-	1.07	1.07	1.07	1.06	1.05	1.04	1.03	1.01	0.98	0.90	0.83	0.79	0.63	-	0.57
01:00	-	1.06	1.06	1.06	1.05	1.05	1.03	1.02	1.00	0.98	0.90	0.83	0.79	0.63	-	0.64
01:20	-	1.06	1.05	1.06	1.04	1.04	1.03	1.02	0.99	0.97	0.91	0.84	0.79	0.65	-	0.68
01:40	-	1.06	1.05	1.05	1.04	1.03	1.02	1.01	0.99	0.97	0.91	0.87	0.81	0.68	-	0.71
02:00	-	1.05	1.05	1.05	1.04	1.03	1.02	1.01	0.99	0.98	0.99	0.96	0.91	0.99	0.99	0.77
02:20	-	1.05	1.05	1.05	1.04	1.04	1.03	1.03	0.93	1.02	1.07	0.99	1.02	1.00	1.00	0.84
02:40	-	1.05	1.05	1.05	1.05	1.07	1.05	1.05	1.04	1.05	1.17	1.02	1.03	0.94	0.94	0.90
03:00	1.04	1.05	1.05	1.06	1.06	1.06	1.06	1.08	1.08	1.10	1.18	1.10	1.09	0.99	-	0.97
03:20	-	1.07	1.11	1.08	1.07	1.08	1.09	1.09	1.08	1.13	1.17	1.06	1.06	1.01	-	1.01
03:40	-	1.06	1.07	1.08	1.08	1.09	1.09	1.11	1.11	1.13	1.20	1.11	1.12	1.05	-	1.04
04:00	1.03	1.07	1.07	1.09	1.09	1.11	1.11	1.14	1.16	1.10	1.26	1.23	1.22	-	-	1.12
04:20	-	1.08	1.09	1.11	1.11	1.12	1.15	1.17	1.21	1.30	1.25	1.21	1.20	1.17	-	1.20
04:40	-	1.08	1.10	1.12	1.13	1.14	1.16	1.19	1.23	1.36	1.29	1.27	1.26	1.19	-	1.26
05:00	1.04	1.09	1.11	1.12	1.15	1.17	1.18	1.22	1.29	1.41	1.32	1.30	1.29	1.25	-	1.27
05:20	-	1.10	1.13	1.16	1.16	1.19	1.20	1.24	1.30	1.39	1.28	1.24	1.23	1.24	-	1.21
05:40	-	1.11	1.14	1.16	1.17	1.19	1.21	1.25	1.32	1.30	1.24	1.16	1.15	1.20	-	1.15
06:00	1.05	1.11	1.14	1.16	1.17	1.20	1.20	1.26	1.25	1.27	1.22	1.10	1.09	1.13	-	1.09
06:20	-	1.12	1.14	1.16	1.16	1.19	1.20	1.22	1.24	1.25	1.23	1.12	1.12	1.09	-	1.05
06:40	-	1.12	1.14	1.17	1.17	1.20	1.19	1.21	1.23	1.24	1.20	1.05	1.04	1.05	-	1.01
07:00	-	1.12	1.15	1.16	1.17	1.18	1.18	1.20	1.21	1.21	1.21	1.04	1.03	1.02	-	0.98
07:20	1.07	1.12	1.14	1.15	1.16	1.16	1.16	1.18	1.18	1.17	1.07	1.04	1.02	0.91	-	0.95
07:40	-	1.12	1.14	1.14	1.14	1.15	1.15	1.16	1.16	1.16	1.04	0.93	0.92	0.84	0.96	0.90
08:00	-	1.11	1.13	1.13	1.14	1.14	1.14	1.14	1.14	1.13	1.02	0.93	0.91	0.77	0.91	0.85
08:20	1.07	1.11	1.12	1.12	1.12	1.13	1.12	1.13	1.13	1.12	1.02	0.92	0.90	0.69	0.82	0.82
08:40	1.07	1.10	1.11	1.11	1.11	1.11	1.10	1.11	1.11	1.09	1.00	0.91	0.83	0.66	0.78	0.72
09:00	-	1.10	1.11	1.10	1.10	1.10	1.09	1.10	1.09	1.08	0.98	0.89	0.79	0.62	0.67	0.63
09:20	-	1.09	1.10	1.09	1.08	1.09	1.09	1.08	1.08	1.06	0.96	0.85	0.74	0.60	0.58	0.58
09:40	-	1.08	1.09	1.08	1.08	1.08	1.07	1.07	1.06	1.05	0.94	0.83	0.72	0.58	0.58	0.55

10:00	1.06	1.07	1.08	1.07	1.07	1.07	1.06	1.06	1.05	1.03	0.92	0.81	0.70	0.57	0.54	0.54
10:20	-	1.07	1.06	1.06	1.06	1.06	1.05	1.05	1.04	1.01	0.91	0.79	0.67	-	0.50	0.50
10:40	-	1.07	1.06	1.06	1.06	1.06	1.05	1.05	1.03	1.01	0.90	0.79	0.68	-	0.52	0.52
11:00	1.05	1.06	1.06	1.05	1.05	1.05	1.04	1.04	1.02	1.00	0.90	0.78	0.68	-	0.57	0.51
11:20	-	1.05	1.04	1.04	1.05	1.03	1.02	1.02	1.00	0.99	0.89	0.80	0.71	0.56	0.59	0.51
11:40	-	1.05	1.04	1.04	1.03	1.02	1.01	1.01	0.99	0.97	0.88	0.79	0.70	0.58	0.64	0.54
12:00	1.03	1.04	1.04	1.03	1.03	1.02	1.01	1.01	0.98	0.96	0.89	0.80	0.72	0.60	0.68	0.58
12:20	-	1.04	1.04	1.03	1.03	1.02	1.00	1.00	0.98	0.96	0.88	0.80	0.72	0.60	0.68	0.59
12:40	-	1.04	1.03	1.02	1.02	1.01	0.99	0.99	0.97	0.95	0.89	0.84	0.90	0.61	0.75	0.65
13:00	1.02	1.03	1.03	1.02	1.02	1.01	0.99	0.99	0.97	0.96	0.92	0.89	0.90	0.62	0.85	0.70
13:20	-	1.03	1.02	1.02	1.02	1.01	1.00	0.99	0.97	0.97	0.95	0.93	0.92	0.69	0.94	0.72
13:40	-	1.03	1.02	1.02	1.01	1.01	1.00	1.00	0.98	0.99	1.00	0.97	0.96	0.75	-	0.75
14:00	1.01	1.03	1.02	1.02	1.03	1.02	1.01	1.01	1.01	1.02	1.11	1.03	1.01	0.83	-	0.83
14:20	1.01	1.02	1.02	1.03	1.03	1.03	1.03	1.04	1.04	1.06	1.22	1.09	1.05	0.91	-	0.91
14:40	-	1.03	1.03	1.04	1.04	1.05	1.06	1.07	1.07	1.13	1.23	1.16	1.12	0.99	-	0.99
15:00	1.01	1.03	1.05	1.06	1.06	1.08	1.09	1.11	1.14	1.23	1.27	1.21	1.19	1.08	-	1.08
Average	**1.04**	**1.08**	**1.10**	**1.11**	**1.11**	**1.13**	**1.13**	**1.16**	**1.17**	**1.17**	**1.09**	**1.01**	**0.97**	**0.84**	**0.64**	**0.83**
Max	1.07	1.15	1.20	1.24	1.27	1.33	1.40	1.55	1.64	1.60	1.48	1.45	1.46	1.32	1.00	1.46
Min	1.01	0.99	0.99	1.01	1.01	1.01	0.99	0.99	0.93	0.95	0.88	0.77	0.65	0.56	0.34	0.34

7.4 Appendix 4- Artificial neural network model to predict the watertable elevation at coast

```
%% Neural network model
clear all; clc; close all;
load beaches
X=beaches;
X(any(isnan(X),2),:) = [];
%Correlation coefficients:: tide-:-distance from coastline-:-
hydraulic conductivity-:-beach slope-:-water elevation
correlations=corrcoef(X);
correlations=correlations(4:end,4:end);
X=X';
p=X(1:7,:);
t=X(8,:);
[p2,ps] = mapminmax(p);
[t2,ts] = mapminmax(t);
[trainV_all,val_all,test_all] = dividevec(p2,t2,0.20,0.20);
%%%
trainV.P=trainV_all.P(4:7,:); % all data
trainV.T=trainV_all.T;
trainV.indices=trainV_all.indices;
%%%
val.P=val_all.P(4:7,:); % all data
val.T=val_all.T;
val.indices=val_all.indices;
%%%
test.P=test_all.P(4:7,:); % all data
test.T=test_all.T;
test.indices=test_all.indices;
%%%
p3=p2(4:7,:); % all data

net = newff(minmax(p3),[20 10
1],{'logsig','logsig','purelin'},'trainrp');
net.trainParam.show = 20;
net.trainParam.lr = 0.01;
net.trainParam.epochs = 1000;
[net,tr]=train(net,trainV.P,trainV.T,[],[],val,test);
saveas(gcf,'performance.emf')
%total data:
sim_total = sim(net,p3);
sim_total_r = mapminmax('reverse',sim_total,ts);
figure; [m_total,b_total,r_total] = postreg(sim_total_r,t);
saveas(gcf,'total_postreg.emf')
g=1:4269;
figure; plot(g,sim_total_r,'r',g,t,':b');
grid on;
legend('Simulated','Real');
xlabel('points')
ylabel('fluctuations (m)')
title('Simulated vs. real data for total data set')
saveas(gcf,'total_xy.emf')
%train:
sim_train = sim(net,trainV.P);
sim_train_r = mapminmax('reverse',sim_train,ts);
t_train_r = mapminmax('reverse',trainV.T,ts);
p_train_r = mapminmax('reverse',trainV_all.P,ps);
figure; [m_train,b_train,r_train] = postreg(sim_train_r,t_train_r);
saveas(gcf,'train_postreg.emf')
```

```
g=1:2563;
figure; plot(g,sim_train_r,'r',g,t_train_r,':b');
grid on;
legend('Simulated','actual');
xlabel('points')
ylabel('fluctuations (m)')
title('Simulated vs. actual data for training data set')
saveas(gcf,'train_xy.emf')
%validation:
sim_val = sim(net,val.P);
sim_val_r = mapminmax('reverse',sim_val,ts);
t_val_r = mapminmax('reverse',val.T,ts);
p_val_r = mapminmax('reverse',val_all.P,ps);
figure; [m_val,b_val,r_val] = postreg(sim_val_r,t_val_r);
saveas(gcf,'val_postreg.emf')
g=1:853;
figure; plot(g,sim_val_r,'r',g,t_val_r,':b');
grid on;
legend('Simulated','actual');
xlabel('Points')
ylabel('Fluctuations (m)')
title('predicted vs. actual data for validation data set')
saveas(gcf,'val_xy.emf')
%test:
sim_test = sim(net,test.P);
sim_test_r = mapminmax('reverse',sim_test,ts);
t_test_r = mapminmax('reverse',test.T,ts);
p_test_r = mapminmax('reverse',test_all.P,ps);
figure; [m_test,b_test,r_test] = postreg(sim_test_r,t_test_r);
saveas(gcf,'test_postreg.emf')
figure; plot(g,sim_test_r,'r',g,t_test_r,':b');
grid on;
legend('predicted','actual');
xlabel('Points')
ylabel('Fluctuations (m)')
title('predicted vs. actual data for testing data set')
saveas(gcf,'test_xy.emf')
```

7.5 Appendix 5- ANN model performance of sensitivity study for watertable elevation prediction at coast

Table 7.8 Performance of developed ANN model (Tide data is removed)

	Well No.	Distance from coastline (m)	Max Water Level (m)	Min Water Level (m)	Mean Water Level (m)	Total Data set			Training data set			Validation data set			Testing data set		
						Number of data	RMSE	R	Number of data	RMSE	R	Number of data	RMSE	R	Number of data	RMSE	R
Kings Beach	-	-	-	-	-	1104	0.24	0.66	671	0.24	0.64	217	0.23	0.73	216	0.25	0.67
Eagers Beach	-	-	-	-	-	805	0.19	0.93	494	0.19	0.93	156	0.17	0.94	155	0.17	0.94
Shelley Beach	-	-	-	-	-	717	0.21	0.96	421	0.21	0.96	146	0.21	0.95	150	0.20	0.96
Brunswick Beach	-	-	-	-	-	624	0.18	0.87	347	0.17	0.86	135	0.18	0.89	142	0.21	0.86
Bribie Island	-	-	-	-	-	1019	0.16	0.57	630	0.16	0.56	199	0.16	0.57	190	0.14	0.62
Kings Beach	1	48.39	0.09	-0.06	0.02	84	0.05	0.00	53	0.05	-	17	0.04	-	14	0.05	-
	2	38.54	0.15	-0.08	0.04	79	0.08	-	43	0.08	-	18	0.07	-	18	0.08	-
	3	33.54	0.18	-0.11	0.04	81	0.09	0.00	47	0.09	-	10	0.09	-	24	0.09	-
	4	28.52	0.25	-0.15	0.06	79	0.12	0.00	46	0.13	-	21	0.12	-	12	0.12	-
	5	23.46	0.40	-0.24	0.05	84	0.20	-	58	0.21	-	13	0.19	-	13	0.19	-
	6	21.51	0.53	-0.26	0.11	43	0.25	-	27	0.21	-	8	0.26	-	8	0.35	-
	7	19.53	0.59	-0.29	0.11	84	0.31	0.00	56	0.31	0.00	12	0.26	-	16	0.34	-
	8	17.53	0.54	-0.33	0.02	58	0.31	-	39	0.30	-	9	0.33	-	10	0.31	-
	9	15.53	0.45	-0.38	0.04	84	0.30	0.00	51	0.29	0.02	15	0.31	-0.49	18	0.30	0.16
	10	13.53	0.39	-0.42	-0.03	84	0.27	0.00	48	0.27	-	20	0.27	-	16	0.25	-
	11	11.58	0.10	-0.46	-0.24	55	0.21	0.00	34	0.22	0.00	11	0.18	-	10	0.19	-
	12	9.62	-0.08	-0.53	-0.36	31	0.22	-0.03	15	0.23	-0.02	9	0.20	-0.11	7	0.21	-0.75
	13	7.64	0.29	-0.59	-0.20	84	0.32	0.00	50	0.30	0.00	18	0.33	0.00	16	0.35	0.00
	14	5.59	0.28	-0.68	-0.36	64	0.32	0.00	39	0.34	0.00	11	0.25	0.00	14	0.32	0.00
	15	3.44	0.14	-0.78	-0.48	61	0.29	0.00	39	0.29	0.03	15	0.26	0.09	7	0.35	0.34
	16	0.00	-0.05	-1.06	-0.73	49	0.29	0.00	26	0.29	0.00	10	0.26	0.00	13	0.32	0.00
Eagers Beach	1	96.75	8.16	8.06	8.11	55	0.05	0.00	34	0.05	0.00	11	0.04	0.00	10	0.05	0.00
	2	86.99	8.09	7.93	8.00	55	0.05	0.00	35	0.05	0.00	9	0.07	0.00	11	0.05	-
	3	77.10	8.03	7.76	7.87	55	0.09	0.00	35	0.09	0.00	15	0.07	0.00	5	0.11	0.00
	4	67.10	8.06	7.57	7.75	55	0.15	0.00	30	0.15	0.00	11	0.11	0.00	14	0.17	0.00
	5	61.99	8.13	7.47	7.68	55	0.19	0.00	40	0.19	0.00	6	0.21	-	9	0.22	0.00
	6	57.98	8.00	7.37	7.60	55	0.21	0.00	29	0.21	0.00	14	0.18	0.00	12	0.23	0.00
	7	54.06	7.81	7.28	7.49	55	0.18	0.00	29	0.18	0.00	7	0.14	0.00	19	0.18	0.00
	8	50.07	7.73	7.21	7.40	55	0.16	0.00	29	0.15	0.00	15	0.17	0.00	11	0.16	0.00
	9	45.81	7.73	7.10	7.28	55	0.17	0.00	35	0.17	0.00	14	0.19	0.00	6	0.12	0.00
	10	41.24	7.68	7.00	7.17	52	0.20	0.00	32	0.22	0.00	9	0.17	0.00	11	0.16	0.00
	11	37.61	7.64	6.93	7.09	51	0.22	0.00	32	0.23	0.00	9	0.19	0.00	10	0.23	-
	12	33.08	7.58	6.83	6.98	48	0.23	0.00	35	0.24	0.01	6	0.27	-0.01	7	0.09	-0.31
	13	28.02	7.57	6.71	6.90	48	0.26	0.00	29	0.30	0.00	11	0.16	-	8	0.17	0.00
	14	20.93	7.54	6.59	6.75	41	0.24	-	23	0.30	0.00	9	0.16	0.00	9	0.14	0.00
	15	10.00	7.20	6.33	6.55	37	0.23	0.00	22	0.21	0.00	7	0.19	0.00	8	0.29	0.00
	16	0.00	6.86	6.09	6.38	33	0.25	0.00	25	0.23	0.00	3	0.38	-	5	0.21	-

Shelley Beach	1	42.46	5.81	5.64	5.72	48	0.07	0.00	30	0.06	0.00	9	0.08	0.00	9	0.07	0.00
	2	38.74	5.89	5.46	5.65	73	0.13	0.00	41	0.12	0.00	17	0.13	0.00	15	0.13	0.00
	3	33.96	6.09	5.37	5.64	73	0.20	0.00	46	0.21	0.00	14	0.15	-	13	0.23	-
	4	28.55	6.15	5.11	5.51	79	0.30	0.00	46	0.31	0.00	19	0.31	0.00	14	0.25	0.00
	5	23.67	5.83	4.87	5.29	79	0.28	0.00	41	0.30	0.00	14	0.23	0.00	24	0.29	0.00
	6	20.54	5.50	4.71	5.10	79	0.23	0.00	48	0.23	-	18	0.27	-	13	0.19	-
	7	16.92	5.19	4.57	4.87	69	0.17	0.00	37	0.18	0.00	12	0.16	0.00	20	0.17	0.00
	8	13.57	4.95	4.33	4.56	48	0.17	0.00	28	0.17	0.00	11	0.10	0.00	9	0.21	0.00
	9	10.01	4.47	4.05	4.24	62	0.12	0.00	41	0.11	0.00	13	0.15	0.00	8	0.12	0.00
	10	6.87	4.21	3.76	3.97	49	0.13	0.00	30	0.14	0.00	9	0.10	-	10	0.13	0.00
	11	3.22	3.97	3.35	3.53	36	0.22	0.00	20	0.22	0.00	7	0.22	-	9	0.23	0.00
	12	0.00	3.97	3.19	3.46	22	0.26	0.00	13	0.24	-	3	0.42	-	6	0.17	-
Brunswick Beach	1	99.00	1.10	0.95	1.03	50	0.05	0.00	26	0.05	0.00	10	0.05	0.00	14	0.05	0.00
	2	86.95	1.28	0.95	1.10	50	0.10	0.00	27	0.09	0.00	14	0.10	0.00	9	0.11	-
	3	75.77	1.57	0.89	1.12	50	0.18	0.00	27	0.19	0.00	15	0.16	0.00	8	0.20	0.00
	4	68.97	1.53	0.82	1.08	50	0.19	0.00	25	0.16	0.00	15	0.25	0.00	10	0.17	0.00
	5	65.85	1.44	0.78	1.04	50	0.19	0.00	27	0.21	0.00	10	0.20	0.00	13	0.15	0.00
	6	63.93	1.36	0.75	1.01	50	0.18	0.00	27	0.15	0.00	5	0.13	0.00	18	0.24	0.00
	7	61.89	1.28	0.85	1.12	7	0.24	0.06	2	0.21	-	3	0.26	-	2	0.22	-
	8	59.88	1.20	0.68	0.92	50	0.16	0.04	28	0.15	-0.05	10	0.20	-0.04	12	0.15	0.17
	9	57.85	1.14	0.82	1.03	7	0.21	0.00	2	0.26	-	4	0.16	-	1	0.26	1.00
	10	55.77	1.15	0.59	0.83	50	0.15	-0.01	35	0.15	-0.04	8	0.16	-0.09	7	0.15	-0.23
	11	53.75	0.99	0.80	0.90	7	0.16	0.00	4	0.18	-	1	0.11	1.00	2	0.13	-
	12	51.66	0.98	0.48	0.70	50	0.13	0.00	36	0.13	0.00	7	0.10	0.00	7	0.14	0.00
	13	49.47	0.97	0.36	0.62	46	0.13	0.00	27	0.14	0.00	10	0.07	0.00	9	0.12	0.00
	14	46.27	0.92	0.33	0.52	40	0.14	0.00	19	0.13	0.00	9	0.15	0.00	12	0.13	0.00
	15	35.62	0.77	0.03	0.21	42	0.18	0.00	23	0.17	-	11	0.16	-	8	0.21	-
	16	18.00	0.50	-0.42	-0.08	19	0.48	-	8	0.40	-	3	0.51	-	8	0.53	-
	17	0.00	0.49	-0.44	0.11	6	0.44	-	4	0.38	-	0	-	-	2	0.55	-
Bribie Island	1	90.40	1.07	1.01	1.04	17	0.07	0.00	11	0.07	0.00	2	0.07	-	4	0.07	-
	2	75.20	1.15	0.99	1.08	76	0.06	0.00	51	0.06	0.00	12	0.04	0.00	13	0.06	0.00
	3	68.50	1.20	0.99	1.10	76	0.06	0.00	46	0.06	0.00	15	0.06	0.00	15	0.06	0.00
	4	65.73	1.24	1.01	1.11	76	0.07	-	45	0.07	-	13	0.06	-	18	0.07	-
	5	63.23	1.27	1.01	1.11	76	0.07	0.00	41	0.07	0.00	17	0.07	0.00	18	0.08	0.00
	6	60.84	1.33	1.01	1.13	76	0.09	0.00	48	0.10	0.00	11	0.09	-	17	0.07	-
	7	58.39	1.40	0.99	1.13	76	0.11	0.00	46	0.11	0.00	16	0.11	0.00	14	0.12	0.00
	8	55.90	1.55	0.99	1.16	76	0.15	0.00	49	0.16	0.00	13	0.15	0.00	14	0.09	0.00
	9	53.39	1.64	0.93	1.17	76	0.18	0.00	49	0.20	0.00	15	0.20	0.00	12	0.06	0.00
	10	50.85	1.60	0.95	1.17	76	0.19	0.00	47	0.20	0.00	19	0.21	-	10	0.11	0.00
	11	48.32	1.48	0.88	1.09	76	0.19	0.00	51	0.19	0.00	14	0.18	0.00	11	0.21	0.00
	12	38.50	1.45	0.77	1.01	76	0.22	0.00	42	0.23	0.00	24	0.20	0.00	10	0.21	0.00
	13	32.01	1.46	0.65	0.97	76	0.25	0.00	56	0.24	0.00	9	0.23	0.19	11	0.30	0.00
	14	21.20	1.32	0.56	0.84	53	0.24	0.00	27	0.23	0.00	11	0.23	0.00	15	0.26	0.00
	15	0.00	1.00	0.34	0.64	37	0.22	0.12	21	0.24	0.01	8	0.22	0.00	8	0.13	0.00

Table 7.9 Performance of developed ANN model (Distance data is removed)

	Well No.	Distance from coastline (m)	Max Water Level (m)	Min Water Level (m)	Mean Water Level (m)	Total Data set			Training data set			Validation data set			Testing data set		
						Number of data	RMSE	R	Number of data	RMSE	R	Number of data	RMSE	R	Number of data	RMSE	R
Kings Beach	-	-	-	-	-	1104	0.25	0.64	671	0.24	0.63	217	0.26	0.63	216	0.25	0.68
Eagers Beach	-	-	-	-	-	805	0.47	0.39	494	0.47	0.42	156	0.46	0.30	155	0.46	0.37
Shelley Beach	-	-	-	-	-	717	0.65	0.44	421	0.66	0.43	146	0.63	0.40	150	0.64	0.50
Brunswick Beach	-	-	-	-	-	624	0.31	0.50	347	0.29	0.48	135	0.32	0.54	142	0.34	0.51
Bribie Island	-	-	-	-	-	1019	0.16	0.59	630	0.16	0.61	199	0.16	0.58	190	0.16	0.52
Kings Beach	1	48.39	0.09	-0.06	0.02	84	0.23	-0.06	53	0.23	-0.01	17	0.25	-0.29	14	0.22	0.07
	2	38.54	0.15	-0.08	0.04	79	0.23	0.12	43	0.22	0.03	18	0.26	0.19	18	0.25	0.10
	3	33.54	0.18	-0.11	0.04	81	0.23	0.28	47	0.24	0.35	10	0.23	-0.02	24	0.21	0.25
	4	28.52	0.25	-0.15	0.06	79	0.22	0.40	46	0.23	0.39	21	0.24	0.37	12	0.18	0.43
	5	23.46	0.40	-0.24	0.05	84	0.22	0.61	58	0.22	0.54	13	0.20	0.78	13	0.22	0.77
	6	21.51	0.53	-0.26	0.11	43	0.25	0.68	27	0.24	0.64	8	0.25	0.84	8	0.29	0.77
	7	19.53	0.59	-0.29	0.11	84	0.27	0.78	56	0.26	0.74	12	0.25	0.82	16	0.29	0.93
	8	17.53	0.54	-0.33	0.02	58	0.23	0.79	39	0.22	0.76	9	0.27	0.65	10	0.24	0.98
	9	15.53	0.45	-0.38	0.04	84	0.19	0.88	51	0.19	0.89	15	0.21	0.82	18	0.20	0.92
	10	13.53	0.39	-0.42	-0.03	84	0.12	0.92	48	0.13	0.91	20	0.10	0.94	16	0.11	0.93
	11	11.58	0.10	-0.46	-0.24	55	0.11	0.85	34	0.11	0.86	11	0.10	0.86	10	0.12	0.81
	12	09.62	-0.08	-0.53	-0.36	31	0.17	0.81	15	0.19	0.78	9	0.16	0.83	7	0.14	0.90
	13	07.64	0.29	-0.59	-0.20	84	0.18	0.96	50	0.19	0.95	18	0.17	0.96	16	0.15	0.97
	14	05.59	0.28	-0.68	-0.36	64	0.27	0.94	39	0.26	0.94	11	0.30	0.90	14	0.30	0.94
	15	03.44	0.14	-0.78	-0.48	61	0.35	0.96	39	0.35	0.96	15	0.36	0.93	7	0.33	0.97
	16	00.00	-0.05	-1.06	-0.73	49	0.54	1.00	26	0.54	0.99	10	0.56	1.00	13	0.51	1.00
Eagers Beach	1	96.75	8.16	8.06	8.11	55	0.76	-0.25	34	0.72	-0.34	11	0.82	-0.22	10	0.81	-0.10
	2	86.99	8.09	7.93	8.00	55	0.65	-0.10	35	0.64	-0.09	9	0.69	-0.37	11	0.64	0.18
	3	77.10	8.03	7.76	7.87	55	0.53	0.07	35	0.50	0.10	15	0.58	0.09	5	0.61	0.02
	4	67.10	8.06	7.57	7.75	55	0.42	0.36	30	0.41	0.35	11	0.42	0.21	14	0.42	0.48
	5	61.99	8.13	7.47	7.68	55	0.35	0.60	40	0.35	0.58	6	0.23	0.57	9	0.39	0.80
	6	57.98	8.00	7.37	7.60	55	0.26	0.74	29	0.25	0.73	14	0.29	0.64	12	0.25	0.86
	7	54.06	7.81	7.28	7.49	55	0.15	0.82	29	0.16	0.81	7	0.10	0.86	19	0.16	0.84
	8	50.07	7.73	7.21	7.40	55	0.11	0.86	29	0.11	0.83	15	0.11	0.90	11	0.12	0.89
	9	45.81	7.73	7.10	7.28	55	0.15	0.87	35	0.15	0.87	14	0.15	0.87	6	0.17	0.85
	10	41.24	7.68	7.00	7.17	52	0.23	0.84	32	0.23	0.85	9	0.25	0.80	11	0.22	0.89
	11	37.61	7.64	6.93	7.09	51	0.30	0.83	32	0.31	0.82	9	0.28	0.89	10	0.31	0.85
	12	33.08	7.58	6.83	6.98	48	0.39	0.83	35	0.40	0.83	6	0.32	0.89	7	0.39	0.85
	13	28.02	7.57	6.71	6.90	48	0.47	0.86	29	0.46	0.86	11	0.50	0.88	8	0.45	0.87
	14	20.93	7.54	6.59	6.75	41	0.56	0.88	23	0.54	0.89	9	0.57	0.95	9	0.62	0.91
	15	10.00	7.20	6.33	6.55	37	0.74	0.97	22	0.74	0.98	7	0.74	0.98	8	0.71	0.96
	16	00.00	6.86	6.09	6.38	33	0.87	1.00	25	0.88	1.00	3	0.77	1.00	5	0.85	1.00
Shelley Beach	1	42.46	5.81	5.64	5.72	48	0.69	0.30	30	0.72	0.04	9	0.66	0.58	9	0.61	0.60
	2	38.74	5.89	5.46	5.65	73	0.64	0.49	41	0.66	0.57	17	0.64	0.71	15	0.60	0.22
	3	33.96	6.09	5.37	5.64	73	0.61	0.72	46	0.61	0.77	14	0.61	0.38	13	0.59	0.78
	4	28.55	6.15	5.11	5.51	79	0.47	0.82	46	0.48	0.87	19	0.48	0.78	14	0.43	0.63
	5	23.67	5.83	4.87	5.29	79	0.27	0.82	41	0.27	0.80	14	0.30	0.69	24	0.27	0.90
	6	20.54	5.50	4.71	5.10	79	0.21	0.72	48	0.19	0.77	18	0.26	0.53	13	0.16	0.88
	7	16.92	5.19	4.57	4.87	69	0.35	0.40	37	0.36	0.43	12	0.35	0.45	20	0.32	0.29

	8	13.57	4.95	4.33	4.56	48	0.42	0.59	28	0.43	0.61	11	0.45	0.66	9	0.31	0.75
	9	10.01	4.47	4.05	4.24	62	0.72	0.63	41	0.72	0.62	13	0.73	0.39	8	0.70	0.59
	10	06.87	4.21	3.76	3.97	49	0.94	0.97	30	0.94	0.98	9	0.93	0.92	10	0.96	0.99
	11	03.22	3.97	3.35	3.53	36	1.33	0.28	20	1.31	0.39	7	1.35	0.05	9	1.36	0.19
	12	00.00	3.97	3.19	3.46	22	1.34	0.99	13	1.36	0.98	3	1.20	1.00	6	1.38	0.99
Brunswick Beach	1	99.00	1.10	0.95	1.03	50	0.24	0.37	26	0.24	0.36	10	0.26	0.30	14	0.22	0.42
	2	86.95	1.28	0.95	1.10	50	0.30	0.50	27	0.29	0.40	14	0.29	0.46	9	0.35	0.78
	3	75.77	1.57	0.89	1.12	50	0.33	0.73	27	0.32	0.77	15	0.31	0.62	8	0.37	0.71
	4	68.97	1.53	0.82	1.08	50	0.29	0.85	25	0.24	0.81	15	0.34	0.93	10	0.29	0.73
	5	65.85	1.44	0.78	1.04	50	0.24	0.90	27	0.25	0.92	10	0.25	0.91	13	0.21	0.83
	6	63.93	1.36	0.75	1.01	50	0.21	0.92	27	0.19	0.87	5	0.18	0.89	18	0.24	0.95
	7	61.89	1.28	0.85	1.12	7	0.22	0.89	2	0.23	1.00	3	0.24	0.97	2	0.15	1.00
	8	59.88	1.20	0.68	0.92	50	0.12	0.93	28	0.11	0.92	10	0.15	0.93	12	0.11	0.95
	9	57.85	1.14	0.82	1.03	7	0.12	0.85	2	0.10	1.00	4	0.14	0.89	1	0.09	1.00
	10	55.77	1.15	0.59	0.83	50	0.05	0.95	35	0.04	0.96	8	0.06	0.96	7	0.06	0.92
	11	53.75	0.99	0.80	0.90	7	0.05	0.88	4	0.05	0.89	1	0.04	1.00	2	0.07	1.00
	12	51.66	0.98	0.48	0.70	50	0.13	0.95	36	0.12	0.96	7	0.14	0.96	7	0.16	0.98
	13	49.47	0.97	0.36	0.62	46	0.19	0.94	27	0.19	0.95	10	0.18	0.83	9	0.19	0.95
	14	46.27	0.92	0.33	0.52	40	0.28	0.93	19	0.28	0.92	9	0.27	0.94	12	0.28	0.96
	15	35.62	0.77	0.03	0.21	42	0.58	0.87	23	0.58	0.87	11	0.61	0.82	8	0.55	0.90
	16	18.00	0.50	-0.42	-0.08	19	0.82	0.99	8	0.76	0.99	3	0.88	1.00	8	0.86	1.00
	17	00.00	0.49	-0.44	0.11	6	0.72	1.00	4	0.68	0.99	0	-	-	2	0.81	1.00
Bribie Island	1	90.40	1.07	1.01	1.04	17	0.10	-0.13	11	0.10	-0.08	2	0.07	-1.00	4	0.12	-0.16
	2	75.20	1.15	0.99	1.08	76	0.13	-0.22	51	0.13	-0.26	12	0.12	-0.18	13	0.12	-0.16
	3	68.50	1.20	0.99	1.10	76	0.12	0.08	46	0.11	0.18	15	0.11	-0.18	15	0.14	-0.07
	4	65.73	1.24	1.01	1.11	76	0.12	0.23	45	0.12	0.29	13	0.14	-0.12	18	0.09	0.24
	5	63.23	1.27	1.01	1.11	76	0.11	0.36	41	0.10	0.45	17	0.12	0.30	18	0.12	0.30
	6	60.84	1.33	1.01	1.13	76	0.11	0.47	48	0.11	0.49	11	0.11	0.46	17	0.10	0.47
	7	58.39	1.40	0.99	1.13	76	0.11	0.56	46	0.09	0.66	16	0.15	0.45	14	0.14	0.56
	8	55.90	1.55	0.99	1.16	76	0.13	0.67	49	0.14	0.68	13	0.13	0.74	14	0.10	0.63
	9	53.39	1.64	0.93	1.17	76	0.14	0.76	49	0.16	0.80	15	0.13	0.85	12	0.08	0.61
	10	50.85	1.60	0.95	1.17	76	0.14	0.87	47	0.14	0.86	19	0.13	0.94	10	0.12	0.47
	11	48.32	1.48	0.88	1.09	76	0.09	0.96	51	0.09	0.95	14	0.07	0.85	11	0.09	0.98
	12	38.50	1.45	0.77	1.01	76	0.13	0.98	42	0.13	0.98	24	0.12	0.98	10	0.14	0.91
	13	32.01	1.46	0.65	0.97	76	0.18	0.98	56	0.18	0.98	9	0.21	0.98	11	0.17	0.99
	14	21.20	1.32	0.56	0.84	53	0.28	0.92	27	0.31	0.91	11	0.20	0.85	15	0.27	0.96
	15	00.00	1.00	0.34	0.64	37	0.40	0.89	21	0.38	0.92	8	0.44	0.87	8	0.41	0.86

Table 7.10 Performance of developed ANN model (Hydraulic conductivity data is removed)

	Well No.	Distance from coastline (m)	Max Water Level (m)	Min Water Level (m)	Mean Water Level (m)	Total Data set			Training data set			Validation data set			Testing data set		
						Number of data	RMSE	R	Number of data	RMSE	R	Number of data	RMSE	R	Number of data	RMSE	R
Kings Beach	-	-	-	-	-	1104	0.12	0.93	671	0.12	0.93	217	0.11	0.94	216	0.11	0.94
Eagers Beach	-	-	-	-	-	805	0.10	0.98	494	0.10	0.98	156	0.09	0.98	155	0.10	0.98
Shelley Beach	-	-	-	-	-	717	0.15	0.98	421	0.14	0.98	146	0.17	0.97	150	0.15	0.98
Brunswick Beach	-	-	-	-	-	624	0.10	0.96	347	0.10	0.95	135	0.12	0.96	142	0.11	0.97
Bribie Island	-	-	-	-	-	1019	0.09	0.90	630	0.09	0.89	199	0.09	0.89	190	0.08	0.91
Kings Beach	1	48.39	0.09	-0.06	0.02	84	0.06	-0.10	53	0.06	-0.08	17	0.05	-0.14	14	0.06	-0.12
	2	38.54	0.15	-0.08	0.04	79	0.07	0.14	43	0.07	0.18	18	0.07	0.16	18	0.08	-0.06
	3	33.54	0.18	-0.11	0.04	81	0.09	0.28	47	0.09	0.34	10	0.10	-0.08	24	0.09	0.27
	4	28.52	0.25	-0.15	0.06	79	0.12	0.40	46	0.12	0.40	21	0.12	0.37	12	0.12	0.40
	5	23.46	0.40	-0.24	0.05	84	0.16	0.62	58	0.17	0.56	13	0.13	0.77	13	0.13	0.76
	6	21.51	0.53	-0.26	0.11	43	0.18	0.70	27	0.17	0.64	8	0.16	0.81	8	0.24	0.84
	7	19.53	0.59	-0.29	0.11	84	0.19	0.82	56	0.20	0.79	12	0.17	0.83	16	0.20	0.94
	8	17.53	0.54	-0.33	0.02	58	0.18	0.84	39	0.18	0.82	9	0.22	0.72	10	0.13	0.98
	9	15.53	0.45	-0.38	0.04	84	0.13	0.90	51	0.13	0.91	15	0.16	0.87	18	0.12	0.93
	10	13.53	0.39	-0.42	-0.03	84	0.09	0.94	48	0.10	0.93	20	0.08	0.96	16	0.09	0.95
	11	11.58	0.10	-0.46	-0.24	55	0.09	0.87	34	0.09	0.88	11	0.09	0.87	10	0.10	0.83
	12	09.62	-0.08	-0.53	-0.36	31	0.09	0.81	15	0.09	0.80	9	0.08	0.83	7	0.10	0.83
	13	07.64	0.29	-0.59	-0.20	84	0.07	1.00	50	0.07	0.99	18	0.07	1.00	16	0.07	1.00
	14	05.59	0.28	-0.68	-0.36	64	0.05	0.99	39	0.05	1.00	11	0.04	0.98	14	0.06	1.00
	15	03.44	0.14	-0.78	-0.48	61	0.03	1.00	39	0.03	1.00	15	0.04	0.99	7	0.02	1.00
	16	00.00	-0.05	-1.06	-0.73	49	0.08	0.98	26	0.08	0.98	10	0.08	0.99	13	0.09	0.99
Eagers Beach	1	96.75	8.16	8.06	8.11	55	0.05	-0.10	34	0.05	-0.10	11	0.06	-0.24	10	0.06	-0.16
	2	86.99	8.09	7.93	8.00	55	0.07	-0.02	35	0.06	0.02	9	0.07	-0.02	11	0.07	-0.13
	3	77.10	8.03	7.76	7.87	55	0.09	0.02	35	0.10	0.05	15	0.08	-0.19	5	0.12	0.27
	4	67.10	8.06	7.57	7.75	55	0.15	0.34	30	0.15	0.34	11	0.13	0.16	14	0.15	0.45
	5	61.99	8.13	7.47	7.68	55	0.16	0.61	40	0.16	0.58	6	0.16	0.57	9	0.19	0.80
	6	57.98	8.00	7.37	7.60	55	0.14	0.78	29	0.13	0.78	14	0.15	0.65	12	0.12	0.89
	7	54.06	7.81	7.28	7.49	55	0.09	0.87	29	0.10	0.86	7	0.07	0.89	19	0.08	0.90
	8	50.07	7.73	7.21	7.40	55	0.08	0.92	29	0.08	0.91	15	0.07	0.95	11	0.08	0.94
	9	45.81	7.73	7.10	7.28	55	0.08	0.94	35	0.08	0.94	14	0.09	0.93	6	0.08	0.94
	10	41.24	7.68	7.00	7.17	52	0.07	0.94	32	0.07	0.95	9	0.08	0.92	11	0.07	0.96
	11	37.61	7.64	6.93	7.09	51	0.08	0.95	32	0.08	0.94	9	0.05	0.97	10	0.08	0.95
	12	33.08	7.58	6.83	6.98	48	0.08	0.95	35	0.09	0.95	6	0.08	0.97	7	0.04	0.88
	13	28.02	7.57	6.71	6.90	48	0.10	0.95	29	0.13	0.96	11	0.06	0.95	8	0.06	0.94
	14	20.93	7.54	6.59	6.75	41	0.12	0.92	23	0.15	0.93	9	0.05	0.96	9	0.05	0.90
	15	10.00	7.20	6.33	6.55	37	0.09	0.94	22	0.06	0.97	7	0.06	0.97	8	0.14	0.92
	16	00.00	6.86	6.09	6.38	33	0.03	0.99	25	0.03	0.99	3	0.03	1.00	5	0.03	0.99
Shelley Beach	1	42.46	5.81	5.64	5.72	48	0.07	0.29	30	0.08	0.02	9	0.06	0.57	9	0.06	0.58
	2	38.74	5.89	5.46	5.65	73	0.13	0.44	41	0.10	0.57	17	0.10	0.70	15	0.19	0.15
	3	33.96	6.09	5.37	5.64	73	0.15	0.69	46	0.14	0.75	14	0.18	0.33	13	0.15	0.78
	4	28.55	6.15	5.11	5.51	79	0.18	0.81	46	0.17	0.86	19	0.21	0.77	14	0.17	0.63
	5	23.67	5.83	4.87	5.29	79	0.17	0.80	41	0.19	0.77	14	0.16	0.64	24	0.13	0.89
	6	20.54	5.50	4.71	5.10	79	0.17	0.70	48	0.15	0.76	18	0.24	0.49	13	0.09	0.87

	7	16.92	5.19	4.57	4.87	69	0.16	0.43	37	0.17	0.46	12	0.15	0.44	20	0.16	0.33
	8	13.57	4.95	4.33	4.56	48	0.12	0.70	28	0.12	0.73	11	0.06	0.81	9	0.18	0.80
	9	10.01	4.47	4.05	4.24	62	0.09	0.68	41	0.08	0.69	13	0.10	0.40	8	0.08	0.73
	10	06.87	4.21	3.76	3.97	49	0.06	0.88	30	0.06	0.92	9	0.07	0.80	10	0.07	0.86
	11	03.22	3.97	3.35	3.53	36	0.21	0.45	20	0.18	0.59	7	0.25	0.19	9	0.23	0.34
	12	00.00	3.97	3.19	3.46	22	0.18	0.99	13	0.16	0.99	3	0.30	1.00	6	0.12	1.00
Brunswick Beach	1	99.00	1.10	0.95	1.03	50	0.07	0.32	26	0.07	0.32	10	0.09	0.22	14	0.07	0.38
	2	86.95	1.28	0.95	1.10	50	0.09	0.48	27	0.09	0.38	14	0.09	0.45	9	0.08	0.79
	3	75.77	1.57	0.89	1.12	50	0.15	0.74	27	0.16	0.78	15	0.14	0.62	8	0.18	0.71
	4	68.97	1.53	0.82	1.08	50	0.15	0.85	25	0.12	0.81	15	0.20	0.93	10	0.14	0.73
	5	65.85	1.44	0.78	1.04	50	0.14	0.89	27	0.15	0.91	10	0.15	0.90	13	0.11	0.82
	6	63.93	1.36	0.75	1.01	50	0.13	0.91	27	0.10	0.85	5	0.07	0.88	18	0.17	0.95
	7	61.89	1.28	0.85	1.12	7	0.15	0.90	2	0.14	1.00	3	0.17	0.97	2	0.14	1.00
	8	59.88	1.20	0.68	0.92	50	0.08	0.92	28	0.08	0.90	10	0.10	0.92	12	0.06	0.95
	9	57.85	1.14	0.82	1.03	7	0.10	0.86	2	0.09	1.00	4	0.10	0.90	1	0.08	1.00
	10	55.77	1.15	0.59	0.83	50	0.05	0.95	35	0.05	0.95	8	0.05	0.96	7	0.06	0.94
	11	53.75	0.99	0.80	0.90	7	0.05	0.88	4	0.04	0.88	1	0.09	1.00	2	0.05	1.00
	12	51.66	0.98	0.48	0.70	50	0.06	0.95	36	0.07	0.95	7	0.04	0.96	7	0.07	0.98
	13	49.47	0.97	0.36	0.62	46	0.06	0.94	27	0.07	0.94	10	0.06	0.83	9	0.06	0.96
	14	46.27	0.92	0.33	0.52	40	0.08	0.92	19	0.09	0.91	9	0.06	0.93	12	0.09	0.96
	15	35.62	0.77	0.03	0.21	42	0.10	0.87	23	0.10	0.87	11	0.11	0.82	8	0.11	0.90
	16	18.00	0.50	-0.42	-0.08	19	0.07	0.99	8	0.06	0.99	3	0.06	1.00	8	0.08	1.00
	17	00.00	0.49	-0.44	0.11	6	0.09	0.98	4	0.09	0.97	0	-	-	2	0.11	1.00
Bribie Island	1	90.40	1.07	1.01	1.04	17	0.16	-0.13	11	0.15	-0.08	2	0.14	-1.00	4	0.17	-0.16
	2	75.20	1.15	0.99	1.08	76	0.08	-0.21	51	0.08	-0.22	12	0.07	-0.22	13	0.08	-0.20
	3	68.50	1.20	0.99	1.10	76	0.06	0.10	46	0.06	0.18	15	0.06	-0.11	15	0.08	-0.05
	4	65.73	1.24	1.01	1.11	76	0.07	0.25	45	0.07	0.30	13	0.08	-0.09	18	0.05	0.28
	5	63.23	1.27	1.01	1.11	76	0.07	0.38	41	0.07	0.49	17	0.07	0.31	18	0.08	0.29
	6	60.84	1.33	1.01	1.13	76	0.08	0.49	48	0.08	0.51	11	0.08	0.49	17	0.06	0.49
	7	58.39	1.40	0.99	1.13	76	0.09	0.58	46	0.08	0.67	16	0.11	0.45	14	0.10	0.56
	8	55.90	1.55	0.99	1.16	76	0.11	0.68	49	0.12	0.69	13	0.10	0.75	14	0.08	0.63
	9	53.39	1.64	0.93	1.17	76	0.12	0.76	49	0.13	0.80	15	0.12	0.86	12	0.09	0.61
	10	50.85	1.60	0.95	1.17	76	0.10	0.87	47	0.11	0.85	19	0.09	0.94	10	0.10	0.47
	11	48.32	1.48	0.88	1.09	76	0.07	0.96	51	0.07	0.95	14	0.08	0.85	11	0.05	0.98
	12	38.50	1.45	0.77	1.01	76	0.05	0.98	42	0.05	0.98	24	0.05	0.98	10	0.06	0.91
	13	32.01	1.46	0.65	0.97	76	0.05	0.98	56	0.05	0.98	9	0.05	0.98	11	0.05	0.99
	14	21.20	1.32	0.56	0.84	53	0.09	0.92	27	0.10	0.91	11	0.09	0.86	15	0.09	0.96
	15	00.00	1.00	0.34	0.64	37	0.12	0.87	21	0.12	0.90	8	0.15	0.86	8	0.10	0.88

Table 7.11 Performance of developed ANN model (Beach slope data is removed)

	Well No.	Distance from coastline (m)	Max Water Level (m)	Min Water Level (m)	Mean Water Level (m)	Total Data set			Training data set			Validation data set			Testing data set		
						Number of data	RMSE	R	Number of data	RMSE	R	Number of data	RMSE	R	Number of data	RMSE	R
Kings Beach	-	-	-	-	-	1104	0.13	0.92	671	0.13	0.91	217	0.13	0.92	216	0.13	0.93
Eagers Beach	-	-	-	-	-	805	0.08	0.99	494	0.08	0.99	156	0.07	0.99	155	0.08	0.99
Shelley Beach	-	-	-	-	-	717	0.14	0.98	421	0.13	0.98	146	0.16	0.97	150	0.14	0.98
Brunswick Beach	-	-	-	-	-	624	0.11	0.96	347	0.10	0.95	135	0.11	0.96	142	0.11	0.96
Bribie Island	-	-	-	-	-	1019	0.10	0.88	630	0.10	0.88	199	0.10	0.88	190	0.10	0.89
Kings Beach	1	48.39	0.09	-0.06	0.02	84	0.18	-0.10	53	0.19	-0.06	17	0.19	-0.32	14	0.15	-0.01
	2	38.54	0.15	-0.08	0.04	79	0.11	0.00	43	0.12	-0.13	18	0.09	0.32	18	0.11	-0.07
	3	33.54	0.18	-0.11	0.04	81	0.11	0.21	47	0.10	0.32	10	0.12	-0.07	24	0.11	0.10
	4	28.52	0.25	-0.15	0.06	79	0.13	0.36	46	0.13	0.41	21	0.12	0.36	12	0.15	0.14
	5	23.46	0.40	-0.24	0.05	84	0.16	0.61	58	0.17	0.59	13	0.14	0.72	13	0.15	0.66
	6	21.51	0.53	-0.26	0.11	43	0.18	0.71	27	0.17	0.60	8	0.18	0.75	8	0.21	0.88
	7	19.53	0.59	-0.29	0.11	84	0.19	0.84	56	0.19	0.84	12	0.20	0.79	16	0.20	0.92
	8	17.53	0.54	-0.33	0.02	58	0.17	0.88	39	0.16	0.87	9	0.21	0.76	10	0.12	0.97
	9	15.53	0.45	-0.38	0.04	84	0.13	0.91	51	0.13	0.91	15	0.15	0.89	18	0.13	0.92
	10	13.53	0.39	-0.42	-0.03	84	0.10	0.94	48	0.10	0.93	20	0.08	0.96	16	0.09	0.95
	11	11.58	0.10	-0.46	-0.24	55	0.09	0.87	34	0.08	0.88	11	0.08	0.88	10	0.10	0.83
	12	09.62	-0.08	-0.53	-0.36	31	0.09	0.80	15	0.08	0.81	9	0.07	0.83	7	0.11	0.78
	13	07.64	0.29	-0.59	-0.20	84	0.07	1.00	50	0.06	0.99	18	0.07	1.00	16	0.07	1.00
	14	05.59	0.28	-0.68	-0.36	64	0.04	0.99	39	0.04	1.00	11	0.04	0.99	14	0.05	1.00
	15	03.44	0.14	-0.78	-0.48	61	0.04	1.00	39	0.04	1.00	15	0.04	0.99	7	0.02	1.00
	16	00.00	-0.05	-1.06	-0.73	49	0.12	0.99	26	0.12	0.99	10	0.12	1.00	13	0.13	0.99
Eagers Beach	1	96.75	8.16	8.06	8.11	55	0.07	-0.19	34	0.07	-0.25	11	0.08	-0.26	10	0.07	-0.15
	2	86.99	8.09	7.93	8.00	55	0.07	0.09	35	0.07	0.11	9	0.07	0.30	11	0.08	-0.26
	3	77.10	8.03	7.76	7.87	55	0.09	0.11	35	0.09	0.08	15	0.06	0.48	5	0.14	-0.48
	4	67.10	8.06	7.57	7.75	55	0.13	0.46	30	0.14	0.41	11	0.12	0.56	14	0.13	0.64
	5	61.99	8.13	7.47	7.68	55	0.13	0.77	40	0.12	0.74	6	0.16	0.58	9	0.11	0.90
	6	57.98	8.00	7.37	7.60	55	0.11	0.88	29	0.11	0.88	14	0.11	0.84	12	0.10	0.92
	7	54.06	7.81	7.28	7.49	55	0.08	0.88	29	0.08	0.90	7	0.08	0.86	19	0.09	0.89
	8	50.07	7.73	7.21	7.40	55	0.06	0.93	29	0.06	0.93	15	0.06	0.94	11	0.07	0.92
	9	45.81	7.73	7.10	7.28	55	0.04	0.98	35	0.04	0.99	14	0.04	0.98	6	0.03	0.98
	10	41.24	7.68	7.00	7.17	52	0.04	0.99	32	0.04	1.00	9	0.03	0.99	11	0.04	0.99
	11	37.61	7.64	6.93	7.09	51	0.03	0.99	32	0.03	0.99	9	0.03	1.00	10	0.04	0.99
	12	33.08	7.58	6.83	6.98	48	0.04	0.99	35	0.04	0.99	6	0.04	1.00	7	0.04	0.87
	13	28.02	7.57	6.71	6.90	48	0.04	0.99	29	0.04	0.99	11	0.03	0.99	8	0.04	0.98
	14	20.93	7.54	6.59	6.75	41	0.05	0.99	23	0.05	0.99	9	0.03	0.99	9	0.06	0.95
	15	10.00	7.20	6.33	6.55	37	0.06	0.99	22	0.06	0.99	7	0.06	0.99	8	0.08	0.99
	16	00.00	6.86	6.09	6.38	33	0.03	1.00	25	0.03	1.00	3	0.04	1.00	5	0.02	1.00
Shelley Beach	1	42.46	5.81	5.64	5.72	48	0.09	0.20	30	0.09	-0.16	9	0.06	0.69	9	0.09	0.44
	2	38.74	5.89	5.46	5.65	73	0.13	0.50	41	0.10	0.64	17	0.08	0.79	15	0.21	0.15
	3	33.96	6.09	5.37	5.64	73	0.14	0.73	46	0.13	0.79	14	0.18	0.33	13	0.13	0.83
	4	28.55	6.15	5.11	5.51	79	0.17	0.85	46	0.16	0.88	19	0.20	0.80	14	0.16	0.69
	5	23.67	5.83	4.87	5.29	79	0.17	0.82	41	0.19	0.80	14	0.15	0.67	24	0.13	0.90
	6	20.54	5.50	4.71	5.10	79	0.16	0.74	48	0.15	0.78	18	0.22	0.58	13	0.08	0.91

	7	16.92	5.19	4.57	4.87	69	0.15	0.52	37	0.15	0.57	12	0.15	0.49	20	0.15	0.40
	8	13.57	4.95	4.33	4.56	48	0.13	0.67	28	0.13	0.68	11	0.08	0.78	9	0.17	0.81
	9	10.01	4.47	4.05	4.24	62	0.09	0.67	41	0.09	0.68	13	0.10	0.36	8	0.09	0.69
	10	06.87	4.21	3.76	3.97	49	0.06	0.90	30	0.06	0.92	9	0.06	0.83	10	0.07	0.87
	11	03.22	3.97	3.35	3.53	36	0.21	0.46	20	0.18	0.59	7	0.25	0.19	9	0.24	0.35
	12	00.00	3.97	3.19	3.46	22	0.13	0.99	13	0.12	0.98	3	0.23	1.00	6	0.07	0.99
Brunswick Beach	1	99.00	1.10	0.95	1.03	50	0.05	0.39	26	0.05	0.39	10	0.06	0.35	14	0.05	0.44
	2	86.95	1.28	0.95	1.10	50	0.09	0.53	27	0.09	0.45	14	0.09	0.47	9	0.08	0.75
	3	75.77	1.57	0.89	1.12	50	0.16	0.60	27	0.17	0.61	15	0.14	0.61	8	0.18	0.66
	4	68.97	1.53	0.82	1.08	50	0.15	0.73	25	0.13	0.69	15	0.19	0.83	10	0.12	0.67
	5	65.85	1.44	0.78	1.04	50	0.13	0.83	27	0.14	0.85	10	0.13	0.85	13	0.10	0.79
	6	63.93	1.36	0.75	1.01	50	0.10	0.89	27	0.08	0.83	5	0.05	0.88	18	0.14	0.94
	7	61.89	1.28	0.85	1.12	7	0.12	0.92	2	0.12	1.00	3	0.13	0.96	2	0.10	1.00
	8	59.88	1.20	0.68	0.92	50	0.07	0.93	28	0.07	0.91	10	0.08	0.92	12	0.06	0.95
	9	57.85	1.14	0.82	1.03	7	0.09	0.87	2	0.05	1.00	4	0.11	0.89	1	0.03	1.00
	10	55.77	1.15	0.59	0.83	50	0.07	0.96	35	0.07	0.96	8	0.07	0.96	7	0.05	0.93
	11	53.75	0.99	0.80	0.90	7	0.09	0.88	4	0.07	0.87	1	0.13	1.00	2	0.09	1.00
	12	51.66	0.98	0.48	0.70	50	0.09	0.95	36	0.09	0.96	7	0.06	0.96	7	0.09	0.98
	13	49.47	0.97	0.36	0.62	46	0.08	0.94	27	0.08	0.95	10	0.08	0.82	9	0.08	0.94
	14	46.27	0.92	0.33	0.52	40	0.09	0.94	19	0.09	0.92	9	0.06	0.96	12	0.11	0.97
	15	35.62	0.77	0.03	0.21	42	0.08	0.92	23	0.08	0.92	11	0.09	0.87	8	0.09	0.96
	16	18.00	0.50	-0.42	-0.08	19	0.16	0.97	8	0.15	0.97	3	0.14	1.00	8	0.17	0.99
	17	00.00	0.49	-0.44	0.11	6	0.13	0.98	4	0.14	0.98	0	-	-	2	0.12	1.00
Bribie Island	1	90.40	1.07	1.01	1.04	17	0.10	-0.15	11	0.10	-0.09	2	0.09	-1.00	4	0.11	-0.20
	2	75.20	1.15	0.99	1.08	76	0.04	0.17	51	0.04	0.18	12	0.03	0.14	13	0.04	0.16
	3	68.50	1.20	0.99	1.10	76	0.05	-0.03	46	0.05	0.09	15	0.05	-0.37	15	0.06	-0.12
	4	65.73	1.24	1.01	1.11	76	0.06	0.16	45	0.07	0.22	13	0.07	-0.16	18	0.06	0.15
	5	63.23	1.27	1.01	1.11	76	0.08	0.30	41	0.07	0.34	17	0.07	0.26	18	0.08	0.29
	6	60.84	1.33	1.01	1.13	76	0.09	0.42	48	0.09	0.43	11	0.10	0.39	17	0.07	0.42
	7	58.39	1.40	0.99	1.13	76	0.11	0.51	46	0.10	0.60	16	0.13	0.42	14	0.11	0.54
	8	55.90	1.55	0.99	1.16	76	0.12	0.62	49	0.13	0.62	13	0.10	0.69	14	0.11	0.61
	9	53.39	1.64	0.93	1.17	76	0.13	0.71	49	0.13	0.76	15	0.13	0.78	12	0.13	0.60
	10	50.85	1.60	0.95	1.17	76	0.11	0.82	47	0.12	0.80	19	0.09	0.91	10	0.11	0.47
	11	48.32	1.48	0.88	1.09	76	0.07	0.94	51	0.07	0.94	14	0.08	0.84	11	0.05	0.97
	12	38.50	1.45	0.77	1.01	76	0.08	0.96	42	0.08	0.96	24	0.08	0.95	10	0.09	0.91
	13	32.01	1.46	0.65	0.97	76	0.09	0.98	56	0.08	0.98	9	0.10	0.97	11	0.09	0.98
	14	21.20	1.32	0.56	0.84	53	0.15	0.92	27	0.13	0.91	11	0.16	0.84	15	0.15	0.95
	15	00.00	1.00	0.34	0.64	37	0.14	0.89	21	0.14	0.92	8	0.17	0.87	8	0.12	0.86