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DEVELOPMENT OF GROUNDWATER LEVEL MODEL USING ARTIFICIAL INTELLIGENCE APPROACH

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Development of Groundwater Level Model Using Artificial Intelligence Approach

وبعد المناقشة العلنية التي تمت اليوم الأربعاء 14 شعبان 1433هـ، الموافق 2012/07/04م الساعة الواحدة والنصف ظهرًا بمبنى طيبة، اجتمعت لجنة الحكم على الأطروحة والمكونة من:

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واللجنة إذ تمنحه هذه الدرجة فإنها توصيه بتقوى الله ولزوم طاعته وأن يسخر علمه في خدمة دينه ووطنه.

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(وَأَنزَلْنَا مِنَ السَّمَاءِ مَاءً بِقَدَرٍ فَأَسْكَنَّاهُ فِي الْأَرْضِ وَإِنَّا عَلَى ذَهَابٍ بِهِ لَقَادِرُونَ)

(المؤمنون/18)

قال تعالى:

(قُلْ أَرَأَيْتُمْ إِنْ أَصْبَحَ مَاؤُكُمْ غَوْرًا فَمَنْ يَأْتِيكُمْ بِمَاءٍ مَعِينٍ)

(الملك/30)

ABSTRACT

Water is a vital source supporting all forms of developments all over the world. In Gaza Strip (GS), Gaza coastal aquifer (GCA) is the most precious natural source where it is the only source of water for different uses. Groundwater crisis in Gaza includes two major folds: shortage of water supply and contamination. The extraction of groundwater currently exceeds the aquifer recharge rate. As a result, the Groundwater level (GWL) is falling continuously and by contamination of many pollutants mainly nitrate and salinity. Therefore, one important requirement for effective management of groundwater is forecasting the GWL fluctuations.

The undertaken research is concerned with the development of GWL model using one of Artificial Intelligence techniques namely Artificial Neural Networks (ANNs).The applicability of ANNs models in simulating groundwater level was investigated in Khanyounis Governorate (KYG). ANNs are being used increasingly as alternative tools to physical based groundwater modeling approaches to predict and forecast water resources variables in complex groundwater systems with limited data as the case of GCA.

In order to model GWL using ANNs it is necessary to gather data for training purposes. Physically, the GWL influenced by many variables such as: recharge from different sources, abstraction, precipitation, return flow. In this study, dependent variable used in the developed ANNs model were the initial (GWL), recharge from rainfall (R), recharge from return flow from water networks system (RRFW), recharge from return flow from wastewater system (RRFWW), recharge from return flow from irrigation water (RRFIW), abstraction from municipal wells (QM), abstraction from agricultural wells (QA). The aforementioned input variables were used to predict the final (GWL) at 17 monitoring wells which distributed over all study area.

After a number of trials, the best neural network was determined to be Radial Basis Function networks with three layers: an input layer of 7 neurons, one hidden layer with 9 neurons and the output layer with 1 neuron. The developed model generated very good results which were clearly appeared through high correlation between the observed and predicted values of GWL. The correlation coefficient (r) between the predicted and the observed output values of the ANNs model was 0.993. The high value of r showed that the simulated GWL values using the ANNs model were in very good agreement with the observed GWL which means that ANNs model is a useful and applicable.

The developed model was utilized as an analytical tool to study influence of the input variables on GWL. It was utilized as simulation and prediction tool of GWL in monitoring wells in KYG. Moreover, ANNs model was utilized as decision support tool by considering two future scenarios based on management of overall abstraction from the aquifer. Two selected management scenarios were tested; (1) work as usual (zero scenario), (2) reduction of overall abstraction by 50%. In the first scenario, the GWL in the cone of depression area will be expected to decrease from -15 m below MSL at year 2015 to -24 m below MSL at year 2025. In addition, it was noticed that seawater intrusion phenomena will increase and its impact will cover more than 60% of total area of KYG in year 2025. For the second scenario, the GWL in the cone of depression area will be expected to increase from -8 m below MSL at year 2015 to -3 m below MSL at year 2025. It was noticed that the effect of seawater intrusion will be reduced where the influenced area will be 25 % of total area of KYG in year 2025. Thus, this study has shown that ANNs are effective tools in forecasting GWL fluctuations in the GCA in spite of GWL model is very difficult since it is affected by many interconnected variables.

الخلاصة

تعتبر المياه مصدر حيوي هام لجميع أشكال التطور في العالم، يعد خزان المياه الجوفي في قطاع غزة أهم مصدر مياه طبيعي بل يعتبر المصدر الوحيد للمياه المستخدمة لعدة أغراض. تعاني المياه الجوفية في قطاع غزة من مشكلتين وهما: شح المياه وتلوثها، و في الوقت الحالي ، يفوق معدل السحب من الخزان الجوفي معدل التغذية ، الأمر الذي يؤدي إلى انحدار مستوى مخزون المياه الجوفية إضافة إلى تلوثها بالملوثات مثل: النترات والملوحة. لذا يستحسن أن يكون هناك رصد ومتابعة للتغيرات التي تحدث في مستوى المياه الجوفية لضمان الإدارة الفعالة للخزان الجوفي.

يقدم هذا البحث نموذجاً مطوراً للتنبؤ بمستوى المياه الجوفية باستخدام إحدى تقنيات الذكاء الاصطناعي وهي "الشبكات العصبية الاصطناعية". وتم تطبيق هذه الدراسة على محافظة خانيونس لمحاكاة مستوى المياه الجوفية. حيث يجري استخدام الشبكات العصبية الاصطناعية بصورة متزايدة كأداة بديلة للنماذج المستندة على الأساس الفيزيائي للتنبؤ بمتغيرات مصادر المياه في أنظمة المياه الجوفية المعقدة والمحدودة البيانات كما في حالة خزان المياه الجوفية في غزة. إن نمذجة مستوى المياه الجوفية باستخدام الشبكات العصبية الاصطناعية تتطلب جمع البيانات اللازمة لعملية التدريب التي تقوم بها الشبكة العصبية، حيث يتأثر مستوى المياه الجوفية بعدة متغيرات طبيعية مثل: التغذية من مصادر مختلفة، السحب، الترسيب، التغذية من المياه العائدة.

تمت عملية النمذجة باستخدام المتغيرات التالية وهي: مستوى المياه الجوفية الابتدائي، التغذية من مياه الأمطار، التغذية من المياه العائدة من شبكات المياه، التغذية من المياه العائدة من أنظمة الصرف الصحي، التغذية من المياه العائدة من مياه الري، سحب المياه من آبار البلدية، و سحب المياه من الآبار الزراعية، وقد تم استخدام هذه المتغيرات في التنبؤ بمستوى المياه الجوفية النهائي في (17) بئر للمراقبة موزعة على منطقة الدراسة.

وبعد إجراء عدة محاولات، تبين أن أفضل شبكة عصبية هي "Radial Basis Function networks" والمكونة من ثلاث طبقات وهي: طبقة المدخلات ويوجد بها عدد (7 نيورون)، والطبقة المخفية و بها عدد (9 نيورون)، وطبقة المخرجات و بها عدد (1 نيورون). وقد أعطت الشبكة العصبية نتائج ممتازة اعتماداً على التقارب الكبير بين القيم الحقيقية والقيم المستخرجة حيث بلغت قيمة معامل الارتباط (0.993) وهذا يعني توافق كبير بين القيم الحقيقية والقيم المستخرجة من النموذج مما يجعله صالحاً للاستخدام والتطبيق.

وقد تم استخدام هذا النموذج كأداة تحليلية لدراسة تأثير المتغيرات المدخلة على مستوى المياه الجوفية و كأداة لتنبؤ و محاكاة مستوى المياه الجوفية لآبار المراقبة في محافظة خانيونس، وأيضا كأداة لدعم اتخاذ القرار من خلال سيناريوهين لإدارة عملية السحب من الخزان الجوفي. وقد تم اختبارهما: الأول بالاستمرار في الوضع القائم والثاني بتقليل السحب بما نسبته (50%).

وقد بين السيناريو الأول أنه يتوقع أن يزيد الاستنزاف في المنطقة الأكثر هبوطاً في مستوى المياه الجوفية من (-15 متر عام 2015 إلى - 24 متر في عام 2025) تحت مستوى سطح البحر. وقد لوحظ أن ظاهرة تداخل ماء البحر مع المياه الجوفية ستزداد وستغطي ما مساحته (60%) من المساحة الإجمالية لمحافظة خانيونس في عام 2025. أما بالنسبة للسيناريو الثاني، فيتوقع أن يقل الاستنزاف في المنطقة الأكثر هبوطاً في مستوى المياه الجوفية من(- 8 متر في عام 2015 إلى - 3 متر في عام 2025) تحت مستوى سطح البحر. وقد لوحظ أن تأثير ظاهرة تداخل ماء البحر مع المياه الجوفية ستقل وستغطي ما مساحته (25%) من المساحة الإجمالية لمحافظة خانيونس في عام 2025.

وبهذا أثبتت الدراسة أن تقنية الشبكات العصبية الاصطناعية هي وسيلة فعالة في التنبؤ بمستوى المياه الجوفية في الخزان الجوفي لقطاع غزة وذلك على الرغم من أن نمذجة مستوى المياه الجوفية يصعب لتأثره بعدة متغيرات متداخلة.

Dedication

This research is dedicated to:

The memory of my father, may Allah grant him mercy…

My mother for her love, pray, and continuous sacrifices…

My beloved wife for her support and encouragement…

My lovely daughter (Dana)…

To all of my brothers and sisters…

To all of my friends and colleagues…

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First, all praises and glory are due to **ALLAH** for all the bounty and support granted to me. This work would not be done without God's endless guidance and support.

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Next, I wish to express my unreserved gratitude to my friend, **Eng. Jawad Alagha**, for his help. His constructive criticisms and ideas have made this research worth reading. It is worth mentioning that Eng. Jawad is a PhD candidates in Universiti Sains Malaysia, the PhD research conducted with a title "Development of Water Resources Management Model Using ANNs and SVMs Case Study – KYG – GS – Palestine".

I will also like to extend my sincere appreciation to **Dr. Mohammed Arafa and Dr. Mamoun Alqedra** since they give me first knowledge about ANNs during Bachelors studying.

I would like to extend my sincere gratitude and appreciation to my mother, brothers, sisters and my wife who gave me love, moral support, and motivation.

I would like to express my grateful appreciation and thanks to everyone who gave me support to bring this research into reality, specially **Dr. Mazen abu Alteaf, Eng. Mohammed Seyam, Eng. Wesam Alashqer, Eng. Mohammed Alhessi, Mr. Bassam abu Dagaa, Mr. Medhat abu Alnaeem.**

Also, I could not forget the role of my colleagues in Ministry of Public Works and Housing for their help and encouragement.

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List of Acronyms and Abbreviations

ANNs	Artificial Neural Networks
BP	Back Propagation
CAMP	Coastal Aquifer Management Plan
CMWU	Coastal Municipalities Water Utility
FFN	Feed forward Neural Network
GA	Genetic Algorithms
GCA	Gaza Coastal Aquifer
GIS	Geographic Information Systems
GRBF	Generalized Radial Basis Function
GS	Gaza Strip
GWL	Groundwater level
IDNN	Input Delay Neural Network
KYG	Khanyounis Governorate
Max	Maximum
MCM	Million Cubic Meter
Min	Minimum
MLP	Multilayer Percepton
MoA	Ministry of Agriculture
MOA	The Ministry of Agriculture
MoP	Ministry of Planning
MSL	Mean Sea Level
PNN	Probabilistic Neural Network
PWA	Palestinian Water Authority
QA	Abstraction from Agriculture wells
QM	Abstraction from Municipal wells
R	Recharge from Rainfall
RBF	Radial Basis Function
RNN	Recurrent Neural Network
RRFIW	Recharge from Return Flow from Irrigation Water
RRFW	Recharge from Return Flow from Water networks
RRFWW	Recharge from Return Flow from Wastewater networks
SVM	Support Vector Machine
WHO	World Health Organization

Chapter (1)

Introduction

1.1. General Background:

Groundwater is one of the most precious natural resources in the Gaza Strip (GS), as it is the only source of drinking water for the majority of the population to meet domestic, industrial, and agricultural needs (Shomar et al.,2005). It is utilized extensively to satisfy agricultural, domestic, and industrial water demands. Groundwater crisis in Gaza includes two major folds: shortage and contamination. The extraction of groundwater currently exceeds the aquifer recharge rate. As a result, the Groundwater level (GWL) is falling continuously and accompanied with it the contamination with many pollutants mainly nitrate and salinity (UNEP, 2003; Weinthal and Vengosh, 2005; Qahman and Larabi, 2006).

For the effective management of groundwater, it is important to predict GWL fluctuations. Thus, there have been many researches on developing GWL prediction models (Alnahhal et al.,2010).GWL can be influenced by many factors, including precipitation, abstraction, lateral flow and intrusion or upconing of brackish or saline water, and return flow from irrigation, wastewater, or urban stormwater (Water Data Banks Project, 2005).The prediction of GWL in a well based on continuous monitoring of selected nearby wells is of an immense importance in the management of groundwater resources (Coulibaly et al., 2001). Two approaches have evolved over the last few decades for hydrological forecasts these include physical and data driven approaches. The first approach is the physically-based models which try to explain the underlying processes, but these approach requires a large quantity of good quality data, sophisticated programs for calibration and a detailed understanding of the underlying physical process. Moreover, complexity and data uncertainty of groundwater systems mostly limit physical-based modeling accuracy of simulation.

The second approach is the data driven approach which model the data rather than the physical process. The main advantage of this approach over physically-based models is that it does not require understanding of the complex nature of the underlying process under consideration to be explicitly described in mathematical form which makes this approach an attractive tool for modeling water table fluctuations (Yoonet et. al.,2010; Coulibaly et al., 2001). Statistical models andArtificial intelligence models such as artificial neural networks(ANNs), support vector machines (SVMs) and genetic algorithms (GA)are considered as data driven models which have the potential to be an effective groundwater modeling tool.

1.2. Problem statement

Gaza coastal aquifer (GCA) is the main source of water for supplying agriculture, domestic, and industrial purposes in GS. According to Ministry of Planning (MoP) report (2010), the Palestinian consumption from the groundwater resources in the GS is about 170 MCM per year and the return water to GCA is equal to 120 MCM per year, so the deficit equal to 50 MCM per year (MoP, 2010). The overdraft in year 2008 estimated at 100 MCM. As a result, there has been a continual decline in the static water level, water quality has been deteriorating, and there is an increase of seawater intrusion. Currently, only 5-10% of the portion of the aquifer underlying Gaza is drinkable, with more than 90% of all 150 municipal wells having salt and nitrate levels above WHO standards and so unfit for human consumption (World bank, 2009) . Thus, the rapid increase on water demand to fulfill the needs of the continuous population growth made the aquifer overexploited, leading to huge crises of water scarcity, seawater intrusion and over-pumping rate. The GWL dropped by as much as 14 meters between 1990 and 2008 in the southern area of the GS (MoP, 2010). This drop is continuous apparent in the GCA until now.

The aforementioned condition affect on GWL inversely, leading to large water table fluctuation in GCA. Monitoring and forecasting the GWL can contribute in an integration of water resources management. So modeling the GWL by ANNs, which is considered as non conventional approaches which provide an easy and efficient tool for prediction and forecasting that help in water resources management.

1.3. Objectives

The main aim of this research is to **provide the decision makers in the field of water resources management with groundwater model based on ANNs applications as an alternative tool for monitoring and forecasting of GWL in Khanyounis Governorate (KYG).**

To be more specific, the objectives of this research are:

- To develop ANNs model studying the relation between GWL (represented by GWL in observation well) and some hydrological variables as: abstraction, recharge rate, rainfall, return flow from agriculture and water networks, and others.
- To predict GWL in future depending various scenarios of future abstraction of ground water and other hydrological and metrological variables .
- To suggest some remedial measures and rational solutions to minimize the groundwater deterioration gradually in Gaze Strip.
- To compare the performance between ANNs and physical models such as MODFLOW model.

1.4. Justification for study area selection

- The study area of this research is KYG, which is the governorate that has largest area among GS five governorates with a total area of 112 km^2.
- KYG was expected to be the second regional center in GS based on regional plan conducted by MOP in year 2007 (MoP, 2007).
- KYG has the most serious situation in relation to groundwater problems. The highest nitrate level in GS was recorded in Khanyounis with the average concentrations of 191 mg/L. The highest chloride concentrations in GS was recorded in Khanyounis with the concentration of 2652 mg/L (Shomar et al. 2008).
- KYG has the largest agricultural activities relatively among GS five governorates. Thus, groundwater is affected by agricultural activities in order to meet agricultural water demand.

- Three years ago, it is witnessed that KYG municipalities drilled more than 17 wells in randomly way to meet water needs which is negatively affected the groundwater storage.
- The core of declination of GWL has the maximum value in the middle of the southern Governorate. That is reflecting the intensive pumping from both municipal wells and agricultural wells and its un balance with the total renewable amount of the aquifer (PWA,2007) .
- The availability of data play an important role in study area selection.
- This research is a part of PhD research currently conducted in Universiti Sains Malaysia with title "Development of Water Resources Management Model Using ANNs and SVMs Case Study – KYG– GS – Palestine".

1.5. Methodology

It is intended to achieve the objectives of the study by the following steps:

a. Literature review

Revision of accessible references as books, studies and researches relative to the topic of this research which may include ANNs, ground water hydrology, GWL on GS .

b. Data collection

Data gathering from relevant institution and ministries that includes details and time series data about different influenced parameters.

c. Data analysis

The data is analyzed using various software such as Microsoft Excel, GIS (ArcView GIS 10.1) and ERDASE 2011. The analysis is required to construct some hundreds of data cases of input and output variables. Data cases are considered as row material to ANNs model.

d. Building a model

Construction ANNs model utilization STATISTICA Neural Networks (SNN) which built in STATISTICA program version 7. This step includes training, validation and testing ANNs model. The validation and testing is achieved using SNN directly after training process.

e. Parametric study

Parametric study means applying the ANNs model to evaluate the degree of effect of each variable on GWL, and interpret the influence of the various combinations of hydrological variables on GWL.

f. Utilization of prediction model

The ANNs model will be utilized to predict GWL in future and considering different logic and possible solutions to minimize the groundwater deterioration gradually.

1.6. Thesis Outline

The thesis is composed of the following six chapters that cover the proposed subject as illustrated below:

1. **Chapter One (Introduction):** chapter one include a general background about GWL and ANNs follows by statement of the problem, objectives, methodology used in order to achieve the objectives and thesis outline.
2. **Chapter Two (Literature Review):** chapter two covers a general literature review on GWL including factors affecting in GWL, then it talks about groundwater modeling approaches in general and some application of groundwater modeling in GS. Furthermore, chapter two presents a general literature review on ANNs including brief introduction to ANNs, architectures of ANNs, types of ANNs and the weakness and strengthen point in ANNs. Finally it discusses some ANNs applications in GWL modeling .
3. **Chapter Three (Study Area):** chapter three describes the study area with respect to its location, population, topography, climate and rainfall, land use geology and hydrology.
4. **Chapter Four (Methodology):** chapter four discuses the methodology of study including data collection, data analysis and preparation, construction data matrix for ANNs model and procedural steps in building ANNs model.
5. **Chapter Five (Results and Discussion):** chapter five presents characters of initial and final ANNs Model including topology, performance, regression statistics, response presentations, sensitivity analysis of ANNs. Then it presents application of ANNs model including utilization ANNs model as analytical tool to study the influence of the input variables on GWL, utilization ANNs model as simulation and prediction tool of GWL on monitoring wells in study area and utilization it as a decision making support tool.
6. **Chapter Six (Conclusions and Recommendations):** chapter six presents the main conclusions and recommendations of study.

Chapter (2)

Literature Review

2.1. Introduction

In many countries, especially in arid and semi arid regions as GS, groundwater is one of the major water resources for domestic and agricultural uses. Aquifers and the contained groundwater are inherently susceptible to pollution from many sources (Abyaneh, 2005).

Recently, the rapid increase on water demand to fulfill the needs of the continuous population growth made the aquifer overexploited, leading to huge crises of water scarcity and seawater intrusion. For effective management of groundwater, it is important to predict GWL fluctuations (Alnahhal et. al., 2010).

2.2. Aquifer GWL:

Aquifer GWL, whether it be the water table of an unconfined aquifer or the piezometric surface of a confined aquifer, indicates the elevation of atmospheric pressure of the aquifer. Any phenomenon that produces a change in pressure on ground water will cause the GWL to vary. Differences between supply and withdrawal of ground water cause levels to fluctuate (Todd and Mays, 2005). Superimposed on natural, climate-related fluctuations in ground-water levels are the effects of human activities that alter the natural rates of ground-water recharge or discharge (Taylor and Alley, 2001)).

As mentioned above, GWL change for many reasons. Some changes are due to natural factors, and others are caused by human's activities. In order to simulate the fluctuation in GWL, it is instructive to identify the natural and human factors induced stresses on the aquifers described and the relative and combined effects of each on GWL as shown in the sketch in Figure (2.1).

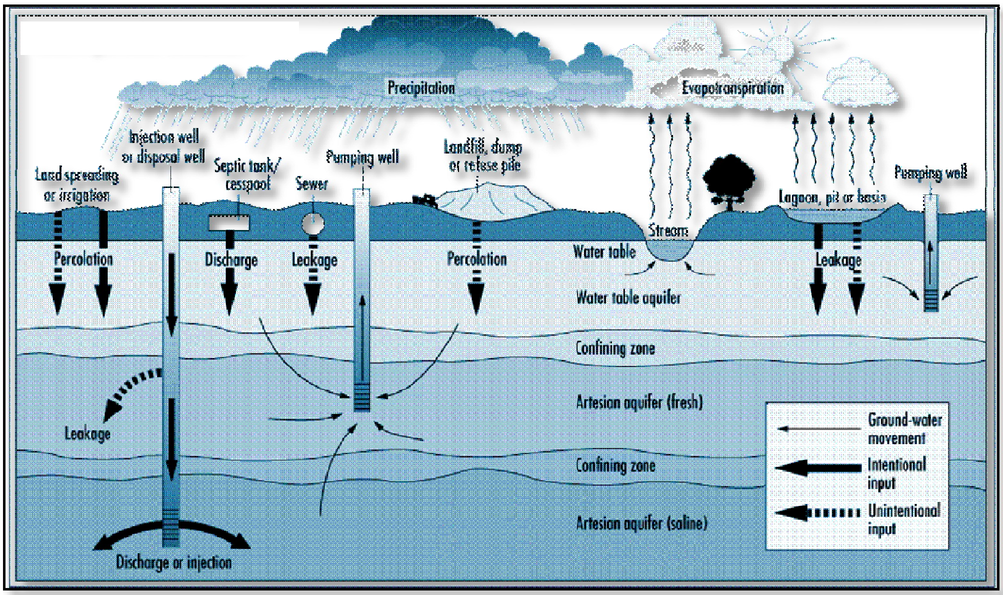


Figure (2.1): A sketch showing the natural and human factors that affect on GWL fluctuation.

2.2.1. Natural Factors Affecting GWL

Groundwater is an inherent part of the hydrological cycle. While precipitation and surface water bodies recharge the underground water bodies, groundwater steadily flows towards a discharge point or is stored in underground geological formations. Provided that the groundwater is primarily influenced by hydro-meteorological processes, the water table fluctuates periodically. Under natural conditions, the aquifer fluctuates around a multi-annual average and there is a balance between annual recharge and withdrawal. Exceptions can also occur depending on precipitation patterns. For example, less frequent but heavier precipitation events during the annual cycle could lead to longer dry periods, even though annual rainfall amounts might have increased (Andreadis and Lettenmaier, 2006).

GWL are controlled by the balance among recharge to, storage in, and discharge from an aquifer. Physical properties such as the porosity, permeability, and thickness of the rocks or sediments that compose the aquifer affect this balance. When the rate of recharge to an aquifer exceeds the rate of discharge, water levels or hydraulic heads will rise. Conversely, when the rate of ground-water withdrawal or discharge is greater than the rate of ground-water recharge, the water stored in the aquifer becomes depleted and water levels or hydraulic heads will decline (Taylor and Alley,2001).

2.2.2. Human Factors Affecting GWL

The human's activities causes change in GWL as a result of change in recharge or discharge such as urbanization development, withdrawal of ground water by pumping, deforestation, draining of wetlands, agricultural tillage, the impoundment of streams, and creation of artificial wetlands.

The process of urbanization often causes changes in GWL as a result of decreased recharge and increased withdrawal. In urban areas, water supplies are usually obtained from shallow wells, while most of the domestic wastewater is returned to the ground through cesspools or septic tanks. On other hand, urbanization can affect GWL such as impervious paved surfaces increased which may prevent precipitation from recharging ground water.

The withdrawal of ground water by pumping is the most significant human activity that alters the amount of ground water in storage and the rate of discharge from an aquifer. The removal of water stored in geologic materials near the well sets up hydraulic gradients that induce flow from more distant parts of the aquifer. As groundwater storage is depleted within the radius of influence of pumping, water levels in the aquifer decline.

Agriculture has been the cause of significant modification of landscapes throughout the world. Tillage of land changes the infiltration and runoff characteristics of the land surface, which affects recharge to ground water, delivery of water and sediment to surface-water bodies, and evapotranspiration. All of these processes either directly or indirectly affect the interaction of ground water (Todd and Mays,2005, Taylor and Alley, 2001and EPA, 2000).

2.3. Groundwater Modeling Approaches :

Groundwater Modeling is one of the main tools used in the hydrogeological sciences for the assessment of the resource potential and prediction of future impact under different circumstances and stresses. Its predictive capacity makes it the most useful tool for planning, design, implementation and management of the groundwater resources. Although it has been widely used by developed countries (Ghosh and Sharma,1999).

Hydrologic models - including groundwater models - are simplified, conceptual representations of a part of the hydrologic cycle. They are primarily used for hydrologic prediction and for understanding hydrologic processes. Two major types of hydrologic models can be distinguished (Gupta, 2011).

2.3.1. Physical -Based Models:

These models try to represent the physical processes observed in the real world. Typically, such models contain representations of surface runoff, subsurface flow, evapotranspiration, and channel flow, but they can be far more complicated. These models are known as deterministic hydrology models or process–based models. Deterministic hydrology models can be subdivided into single-event models and continuous simulation models. Recent research in hydrologic modeling tries to have a more global approach to the understanding of the behavior of hydrologic systems to make better predictions and to face the major challenges in water resources management(Gupta, 2011 and Solomatine et al., 2002)

In the last few decades, tens of computer models for simulating various aspects of soil - groundwater systems have been developed such as MODFLOW, MODPATH, SURFACT and POLLUTION (Saghravani et al., 2010). MODFLOW is considered as the most widely used model for groundwater modeling all over the world (Mohamed et al., 2009, Singh et al., 2008).The modular finite-difference groundwater flow model (MODFLOW) is a computer program for simulating common features in ground-water systems. It was developed by the U.S. Geological Survey (USGS) in 1988. MODFLOW is an effective management tool of groundwater resources (Green et al., 2006). It is able to simulate a wide range of flow in porous media with wide varieties of systems and standards including groundwater flow, transport of contamination and mine dewatering (Saghravani et al, 2010). The popularity of the model is attributed to many factors such as:

- It is relatively easy to be understood and applied to a wide variety of real world conditions
- It works on many different computer systems.
- It can be applied as a one, two, or three-dimensional model.
- Each simulation feature of MODFLOW has been extensively tested.
- Data input instructions and theory are well documented.
- The modular program design of MODFLOW allows for new simulation features to be added with relative ease.
- A wide variety of computer programs written by the many companies are available to analyze field data and construct input data sets for MODFLOW.
- A wide variety of programs are available to read output from MODFLOW and graphically present model results in ways that are easily understood.

2.3.2. Stochastic Approach

These models are data driven models, based on data and using mathematical and statistical concepts to link a certain input (e.g. rainfall) to the model output (e. g. runoff). These models involve mathematical equations that are not derived from physical processes in the field but from analysis of time series data. Commonly used techniques are regression, transfer functions, neural networks and system identification (Bhatt, 2002).

This approach, which are known as statistical or data driven or empirical or artificial intelligence based methods - is based on analyzing the data about a system, in particular finding connections between the system state variables (input, internal and output variables) without explicit knowledge of the physical behavior of the system (Bhatt, 2002).

Stochastic modeling is therefore focused on computational intelligence and machine learning methods that can be used to build models for complementing or replacing physically based models. A machine-learning algorithm is used to determine the relationship between a system's inputs and outputs using a training data set that is representative of all the behavior found in the system as shown in Figure (2.2). Once the model is trained, it can be tested using an independent data set to determine how well it can generalize to unseen data (Gupta, 2011andSolomatine et. al., 2002).

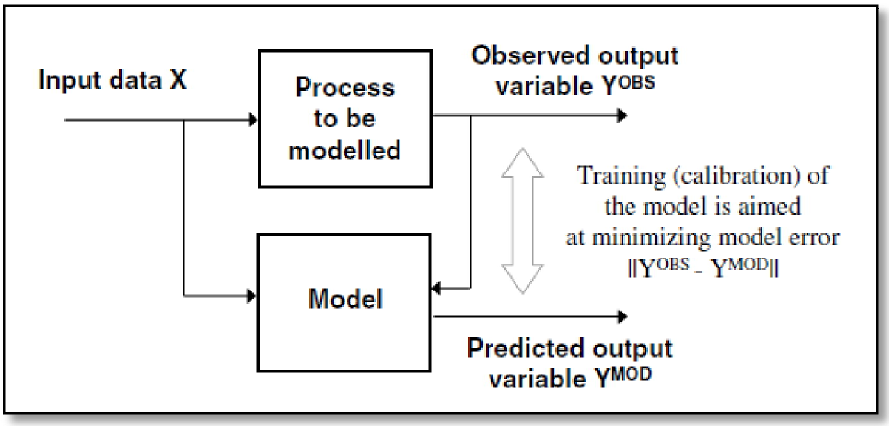


Figure (2.2): General approach to modelling (Solomatine et. al., 2002)

To develop a stochastic model, it is required to have time series and other related data sets about the specific contaminant or several contaminants under question (Harter and Walker, 2001). However the required data is less than that is required for process – based approach (Solomatine et. al., 2002, Palani etal. 2008). The application of statistical analysis helps to explore the hidden relationships among different parameters especially if a large amount of groundwater data is available leading to difficulties in the integration, interpretation and representation of these data (Prasanna et al. 2010). Many statistical techniques have been effectively used for groundwater modelling such as multivariate statistical techniques and ANNs **(**Singh et al. 2008**)**. The most popular computational intelligence techniques used in hydrological modeling, including neural networks, fuzzy rule-based systems, genetic algorithms, as well as approaches to model integration (Solomatine and et al., 2002). ANNs techniques will be used in this research.

2.4. Introduction to Artificial Neural Networks

In analogy to the biological system ANNs is being applied to solve a wide variety of water recourses problems. A neural network is an information processing system modeled on the structure of human brain. The biggest merit is its ability to deal with fuzzy information whose interrelation is ambiguous or whose functional relationship is not clear. A neural network has capability of learning and adjusts with the outside environment. Training the network is a kind of learning process. Method of learning is done with specified examples. A neural network possesses the ability to learn and able to memorize a large amount of various information and then to formalize it. Furthermore, the most precious quality of a neural network is its ability to provide forecasts based on the data it has processed. A neural network is a powerful tool because of its high functioning with fast computation and high memory to solve problems of non-linear interactions that involves complex variables. It is a data oriented modeling technique which finds the good relationship between the input and output system at faster rate of approach. These networks have good capability of learning, and predict better compared to mathematical models. A network has model free solutions, data error tolerance built in dynamism and lack of any exogenous input requirement, which makes the network attractive and reliable. These unique qualities have made neural networks to be used increasingly to predict and forecast water resources variables (Mandalet al., 2008; Manisha et al., 2008; Jain et al., 2004 and Maier and Dandy, 2000). Artificial neurons connected together form a network. The structure of ANNs is, as rule, layered. Three functional group can be distinguished in the ANNs i.e. the inputs receiving signals from the network's outside and introducing them into its inside, the neuron which process information and the neurons which generate results. A model of the artificial neuron is shown in the Figure (2.3). The model include N inputs, one output, a summation block and an activation block (Hola and Schabowicz, 2005).

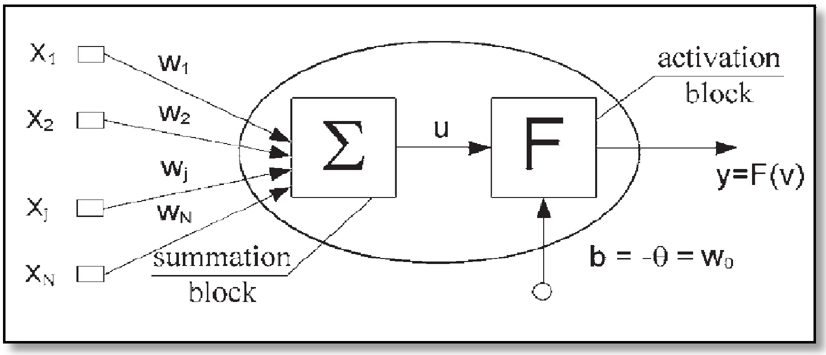


Figure (2.3): Model of artificial neurons (Hola and Schabowicz, 2005)

The network topology consists of a set of nodes (neurons) connected by links and usually organized in a number of layers. Each node in a layer receives and processes weighted input from a previous layer and transmits its output to nodes in the following layer through links. Each link is assigned a weight, which is a numerical estimate of the connection strength. The weighted summation of inputs to a node is converted to an output according to a transfer function .

Most ANNs has three layers or more: an input layer, which is used to present data to the network; an output layer, which is used to produce an appropriate response to the given input; and one or more intermediate layers, which are used to act as a collection of feature detectors. Determination of appropriate network architecture is one of the most important, but also one of the most difficult, tasks in the model-building process. Unless carefully designed an ANNs model can lead to over parameterization, resulting in an unnecessarily large network (Sudheer et al., 2002). Figure (2.4) demonstrated schematic description of a general ANNs model of three layers.

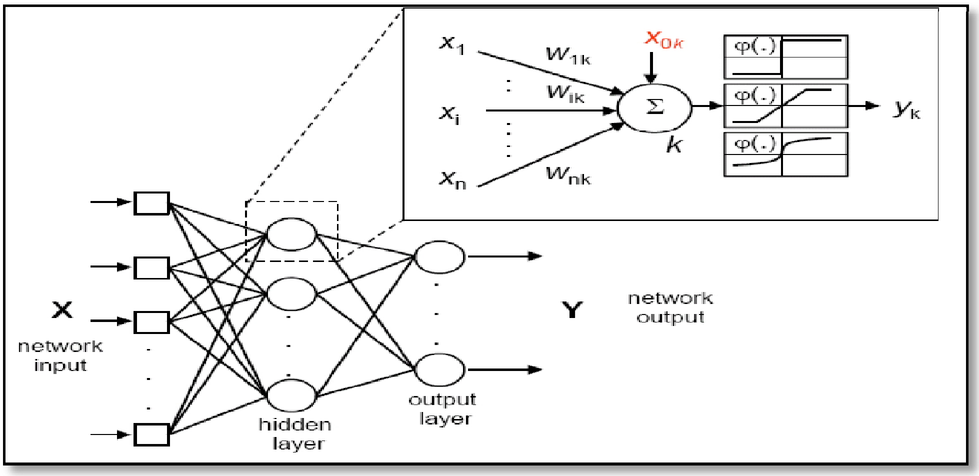


Figure (2.4): Schematic description of a three layer ANNs and of the elements of its (mathematical) neurons (Claudius et al., 2005)

In the ANNs methodology, the sample data is often subdivided into training, validation, and test sets. The distinctions among these subsets are crucial. As the following definitions:

- **Training set:** A set of examples used for learning that is to fit the parameters weights of the classifier.
- **Validation set:** A set of examples used to tune the parameters of a classifier, for example to choose the number of hidden units in a neural network.
- **Test set:** A set of examples used only to assess the performance generalization of a fully specified classifier.

2.4.1. Architectures of ANNs

ANNs architecture requires determination of the number of connection weights and the way information flows through the network which is done by choosing the number of layers, number of nodes in each layer and their connectivity. A number of output nodes is fixed by the quantities to be estimated. But number of input nodes is dependent on problem under consideration and the modeler's discretion to utilize domain knowledge. The number of neurons in hidden layer is increased gradually and the performance of the network in the form of an error is monitored . It is observed that error goes on reducing as the hidden neurons are increased up to a certain limit beyond which network performance goes down in validation (Rogers and Dowla, 1994, Shigdi and Gratia, 2003). There are several types of architecture of ANNs. However, the two most widely used ANNs are discussed below:

2.4.1.1. Feedforward Networks:

Feedforward ANNs allow signals to travel one way; from input to output. There is no feedback (loops) i.e. the output of any layer does not affect that same layer. They are extensively used in pattern recognition (Jha,2005).

2.4.1.2. Feedback/Recurrent Networks:

Feedback networks can have signals traveling in both direction by introducing loops in the network. Feedback networks are dynamic; their state is changing continuously until they reach an equilibrium point. They remain at the equilibrium point until the input changes and a new equilibrium needs to be found (Jha,2005).

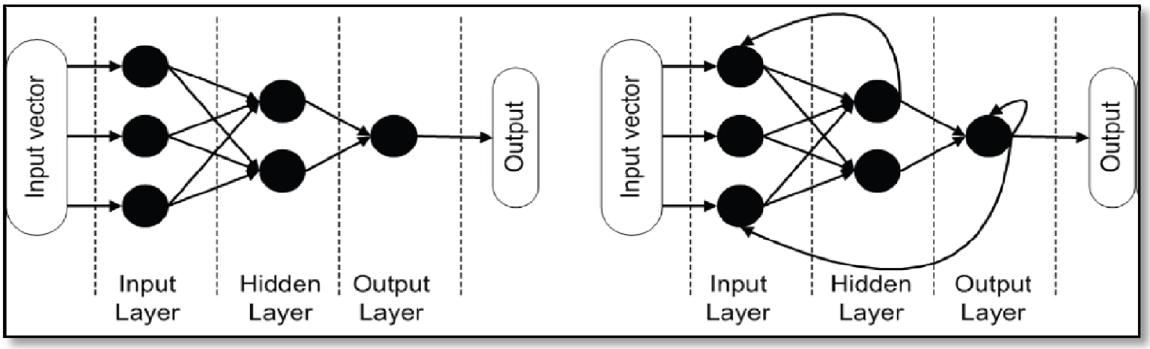


Figure (2.5): Feed-forward and recurrent Networks topology of an artificial neural network (Jha,2005)..

Figure (2.5) shows these two topologies; the left side of the figure represent simple feedforward topology (acyclic graph) where information flows from inputs to outputs in only one direction and the right side of the figure represent simple recurrent topology (semicyclic graph) where some of the information flows not only in one direction from input to output but also in opposite direction (Krenker, 2009) .

2.4.1.3. Multilayer perceptron

The multilayer perceptron (MLP) networks are currently the most widely used neural networks. These networks can do the classification for patterns having nonlinearly separable boundaries since the network consists of many neurons.

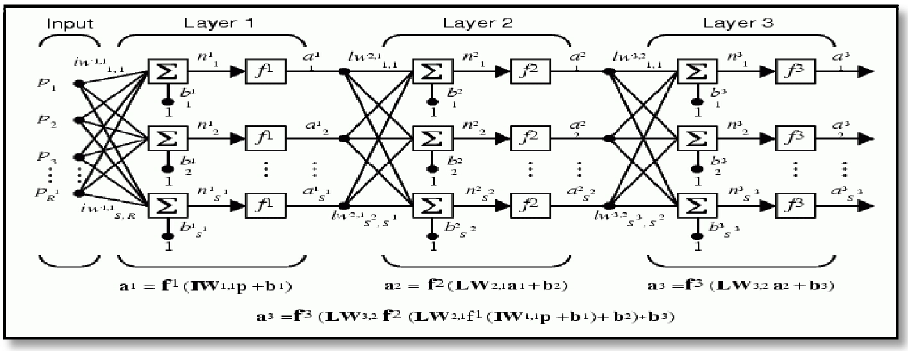


Figure (2.6): Multiple Layers of Neurons (Matlab, 1994)

2.4.2. Learning of Artificial Neural Network

A learning rule or training algorithm is the procedure for modifying the weights and biases of a network. There are many types of learning algorithms that can be arranged into three main classes:

- **Supervised learning**: The learning rule is provided with a set of examples of proper network behavior with inputs and outputs. As the inputs are applied to the network, the network outputs are compared to the targets. The learning rule is then used to adjust the weights and biases of the network in order to move the network outputs closer to the targets.
- **Reinforcement learning**: This is similar to supervised learning except that instead of being provided with a correct output for each network input the algorithm is only given a grade. The grade is a measure of the network performance over some sequence of inputs.
- **Unsupervised learning**: In this type of learning the weights and biases are adjusted in response to network inputs only. There are no target outputs available. Most of these algorithms perform some kind of clustering operation. They learn to categories the input patterns into a finite number of classes (Bhatt, 2002).

When Neural networks are trained, a particular input leads to a specific target output. Such a situation is shown Figure (2.7) There, the network is adjusted, based on a comparison of the output and the target, until the network output matches the target. Typically many such input/target pairs are used, in this supervised learning, to train a network

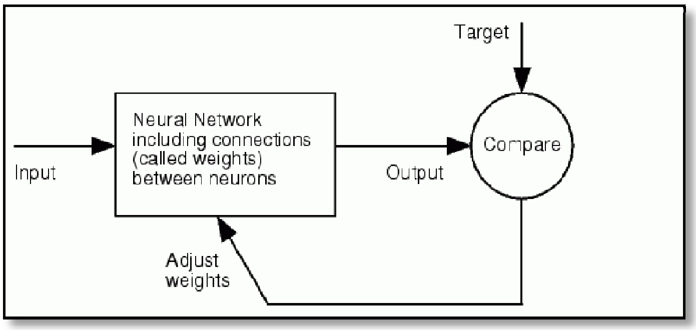


Figure (2.7): Neural Network Mechanism (Matlab, 1994)

The network adopts as follows, change the weight by an amount proportional to the difference between the desired output and the actual output. As an Equation (2.1)

Delta $W_i = L * (D-Y).I_i$……………………………………………………………Eq. 2.1

Where L is the learning rate, D is the desired output, and Y is the actual output.

This is called the Perceptron Learning Rule, and goes back to the early 1960's. BP which sometimes known as MLP and Radial Basis Function (RBF) Networks are both well-known developments of the Delta rule for single layer networks that is a development of the Perceptron Learning Rule. There are many other methods of training as the Generalized Regression Neural Networks and Hopfield Networks. In this study only MLP and RBF were used in modeling process.

2.4.3. The BP Method

BP which sometimes known as MLP distinguishes itself by the presence of one or more hidden layers, whose computation nodes are correspondingly called hidden neurons of hidden units. The function of hidden neurons is to intervene between the external input and the network output in some useful manner. By adding one or more hidden layers, the network is able to extract higher order statistics. In a rather loose sense, the network acquires a global perspective despite its local connectivity due to the extra set of synaptic connections and the extra dimension of the network interconnections (Haykin, 1994).

The ability of hidden neurons to extract higher order statistics is particularly valuable when the size of the input layer is large. The source nodes in the input layer of the network supply respective elements of the activation pattern (input vector), which constitute the input signals applied to the neurons (computation nodes) in the second layer (i.e., the first hidden layer). The output signals of the second layer are used as inputs to the third layer, and so on for the rest of the network. Typically, the neurons in each layer of the network have as their inputs the output signals of the preceding layer only. The set of the output signals of the neurons in the output layer of the network constitutes the overall response of the network to the activation patterns applied by the source nodes in the input (first) layer. BP is trained using the Levenberg–Marquardt optimization technique. Throughout all BP simulations, the learning rate and the momentum rate parameters were taken adaptively (Cigizoglu et al., 2007). Generally the Figure (3.8) shows the Architectures of BP method.

Training BP: Networks The weight change rule is a development of the perceptron learning rule. Weights are changed by an amount proportional to the error at that unit times the output of the unit feeding into the weight. Running the network consists of

1- Forward pass: The outputs are calculated and the error at the output units calculated.

2- Backward pass: The output unit error is used to alter weights on the output units. Then the error at the hidden nodes is calculated (by back-propagating the error at the output units through the weights), and the weights on the hidden nodes altered using these values.

For each data pair to be learned a forward pass and backwards pass is performed. This is repeated over and over again until a given number of epochs elapse, or when the error reaches an acceptable level, or when the error stops improving (you can select which of these stopping conditions to use).

2.4.4. The RBF Networks

RBF were introduced into the neural network by Broomhead and Lowe in 1988. The RBF consists of two layers whose output nodes form a linear combination of the basis functions. The basis functions in the hidden layer produce a significant non-zero response to input stimulus only when the input falls within a small localized region of the input space. Hence, this paradigm is also known as a localized receptive field network.

Transformation of the inputs is essential for fighting the curse of dimensionality in empirical modeling. The type of input transformation of the RBF is the local nonlinear projection using a radial fixed shape basis function. After nonlinearly squashing the multi-dimensional inputs without considering the output space, the RBF play a role as regressors. Since the output layer implements a linear regressor the only adjustable parameters are the weights of this regressor. These parameters can therefore be determined using the linear least square method, which gives an important advantage for convergence (Cigizoglu et al., 2007).

RBF networks consist of two layers: a hidden radial basis layer of S^1 neurons, and an output linear layer of S^2 neurons as shown in Figure (2.8).

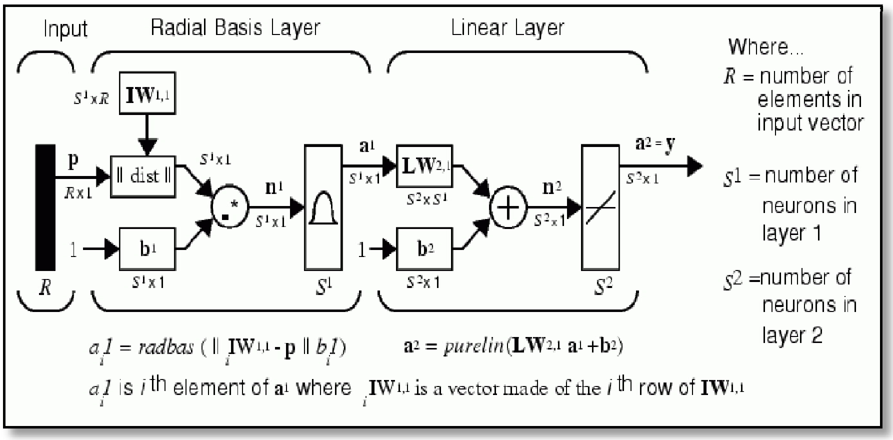


Figure (2.8): RBF Networks (Matlab, 1994)

2.4.5. Merits and Demerits Of ANNs

Manish et al.,(2008) carried out a study in order to review of application of ANNs in groundwater hydrology. Thus Manish et. al., 2008 summarizes the strengths and weaknesses of ANNs for a meaningful understanding of applicability of the technique.

2.4.5.1. Strength of ANNs

- ANNs are better in terms of result accuracy than almost all prevalent analytical, statistical or stochastic schemes.
- ANNs methodology has been reported to have capability of adapting to a nonlinear and multivariate system having complex interrelationships which may be poorly defined and not clearly understood using mathematical equations.
- Input data that are incomplete and ambiguous or data with noise, can be handled properly by ANNs because of their parallel processing.
- ANNs are able to recognize the relation between the input and output variables without explicit physical consideration of the system or knowing underlying principle because of the generalizing capabilities of the activation function.
- Accuracy of ANNs increases as more and more input data is made available to it .
- The time is consumed in arriving at best network and training but ANNs once trained, are easy to use. It is much faster than a physical based model which it approximates .
- ANNs are able to adapt to solutions over time to compensate for changing circumstances (suitable for time variant problems).

- ANNs are most suitable for dynamic forecasting problems because the weights can be updated when fresh observations are made available .
- Neural networks can be complimentary or alternative to many complex numerical schemes.

2.4.5.2. Weakness of ANNs

- ANNs's extrapolation capabilities, beyond its calibration range, are not reliable. During prediction ANNs is likely to perform poorly if it faces inputs that are far different from the examples it is exposed to during training. Therefore prior information of the system is of utmost importance to obtain reasonably accurate estimates.
- It is not always possible to determine significance of the input variables prior to the exercise and it is important to identify and eliminate redundant input variables that do not make a significant contribution to the model. This would result in a more efficient model.
- The knowledge contained in the trained networks is difficult to interpret because it is distributed across the connection weights in a complex manner.
- The success of ANNs application depends both on the quality and quantity of data available , type and structure of the neural network adopted and method of training .
- Determining the ANNs architecture is problem dependent trial-and-error process. The choice of network architecture, training algorithm and definition of error are usually determined by the users past experience and preference, rather than the physical aspects of the problem
- Initialization of weights and threshold values are an important consideration. This problem is faced particularly while implementing BP training algorithm. Some of the researchers have tried to overcome this problem by using GA global search method.

2.5. Application of ANNs in groundwater modeling:

Since a large number of factors affecting the water quality, as well as, the relationship between these factors are complicated and non-linear, traditional statistical models are no longer good enough for solving the problem, which necessitates looking for more effective methods. Over the past decade, ANNs has become increasingly popular in many disciplines as a problem solving tool. ANNs widely usage is referred to its capability of imitating the basic characteristics of the human brain such as self-adaptability, self-organization and error tolerant, these characteristics make ANNs widely adopted for model identification, analysis and forecast, system recognition and design optimization **(**Singh et al. 2009**)**. ANNs has the ability to solve extremely complex problems with highly non-linear relationships. Its flexible structure is capable of approximating almost any input-output relationships. Particularly ANNs has been extensively used as a predicting and forecasting tool in many different areas **(**Rajanayaka et al. 2001**).**In the recent years, researchers have utilized the capabilities of ANNs in the fields for groundwater and surface water modeling **(**Tabach et al. 2007**,** Singh et al. 2009**,** Palani et al. 2008andStarrett et al. 1996**)**.

2.5.1. Applications of ANNs in GWL Modeling :

The artificial intelligence approach is used for predicting GWL fluctuations via uses data based time series models. These models require time-series data of the GWL and relevant input variables only. In recent years, ANNs have been applied to solving various water resource problems including time-series forecasting (ASCE, 2000a and Yoon et al.,2010).

These approaches have become increasingly popular in many disciplines as a powerful problem-solving tool for modeling complicated, nonlinear, and interrelated processes. They have been also proven to be highly efficient in solving data-intensive problems, especially when the algorithms or the rules to solve such problems are unknown or difficult to express (Rajanayaka et al., 2001,May and Sivakumar, 2009, Dixon, 2009 and Chen et al.,2008).

Many researchers have successfully utilized ANNs to simulate GWL fluctuation. The following are samples of available studies on ANNs in GWL in reputed journals up to 2011.

- Coulibaly et. al., (2001) conducted an ANNs model to predict water table depth fluctuations taking in consideration the water table depth records obtained from four observation wells, daily average precipitation and daily minimum, maximum, and mean temperature. The research test three types of functionally different ANNs models which calibrated using a relatively short length of data to simulate water table fluctuations in the Gondo aquifer, Burkina Faso. Type of models was input delay neural networks (IDNN), RNN, RBF, generalized RBF (GRBF) and probabilistic neural networks (PNN) . Overall, simulation results suggest that the RNN is the most efficient of the ANNs models tested for a calibration period as short as 7 years. The results of the IDNN and the PNN are almost equivalent despite their basically different learning procedures. The GRBF performs very poorly as compared to the other models. Furthermore, the study shows that RNN may offer a robust framework for improving water supply planning in semiarid areas where aquifer information is not available.
- Coppola et. al.,(2005) developed ANNs a model to predict water level elevations in monitoring wells in a semiconfined glacial sand and gravel aquifer under variable state, pumping extraction, and climate conditions. In this study, the ANNs used the initial water level measurements, production well extractions, and climate conditions to predict the final water level elevations 30 days into the future at two monitoring wells. A sensitivity analysis was conducted with the ANNs that quantified the importance of the various input predictor variables on final water level elevations. This study demonstrates that ANNs can provide both excellent prediction capability and valuable sensitivity analyses, which can result in more appropriate ground water management strategies.
- Daliakopoulos et. al., (2005) conducted a various architectures and variable configurations of ANNs models in order to determine which gives better predictions of the behavior of the GWL of the Messara Valley, Crete, Greece. A total of seven different ANNs configurations were tested in terms of optimum results for a prediction limited to 18 months. The most suitable configuration for this task consist of three layers: an input layer of 20 neurons, one hidden layer with 3 neurons, and the output layer with 1 neuron with Feedforward Neural Network trained with the Levenberg–Marquardt method as it showed the most accurate predictions of the decreasing GWL when working with monthly data with five input variables (precipitation, temperature, runoff, GWL and specific yield). It was inferred that ANNs can be applied in cases where the datasets manifest trends and shifts and the desired output lies outside of the range of previously introduced input.

- Mohammadi (2008) investigated the applicability of ANNs models in simulating GWL .In order to be able to use ANNs models for aquifers with limited data, MODFLOW was used to simulate the groundwater flow and the calibrated model was then applied to generate hundreds of data sets for the training of the ANNs model MODFLOW outputs and measured water table elevations were used to compare the performance of the ANNs models. The average regression coefficients for multi-layer perceptrons and time lag recurrent neural networks were 0.865 and 0.958, respectively.
- Tsanis and et. al. 2008, developed a model that uses neural networks for forecasting the groundwater changes in an aquifer, based on a research carried out by Daliakopoulos et al. (2005). But Ioannis et. al.,(2005) carried out this study to take in consideration the effect of time lage in dat up to 5 month. The model had a good performance with a correlation coefficient of 0.982.
- Sreekanth et. al., (2009), carried out a reliable forecasting model for predicting the GWL using weather parameters like (Monthly water levels, evaporation, rainfall, relative humidity and temperature) as input variable on ANNs model. In this study, the researcher used the standard feed-forward neural network trained with Levenberg–Marquardt algorithm, was examined for forecasting GWL at Maheshwaram watershed, Hyderabad, India , as it showed the most accurate prediction, and the overall accuracy of this model is around 93%. Further, a significant advantage of this model is that it can provide satisfactory predictions with limited GWL records also.
- Abrishamchi et. al., (2010) conducted a research to identify the need of ANNs models that can capture the complex dynamics of urban groundwater table fluctuations. In this study, the researcher investigate the capability of two ANNs models to predict the urban GWL using different sets of available input data such as GWL, precipitation, temperature and in-city stream flow time-series, and then compare the results of these two models. A multi-input-single-output network has been trained using Levenberg-Marquardt algorithm. The results show the importance of input data selection and its effect on prediction accuracy. The model had a good performance with a correlation coefficient of 0.98. Also, this study confirms that ANNs models are capable in predicting the GWL even in complicated urban water cycles by using common hydrological data .
- Sethi et. al., (2010) have carried out a study to determine the factors that influence and control the water table fluctuation in a specific geomorphologic situation, to develop a forecasting model and examine its potential in predicting water table depth using limited data. The model performed to predict water table depth by using ANNs techniques with monthly rainfall, potential evapotranspiration, and water table depth from nearby influencing wells data as input and one month ahead water table depth as output. The study employed multilayer feed forward neural network with BP learning method to develop the model. The neural networks with different numbers of hidden layer neurons were developed. The results of the study clearly showed that ANNs can be used to predict water table depth in a hard rock aquifer with reasonably good accuracy reach 0.98 ,even in case of limited data situation .
- Yoon et. al.,(2010) developed two nonlinear time-series models for predicting GWL fluctuations using ANNs and SVMs. The models were applied to GWL prediction of two

wells at a coastal aquifer in Korea. Among the possible variables (past GWL, precipitation, and tide level) for an input structure, the past GWL was the most effective input variable for this study site. Tide level was more frequently selected as an input variable than precipitation. However, the overall model performance criteria of the SVM are similar to or even better than those of the ANNs in model prediction stage. The generalization ability of a SVM model is superior to an ANNs model for input structures and lead times. The uncertainty analysis for model parameters detects an equifinality of model parameter sets and higher uncertainty for ANNs model than SVM in this case. These results imply that the model-building process should be carefully conducted, especially when using ANNs models for GWL forecasting in a coastal aquifer .

- Jalalkamali et al.,(2011) employed a research to improve a decision support systems of groundwater resources exploitation. The study investigates the ability of a hybrid model of ANNs and GA in forecasting GWL in an individual well (target well). A standard feed forward networks (FFN) and RNN are utilized for performing the prediction task. Moreover, GA is used in order to determine the optimal structure of ANNs (that is, number of neurons for each hidden layer). Air temperature, rainfall depth and GWL in neighboring wells in Kerman plain, Kerman, Iran were used as input data of the hybrid model. This study indicates that the ANNs-GA model can be used successfully to forecast GWL of individual wells. In addition, a comparative study of both hybrid models indicates that the feed forward networks performed better than the recurrent neural networks .

2.6. Groundwater situation in Gaza Strip

Groundwater is one of the most precious natural resources in the GS as it is the only source of drinking water for the majority of the population (Shomar et. al., 2005). It is utilized extensively to satisfy agricultural, domestic, and industrial water demands. Groundwater crisis in Gaza includes two major folds: shortage and contamination. The extraction of groundwater currently exceeds the aquifer recharge rate. As a result, the GWL is falling continuously and accompanied with it the contamination with many pollutants mainly nitrate and seawater intrusion (UNEP, 2003, Weinthal and Vengosh, 2005 and Qahman and Larabi, 2006).

2.6.1. Groundwater monitoring system in Gaza strip

GWL system in GS has been carried out since 1970.In the time being, in our database, there are some wells have long term water level records, and other are recently merged into the system Coastal Aquifer Management Program (CAMP) wells to have better understanding of ground water movement. Most of the monitoring wells are agricultural wells, 2 inches steel piezometer and 4 inches PVC CAMP wells. The agricultural wells are almost shallow, only few meters below groundwater table, while the CAMP wells and piezometers are penetrating the different water bearing horizons either shallow or deep. Historically, it has been reported that the GWL has been measured at 177 sites. However and due to the damages of many of two inches steel piezometer since the year 2000, the total number of the monitoring wells were reduced to 139 (106 agricultural wells and 33 piezometer). In the year 2000, GWL monitoring system was evaluated and redesign to have in total 127 wells (98 agricultural wells and 29 piezometer). Through the CAMP project the PWA drilled 16 monitoring wells at 12 location distributed over the area of GS. These wells were used for both GWL and groundwater quality monitoring. Moreover, the CAMP project rehabilitated some existing 2 inches steel piezometer to be used for the same purpose. All the water levels are measured on monthly basis manually by using water indicator as shown in Figure (2.1), except 2 sites are measured automatically through water level loggers (CAMP_3 and CAMP_7). At present the total number of the monitoring wells in existing network is 108 wells,((72 agricultural wells, 20 piezometer and 16 CAMP monitoring wells) as shown in Figure (2.8) (PWA,2007).

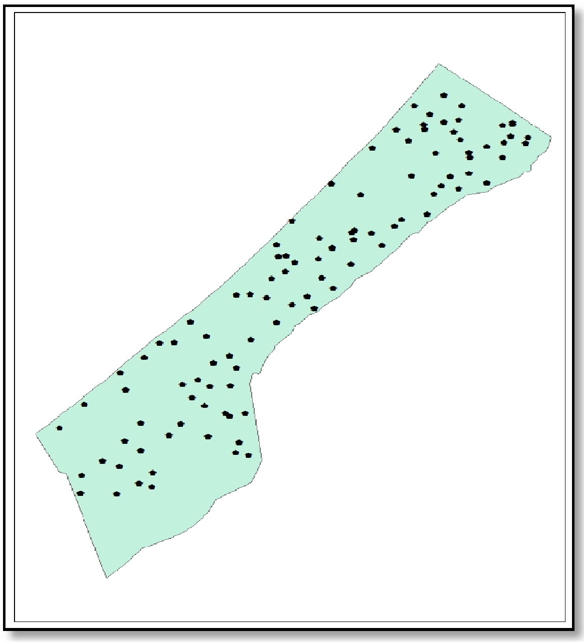


Figure (2.9): Monitoring wells in GS for year 2000 (PWA, 2007)

The GWL is computed from field measurements (water depth) and the elevation of the top of the wells according to the mean sea level. Water level monitoring in the GS is complicated by the fact that the aquifer contains fluids of different densities (e.g., seawater). The density effects have to be accounted for when interpreting hydraulic head data and flow directions (Mogheir, 2003).

2.6.2. GWL trends in Gaza Strip:

The historical data of the GWL between the year of 1990 and 2008 indicates gradually decline as much as 14 meters in the southern area of the GS. This decline is continuous apparent in the GCA until now. Thus the trend of the drop is so obvious and alarming (MoP,2010).

Generally, the rate of declination varies from place to place. There is a clear relation between the rate of decline and the hydrological characteristics of the water bearing formation as well as pumping rate. Accordingly, that high decline is due to the unbalanced between the recharge and discharge of the aquifer. The total pumped water is generally more than the total recharge from different sources (lateral flow and rainfall) (PWA, 2007).The core of declination has the maximum value in the middle of the southern Governorate. That is reflecting the intensive pumping from both municipal wells and agricultural wells and its un balance with the total renewable amount of the aquifer (PWA, 2007).

Within the GS, large cones of depression have formed in the largest well fields within the urban centers in the Northern and the Southern Governorates. Water level is presently below the mean sea level in many places, inducing a direct (negative) hydraulic gradient from the Mediterranean Sea towards the municipal wells (seawater intrusion).

Between 1970-1993, GWL dropped by almost 2-meters on average. This drop is most apparent in the South, and is a reflection of lower R in this area (Mogheir,2003).

2.6.3. Groundwater Modeling in Gaza Strip

In recent years, groundwater modeling has become a principal part of many projects and studies dealing with groundwater exploitation, protection and remediation. Therefore, the groundwater model is considered as a best management tool for water resources; aims to regulate and optimize annual groundwater extraction without adversely impacting groundwater. This new technique is based on assumptions and approximations that simplify the actual system and cannot simulate exactly the inherent complexity of the hydrogeological framework. Therefore, the results of the any model simulation are only an approximation and expectation of actual conditions and are only as accurate or realistic as the assumptions and data used in its development (PWA, 2005).

2.6.4. Process-Based Groundwater Modeling in Gaza Strip

Since its establishment in 1995, Palestinian Water Authority (PWA) has forced to use this modern technique in water resources management program in order to simplify the complex hydrogeological situation of groundwater aquifers and tries to understand the water regime within the entire aquifers. The ultimate goals of the PWA is to produce a long-term management plan that will provide rational and practical tools for management of groundwater extraction in GS and West Bank aquifers and to identify the most potential zones that are suitable for future development (PWA, 2005).

- PWA carried out many reports in water resources management in Gaza governorates. CAMP introduced integrated aquifer management plan, it explained also the current balance for the Gaza coastal aquifer, and defined the net negative balance between inflows and outflows (Metcalf and Eddy, 2000).
- In recognition the worsening situation of the water in GS, PWA and United State Agency for International Development (USAID) have jointly developed the implementation of an Integrated Aquifer Management Plan (IAMP). The IAMP presented overall planning guidelines for water supply and usage through year 2020. As a result to this jointly, new model depending on Coupled Flow-Transport Modeling Code (DYNCFT) was conducted to simulate the effect of IAMP. DYNCFT is a model able to simulate 3-dimensional contaminant transport with dispersion and first-order decay and/or linear equilibrium adsorption. Conservative constituents (such as chloride and tritium) may be simulated as well. DYNCFT is based on the Lagrangian approach ('Random Walk" method for statistically significant number of particles, each particle having an associated weight, decay rate, and retardation). DYNCFT can also be used for transport modeling of dissolved contaminants, without variable density fluids. With the existing model PWA has an added capability to

manage its resource, and equally importantly, to demonstrate what will happen if required investment are not made (Moe et al., 2001).

- There are some researchers attempted to model the groundwater in GS. Aish (2004) used GIS and MODFLOW in Artificial Recharge Modeling of the Gaza Coastal Aquifer. This research work investigates the first phase of a feasibility study on the impact of artificial recharge from a planned wastewater treatment plant on the groundwater quantity and quality of the coastal aquifer in the GS. In the analysis of the results, the 100 mg/l of solute will be considered as the reference concentration (100% injected water) and the simulated concentration in the aquifer will be expressed relative to this value. The results indicate that 90% of the infiltrated water will be mixed with the aquifer water after 1 year beneath the recharge area with decreasing percentages in the surrounding area.
- Qahman (2004) achieve a numerical assessment of seawater intrusion in GS by applying a 3-D variable density groundwater flow model. A two-stage finite difference simulation algorithm was used in steady state and transient models. SEAWAT computer code was used for simulating the spatial and temporal evolution of hydraulic heads and solute concentrations of groundwater. A regular finite difference grid with a 400 m2 cell in the horizontal plane, in addition to a 12-layer model were chosen. The model has been calibrated under steady state and transient conditions. Simulation results indicate that the proposed schemes successfully simulate the intrusion mechanism. Two pumpage schemes were designed to use the calibrated model for prediction of future changes in water levels and solute concentrations in the groundwater for a planning period of 17 years. The results show that seawater intrusion would worsen in the aquifer if the current rates of groundwater pumpage continue. The alternative, to eliminate pumpage in the intruded area, to moderate pumpage rates from water supply wells far from the seashore and to increase the aquifer replenishment by encouraging the implementation of suitable solutions like artificial recharge, may limit significantly seawater intrusion and reduce the current rate of decline of the water levels.
- Mushtaha et. al. (2007) used the finite difference code (MODFLOW) to quantify the impacts of controlled infiltration of the partially treated sewage from the new Beit-Lahia wastewater treatment plant on the aquifer water quality with respect to chloride and nitrate. The untreated effluent from the old Beit-Lahia wastewater treatment plant was allowed to accumulate forming huge lake allowing the infiltrated sewage water reaches the groundwater and may contaminate the aquifer. The partially treated effluents will be transferred to the new infiltration site located at the north eastern borders of GS. Water level was calibrated based on steady the steady state simulation for the year 2000 and the transient calibration was for the period 2000 to 2004. Transport model to simulate nitrate was performed using MT3D model, zero concentration was set to the model as initial concentration. The calibrated effective porosity was 0.25 and calibrated dispersivity ranged from 3 to 12 m. The study had showed that the difference in dispersivity did not give and significant changes in results. Also, the study showed that water quantity would be improved slightly but the nitrate concentration around the basins site would increase significantly .
- Jaber (2008) performed a study to model the fate and transport of nitrate in the costal aquifer of GS and the feasible management options. A coupled flow and transport model using a

three-dimensional, finite difference simulation model (VMODFLOW Pro.) was applied to simulate the Gaza coastal aquifer. The result gave an impression about the situation in Gaza aquifer regarding groundwater contamination by nitrate in the next 30 years.

- Alghamri (2009) carried out a research to study the impact of land use and over pumping on nitrate concentration in groundwater in KYG area. A coupled flow and transport model was conducted by using a three-dimensional, finite difference simulation model (VMODFLOW Pro.) Seven selected management scenarios were tested to reduce the transport of nitrate into the aquifer system during the next 30 years.
- Hajhamad and Almasri (2009) performed a study in order to develop and utilize lumped-parameter models to simulate nitrate concentration in the groundwater of Gaza City and Jabalia Camp in the GCA in Palestine. The main outcomes of the lumped-parameter models are the average temporal water table elevation and nitrate concentration. In order to demonstrate LPMs usability, a set of management options to reduce nitrate concentration in the groundwater of the study area were proposed and evaluated using the developed LPMs.

2.6.5. Artificial Intelligence Groundwater Modeling in Gaza Strip:

The use of Artificial Intelligence approach in groundwater modeling in GS doesn't found in large scale, till now, only a few researchers used it.

- Ghabayen (2004) developed a model using Bayesian belief networks, for Identification of salinity origin. The Bayesian belief networks model incorporates the theoretical background of salinity sources, area specific monitoring data that are characteristically incomplete in their coverage, expert judgment, and common sense reasoning to produce a geographic distribution for the most probable sources of Stalinization. The model showed areas where additional data on chemical and isotopic parameters are needed to understand the contribution of each of these sources to the problem. The model has successfully identified areas where seawater intrusion, deep brines, wastewater leakage, agricultural return flows, and Eocene waters exist with high probability. It has also identified areas where there is missing information or incomplete data especially in the eastern part of the coastal aquifer outside GS.
- Al Mahalawi (2007) developed a model to examines the relation between nitrate concentration of urban groundwater and hydrological and land use factors in the GS coastal aquifer using ANNs. Nine explanatory variables were used as input data for ANNs models. The variables used were total well depth, depth to initial water level, depth to the screen level, well screen length, rainfall intensity, well discharge, well distance from the seashore, population density within 250m buffer zone, and population density within 500m buffer zone. The results show that the MLP model is the best network for simulating nitrate concentration. The model had a good performance with a correlation coefficient of 0.9773. Based on the ANNs model, groundwater quality with respect to nitrate depends on a combination of the hydrological and land use factors. Because coastal aquifer areas are typically stressed throughout the world, this approach for nitrate modeling of groundwater can be applied to other aquifers on a regional scale.
- Seyam and Mogheir (2011) conducted a research to model the salinity spatial distribution in GCA. The developed ANNs model proved that chloride concentration in groundwater is

positively affected by abstraction average rate and well's life time, and it was inversely affected by recharge rate, and aquifer thickness. The results present the best neural network was determined to be MLP with four layers: an input layer of 6 neurons, first hidden layer with 10 neurons, second hidden layer with 7 neurons and the output layer with 1 neuron which gives the final chloride concentration. The ANNs model generated very good results depending on the high correlation between the observed and simulated values of chloride concentration. The correlation coefficient was 0.9848. The high value of correlation coefficient showed that the simulated chloride concentration values using the ANNs model were in very good agreement with the observed chloride concentration which mean that ANNs model is useful and applicable for groundwater salinity modeling. ANNs model was successfully utilized as analytical tool to study influence of the input variables on chloride concentration. It proved that chloride concentration in groundwater is reduced by decreasing abstraction, abstraction average rate and life time. Furthermore, it is reduced by increasing recharge rate and aquifer thickness .

- Jalala (2011) carried out a research in order to develop an integrated groundwater quantity management model for GS based on consider appropriate control measures of the socio economic needs.the effective variables have been characterized and prioritized using multi-criteria analysis with ANNs and expert opinion and judgment.The selected variables were classified and organized using the multivariate techniques of cluster analysis, factor analysis, principal components and classification analysis. The result shows a significant discrepancies between the results of ANNs analysis and expert opinion and judgment in terms of ranking and prioritizing the socio-economic variables. On other hand, Characterization of the priority effective socio-economic driving forces indicates that water managers and planners can introduce demand-based groundwater management in place of the existing supply based groundwater management. This ensures the success of undertaking responsive technical, managerial and regulatory measures.

2.6.6. Mix-mode Groundwater Modeling in Gaza Strip

Some research was conducted based on a combined simulation/optimization techniques which used to predict aquifer behavior while simultaneously select the optimal set of management alternatives.

- Barakat (2005) developed a model to find optimal values of water quantities from different resources in the southern GS. Visual MODFLOW and its integrated modules, was developed to quantify, and analyze the raw input data. Many scenarios for domestic supply and demand reconfiguration are introduced. GA is used as a global optimization method, to find optimal values of water quantities from different resources. The resulted optimal values for water quantities were introduced into the groundwater model to predict water level contour maps in the next years .

- Alnahhal and et. al., 2010 has developed a decision support system based on a simulation - optimization approach to be applied to an area of 4 km^2 in GCA to manage sustainable aquifer development under effective recharge operations and groundwater salinity constraint. They linked physical groundwater simulation model (flow and salt transport CODESA-3D model) with optimization techniques Carroll's FORTRAN GA Driver. The results present the optimum spatial distribution of pumping rates for two aquifer management models (with and without artificial recharge) for the inner region of the coastal aquifer within a one year time interval .

It is clear from the previous research that GWL modeling by artificial intelligence doesn't be conducted in GS, till now. Thus, this new research (*Development GWL Modeling Using ANNs–Khanyounis governorate as a case study*) might be considered as the first contributions in modeling of the relation between GWL and the influenced variables that affect on it in spatial scale using ANNs.

Chapter (3)

Study Area

3.1. Introduction

KYG is one of the five governorates of the GS. GS is located in a semi-arid area with scarce water resources. It is a part of the Palestinian coastal plain in the south west of Palestine as shown in Figure (3.1), where it forms a long and narrow rectangular area of about 365 km^2, with 45 km length, and between 5 and 12 km width. Nowadays, its five governorates are: Northern, Gaza, Middle, Khanyounis and Rafah as shown in Figure (3.2). It is located on the south-eastern coast of the Mediterranean Sea, between longitudes 34° 2’’ and 34° 25’’ east, and latitudes 31° 16’’ and 31° 45’’ north. The GS is confined between the Mediterranean Sea in the west, Egypt in the south. (UNEP, 2003). Figure (3.1) showed regional and location map of GS.

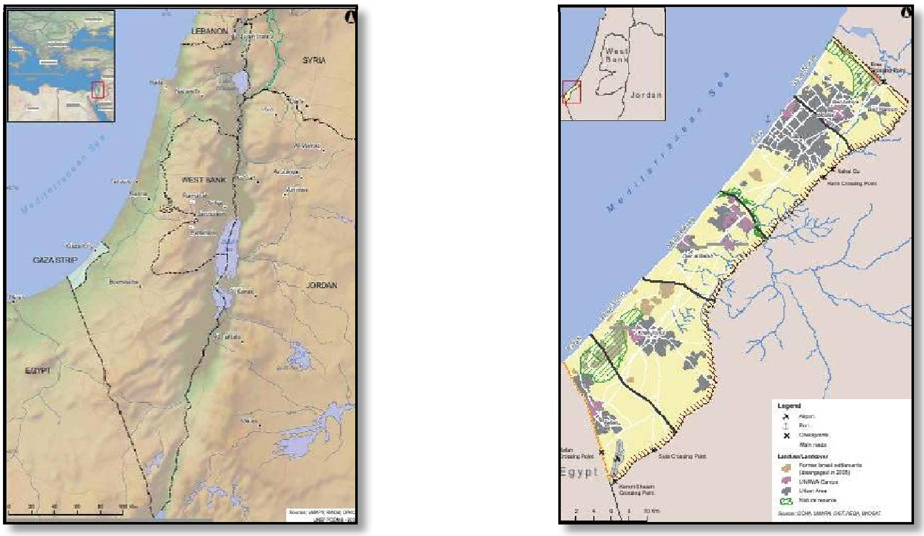


Figure (3.1): Regional and location map of GS (UNEP, 2009)

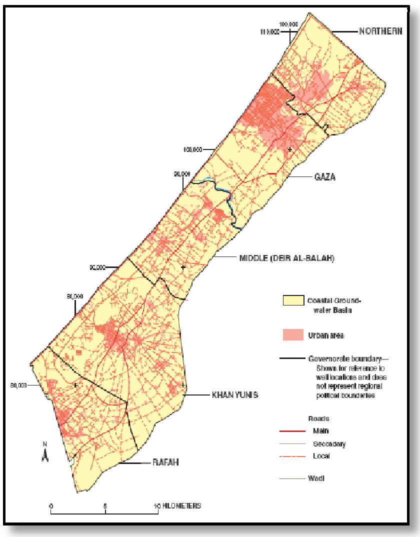


Figure (3.2): GS Governorates (PWA, 2000)

KYG is located in the southern part of GS as shown in Figure (3.2). Its district capital is Khanyounis City. In 2007, About 280 thousand inhabitants are living in Khanyounis. The

KYGconsists of six municipalities: Khanyounis, Bani Suhaila, Abasan El-Kabira, Abasan El-Saghira, Quarrara, Al Fakhari and the Khaza'a as shown in Figure (3.3).

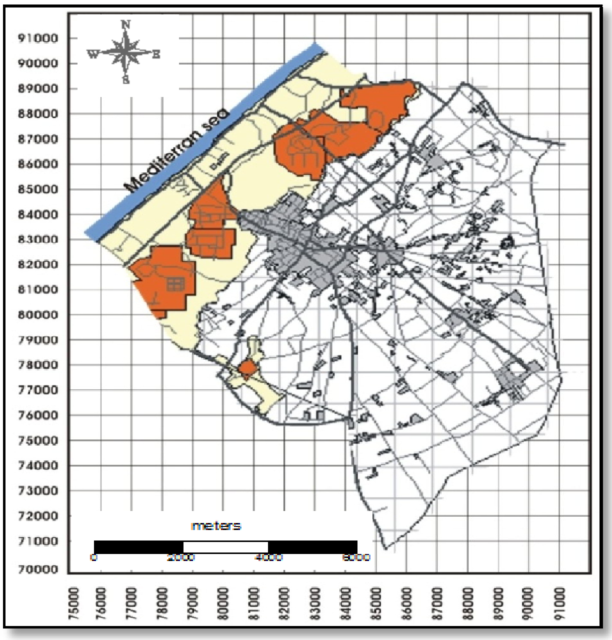


Figure (3.3): KYG map (PWA, 2007b)

3.2. Physical Settings

3.2.1. Climate

KYG as a part of GS area has a characteristically semi-arid Mediterranean Sea climate. It is located in transitional zone between a temperate Mediterranean climate to the west and north, and the arid Negev and Sinai deserts to the east and south and there are two distinct seasons; cool and relatively wet season (October-March), and hot and dry season (April-September). Figure (3.4) presents the maximum, minimum and mean monthly air temperatures as observed in the meteorological station of Gaza city which closed to Khanyounis temperature for the period lasting from 1999 until 2005. Temperature gradually changes throughout the year, reaches it's maximum in August (summer) and its minimum in January (winter), average of the monthly maximum temperature range from about 15.6 C° for January to 27.84 C° for August. The average of the monthly minimum temperature for January is about 12.85 C° and 27.6 for August. (GMS, 2005).The daily relative humidity of this coastal area ranges from 65% to 85%in summer and from 60% to 80% in winter in the day time and at night respectively (GMS, 2005).The wind velocity with northwest direction at 2 meter above the surface in the summer is about 1.5 m s^{-1}, which is less than that's during winter months where velocity reaches values of 2.8 m s^{-1} (Haeyer, 2000). The mean monthly evaporation varies significantly throughout the year. The monthly average evaporation varies between maximum of 174 mm in July and minimum of 63 mm in January, with an annual average evaporation of 1300 mm. (GMS, 2005).

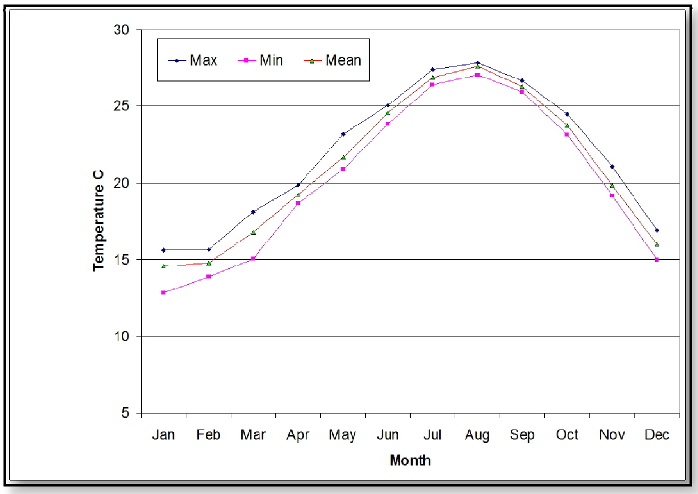


Figure (3.4): Mean monthly maximum, minimum and average temperature (C°)for the GS (period 1999 – 2005)

3.2.2. Rainfall

The rainfall data of the Khanyounis is based on the data collected from the main two rain stations located in Khanyounis city and Khaza'a as shown in Figure (3.5). Daily rainfall data are available for Khanyounis station since 1985 but for Khaza'a station since 1999.The average rainfall in KYG from 1999 to 2008 was 263.5 (mm/year) as an annual precipitation as shown in Table (3.1).

Table (3.1): Average yearly precipitation in KYG from 1999-2009 (source: MoA, 2009)

Year	Readings of Khanyounis Station (mm/ year)	Readings of Khaza'a Station (mm/ year)
1999/2000	191.80	142.20
2000/2001	381.00	284.30
2001/2002	311.70	258.50
2002/2003	298.00	261.20
2003/2004	204.40	184.00
2004/2005	373.00	367.70
2005/2006	270.5	214.0
2006/2007	252	256.1
2007/2008	178	137.8
2008/2009	309	261.8
Avg. yearly prec.	**276.94**	**236.69**
Approximated Area	**86.70**	**43.40**
Annual Precipitation (mm/year)	***263.5***	***Approximated from last 10 years(1999-2009)***

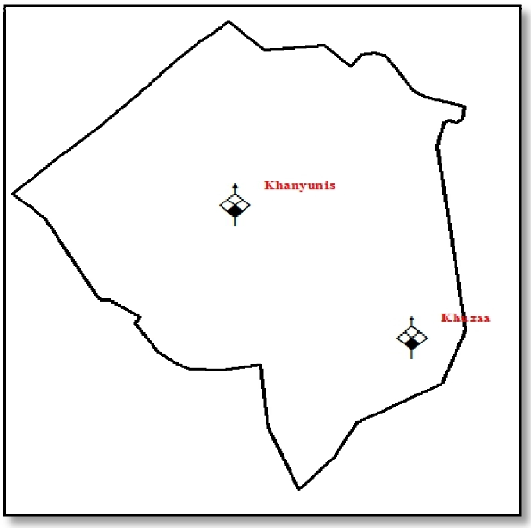


Figure (3.5): Locations of rain stations in KYG (PWA, 2000)

3.2.3. Topography and Soil

Topography refers to the altitude of the land surface, KYG as a part of GS area which is a coastal foreshore plain gradually sloping westward toward the sea allowing for surface run-off to rein filtrates the soil. A sandy beach stretches all along the coast, bound in the east by a ridge of sand dunes known as Kurkar ridges .The altitude of the GS land surface ranges between zero meters at the shore line to about 90 meters above mean sea level in some places, as shown in Figure (3.6). The soil of the study area consists of dark to reddish brown silty, clayey soil types and loess soils with different sand content, as shown in Figure (3.7)

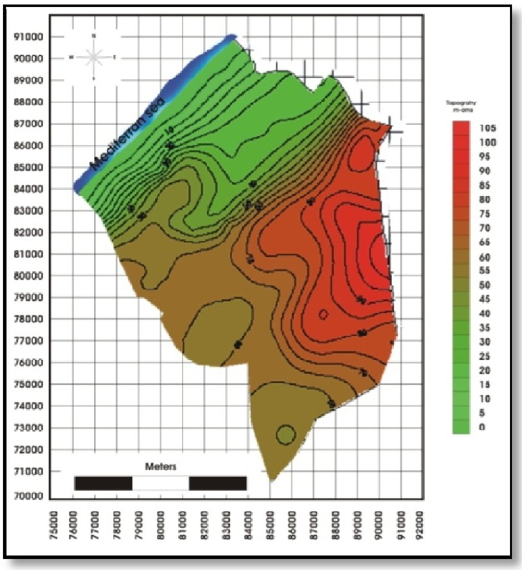


Figure (3.6): Topographical map of KYG (MOPIC, 2004)

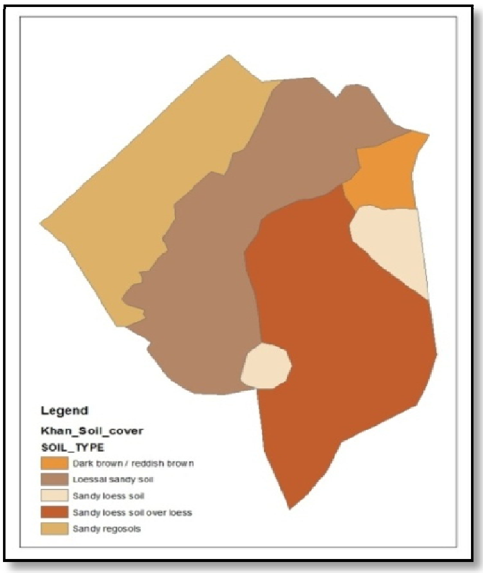


Figure (3.7): Soil Classifications in Khanyounis Governorate (MOPIC, 2004)

Table (3.2): Classification & characteristics of different soil types in GS.Adopted from (MOPIC, 1997; Goris and Samain, 2001)

Local Classification	Location	Description	Texture
Loess soil	Between the Gaza city and the Wadi Gaza	Loess soils sedimented in Pleistocene until Holocene Series. The grain size of loess fluctuates from 0.002 to 0.068 mm. Loess has been transported by winds and sedimented in loose form in the upper part, and in hard form in the lower part of the layers. They are brownish yellow-colored often with accumulation of lime concretions in the subsoil and containing 8 – 12 % calcium carbonate.	Sandy loam (6% clay, silt 34% , sand 58%)
Dark brown /reddish brown	Beit Hanoun and Wadi Gaza	These alluvial soils are Usually dark brown to reddish in colour, with a well-developed structure. At some depth, lime concretions can be found. The calcium carbonate content can be around 15–20%	Sandy clay loam (25% clay, 13% silt, 62% sand)
Sandy loess soil	Deir el Balah and Abssan	This is a transitional soil, characterized by a rather uniform, lighter texture. Apparently, windblown sands have been mixed with loessial deposits.	Sandy clay loam (23% clay, 21% silt, 56% sand)
Loessial sandy soil	It is found in the central and southern part of the strip	Forms a transitional zone between the sandy soil and the loess soil, usually with a calcareous loamy sandy texture and a deep uniform pale brown soil profile.	The top layer is sandy loam (14% clay, 20% silt, 66% sand). The lower profile is loam (21% clay, 30% silt, 49% sand)
Sandy loess soil over loess	It is found east of Rafah and Khan	It is loess or loessial soils which have been covered by a 20 to 50 cm thick layer of sand dune	Sandy loam (17.5% clay, 16.5% silt,

Local Classification	Location	Description	Texture
	Younis		66% sand)
Sandy regosol	It is found a long the coast of GS	Soil without a marked profile. Texture in the top meters is usually uniform and consists of medium to coarse quartz sand with a very low water holding capacity. The soils are moderately calcareous, very low matter and chemically poor, but physically suitable for intensive horticulture in greenhouses. In the deeper subsurface occasionally loam or clay loam layers of alluvial origin can be found	Top layer is loamy sand (9% clay, 4% silt, 87% sand). Deeper profile is sand (7.5% clay, 0% silt, 92.5% sand)

3.2.4. Land Use

The land use map of Khanyounis as shown in Figure (3.8) is based on the regional plan developed by central committee in the Ministry of the local government for GS for year 2005 (MoLG, 2005).

The land as shown in Figure (3.8) is scarce and the pressure on it is increasing rapidly for all kinds of uses; urban, industrial, and agricultural uses. Agricultural land occupies about 72 km^2, which is about to 65% of the total area of the Khanyounis governorate. It is expected that future expansion will be for the domestic use only.

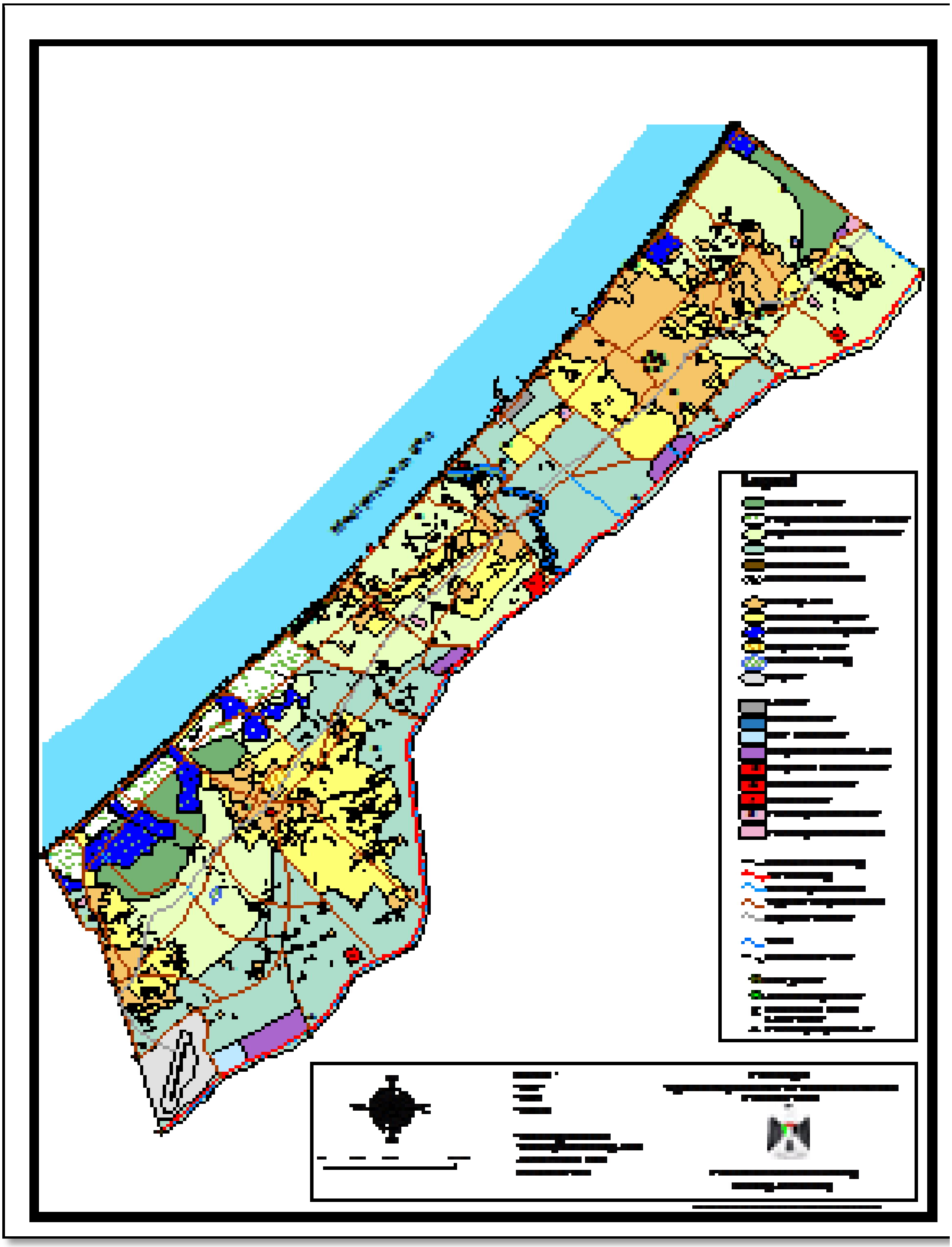


Figure (3.8): Regional plan for Gaza Governorates (MoP, 2005).

3.3. Hydrogeology

3.3.1. Description of the Coastal Aquifer

The coastal aquifer of the GS (included KYG) is part of a regional groundwater aquifer system that extends north up to Haifa, and south into Sinai coast of Egypt. The coastal aquifer consists primarily of Pleistocene age Kurkar group deposits including calcareous and silty sandstones, silts, clays, unconsolidated sands, and conglomerates. The coastal aquifer is generally 10-15 kilometers wide; the Kurkar group forms a seaward sloping plain, which ranges in thickness from 0 m in the east, and about 100 m at the shore in the south, and about 200 m near Gaza City. At the eastern Gaza border, the saturated thickness is about 60-70 m in the north, and only a few meters in the south near Rafah. Near the coast, coastal clay layers extend about 2-5 km inland, and divide the main aquifer into three subaquifers, referred to as subaquifers A, B1, B2, and C. A conceptual geological cross-section of the coastal plain geology is presented in Figure (3.9).The base of the aquifer is marked by the top of Saqiya formation (Tertiary age), it is a thick sequence of marls, clay stones and shale that slopes towards the sea, with low permeability and approximately 400-1000 m thick wedge beneath the GS (Metcalf & Eddy, 2000; Qahman and Zhou, 2001).

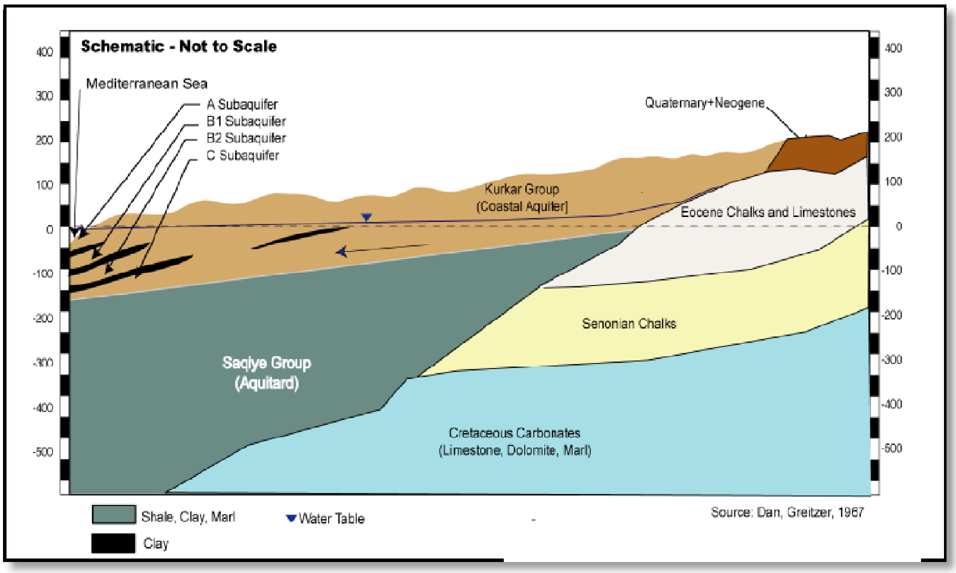


Figure (3.9): Generalized Cross-Section of the Coastal Plain(Adapted after Metcalf & Eddy, 2000).

3.3.2. Groundwater Flow and Water Levels

Under natural conditions, groundwater flow in the KYG is towards the Mediterranean Sea, where fresh groundwater discharges to the sea. However, natural flow patterns have been significantly disturbed by increasing population and over pumping in the past 40 years (Metcalf & Eddy, 2000). Within the southern part of GS, large cone of depression has formed over large area. Water levels are presently below mean sea level in many places, inducing a hydraulic gradient from the Mediterranean Sea towards the major pumping centers and municipal supply wells as shown in Figure (3.10). In Khanyounis, water levels range from greater than 3 meters above sea level near the eastern border to less than -6 meters in the area of cone of depression.

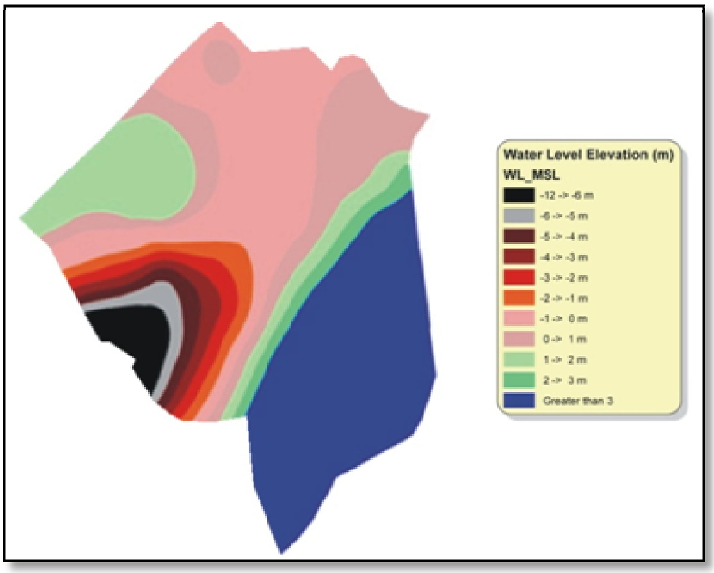


Figure (3.10): Water level elevation map for hydrological year 2007 (CMWU, 2008).

3.4. Water Quality

Ongoing deterioration of the water supply of GS poses a major challenge for water planners and sustainable management of the coastal aquifer. The aquifer is presently being overexploited, with total pumping exceeding total recharge. In addition, anthropogenic sources of pollution threaten the water supplies in major urban centers. Many water quality parameters presently exceed World Health Organization (WHO) drinking water standards. The major documented water quality problems are elevated chloride (salinity) and nitrate concentrations in the aquifer (Aish, 2004).

3.4.1. Groundwater Salinity (Chloride)

Salinity in the GCA is most often described by the concentration of chloride in groundwater. Sea water intrusion and intensive exploitation of groundwater have resulted in increased salinity in the most areas in GS. According to Coastal Municipalities Water Utility(CMWU), a generalized contour map of year 2007 is shown in Figure (3.11). Chloride concentrations are the highest along the Gaza border in the middle and south areas with concentrations exceeding 1500 mg/l. The best water quality is founded in the sand dune areas in the north of GS, mainly in the range of 50 – 250 mg/l.

There are three major sources of groundwater salinity; leakage of brackish saline water lowing from adjacent aquifers along the eastern boundary of the coastal aquifer (600-2000 mg/l Chloride), sea water intrusion along the coast from the west and mixing with deeper very saline water from below and the over-exploitation of the coastal aquifer resulting in the creation of water level depressions while preventing the flushing of accumulated salts (Qahman, 2004). Seawater Intrusion is defined as the migration of saltwater into fresh water aquifers under the influence of groundwater development. Seawater intrusion began in the late-1960s and the wedge continued to migrate inland at high rates due to increasing in municipal pumping and abstractions. Many modern studies indicate that seawater intrusion extends from 1 to 2.5 km along the western boundaries of GS along the sea, especially in Gaza city-Jabalia and Khanyounis-Rafah. These areas correspond to the largest pumping quantities where the GWL are 1-6 m below the mean sea level (Metcalf & Eddy, 2000; Qahman, 2004).

Each Municipality in KYG has it own wells, network distribution and operational system therefore the equity of consumption varies from municipality to another either in term of quantity and/or in quality (PWA, 2007b).

Concerning the pumped water quality, the chloride ion concentration of the Khanyounis municipality is in the range of 350-1250 mg/l. Only 2-wells are with chloride of about 350 mg/l and 3-wells are 500-600 mg/l and the remaining 15-wells are 600-1250mg/l. This means that 90% of the wells with chloride exceed the WHO limit (PWA, 2007b).

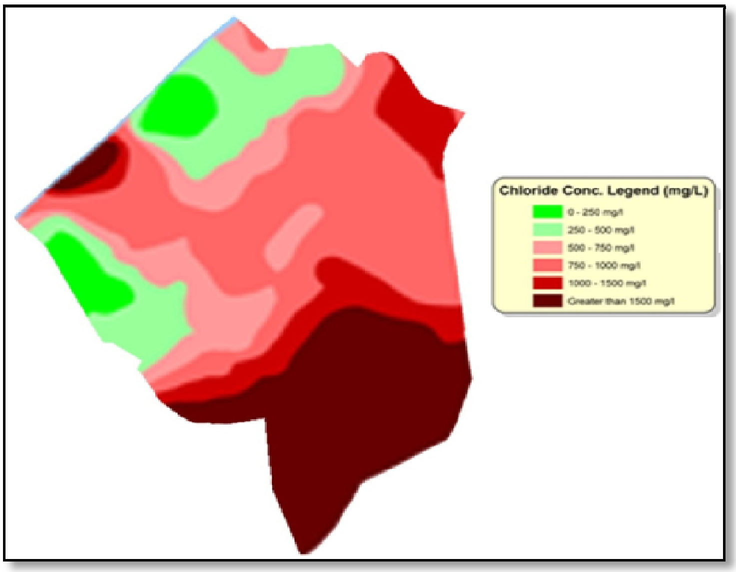


Figure (3.11): Chloride concentration map for the year 2007 (CMWU, 2008)

3.4.2. Nitrate Pollution

Increasing of nitrate is one of the most important and widespread of the numerous potential groundwater contaminants. The main causes of nitrate pollution are the excessive use of fertilizers in intensive agriculture, the irrigation with domestic wastewater and livestock farming (Rocca et. al., 2005).

The problem of high nitrate concentrations in drinking water constitutes a major health risk to both humans and stock life. Nitrite reacts directly with hemoglobin in human blood and other warm-blooded animals to produce methaemoglobin. Methaemoglobin destroys the ability of red blood cells to transport oxygen. This condition is especially serious for babies under three months of age. It causes a condition known as methaemoglobinemia or "blue baby" disease. The WHO assigned the nitrate of 50 mg/L as a health significant value in drinking water .

Most municipal wells in GS especially those are located in KYG show nitrate levels in excess of the WHO drinking water standard of 50 mg/l. In the worst affected areas (urban centers), NO_3^- concentrations are increasing at rates of up to 10 mg/l per year. The main sources of NO_3^- are fertilizers and domestic sewage effluents. The quantities of sewage that infiltrate to the water table on an annual basis through cesspits and septic tanks are significant, about $12*10^6$ m^3/y. In contrast to salinity, groundwater flowing from the east has relatively low NO_3^- levels (Mogheir, 2006). Figure (3.12) shows nitrate concentration in the Gaza Governorates for the year 2007.

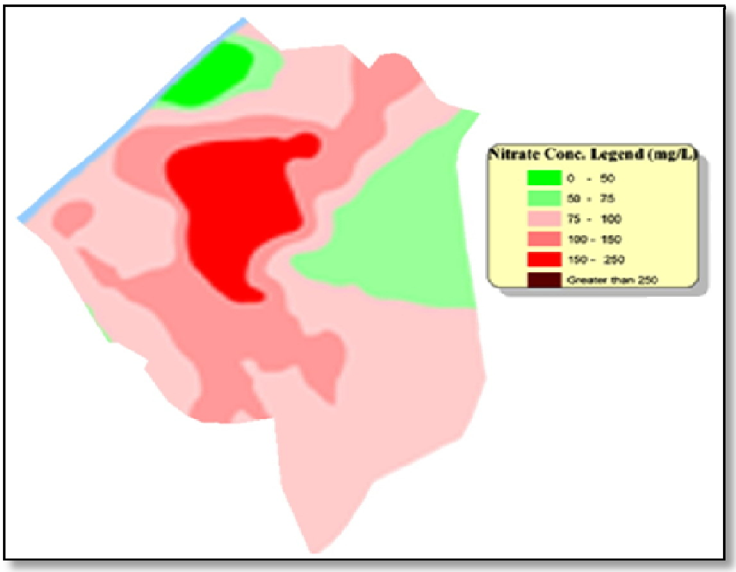


Figure (3.12): Nitrate concentration map for the year 2007 (CMWU, 2008)

Chapter (4)

Methodology

4.1. Introduction

This chapter discussed the methodology that used in this research. The methodology described the techniques, approaches and tools which were used to achieve the objectives of this research. An important step in developing ANNs models is to select the model input variables that have the most significant impact on model performance. A comprehensive literature review was conducted to determine which input variables are likely to be influential.

Physically, the GWL may be influenced by some variables such as: recharge from many sources, abstraction, precipitation, return flow, evaporation, temperature and lateral inflow. In order to model the GWL in GS using ANNs it is necessary to gather time series data for training purposes about these variables.

4.2. Data Collection and Preparation

The water level measurements is usually measured monthly, therefore, the data about inputs was collected on monthly basis. So in this research all required data, in study area, have been surveyed for the period of 2000-2008. The needed data was collected mainly from institutions such as Khanyounis Municipality , PWA, CMWU and Ministry of Agriculture (MoA) .

It is noted that the raw data available in institutions may have some errors and noise which are mainly related to human error and many necessary data had been lost or not found specially, the data after 2007 according to the political situation in GS. This problem has been tackled by excluding the noisy data and make double check on data from other source or make a linear interpolation. Different variables have different amounts of missing data. However, missing data treatment should be carefully thought this research. Therefore, the missing data was treated at the beginning of analysis. Thus, a large effort was conducted during screening, filtration and double check on the row data. The methodology of gathering and preprocessing data steps on raw sets of required data is discussed in the following sections.

4.2.1. Water Level in Monitoring Wells

The existing groundwater monitoring wells network in the study area consist of 31 monitoring wells, which distributed over all area since 1972. These monitoring wells are agriculture and piezometric wells (PWA, 1997). Figure (4.1) presents the GWL contour map for the year 2010.

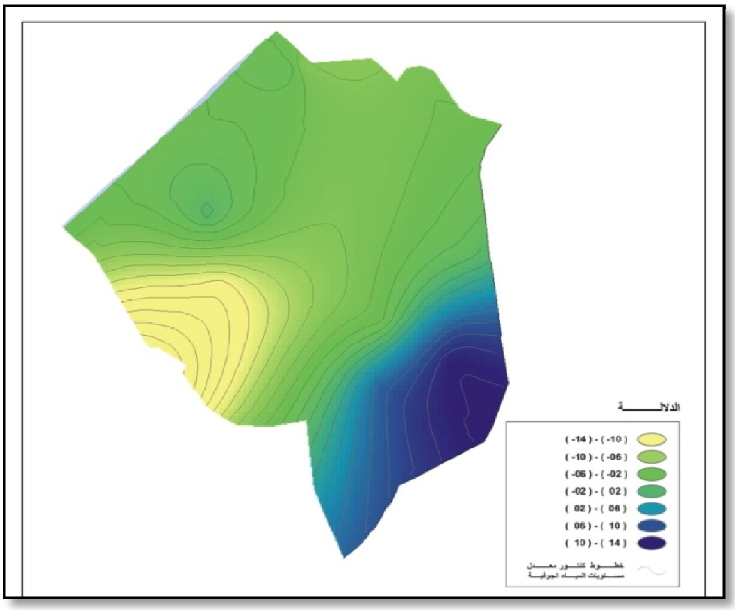


Figure (4.1): GWL contour map of KYG area for the year 2010 (MoP, 2010)

Preliminary analysis of GWL data that reveals many monitoring wells have complete data sets for 8 years that could be utilized in the model while other wells have been constructed for few years or for specific tasks and closed after that. Therefore, only 17 monitoring wells were selected for analysis in this research. Figure (4.2) shows distribution of these wells over the study area. It is clear from Figure (4.2) that the 17 monitoring wells are distributed over the study area.

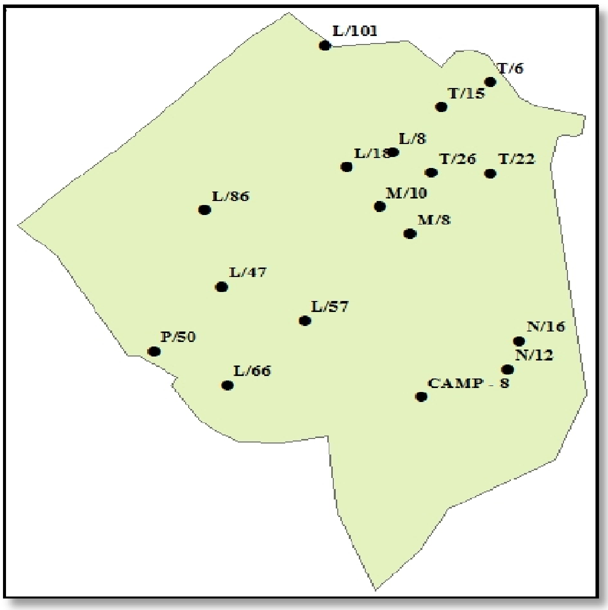


Figure (4.2): The distribution of the monitoring wells over the study area.

Excel sheets from PWA including the monthly recordings of water levels for the 17 observation wells were available with some missing records. The missing date should be estimated to make the series complete for modeling. Since the missing data were small and the GWL data were highly correlated, simple linear interpolation between available records was used to estimate the missing values. Table (4.1) presents the GWL data of monitoring wells for April,2005. Complete data of GWL for all wells are found in Appendix (1).

Table (4.1) : GWL of monitoring wells in April, 2005.

No.	Well ID	Wells coordinates			WL/MSL
		X	Y	Z	
1.	**L/18**	85277.44	85821.60	32.201	-0.509
2.	**L/47**	82610.31	82589.34	62.95	-4.55
3.	**L/57**	84368.98	81663.11	70.179	-2.841
4.	**L/66**	83310.37	78719.78	59.43	-2.91
5.	**L/8**	86254.41	86212.13	41.615	-0.565
6.	**L/86**	82244.33	84658.55	47.720	3.29
7.	**M/10**	85967.49	84740.36	65.605	-0.815
8.	**M/8**	86607.72	84009.51	85.237	-0.613
9.	**N/12**	88701.25	80356.73	92.536	10.146
10.	**N/16**	88941.39	81122.74	89.899	8.439
11.	**T/15**	87279.12	87444.48	35.312	-0.098
12.	**T/22**	88337.98	85643.53	82.196	0.066
13.	**T/26**	87080.51	85663.61	65.815	-0.305
14.	**T/6**	88321.99	88116.69	44.58	0.17
15.	**L/101**	84805.69	89100.40	4.485	-1.217
16.	**CAMP - 8**	86858.81	79606.82	82	6.341
17.	**P/50**	81167.09	80838.04	67.355	-9.58

In order to describe the area of influence for different input variable of each monitoring wells, the study area was divided into 17 parts based on the polygons created by the Thiessen method according to the locations of each monitoring wells stations shown in Figure (4.3).This technique is widely used in hydrology (Coulibaly, M. and Becker, S. 2007, Baalousha, 2005 and Fiedler,2003). It defines individual areas of influence around each of a set of points. Thiessen polygons are polygons whose boundaries define the area that is closest to each point relative to all other points (Fiedler,2003). They are mathematically defined by the perpendicular bisectors of the lines between all points. The monitoring wells consider as Thessin polygons centers as shown in Figure (4.3) using ArcGIS program.

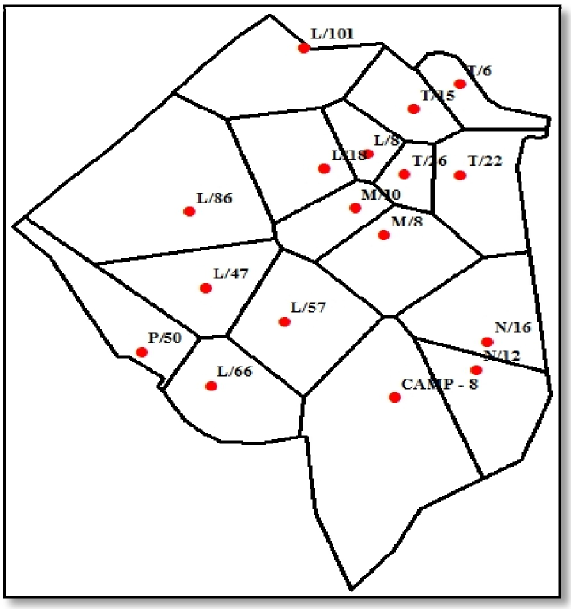


Figure (4.3) : Influence area of each monitoring well over the study area.

4.2.2. Rainfall data

Rainfall is one of the most important influencing parameters of the water resources and it is an essential component of scientific investigation of the hydrologic cycle**.** The pattern, the amount beside the intensity of rainfall are the most important factors that directly affect groundwater balance and replenishment (PWA, 2007). Monthly rainfall data during 2000-2008 was collected for Khanyounis and Khuza rainfall stations as shown on Table (4.2). Khanyounis station rainfall measurements represented all influence areas except N16 ,N12 and Camp_8 which were represented by Khuza station.

Table (4.2): Monthly Rainfall values in Khanyounis meteorological stations for year 2006

Date	Year	Khanyounis station(mm)	Khuza station(mm)
January	2006	27.00	21.5
February	2006	49.50	43.5
March	2006	7.00	5.5
April	2006	35.00	35
May	2006	0.00	0
June	2006	0.00	0
July	2006	0.00	0
August	2006	0.00	0
September	2006	0.00	0
October	2006	0.00	48.5
November	2006	25.50	28.5
December	2006	36.50	82

Figure (4.4) shows seasonal average rainfall depth at rainfall station of KYG. Values between (2000-2008) are clearly shown the variation in rainy season during the study period. Complete data of rainfall are found in Appendix (1).

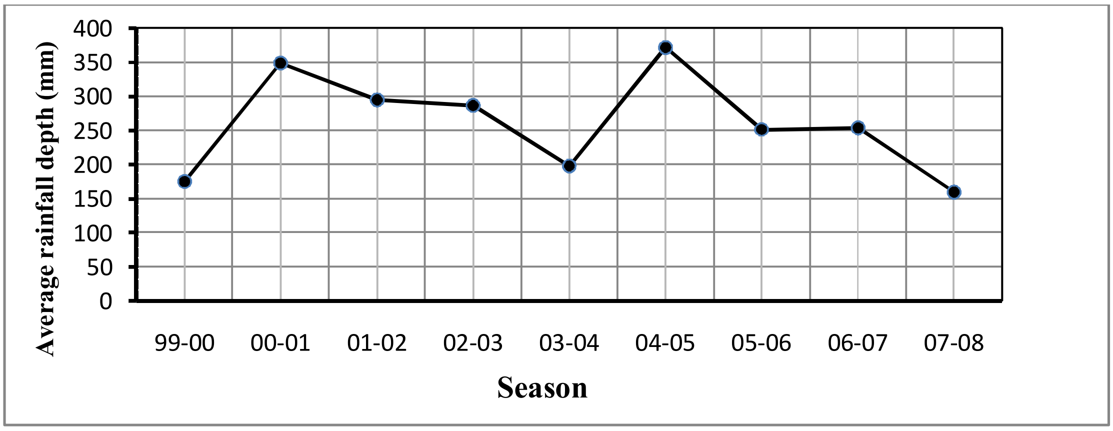


Figure (4.4): Seasonal variation of rainfall depth average in KYG between (2000-2008)

4.2.3. Soil Category of KYG

The soil of the study area consists of dark to reddish brown silty, clayey soil types and loess soils with different sand content. The coastal area is characterized by sandy regosols showing poorly developed soil horizons. Ministry of Local Governorate in Gaza has published a modified soil map for GS as shown in Figure (4.5) which is used in this research. It classifies the soil into five categories:

- Sandy regosol.
- Loessial sandy soil.
- Sandy loessial soil.
- Sandy loess soil over loess.
- Dark brown / reddish brown.

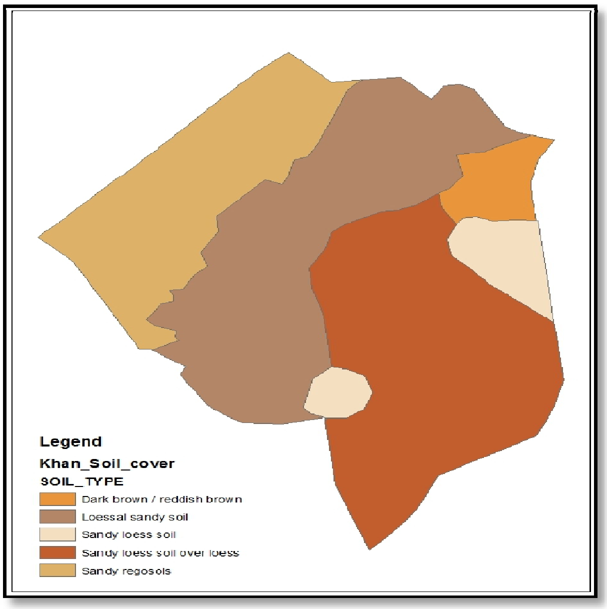


Figure (4.5): Soil Classifications in GS (MoLG, 2004)

Intersection between influence area for each well and soil type maps was obtained using ArcGIS 10.0, each area has more than one soil type area as illustrated in Table (4.3).

Table (4.3): Soil types for each influence areas.

Influence Areas	Soil Type	Area m^2
CAMP - 8	Loessal sandy soil	6,134
	Sandy loess soil over loess	15,553,635
	Sandy loess soil	1,415,693
L/101	Loessal sandy soil	1,505,512
	Sandy regosols	5,843,460
L/18	Loessal sandy soil	4,134,496
	Sandy regosols	1,419,559
L/47	Loessal sandy soil	4,658,930
	Sandy regosols	1,299,111
L/57	Loessal sandy soil	3,847,102
	Sandy loess soil over loess	3,544,028
	Sandy loess soil	120,086
L/66	Loessal sandy soil	5,936,198
	Sandy loess soil	331,033
L/8	Loessal sandy soil	2,217,754
L/86	Loessal sandy soil	2,919,605
	Sandy regosols	12,268,512
M/10	Loessal sandy soil	1,480,632
	Sandy loess soil over loess	1,623,002
M/8	Sandy loess soil over loess	5,524,505
	Sandy loess soil	794,323
N/12	Sandy loess soil over loess	5,987,056
N/16	Sandy loess soil over loess	4,742,585
	Sandy loess soil	1,788,512
P/50	Loessal sandy soil	1,848,600
	Sandy regosols	3,419,652
T/15	Loessal sandy soil	3,612,902
	Dark brown / reddish brown	48,160
T/22	Loessal sandy soil	136,112
	Dark brown / reddish brown	3,827,072
	Sandy loess soil over loess	24,838
	Sandy loess soil	2,028,265
	Dark brown / reddish brown	3,997
	Sandy loess soil	3,997
T/26	Loessal sandy soil	1,204,476
	Dark brown / reddish brown	162,236
	Sandy loess soil over loess	521,902
T/6	Loessal sandy soil	2,055,829
	Dark brown / reddish brown	465,451

4.2.4. Land use of KYG

4.2.4.1. Spatial Analysis

The land use requires studying and analyzing the trend to assess its impact upon the agricultural land and natural resources of the study area. Analysis of land use variation over the study area was performed using Erdas11 and ArcGIS10. The area and direction of land use trends were investigated in the KYG. Three aerial photos for the years 1999, 2003 and 2007 were utilized in this analysis. It is assumed that each aerial photo represents three years as shown in Table (4.4).

Table (4.4): Proposed represented aerial photo for each year

Date of Aerial photo	1999 aerial photo			2003 aerial photo			2007 aerial photo		
Years represented	2000	2001	2002	2003	2004	2005	2006	2007	2008

For landuse analysis, several technical steps in the remote sensing (ERDAS) and GIS framework were completed. These involved data organization, processing, interpretation and analysis. The resultant output was used to synthesize the observed trend of land use in the region. The technical steps include:

4.2.4.2. Image pre-processing

Before the different land use types were classified, it was necessary to preprocess the data, to fit it to the study area and to ensure that the data is compatible with all datasets involved in this research. The satellite images for years 1999, 2003 and 2007 were georeferenced and processed in ERDAS Imagine 2011 software.

4.2.4.3. Image analysis

As mentioned above, ERDAS Imagine program version 2011 was used to perform a classification for the land cover that appears in KYG aerial photos. ERDAS Imagine is a remote sensing application with raster graphics editor capabilities aimed primarily at geospatial raster data processing and allows the user to prepare, display and enhance digital images for mapping use. Supervised classification was performed for three land use categories: build up, open, and agriculture areas. It is important that training samples be representative of the class that you are trying to identify. Great efforts were spent during the training area selection since the training areas were collected from the most represented homogenous areas as presented in Figure (4.7) for 2003.

4.2.4.4. Implementing the GIS

The classified images presenting the three land cover classes were imported into the GIS system as images and shapefiles. These types of data are compatible with other GIS data and can be presented in GIS as layers for further analysis. It is worth mentioning that the obtained layers of land use / land cover were cropped using the influence area for each monitoring wells (Figure 4.3) borders in order to calculate the areas of each land cover type in each area in the analysis time period by using the computational functionalities available in GIS. These included; determination of the total amount of built-up area, open space area and agricultural area as shown in Tables (4.5). Figure (4.8) shows the influence area of N/16 as aerial photo and classified photo for year 2003. Based on a study carried out by Khalf,2005 the distribution of existing land use within the study area per type of land use is illustrated in Table (4.6).

Table (4.6): Land use distribution in KYG(Khalf,2005)

Year	Buildup Area m^2	Agricultural Area m^2	Open space Area m^2
Before September, 2000	10,388,624	73,339,147	26,340,802
From September 2000 until August 2004	10,388,624	64,096,147	35,583,802

As shown in Table (4.7), it is clear that performed classification by using ERDAS show a good agreement with Khalf (2005) study. On the other hand, the properties of each photo play a role in classification accuracy but overall. The results in Table (4.7) are comparable of that by Khalf (2005)despite the different approach used. The quality of aerial photos leads to conduct a modification on ERDAS classification. So that, manual modification has been made based on knowledge of study area and verification of the result with related official reports. Complete data of land use classification for each influence areas are found in Appendix (2).

Table (4.7): Land use distribution in KYG using ERDAS

Year	Buildup Area m^2	Agricultural Area m^2	Open space Area m^2
1999	11,739,627	70,306,879	26,442,651
2003	11,913,254	63,141,215	33,434,688
2007	11,075,910	57,860,734	39,552,513

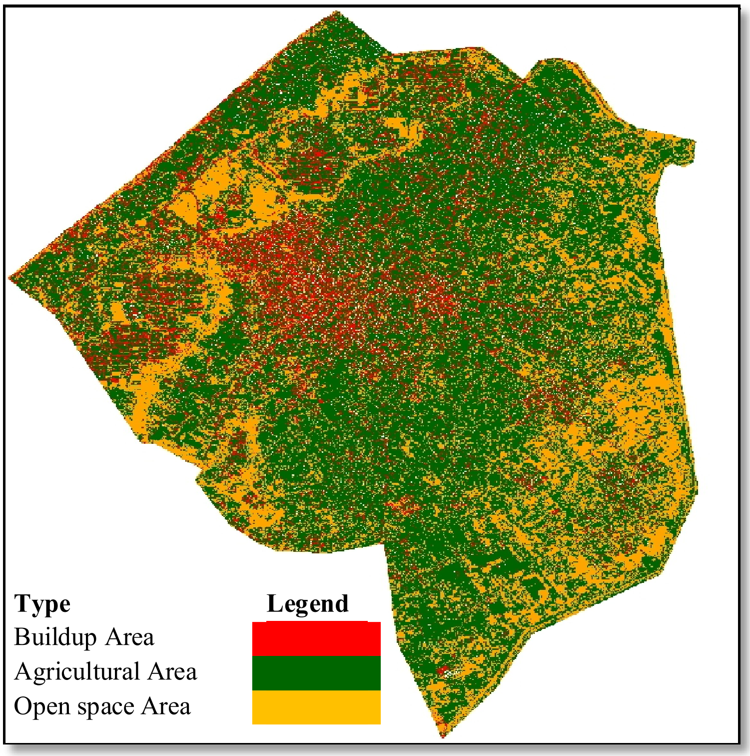


Figure (4.7): Land use classification of KYG for year 2003 by ERDAS

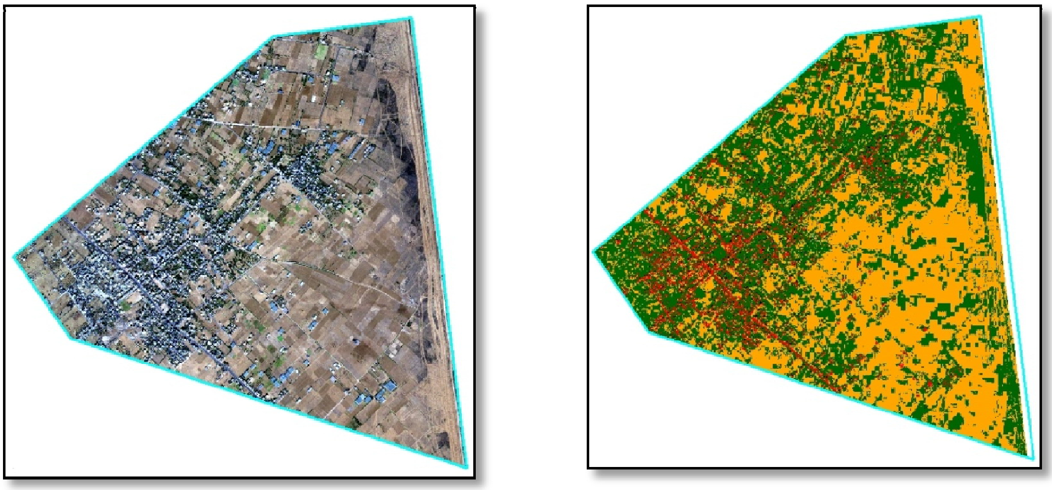


Figure (4.8): Aerial photo and land use classification of N/16 influence area for year2003

Table(4.5) : Landuse classification and Soil type for each influence areas in KYGfor year 2003.

Influence Areas	Soil Type	Buildup Area m^2	Agricultural Area m^2	Open Space Area m^2
CAMP - 8	Loessal sandy soil	159	4,043	1,929
	Sandy loess soil over loess	402,022	10,250,544	4,890,752
	Sandy loess soil	36,592	933,005	445,157
L/101	Loessal sandy soil	62,807	1,080,791	356,178
	Sandy regosols	243,779	4,194,956	1,382,462
L/18	Loessal sandy soil	457,058	2,980,219	697,218
	Sandy regosols	156,929	1,023,244	239,386
L/47	Loessal sandy soil	998,419	2,428,332	1,232,179
	Sandy regosols	278,402	677,124	343,585
L/57	Loessal sandy soil	221,961	2,931,752	693,389
	Sandy loess soil over loess	204,475	2,700,789	638,764
	Sandy loess soil	6,928	91,513	21,644
L/66	Loessal sandy soil	98,179	2,670,242	3,167,777
	Sandy loess soil	5,475	148,907	176,652
L/8	Loessal sandy soil	107,984	1,810,053	299,717
L/86	Loessal sandy soil	597,936	1,024,670	1,297,000
	Sandy regosols	2,512,596	4,305,777	5,450,139
M/10	Loessal sandy soil	633,754	629,195	217,683
	Sandy loess soil over loess	694,693	689,695	238,614
M/8	Sandy loess soil over loess	2,178,312	2,682,866	663,326
	Sandy loess soil	313,202	385,747	95,374
N/12	Sandy loess soil over loess	185,423	2,899,048	3,066,788
N/16	Sandy loess soil over loess	84,129	2,276,583	2,381,872
	Sandy loess soil	31,727	858,540	898,246
P/50	Loessal sandy soil	103,818	1,110,758	644,514
	Sandy regosols	192,048	2,054,748	1,192,261
T/15	Loessal sandy soil	751,797	2,216,949	644,156
	Dark brown / reddish brown	10,021	29,552	8,587
T/22	Loessal sandy soil	4,427	101,152	30,534
	Dark brown / reddish brown	124,471	2,844,086	858,515
	Sandy loess soil over loess	808	18,458	5,572
	Sandy loess soil	65,967	1,507,304	454,994
	Dark brown / reddish brown	130	2,970	897
	Sandy loess soil	130	2,970	897
T/26	Loessal sandy soil	25,734	912,999	265,743

Influence Areas	Soil Type	Buildup Area m^2	Agricultural Area m^2	Open Space Area m^2
	Dark brown / reddish brown	3,466	122,975	35,794
	Sandy loess soil over loess	11,151	395,605	115,147
T/6	Loessal sandy soil	86,712	1,747,427	221,691
	Dark brown / reddish brown	19,632	395,627	50,192

4.3. Recharge

Groundwater recharge is a hydrologic process where water moves downward from surface water to groundwater. Recharge occurs both naturally and artificially, where rainwater and or reclaimed water is routed to the subsurface. Major component of recharge in the Gaza coastal aquifer include:

- Rainfall recharge.
- Return flows from irrigation.
- Return flow from other sources (water distribution systems, septic systems, and wastewater collection systems, wadi Gaza and infiltration basins) (METCALF AND EDDY, 2000).

4.3.1. Recharge from rainfall (R)

Rainfall recharge accounts for most of the renewable resources of the Gaza costal aquifer. A fraction of rainfall infiltrates and replenishes the aquifer system (effective recharge), and the remainder is lost to evapotranspiration and runoff. Recharge from rainfall is perhaps the most difficult parameter to quantify in the GS due to all of potential factors that affect infiltration of rainwater. This include land use, soil type, as well as other influencing factors (METCALF AND EDDY, 2000). As previously shown, monthly total rainfall for Khanyounis and Khuzza'a stations was utilized to estimate the total rainfall recharge. Values of total rainfall were simply multiplied by certain coefficients reflecting mainly the effect of soil type, land uses, to calculate the amount of infiltrated rainfall. Those coefficients are presented in Tables (4.8,4.9).

Table (4.8): Recharge coefficient according to soil type (Metcalf AND Eddy, 2000)

Type of Soil	Coefficient of Recharge
Dark brown / reddish brown	0.025
Sandy regosols	0.7
Loess soils	0.15
Loessal sandy soil	0.25
Sandy loess soil	0.3
Sandy loess soil over loess	0.35

Table (4.9): Recharge coefficient according to land use (Hamdan,2007)

Type of Land use	Coefficient of Recharge
Built-up areas	0.135
Cultivated (Irrigation areas)	0.85
Natural zones (Open space areas)	0.925

Table (4.10) shows the calculation of rainfall recharge for 2003. Complete data of recharge from rainfall for each influence areas are found in Appendix (3).

Table (4.10) : Computation of R for January, 2003

Influence Areas	SOIL_TYPE	Rainfall mm	Build Area m^2	Effective Recharge from Build m^3	Agr. Area m^2	Effective Recharge from Agr. m^3	Open Area m^2	Effective Recharge from Open m^3	Summation of Recharge volume (m^3)	
CAMP - 8	Loessal sandy soil	21.20	159	0.1	4,043	18	1,929	9	28	**106,342**
	Sandy loess soil	21.20	402,022	403	10,250,54	64,650	4,890,75	33,568	98,621	
	Sandy loess soil	21.20	36,592	31	933,005	5,044	445,157	2,619	7,694	
L/101	Loessal sandy soil	26.70	62,807	57	1,080,791	6,132	356,178	2,199	8,388	**99,547**
	Sandy regosols	26.70	243,779	615	4,194,956	66,643	1,382,46	23,900	91,159	
L/18	Loessal sandy soil	26.70	457,058	412	2,980,219	16,909	697,218	4,305	21,626	**42,416**
	Sandy regosols	26.70	156,929	396	1,023,244	16,256	239,386	4,139	20,790	
L/47	Loessal sandy soil	26.70	998,419	900	2,428,332	13,778	1,232,17	7,608	22,285	**39,685**
	Sandy regosols	26.70	278,402	702	677,124	10,757	343,585	5,940	17,400	
L/57	Loessal sandy soil	26.70	221,961	200	2,931,752	16,634	693,389	4,281	21,115	**49,139**
	Sandy loess soil	26.70	204,475	258	2,700,789	21,453	638,764	5,522	27,233	
	Sandy loess soil	26.70	6,928	7	91,513	623	21,644	160	791	
L/66	Loessal sandy soil	26.70	98,179	88	2,670,242	15,150	3,167,77	19,559	34,798	**37,126**
	Sandy loess soil	26.70	5,475	6	148,907	1,014	176,652	1,309	2,329	
L/8	Loessal sandy soil	26.70	107,984	97	1,810,053	10,270	299,717	1,851	12,218	**12,218**
L/86	Loessal sandy soil	26.70	597,936	539	1,024,670	5,814	1,297,00	8,008	14,361	**183,327**
	Sandy regosols	26.70	2,512,59	6,340	4,305,777	68,404	5,450,13	94,223	168,967	
M/10	Loessal sandy soil	26.70	633,754	571	629,195	3,570	217,683	1,344	5,485	**13,902**
	Sandy loess soil	26.70	694,693	876	689,695	5,478	238,614	2,063	8,417	
M/8	Sandy loess soil	26.70	2,178,31	2,748	2,682,866	21,311	663,326	5,734	29,793	**33,464**

Influence Areas	SOIL_TYPE	Rainfall mm	Build Area m^2	Effective Recharge from Build m^3	Agr. Area m^2	Effective Recharge from Agr. m^3	Open Area m^2	Effective Recharge from Open m^3	Summation of Recharge volume (m^3)	
	Sandy loess soil	26.70	313,202	339	385,747	2,626	95,374	707	3,672	
N/12	Sandy loess soil	21.20	185,423	186	2,899,048	18,284	3,066,78	21,049	39,519	**39,519**
N/16	Sandy loess soil	21.20	84,129	84	2,276,583	14,358	2,381,87	16,348	30,791	**40,744**
	Sandy loess soil	21.20	31,727	27	858,540	4,641	898,246	5,284	9,953	
P/50	Loessal sandy soil	26.70	103,818	94	1,110,758	6,302	644,514	3,979	10,375	**64,115**
	Sandy regosols	26.70	192,048	485	2,054,748	32,643	1,192,26	20,612	53,739	
T/15	Loessal sandy soil	26.70	751,797	677	2,216,949	12,578	644,156	3,977	17,233	**17,463**
	Dark brown /	26.70	10,021	9	29,552	168	8,587	53	230	
T/22	Loessal sandy soil	26.70	4,427	4	101,152	574	30,534	189	766	**36,266**
	Dark brown /	26.70	124,471	112	2,844,086	16,137	858,515	5,301	21,550	
	Sandy loess soil	26.70	808	1	18,458	147	5,572	48	196	
	Sandy loess soil	26.70	65,967	71	1,507,304	10,262	454,994	3,371	13,705	
	Dark brown /	26.70	130	0	2,970	17	897	6	23	
	Sandy loess soil	26.70	130	0	2,970	20	897	7	27	
T/26	Loessal sandy soil	26.70	25,734	23	912,999	5,180	265,743	1,641	6,844	**11,918**
	Dark brown /	26.70	3,466	3	122,975	698	35,794	221	922	
	Sandy loess soil	26.70	11,151	14	395,605	3,142	115,147	995	4,152	
T/6	Loessal sandy soil	26.70	86,712	78	1,747,427	9,914	221,691	1,369	11,361	**13,934**
	Dark brown /	26.70	19,632	18	395,627	2,245	50,192	310	2,572	

4.3.2. Recharge from Return Flow

There are three primary sources of return flow in the Gaza Strip: leakage from municipal water distribution system, wastewater return flows and irrigation return flow. According to the Palestinian Water authority the recharge from return flow was estimated as follows:

4.3.2.1. Return flow from water distribution systems (RRFW)

The leakage from water distribution system was estimated as a percentage of the total abstraction. The leakage from municipal water distribution system was estimated to include the physical losses 23 % of the total abstraction (Al Mahallawi, 2005). Moreover, KYG was provided the water from two sources, the first one was the abstraction from municipal wells and second was MEKKEROT water, MEKKEROT water was provided by an Israeli company to KYG especially eastern part of KYG .As a result of the aforementioned situation the recharge from retain flow was calculated based on the following steps:

1. Determine the total water consumption from municipal wells and MEKKEROT water for all KYG.
2. Divide the total water consumption obtained from (step 1) on total build up area in all KYG.
3. Multiply the buildup area in each influence area with the ratio obtained from (step 2) to estimate the water consumption for each influence area.
4. Consider the physical losses 23% from the water consumption.
5. Using the following equation (Eq. 4.1) to estimate RRFW.

$$\boldsymbol{Leakage\ from\ water\ distribution\ networks} = Water\ consumption\ per\ influnce\ area(\ step\ 3) \times physical\ losses\ of\ networks \ldots\ldots \quad \text{Eq .4.1}$$

Table (4.11) show the estimation for return flow from water distribution systems for year 2003. Complete data of calculation RRFW are found in Appendix (4).

4.3.2.2. Return Flow from wastewater distribution systems (RRFWW)

The leakage from wastewater distribution system was recharge from unsewered areas where cesspits system exists is significant, especially in Khanyounis city. These cesspits serve one house or a number of houses. This system lets water to percolate through soil to the groundwater. After some years of construction the soil permeability decreases and these systems must be evacuated two to three times per year that depends on water consumption. When these systems become filled they are pumped by vacuum tankers and discharged mainly into uncontrolled areas and sometimes to the near wastewater treatment plant (Al Mahallawi, 2005). As mentioned before, about 40 % of the population in the study area are connected to sewer networks after the middle of 2007(MoP,2009). So as a result of complex situation and for simplicity estimation the sewer networks was neglected after the middle of 2007 and assumed the cesspits system still exists for all area of KYG.

There are no estimations for the leakage from the sewer systems, so 20% leakage from the total flow was made according to Rabah (1996), in addition, 80% converted water to wastewater was taken according to Almasri (2008) and 90% remain after pumper by vacuum was taken in consideration according to Khanyounis municipality estimation. In addition, the water networks efficiency was estimated as 48% (Al Mahallawi, 2005). The total quantity of recharge from wastewater was calculated for each influence area according to the following steps:

1. Determine the water consumption from municipal wells and MEKKEROT water for each influence area which was obtained from (step 3) in previous section.
2. Using the following equation (Eq. 4.2) with previous percentages to RRFWW .

$$\boldsymbol{Leakage\ from\ wastewater\ cesspits} = (Water\ consumption\ per\ influnce\ area \times \%efficiency \times \%\ converted\ to\ waste\ water) \times \%\ Remain\ after\ \text{pumped by vacuum tankers} \ldots\ldots \text{Eq. 4.2}$$

Table (4.12) show the calculation for return flow from wastewater distribution systems for 2003. Complete data of calculation for RRFWW for each influence area are found in Appendix (4).

4.3.2.3. Return Flow from Irrigation (RRFIW)

Irrigation return flow has been estimated as a percentage of the total agricultural abstraction, so irrigation return flow has been estimated to be about 25 % of the total agricultural abstraction (Metcalf and Eddy, 2000). The total quantity of recharge from irrigation water was calculated for each influence area from equation (4.3):

$$\textbf{Return flow from irrigation water} = Agricultural\ \text{abstraction} \times \%\ return\ flow\ from\ irrigation \ldots\ldots \text{Eq.4.3}$$

Table (4.13) show the calculation for return flow from irrigation water for 2007. Complete data of calculation RRFIW are found in Appendix (4).

Table (4.11) : RRFW estimation for year 2003 in m^3/month

Influence Areas	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
CAMP - 8	6,368	6,104	6,819	7,732	2,451	9,009	9,656	9,358	9,271	9,314	7,943	7,369
L/101	11,662	11,178	12,487	14,159	4,488	16,498	17,683	17,137	16,978	17,056	14,546	13,494
L/18	11,773	11,285	12,606	14,294	4,531	16,655	17,852	17,301	17,140	17,219	14,685	13,623
L/47	15,164	14,536	16,237	18,411	5,836	21,453	22,994	22,284	22,077	22,179	18,915	17,546
L/57	11,488	11,012	12,301	13,948	4,422	16,253	17,421	16,882	16,725	16,803	14,330	13,293
L/66	5,357	5,135	5,736	6,504	2,062	7,579	8,123	7,873	7,799	7,835	6,682	6,199
L/8	4,481	4,295	4,798	5,440	1,725	6,339	6,794	6,584	6,523	6,553	5,589	5,185
L/86	42,066	40,323	45,043	51,074	16,191	59,512	63,788	61,818	61,242	61,525	52,472	48,675
M/10	9,210	8,828	9,861	11,182	3,545	13,029	13,965	13,534	13,408	13,470	11,488	10,657
M/8	10,041	9,625	10,752	12,191	3,865	14,205	15,226	14,756	14,618	14,686	12,525	11,619
N/12	4,036	3,869	4,322	4,900	1,553	5,710	6,120	5,931	5,876	5,903	5,034	4,670
N/16	4,718	4,522	5,052	5,728	1,816	6,675	7,154	6,933	6,869	6,901	5,885	5,459
P/50	7,921	7,593	8,482	9,617	3,049	11,206	12,012	11,641	11,532	11,586	9,881	9,166
T/15	5,929	5,683	6,349	7,199	2,282	8,388	8,991	8,713	8,632	8,672	7,396	6,861
T/22	658	631	705	799	253	931	998	967	958	962	821	761
T/26	1,916	1,836	2,051	2,326	737	2,710	2,905	2,815	2,789	2,802	2,390	2,217
T/6	1,528	1,465	1,636	1,856	588	2,162	2,318	2,246	2,225	2,235	1,906	1,768

Table (4.12) : RRFWW estimation for year 2003 in m^3/month

Influence Areas	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
CAMP - 8	9,569	9,172	10,246	11,618	3,683	13,537	14,510	14,062	13,931	13,995	11,936	11,072
L/101	17,523	16,797	18,763	21,275	6,744	24,790	26,571	25,751	25,511	25,629	21,858	20,276
L/18	17,690	16,957	18,942	21,478	6,809	25,026	26,825	25,996	25,754	25,873	22,066	20,469
L/47	22,786	21,841	24,398	27,665	8,770	32,235	34,551	33,484	33,173	33,326	28,422	26,365
L/57	17,262	16,547	18,484	20,959	6,644	24,421	26,176	25,368	25,132	25,248	21,533	19,975
L/66	8,050	7,716	8,619	9,773	3,098	11,388	12,206	11,829	11,719	11,773	10,041	9,314
L/8	6,733	6,454	7,209	8,174	2,591	9,525	10,209	9,894	9,802	9,847	8,398	7,790
L/86	63,209	60,589	67,681	76,744	24,329	89,423	95,848	92,888	92,023	92,448	78,845	73,140
M/10	13,839	13,265	14,818	16,802	5,326	19,578	20,984	20,336	20,147	20,240	17,262	16,013
M/8	15,088	14,462	16,155	18,318	5,807	21,345	22,879	22,172	21,966	22,067	18,820	17,458
N/12	6,064	5,813	6,494	7,363	2,334	8,579	9,196	8,912	8,829	8,870	7,565	7,017
N/16	7,089	6,796	7,591	8,607	2,729	10,029	10,750	10,418	10,321	10,369	8,843	8,203
P/50	11,903	11,409	12,745	14,451	4,581	16,839	18,049	17,491	17,329	17,409	14,847	13,773
T/15	8,909	8,540	9,540	10,817	3,429	12,604	13,510	13,092	12,971	13,030	11,113	10,309
T/22	989	948	1,059	1,201	381	1,399	1,499	1,453	1,440	1,446	1,233	1,144
T/26	2,879	2,760	3,083	3,495	1,108	4,073	4,365	4,231	4,191	4,211	3,591	3,331
T/6	2,297	2,201	2,459	2,788	884	3,249	3,482	3,375	3,343	3,359	2,865	2,657

Table (4.13) : RRFIW estimation for 2003 in m^3/month

Influence Areas	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
CAMP - 8	83,078	83,145	81,873	79,572	111,848	119,278	117,840	119,455	96,519	71,693	73,992	81,691
L/101	39,177	39,209	38,609	37,524	52,744	56,248	55,570	56,332	45,516	33,809	34,892	38,523
L/18	29,729	29,753	29,298	28,475	40,025	42,683	42,169	42,747	34,539	25,655	26,478	29,233
L/47	23,061	23,079	22,726	22,088	31,047	33,109	32,710	33,158	26,792	19,901	20,539	22,676
L/57	42,506	42,541	41,890	40,713	57,226	61,028	60,292	61,119	49,383	36,681	37,857	41,797
L/66	20,935	20,952	20,631	20,051	28,184	30,057	29,694	30,101	24,322	18,066	18,645	20,585
L/8	13,441	13,452	13,246	12,874	18,096	19,298	19,066	19,327	15,616	11,599	11,971	13,217
L/86	39,583	39,615	39,009	37,913	53,291	56,831	56,146	56,916	45,987	34,159	35,254	38,923
M/10	9,794	9,802	9,652	9,381	13,186	14,061	13,892	14,082	11,378	8,452	8,723	9,630
M/8	22,787	22,806	22,457	21,826	30,678	32,716	32,322	32,765	26,474	19,665	20,295	22,407
N/12	21,528	21,545	21,216	20,620	28,983	30,909	30,536	30,955	25,011	18,578	19,173	21,169
N/16	23,281	23,300	22,943	22,299	31,343	33,425	33,023	33,475	27,048	20,091	20,735	22,892
P/50	23,507	23,526	23,166	22,515	31,647	33,749	33,343	33,800	27,310	20,286	20,936	23,114
T/15	16,682	16,696	16,440	15,978	22,459	23,951	23,663	23,987	19,381	14,396	14,858	16,404
T/22	33,245	33,272	32,763	31,842	44,758	47,731	47,156	47,803	38,624	28,690	29,609	32,690
T/26	10,631	10,639	10,477	10,182	14,312	15,263	15,079	15,286	12,351	9,174	9,468	10,453
T/6	15,914	15,927	15,683	15,243	21,425	22,848	22,573	22,882	18,489	13,733	14,174	15,648

4.4. Abstraction:

The abstraction from the coastal aquifer in the study area takes place by about 1500 production wells distributed between agricultural (legal and illegal) and municipal wells. According to PWA (2006) and CWMU (2009), there are around 30 municipal wells and 1450 agricultural wells within Khanyounis Governorate. The estimated municipal abstraction (QM) totals about 12.9 MCM per year, while agricultural abstraction (QA) is estimated to account for about 25.1 MCM for year 2006.

4.4.1. Municipal Abstraction

Based on the available abstraction data from PWA and CWMU, accurate monthly municipal production in the study area for the year 2000 to 2008 was collected. Due to limitation in the available fresh groundwater resources some municipalities located in the study area consume water that is sold by the Israeli company MEKKEROT (2 MCM/yr, municipalities like Khuzz'a, Abassan and Bani Suhaila).

Table (4.14) presented the QM for L47 influence area as an example. It is noted that the QM are varies from month to another. In summer season there are huge abstraction specially in August and the abstraction decreases in winter specially in February. The QM of wells which located in each influence area was summed for the analysis' time period as shown in Figure (4.9) which illustrates each municipal wells which locate in influence area buffer for monitoring well L/47 was summed to represent the QM for this influence area . Complete data of QM for each influence areas are found in Appendix (5).

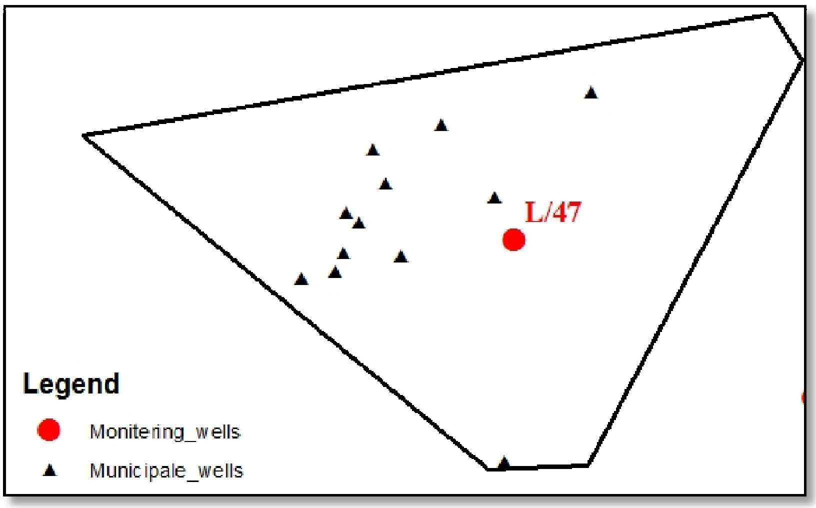


Figure (4.9):Municipal wells located in influence area buffer for monitoring well L/47

4.4.2. Agricultural Abstraction

At the present time the abstraction from the coastal aquifer in GS by the agricultural wells is not monitored. The only available data about QA was during the interval 1986-1993 (PWA/Metcalf AND Eddy, 2000). These data were collected by the water division during the civil administration decade of the Israeli occupation of Gaza Strip. The approximate estimation of irrigation water demand based on quota allowed and available irrigated lands is about 25.5 MCM per year 2006 for KYG (PWA, 2006). As mentioned above, each agricultural well in study area has not any record about their abstraction available, instead agricultural areas were used to estimate agricultural abstraction.

Thus, it was observed that the agricultural water demand was roughly estimated from Ministry of Agriculture. However during the period 2000-2008 KYG land use was exposed to different change in cultivated area. Based on the above, it is reasonable to estimate the QA per month to stand up on the above mentioned land use change influence .So, based on the land use classification as illustrated previously, the available agricultural areas for each influence area will multiplied by the irrigation water needs per dunum and distributed for each month.

According to irrigation behavior in the study area, the water needed for one dunum is assumed to be in average about 500 m^3/yr (MoP,2010). Moreover, crop water demands varies throughout the year with minimum demands in winter months and peak demands occur during summer months, the percentage of average irrigation water requirements for each month are given in Table (4.15) (CEP and FCG, 2010). Table (4.16) presents the QA estimation for year 2003. Complete data of QA for each influence areas are found in Appendix (5).

Table(4.14) : QM for L47 influence area in m^3/month.

Month	2000	2001	2002	2003	2004	2005	2006	2007	2008
Jan	152,548	222,688	239,716	223,780	308,285	258,446	274,570	322,301	213,419
Feb	170,646	208,771	218,293	198,148	298,671	260,756	275,750	251,863	213,973
Mar	183,306	221,900	286,638	258,628	365,883	294,614	352,223	307,245	285,678
Apr	184,886	261,521	256,702	321,693	362,094	301,532	293,760	313,129	327,637
May	196,557	264,814	325,276	338,859	409,757	309,455	337,760	346,436	316,104
Jun	214,151	301,358	298,193	376,998	404,633	351,458	358,720	385,568	374,080
Jul	292,668	324,396	291,539	399,645	389,547	412,503	358,000	387,899	411,806
Aug	296,218	300,035	306,137	400,894	435,059	424,226	355,130	398,949	393,360
Sep	272,460	265,949	317,002	374,559	412,895	433,929	370,185	384,731	366,414
Oct	269,363	281,236	313,943	354,834	392,509	359,370	395,287	415,949	310,650
Nov	237,138	276,220	288,987	364,558	329,150	319,876	358,137	376,519	230,926
Dec	204,234	255,245	278,111	325,706	239,366	307,590	317,681	310,810	255,524

Table (4.15): The percentage of average irrigation water requirements for each month, adopted from (CEP and FCG, 2010)

Month	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
% Average irrigation water	7.43	7.43	7.32	7.11	10.00	10.66	10.53	10.68	8.63	6.41	6.61	7.30

Table (4.16): QA estimation for year 2003 in m^3/month.

Influence Areas	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Camp_8	415,388	415,725	409,365	397,861	559,239	596,389	589,202	597,277	482,594	358,467	369,958	408,456
L-101	195,885	196,044	193,045	187,620	263,721	281,240	277,851	281,659	227,578	169,043	174,461	192,616
L-18	148,646	148,767	146,491	142,374	200,123	213,417	210,845	213,735	172,696	128,277	132,389	146,165
L-47	115,303	115,397	113,632	110,438	155,234	165,546	163,551	165,792	133,959	99,503	102,693	113,379
L-57	212,530	212,703	209,449	203,563	286,131	305,138	301,461	305,593	246,916	183,407	189,286	208,984
L-66	104,673	104,758	103,155	100,257	140,922	150,283	148,472	150,507	121,608	90,330	93,225	102,926
L-8	67,206	67,261	66,232	64,370	90,480	96,490	95,328	96,634	78,079	57,997	59,856	66,085
L-86	197,916	198,077	195,046	189,565	266,455	284,156	280,732	284,579	229,937	170,796	176,270	194,613
M-10	48,970	49,009	48,260	46,903	65,928	70,307	69,460	70,412	56,892	42,259	43,614	48,152
M-8	113,936	114,028	112,284	109,128	153,392	163,582	161,611	163,826	132,369	98,323	101,475	112,034
N-12	107,640	107,727	106,079	103,098	144,916	154,543	152,680	154,773	125,055	92,890	95,867	105,843
N-16	116,405	116,499	114,717	111,493	156,717	167,127	165,113	167,376	135,238	100,454	103,674	114,462
P-50	117,533	117,629	115,829	112,574	158,236	168,747	166,714	168,998	136,549	101,428	104,679	115,572
T-15	83,411	83,479	82,202	79,892	112,297	119,757	118,314	119,935	96,906	71,981	74,289	82,019
T-22	166,226	166,361	163,816	159,212	223,791	238,657	235,781	239,013	193,120	143,448	148,046	163,452
T-26	53,154	53,197	52,383	50,911	71,561	76,315	75,395	76,428	61,753	45,870	47,340	52,267
T-6	79,570	79,635	78,416	76,213	107,126	114,242	112,865	114,412	92,444	68,667	70,868	78,242

4.5. Lateral inflow and Discharge to the sea outflow

Lateral flow and discharge to the sea are two parameters contributing to overall water balance in GS. These two parameters are subjected to considerable temporal variation from year to another. Alghamri (2009) estimated that inflow from lateral inflow at year 2004 was 3 MCM where as outflow from discharge to the sea for the same year was 1.5 MCM. Consequently, the net balance for these two parameters was 1.5 MCM. These two parameters were neglected in this study due to the following justification:

- Net balance for these parameters was very small compared with other parameters.
- Accurate estimation for these parameters was very difficult and very limited data were available.
- The developed model gave very satisfactory results even though these two parameters were neglected.

4.6. Comparison between this study variables estimation and estimation from another related study

The aforementioned variables estimation in this research was compared with the same variables estimation conducted in a related study. The comparison was carried out with Alghamri (2009). According to the inflow and outflow components in Alghamri (2009)model domain, a water balance for the year 2004 was estimated as shown in the Table (4.17) which also includes the variables estimated in this research for the same year.

Table (4.17): Variables estimation conducted by Alghamri (2009) and this research.

Variable	Alghamri (2009) MCM	This research estimation MCM
Inflow		
• Recharge from rainfall	12.35	11.22
• Leakage from water supply system.	2	2.67
• Leakage from wastewater system	3.4	4.03
• Agricultural return flow	7.5	6.2
Total estimated inflow	**25.7**	**24.12**
Outflow		
• Overall abstraction	48.4	43.90
Total estimated outflow	**48.4**	**43.90**

It is noticed that the variables estimations for both studies are almost the same with very minor differences indicating the reliability of the conducted estimation for further analysis.

4.7. Construction Data Matrix for ANNs Model

4.7.1. Selection the Variables of ANNs Model

One of the critical issues in training the ANNs model is to select input variables that are highly correlated with the studied problem. The choice of variables is guided by intuition and physical relations. Understanding the physical system and expertise in the problem domain and conditions gives an idea of which input variables are likely to be influential. Once in ANNs, variables can be selected and deselect, and ANNs can also determine useful variables (Jiang and Cotton, 2004).

Hydro-geologically, the GWL may be affected by some variables such as: recharge, abstraction, precipitation, return flow, and others. The variables were chosen to predict the GWL which is a dependent of other variables. The chosen variables are described in Table (4.18).

Table (4.18): ANNs model input variables

Variable	Sym.	Unit	Type
Final groundwater level.	GWL_f	m	Dependent
Initial groundwater level.	GWL_o	m	Independent
Recharge from rainfall.	R	m^3/month	Independent
Recharge from return flow from water networks.	RRFW	m^3/month	Independent
Recharge from return flow from wastewater networks.	RRFWW	m^3/month	Independent
Recharge from return flow from irrigation water.	RFIW	m^3/month	Independent
Abstraction from municipal wells.	QM	m^3/ month	Independent
Abstraction from agricultural wells.	QA	m^3/ month	Independent

The ANNs model operated under black box, that includes large number of complex mathematical functions as discussed in Chapter (2). Equation (4.5) represents -in simple way- the ANNs model.

$\mathbf{GWL_f = \mathit{f}\,(GWL_o, R, RFW, RFWW, RFIW, QM, QA)}$ .... Eq. 4.5

4.7.2. Time Distribution Phases of ANNs Model Data

Firstly, the model matrix was prepared in monthly base based on GWL available from selected monitoring wells in the study area. The matrix was consisted of 1626 cases. Several trials were conducted to simulate the monthly GWL. The preliminary results reveals unsatisfactory results and poor model performance.

Therefore, the matrix was prepared in quarterly base to minimize the missing value and to take a time lag in physical process in consideration. Accordingly, the matrix consists of 542 cases. The time distribution was divided into four phases A, B, C and D. The phase A starts from January to March, the phase B starts from April to June, the phase C starts from July to September and the phase D starts from October to December. For example, time phase 2000-A extends from January 2000 to March 2000 and time phase 2000-B extends from April 2000 to June 2000, etc. So all other factors were organized according to this time distribution. Table (4.19) presented the time distribution phase of the ANNs model for the year 2000

Table (4.19) The time distribution phase of the ANNs model for the year 2000

Year	Month	Time phase
2000	January	2000-A
2000	February	
2000	March	
2000	April	2000-B
2000	May	
2000	June	
2000	July	2000-C
2000	August	
2000	September	
2000	October	2000-D
2000	November	
2000	December	

4.7.3. Organizing of ANNs Model Data

The organizing of ANNs model data are required to construct some hundreds of data cases of input and output variables. These cases construct data matrix. Data organizing was carried out using software Ms. Excel and Access software. The data matrix is considered as raw material to ANNs model. Table (4.20) summarizes procedures of calculating and organizing ANNs model variables.

Table (4.20): The procedures of organizing ANNs model variables

	Variable	Sym.	Summarization of calculation procedures
1.	Final groundwater level	GWL_f	It is represented the level at the end of each time phase and it is collected from PWA data bank. It is presented in Appendix (1).
2.	Initial groundwater level	GWL_o	It is represented the level at the beginning of each time phase and it is collected from PWA data bank. It is presented in Appendix (1).
3.	Recharge from rainfall	R	It is calculated in monthly base, as total rainfall were simply multiplied by certain coefficients reflecting mainly the effect of soil type, land uses and then it is summed for each influence area. Then it is summed for each time phase. It is presented in Appendix (3).

	Variable	Sym.	Summarization of calculation procedures
4.	Recharge from return flow from water networks	RRFW	It is calculated in monthly base, as water consumption multiplied by certain coefficients reflecting mainly the effect of physical losses in networks and then it is summed for each influence area. Then it is summed for each time phase. It is presented in Appendix (4).
5.	Recharge from return flow from wastewater networks	RRFWW	It is calculated in monthly base, as water consumption multiplied by certain coefficients reflecting mainly the effect sewer situation either cesspits or networks and then it is summed for each influence area. Then it is summed for each time phase. It is presented in Appendix (4).
6.	Recharge from return flow from irrigation water	RRFIW	It is calculated in monthly base, as agricultural area in each influence area multiplied by irrigation water need for year and then distribute it for each month during the year. Then it is summed for each time phase. It is presented in Appendix (4).
7.	Abstraction from municipal wells	QM	Monthly abstraction quantities for study area municipal wells is collected from PWA data bank. Then it is summed for each well located in influence area. Then it is summed for each time phase . It is presented in Appendix (5).
8.	Abstraction from agricultural wells	QA	It is calculated in monthly base, as agricultural area in each influence area multiplied by irrigation water need for year. Then it is summed for each time phase. It is presented in Appendix (5).

By application the procedures in Table (4.20), the data matrix for ANNs model were obtained. The entire data matrix is presented in Appendix (6). Table (4.21) presented a side of ANNs model matrix. Moreover, the shaded row in Table (4.21) was obtained as the following in Table (4.22).

Table (4.21) : Side of ANNs model matrix

Well No.	Time phase		GWL_o	GWL_f	QM	QA	R	RRFW	RRFWW	RRFIW
L/47	2000	A	-1.53	-1.77	506,500	414,856	262,522	16,376	24,606	82,971
L/47	2000	B	-1.77	-1.79	595,594	519,537	0	21,073	31,664	103,907
L/47	2000	C	-1.79	-2.22	861,346	558,192	0	26,644	40,035	111,638
L/47	2000	D	-2.22	-2.1	710,735	380,210	279,496	21,617	32,481	76,042
L/47	2001	A	-2.1	-2.13	653,359	414,856	258,863	20,275	30,465	82,971
L/47	2001	B	-2.13	-2.57	827,693	519,537	18,292	27,351	41,098	103,907
L/47	2001	C	-2.57	-2.94	890,380	558,192	0	30,046	45,147	111,638
L/47	2001	D	-2.94	-2.73	812,701	380,210	133,163	26,288	39,501	76,042
L/47	2002	A	-2.73	-2.565	744,647	414,856	305,397	23,662	35,555	82,971
L/47	**2002**	**B**	**-2.565**	**-3.27**	**880,171**	**519,537**	**17,560**	**28,433**	**42,723**	**103,907**
L/47	2002	C	-3.27	-3.33	914,678	558,192	0	31,408	47,193	111,638
L/47	2002	D	-3.33	-3.25	881,041	380,210	229,158	28,983	43,551	76,042
L/47	2003	A	-3.25	-3	680,556	344,332	231,421	45,937	69,025	68,866
L/47	2003	B	-3	-3.55	1,037,550	431,218	15,458	45,700	68,670	86,244
L/47	2003	C	-3.55	-4.46	1,175,098	463,302	0	67,355	101,208	92,660
L/47	2003	D	-4.46	-3.95	1,045,098	315,576	72,681	58,640	88,113	63,115
L/47	2004	A	-3.95	-4.37	972,839	344,332	223,544	50,928	76,525	68,866
L/47	2004	B	-4.37	-4.15	1,176,484	431,218	5,499	64,912	97,537	86,244
L/47	2004	C	-4.15	-4.83	3,590,469	325,738	10,999	204,239	306,891	265,148
L/47	2004	D	-4.83	-4.5	961,025	315,576	303,954	63,251	95,042	63,115
L/47	2005	A	-4.5	-4.55	813,816	344,332	287,604	50,998	76,630	68,866
L/47	2005	B	-4.55	-4.75	962,445	431,218	0	66,879	100,494	86,244
L/47	2005	C	-4.75	-5.2	1,270,658	463,302	0	79,102	118,860	92,660
L/47	2005	D	-5.2	-4.95	986,836	315,576	180,589	64,732	97,267	63,115
L/47	2006	A	-4.95	-4.74	902,543	354,944	123,797	64,632	97,117	70,989
L/47	2006	B	-4.74	-5.48	990,240	444,507	55,597	76,185	114,476	88,901
L/47	2006	C	-5.48	-5.41	1,083,315	477,580	2,224	88,410	132,846	95,516
L/47	2006	D	-5.41	-5.45	1,071,105	325,301	167,681	82,523	123,999	65,060
L/47	2007	A	-5.45	-5.52	881,409	354,944	172,722	64,359	96,707	70,989
L/47	2007	B	-5.52	-6.2	1,045,133	444,507	8,154	87,937	132,135	88,901
L/47	2007	C	-6.2	-6.68	1,171,579	477,580	0	101,502	152,518	95,516
L/47	2007	D	-6.68	-6.28	1,103,278	325,301	83,025	85,335	128,225	65,060
L/47	2008	A	-6.28	-6.3	713,070	354,944	153,152	57,926	87,039	70,989

Table (4.22): Illustrates one case in the entire data matrix.

Items	Description
L/ 47	The monitoring well L/47 .
2002-B	The second time phase on year 2002 which extended from April-2002 to June-2002.
-2.565	The GWL in April-2002.
-3.27	The GWL in June-2002.
880,171	The summation of municipal abstraction for April, may and June in year 2002.
519,537	The summation of agricultural abstraction estimation for April, may and June in year 2002.
17,560	The summation of recharge from rainfall estimation for April, May and June in year 2002.
28,433	The summation of recharge from return flow from water networks estimation for April, May and June in year 2002.
42,723	The summation of recharge from return flow from wastewater networks estimation for April, May and June in year 2002.
103,907	The summation of recharge from return flow from irrigation water estimation for April, May and June in year 2002.

4.7.4. Analysis of input data for ANNs Model.

Considering only those cases that have complete numeric values for all variables, only 542 cases satisfy the above-mentioned criteria from year 2000 to year 2008. ANNs model can performwell over an entire space only when the training data are evenly distributed in the space. As the current data are collected from limited sources, they may constitute clusters. Therefore, the distribution of each variables across its range in the database is examined.

The frequency distribution of different variables studied across the range of the 542 cases are represented graphically as histograms with normal distribution curve in Figure (4.10). The mean, standard deviation and ranges of different variables used in ANNs training is shown in Table (4.23). The entire data matrix is presented in Appendix (6).

Table (4.23): Mean , standard deviation and ranges of variables used to train the ANNs model

Variable	Sym.	Unit	Mean	Min.	Max.	Std. Dev.
Final Groundwater Level	GWL_f	m	0.155	-11.9	11	4.3
Initial Groundwater Level	GWL_o	m	0.155	-11.9	11	4.3
Recharge from rainfall	R	m^3/ 3month	136317.7	0.0	1428717	223160.5
Recharge from return flow from Water Networks	RRFW	m^3/ 3month	40190.1	1983.3	219436	36498.4
Recharge from return flow from Wastewater Networks	RRFWW	m^3/ 3month	60390.0	2980.1	329727	54842.8
Recharge from return flow from irrigation water	RFIW	m^3/ 3month	90736.9	25940.1	389214	54008.3
Abstraction from municipal wells	QM	m^3/ 3month	140938.7	0.0	3590469	304609.4
Abstraction from agricultural wells	QA	m^3/ 3month	453684.6	129700.3	1946068	270041.5

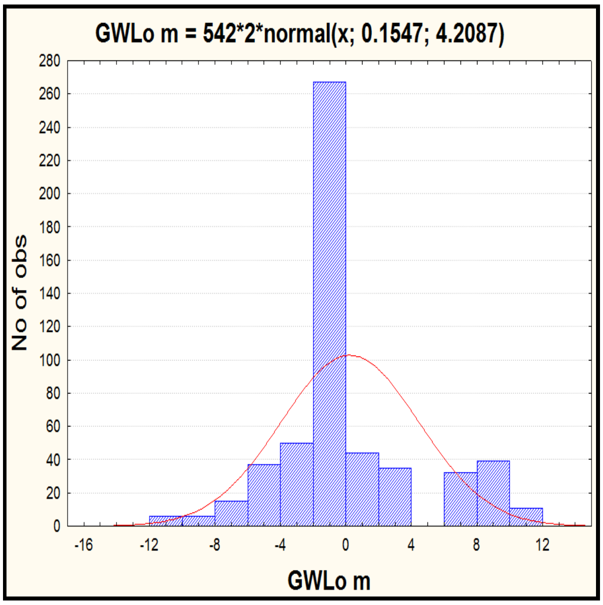


Figure (4.11.a): Frequency distribution of initial GWL.

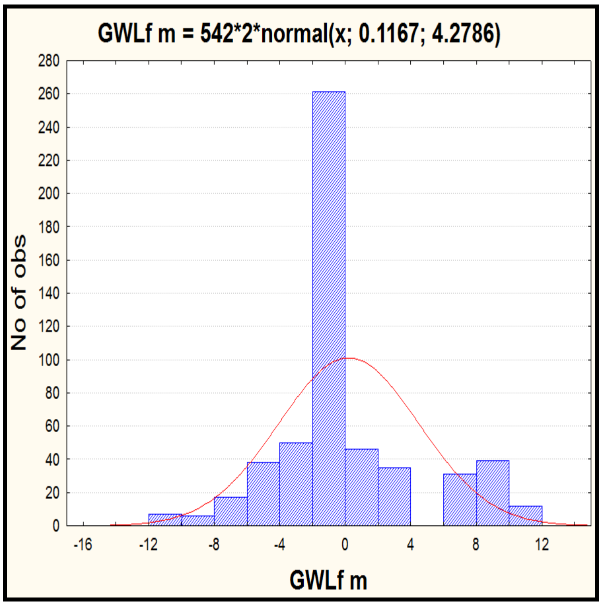


Figure (4.11.b): Frequency distribution of final GWL.

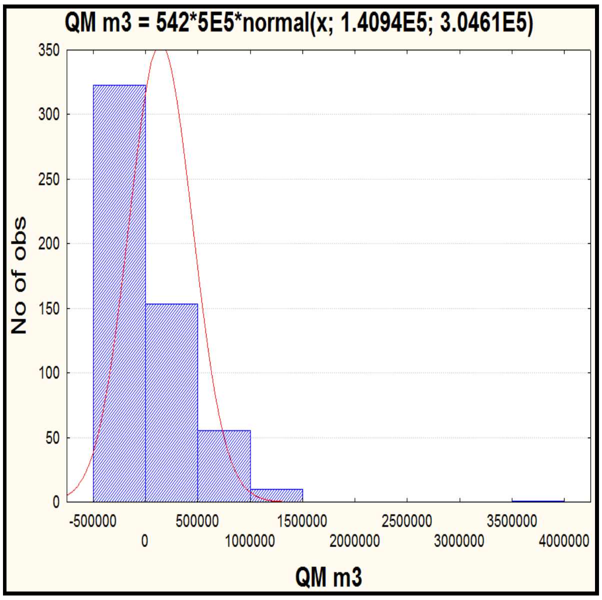


Figure (4.11.c): Frequency distribution of QM

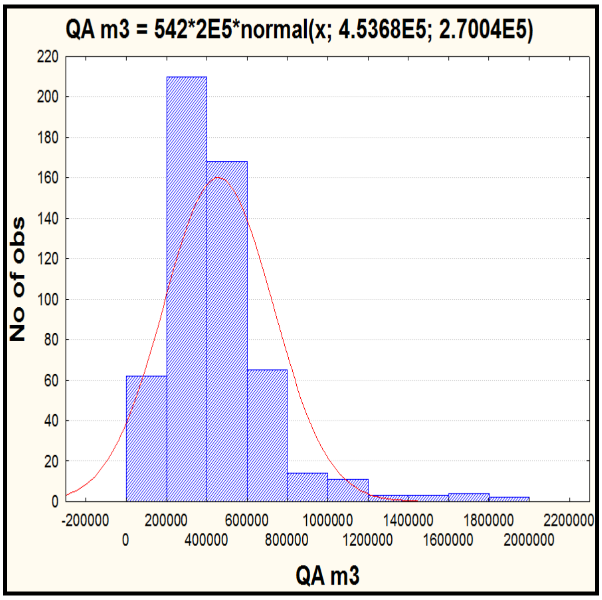


Figure (4.11.d): Frequency distribution of QA.

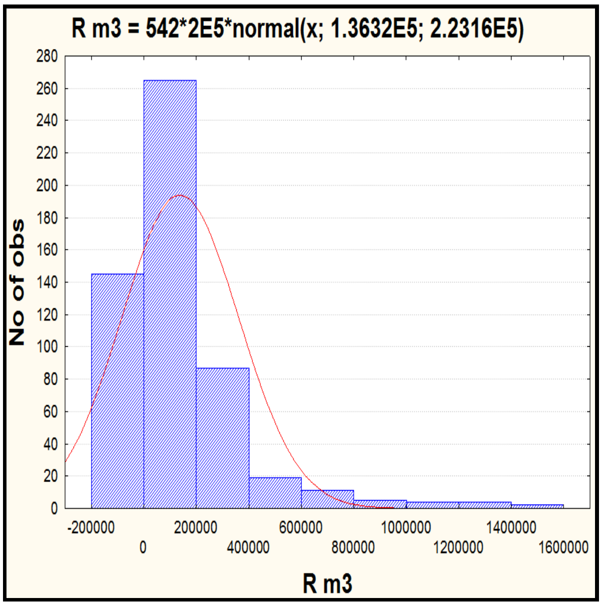


Figure (4.11.e): Frequency distribution of R.

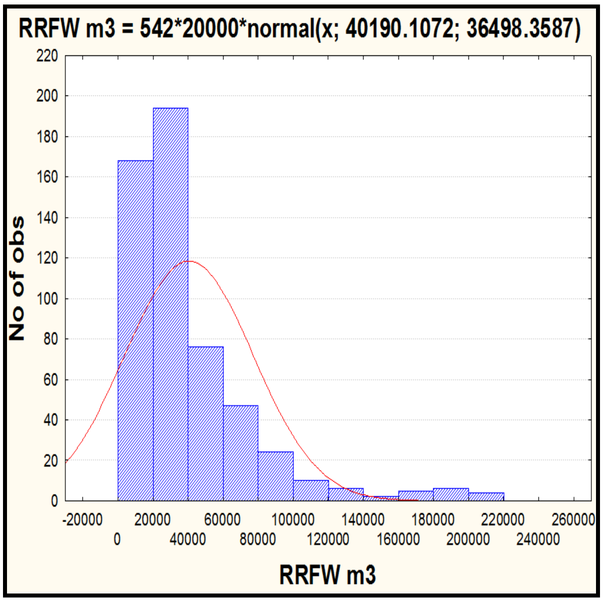


Figure (4.11.f): Frequency distribution of RRFW.

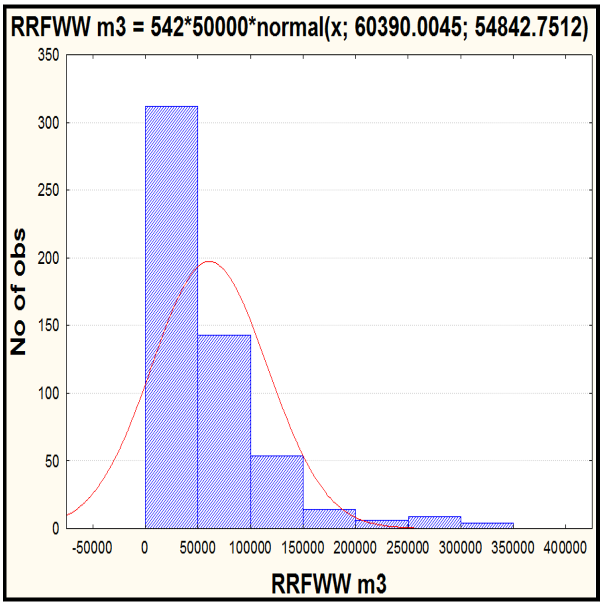


Figure (4.11.g): Frequency distribution of RRFWW.

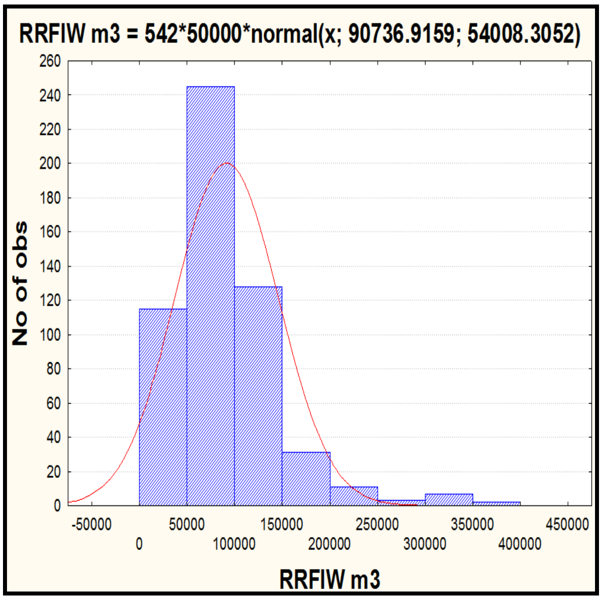


Figure (4.11.h): Frequency distribution of RRFIW.

4.7.5. Procedural Steps in Building ANNs Model

The ANNs model was designed using the STATISTICA Neural Networks (SNN) which is built in STATISTICA program version 7. STATISTICA, is a program where every analysis needed is at fingertips. Used around the world in more than 20 countries, StatSoft's STATISTICA line of software has gained unprecedented recognition by users and reviewers. In addition to both basic and advanced statistics, STATISTICA products offer specialized tools for analyzing neural networks, determining sample size, designing experiments, creating real-time quality control charts, reporting via the Web, and much more of the possibilities. The procedural steps in building and applying for ANNs model varies according to the tool used in building ANNs models. Using SNN, the procedural steps involves the following procedures:

4.7.5.1. Data Importation

Feed the data matrix for SNN to train the Network by "importing" or through the data entry process. The data must be in acceptable format such as spreadsheet. The input data is the cases that the network uses to train itself.

4.7.5.2. Problem Definition

Specify the inputs (Independent) and the output (Dependent) variable for the ANNs model. Initially, there are seven inputs variables and one output variables.

4.7.5.3. Extraction of the Test Set

In SNN, The test set extraction is about 50% of cases for training. 25% for calibration and 25% for testing and it is randomly selected and the user can change these percentage. Test set provide a means by which the network knows when to stop training and used for calibration and Testing.

4.7.5.4. Network Design

Choose the appropriate architecture of network among the available networks based on the type of the data and the problem. This step was previously presented in section 2.4. After many trials, A RBF network has been chosen because of its high capabilities to generalize well in problems plagued with significant heterogeneity and nonlinearity.

4.7.5.5. Network Training

Once the type of network has been chosen, the conditions to stop training processes was set before the network is trained. Training was controlled by some of conditions as: the maximum number of iterations, target performance which specifies the tolerance between the neural network prediction and actual output, the maximum run time and the minimum allowed gradient and .The overall training of the ANNs will involve the following processes; the input values of the first layer are weighted and passed on to the hidden layer; the neurons in the hidden layer will produce outputs by applying an activation function to the sum of the weighted input values; the resulting outputs are then weighted by the connections between the hidden and output layer. The desired results are generated in the output layer.

The network achieves the desired learning by adjusting its interconnected weights continuously until there is a close match between the output from the neurons and the output from the training data. The difference between the predicted outputs and the original outputs is referred to as error.

4.7.5.6. Network Calibration

A trained network will continuously train in order to make a model perform best on the training set. However, after some time, it is very possible for the network to "memorize" the training set instead of learning it. In order to prevent the possibility of memorization to occur, calibration is utilized. Calibration is a parameter, which indicates that the network has trained enough thus stopping the iteration process. This can be achieved in two ways;

4.7.5.7. Calibration Based on Best Test Set

When training begins at the interval specified, the Network stops to read the test set and computes an average error for it. The error of the training set continues to decrease until it becomes flat whereas the test set error decreases to an optimal point after which it slowly increases. The Network could be saved at this optimal point based on the best test set.

4.7.5.8. Calibration Based on Minimum Error Events

Training was ordered to stop when the number of invents since minimum error for test set reaches a particular value. Calibration thus prevents over training of the network and thus reduces the training time.

4.7.5.9. Testing of Network

After the network has been successfully trained well, it is then tested against a set of cases withheld from it during its training session. The ANNs is then ready to be applied to any other values of variables.

The results are then presented in statistical manner. Regression analysis is utilized to measure the degree of correlation between the actual output and the network output. Correlation factor (r) of 1 gives an indication of a perfect model while an (r) of 0 indicates a very bad model. Mathematically the values of (r) represented in Equation (4.6).

$$R^2 = 1 - \frac{\sum_{i=1}^{n} \left(actual_i - predicted_i\right)^2}{\sum_{i=1}^{n} \left(actual_i - mean\right)^2} \qquad \text{.......Eq. 4.6}$$

4.7.5.10. Application of the Network:

The built Network is then applied to any other values of input variables. The results can be displayed in statistical form to determine the correlation between the actual output and the predicted output. Detailed description about ANNs model result will be presented in the next chapter.

Chapter (5)

Results and Discussion

5.1. Characterization of ANNs Model

5.1.1. Introduction

In this section, the procedural steps in building ANNs model were applied in order to create ANNs model that was able to predict GWL using the input variables which previously discussed in Chapter (2). Many trials were applied to get best performance model. The modeling trials were made using all input variables. From created ANNs models, the importance and effect of each variables were studied and represented, also the sensitivity analysis was applied. The predicted values of GWL were compared with the observed values of GWL and the results were presented in contour maps.

5.1.2. Topology of ANNs model

Several ANNs models were created and tested using SNN by varying the neural networks type, the number of hidden layers, number of neurons in hidden layers and stop training conditions parameters.

After a number of trials, the best neural network was determined to be **RBF networks** with three layers: an input layer of 7 neurons, one hidden layer with 9 neurons and the output layer with 1 neuron as shown in Figure (5.1). The Seven input neurons are: initial GWL, R, RRFW, RRFWW, RRFIW, QM, QA. The output neuron gives the final GWL. Figure (5.1) presented the topology of the ANNs model.

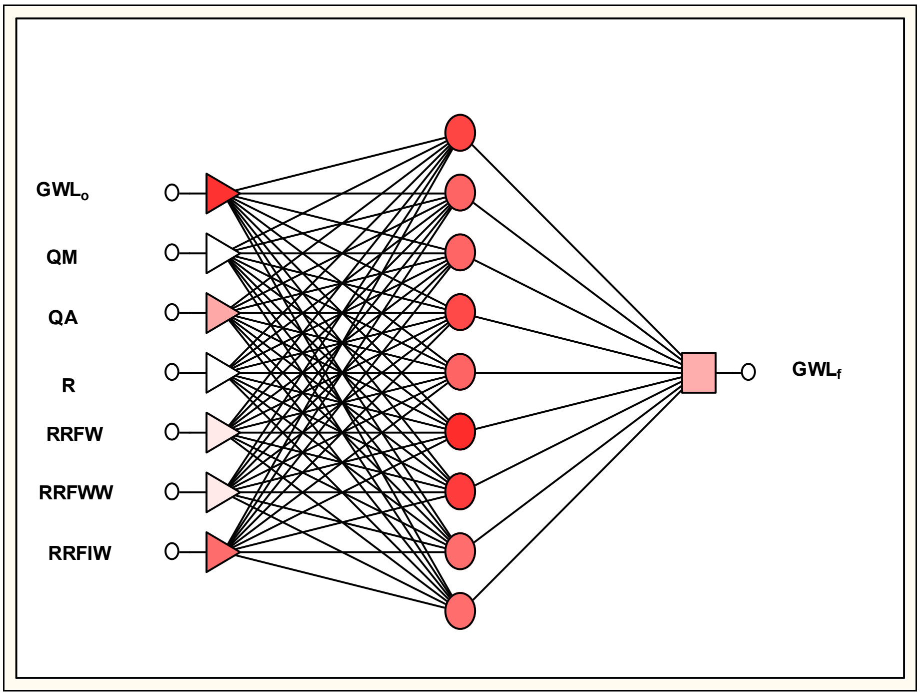


Figure (5.1): Topology of the ANNs model

5.1.3. Performance of ANNs

The progress of the training was checked by plotting the mean square errors for both training, and test versus the performed number of iterations, as presented in Figure (5.2).

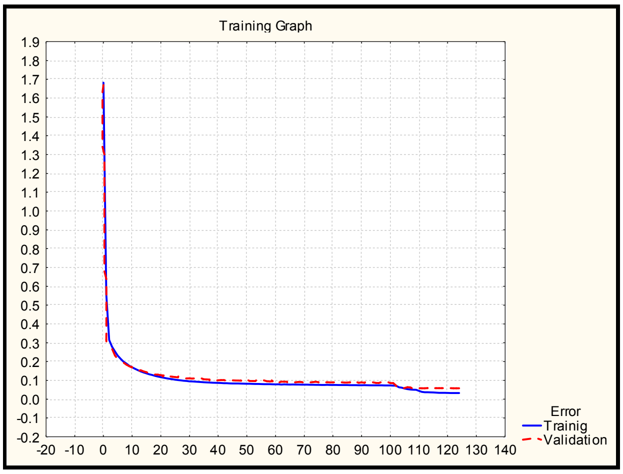


Figure (5.2): Training progress of ANNs model

Figure (5.3) presented a comparison of predicted GWL using ANNs and the observed GWL. It is clear from Figure (5.3) a high correlation between observed and predicted values of GWL. The correlation coefficient (r) between the predicted and observed output values of the ANNs model is (r) = 0.993. Other Regression Statistics of ANNs model were discussed and presented in section 5.1.4.

The high value of correlation coefficient (r) indicates that the predicted GWL values using the ANNs model are in good agreement with the observed GWL which gives initial impression that ANNs model is useful and applicable.

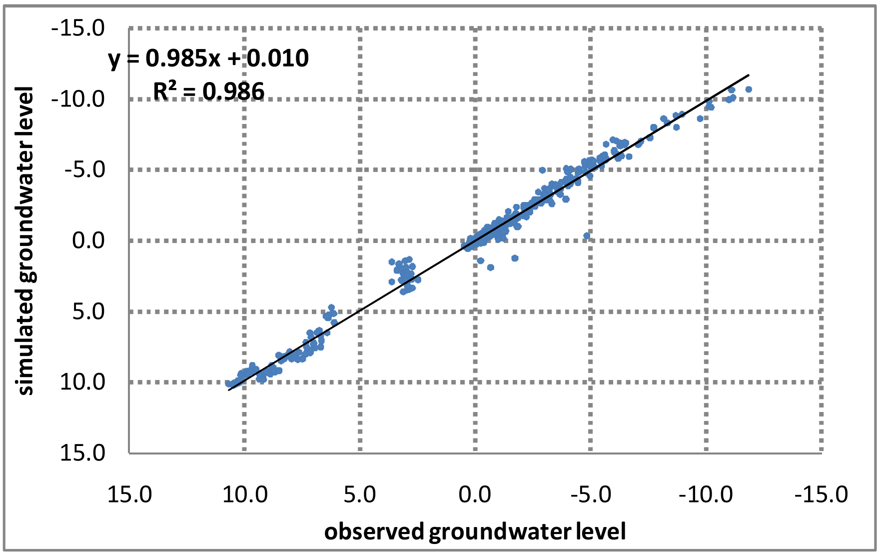
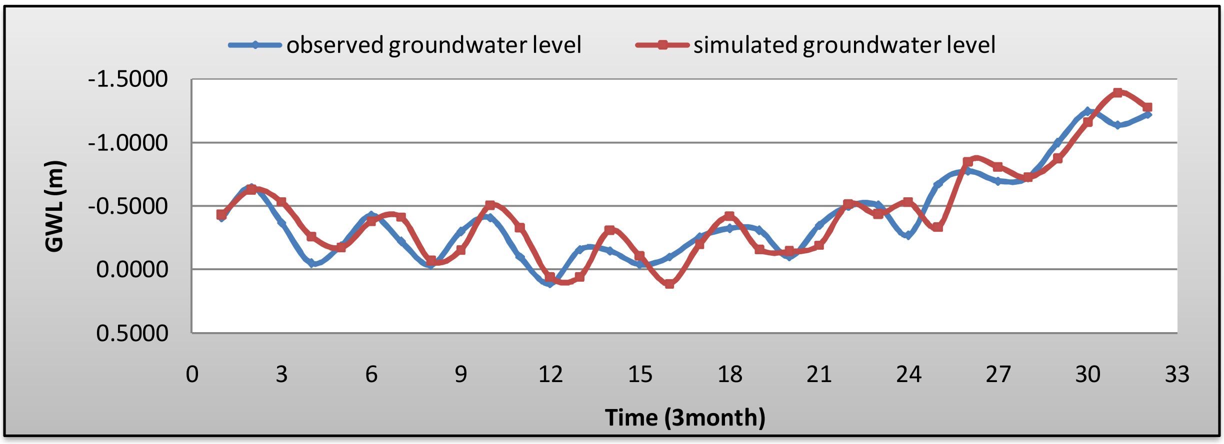


Figure (5.3): Comparison of simulated GWL using ANNs and the observed GWL

To provide a visual interpretation and appreciation of the results, Figures (5.4.a, b, c, d, e and f) showed the variations of observed GWL and those estimated by ANNs model for selected monitoring wells. These figures showed good agreement between observed and predicted value of GWL in monitoring wells located in study area . From this figure it may be concluded that the given ANNs model was able to predict actual result satisfactory. In general, the results indicate the potential of neural computing techniques in forecasting the groundwater levels in monitoring wells. Complete data of predicted GWL for all monitoring wells are found in Appendix (6).



Figure(5.4.a): Comparison between ANNs simulated GWL and observed GWL in well T/15

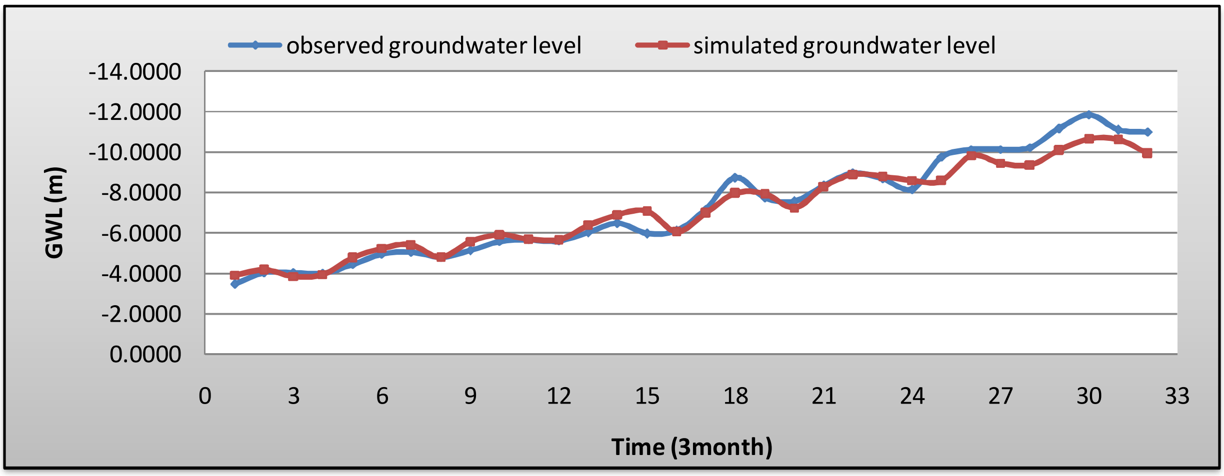


Figure (5.4.b): Comparison between ANNs simulated GWL and observed GWL in well P/50.

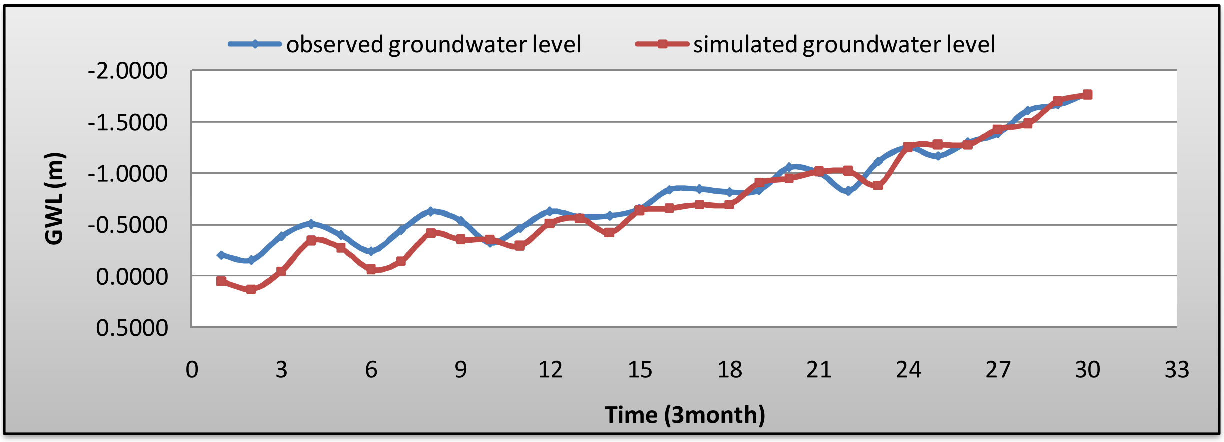


Figure (5.4.d): Comparison of simulated GWL using ANNs and the observed GWL for M/10.

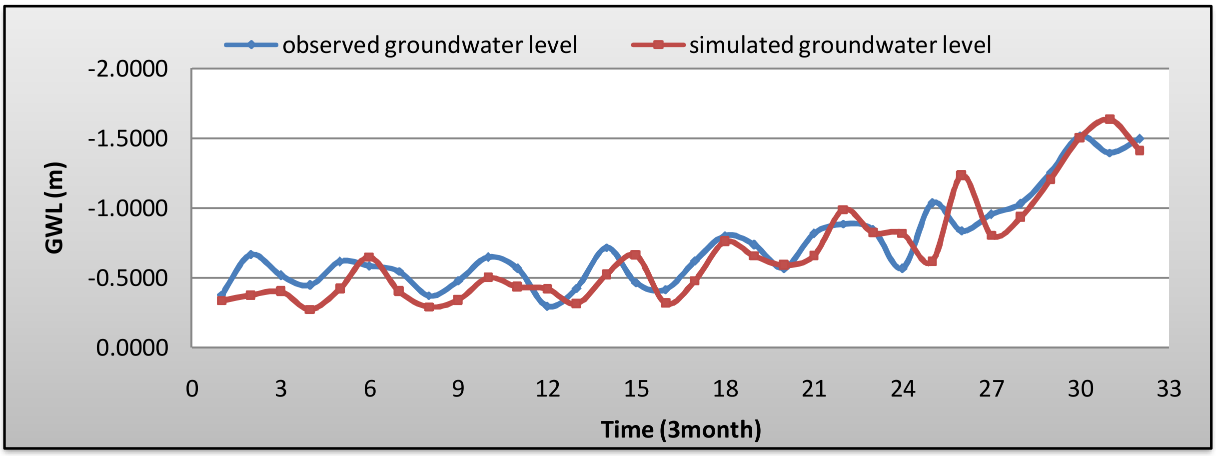


Figure (5.4.e): Comparison of simulated GWL using ANNs and the observed GWL for L/8.

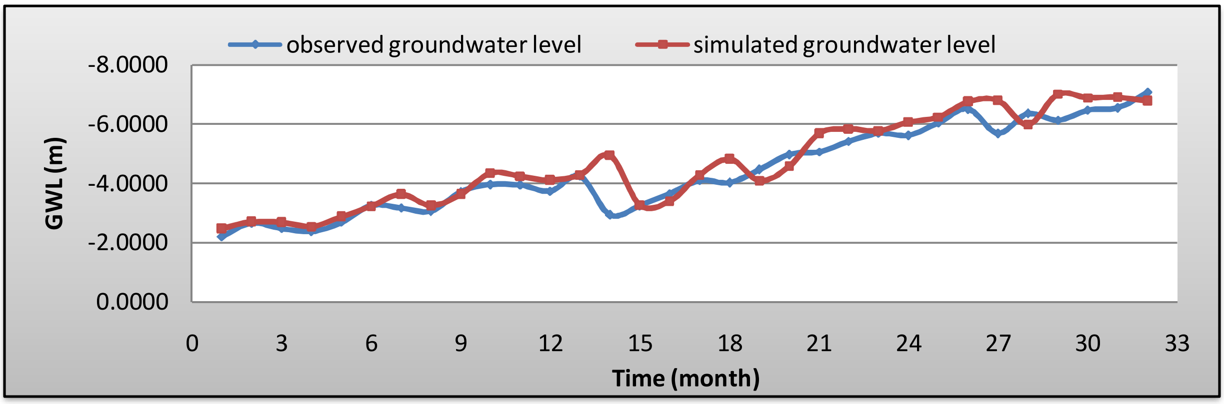


Figure (5.4.f): Comparison of simulated GWL using ANNs and the observed GWL for L/66.

5.1.4. Regression Statistics of ANNs Model

In regression problems, the purpose of the neural network is to learn a mapping from the input variables to a continuous output variable. A network is successful at regression if it makes predictions with accepted accuracy.

SNN automatically calculates the mean and standard deviation of the training and other subsets, when the entire data set is run. It also calculates the mean and standard deviations of the prediction errors. The error ratio of the prediction to data standard deviations is displayed **(S.D. Ratio)** if it is 1.0, then the network is bad performance. A lower ratio indicates a better estimate.

In addition, SNN displays correlation coefficient (r) between the actual and predicted outputs. A perfect prediction will have a correlation coefficient of 1.0. A correlation of 1.0 does not necessarily indicate a perfect prediction (only a prediction which is perfectly linearly correlated with the actual outputs), although in practice the correlation coefficient is a good indicator of performance. It also provides a simple and familiar way to compare the performance of neural networks with standard least squares linear fitting procedures. The degree of predictive accuracy needed varies from application to application.

Regression statistics are listed as follows:

- **Data Mean**: Average value of the target output variable.
- **Data S.D.**: Standard deviation of the target output variable.
- **Error Mean**: Average error (residual between target and actual output values) of the output variable.
- **Abs. E. Mean**: Average absolute error (difference between target and actual output values) of the output variable.
- **Error S.D.**: Standard deviation of errors for the output variable.
- **S.D. Ratio**: The error/data standard deviation ratio.
- **Correlation**: The correlation coefficient (r) between the predicted and observed output values.

Table (5.1) present the values of regression statistics for the ANNs model.

Table (5.1): The values of regression statistics for the ANNs model

Regression statistics	Training data set	Validation data set	Test data set
Data Mean	0.152555	-0.267470	0.257785
Data S.D.	4.215948	4.425116	4.223556
Error Mean	-0.000000	-0.000043	0.037059
Error S.D.	0.512841	0.468387	0.497541
Abs E. Mean	0.303770	0.311526	0.323434

S.D. Ratio	0.121643	0.105848	0.117801
Correlation (r)	0.992574	0.994388	0.993038

It was noted that the values of regression statistics for the ANNs model refers that performance of ANNs model is excellent as follows:

- Low value of **S.D. Ratio** shows that the error between observed and predicted GWL values using the ANNs model are small.
- High value of **correlation coefficient (r)** shows that the predicted GWL values using the ANNs model are in good agreement with the observed GWL.

5.1.5. Response Presentations

Response presentations of ANNs model include two types of figures, response graph and response surfaces.

5.1.5.1. Response Graph

Response presentations of ANNs model are represented by response graph. which shows the effect on the output variable prediction of adjusting input (independent) variables. The ANNs model was utilized to study the influence of the input variables on output variable which is Final GWL.

Figures (5.5.a) indicated that the GWL increased as initial GWL increased. Figures (5.5.b) indicated that the final GWL nonlinearly decreased as QM increased. However, at very high QM the behavior of GWL dramatically changed. This change in behavior may be related to the up coning phenomena where at huge and continuous QM up coning phenomena would be very obvious specially that most monitoring wells are very close to abstraction wells.

Figures (5.5.c) indicated that the final GWL nonlinearly decreased as QA increased. However, at very high QA the behavior of GWL dramatically changed. This change in behavior may be related to the up coning phenomena. In addition, considerable amount of agricultural wells are located in the eastern part of study area, therefore at high QA the effect of lateral inflow from eastern aquifer will increase to replenished of QA. Furthermore, as QA increase the RRFIW which also contribute in increasing GWL.

Figures (5.5.d) indicated that the final GWL increased as R increased, However, at very high R the behavior of GWL changed. This change in behavior occurred at high R because the soil will become oversaturated which in turn lead to increase surface run off compared with recharge.

Figures (5.5.e, f, and g) indicated that final GWL increases as initial RRFW, RRFWW and RRFIW increase.

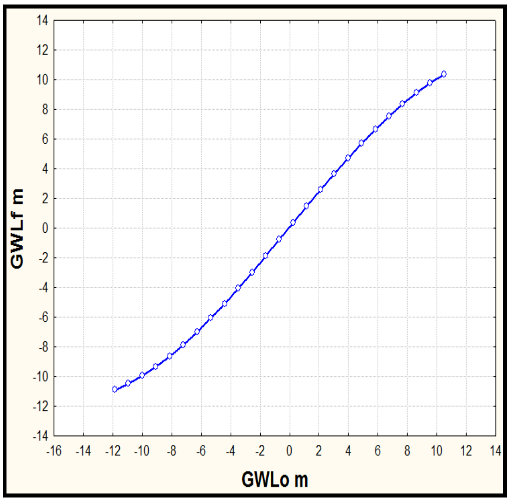


Figure (5.5.a): Response graph of initial GWL

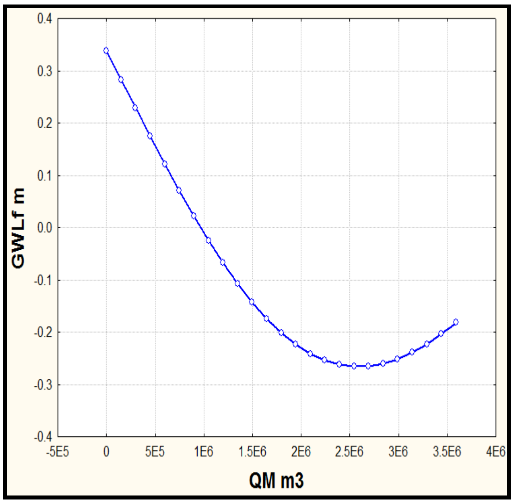


Figure (5.5.b): Response graph of QM

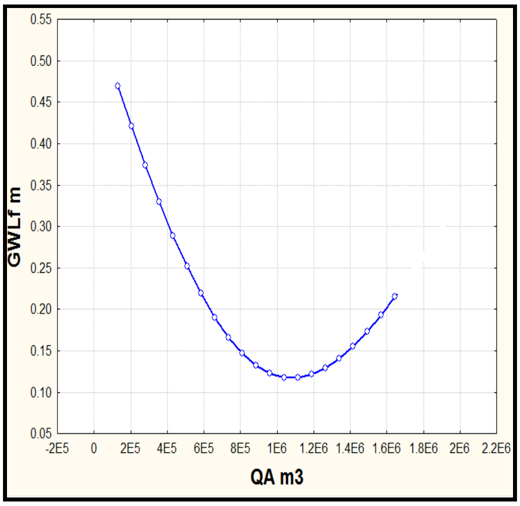


Figure (5.5.c): Response graph of QA

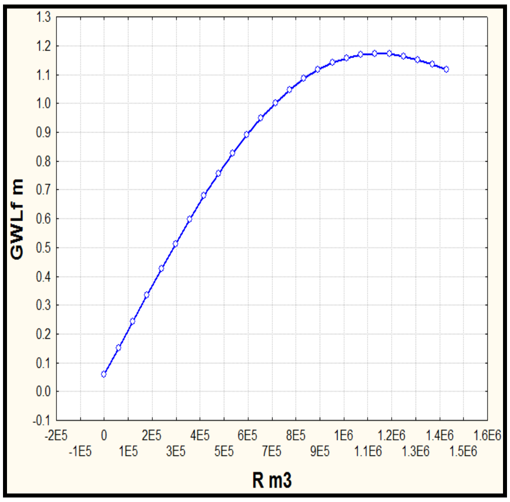


Figure (5.5.d): Response graph of R

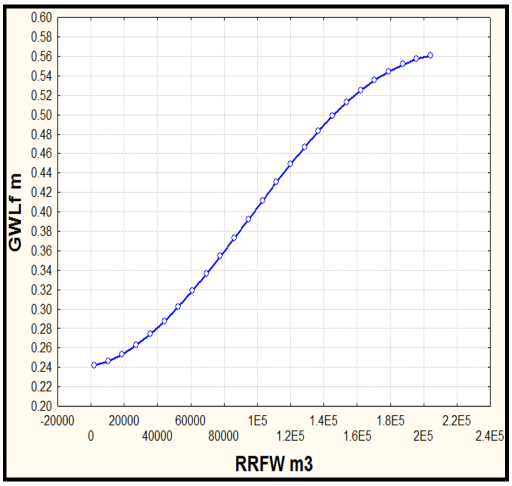


Figure (5.5.e): Response graph of RRFW

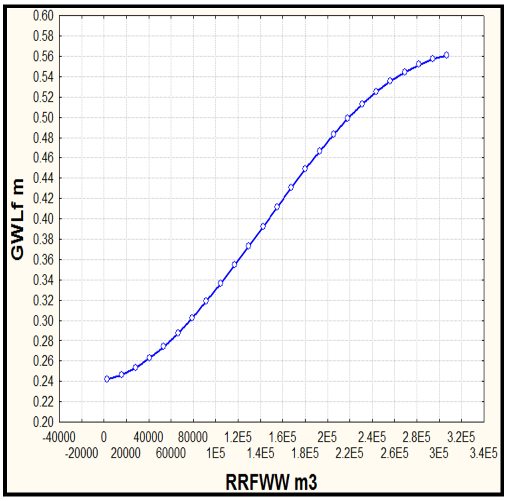


Figure (5.5.f): Response graph of RRFWW

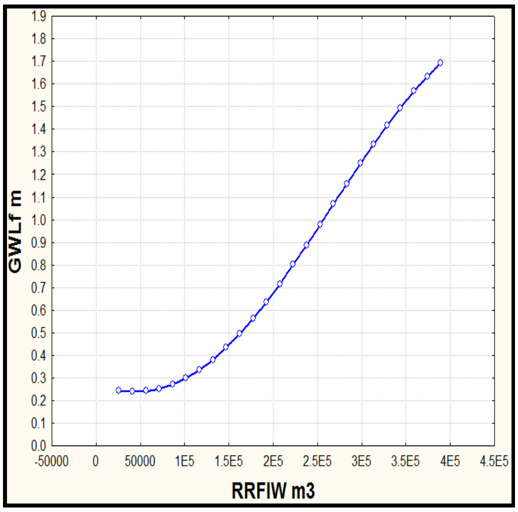


Figure (5.5.g): Response graph of RRFIW

5.1.5.2. Response Surface

A response surface is a figure shows the effect on the output variable prediction of adjusting two input (independent) variables. The ANNs model was utilized to study the influence of each two input variables on GWL. Figures (5.6) presented response surface of each two input variables of ANNs model

Figures (5.6.a) indicated that the GWL increased nonlinearly as QA decreased and initial GWL increased and the effect of initial GWL is stronger than effect of QA. Figure (5.6.b) indicated that the GWL increased nonlinearly as QM decreased and initial GWL increased and the effect of initial GWL. Figure (5.6.c) indicated that the GWL decreased nonlinearly as QM and QA increased and the effect of QM is stronger than effect of QA.

Figures (5.6.d) indicated that the GWL increased nonlinearly as QM decrease and R increase and the effect of R is stronger than effect QM. Figure (5.6.e) indicated that the GWL increased nonlinearly as RRFWW and QM decrease. Figure (5.6.f) indicated that the GWL increased nonlinearly as RRFWW increase and QM decrease.

Figure (5.6.g) indicated that the GWL increased nonlinearly as R increased and QA decreases. In addition, it was noted that effect of R is stronger than effect of QA. Figure (5.6.h) indicated that the GWL increased nonlinearly RRFIW increased and QM decrease. Figure (5.6.i) indicated that the GWL increased nonlinearly as QA decreased and RRFWW increases.

Figure (5.6.j) indicated that the GWL increased nonlinearly as recharge from retain flow from water networks increased and QM decrease. Figure (5.6.k) indicated that the GWL increased nonlinearly as RRFWW increased and R increases. In addition, it was noted that effect of R is stronger than effect of RRFWW. Figure (5.6.l) indicated that the GWL increased nonlinearly as RRFW increased and R increases. In addition, it was noted that effect of R is stronger than effect of RRFWW.

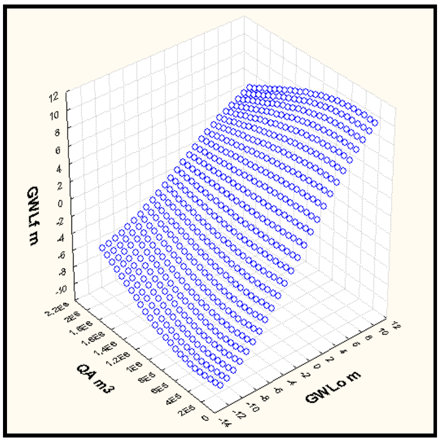


Figure (5.6.a) Response surface of initial GWL and QA

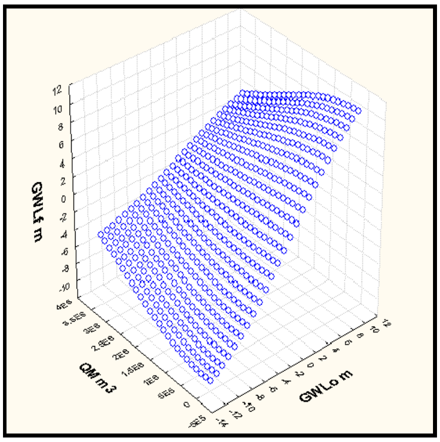


Figure (5.6.b) Response surface of initial GWL and QM

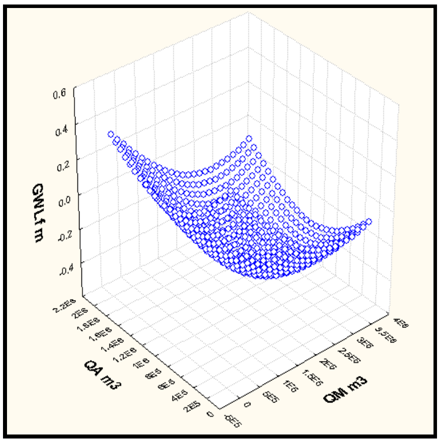


Figure (5.6.c) Response surface of QM and QA

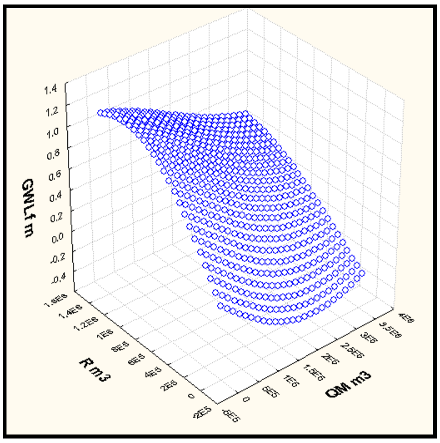


Figure (5.6.d) Response surface of R and QM

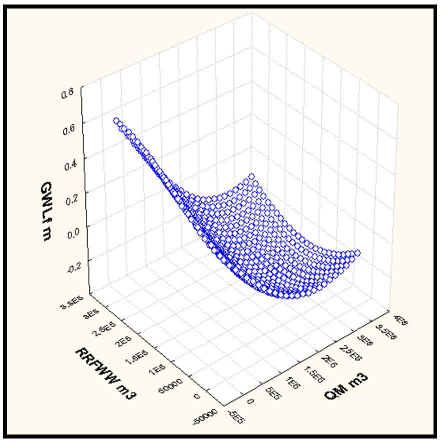


Figure (5.6.e) Response surface of RRFWW and QM

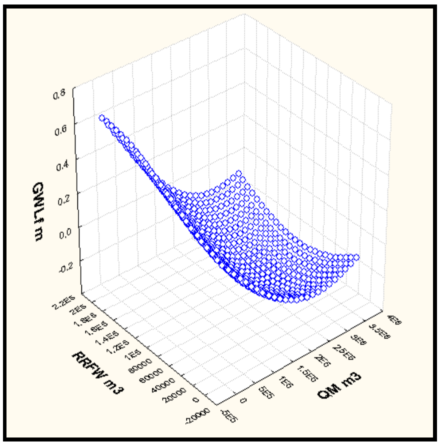


Figure (5.6.f) Response surface of RRFW and QM

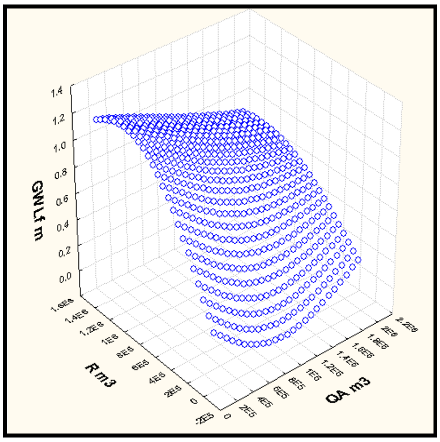


Figure (5.6.g) Response surface of R and QA

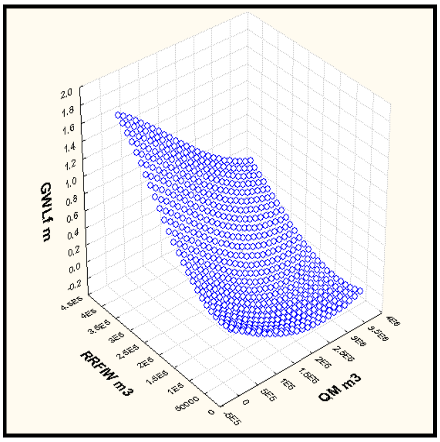


Figure (5.6.h) Response surface of RRFIW and QM

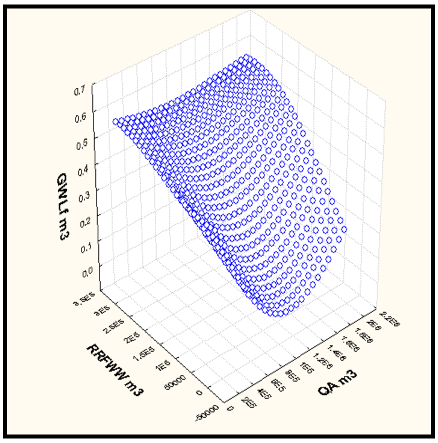


Figure (5.6.k) Response surface of RRFWW and QA

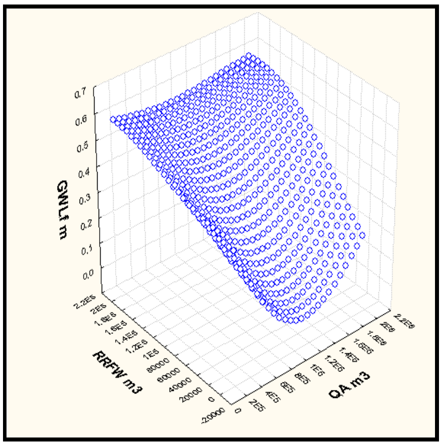


Figure (5.6.l) Response surface of RRFW and QA

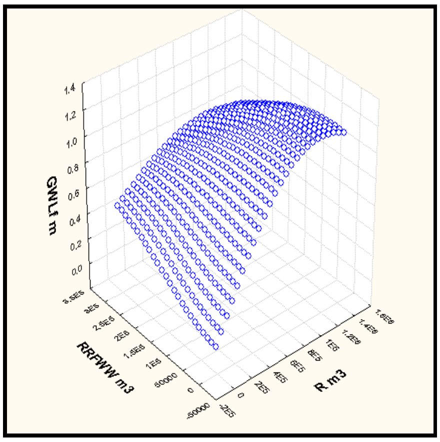


Figure (5.6.m) Response surface of RRFWW and R

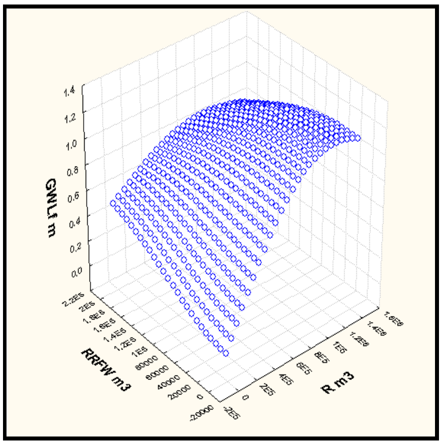


Figure (5.6.n) Response surface of RRFW and R

5.1.6. Sensitivity Analysis

SNN conducts a sensitivity analysis on the inputs to a neural network. This indicates which input variables are considered most important by that particular neural network. Sensitivity analysis can be used purely for informative purposes. Sensitivity analysis can give important insights into the usefulness of individual variables. It often identifies variables that can be safely ignored in subsequent analyses, and key variables that must always be retained. However, it must be deployed with some care, for reasons that are explained below.

Input variables are not, in general, independent that is, there are interdependencies between variables. Sensitivity analysis rates variables according to the deterioration in modeling performance that occurs if that variable is no longer available to the model. In so doing, it assigns a single rating value to each variable. However, the interdependence between variables means that no scheme of single ratings per variable can ever reflect the subtlety of the true situation.

Consider, for example, the case where two input variables encode the same information (they might even be copies of the same variable). A particular model might depend wholly on one, wholly on the other, or on some arbitrary combination of them. Then sensitivity analysis produces an arbitrary relative sensitivity to them. Moreover, if either is eliminated the model may compensate adequately because the other still provides the key information. It may therefore rate the variables as of low sensitivity, even though they might encode key information. Similarly, a variable that encodes relatively unimportant information, but is the only variable to do so, may have higher sensitivity than any number of variables that mutually encode more important information.

SNN conducts sensitivity analysis by treating each input variable in turn as if it were "unavailable". SNN has defined a missing value substitution procedure, which is used to allow predictions to be made in the absence of values for one or more inputs. To define the sensitivity of a particular variable, v, the network first was run on a set of test cases, and the network error was accumulated. Then the network was run again using the same cases, but this time replacing the observed values of v with the value estimated by the missing value procedure, and again the network error was accumulated. (STATISTICA, 2004).

After that, It is expected some deterioration in error to occur. The basic measure of sensitivity is the ratio of the error with missing value substitution to the original error. The more sensitive the network is to a particular input, the greater the deterioration we can expect, and therefore the greater the ratio. Once sensitivities have been calculated for all variables, they may be ranked in order. SNN provides these rankings, for convenience in interpreting the sensitivities. Table (5.2) presented the value of error ratio and rank of input variables.

Table (5.2): The value of error ratio and rank of input variables

Variables	GWL_o	R	RFW	RFWW	RFIW	QM	QA
Error Ratio	**8.454019**	**1.033463**	**0.893964**	**0.893964**	**0.924934**	**0.983301**	**0.976518**
Variables Rank	**1**	**2**	**6**	**7**	**5**	**3**	**4**
Training error ratio	8.076592	1.023389	0.921196	0.921196	0.929167	0.991854	0.981891

Training variables Rank	1	2	6	7	5	3	4
Validation error ratio	9.360775	1.022814	0.839532	1.002814	0.934441	0.984613	0.982641
Validation variables Rank	1	2	7	3	6	4	5
Test error ratio	8.397338	1.063701	0.881535	1.003701	0.907312	0.963662	0.959487
Test variables Rank	1	2	7	3	6	4	5

It was noted that value of Error Ratio of the initial GWL is the highest value of Error Ratio which means that the final GWL is high correlated to initial GWL. The most other important variables for this model are R, QM, QA. Other variables ranks are presented in Table (5.2).

5.2. Comparison of ANNs model results with other related studies

The model results were then compared with other studies conducted on the same area of study area. The comparison was carried out between this research result and a research results conducted recently by Alghamri (2009). Figures (5.7.a and b) presented the simulated GWL for year 2004 for two models. The figures show high degree of similarity between the result of two models. However, the previous study used larger data set through process-based model. The results from this study suggest that ANNs can provide a reliable method to forecast groundwater level with good accuracy even with limited data. So, it may be concluded that the ANNs model have powerful as physical based model to predict satisfactory result.

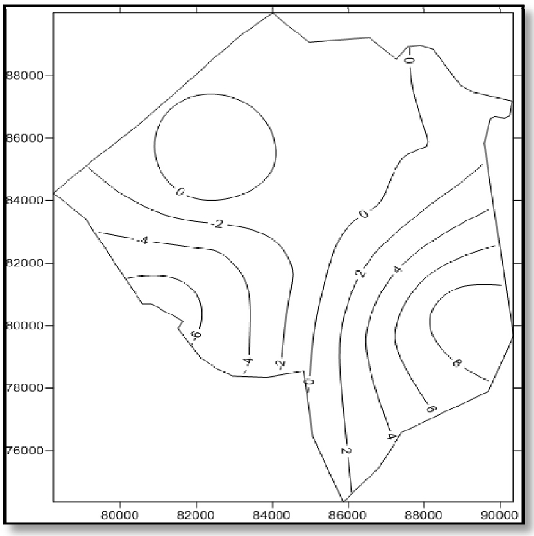


Figure (5.7.a): Simulated GWL for year 2004-calculated by ANNs model.

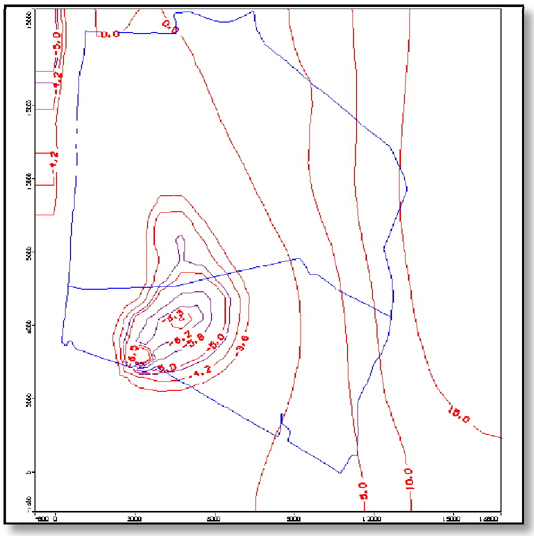


Figure (5.7.b): Simulated water table for year 2004-calculated by VMODFLOW.(Adopted from Alghamri, 2009)

5.3. Utilizing ANNs Model as a Simulation Tool

The ANNs model was utilized to simulate GWL in monitoring wells in KYG for the years exist in the time range of ANNs model. Contour map of GWL was prepared for ANNs simulated results. Another contour map of observed GWL was prepared in order to compare between the observed and simulated values of GWL. These steps were prepared for years 2000 and 2007. Figures (5.8.a and b), (5.9.a and b) presented the observed and simulated GWL in KYG in years 2000 and 2007. The figures show high degree of similarity between the simulated and the observed contour maps.

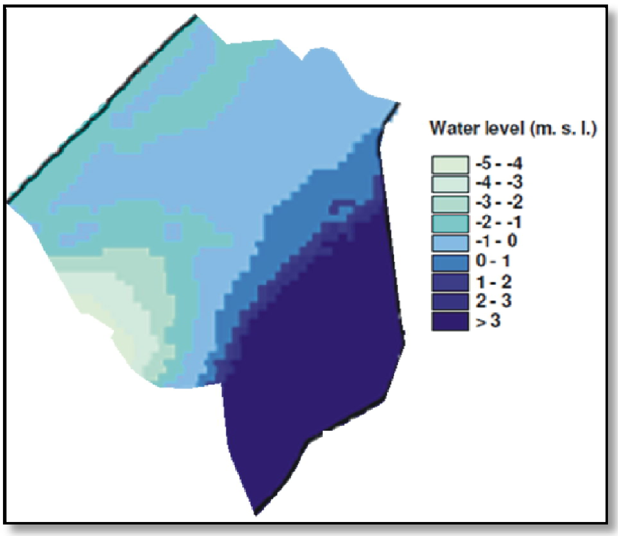


Figure (5.8.a): Observed GWL in KYG (2000)(Adopted from PWA,2000).

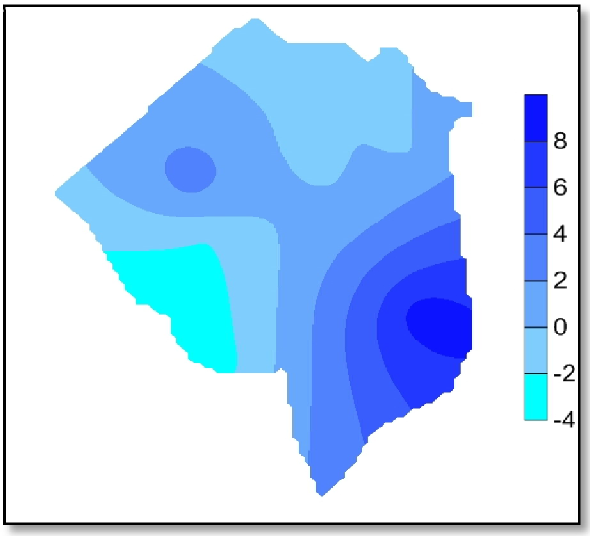


Figure (5.8.b): ANNs simulated GWL in KYG (2000).

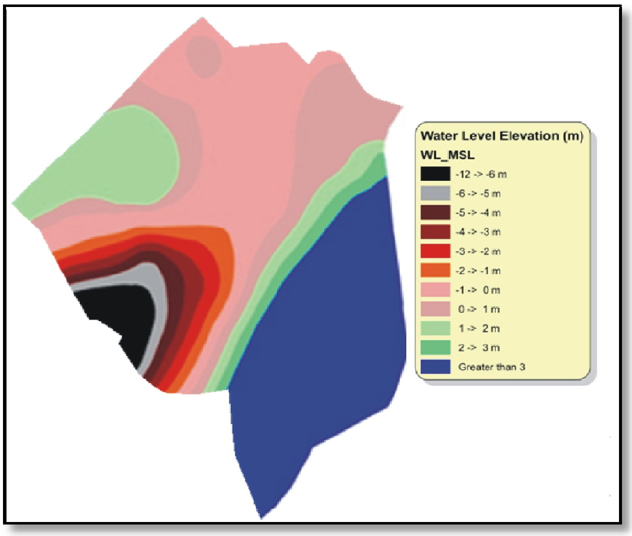


Figure (5.9.a): Observed GWL in KYG (2005) (Adapted from PWA,2005).

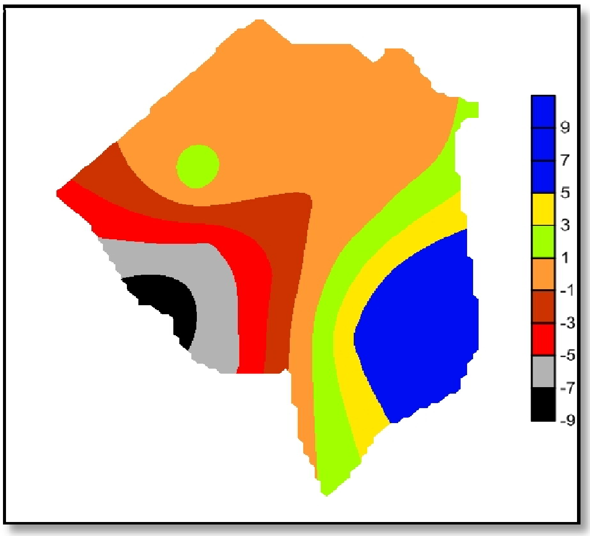


Figure (5.9.b): ANNs simulated GWL in KYG (2005).

5.4. Utilizing ANNs Model as a Prediction Tool

The ANNs model was utilized to predict GWL in monitoring wells in KYG for the years do not exist in the time range of ANNs model. Contour map of GWL was prepared for ANNs predicted results. Another contour map of observed GWL was prepared in order to compare between the observed and simulated values of GWL. These steps were prepared for year 2010. Figures (5.10.a and b) presented the observed and predicted GWL in KYG in 2010. The figures show high degree of similarity between the predicted and the observed contour maps. The GWL data of monitoring wells for year 2010 are represented in Appendix (7).

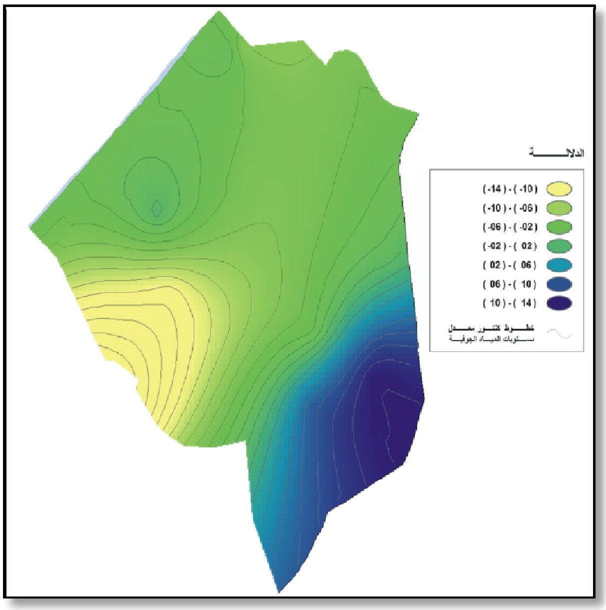


Figure (5.10.a): Observed GWL in KYG (2010)((Adapted from PWA, 2010).

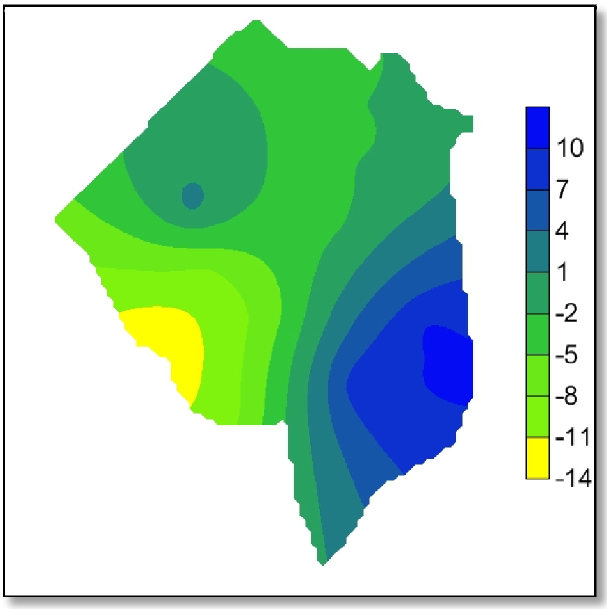


Figure (5.10.b): ANNs simulated GWL in KYG (2010).

5.5. Utilizing ANNs Model as Analytical Tool

The ANNs model was utilized to study the influence of the input variables on GWL. Seyam and Mogheir (2011) carried out a research using ANNs model as analytical tool to study influence of the input variables on chloride concentration based on three hypothetical cases. Hypothetical cases consist of three level of confidence. By application the same analysis, the first one was consolidating the values of input variables on the mean value and changing the value of studied variable gradually from minimum value to maximum value in the range of input variable. The second level of confidence was consolidating the values of R, RRFW, RRFWW and RRFIW on the mean plus the value of standard deviation. In addition it was consolidating the values of QM and QA on the mean subtract the value of standard deviation which produce conditions lead to increase GWL.

The third level of confidence was consolidating the values of R, RRFW, RRFWW and RRFIW on the mean subtract the value of standard deviation and consolidating the values of QM and QA on the mean plus the value of standard deviation which produce conditions lead to decrease GWL.

To obtain the values of gradual changing for input variable from minimum value to maximum value in the range of input variable, the range was divided to ten steps and the value gradually was increased from minimum value to maximum value in the range. Table (5.3) presented the hypothetical values of gradual change of input variables. Hypothetical values of input variables for the three analysis conditions were computed as explained above and they were presented in Table (5.4).

Table (5.3): Hypothetical values of gradual change for input variables

	GWL_o	R	RFW	RFWW	RFIW	QM	QA
Unit	**m**	**m^3/month**	**m^3/month**	**m^3/month**	**m^3/month**	**m^3/month**	**m^3/month**
Min.	**-11.9**	**0**	**1983.3**	**2980.1**	**25940.1**	**0**	**129700.3**
Max.	**11**	**1428717**	**219436**	**329727**	**389214**	**3590469**	**1946068**
1	0.155	0	1980	2980	25940	0	129700
2	0.155	14300	23730	35655	62270	359000	311300
3	0.155	28600	45480	68330	98600	718000	492900
4	0.155	42900	67230	101005	134930	1077000	674500
5	0.155	57200	88980	133680	171260	1436000	856100
6	0.155	71500	110730	166355	207590	1795000	1037700
7	0.155	85800	132480	199030	243920	2154000	1219300
8	0.155	100100	154230	231705	280250	2513000	1400900
9	0.155	114400	175980	264380	316580	2872000	1582500
10	0.155	128700	197730	297055	352910	3231000	1764100
11	0.155	143000	219480	329730	389240	3590000	1945700

Table (5.4): Hypothetical values of input variables for the three analysis conditions

	GWL_o	R	RFW	RFWW	RFIW	QM	QA
Min.	**-11.9**	**0**	**1983.3**	**2980.1**	**25940.1**	**0**	**129700.3**
Max.	**11**	**1428717**	**219436**	**329727**	**389214**	**3590469**	**1946068**
Mean	0.155	136317.7	40190.1	60390	90736.9	140938.7	453684.6
S.D	4.3	223160.5	36498.4	54842.8	54008.3	304609.4	270041.5
M+S.D	4.4	359478.2	76688.5	115232.8	144745.2	445548.1	723726.1
M-S.D	-4.2	-86842.8	3691.7	5547.2	36728.6	-163671	183643.1
Normal Condition	0.155	136300	40190	60390	90735	140935	453685
Decreasing Condition	0.155	0	3691.7	5547.2	36728.6	445548.1	723726.1
Increasing Condition	0.155	359478.2	76688.5	115232.8	144745.2	0	183643.1

5.5.1. Influence of R on GWL

By application the abovementioned procedure and using ANNs model to calculate the value of final GWL for each hypothetical case, the effect of Ron GWL was investigated. Results of the three conditions (normal, increasing and decreasing) were presented in Figure (5.11) and Table (5.5). Results of ANNs model for hypothetical cases studied the effect of R on GWL are presented in Appendix (6)

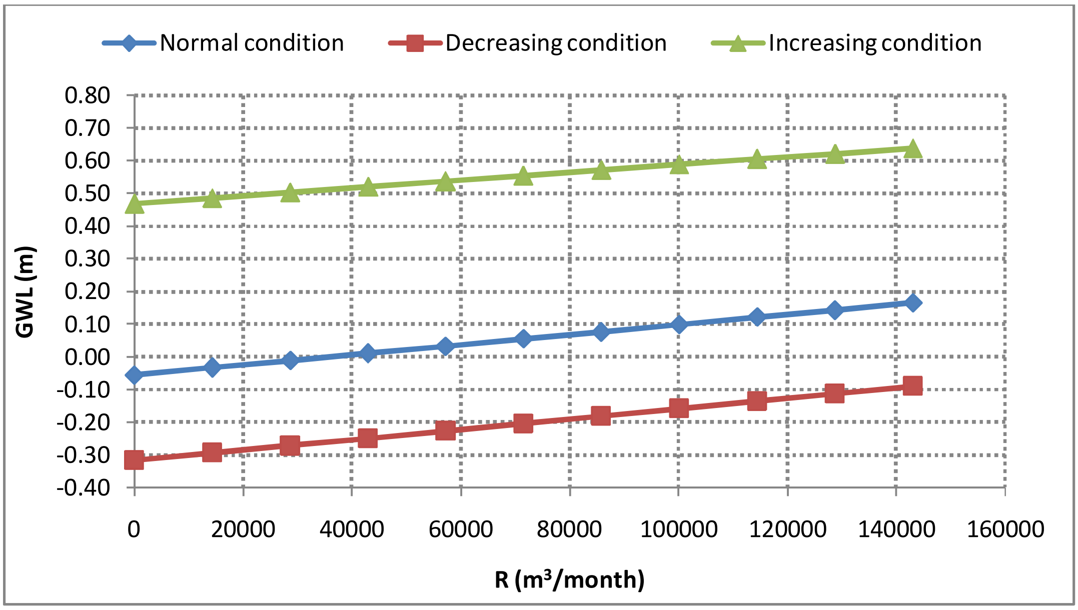


Figure (5.11): Impact of R on GWL

Table (5.5): Summary of results of ANNs model for hypothetical cases studied the effect of R on GWL

R	GWL_f (Normal condition)	GWL_f (Decreasing condition)	GWL_f (Increasing condition)
0	-0.055113	-0.315958	0.468946
14300	-0.033298	-0.293852	0.486052
28600	-0.011390	-0.271606	0.503152
42900	0.010597	-0.249232	0.520236
57200	0.032651	-0.226745	0.537293
71500	0.054759	-0.204158	0.554314
85800	0.076906	-0.181485	0.571287
100100	0.099079	-0.158739	0.588204
114400	0.121266	-0.135934	0.605053
128700	0.143452	-0.113083	0.621824
143000	0.165625	-0.090201	0.638509

It was noted that increasing R from 0 to 143,000 m^3/month resulted in a large influence in GWL as follows:

- In **normalcondition**, when the initial GWL = 0.155 m, RRFW = 40.190 m^3/month, RRFWW = 60.390 m^3/month, RRFIW = 90,735 m^3/month, QMwells = 140,935 m^3/month and QA = 453,685 m^3/month. Final GWL increase from -0.055113 m to 0.165625 m. Final GWL stayed stable of 0.155 m on R of 110000 m^3/month.
- In **increasingcondition**, when the initial GWL = 0.155 m , RRFW = 76688.5 m3/month, RRFWW = 115232.8 m^3/month, RRFIW = 144745.2 m3/month, QMwells = 0 m^3/month and QA = 183643.1 m^3/month. Final GWL increased from 0.468946 m to 0.638509 m. Final GWL stayed more than 0.155 m for all values of R.
- In **decreasingcondition**, when initial GWL = 0.155 m , RRFW = 3691.7 m^3/month, RRFWW = 5547.2 m^3/month, RRFIW = 36728.6 m^3/month, QMwells = 445548.1 m^3/month and QA = 723726.1 m^3/month. Final GWL increased from -0.315958 m to -0.090201 m. In this condition final GWL stayed less than 0.155 m for all values of R.
- It is noted that stabilization point of GWL for normal condition occurred at R = 110000 m^3/month. In increasing condition final GWL stayed more than 0.155 m with values 0.468946 m to 0.638509 m for all values of R. In decreasing condition final GWL stayed less than 0.155 m with values -0.315958 m to -0.090201 m for all values of R.

5.5.2. Influence of RRFW on GWL

By application the abovementioned procedure and using ANNs model to calculate the value of final GWL for each hypothetical case, the effect of RRFWon GWL was investigated. Results of the three conditions (normal, increasing and decreasing) were presented in Figure (5.12) and Table (5.6).

Results of ANNs model for hypothetical cases studied the effect of RRFW on GWL are presented in Appendix (6).

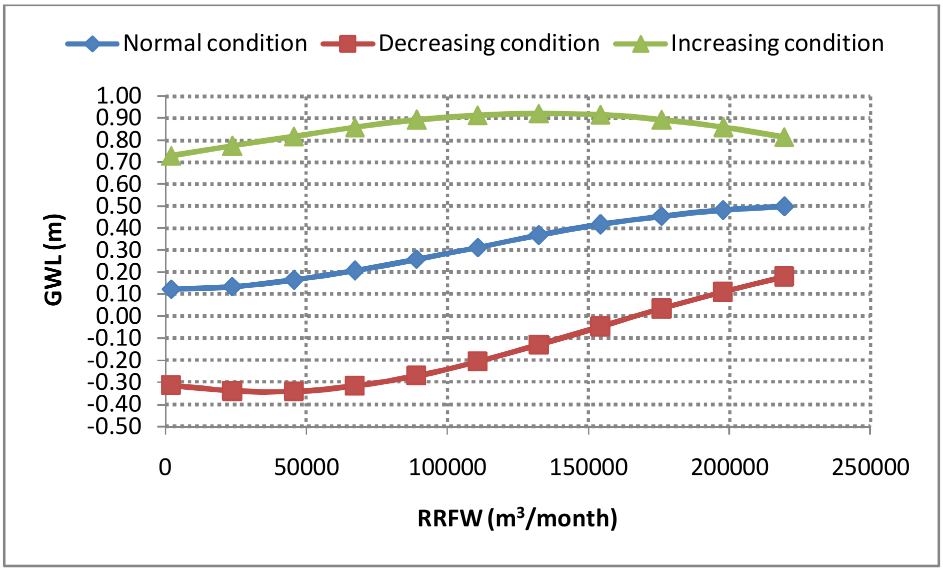


Figure (5.12): Impact of RRFW on GWL

Table (5.6): **Summary of results of ANNs model for hypothetical cases studied the effect of RRFW on GWL**

RRFW	GWL_f (Normal condition)	GWL_f (Decreasing condition)	GWL_f (Increasing condition)
1980	0.122248	-0.312870	0.729011
23730	0.134656	-0.340288	0.772589
45480	0.163687	-0.341314	0.816935
67230	0.206291	-0.316799	0.857991
88980	0.257981	-0.269868	0.891537
110730	0.313509	-0.205411	0.913825
132480	0.367643	-0.129351	0.922152
154230	0.415876	-0.047842	0.915269
175980	0.454959	0.033463	0.893534
197730	0.483178	0.109973	0.858817
219480	0.500340	0.178471	0.814157

It was noted that increasing RRFW from 1980 to 219480 m^3/month resulted in a large influence in GWL as follows:

- In **normalcondition**, when the initial GWL = 0.155 m, R = 136300 m^3/month, RRFWW = 60390 m^3/month, RRFIW = 90735 m^3/month, QM = 140935 m^3/month and QA = 453685 m^3/month. Final GWL increase from 0.122248 m to 0.500340 m. Final GWL stayed more than 0.155 m for all values of RRFW.
- In **increasingcondition**, when the initial GWL = 0.155 m , R = 359478.2 m^3/month, RRFWW = 115232.8 m^3/month, RRFIW = 144745.2 m^3/month, QM = 0 m^3/month and QA = 183643.1 m^3/month. Final GWL increased from 0.729011 m to 0.814157 m. Final GWL stayed more than 0.155 m for all values of RRFW.
- In **decreasingcondition**, when initial GWL = 0.155 m , R = 0 m^3/month, RRFWW = 5547.2 m^3/month, RRFIW = 36728.6 m^3/month, QM = 445548.1 m^3/month and QA = 723726.1 m^3/month. Final GWL increased from -0.312870 m to 0.178471 m. Final GWL stayed stable of 0.155 m on RRFW of 200000 m^3/month.

5.5.3. Influence of RRFWW on GWL

By application the abovementioned procedure and using ANNs model to calculate the value of final GWL for each hypothetical case, the effect of RRFWWon GWL was investigated. Results of the three conditions (normal, increasing and decreasing) were presented in Figure (5.13) and Table (5.7).

Results of ANNs model for hypothetical cases studied the effect of RRFWW on GWL are presented in Appendix (6).

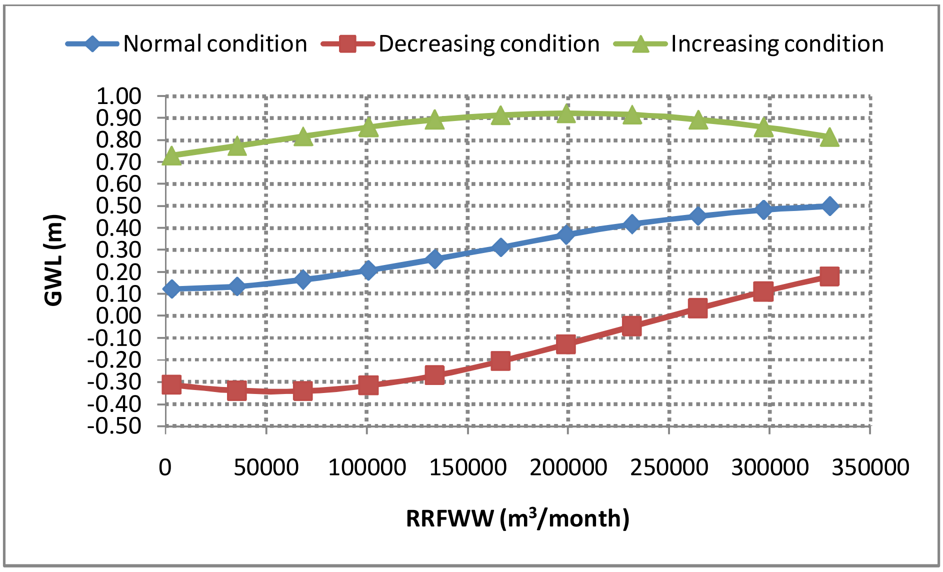


Figure (5.13): Impact of RRFWW on GWL

Table (5.7): Summary of results of ANNs model for hypothetical cases studied the effect of RRFWW on GWL

RRFWW	GWL_f (Normal condition)	GWL_f (Decreasing condition)	GWL_f (Increasing condition)
2980	0.122248	-0.312870	0.729011
35655	0.134656	-0.340288	0.772589
68330	0.163687	-0.341314	0.816935
101005	0.206291	-0.316799	0.857991
133680	0.257981	-0.269868	0.891537
166355	0.313509	-0.205411	0.913825
199030	0.367643	-0.129351	0.922152
231705	0.415876	-0.047842	0.915269
264380	0.454959	0.033463	0.893534
297055	0.483178	0.109973	0.858817
329730	0.500340	0.178471	0.814157

It was noted that increasing recharge from return flow from wastewater networks from 2980 to 329730 m^3/month resulted in a large influence in GWL as follows:

- In **normalcondition**, when the initial GWL = 0.155 m, R = 136300 m^3/month, RRFW = 40190 m^3/month, RRFIW = 90735 m^3/month, QM = 140935 m^3/month and QA = 453685 m^3/month. Final GWL increase from 0.122248 m to 0.500340 m. Final GWL stayed more than 0.155 m for all values of RRFWW.
- In **increasingcondition**, when the initial GWL = 0.155 m , R = 359478.2 m^3/month, RRFW = 76688.5 m^3/month, RRFIW = 144745.2 m^3/month, QM = 0 m^3/month and QA = 183643.1 m^3/month. Final GWL increased from 0.729011 m to 0.814157 m. Final GWL stayed more than 0.155 m for all values of RRFWW.

- In **decreasingcondition**, when initial GWL = 0.155 m , R = 0 m^3/month, RRFW = 3691.7 m^3/month, RRFIW = 36728.6 m^3/month, QM = 445548.1 m^3/month and QA = 723726.1 m^3/month. Final GWL increased from -0.312870 m to 0.178471 m. Final GWL stayed stable of 0.155 m on RRFWW of 300000 m^3/month.

5.5.4. Influence of RRFIW on GWL

By application the abovementioned procedure and using ANNs model to calculate the value of final GWL for each hypothetical case, the effect of RRFIWon GWL was investigated. Results of the three conditions (normal, increasing and decreasing) were presented in Figure (5.14) and Table (5.8).

Results of ANNs model for hypothetical cases studied the effect of RRFIWon GWL are presented in Appendix (6).

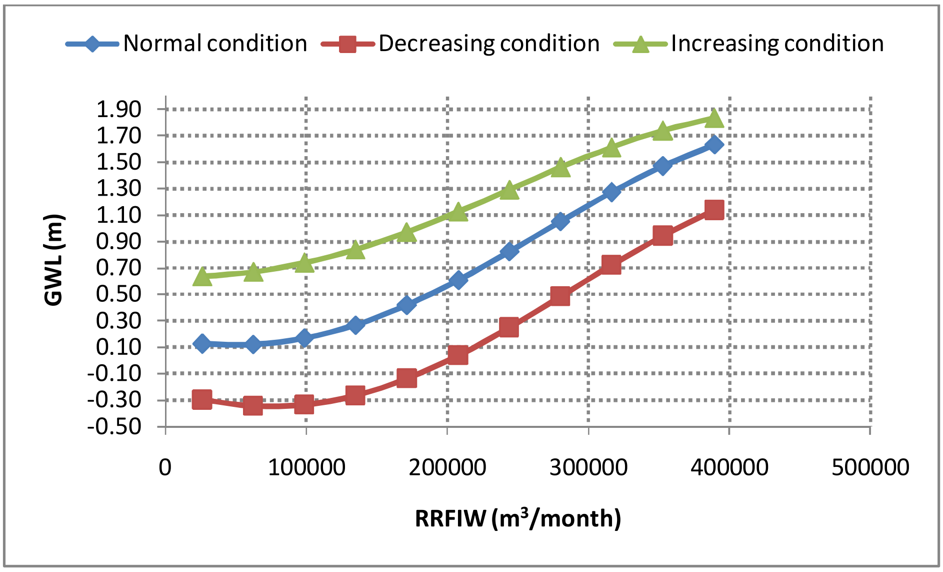


Figure (5.14): Impact of RRFIW on GWL

Table (5.8): Summary of results of ANNs model for hypothetical cases studied the effect of RRFIW on GWL

RRFIW	GWL_f (Normal condition)	GWL_f (Decreasing condition)	GWL_f (Increasing condition)
25940	0.124865	-0.296492	0.634998
62270	0.122178	-0.343616	0.670203
98600	0.170064	-0.334344	0.738759
134930	0.270289	-0.265264	0.840822
171260	0.419279	-0.138652	0.972723
207590	0.608276	0.037594	1.127117
243920	0.824182	0.250765	1.293664
280250	1.050999	0.484772	1.460133
316580	1.271638	0.721980	1.613778

352910	1.469825	0.945176	1.742783
389240	1.631845	1.139378	1.837560

It was noted that increasing RRFIWfrom 25940 to 389240 m^3/month resulted in a large influence in GWL as follows:

- In **normalcondition**, when the initial GWL = 0.155 m, R = 136300 m^3/month, RRFW = 40190 m^3/month, RRFWW = 60390 m^3/month, QM = 140935 m^3/month and QA = 453685 m^3/month. Final GWL increase from 0.124865 m to 1.631845 m. Final GWL stayed more than 0.155 m for all values of recharge from return flow from from irrigation water .
- In **increasingcondition**, when the initial GWL = 0.155 m , R = 359478.2 m^3/month, RRFW = 76688.5 m^3/month, RRFWW = 115232.8 m^3/month, QM = 0 m^3/month and QA = 183643.1 m^3/month. Final GWL increased from 0.634998 m to 1.837560 m. Final GWL stayed more than 0.155 m for all values of recharge from return flow from from irrigation water .
- In **decreasingcondition**, when initial GWL = 0.155 m , R = 0 m^3/month, RRFW = 3691.7 m^3/month, RRFWW = 5547.2 m^3/month, QM = 445548.1 m^3/month and QA = 723726.1 m^3/month. Final GWL increased from -0.296492 m to 1.139378 m. Final GWL stayed stable of 0.155 m on RRFIWof 220000 m^3/month.

5.5.5. Influence of QM on GWL

By application the abovementioned procedure and using ANNs model to calculate the value of final GWL for each hypothetical case, the effect of QM on GWL was investigated. Results of the three conditions (normal, increasing and decreasing) were presented in Figure (5.15) and Table (5.9).

Results of ANNs model for hypothetical cases studied the effect of QM on GWL are presented in Appendix (6).

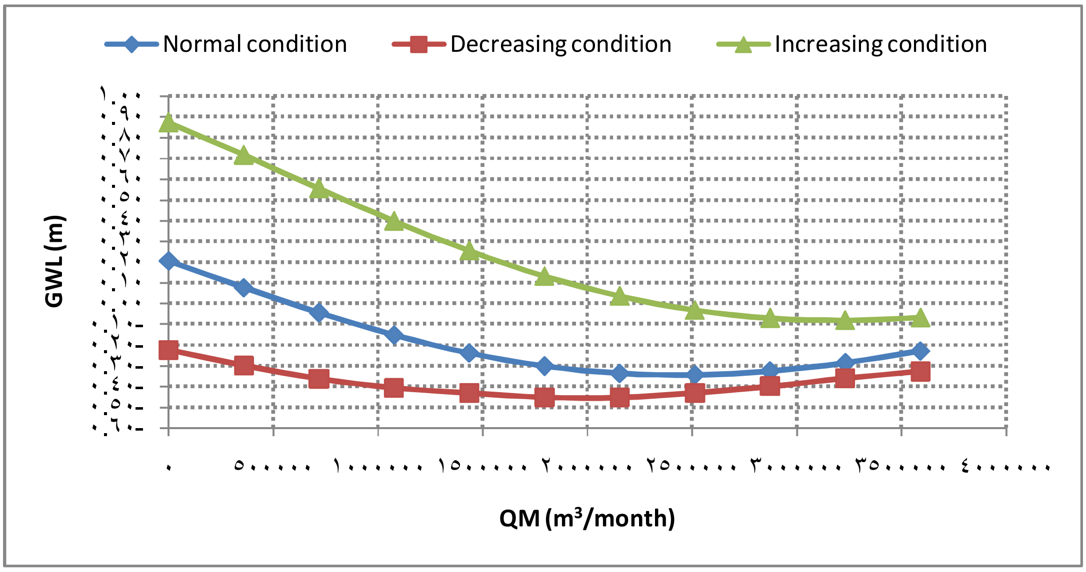


Figure (5.15): Impact of QM on GWL

Table (5.9): Summary of results of ANNs model for hypothetical cases studied the effect of QM on GWL

QM	GWL_f (Normal condition)	GWL_f (Decreasing condition)	GWL_f (Increasing condition)
0	0.206267	-0.223689	0.873760
359000	0.077189	-0.299590	0.717110
718000	-0.044823	-0.361540	0.555574
1077000	-0.152534	-0.405823	0.398681
1436000	-0.239822	-0.429867	0.255294
1795000	-0.302248	-0.450992	0.132777
2154000	-0.337429	-0.451903	0.036383
2513000	-0.345148	-0.430498	-0.031084
2872000	-0.327223	-0.398819	-0.069301
3231000	-0.287148	-0.360159	-0.080173
3590000	-0.229601	-0.327328	-0.067369

It was noted that increasing QM from 0 to 3,590,000 m^3/month resulted in a large influence in GWL as follows:

- In **normalcondition**, when the initial GWL = 0.155 m, R = 136300 m^3/month, RRFW = 40190 m^3/month, RRFWW = 60390 m^3/month, RRFIW = 90735 m^3/month and QA = 453685 m^3/month. Final GWL decrease from 0.206267 m to -0.229601 m. Final GWL stayed stable of 0.155 m on QM of 300000 m^3/month.
- In **increasingcondition**, when the initial GWL = 0.155 m , R = 359478.2 m^3/month, RRFW = 76688.5 m^3/month, RRFWW = 115232.8 m^3/month, RRFIW = 144745.2 m^3/month and QA = 183643.1 m^3/month. Final GWL decreased from 0.873760 m to -0.067369 m. Final GWL stayed stable of 0.155 m on QM of 190,000 m^3/month.

- In **decreasingcondition**, when initial GWL = 0.155 m , R = 0 m^3/month, RRFW = 3691.7 m^3/month, RRFWW = 5547.2 m^3/month, RRFIW = 36728.6 m^3/month and QA = 723726.1 m^3/month. Final GWL decreased from -0.223689 m to -0.327328 m. Final GWL stayed less than 0.155 m for all values of QM.

5.5.6. Influence of QA on GWL

By application the abovementioned procedure and using ANNs model to calculate the value of final GWL for each hypothetical case, the effect of QA on GWL was investigated. Results of the three conditions (normal, increasing and decreasing) were presented in Figure (5.16) and Table (5.10). Results of ANNs model for hypothetical cases studied the effect of QA on GWL are presented in Appendix (6).

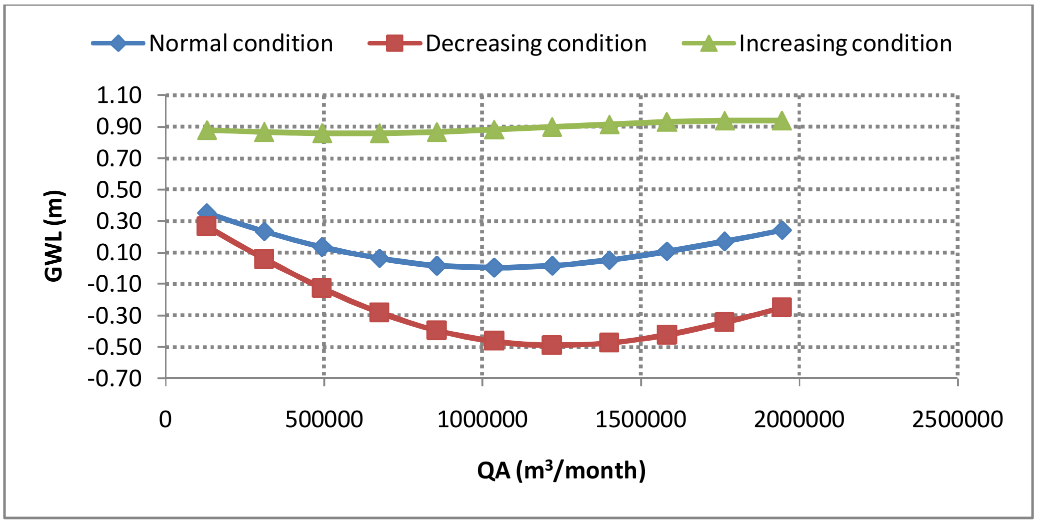


Figure (5.16): Impact of QA on GWL

Table (5.10): Summary of results of ANNs model for hypothetical cases studied the effect of QA on GWL

QA	GWL_f (Normal condition)	GWL_f (Decreasing condition)	GWL_f (Increasing condition)
129700	0.352563	0.264098	0.878017
311300	0.234695	0.057945	0.865501
492900	0.135854	-0.127399	0.859197
674500	0.062255	-0.280941	0.860154
856100	0.017578	-0.394698	0.868167
1037700	0.002673	-0.464376	0.881807
1219300	0.015637	-0.489571	0.898643
1400900	0.052233	-0.473490	0.915622
1582500	0.106574	-0.422279	0.929517
1764100	0.171939	-0.344064	0.937394
1945700	0.241601	-0.247896	0.937000

It was noted that increasing QA from129,700 to 1,945,700 m^3/month resulted in a large influence in GWL as follows:

- In **normalcondition**, when the initial GWL = 0.155 m, R = 136,300 m^3/month, RRFW = 40,190 m^3/month, RRFWW = 60,390 m^3/month, RRFIW = 90,735 m^3/month and QM = 140,935 m^3/month. Final GWL decrease from 0.352563 m to 0.241601 m. Final GWL stayed stable of 0.155 m on QA of 500,000 m^3/month.
- In **increasingcondition**, when the initial GWL = 0.155 m , R = 359478.2 m^3/month, RRFW = 76688.5 m^3/month, RRFWW = 115232.8 m^3/month, RRFIW = 144745.2 m^3/month and QM = 0 m^3/month. Final GWL increased from 0.878017 m to 0.937000m. Final GWL stayed more than 0.155 m for all values of QA..
- In **decreasingcondition**, when initial GWL = 0.155 m , R = 0 m^3/month, RRFW = 3691.7 m^3/month, RRFWW = 5547.2 m^3/month, RRFIW = 36728.6 m^3/month and QM = 445548.1 m^3/month. Final GWL decreased from 0.264098m to -0.247896 m.Final GWL stayed stable of 0.155 m on QA of 270000 m^3/month.

5.6. Utilizing ANNs Model for Future Scenarios Predictions

The ANNs model was utilized to predict GWL in KYG by considering two future scenarios based on management the pumping from the aquifer. It is difficult to enumerate all available and feasible alternatives needed to increase the GWL. These future scenarios considered mainly the influence of both abstraction type on GWL because the effect of abstraction from agricultural and domestic wells have a large negative impact on GWL change. In developing the scenarios the following assumptions were considered:

- Target period for prediction is from 2010-2025.
- For the period 2010-2025, R was set to the model as year 2007 for simplicity. Also, recharge from wastewater networks was kept the same as year 2007 based on cesspits system for simplicity.
- Future abstraction estimation was conducted according to the Palestinian Central Bureau of Statistics report which published in 2006 and Sectoral planning report which published by ministry of planning in 2010.

In the contest, it was necessary to take into consideration ANNs data limitation in order to avoid overtraining problem. Therefore, the prediction in the following scenarios are conducted in stepwise for each season from year 2015 to 2025 because when the model run directly and used an input data larger than training data the result may be unacceptable.

5.6.1. First scenario : No Change of Abstraction Condition (Zero Scenario)

This scenario included that abstraction quantity and abstraction rates will continue as in 2010 abstraction conditions. The ANNs model was utilized to predict GWL in the groundwater monitoring wells for years 2015, 2020 and 2025. Figures (5.17.a ,b and c) presented the predicted GWL for first scenario in years 2015, 2020 and 2025. The figures show that GWL decreases very rapidly in most areas of KYG. It was noted that cone of depression will increase rapidly in year

2020 and 2025. Moreover, the effect of lateral inflow appeared strongly due to increased GWL at the east of KYG. From other side, it was noticed that seawater intrusion phenomena will increase and cover more than 60% of total area of KYG in year 2025,as the GWL below MSL enlarges due to the over abstraction and the recharge water replenishment cannot balance that drop.

The cone of depression area will increase in depletion from -15 m below MSL at year 2015 to -24 m below MSL at year 2025. At the eastern side of KYG the GWL will increase from 12 m to 18 m above MSL. The model result present the effect of high abstraction rate well (municipal wells) which may be concentrated or close to the cone of depression area. The GWL in KYG area will be varied from -24 m below MSL to 18 m above MSL during the period from 2015 to 2025.

Complete data of GWL for first scenario are found in Appendix (7).

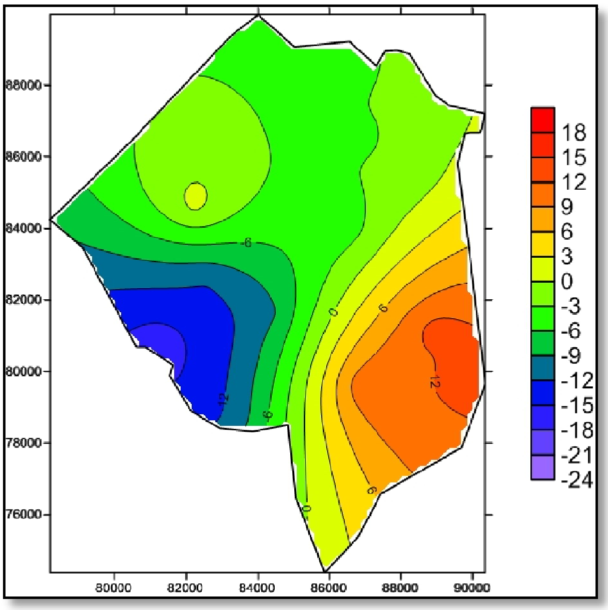


Figure (5.17.a): Predicted GWL in KYG in 2015 for first scenario

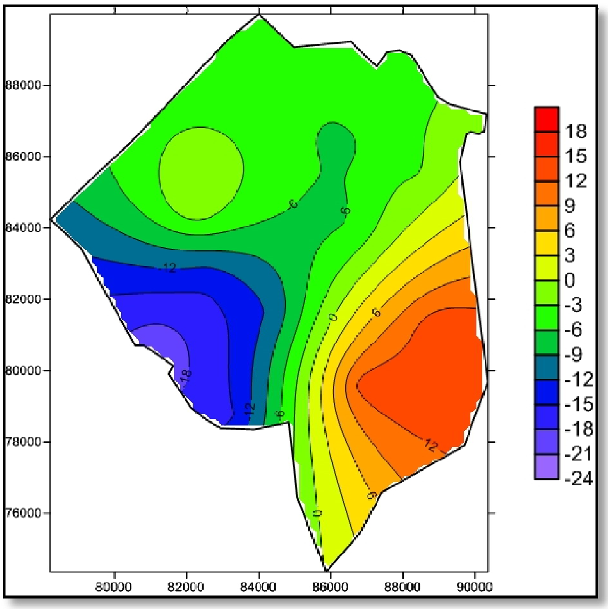


Figure (5.17.b): Predicted GWL in KYG in 2020 for first scenario

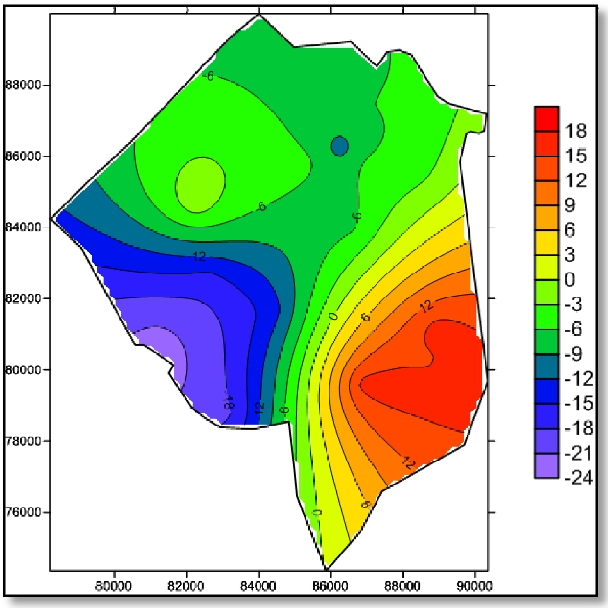


Figure (5.17.c): Predicted GWL in KYG in 2025 for first scenario

5.6.2. Second scenario : The Abstraction Will be Reduced by Half

Second scenario considered that both abstraction type, agricultural and domestic quantity fixed in half value of abstraction in year 2010. The ANNs model was utilized to GWL in the groundwater monitoring wells for years 2015, 2020 and 2025 for this scenario. Figures (5.18.a ,b and c) presented predicted GWL for second scenario 2015, 2020 and 2025. The figures showed that GWL increases rabidly in most areas of KYG except of sum areas increases in slowly rates due to the over abstraction and the recharge water replenishment cannot balance that drop.

The cone of depression will reduce in depletion from -8 m below MSL at year 2015 to -3 m below MSL at year 2025. At the eastern side of KYG the GWL will be increased from 8 m to 11 m above MSL. It was noticed that the seawater intrusion phenomena will reduce and cover more than 25% of total area of KYG in year 2025, as GWL increased from -3m below MSL to 1 m above MSL at the shore line of the sea. The GWL in KYG area will be varied from -8 m below MSL to 11 m above MSL during the period from 2015 to 2025.

Complete data of GWL for seconed scenario are found in Appendix (7).

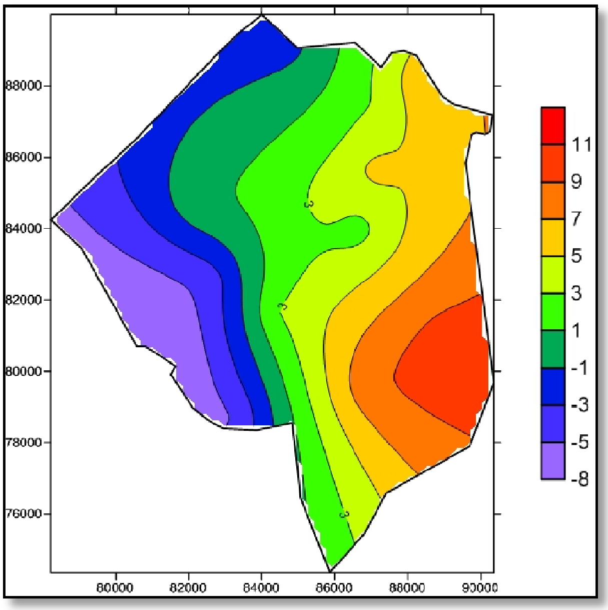


Figure (5.18.a): Predicted GWL in KYG in 2015 for second scenario

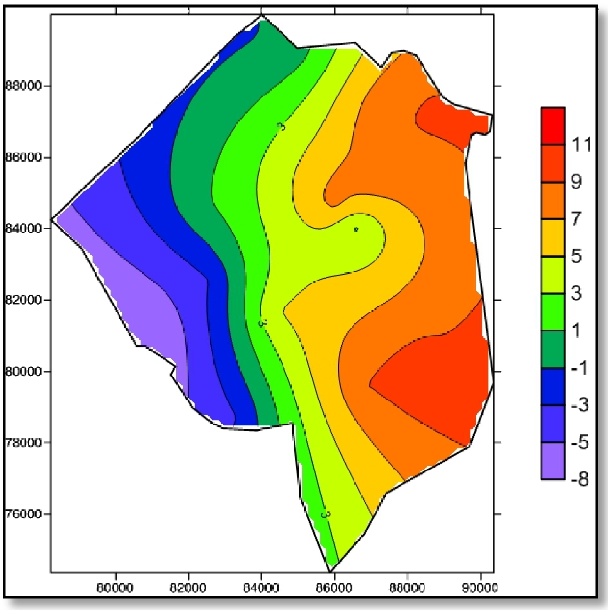


Figure (5.18.b): Predicted GWL in KYG in 2020 for second scenario

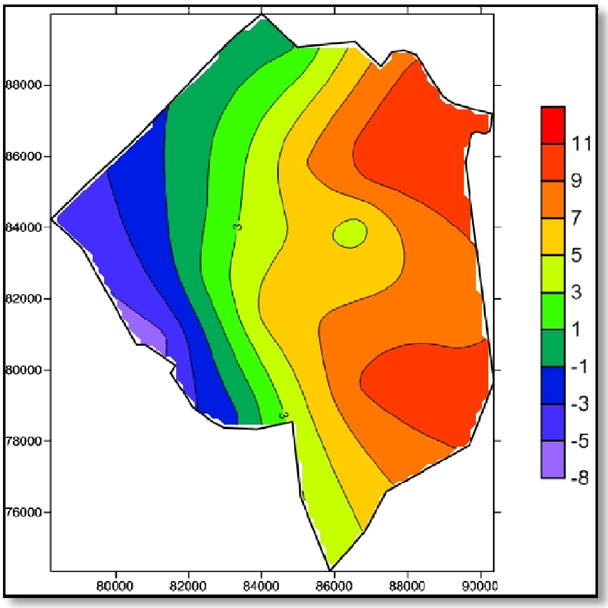


Figure (5.18.c): Predicted GWL in KYG in 2025 for second scenario

From the abovementioned scenario, it has been proven that groundwater level will improve when the overall abstraction from the aquifer reduced by half . Therefore, the previous scenario may be a realistic scenario, effective and easy to achieve .So there is a potential for decreasing overall abstraction by using a water from different sources such as a desalination water and treatment water. In addition, it is recommended to increase public awareness to rationalize of water consumption and using artificial recharge techniques. Therefore, the previous remedial and rational solutions aimed to increase the groundwater aquifer storage to overcome the depletion deterioration.

Chapter (6)

Conclusion and Recommendations

6.1. Conclusions

An ANNs model has been developed to simulate the GWL fluctuation in an observation wells with a case study of an observation well in KYG. The following conclusions were made based on the results obtained from the current study:

1. A new approach for GWL modelling in KYG utilizing ANNs was successfully developed and applied. ANNs model was developed to study the relation between GWL(represented by GWL in monitoring wells) and some related hydrological variables such as R, RRFW, RRFWW, RRFIW, QM, QA.
2. After testing different network topologies, the best neural network was RBF networks with three layers: an input layer of 7 neurons, one hidden layer with 9 neurons and the output layer with 1 neuron. The seven input neurons represented the input variables which are: initial GWL, R, RRFW, RRFWW, RRFIW, QM, QA .The output neuron gives the final GWL.
3. The developed model resulted in satisfaction results depending high correlation between the observed and predicted values of GWL. The correlation coefficient (r) between the predicted and the observed output values of the ANNs model was 0.993. The high value of correlation coefficient (r) showed that the simulated GWL values using the ANNs model were in very good agreement with the observed GWL which mean that ANNs model are useful and applicable. Thus, this study has shown that neural networks are effective at predicting GWL fluctuations in the Coastal aquifers
4. The ANNs model proved that GWL is directly affected by initial GWL, R, RRFW, RRFWW, RRFIW. Furthermore, it was adversely affected by QM, QA.
5. The ANNs model was successfully utilized in many practical and theoretical applications. It was utilized as analytical tool to study influence of the input variables on GWL. Furthermore, it was utilized as simulation and prediction tool of GWL in monitoring wells in KYG. Other important application of ANNs model that it was utilized as decision making support tool.
6. The developed ANNs model showed that if the abstraction kept the same as in 2010, GWL decreases very rapidly in most areas of KYG. It was noted that cone of depression will increase rapidly in year 2020 and 2025. Moreover, the effect of lateral inflow clearly appeared due to increased GWL at the east of KYG so the availability of fresh water will decrease in disquieting rates by year 2025. It was noticed that the seawater intrusion phenomena will be increased.
7. The developed ANNs model showed that if the abstraction is decreased with 50% of 2010 abstraction, the GWL will increase rabidly in most areas of KYG except of sum areas increases in slowly rates due to the over abstraction and the recharge water replenishment cannot balance that drop. It was noticed that the seawater intrusion phenomena will be reduced.
8. Comparison of results of the ANNs model and previous studies carried out by using process based modelling approach shows good agreement and indicates the validity of ANNs model

to solve complex situation as coastal aquifer there for it is a potential to used ANNs model in groundwater hydrology modelling..

9. Therefore, the current research showed that ANNs model can be used in groundwater management and it is comparable to other used approaches such as groundwater modelling and statistical modelling. It showed that the strong remedial actions for solving the GWL depletion problem in the aquifer of KYG are reducing the abstraction and increasing the recharge quantities to the aquifer.

6.2. Recommendations

The following recommendations were made based on the results obtained from the study:

1. New water sources should be found and the abstraction from the aquifer should be reduced with more than 50% at least, to solve GWL depletion problem. This action can reduce the problem gradually with time.
2. New wells should be constructed in appropriate areas that have high ability to infiltrate rainfall to groundwater depending on their direct relation with GWL.
3. In addition to redistribution of pumping wells and a lower rate of abstraction is preferred to avoid increasing the cone of depression area and decreasing the seawater intrusion.
4. It is recommended to construct additional monitoring wells to increase groundwater aquifer monitoring in over all area. In addition, to construct a series of monitoring wells especially at the east and west to monitor the effect of lateral inflow and seawater intrusion respectively.
5. Although, the ANNs model performed well, further studies about hydrological processes using ANNs in Gaza strip will enhance the utilizing ANNs as modelling and management approach.
6. Although, the ANNs model performed well, further studies about using ANNs model in groundwater management approach is recommended. An example of these studies is the effect of increasing recharge areas such as stormwater and treated wastewater infiltration basins, on GWL. In contrast, the extension of urbanized areas and their influence on GWL can be also a future study.
7. Due to the fact that seawater intrusion modelling using hydrogeological approach is data and time consuming, it is recommended to analyse the phenomena using ANNs if there is enough related data in future.
8. It is recommended – in case of data available - a new ANNs model to be developed in order to study the influence of other hydrological factors on GWL such as lateral inflow, evapotranspiration, and others.
9. It is recommended – in case of data available - a new ANNs model to be developed in order to study the influence of wastewater sewer system and improvement of water networks system efficiency on GWL.
10. Further studies are recommended for using different techniques instead Thessian polygons to represent the best buffer zone or influence area for each monitoring well.
11. It is recommended to find data bank to facilitatethe scientific research task in the future.

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APPENDIX 1 : Groundwater Level and Rainfall Data

PWA Number		L/18	L/47	L/57	L/8	M/10	M/8	N/12	N/16	T/15
Year	*Date*	*WL/MSL*	*WL/MSL*	*WL/MSL*	*WL/MSL*	*WL/MSL*	*WL/MSL*	*WL/MSL*	*WL/MSL*	*WL/MSL*
2000	Jan	-0.319	-1.53	-0.421	-0.165	-0.225	0.117	8.686	6.929	-0.328
2000	Feb	-0.169	-1.34	-0.451	-0.115	-0.295	0.167	8.686	6.989	-0.178
2000	Mar	-0.199	-1.48	-0.491	-0.225	-0.265	0.167	8.736	7.119	-0.218
2000	Apr	-0.269	-1.77	-0.521	-0.375	-0.305	0.167	8.756	6.949	-0.268
2000	May	-0.309	-1.76	-0.541	-0.415	-0.345	0.157	8.716	7.159	-0.298
2000	Jun	-0.459	-1.74	-0.511	-0.415	-0.305	0.167	8.736	7.119	-0.428
2000	Jul	-0.449	-1.79	-0.531	-0.375	-0.205	0.157	8.836	7.019	-0.408
2000	Aug	-0.499	-2	-0.751	-0.495	-0.155	0.077	8.806	6.749	-0.518
2000	Sep	-0.539	-2.09	-0.821	-0.475	-0.125	0.027	8.816	6.749	-0.568
2000	Oct	-0.619	-2.22	-0.921	-0.665	-0.155	-0.003	8.786	6.699	-0.648
2000	Nov	-0.709	-2.24	-0.941	-0.705	-0.175	0.057	8.816	6.934	-0.518
2000	Dec	-0.579	-2.34	-0.931	-0.735	-0.355	-0.123	8.756	7.169	-0.508
2001	Jan	-0.299	-2.1	-0.871	-0.515	-0.385	-0.043	8.906	7.319	-0.368
2001	Feb	-0.194	-1.93	-0.831	-0.375	-0.405	-0.013	9.036	7.339	-0.148
2001	Mar	-0.159	-1.95	-0.821	-0.335	-0.465	-0.043	8.906	7.289	-0.168
2001	Apr	-0.269	-2.13	-0.861	-0.445	-0.505	0.087	8.906	7.359	-0.048
2001	May	-0.299	-2.19	-0.891	-0.485	-0.545	0.027	8.896	7.429	-0.128
2001	Jun	-0.459	-2.44	-0.981	-0.605	-0.495	-0.033	8.956	7.289	-0.248
2001	Jul	-0.509	-2.57	-0.991	-0.615	-0.395	-0.063	8.976	7.169	-0.188
2001	Aug	-0.589	-2.69	-1.081	-0.635	-0.335	-0.073	9.046	7.259	-0.298
2001	Sep	-0.639	-2.79	-1.211	-0.665	-0.25	-0.143	8.986	7.149	-0.368
2001	Oct	-0.659	-2.94	-1.231	-0.585	0.24	-0.133	8.936	7.099	-0.428
2001	Nov	-0.739	-2.97	-1.321	-0.785	-0.245	-0.183	9.026	7.169	-0.408
2001	Dec	-0.499	-2.87	-1.321	-0.715	-0.38	-0.183	9.116	7.459	-0.348
2002	Jan	-0.409	-2.73	-1.251	-0.545	-0.445	-0.143	9.316	7.649	-0.218
2002	Feb	-0.219	-2.55	-1.211	-0.405	-0.575	-0.113	9.136	7.689	-0.128
2002	Mar	-0.159	-2.44	-1.246	-0.315	-0.495	-0.103	9.2	7.654	-0.166
2002	Apr	-0.249	-2.565	-1.291	-0.37	-0.625	-0.058	9.211	7.704	-0.032
2002	May	-0.299	-2.87	-1.321	-0.43	-0.56	-0.083	9.226	7.729	0.002
2002	Jun	0.439	-2.96	-1.351	-0.55	-0.575	-0.123	9.286	7.674	-0.173
2002	Jul	-0.499	-3.27	-1.411	-0.475	-0.535	-0.183	9.236	7.869	-0.298
2002	Aug	-0.679	-3.3	-1.521	-0.515	-0.435	-0.193	9.296	7.929	-0.228
2002	Sep	-0.679	-3.56	-1.561	-0.59	-0.375	-0.213	9.341	7.574	-0.233
2002	Oct	-0.899	-3.33	-1.701	-0.645	-0.325	-0.263	9.356	7.499	-0.408

PWA Number		L/18	L/47	L/57	L/8	M/10	M/8	N/12	N/16	T/15
Year	**Date**	**WL/MSL**	**WL/MSL**	**WL/MSL**	**WL/MSL**	**WL/MSL**	**WL/MSL**	**WL/MSL**	**WL/MSL**	**WL/MSL**
2002	Nov	-0.729	-3.765	-1.711	-0.7	-0.315	-0.258	9.381	7.574	-0.328
2002	Dec	-0.539	-3.48	-1.791	-0.645	-0.405	-0.283	9.376	7.829	-0.228
2003	Jan	-0.519	-3.25	-1.671	-0.565	-0.465	-0.263	9.376	7.979	-0.098
2003	Feb	-0.519	-3	-1.721	-0.375	-0.435	-0.223	9.466	7.949	-0.078
2003	Mar	-0.159	-2.93	-1.671	-0.295	-0.525	-0.163	9.496	8.019	0.002
2003	Apr	-0.229	-3	-1.721	-0.295	-0.625	-0.203	9.516	8.049	0.112
2003	May	-0.299	-3.55	-1.751	-0.375	-0.575	-0.193	9.556	8.029	0.132
2003	Jun	-0.419	-3.47	-1.721	-0.495	-0.625	-0.213	9.616	8.059	-0.098
2003	Jul	-0.479	-3.55	-1.761	-0.425	-0.575	-0.163	9.666	8.059	-0.158
2003	Aug	-0.599	-4.1	-1.891	-0.565	-0.535	-0.203	9.686	7.849	-0.098
2003	Sep	-0.719	-4.3	-1.911	-0.515	-0.505	-0.283	9.696	7.999	-0.098
2003	Oct	-0.749	-4.46	-2.051	-0.715	-0.585	-0.313	9.696	7.869	-0.148
2003	Nov	-0.719	-4.56	-2.101	-0.615	-0.625	-0.333	9.736	7.979	-0.248
2003	Dec	-0.619	-4.6	-2.121	-0.535	-0.665	-0.323	9.706	8.109	-0.148
2004	Jan	-0.529	-3.95	-2.101	-0.465	-0.65	-0.353	9.706	8.129	-0.038
2004	Feb	-0.289	-3.75	-2.101	-0.405	-0.755	-0.353	9.786	8.189	0.062
2004	Mar	-0.479	-4.17	-2.061	-0.405	-0.855	-0.323	9.816	8.279	0.062
2004	Apr	-0.699	-4.37	-2.151	-0.415	-0.84	-0.343	9.886	8.299	-0.098
2004	May	-0.669	-4.38	-2.221	-0.455	-0.935	-0.413	9.916	8.149	-0.098
2004	Jun	-0.879	-4.55	-2.351	-0.475	-0.895	-0.413	9.896	8.219	-0.238
2004	Jul	-0.614	-4.15	-2.386	-0.62	-0.845	-0.398	9.908	8.239	-0.253
2004	Aug	-0.859	-5.1	-2.521	-0.675	-0.765	-0.463	9.886	8.169	-0.398
2004	Sep	-0.859	-4.86	-2.561	-0.895	-0.725	-0.493	9.866	8.069	-0.548
2004	Oct	-0.814	-4.83	-2.596	-0.8	-0.815	-0.563	9.791	7.799	0.323
2004	Nov	-0.999	-5.1	-2.751	-0.955	-0.745	-0.513	9.926	8.009	-0.578
2004	Dec	-0.779	-4.8	-2.851	-0.805	-0.785	-0.553	9.946	8.299	-0.438
2005	Jan	-0.579	-4.5	-2.851	-0.735	-0.835	-0.583	9.996	8.299	-0.308
2005	Feb	-0.489	-4.2	-2.791	-0.515	-0.885	-0.583	10.116	8.249	-0.208
2005	Mar	-0.439	-4.3	-2.791	-0.435	-0.995	-0.613	10.116	8.439	-0.138
2005	Apr	-0.509	-4.55	-2.841	-0.565	-1.055	-0.613	10.146	8.439	-0.098
2005	May	-0.589	-4.52	-2.871	-0.645	-1.025	-0.613	10.116	8.419	-0.198
2005	Jun	-0.679	-4.61	-2.951	-0.745	-1.015	-0.593	10.156	8.399	-0.318
2005	Jul	-0.749	-4.75	-3.011	-0.815	-1.005	-0.633	10.156	8.419	-0.348

PWA Number		L/18	L/47	L/57	L/8	M/10	M/8	N/12	N/16	T/15
Year	***Date***	***WL/MSL***	***WL/MSL***	***WL/MSL***	***WL/MSL***	***WL/MSL***	***WL/MSL***	***WL/MSL***	***WL/MSL***	***WL/MSL***
2005	Aug	-0.939	-4.88	-3.081	-0.835	-0.925	-0.703	9.956	8.229	-0.398
2005	Sep	-0.879	-5.17	-3.141	-0.985	-0.845	-0.713	9.936	8.399	-0.458
2005	Oct	-0.879	-5.2	-3.141	-0.885	-0.825	-0.813	9.886	7.699	-0.498
2005	Nov	-0.679	-5.325	-2.946	-0.815	-1.025	-0.653	10.101	8.284	-0.663
2005	Dec	-0.726	-4.95	-2.998	-0.83	-0.805	-0.7005	10.143	8.406	-0.583
2006	Jan	-0.774	-4.95	-3.051	-0.845	-1.11	-0.748	10.186	8.529	-0.503
2006	Feb	-0.529	-4.65	-3.021	-0.715	-0.915	-0.763	10.086	8.549	-0.4355
2006	Mar	-0.399	-4.59	-2.971	-0.665	-1.125	-0.793	10.086	8.619	-0.368
2006	Apr	-0.519	-4.74	-3.001	-0.565	-1.25	-0.763	10.136	8.649	-0.268
2006	May	-1.044	-5.13	-3.226	-0.875	-1.125	-0.828	10.286	8.649	-0.523
2006	June	-0.699	-4.91	-3.041	-0.955	-1.145	-0.813	10.136	8.579	-0.398
2006	July	-1.124	-5.48	-3.071	-1.035	-1.165	-0.868	10.321	8.694	-0.673
2006	Aug	-0.899	-5.05	-3.071	-0.755	-1.155	-0.813	10.206	8.549	-0.558
2006	Sep	-1.129	-5.28	-3.506	-0.835	-1.145	-0.843	10.206	8.489	-0.798
2006	Oct	-1.089	-5.41	-3.325	-0.835	-1.3	-0.818	10.241	8.524	-0.773
2006	Nov	-1.049	-5.55	-3.141	-0.835	-1.305	-0.793	10.276	8.559	-0.748
2006	Dec	-1.009	-5.5	-3.331	-0.895	-1.345	-0.853	10.321	8.659	-0.723
2007	Jan	-0.969	-5.45	-3.251	-0.955	-1.385	-0.913	10.376	8.759	-0.698
2007	Feb	-0.944	-5.375	-3.301	-0.91	-1.47	-0.928	10.401	8.824	-0.648
2007	Mar	-0.919	-5.3	-3.351	-0.865	-1.555	-0.943	10.426	8.889	-0.598
2007	Apr	-1.039	-5.52	3.561	-1.03	-1.61	-0.993	10.441	8.884	-0.723
2007	May	-1.499	-5.74	-3.581	-1.105	-1.665	-1.043	10.456	8.879	-0.848
2007	Jun	-1.499	-5.97	-3.636	-1.18	-1.665	-1.073	10.471	8.924	-0.923
2007	Jul	-1.499	-6.2	-3.691	-1.255	-1.665	-1.103	10.486	8.969	-0.998
2007	Aug	-1.699	-4.211	-3.781	-1.35	-1.65	-1.148	10.486	9.024	-1.098
2007	Sep	-1.899	-6.57	-3.871	-1.445	-1.65	-1.193	10.486	9.079	-1.198
2007	Oct	-1.834	-6.68	-3.931	-1.515	-1.775	-1.228	10.486	9.079	-1.243
2007	Nov	-1.769	-6.78	-3.991	-1.585		-1.263	10.486	9.079	-1.288
2007	Dec	1.599	-6.53	-4.052	-1.49		-1.188	10.486	9.214	-1.213
2008	Jan	-1.429	-6.28	-4.121	-1.395		-1.113	10.696	9.349	-1.138
2008	Feb	-1.606	-6.14	4.05	-1.495		1.198	10.538	9.181	-1.221
2008	Mar	-1.583	-6	4.05	-1.495		1.198	10.538	9.181	-1.221
2008	Apr	-1.559	-6.3	-4.121	-1.495		1.198	10.538	9.181	-1.221

PWA Number		T/22	T/26	T/6	L/101	L/66	L/86	P/50	CAMP - 8
Year	Date	WL/MSL	WL/MSL	WL/MSL	WL/MSL	WL/MSL	WL/MSL	WL/MSL	WL/MSL
2000	Jan	-0.104	-0.085	-0.11	-1.427	-1.811	3.1	-3.005	
2000	Feb	0.026	0.055	0.03	-1.197	-1.781	3.12	-2.925	
2000	Mar	-0.044	0.045	0.04	-1.247	-1.871	3.04	-2.915	
2000	Apr	-0.034	0.015	-0.01	-1.327	-2.011	3	-3.245	
2000	May	0.006	-0.045	0.01	-1.417	-2.091	2.97	-3.245	
2000	Jun	-0.144	-0.085	0.015	-1.527	-2.161	2.97	-3.515	
2000	Jul	-0.104	-0.085	0.03	-1.477	-2.201	2.96	-3.475	
2000	Aug	-0.274	-0.165	-0.16	-1.557	-2.261	2.88	-3.645	
2000	Sep	-0.294	-0.215	-0.23	-1.667	-2.311	2.95	-3.745	
2000	Oct	-0.254	-0.285	-0.27	-1.707	-2.651	2.92	-4.045	
2000	Nov	-0.184	-0.365	-0.15	-1.627	-2.641	2.91	-4.095	
2000	Dec	-0.129	-0.315	-0.17	-1.497	-2.701	2.99	-4.0625	
2001	Jan	-0.074	-0.215	-0.08	-0.937	-2.471	3.07	-4.03	
2001	Feb	0.091	-0.115	0.125	-0.517	-2.271	3.09	-3.795	
2001	Mar	0.006	-0.135	0.09	-0.697	-2.281	3.12	-3.915	
2001	Apr	-0.024	-0.135	0.14	-0.967	-2.371	3.15	-4.015	
2001	May	0.006	-0.115	0.14	-1.067	-2.501	3.25	-4.095	
2001	Jun	-0.004	-0.145	0.14	-1.217	-2.651	3.17	-4.295	
2001	Jul	-0.044	-0.155	0.07	-1.197	-2.681	3.12	-4.455	
2001	Aug	-0.044	-0.255	0.03	-1.257	-2.981	3.02	-4.595	
2001	Sep	-0.044	-0.405	0.03	-1.347	-3.151	2.95	-4.805	
2001	Oct	-0.104	-0.465	-0.05	-1.357	-3.251	2.86	-4.965	
2001	Nov	-0.084	-0.435	-0.05	-1.207	-3.421	2.79	-5.145	
2001	Dec	0.016	-0.265	0.04	-1.117	-3.401	2.72	-5.095	
2002	Jan	0.036	-0.235	0.11	-0.987	-3.171	2.74	-5.055	
2002	Feb	0.156	-0.115	0.22	-0.867	-3.221	2.85	-4.825	
2002	Mar	0.086	-0.11	0.28	-0.807	-3.046	2.945	-4.665	
2002	Apr	0.136	0.085	0.305	-0.992	3.051	2.975	-4.815	
2002	May	0.186	-0.065	0.28	-1.117	-2.961	3.035	-4.995	
2002	Jun	0.136	-0.105	0.275	-1.167	-3.031	2.995	-5.145	
2002	Jul	0.056	-0.245	0.22	-1.257	-3.701	2.89	-5.135	
2002	Aug	0.026	-0.275	0.18	-1.337	-3.701	2.83	-5.415	
2002	Sep	0.021	-0.31	0.14	-1.397	-3.078	2.975	-5.58	

PWA Number		T/22	T/26	T/6	L/101	L/66	L/86	P/50	CAMP - 8
Year	**Date**	**WL/MSL**	**WL/MSL**	**WL/MSL**	**WL/MSL**	**WL/MSL**	**WL/MSL**	**WL/MSL**	**WL/MSL**
2002	Oct	-0.084	-0.385	0.04	-1.417	-3.951	2.93	-5.595	
2002	Nov	0.006	-0.395	0.14	-1.267	-3.168	2.855	-7.1225	
2002	Dec	0.076	-0.275	0.13	-1.207	-3.991	2.69	-5.755	
2003	Jan	0.146	-0.245	0.17	-1.017	-3.931	2.77	-5.685	
2003	Feb	0.166	-0.135	0.31	-0.967	-3.771	2.800	-5.475	
2003	Mar	0.166	-0.085	0.47	-0.917	-3.811	2.77	-5.415	
2003	Apr	0.296	-0.035	0.47	-1.017	-3.731	2.8	-5.615	
2003	May	0.366	-0.015	0.42	-1.137	-3.871	2.82	-5.815	
2003	Jun	0.276	-0.065	0.41	-1.157	-3.951	2.82	-5.995	
2003	Jul	0.226	-0.265	0.37	-1.247	-4.241	2.92	-6.035	
2003	Aug	0.196	-0.225	0.24	-1.247	-4.391	2.88	-6.225	
2003	Sep	0.086	-0.215	0.25	-1.367	-3.005	3	-6.355	
2003	Oct	0.056	-0.315	0.2	-1.387	-2.925	3	-6.495	
2003	Nov	0.096	-0.355	0.33	-1.257	-2.915	2.92	-9.1	
2003	Dec	0.156	-0.205	0.28	-1.257	-3.245	2.96	-9.18	
2004	Jan	0.156	-0.205	0.35	-1.027	-3.245	2.96	-8.98	
2004	Feb	0.196	-0.165	0.47	-0.927	-3.515	2.96	-8.76	
2004	Mar	0.196	-0.165	0.47	-1.147	-3.475	2.96	-8.81	
2004	Apr	0.226	-0.225	0.32	-1.177	-3.645	3.14	-9.13	6.041
2004	May	-0.044	-0.225	0.35	-1.337	-3.745	3.04	-7.8475	6.081
2004	Jun	-0.074	-0.325	0.25	-1.447	-4.045	2.96	-9.68	6.111
2004	Jul	0.036	0.35	0.195	-1.487	-4.095	3.155	-8.1875	6.116
2004	Aug	-0.084	-0.435	0.02	-1.467	-3.795	2.85	-10.01	6.121
2004	Sep	-0.064	-0.495	0.04	-1.597	-3.915	2.85	-10.1	6.121
2004	Oct	-0.074	-0.46	0.055	-1.557	-4.015	3.31	-8.738	6.146
2004	Nov	-0.164	-0.605	0.105	-1.527	-4.095	2.89	-9.399	6.171
2004	Dec	-0.104	-0.535	0.178	-1.317	-4.295	2.94	-10.06	6.201
2005	Jan	-0.074	-0.425	0.2	-0.997	-4.455	3.04	-9.74	6.241
2005	Feb	-0.004	-0.365	0.25	-0.947	-4.595	3.13	-9.33	6.271
2005	Mar	-0.004	-0.345	0.14	-1.067	-4.805	3.23	-9.18	6.301
2005	Apr	0.066	-0.305	0.17	-1.217	-4.965	3.29	-9.58	6.341
2005	May	0.006	-0.315	0.14	-1.337	-5.145	3.36	-9.88	6.361
2005	Jun	-0.094	-0.375	0.11	-1.447	-5.095	3.36	-10.18	6.381

PWA Number		T/22	T/26	T/6	L/101	L/66	L/86	P/50	CAMP - 8
Year	Date	WL/MSL	WL/MSL	WL/MSL	WL/MSL	WL/MSL	WL/MSL	WL/MSL	WL/MSL
2005	Jul	-0.154	-0.435	0.02	-1.487	-5.055	3.39	-10.34	6.391
2005	Aug	-0.174	-0.475	-0.05	-1.467	-4.825	3.44	-10.54	6.411
2005	Sep	-0.174	-0.545	-0.08	-1.517	-5.135	3.49	-10.8	6.441
2005	Oct	-0.204	-0.605	-0.09	-1.467	-5.415	3.62	-10.98	6.471
2005	Nov	-0.184	-0.605	-0.12	-1.427	-5.595	3.005	-10.84	6.3605
2005	Dec	-0.1615	-0.58	-0.045	-1.367	-5.755	3.065	-10.75	6.25
2006	Jan	-0.139	-0.555	0.01	-1.307	-5.685	3.125	-10.695	6.4255
2006	Feb	-0.104	-0.415	0.03	-1.227	-5.475	3.72	-10.08	6.601
2006	Mar	-0.054	-0.355	0.09	-1.167	-5.415	3.62	-9.86	6.641
2006	Apr	-0.054	-0.355	0.07	-1.137	-5.615	3.62	-10.18	6.671
2006	May	-0.124	-0.54	0.02	-1.702	-5.815	3.26	-11.33	6.671
2006	June	-0.094	-0.455	-0.03	-1.567	-5.995	3.51	-10.72	6.671
2006	July	0.204	0.655	-0.285	-1.852	-6.035	3.21	-11.76	6.701
2006	Aug	-0.154	-0.565	-0.13	-1.697	-6.225	3.36	-10.98	6.731
2006	Sep	-0.234	-0.665	-0.33	-1.927	-6.355	3.25	-10.98	6.731
2006	Oct	-0.219	-0.665	-0.36	-1.822	-6.495	3.185	-11.44	6.766
2006	Nov	-0.204	-0.665	-0.39	-1.717	-6.073	3.12	-11.9	6.801
2006	Dec	-0.204	-0.675	-0.365	-1.667	-5.877	3.165	-11.775	6.836
2007	Jan	-0.204	-0.685	-0.32	-1.617	-5.681	3.21	-11.65	6.871
2007	Feb	-0.154	-0.64	0.28	-1.617	-5.681	3.205	-11.48	6.931
2007	Mar	-0.104	-0.595	-0.23	-1.617	-5.681	3.28	-11.44	6.991
2007	Apr	-0.179	-0.68	0.34	-1.682	-6.343	3.055	-12.11	7.006
2007	May	-0.254	-0.765	-0.45	-2.067	-5.951	3.16	-12.78	7.021
2007	Jun	-0.254	-0.82	-0.52	-2.142	-6.014	3.095	-12.98	7.071
2007	Jul	-0.254	-0.875	-0.59	-2.217	-6.131	3.03	-13.18	7.121
2007	Aug	-0.294	-0.955	-0.67	-2.292	-6.256	3.01	-13.41	7.136
2007	Sep	-0.334	-1.035	-0.75	-2.367	-6.381	2.99	-13.64	7.151
2007	Oct	-0.364	-1.085	-0.8	-2.377	-6.466	2.865	-13.865	7.176
2007	Nov	-0.394	-1.135	-0.84	-2.387	-6.551	2.74	-14.09	7.201
2007	Dec	-0.374	-1.11	-0.79	-2.277	-6.546	2.72	-13.75	7.266
2008	Jan	-0.354	-1.085	-0.73	-2.167	-6.541	2.72	-13.23	7.331
2008	Feb	-0.3715	1.11	0.71	-2.197	-6.496	2.69	-12.78	7.3305
2008	Mar	-0.3715	1.11	0.71	-2.197	-6.451	2.59	-12.55	7.33

PWA Number		*T/22*	*T/26*	*T/6*	*L/101*	*L/66*	*L/86*	*P/50*	*CAMP - 8*
Year	*Date*	*WL/MSL*	*WL/MSL*	*WL/MSL*	*WL/MSL*	*WL/MSL*	*WL/MSL*	*WL/MSL*	*WL/MSL*
2008	Apr	-0.3715	1.11	0.71	-2.227	-7.071	2.49	-12.1	7.351

Rainfall Data

Year	Month	Khanyounis station _ Monthly Rainfall (mm)	Khuza station _ Monthly Rainfall (mm)	Year	Month	Khanyounis station _ Monthly Rainfall (mm)	Khuza station _ Monthly Rainfall (mm)	Year	Month	Khanyounis station _ Monthly Rainfall (mm)	Khuza station _ Monthly Rainfall (mm)
2000	Jan	164.10	59.1	2002	Oct	21.00	20.50	2005	Jul	0.00	0
2000	Feb	5.60	65	2002	Nov	8.30	1.50	2005	Aug	0.00	0
2000	Mar	9.70	3.1	2002	Dec	127.30	144.00	2005	Sep	0.00	0
2000	Apr	0.00	0	2003	Jan	26.70	21.2	2005	Oct	0.00	0
2000	May	0.00	0	2003	Feb	50.00	32	2005	Nov	59.00	44.5
2000	Jun	0.00	0	2003	Mar	79.00	62.1	2005	Dec	62.50	43.5
2000	Jul	0.00	0	2003	Apr	10.40	4	2006	Jan	27.00	21.5
2000	Aug	0.00	0	2003	May	0.00	0	2006	Feb	49.50	43.5
2000	Sep	0.00	0	2003	Jun	0.00	0	2006	Mar	7.00	5.5
2000	Oct	44.00	38.7	2003	Jul	0.00	0	2006	Apr	35.00	35
2000	Nov	13.00	7	2003	Aug	0.00	0	2006	May	0.00	0
2000	Dec	134.60	96	2003	Sep	0.00	0	2006	Jun	0.00	0
2001	Jan	108.80	76.8	2003	Oct	0.00	0	2006	Jul	0.00	0
2001	Feb	66.50	52.1	2003	Nov	0.00	2	2006	Aug	0.00	0
2001	Mar	1.60	0.2	2003	Dec	48.90	46.5	2006	Sep	1.50	0
2001	Apr	11.20	10	2004	Jan	102.20	92	2006	Oct	51.10	48.5
2001	May	1.30	3.5	2004	Feb	28.70	26.5	2006	Nov	25.50	28.5
2001	Jun	0.00	0	2004	Mar	19.50	18	2006	Dec	36.50	82
2001	Jul	0.00	0	2004	Apr	1.70	0.5	2007	Jan	28.00	32.5
2001	Aug	0.00	0	2004	May	2.00	0.5	2007	Feb	36.80	30.3
2001	Sep	0.00	0	2004	Jun	0.00	0	2007	Mar	51.70	32.5
2001	Oct	3.90	7	2004	Jul	0.00	0	2007	Apr	3.00	1
2001	Nov	19.60	12	2004	Aug	0.00	0	2007	May	2.50	0.5
2001	Dec	67.50	57	2004	Sep	0.00	0	2007	Jun	0.00	0
2002	Jan	152.50	132.00	2004	Oct	37.00	0	2007	Jul	0.00	0
2002	Feb	8.70	11.50	2004	Nov	58.50	123	2007	Aug	0.00	0
2002	Mar	47.50	29.50	2004	Dec	109.00	93	2007	Sep	0.00	0
2002	Apr	12.00	9.5	2005	Jan	83.00	79.5	2007	Oct	0.70	0.5
2002	May	0.00	0	2005	Feb	55.50	49	2007	Nov	19.00	10.5

Year	Month	Khanyounis station _ Monthly Rainfall (mm)	Khuza station _ Monthly Rainfall (mm)	Year	Month	Khanyounis station _ Monthly Rainfall (mm)	Khuza station _ Monthly Rainfall (mm)	Year	Month	Khanyounis station _ Monthly Rainfall (mm)	Khuza station _ Monthly Rainfall (mm)
2002	Jun	0.00	0.00	2005	Mar	55.00	39	2007	Dec	36.30	18.5
2002	Jul	0.00	0.00	2005	Apr	0.00	2	2008	Jan	48.70	52
2002	Aug	0.00	0.00	2005	May	0.00	0	2008	Feb	54.60	71.5
2002	Sep	0.00	0.00	2005	Jun	0.00	0	2008	Mar	0.00	1
								2008	Apr	0.00	0.00

APPENDIX 2 : Data of land use classification for each influence areas

For aerial photo 1999

Influence Areas	Soil Type	Buildup Area m^2	Agricultural Area m^2	Open Space Area m^2
CAMP - 8	Loessal sandy soil	158	4,156	1,821
	Sandy loess soil over loess	399,483	10,536,392	4,617,760
	Sandy loess soil	36,361	959,023	420,309
L/101	Loessal sandy soil	63,229	1,071,617	370,666
	Sandy regosols	245,416	4,159,352	1,438,693
L/18	Loessal sandy soil	458,509	3,324,979	351,008
	Sandy regosols	157,427	1,141,615	120,517
L/47	Loessal sandy soil	1,016,587	2,925,684	716,659
	Sandy regosols	283,468	815,807	199,836
L/57	Loessal sandy soil	215,138	3,304,804	327,160
	Sandy loess soil over loess	198,190	3,044,452	301,386
	Sandy loess soil	6,715	103,158	10,212
L/66	Loessal sandy soil	96,993	3,439,421	2,399,785
	Sandy loess soil	5,409	191,800	133,824
L/8	Loessal sandy soil	108,889	1,671,650	437,215
L/86	Loessal sandy soil	579,963	1,299,222	1,040,420
	Sandy regosols	2,437,070	5,459,478	4,371,964
M/10	Loessal sandy soil	624,441	673,263	182,927
	Sandy loess soil over loess	684,485	738,001	200,517
M/8	Sandy loess soil over loess	2,117,394	3,166,594	240,517
	Sandy loess soil	304,443	455,299	34,582
N/12	Sandy loess soil over loess	184,070	3,351,872	2,615,318
N/16	Sandy loess soil over loess	83,776	2,637,617	2,021,191
	Sandy loess soil	31,594	994,692	762,227
P/50	Loessal sandy soil	103,575	1,306,813	438,212
	Sandy regosols	191,600	2,417,421	810,632
T/15	Loessal sandy soil	750,840	2,500,714	361,349
	Dark brown / reddish brown	10,009	33,334	4,817
T/22 -1	Loessal sandy soil	4,426	104,237	27,449
	Dark brown / reddish brown	124,449	2,930,839	771,783
	Sandy loess soil over loess	808	19,021	5,009
	Sandy loess soil	65,955	1,553,281	409,028

	Dark brown / reddish brown	130	3,061	806
	Sandy loess soil	130	3,061	806
T/26 -1	Loessal sandy soil	26,293	999,408	178,775
	Dark brown / reddish brown	3,542	134,614	24,080
	Sandy loess soil over loess	11,393	433,046	77,464
T/6 -1	Loessal sandy soil	87,467	1,955,374	12,988
	Dark brown / reddish brown	19,803	442,708	2,940

For aerial photo 2003

Influence Areas	Soil Type	Buildup Area m^2	Agricultural Area m^2	Open Space Area m^2
CAMP - 8	Loessal sandy soil	159	4,043	1,929
	Sandy loess soil over loess	402,022	10,250,544	4,890,752
	Sandy loess soil	36,592	933,005	445,157
L/101	Loessal sandy soil	62,807	1,080,791	356,178
	Sandy regosols	243,779	4,194,956	1,382,462
L/18	Loessal sandy soil	457,058	2,980,219	697,218
	Sandy regosols	156,929	1,023,244	239,386
L/47	Loessal sandy soil	998,419	2,428,332	1,232,179
	Sandy regosols	278,402	677,124	343,585
L/57	Loessal sandy soil	221,961	2,931,752	693,389
	Sandy loess soil over loess	204,475	2,700,789	638,764
	Sandy loess soil	6,928	91,513	21,644
L/66	Loessal sandy soil	98,179	2,670,242	3,167,777
	Sandy loess soil	5,475	148,907	176,652
L/8	Loessal sandy soil	107,984	1,810,053	299,717
L/86	Loessal sandy soil	597,936	1,024,670	1,297,000
	Sandy regosols	2,512,596	4,305,777	5,450,139
M/10	Loessal sandy soil	633,754	629,195	217,683
	Sandy loess soil over loess	694,693	689,695	238,614
M/8	Sandy loess soil over loess	2,178,312	2,682,866	663,326
	Sandy loess soil	313,202	385,747	95,374
N/12	Sandy loess soil over loess	185,423	2,899,048	3,066,788
N/16	Sandy loess soil over loess	84,129	2,276,583	2,381,872
	Sandy loess soil	31,727	858,540	898,246
P/50	Loessal sandy soil	103,818	1,110,758	644,514

Influence Areas	Soil Type	Buildup Area m^2	Agricultural Area m^2	Open Space Area m^2
	Sandy regosols	192,048	2,054,748	1,192,261
T/15	Loessal sandy soil	751,797	2,216,949	644,156
	Dark brown / reddish brown	10,021	29,552	8,587
T/22	Loessal sandy soil	4,427	101,152	30,534
	Dark brown / reddish brown	124,471	2,844,086	858,515
	Sandy loess soil over loess	808	18,458	5,572
	Sandy loess soil	65,967	1,507,304	454,994
	Dark brown / reddish brown	130	2,970	897
	Sandy loess soil	130	2,970	897
T/26	Loessal sandy soil	25,734	912,999	265,743
	Dark brown / reddish brown	3,466	122,975	35,794
	Sandy loess soil over loess	11,151	395,605	115,147
T/6	Loessal sandy soil	86,712	1,747,427	221,691
	Dark brown / reddish brown	19,632	395,627	50,192

<u>For aerial photo 2007</u>

Influence Areas	Soil Type	Buildup Area m^2	Agricultural Area m^2	Open Space Area m^2
CAMP - 8	Loessal sandy soil	159	3,854	2,095
	Sandy loess soil over loess	401,992	9,771,948	5,310,671
	Sandy loess soil	36,589	889,444	483,378
L/101	Loessal sandy soil	270	954,408	550,834
	Sandy regosols	1,047	3,704,418	2,137,996
L/18	Loessal sandy soil	376,708	2,635,086	1,122,702
	Sandy regosols	129,341	904,744	385,474
L/47	Loessal sandy soil	1,001,928	2,503,168	1,153,835
	Sandy regosols	279,381	697,991	321,739
L/57	Loessal sandy soil	222,553	2,862,172	762,377
	Sandy loess soil over loess	205,021	2,636,690	702,317
	Sandy loess soil	6,947	89,342	23,797
L/66	Loessal sandy soil	94,146	2,374,684	3,345,182
	Sandy loess soil	5,250	132,425	186,545
L/8	Loessal sandy soil	108,132	1,518,492	591,130
L/86	Loessal sandy soil	486,244	929,597	1,503,764
	Sandy regosols	2,043,252	3,906,272	6,318,989
M/10	Loessal sandy soil	639,258	608,891	232,483

Influence Areas	Soil Type	Buildup Area m^2	Agricultural Area m^2	Open Space Area m^2
	Sandy loess soil over loess	700,726	667,439	254,838
M/8	Sandy loess soil over loess	2,165,267	2,570,055	789,183
	Sandy loess soil	311,326	369,527	113,470
N/12	Sandy loess soil over loess	184,824	2,465,523	3,500,913
N/16	Sandy loess soil over loess	137,102	2,257,574	2,347,909
	Sandy loess soil	51,704	851,371	885,438
P/50	Loessal sandy soil	60,066	827,502	961,032
	Sandy regosols	111,113	1,530,763	1,777,776
T/15	Loessal sandy soil	731,307	2,123,317	758,278
	Dark brown / reddish brown	9,748	28,304	10,108
T/22	Loessal sandy soil	4,623	82,901	48,589
	Dark brown / reddish brown	129,974	2,330,922	1,366,175
	Sandy loess soil over loess	844	15,128	8,866
	Sandy loess soil	68,883	1,235,338	724,043
	Dark brown / reddish brown	136	2,434	1,427
	Sandy loess soil	136	2,434	1,427
T/26	Loessal sandy soil	37,001	920,039	247,437
	Dark brown / reddish brown	4,984	123,924	33,328
	Sandy loess soil over loess	16,033	398,655	107,215
T/6	Loessal sandy soil	87,708	1,576,936	391,185
	Dark brown / reddish brown	19,858	357,027	88,567

APPENDIX 3 : Recharge from rainfall estimation m^3/month

For year 2000												
Influence Areas	**Jan**	**Feb**	**Mar**	**Apr**	**May**	**Jun**	**Jul**	**Aug**	**Sep**	**Oct**	**Nov**	**Dec**
CAMP - 8	296,234	325,807	15,539	0	0	0	0	0	0	193,981	35,087	481,192
L/101	614,576	20,973	36,328	0	0	0	0	0	0	164,786	48,687	501,847
L/18	258,519	8,822	15,281	0	0	0	0	0	0	69,317	20,480	211,100
L/47	240,133	8,195	14,194	0	0	0	0	0	0	64,387	19,023	196,086
L/57	299,854	10,233	17,724	0	0	0	0	0	0	80,400	23,754	244,853
L/66	225,697	7,702	13,341	0	0	0	0	0	0	60,516	17,880	184,299
L/8	75,487	2,576	4,462	0	0	0	0	0	0	20,240	5,980	61,641
L/86	1,123,395	38,336	66,404	0	0	0	0	0	0	301,215	88,995	917,336
M/10	85,867	2,930	5,076	0	0	0	0	0	0	23,023	6,802	70,117
M/8	206,438	7,045	12,203	0	0	0	0	0	0	55,352	16,354	168,572
N/12	109,488	120,418	5,743	0	0	0	0	0	0	71,695	12,968	177,848
N/16	112,849	124,115	5,919	0	0	0	0	0	0	73,896	13,366	183,308
P/50	387,914	13,238	22,930	0	0	0	0	0	0	104,011	30,731	316,761
T/15	106,475	3,634	6,294	0	0	0	0	0	0	28,549	8,435	86,945
T/22	222,447	7,591	13,149	0	0	0	0	0	0	59,645	17,622	181,645
T/26	72,753	2,483	4,300	0	0	0	0	0	0	19,507	5,763	59,408
T/6	84,823	2,895	5,014	0	0	0	0	0	0	22,743	6,720	69,264

For year 2001												
Influence Areas	**Jan**	**Feb**	**Mar**	**Apr**	**May**	**Jun**	**Jul**	**Aug**	**Sep**	**Oct**	**Nov**	**Dec**
CAMP - 8	384,954	261,147	1,002	50,124	17,543	0	0	0	0	35,087	60,149	285,708
L/101	407,470	249,051	5,992	41,945	4,869	0	0	0	0	14,606	73,405	252,796
L/18	171,401	104,762	2,521	17,644	2,048	0	0	0	0	6,144	30,877	106,338
L/47	159,210	97,312	2,341	16,389	1,902	0	0	0	0	5,707	28,681	98,775
L/57	198,806	121,513	2,924	20,465	2,375	0	0	0	0	7,126	35,814	123,340
L/66	149,640	91,462	2,201	15,404	1,788	0	0	0	0	5,364	26,957	92,837
L/8	50,049	30,590	736	5,152	598	0	0	0	0	1,794	9,016	31,050
L/86	744,822	455,245	10,953	76,673	8,900	0	0	0	0	26,699	134,178	462,091
M/10	56,931	34,797	837	5,861	680	0	0	0	0	2,041	10,256	35,320
M/8	136,871	83,657	2,013	14,090	1,635	0	0	0	0	4,906	24,657	84,915
N/12	142,279	96,520	371	18,526	6,484	0	0	0	0	12,968	22,231	105,598
N/16	146,646	99,483	382	19,095	6,683	0	0	0	0	13,366	22,913	108,839
P/50	257,191	157,198	3,782	26,476	3,073	0	0	0	0	9,219	46,332	159,562

For year 2001												
Influence Areas	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
T/15	70,594	43,148	1,038	7,267	843	0	0	0	0	2,530	12,717	43,797
T/22	147,485	90,145	2,169	15,182	1,762	0	0	0	0	5,287	26,569	91,500
T/26	48,236	29,482	709	4,965	576	0	0	0	0	1,729	8,690	29,926
T/6	56,238	34,374	827	5,789	672	0	0	0	0	2,016	10,131	34,890

For year 2002												
Influence Areas	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
CAMP - 8	661,640	57,643	147,866	47,618	0	0	0	0	0	102,755	7,519	721,789
L/101	571,132	32,583	177,894	44,942	0	0	0	0	0	78,648	31,085	476,755
L/18	240,245	13,706	74,830	18,905	0	0	0	0	0	33,083	13,076	200,545
L/47	223,158	12,731	69,508	17,560	0	0	0	0	0	30,730	12,146	186,282
L/57	278,657	15,897	86,795	21,927	0	0	0	0	0	38,372	15,166	232,610
L/66	209,743	11,966	65,330	16,504	0	0	0	0	0	28,883	11,416	175,084
L/8	70,151	4,002	21,850	5,520	0	0	0	0	0	9,660	3,818	58,559
L/86	1,043,984	59,558	325,175	82,150	0	0	0	0	0	143,762	56,820	871,470
M/10	79,797	4,552	24,855	6,279	0	0	0	0	0	10,988	4,343	66,611
M/8	191,846	10,945	59,755	15,096	0	0	0	0	0	26,418	10,441	160,144
N/12	244,542	21,305	54,651	17,600	0	0	0	0	0	37,978	2,779	266,773
N/16	252,048	21,959	56,329	18,140	0	0	0	0	0	39,144	2,864	274,961
P/50	359,311	20,566	112,285	28,367	0	0	0	0	0	49,642	19,620	300,923
T/15	98,624	5,645	30,820	7,786	0	0	0	0	0	13,626	5,385	82,597
T/22	206,045	11,793	64,389	16,267	0	0	0	0	0	28,467	11,251	172,563
T/26	67,388	3,857	21,059	5,320	0	0	0	0	0	9,310	3,680	56,438
T/6	78,568	4,497	24,553	6,203	0	0	0	0	0	10,855	4,290	65,801

For year 2003												
Influence Areas	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
CAMP - 8	106,342	160,517	311,503	20,065	0	0	0	0	0	0	0	233,251
L/101	99,547	186,417	294,538	38,775	0	0	0	0	0	0	0	182,316
L/18	42,416	79,431	125,501	16,522	0	0	0	0	0	0	0	77,683
L/47	39,685	74,316	117,420	15,458	0	0	0	0	0	0	0	72,681
L/57	49,139	92,020	145,392	19,140	0	0	0	0	0	0	0	89,996
L/66	37,126	69,525	109,850	14,461	0	0	0	0	0	0	0	67,996

For year 2003												
Influence Areas	**Jan**	**Feb**	**Mar**	**Apr**	**May**	**Jun**	**Jul**	**Aug**	**Sep**	**Oct**	**Nov**	**Dec**
L/8	12,218	22,880	36,150	4,759	0	0	0	0	0	0	0	22,376
L/86	183,327	343,310	542,430	71,408	0	0	0	0	0	0	0	335,757
M/10	13,902	26,035	41,135	5,415	0	0	0	0	0	0	0	25,462
M/8	33,464	62,667	99,014	13,035	0	0	0	0	0	0	0	61,289
N/12	39,519	59,651	115,761	7,456	0	0	0	0	0	0	0	86,681
N/16	40,744	61,500	119,348	7,687	0	0	0	0	0	0	0	89,367
P/50	64,115	120,065	189,702	24,973	0	0	0	0	0	0	0	117,423
T/15	17,463	32,702	51,669	6,802	0	0	0	0	0	0	0	31,983
T/22	36,266	67,914	107,305	14,126	0	0	0	0	0	0	0	66,420
T/26	11,918	22,318	35,262	4,642	0	0	0	0	0	0	0	21,827
T/6	13,934	26,093	41,227	5,427	0	0	0	0	0	0	0	25,519

For year 2004												
Influence Areas	**Jan**	**Feb**	**Mar**	**Apr**	**May**	**Jun**	**Jul**	**Aug**	**Sep**	**Oct**	**Nov**	**Dec**
CAMP - 8	461,486	132,928	90,291	2,508	2,508	0	0	0	0	0	616,987	466,502
L/101	381,036	107,003	72,703	6,338	7,457	0	0	0	0	137,948	218,108	406,388
L/18	162,357	45,593	30,978	2,701	3,177	0	0	0	0	58,779	92,934	173,159
L/47	151,903	42,658	28,983	2,527	2,973	0	0	0	0	54,994	86,950	162,010
L/57	188,089	52,820	35,888	3,129	3,681	0	0	0	0	68,095	107,664	200,604
L/66	142,109	39,907	27,115	2,364	2,781	0	0	0	0	51,449	81,344	151,565
L/8	46,766	13,133	8,923	778	915	0	0	0	0	16,931	26,769	49,877
L/86	701,725	197,060	133,891	11,673	13,732	0	0	0	0	254,049	401,672	748,415
M/10	53,215	14,944	10,153	885	1,041	0	0	0	0	19,266	30,460	56,755
M/8	128,092	35,971	24,440	2,131	2,507	0	0	0	0	46,374	73,321	136,615
N/12	171,497	49,399	33,554	932	932	0	0	0	0	0	229,284	173,361
N/16	176,812	50,929	34,594	961	961	0	0	0	0	0	236,389	178,733
P/50	245,412	68,917	46,825	4,082	4,803	0	0	0	0	88,848	140,476	261,741
T/15	66,843	18,771	12,754	1,112	1,308	0	0	0	0	24,199	38,261	71,290
T/22	138,817	38,983	26,487	2,309	2,717	0	0	0	0	50,257	79,460	148,053
T/26	45,618	12,810	8,704	759	893	0	0	0	0	16,515	26,112	48,653
T/6	53,334	14,977	10,176	887	1,044	0	0	0	0	19,309	30,529	56,883

For year 2005												
Influence Areas	**Jan**	**Feb**	**Mar**	**Apr**	**May**	**Jun**	**Jul**	**Aug**	**Sep**	**Oct**	**Nov**	**Dec**

CAMP - 8	398,784	245,792	195,630	10,032	0	0	0	0	0	0	223,219	218,203
L/101	309,452	206,923	205,058	0	0	0	0	0	0	0	219,972	233,021
L/18	131,855	88,168	87,374	0	0	0	0	0	0	0	93,728	99,289
L/47	123,365	82,491	81,748	0	0	0	0	0	0	0	87,693	92,895
L/57	152,753	102,142	101,222	0	0	0	0	0	0	0	108,584	115,025
L/66	115,412	77,173	76,478	0	0	0	0	0	0	0	82,040	86,906
L/8	37,980	25,396	25,167	0	0	0	0	0	0	0	26,998	28,599
L/86	569,894	381,074	377,641	0	0	0	0	0	0	0	405,106	429,137
M/10	43,217	28,898	28,638	0	0	0	0	0	0	0	30,721	32,543
M/8	104,028	69,561	68,934	0	0	0	0	0	0	0	73,947	78,334
N/12	148,196	91,341	72,700	3,728	0	0	0	0	0	0	82,952	81,088
N/16	152,788	94,171	74,953	3,844	0	0	0	0	0	0	85,523	83,601
P/50	199,308	133,272	132,071	0	0	0	0	0	0	0	141,676	150,081
T/15	54,285	36,299	35,972	0	0	0	0	0	0	0	38,588	40,877
T/22	112,738	75,385	74,706	0	0	0	0	0	0	0	80,139	84,893
T/26	37,048	24,773	24,550	0	0	0	0	0	0	0	26,335	27,897
T/6	43,314	28,963	28,702	0	0	0	0	0	0	0	30,790	32,616

For year 2006

Influence Areas	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
CAMP - 8	107,698	217,901	27,551	175,323	2,505	0	0	0	0	242,947	142,763	410,756
L/101	105,807	193,980	27,431	137,157	9,797	0	0	0	5,878	200,250	99,929	143,036
L/18	44,076	80,806	11,427	57,135	4,081	0	0	0	2,449	83,417	41,627	59,584
L/47	40,030	73,388	10,378	51,891	3,706	0	0	0	2,224	75,761	37,806	54,115
L/57	49,766	91,237	12,902	64,511	4,608	0	0	0	2,765	94,186	47,001	67,276
L/66	36,912	67,672	9,570	47,849	3,418	0	0	0	2,051	69,860	34,862	49,900
L/8	12,502	22,920	3,241	16,206	1,158	0	0	0	695	23,661	11,807	16,901
L/86	193,605	354,943	50,194	250,970	17,926	0	0	0	10,756	366,416	182,849	261,725
M/10	14,010	25,686	3,632	18,162	1,297	0	0	0	778	26,516	13,232	18,940
M/8	34,040	62,406	8,825	44,125	3,152	0	0	0	1,891	64,423	32,148	46,016
N/12	40,326	81,591	10,316	65,648	938	0	0	0	0	90,969	53,456	153,803
N/16	40,918	82,787	10,467	66,610	952	0	0	0	0	92,302	54,240	156,058
P/50	66,758	122,390	17,308	86,538	6,181	0	0	0	3,709	126,346	63,049	90,247
T/15	17,818	32,666	4,619	23,097	1,650	0	0	0	990	33,722	16,828	24,087
T/22	37,062	67,946	9,609	48,043	3,432	0	0	0	2,059	70,143	35,003	50,102
T/26	11,941	21,892	3,096	15,479	1,106	0	0	0	663	22,599	11,277	16,142

T/6	14,190	26,014	3,679	18,394	1,314	0	0	0	788	26,855	13,401	19,182

For year 2007												
Influence Areas	**Jan**	**Feb**	**Mar**	**Apr**	**May**	**Jun**	**Jul**	**Aug**	**Sep**	**Oct**	**Nov**	**Dec**
CAMP - 8	162,799	151,779	162,799	5,009	2,505	0	0	0	0	2,505	52,597	92,670
L/101	109,726	144,211	202,601	11,756	9,797	0	0	0	0	2,743	74,457	142,252
L/18	45,708	60,074	84,397	4,897	4,081	0	0	0	0	1,143	31,016	59,257
L/47	41,513	54,559	76,650	4,448	3,706	0	0	0	0	1,038	28,169	53,818
L/57	51,609	67,829	95,292	5,530	4,608	0	0	0	0	1,290	35,020	66,907
L/66	38,279	50,310	70,680	4,101	3,418	0	0	0	0	957	25,975	49,626
L/8	12,965	17,039	23,939	1,389	1,158	0	0	0	0	324	8,798	16,808
L/86	200,776	263,877	370,718	21,512	17,926	0	0	0	0	5,019	136,241	260,291
M/10	14,529	19,096	26,827	1,557	1,297	0	0	0	0	363	9,859	18,836
M/8	35,300	46,395	65,179	3,782	3,152	0	0	0	0	883	23,954	45,764
N/12	60,959	56,832	60,959	1,876	938	0	0	0	0	938	19,694	34,699
N/16	61,852	57,665	61,852	1,903	952	0	0	0	0	952	19,983	35,208
P/50	69,231	90,989	127,830	7,418	6,181	0	0	0	0	1,731	46,978	89,753
T/15	18,478	24,285	34,118	1,980	1,650	0	0	0	0	462	12,538	23,955
T/22	38,434	50,514	70,966	4,118	3,432	0	0	0	0	961	26,080	49,827
T/26	12,383	16,275	22,865	1,327	1,106	0	0	0	0	310	8,403	16,054
T/6	14,715	19,340	27,170	1,577	1,314	0	0	0	0	368	9,985	19,077

For year 2008			
Influence Areas	**Jan**	**Feb**	**Mar**
CAMP - 8	260,479	358,159	5,009
L/101	190,845	213,965	0
L/18	79,500	89,131	0
L/47	72,202	80,950	0
L/57	89,762	100,637	0
L/66	66,579	74,645	0
L/8	22,549	25,281	0
L/86	349,206	391,513	0
M/10	25,271	28,332	0
M/8	61,397	68,836	0
N/12	97,534	134,109	1,876
N/16	98,964	136,075	1,903

P/50	120,412	135,000	0
T/15	32,138	36,032	0
T/22	66,848	74,947	0
T/26	21,538	24,147	0
T/6	25,594	28,694	0

APPENDIX 4 : Recharge from return flow

<u>water distribution systems estimation in m^3/month</u>

For year 2000												
Influence Areas	**Jan**	**Feb**	**Mar**	**Apr**	**May**	**Jun**	**Jul**	**Aug**	**Sep**	**Oct**	**Nov**	**Dec**
CAMP - 8	10,186	10,212	12,015	13,151	14,342	14,217	16,712	17,766	18,259	15,435	14,539	12,812
L/101	5,430	5,444	6,404	7,010	7,645	7,578	8,908	9,470	9,733	8,227	7,750	6,829
L/18	5,119	5,132	6,038	6,609	7,208	7,145	8,399	8,929	9,177	7,757	7,307	6,439
L/47	5,146	5,159	6,070	6,644	7,246	7,183	8,443	8,976	9,225	7,798	7,346	6,473
L/57	3,292	3,301	3,883	4,250	4,635	4,595	5,401	5,742	5,901	4,988	4,699	4,141
L/66	3,511	3,520	4,141	4,533	4,944	4,901	5,761	6,124	6,294	5,320	5,012	4,416
L/8	1,891	1,895	2,230	2,441	2,662	2,639	3,102	3,297	3,389	2,865	2,699	2,378
L/86	18,476	18,524	21,793	23,854	26,015	25,787	30,313	32,225	33,119	27,997	26,372	23,239
M/10	2,258	2,264	2,663	2,915	3,179	3,152	3,705	3,938	4,048	3,422	3,223	2,840
M/8	7,007	7,025	8,264	9,046	9,865	9,779	11,495	12,220	12,560	10,617	10,001	8,813
N/12	7,760	7,780	9,153	10,019	10,926	10,830	12,731	13,534	13,910	11,759	11,076	9,760
N/16	7,376	7,395	8,700	9,523	10,386	10,295	12,102	12,865	13,222	11,177	10,529	9,278
P/50	5,319	5,332	6,273	6,867	7,489	7,423	8,726	9,276	9,534	8,059	7,592	6,690
T/15	3,845	3,854	4,535	4,964	5,413	5,366	6,308	6,705	6,892	5,826	5,488	4,836
T/22	4,389	4,401	5,177	5,667	6,180	6,126	7,201	7,655	7,868	6,651	6,265	5,521
T/26	1,936	1,941	2,283	2,499	2,725	2,702	3,176	3,376	3,470	2,933	2,763	2,435
T/6	2,088	2,094	2,463	2,696	2,940	2,915	3,426	3,642	3,743	3,164	2,981	2,627
For year 2001												
Influence Areas	**Jan**	**Feb**	**Mar**	**Apr**	**May**	**Jun**	**Jul**	**Aug**	**Sep**	**Oct**	**Nov**	**Dec**
CAMP - 8	12,678	11,686	15,767	17,152	17,827	19,158	20,204	20,683	18,583	18,784	17,695	15,554
L/101	6,758	6,229	8,404	9,143	9,502	10,212	10,770	11,025	9,906	10,013	9,432	8,291
L/18	6,372	5,873	7,924	8,620	8,959	9,628	10,154	10,395	9,339	9,441	8,893	7,817
L/47	6,405	5,904	7,966	8,666	9,006	9,679	10,208	10,450	9,389	9,490	8,940	7,858
L/57	4,097	3,777	5,096	5,543	5,761	6,192	6,530	6,685	6,006	6,071	5,719	5,027
L/66	4,370	4,028	5,435	5,912	6,145	6,604	6,964	7,130	6,406	6,475	6,099	5,362
L/8	2,353	2,169	2,926	3,184	3,309	3,556	3,750	3,839	3,449	3,487	3,284	2,887
L/86	22,996	21,196	28,598	31,112	32,335	34,750	36,647	37,516	33,707	34,072	32,096	28,213
M/10	2,810	2,591	3,495	3,802	3,952	4,247	4,479	4,585	4,120	4,164	3,923	3,448
M/8	8,721	8,038	10,845	11,798	12,262	13,178	13,898	14,227	12,783	12,921	12,171	10,699
N/12	9,658	8,902	12,011	13,067	13,581	14,595	15,392	15,757	14,157	14,310	13,480	11,850
N/16	9,181	8,462	11,417	12,421	12,909	13,873	14,631	14,978	13,457	13,603	12,814	11,264

P/50	6,620	6,102	8,232	8,956	9,308	10,003	10,550	10,800	9,703	9,808	9,239	8,122
T/15	4,785	4,411	5,951	6,474	6,728	7,231	7,626	7,807	7,014	7,090	6,679	5,871
T/22	5,463	5,035	6,794	7,391	7,682	8,255	8,706	8,913	8,008	8,094	7,625	6,703
T/26	2,409	2,221	2,996	3,259	3,388	3,640	3,839	3,930	3,531	3,570	3,362	2,956
T/6	2,599	2,396	3,232	3,517	3,655	3,928	4,142	4,241	3,810	3,851	3,628	3,189
For year 2002												
Influence Areas	**Jan**	**Feb**	**Mar**	**Apr**	**May**	**Jun**	**Jul**	**Aug**	**Sep**	**Oct**	**Nov**	**Dec**
CAMP - 8	14,364	14,376	18,095	17,062	19,886	19,330	20,693	20,479	20,994	20,647	19,189	17,532
L/101	7,657	7,663	9,646	9,094	10,600	10,304	11,030	10,916	11,191	11,005	10,228	9,345
L/18	7,219	7,225	9,094	8,575	9,994	9,715	10,400	10,292	10,551	10,376	9,644	8,811
L/47	7,257	7,263	9,142	8,620	10,047	9,766	10,454	10,346	10,607	10,431	9,695	8,858
L/57	4,642	4,646	5,848	5,514	6,427	6,247	6,688	6,619	6,785	6,673	6,202	5,666
L/66	4,951	4,955	6,238	5,881	6,855	6,663	7,133	7,059	7,237	7,117	6,614	6,043
L/8	2,666	2,668	3,359	3,167	3,691	3,588	3,841	3,801	3,897	3,832	3,562	3,254
L/86	26,054	26,076	32,822	30,947	36,070	35,062	37,534	37,146	38,081	37,450	34,806	31,801
M/10	3,184	3,187	4,011	3,782	4,408	4,285	4,587	4,540	4,654	4,577	4,254	3,887
M/8	9,880	9,889	12,447	11,736	13,679	13,296	14,234	14,087	14,441	14,202	13,199	12,060
N/12	10,943	10,952	13,785	12,998	15,149	14,726	15,764	15,601	15,994	15,729	14,618	13,356
N/16	10,402	10,410	13,104	12,355	14,400	13,998	14,985	14,830	15,203	14,951	13,896	12,696
P/50	7,500	7,506	9,448	8,909	10,383	10,093	10,805	10,693	10,962	10,781	10,019	9,154
T/15	5,421	5,426	6,830	6,440	7,506	7,296	7,810	7,729	7,924	7,793	7,243	6,617
T/22	6,190	6,195	7,798	7,352	8,569	8,330	8,917	8,825	9,047	8,897	8,269	7,555
T/26	2,730	2,732	3,439	3,242	3,779	3,673	3,932	3,891	3,989	3,923	3,646	3,332
T/6	2,945	2,947	3,710	3,498	4,077	3,963	4,242	4,199	4,304	4,233	3,934	3,594
For year 2003												
Influence Areas	**Jan**	**Feb**	**Mar**	**Apr**	**May**	**Jun**	**Jul**	**Aug**	**Sep**	**Oct**	**Nov**	**Dec**
CAMP - 8	6,368	6,104	6,819	7,732	2,451	9,009	9,656	9,358	9,271	9,314	7,943	7,369
L/101	11,662	11,178	12,487	14,159	4,488	16,498	17,683	17,137	16,978	17,056	14,546	13,494
L/18	11,773	11,285	12,606	14,294	4,531	16,655	17,852	17,301	17,140	17,219	14,685	13,623
L/47	15,164	14,536	16,237	18,411	5,836	21,453	22,994	22,284	22,077	22,179	18,915	17,546
L/57	11,488	11,012	12,301	13,948	4,422	16,253	17,421	16,882	16,725	16,803	14,330	13,293
L/66	5,357	5,135	5,736	6,504	2,062	7,579	8,123	7,873	7,799	7,835	6,682	6,199
L/8	4,481	4,295	4,798	5,440	1,725	6,339	6,794	6,584	6,523	6,553	5,589	5,185
L/86	42,066	40,323	45,043	51,074	16,191	59,512	63,788	61,818	61,242	61,525	52,472	48,675
M/10	9,210	8,828	9,861	11,182	3,545	13,029	13,965	13,534	13,408	13,470	11,488	10,657

M/8	10,041	9,625	10,752	12,191	3,865	14,205	15,226	14,756	14,618	14,686	12,525	11,619
N/12	4,036	3,869	4,322	4,900	1,553	5,710	6,120	5,931	5,876	5,903	5,034	4,670
N/16	4,718	4,522	5,052	5,728	1,816	6,675	7,154	6,933	6,869	6,901	5,885	5,459
P/50	7,921	7,593	8,482	9,617	3,049	11,206	12,012	11,641	11,532	11,586	9,881	9,166
T/15	5,929	5,683	6,349	7,199	2,282	8,388	8,991	8,713	8,632	8,672	7,396	6,861
T/22	658	631	705	799	253	931	998	967	958	962	821	761
T/26	1,916	1,836	2,051	2,326	737	2,710	2,905	2,815	2,789	2,802	2,390	2,217
T/6	1,528	1,465	1,636	1,856	588	2,162	2,318	2,246	2,225	2,235	1,906	1,768
For year 2004												
Influence Areas	**Jan**	**Feb**	**Mar**	**Apr**	**May**	**Jun**	**Jul**	**Aug**	**Sep**	**Oct**	**Nov**	**Dec**
CAMP - 8	6,545	6,813	8,029	8,355	9,037	9,868	10,151	10,669	10,430	10,270	8,988	7,304
L/101	11,985	12,477	14,703	15,301	16,548	18,070	18,590	19,538	19,101	18,807	16,460	13,375
L/18	12,099	12,596	14,844	15,447	16,706	18,243	18,767	19,724	19,283	18,987	16,617	13,503
L/47	15,585	16,224	19,119	19,896	21,518	23,497	24,173	25,405	24,837	24,456	21,404	17,392
L/57	11,807	12,292	14,485	15,074	16,302	17,802	18,313	19,247	18,817	18,528	16,216	13,176
L/66	5,506	5,732	6,755	7,029	7,602	8,301	8,540	8,975	8,775	8,640	7,562	6,144
L/8	4,605	4,794	5,649	5,879	6,358	6,943	7,143	7,507	7,339	7,226	6,324	5,139
L/86	43,233	45,008	53,039	55,194	59,693	65,183	67,058	70,476	68,900	67,842	59,376	48,246
M/10	9,465	9,854	11,612	12,084	13,069	14,271	14,681	15,430	15,084	14,853	12,999	10,563
M/8	10,320	10,743	12,660	13,175	14,249	15,559	16,006	16,822	16,446	16,194	14,173	11,516
N/12	4,148	4,318	5,089	5,295	5,727	6,254	6,434	6,762	6,610	6,509	5,697	4,629
N/16	4,849	5,048	5,949	6,190	6,695	7,311	7,521	7,904	7,728	7,609	6,659	5,411
P/50	8,141	8,475	9,988	10,393	11,241	12,274	12,627	13,271	12,974	12,775	11,181	9,085
T/15	6,094	6,344	7,476	7,780	8,414	9,187	9,452	9,934	9,711	9,562	8,369	6,800
T/22	676	704	830	863	934	1,020	1,049	1,103	1,078	1,061	929	755
T/26	1,969	2,050	2,416	2,514	2,719	2,969	3,054	3,210	3,138	3,090	2,704	2,197
T/6	1,571	1,635	1,927	2,005	2,169	2,368	2,436	2,561	2,503	2,465	2,157	1,753
For year 2005												
Influence Areas	**Jan**	**Feb**	**Mar**	**Apr**	**May**	**Jun**	**Jul**	**Aug**	**Sep**	**Oct**	**Nov**	**Dec**
CAMP - 8	7,042	6,709	7,666	8,519	9,198	10,368	10,931	10,869	11,419	9,473	8,918	8,793
L/101	12,896	12,285	14,038	15,601	16,845	18,987	20,017	19,905	20,911	17,348	16,332	16,102
L/18	13,019	12,402	14,172	15,750	17,005	19,168	20,208	20,095	21,110	17,513	16,487	16,255
L/47	16,769	15,975	18,255	20,287	21,903	24,689	26,029	25,883	27,191	22,558	21,236	20,938
L/57	12,704	12,103	13,830	15,369	16,594	18,705	19,719	19,609	20,600	17,090	16,089	15,862
L/66	5,924	5,644	6,449	7,167	7,738	8,722	9,195	9,144	9,606	7,969	7,502	7,397

L/8	4,955	4,720	5,394	5,994	6,472	7,295	7,691	7,648	8,034	6,665	6,275	6,187
L/86	46,518	44,315	50,640	56,277	60,762	68,490	72,205	71,801	75,429	62,577	58,912	58,083
M/10	10,184	9,702	11,087	12,321	13,303	14,995	15,808	15,720	16,514	13,700	12,898	12,716
M/8	11,104	10,578	12,088	13,433	14,504	16,348	17,235	17,139	18,005	14,937	14,062	13,864
N/12	4,463	4,252	4,859	5,399	5,830	6,571	6,928	6,889	7,237	6,004	5,652	5,573
N/16	5,217	4,970	5,680	6,312	6,815	7,682	8,098	8,053	8,460	7,019	6,607	6,514
P/50	8,760	8,345	9,536	10,597	11,442	12,897	13,597	13,521	14,204	11,784	11,093	10,937
T/15	6,557	6,246	7,138	7,932	8,564	9,654	10,177	10,120	10,632	8,820	8,304	8,187
T/22	728	693	792	880	951	1,071	1,130	1,123	1,180	979	922	909
T/26	2,119	2,018	2,306	2,563	2,767	3,119	3,289	3,270	3,435	2,850	2,683	2,645
T/6	1,690	1,610	1,840	2,045	2,208	2,488	2,623	2,609	2,741	2,274	2,140	2,110

For year 2006												
Influence Areas	**Jan**	**Feb**	**Mar**	**Apr**	**May**	**Jun**	**Jul**	**Aug**	**Sep**	**Oct**	**Nov**	**Dec**
CAMP - 8	20,747	17,567	22,252	21,347	24,439	25,606	27,432	28,585	26,832	29,521	25,477	22,333
L/101	19,116	16,186	20,503	19,669	22,518	23,593	25,275	26,338	24,722	27,200	23,474	20,578
L/18	18,865	15,974	20,234	19,410	22,222	23,283	24,943	25,992	24,398	26,843	23,166	20,307
L/47	22,139	18,747	23,746	22,780	26,080	27,325	29,273	30,504	28,633	31,503	27,187	23,832
L/57	24,817	21,014	26,618	25,535	29,233	30,630	32,813	34,193	32,095	35,312	30,475	26,715
L/66	6,793	5,752	7,287	6,990	8,003	8,385	8,982	9,360	8,786	9,667	8,342	7,313
L/8	9,474	8,022	10,161	9,748	11,160	11,693	12,526	13,053	12,252	13,480	11,634	10,198
L/86	47,120	39,899	50,540	48,483	55,506	58,157	62,303	64,923	60,940	67,049	57,864	50,724
M/10	17,033	14,422	18,269	17,525	20,064	21,022	22,521	23,468	22,028	24,236	20,916	18,335
M/8	29,000	24,556	31,105	29,839	34,161	35,793	38,344	39,957	37,505	41,265	35,612	31,218
N/12	9,444	7,997	10,130	9,717	11,125	11,656	12,487	13,012	12,214	13,438	11,598	10,166
N/16	18,035	15,271	19,344	18,557	21,245	22,259	23,846	24,849	23,325	25,662	22,147	19,414
P/50	9,259	7,840	9,931	9,527	10,907	11,428	12,243	12,758	11,975	13,175	11,370	9,967
T/15	15,154	12,832	16,254	15,592	17,851	18,704	20,037	20,880	19,599	21,563	18,609	16,313
T/22	9,249	7,832	9,920	9,517	10,895	11,416	12,229	12,744	11,962	13,161	11,358	9,956
T/26	6,287	5,323	6,743	6,469	7,406	7,759	8,312	8,662	8,131	8,945	7,720	6,767
T/6	4,901	4,150	5,257	5,043	5,773	6,049	6,480	6,753	6,339	6,974	6,019	5,276

For year 2007												
Influence Areas	**Jan**	**Feb**	**Mar**	**Apr**	**May**	**Jun**	**Jul**	**Aug**	**Sep**	**Oct**	**Nov**	**Dec**
CAMP - 8	20,446	17,365	22,501	25,351	27,469	29,585	31,606	32,215	31,295	29,403	27,977	22,587

L/101	18,838	16,000	20,732	23,358	25,310	27,259	29,122	29,683	28,835	27,091	25,778	20,811
L/18	18,591	15,789	20,459	23,051	24,977	26,901	28,739	29,293	28,456	26,735	25,439	20,538
L/47	21,818	18,530	24,011	27,052	29,313	31,571	33,728	34,378	33,396	31,377	29,856	24,103
L/57	24,456	20,771	26,915	30,324	32,858	35,389	37,807	38,535	37,435	35,171	33,466	27,018
L/66	6,695	5,686	7,368	8,301	8,995	9,688	10,349	10,549	10,248	9,628	9,161	7,396
L/8	9,336	7,929	10,275	11,576	12,543	13,510	14,433	14,711	14,291	13,426	12,775	10,314
L/86	46,436	39,439	51,104	57,577	62,389	67,194	71,785	73,168	71,078	66,780	63,543	51,299
M/10	16,785	14,256	18,472	20,812	22,552	24,289	25,948	26,448	25,693	24,139	22,969	18,543
M/8	28,579	24,272	31,451	35,435	38,397	41,354	44,179	45,031	43,745	41,099	39,107	31,572
N/12	9,307	7,905	10,243	11,540	12,505	13,468	14,388	14,665	14,246	13,385	12,736	10,282
N/16	17,773	15,095	19,560	22,037	23,879	25,718	27,475	28,005	27,205	25,560	24,321	19,635
P/50	9,125	7,750	10,042	11,314	12,260	13,204	14,106	14,378	13,967	13,122	12,486	10,080
T/15	14,934	12,684	16,435	18,517	20,065	21,610	23,086	23,531	22,859	21,477	20,436	16,498
T/22	9,115	7,741	10,031	11,302	12,246	13,189	14,090	14,362	13,952	13,108	12,473	10,069
T/26	6,195	5,262	6,818	7,682	8,324	8,965	9,577	9,762	9,483	8,910	8,478	6,844
T/6	4,830	4,102	5,315	5,989	6,489	6,989	7,467	7,610	7,393	6,946	6,609	5,336

For year 2008				
Influence Areas	**Jan**	**Feb**	**Mar**	**Apr**
CAMP - 8	17,233	16,410	20,639	24,270
L/101	15,878	15,120	19,016	22,362
L/18	15,670	14,921	18,766	22,068
L/47	18,390	17,511	22,024	25,899
L/57	20,614	19,629	24,688	29,032
L/66	5,643	5,373	6,758	7,947
L/8	7,869	7,493	9,424	11,083
L/86	39,140	37,270	46,875	55,123
M/10	14,148	13,472	16,944	19,925
M/8	24,089	22,938	28,849	33,925
N/12	7,845	7,470	9,395	11,048
N/16	14,981	14,265	17,941	21,098
P/50	7,691	7,324	9,211	10,832
T/15	12,588	11,986	15,075	17,728
T/22	7,683	7,316	9,201	10,820
T/26	5,222	4,972	6,254	7,354

For year 2008				
Influence Areas	**Jan**	**Feb**	**Mar**	**Apr**
T/6	4,071	3,877	4,876	5,734

wastewater distribution systems estimation in m^3/month

For year 2000												
Influence Areas	**Jan**	**Feb**	**Mar**	**Apr**	**May**	**Jun**	**Jul**	**Aug**	**Sep**	**Oct**	**Nov**	**Dec**
CAMP - 8	15,306	15,345	18,053	19,761	21,551	21,362	25,111	26,695	27,436	23,193	21,847	19,251
L/101	8,159	8,180	9,623	10,533	11,487	11,387	13,385	14,229	14,624	12,363	11,645	10,262
L/18	7,692	7,712	9,073	9,931	10,831	10,736	12,620	13,416	13,789	11,656	10,980	9,675
L/47	7,733	7,753	9,121	9,984	10,888	10,793	12,687	13,487	13,861	11,717	11,038	9,726
L/57	4,947	4,959	5,835	6,387	6,965	6,904	8,116	8,628	8,867	7,496	7,061	6,222
L/66	5,276	5,289	6,223	6,812	7,429	7,364	8,656	9,202	9,457	7,995	7,531	6,636
L/8	2,841	2,848	3,351	3,668	4,000	3,965	4,661	4,955	5,092	4,305	4,055	3,573
L/86	27,762	27,834	32,746	35,843	39,090	38,748	45,548	48,421	49,765	42,068	39,627	34,919
M/10	3,393	3,402	4,002	4,381	4,777	4,736	5,567	5,918	6,082	5,141	4,843	4,268
M/8	10,528	10,555	12,418	13,593	14,824	14,694	17,273	18,362	18,872	15,953	15,028	13,242
N/12	11,660	11,690	13,753	15,054	16,418	16,274	19,130	20,337	20,901	17,669	16,643	14,666
N/16	11,084	11,112	13,073	14,310	15,606	15,469	18,184	19,331	19,868	16,795	15,821	13,941
P/50	7,992	8,012	9,426	10,318	11,253	11,154	13,112	13,939	14,326	12,110	11,407	10,052
T/15	5,777	5,792	6,814	7,458	8,134	8,063	9,478	10,076	10,355	8,754	8,246	7,266
T/22	6,595	6,612	7,779	8,515	9,286	9,205	10,821	11,503	11,822	9,994	9,414	8,296
T/26	2,908	2,916	3,431	3,755	4,095	4,059	4,772	5,073	5,214	4,407	4,151	3,658
T/6	3,138	3,146	3,701	4,051	4,418	4,380	5,148	5,473	5,625	4,755	4,479	3,947
For year 2001												
Influence Areas	**Jan**	**Feb**	**Mar**	**Apr**	**May**	**Jun**	**Jul**	**Aug**	**Sep**	**Oct**	**Nov**	**Dec**
CAMP - 8	19,050	17,559	23,691	25,773	26,787	28,787	30,359	31,079	27,923	28,226	26,588	23,372
L/101	10,154	9,360	12,628	13,738	14,278	15,345	16,182	16,566	14,884	15,045	14,173	12,458
L/18	9,574	8,825	11,907	12,953	13,462	14,468	15,258	15,619	14,034	14,186	13,363	11,746
L/47	9,624	8,871	11,969	13,021	13,533	14,544	15,338	15,702	14,107	14,260	13,433	11,808
L/57	6,157	5,675	7,657	8,330	8,657	9,304	9,812	10,044	9,025	9,122	8,593	7,554
L/66	6,566	6,053	8,166	8,884	9,233	9,923	10,465	10,713	9,625	9,729	9,165	8,056
L/8	3,536	3,259	4,397	4,784	4,972	5,343	5,635	5,768	5,183	5,239	4,935	4,338
L/86	34,553	31,849	42,972	46,749	48,587	52,215	55,067	56,373	50,649	51,197	48,227	42,394
M/10	4,223	3,893	5,252	5,713	5,938	6,382	6,730	6,890	6,190	6,257	5,894	5,181
M/8	13,103	12,078	16,296	17,728	18,425	19,801	20,883	21,378	19,207	19,415	18,289	16,077
N/12	14,512	13,377	18,048	19,634	20,406	21,930	23,128	23,676	21,272	21,503	20,255	17,805
N/16	13,795	12,715	17,156	18,664	19,398	20,846	21,984	22,506	20,221	20,440	19,254	16,925

P/50	9,947	9,168	12,370	13,457	13,987	15,031	15,852	16,228	14,580	14,738	13,883	12,204
T/15	7,190	6,627	8,942	9,728	10,110	10,865	11,458	11,730	10,539	10,653	10,035	8,821
T/22	8,209	7,566	10,209	11,106	11,543	12,405	13,082	13,392	12,032	12,163	11,457	10,071
T/26	3,620	3,337	4,502	4,898	5,090	5,470	5,769	5,906	5,306	5,364	5,052	4,441
T/6	3,906	3,600	4,857	5,284	5,492	5,902	6,224	6,372	5,725	5,787	5,451	4,792
For year 2002												
Influence Areas	**Jan**	**Feb**	**Mar**	**Apr**	**May**	**Jun**	**Jul**	**Aug**	**Sep**	**Oct**	**Nov**	**Dec**
CAMP - 8	21,583	21,601	27,190	25,637	29,881	29,046	31,093	30,772	31,546	31,024	28,834	26,344
L/101	11,505	11,514	14,493	13,665	15,927	15,482	16,574	16,402	16,815	16,537	15,369	14,042
L/18	10,847	10,856	13,665	12,885	15,017	14,598	15,627	15,465	15,854	15,592	14,491	13,240
L/47	10,904	10,913	13,737	12,952	15,096	14,675	15,709	15,547	15,938	15,674	14,567	13,309
L/57	6,976	6,981	8,788	8,286	9,657	9,387	10,049	9,945	10,196	10,027	9,319	8,514
L/66	7,440	7,446	9,373	8,837	10,300	10,012	10,718	10,607	10,874	10,694	9,939	9,081
L/8	4,006	4,009	5,047	4,758	5,546	5,391	5,771	5,711	5,855	5,758	5,352	4,890
L/86	39,149	39,181	49,319	46,502	54,199	52,685	56,399	55,815	57,221	56,272	52,300	47,784
M/10	4,785	4,789	6,028	5,683	6,624	6,439	6,893	6,822	6,993	6,877	6,392	5,840
M/8	14,846	14,859	18,703	17,635	20,554	19,979	21,388	21,167	21,700	21,340	19,833	18,121
N/12	16,443	16,456	20,714	19,531	22,764	22,127	23,687	23,442	24,033	23,634	21,966	20,069
N/16	15,630	15,643	19,690	18,565	21,638	21,033	22,516	22,283	22,844	22,466	20,880	19,077
P/50	11,270	11,279	14,197	13,386	15,602	15,166	16,235	16,067	16,472	16,199	15,055	13,755
T/15	8,146	8,153	10,263	9,676	11,278	10,963	11,736	11,614	11,907	11,709	10,883	9,943
T/22	9,301	9,308	11,717	11,047	12,876	12,516	13,398	13,260	13,594	13,368	12,425	11,352
T/26	4,101	4,105	5,167	4,872	5,678	5,519	5,908	5,847	5,995	5,895	5,479	5,006
T/6	4,425	4,429	5,575	5,256	6,126	5,955	6,375	6,309	6,468	6,361	5,911	5,401

For year 2003												
Influence Areas	**Jan**	**Feb**	**Mar**	**Apr**	**May**	**Jun**	**Jul**	**Aug**	**Sep**	**Oct**	**Nov**	**Dec**
CAMP - 8	9,569	9,172	10,246	11,618	3,683	13,537	14,510	14,062	13,931	13,995	11,936	11,072
L/101	17,523	16,797	18,763	21,275	6,744	24,790	26,571	25,751	25,511	25,629	21,858	20,276
L/18	17,690	16,957	18,942	21,478	6,809	25,026	26,825	25,996	25,754	25,873	22,066	20,469
L/47	22,786	21,841	24,398	27,665	8,770	32,235	34,551	33,484	33,173	33,326	28,422	26,365
L/57	17,262	16,547	18,484	20,959	6,644	24,421	26,176	25,368	25,132	25,248	21,533	19,975
L/66	8,050	7,716	8,619	9,773	3,098	11,388	12,206	11,829	11,719	11,773	10,041	9,314
L/8	6,733	6,454	7,209	8,174	2,591	9,525	10,209	9,894	9,802	9,847	8,398	7,790
L/86	63,209	60,589	67,681	76,744	24,329	89,423	95,848	92,888	92,023	92,448	78,845	73,140

For year 2003												
Influence Areas	**Jan**	**Feb**	**Mar**	**Apr**	**May**	**Jun**	**Jul**	**Aug**	**Sep**	**Oct**	**Nov**	**Dec**
M/10	13,839	13,265	14,818	16,802	5,326	19,578	20,984	20,336	20,147	20,240	17,262	16,013
M/8	15,088	14,462	16,155	18,318	5,807	21,345	22,879	22,172	21,966	22,067	18,820	17,458
N/12	6,064	5,813	6,494	7,363	2,334	8,579	9,196	8,912	8,829	8,870	7,565	7,017
N/16	7,089	6,796	7,591	8,607	2,729	10,029	10,750	10,418	10,321	10,369	8,843	8,203
P/50	11,903	11,409	12,745	14,451	4,581	16,839	18,049	17,491	17,329	17,409	14,847	13,773
T/15	8,909	8,540	9,540	10,817	3,429	12,604	13,510	13,092	12,971	13,030	11,113	10,309
T/22	989	948	1,059	1,201	381	1,399	1,499	1,453	1,440	1,446	1,233	1,144
T/26	2,879	2,760	3,083	3,495	1,108	4,073	4,365	4,231	4,191	4,211	3,591	3,331
T/6	2,297	2,201	2,459	2,788	884	3,249	3,482	3,375	3,343	3,359	2,865	2,657
For year 2004												
Influence Areas	**Jan**	**Feb**	**Mar**	**Apr**	**May**	**Jun**	**Jul**	**Aug**	**Sep**	**Oct**	**Nov**	**Dec**
CAMP - 8	9,834	10,238	12,065	12,555	13,578	14,827	15,253	16,031	15,673	15,432	13,506	10,974
L/101	18,009	18,748	22,094	22,991	24,866	27,152	27,933	29,357	28,701	28,260	24,733	20,097
L/18	18,181	18,927	22,304	23,211	25,103	27,411	28,200	29,637	28,974	28,530	24,969	20,289
L/47	23,417	24,379	28,729	29,896	32,334	35,307	36,322	38,174	37,320	36,748	32,162	26,133
L/57	17,741	18,469	21,765	22,650	24,496	26,749	27,518	28,921	28,274	27,840	24,366	19,798
L/66	8,273	8,613	10,149	10,562	11,423	12,473	12,832	13,486	13,185	12,982	11,362	9,232
L/8	6,919	7,203	8,489	8,834	9,554	10,432	10,732	11,280	11,027	10,858	9,503	7,722
L/86	64,962	67,629	79,696	82,935	89,696	97,945	100,761	105,898	103,530	101,941	89,219	72,495
M/10	14,222	14,806	17,448	18,157	19,637	21,443	22,060	23,185	22,666	22,318	19,533	15,872
M/8	15,506	16,143	19,023	19,796	21,410	23,379	24,051	25,278	24,712	24,333	21,296	17,304
N/12	6,233	6,489	7,646	7,957	8,606	9,397	9,667	10,160	9,933	9,781	8,560	6,955
N/16	7,286	7,585	8,939	9,302	10,060	10,985	11,301	11,877	11,612	11,433	10,007	8,131
P/50	12,233	12,735	15,007	15,617	16,890	18,444	18,974	19,941	19,495	19,196	16,801	13,651
T/15	9,156	9,532	11,233	11,690	12,643	13,805	14,202	14,926	14,592	14,368	12,575	10,218
T/22	1,016	1,058	1,247	1,297	1,403	1,532	1,576	1,657	1,620	1,595	1,396	1,134
T/26	2,959	3,080	3,630	3,777	4,085	4,461	4,589	4,823	4,715	4,643	4,063	3,302
T/6	2,360	2,457	2,896	3,013	3,259	3,559	3,661	3,848	3,761	3,704	3,242	2,634
For year 2005												
Influence Areas	**Jan**	**Feb**	**Mar**	**Apr**	**May**	**Jun**	**Jul**	**Aug**	**Sep**	**Oct**	**Nov**	**Dec**
CAMP - 8	10,581	10,080	11,519	12,801	13,821	15,579	16,424	16,333	17,158	14,234	13,401	13,212
L/101	19,378	18,460	21,094	23,442	25,311	28,530	30,078	29,909	31,421	26,067	24,540	24,195
L/18	19,562	18,636	21,295	23,666	25,552	28,802	30,364	30,195	31,720	26,316	24,774	24,425

For year 2003												
Influence Areas	**Jan**	**Feb**	**Mar**	**Apr**	**May**	**Jun**	**Jul**	**Aug**	**Sep**	**Oct**	**Nov**	**Dec**
L/47	25,197	24,004	27,429	30,483	32,912	37,099	39,111	38,892	40,857	33,896	31,910	31,461
L/57	19,089	18,185	20,781	23,094	24,934	28,106	29,630	29,465	30,953	25,679	24,175	23,835
L/66	8,902	8,480	9,690	10,769	11,627	13,106	13,817	13,740	14,434	11,975	11,273	11,115
L/8	7,445	7,093	8,105	9,007	9,725	10,962	11,556	11,492	12,072	10,015	9,429	9,296
L/86	69,899	66,589	76,091	84,562	91,302	102,914	108,496	107,890	113,341	94,029	88,521	87,275
M/10	15,303	14,578	16,659	18,513	19,989	22,531	23,753	23,621	24,814	20,586	19,380	19,107
M/8	16,685	15,894	18,163	20,185	21,793	24,565	25,898	25,753	27,054	22,445	21,130	20,832
N/12	6,706	6,389	7,300	8,113	8,760	9,874	10,409	10,351	10,874	9,021	8,493	8,373
N/16	7,840	7,468	8,534	9,484	10,240	11,543	12,169	12,101	12,712	10,546	9,928	9,789
P/50	13,162	12,539	14,329	15,924	17,193	19,379	20,431	20,316	21,343	17,706	16,669	16,435
T/15	9,852	9,386	10,725	11,919	12,869	14,506	15,292	15,207	15,975	13,253	12,477	12,301
T/22	1,093	1,042	1,190	1,323	1,428	1,610	1,697	1,688	1,773	1,471	1,385	1,365
T/26	3,184	3,033	3,466	3,851	4,158	4,687	4,941	4,914	5,162	4,283	4,032	3,975
T/6	2,540	2,419	2,765	3,072	3,317	3,739	3,942	3,920	4,118	3,416	3,216	3,171

For year 2006												
Influence Areas	**Jan**	**Feb**	**Mar**	**Apr**	**May**	**Jun**	**Jul**	**Aug**	**Sep**	**Oct**	**Nov**	**Dec**
CAMP - 8	31,174	26,397	33,437	32,076	36,722	38,476	41,219	42,953	40,318	44,359	38,282	33,558
L/101	28,723	24,322	30,808	29,554	33,835	35,451	37,979	39,576	37,148	40,871	35,273	30,920
L/18	28,346	24,002	30,403	29,166	33,391	34,986	37,480	39,056	36,660	40,334	34,809	30,514
L/47	33,267	28,169	35,681	34,229	39,187	41,059	43,986	45,836	43,024	47,336	40,852	35,811
L/57	37,290	31,576	39,996	38,368	43,926	46,025	49,306	51,379	48,227	53,061	45,792	40,142
L/66	10,208	8,644	10,949	10,503	12,025	12,599	13,497	14,065	13,202	14,525	12,535	10,989
L/8	14,235	12,054	15,268	14,647	16,769	17,570	18,822	19,614	18,410	20,256	17,481	15,324
L/86	70,803	59,953	75,942	72,851	83,404	87,388	93,617	97,554	91,570	100,748	86,947	76,218
M/10	25,593	21,671	27,451	26,333	30,148	31,588	33,840	35,263	33,100	36,417	31,429	27,550
M/8	43,575	36,898	46,738	44,836	51,331	53,782	57,616	60,039	56,356	62,005	53,511	46,908
N/12	14,191	12,016	15,221	14,601	16,717	17,515	18,764	19,553	18,353	20,193	17,427	15,276
N/16	27,099	22,947	29,066	27,883	31,922	33,447	35,831	37,338	35,048	38,561	33,278	29,172
P/50	13,913	11,781	14,923	14,315	16,389	17,172	18,396	19,170	17,994	19,797	17,085	14,977
T/15	22,771	19,281	24,423	23,429	26,823	28,104	30,108	31,374	29,449	32,401	27,963	24,512
T/22	13,898	11,768	14,907	14,300	16,371	17,153	18,376	19,149	17,974	19,776	17,067	14,961
T/26	9,446	7,999	10,132	9,720	11,128	11,659	12,490	13,016	12,217	13,442	11,600	10,169

For year 2006												
Influence Areas	**Jan**	**Feb**	**Mar**	**Apr**	**May**	**Jun**	**Jul**	**Aug**	**Sep**	**Oct**	**Nov**	**Dec**
T/6	7,364	6,236	7,899	7,577	8,675	9,090	9,737	10,147	9,524	10,479	9,044	7,928

For year 2007												
Influence Areas	**Jan**	**Feb**	**Mar**	**Apr**	**May**	**Jun**	**Jul**	**Aug**	**Sep**	**Oct**	**Nov**	**Dec**
CAMP - 8	30,722	26,092	33,810	38,092	41,276	44,455	47,492	48,407	47,025	44,181	42,039	33,939
L/101	28,306	24,041	31,152	35,097	38,031	40,960	43,758	44,601	43,328	40,708	38,734	31,271
L/18	27,935	23,725	30,742	34,636	37,531	40,422	43,184	44,016	42,759	40,173	38,225	30,860
L/47	32,784	27,844	36,079	40,649	44,047	47,439	50,680	51,657	50,181	47,147	44,861	36,217
L/57	36,749	31,211	40,442	45,565	49,373	53,176	56,809	57,904	56,250	52,848	50,286	40,597
L/66	10,060	8,544	11,071	12,473	13,516	14,557	15,551	15,851	15,398	14,467	13,766	11,113
L/8	14,029	11,915	15,439	17,394	18,848	20,300	21,686	22,104	21,473	20,175	19,197	15,498
L/86	69,775	59,261	76,789	86,515	93,746	100,967	107,864	109,943	106,803	100,345	95,480	77,083
M/10	25,222	21,421	27,757	31,273	33,886	36,496	38,990	39,741	38,606	36,272	34,513	27,863
M/8	42,943	36,472	47,259	53,245	57,696	62,139	66,384	67,664	65,731	61,756	58,762	47,440
N/12	13,985	11,878	15,391	17,340	18,789	20,237	21,619	22,036	21,406	20,112	19,137	15,450
N/16	26,706	22,682	29,390	33,113	35,881	38,644	41,284	42,080	40,878	38,406	36,544	29,503
P/50	13,711	11,645	15,089	17,000	18,421	19,840	21,196	21,604	20,987	19,718	18,762	15,147
T/15	22,440	19,059	24,696	27,824	30,149	32,471	34,690	35,358	34,348	32,271	30,707	24,790
T/22	13,696	11,632	15,073	16,982	18,401	19,819	21,173	21,580	20,964	19,696	18,742	15,130
T/26	9,309	7,907	10,245	11,543	12,507	13,471	14,391	14,668	14,249	13,388	12,739	10,284
T/6	7,258	6,164	7,987	8,999	9,751	10,502	11,219	11,436	11,109	10,437	9,931	8,018

For year 2008				
Influence Areas	**Jan**	**Feb**	**Mar**	**Apr**
CAMP - 8	25,895	24,657	31,012	36,469
L/101	23,859	22,719	28,574	33,602
L/18	23,546	22,420	28,199	33,160
L/47	27,633	26,313	33,094	38,917
L/57	30,975	29,495	37,096	43,623
L/66	8,479	8,074	10,155	11,942
L/8	11,824	11,259	14,161	16,653
L/86	58,813	56,002	70,435	82,828
M/10	21,259	20,243	25,460	29,940
M/8	36,196	34,466	43,349	50,976

For year 2008				
Influence Areas	**Jan**	**Feb**	**Mar**	**Apr**
N/12	11,788	11,224	14,117	16,601
N/16	22,510	21,434	26,959	31,702
P/50	11,557	11,005	13,841	16,276
T/15	18,914	18,011	22,652	26,638
T/22	11,544	10,993	13,826	16,258
T/26	7,847	7,472	9,397	11,051
T/6	6,117	5,825	7,326	8,615

return flow from irrigation water estimation in m3/month

For year 2000 - 2002												
Influence Areas	**Jan**	**Feb**	**Mar**	**Apr**	**May**	**Jun**	**Jul**	**Aug**	**Sep**	**Oct**	**Nov**	**Dec**
Camp_8	85,394	85,464	84,156	81,791	114,967	122,604	121,127	122,787	99,210	73,693	76,055	83,969
L-101	38,844	38,876	38,281	37,205	52,297	55,771	55,099	55,854	45,129	33,522	34,596	38,196
L-18	33,168	33,195	32,687	31,769	44,655	47,621	47,047	47,692	38,535	28,623	29,541	32,615
L-47	27,784	27,806	27,381	26,612	37,406	39,890	39,410	39,950	32,279	23,977	24,745	27,320
L-57	47,915	47,954	47,220	45,893	64,508	68,793	67,964	68,896	55,667	41,349	42,674	47,115
L-66	26,965	26,987	26,574	25,827	36,303	38,715	38,248	38,772	31,328	23,270	24,016	26,515
L-8	12,413	12,424	12,233	11,890	16,712	17,822	17,608	17,849	14,422	10,712	11,056	12,206
L-86	50,189	50,230	49,462	48,072	67,570	72,059	71,190	72,166	58,309	43,312	44,700	49,352
M-10	10,480	10,488	10,328	10,038	14,109	15,046	14,865	15,069	12,175	9,044	9,334	10,305
M-8	26,896	26,918	26,506	25,761	36,210	38,615	38,150	38,673	31,247	23,210	23,954	26,447
N-12	24,891	24,911	24,530	23,840	33,510	35,736	35,306	35,790	28,918	21,480	22,168	24,475
N-16	26,973	26,995	26,582	25,835	36,314	38,726	38,260	38,784	31,337	23,277	24,023	26,523
P-50	27,656	27,678	27,255	26,489	37,233	39,706	39,228	39,765	32,130	23,866	24,631	27,194
T-15	18,818	18,833	18,545	18,024	25,334	27,017	26,691	27,057	21,862	16,239	16,759	18,503
T-22	34,259	34,287	33,763	32,814	46,123	49,187	48,595	49,261	39,802	29,565	30,512	33,688
T-26	11,637	11,646	11,468	11,146	15,667	16,707	16,506	16,732	13,520	10,042	10,364	11,443
T-6	17,808	17,822	17,550	17,056	23,975	25,567	25,259	25,606	20,689	15,368	15,860	17,511
For year 2003 - 2005												
Influence Areas	**Jan**	**Feb**	**Mar**	**Apr**	**May**	**Jun**	**Jul**	**Aug**	**Sep**	**Oct**	**Nov**	**Dec**
Camp_8	83,078	83,145	81,873	79,572	111,848	119,278	117,840	119,455	96,519	71,693	73,992	81,691
L-101	39,177	39,209	38,609	37,524	52,744	56,248	55,570	56,332	45,516	33,809	34,892	38,523
L-18	29,729	29,753	29,298	28,475	40,025	42,683	42,169	42,747	34,539	25,655	26,478	29,233
L-47	23,061	23,079	22,726	22,088	31,047	33,109	32,710	33,158	26,792	19,901	20,539	22,676
L-57	42,506	42,541	41,890	40,713	57,226	61,028	60,292	61,119	49,383	36,681	37,857	41,797
L-66	20,935	20,952	20,631	20,051	28,184	30,057	29,694	30,101	24,322	18,066	18,645	20,585
L-8	13,441	13,452	13,246	12,874	18,096	19,298	19,066	19,327	15,616	11,599	11,971	13,217
L-86	39,583	39,615	39,009	37,913	53,291	56,831	56,146	56,916	45,987	34,159	35,254	38,923
M-10	9,794	9,802	9,652	9,381	13,186	14,061	13,892	14,082	11,378	8,452	8,723	9,630
M-8	22,787	22,806	22,457	21,826	30,678	32,716	32,322	32,765	26,474	19,665	20,295	22,407
N-12	21,528	21,545	21,216	20,620	28,983	30,909	30,536	30,955	25,011	18,578	19,173	21,169
N-16	23,281	23,300	22,943	22,299	31,343	33,425	33,023	33,475	27,048	20,091	20,735	22,892

P-50	23,507	23,526	23,166	22,515	31,647	33,749	33,343	33,800	27,310	20,286	20,936	23,114
T-15	16,682	16,696	16,440	15,978	22,459	23,951	23,663	23,987	19,381	14,396	14,858	16,404
T-22	33,245	33,272	32,763	31,842	44,758	47,731	47,156	47,803	38,624	28,690	29,609	32,690
T-26	10,631	10,639	10,477	10,182	14,312	15,263	15,079	15,286	12,351	9,174	9,468	10,453
T-6	15,914	15,927	15,683	15,243	21,425	22,848	22,573	22,882	18,489	13,733	14,174	15,648

For year 2006 - 2008

Influence Areas	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Camp_8	98,998	99,079	97,563	94,821	133,282	142,136	140,423	142,348	115,016	85,433	88,171	97,346
L-101	43,245	43,280	42,618	41,420	58,221	62,088	61,340	62,181	50,241	37,319	38,515	42,523
L-18	32,858	32,885	32,381	31,471	44,237	47,175	46,607	47,246	38,174	28,355	29,264	32,310
L-47	29,714	29,738	29,283	28,460	40,004	42,662	42,148	42,725	34,522	25,642	26,464	29,218
L-57	51,872	51,914	51,119	49,683	69,835	74,474	73,577	74,585	60,264	44,764	46,198	51,006
L-66	23,272	23,291	22,934	22,290	31,331	33,412	33,010	33,462	27,037	20,083	20,727	22,883
L-8	14,095	14,107	13,891	13,500	18,976	20,237	19,993	20,267	16,376	12,164	12,554	13,860
L-86	44,888	44,925	44,237	42,994	60,433	64,448	63,671	64,544	52,151	38,737	39,979	44,139
M-10	11,847	11,857	11,676	11,347	15,950	17,010	16,805	17,035	13,764	10,224	10,552	11,650
M-8	27,286	27,308	26,891	26,135	36,736	39,176	38,704	39,234	31,701	23,547	24,302	26,831
N-12	22,886	22,904	22,554	21,920	30,811	32,858	32,462	32,907	26,589	19,750	20,383	22,504
N-16	28,858	28,882	28,440	27,641	38,852	41,433	40,934	41,495	33,527	24,904	25,702	28,377
P-50	21,890	21,908	21,573	20,967	29,471	31,429	31,050	31,475	25,432	18,891	19,496	21,525
T-15	19,972	19,988	19,682	19,129	26,889	28,675	28,329	28,717	23,203	17,235	17,788	19,639
T-22	34,058	34,086	33,565	32,621	45,853	48,899	48,310	48,972	39,569	29,391	30,333	33,490
T-26	13,391	13,402	13,197	12,826	18,028	19,226	18,994	19,254	15,557	11,556	11,926	13,167
T-6	17,952	17,966	17,691	17,194	24,168	25,774	25,463	25,812	20,856	15,492	15,988	17,652

APPENDIX 5: Data of municipal abstraction and agricultural abstraction

Data of municipal abstraction

L18									
Month	2000	2001	2002	2003	2004	2005	2006	2007	2008
Jan	9,808	13,007	12,438	6,270	16,622	8,635	8,622	9,845	0
Feb	17,580	12,092	25,112	6,247	19,561	9,007	10,171	14,215	0
Mar	15,563	17,615	43,019	6,728	34,767	11,589	16,567	17,925	0
Apr	18,115	25,283	32,545	11,985	17,052	18,234	21,590	23,656	9,909
May	19,407	24,264	39,023	22,160	8,522	21,083	29,280	30,944	22,156
Jun	19,393	38,459	38,891	29,847	19,715	40,724	31,090	36,718	24,551
Jul	24,019	25,905	47,284	23,489	21,707	41,364	32,740	39,145	20,509
Aug	25,213	35,090	46,937	23,612	27,345	40,446	32,987	45,677	0
Sep	22,840	37,620	22,772	36,762	19,947	42,075	34,543	35,145	0
Oct	17,054	28,655	25,963	36,146	25,188	35,310	39,665	35,250	0
Nov	15,839	22,330	20,994	37,269	19,434	20,240	16,490	20,513	0
Dec	13,489	12,042	9,220	23,739	8,021	10,905	17,885	7,168	8,144

L47									
Month	2000	2001	2002	2003	2004	2005	2006	2007	2008
Jan	152,548	222,688	239,716	223,780	308,285	258,446	274,570	322,301	213,419
Feb	170,646	208,771	218,293	198,148	298,671	260,756	275,750	251,863	213,973
Mar	183,306	221,900	286,638	258,628	365,883	294,614	352,223	307,245	285,678
Apr	184,886	261,521	256,702	321,693	362,094	301,532	293,760	313,129	327,637
May	196,557	264,814	325,276	338,859	409,757	309,455	337,760	346,436	316,104
Jun	214,151	301,358	298,193	376,998	404,633	351,458	358,720	385,568	374,080
Jul	292,668	324,396	291,539	399,645	389,547	412,503	358,000	387,899	411,806
Aug	296,218	300,035	306,137	400,894	435,059	424,226	355,130	398,949	393,360
Sep	272,460	265,949	317,002	374,559	412,895	433,929	370,185	384,731	366,414
Oct	269,363	281,236	313,943	354,834	392,509	359,370	395,287	415,949	310,650
Nov	237,138	276,220	288,987	364,558	329,150	319,876	358,137	376,519	230,926
Dec	204,234	255,245	278,111	325,706	239,366	307,590	317,681	310,810	255,524

L8							
Month	2002	2003	2004	2005	2006	2007	2008
Jan	0	7,545	0	0	5,763	23,530	6,820

Feb	0	7,687	602	0	7,051	21,156	6,320
Mar	0	7,875	0	6,176	8,382	29,197	9,929
Apr	0	11,229	4,060	8,265	7,130	27,524	14,261
May	0	13,141	19,392	20,072	10,826	29,008	16,490
Jun	0	15,876	25,595	26,085	11,800	29,965	18,921
Jul	0	17,010	27,550	25,791	36,090	27,930	25,252
Aug	0	15,515	23,683	26,748	16,216	18,094	27,283
Sep	14,530	15,959	20,212	25,469	15,222	25,186	18,809
Oct	13,202	9,896	25,530	25,619	26,516	27,790	14,115
Nov	9,671	0	19,629	23,634	7,504	13,910	9,110
Dec	8,467	0	0	12,618	8,440	13,280	11,170

M10		
Month	**2006**	**2007**
Jan	0	0
Feb	0	1,500
Mar	0	8,830
Apr	0	8,640
May	0	22,310
Jun	0	27,290
Jul	15,320	28,800
Aug	23,170	11,800
Sep	27,990	23,340
Oct	22,010	20,760
Nov	12,630	5,300
Dec	8,480	7,130

P50										
Month	**2000**	**2001**	**2002**	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**	**2009**
Jan	66,155	59,250	54,344	419	63,911	45,536	69,424	46,276	54,376	66,155
Feb	57,741	54,360	37,983	8	67,269	43,183	68,264	48,583	38,971	57,741
Mar	58,278	76,227	36,901	8,256	68,256	31,613	59,132	44,451	46,721	58,278
Apr	67,340	81,836	59,779	49,786	86,807	60,249	66,958	57,432	73,201	67,340
May	63,958	93,899	40,653	58,978	81,196	75,432	8,299	68,406	85,185	63,958
Jun	72,103	87,437	32,580	86,023	89,831	85,984	88,954	76,344	79,797	72,103

Jul	73,333	95,669	47,763	108,949	82,073	100,890	56,137	81,694	87,982	73,333
Aug	69,915	80,098	42,700	81,394	91,422	98,599	68,138	88,140	94,208	69,915
Sep	58,500	58,436	46,910	75,818	99,759	84,570	73,275	82,231	99,027	58,500
Oct	56,035	11,842	17,767	57,171	71,132	87,548	73,815	90,115	74,995	56,035
Nov	50,820	58,642	19,568	63,208	76,172	78,309	54,689	77,926	57,394	50,820
Dec	39,419	48,372	332	80,864	57,346	71,953	52,535	59,708	37,130	39,419

T15								
Month	**2000**	**2001**	**2002**	**2003**	**2004**	**2006**	**2007**	**2008**
Jan	15,684	10,021	12,716	16,023	11,400	1,440	2,400	29,500
Feb	14,514	10,472	14,819	16,769	27,840	2,160	5,400	28,400
Mar	21,634	17,449	19,317	11,669	10,800	1,800	7,200	34,200
Apr	23,945	22,460	18,039	9,840	2,520	2,880	9,000	35,200
May	25,191	21,300	26,487	25,270	10,800	3,840	9,000	31,500
Jun	27,580	22,814	26,885	28,080	15,660	3,840	10,800	37,000
Jul	29,112	29,081	34,506	35,450	20,160	3,840	12,040	36,130
Aug	30,636	33,900	32,419	40,200	9,360	17,550	21,600	34,070
Sep	28,744	23,657	28,900	24,570	38,118	7,280	27,000	33,300
Oct	6,450	22,768	24,409	24,570	46,138	7,720	19,800	34,100
Nov	18,309	16,741	20,127	18,000	26,370	7,200	17,556	29,336
Dec	10,226	14,553	15,902	16,200	21,540	7,200	16,119	30,510

L57									
Month	**2000**	**2001**	**2002**	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**
Jan	40,805	44,168	53,770	78,642	60,002	103,631	124,468	115,710	101,730
Feb	45,534	40,290	52,085	72,863	73,901	103,558	123,947	87,649	87,802
Mar	36,450	57,763	55,665	72,070	80,552	130,512	143,085	138,925	102,971
Apr	59,708	53,793	55,519	78,978	108,518	151,133	121,996	145,812	84,630
May	59,264	56,792	58,788	91,224	130,845	157,816	126,000	161,163	101,848
Jun	57,528	54,594	50,936	89,430	124,899	166,850	153,710	182,263	123,680
Jul	55,623	58,218	55,653	93,814	131,414	166,851	176,860	179,320	145,124
Aug	58,178	53,850	54,502	89,515	141,582	157,910	130,100	170,237	153,966
Sep	57,926	57,264	90,271	102,285	150,063	160,957	138,515	167,992	133,141

Oct	55,264	56,983	79,498	107,714	143,755	151,996	130,950	158,100	128,205
Nov	54,385	54,334	74,081	95,400	136,942	140,700	165,147	154,747	94,133
Dec	54,227	51,724	74,018	84,959	136,381	144,442	122,429	113,712	80,731

L86									
Month	**2000**	**2001**	**2002**	**2003**	**2004**	**2005**	**2006**	**2007**	**2008**
Jan	102,844	159,426	176,612	214,293	182,131	229,064	229,194	200,446	199,495
Feb	98,505	120,567	181,256	224,236	176,892	194,092	190,755	189,137	187,430
Mar	141,995	195,379	197,482	210,551	193,308	210,010	217,676	237,178	213,046
Apr	157,043	200,327	195,541	234,020	190,213	238,962	241,130	247,516	248,391
May	175,879	209,853	207,218	232,081	209,730	243,516	293,495	264,612	271,684
Jun	194,536	207,422	203,857	240,215	209,506	263,887	271,330	284,228	311,706
Jul	181,661	224,041	217,506	245,941	238,386	256,153	195,480	302,183	326,654
Aug	195,845	211,553	188,659	233,041	234,259	193,671	256,842	312,966	353,273
Sep	196,800	223,667	216,725	234,831	225,915	275,607	257,385	312,838	356,043
Oct	181,946	213,471	222,061	260,792	256,686	230,283	244,794	308,976	339,606
Nov	191,333	216,664	222,124	162,738	246,704	250,651	262,886	281,534	279,911
Dec	178,645	188,476	229,670	202,368	240,130	235,041	203,683	259,158	270,507

Data of agricultural abstraction

For year 2000 - 2002												
Influence Areas	**Jan**	**Feb**	**Mar**	**Apr**	**May**	**Jun**	**Jul**	**Aug**	**Sep**	**Oct**	**Nov**	**Dec**
Camp_8	426,971	427,318	420,781	408,956	574,834	613,020	605,633	613,933	496,052	368,464	380,274	419,846
L-101	194,222	194,380	191,406	186,027	261,483	278,853	275,493	279,268	225,646	167,608	172,981	190,981
L-18	165,842	165,976	163,437	158,844	223,274	238,105	235,236	238,460	192,674	143,116	147,704	163,074
L-47	138,919	139,032	136,905	133,058	187,028	199,452	197,048	199,749	161,395	119,883	123,726	136,601
L-57	239,574	239,768	236,100	229,465	322,540	343,966	339,821	344,478	278,335	206,745	213,372	235,576
L-66	134,825	134,934	132,870	129,136	181,516	193,573	191,241	193,862	156,638	116,350	120,079	132,575
L-8	62,067	62,118	61,167	59,448	83,562	89,112	88,039	89,245	72,109	53,562	55,279	61,031
L-86	250,946	251,150	247,308	240,358	337,850	360,293	355,952	360,830	291,547	216,559	223,501	246,758
M-10	52,399	52,442	51,640	50,188	70,546	75,232	74,325	75,344	60,877	45,219	46,669	51,525
M-8	134,478	134,588	132,529	128,804	181,049	193,076	190,750	193,364	156,236	116,051	119,771	132,234
N-12	124,453	124,554	122,648	119,202	167,552	178,682	176,529	178,948	144,588	107,399	110,842	122,376
N-16	134,865	134,975	132,910	129,175	181,570	193,631	191,298	193,920	156,685	116,385	120,115	132,615
P-50	138,278	138,391	136,273	132,444	186,165	198,532	196,139	198,827	160,651	119,330	123,155	135,971
T-15	94,088	94,164	92,723	90,118	126,671	135,085	133,457	135,286	109,310	81,195	83,797	92,517
T-22	171,296	171,435	168,813	164,069	230,617	245,937	242,973	246,303	199,011	147,823	152,562	168,438
T-26	58,184	58,231	57,341	55,729	78,334	83,537	82,531	83,662	67,598	50,211	51,821	57,213
T-6	89,039	89,111	87,748	85,282	119,874	127,837	126,297	128,028	103,445	76,838	79,301	87,553

For year 2003 - 2005												
Influence Areas	**Jan**	**Feb**	**Mar**	**Apr**	**May**	**Jun**	**Jul**	**Aug**	**Sep**	**Oct**	**Nov**	**Dec**
Camp_8	415,388	415,725	409,365	397,861	559,239	596,389	589,202	597,277	482,594	358,467	369,958	408,456
L-101	195,885	196,044	193,045	187,620	263,721	281,240	277,851	281,659	227,578	169,043	174,461	192,616
L-18	148,646	148,767	146,491	142,374	200,123	213,417	210,845	213,735	172,696	128,277	132,389	146,165
L-47	115,303	115,397	113,632	110,438	155,234	165,546	163,551	165,792	133,959	99,503	102,693	113,379
L-57	212,530	212,703	209,449	203,563	286,131	305,138	301,461	305,593	246,916	183,407	189,286	208,984
L-66	104,673	104,758	103,155	100,257	140,922	150,283	148,472	150,507	121,608	90,330	93,225	102,926
L-8	67,206	67,261	66,232	64,370	90,480	96,490	95,328	96,634	78,079	57,997	59,856	66,085
L-86	197,916	198,077	195,046	189,565	266,455	284,156	280,732	284,579	229,937	170,796	176,270	194,613
M-10	48,970	49,009	48,260	46,903	65,928	70,307	69,460	70,412	56,892	42,259	43,614	48,152
M-8	113,936	114,028	112,284	109,128	153,392	163,582	161,611	163,826	132,369	98,323	101,475	112,034
N-12	107,640	107,727	106,079	103,098	144,916	154,543	152,680	154,773	125,055	92,890	95,867	105,843

For year 2003 - 2005												
Influence Areas	**Jan**	**Feb**	**Mar**	**Apr**	**May**	**Jun**	**Jul**	**Aug**	**Sep**	**Oct**	**Nov**	**Dec**
N-16	116,405	116,499	114,717	111,493	156,717	167,127	165,113	167,376	135,238	100,454	103,674	114,462
P-50	117,533	117,629	115,829	112,574	158,236	168,747	166,714	168,998	136,549	101,428	104,679	115,572
T-15	83,411	83,479	82,202	79,892	112,297	119,757	118,314	119,935	96,906	71,981	74,289	82,019
T-22	166,226	166,361	163,816	159,212	223,791	238,657	235,781	239,013	193,120	143,448	148,046	163,452
T-26	53,154	53,197	52,383	50,911	71,561	76,315	75,395	76,428	61,753	45,870	47,340	52,267
T-6	79,570	79,635	78,416	76,213	107,126	114,242	112,865	114,412	92,444	68,667	70,868	78,242

For year 2006 - 2008												
Influence Areas	**Jan**	**Feb**	**Mar**	**Apr**	**May**	**Jun**	**Jul**	**Aug**	**Sep**	**Oct**	**Nov**	**Dec**
Camp_8	395,993	396,315	390,252	379,285	533,129	568,543	561,693	569,391	460,062	341,730	352,685	389,385
L-101	172,979	173,119	170,471	165,680	232,883	248,353	245,360	248,723	200,966	149,276	154,061	170,092
L-18	131,432	131,538	129,526	125,886	176,947	188,701	186,428	188,983	152,696	113,421	117,057	129,238
L-47	118,857	118,953	117,134	113,842	160,018	170,648	168,591	170,902	138,087	102,570	105,858	116,873
L-57	207,486	207,655	204,478	198,732	279,340	297,896	294,307	298,340	241,056	179,054	184,794	204,024
L-66	93,087	93,163	91,738	89,160	125,324	133,649	132,039	133,848	108,148	80,332	82,907	91,534
L-8	56,381	56,426	55,563	54,002	75,906	80,948	79,972	81,068	65,503	48,655	50,214	55,440
L-86	179,553	179,698	176,949	171,977	241,733	257,791	254,684	258,175	208,603	154,948	159,915	176,556
M-10	47,389	47,428	46,702	45,390	63,800	68,039	67,219	68,140	55,056	40,896	42,206	46,598
M-8	109,145	109,233	107,562	104,539	146,942	156,703	154,815	156,937	126,804	94,189	97,208	107,323
N-12	91,543	91,618	90,216	87,681	123,245	131,432	129,849	131,628	106,354	78,999	81,531	90,016
N-16	115,433	115,527	113,759	110,562	155,408	165,732	163,735	165,979	134,109	99,615	102,808	113,507
P-50	87,561	87,632	86,291	83,866	117,884	125,714	124,200	125,902	101,727	75,562	77,984	86,100
T-15	79,888	79,953	78,730	76,517	107,554	114,699	113,317	114,870	92,814	68,941	71,151	78,555
T-22	136,233	136,344	134,258	130,485	183,412	195,596	193,239	195,887	158,275	117,565	121,334	133,960
T-26	53,563	53,607	52,787	51,303	72,113	76,903	75,976	77,018	62,230	46,224	47,705	52,670
T-6	71,807	71,865	70,766	68,777	96,674	103,096	101,854	103,249	83,425	61,967	63,953	70,608

APPENDIX 6 : Data matrix for ANNs model and results

<u>Data matrix for ANNs model and results</u>

Well No.	Time phase		GWL_o	GWL_f	QM	QA	R	RRFWW	RRFI	RRFW	$GWL_{fpredicted}$
CAMP - 8	2004	B	6.081	6.116	0	1,171,115	2,508	28,405	234,223	18,904	**5.7867**
CAMP - 8	2004	C	6.116	6.146	0	1,691,442	0	46,957	338,288	31,250	**5.1502**
CAMP - 8	2004	D	6.146	6.241	0	1,152,117	1,083,489	39,913	230,423	26,562	**4.7248**
CAMP - 8	2005	A	6.241	6.341	0	1,257,102	840,206	32,181	251,420	21,417	**5.2484**
CAMP - 8	2005	B	6.341	6.391	0	1,574,307	10,032	42,202	314,861	28,086	**5.4708**
CAMP - 8	2005	C	6.391	6.471	0	1,691,442	0	49,915	338,288	33,219	**5.3335**
CAMP - 8	2005	D	6.471	6.4255	0	1,152,117	441,421	40,847	230,423	27,184	**6.5281**
CAMP - 8	2006	A	6.4255	6.671	0	1,198,408	353,150	91,008	239,682	60,567	**7.0676**
CAMP - 8	2006	B	6.671	6.701	0	1,500,803	177,827	107,274	300,161	71,392	**6.7068**
CAMP - 8	2006	C	6.701	6.766	0	1,612,469	0	124,489	322,494	82,849	**6.3515**
CAMP - 8	2006	D	6.766	6.871	0	1,098,324	796,465	116,199	219,665	77,331	**6.4897**
CAMP - 8	2007	A	6.871	7.006	0	1,198,408	477,378	90,623	239,682	60,311	**7.2331**
CAMP - 8	2007	B	7.006	7.121	0	1,500,803	7,514	123,823	300,161	82,405	**6.8331**
CAMP - 8	2007	C	7.121	7.176	0	1,612,469	0	142,924	322,494	95,117	**6.5021**
CAMP - 8	2007	D	7.176	7.331	0	1,098,324	147,772	120,159	219,665	79,967	**7.8915**
CAMP - 8	2008	A	7.331	7.351	0	1,198,408	623,647	81,564	239,682	54,282	**7.1602**
L/101	2000	A	-1.427	-1.327	0	580,009	671,876	25,961	116,002	17,277	**-0.6654**
L/101	2000	B	-1.327	-1.477	0	726,363	0	33,407	145,273	22,233	**-1.5747**
L/101	2000	C	-1.477	-1.707	0	780,407	0	42,239	156,081	28,111	**-1.6312**
L/101	2000	D	-1.707	-0.937	0	531,570	715,320	34,270	106,314	22,807	**-0.8724**
L/101	2001	A	-0.937	-0.967	0	580,009	662,513	32,142	116,002	21,391	**-0.1999**
L/101	2001	B	-0.967	-1.197	0	726,363	46,814	43,361	145,273	28,857	**-1.0913**
L/101	2001	C	-1.197	-1.357	0	780,407	0	47,633	156,081	31,700	**-1.3077**
L/101	2001	D	-1.357	-0.987	0	531,570	340,807	41,676	106,314	27,736	**-1.2104**
L/101	2002	A	-0.987	-0.992	0	580,009	781,608	37,512	116,002	24,965	**-0.0748**
L/101	2002	B	-0.992	-1.257	0	726,363	44,942	45,075	145,273	29,998	**-1.1160**
L/101	2002	C	-1.257	-1.417	0	780,407	0	49,792	156,081	33,137	**-1.3647**
L/101	2002	D	-1.417	-1.017	0	531,570	586,487	45,948	106,314	30,579	**-0.8295**
L/101	2003	A	-1.017	-1.017	0	584,974	580,502	53,082	116,995	35,327	**-0.4010**
L/101	2003	B	-1.017	-1.247	0	732,581	38,775	52,809	146,516	35,145	**-1.1143**
L/101	2003	C	-1.247	-1.387	0	787,087	0	77,833	157,417	51,798	**-1.1934**
L/101	2003	D	-1.387	-1.027	0	536,120	182,316	67,762	107,224	45,096	**-1.4845**
L/101	2004	A	-1.027	-1.177	0	584,974	560,741	58,851	116,995	39,166	**-0.4362**

Well No.	Time phase		GWL_o	GWL_f	QM	QA	R	RRFWW	RRFI	RRFW	$GWL_{fpredicted}$
L/101	2004	B	-1.177	-1.487	0	732,581	13,795	75,009	146,516	49,920	**-1.2178**
L/101	2004	C	-1.487	-1.557	0	787,087	0	85,991	157,417	57,228	**-1.4084**
L/101	2004	D	-1.557	-0.997	0	536,120	762,444	73,091	107,224	48,643	**-0.6520**
L/101	2005	A	-0.997	-1.217	0	584,974	721,433	58,932	116,995	39,220	**-0.1593**
L/101	2005	B	-1.217	-1.487	0	732,581	0	77,283	146,516	51,433	**-1.2663**
L/101	2005	C	-1.487	-1.467	0	787,087	0	91,407	157,417	60,833	**-1.3709**
L/101	2005	D	-1.467	-1.307	0	536,120	452,993	74,802	107,224	49,781	**-1.1020**
L/101	2006	A	-1.307	-1.137	0	516,570	327,218	83,853	103,314	55,805	**-1.1173**
L/101	2006	B	-1.137	-1.852	0	646,916	146,954	98,841	129,383	65,780	**-0.9947**
L/101	2006	C	-1.137	-1.822	0	695,049	5,878	114,702	139,010	76,336	**-0.9798**
L/101	2006	D	-1.822	-1.617	0	473,429	443,214	107,064	94,686	71,252	**-1.4473**
L/101	2007	A	-1.617	-1.682	0	516,570	456,538	83,499	103,314	55,569	**-1.2541**
L/101	2007	B	-1.682	-2.217	0	646,916	21,553	114,089	129,383	75,927	**-1.6687**
L/101	2007	C	-2.217	-2.377	0	695,049	0	131,688	139,010	87,639	**-2.0365**
L/101	2007	D	-2.377	-2.167	0	473,429	219,452	110,713	94,686	73,680	**-2.4369**
L/101	2008	A	-2.167	-2.227	0	516,570	404,810	75,152	103,314	50,014	**-1.9977**
L/18	2000	A	-0.319	-0.269	42,951	495,255	282,622	24,477	99,051	16,290	**-0.1240**
L/18	2000	B	-0.269	-0.449	56,915	620,223	0	31,498	124,045	20,962	**-0.5124**
L/18	2000	C	-0.449	-0.619	72,072	666,370	0	39,825	133,274	26,504	**-0.6711**
L/18	2000	D	-0.619	-0.299	46,382	453,894	300,897	32,311	90,779	21,503	**-0.4220**
L/18	2001	A	-0.299	-0.269	42,714	495,255	278,684	30,305	99,051	20,168	**-0.1071**
L/18	2001	B	-0.269	-0.509	88,006	620,223	19,692	40,883	124,045	27,208	**-0.4689**
L/18	2001	C	-0.509	-0.659	274,627	1,906,817	39,384	126,676	381,363	84,304	**1.9143**
L/18	2001	D	-0.659	-0.409	63,027	453,894	143,359	39,294	90,779	26,151	**-0.7388**
L/18	2002	A	-0.409	-0.249	80,569	495,255	328,781	35,369	99,051	23,538	**-0.1622**
L/18	2002	B	-0.249	-0.499	110,459	620,223	18,905	42,500	124,045	28,284	**-0.4500**
L/18	2002	C	-0.499	-0.899	116,993	666,370	0	46,946	133,274	31,243	**-0.7203**
L/18	2002	D	-0.899	-0.519	56,177	453,894	246,704	43,323	90,779	28,832	**-0.8500**
L/18	2003	A	-0.519	-0.229	131,599	1,351,692	740,755	140,234	270,338	93,327	**1.4191**
L/18	2003	B	-0.229	-0.479	63,992	555,914	16,522	53,313	111,183	35,480	**-0.4059**
L/18	2003	C	-0.479	-0.749	83,863	597,276	0	78,575	119,455	52,292	**-0.6092**
L/18	2003	D	-0.749	-0.529	97,154	406,831	77,683	68,409	81,366	45,527	**-0.9248**
L/18	2004	A	-0.749	-0.699	70,950	443,903	238,928	59,412	88,781	39,539	**-0.6825**
L/18	2004	B	-0.699	-0.614	45,289	555,914	5,878	75,725	111,183	50,396	**-0.8917**

Well No.	Time phase		GWL_o	GWL_f	QM	QA	R	RRFWW	RRFI	RRFW	$GWL_{fpredicted}$
L/18	2004	C	-0.614	-0.814	68,999	597,276	0	86,812	119,455	57,774	**-0.7214**
L/18	2004	D	-0.814	-0.579	52,643	406,831	324,872	73,788	81,366	49,107	**-0.5919**
L/18	2005	A	-0.579	-0.509	29,231	443,903	307,397	59,494	88,781	39,594	**-0.3540**
L/18	2005	B	-0.509	-0.749	80,041	555,914	0	78,020	111,183	51,923	**-0.6767**
L/18	2005	C	-0.749	-0.879	123,885	597,276	0	92,279	119,455	61,413	**-0.8776**
L/18	2005	D	-0.879	-0.774	66,455	406,831	193,017	75,515	81,366	50,256	**-0.8829**
L/18	2006	A	-0.774	-0.519	35,360	392,496	136,308	82,752	78,499	55,072	**-0.8117**
L/18	2006	B	-0.519	-1.124	81,960	491,534	61,216	97,543	98,307	64,915	**-0.5568**
L/18	2006	C	-1.124	-1.089	100,270	528,106	2,449	113,196	105,621	75,333	**-1.2468**
L/18	2006	D	-1.089	-0.969	74,040	359,717	184,628	105,657	71,943	70,316	**-1.0628**
L/18	2007	A	-0.969	-1.039	41,985	392,496	190,179	82,402	78,499	54,839	**-0.9705**
L/18	2007	B	-1.039	-1.499	91,318	491,534	8,978	112,590	98,307	74,930	**-1.1667**
L/18	2007	C	-1.499	-1.834	119,967	528,106	0	129,958	105,621	86,488	**-1.5701**
L/18	2007	D	-1.834	-1.429	62,931	359,717	91,416	109,259	71,943	72,713	**-2.0466**
L/18	2008	A	-1.429	-1.559	0	392,496	168,630	74,165	78,499	49,357	**-1.5594**
L/47	2000	A	-1.53	-1.77	506,500	414,856	262,522	24,606	82,971	16,376	**-1.5738**
L/47	2000	B	-1.77	-1.79	595,594	519,537	0	31,664	103,907	21,073	**-2.3464**
L/47	2000	C	-1.79	-2.22	861,346	558,192	0	40,035	111,638	26,644	**-2.3964**
L/47	2000	D	-2.22	-2.1	710,735	380,210	279,496	32,481	76,042	21,617	**-2.3271**
L/47	2001	A	-2.1	-2.13	653,359	414,856	258,863	30,465	82,971	20,275	**-2.2537**
L/47	2001	B	-2.13	-2.57	827,693	519,537	18,292	41,098	103,907	27,351	**-2.7544**
L/47	2001	C	-2.57	-2.94	890,380	558,192	0	45,147	111,638	30,046	**-3.2448**
L/47	2001	D	-2.94	-2.73	812,701	380,210	133,163	39,501	76,042	26,288	**-3.4083**
L/47	2002	A	-2.73	-2.565	744,647	414,856	305,397	35,555	82,971	23,662	**-2.8751**
L/47	2002	B	-2.565	-3.27	880,171	519,537	17,560	42,723	103,907	28,433	**-3.2252**
L/47	2002	C	-3.27	-3.33	914,678	558,192	0	47,193	111,638	31,408	**-3.9813**
L/47	2002	D	-3.33	-3.25	881,041	380,210	229,158	43,551	76,042	28,983	**-3.6687**
L/47	2003	A	-3.25	-3	680,556	344,332	231,421	69,025	68,866	45,937	**-3.6763**
L/47	2003	B	-3	-3.55	1,037,550	431,218	15,458	68,670	86,244	45,700	**-3.7210**
L/47	2003	C	-3.55	-4.46	1,175,098	463,302	0	101,208	92,660	67,355	**-4.1947**
L/47	2003	D	-4.46	-3.95	1,045,098	315,576	72,681	88,113	63,115	58,640	**-5.0635**
L/47	2004	A	-3.95	-4.37	972,839	344,332	223,544	76,525	68,866	50,928	**-4.3894**
L/47	2004	B	-4.37	-4.15	1,176,484	431,218	5,499	97,537	86,244	64,912	**-5.0119**
L/47	2004	C	-4.15	-4.83	3,590,469	1,325,738	10,999	306,891	265,148	204,239	**-0.3376**

Well No.	Time phase		GWL_o	GWL_f	QM	QA	R	RRFWW	RRFI	RRFW	$GWL_{fpredicted}$
L/47	2004	D	-4.83	-4.5	961,025	315,576	303,954	95,042	63,115	63,251	**-5.0527**
L/47	2005	A	-4.5	-4.55	813,816	344,332	287,604	76,630	68,866	50,998	**-4.8711**
L/47	2005	B	-4.55	-4.75	962,445	431,218	0	100,494	86,244	66,879	**-5.2692**
L/47	2005	C	-4.75	-5.2	1,270,658	463,302	0	118,860	92,660	79,102	**-5.1575**
L/47	2005	D	-5.2	-4.95	986,836	315,576	180,589	97,267	63,115	64,732	**-5.6260**
L/47	2006	A	-4.95	-4.74	902,543	354,944	123,797	97,117	70,989	64,632	**-5.5479**
L/47	2006	B	-4.74	-5.48	990,240	444,507	55,597	114,476	88,901	76,185	**-5.2885**
L/47	2006	C	-5.48	-5.41	1,083,315	477,580	2,224	132,846	95,516	88,410	**-5.7263**
L/47	2006	D	-5.41	-5.45	1,071,105	325,301	167,681	123,999	65,060	82,523	**-5.5908**
L/47	2007	A	-5.45	-5.52	881,409	354,944	172,722	96,707	70,989	64,359	**-5.9659**
L/47	2007	B	-5.52	-6.2	1,045,133	444,507	8,154	132,135	88,901	87,937	**-5.7980**
L/47	2007	C	-6.2	-6.68	1,171,579	477,580	0	152,518	95,516	101,502	**-5.9276**
L/47	2007	D	-6.68	-6.28	1,103,278	325,301	83,025	128,225	65,060	85,335	**-6.6717**
L/47	2008	A	-6.28	-6.3	713,070	354,944	153,152	87,039	70,989	57,926	**-6.8835**
L/57	2000	A	-0.421	-0.521	122,789	715,442	327,811	15,741	143,088	10,476	**-0.1931**
L/57	2000	B	-0.521	-0.531	176,500	895,971	0	20,256	179,194	13,480	**-0.5709**
L/57	2000	C	-0.531	-0.921	171,727	962,634	0	25,611	192,527	17,044	**-0.4357**
L/57	2000	D	-0.921	-0.871	163,876	655,693	349,007	20,779	131,139	13,828	**-0.7217**
L/57	2001	A	-0.871	-0.861	142,221	715,442	323,243	19,488	143,088	12,970	**-0.6745**
L/57	2001	B	-0.861	-0.991	165,179	895,971	22,841	26,291	179,194	17,497	**-0.8556**
L/57	2001	C	-0.991	-1.231	169,332	962,634	0	28,881	192,527	19,221	**-0.8642**
L/57	2001	D	-1.231	-1.251	163,041	655,693	166,281	25,269	131,139	16,817	**-1.3619**
L/57	2002	A	-1.251	-1.291	161,520	715,442	381,349	22,745	143,088	15,137	**-0.9821**
L/57	2002	B	-1.291	-1.411	165,243	895,971	21,927	27,330	179,194	18,189	**-1.2840**
L/57	2002	C	-1.411	-1.701	200,426	962,634	0	30,190	192,527	20,092	**-1.2749**
L/57	2002	D	-1.701	-1.671	227,597	655,693	286,149	27,860	131,139	18,541	**-1.6966**
L/57	2003	A	-1.671	-1.721	678,769	1,946,068	858,849	108,012	389,214	71,883	**1.2355**
L/57	2003	B	-1.721	-1.761	259,632	794,832	19,140	52,024	158,966	34,623	**-1.9093**
L/57	2003	C	-1.761	-2.051	285,614	853,970	0	76,676	170,794	51,028	**-1.7362**
L/57	2003	D	-2.051	-2.101	288,073	581,677	89,996	66,755	116,335	44,426	**-2.4816**
L/57	2004	A	-2.101	-2.151	214,455	634,682	276,797	57,976	126,936	38,583	**-2.1792**
L/57	2004	B	-2.151	-2.386	364,262	794,832	6,809	73,894	158,966	49,177	**-2.3395**
L/57	2004	C	-2.386	-2.596	423,059	853,970	0	84,713	170,794	56,377	**-2.4029**
L/57	2004	D	-2.596	-2.851	417,078	581,677	376,363	72,004	116,335	47,920	**-2.6294**

Well No.	Time phase		GWL_o	GWL_f	QM	QA	R	RRFWW	RRFI	RRFW	$GWL_{fpredicted}$
L/57	2005	A	-2.851	-2.841	337,701	634,682	356,118	58,055	126,936	38,636	**-2.8926**
L/57	2005	B	-2.841	-3.011	475,799	794,832	0	76,134	158,966	50,668	**-3.1052**
L/57	2005	C	-3.011	-3.141	485,718	853,970	0	90,049	170,794	59,928	**-3.0359**
L/57	2005	D	-3.141	-3.051	437,138	581,677	223,609	73,690	116,335	49,041	**-3.5381**
L/57	2006	A	-3.051	-3.001	391,500	619,619	153,904	108,862	123,924	72,449	**-3.3096**
L/57	2006	B	-3.001	-3.071	401,706	775,968	69,119	128,319	155,194	85,398	**-2.8439**
L/57	2006	C	-3.071	-3.325	445,475	833,703	2,765	148,911	166,741	99,102	**-2.5974**
L/57	2006	D	-3.325	-3.251	418,526	567,872	208,462	138,995	113,574	92,502	**-3.3190**
L/57	2007	A	-3.251	3.561	342,284	619,619	214,729	108,402	123,924	72,142	**-3.4259**
L/57	2007	B	3.561	-3.691	489,238	775,968	10,137	148,114	155,194	98,572	**-3.2474**
L/57	2007	C	-3.691	-3.931	517,549	833,703	0	170,962	166,741	113,777	**-2.9075**
L/57	2007	D	-3.931	-4.121	426,559	567,872	103,217	143,732	113,574	95,655	**-4.0091**
L/57	2008	A	-4.121	-4.121	292,503	619,619	190,399	97,565	123,924	64,931	**-4.4698**
L/66	2000	A	-1.811	-2.011	0	402,629	246,740	16,788	80,526	11,173	**-1.7741**
L/66	2000	B	-2.011	-2.201	0	504,225	0	21,604	100,845	14,377	**-2.4637**
L/66	2000	C	-2.201	-2.651	0	541,741	0	27,315	108,348	18,178	**-2.6910**
L/66	2000	D	-2.651	-2.471	0	369,004	262,695	22,161	73,801	14,749	**-2.6754**
L/66	2001	A	-2.471	-2.371	0	402,629	243,302	20,785	80,526	13,833	**-2.5370**
L/66	2001	B	-2.371	-2.681	0	504,225	17,192	28,040	100,845	18,661	**-2.8670**
L/66	2001	C	-2.681	-3.251	0	541,741	0	30,803	108,348	20,500	**-3.2328**
L/66	2001	D	-3.251	-3.171	0	369,004	125,158	26,951	73,801	17,936	**-3.6178**
L/66	2002	A	-3.171	3.051	0	402,629	287,039	24,258	80,526	16,144	**-3.2425**
L/66	2002	B	3.051	-3.701	0	504,225	16,504	29,149	100,845	19,399	**-3.6224**
L/66	2002	C	-3.701	-3.951	0	541,741	0	32,199	108,348	21,429	**-4.3421**
L/66	2002	D	-3.951	-3.931	0	369,004	215,382	29,714	73,801	19,775	**-4.2414**
L/66	2003	A	-3.931	-3.731	0	312,587	216,501	24,385	62,517	16,229	**-4.0967**
L/66	2003	B	-3.731	-4.241	0	391,462	14,461	24,260	78,292	16,145	**-4.2840**
L/66	2003	C	-4.241	-2.925	0	420,588	0	35,755	84,118	23,795	**-4.9463**
L/66	2003	D	-2.925	-3.245	0	286,481	67,996	31,129	57,296	20,717	**-3.2664**
L/66	2004	A	-3.245	-3.645	0	312,587	209,132	27,035	62,517	17,992	**-3.3967**
L/66	2004	B	-3.645	-4.095	0	391,462	5,145	34,458	78,292	22,932	**-4.2794**
L/66	2004	C	-4.095	-4.015	0	420,588	0	39,503	84,118	26,290	**-4.8151**
L/66	2004	D	-4.015	-4.455	0	286,481	284,358	33,577	57,296	22,346	**-4.0900**
L/66	2005	A	-4.455	-4.965	0	312,587	269,062	27,072	62,517	18,017	**-4.5650**

Well No.	Time phase		GWL_o	GWL_f	QM	QA	R	RRFWW	RRFI	RRFW	$GWL_{fpredicted}$
L/66	2005	B	-4.965	-5.055	0	391,462	0	35,503	78,292	23,627	**-5.6747**
L/66	2005	C	-5.055	-5.415	0	420,588	0	41,991	84,118	27,945	**-5.8289**
L/66	2005	D	-5.415	-5.685	0	286,481	168,946	34,363	57,296	22,869	**-5.7677**
L/66	2006	A	-5.685	-5.615	0	277,988	114,154	29,800	55,598	19,832	**-6.0511**
L/66	2006	B	-5.615	-6.035	0	348,133	51,267	35,127	69,627	23,377	**-6.2293**
L/66	2006	C	-6.035	-6.495	0	374,035	2,051	40,764	74,807	27,129	**-6.7513**
L/66	2006	D	-6.495	-5.681	0	254,772	154,621	38,049	50,954	25,322	**-6.7971**
L/66	2007	A	-5.681	-6.343	0	277,988	159,269	29,675	55,598	19,749	**-5.9761**
L/66	2007	B	-6.343	-6.131	0	348,133	7,519	40,546	69,627	26,984	**-7.0075**
L/66	2007	C	-6.131	-6.466	0	374,035	0	46,800	74,807	31,146	**-6.8880**
L/66	2007	D	-6.466	-6.541	0	254,772	76,559	39,346	50,954	26,185	**-6.8904**
L/66	2008	A	-6.541	-7.071	0	277,988	141,223	26,708	55,598	17,774	**-6.7698**
L/8	2000	A	-0.165	-0.375	0	185,352	82,525	9,040	37,070	6,016	**0.1201**
L/8	2000	B	-0.375	-0.375	0	232,122	0	11,633	46,424	7,742	**-0.3354**
L/8	2000	C	-0.375	-0.665	0	249,393	0	14,708	49,879	9,788	**-0.3749**
L/8	2000	D	-0.665	-0.515	0	169,873	87,861	11,933	33,975	7,941	**-0.3992**
L/8	2001	A	-0.515	-0.445	0	185,352	81,375	11,192	37,070	7,448	**-0.2718**
L/8	2001	B	-0.445	-0.615	0	232,122	5,750	15,098	46,424	10,048	**-0.4170**
L/8	2001	C	-0.615	-0.585	0	249,393	0	16,586	49,879	11,038	**-0.6475**
L/8	2001	D	-0.585	-0.545	0	169,873	41,861	14,512	33,975	9,658	**-0.4009**
L/8	2002	A	-0.545	-0.37	0	185,352	96,003	13,062	37,070	8,693	**-0.2898**
L/8	2002	B	-0.37	-0.475	0	232,122	5,520	15,695	46,424	10,445	**-0.3370**
L/8	2002	C	-0.475	-0.645	14,530	249,393	0	17,338	49,879	11,538	**-0.4986**
L/8	2002	D	-0.645	-0.565	31,340	169,873	72,037	15,999	33,975	10,648	**-0.4314**
L/8	2003	A	-0.565	-0.295	23,107	200,698	71,247	20,395	40,140	13,573	**-0.4191**
L/8	2003	B	-0.295	-0.425	40,246	251,341	4,759	20,290	50,268	13,503	**-0.3094**
L/8	2003	C	-0.425	-0.715	48,484	270,041	0	29,905	54,008	19,902	**-0.5194**
L/8	2003	D	-0.715	-0.465	9,896	183,937	22,376	26,035	36,787	17,327	**-0.6583**
L/8	2004	A	-0.465	-0.415	602	200,698	68,822	22,611	40,140	15,048	**-0.3157**
L/8	2004	B	-0.415	-0.62	49,047	251,341	1,693	28,820	50,268	19,180	**-0.4773**
L/8	2004	C	-0.62	-0.8	71,445	270,041	0	33,039	54,008	21,988	**-0.7569**
L/8	2004	D	-0.8	-0.735	45,159	183,937	93,577	28,083	36,787	18,689	**-0.6572**
L/8	2005	A	-0.735	-0.565	6,176	200,698	88,544	22,643	40,140	15,069	**-0.5874**
L/8	2005	B	-0.565	-0.815	54,422	251,341	0	29,694	50,268	19,761	**-0.6546**

Well No.	Time phase		GWL_o	GWL_f	QM	QA	R	RRFWW	RRFI	RRFW	$GWL_{fpredicted}$
L/8	2005	C	-0.815	-0.885	78,008	270,041	0	35,120	54,008	23,373	**-0.9885**
L/8	2005	D	-0.885	-0.845	61,871	183,937	55,597	28,740	36,787	19,127	**-0.8207**
L/8	2006	A	-0.845	-0.565	21,196	168,370	38,663	41,557	33,674	27,657	**-0.8181**
L/8	2006	B	-0.565	-1.035	29,756	210,855	17,364	48,985	42,171	32,600	**-0.6136**
L/8	2006	C	-1.035	-0.835	67,528	226,543	695	56,846	45,309	37,832	**-1.2317**
L/8	2006	D	-0.835	-0.955	42,460	154,309	52,368	53,060	30,862	35,312	**-0.8044**
L/8	2007	A	-0.955	-1.03	73,883	168,370	53,943	41,382	33,674	27,540	**-0.9328**
L/8	2007	B	-1.03	-1.255	86,497	210,855	2,547	56,542	42,171	37,629	**-1.2073**
L/8	2007	C	-1.255	-1.515	71,210	226,543	0	65,264	45,309	43,434	**-1.5005**
L/8	2007	D	-1.515	-1.395	54,980	154,309	25,930	54,869	30,862	36,516	**-1.6325**
L/8	2008	A	-1.395	-1.495	23,069	168,370	47,831	37,245	33,674	24,787	**-1.4116**
L/86	2000	A	3.1	3	343,344	753,125	1,228,136	88,342	150,625	58,792	**2.9016**
L/86	2000	B	3	2.96	527,458	943,162	0	113,680	188,632	75,655	**3.4724**
L/86	2000	C	2.96	2.92	574,306	1,013,337	0	143,735	202,667	95,657	**3.4334**
L/86	2000	D	2.92	3.07	551,924	690,229	1,307,547	116,615	138,046	77,608	**2.5311**
L/86	2001	A	3.07	3.15	475,372	753,125	1,211,021	109,375	150,625	72,790	**2.8469**
L/86	2001	B	3.15	3.12	617,602	943,162	85,572	147,551	188,632	98,196	**3.6164**
L/86	2001	C	3.12	2.86	659,261	1,013,337	0	162,088	202,667	107,871	**3.4354**
L/86	2001	D	2.86	2.74	618,611	690,229	622,967	141,818	138,046	94,381	**3.3430**
L/86	2002	A	2.74	2.975	555,350	753,125	1,428,717	127,650	150,625	84,952	**2.1685**
L/86	2002	B	2.975	2.89	606,616	943,162	82,150	153,386	188,632	102,080	**3.4394**
L/86	2002	C	2.89	2.93	622,890	1,013,337	0	169,435	202,667	112,760	**3.2303**
L/86	2002	D	2.93	2.77	673,855	690,229	1,072,051	156,356	138,046	104,056	**2.7163**
L/86	2003	A	2.77	2.8	649,080	593,974	1,069,067	191,480	118,795	127,432	**2.3409**
L/86	2003	B	2.8	2.92	706,316	743,853	71,408	190,495	148,771	126,776	**2.8527**
L/86	2003	C	2.92	3	713,813	799,198	0	280,760	159,840	186,848	**1.9125**
L/86	2003	D	3	2.96	625,898	544,369	335,757	244,433	108,874	162,673	**2.4414**
L/86	2004	A	2.96	3.14	552,331	593,974	1,032,676	212,287	118,795	141,279	**2.3376**
L/86	2004	B	3.14	3.155	609,449	743,853	25,405	270,576	148,771	180,071	**2.2173**
L/86	2004	C	3.155	3.31	698,560	799,198	0	310,190	159,840	206,434	**1.6638**
L/86	2004	D	3.31	3.04	743,520	544,369	1,404,137	263,655	108,874	175,465	**1.4147**
L/86	2005	A	3.04	3.29	633,166	593,974	1,328,609	212,579	118,795	141,473	**1.9042**
L/86	2005	B	3.29	3.39	746,365	743,853	0	278,777	148,771	185,529	**2.0934**
L/86	2005	C	3.39	3.62	725,431	799,198	0	329,727	159,840	219,436	**1.5025**

Well No.	Time phase		GWL_o	GWL_f	QM	QA	R	RRFWW	RRFI	RRFW	$GWL_{fpredicted}$
L/86	2005	D	3.62	3.125	715,975	544,369	834,243	269,826	108,874	179,572	**2.0908**
L/86	2006	A	3.125	3.62	637,625	538,863	598,742	206,698	107,773	137,560	**2.9119**
L/86	2006	B	3.62	3.21	805,955	674,835	268,896	243,643	134,967	162,147	**2.7935**
L/86	2006	C	3.21	3.185	709,707	725,045	10,756	282,741	145,009	188,167	**2.0195**
L/86	2006	D	3.185	3.21	711,363	493,861	810,990	263,912	98,772	175,636	**1.9833**
L/86	2007	A	3.21	3.055	626,761	538,863	835,370	205,825	107,773	136,979	**2.7591**
L/86	2007	B	3.055	3.03	796,356	674,835	39,438	281,228	134,967	187,160	**1.9011**
L/86	2007	C	3.03	2.865	927,987	725,045	0	324,610	145,009	216,031	**1.3330**
L/86	2007	D	2.865	2.72	849,668	493,861	401,551	272,907	98,772	181,622	**1.8391**
L/86	2008	A	2.72	2.49	599,971	538,863	740,719	185,250	107,773	123,285	**2.7574**
M/10	2000	C	-0.225	-0.305	0	210,546	0	17,567	42,109	11,691	**-0.1582**
M/10	2000	D	-0.305	-0.205	0	143,412	99,943	14,252	28,682	9,485	**0.0497**
M/10	2001	A	-0.205	-0.155	0	156,481	92,565	13,368	31,296	8,896	**0.1263**
M/10	2001	B	-0.155	-0.385	0	195,966	6,541	18,033	39,193	12,001	**-0.0483**
M/10	2001	C	-0.385	-0.505	0	210,546	0	19,810	42,109	13,184	**-0.3433**
M/10	2001	D	-0.505	-0.395	0	143,412	47,617	17,333	28,682	11,535	**-0.2690**
M/10	2002	A	-0.395	0.24	0	156,481	109,204	15,601	31,296	10,383	**-0.0635**
M/10	2002	B	0.24	-0.445	0	195,966	6,279	18,746	39,193	12,476	**-0.1449**
M/10	2002	C	-0.445	-0.625	0	210,546	0	20,708	42,109	13,781	**-0.4133**
M/10	2002	D	-0.625	-0.535	0	143,412	81,942	19,109	28,682	12,718	**-0.3534**
M/10	2003	A	-0.535	-0.325	0	146,238	81,072	41,921	29,248	27,899	**-0.3573**
M/10	2003	B	-0.325	-0.465	0	183,139	5,415	41,706	36,628	27,755	**-0.2926**
M/10	2003	C	-0.465	-0.625	0	196,765	0	61,468	39,353	40,907	**-0.5135**
M/10	2003	D	-0.625	-0.575	0	134,025	25,462	53,515	26,805	35,614	**-0.5616**
M/10	2004	A	-0.575	-0.585	0	146,238	78,312	46,477	29,248	30,931	**-0.4221**
M/10	2004	B	-0.585	-0.65	0	183,139	1,927	59,238	36,628	39,423	**-0.6314**
M/10	2004	C	-0.585	-0.84	0	196,765	0	67,911	39,353	45,195	**-0.6579**
M/10	2004	D	-0.84	-0.845	0	134,025	106,482	57,723	26,805	38,415	**-0.6962**
M/10	2005	A	-0.845	-0.815	0	146,238	100,754	46,541	29,248	30,973	**-0.6966**
M/10	2005	B	-0.815	-0.835	0	183,139	0	61,034	36,628	40,618	**-0.9040**
M/10	2005	C	-0.835	-1.055	0	196,765	0	72,188	39,353	48,042	**-0.9518**
M/10	2005	D	-1.055	-1.005	0	134,025	63,264	59,074	26,805	39,314	**-1.0128**
M/10	2006	A	-1.005	-0.825	0	141,519	43,328	74,715	28,304	49,724	**-1.0200**
M/10	2006	B	-0.825	-1.11	0	177,229	19,459	88,070	35,446	58,611	**-0.8843**

Well No.	Time phase		GWL_o	GWL_f	QM	QA	R	RRFWW	RRFI	RRFW	$GWL_{fpredicted}$
M/10	2006	C	-1.11	-1.25	66,480	190,415	778	102,203	38,083	68,017	**-1.2491**
M/10	2006	D	-1.25	-1.165	43,120	129,700	58,688	95,396	25,940	63,487	**-1.2750**
M/10	2007	A	-1.25	-1.3	0	141,519	60,452	74,400	28,304	49,514	**-1.2789**
M/10	2007	B	-1.3	-1.385	0	177,229	2,854	101,656	35,446	67,653	**-1.4280**
M/10	2007	C	-1.385	-1.61	0	190,415	0	117,337	38,083	78,089	**-1.4818**
M/10	2007	D	-1.61	-1.665	0	129,700	29,059	98,648	25,940	65,651	**-1.6994**
M/10	2008	A	-1.665	-1.775	10,330	141,519	53,603	66,962	28,304	44,564	**-1.7596**
M/8	2000	A	0.117	0.167	0	401,595	225,686	33,502	80,319	22,296	**0.3548**
M/8	2000	B	0.167	0.157	0	502,929	0	43,110	100,586	28,690	**0.0244**
M/8	2000	C	0.157	-0.003	0	540,349	0	54,508	108,070	36,275	**0.0514**
M/8	2000	D	-0.003	-0.043	0	368,056	240,279	44,223	73,611	29,431	**0.2622**
M/8	2001	A	-0.003	0.087	0	401,595	222,541	41,478	80,319	27,604	**0.2113**
M/8	2001	B	0.087	-0.063	0	502,929	15,725	55,955	100,586	37,239	**-0.0086**
M/8	2001	C	-0.063	-0.133	0	540,349	0	61,468	108,070	40,907	**-0.1845**
M/8	2001	D	-0.133	-0.143	0	368,056	114,478	53,781	73,611	35,792	**-0.0902**
M/8	2002	A	-0.143	-0.058	0	401,595	262,545	48,408	80,319	32,216	**0.1116**
M/8	2002	B	-0.058	-0.183	0	502,929	15,096	58,168	100,586	38,711	**-0.1761**
M/8	2002	C	-0.058	-0.263	0	540,349	0	64,254	108,070	42,762	**-0.1677**
M/8	2002	D	-0.263	-0.263	0	368,056	197,003	59,294	73,611	39,461	**-0.1126**
M/8	2003	A	-0.263	-0.203	0	340,247	195,146	45,706	68,049	30,418	**-0.0981**
M/8	2003	B	-0.203	-0.163	0	426,102	13,035	45,471	85,220	30,261	**-0.3695**
M/8	2003	C	-0.163	-0.313	0	457,806	0	67,016	91,561	44,600	**-0.3005**
M/8	2003	D	-0.313	-0.353	0	311,832	61,289	58,345	62,366	38,829	**-0.3509**
M/8	2004	A	-0.353	-0.343	0	340,247	188,503	50,672	68,049	33,723	**-0.2182**
M/8	2004	B	-0.343	-0.398	0	426,102	4,637	64,586	85,220	42,982	**-0.5158**
M/8	2004	C	-0.398	-0.563	0	457,806	0	74,041	91,561	49,275	**-0.5620**
M/8	2004	D	-0.563	-0.583	0	311,832	256,309	62,934	62,366	41,883	**-0.3434**
M/8	2005	A	-0.583	-0.613	0	340,247	242,523	50,742	68,049	33,769	**-0.4047**
M/8	2005	B	-0.613	-0.633	0	426,102	0	66,543	85,220	44,285	**-0.8433**
M/8	2005	C	-0.633	-0.813	0	457,806	0	78,705	91,561	52,379	**-0.8297**
M/8	2005	D	-0.813	-0.748	0	311,832	152,282	64,407	62,366	42,863	**-0.8096**
M/8	2006	A	-0.748	-0.763	0	325,940	105,270	127,211	65,188	84,660	**-0.6416**
M/8	2006	B	-0.763	-0.868	0	408,185	47,277	149,949	81,637	99,792	**-0.5783**
M/8	2006	C	-0.868	-0.818	0	438,556	1,891	174,011	87,711	115,806	**-0.5570**

Well No.	Time phase		GWL_o	GWL_f	QM	QA	R	RRFWW	RRFI	RRFW	$GWL_{fpredicted}$
M/8	2006	D	-0.818	-0.913	0	298,720	142,588	162,423	59,744	108,094	**-0.5057**
M/8	2007	A	-0.913	-0.993	0	325,940	146,874	126,674	65,188	84,303	**-0.7837**
M/8	2007	B	-0.993	-1.103	0	408,185	6,934	173,080	81,637	115,186	**-0.7049**
M/8	2007	C	-1.103	-1.228	0	438,556	0	199,779	87,711	132,955	**-0.6042**
M/8	2007	D	-1.228	-1.113	0	298,720	70,601	167,959	59,744	111,778	**-0.9626**
M/8	2008	A	-1.113	1.198	0	325,940	130,233	114,011	65,188	75,875	**-1.0950**
N/12	2000	A	8.686	8.756	0	371,655	235,649	37,104	74,331	24,693	**8.9734**
N/12	2000	B	8.756	8.836	0	465,435	0	47,746	93,087	31,775	**8.8264**
N/12	2000	C	8.836	8.786	0	500,065	0	60,368	100,013	40,176	**9.0438**
N/12	2000	D	8.786	8.906	0	340,617	262,512	48,978	68,123	32,595	**9.2164**
N/12	2001	A	8.906	8.906	0	371,655	239,169	45,937	74,331	30,572	**9.2581**
N/12	2001	B	8.906	8.976	0	465,435	25,010	61,971	93,087	41,242	**9.1848**
N/12	2001	C	8.976	8.936	0	500,065	0	68,077	100,013	45,306	**9.2351**
N/12	2001	D	8.936	9.316	0	340,617	140,797	59,563	68,123	39,640	**9.3650**
N/12	2002	A	9.316	9.211	0	371,655	320,498	53,613	74,331	35,680	**9.6191**
N/12	2002	B	9.211	9.236	0	465,435	17,600	64,422	93,087	42,873	**9.4159**
N/12	2002	C	9.236	9.356	0	500,065	0	71,162	100,013	47,359	**9.4523**
N/12	2002	D	9.356	9.376	0	340,617	307,530	65,669	68,123	43,704	**9.7552**
N/12	2003	A	9.376	9.516	0	321,446	214,931	18,371	64,289	12,226	**9.0825**
N/12	2003	B	9.516	9.666	0	402,557	7,456	18,277	80,511	12,163	**8.8195**
N/12	2003	C	9.666	9.696	0	432,508	0	26,937	86,502	17,927	**9.0682**
N/12	2003	D	9.696	9.706	0	294,601	90,409	23,452	58,920	15,607	**9.2353**
N/12	2004	A	9.706	9.886	0	321,446	254,450	20,368	64,289	13,555	**9.3353**
N/12	2004	B	9.886	9.908	0	402,557	1,864	25,960	80,511	17,277	**9.2009**
N/12	2004	C	9.908	9.791	0	432,508	0	29,761	86,502	19,806	**9.2752**
N/12	2004	D	9.791	9.996	0	294,601	402,646	25,296	58,920	16,835	**9.4065**
N/12	2005	A	9.996	10.146	0	321,446	312,237	20,396	64,289	13,573	**9.4930**
N/12	2005	B	10.146	10.156	0	402,557	3,728	26,747	80,511	17,800	**9.3728**
N/12	2005	C	10.156	9.886	0	432,508	0	31,635	86,502	21,053	**9.4602**
N/12	2005	D	9.886	10.186	0	294,601	164,041	25,888	58,920	17,229	**9.4939**
N/12	2006	A	10.186	10.136	0	273,377	132,233	41,428	54,675	27,571	**9.8940**
N/12	2006	B	10.136	10.321	0	342,358	66,585	48,833	68,472	32,499	**9.9137**
N/12	2006	C	10.321	10.241	0	367,831	0	56,669	73,566	37,714	**10.0021**
N/12	2006	D	10.241	10.376	0	250,546	298,228	52,895	50,109	35,202	**10.1161**

Well No.	Time phase		GWL_o	GWL_f	QM	QA	R	RRFWW	RRFI	RRFW	$GWL_{fpredicted}$
N/12	2007	A	10.376	10.441	0	273,377	178,749	41,253	54,675	27,454	**10.0424**
N/12	2007	B	10.441	10.486	0	342,358	2,813	56,366	68,472	37,512	**10.0644**
N/12	2007	C	10.486	10.486	0	367,831	0	65,061	73,566	43,299	**10.1975**
N/12	2007	D	10.486	10.696	0	250,546	55,332	54,698	50,109	36,402	**10.1035**
N/12	2008	A	10.696	10.538	0	273,377	233,518	37,129	54,675	24,710	**10.1689**
N/16	2000	A	6.929	6.949	0	410,485	242,883	35,269	82,097	23,472	**7.5623**
N/16	2000	B	6.949	7.019	0	514,063	0	45,385	102,813	30,204	**7.3033**
N/16	2000	C	7.019	6.699	0	552,312	0	57,384	110,462	38,189	**7.4962**
N/16	2000	D	6.699	7.319	0	376,204	270,570	46,557	75,241	30,984	**7.5258**
N/16	2001	A	7.319	7.359	0	410,485	246,511	43,666	82,097	29,060	**8.0042**
N/16	2001	B	7.359	7.169	0	514,063	25,778	58,907	102,813	39,203	**7.8914**
N/16	2001	C	7.169	7.099	0	552,312	0	64,711	110,462	43,066	**7.7124**
N/16	2001	D	7.099	7.649	0	376,204	145,119	56,619	75,241	37,680	**7.8783**
N/16	2002	A	7.649	7.704	0	410,485	330,336	50,962	82,097	33,916	**8.3656**
N/16	2002	B	7.704	7.869	0	514,063	18,140	61,237	102,813	40,754	**8.1958**
N/16	2002	C	7.869	7.499	0	552,312	0	67,644	110,462	45,018	**8.3400**
N/16	2002	D	7.499	7.979	0	376,204	316,969	62,423	75,241	41,543	**8.3533**
N/16	2003	A	7.979	8.049	0	354,299	221,591	21,476	70,860	14,292	**8.1970**
N/16	2003	B	8.049	8.059	0	443,699	7,687	21,365	88,740	14,219	**7.8606**
N/16	2003	C	8.059	7.869	0	476,712	0	31,489	95,342	20,956	**8.0184**
N/16	2003	D	7.869	8.129	0	324,710	93,210	27,415	64,942	18,245	**8.0696**
N/16	2004	A	8.129	8.299	0	354,299	262,335	23,810	70,860	15,846	**8.3695**
N/16	2004	B	8.299	8.239	0	443,699	1,922	30,347	88,740	20,196	**8.2080**
N/16	2004	C	8.239	7.799	0	476,712	0	34,790	95,342	23,153	**8.2158**
N/16	2004	D	7.799	8.299	0	324,710	415,123	29,571	64,942	19,680	**8.1879**
N/16	2005	A	8.299	8.439	0	354,299	321,912	23,842	70,860	15,867	**8.4960**
N/16	2005	B	8.439	8.419	0	443,699	3,844	31,267	88,740	20,808	**8.3329**
N/16	2005	C	8.419	7.699	0	476,712	0	36,981	95,342	24,611	**8.3901**
N/16	2005	D	7.699	8.529	0	324,710	169,124	30,263	64,942	20,140	**8.0906**
N/16	2006	A	8.529	8.649	0	351,340	134,172	79,112	70,268	52,650	**9.1909**
N/16	2006	B	8.649	8.694	0	439,994	67,562	93,253	87,999	62,061	**9.2666**
N/16	2006	C	8.694	8.524	0	472,731	0	108,217	94,546	72,020	**9.1742**
N/16	2006	D	8.524	8.759	0	321,998	302,600	101,011	64,400	67,224	**9.1916**
N/16	2007	A	8.759	8.884	0	351,340	181,370	78,778	70,268	52,428	**9.4038**

Well No.	Time phase		GWL_o	GWL_f	QM	QA	R	RRFWW	RRFI	RRFW	$GWL_{fpredicted}$
N/16	2007	B	8.884	8.969	0	439,994	2,855	107,638	87,999	71,634	**9.3133**
N/16	2007	C	8.969	9.079	0	472,731	0	124,242	94,546	82,684	**9.2832**
N/16	2007	D	9.079	9.349	0	321,998	56,143	104,453	64,400	69,515	**9.4646**
N/16	2008	A	9.349	9.181	0	351,340	236,941	70,903	70,268	47,187	**9.8057**
P/50	2000	A	-3.005	-3.245	182,174	414,391	424,081	25,431	82,878	16,924	**-2.8143**
P/50	2000	B	-3.245	-3.475	203,401	518,955	0	32,725	103,791	21,779	**-3.9203**
P/50	2000	C	-3.475	-4.045	201,747	557,567	0	41,376	111,513	27,536	**-4.1856**
P/50	2000	D	-4.045	-4.03	146,274	379,784	451,502	33,569	75,957	22,341	**-3.8604**
P/50	2001	A	-4.03	-4.015	189,837	414,391	418,171	31,485	82,878	20,954	**-3.9514**
P/50	2001	B	-4.015	-4.455	263,173	518,955	29,549	42,475	103,791	28,267	**-4.7756**
P/50	2001	C	-4.455	-4.965	234,203	557,567	0	46,660	111,513	31,052	**-5.2500**
P/50	2001	D	-4.965	-5.055	118,856	379,784	215,114	40,825	75,957	27,169	**-5.4366**
P/50	2002	A	-5.055	-4.815	129,228	414,391	492,161	36,746	82,878	24,455	**-4.7982**
P/50	2002	B	-4.815	-5.135	133,012	518,955	28,367	44,154	103,791	29,385	**-5.5960**
P/50	2002	C	-5.135	-5.595	137,373	557,567	0	48,774	111,513	32,460	**-5.9300**
P/50	2002	D	-5.595	-5.685	37,667	379,784	370,184	45,010	75,957	29,954	**-5.7099**
P/50	2003	A	-5.685	-5.615	8,682	352,222	373,882	36,057	70,444	23,996	**-5.6800**
P/50	2003	B	-5.615	-6.035	194,787	441,099	24,973	35,871	88,220	23,873	**-6.3688**
P/50	2003	C	-6.035	-6.495	266,160	473,918	0	52,869	94,784	35,185	**-6.9101**
P/50	2003	D	-6.495	-5.98	201,243	322,807	117,423	46,028	64,561	30,632	**-7.0923**
P/50	2004	A	-5.98	-6.13	199,436	352,222	361,155	39,975	70,444	26,604	**-6.0674**
P/50	2004	B	-6.13	-7.187	257,834	441,099	8,885	50,951	88,220	33,908	**-6.9892**
P/50	2004	C	-7.187	-8.738	273,254	473,918	0	58,411	94,784	38,873	**-7.9740**
P/50	2004	D	-8.738	-7.74	204,650	322,807	491,065	49,648	64,561	33,041	**-7.9587**
P/50	2005	A	-7.74	-7.58	120,332	352,222	464,651	40,030	70,444	26,640	**-7.2561**
P/50	2005	B	-7.58	-8.34	221,665	441,099	0	52,496	88,220	34,936	**-8.2836**
P/50	2005	C	-8.34	-8.98	284,059	473,918	0	62,090	94,784	41,321	**-8.9161**
P/50	2005	D	-8.98	-8.695	237,810	322,807	291,758	50,810	64,561	33,815	**-8.8257**
P/50	2006	A	-8.695	-8.18	196,819	262,401	206,456	40,617	52,480	27,031	**-8.6021**
P/50	2006	B	-8.18	-9.76	164,211	328,613	92,720	47,876	65,723	31,862	**-8.5847**
P/50	2006	C	-9.76	-10.15	197,550	353,063	3,709	55,559	70,613	36,975	**-9.8394**
P/50	2006	D	-10.15	-10.15	181,040	240,487	279,643	51,859	48,097	34,513	**-9.4611**
P/50	2007	A	-10.15	-10.24	139,310	262,401	288,049	40,445	52,480	26,917	**-9.3765**
P/50	2007	B	-10.24	-11.18	202,182	328,613	13,599	55,262	65,723	36,777	**-10.0936**

Well No.	Time phase		GWL_o	GWL_f	QM	QA	R	RRFWW	RRFI	RRFW	$GWL_{fpredicted}$
P/50	2007	C	-11.18	-11.86	252,065	353,063	0	63,787	70,613	42,451	**-10.6554**
P/50	2007	D	-11.86	-11.12	227,749	240,487	138,461	53,627	48,097	35,689	**-10.6212**
P/50	2008	A	-11.12	-11.01	140,067	262,401	255,412	36,402	52,480	24,226	**-9.9371**
T/15	2000	A	-0.328	-0.268	51,832	280,975	116,402	18,383	56,195	12,234	**-0.2017**
T/15	2000	B	-0.268	-0.408	76,716	351,873	0	23,655	70,375	15,743	**-0.4298**
T/15	2000	C	-0.408	-0.648	88,492	378,054	0	29,909	75,611	19,905	**-0.6271**
T/15	2000	D	-0.648	-0.368	34,985	257,509	123,928	24,266	51,502	16,149	**-0.5348**
T/15	2001	A	-0.368	-0.048	37,942	280,975	114,780	22,759	56,195	15,146	**-0.2599**
T/15	2001	B	-0.048	-0.188	66,574	351,873	8,110	30,703	70,375	20,433	**-0.1699**
T/15	2001	C	-0.188	-0.428	86,638	378,054	0	33,728	75,611	22,446	**-0.3749**
T/15	2001	D	-0.428	-0.218	54,062	257,509	59,044	29,510	51,502	19,639	**-0.4118**
T/15	2002	A	-0.218	-0.032	46,852	280,975	135,088	26,562	56,195	17,677	**-0.0668**
T/15	2002	B	-0.032	-0.298	71,411	351,873	7,786	31,917	70,375	21,241	**-0.1540**
T/15	2002	C	-0.298	-0.408	95,825	378,054	0	35,257	75,611	23,464	**-0.5064**
T/15	2002	D	-0.408	-0.098	60,438	257,509	101,608	32,535	51,502	21,652	**-0.3290**
T/15	2003	A	-0.098	0.112	44,461	249,092	101,834	26,989	49,818	17,961	**0.0572**
T/15	2003	B	0.112	-0.158	63,190	311,945	6,802	26,850	62,389	17,869	**0.0570**
T/15	2003	C	-0.158	-0.148	100,220	335,155	0	39,573	67,031	26,336	**-0.3108**
T/15	2003	D	-0.148	-0.038	58,770	228,289	31,983	34,453	45,658	22,929	**-0.1082**
T/15	2004	A	-0.038	-0.098	50,040	249,092	98,368	29,922	49,818	19,913	**0.1121**
T/15	2004	B	-0.098	-0.253	28,980	311,945	2,420	38,137	62,389	25,381	**-0.1937**
T/15	2004	C	-0.253	0.323	67,638	335,155	0	43,721	67,031	29,097	**-0.4146**
T/15	2004	D	0.323	-0.308	94,048	228,289	133,751	37,162	45,658	24,732	**-0.1591**
T/15	2005	A	-0.308	-0.098	5,400	249,092	126,557	29,963	49,818	19,940	**-0.1407**
T/15	2005	B	-0.098	-0.348	10,560	311,945	0	39,293	62,389	26,150	**-0.1930**
T/15	2005	C	-0.348	-0.498	28,670	335,155	0	46,475	67,031	30,929	**-0.5155**
T/15	2005	D	-0.498	-0.503	22,120	228,289	79,466	38,032	45,658	25,310	**-0.4344**
T/15	2006	A	-0.503	-0.268	15,000	238,571	55,103	66,475	47,714	44,240	**-0.5289**
T/15	2006	B	-0.268	-0.673	28,800	298,770	24,747	78,357	59,754	52,147	**-0.3341**
T/15	2006	C	-0.673	-0.773	60,640	321,000	990	90,931	64,200	60,516	**-0.8482**
T/15	2006	D	-0.773	-0.698	53,475	218,647	74,637	84,876	43,729	56,485	**-0.8099**
T/15	2007	A	-0.698	-0.723	0	238,571	76,881	66,194	47,714	44,053	**-0.7232**
T/15	2007	B	-0.723	-0.998	0	298,770	3,630	90,444	59,754	60,192	**-0.8723**
T/15	2007	C	-0.998	-1.243	0	321,000	0	104,396	64,200	69,477	**-1.1629**

Well No.	Time phase		GWL_o	GWL_f	QM	QA	R	RRFWW	RRFI	RRFW	$GWL_{fpredicted}$
T/15	2007	D	-1.243	-1.138	0	218,647	36,955	87,768	43,729	58,411	**-1.3926**
T/15	2008	A	-1.138	-1.221	92,100	238,571	68,170	59,577	47,714	39,649	**-1.2810**
T/22	2000	A	-0.104	-0.034	0	528,992	243,187	20,987	105,798	13,967	**0.0527**
T/22	2000	B	-0.034	-0.104	0	662,473	0	27,007	132,495	17,973	**-0.2254**
T/22	2000	C	-0.104	-0.254	0	711,763	0	34,146	142,353	22,725	**-0.2439**
T/22	2000	D	-0.254	-0.074	0	484,814	258,912	27,704	96,963	18,437	**-0.0718**
T/22	2001	A	-0.074	-0.024	0	528,992	239,798	25,984	105,798	17,292	**0.0861**
T/22	2001	B	-0.024	-0.044	0	662,473	16,944	35,053	132,495	23,328	**-0.1606**
T/22	2001	C	-0.044	-0.104	0	711,763	0	38,507	142,353	25,627	**-0.1580**
T/22	2001	D	-0.104	0.036	0	484,814	123,356	33,691	96,963	22,422	**-0.1128**
T/22	2002	A	0.036	0.136	0	528,992	282,227	30,325	105,798	20,182	**0.2838**
T/22	2002	B	0.136	0.056	0	662,473	16,267	36,439	132,495	24,251	**0.0246**
T/22	2002	C	0.056	-0.084	0	711,763	0	40,252	142,353	26,788	**-0.0380**
T/22	2002	D	-0.084	0.146	0	484,814	212,280	37,145	96,963	24,720	**0.0571**
T/22	2003	A	0.146	0.296	0	513,334	211,486	2,995	102,667	1,994	**0.2765**
T/22	2003	B	0.296	0.226	0	642,864	14,126	2,980	128,573	1,983	**0.0791**
T/22	2003	C	0.226	0.056	0	690,695	0	4,392	138,139	2,923	**-0.0063**
T/22	2003	D	0.056	0.156	0	470,463	66,420	3,824	94,093	2,545	**-0.0251**
T/22	2004	A	0.156	0.226	0	513,334	204,287	3,321	102,667	2,210	**0.2759**
T/22	2004	B	0.226	0.036	0	642,864	5,026	4,233	128,573	2,817	**-0.0052**
T/22	2004	C	0.036	-0.074	0	690,695	0	4,853	138,139	3,229	**-0.2018**
T/22	2004	D	-0.074	-0.074	0	470,463	277,770	4,125	94,093	2,745	**0.1763**
T/22	2005	A	-0.074	0.066	0	513,334	262,829	3,326	102,667	2,213	**0.1209**
T/22	2005	B	0.066	-0.154	0	642,864	0	4,361	128,573	2,902	**-0.1805**
T/22	2005	C	-0.154	-0.204	0	690,695	0	5,158	138,139	3,433	**-0.3983**
T/22	2005	D	-0.204	-0.139	0	470,463	165,032	4,221	94,093	2,809	**-0.1483**
T/22	2006	A	-0.139	-0.054	0	420,712	114,616	40,572	84,142	27,001	**-0.1349**
T/22	2006	B	-0.054	0.204	0	526,870	51,474	47,824	105,374	31,827	**-0.1446**
T/22	2006	C	0.204	-0.219	0	566,071	2,059	55,499	113,214	36,935	**0.1211**
T/22	2006	D	-0.219	-0.204	0	385,577	155,247	51,803	77,115	34,475	**-0.1398**
T/22	2007	A	-0.204	-0.179	0	420,712	159,914	40,401	84,142	26,887	**-0.1389**
T/22	2007	B	-0.179	-0.254	0	526,870	7,550	55,202	105,374	36,737	**-0.3374**
T/22	2007	C	-0.254	-0.364	0	566,071	0	63,717	113,214	42,404	**-0.3928**
T/22	2007	D	-0.364	-0.354	0	385,577	76,869	53,568	77,115	35,650	**-0.4368**

Well No.	Time phase		GWL_o	GWL_f	QM	QA	R	RRFWW	RRFI	RRFW	$GWL_{fpredicted}$
T/22	2008	A	-0.354	-0.371	0	420,712	141,795	36,362	84,142	24,199	**-0.3462**
T/26	2000	A	-0.085	0.015	0	173,756	79,536	9,255	34,751	6,159	**0.2212**
T/26	2000	B	0.015	-0.085	0	217,600	0	11,909	43,520	7,926	**0.1125**
T/26	2000	C	-0.085	-0.285	0	233,790	0	15,058	46,758	10,021	**-0.0323**
T/26	2000	D	-0.285	-0.215	0	159,245	84,679	12,217	31,849	8,130	**0.0265**
T/26	2001	A	-0.215	-0.135	0	173,756	78,428	11,458	34,751	7,626	**0.0693**
T/26	2001	B	-0.135	-0.155	0	217,600	5,542	15,458	43,520	10,287	**-0.0540**
T/26	2001	C	-0.155	-0.465	0	233,790	0	16,981	46,758	11,301	**-0.1155**
T/26	2001	D	-0.465	-0.235	0	159,245	40,344	14,857	31,849	9,888	**-0.2546**
T/26	2002	A	-0.235	0.085	0	173,756	92,304	13,373	34,751	8,900	**0.0623**
T/26	2002	B	0.085	-0.245	0	217,600	5,320	16,069	43,520	10,694	**0.1857**
T/26	2002	C	-0.245	-0.385	0	233,790	0	17,750	46,758	11,813	**-0.2177**
T/26	2002	D	-0.385	-0.245	0	159,245	69,428	16,380	31,849	10,901	**-0.1270**
T/26	2003	A	-0.245	-0.035	0	158,733	69,498	8,721	31,747	5,804	**0.0618**
T/26	2003	B	-0.035	-0.265	0	198,787	4,642	8,676	39,757	5,774	**0.1083**
T/26	2003	C	-0.265	-0.315	0	213,577	0	12,787	42,715	8,510	**-0.1892**
T/26	2003	D	-0.315	-0.205	0	145,477	21,827	11,133	29,095	7,409	**-0.0788**
T/26	2004	A	-0.205	-0.225	0	158,733	67,132	9,669	31,747	6,435	**0.0964**
T/26	2004	B	-0.225	0.35	0	198,787	1,652	12,323	39,757	8,201	**-0.1162**
T/26	2004	C	0.35	-0.46	0	213,577	0	14,127	42,715	9,402	**-0.2875**
T/26	2004	D	-0.46	-0.425	0	145,477	91,280	12,008	29,095	7,991	**-0.1251**
T/26	2005	A	-0.425	-0.305	0	158,733	86,370	9,682	31,747	6,443	**-0.1086**
T/26	2005	B	-0.305	-0.435	0	198,787	0	12,697	39,757	8,450	**-0.2073**
T/26	2005	C	-0.435	-0.605	0	213,577	0	15,017	42,715	9,994	**-0.3843**
T/26	2005	D	-0.605	-0.555	0	145,477	54,233	12,289	29,095	8,179	**-0.3438**
T/26	2006	A	-0.555	-0.355	0	159,957	36,928	27,577	31,991	18,353	**-0.4191**
T/26	2006	B	-0.355	0.655	0	200,319	16,585	32,506	40,064	21,633	**-0.3098**
T/26	2006	C	0.655	-0.665	0	215,224	663	37,723	43,045	25,105	**-0.7143**
T/26	2006	D	-0.665	-0.685	0	146,598	50,019	35,211	29,320	23,433	**-0.5299**
T/26	2007	A	-0.685	-0.68	0	159,957	51,523	27,461	31,991	18,275	**-0.5404**
T/26	2007	B	-0.68	-0.875	0	200,319	2,432	37,521	40,064	24,971	**-0.7172**
T/26	2007	C	-0.875	-1.085	0	215,224	0	43,309	43,045	28,822	**-0.9835**
T/26	2007	D	-1.085	-1.085	0	146,598	24,766	36,411	29,320	24,232	**-1.0468**
T/26	2008	A	-1.085	1.11	0	159,957	45,685	24,716	31,991	16,448	**-0.9807**

Well No.	Time phase		GWL_o	GWL_f	QM	QA	R	RRFWW	RRFI	RRFW	$GWL_{fpredicted}$
T/6	2000	A	-0.11	-0.01	0	277,375	92,731	9,985	55,475	6,645	**0.0445**
T/6	2000	B	-0.01	0.03	0	347,365	0	12,849	69,473	8,551	**-0.0975**
T/6	2000	C	0.03	-0.27	0	373,210	0	16,246	74,642	10,812	**-0.0853**
T/6	2000	D	-0.27	-0.08	0	254,210	98,727	13,181	50,842	8,772	**-0.0982**
T/6	2001	A	-0.08	0.14	0	277,375	91,439	12,363	55,475	8,228	**0.0687**
T/6	2001	B	0.14	0.07	0	347,365	6,461	16,678	69,473	11,099	**0.0754**
T/6	2001	C	0.07	-0.05	0	373,210	0	18,321	74,642	12,193	**-0.0422**
T/6	2001	D	-0.05	0.11	0	254,210	47,038	16,030	50,842	10,668	**0.0513**
T/6	2002	A	0.11	0.305	0	277,375	107,618	14,428	55,475	9,602	**0.3023**
T/6	2002	B	0.305	0.22	0	347,365	6,203	17,337	69,473	11,538	**0.2595**
T/6	2002	C	0.22	0.04	0	373,210	0	19,151	74,642	12,745	**0.1264**
T/6	2002	D	0.04	0.17	0	254,210	80,946	17,673	50,842	11,762	**0.2043**
T/6	2003	A	0.17	0.47	0	247,877	81,254	6,957	49,575	4,630	**0.3854**
T/6	2003	B	0.47	0.37	0	310,424	5,427	6,921	62,085	4,606	**0.4930**
T/6	2003	C	0.37	0.2	0	333,521	0	10,201	66,704	6,789	**0.3421**
T/6	2003	D	0.2	0.35	0	227,176	25,519	8,881	45,435	5,910	**0.3504**
T/6	2004	A	0.35	0.32	0	247,877	78,488	7,713	49,575	5,133	**0.5749**
T/6	2004	B	0.32	0.195	0	310,424	1,931	9,831	62,085	6,542	**0.3197**
T/6	2004	C	0.195	0.055	0	333,521	0	11,270	66,704	7,500	**0.1481**
T/6	2004	D	0.055	0.2	0	227,176	106,721	9,579	45,435	6,375	**0.3278**
T/6	2005	A	0.2	0.17	0	247,877	100,980	7,723	49,575	5,140	**0.4494**
T/6	2005	B	0.17	0.02	0	310,424	0	10,129	62,085	6,741	**0.1513**
T/6	2005	C	0.02	-0.09	0	333,521	0	11,980	66,704	7,973	**-0.0464**
T/6	2005	D	-0.09	0.01	0	227,176	63,406	9,803	45,435	6,524	**0.0957**
T/6	2006	A	0.01	0.07	0	223,692	43,883	21,499	44,738	14,308	**0.1432**
T/6	2006	B	0.07	-0.285	0	280,137	19,708	25,342	56,027	16,865	**0.0858**
T/6	2006	C	-0.285	-0.36	0	300,980	788	29,409	60,196	19,572	**-0.3823**
T/6	2006	D	-0.36	-0.32	0	205,011	59,439	27,450	41,002	18,268	**-0.2374**
T/6	2007	A	-0.32	0.34	0	223,692	61,225	21,409	44,738	14,248	**-0.1978**
T/6	2007	B	0.34	-0.59	0	280,137	2,890	29,251	56,027	19,467	**-0.4166**
T/6	2007	C	-0.59	-0.8	0	300,980	0	33,764	60,196	22,470	**-0.7429**
T/6	2007	D	-0.8	-0.73	0	205,011	29,430	28,386	41,002	18,891	**-0.7861**
T/6	2008	A	-0.73	0.71	0	223,692	54,288	19,268	44,738	12,823	**-0.6592**

ANNs model Results of hypothetical cases studied the effect of input variables on GWL

Normal Condition							
GWL_o	R	RFW	RFWW	RFIW	QM	QA	GWLf
0.155	0	40,190	60,390	90,735	140,935	453,685	-0.055113
0.155	14,300	40,190	60,390	90,735	140,935	453,685	-0.033298
0.155	28,600	40,190	60,390	90,735	140,935	453,685	-0.011390
0.155	42,900	40,190	60,390	90,735	140,935	453,685	0.010597
0.155	57,200	40,190	60,390	90,735	140,935	453,685	0.032651
0.155	71,500	40,190	60,390	90,735	140,935	453,685	0.054759
0.155	85,800	40,190	60,390	90,735	140,935	453,685	0.076906
0.155	100,100	40,190	60,390	90,735	140,935	453,685	0.099079
0.155	114,400	40,190	60,390	90,735	140,935	453,685	0.121266
0.155	128,700	40,190	60,390	90,735	140,935	453,685	0.143452
0.155	143,000	40,190	60,390	90,735	140,935	453,685	0.165625
0.155	136,300	1,980	60,390	90,735	140,935	453,685	0.122248
0.155	136,300	23,730	60,390	90,735	140,935	453,685	0.134657
0.155	136,300	45,480	60,390	90,735	140,935	453,685	0.163696
0.155	136,300	67,230	60,390	90,735	140,935	453,685	0.206314
0.155	136,300	88,980	60,390	90,735	140,935	453,685	0.258018
0.155	136,300	110,730	60,390	90,735	140,935	453,685	0.313559
0.155	136,300	132,480	60,390	90,735	140,935	453,685	0.367700
0.155	136,300	154,230	60,390	90,735	140,935	453,685	0.415933
0.155	136,300	175,980	60,390	90,735	140,935	453,685	0.455010
0.155	136,300	197,730	60,390	90,735	140,935	453,685	0.483216
0.155	136,300	219,480	60,390	90,735	140,935	453,685	0.500363
0.155	136,300	40,190	2,980	90,735	140,935	453,685	0.122248
0.155	136,300	40,190	35,655	90,735	140,935	453,685	0.134656
0.155	136,300	40,190	68,330	90,735	140,935	453,685	0.163687
0.155	136,300	40,190	101,005	90,735	140,935	453,685	0.206291
0.155	136,300	40,190	133,680	90,735	140,935	453,685	0.257981
0.155	136,300	40,190	166,355	90,735	140,935	453,685	0.313509
0.155	136,300	40,190	199,030	90,735	140,935	453,685	0.367643
0.155	136,300	40,190	231,705	90,735	140,935	453,685	0.415876
0.155	136,300	40,190	264,380	90,735	140,935	453,685	0.454959
0.155	136,300	40,190	297,055	90,735	140,935	453,685	0.483178
0.155	136,300	40,190	329,730	90,735	140,935	453,685	0.500340
0.155	136,300	40,190	60,390	25,940	140,935	453,685	0.124865
0.155	136,300	40,190	60,390	62,270	140,935	453,685	0.122178
0.155	136,300	40,190	60,390	98,600	140,935	453,685	0.170064
0.155	136,300	40,190	60,390	134,930	140,935	453,685	0.270289
0.155	136,300	40,190	60,390	171,260	140,935	453,685	0.419279
0.155	136,300	40,190	60,390	207,590	140,935	453,685	0.608276
0.155	136,300	40,190	60,390	243,920	140,935	453,685	0.824182
0.155	136,300	40,190	60,390	280,250	140,935	453,685	1.050999
0.155	136,300	40,190	60,390	316,580	140,935	453,685	1.271638
0.155	136,300	40,190	60,390	352,910	140,935	453,685	1.469825
0.155	136,300	40,190	60,390	389,240	140,935	453,685	1.631845
0.155	136,300	40,190	60,390	90,735	0	453,685	0.206267
0.155	136,300	40,190	60,390	90,735	359,000	453,685	0.077189
0.155	136,300	40,190	60,390	90,735	718,000	453,685	-0.044823
0.155	136,300	40,190	60,390	90,735	1,077,000	453,685	-0.152534
0.155	136,300	40,190	60,390	90,735	1,436,000	453,685	-0.239822
0.155	136,300	40,190	60,390	90,735	1,795,000	453,685	-0.302248
0.155	136,300	40,190	60,390	90,735	2,154,000	453,685	-0.337429
0.155	136,300	40,190	60,390	90,735	2,513,000	453,685	-0.345148
0.155	136,300	40,190	60,390	90,735	2,872,000	453,685	-0.327223

Normal Condition							
GWL_o	R	RFW	RFWW	RFIW	QM	QA	GWLf
0.155	136,300	40,190	60,390	90,735	3,231,000	453,685	-0.287148
0.155	136,300	40,190	60,390	90,735	3,590,000	453,685	-0.229601
0.155	136,300	40,190	60,390	90,735	140,935	129,700	0.352563
0.155	136,300	40,190	60,390	90,735	140,935	311,300	0.234695
0.155	136,300	40,190	60,390	90,735	140,935	492,900	0.135854
0.155	136,300	40,190	60,390	90,735	140,935	674,500	0.062255
0.155	136,300	40,190	60,390	90,735	140,935	856,100	0.017578
0.155	136,300	40,190	60,390	90,735	140,935	1,037,700	0.002673
0.155	136,300	40,190	60,390	90,735	140,935	1,219,300	0.015637
0.155	136,300	40,190	60,390	90,735	140,935	1,400,900	0.052233
0.155	136,300	40,190	60,390	90,735	140,935	1,582,500	0.106574
0.155	136,300	40,190	60,390	90,735	140,935	1,764,100	0.171939
0.155	136,300	40,190	60,390	90,735	140,935	1,945,700	0.241601
Decreasing Condition							
GWL_o	R	RFW	RFWW	RFIW	QM	QA	GWLf
0.155	0	3,692	5,547	36,729	445,548	723,726	-0.315958
0.155	14,300	3,692	5,547	36,729	445,548	723,726	-0.293852
0.155	28,600	3,692	5,547	36,729	445,548	723,726	-0.271606
0.155	42,900	3,692	5,547	36,729	445,548	723,726	-0.249232
0.155	57,200	3,692	5,547	36,729	445,548	723,726	-0.226745
0.155	71,500	3,692	5,547	36,729	445,548	723,726	-0.204158
0.155	85,800	3,692	5,547	36,729	445,548	723,726	-0.181485
0.155	100,100	3,692	5,547	36,729	445,548	723,726	-0.158739
0.155	114,400	3,692	5,547	36,729	445,548	723,726	-0.135934
0.155	128,700	3,692	5,547	36,729	445,548	723,726	-0.113083
0.155	143,000	3,692	5,547	36,729	445,548	723,726	-0.090201
0.155	0	1,980	5,547	36,729	445,548	723,726	-0.312865
0.155	0	23,730	5,547	36,729	445,548	723,726	-0.340289
0.155	0	45,480	5,547	36,729	445,548	723,726	-0.341311
0.155	0	67,230	5,547	36,729	445,548	723,726	-0.316781
0.155	0	88,980	5,547	36,729	445,548	723,726	-0.269830
0.155	0	110,730	5,547	36,729	445,548	723,726	-0.205348
0.155	0	132,480	5,547	36,729	445,548	723,726	-0.129264
0.155	0	154,230	5,547	36,729	445,548	723,726	-0.047736
0.155	0	175,980	5,547	36,729	445,548	723,726	0.033582
0.155	0	197,730	5,547	36,729	445,548	723,726	0.110098
0.155	0	219,480	5,547	36,729	445,548	723,726	0.178594
0.155	0	3,692	2,980	36,729	445,548	723,726	-0.312870
0.155	0	3,692	35,655	36,729	445,548	723,726	-0.340288
0.155	0	3,692	68,330	36,729	445,548	723,726	-0.341314
0.155	0	3,692	101,005	36,729	445,548	723,726	-0.316799
0.155	0	3,692	133,680	36,729	445,548	723,726	-0.269868
0.155	0	3,692	166,355	36,729	445,548	723,726	-0.205411
0.155	0	3,692	199,030	36,729	445,548	723,726	-0.129351
0.155	0	3,692	231,705	36,729	445,548	723,726	-0.047842
0.155	0	3,692	264,380	36,729	445,548	723,726	0.033463
0.155	0	3,692	297,055	36,729	445,548	723,726	0.109973
0.155	0	3,692	329,730	36,729	445,548	723,726	0.178471
0.155	0	3,692	5,547	25,940	445,548	723,726	-0.296492
0.155	0	3,692	5,547	62,270	445,548	723,726	-0.343616
0.155	0	3,692	5,547	98,600	445,548	723,726	-0.334344
0.155	0	3,692	5,547	134,930	445,548	723,726	-0.265264
0.155	0	3,692	5,547	171,260	445,548	723,726	-0.138652
0.155	0	3,692	5,547	207,590	445,548	723,726	0.037594

Normal Condition							
GWL_o	R	RFW	RFWW	RFIW	QM	QA	GWLf
0.155	0	3,692	5,547	243,920	445,548	723,726	0.250765
0.155	0	3,692	5,547	280,250	445,548	723,726	0.484772
0.155	0	3,692	5,547	316,580	445,548	723,726	0.721980
0.155	0	3,692	5,547	352,910	445,548	723,726	0.945176
0.155	0	3,692	5,547	389,240	445,548	723,726	1.139378
0.155	0	3,692	5,547	36,729	0	723,726	-0.223689
0.155	0	3,692	5,547	36,729	359,000	723,726	-0.299590
0.155	0	3,692	5,547	36,729	718,000	723,726	-0.361540
0.155	0	3,692	5,547	36,729	1,077,000	723,726	-0.405823
0.155	0	3,692	5,547	36,729	1,436,000	723,726	-0.429867
0.155	0	3,692	5,547	36,729	1,795,000	723,726	-0.432486
0.155	0	3,692	5,547	36,729	2,154,000	723,726	-0.413980
0.155	0	3,692	5,547	36,729	2,513,000	723,726	-0.376057
0.155	0	3,692	5,547	36,729	2,872,000	723,726	-0.321615
0.155	0	3,692	5,547	36,729	3,231,000	723,726	-0.254412
0.155	0	3,692	5,547	36,729	3,590,000	723,726	-0.178664
0.155	0	3,692	5,547	36,729	445,548	129,700	0.264098
0.155	0	3,692	5,547	36,729	445,548	311,300	0.057945
0.155	0	3,692	5,547	36,729	445,548	492,900	-0.127399
0.155	0	3,692	5,547	36,729	445,548	674,500	-0.280941
0.155	0	3,692	5,547	36,729	445,548	856,100	-0.394698
0.155	0	3,692	5,547	36,729	445,548	1,037,700	-0.464376
0.155	0	3,692	5,547	36,729	445,548	1,219,300	-0.489571
0.155	0	3,692	5,547	36,729	445,548	1,400,900	-0.473490
0.155	0	3,692	5,547	36,729	445,548	1,582,500	-0.422279
0.155	0	3,692	5,547	36,729	445,548	1,764,100	-0.344064
0.155	0	3,692	5,547	36,729	445,548	1,945,700	-0.247896
Increasing Condition							
GWL_o	R	RFW	RFWW	RFIW	QM	QA	GWLf
0.155	0	76,689	115,233	144,745	0	183,643	0.468946
0.155	14,300	76,689	115,233	144,745	0	183,643	0.486052
0.155	28,600	76,689	115,233	144,745	0	183,643	0.503152
0.155	42,900	76,689	115,233	144,745	0	183,643	0.520236
0.155	57,200	76,689	115,233	144,745	0	183,643	0.537293
0.155	71,500	76,689	115,233	144,745	0	183,643	0.554314
0.155	85,800	76,689	115,233	144,745	0	183,643	0.571287
0.155	100,100	76,689	115,233	144,745	0	183,643	0.588204
0.155	114,400	76,689	115,233	144,745	0	183,643	0.605053
0.155	128,700	76,689	115,233	144,745	0	183,643	0.621824
0.155	143,000	76,689	115,233	144,745	0	183,643	0.638509
0.155	359,478	1,980	115,233	144,745	0	183,643	0.729005
0.155	359,478	23,730	115,233	144,745	0	183,643	0.772591
0.155	359,478	45,480	115,233	144,745	0	183,643	0.816947
0.155	359,478	67,230	115,233	144,745	0	183,643	0.858009
0.155	359,478	88,980	115,233	144,745	0	183,643	0.891557
0.155	359,478	110,730	115,233	144,745	0	183,643	0.913839
0.155	359,478	132,480	115,233	144,745	0	183,643	0.922153
0.155	359,478	154,230	115,233	144,745	0	183,643	0.915250
0.155	359,478	175,980	115,233	144,745	0	183,643	0.893491
0.155	359,478	197,730	115,233	144,745	0	183,643	0.858748
0.155	359,478	219,480	115,233	144,745	0	183,643	0.814065
0.155	359,478	76,689	2,980	144,745	0	183,643	0.729011
0.155	359,478	76,689	35,655	144,745	0	183,643	0.772589
0.155	359,478	76,689	68,330	144,745	0	183,643	0.816935

Normal Condition							
GWL_o	R	RFW	RFWW	RFIW	QM	QA	GWLf
0.155	359,478	76,689	101,005	144,745	0	183,643	0.857991
0.155	359,478	76,689	133,680	144,745	0	183,643	0.891537
0.155	359,478	76,689	166,355	144,745	0	183,643	0.913825
0.155	359,478	76,689	199,030	144,745	0	183,643	0.922152
0.155	359,478	76,689	231,705	144,745	0	183,643	0.915269
0.155	359,478	76,689	264,380	144,745	0	183,643	0.893534
0.155	359,478	76,689	297,055	144,745	0	183,643	0.858817
0.155	359,478	76,689	329,730	144,745	0	183,643	0.814157
0.155	359,478	76,689	115,233	25,940	0	183,643	0.634998
0.155	359,478	76,689	115,233	62,270	0	183,643	0.670203
0.155	359,478	76,689	115,233	98,600	0	183,643	0.738759
0.155	359,478	76,689	115,233	134,930	0	183,643	0.840822
0.155	359,478	76,689	115,233	171,260	0	183,643	0.972723
0.155	359,478	76,689	115,233	207,590	0	183,643	1.127117
0.155	359,478	76,689	115,233	243,920	0	183,643	1.293664
0.155	359,478	76,689	115,233	280,250	0	183,643	1.460133
0.155	359,478	76,689	115,233	316,580	0	183,643	1.613778
0.155	359,478	76,689	115,233	352,910	0	183,643	1.742783
0.155	359,478	76,689	115,233	389,240	0	183,643	1.837560
0.155	359,478	76,689	115,233	144,745	0	183,643	0.873760
0.155	359,478	76,689	115,233	144,745	359,000	183,643	0.717110
0.155	359,478	76,689	115,233	144,745	718,000	183,643	0.555574
0.155	359,478	76,689	115,233	144,745	1,077,000	183,643	0.398681
0.155	359,478	76,689	115,233	144,745	1,436,000	183,643	0.255294
0.155	359,478	76,689	115,233	144,745	1,795,000	183,643	0.132777
0.155	359,478	76,689	115,233	144,745	2,154,000	183,643	0.036383
0.155	359,478	76,689	115,233	144,745	2,513,000	183,643	-0.031084
0.155	359,478	76,689	115,233	144,745	2,872,000	183,643	-0.069301
0.155	359,478	76,689	115,233	144,745	3,231,000	183,643	-0.080173
0.155	359,478	76,689	115,233	144,745	3,590,000	183,643	-0.067369
0.155	359,478	76,689	115,233	144,745	0	129,700	0.878017
0.155	359,478	76,689	115,233	144,745	0	311,300	0.865501
0.155	359,478	76,689	115,233	144,745	0	492,900	0.859197
0.155	359,478	76,689	115,233	144,745	0	674,500	0.860154
0.155	359,478	76,689	115,233	144,745	0	856,100	0.868167
0.155	359,478	76,689	115,233	144,745	0	1,037,700	0.881807
0.155	359,478	76,689	115,233	144,745	0	1,219,300	0.898643
0.155	359,478	76,689	115,233	144,745	0	1,400,900	0.915622
0.155	359,478	76,689	115,233	144,745	0	1,582,500	0.929517
0.155	359,478	76,689	115,233	144,745	0	1,764,100	0.937394
0.155	359,478	76,689	115,233	144,745	0	1,945,700	0.937000

APPENDIX 7 : ANNs model scenarios results

Zero Scenario							
Well No.	Time Phase	2015		2020		2025	
		GWL_o	GWL_f	GWL_o	GWL_f	GWL_o	GWL_f
Camp_8	A	9.21	9.96	11.52	11.94	14.42	14.86
L-101	A	-3.74	-3.98	-5.02	-5.68	-6.75	-7.40
L-18	A	-3.82	-3.26	-4.88	-4.26	-5.54	-5.18
L-47	A	-11.39	-11.05	-13.23	-13.64	-15.41	-15.56
L-57	A	-8.05	-8.36	-10.67	-10.23	-13.78	-13.29
L-66	A	-11.41	-11.19	-13.68	-13.89	-17.02	-16.66
L-8	A	-5.26	-5.06	-6.80	-6.32	-9.11	-9.47
L-86	A	1.15	1.39	0.32	0.48	-0.29	0.08
M-10	A	-4.69	-4.17	-5.90	-6.16	-7.47	-7.17
M-8	A	-3.34	-3.98	-5.33	-5.07	-6.19	-5.98
N-12	A	10.90	11.14	12.09	12.15	14.26	14.32
N-16	A	12.78	12.96	14.25	14.73	16.16	16.42
P-50	A	-16.51	-16.21	-19.56	-19.24	-22.39	-22.17
T-15	A	-2.82	-2.58	-3.69	-3.48	-4.77	-4.96
T-22	A	-2.64	-2.39	-3.48	-3.53	-4.01	-3.88
T-26	A	-2.68	-2.37	-3.75	-3.59	-4.06	-3.90
T-6	A	-2.89	-3.21	-3.65	-3.88	-5.38	-5.20
Camp_8	B	9.96	10.08	11.94	12.38	14.86	15.02
L-101	B	-3.98	-4.28	-5.68	-5.94	-7.40	-7.85
L-18	B	-3.26	-3.66	-4.26	-4.79	-5.18	-5.39
L-47	B	-11.05	-11.69	-13.64	-13.93	-15.56	-15.91
L-57	B	-8.36	-8.91	-10.23	-10.85	-13.29	-13.68
L-66	B	-11.19	-11.57	-13.89	-14.18	-16.66	-16.91
L-8	B	-5.06	-5.57	-6.32	-6.92	-9.47	-9.86
L-86	B	1.39	1.21	0.48	0.28	0.08	-0.24
M-10	B	-4.17	-4.38	-6.16	-6.85	-7.17	-7.50
M-8	B	-3.98	-4.33	-5.07	-5.37	-5.98	-6.44
N-12	B	11.14	11.56	12.15	12.44	14.32	14.29
N-16	B	12.96	13.13	14.73	14.35	16.42	16.17
P-50	B	-16.21	-16.64	-19.24	-19.51	-22.17	-22.41
T-15	B	-2.58	-2.88	-3.48	-3.67	-4.96	-5.13
T-22	B	-2.39	-2.60	-3.53	-3.23	-3.88	-4.03
T-26	B	-2.37	-2.19	-3.59	-3.77	-3.90	-4.16
T-6	B	-3.21	-2.46	-3.88	-4.08	-5.20	-5.36
Camp_8	C	10.08	10.35	12.38	12.95	15.02	15.47
L-101	C	-4.28	-4.57	-5.94	-6.27	-7.85	-8.24
L-18	C	-3.66	-4.13	-4.79	-5.22	-5.39	-5.71
L-47	C	-11.69	-11.99	-13.93	-14.17	-15.91	-16.23
L-57	C	-8.91	-9.29	-10.85	-11.03	-13.68	-13.84
L-66	C	-11.57	-11.89	-14.18	-14.83	-16.91	-17.29
L-8	C	-5.57	-5.99	-6.92	-7.25	-9.86	-10.17
L-86	C	1.21	1.04	0.28	0.37	-0.24	-0.57
M-10	C	-4.38	-4.84	-6.85	-7.13	-7.50	-7.96
M-8	C	-4.33	-4.84	-5.37	-5.75	-6.44	-6.80
N-12	C	11.56	11.15	12.44	12.58	14.29	14.38
N-16	C	13.13	13.06	14.35	14.57	16.17	16.36
P-50	C	-16.64	-16.89	-19.51	-19.57	-22.41	-22.37
T-15	C	-2.88	-3.13	-3.67	-3.74	-5.13	-5.48
T-22	C	-2.60	-2.27	-3.23	-3.56	-4.03	-4.32
T-26	C	-2.19	-2.46	-3.77	-3.98	-4.16	-4.43
T-6	C	-2.46	-2.76	-4.08	-4.30	-5.36	-5.55
Camp_8	D	10.35	10.84	12.95	13.26	15.47	15.95
L-101	D	-4.57	-4.15	-6.27	-5.98	-8.24	-7.71
L-18	D	-4.13	-3.79	-5.22	-4.79	-5.71	-5.10

L-47	D	-11.99	-11.54	-14.17	-13.95	-16.23	-16.03
L-57	D	-9.29	-9.72	-11.03	-11.40	-13.84	-13.65
L-66	D	-11.89	-11.26	-14.83	-15.03	-17.29	-17.83
L-8	D	-5.99	-5.43	-7.25	-7.64	-10.17	-10.08
L-86	D	1.04	0.92	0.37	0.12	-0.57	-0.98
M-10	D	-4.84	-4.43	-7.13	-6.86	-7.96	-7.49
M-8	D	-4.84	-4.21	-5.75	-5.52	-6.80	-6.42
N-12	D	11.15	11.42	12.58	12.77	14.38	14.57
N-16	D	13.06	13.35	14.57	14.62	16.36	16.44
P-50	D	-16.89	-16.34	-19.57	-19.32	-22.37	-22.16
T-15	D	-3.13	-2.74	-3.74	-3.50	-5.48	-5.88
T-22	D	-2.27	-2.15	-3.56	-3.40	-4.32	-4.57
T-26	D	-2.46	-2.36	-3.98	-3.84	-4.43	-4.68
T-6	D	-2.76	-2.55	-4.30	-4.16	-5.55	-5.40

Half Abstraction Scenario							
Well No.	**Time Phase**	**2015**		**2020**		**2025**	
		GWL_o	**GWL_f**	**GWL_o**	**GWL_f**	**GWL_o**	**GWL_f**
Camp_8	A	7.05	7.30	9.92	8.58	9.76	9.15
L-101	A	-1.59	-1.79	-0.94	-1.22	2.00	2.00
L-18	A	2.15	2.69	5.78	6.30	6.93	7.72
L-47	A	-4.27	-4.52	-2.76	-3.25	1.76	2.25
L-57	A	2.68	3.33	5.13	5.83	5.78	6.72
L-66	A	-5.78	-5.51	-4.99	-4.78	-5.20	-5.00
L-8	A	3.20	3.35	6.55	6.62	8.60	8.61
L-86	A	0.52	0.89	0.43	0.65	0.38	0.53
M-10	A	2.84	3.43	7.76	8.11	6.36	6.86
M-8	A	2.21	2.59	1.76	2.34	4.17	4.78
N-12	A	9.79	9.79	9.93	9.99	10.08	10.15
N-16	A	9.57	9.95	9.01	9.48	7.42	8.16
P-50	A	-8.91	-8.47	-8.98	-8.62	-8.89	-8.61
T-15	A	2.08	2.60	8.29	8.74	9.16	9.40
T-22	A	4.94	4.93	8.20	8.23	10.39	10.40
T-26	A	5.49	5.45	8.80	8.75	10.09	10.01
T-6	A	6.38	6.34	8.64	8.61	9.98	9.89
Camp_8	B	7.30	7.86	8.58	9.80	9.15	9.35
L-101	B	-1.79	-1.76	-1.22	-0.89	2.00	2.00
L-18	B	2.69	2.63	6.30	5.88	7.72	7.46
L-47	B	-4.52	-4.37	-3.25	-3.12	2.25	2.12
L-57	B	3.33	3.13	5.83	5.29	6.72	6.75
L-66	B	-5.51	-5.70	-4.78	-4.98	-5.00	-5.17
L-8	B	3.35	3.35	6.62	6.52	8.61	8.53
L-86	B	0.89	0.66	0.65	0.43	0.53	0.39
M-10	B	3.43	3.89	8.11	7.87	6.86	6.68
M-8	B	2.59	2.28	2.34	2.70	4.78	4.51
N-12	B	9.79	9.76	9.99	9.99	10.15	10.13
N-16	B	9.95	9.83	9.48	9.12	8.16	7.93
P-50	B	-8.47	-8.76	-8.62	-8.89	-8.61	-8.86
T-15	B	2.60	3.08	8.74	8.62	9.40	9.25
T-22	B	4.93	4.92	8.23	8.22	10.40	10.36
T-26	B	5.45	5.49	8.75	8.82	10.01	10.06
T-6	B	6.34	6.36	8.61	8.66	9.89	9.93
Camp_8	C	7.86	9.57	9.80	9.25	9.35	9.32
L-101	C	-1.76	-1.34	-0.89	-0.02	2.00	2.00
L-18	C	2.63	2.23	5.88	5.00	7.46	6.59
L-47	C	-4.37	-3.79	-3.12	-2.56	2.12	1.56
L-57	C	3.13	2.46	5.29	4.18	6.75	6.17

L-66	C	-5.70	-5.91	-4.98	-5.16	-5.17	-5.30
L-8	C	3.35	3.32	6.52	6.49	8.53	8.57
L-86	C	0.66	0.46	0.43	0.39	0.39	0.40
M-10	C	3.89	4.27	7.87	7.28	6.68	6.08
M-8	C	2.28	1.69	2.70	2.87	4.51	3.75
N-12	C	9.76	9.83	9.99	10.03	10.13	10.12
N-16	C	9.83	9.48	9.12	8.36	7.93	7.15
P-50	C	-8.76	-9.01	-8.89	-9.03	-8.86	-8.92
T-15	C	3.08	3.59	8.62	8.14	9.25	8.85
T-22	C	4.92	4.98	8.22	8.25	10.36	10.33
T-26	C	5.49	5.61	8.82	8.94	10.06	10.17
T-6	C	6.36	6.45	8.66	8.79	9.93	10.05
Camp_8	D	9.57	9.15	9.25	8.31	9.32	9.78
L-101	D	-1.34	-1.59	-0.02	-0.19	2.00	2.00
L-18	D	2.23	2.35	5.00	5.03	6.59	6.65
L-47	D	-3.79	-3.70	-2.56	-2.56	1.56	1.56
L-57	D	2.46	2.44	4.18	4.08	6.17	6.38
L-66	D	-5.91	-5.79	-5.16	-5.06	-5.30	-5.21
L-8	D	3.32	3.41	6.49	6.57	8.57	8.63
L-86	D	0.46	0.52	0.39	0.39	0.40	0.38
M-10	D	4.27	4.77	7.28	7.26	6.08	6.07
M-8	D	1.69	1.67	2.87	3.23	3.75	3.70
N-12	D	9.83	9.78	10.03	9.99	10.12	10.08
N-16	D	9.48	9.51	8.36	8.36	7.15	7.18
P-50	D	-9.01	-8.89	-9.03	-8.94	-8.92	-8.87
T-15	D	3.59	4.20	8.14	8.16	8.85	8.83
T-22	D	4.98	5.03	8.25	8.30	10.33	10.40
T-26	D	5.61	5.58	8.94	8.91	10.17	10.12
T-6	D	6.45	6.43	8.79	8.77	10.05	10.01