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Assessment of spatial representation of Groundwater monitoring and meteorological data in Gaza Strip

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ABSTRACT

The Groundwater aquifer in Gaza Strip (semi-arid region) is considered to be the sole source of water exploitation that is extensively deteriorated and may take long time to restore its fresh water conditions. For protecting the groundwater quality and quantity, understanding the data on spatial and temporal distribution of water quality, groundwater level, and rainfall (the only source of natural recharge) are very important. Geostatistics methods are one of the most advanced techniques for interpolation of groundwater related parameters. Accordingly, perceptive spatial variation in groundwater and climate representation is a key decision to many water resource management specialists. However, the most common sources of groundwater and climatic data in Gaza Strip are the domestic water wells including some of the monitoring wells and the meteorological/rainfall stations respectively.

This study examines some of the statistical approaches for interpolating both groundwater parameters represented by chloride concentration "and water level and climatic data represented by rainfall rates over Gaza Strip. It also provides a brief introduction to the applicable interpolation techniques for groundwater & climate variables for use in Water resources studies and in addition, draws recommendations for future research to assess interpolation techniques.

Basically, one of the problems which often arise in any hydrogeological studies is to estimate data at a given site because either the data are missing or the site is un-gauged or not accessible as Gaza Strip case. Such estimates can be made by spatial interpolation of data available at other sites. A number of spatial interpolation techniques are available today with varying degrees of complexity. In this study, different interpolation methods (IDW, Kriging, and Spline) were applied for predicting the spatial distribution of water quality and rainfall data generated for more than 170 domestic and monitoring water wells as well as 12 rainfall stations. Statistical investigations through normalization of data, modeling of semivariogram, examining powers, tuning smoothing factors were conducted. RMSE and/or R^2 were used to select the best fitted model for each interpolation method, and then cross-validation of the best fitted models was using two independent sets of data (modeling data and calibration data). The best method for interpolation was selected based on the lowest RMSE and the highest R^2.

Results showed that for interpolation of groundwater quality and water level, Kriging method is superior to IDW & Spline methods. In addition to that, the study recommended using Kriging method for the interpolation of the annual rainfall spatial variability unlike what is practiced locally. Finally, using the best fitted interpolation methods and GIS tools, prediction maps of groundwater parameters and rainfall data were prepared.

Keywords: GIS, Interpolation, spatial distribution models, groundwater quality, groundwater level, rainfall, Gaza Strip

ملخــص الدراســـة

يعتبر خزان المياه الجوفي في قطاع غزة (المنطقة شبه القاحلة) أحد المصادر الرئيسية لاستهلاك مياه الشرب وهو ذو نوعية متدهورة والذي قد يستغرق وقتا طويلا لاستعادة حالة المياه العذبة. و لحماية المياه الجوفية (من حيث النوعية وكمنسوب للمياه) وكميات الأمطار المناخية (مصدر المياه العذبة) فإن البيانات والمعلومات عن التوزيع المكاني والزماني لهذه المعايير تعتبر ذو أهمية خاصة. ولذلك فإن الإحصائيات الجيولوجية (Geostatistics) هلي واحدة من أكثر التقنيات تطورا لاستخراج وتمثيلالمعلومات والبيانات المكانية للمياه الجوفية (كنوعية ومنسوب المياه) ولكميات الأمطار المناخية. وبالتالي فإن إدراك التباين والتوزيع المكاني لنوعية ولمنسوب المياه الجوفية والتمثيل المناخي للأمطار هو أمر رئيسي لقرار كثير من المتخصصين في إدارة الموارد والمصادر المائية. وللعلم فإن مصدر المعلومات المشترك للمياه الجوفية والبيانات المناخية في قطاع غزة يأتي من الآبار بما في ذلك آبار المراقبة ومحطات الأرصاد الجوية.

هذه الدراسة تفحص بعض الأساليب الإحصائية لاستخراج كلا من معلومات المياه الجوفية (الكلور ومنسوب المياه) و البيانات المناخية "الأمطار" في قطاع غزة ، فضلا عن ذلك فالدراسة توفر مقدمة موجزة لتقنيات الاستخراج (Interpolation methods) للمياه الجوفية والمتغيرات المناخية للاستخدام في بحوث الموارد المائية ، وكذلك قدمت الدراسة بعض التوصيات لتقييم تقنيات وطرق المقارنة والتمثيل والتقييم ليتم استخدامها في المستقبل.

أحد المشاكل التي غالبا ما تنشأ في أي دراسات هيدروجيولوجية هو تقدير قيم البيانات في موقع معين، إما لأن البيانات مفقودة أو أن الموقع لا توجد به أدوات قياس أو هناك مناطق لا يمكن الوصول إليها كما في قطاع غزة. وهذه التقديرات يمكن أن يتم معرفتها عن طريقة الاستيفاء المكاني (Spatial Interpolation) للبيانات المتاحة و المقاسة في مواقع أخرى .هناك عدد من تقنيات الاستيفاء المكانية المتاحة اليوم مع درجات متفاوتة من التعقيد. في هذه الدراسة ، يوجد أكثر من طريقة تمثيل مكاني للبيانات كـ (IDW ، Kriging، Spline)، حيث تم استخدام الطرق المذكورة للتنبؤ بالتوزيع المكاني للبيانات لأكثر من 170 من آبار البلديات بالإضافة إلى آبار المراقبة و 12 محطة للأرصاد الجوية. بعد فحص وفرز وتقييم البيانات ، واستخدام أدوات تصحيح النمذجة التجريبية (semivariogram)، وتعديل معادلات القوة ومعيار الدقة ومعاملات السلاسة وبالتالي فإن أفضل نموذج معدل قد تم اختياره بناء على أقل قيمة للخطأ تم احتسابها لكل طريقة استخراج واستخدامه بعد ذلك. ثم عبر المقارنة والتقييم بين تلك الأسطح المكانية باستخدام مجموعتين مستقلتين للبيانات (بيانات للنمذجة و بيانات للمعايرة) وبالاستدلال عن مقدار الجذر التربيعي للخطأ واعلى قيمة ارتباط بين القيم المقاسة والقيم التي تم التنبؤ بها، فقد تم اختيار أفضل طريقة للتمثيل.

أظهرت نتائج الدراسة أن لتمثيل بيانات نوعية المياه الجوفية ومنسوبها مكانيا فإن استخدام طريقة Kriging هي أفضل من IDW و Spline. بالإضافة إلى أن الدراسة أوصت باستخدام Kriging لتمثيل التغير المكاني لكميات هطول الأمطار السنوي على عكس ما يحدث في قطاع غزة. أخيراً، وباستخدام طرق التمثيل التي تم اختيارها وبمساعدة نظم المعلومات الجغرافية، فقد تم إعداد الخرائط الخاصة بالتمثيل المكاني لمعلومات المياه الجوفية ومنسوب المياه الجوفية و الأمطار.

الكلمات الأساسية : نظم المعلومات الجغرافية ، الاستخراج ، نماذج التوزيع المكاني ، نوعية المياه الجوفية ، مستوى المياه الجوفية ، هطول الأمطار ، قطاع غزة.

DEDICATIONS

To my sincere father and my sincere mother for their unbounded kindness,

To my wife for her support and encouragement,

To my lovely son (Abdelkader) and lovely daughter (Batol),

To all of my brothers and sisters,

and to my friends and colleagues.

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CAMP	: Coastal Aquifer Management Program
Cl	: Chloride
CMWU	: Coastal Municipalities Water Utility
C^o	: Degrees Celsius
DEM	: Digital elevation models
EC	: Electrical conductivity
EQA	: Environment Quality Authority
ESRI	: Environmental Systems Research Institute
FAO	: Food & Agriculture Organization
GIS	: Geographic Information System
GS	: Gaza strip
ha	: 10.000 m^2
IAMP	: Integrated Aquifer Management Plan
IDW	: Inverse distance weighted
km^2	: Square kilometers
m/d	: meter per day
m^2/d	: square meters per day
m^3/d	: Cubic meter per day
m^3/yr	: cubic meters per year
MCM	: Million Cubic Meters
ME	: Mean error
mg/L	: Milligram Per Liter
Mm	: millimeters
MoA	: Ministry of Agriculture
MoH	: Ministry of Health
MOPIC	: Ministry of Planning and International Cooperation
MSL	: mean sea level
OK	: Ordinary Kriging
PCBS	: Palestinian Central Bureau of Statistics
PHG	: Palestinian Hydrology Group
ppm	: Part Per Million
PWA	: Palestinian Water Authority
RBF	: Radial Basis Functions
RMSE	: Root Mean Squared Error
SAR	: Sodium Adsorption Ratio
TDS	: Total Dissolved Solid
TH	: Total hardness
TIN	: Triangulated irregular networks
UNRWA	: United Nations Welfare Relief Agency
USAID	: U.S. Agency for International Development
UV	: Ultra Violet

WHO	: World Health Organization
WL	: Water Level

CHAPTER (1): INTRODUCTION

1.1 Background

Water is a precious, finite, and scarce resource in our region, and competition for water from industrial and domestic users continues to grow. No resource is more crucial than water, and no resource in Gaza Strip (GS) is surrounded by more controversy. Basically, groundwater "Coastal Aquifer" is the only source of fresh water in the Gaza Strip. Municipal groundwater wells are currently being used for drinking and domestic purposes while private wells are being used for irrigation not to mention the increasing number of household water wells.

The GS is one of the most densely populated areas in the world population of 1,480,000 inhabitants **(PCBS, 2007)** More than 90% of the population is connected to the municipal drinking water network while the other 10%, mainly rural or distant areas is dependent on the private wells.

Generally, GS is a semi arid area with an average annual rainfall ranging between 200-mm/ year in the southern part of the area and 400-mm/ year in the north. Ground water is the only source of water in GS, and many estimation of the annual groundwater recharge in the GS have been mentioned in different references. Although different values for this recharge are given, all of these references agree on one fact, that the annual recharge is less than the abstracted quantities for along time, resulting in a serious mining of the groundwater resources and a net deficit of about 30-40 Million cubic meters (MCM)/year. (**CMWU, 2008**)

In GS the only resource of water for domestic, industry and agriculture use is groundwater. Surface water is not considered as a source of water because Wadi Gaza has the run-off only in winter season and the Israelis turned the direction before it reaches the Palestinian boarder. There are an estimated 4000 wells within the GS. Almost all of these are privately owned and used for agricultural purposes. (**PWA, 2000b).**

Throughout the water studies implemented in GS at the beginning of 1994 and during the implementation of different management programs at especially via the Palestinian Water Authority (PWA) (in particular, Integrated Aquifer Management Plan study (IAMP) and related master plan studies in water and wastewater section, several software systems were used in for modeling, simulating, monitoring, and mapping different characteristics of Gaza aquifer parameters along with the meteorological data over the Gaza strip.

The success of these management programs and studies was primarily reliant on the quality and the quantity of data obtained and the associated monitoring system (data collection system). Monitoring system in GS consists of monitoring wells and networks that were established to characterize Gaza coastal aquifer on a quantitatively and qualitatively respects. The establishment of monitoring system was mainly prolonged during the IAMP study and Coastal Aquifer Management Program

(CAMP) implementation plan, as many wells were rehabilitated and utilized for monitoring issues **(IAMP, 2000).**

Currently, there are more than 140 wells (domestic) are now used in fresh groundwater abstraction, monitoring and data fetching, but before, that figure reached 600 wells (domestic and agricultural) in early of 2000 but due to many financial, technical, and political matters, the monitoring system was finally based on some of the above municipal wells and monitoring wells with total of 103 Wells **(CMWU, 2009).**

The obtained data from these domestic and monitoring wells were used in mapping the characteristics of Gaza groundwater subjected to water quality, water levels, groundwater flow, and recharge zones…etc to be used in formulating the strategic plans and required project needed for groundwater sustainability. The mapping output had been conducted by using Geographic Information System (GIS) based packages using ArcGIS ArcMap software.

Wise management, development, protection, and allocation of water resources is based on sound data regarding the location, quantity, quality, and use of water and how these characteristics are changing over time. The quantity and quality of available water varies over space and time, and is influenced by multifaceted natural and man-made factors including climate, hydrogeology, management practices, pollution…etc. As the foundation for water-resources decision-making, sound data must be continuous over space and time. (**PWA, 2000a**).

GIS applications were first used locally in the beginning of 1995 in different ministries for different purposes (planning, land use, urbanization, road networks …etc) but it was intensively utilized in 1997, in a study funded by the USAID titled as (IAMP), implemented through PWA and other institution with concern, where mapping the groundwater and demonstrating its characteristics was one of the core outputs of that study and a keystone for further groundwater prospected projects, spatial interpretation of Gaza Aquifer quality parameters (mainly Chloride and Nitrate), hydrogeological distribution analysis and other related monitoring issues.

1.2 Statement of the problem

It is worth mentioning that Groundwater quality mapping over extensive areas is the first step in water resources planning **(Todd, 1980).** So, data for generating the required mapping surfaces are usually collected through field sampling and surveying of the established collection system (domestic and monitoring wells). After conducting all required analyzing and screening processing, the resulted mapping output and existing situation representation for different groundwater parameters (e.g. chloride, nitrate and water levels) proved on long term of not having an accurate representation for the whole GS due to either lack of available data in some areas, error in the sampling process or false representation of data in some other areas in the GS, yet many issues were behind these representation problems;

1. Uncertainties concerning monitoring wells' records affect the spatial representation accuracy and efficiency where many locations with no available data.

2. High cost and limited resources availability, the data collection can be conducted only in selected point locations with limited numbers e.g. domestic and monitoring wells.
3. To generate a continuous surface of a property (i.e. groundwater table), some kind of interpolation methods have to be used to estimate surface values at those locations where no samples or measurements were taken.
4. To our knowledge, the evaluation of different interpolation methods and performance for higher accuracy has not taken place in any research or study about Gaza Strip.

An important part of groundwater modeling is the accuracy of input data such as hydraulic head and sink or source that should be assigned to each node of the network. On the other hand, in groundwater, due to aspects of time and cost, data monitoring (such as observation wells) is conducted at a limited number of sites. As a result, non-sampled values should be usually interpolated. Statistics based on spatial distribution, which is usually referred to as geostatistics, is a very useful tool for handling spatially distributed data (**Kholghi & Hosseini, 2008**).

1.3 Study Objectives

The main objective of this study is to evaluate the different interpolation method subjected to spatial representation of groundwater data and meteorological data in GS under the current collection monitoring system along with setting up recommendation for the best suited method for GS status.

Yet, this study has three primary objectives:

- To conduct comparative evaluation of the different interpolation methods and provide some insights on how these methods should be used properly to generate surface mapping for different sets of data under the existing monitoring programme.
- To recommend data managing and processing and provide suggestion as how the data set should be prepared and preprocessed prior to surface generation
- To optimize the interpolation methods or techniques examined in order to be utilized for accurate surface representation of areas with missing data points under the available data.

1.4 Study Methodology

1.4.1 Mobilization and Data collection phase;

- Mobilization of the required tools and software needed for study purpose and objectives.
- Communication with PWA, CMWU, Ministry of Agriculture (MoA), Ministry of Health (MoH), Meteo stations and others.
- Collection and review of all relevant literature, reports, and projects and any other documents pertaining to the study's objectives.
- Collection of Gaza Coastal Aquifer data and the historical data of different groundwater parameters for the last 8 years (i.e. 2000 - 2007). These data are chloride, and water levels along with meteorological rainfall parameter.

- Introducing the different interpolation methods used for surface mapping and a theoretical comparison is to be made.
- Interpreting different sets of data and its quantity-distance relationship to as basis for selection the appropriate interpolation method and to evaluation the distribution of the existing monitoring system.

1.4.2 Data Evaluation and Preparation phase;

- The collected data shall be evaluated and checked against its accuracy, recording, location, documentation and historical background.
- Pre-processing activities such as verifying, modifying, emerging, screening for the different collected data in order to be used for GIS based application.
- Data shall be in form of excel (tables), access (queries) office files and based shape GIS files and themes.

1.4.3 Spatial Analyst based GIS application and Output Modeling;

- The Major technique used in comparing the different interpolation methods adequacy and how spatially is speared in based GIS system.
- Converting different data themes and shape files into grid maps for purpose of calculations and value mapping output.
- Setting out the boundaries, different assumptions and margins of model output accuracy.
- Spatial Analyst based GIS application for each of selected parameter based on its data set arrangement and resulted surface mapping output.

1.4.4 Model investigation and verification;

- The resulted output surface mapping shall be investigated and verified for its validity and accuracy through comparing the output results with actual measured data from the field in different locations.
- Margins of accuracy and errors will be computed as criteria for final decision of recommended interpolation method using the correlation factor criteria.

1.4.5 Review of applied different interpolations;

- As a result, different interpolation models and mapping output shall be demonstrated and interpreted in detailed against the proposed following items;
  - Monitoring data set criteria.
  - Interpolation method used.
  - Model accuracy and investigation result.
  - Comparison tables, and images output.

1.4.6 Final Results review and demonstration;

- Finally the recommended interpolation method will be summarized describing factor of validation and obstacles to be overcome by optimizing the maximum correlation factor "R^2" and minimization of "RMSE".
- Exploring a relationship between the existing monitoring system and the needed spatial representation of different sets of groundwater data.
- Recommendation regarding the most applicable interpolation method under the existing monitoring system in GS and prospected improvements in terms of interpolation method, spatial distribution, and sampling issues.

1.5 Study Layout

The study layout as shown in Fig. 1-1, consists of the introductory work, background information about the status of the GS groundwater, As the problem is identified and stated with respect to the representation of the variables and what its rule in the decision making process under discussed scenarios and various options. The result of such discussions and scenarios are listed, analyzed and based on that conclusion, recommendations were followed with respect to the results.

Chapter one presents the introduction about GS aquifer condition and situation with regard to mapping and spatial representation. It also presents the problem definition, study justification, main goal and purposes of this study. Methodology and study outline.

Chapter two describes the GS area, its location, population, climate, and hydrology. The Project study area and its parameters were also addressed that will be used for more interpolation techniques exploration and mapping.

Chapter three reviews the literature related to the Geostatistics methods in addition to the different interpolation techniques for mapping the groundwater quality parameters and the meteorological data in GS.

Chapter four deals with the data sampled and collected, the process applied for dataset processing through screening, scheduling, correction, and finalization to be used later. The related interpolation analysis methods that have been followed in this study were addressed. Also there will be an introduction to the different processes that will be applied in each interpolation method. All related validation, cross validation and model fitting techniques were discussed and highlighted.

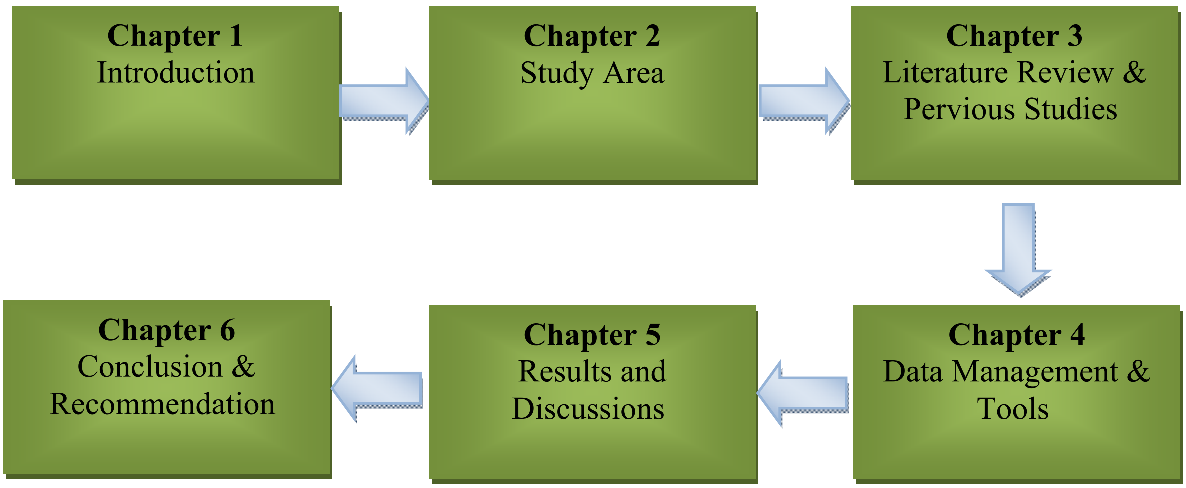


Figure 0-1. Disposition of the study

Chapter five presented the results and discussion, different interpolation methods (IDW, Kriging, and Spline methods) were applied for predicting the spatial distribution of the above data generated for more than 170 domestic and monitoring water wells & 12 meteorological stations. Statistical investigation through normalization of data, modeling of semivariogram, optimizing powers, and tuning smoothing factors were conducted. The least RMSE value was used to select the best fitted model for each interpolation method and the for next step process. Then cross-validation of the best fitted models was using two independent sets of data (modeling data and calibration data) where the lowest RMSE and the highest R^2, the best method for interpolation was selected. Results showed that for interpolation of Groundwater quality and water level Kriging method is superior to IDW & Spline methods. In addition the study recommended using the Kriging interpolation method interpolating annual climate rainfall spatial variability unlike what is practiced locally. Finally, using the best fitted interpolation methods and GIS tools, prediction maps of Groundwater parameters and rainfall data were prepared and compared among each other towards acceptable assessment of the current situation and hence correct decision being made aftermath.

Chapter six stated the conclusions and recommendations resulting from the study.

CHAPTER (2): STUDY AREA

2.1 Introduction

The Palestinian territories consist of the West Bank with approximately 5,800 km^2 and the GS with about 365 km^2. The West Bank area is made up of a hilly region in the West and the Jordan Valley in the East. The climate in the West Bank can be characterized as hot and dry during summer and cool and wet in winter. The GS has a Mediterranean climate and consists mainly of coastal dune sands, being located between the coast and the Negev and Sinai Deserts (**MOPIC, 1998**)

2.2 Location

The Gaza Strip (GS) is located at the south-eastern coast of the Mediterranean Sea as show in Fig. 2-1 below, on the edge of the Sinai Desert between longitudes 34° 2" and 34° 25" east, and latitudes 31° 16" and 31° 45" north. It has an area of about 365 km^2 and its longest width is about 45 m. (**MOPIC, 1998**)

The GS is confined between the Mediterranean Sea in the west, Egypt in the south and the 1950 Armistice line drawn by Rhodes Agreement of 1949 between the Arab States and Israel. Until 1948, the GS was part of Palestine under the British Mandate. From 1948 to 1967, it was under Egyptian administration (**Qahman, 2003**).

Figure 0-1. National Geographic location of GS (Courtesy of Wikipedia)

2.3 Population

GS is considered one of the most overpopulated areas all over the world. As it was stated, the area of GS is about 365 square kilometer with a population of 1,480,000 inhabitants most of them are refugees (**PCBS, 2007**). According to Palestinian bureau statistics council (**PCBS**) population growth rate in GS is 3.8 % which means that the available sources in GS are facing high threat. Moreover the unevenly distribution of population makes the problem of sources allocation more complicated.

Nowadays, Gaza city is the biggest population centre and has about 496,410 inhabitants. Gaza's other two main population centers are southern area (Khanyounis and Rafah) with population of 270,979, followed by northern area with 270,245 inhabitants **(PCBS, 2007).** Moreover Fig. 2-2 shows the population projection up to year 2025 in Gaza Strip which will impose a true challenge to PWA/CMWU and other utilities for providing adequate water.

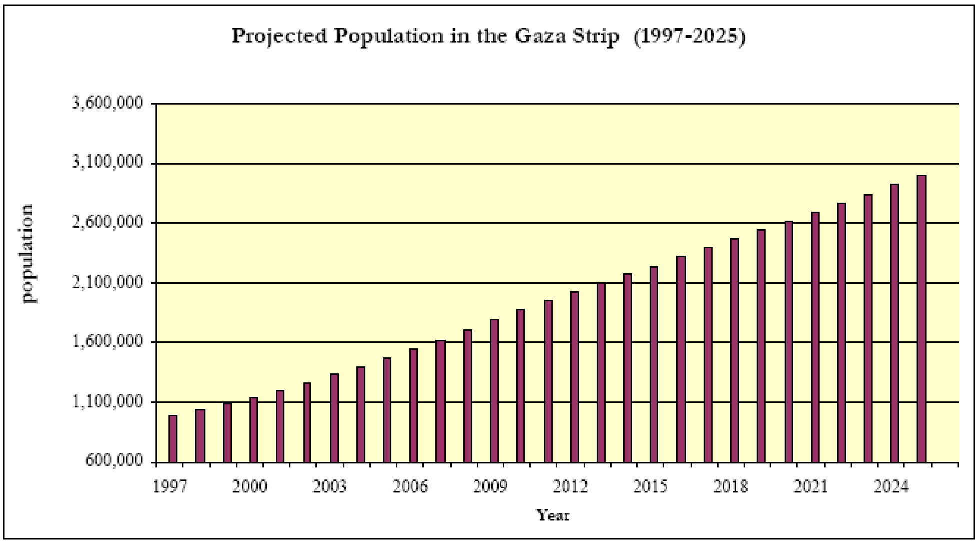


Figure 0-2. Projected population in the GS 1997 – 2025. (PCBS, 2007)

2.4 Climate

GS climate is typical Eastern Mediterranean with hot dry summers and mild winters. Temperature gradually changes throughout the year, reaches its maximum in August (summer) and its minimum in January (winter), the average monthly maximum temperature range from about 17.6 C° for January to 29.4 °C for August while the average monthly minimum temperature for January is about 9.6 °C and 22.7 for August. Gaza Northern area has the highest rainfall rate over GS as on average it has 429mm annually.

The average daily mean temperature ranges from 25 °C in summer to 13 °C in winter. Average daily maximum temperatures range from 29 °C to 17 °C and minimum temperatures from 21 °C to 9 °C in the summer and winter respectively. The daily relative humidity fluctuates between 65% in the daytime and 85% at night in the summer, and between 60% and 80% respectively in winter. The mean annual solar radiation amounts to 2200 J/cm^2/day **(Qahman, 2003).**

The GS is located in the transitional zone between the arid desert climate of the Sinai Peninsula in Egypt and the temperate and semi-humid Mediterranean climate along the coast. This fact could explain the sharp decrease in rainfall quantities of more than

200 mm/year between Beit-Lahia in the north and Rafah in the South of GS. **(Shahen, 2007)**

The rainfall data of the GS is based on the data collected from 12 rain stations. The average annual rainfall varies from 450 mm/yr in the north to 200 mm/yr in the south of the GS. Most of the rainfall occurs in the period from October to March, the rest of the year being completely dry.

2.5 Gaza Coastal Aquifer

The entire GS lies within the Coastal groundwater basin over the Coastal Aquifer. The Coastal Basin covers an area of 2,000 square kilometers as shown in Fig. 2-3, and is located in the Coastal Plain physiographic province. The Coastal Aquifer is comprised of water-bearing sand, sandstone, gravel, and conglomerate that typically overlie relatively impervious clay, marl, limestone, and chalk **(EXACT, 1998)**.

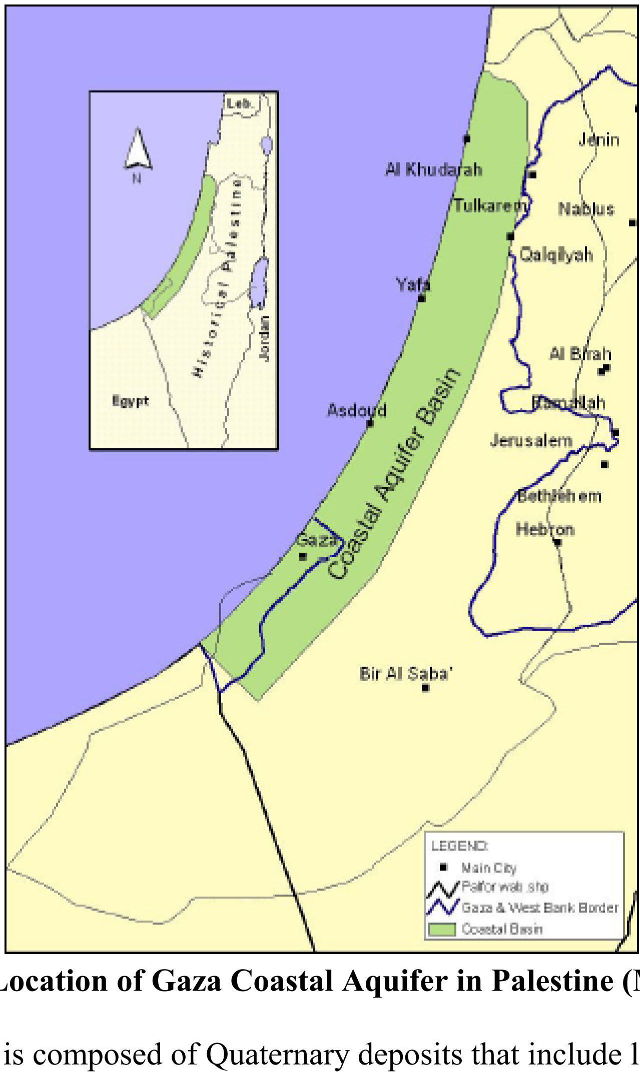


Figure 0-3. Location of Gaza Coastal Aquifer in Palestine (MEDA, 2007)

The Gaza aquifer is composed of Quaternary deposits that include layer of loess, dune sand, calcareous sandstone, silt, and clay. Clay layers, which begin at the coast and feather out approximately 4 km from the sea, separate the main aquifer into various sub-aquifers near the shore. The base of the aquifer is the low-permeability Saqiya Formation (Tertiary age), and approximately 1 km thick wedge of marine clay, shale, and marl. **(Qahman, 2001).**

The thickness of the saturated groundwater aquifer underneath the GS ranges from few meters in the eastern and south east of the GS to about 120- 150m in the west and along the Mediterranean Sea as shown in Figs. 2.4 and 2.5. The aquifer is mainly composed of unconsolidated sand stone known as Kurkar formation, which overlaying the impermissible layer called Saqiya formation which is considered as the bottom of the Gaza Coastal Aquifer with thickness varies from 800-1000m. The thickness of the unsaturated aquifer which is the overlaying part of the saturated groundwater aquifer ranges from 70–80m in the eastern and south-eastern part of the GS to about few meters in the western and along the coast.

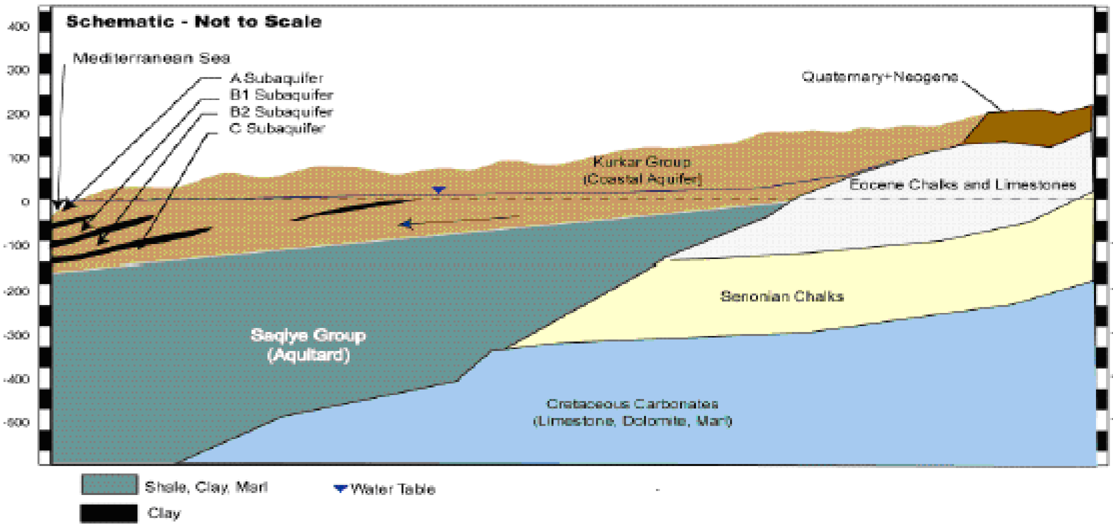


Figure 0-4. Schematic Drawing of Gaza Aquifer HydroGeologic Cross Section (CMWU, 2008)

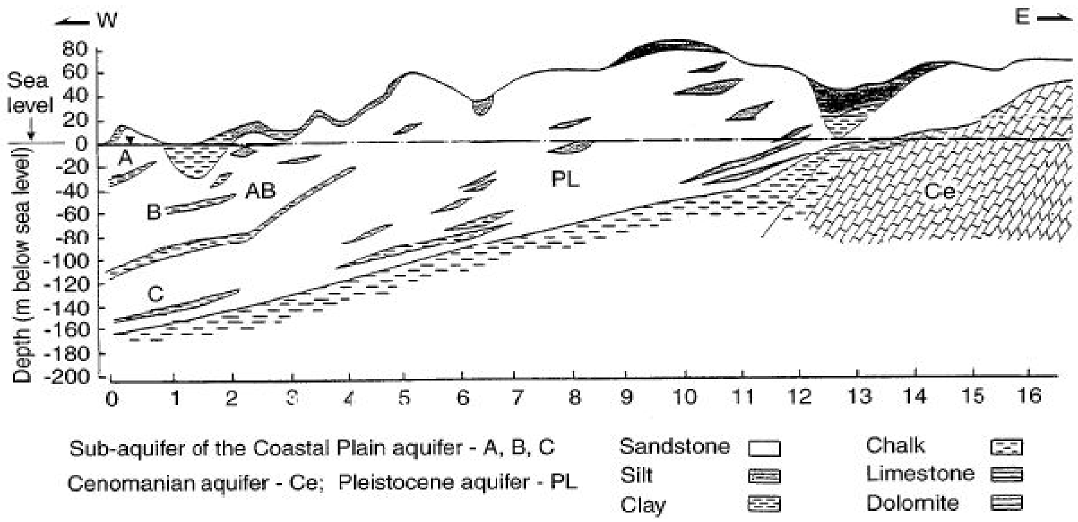


Figure 0-5. Section profile details sub-aquifers of the coastal aquifer (Baalousha, 2003)

Groundwater flows naturally from east to west. In the northern part of Gaza, water levels range from about 2 meters above mean sea level at the eastern border with Israel to mean sea level along the shore. In the southern part, the water level gradient is steeper, from about 10 meters above sea level near the eastern border to mean sea level along the shore. Municipal and agricultural pumping interrupts seaward flow. In some places, flow directions have been reversed as a result of over-pumping. The total estimated production pumping in 1996 was about 40 million m^3/yr from municipal wells supply and about 80 million m^3/yr from agricultural supply (irrigation). Extractions by Israeli settlements have been estimated to approach 10 million m^3/yr **(Qahman, 2001).**

The transmissivity values ranges between 700 and 5000 m^2/d. Corresponding values of hydraulic conductivity are mostly within a range of 20-80 m/d. Specific yield values are estimated to be about 15-30 % while specific storativity is about 10-4 from tests conducted in GS (**Metcalf & Eddy, 2000**).

2.6 GS Groundwater Characteristics

2.6.1 Quantity

The only source of water in GS is groundwater which is used for domestic, agricultural and agricultural consumption. In 2007 the total production of water in GS was 173 MCM; the domestic consumption was 85 MCM while the remaining 87MCM for the agriculture sector. 97.5 % of this quantities produced by water wells while 2.5% was imported from Israel Company called Mekerot (**PCBS, 2007**).

The coastal aquifer holds approximately 5000×106 m^3 of groundwater of different quality. However, only 1400×106 m^3 of this is "freshwater", with Chloride (Cl^-) content of less than 500 mg/l. This fresh groundwater typically occurs in the form of lenses that float on the top of the brackish and/or saline groundwater. That means approximately 70% of the aquifer are brackish or saline water and only 30% are fresh water found mainly in the Northern Governorate. The lateral inflow from the GS borders to the aquifer is estimated at between 18 to 30 ×106 m^3/y. Some recharge is available from the major surface flow (Wadi Gaza). However, the extraction from Wadi Gaza, in Israel, limits this recharge to 1.5 to 2 ×106 m^3. As a result, the total freshwater recharge at present is limited to approximately 56 to 62×106 m^3/y **(Metcalf & Eddy, 2000)**.

The aquifer is recharged mainly by rainfall and other minor sources such as leakage of water system, irrigation return flow, and wastewater discharge. The average annual rainfall in the GS varies between 500 mm in the north to 200 mm in the south. Thus, the average annual rainfall in the GS based on 20 years average is 320 mm y-1. The total amount of groundwater recharge from rainfall is about 43 million m^3 per year (**Baalousha, 2005).**

According to Metcalf and Eddy 2000 study**,** the irrigation return flow in the GS varies between 20 and 25 million m^3. The available groundwater quantity could be identified if the saturated aquifer reservoir thickness is known in addition to the hydrological parameters of the aquifer such as effective porosity. The area of the groundwater reservoir is limited to the area of the political border of the GS. The area where the groundwater quantity less than 250mg/L is about 44.8 km^2, and with an effective porosity of 20%, also with a saturated groundwater ranging from 10 to 50m, hence the stored fresh groundwater quantity is ranging from 100MCM to 450MCM. In previous studies in year 2000, the same calculation has been performed where the groundwater quantity was ranging from 450MCM to 600MCM, which led to a depletion of about

250MCM from freshwater since year 2000. It is observed that the domestic and industrial usage were about 83MCM (**CMWU, 2008**).

2.6.2 Quality

The groundwater quality is monitored through all municipal wells and some agricultural wells distributed all over the GS. The agricultural monitoring wells are tested against chloride and nitrate ions twice a year by the MoA, while the municipal wells are monitored through all the cations and anions twice a year with the cooperation of both MoH and CMWU. The groundwater quality is varies from place to another and from depth to another as presented in Fig. 2-6 below.

The chloride ion concentration varies from less than 250mg/l in the sand dune areas as the northern and south-western area of the GS to about more than10,000 mg/l where the seawater intrusion has occurred (**CMWU, 2008**).

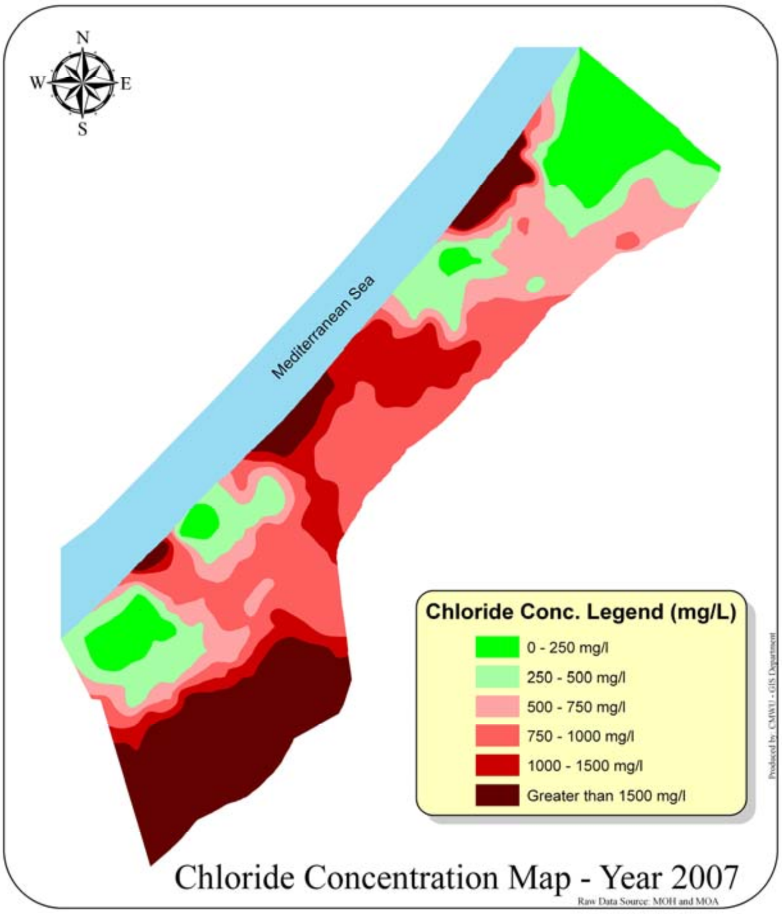


Figure 0-6. Spatial Chloride concentration in GS for the year 2007 (CMWU, 2008)

Quality of the groundwater is a major problem in GS. The aquifer is highly vulnerable to pollution. The domestic water is becoming more saline every year and average chloride concentrations of 500 mg/l or more is no longer an exception. The permissible limits for nitrate are exceeded by a factor of eight for a number of public wells. Most of the public water supply wells don't comply with the drinking water quality standards and concentrations of chloride and nitrate of the water exceed the World Health Organization (WHO) standards in most drinking water wells of the area and represent the main problem of groundwater quality. Over pumping of groundwater and salt water intrusion are the main reasons behind high chloride concentration **(CAMP, 2000).**

Figure 2.7, shows the variation of the concentration of chloride parameter in mg/l for the municipal wells operated in Gaza Strip.

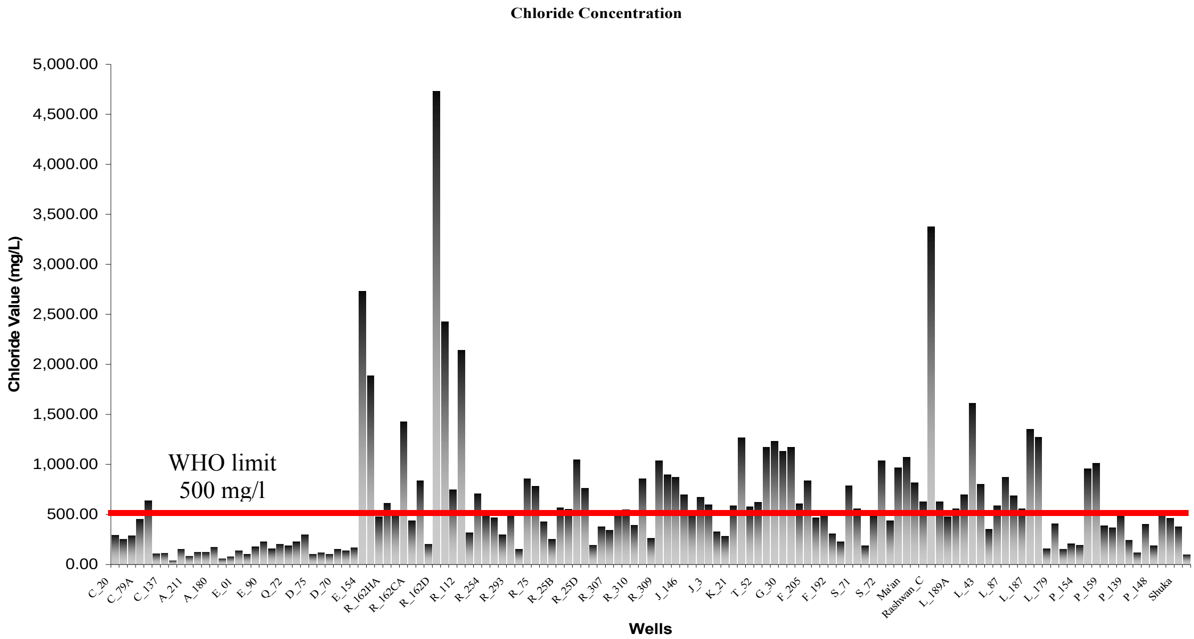


Figure 0-7. Chloride concentration in 2008 for municipal wells in GS

Moreover, it is worth mentioning that Groundwater quality in the Gaza aquifer is generally poor. Over-exploitation has resulted in saltwater intrusion and up-coning. In most areas of Gaza, a slow, continuing decline in groundwater levels has been observed since the mid-1970s **(Qahman, 2003).**

Thus, the uncontrolled discharge of untreated sewage to the ground surface and excessive use of fertilizers led to high nitrate levels in certain areas. With the limited rainfall and high evapotranspiration of the GS it may take long time to restore fresh water conditions in the aquifer (**EQA, 2004**).

Which take us to the point that the water quality in Gaza is affected by many different water sources including soil/water interaction in the unsaturated zone due to recharge and return flows, mobilization of deep brines, sea water intrusion or upconing and disposal of domestic and industrial wastes into the aquifer (**Ghabayen et al. 2006**)

2.6.3 Water Level

The groundwater elevation map in Fig. 2-8 below with respect to the mean sea level (MSL) shows two sensitive areas for groundwater depression; the north and the south areas. As the groundwater level elevation drops 3m in the north and more than 12m in the south below mean sea level. This drop in the groundwater will led to lateral invasion of seawater due to pressure difference and direct contact with the aquifer, and also vertical invasion from deep saline water (**CMWU, 2008).**

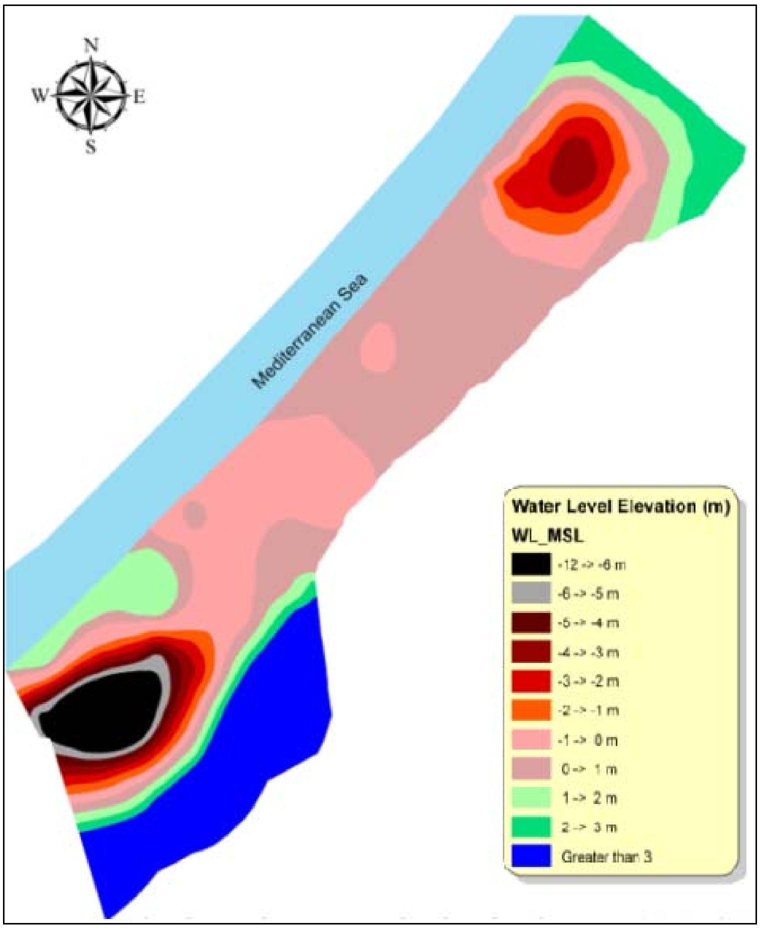


Figure 0-8. Spatial Water Level Elevation in GS for year 2007 (CMWU, 2008)

The extraction from coastal aquifer is almost twice the available recharge that has resulted in dropping the water level by 20-30 cm per year **(PWA, 2003).** In general term, the water level in Gaza Aquifer dropped on average of 1.6 meters per year, but mostly in the south (**Rabi, 2008).**

As quoted, the active wells are shallow wells and typically their screens are 10-20 m below the water table. Of these wells, about 140 agricultural wells and 39 piezometric wells are presently used to monitor the water levels every month. The agriculture wells of about 10 inches diameters are used as water level monitoring wells. The total depth of most of the wells is not defined clearly. Generally, the total penetrated saturated thickness of these wells is ranging between 30 and 40 m. Most of the piezometric wells are located mainly along the coastal zone and range in depth from 20 to 200 m. Many of these wells have screens at different depths. The piezometric wells have deteriorated and many of these wells have been damaged. **(Mogheir, 2003).**

Figure 2.9 shows clearly the drop in water level in meters with respect to MSL considerably in the monitoring and some of the municipal wells for year 2007

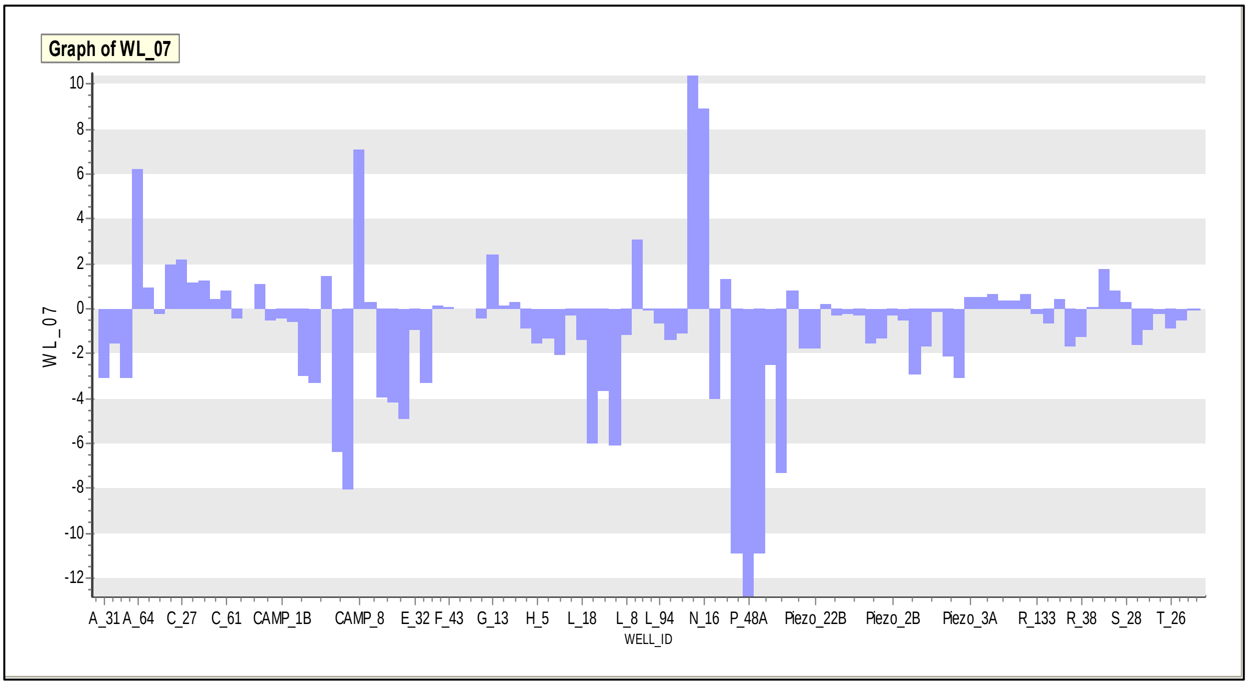


Figure 0-9. Water Level Elevation for Municipal Wells in GS for year 2007

2.6.4 Meteorological Data / Rainfall

Rainfall is a main component for charging and renewal of groundwater resources in the GS. Estimation of rainfall data is necessary in many natural resources and agricultural studies **(Chegini, 2001)**.

Rainfall is one of the most important parts of the water resource. It is an essential component of scientific investigation of the hydrologic cycle. The pattern and the amount beside the intensity of rainfall are the most important factors that directly affect to groundwater balance and replenishment **(PWA, 2007)**.

Rainfall in GS is the main source of groundwater recharge area. The area is located in the semi-arid zone and there is no source of recharge other than rainfall therefore a detailed knowledge of rainfall regime and its distribution is a perquisite for water resources planning and management in GS.

Considering the amount of rainfall quantity is about 110MCM/year, where part of that is feeding the groundwater aquifer through natural recharging process. The recharge rate is varying in accordance to the soil porosity and the thickness of the unsaturated zone that overlaying the groundwater aquifer. Previous studies showed that the recharge rate is about 25% in the low porous area like the eastern part of the GS, and about 75% in porous area where the sand dunes are still found in the north and south of the GS. Also the rainfall intensity plays an important role in the recharge quantity to the aquifer **(CMWU, 2008)**

The long term average recharge is considered to be 40% of the whole rainfall quantity **(PWA, 2005).**

In GS there are 12 manual rainfall stations distributed through different governorates as shown in Fig.2-10. Data from these stations are collected on a daily basis, these stations are operated by ministry of agriculture and data obtained from these stations are entered manually in Palestinian water authority database.

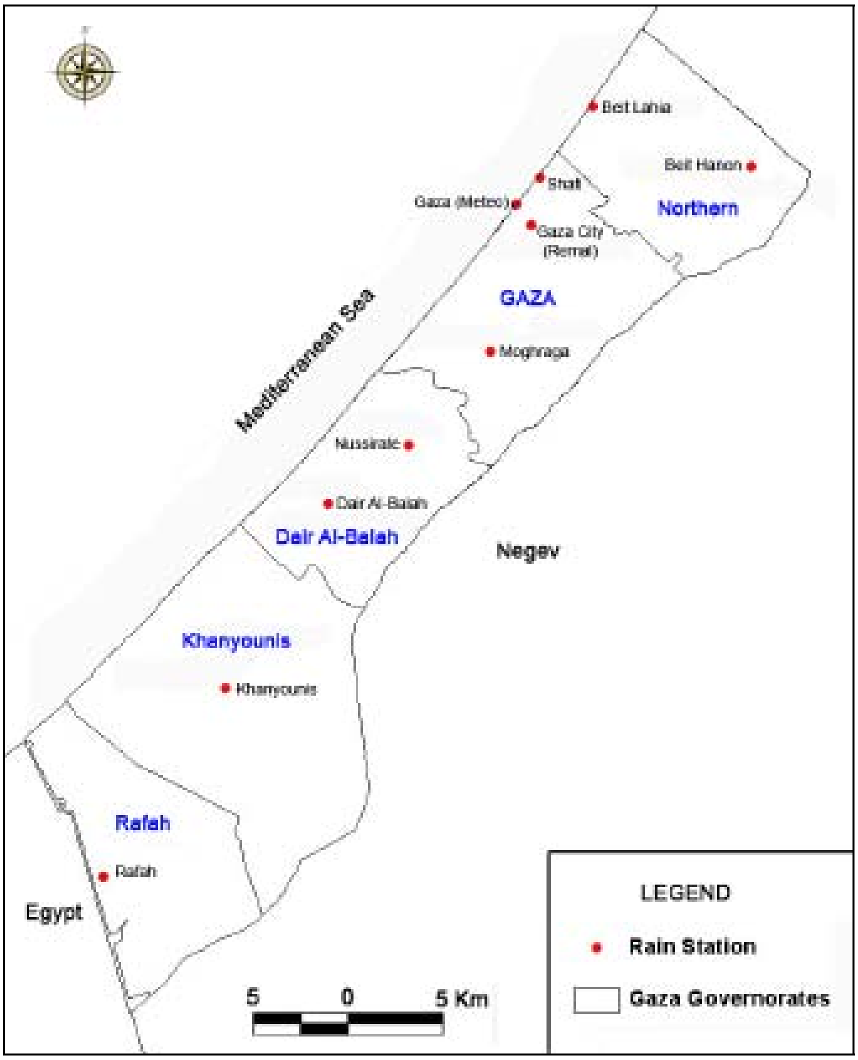


Figure 0-10. Location of rain gauging stations within in GS (Hallaq, 2008)

In 2006-2007 season, the average rainfall depth over GS area is estimated about 364.7 mm with total amount 133.1 MCM received through 46 rainy days. Despite of the small area of GS (365km^2), the level of rainfall varies significantly from one area to the next with an average seasonal rainfall of 521.9 mm in north area (north governorate), to 225 mm in the southern area (Rafah governorate) **(PWA, 2007)**, Only 60 MCM was infiltrate into the ground aquifer while the total abstracted quantity was 166MCM **(PCBS, 2007).**

CHAPTER (3): LITERATURE REVIEW

3.1 Introduction

A Geographical Information System "GIS" is defined as “an organized collection of computer hardware, software, geographic data, and personnel designed to efficiently capture, store, update, manipulate, analyze, and display all forms of geographically referenced information”. GIS technology has been widely used in various fields, such as agriculture, business geographic, ecology, electricity and gas, emergency management and public safety, environmental management, forestry, health care, education, mining and geosciences, real estate, remote sensing, telecommunications, transportation and water distribution and resources **(ESRI, 1992).**

In addition, GIS is a system of hardware, software, data, people, organizations and institutional arrangements for collecting, storing, analyzing and disseminating information about areas of the earth. (**Dueker & Kjerne, 1989**)

Thus, accurate and reliable groundwater resource information is critical to planners and decision-makers at all levels of government, researchers, developers and the business community (**Shivraj & Jothimani, 2002**).

With the advent of Geographical Information Systems (GIS) has added new vistas in the field of ground water resources mapping and management. It helps in the integrating remotely sensed derived data with ancillary data to have more precise and correct information about various factors involved in the ground water resources management. **(Toleti & Chaudhary, 2000).**

The last decade has seen a phenomenal growth in the use of remote sensing and GIS technology in ground water studies as the ground water has become the most sought after natural resources by the mankind due to tremendous pressure on the ground water system by the ever-increasing population and individual growth **(Srivastav & Ahmed, 2003).**

By adopting a GIS platform the result obtained will be faster and more accurate. Till recently, ground water assessment was based on laboratory investigation, but the advent of Satellite Technology and GIS has made it very easy to integrate various databases. Groundwater is a most important natural resource required for drinking, irrigation and industrialization. The resource can be optimally used and sustained only when quantity and quality of groundwater is assessed. It has been observed that lack of standardization of methodology in estimating the groundwater and improper tools for handling the same, leads to miscalculation of estimation of groundwater **(Kharad & Rao, 1999)**

Assessing groundwater parameters and determination of its characteristics on a spatial scale is an essential prerequisite to understand and to mitigate any economical and social impacts. The main coupling aspect of water availability and water use/management is achieved by balancing the water resources available for water use. Thus it is really important to understand the condition and the status of groundwater parameters and to be distinguished.

The use of geographic information system (GIS) and remote sensing to facilitate the estimation of hydrologic parameters for watersheds has gained increasing attention in recent years. This is mainly due to the fact that hydrologic models include both spatial and geomorphic variations. GIS technology provides suitable alternatives for efficient management of large and complex databases (**Melesse et al, 2002**).

Several studies have been done to incorporate GIS in hydrologic modeling of watersheds. These studies have different scopes and can be generally grouped into four categories. Computation of input parameters for existing hydrologic models is the most active area in GIS related hydrology (**Djokic & Maidment, 1991; Olivera & Maidment, 1999).** Hydrologic assessment refers to the mapping and display in GIS of hydrologic factors that pertain to some situation **(Ragan & Kossicki, 1991)**. Measuring the spatial extent of hydrologic variables from paper maps may be tedious, labor-intensive and error prone. Watershed surface mapping refers to the uses of GIS in representation of watershed surface through the use of digital elevation model and girded geographic data (**Sasowsky & Gardner, 1991; Smith & Brilly, 1992**).

The application of any hydrologic model requires efficient management of large spatial data. This is done by integrating watershed simulation models and GIS which generates the capacity to manage large volumes of data in a common spatial structure (**Al-Sabhan et al, 2003).**

3.2 GIS Applications in Water Management

Good quality societal and technical information is a pre-requisite for successful integrated water management **(GWP, 2000).** Many studies have shown that GIS can play a very important role in water management in aspects that include analysis and presentation of societal and technical information, identifying the root causes of problems and planning activities and interventions aimed at solving these problems **(Rama et al, 2003).**

Theoretically, in GIS applications for water sector, generating surfaces is a frequently imposed requirement in the early stage of analyses. Topographic surfaces, bedrock surfaces, groundwater tables, and contamination plumes are examples of surfaces which need to be generated from available data sources. The importance of generating these surfaces is that these surfaces are used as the basic information to perform further spatial analyses in environmental applications. Based on these surfaces, we can carry out additional analyses to answer questions such as what is the water level here or there, or how the contamination is distributed in subsurface soil. Thus, the accuracy of subsequent analyses directly depends on the accuracy of the surfaces built in the early stage of analyses.

GIS applications for the water industry started evolving in the late 1980s. In the early 1990s, the water industry had started to use GIS in mapping, modeling, facilities management, and work-order management for developing capital improvement programs and operations and maintenance plans (**Morgan & Polcari, 1991).**

In the mid-1990s, GIS started to see wide applicability to drinking water studies. Potential applications identified at that time included **(Schock & Clement, 1995):**

- GIS can provide the basis for investigating the occurrence of regulated contaminants for estimating the compliance cost or evaluating human health impacts.
- Mapping can be used to investigate process changes for a water utility or to determine the effectiveness of some existing treatment such as corrosion control or chlorination.
- GIS can assist in assessing the feasibility and impact of system expansion.
- GIS can assist in developing wellhead protection plans.

GIS technology has eased previously laborious procedures. Exchange of data between GIS, CAD, supervisory control and data acquisition (SCADA), and hydrologic and hydraulic (H&H) models is becoming much simpler. For example, delineating watersheds and stream networks has been simplified and the difficulty of conducting spatial data management and model parameterization reduced **(Miller et al., 2004).**

The GIS assisted database system would help to apply groundwater management practices such as; proper groundwater resource management in terms of groundwater quality & quantity, Integrated management of water, land use and the environment; to optimize pumping rates with respect to the capacity of the aquifer system, and to prevent groundwater quality deterioration through proper monitoring & evaluation **(Maruo, 2004).** Yet GIS technology has played critical roles in all aspects of watershed management, from assessing watershed conditions through modeling impacts of human activities on water quality and to visualizing impacts of alternative management scenarios **(Tim & Mallavaram, 2003).**

Representation and analysis of water-related phenomena by GIS facilitates their management. GIS applications that are of particular importance to water industry professionals are: mapping, monitoring, modeling, and maintenance **(Shamsi, 2005).**

The GIS has the ability to store, arrange, retrieve, classify, manipulate, analyze and present huge spatial data and information in a simple manner Application of GIS and Remote Sensing Techniques in Identification, Assessment and Development of Groundwater Resources. **(Howari et al., 2007).**

GIS provides a common framework – spatial location – for watershed management data obtained from a variety of sources. Because watershed data and watershed biophysical processes have spatial dimensions, GIS can be a powerful tool for understanding these processes and for managing potential impacts of human activities. The modeling and visualization capabilities of modern GIS, coupled with the explosive growth of the Internet and the World Wide Web, offer fundamentally new tools to understand the processes and dynamics that shape the physical, biological and chemical environment of watersheds. The linkage between GIS, the Internet, and environmental databases is especially helpful in planning studies where information exchange and feedback on a timely basis is very crucial and more so when there are several different agencies and stakeholders involved. **(Tim & Mallavaram, 2003).**

At the highest level of technology, a GIS can provide a spatial database of information to support modeling of phenomena. The GIS supplies the spatial data in a form that can be input to deterministic or statistical models. The spatial power of the GIS database is used in full by the model, and more detailed and spatially averaged results are produced. This represents a high level of integration and achievement that is now seen in the industry. It has taken a while for such applications to develop, however. This is due to the absence of spatially integrated models for water resource phenomena. Many models use spatial data but average or summarize these data by watershed and/or sub-watershed, and thereby lose much of the detail of spatial variability that often influences phenomena. This is the same level of detail necessary to provide high quality model simulations. In general, the strength of GIS is that it is possible to process the data sets using any type of numerical analysis procedure. In particular, certain procedures are valuable for data visualization and analysis, including image processing techniques, virtual reality, and simulation modeling. **(Naamani, 2002).**

As we can finally summarize it as the integrating capabilities of a GIS can provide an interface to translate and emulate the complexities of a real world system within the confines of a digital world accurately and efficiently **(Tim & Mallavaram, 2003).**

In Gaza Strip, new technique about the integration of applications of geographic information systems and Water Information System in the PWA Offices in Gaza Strip and West Bank which have been used to provide information in water resource management, Licenses Management and Technical issues.

The contribution of geographic information system is mainly focus on generation, management, and delivery of spatially distributed data, in Gaza Strip. PWA spatial data vision is building of layers for various water related features its input values from oracle database and connected completely with GIS as shown in Fig. 3-1. GIS was useful in Management of large data sets as GIS proved to be efficient in managing large amounts of Water data. **(Obaid, 2007).**

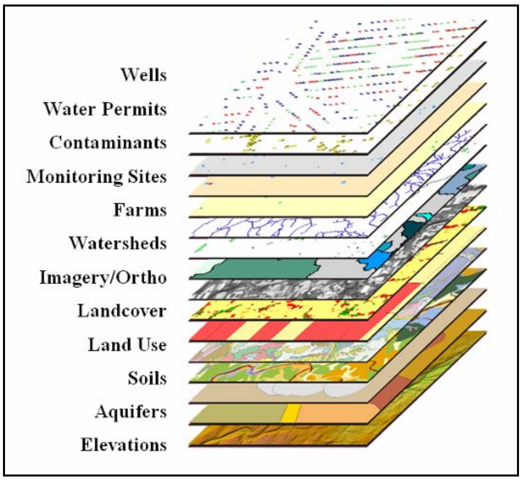


Figure 0-1. Several layers used in GIS application in GS by PWA (Obaid, 2007)

3.3 GIS Interpolation Techniques

Often geographic data are sampled at various locations, rather than a complete census, because of time or money constraints. To create a surface from sampled data, that is to estimate the values at all non-sampled locations, one needs to interpolate. There is a variety of interpolation methods, but all make use of the First Law of Geography, that things closer together tend to be more similar than those farther away **(Theobald, 2007)**.

Interpolation is the process by which a surface is created, usually a raster dataset, through the input of data collected at a number of sample points. There are several forms of interpolation, each which treats the data differently, depending on the properties of the data set. In comparing interpolation methods, the first consideration should be whether or not the source data will change (exact or approximate). Interpolation is a justified measurement because of a Spatial Autocorrelation Principle that recognizes that data collected at any position will have a great similarity to, or influence of those locations within its immediate vicinity. Digital elevation models (DEM), triangulated irregular networks (TIN), Edge finding algorithms, Theissen Polygons, Fourier analysis, Weighted moving averages, Inverse Distance Weighted, Moving averages, Kriging, Spline, and Trend surface analysis are all mathematical methods to produce interpolative data **(Wikipedia, 2009a).**

GIS based packages, offers several interpolation methods for creating surfaces. These methods include but not limited to: trend surface (trend), inverse distance weighted (IDW), triangulation, Kriging and others. Each of these methods has its own advantages and disadvantages in terms of data interpolation processing. None of these method works universally as the best for all the data set. Selection of a particular method depends on the distribution of data points and the study objectives (**Jun, 2001**).

Spatial interpolators may be used to estimate values at non-sampled sites. Spatial interpolation can also be used when preparing irregularly scattered data to construct a contour map or contour surface, which is a two-dimensional representation of a three dimensional surface. All spatial interpolation methods investigated accept irregularly scattered data and can create a regular grid of interpolated points amenable to contouring.

Methods that produce smooth surfaces include various approaches that may combine regression analyses and distance-based weighted averages. As explained in more detail below, a key difference among these approaches is the criteria used to weight values in relation to distance. Criteria may include simple distance relations (e.g., inverse distance methods), minimization of variance (e.g., Kriging and cokriging), minimization of curvature, and enforcement of smoothness criteria (splining). On the basis of how weights are chosen, methods are “deterministic” or “stochastic.” Stochastic methods use statistical criteria to determine weight factors **(Hartkamp et al., 1999).**

Interpolation methods can also be described as “global” or “local.” Global techniques (e.g. inverse distance weighted averaging; (IDWA) fit a model through the prediction variable over all points in the study area. Typically, global techniques do not accommodate local features well and are most often used for modeling long-range variations. Local techniques, such as splining, estimate values for a non-sampled point from a specific number of neighboring points. Consequently, local anomalies can be accommodated without affecting the value of interpolation at other points on the surface (**Burrough, 1986**). Splining, for example, can be described as deterministic with a local stochastic component (**Burrough & McDonnell, 1998**).

In ArcGIS Geostatistical Analyst, it provides a variety of interpolation methods for the creation of an optimal interpolated surface from your data. A friendly wizard helps you through the interpolation process. There are two main groupings of interpolation techniques: deterministic and Geostatistical. Deterministic interpolation techniques are used for creating surfaces from measured points based on either the extent of similarity (e.g., Inverse Distance Weighted) or the degree of smoothing (e.g., Radial Basis Functions). Geostatistical interpolation techniques are based on statistics and are used for more advanced prediction surface modeling, which also includes error or uncertainty of predictions **(ESRI, 2000).** Fig 3.2 below shows different spatial representation through applying different interpolation method.

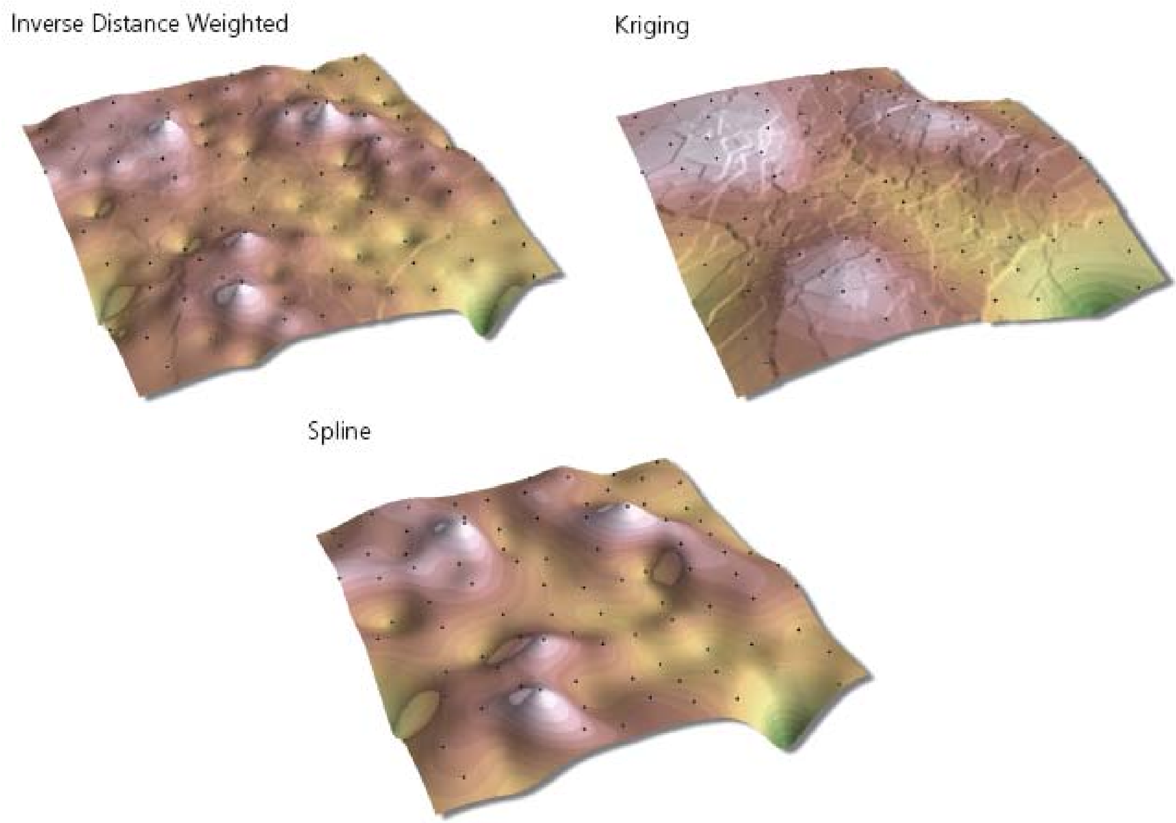


Figure 0-2. Different applied Geostatistical application in GIS (ESRI, 2009a)

Surface interpolation functions create a continuous (or prediction) surface from sampled point values. There is a variety of ways to derive a prediction for each location; each method is referred to as a model. With each model, there are different assumptions made of the data, and certain models are more applicable for specific data—for example, one model may account for local variation better than another. Each model produces predictions using different calculations **(ESRI, 2009a).**

Main commonly used interpolation methods can be summarized as following;

3.3.1 Trend Surface

The linear trend surface interpolator creates a floating-point grid as shown in Fig. 3-3. It uses a polynomial regression to fit a least-squares surface to the input points. It allows the user to control the order of the polynomial used to fit the surface. Trend interpolation is easy to understand by considering a first-order polynomial **(Naoum & Tsanis, 2004).**

The idea behind the trend surface interpolation is to fit a least-squares surface to observational data points by using polynomial regression. The advantage of this method is that it is superficially easy to understand, at least with respect to the way the surfaces are estimated.

It can be used to show broad features of the observational data points, such as the overall flow direction of groundwater **(Jun, 2001).**

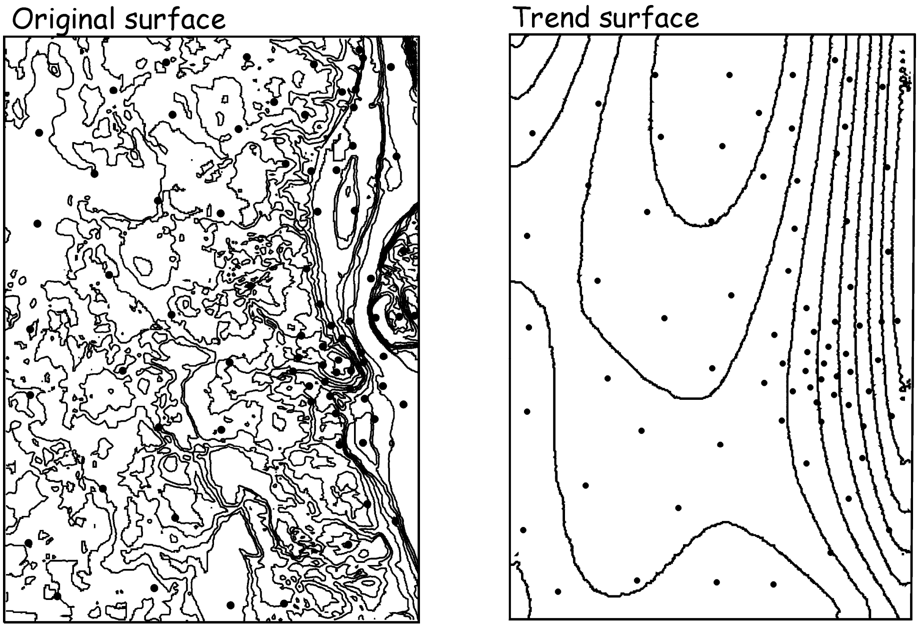


Figure 0-3. Spatial representation with Trend Surface method

3.3.2 Inverse Distance Weighted

IDWA is a deterministic estimation method whereby values at non-sampled points are determined by a linear combination of values at known sampled points **(Hartkamp et al., 1999).**

In this interpolation method, observational points are weighted during interpolation such that the influence of one point relative to another declines with distance from the new point. Weighting is assigned to observational points through the use of a weighting power that controls how weighting factors drop off as the distance from new point increases. The greater the weighting powers, the less effect points far from the new point have during interpolation. As the power increases, the value of new point approaches the value of the nearest observational point **(Jun, 2001).**

The inverse-distance weighted procedure is versatile, easy to program and understand, and is fairly accurate under a wide range of conditions **(Lam, 1983).** Using this method, the property at each unknown location for which a solution is sought is given by:

$$P_i = \frac{\sum_{j=1}^{G} P_i / D_{ij}^n}{\sum_{j=1}^{G} 1 / D_{ij}^n})$$

Where P_i is the property at location i; P_j is the property at sampled location j; D_{ij} is the distance from i to j; G is the number of sampled locations; and n is the inverse-distance weighting power.

The value of n, in effect, controls the region of influence of each of the sampled locations. As n increases, the region of influence decreases until, in the limit, it becomes the area which is closer to point i than to any other. When n is set equal to zero, the method is identical to simply averaging the sampled values. **(Watson & Philip, 1985).**

The interpolation technique used in the analysis is inverse distance weighted (IDW) method. IDW is an algorithm for spatially interpolating, or estimating values between measurements. Each value estimated in an IDW interpolation is a weighted average of the surrounding sample points. Weights are computed by taking the inverse of the distance from an observation's location to the location of the point being estimated (**Burrough & McDonnell, 1998).**

The IDW method is fast, easy to implement and easily "tailored" for specific needs. The method allows anisotropy in the source data. Ancillary data cannot be incorporated. Measure of success is through cross validation. There is no extrapolation: all interpolated values are within the range of the data points **(De Smith et al., 2007).** Fig. 3-4 shows the spatial representation of a surface using IDW interpolation.

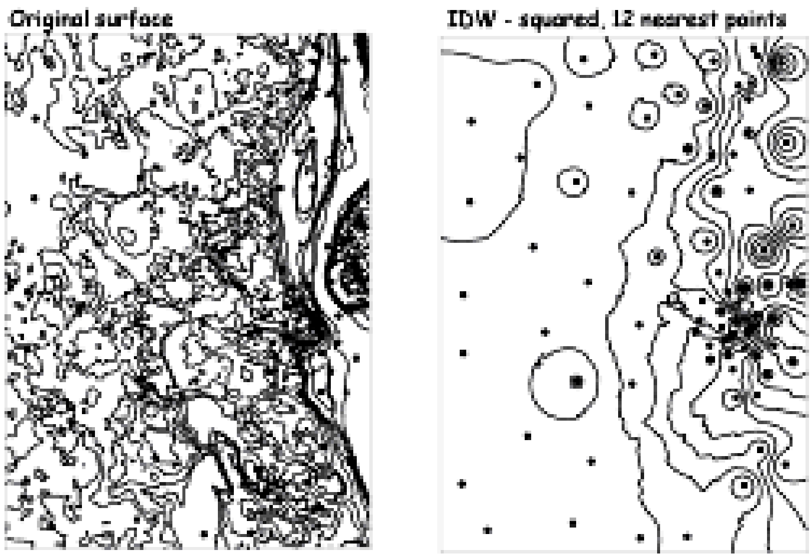


Figure 0-4. Spatial representation with IDW method (Bolstad, 2002)

3.3.3 Triangulation

Triangulation is the most flexible interpolation method. It can generate interpolated surfaces from many different data sources such as point data, lines, break lines, and polygons (erase, replace, or clip). Because of this flexibility and the speed of interpolation, triangulation has become a popular interpolation method for GIS users (**Jun, 2001).**

There are several triangulation methods available **(Watson, 1992).** Delaunay triangulation is the method adopted where value for a new node is ensured to be as close as possible to a known observation point, and triangulation is not affected by the order of observational points to be considered.

The main disadvantage is that the surfaces are not smooth and may give jagged appearance. This is caused by discontinuous slopes at the triangle edges and data points. In addition, triangulation is generally not suitable for extrapolation beyond the domain of observed data points.

3.3.4 Spline (Regularized & Tension):

Spline interpolation consists of the approximation of a function by means of series of polynomials over adjacent intervals with continuous derivatives at the end-point of the intervals. Smoothing Spline interpolation enables to control the variance of the residuals over the data set. The solution is estimated by an iterative process. It is also referred to as the basic minimum curvature technique or thin plate interpolation **(Naoum & Tsanis, 2004).**

There are two Spline methods: Regularized and Tension. The Regularized method creates a smooth, gradually changing surface with values that may lie outside the sample data range. The Tension method controls the stiffness of the surface according to the character of the modeled phenomenon. It creates a less smooth surface with values more closely constrained by the sample data range.

Spline technique has been described by **(Wahba 1980)** and computationally developed by **(Hutchinson 1991)** for use with climate data principally in mind. The degree of smoothness, or inversely the degree of complexity, of the fitted function is usually determined automatically from the data by minimizing a measure of predictive error of the fitted surface given by the generalized cross validation.

Below in Fig. 3-5 shows the spatial representation features and the lines where mapped by using Spline interpolation method.

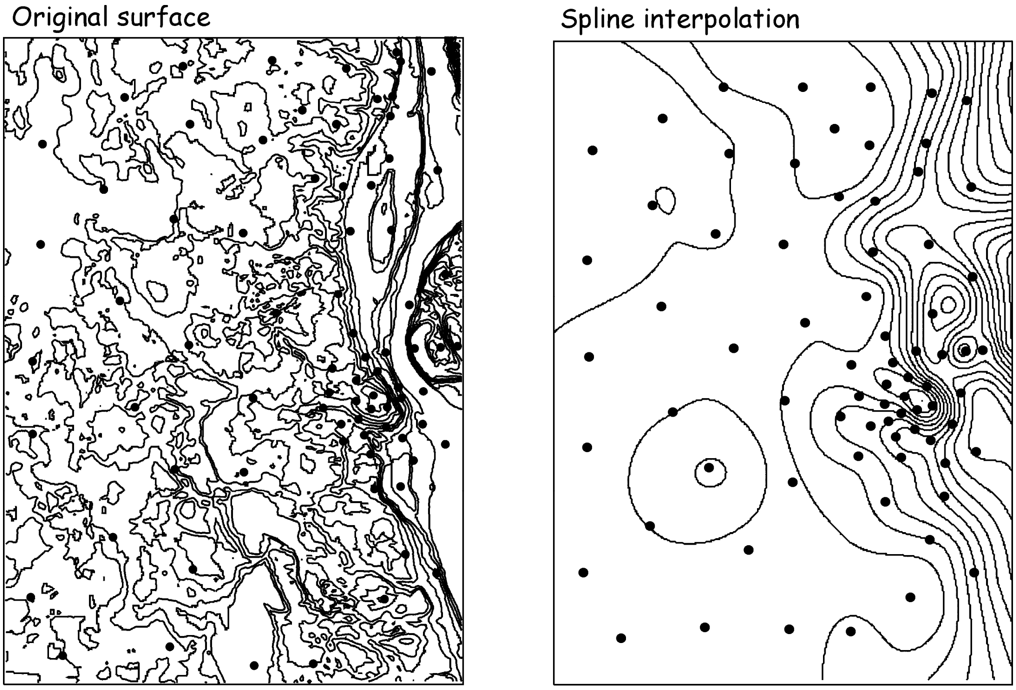


Figure 0-5. Spatial representation with Spline method (Bolstad, 2002)

The Spline method can be thought of as fitting a rubber-sheeted surface through the known points using a mathematical function. In ArcGIS, the Spline interpolation is the Radial Basis Function (RBF). These functions allow analysts to decide between smooth curves or tight straight edges between measured points. Advantages of splining functions are that they can generate sufficiently accurate surfaces from only a few sampled points and they retain small features. A disadvantage is that they may have different minimum and maximum values than the data set and the functions are sensitive to outliers due to the inclusion of the original data values at the sample points (**Sharolyn, 2003**).

3.3.5 Kriging

Kriging is a term coined by G. Matheron in 1963 after the name of D.G. Krige. Kriging is based on a statistical model of a phenomenon instead of an interpolating function. It uses a model for a spatial continuity in the interpolation of unknown values based on values at neighboring points **(Sunila et al., 2004).**

Kriging is a weighted moving averaging method of interpolation. It is derived from regionalized variable theory which assume that the spatial variation of any geological, soil, or hydrological property, known as a 'regionalized variable' is statistically homogenous throughout the surface,; that is, the same pattern of variation can be observed at all locations on the surface **(Jun, 2001).**

Kriging provides a means of interpolating values for points not physically sampled using knowledge about the underlying spatial relationships in a data set to do so. Variograms provide this knowledge. Kriging is based on regionalized variable theory which provides an optimal interpolation estimate for a given coordinate location, as well as a variance estimate for the interpolation value. It involves an interactive investigation of the spatial behavior of the phenomenon before generating the output surface. **(Burrough, 1986).**

The general formula for interpolator method is formed as a weighted sum of the data **(ESRI, 2009b),**

$$Z(s_o) = \sum_{i=1}^{n} \lambda_i Z(s_i)$$

Where:

$Z(s_i)$ = the measured value at the i^{th} location.
λ_i = an unknown weight for the measured value at the i^{th} location.
s_o = the prediction location.
N = the number of measured values.

It is based on the regionalized variable theory, which assumes that the spatial variation in the phenomenon is statistically homogeneous throughout the surface; that is, the same pattern of variation can be observed at all locations on the surface. This hypothesis of spatial homogeneity is fundamental to the regionalized variable theory. Data sets known to have spikes or abrupt changes are not appropriate for the Kriging technique. In some cases, the data can be pre-stratified into regions of uniform surface behavior for separate analysis**. (Oliver, 1990).**

The presence of a spatial structure where observations close to each other are more alike than those that are far apart (spatial autocorrelation) is a prerequisite to the application of geostatistics **(Robinson & Metternicht, 2006).**

More information about Kriging interpolation method can be found in Appendix 10.

2.3.6 Theissen Polygons

Thiessen polygons, also referred to as the Dirichlet Tessellations or the Voronoi Diagrams, are an exact method of interpolation that assumes that the values of non-sampled locations are equal to the value of the nearest sampled point. This method is commonly used in the analysis of climatic data when the local observations are not available, and so the data from the nearest weather stations are used. Thiessen polygons define the individual 'regions of influence' around each of a set of points such that any location within particular polygon is nearer to that polygon's point than to any other point, and therefore, has the same value **(Heywood et al., 1998).**

Fig. 3-6 shows the spatial representation of a surface using Thiessen Polygons interpolation method.

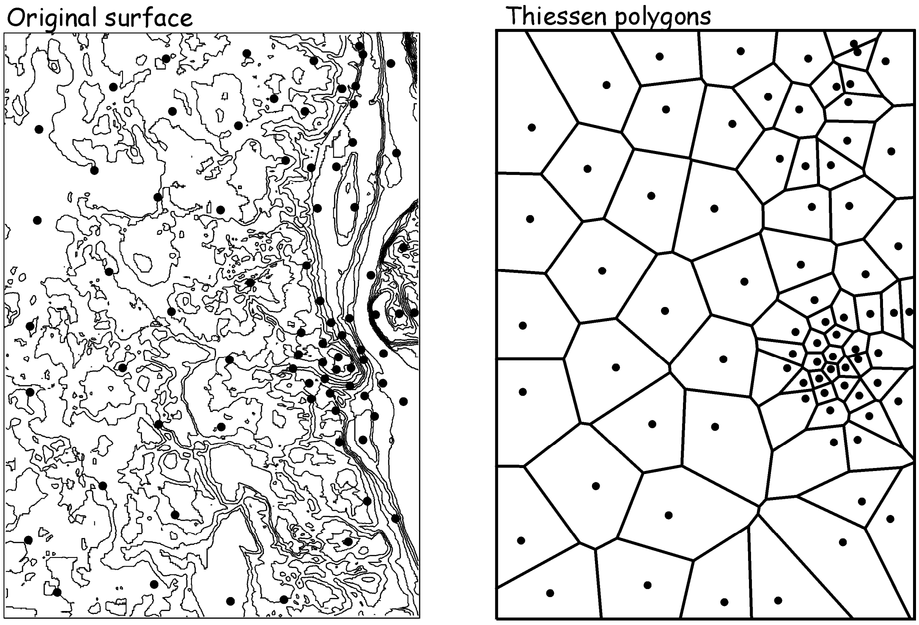


Figure 0-6. Spatial representation with Thiessen Polygons method (Bolstad, 2002).

3.4 Model Evaluation & Validation

3.4.1 Accuracy & Model performance Testing

The accuracy of model predictions generated by several interpolation procedures in this study will be assessed based on the magnitude and distribution of errors – the difference between observed values and model predicted values - in three ways:

(1) The root mean square error (**RMSE**) was calculated for each model prediction using the formula:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(\hat{Z}(x_i) - Z(x_i)\right)^2}$$

Where, Z (xi) is observed value at point xi, $\hat{Z}$ (xi) is predicted value at point xi , N is number of samples (sum of squared errors (observed - estimated values) and n is the number of pairs (errors).)

RMSE is frequently used as an important parameter that indicates the accuracy of spatial analysis in GIS and remote sensing (**Siska and Hung 2005**). Low (RMSE) indicates an interpolator that is likely to give most reliable estimates in the areas with no data. The minimum RMSE calculated by Cross Validation can be used to find the optimum interpolation control parameters (**Mitasova et al, 1995**).

(2) The mean error (ME), The ME is used for determining the degree of bias in the estimates and it is calculated with equation. Large Mean Error (The ME provides an absolute measure of the size of the error) values and comparably

large VE indicate larger discrepancies between predicted and observed values (**Tatalovich, 2006**).

The ME formula as below

$$ME = \frac{1}{n}\sum_{i=1}^{n}\left(\hat{Z}(x_i) - Z(x_i)\right)$$

Where, Z (xi) is observed value at point xi, $\hat{Z}$ (xi) is predicted value at point xi, N is number of samples

The overall performance of the interpolator is then evaluated by statistical means such as the root mean of squared residuals or mean error (ME) (**Tomczak, 1998**). Low root mean squared error (RMSE) indicates an interpolator that is likely to give most reliable estimates in the areas with no data. The minimum RMSE calculated by Cross Validation can be used to find the optimum interpolation control parameters (**Mitasova et al, 1995**).

(3) Correlation (R)
R (Correlation Coefficient) is the measure of the degree of relationship between the X (measured) and Y (predicted) variables. R^2 (Coefficient of determination) explains the percent of the variability in Y (predicted) that can be explained by the regression equation. Correlation coefficients were calculated between observed and predicted values and between errors and observed values. Better model performance is indicated by higher coefficients between observed and predicted, and lower coefficients between errors and observed values.

Further, the quantity R, called the linear correlation coefficient, measures the strength and the direction of a linear relationship between two variables. The linear correlation coefficient is sometimes referred to as the Pearson product moment correlation coefficient in honor of its developer Karl Pearson. The mathematical formula for computing R Where n is the number of pairs of data is:

$$R = \frac{n\sum xy - \left(\sum x\right)\left(\sum y\right)}{\sqrt{n\left(\sum x^2\right) - \left(\sum x\right)^2}\sqrt{n\left(\sum y^2\right) - \left(\sum y\right)^2}}$$

Generally, the best model is the one that has standardized mean nearest to zero, the smallest root mean square prediction error. **(Johnston et al., 2001).**

3.4.3 Cross validation

Cross validation is a model evaluation method for checking validity of the spatial interpolation method used. The most rigorous way to assess the quality of an output surface is to compare the predicted values for specified locations with those measured in the field. It is not always possible to go back to the study area to collect an independent validation dataset. One solution is to divide the original dataset into two parts. One part can be used for modeling, that is, to create the output surface, and the other can be used for testing, that is, to validate the output surface.

There are several validation techniques e.g. holdout set method, 5-fold, 10-fold, K-fold and N-fold. In N-fold cross-validation, the data set is split into N subsets of roughly equal size. The classification algorithm is them tested N times, each time training with N-1 of the subsets and testing with the remaining subset **(Weiss & Kulikowski, 1991).**

3.5 Software processing

Many software packages exist for interpolation of point data. A distinction can be made between automatic processing and manual processing (processing with user intervention). Based on this literature review and the software available the following software may be considered for processing, as we find that ESRI ArcGIS **(ESRI, 2009a)** is the most widely used commercial GIS in the world and the most important module.

3.5.1 ArcMap

ArcMap is the main component of ESRI's ArcGIS suite of geospatial processing programs, and it is used primarily to view, edit, create, and analyze geospatial data. ArcMap allows the user to explore data within a data set, symbolize features accordingly, and create maps for clients. **(Wikipedia, 2009b).** Fig. 3-7 below presents the ArcMap window under ArcGIS 9.2 software that been utilized during the study.

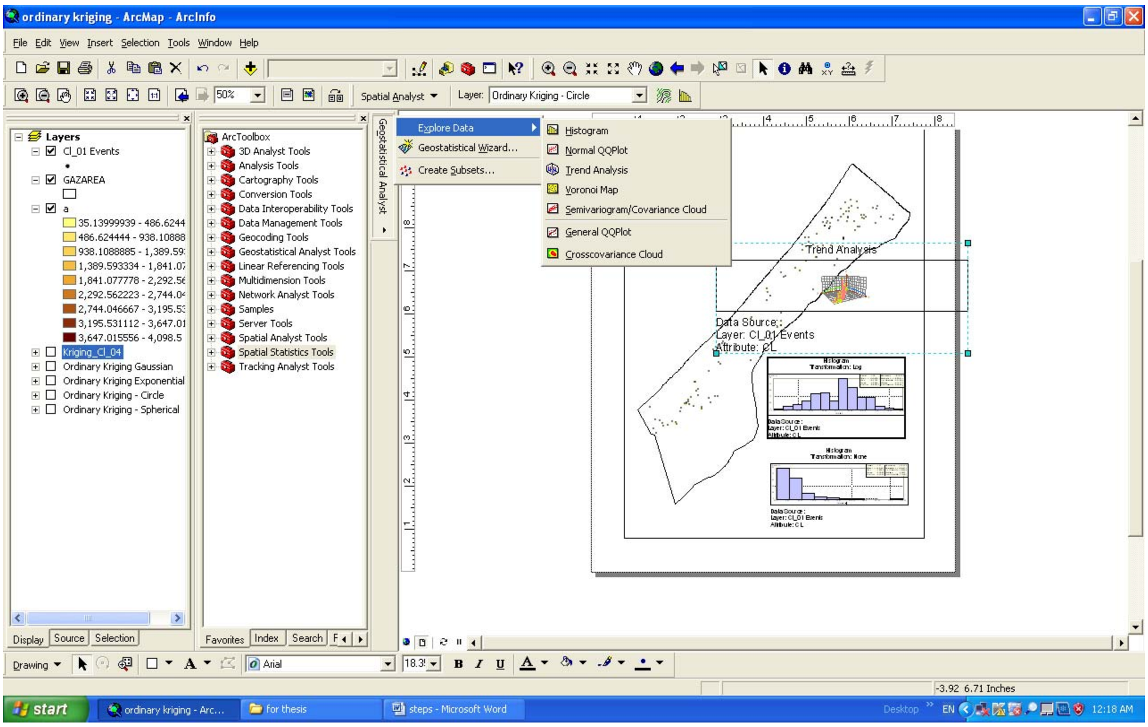


Figure 0-7. ArcMap window and related features.

3.5.2 ArcView

ArcView 8.x and 9.x are part of the ArcGIS Desktop software suite. ArcView is the entry level of licensing offered, it is able to view & edit GIS data held in a flat file database or, through ArcSDE view data held in a relational database management system. Other licensing levels in the suite, namely ArcEditor and ArcInfo have greater functionality. All components are installed on the system, with only those that are licensed being made functional. **(Wikipedia, 2009c).**

3.6 Recommended interpolation methods in the study

In practice, selection of a particular interpolation method should depend upon the configuration of the data set, the type of surfaces to be generated, and tolerance of estimation errors. In generating surfaces, a three step procedure is recommended: the first step is to evaluate the data set. This give idea on how data are spatial distributed, and may provide hints on which interpolation method should be used. The second step is adopted and applies an interpolation method which is most suitable to both the data set and the study objectives. The third step is compare the results using descriptive tools and determines the most stratifying result and the most suitable method.

Burrough & McDonnell, 1998 state that when data are abundant most interpolation techniques give similar results. When data are sparse, the underlying assumptions about the variation among sampled points may differ and the choice of interpolation method and parameters may become critical.

There are many interpolation methods available **(Watson, 1992); (Burrough, 1986); (Lam, 1983); and (Ripley, 1981).** Each of these methods works best for a particular data set because of its inherent assumptions and algorithm design for estimation. For a given data set, different interpolation methods may work best for different study objectives (i.e. smooth surface vs. accurate surface).

There is no general method that is suitable for all problems: it depends on the nature of the variable and on the time-scale on which the variable is represented. According to **(Tveito, 2007)**, climate reference maps should be based on the interpolation of absolute values.

Taking into consideration several papers and studies regarding the comparison of interpolation methods and the best fitted models, where each study a/o paper is investigating a wide variety of spatial interpolation techniques, it can be briefed as following:

In recent study in 2008 done by Mehrjardi and others titled as: Application of Geostastical Methods for Mapping Groundwater Quality in Azarbayjan Province, Iran. They have compared efficiency of three interpolation techniques included IDW, Kriging and cokriging for predicting of some groundwater quality indices such as: Na^+, TH, EC, SAR, Cl^- , Ca^{+2}, Mg^{+2} and SO_4, as a prerequisite of ecosystem management decisions is monitoring of soil and waters that geostatistics methods are one of the most advanced techniques for monitoring of them. The data were taken from 625 wells in Azarbayjan Province, Iran. After normalization of data, variograme was computed. Suitable model for fitness on experimental variograme was selected based on less RMSE value. Then the best method for interpolation was selected, using cross-validation and RMSE. The results showed that for all groundwater quality indices, cokriging performed better than other methods to simulate groundwater quality indices.

Moreover, Coulibaly M. and S. Becker S. in 2007 have done a study named: Spatial Interpolation of Annual Precipitation in South Africa - Comparison and Evaluation of Methods. The data from 545 rainfall gauges were used to interpolate the spatial distribution of annual rainfall in South Africa. Several spatial interpolation methods (inverse distance weighting (IDW), ordinary Kriging, universal Kriging, and cokriging) were tested by variation analyses and cross-validation to determine the most suitable one. The best results were achieved by ordinary Kriging.

Additionally, Christos G. and others in year 2010, have investigated in a study paper the Evaluation of Spatial Interpolation Techniques for Mapping Agricultural Topsoil Properties in Crete, as the aim of their work was to evaluate prediction maps created with interpolation for five common topsoil properties, namely organic matter, total $CaCO_3$, electric conductivity (EC), Fe^{+2} content, and clay content in a Mediterranean agricultural system. 106 topsoil samples were collected on a 50×50 m^2 grid and then analyzed in the laboratory. Three well-known spatial interpolation techniques, namely Ordinary Kriging (OK), Inverse Distance Weighting (IDW), and Radial Basis Functions (RBF) were applied for generating the prediction maps, which then were assessed for their accuracy and effectiveness with a new, independent set of samples. The results indicated that there was not a method clearly more accurate than the other methods for any of the tested properties. But IDW has shown better Goodness of prediction had positive values for Fe content and total $CaCO_3$.

Recent study named: Spatial Distribution of Groundwater Quality with Geostatistics (Case Study: Yazd-Ardakan Plain prepared by Mehrjardi M. and others in 2008, explored in their research that IDW, Kriging and cokriging methods were used for predicting spatial distribution of some Groundwater characteristics such as: TDS, TH, EC, SAR, Cl^- and SO_4. the data were related to 73 wells in Ardakan-Yaz plain. After normalization of data, variograme was drawn, for selecting suitable model for fitness on experimental variograme, less RSS value was used. Then using cross-validation and RMSE, the best method for interpolation was selected. Results showed that for interpolation of Groundwater quality, Kriging and cokriging methods are superior to IDW method; maps of Groundwater were prepared using cokriging

Also, we can see that Sheikhhasan H. in 2006 has done a comprehensive study and evaluation of spatial techniques for rainfall estimation in his Master's Thesis in Computer Science titled as A Comparison of Interpolation Techniques for Spatial Data Prediction. He has done a comprehensive study and evaluation of spatial techniques for rainfall estimation. The data were tested using three kinds of measurements, Residuals, RMSE, and prediction maps. As he has assured that there are a small number of projects that have provided a comparison and superiority of some spatial techniques over others. The objective of their thesis was to provide a comparison between eight interpolation and regression techniques for Rainfall Estimation. Finally the Predication maps made were clear that inverse distance weighted interpolations produced smoother maps.

Further, Tatalovich Z. in 2006 has studied the performance of Thiessen-polygon and Kriging procedures from the standard GIS package in a paper called: Comparison of Thiessen-polygon, Kriging, and Spline Models of UV Exposure. The objective of his study was to identify model that produces least amount of uncertainties in predictions, and utilize that model to generate UV exposure estimates at non-sampled locations across United States. Input data included average global radiation measures computed from hourly data for period 1961-1990 for 215 stations in the U.S. The Spline model produced results with the smallest mean absolute error, smallest variance of error, smallest root mean square error, the highest correlation coefficient between the predicted and observed values and the smallest correlation between the errors and observed values.

Moreover, a study prepared by Largueche F. in 2006 about Estimating Soil Contamination with Kriging Interpolation Method, where she has proved that Kriging is a useful tool to estimate the spatial distribution of ground pollutants in contaminated land. A spatial analysis has been carried out. It consists essentially of: Firstly a primary process of the data which means that histograms and an unprocessed representation of the pollutant's distribution has been plotted for each contaminant, and secondly a graphic presentation of the pollution by using Kriging interpolation technique.

In 2003 a paper prepared by Anderson S. titled as An Evaluation of Spatial Interpolation Methods on Air Temperature in Phoenix, AZ, where it reviews three methods of interpolation to be used on air temperature data from the Phoenix Metropolitan area. The air temperature measurements were taken at thirty-six discrete locations. Much of the geographical spatial analysis requires a continuous data set and this study is designed to create that surface. This study identifies the best spatial interpolation method to use for the creation of continuous data for air temperatures. The reviewed techniques include Spline, inverse distance weighting (IDW) and Kriging. A statistical assessment of the resultant continuous surfaces indicates that there is little difference between the estimating ability of the three interpolation methods with Kriging performing better overall.

Whereas, paper presented by Meyer C. in 2003 titled as Evaluating water quality using spatial interpolation methods, in Pinellas County, Florida, U.S.A, to visualize the spatial trends of water quality monitoring data, spatial interpolation methods were applied to the chlorophyll and dissolved oxygen data from 45 fixed monitoring stations across the county. Investigation determined that inverse distance weighting IDW was the best interpolation method for the data. The IDW surfaces displayed overall trends and hotspots for extreme high and low values as it worked best with limited sample size and random data points.

Recent paper prepared & published in International Journal of Environmental Science and Engineering by F. J. Moral García F.J. and others in 2010, titled as Geostatistical Analysis and Mapping of Ground level Ozone in a Medium Sized Urban Area in Badajoz, City southwest of Spain, where Ground-level tropospheric ozone is one of the air pollutants of most concern. Later, to evaluate the ozone distribution at the city, the measured ozone data (138 urban locations) were analyzed using Geostatistical techniques. During the exploratory analysis of data, it was revealed that they were distributed normally, which is a desirable property for the subsequent stages of the

Geostatistical study. Yet and during the structural analysis of data, theoretical spherical models provided the best fit for all monthly experimental variograms. Finally, predictive ozone maps were derived for all points of the experimental study area, by use of Geostatistical algorithms (Kriging) and high prediction accuracy was obtained in all cases as cross-validation showed.

A paper in year 2007 prepared by Ibrakhimov M. and others titled as Spatial and temporal distribution and influence on soil Stalinization in Khorezm region (Uzbekistan, Aral Sea Basin), has analyzed the temporal dynamics of GW table and salinity in Khorezm, a region of Uzbekistan which is situated on the lower Amu Darya River in the Aral Sea Basin and suffering from severe soil salinization. Data of GW table and salinity were measured during 1990–2000 in 1,972 wells, covering the entire region. Over the entire area, GW was only moderately saline. However, GW levels were generally very shallow and thus likely to prompt secondary soil salinization. Maps interpolated from the regional dataset revealed that GW was significantly shallower and more saline in the western and southern parts of Khorezm using Kriging interpolation method.

Shamsudduha M. in 2007, investigated in a study called: Spatial Variability and Prediction Modeling of Groundwater Arsenic Distributions in the Shallowest Alluvial Aquifers in Bangladesh, the Spatial variability of arsenic in groundwater has been examined by semivariogram analysis that revealed high degree of small-scale spatial variability in alluvial aquifers. Small-scale variability of arsenic concentrations, indicated by high "nugget" values in semivariograms, is associated with heterogeneity in local-scale geology and geochemical processes. In non-sampled locations, arsenic concentrations have been predicted using both deterministic and stochastic prediction methods. Natural neighbor (NN) method predicted better than inverse distance to power (IDW) method, and small-scale variations of arsenic concentrations are preserved. Predicted results are evaluated by cross-validation, mean prediction error, and root mean square methods. Ordinary Kriging (OK) method on the untransformed arsenic data and their residual values performed considerably in predicting spatial arsenic distributions on regional scale.

In 2005, Salih M. and others in a study titled as Spatial correlation between radon in groundwater and bedrock uranium: GIS and Geostatistical analyses; described approaches to create surface maps of radon in groundwater based on measurements of radon in drilled bedrock wells at unevenly distributed sites and uranium bedrock maps from the South East of Sweden. Geostatistical techniques of inverse distance weighted (IDW), Kriging and cokriging were compared in terms of their interpolation power and correlation between the produced radon in the water layer and the bedrock uranium layer. Good interpolation layers (with least root mean square errors RMSE) were obtained by Kriging. However, the kriged radon surface showed poor correlation with bedrock uranium layers. The best radon in water layer that match with uranium in bedrock layer was produced using IDW interpolator.

In parallel, Mueller R. Jr. in his study in 2005 called: Utilizing Geographic Information Science Advancements for Bathymetric Mapping and Dredging Assessment of a Small Urban Lake in Southeastern Minnesota, which is a small Mississippi River floodplain lake in Winona, Minnesota USA. Lake Winona was the site of recent dredging operations aimed at decreasing littoral zone areas to reduce plant growth and stunted fish populations. To assess potential effectiveness of dredging operations, bathymetric data were collected with a Garmin depthfinder and GPS unit, and interpolation techniques to produce Lake Morphometric characteristics (splining, Kriging, and inverse distance weighting (IDW)) were compared within ESRI's ArcMap 9.0. All interpolation methods produced similar outputs for cross validation statistical comparisons, although Kriging produced the best predictive output of actual bathymetric contouring for Lake Winona.

But Valley R. D. and others in 2004, in their research: Evaluation of alternative interpolation techniques for the mapping of remotely-sensed submersed vegetation abundance, have evaluated a hydroacoustics global positioning system to map the percent of the water column occupied by submersed vegetation (referred to here as biovolume) in three Minnesota (USA) lakes. As they evaluated the relative accuracy and precision of digital biovolume maps produced by three interpolation methods (inverse distance weighted (IDW), Kriging and Spline) after using a non-parametric regression smoother to remove a non-linear depth trend. Interpolated predictions with all methods were relatively accurate in all lakes; however, precision varied among lakes. In all cases, Kriging interpolation produced the best predictions when compared with observations in independent verification data sets.

Comprehensive paper released in 1999 and prepared by Hartkamp, A.D. and others titled as Interpolation Techniques for Climate Variables. NRG (Natural Resources Group)-GIS Series 99-01. Mexico has examined statistical approaches for interpolating climatic data over large regions, providing a brief introduction to interpolation techniques for climate variables of use in agricultural research, as well as general recommendations for future research to assess interpolation techniques. Three approaches: 1) inverse distance weighted averaging (IDWA), 2) thin plate smoothing splines, and 3) co-kriging; were evaluated for a 20,000 km^2 square area covering the state of Jalisco, Mexico. Validation of the surfaces using two independent sets of test data showed no difference among the three techniques for predicting precipitation. For maximum temperature, splining performed best. Taking into account valued error prediction, data assumptions, and computational simplicity; the results recommended using of thin-plate smoothing Spline for interpolating climate variables.

In conclusion, the techniques assessed previously and that will be practiced in the study are deterministic interpolation methods of *SPLINE* and *INVERSE DISTANCE WEIGHTING (IDW)* and the stochastic method of *KRIGING* in an effort to retain actual measurement in a final surface. Each method selected requires that the exact data values for the sample points are included in the final output surface.

CHAPTER (4): METHOD AND MATERIALS

4.1 Data employed

The dataset comprised of three categories, groundwater quality parameter (Chloride (Cl^-), Groundwater level (WL), and meteorological rainfall data. The dataset obtained in years from 2000 – 2007 from Palestinian Water Authority (PWA) and Coastal Municipalities Water Utility (CMWU) data bank's departments.

In this chapter, the municipal well lists which were obtained from the PWA & CMWU; it was difficult to distinguish between municipal wells and domestic wells. It was found that there were some domestic wells (private wells) used by the municipality for some time. The evaluation only considered the working wells while there were many wells recently closed due to increasing salinity in the water or damaging and faulting of the mechanical parts of these wells. Appendix 1 shows also a summary of municipal wells and some of the domestic wells (use for domestic purposes but not belongs to the municipality) in each Governorate.

4.1.1 Groundwater Quality (Chloride - Cl^- in mg/l)

Water quality in Gaza is tested by different agencies for different reasons. The Ministry of Health (MoH) tests all of the approximately more than 130 Municipal wells twice a year (during June/July and Jan. /December months) for the major ions, nitrates, and coliform to insure that the drinking water is safe for public consumption. The MoA tests more than 400 wells twice a year for Chloride and Nitrate and some additional ions to assess the quality of the irrigation water in Gaza. In addition, the United Nations Welfare Relief Agency (UNWRA) tests their wells on a regular basis. Reportedly this testing is similar to that of the MoH. UNWRA administers the drinking water wells in the refugee camps, yet it will not be considered in the study **(CAMP, 2000).**

It is worth mentioning that measurements in 2001, 2003, 2005 & 2007 were considered in the study. Reasons for consistent data, sampling accuracy, regular monitoring, harmonized wells development and extension, were behind choosing the Chloride concentration in mg/l as testing groundwater quality parameter, though these years to be briefed as following:

The following table 4-1 details the study wells in 2001 and Fig. 4-1 below demonstrates the distribution of municipal wells over Gaza Strip's governorates, as more details about Chloride dataset in year 2001 can be found in Appendix 2.1 - Chloride Dataset in 2001.

Table 0-1. Summary of Chloride dataset in year 2001

Study Area Data in 2001	**No.**
No. of Total Wells in Gaza Strip in 2001	71
No. of Wells used for Calibration	**10**
No. of Wells used for Modeling	**61**

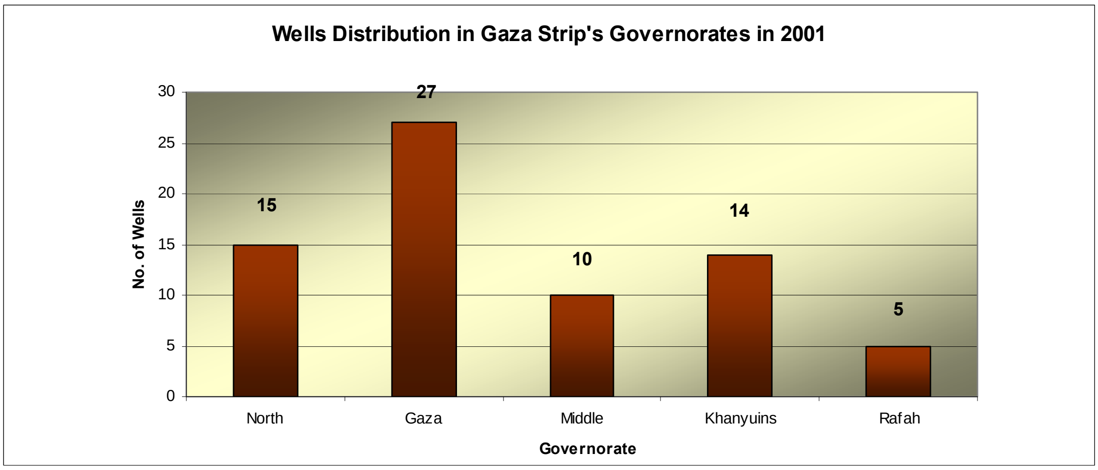


Figure 0-1. Wells Distribution in Gaza Strip's Governorate in year 2001

The following table 4-2 details the study wells in 2003 and Fig. 4-2 below demonstrates the distribution of municipal wells over Gaza Strip's governorates, as more details about Chloride dataset in year 2003 can be found in Appendix 2.2 - Chloride Dataset in 2003.

Table 0-2. Summary of Chloride dataset in year 2003

Study Area Data	No.
No. of Total Wells in Gaza Strip in 2003	88
No. of Wells used for Calibration	**15**
No. of Wells used for Modeling	**73**

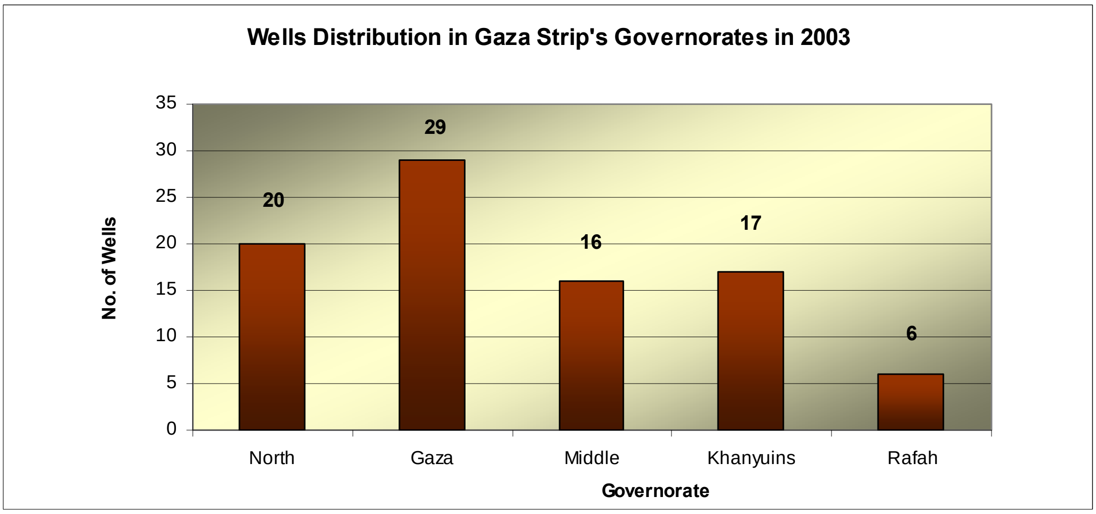


Figure 0-2. Wells Distribution in Gaza Strip's Governorate in year 2003

The following table 4-3 details the study wells in 2005 and Fig. 4-3 demonstrates the distribution of municipal wells over Gaza Strip's governorates, as more details about Chloride dataset in year 2005 can be found in Appendix 2.3 - Chloride Dataset in 2005.

Table 0-3. Summary of Chloride dataset in year 2005

Study Area Data	No.
No. of Total Wells in Gaza Strip in 2005	104
No. of Wells used for Calibration	**20**
No. of Wells used for Modeling	**84**

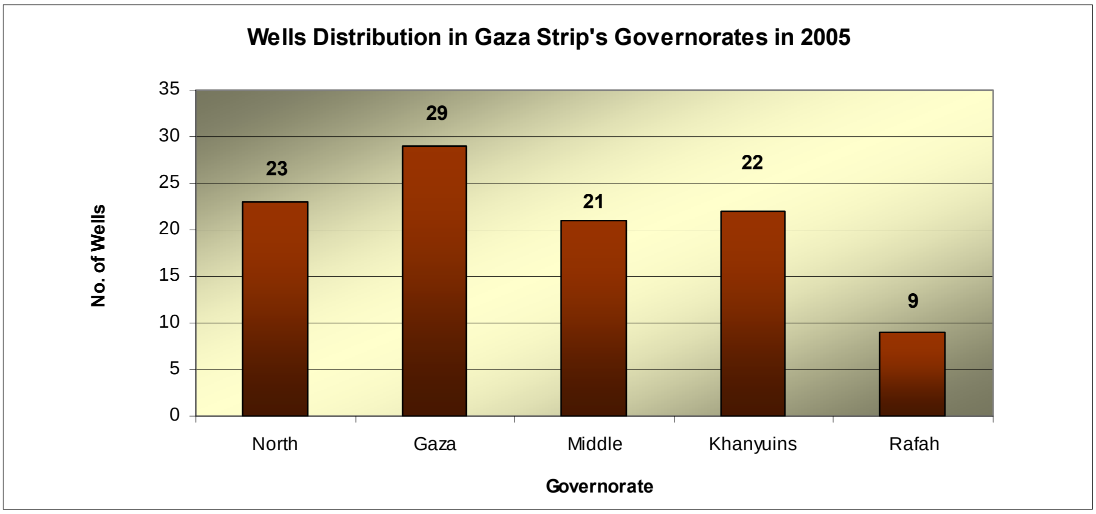


Figure 0-3. Wells Distribution in Gaza Strip's Governorate in year 2005

Table 4-4 below details the study wells in 2007 and Fig. 4-4 below demonstrates the distribution of municipal wells over Gaza Strip's governorates, as more details about Chloride dataset in year 2007 can be found in Appendix 2.4 - Chloride Dataset in 2007.

Table 0-4. Summary of Chloride dataset in year 2007

Study Area Data	**No.**
No. of Total Wells in Gaza Strip in 2001	129
No. of Wells used for Calibration	**23**
No. of Wells used for Modeling	**106**

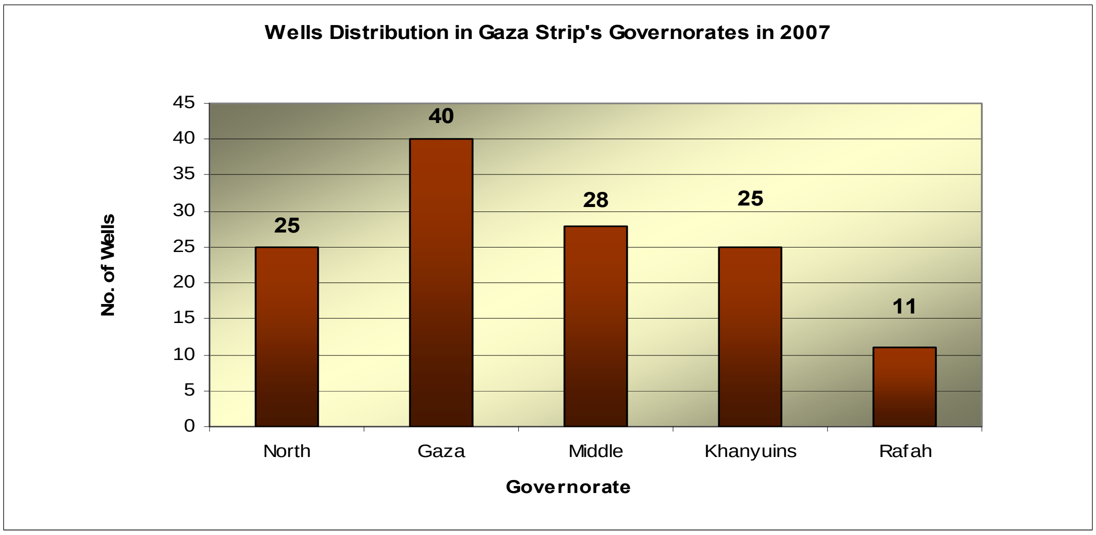


Figure 0-4. Wells Distribution in Gaza Strip's Governorate in year 2007

4.1.2 Groundwater water level (WL in meters)

Groundwater level Data was obtained from PWA-Water Resources Directorate and CMWU-Data Bank. The data collected was mainly concerned in years 2000-2007.

The collected data were based on average values (yearly records in meters) for each year through different readings through the same year.

In terms of historical hydrogeological data related to the depth of groundwater levels, it was noted that the water level was above the ground level with 5-15 meters, and there was a clear slope and flow of groundwater encountered from the southeastern side to the northwestern with no observations of any phenomena related to any upcoming issues. **(Yaqoubi, 2006).**

Two types of wells used to monitor the groundwater level: 1) Monitoring Wells, which can be municipal or domestic wells with shallow depths ranged down to 40 meters. The other type is 2) Piezometer Wells, which mainly were constructed for monitoring purposes and depths range from 20-200 m.

It was clear that after several years of operation, part of the wells encountered different function-affecting problems including clogging, scaling, fouling, and high turbidity. The problems mentioned previously may affect the function of Monitoring and Piezometer wells and the accuracy of groundwater level monitoring.

The active wells are shallow wells and typically their screens are 10-20 m below the water table. Of these wells, about 140 monitoring wells and 39 piezometric wells are presently used to monitor the water levels every month. The agriculture wells of about 10 inches diameters are used as water level monitoring wells. The total depth of most of the wells is not defined clearly. Generally, the total penetrated saturated thickness of these wells is ranging between 30 and 40 m. Most of the piezometric wells are located mainly along the coastal zone and range in depth from 20 to 200 m. Many of these wells have screens at different depths. The piezometric wells have deteriorated and many of these wells have been damaged. (**Mogheir, 2003**).

It is worth mentioning that the records in 2001, 2003, 2005 & 2007 were considered in the study. Reasons for consistent data, sampling accuracy, regular and monitoring activities were behind choosing of the said years. Table 4-5 illustrates the number of monitoring and piezometer wells in Gaza Strip through the different years of study. More details about water level dataset will be found in Appendix 3 – Water Level Dataset:

Table 0-5. Number of wells used for Water level study dataset

Description / Year	2001	2003	2005	2007
No. of Monitoring Wells	96	88	71	66
No. of Piezometer Wells	15	14	34	33
Total No. of Wells used for Groundwater Water Level Monitoring	111	102	105	99

During our investigation and exploring the Water Level data, the following were raised as points of interests:

1) Full records of water level were decreased during years from 2001 to 2007 (111 to 99) in many monitoring wells either due to lack of frequent maintenance and shortage of spare parts needed for rehabilitation process or

due to accessibility issues under security concerns considered as dangerous zone.

2) No. of Piezometer wells were increased in 2004/2005 under a program funded by USAID and implemented through PWA under IAMP study outputs.

4.1.3 Meteorological data (Rainfall in mm)

In Gaza Strip there are 12 rainfall stations distributed through different governorates, these stations are operated by ministry of agriculture and data obtained from these stations are entered manually in Palestinian water authority database.

The data was obtained from PWA and CMWU data bank departments as yearly average rainfall data in mm for the years from 2000 to 2007. The records in PWA and MOA were based on monthly rainfall depth collected measurements from rain gauges that start in July of particular year and ends in June of next year.

It is worth mentioning that the records in 2000/01, 2002/03, 2004/05 & 2006/07 were considered in this study as shown in table 4-6. Reasons for consistent data, sampling accuracy, regular and monitoring were behind choosing the said years. More details about the rainfall data can be found in Appendix 4 – Rainfall Dataset:

Table 0-6. Rainfall dataset in study years (mm/year)

Station_Name	00-01'	02-03'	04-05'	06-07'
Beit Hanoun	497.50	801.50	358.70	509.90
Beit Lahia	490.40	724.00	320.60	530.30
Jabalia	540.00	692.60	345.50	536.70
Shati	478.90	627.00	296.60	469.00
Gaza City	511.90	599.00	316.00	501.20
Tuffah	533.40	653.50	345.40	545.50
Gaza South	563.60	790.70	323.60	388.20
Nusseirat	558.30	446.20	405.00	403.00
Deir Al Balah	550.50	372.60	345.50	418.00
Khan Younis	381.00	298.00	373.00	252.00
Khuzaa	284.30	261.20	367.70	256.10
Rafah	308.00	220.80	360.20	225.00

4.1.4 ArcGIS documents

The major file needed to assess the extent of any data in space and time was the GazaStrip.shp file (National Grids-Palestinian Grid 1923) which was obtained from CMWU-data bank, which details the boundaries of Gaza Strip where the spatial extension ends. The study area matches these maps which cover the entire Gaza Strip area.

4.2 Dataset Processing

The data required some processing before it could be used in ArcGIS. First, the data was opened using Excel and saved in several Excel spreadsheets. The dataset was verified, sieved and stored in three main categories: Water Quality data, Water Level Data, and Rainfall Data. In each category, the dataset was compiled into four main tables for years of 2001, 2003, 2005 and 2007.

As for the Water Quality data, the information stored was mainly about Well_ID, Well_Name, Municipality, Governorate, X, Y data (Longitude, Latitude), and yearly average of Chloride Concentration in mg/l. The Water Level data, it was about Well_ID, Well_Type, X, Y data (Longitude, Latitude), and yearly average of Water Level in meters, while, the Rainfall data was stored as Station_Location, Station_Name, X, Y data (Longitude, Latitude), and yearly average of rainfall amount in mm. The above selected data, were organized in several Excel spreadsheets and saved as a DBF 4 *.dbf files. These file were imported into the geodatabase and then added to an ArcMap document. But, prior to any temporal analyses, the aforementioned data were checked for the distributional assumptions and descriptive statistics, as exploratory spatial data analysis was applied for the chloride, water level and rainfall to check data consistency, removing outliers and identifying statistical distribution where data came from.

It is worth mentioning that during the exploratory phase, transformation of data shall be a necessity once the data was not distributed normally, as the goal of transformations is to normalize the available datasets we have, as it enable us to re-check the different datasets for normality after performing the transformation whose distribution is most normal (log transformation is the technique that shall be used in the Geostatistical Analysis tools), as stated in (**Lutkepohl, H., 2009**) that for a range of economic variables substantial forecast improvements from taking logs are found if the log transformation actually stabilizes the variance of the underlying series. It can be damaging for the forecast precision if a stable variance is not achieved.

Furthermore, statistics provide additional numerical information to confirm the graphical tendencies shown with the histograms **(Johnston et al., 2001).**

4.2.1 Groundwater Quality (Chloride (Cl^-) in mg/l)

Descriptive statistics of the Chloride dataset can be demonstrated in table 4-7 as following:

Table 0-7. Statistics analysis of Chloride Dataset

Year	Count	Min.	Max.	Mean	Median	Skew	SD	Kurtosis
2001	71	35.4	1,175.75	394.68	308.40	0.783	297.873	2.592
2003	88	29.32	2,009.65	428.31	305.90	1.456	353.189	6.082
2005	104	43.06	2,031.00	476.00	350.08	1.459	397.918	5.461
2007	129	35.14	2,077.00	527.17	444.60	1.600	424.472	5.865

The chloride ion concentration dataset varies from less than 250mg/l in the sand dune areas as the northern and south-western area of the Gaza Strip to about more than 1500 mg/l along the coastal areas as shown in the figures listed in Appendix 8. The general trend of chloride concentration is notably increasing due to many factors but not limited to freshwater source represented in rainfall intensity, seawater intrusion, high pumping capacities, and deep penetrated wells.

Moreover, it is clear that in all years (2001, 2003, 2005, and 2007) the data are not quite normally distributed due to positive skewed values increasing gradually (0.783, 1.456, 1.459, and 1.600. The distribution showed positive peaked shape in 2001, 2003, 2005 and 2007 with kurtosis of 2.5915, 6.082, 5.461, and 5,865 respectively. More details can be referred to Appendix 8**.**

4.2.2 Groundwater water level (WL in meters)

Descriptive statistics of the Water Level dataset can be demonstrated in table 4-8 as following:

Table 0-8. Statistics analysis of Water Level Dataset

Year	Count	Min.	Max.	Mean	Median	Skew	SD	Kurtosis
2001	111	-6.469	12.885	-0.121	-0.066	1.595	2.452	8.470
2003	102	-8.173	9.601	-0.452	-0.242	-0.009	2.593	3.572
2005	105	-10.055	10.058	-0.497	-0.190	-0.042	2.900	3.430
2007	99	-12.797	10.453	-0.925	-0.438	-0.394	3.313	4.176

Water level dataset in years of 2001, 2003, 2005 and 2007 have demonstrated obvious problem in the northern and southern side of Gaza Strip due to imbalance between replenishment and consumption averages with comprehensible groundwater levels drop with reference to MSL. As shown below in Figs 4-5, 4-6, 4-7, and 4-8 the drop increased from 6.469 down to 12.797 meters below MSL. The situation is worse in the southern side due to less replenishment process escorted by low annual precipitations as the recharge rate is about 25% in the low porous area like the eastern part of the Gaza Strip, and about 75% in porous area where the sand dunes are still found in the north and south of GS **(CMWU, 2008)** and higher population demand with more urban expansions.

Statistically, the distribution of 2001 data is characterized by positive high skewness (1.595) and really high peaked positive kurtosis (8.470) due to infrequent extreme deviations. In 2003 & 2005, we can define the data are entirely normally distributed due to negative skewness near zero of (-0.009 & -0.042), while we have left sided distributed data in 2007 with negative skewness (-0.394) and positive kurtosis (4.176).

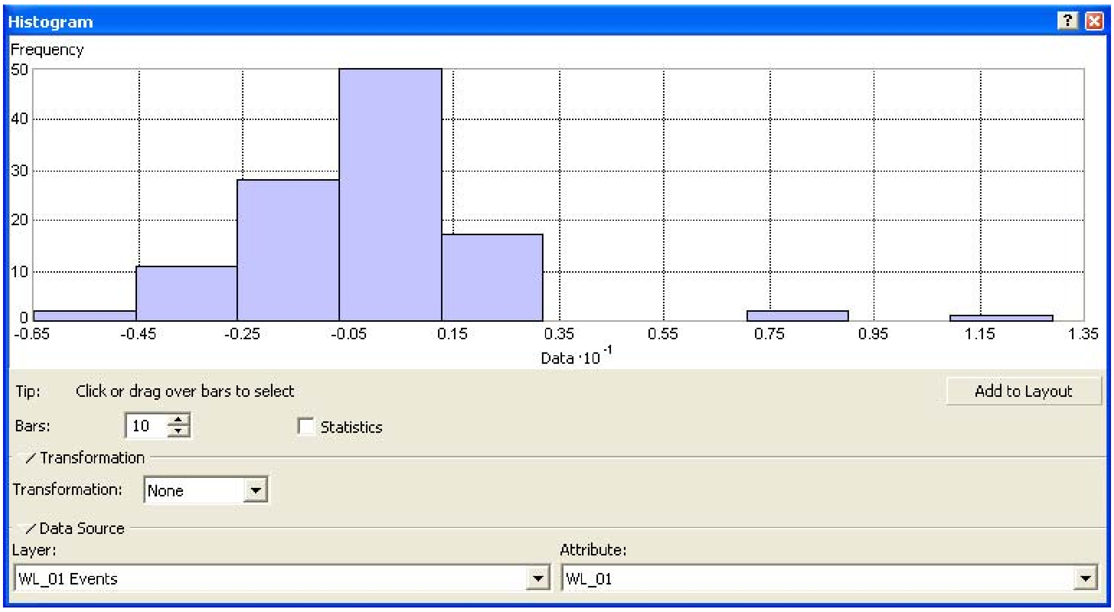


Figure 0-5. Histogram Graph for Water Level in year 2001

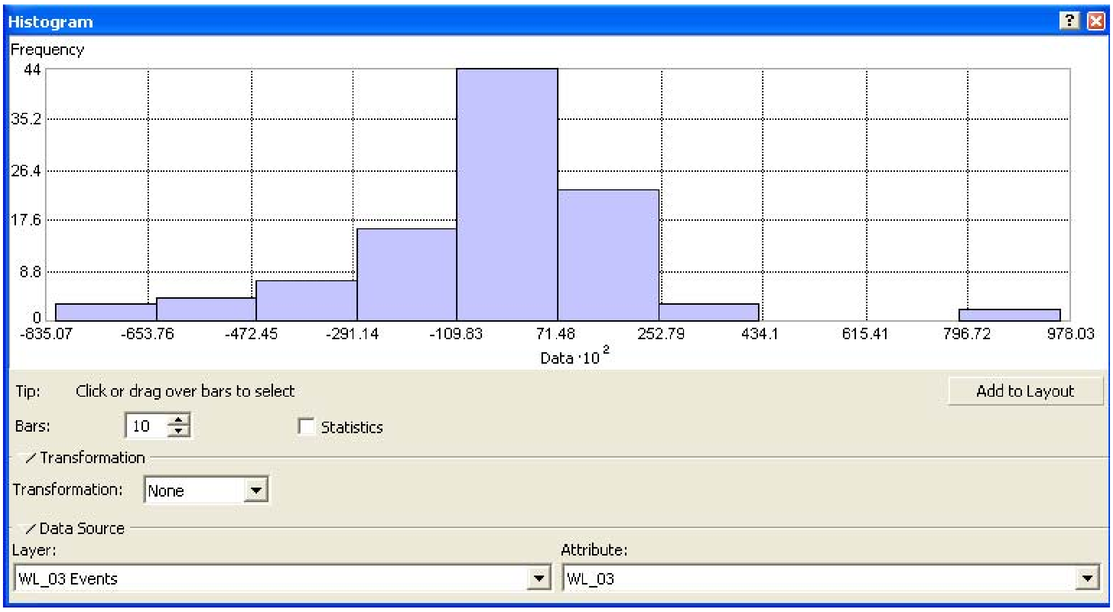


Figure 0-6. Histogram Graph for Water Level in year 2003

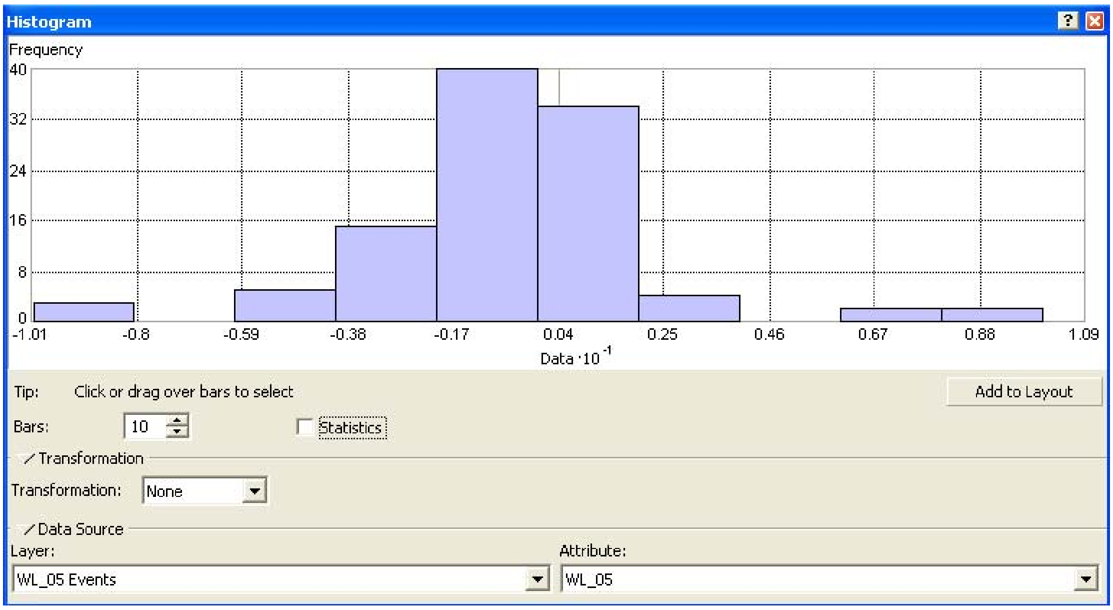


Figure 0-7. Histogram Graph for Water Level in year 2005

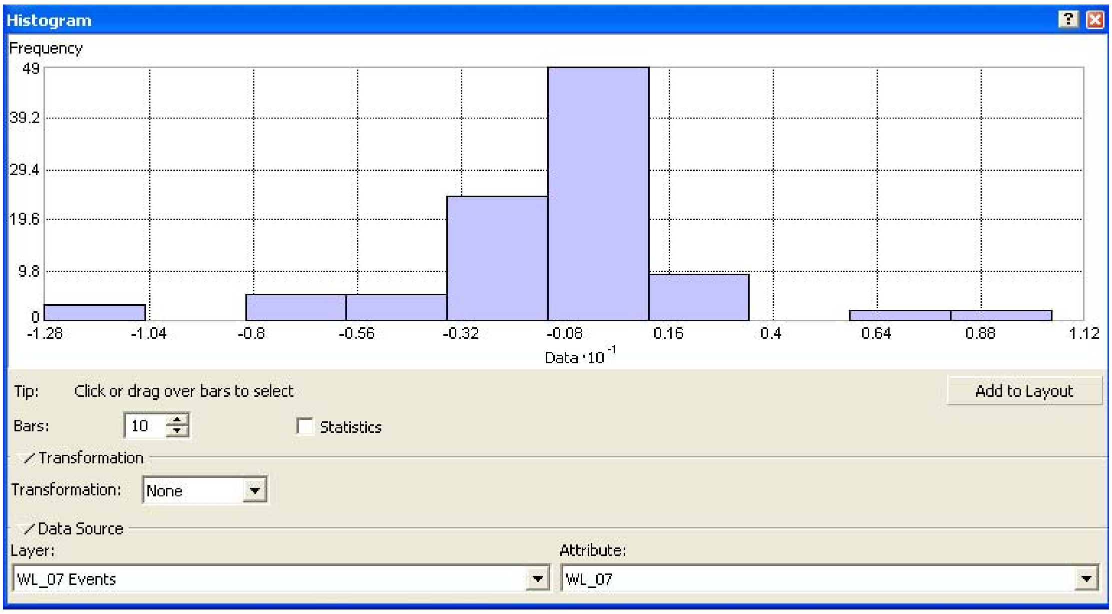


Figure 0-8. Histogram Graph for Water Level in year 2007

4.2.3 Meteorological data (Rainfall in mm)

Descriptive statistics of the Rainfall dataset can be demonstrated in table 4-9 as following:

Table 0-9. Statistics analysis of Rainfall Dataset

Year	Count	Min.	Max.	Mean	Median	Skew	SD	Kurtosis
2000/01	12	284.30	563.60	474.82	504.7	-1.213	96.924	0.154
2002/03	12	220.80	801.50	540.59	613.0	-0.339	210.477	-1.518
2004/05	12	296.60	405.00	346.48	345.5	0.219	29.433	0.220
2006/07	12	225.00	545.50	419.58	443.5	-0.672	117.947	-1.066

The rainfall dataset demonstrated close rainfall dataset average but with high rainfall intensity occurred in 2002/03 year unlike the average occurred in 2004/05. Moreover, there is a regional trend in the rainfall dataset where the general concentrations increase toward the north from south of the Gaza Strip.

The distribution of 2000/01 data is characterized by negative skewness of (-1.213) tended to the left side and positive kurtosis of (0.154) with peaked distribution. Flat distribution of 2002/03 data were noticed due to negative kurtosis with negative skewness of (-0.339). The 2004/05 data have shown normal flat distribution characterized by positive skewness (0.219) and low positive kurtosis (0.220). The distribution of 2006/07 showed flat distribution of negative kurtosis (-1.066) and slight left sided location of data of negative skewness (-0.672). More details regarding Rainfall dataset histograms and normalization process can be found in Appendix 9.

4.3 Methods

The dataset including water quality parameters & rainfall amounts were imported into ESRI ArcMap software. The ESRI Geographic information system (GIS) was used for the construction of creation of the interpolation surfaces through applying the 'Geostatistical Analyst' extensions of ArcGIS 9.2 software package.

ESRI ArcGIS (**ESRI, 2009c**) is the most widely used commercial GIS in the world and the most important module, ArcMap, supports most interpolation methods except linear regression modeling which should be done using an external statistical package. ESRI ArcMap is very powerful for visualization and processing with user intervention **(Sluiter, 2008).**

GIS modules are described to spatially interpolate data of radon concentration in water. Two interpolation techniques, Spline, inverse distance weighted (IDW) and Kriging, used in the present study are briefly summarized below:

The application of any interpolation method for the spatial interpolation of data assumes a normal distribution. It is a pre-requisite to transform skewed data into a normal distribution before applying to any geostatistical analysis. Logtransformation is one of the widely used methods for data normalization. Three interpolation procedures used to generate a set of predicted values at known locations. In each instance the predicted values were generated by systematically removing some of the input data (Calibration data) for Chloride, WL, and rainfall then calculating their values based on other data (Modeling data), where the goal of the study geostatistical analysis is to predict values where no data have been collected.

IDW, Kriging and Spline (RBF) procedures are evidently very different not only statistically, but also in terms of computational complexity, and their ability to incorporate additional variables, all of which may differentially affect the predictions. One way to assess the performance of different exposure models would be to examine the magnitude and distribution of prediction errors.

4.3.1 Applied Interpolation Techniques

4.3.1.1 Spline (RBF)

Spline which described as RBF is moderately quick deterministic interpolators that are exact. There is no assessment of prediction errors. The method provides prediction surfaces that are comparable to the exact form of Kriging & IDW. Radial Basis Functions do not allow you to investigate the autocorrelation of the data, making it less flexible and more automatic than Kriging & IDW. Radial Basis Functions make no assumptions about the data. The RBF (Spline) interpolation was performed and the produced layer was compared. Finally, and as per the process above, cross validation parameters (error estimates) and correlation coefficients between the generated models were tabulated for comparison and evaluation.

4.3.1.2 IDW

The points are weighted during interpolation such that the influence of one point relative to another is a function of inverse distance. Weighting is assigned to points through the use of a weighting power and the radius object. The greater power means that the nearby points have the greater influence. As a part of this study a fixed radius option was selected to test locality or globalization of data. The input value of the radius was changed systematically and at each radius the interpolation was performed and the produced layer was compared. Finally, cross validation parameters (error estimates) and correlation coefficients between the generated models were tabulated for comparison and evaluation.

4.3.1.3 Kriging

Kriging is an advanced interpolation procedure that generates an estimated surface from an x-y scattered set of points with z values (radon concentration). It is a weighted moving averaging method of interpolation derived from regionalized variable theory, which assume that the spatial variation of a property, known as a ‘regionalized variable’, is statistically homogenous throughout the surface. Kriging derive weights from the semivariogram that measures the degree of spatial correlation among data points in a study area as a function of distance and direction between data points. Finally, and as per the process above, cross validation parameters (error estimates) and correlation coefficients between the generated models were tabulated for comparison and evaluation.

4.3.2 Model Validation & Evaluation

4.3.2.1 Validation

In Model Validation process, we first remove part of the data, call it the calibration dataset, then uses the rest of the data, call it the modeling dataset, to develop the trend and autocorrelation models to be used for prediction. In Geostatistical Analyst, you create the test and training (Calibration) datasets using the Create Subset tools. Validation creates a model for only a subset of the data, so it does not directly check the final model, which should include all available data.

4.3.2.2 Cross-validation

Cross-validation uses all of the data to estimate the trend and autocorrelation models. It removes each data location, one at a time, and predicts the associated data value. The predicted and actual values at the location of the omitted point are compared. For all points, cross-validation compares the measured and predicted values. After completing cross-validation, some data locations may be set aside as unusual, requiring the trend and autocorrelation models to be refit.

4.3.2.3 Evaluation

The choice of the “best fitted” model for each interpolation method and its corresponding parameters was based on the evaluation of the errors estimates (the residuals, or estimated errors, are the differences between the observed data and fitted model) as it can be briefed as the lowest RMSE among the models performed in each interpolation method.

Moreover, the accuracy of the best fitted predictions model generated by IDW, Kriging and Spline procedures in this study was assessed among each other based on the magnitude and distribution of errors – the difference between observed values and model predicted values as following: The root mean square error (RMSE) and the mean error (ME) were calculated for each model prediction. In addition to the R (Correlation Coefficient) that was measured between the measured and predicted variables as well as R^2 (Coefficient of determination).

The overall approach and methodology can be briefed in Fig. 4-9 next, where it illustrates the stages that the study went through and the modeling techniques applied for the three datasets for the different study years.

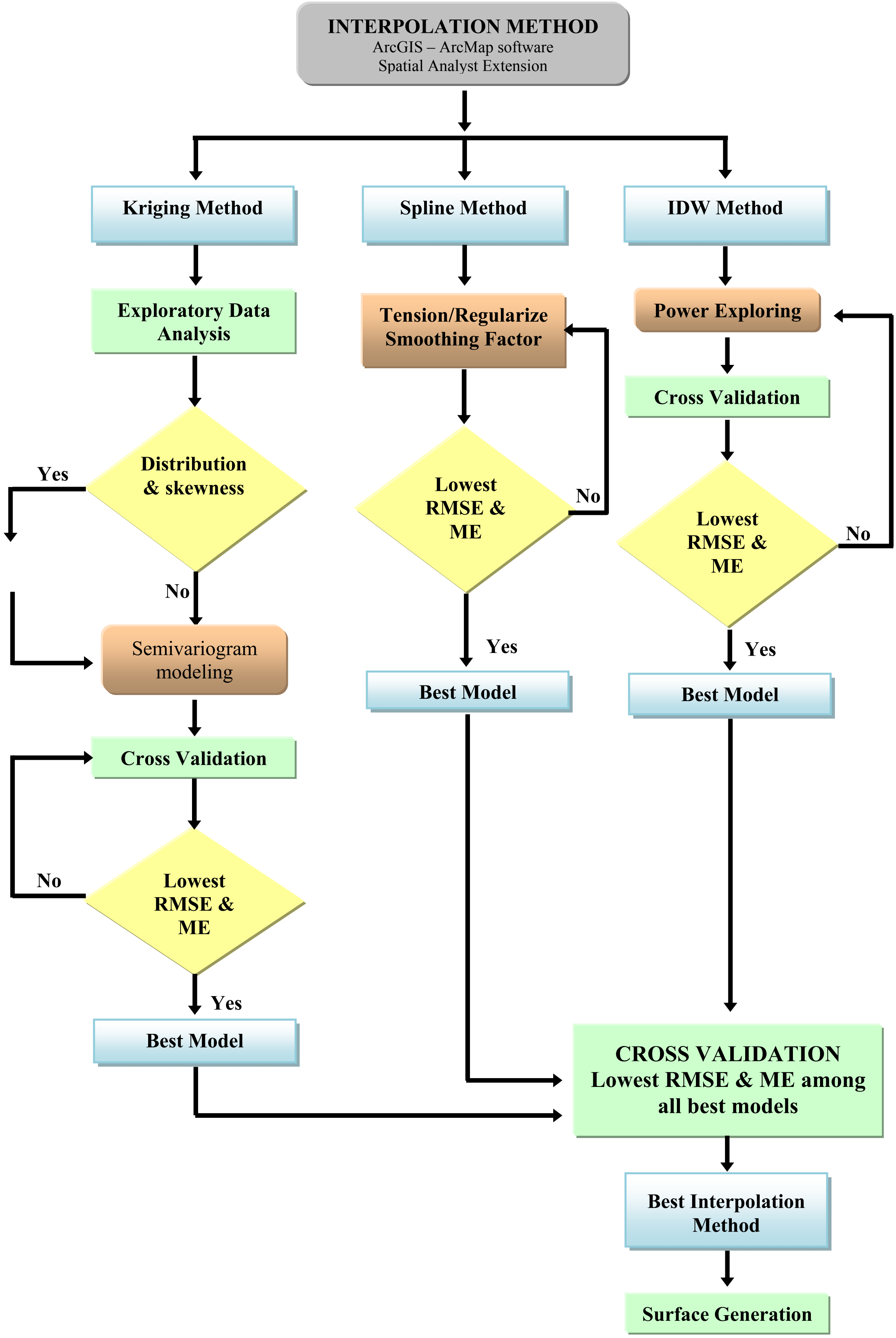


Figure 0-9. Study flowchart in selection the best interpolation method

CHAPTER (5): RESULTS & DISCUSSIONS

5.1 Introduction

The main objective of this study is to evaluate the spatial representation of groundwater data (Chloride & Water level) and meteorological data (Rainfall) in GS under the current different collection monitoring system dataset so as to optimize the interpolation methods or techniques examined in order to be utilized for accurate surface representation of areas with missing data points along with setting up recommendation for the future monitoring programme of GS aquifer.

The quality of the interpolation methods are assessed by evaluating various prediction errors that are derived from the cross validation process **(Coulibaly & Becker, 2007).** The estimated value is then compared to the measured one for error estimation; three of the five types of prediction errors presented by **Johnston et al. (2001)** were taken into consideration.

5.2 Interpolation Application

Specifically a statistical summary of the groundwater quality properties (Chloride and Water Level dataset) and Rainfall dataset was presented in Chapter 4. Based on their skewness and histogram, some of the data were normalized using logarithmic transformation. After data normalizing (once needed), experimental semivariogram, powering and smoothing factors were computed and recorded. The best model for fitting on experimental semivariogram, powering and smoothing was selected based on less RMSE value and other supporting factors like ME value.

In order to validate the results obtained through applying the selected above different interpolation methods, of the total available dataset, few samples were randomly selected but geographically covering the whole dataset and kept as calibration dataset. They are not used for prediction or semivariogram estimation, so it is possible to compare predicted points with independent observations. In this study two test sets were used. The resulted surface mapping were evaluated using the cross-validation process, the resulted predicted data was compared with the measured data (calibration) and was subjected to correlation investigation. The best calibrated model that will be used for final surface map was selected based on highest correlation (R^2) among all.

It is really important to mention that all trials and fitting techniques results can be found in Appendix 11 (Chloride dataset), Appendix 12 (Water level Dataset), and in Appendix 13 (Rainfall Dataset) where in these appendixes the recommended final parameters that were optimized and recorded for the Kriging, IDW, and Spline (RBF) interpolation methods were highlighted. The Spline (RBF) method had two categories with optimizing factor to choose, while in the IDW method the smoothing factor along with powering parameter were verified. In the Kriging, different semivariogram parameters were tackled like partial sill, nugget, lag size, and smoothing factor for modeling techniques. Where the combination and the trails of the above multi associated parameters in the different interpolation methods is to interpolate a map that reflects more accurate predicted values and surface smoothing.

Moreover, it is better to point out that in the interpolation mechanism, the objects are rasterized into two-dimensional images from their corner points (vertices), all the pixels between those points are filled in by the defined interpolation algorithm (Spline, IDW or Kriging), which determines their attributes as described in the creation of new values that lie between known values, and that's what happened clearly in the above cases and results.

Finally, couple of factors has already affected the interpolation process and gaining more reliable predicted data:

(1) Unreasonable distribution of monitoring points.
(2) Monitoring frequency is roughly unreasonable.
(3) Monitoring tools are out of date and measure errors existed.
(4) High risks of data storage loss.

5.3 Results

5.3.1Chloride Dataset Results

5.3.1.1 2001 dataset

The Chloride dataset was divided into two sets of data, modeling data and calibration data. The modeling data (61 samples) as shown in (Appendix 5.1 - Chloride Modeling Dataset in 2001) was applied in the three interpolation techniques, yet the Calibration dataset used can be demonstrated in table 5-1 below. Each interpolation technique was best fitted in the validation process, was evaluated through cross-validation process using calibration data with total no. of 10 samples.

Table 0-1. Calibration dataset of Chloride dataset for year 2001

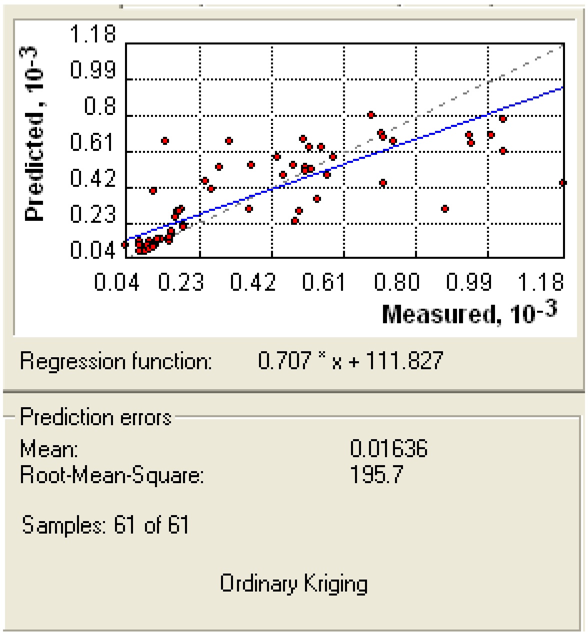
Well_ID	Well_Name	X	Y	Cl_01
C_76	Industrial_Area_Well	104667.09	104336.57	578.90
D_73	Salateen_Well	101036.18	106827.16	70.75
D_70	Sheikh_Radwan_No._12	101440.34	105833.46	99.05
R_162CA	Sheikh_Radwan_No._4	98867.35	104590.00	280.00
R_254	Sheikh_Ejleen_No._2	96540.88	102055.55	407.65
S_69	Abu_Merwan_Well	91769.92	90702.26	466.00
G_30	Hertani_Well	91478.84	95975.57	973.70
L_176	El_Sha'e _Old_Southern_Well	82187.00	83276.00	779.05
L_179	Western_well	85572.00	87460.00	650.00
P_138	Abu_Zohri_Well	78773.00	79764.00	128.60

The models for 2001 dataset were subjected for fitting process based on experimental semivariogram, powering and smoothing process and trails. As it can be summarized in the table 5-2, where the final models were selected based on least RMSE value.

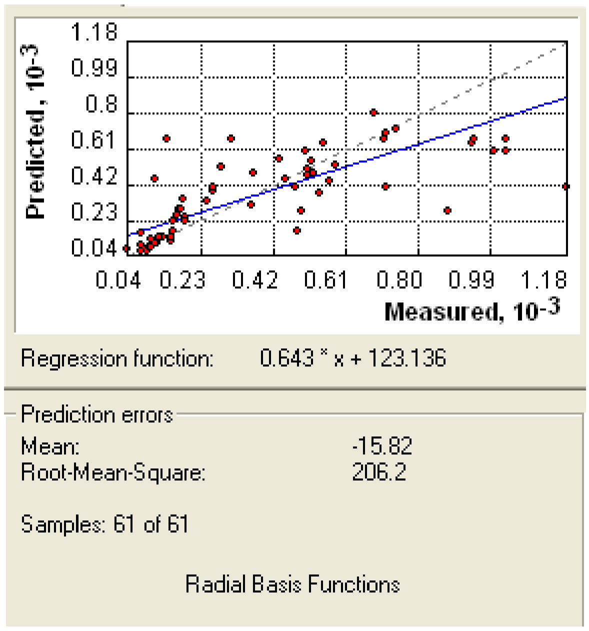
Table 0-2. Summary of Validation results for Chloride in year 2001

Measurements of Errors	Spline	IDW	Kriging
Mean:	-15.82	-10.99	0.016
Root-Mean-Square:	206.2	187.5	195.7

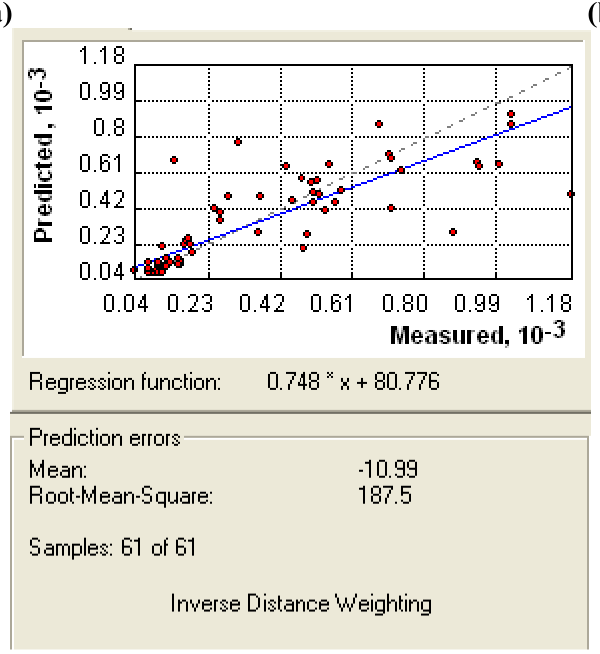
As we can find in Fig. 5-1 the summary of statistical errors for Chloride in Year 2001 resulted from applying Kriging, Spline (RBF), and IDW interpolation methods.



(a)



(b)



(c)

Figure 0-1. Prediction error statistics Vs Measured for Chloride in Year 2001 resulted from: (a) Kriging, (b) Spline (RBF), and (c) IDW interpolation methods

The best fitted above models were further evaluated using the calibration dataset, the results was summarized in table 5-3 and table 5-4.

Table 0-3. Predicted values vs. measured Chloride values for year 2001

Well_ID	Well_Type	Cl_01	Spline	IDW	Kriging
		Measured		Predicted	
C_76	Industrial_Area_Well	578.90	291.08	313.17	339.20
D_73	Salateen_Well	70.75	80.49	85.36	72.40
D_70	Sheikh_Radwan_No._12	99.05	95.77	96.67	103.52
R_162CA	Sheikh_Radwan_No._4	280.00	531.53	503.84	567.45
R_254	Sheikh_Ejleen_No._2	407.65	297.52	333.79	295.09
S_69	Abu_Merwan_Well	466.00	544.29	536.44	611.03
G_30	Hertani_Well	973.70	953.46	1018.40	1073.71
L_176	El_Sha'er_Old_Southern_Well	779.05	453.88	454.89	375.12
L_179	Western_well_	650.00	561.47	473.07	444.63
P_138	Abu_Zohri_Well	128.60	343.60	301.78	365.92

Table 0-4. Summary of Cross Validation values for Chloride in year 2001

Measurements of Correlation	Spline	IDW	Kriging
R	0.791	0.811	0.721
R^2	0.625	0.658	0.520

Figure 5-2 below illustrates the tendency of each predicted values resulted from applying the three interpolation methods against the measured values for Chloride dataset in year 2001.

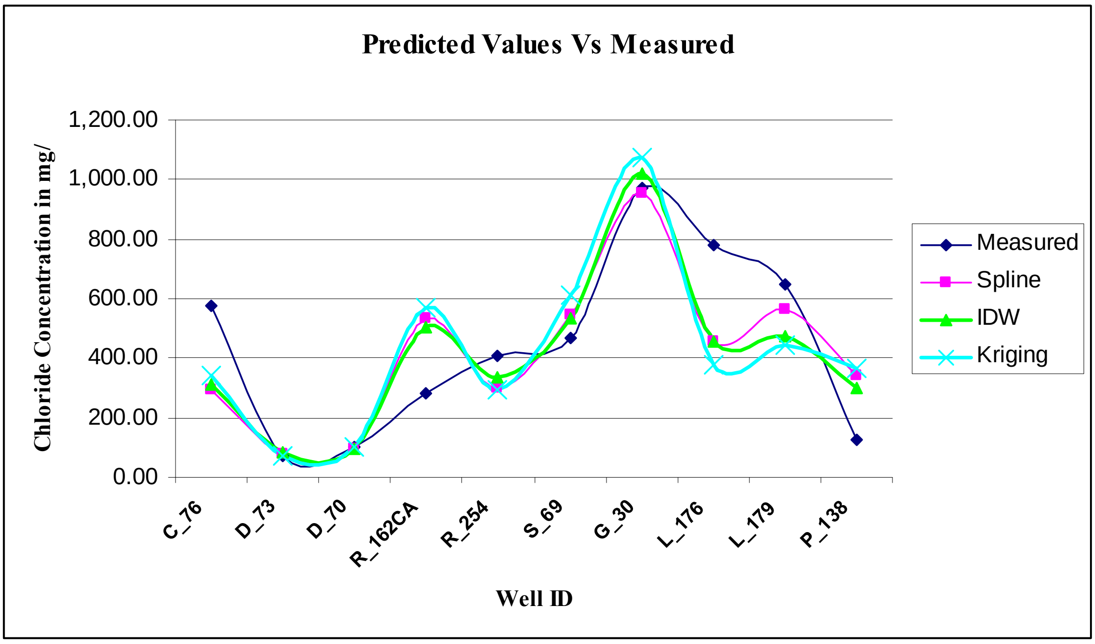


Figure 0-2. Correlation Analysis for Chloride in Year 2001

It is useful to clarify that the absolute value of errors (R) shows strong positive correlation with the magnitude of the Chloride predicted values at year 2001 as shown in table 5-4. While during the interpolation process and as shown in Fig 5-2, the predicted values at P_138 and R_162CA wells went underestimated unlike the L_179 well which was overestimated, in view of the fact that the interpolation process was affected by nearby locally extreme modeled values in which they were surrounded spatially by smaller values. As in this situation, there will be huge spatial variation among observations over a short distance. Yet, one strong factor can be added to this variation is the presence of local measuring error that associated in this case during the sampling process.

5.3.1.2 2003 dataset

The Chloride dataset was divided into two sets of data, modeling data and calibration data. The modeling data (73 samples) as shown in (Appendix 5.2 - Chloride Modeling Dataset in 2003) was applied in the three interpolation techniques yet the Calibration dataset used can be demonstrated in table 5-5 below. Each interpolation technique was best fitted in the validation process, was evaluated through cross-validation process using calibration data with total no. of 15 samples.

Table 0-5. Calibration dataset of Chloride dataset in for year 2003

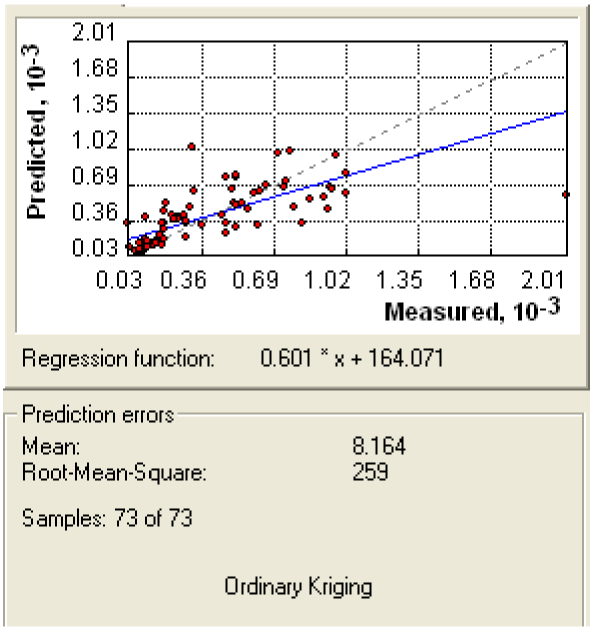
Well_ID	Well_Name	X	Y	Cl_03
C_127A	Ezba New Well	104785.02	106154.68	57.20
A_205	Sheikh Zaid East Well	103497.36	105126.10	51.99
D_72	Sheikh Radwan No. 16	101739.33	106462.51	78.40
R_162LA	Sheikh Radwan No. 1-A	98480.71	104045.75	766.80
R_270	Maslahk Well	96230.00	99750.00	443.05
R_25A	Safa-02	100758.64	102581.70	490.90
R_280	Sheikh Ejleen No. 6	95760.88	101154.53	60.49
K_20	El-Berka No. 2	86265.41	89777.53	293.20
G_49	Nusirat New Well (Municipal Well)	91378.53	96449.25	1041.00
H_60	Fallet Well	91380.00	94950.00	994.50
L_43	Aia Well	83063.19	83461.45	744.60
L_179	Western well	85572.00	87460.00	404.70
S_69	Abu Merwan Well	91769.92	90702.26	436.00
P_138	Abu Zohri Well	78773.00	79764.00	179.00
L_187	El-Satar Well	84364.00	86335.00	1285.50

The models for 2003 dataset were subjected for fitting process based on experimental semivariogram, powering and smoothing process and trails. As it can be summarized in the table 5-6, where the final models were selected based on least RMSE value.

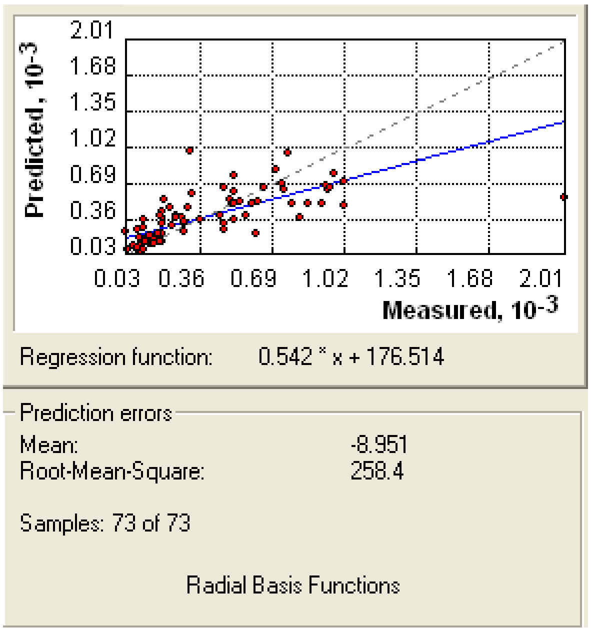
Table 0-6. Summary of Validation results for Chloride in year 2003

Measurements of Errors	Spline	IDW	Kriging
Mean:	-8.951	-28.95	8.16
Root-Mean-Square:	258.4	245.9	259.0

As we can find in Fig. 5-3 the summary of statistical errors for Chloride in Year 2003 resulted from applying Kriging, Spline (RBF), and IDW interpolation methods.



(a)



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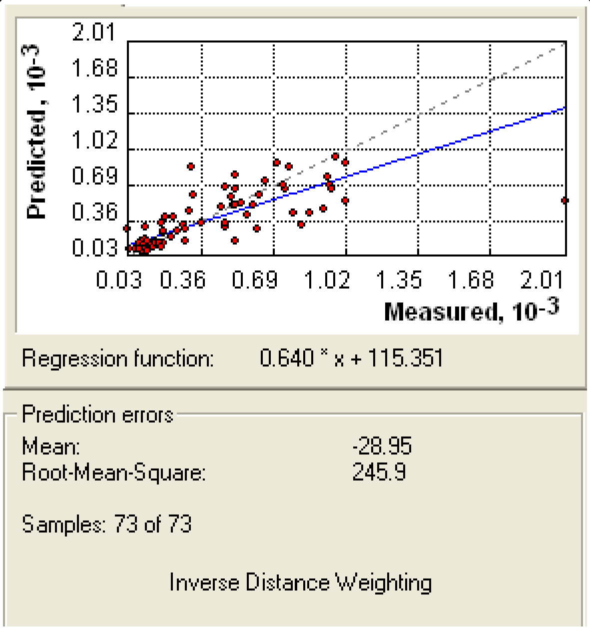


(c)

Figure 0-3. Prediction error statistics for Chloride in Year 2003 resulted from: (a) Kriging, (b) Spline (RBF), and (c) IDW interpolation methods

The best fitted above models were further evaluated using the calibration dataset, where t tables 5-7 & 5-8 summarize it:

Table 0-7. Predicted values vs. measured Chloride values for year 2003

Well_ID	Well_Type	Cl_03	Spline	IDW	Kriging
		Measured	Predicted		
C_127A	Ezba New Well	57.20	147.28	49.27	72.69
A_205	Sheikh Zaid East Well	51.99	168.71	119.45	147.66
D_72	Sheikh Radwan No. 16	78.40	86.67	92.90	91.16
R_162LA	Sheikh Radwan No. 1-A	766.80	684.55	694.95	736.50
R_270	Maslahk Well	443.05	323.65	313.37	373.61
R_25A	Safa-02	490.90	432.29	577.43	577.47
R_280	Sheikh Ejleen No. 6	60.49	271.17	226.03	258.96
K_20	El-Berka No. 2	293.20	314.76	228.73	286.58
G_49	Nusirat New Well	1,041.00	735.79	915.57	833.23
H_60	Fallet Well	994.50	712.52	883.42	906.66
L_43	Aia Well	744.60	753.05	750.34	951.60
L_179	Western well	404.70	428.31	277.12	430.80
S_69	Abu Merwan Well	436.00	552.69	539.08	633.58
P_138	Abu Zohri Well	179.00	350.02	307.60	395.11
L_187	El-Satar Well	1,285.50	480.13	538.99	530.23

Table 0-8. Summary of Cross Validation results for Chloride in year 2003

Measurements of Correlation	Spline	IDW	Kriging
R	0.810	0.850	0.799
R^2	0.657	0.723	0.638

Figure 5-4 below illustrates the tendency of each predicted values resulted from applying the three interpolation methods against the measured values for Chloride dataset in year 2003.

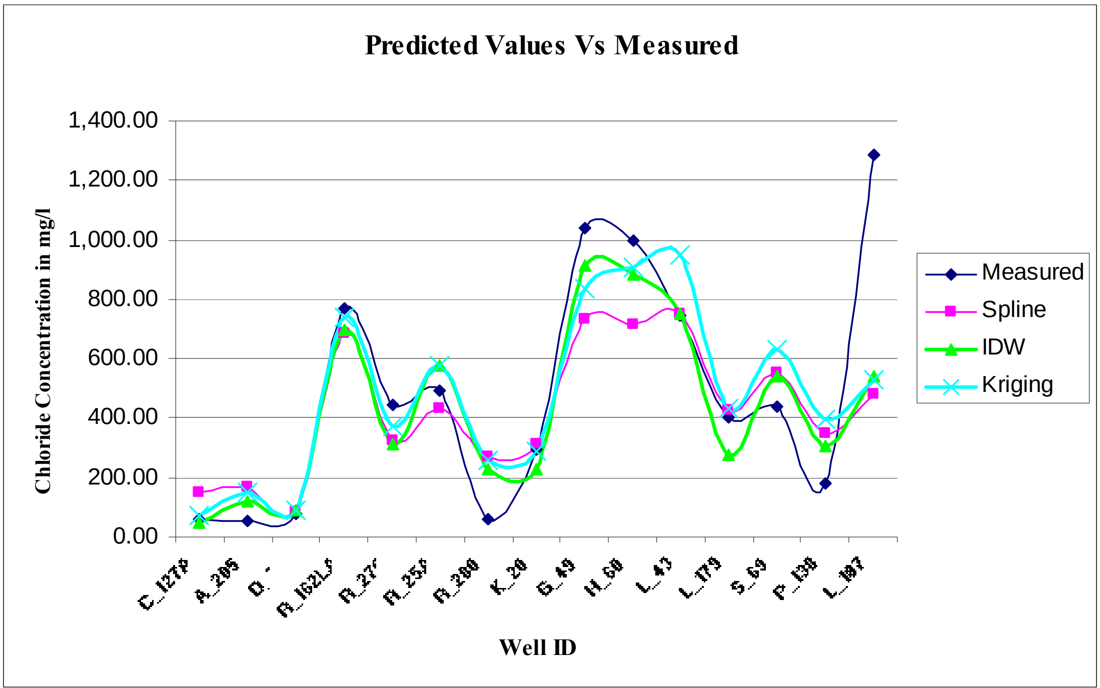


Figure 0-4. Correlation Analysis for Chloride in Year 2003

In table 5-8 above, the absolute value of errors (R) shows strong positive correlation with the magnitude of the Chloride predicted values at year 2003. While during the interpolation process the predicted value in Fig. 5-4 at L_187 well went underestimated, it was clear that during interpolating the modeling dataset the process was affected by the nearby locally low values (surrounded wells) thus there will be huge spatial variation among observations over a short distance. Moreover, a local measuring error factor had associated in the above case.

5.3.1.3 2005 dataset

The Chloride dataset was divided into two sets of data, modeling data and calibration data. The modeling data (85 samples) as shown in (Appendix 5.3 - Chloride Modeling Dataset in 2005) was applied in the three interpolation techniques, yet the Calibration dataset used can be demonstrated in table 5-9 below. Each interpolation technique was best fitted in the validation process, was evaluated through cross-validation process using calibration data with total no. of 20 samples.

Table 0-9. Calibration dataset of Chloride dataset for year 2005

Well_ID	Well_Name	X	Y	Cl_05
C_128	Abu Gazalah	106477.56	104891.26	249.35
C_76	Industrial Area Well	104667.09	104336.57	713.20
A_211	Shekh Zaid West Well	103328.60	105390.98	52.47
E_90	Hawooz Well (Paris)	101280.23	104587.48	208.80
R_280	Sheikh Ejleen No. 6	95760.88	101154.53	107.49
R_25C	Safa-03	100775.79	102454.93	994.20
J_146	Abo Naser Well	91199.81	90460.94	640.60
K_20	El-Berka No. 2	86265.41	89777.53	357.70

G_49	Nusirat New Well	91378.53	96449.25	1093.00
F_203	Moghraqa Well No. 3	93719.69	97945.33	272.60
F_191	Moghraqa Well No. 1 - JC	94959.67	98953.18	306.30
L_41	Mahata Eastern Well	84345.62	83160.60	957.80
L_190	El-Satar New Well (Northern)	85758.00	87281.00	1385.00
L_189A	Tahadi Well	81832.00	82693.00	454.00
L_159A	Al-Amal New Well	82680.00	85080.00	324.30
L_159	Al-Amal Old Well	82607.00	85049.00	514.20
P_144A	Canada Well	78314.07	80366.60	307.80
R_162CA	Sheikh Radwan No. 4	98867.35	104590.00	833.60
D_73	Salateen Well	101036.18	106827.16	70.10
Shuka	Shuka Well	80266.00	80177.00	232.40

The models for 2005 dataset were subjected for fitting process based on experimental semivariogram, powering and smoothing process and trails. As it can be summarized in table 5-10, where the final models were selected based on least RMSE value.

Table 0-10. Summary of Validation results for Chloride in year 2005

Measurements of Errors	Spline	IDW	Kriging
Mean:	-30.44	-50.01	-8.78
Root-Mean-Square:	333.4	349.5	332.4

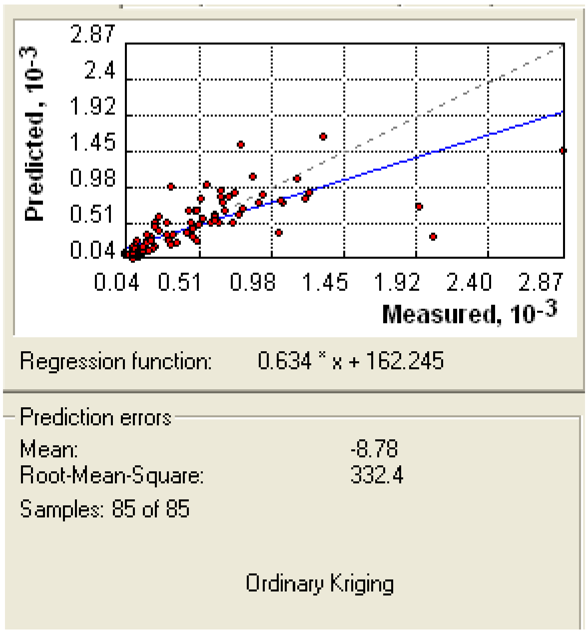
The best fitted above models were further evaluated using the calibration dataset, where tables 5-11 & 5-12 summarize it:

Table 0-11. Predicted values vs. measured Chloride values for year 2005

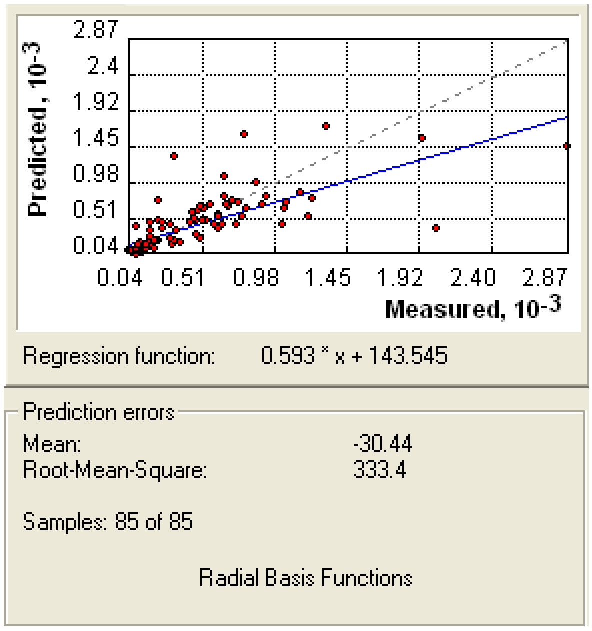
Well_ID	Well_Type	Cl_05	Spline	IDW	Kriging
		Measured	Predicted		
C_128	Abu Gazalah	249.35	208.32	205.07	215.02
C_76	Industrial Area Well	713.20	610.20	645.27	683.59
A_211	Shekh Zaid West Well	52.47	97.19	104.41	103.87
E_90	Hawooz Well (Paris)	208.80	165.05	148.03	186.39
R_280	Sheikh Ejleen No. 6	107.49	171.40	375.42	295.97
R_25C	Safa-03	994.20	730.27	821.56	884.53
J_146	Abo Naser Well	640.60	515.05	536.77	616.52
K_20	El-Berka No. 2	357.70	404.94	404.67	406.07
G_49	Nusirat New Well	1,093.00	862.46	898.35	902.94
F_203	Moghraqa Well No. 3	272.60	264.60	300.86	300.26
F_191	Moghraqa Well No. 1 - JC	306.30	281.04	348.42	318.91
L_41	Mahata Eastern Well	957.80	1054.92	856.49	1167.04
L_190	El-Satar New Well (Northern)	1,385.00	713.99	691.07	741.42
L_189A	Tahadi Well	454.00	561.40	472.64	484.55
L_159A	Al-Amal New Well	324.30	903.00	736.29	955.73
L_159	Al-Amal Old Well	514.20	879.23	730.41	929.65
P_144A	Canada Well	307.80	83.66	205.66	136.99

R_162CA	Sheikh Radwan No. 4	833.60	1275.98	1125.17	1234.99
D_73	Salateen Well	70.10	85.91	127.05	84.44
Shuka	Shuka Well	232.40	330.77	300.01	356.96

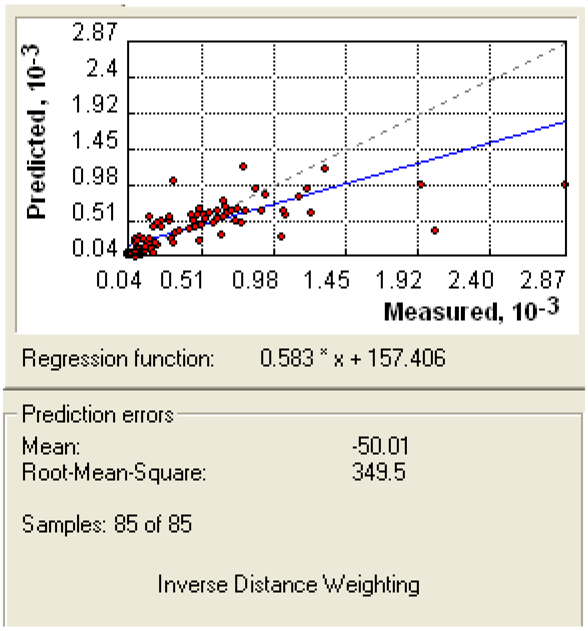
As we can find in Fig. 5-5 the summary of statistical errors for Chloride in Year 2005 resulted from applying Kriging, Spline (RBF), and IDW interpolation methods.



(a)



(b)



(c)

Figure 0-5. Prediction error statistics for Chloride in Year 2005 resulted from: (a) Kriging, (b) Spline (RBF), and (c) IDW interpolation methods

Table 0-12. Summary of Cross Validation results for Chloride in year 2005

Measurements of Correlation	Spline	IDW	Kriging
R	0.810	0.850	0.799
R^2	0.657	0.723	0.638

Moreover, figure 5-6 below illustrates the tendency of each predicted values resulted from applying the three interpolation methods against the measured values for Chloride dataset in year 2005.

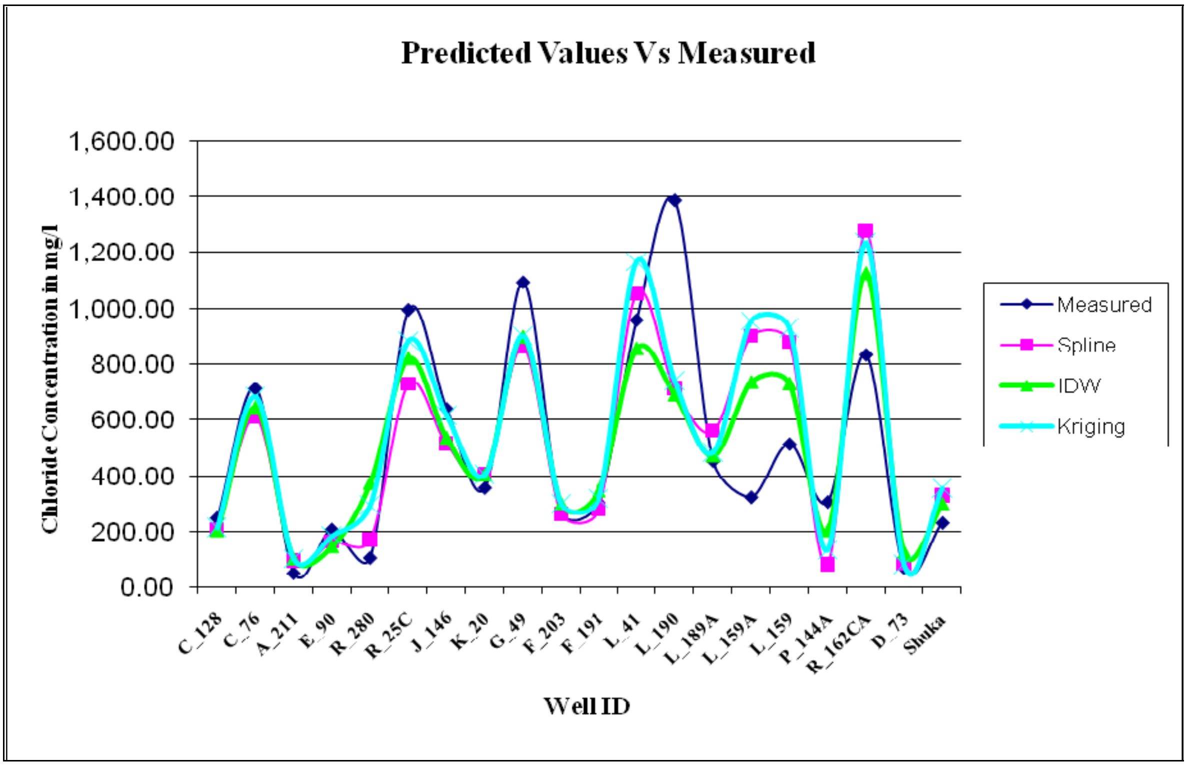


Figure 0-6. Correlation Analysis for Chloride in Year 2005

Despite the fact that the absolute value of errors (R) shows strong positive correlation with the magnitude of the Chloride predicted values at year 2005 in table 5-12, the predicted values in Fig. 5-6 at L_195A and L_190 wells went over and underestimated, this is due to the interpolation process of the modeled dataset, as they were affected by the nearby locally low and high values of the wells that surrounded the intended calibration dataset. As in this situation, there will be huge spatial variation among observations over the distance between.

5.3.1.4 2007 dataset

The Chloride dataset was divided into two sets of data, modeling data and calibration data. The modeling data (106 samples) as shown in (Appendix 5.4 - Chloride Modeling Dataset in 2007) was applied in the three interpolation techniques, yet the Calibration dataset used can be demonstrated in table 5-13 below. Each interpolation technique was best fitted in the validation process, was evaluated through cross-validation process using calibration data with total no. of 25 samples.

Table 0-13. Calibration data of Chloride dataset for year 2007

Well_ID	Well_Name	X	Y	Cl_07
C_137	Nada Well	104987.96	106485.52	60.96
A_211	Shekh Zaid West Well	103328.60	105390.98	86.05
D_72	Sheikh Radwan No. 16	101739.33	106462.51	86.70
E_156	Abu Talal Well	102067.20	104589.25	170.55
R_270	Maslahk Well	96230.00	99750.00	530.70
R_75	Shijaia No. 2 (Abu Abali Well)	100416.47	101298.12	878.45
R_314	Remal No.2 (Kamal Naser)	99164.44	104391.10	177.65
R_306	Sabra-01 (Dogmosh Well)	97075.52	101805.57	261.52
H_95	Zawaida New Well	89462.12	92752.93	1109.00
T_46	Abu Hamam Well	91983.77	90273.16	674.10
K_20	El-Berka No. 2	86265.41	89777.53	433.85
T_52	Wadi El-Salga Well	89412.94	87720.22	623.20
G_30	Hertani Well	91478.84	95975.57	1004.00
S_80	Magazi Well No. S-80	93117.84	91923.24	717.10
S_72	Karaj Well	93199.94	93513.76	1083.00
L_198	Cultural Center Well	83462.39	81977.16	659.70
Rashwan_C	Abu Rashwan Well No. "C"	81953.89	82385.25	2004.00
L_184	Abu Rashwan Well No. "A"	81608.00	82519.00	425.10
L_159	Al-Amal Old Well	82607.00	85049.00	580.85
L_179	Western well	85572.00	87460.00	410.00
M_12	An-Najar Well	85384.00	83299.00	956.10
M_11	Abu-Shahla Well	85100.00	83358.00	467.10
P_144A	Canada Well	78314.07	80366.60	444.60
P_145	El-Hashash Well	79368.23	79856.17	431.00
Shuka	Shuka Well	80266.00	80177.00	358.60

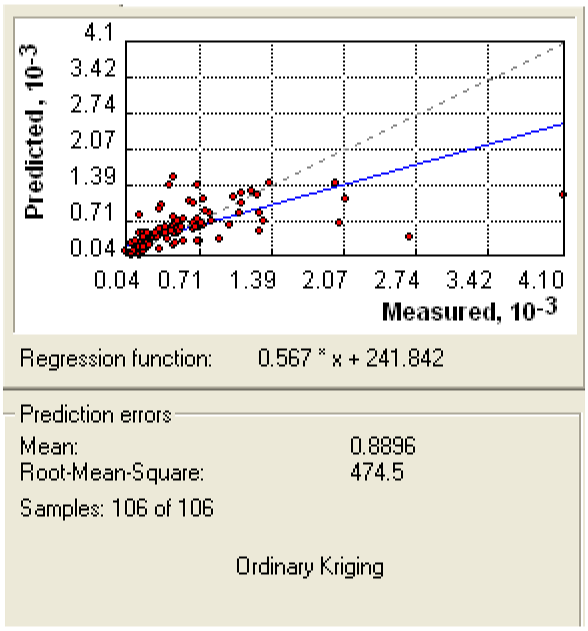
The models for 2007 dataset were subjected for fitting process based on experimental semivariogram, powering and smoothing process and trails. As it can be summarized in table 5-14, where the final models were selected based on least RMSE value.

Table 0-14. Summary of Validation results for Chloride in year 2007

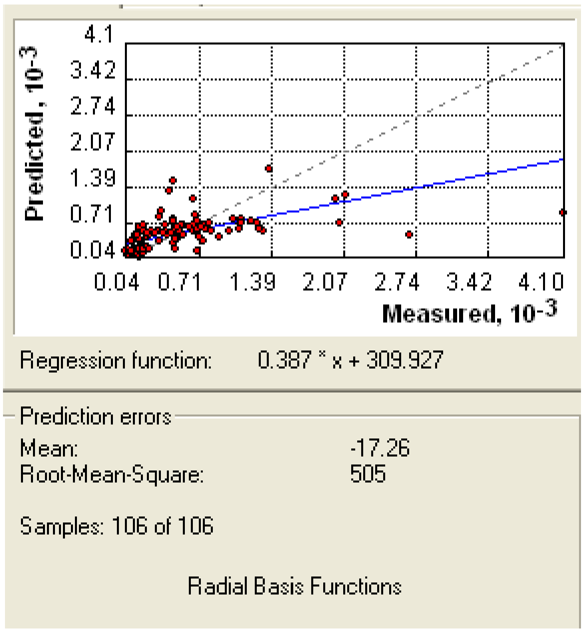
Measurements of Errors	Spline	IDW	Kriging
Mean:	-17.26	-36.97	0.89
Root-Mean-Square:	505	511.1	474.5

As we can find in Fig. 5-7 summary of statistical errors for Chloride in Year 2007 resulted from applying Kriging, Spline (RBF), and IDW interpolation methods.

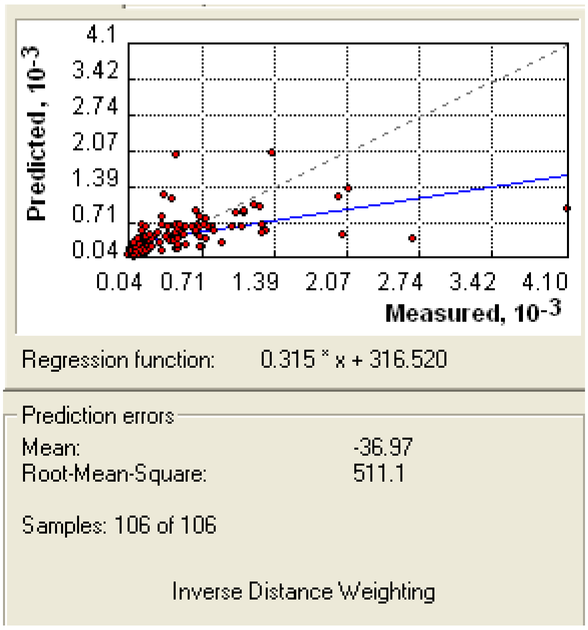
Moreover, the best fitted above models were further evaluated using the calibration dataset, as summarized in tables 5-15 & 5-16 below.



(a)



(b)



(c)

Figure 0-7. Prediction error statistics for Chloride in Year 2007 resulted from: (a) Kriging, (b) Spline (RBF), and (c) IDW interpolation methods

Table 0-15. Predicted values vs. measured Chloride values for year 2007

Well_ID	Well_Type	Cl_07	Spline	IDW	Kriging
		Measured	Predicted		
C_137	Nada Well	60.96	188.61	125.47	120.80
A_211	Shekh Zaid West Well	86.05	162.34	135.15	123.75
D_72	Sheikh Radwan No. 16	86.70	119.78	149.34	106.27
E_156	Abu Talal Well	170.55	164.27	250.86	195.37
R_270	Maslahk Well	530.70	418.04	444.36	314.03

R_75	Shijaia No. 2 (Abu Abali Well)	878.45	695.28	748.81	910.38
R_314	Remal No.2 (Kamal Naser)	177.65	994.11	895.61	762.74
R_306	Sabra-01 (Dogmosh Well)	261.52	553.19	497.80	450.68
H_95	Zawaida New Well	1,109.00	657.46	638.58	753.57
T_46	Abu Hamam Well	674.10	564.32	521.84	630.83
K_20	El-Berka No. 2	433.85	573.88	652.32	561.97
T_52	Wadi El-Salga Well	623.20	612.60	601.35	799.09
G_30	Hertani Well	1,004.00	875.08	1132.21	1357.20
S_80	Magazi Well No. S-80	717.10	213.40	213.40	213.40
S_72	Karaj Well	1,083.00	634.76	511.94	651.40
L_198	Cultural Center Well	659.70	762.72	724.25	974.29
Rashwan_C	Abu Rashwan Well No. "C"	2,004.00	668.70	647.28	769.69
L_184	Abu Rashwan Well No. "A"	425.10	573.41	658.31	539.22
L_159	Al-Amal Old Well	580.85	635.32	485.37	564.69
L_179	Western well	410.00	830.51	1237.71	984.07
M_12	An-Najar Well	956.10	926.69	921.57	1187.18
M_11	Abu-Shahla Well	467.10	927.32	952.04	1213.46
P_144A	Canada Well	444.60	336.90	262.05	210.05
P_145	El-Hashash Well	431.00	362.25	319.95	291.63
Shuka	Shuka Well	358.60	342.28	306.47	244.47

Table 0-16. Summary of Cross Validation results for Chloride in year 2007

Measurements of Correlation	Spline	IDW	Kriging
R	0.428	0.362	0.505
R^2	0.183	0.131	0.255

Fig 5-8 below illustrates the tendency of predicted values for Chloride dataset in year 2007.

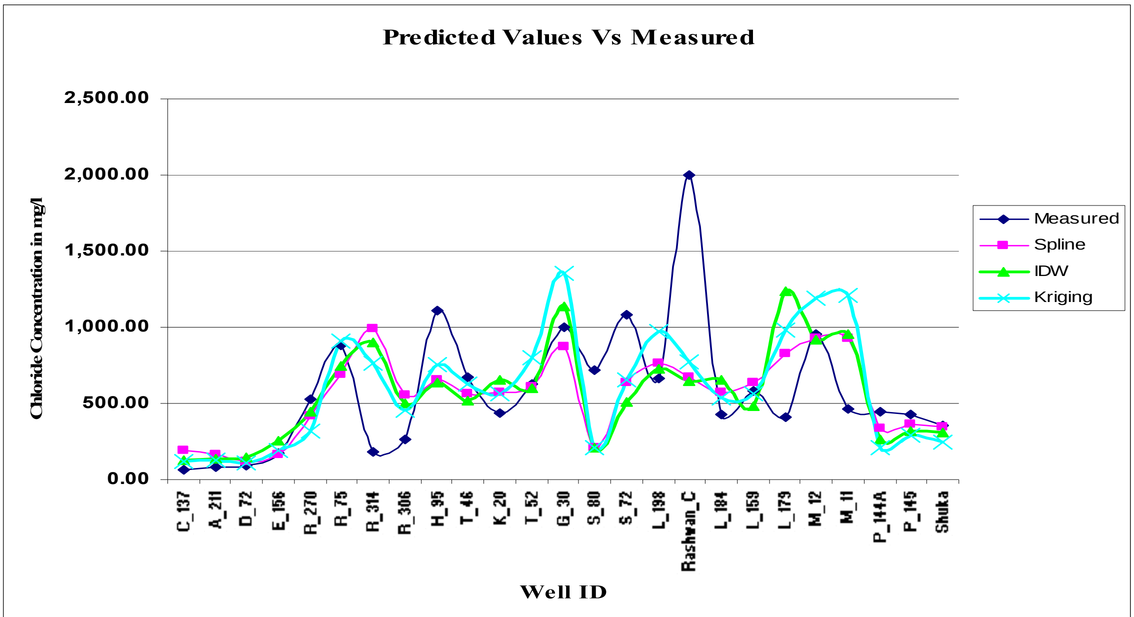


Figure 0-8. Correlation Analysis for Chloride in Year 2007

In table 5-16 the absolute value of errors (R) shows fair positive correlation with the magnitude of the Chloride predicted values at year 2007 and during the interpolation process the predicted values in Fig. 5-8 at R_314 and R_306 wells went all overestimated due to nearby locally high values in which it surrounded them and let the interpolation tendency follow them over the distance between them. Moreover, the predicted value at Rachwan C well , this is due to the nearby locally low values at L_198, L_184, and L_159 wells and in this situation; there will be huge spatial variation among these observations over the distance between them. Besides, a local measurement error during the sampling process might be an associated factor.

5.3.2 Water Level Dataset Results

5.3.2.1 2001 dataset

The Chloride dataset was divided into two sets of data, modeling data and calibration data. The modeling data (101 samples) as shown in (Appendix 6.1 – Water Level Modeling Dataset in 2001) was applied in the three interpolation techniques, yet the Calibration dataset used can be demonstrated in table 5-17 below. Each interpolation technique was best fitted in the validation process, was evaluated through cross-validation process using calibration data with total no. of 10 samples.

Table 0-17. Calibration dataset of Water Level dataset for year 2001

Well_ID	Well_Type	X	Y	WL_01
A_64	Monitoring	103330.19	108096.81	-0.937
C_49	Monitoring	106002.82	105244.83	-0.327
G_24B	Monitoring	92376.56	98908.88	0.379
H_5	Monitoring	89613.29	92965.11	0.083
L_86	Monitoring	82244.33	84658.55	3.026
P_94	Monitoring	80941.85	76960.21	-0.713
Piezo_27	Piezometer	100870.10	107857.73	-1.273
Piezo_36A	Piezometer	98978.74	105215.04	-1.747
S_15	Monitoring	94278.40	94366.74	1.503
T_15	Monitoring	87279.12	87444.48	-0.262

The models for 2001 dataset were subjected for fitting process based on experimental semivariogram, powering and smoothing process and trails. As it can be summarized in table 5-18, where the final models were selected based on least RMSE value.

Table 0-18. Summary of Validation results for Water Level in year 2001

Measurements of Errors	Spline	IDW	Kriging
Mean:	0.0082	0.0327	0.0174
Root-Mean-Square:	1.200	1.219	1.116

As we can find in Fig. 5-9 summary of statistical errors for Water Level in Year 2001 resulted from applying Kriging, Spline (RBF), and IDW interpolation methods.

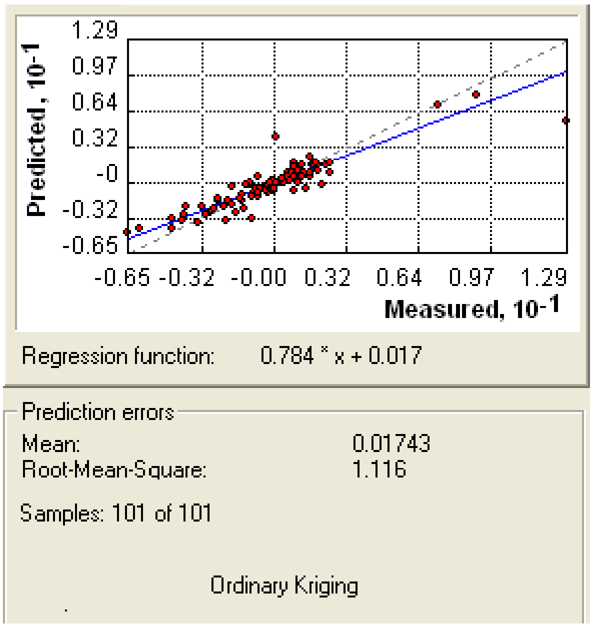
The best fitted above models were further evaluated using the calibration dataset, where tables 5-19 & 5-20 summarize it:

Table 0-19. Predicted values vs. measured Water Level values for year 2001

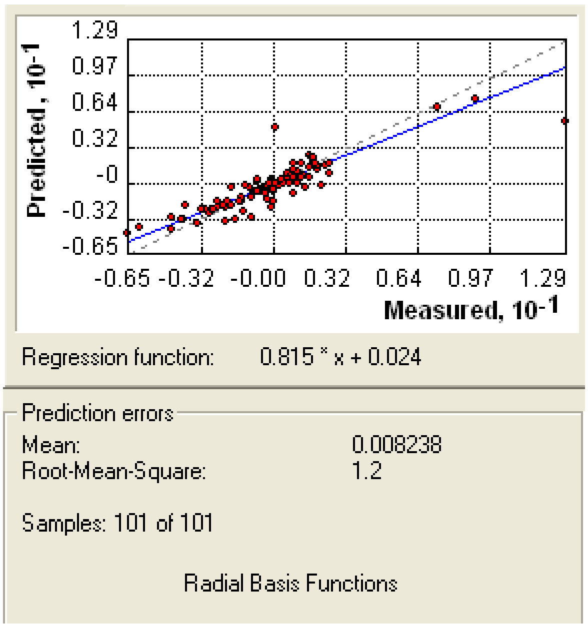
Well_ID	Well_Type	WL_01	Spline	IDW	Kriging
		Measured	Predicted		
A_64	Monitoring	-0.937	-0.544	-0.881	-0.374
C_49	Monitoring	-0.327	0.103	0.049	0.115
G_24B	Monitoring	0.379	0.980	1.072	0.703
H_5	Monitoring	0.083	0.084	0.199	0.102
L_86	Monitoring	3.026	-1.849	-1.304	-1.034
P_94	Monitoring	-0.713	-2.289	-2.779	-1.988
Piezo_27	Piezometer	-1.273	-1.421	-1.629	-1.292
Piezo_36A	Piezometer	-1.747	-2.429	-2.429	-2.429
S_15	Monitoring	1.503	1.738	1.562	1.786
T_15	Monitoring	-0.262	-0.274	-0.122	-0.183

Table 0-20. Summary of Cross Validation results for Water Level in year 2001

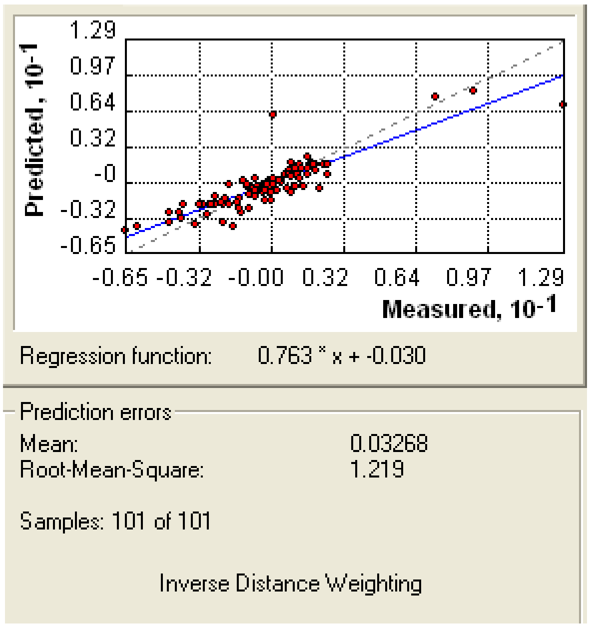
Measurements of Correlation	Spline	IDW	Kriging
R	0.310	0.430	0.461
R^2	0.096	0.185	0.213



(a)



(b)



(c)

Figure 0-9. Prediction error statistics for Water level in Year 2001 resulted from: (a) Kriging, (b) Spline (RBF), and (c) IDW interpolation methods

Figure 5-10 below illustrates the tendency of each predicted values resulted from applying the three interpolation methods against the measured values for Water level dataset in year 2001.

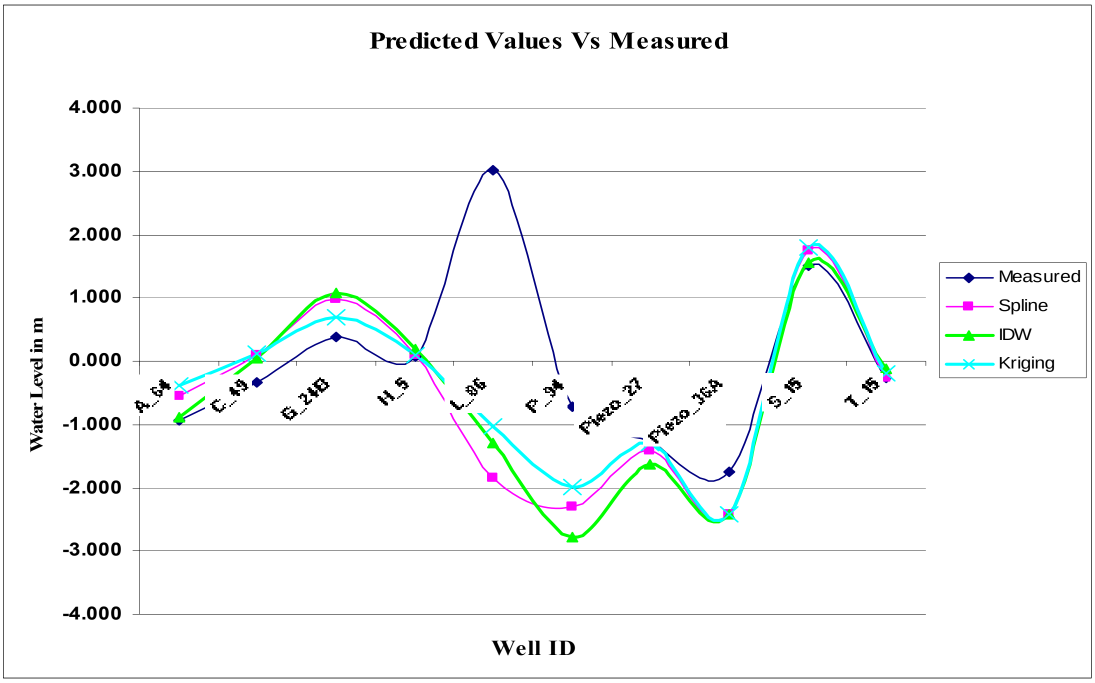


Figure 0-10.Correlation Analysis for Water Level in Year 2001

The absolute value of errors (R) shows weak positive correlation with the magnitude of the Water level predicted values at year 2001 in table 5-20, this can affect the interpolation process, as we can see in Fig. 5-10 above that at L_86 well and during the interpolation process its predicted value went all down underestimated due to the nearby locally low values in which it surrounded it and let the interpolation tendency catch the values over the distance between them. Besides, a local measurement error during the sampling process might be an associated factor in this case.

5.3.2.2 2003 dataset

The Chloride dataset was divided into two sets of data, modeling data and calibration data. The modeling data 92 samples) as shown in (Appendix 6.2 – Water Level Modeling Dataset in 2003) was applied in the three interpolation techniques, yet the Calibration dataset used can be demonstrated in table 5-21 below. Each interpolation technique was best fitted in the validation process, was evaluated through cross-validation process using calibration data with total no. of 11 samples.

Table 0-21. Calibration dataset of Water Level dataset for year 2003

Well_ID	Well_Type	X	Y	WL_03
A_64	Monitoring	103330.19	108096.81	-0.299
C_49	Monitoring	106002.82	105244.83	-0.557
G_24B	Monitoring	92376.56	98908.88	0.407
H_5	Monitoring	89613.29	92965.11	-0.090
L_86	Monitoring	82244.33	84658.55	2.872
P_94	Monitoring	80941.85	76960.21	-1.421
Piezo_27	Piezometer	100870.10	107857.73	-0.798
Piezo_36A	Piezometer	98978.74	105215.04	-1.703
R_133	Monitoring	96773.31	101064.29	1.176
S_15	Monitoring	94278.40	94366.74	1.792
T_15	Monitoring	87279.12	87444.48	-0.077

The models for 2003 dataset were subjected for fitting process based on experimental semivariogram, powering and smoothing process and trails. As it can be summarized in the table 5-22, where the final models were selected based on least RMSE value.

Table 0-22. Summary of Validation results for Water Level in year 2003

Measurements of Errors	Spline	IDW	Kriging
Mean:	0.008	0.033	0.017
Root-Mean-Square:	1.20	1.22	1.12

As we can find in Fig. 5-11 next, summary of statistical errors for Water Level in year 2003 resulted from applying Kriging, Spline (RBF), and IDW interpolation methods.

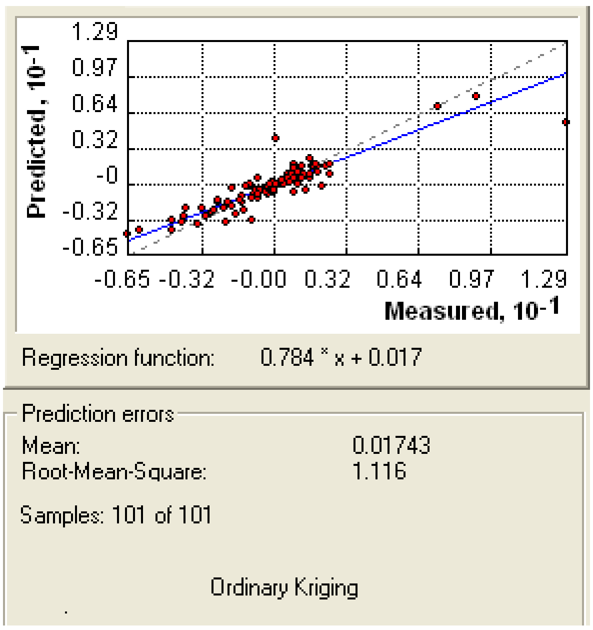
The best fitted above models were further evaluated using the calibration dataset, where tables 5-23 & 5-24 summarize it:

Table 0-23. Predicted values vs. measured Water Level values for year 2003

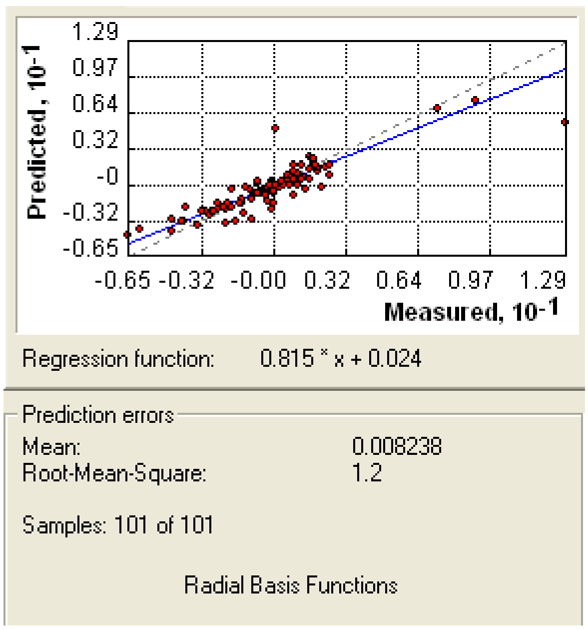
Well_ID	Well_Type	WL_03	Spline	IDW	Kriging
		Measured	Predicted		
A_64	Monitoring	-0.299	-0.490	-1.293	-0.572
C_49	Monitoring	-0.557	-0.306	-0.330	-0.314
G_24B	Monitoring	0.407	0.669	0.804	0.099
H_5	Monitoring	-0.090	0.132	0.219	0.069
L_86	Monitoring	2.872	2.872	2.872	2.872
P_94	Monitoring	-1.421	-3.380	-3.865	-2.810
Piezo_27	Piezometer	-0.798	0.582	-1.092	-0.895
Piezo_36A	Piezometer	-1.703	-2.467	-2.467	-2.467
R_133	Monitoring	1.176	0.878	1.434	1.176
S_15	Monitoring	1.792	1.983	1.851	2.278
T_15	Monitoring	-0.077	-0.084	0.005	-0.095

Table 0-24. Summary of Cross Validation results for Water Level in year 2003

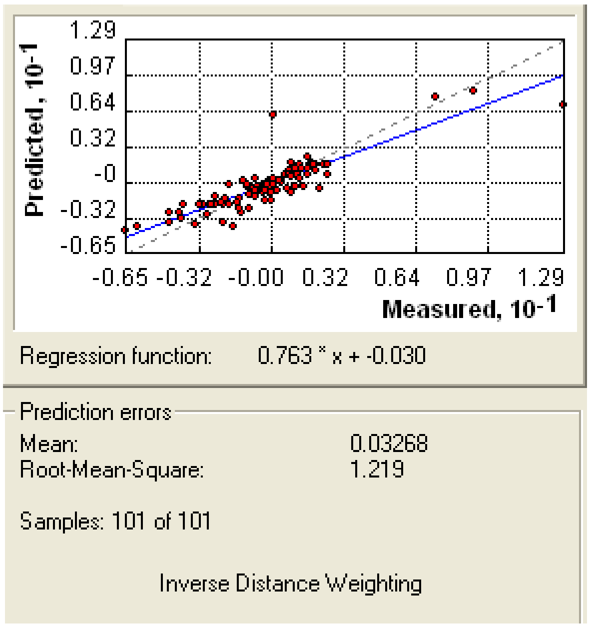
Measurements of Correlation	Spline	IDW	Kriging
R	0.899	0.930	0.971
R^2	0.807	0.865	0.943



(a)



(b)



(c)

Figure 0-11. Prediction error statistics for Water level in Year 2003 resulted from: (a) Kriging, (b) Spline (RBF), and (c) IDW interpolation methods

Figure 5-12 below illustrates the tendency of each predicted values resulted from applying the three interpolation methods against the measured values for Water level dataset in year 2003.

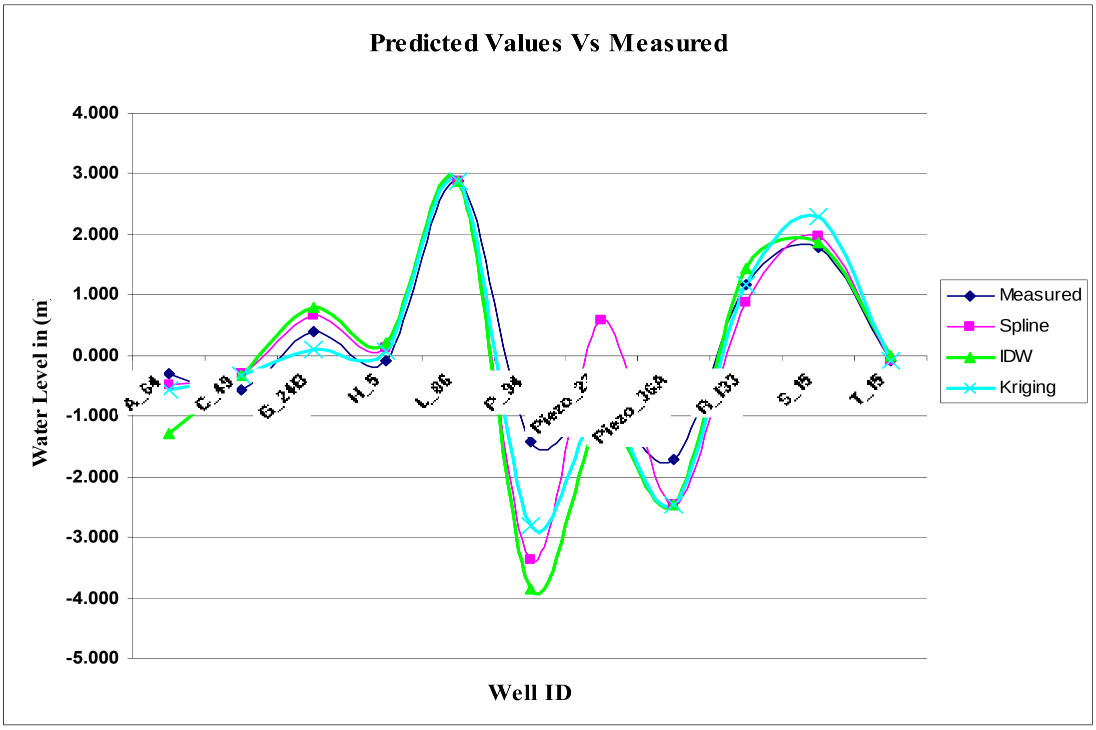


Figure 0-12.Correlation Analysis for Water Level in Year 2003

5.3.2.3 2005 dataset

The Chloride dataset was divided into two sets of data, modeling data and calibration data. The modeling data 94 samples) as shown in (Appendix 6.3 – Water Level Modeling Dataset in 2005) was applied in the three interpolation techniques, yet the Calibration dataset used can be demonstrated in table 5-25 below. Each interpolation technique was best fitted in the validation process, was evaluated through cross-validation process using calibration data with total no. of 11 samples.

Table 0-25. Calibration dataset of Water Level dataset for year 2005

Well_ID	Well_Type	X	Y	WL_05
A_64	Monitoring	103330.19	108096.81	6.315
C_49	Monitoring	106002.82	105244.83	0.581
G_24B	Monitoring	92376.56	98908.88	0.238
H_5	Monitoring	89613.29	92965.11	-0.787
L_86	Monitoring	82244.33	84658.55	3.335
P_94	Monitoring	80941.85	76960.21	-2.125
Piezo_27	Piezometer	100870.10	107857.73	-0.160
Piezo_36A	Piezometer	98978.74	105215.04	-1.956
R_133	Monitoring	96773.31	101064.29	0.655
S_15	Monitoring	94278.40	94366.74	1.400
T_15	Monitoring	87279.12	87444.48	-0.297

The models for 2005 dataset were subjected for fitting process based on experimental semivariogram, powering and smoothing process and trails. As it can be summarized in table 5-26, where the final models were selected based on least RMSE value.

Table 0-26. Summary of Validation results for Water Level in year 2005

Measurements of Errors	Spline	IDW	Kriging
Mean:	0.1222	0.0561	0.0073
Root-Mean-Square:	1.677	1.35	1.064

The best fitted above models were further evaluated using the calibration dataset, where tables 5-27 & 5-28 summarize it:

Table 0-27. Predicted values vs. measured Water Level values for year 2005

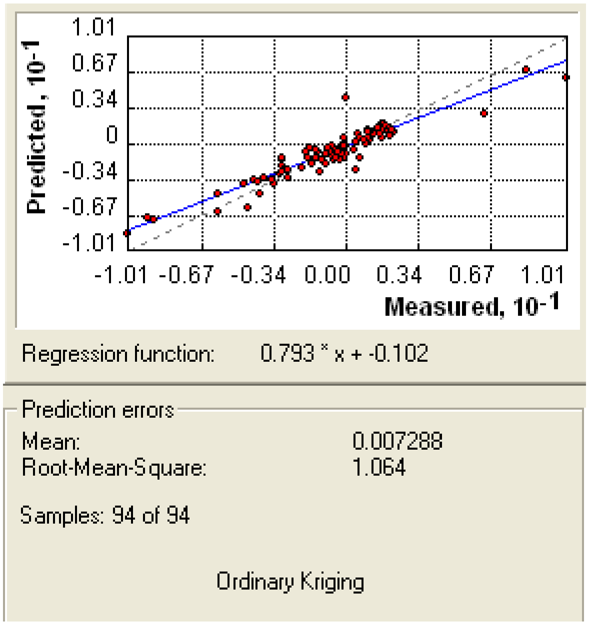
Well_ID	Well_Type	WL_01	Spline	IDW	Kriging
		Measured	Predicted		
A_64	Monitoring	6.315	-1.153	-0.792	-0.398
C_49	Monitoring	0.581	0.592	0.809	0.778
G_24B	Monitoring	0.238	1.182	1.469	1.172
H_5	Monitoring	-0.787	-0.261	-0.490	-0.564
L_86	Monitoring	3.335	-2.906	-2.767	-2.769
P_94	Monitoring	-2.125	-3.341	-3.487	-2.467
Piezo_27	Piezometer	-0.160	-1.533	-1.533	-1.533
Piezo_36A	Piezometer	-1.956	-2.881	-2.881	-2.881

R_133	Monitoring	0.655	0.456	1.254	0.808
S_15	Monitoring	1.400	1.188	1.412	1.476
T_15	Monitoring	-0.297	-0.453	-0.295	-0.344

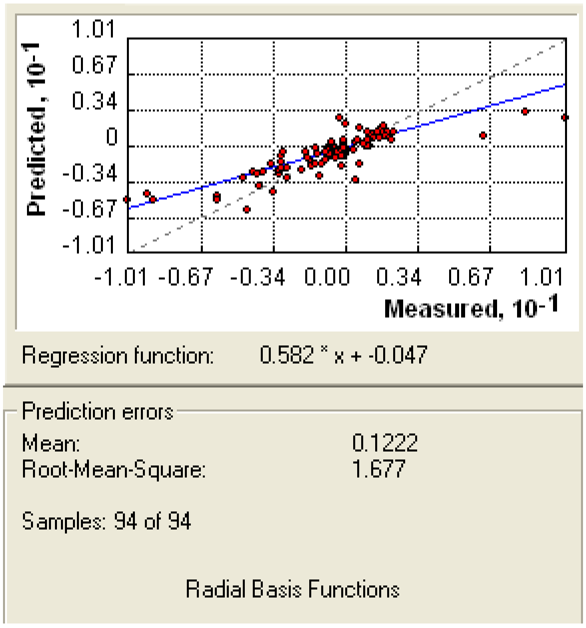
Table 0-28. Summary of Cross Validation results for Water Level in year 2005

Measurements of Correlation	Spline	IDW	Kriging
R	0.122	0.181	0.198
R^2	0.015	0.033	0.039

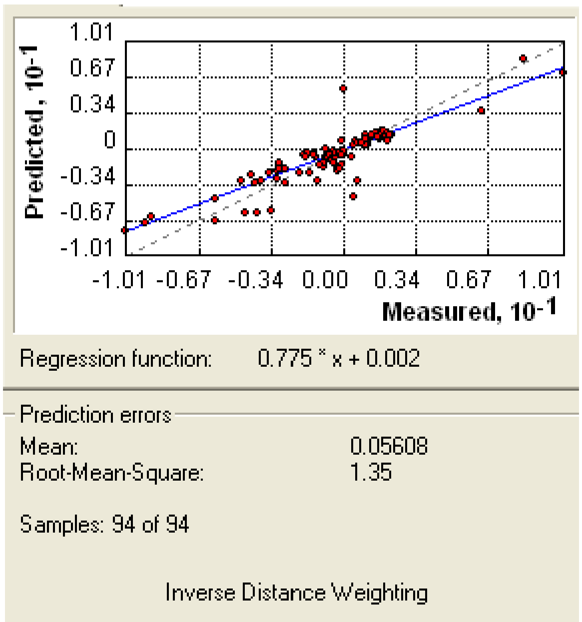
As we can find in Fig. 5-13 next, summary of statistical errors for Water Level in year 2005 resulted from applying Kriging, Spline (RBF), and IDW interpolation methods.



(a)



(b)



(c)

Figure 0-13. Prediction error statistics for Water level in Year 2005 resulted from: (a) Kriging, (b) Spline (RBF), and (c) IDW interpolation methods

Figure 5-14 below illustrates the tendency of each predicted values resulted from applying the three interpolation methods against the measured values for Water level dataset in year 2005.

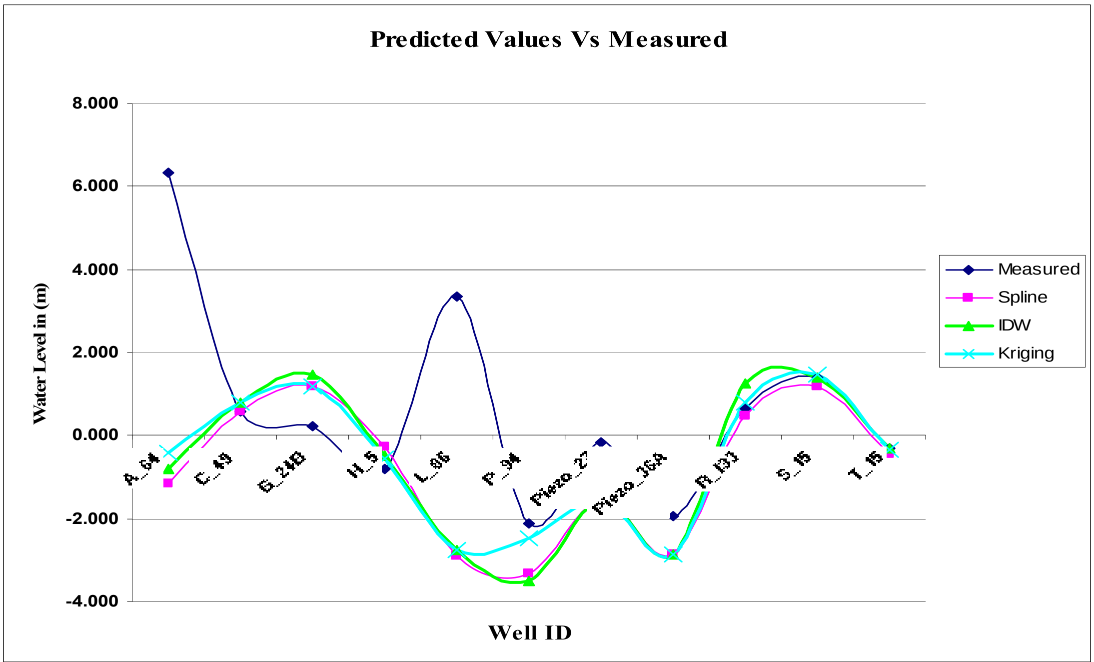


Figure 0-14. Correlation Analysis for Water Level in Year 2005

The absolute value of errors (R) shows very weak positive correlation with the magnitude of the Water level predicted values at year 2003 in table 5-28, this can affect the interpolation process, as clearly we can see in Fig. 5-14 above that at L_86 well and during the interpolation process; its predicted value went underestimated due to the nearby locally low values of the modeled wells surrounded. The different interpolation tendencies caught the values over the distance between them and their associated weights. Besides, a local measurement error during the sampling process might be an associated factor in this case as proved at A_64 well.

5.3.2.4 2007 dataset

The Chloride dataset was divided into two sets of data, modeling data and calibration data. The modeling data 87 samples) as shown in (Appendix 6.4 – Water Level Modeling Dataset in 2007) was applied in the three interpolation techniques, yet the Calibration dataset used can be demonstrated in table 5-29 below. Each interpolation technique was best fitted in the validation process, was evaluated through cross-validation process using calibration data with total no. of 12 samples.

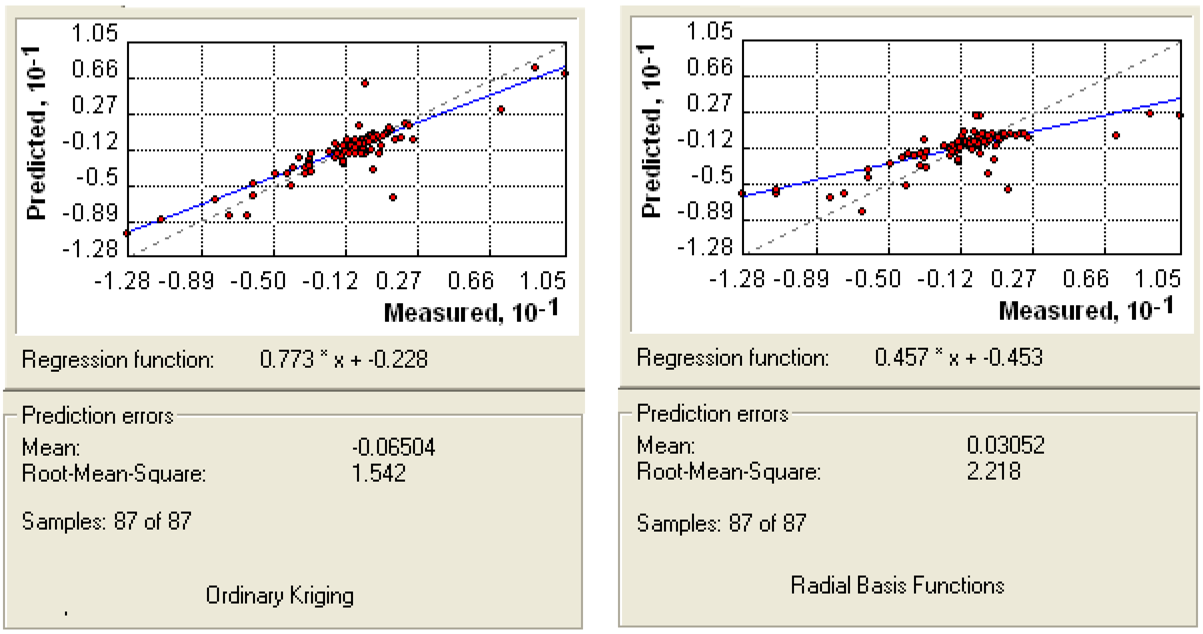
Table 0-29. Calibration data of Water Level dataset for year 2007

Well_ID	Well_Type	X	Y	WL_07
A_64	Monitoring	103330.19	108096.81	6.229
C_49	Monitoring	106002.82	105244.83	0.427
G_24B	Monitoring	92376.56	98908.88	0.114
H_5	Monitoring	89613.29	92965.11	-1.544
L_86	Monitoring	82244.33	84658.55	3.068
P_94	Monitoring	80941.85	76960.21	-2.491
Piezo_27	Piezometer	100870.10	107857.73	-1.538
Piezo_36A	Piezometer	98978.74	105215.04	-2.139
R_133	Monitoring	96773.31	101064.29	-0.234
R_216	Monitoring	101523.17	101059.39	-1.654
S_15	Monitoring	94278.40	94366.74	0.776
T_15	Monitoring	87279.12	87444.48	-0.938

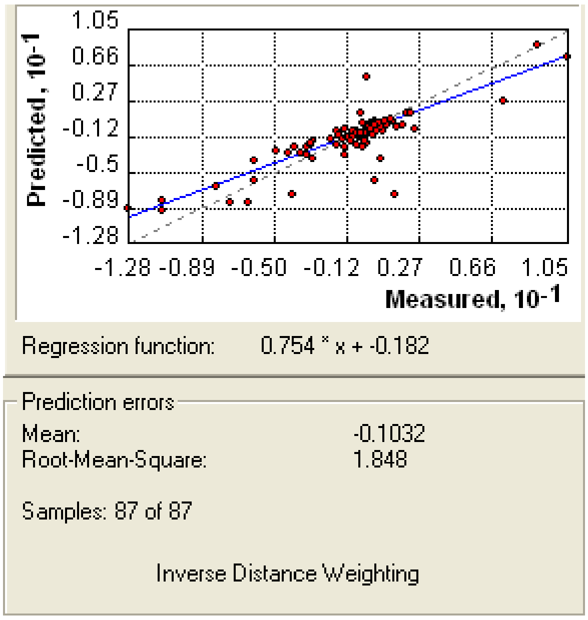
Table 0-30. Summary of Validation results for Water Level in year 2007

Measurements of Errors	Spline	IDW	Kriging
Mean:	0.030	-0.103	-0.065
Root-Mean-Square:	2.218	1.848	1.542

As we can find in Fig. 5-15 next, summary of statistical errors for Water Level in year 2007 resulted from applying Kriging, Spline (RBF), and IDW interpolation methods.



(a) (b)



(c)

Figure 0-15. Prediction error statistics for Water level in Year 2007 resulted from: (a) Kriging, (b) Spline (RBF), and (c) IDW interpolation methods

The best fitted above models were further evaluated using the calibration dataset, where tables 5-31 & 5-32 that summarize it:

Table 0-31. Predicted values vs. measured Water Level values for year 2007

Well_ID	Well_Type	WL_07	Spline	IDW	Kriging
		Measured		Predicted	
A_64	Monitoring	6.229	-1.172	-1.035	-0.544
C_49	Monitoring	0.427	0.417	0.713	0.808
G_24B	Monitoring	0.114	0.541	0.623	0.685
H_5	Monitoring	-1.544	-0.634	-0.858	-0.976
L_86	Monitoring	3.068	-2.861	-2.639	-2.802
P_94	Monitoring	-2.491	-4.075	-3.761	-3.547
Piezo_27	Piezometer	-1.538	-1.809	-0.827	-1.323
Piezo_36A	Piezometer	-2.139	-3.083	-3.083	-3.083
R_133	Monitoring	-0.234	-0.440	-0.060	-0.282
R_216	Monitoring	-1.654	-1.743	-1.412	-1.066
S_15	Monitoring	0.776	0.5906	0.786	0.978
T_15	Monitoring	-0.938	-0.945	-0.849	-0.834

Table 0-32. Summary of Cross Validation results for Water Level in year 2007

Measurements of Correlation	Spline	IDW	Kriging
R	0.220	0.201	0.263
R^2	0.048	0.040	0.069

Figure 5.16 below illustrates the tendency of each predicted values resulted from applying against the measured values for Water Level dataset in year 2007.

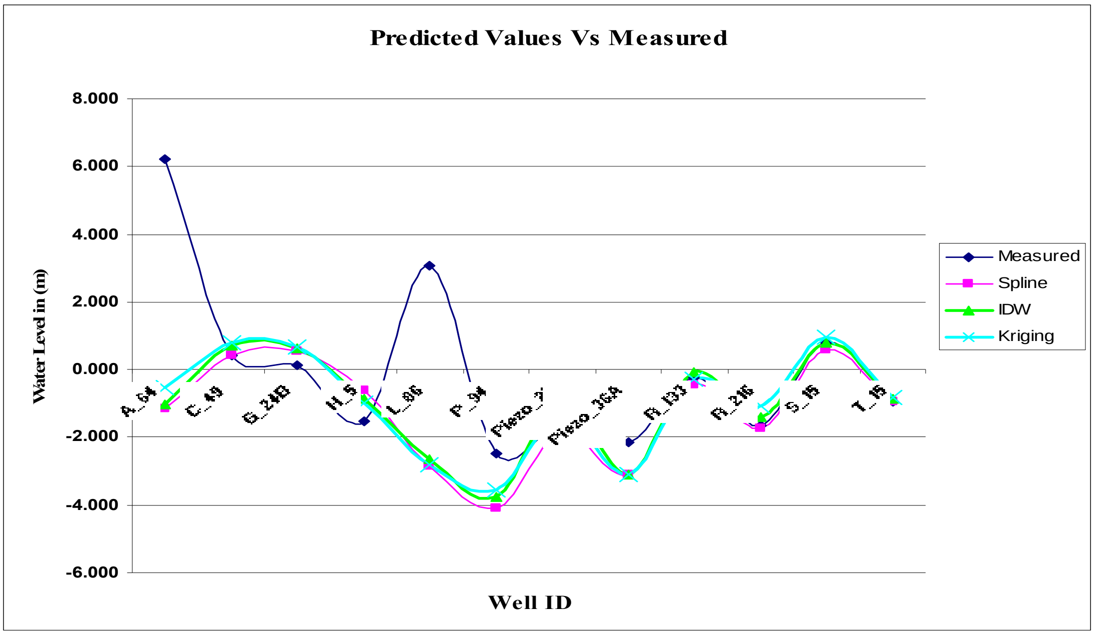


Figure 0-16. Correlation Analysis for Water Level in Year 2007

Again, the absolute value of errors (R) shows very weak positive correlation with the magnitude of the Water level predicted values at year 2007 in table 5-32, this can affect the interpolation process, as clearly we can see this in Fig. 5-16 above that at L_86 well and during the interpolation process its predicted value went all down underestimated due to the nearby locally low values in which it surrounded it and let the interpolation tendency catch the values over the distance between them. Besides, a local measurement error during the sampling process might be an associated factor in this case as proved at A_64 well case.

5.3.3 Rainfall Dataset Results

2.3.3.1 2001 dataset

The Chloride dataset was divided into two sets of data, modeling data and calibration data. The modeling data (10 samples) as shown in (Appendix 7.1 – Rainfall Modeling Dataset in 2001) was applied in the three interpolation techniques, yet the Calibration dataset used can be demonstrated in table 5-33 below. Each interpolation technique was best fitted in the validation process, was evaluated through cross-validation process using calibration data with total no. of 3 samples.

Table 0-33. Calibration dataset of Rainfall dataset for year 2001

Station_Name	Station_Location	X	Y	Rainfall_in_mm
JB	Jabalia	99850	105100	540.00
TUFFAH	Tuffah	100500	101700	533.40
KHUZ.	Khuzaa	83700	76350	284.30

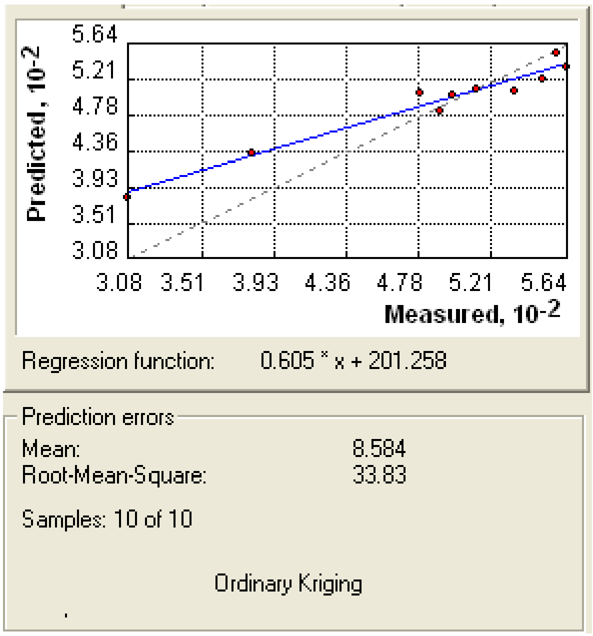
The models for 2001 dataset were subjected for fitting process based on experimental semivariogram, powering and smoothing process and trails. As it can be summarized in the table 5.34, where the final models were selected based on least RMSE value.

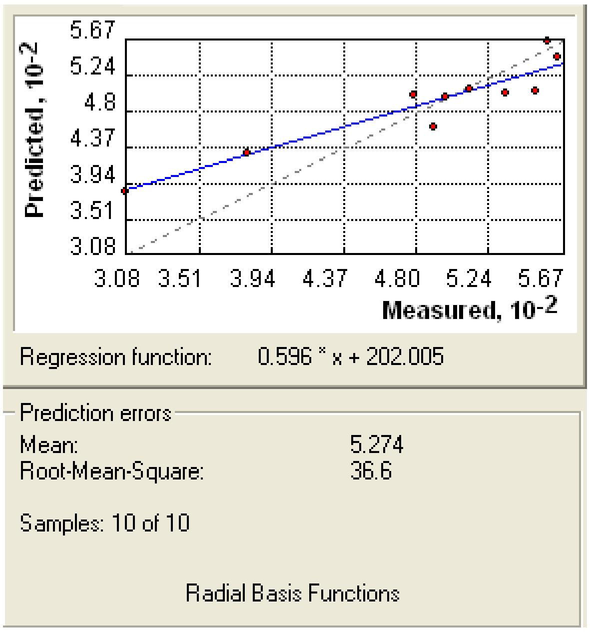
Table 0-34. Summary of Validation results for Rainfall in year 2001

Measurements of Errors	Spline	IDW	Kriging
Mean:	0.0082	0.0327	0.0174
Root-Mean-Square:	1.200	1.219	1.116

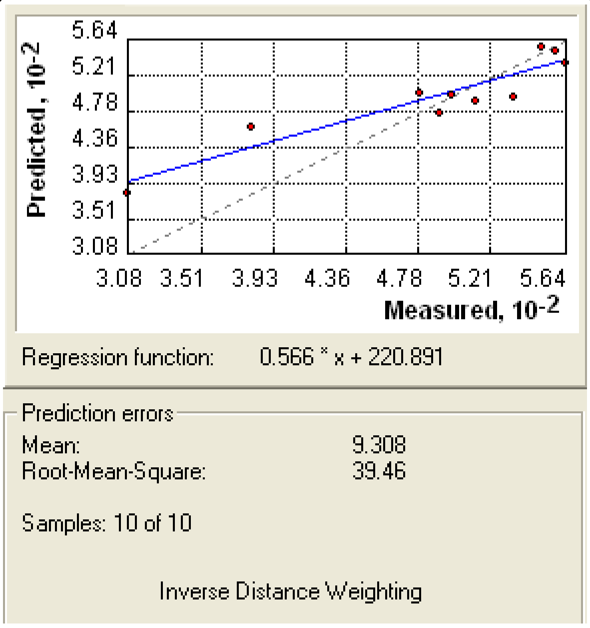
As we can find next in Fig. 5-17, summary of statistical errors for Rainfall in year 2001 resulted from applying Kriging, Spline (RBF), and IDW interpolation methods.

Moreover, the best fitted above models were further evaluated using the calibration dataset, and the results can be shown next in tables 5-35 & 5-36.





(a) (b)



(c)

Figure 0-17. Prediction error statistics for Rainfall in Year 2001 resulted from: (a) Kriging, (b) Spline (RBF), and (c) IDW interpolation methods

Table 0-35. Predicted values vs. measured Rainfall values for year 2001

Station_Name	Station_Location	Rainfall_in_mm	Spline	IDW	Kriging
		Measured	Predicted		
JB	Jabalia	540.00	481.31	478.90	483.58
TUFFAH	Tuffah	533.40	533.40	533.40	533.40
KHUZ.	Khuzaa	284.30	332.45	310.83	327.85

Table 0-36. Summary of Cross Validation results for Rainfall in year 2001

Measurements of Correlation	Spline	IDW	Kriging
R	0.962	0.966	0.967
R^2	0.926	0.934	0.935

Figure 5-18 below illustrates the tendency of each predicted values resulted from applying the three interpolation methods against the measured values for Rainfall dataset in year 2001.

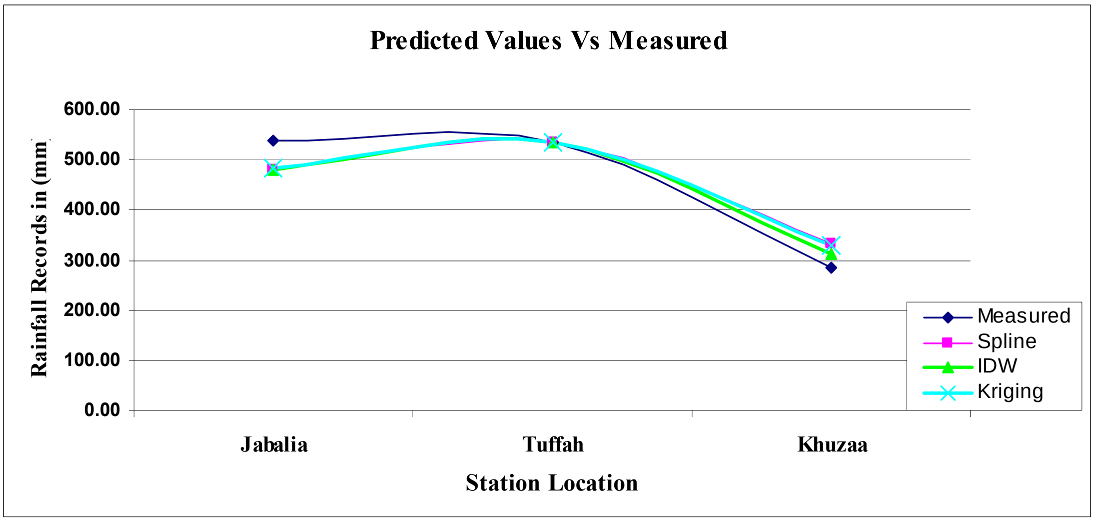


Figure 0-18. Correlation Analysis for Rainfall in Year 2001

5.3.3.2 2003 dataset

The Chloride dataset was divided into two sets of data, modeling data and calibration data. The modeling data (10 samples) as shown in (Appendix 7.2 – Rainfall Modeling Dataset in 2003) was applied in the three interpolation techniques, yet the Calibration dataset used can be demonstrated in table 5-37 below. Each interpolation technique was best fitted in the validation process, was evaluated through cross-validation process using calibration data with total no. of 3 samples.

Table 0-37. Calibration dataset of Rainfall dataset in mm for year 2003

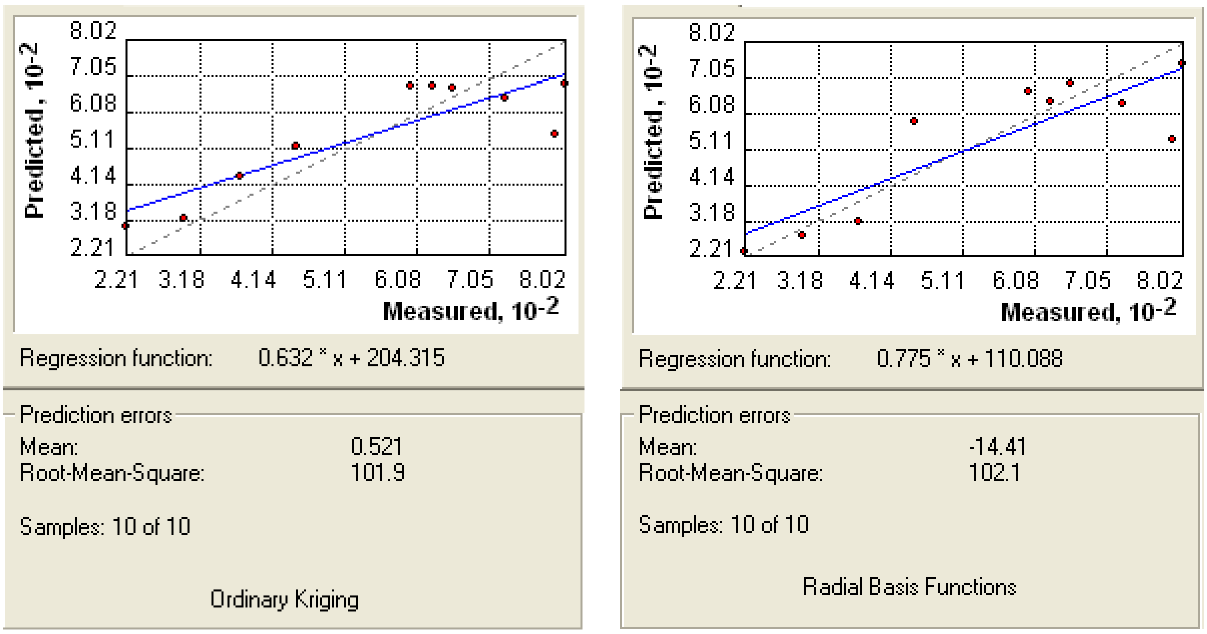
Station_Name	Station_Location	X	Y	Rainfall_in_mm
JB	Jabalia	99850	105100	692.60
TUFFAH	Tuffah	100500	101700	653.50
KHUZ.	Khuzaa	83700	76350	261.20

The models for 2003 dataset were subjected for fitting process based on experimental semivariogram, powering and smoothing process and trails. As it can be summarized in table 5-38, where the final models were selected based on least RMSE value.

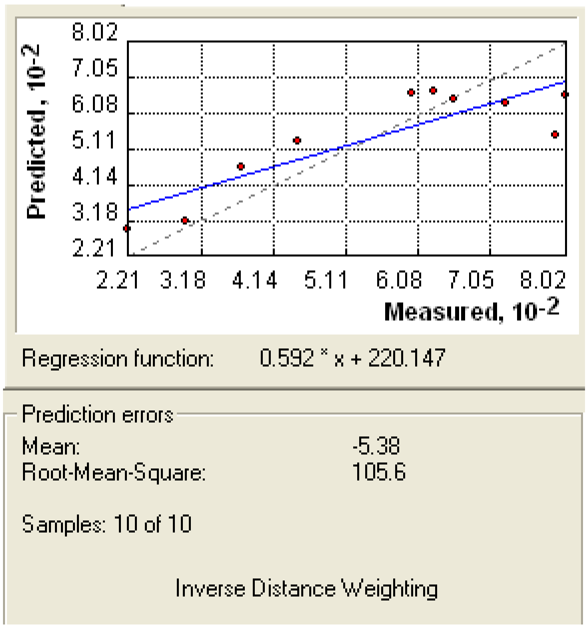
Table 0-38. Summary of Validation results for Rainfall in year 2003

Measurements of Errors	Spline	IDW	Kriging
Mean:	-14.41	-5.38	0.521
Root-Mean-Square:	102.1	105.6	101.9

As we can find next in Fig. 5-19, summary of statistical errors for Rainfall in year 2003 resulted from applying Kriging, Spline (RBF), and IDW interpolation methods.



(a) (b)



(c)

Figure 0-19. Prediction error statistics for Rainfall in Year 2003 resulted from: (a) Kriging, (b) Spline (RBF), and (c) IDW interpolation methods

The best fitted above models were further evaluated using the calibration dataset, where tables 5-39 & 5-40 summarize it:

Table 0-39. Predicted values vs. measured Rainfall values for year 2003

Station_Name	Station_Location	Rainfall_in_mm	Spline	IDW	Kriging
		Measured	Predicted		
JB	Jabalia	692.60	630.29	629.20	636.11
TUFFAH	Tuffah	653.50	653.50	653.50	653.50
KHUZ.	Khuzaa	261.20	261.10	240.03	245.74

Table 0-40. Summary of Cross Validation results for Rainfall in year 2003

Measurements of Correlation	Spline	IDW	Kriging
R	0.991	0.991	0.993
R^2	0.982	0.982	0.986

Figure 5-20 below illustrates the tendency of each predicted values resulted from applying the three interpolation methods against the measured values for Rainfall dataset in year 2003.

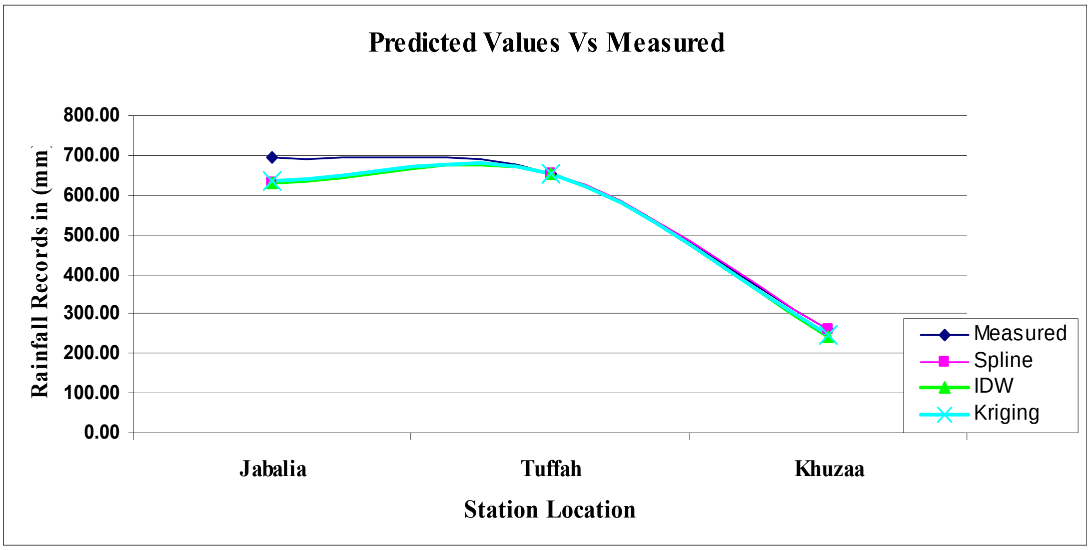


Figure 0-20.Correlation Analysis for Rainfall in Year 2003

5.3.3.3 2005 dataset

The Chloride dataset was divided into two sets of data, modeling data and calibration data. The modeling data (10 samples) as shown in (Appendix 7.3 – Rainfall Modeling Dataset in 2005) was applied in the three interpolation techniques, yet the Calibration dataset used can be demonstrated in table 5-41 below. Each interpolation technique was best fitted in the validation process, was evaluated through cross-validation process using calibration data with total no. of 3 samples.

Table 0-41. Calibration dataset of Rainfall dataset for year 2005

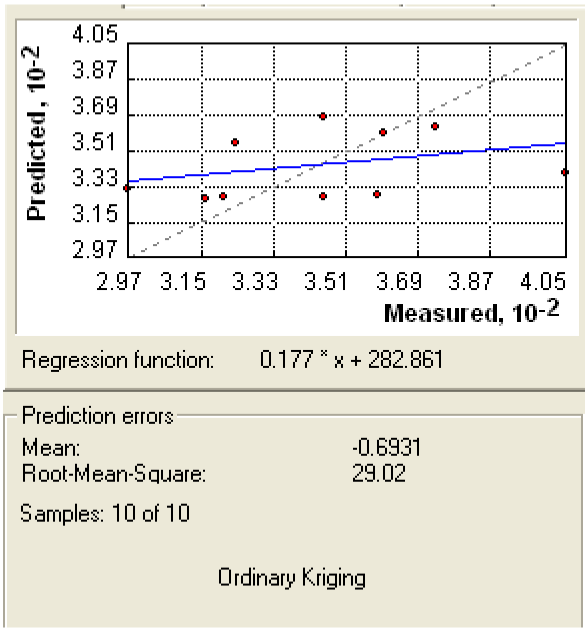
Station_Name	Station_Location	X	Y	Rainfall_in_mm
JB	Jabalia	99850	105100	345.50
TUFFAH	Tuffah	100500	101700	345.40
KHUZ.	Khuzaa	83700	76350	367.70

The models for 2005 dataset were subjected for fitting process based on experimental semivariogram, powering and smoothing process and trails. As it can be summarized in table 5-42, where the final models were selected based on least RMSE value.

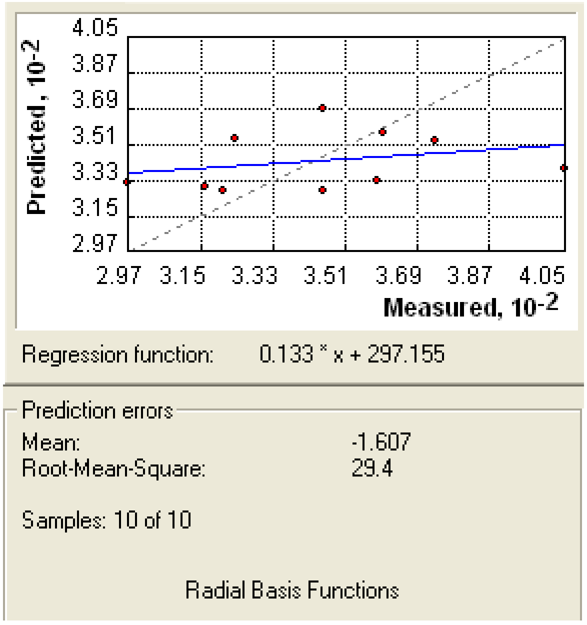
Table 0-42. Summary of Validation results for Rainfall in year 2005

Measurements of Errors	Spline	IDW	Kriging
Mean:	-1.61	-3.19	-0.69
Root-Mean-Square:	29.4	32.13	29.02

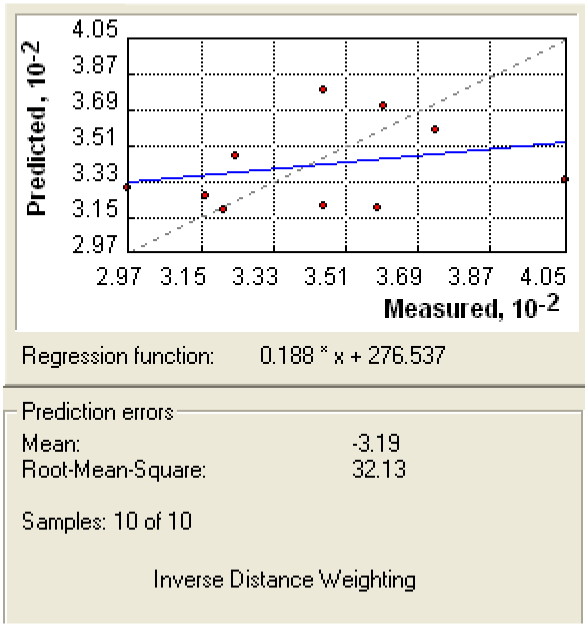
As we can find in Fig. 5-21, summary of statistical errors for Rainfall in year 2005 resulted from applying Kriging, Spline (RBF), and IDW interpolation methods.



(a)



(b)



(c)

Figure 0-21. Prediction error statistics for Rainfall in Year 2005 resulted from: (a) Kriging, (b) Spline (RBF), and (c) IDW interpolation methods

The best fitted above models were further evaluated using the calibration dataset, where tables 5-43 & 5-44 summarize it:

Table 0-43. Predicted values vs. measured Rainfall values for year 2005

Station_Name	Station_Location	Rainfall_in_mm	Spline	IDW	Kriging
		Measured	Predicted		
JB	Jabalia	345.50	305.22	307.59	314.82
TUFFAH	Tuffah	345.40	345.40	345.40	345.40
KHUZ.	Khuzaa	367.70	359.68	364.13	362.08

Table 0-44. Summary of Cross Validation results for Rainfall in year 2005

Measurements of Correlation	Spline	IDW	Kriging
R	0.70	0.75	0.77
R^2	0.49	0.57	0.59

Figure 5-22 below illustrates the tendency of each predicted values resulted from applying the three interpolation methods against the measured values for Rainfall dataset in year 2005.

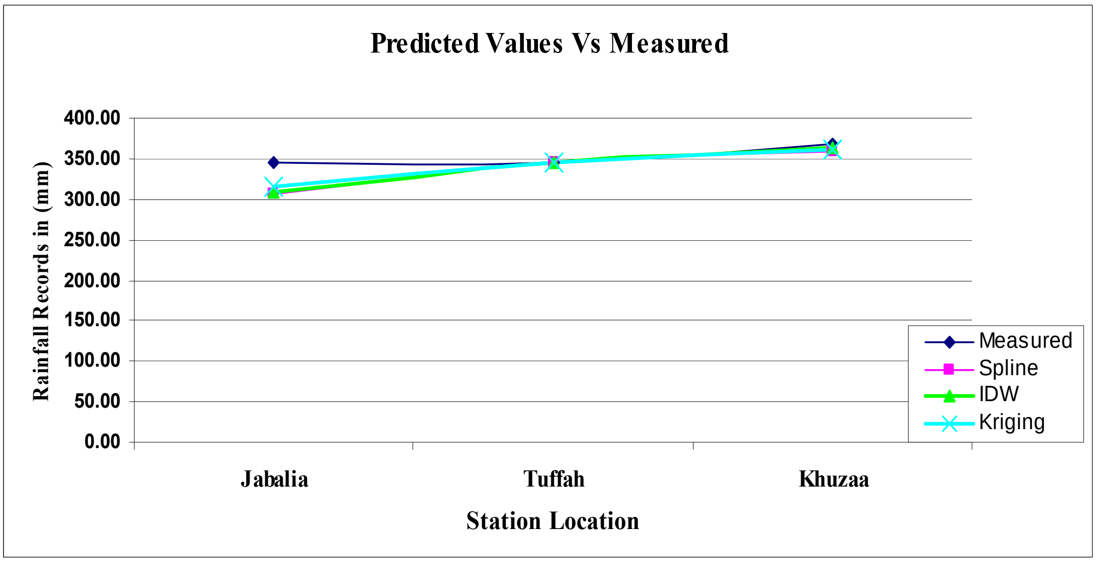


Figure 0-22. Correlation Analysis for Rainfall in Year 2005

5.3.3.4 2007 dataset

The Chloride dataset was divided into two sets of data, modeling data and calibration data. The modeling data (10 samples) as shown in (Appendix 7.4 – Rainfall Modeling Dataset in 2007) was applied in the three interpolation techniques, yet the Calibration dataset used can be demonstrated in table 5-45 below. Each interpolation technique was best fitted in the validation process, was evaluated through cross-validation process using calibration data with total no. of 3 samples.

Table 0-45. Calibration dataset of Rainfall dataset for year 2007

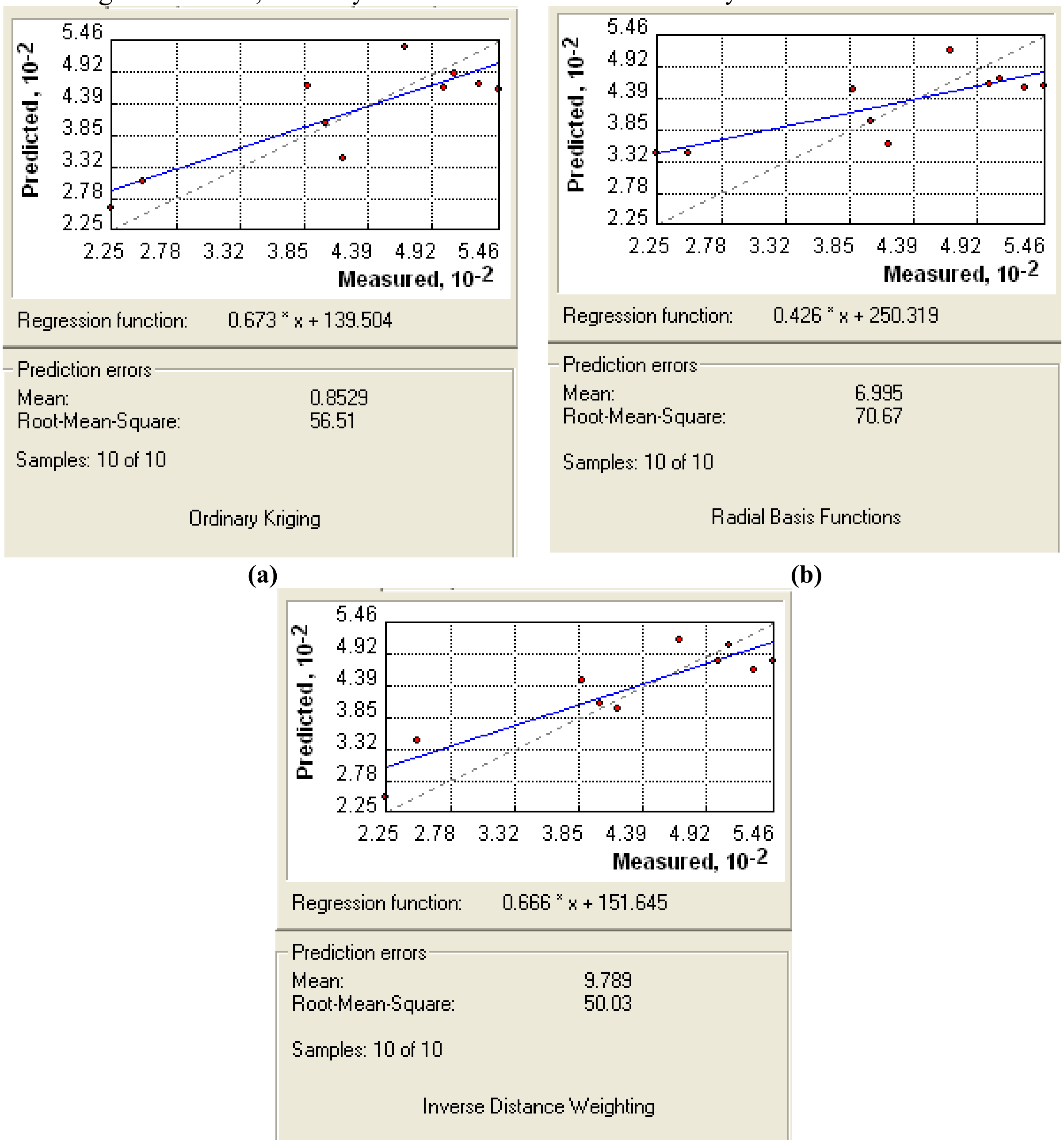
Station_Name	Station_Location	X	Y	Rainfall_in_mm
JB	Jabalia	99850	105100	536.70
TUFFAH	Tuffah	100500	101700	545.50
KHUZ.	Khuzaa	83700	76350	256.10

The models for 2007 dataset were subjected for fitting process based on experimental semivariogram, powering and smoothing process and trails. As it can be summarized in table 5-46, where the final models were selected based on least RMSE value.

Table 0-46. Summary of Validation results for Rainfall in year 2007

Measurements of Errors	Spline	IDW	Kriging
Mean:	6.99	9.79	0.85
Root-Mean-Square:	70.67	50.03	56.51

In Fig. 5-23 below, summary of statistical errors for Rainfall in year 2005.



(c)

Figure 0-23. Prediction error statistics for Rainfall in Year 2007 resulted from: (a) Kriging, (b) Spline (RBF)**, and (c) IDW interpolation methods**

The best fitted above models were further evaluated using the calibration dataset, where tables 5-47 & 5-48 summarize it:

Table 0-47. Predicted values vs. measured Rainfall values in mm for year 2007

Station_Name	Station_Location	Rainfall_in_mm	Spline	IDW	Kriging
		Measured	Predicted		
JB	Jabalia	536.70	474.38	469.00	479.98
TUFFAH	Tuffah	545.50	545.50	545.50	545.50
KHUZ.	Khuzaa	256.10	274.81	225.63	240.51

Table 0-48. Summary of Cross Validation results for Rainfall in year 2007

Measurements of Correlation	Spline	IDW	Kriging
R	0.97	0.98	0.98
R^2	0.95	0.96	0.97

Figure 5-24 below illustrates the tendency of each predicted values resulted from applying the three interpolation methods against the measured values for Rainfall dataset in year 2007.

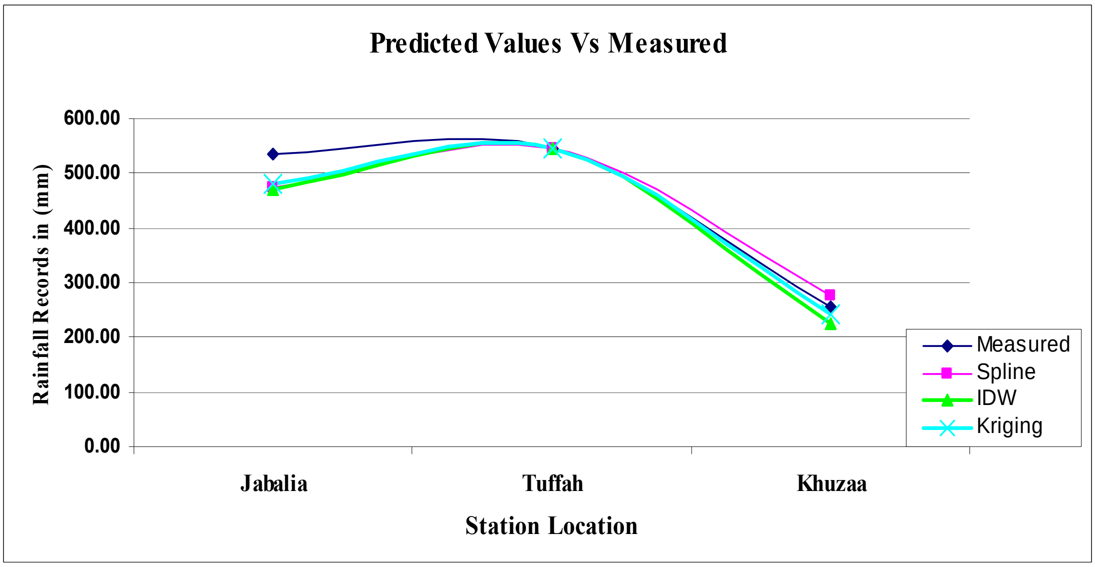


Figure 0-24. Correlation Analysis for Rainfall in Year 2007

5.4 Discussion & Interpretation

In general the three interpolation methods have expressed good representation of the three different datasets for the different study years but with poor accuracy except in some cases like Rainfall dataset. It was noticed that Kriging method performed spatially better in the rainfall and water level as well measure of errors and its predicted values rather than the IDW and Spline methods. IDW and Kriging methods had expressed strong performance in modeling Chloride datasets with low accuracy in the predicted data rather than the Spline method.

In the Spline interpolation, and after trials, it was found out that the more weight given to the optimized Regularized method, the more data that can be anticipated and it could go beyond the range, which makes the surface produced questionable. Thus the chosen Spline with tension surface that was optimized for most of the three different datasets has gone within the range of the modeled data and provided more accurate predicted values and less RMSE values rather than the Regularized method

The power parameter in the IDW (with fixed radius) interpolator was controlling the significance of the surrounding points upon the interpolated value. A higher power results in less influence from distant points, while using the optimized power and smoothing factor have resulted in less RMSE values.

In Kriging interpolation, it was validated through serial of trials in the semivariogram (lag, nugget, and sill ratio with smoothing factors) where it helps in making an informed decision as to which model provides the best predictions should have. Ordinary Kriging with Prediction mapping tools has expressed the most accurate and reliable spatial representation of the datasets rather than the Universal Kriging, moreover, the Spherical and Exponential models expressed the least RMSE among all techniques in Kriging interpolation. However, data were normalized using logarithmic method in only the Chloride and Rainfall datasets.

5.4.1 Chloride Dataset Discussion

The applicable interpolation methods used in this type of dataset were IDW and Kriging with advantage to Kriging due to its smaller values of ME and RMSE which confirms the unbiased dataset presentation. It is worth to mention that Spline has expressed high ME and RMSE values during the same years and made its spatial mapping questionable despite the close values of correlation with both IDW and Kriging.

With reference to table 5-49 below, IDW and Kriging have close correlation values during the different years of the study. It is fair to say that both methods produces good estimates, but neither estimates every unknown value with perfect accuracy. This confirms that with the available sampling locations, neither of the methods was able to predict or interpolate values accurately at relatively distant points or at locations where sampling points were not available.

Table 0-49. Summary of statistical errors for for Chloride Datasets

Method	Years	ME	RMSE	R^2
	2001			
Spline		-15.82	206.2	0.625
IDW		-10.99	187.5	0.658
Kriging		0.02	195.7	0.520
	2003			
Spline		-8.95	258.4	0.657
IDW		-28.95	245.9	0.723
Kriging		8.16	259.0	0.638
	2005			
Spline		-30.44	333.4	0.423

IDW	-50.01	349.5	0.483
Kriging	-8.78	332.4	0.449
2007			
Spline	-17.26	505.0	0.183
IDW	-36.97	511.1	0.131
Kriging	0.89	474.5	0.255

As it shows above, the more data used in the modeling phase the more RMSE results and the less ME results it is obtained due to the huge spatial variation among observations over a short distance as we do have measures ranged between 50-2000 mg/l.

The results did not indicate obvious advantage in using IDW over Kriging. However, we must remember that cross validation only provides information about model bias and not about the accuracy, thus both statistical analyses and visual presentations of error can be used as solid guide for selecting the best method which concluded in Kriging.

5.4.2 Water Level Dataset Discussion

The three interpolation methods were close in ME and RMSE values with advantage to Kriging in this regard, the errors between Spline, IDW and Kriging were similar. The Cross validation process revealed that Kriging will perform better than Spline and IDW due to its highest value of correlation, this result was kept uniform for all the dataset processed during the different study years, as table 5-50 below illustrates the resulted statistical errors for the three applied interpolation methods for Water level datasets.

Table 0-50. Summary of statistical errors for Water Level Datasets

Method Years	ME	RMSE	R^2
2001			
Spline	0.01	1.2	0.096
IDW	0.03	1.2	0.185
Kriging	0.02	1.1	0.213
2003			
Spline	0.01	1.2	0.807
IDW	0.03	1.2	0.865
Kriging	0.02	1.1	0.943
2005			
Spline	0.12	1.7	0.015
IDW	0.06	1.4	0.033
Kriging	0.01	1.1	0.039
2007			
Spline	0.03	2.2	0.048
IDW	-0.10	1.8	0.040
Kriging	-0.07	1.5	0.069

The results indicated obvious advantage in using Kriging over Spline and IDW as interpolator that can be the most suitable for surface mapping the Water Level dataset as proven for the different study years.

5.4.3 Rainfall Dataset Discussion

Both interpolation methods (Kriging and IDW) could not be utilized since the available data that ought to be modeled were less than 10 samples where this could be a disadvantage aspect unlike the Spline method, accordingly 10 samples were modeled out of the available 12 samples, while the calibration dataset used 3 distributed samples to carry on the required analysis and errors exploration.

It can lead us to the fact that there should be more adequate dataset (more stations) for more reliable spatial modeling so as it can be geostatistically analyzed and to obtain better results and surface mapping output.

In comparing the cross validation results, it was found that the errors were unbiased in Kriging method despite that both cross-validation and validation results indicated that errors increased as data density increased during the different study years, as table 5-51 below illustrates the resulted statistical errors for the three applied interpolation methods for Rainfall datasets.

Table 0-51.Summary of statistical errors for Rainfall Datasets

Method	Years	ME	RMSE	R^2
	2001			
Spline		0.01	1.2	0.926
IDW		0.03	1.2	0.934
Kriging		0.02	1.1	0.935
	2003			
Spline		-14.41	102.1	0.982
IDW		-5.38	105.6	0.982
Kriging		0.52	101.9	0.986
	2005			
Spline		-1.61	29.4	0.490
IDW		-3.19	32.1	0.565
Kriging		-0.69	29.0	0.589
	2007			
Spline		7.00	70.7	0.948
IDW		9.79	50.0	0.959
Kriging		0.85	56.5	0.968

As we notice that the results in year 2005 have considerably changed in terms of R2 values, that's due to the fact that there high possibility of local measurement error in the Jabalia gauge (345.50 mm), since the simulation by the different interpolation method did not get close enough of that value (305.22/Spline, 307.59/IDW, 314.82/Kriging)., unlike the other years where good results proved accurate simulation.

The results above indicated to somehow obvious advantage in using Kriging over Spline and IDW as interpolator that can be the most suitable for surface mapping the Rainfall dataset as proven during the study years.

In conclusion, Kriging performed slightly better than Spline and IDW due to its quietly higher correlation values and less RMSE values, thus more accuracy and proper surface mapping we can generate by using Kriging interpolation method.

5.5 Surface Mapping

For each dataset and after the validation and cross validation process, the Surface generation was conducted using the three interpolation methods for year 2007 to produce the Chloride, Water Level and Rainfall maps that show the spatial variation in the concentration, groundwater level, and rainfall amounts in the study area (Gaza Strip) in which we can summarize them in the following manner:

- The chloride ion concentration varies from less than 250mg/l in the sand dune areas as the northern and south-western area of the GS to about more 1,500 mg/l where the seawater intrusion has occurred on the coastal areas.
- The groundwater is at a deeper position in the southern parts of the study area, decreasing gradually to the middle but goes deeper again in the northern parts (more than -6 meters) due to huge consumption ratios and other factors like deficient natural recharge.
- The rainfall varies significantly as it decreases from northern governorates (more than 500 mm) down to southern governorates (less than 300 mm).

In the following, is the final surface mapping for the different datasets utilized in this study (i.e. Chloride, Water Level, and Rainfall) where it can be shown that in the next figures:

- In Fig 5-25 different Spatial representation of Chloride concentration for Year 2007 were generated and compared against each other by using a) IDW, b) Spline (RBF), and c) Kriging and d) the officially released CMWU map in 2007.

- While in Fig 5-26 the maps of different Spatial representation of Water Level for Year 2007 were produced and compared against each other by using a) IDW, b) Spline (RBF), and c) Kriging and d)the officially released CMWU map in 2007.

- Finally, in Fig 5-27 different Spatial representation of Chloride concentration for Year 2007 were generated and comparison against each other by using a) IDW, b) Spline (RBF), and c) Kriging, where no maps were officially released by CMWU in this regard.

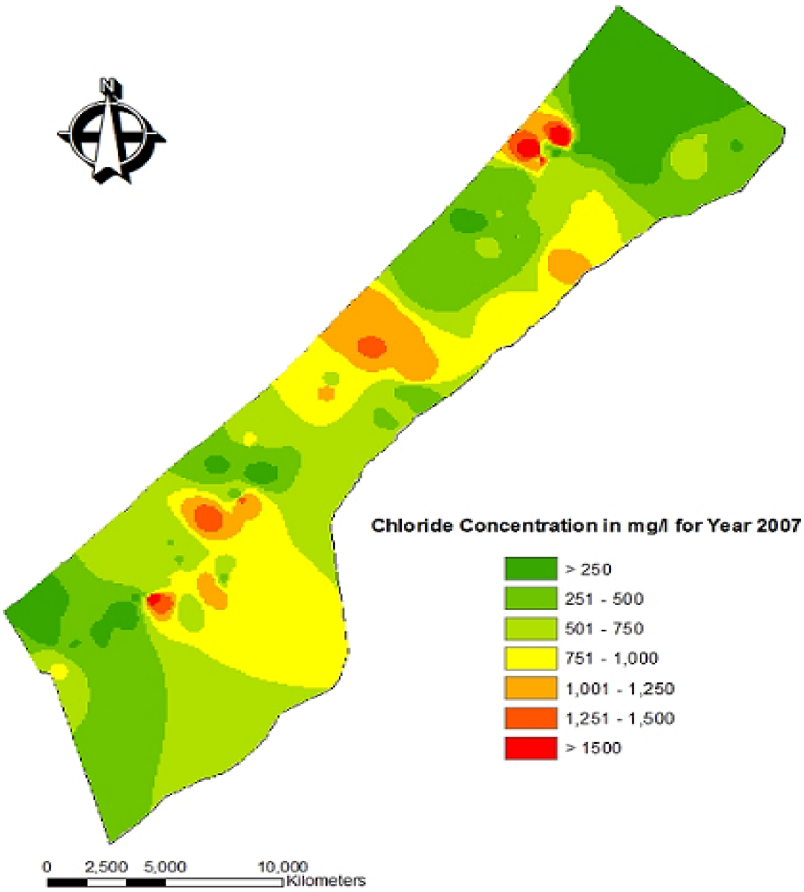


Fig 5-25 (a)

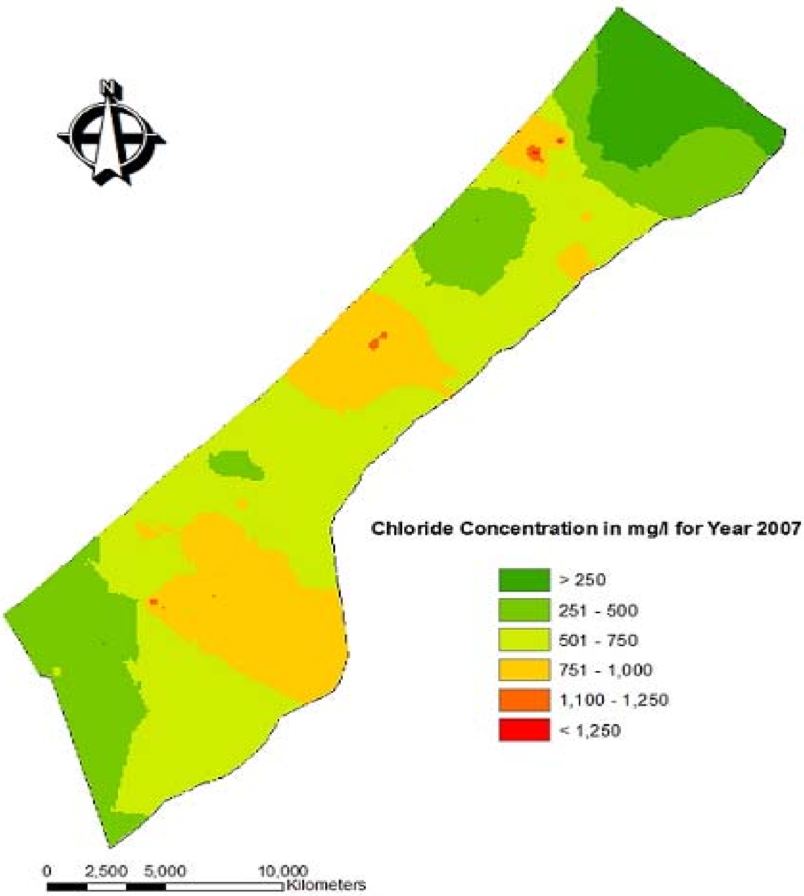


Fig 5-25 (b)

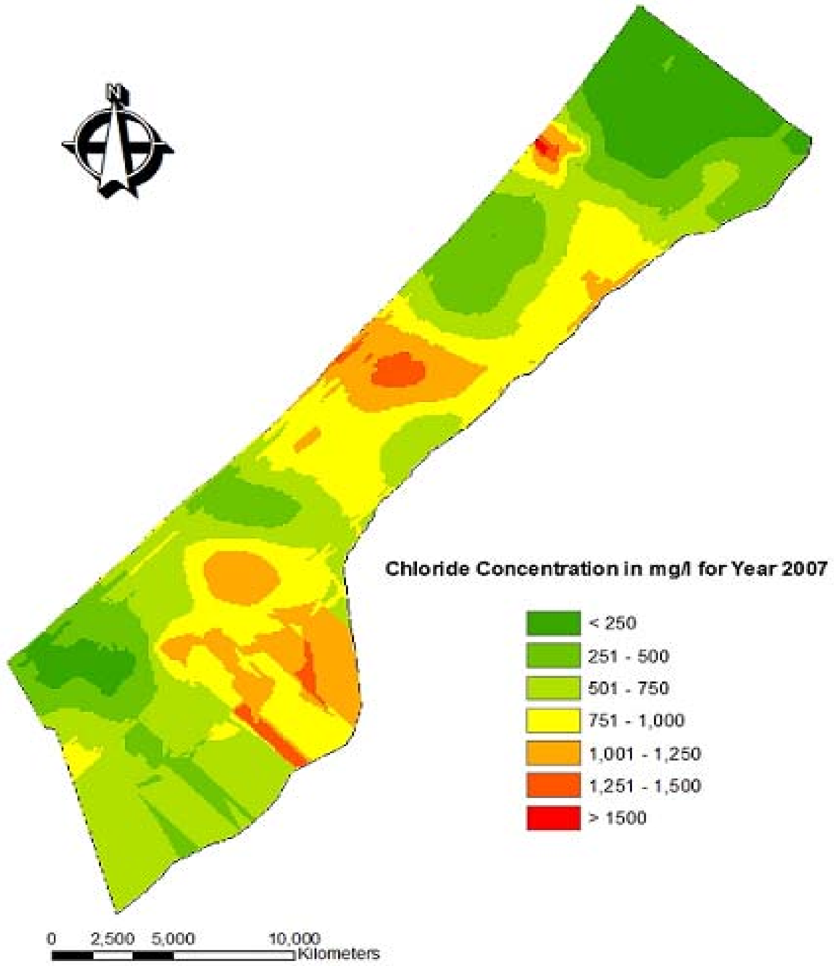


Fig. 5-25 (c)

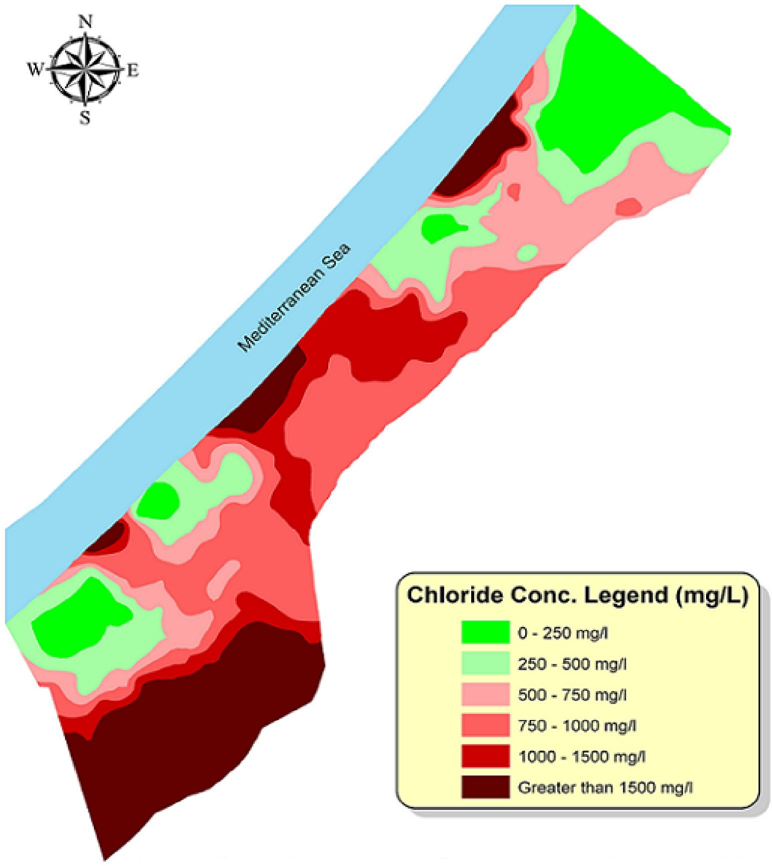


Fig. 5-25 (d)

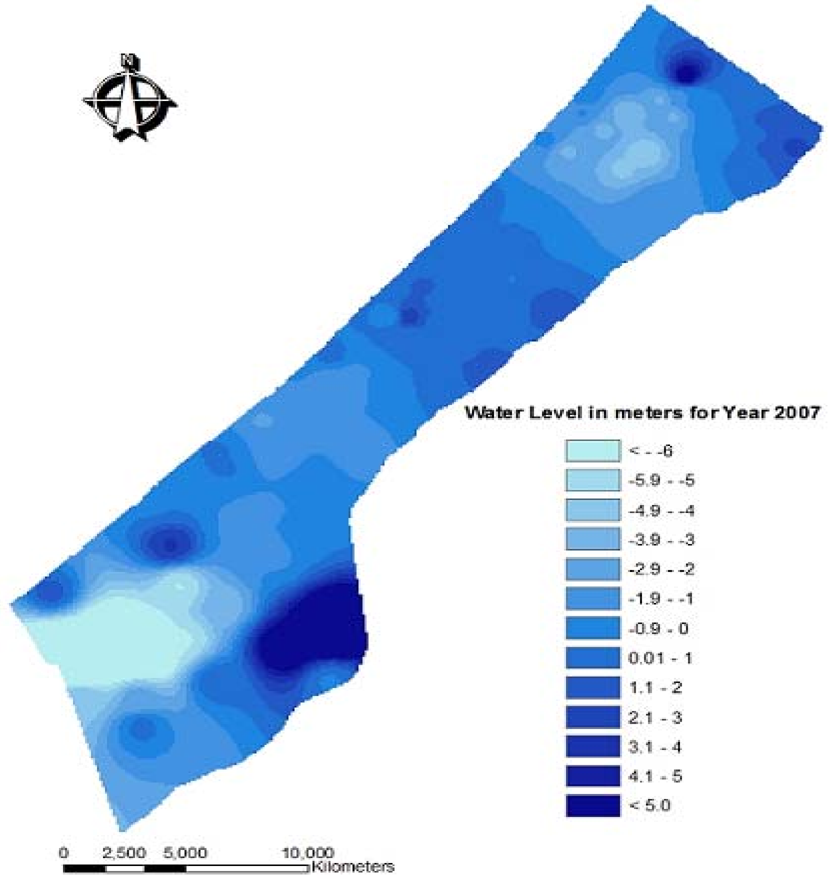


Fig. 5-26 (a)

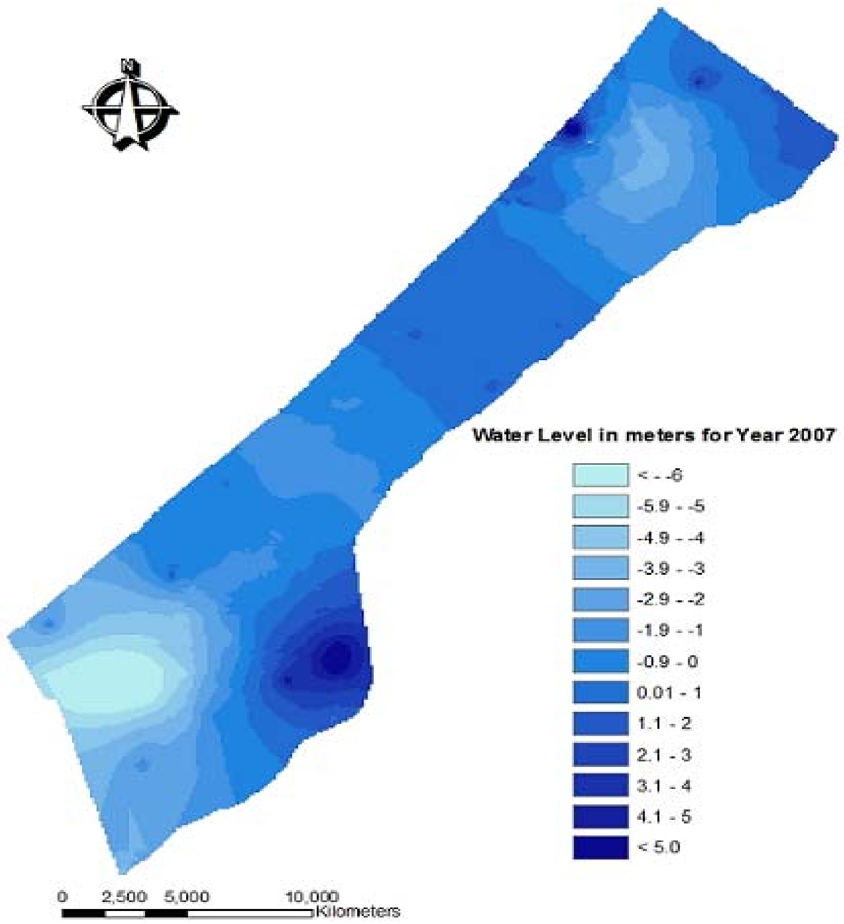


Fig. 5-26 (b)

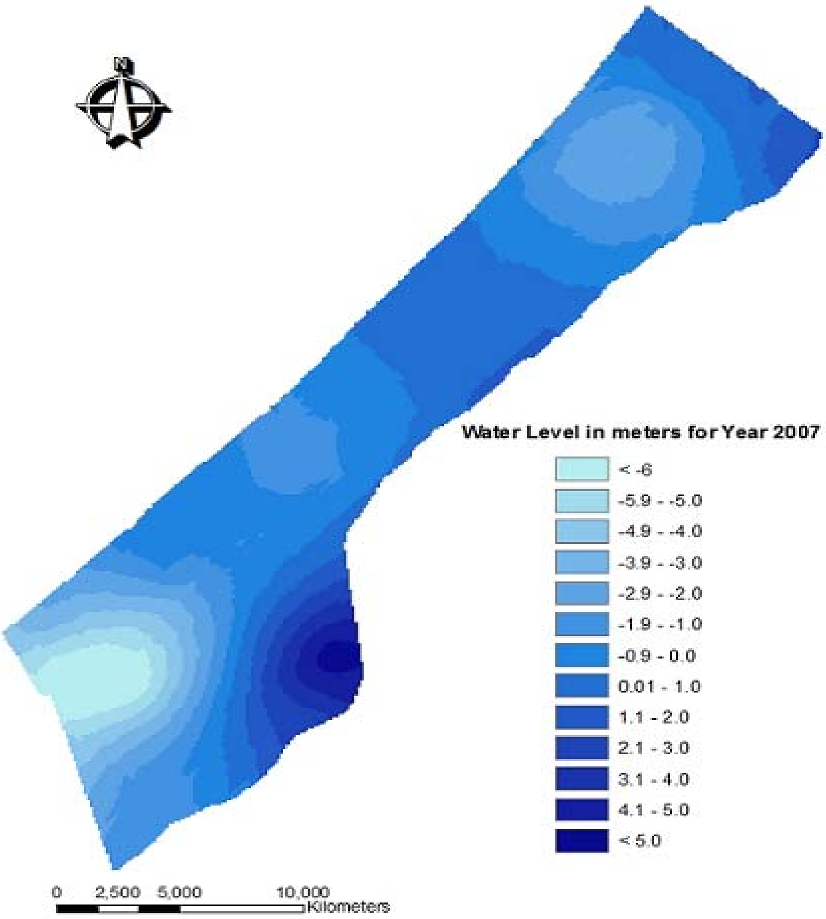


Fig. 5-26 (c)

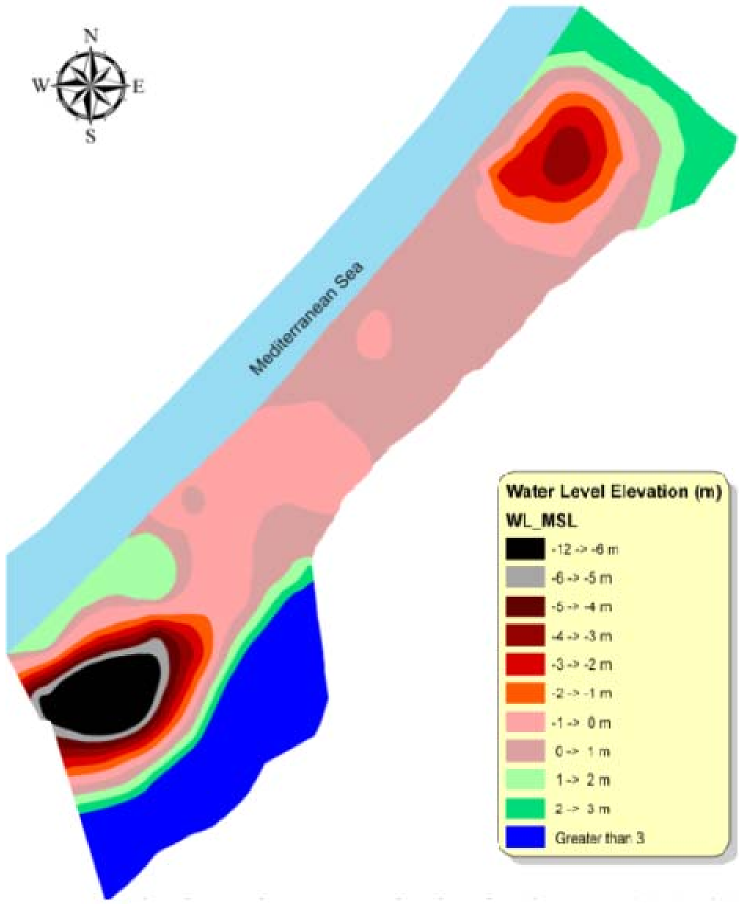


Fig. 5-26 (d)

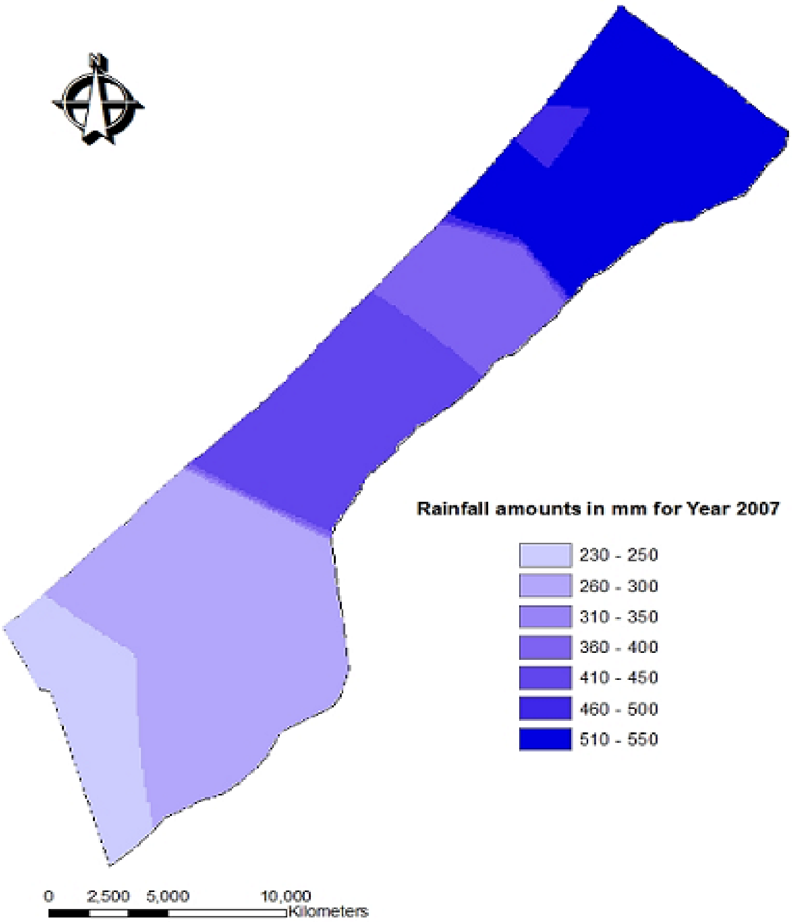


Fig. 5-27 (a)

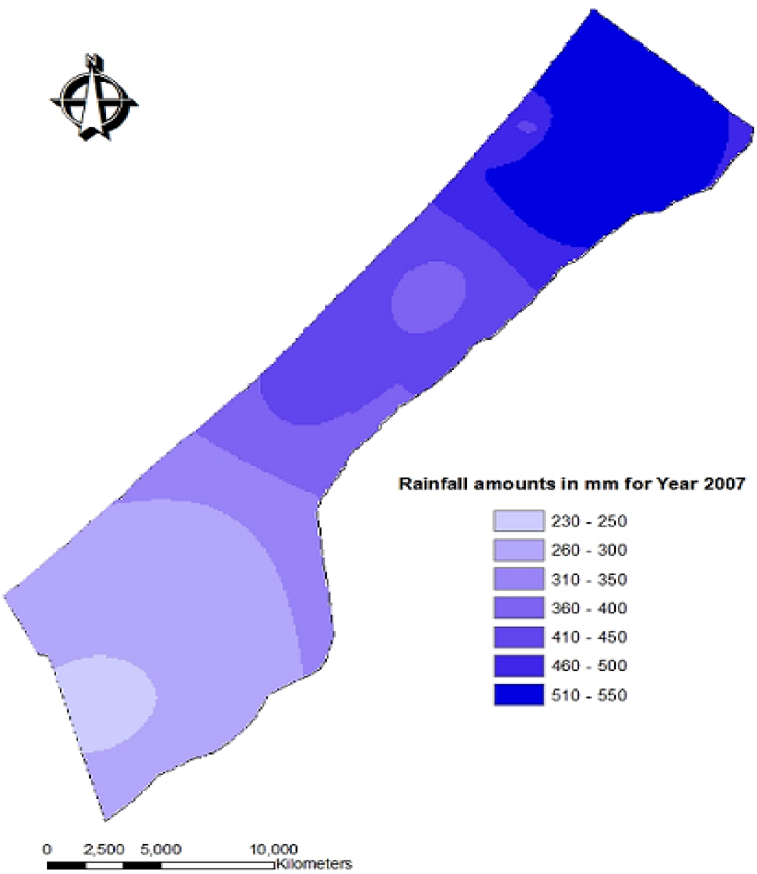


Fig. 5-27 (b)

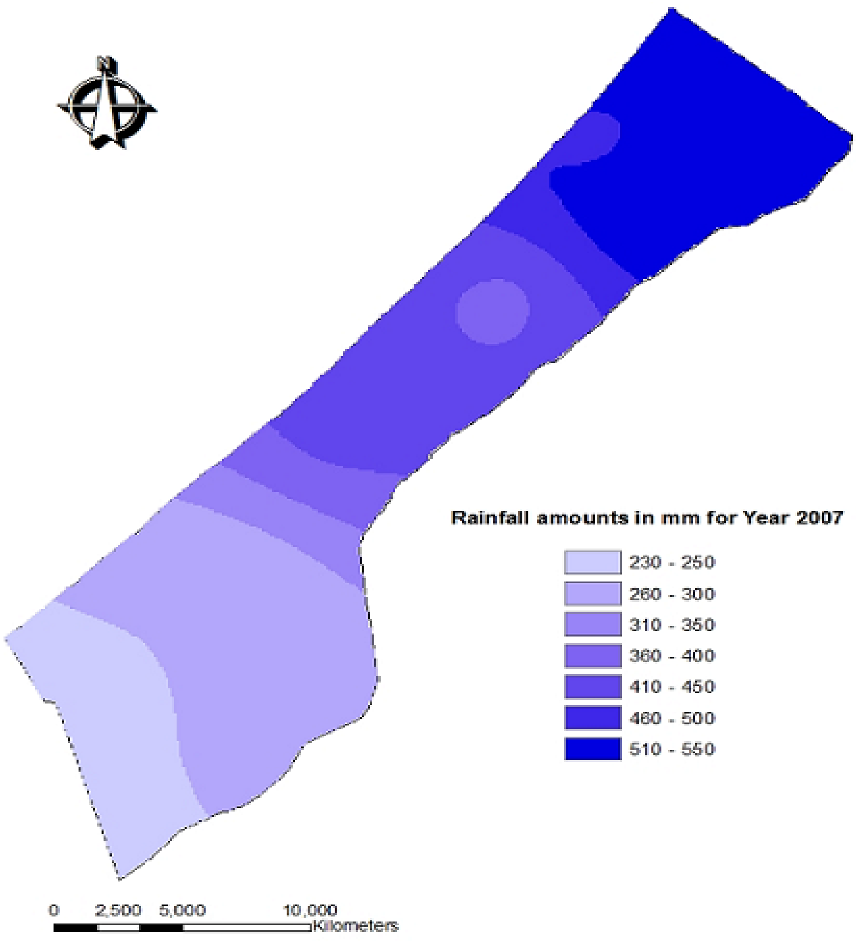

Rainfall amounts in mm for Year 2007
230 - 250
260 - 300
310 - 350
360 - 400
410 - 450
460 - 500
510 - 550
0
2,500
5,000
10,000
Kilometers

Fig. 5-27 (c)

5.6 Optimized Interpolation Method

To maximize success with datasets investigations, it is important to understand the extent to which limited data from Gaza Strip geographic area can affect the decision to use spatial interpolation methods. The other objective of this study was to investigate the appropriateness of using the best suited spatial interpolation method with limited data for Chloride and/or Water level prediction models.

This will be applied on the Kriging and IDW method for year 2007, so as to find the relationship between the no. of samples and the related correlation, (meaning for example 50 wells with good distribution might give the same results as 129 wells), so why waste resources and money, so after you select the best model try 4 or 5 runs and every time you increase the number of wells and see the difference, see if RMSE will increase or not or little difference.

5.6.1 Chloride Dataset 2007

The dataset comprised of 129 municipal wells, through the Geostatsitical analysis, the dataset was turned into five subsets out of the 129: 25, 50, 75, 100, and 129 samples. These subsets data were spatially distributed covering the study area and they were produced through utilizing Geotechnical Analysis wizard tool in the ArcGIS software.

These subsets data will be evaluated through Kriging and IDW interpolation method, as the interpolation will be optimized and the best fitted model will have to validate and to check the performance of the related RMSE and R^2 each time we model theses subsets in terms in reflection to the current status of limited data available in the Gaza Strip.

The following tables 5-52 & 5-53 are the summary results of the validated applied both interpolation methods (Kriging & IDW):

Table 0-52. Summary of Statistical errors for Kriging Method for Chloride subsets in year 2007

No. of Modeled Samples	RMSE	R^2
25	384.5	0.039
50	383.9	0.195
75	336.0	0.258
100	320.3	0.347
129	331.5	0.406

Table 0-53. Summary of Statistical errors for IDW Method for Chloride subsets in Year 2007

No. of Modeled Samples	RMSE	R^2
25	391.4	0.012
50	393.6	0.229

75	381.3	0.129
100	350.7	0.195
129	258.4	0.378

Moreover, Fig. 5-28 and 5-29, demonstrates the relationship between the number of modeled samples for Chloride subsets data in year 2007 and the performance of IDW and Kriging interpolation method during this process.

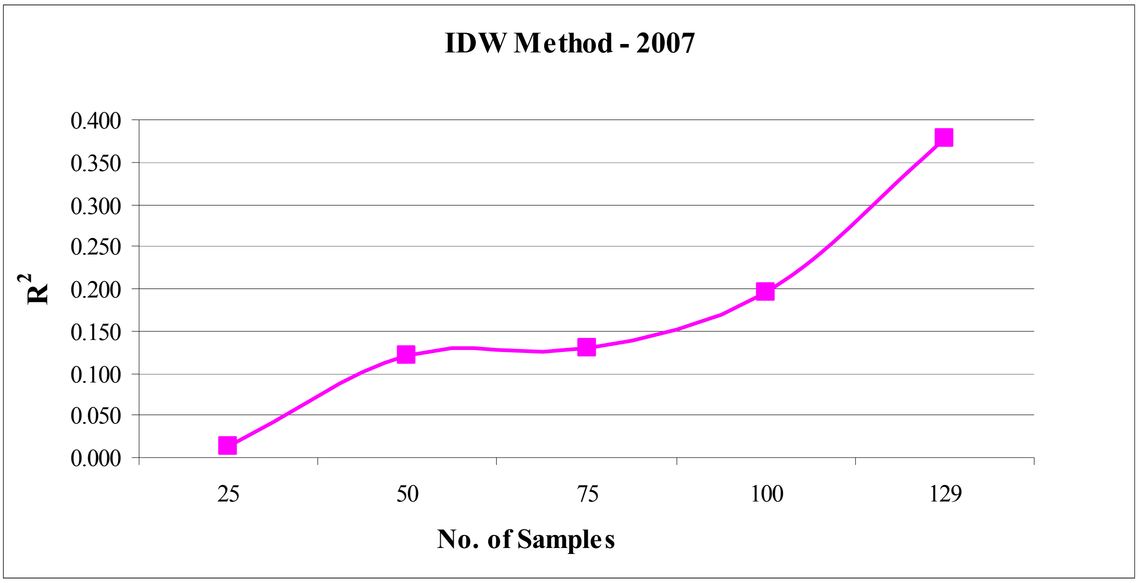


Figure 0-25. R^2 vs. number of modeled samples in IDW method for Chloride subsets in Year 2007

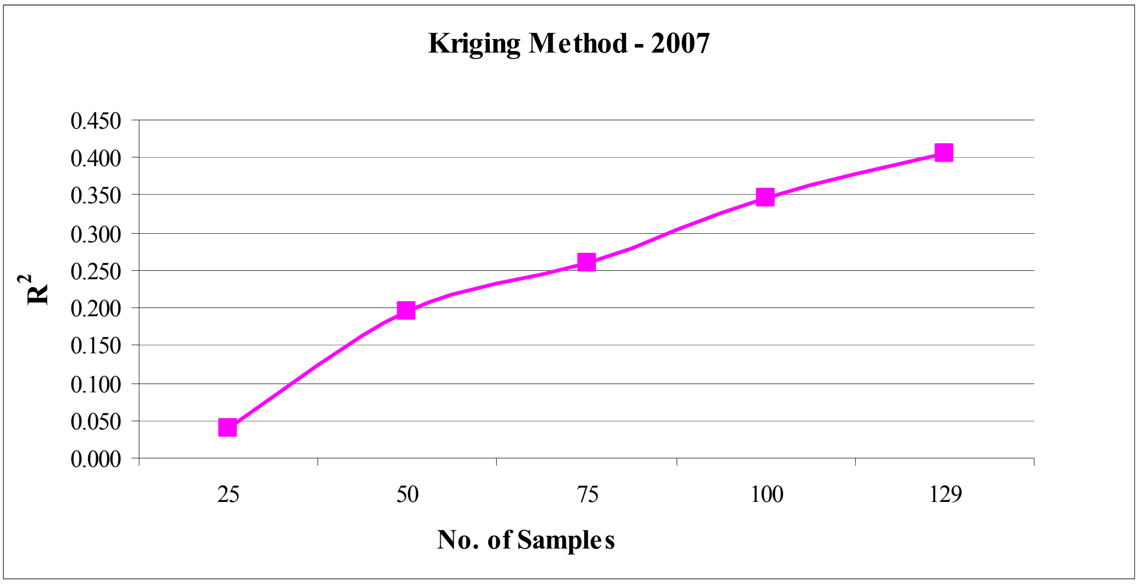


Figure 0-26. R^2 vs. number of modeled samples in Kriging method for Chloride subset in Year 2007

As indicted above, it is confirmed that there are fitted increase in the relationship between the no. of sampling and the spatial representation performance of the methods in GZ, when the no. of modeled samples increased from 25 up to 129 the results given were 0.039 up to 0.406 (Kriging), and 0.012 up to 0.378 (IDW). While we see quite decrease in the RMSE indicating that the predicted values are getting closer to the measured real ones.

Moreover, the following Fig. 5-30 has proved that Kriging is a prevailing interpolation tool for spatial representation of Chloride dataset in Gaza Strip, in terms of predictions and errors estimated (i.e. R^2),

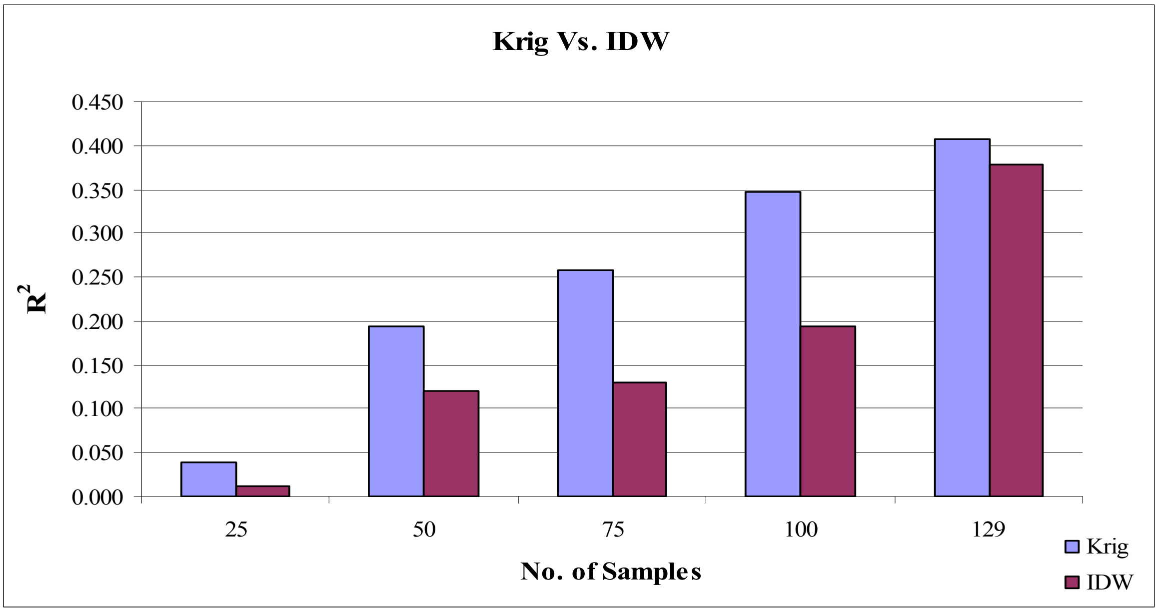


Figure 0-27. Performance of Kriging and IDW for modeled Chloride subsets in Year 2007

5.6.2 Water Level Dataset 2007

The dataset comprised of 99 monitoring wells, through the Geostatsitical analysis, the data was turned into four subsets out of the 99: 25, 50, 75, and 99 samples.

These subsets data will be evaluated through Kriging and IDW interpolation method, as the interpolation will be optimized and the best fitted model will have to validate and to check the performance of the related RMSE and R^2 each time we model theses subsets in terms in reflection to the current status of limited data available in the Gaza Strip.

Following tables 5-54 and 5-55 are summarizing the results of applying both validated interpolation methods (Kriging & IDW):

Table 0-54. Summary of Statistical errors for Kriging method for Water Level datasets in Year 2007

No. of Modeled Samples	RMSE	R^2
25	2.600	0.000
50	2.614	0.505

75	1.800	0.648
99	1.655	0.749

Table 0-55. Summary of Statistical errors for IDW method for Water Level subsets in Year 2007

No. of Modeled Samples	RMSE	R^2
25	2.598	0.004
50	2.704	0.464
75	2.057	0.564
99	2.028	0.664

Moreover, Fig. 5-31 and 5-32 demonstrates the relationship between the number of modeled samples for Water Level subsets data in year 2007 and the performance of IDW and Kriging interpolation method during this process.

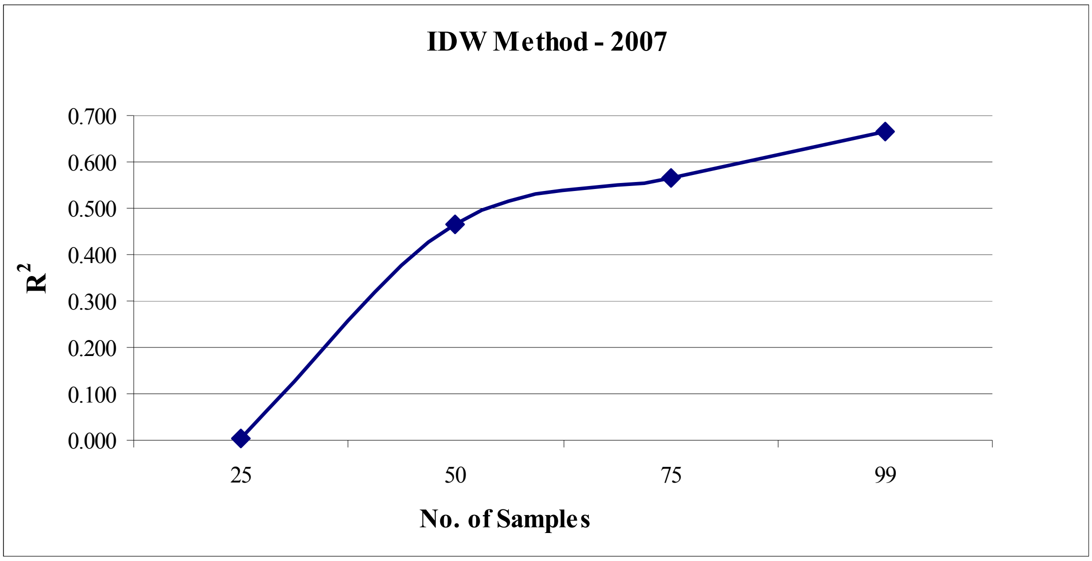


Figure 0-28. R^2 vs. number of modeled samples in IDW method for Water Level subset in Year 2007

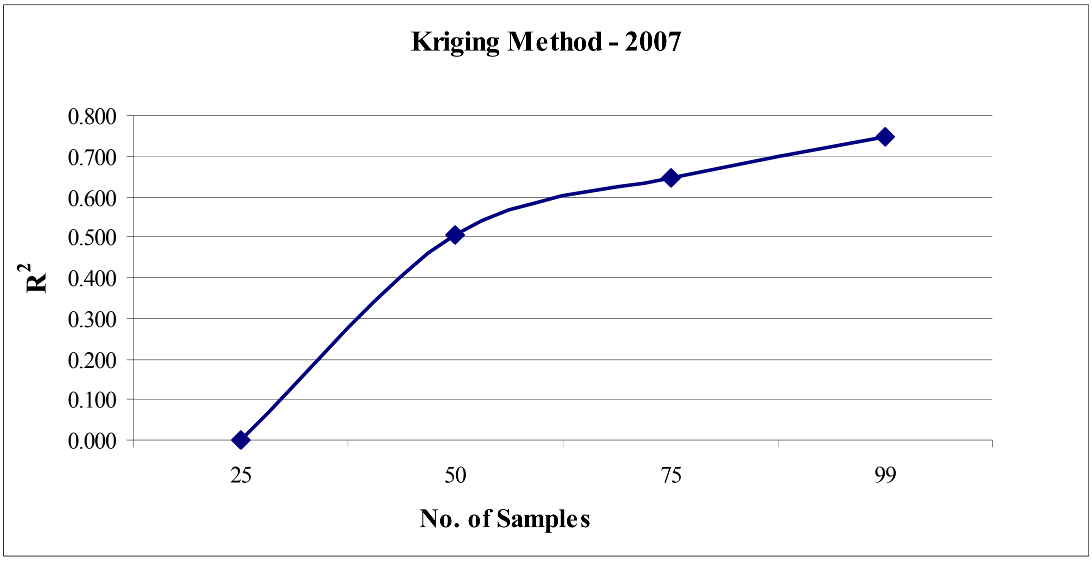


Figure 0-29. R^2 vs. number of modeled samples in Kriging method for Chloride subsets in Year 2007

As indicted above, it is confirmed again that there are fitted increase in the relationship between the no. of sampling and the spatial representation performance of the methods in GZ, when the no. of modeled samples increased from 25 up to 99 the results given were 0.00 up to 0.749 (Kriging), and 0.004 up to 0.664 (IDW). While we see quite decrease in the RMSE indicating that the predicted values are getting closer to the measured real ones.

Moreover, Fig. 5-33 below has proved again that Kriging is a prevailing interpolation tool for spatial representation of Water Level dataset in Gaza Strip, in terms of predictions and errors estimated (i.e. R^2),

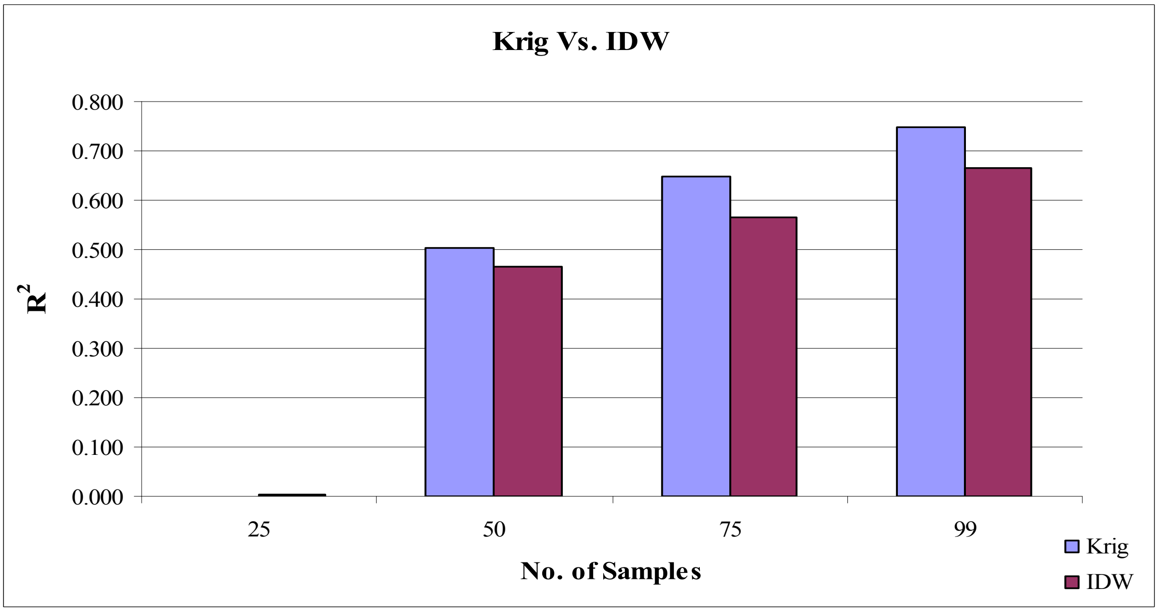


Figure 0-30. Performance of Kriging and IDW for modeled Water Level subsets in Year 2007

CHAPTER (6): CONCLUSIONS AND RECOMMENDATIONS

6.1 Conclusions

This study that has conducted comprehensive comparative evaluation for the three different interpolation methods for generating surface mapping of groundwater parameters in Gaza Strip: Kriging (with Ordinary Kriging (OK) model subjected to semivariogram, and smoothing fact under exponential, and spherical techniques), IDW with optimized power and smoothing factor, Spline (RBF) with optimized tension power and smoothing factor were applied frequently for each dataset and for each year (2001, 2003, 2005, and 2007) in this study. The main conclusions of this study can be summarized as following:

1. It is concluded that after the best-fit model was selected for each interpolation method based on the least RMSE values in each interpolation process, these models were validated and checked under cross validation analysis in which the highest finalized correlation (R^2) value among these applied interpolation methods for each parameter (dataset) was considered, and this can be summarized as following during the different study years:

   - During the interpolation of Chloride dataset, it was found that IDW had been slightly superior to OK and Spline methods during years 2001, 2003, and 2005. But, in 2007 OK (R^2 = 26% in year 2007) had better predicted values with highest correlation results than IDW (R^2 = 13% in year 2007) and Spline (R^2 = 18% in year 2007).

   - OK (R^2 = 7% in year 2007) had given better error measurements with high correlation values and also better visualization of the results than IDW (R^2 = 4% in year 2007) and Spline (R^2 = 5% in year 2007) approaches during the interpolation of Water level dataset.

   - Few differences existed between the employed interpolation techniques during interpolating the rainfall dataset; OK (R^2 = 97% in year 2007) had expressed unbiased data with small errors and relatively high correlation results greater than IDW (R^2 = 96% in year 2007) and Spline (R^2 = 95% in year 2007).

2. It was found that the advantage of using IDW and Spline is the easy-friendly application of their interpolation method in surface mapping the study parameters. While in Kriging for example, fitting semivariogram models can be time consuming because it requires skill and judgment. The computational process is also demanding despite the fact that Kriging is superior to other means of interpolation because it provided an optimal interpolation estimate for the coordinate location, as well as a variance estimate for the interpolation value.

3. It was concluded out of this study that in the presence of limited available data, Kriging interpolation method performed better than IDW. Moreover, the more samples modeled the higher R^2 was reached in both the Chloride and Water level datasets, where the no. of modeled samples increased from 25 up to 129 the results given were 4% up to 41% (Kriging), and 1% up to 37% (IDW).

4. It is comprehended out of this study and in order to have more reliable surface maps, the data should be adequate geographically and spatially covering the required study area. (12 sampling point for rainfall is adequate, 99 sampling points for Water level is adequate, 129 sampling points in Chloride is quite adequate but needs more in the southern side since the no. of the domestic municipal wells is concentrated in the western and middle side of southern governorates).

5. It was taken out of this study and in terms of optimizing the monitoring system for Water level datasets, if there are 70-80 properly spatially distributed samples, we can reach R^2 value ranges from 65-75%. This can save time and cost, as no need to waste more time in sampling due to slight increase in R^2 that could be reached if the no. of samples increased.

6.2 Recommendation

Comparisons of various methods based on different approaches are useful for model construction and final surface mapping. Each method or technique has its own advantages and disadvantages. It gives us alternatives for choosing a suitable model for data analysis. Yet, a best-fit model for one kind of data may not fit with another kind of data, the followings are the main recommendations reached:

1. It is recommended that in order to have more reliable surface maps that can simulate the real values on ground, Kriging interpolation method (subjected to Ordinary Prediction Map with Spherical and Exponential modeling techniques) can be described as the best suited interpolator for surface mapping the study datasets.

2. If time is of main concern and massive data need to be mapped, using IDW interpolation method can be an alternative in order to produce surface mapping of other parameters that have the same nature of Chloride and Water level of data size and variance (i.e. TDS, EC, and nitrate).

3. The study recommends strongly producing these maps through utilizing the Geostatistical Analyst tools rather than utilizing the common interpolation extension tools in producing different spatial representation maps for the different datasets, taking into consideration investigate the data trend, normality consistency, removing outliers and identifying statistical distribution where data came from, this will minimize the errors and produce more accurate predicted values.

4. The optimization of the monitoring network can be based on monitoring sites number and spatial distribution, as shown in the study, the more spatially distributed monitoring samples, the more accurate and reliable spatial representation of Groundwater parameters (i.e. c water level) even if there limited available datasets, thus it is recommended to investigate the monitoring and municipal wells spatial location and to optimize the needed wells to be sampled in away to minimize the time-cost needed.

5. It is taking out from the study that the spatial representation of Chloride parameter in the southern areas of Gaza Strip was performed poorly by the different interpolation, accordingly, and in recommending to have more accurate mapping than the current mapping outputs and to achieve higher R^2, more wells needed to be distributed spatially in the southern part of Gaza Strip.

6. Further studies have to be performed to investigate deeply the interpolation methods applied on other Groundwater parameters (i.e. nitrate) as well as other metrological data in Gaza Strip in terms of programming and fitting procedures related to interpolation modeling basics that that can also minimize the errors and produce higher accurate predicted values.

7. Applying the ArcMap-GIS (spatial interpolation and analyze of surfaces) with the above recommendation can contribute to the achievement of:
    - Hydrogeological studies regarding quantitative and the qualitative groundwater estimation in Gaza Strip,
    - Hydrogeological studies for water supply,
    - Hydrogeological studies for delimitation of the hydrogeological protection areas and for sanitary protection areas
    - Elaboration of the hydrogeological forecast.
    - Assessment the distribution reasonableness of the groundwater monitoring points.

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APPENDIXES

Appendix 1 – Study Wells' Data

Well_Name	Well_ID	Govern	Municipal	X	Y
Aida Abu Gazalah	C_20	North	Beit Hanoun	106738.419	104856.817
Abu Gazalah	C_128	North	Beit Hanoun	106477.556	104891.263
Khadija	C_155	North	Beit Hanoun	106857.426	105351.288
Al Awqaf well	C_79A	North	Beit Hanoun	105350.281	105094.134
Industrial Area Well	C_76	North	Beit Hanoun	104667.093	104336.570
Ezba New Well	C_127A	North	Beit Hanoun	104785.023	106154.679
Nada Well	C_137	North	Beit Hanoun	104987.959	106485.517
Om El-Naser Well	A_210	North	Om Enaser	104434.599	106243.541
Mashro Well	A_185	North	Beit Lahia	102529.950	106252.123
Shekh Zaid West Well	A_211	North	Beit Lahia	103328.602	105390.978
Sheikh Zaid East Well	A_205	North	Beit Lahia	103497.357	105126.104
Shawa Well	E_06	North	Beit Lahia	103012.159	105333.978
Gabin Well	A_180	North	Beit Lahia	102459.196	107033.005
Atatra Well	D_67	North	Beit Lahia	101715.425	107217.505
Salateen Well	D_73	North	Beit Lahia	101036.182	106827.164
Abu Hasira Well	E_01	North	Jabalia	103273.717	104897.703
Bahtimi Well	E_04	North	Jabalia	103034.144	105064.223
Abu Talal Well	E_156	North	Jabalia	102067.198	104589.246
Hawooz Well (Paris)	E_90	North	Jabalia	101280.226	104587.480
Abu Sharikh Eastern Well	D_20	North	Jabalia	101379.650	105027.493
Nammar / Edara Well	Q_40C	North	Jabalia	102773.848	103960.567
El - Hissi Well	Q_72	North	Jabalia	102528.930	103933.565
Abu Sharikh Western Well	D_60	North	Jabalia	101286.467	105111.237
Amer Well (17 Well)	D_74	North	Jabalia	100503.704	106104.088
Zohour Well	D_75	North	Jabalia	101085.391	105814.549
Sheikh Radwan No. 15	D_71	Gaza	Gaza	101457.632	106193.151
Sheikh Radwan No. 16	D_72	Gaza	Gaza	101739.331	106462.512
Sheikh Radwan No. 12	D_70	Gaza	Gaza	101440.342	105833.464
Sheikh Radwan No. 11	D_69	Gaza	Gaza	100836.179	105464.148
Sheikh Radwan No. 10	D_68	Gaza	Gaza	100513.384	105180.887
Sheikh Radwan No. 8	E_154	Gaza	Gaza	99329.682	105051.664
Sheikh Radwan No. 8-A	E_154A	Gaza	Gaza	99336.835	105056.140
Sheikh Radwan No. 7	R_162H	Gaza	Gaza	99056.143	103668.501
Sheikh Radwan No. 7-A	R_162HA	Gaza	Gaza	99048.735	103698.189
Sheikh Radwan No. 1-B	R_162LB	Gaza	Gaza	98453.297	104044.530
Sheikh Radwan No. 1-A	R_162LA	Gaza	Gaza	98480.709	104045.751
Sheikh Radwan No. 4	R_162CA	Gaza	Gaza	98867.347	104589.998
Sheikh Radwan No. 3	R_162BA	Gaza	Gaza	98727.630	104412.150
Sheikh Radwan No. 9	E_157	Gaza	Gaza	100156.242	104670.263
Sheikh Radwan No. 2	R_162EA	Gaza	Gaza	98247.667	104479.677
Sheikh Radwan No. 13	R_162G	Gaza	Gaza	99166.221	103951.902
Sheikh Ejleen No. 5	R_277	Gaza	Gaza	96236.996	101529.748
Maslahk Well	R_270	Gaza	Gaza	96230.000	99750.000
Sheikh Ejleen No. 2	R_254	Gaza	Gaza	96540.877	102055.549
Sheikh Ejleen No. 4	R_113A	Gaza	Gaza	96532.492	102589.653

Well_Name	Well_ID	Govern	Municipal	X	Y
Sheikh Ejleen No. 3	R_265	Gaza	Gaza	95808.755	101707.838
Sheikh Ejleen No. 7	R_293	Gaza	Gaza	96713.479	101394.692
Sheikh Ejleen No. 6	R_280	Gaza	Gaza	95760.876	101154.530
Al Shijaia No. 6 (Al Montar)	R_312	Gaza	Gaza	100004.184	100005.239
Shijaia No. 2 (Abu Abali Well)	R_75	Gaza	Gaza	100416.471	101298.121
Shijaia No. 3(Abu Lafi)	R_74	Gaza	Gaza	100659.744	101542.207
Safa-05 (Zimmo Well)	Q_68	Gaza	Gaza	102220.996	103530.894
Safa-01	R_25B	Gaza	Gaza	100777.863	102527.824
Safa-02	R_25A	Gaza	Gaza	100758.643	102581.703
Safa-03	R_25C	Gaza	Gaza	100775.793	102454.926
Safa-04	R_25D	Gaza	Gaza	100820.083	102495.564
Remal No.2 (Kamal Naser)	R_314	Gaza	Gaza	99164.439	104391.099
Remal-01 (Al Jundi Garden - Well)	R_313	Gaza	Gaza	97563.923	103022.306
Sabra-02 (Dairi Well)	R_307	Gaza	Gaza	97602.376	101510.214
Sabra-03 (Sh'haiber Well)	R_308	Gaza	Gaza	98262.823	101598.399
Zaiton-02 (Om El-Laymon-Abu Khosa)	R_305	Gaza	Gaza	97547.626	100274.629
Zaiton-01	R_310	Gaza	Gaza	97415.859	100282.770
Daraj-01(Basha Well)	R_311	Gaza	Gaza	99287.488	101643.335
Sabra-01 (Dogmosh Well)	R_306	Gaza	Gaza	97075.516	101805.570
Sheja'ia No.5 -Soq Al Halal	R_309	Gaza	Gaza	99687.000	99203.000
Zawaida New Well	H_95	Middle	Zawaida	89462.115	92752.927
Aisha Well	Aisha	Middle	Zawaida	89518.317	92949.763
Abo Naser Well	J_146	Middle	Deir El Balah	91199.807	90460.942
Abu Merwan Well	S_69	Middle	Deir El Balah	91769.916	90702.258
Abu Hamam Well	T_46	Middle	Deir El Balah	91983.766	90273.159
El-Sahel No. 3	J_3	Middle	Deir El Balah	85589.714	89657.360
El-Sahel No. 4	J_4	Middle	Deir El Balah	85253.031	89308.798
El-Sahel No. 5	J_5	Middle	Deir El Balah	84876.365	89043.249
El-Berka No. 1	K_21	Middle	Deir El Balah	85915.694	89758.346
El-Sahel No. 2	J_2	Middle	Deir El Balah	86073.590	90006.285
El-Berka No. 2	K_20	Middle	Deir El Balah	86265.407	89777.531
Wadi El-Salga Well	T_52	Middle	Wadi El Salga	89412.942	87720.219
Nusirat New Well (Municipal Well)	G_49	Middle	Nussirat	91378.528	96449.254
Fallet Well	H_60	Middle	Nussirat	91380.000	94950.000
Hertani Well	G_30	Middle	Nussirat	91478.840	95975.570
Abu Ereban Well	G_45	Middle	Nussirat	91853.380	95529.720
Nusirat F-208 (Zahra'a Well)	F_208	Middle	Nussirat	93493.157	97839.178
Wadi Gaza Well	F_205	Middle	Wadi Gaza	97083.010	96337.176
Al-Zahra Well	G_50	Middle	Zahra	93154.175	98410.772
Moghraqa Well No. 3	F_203	Middle	Moghraqa	93719.685	97945.334
Moghraqa Well No. 2 - JC	F_192	Middle	Moghraqa	95405.166	98642.566
Moghraqa Well No. 1 - JC	F_191	Middle	Moghraqa	94959.667	98953.183
Magazi Well No. S-80	S_80	Middle	Maghazi	93117.838	91923.243
Magazi Well No. S-71	S_71	Middle	Maghazi	92674.599	91699.851
Magazi Well No. S-82	S_82	Middle	Maghazi	93117.838	91923.243
Makbola Well	Makbola	Middle	Buraij	93108.102	92454.610
Karaj Well	S_72	Middle	Buraij	93199.944	93513.760
Musadar Well (Yusif Thabet Well)	Musadar	Middle	Musader	91874.427	90945.884
Mahata Eastern Well	L_41	Khanyuins	Khan Younis	84345.622	83160.595
Ma'an Eastern Well	Ma'an	Khanyuins	Khan Younis	84544.985	82616.927

Well_Name	Well_ID	Govern	Municipal	X	Y
Al Madena Al Riyadia	MadenaRiyadia	Khanyuins	Khan Younis	83496.769	81790.166
Cultural Center Well	L_198	Khanyuins	Khan Younis	83462.388	81977.159
Abu Rashwan Well No. "C"	Rashwan_C	Khanyuins	Khan Younis	81953.889	82385.253
Abu Rashwan Well No. "B"	L_286	Khanyuins	Khan Younis	81564.289	82410.458
Abu Rashwan Well No. "A"	L_184	Khanyuins	Khan Younis	81608.000	82519.000
Tahadi Well	L_189A	Khanyuins	Khan Younis	81832.000	82693.000
New Southern Well	L_182	Khanyuins	Khan Younis	81858.000	82927.000
Al-Najar Well	Al_Najar	Khanyuins	Khan Younis	82430.000	82100.000
Aia Well	L_43	Khanyuins	Khan Younis	83063.193	83461.450
Al-Amal New Well	L_159A	Khanyuins	Khan Younis	82680.000	85080.000
Al-Amal Old Well	L_159	Khanyuins	Khan Younis	82607.000	85049.000
El-Sa'ada Well	L_87	Khanyuins	Khan Younis	83040.000	84200.000
El-Ahrash Well	L_127	Khanyuins	Khan Younis	82852.000	83935.000
El-Sha'er Well / Old Southern Well	L_176	Khanyuins	Khan Younis	82187.000	83276.000
El-Satar Well	L_187	Khanyuins	Khan Younis	84364.000	86335.000
El-Satar New Well (Northern)	L_190	Khanyuins	Khan Younis	85758.000	87281.000
AL Matahen Well	K_19	Khanyuins	Qarara	86461.000	88592.000
Western well	L_179	Khanyuins	Qarara	85572.000	87460.000
EV01 - Eastern Village No. 1	L_181	Khanyuins	Bani Sohila	81358.761	82404.408
EV02 - Eastern Village No. 2	P_146	Khanyuins	Bani Sohila	80949.000	81865.000
EV03 - Eastern Village No. 3	P_154	Khanyuins	Bani Sohila	80847.000	81468.000
An-Najar Well	M_12	Khanyuins	Bani Sohila	85384.000	83299.000
Abu-Shahla Well	M_11	Khanyuins	Bani Sohila	85100.000	83358.000
El-Fakhari Well (Khazzan well)	P_159	Rafah	Fakhari	80359.000	79965.000
Hejazi Well (Zu'rub)	P_15	Rafah	Rafah	77925.638	78903.921
Western Abu Hashem Well	P_124	Rafah	Rafah	77599.000	79414.000
Al Bahar Well	P_139	Rafah	Rafah	77165.000	82011.000
El-Iskan Well	P_153	Rafah	Rafah	77736.215	80519.752
Canada Well	P_144A	Rafah	Rafah	78314.071	80366.603
Tal Al Sultan -PWA	P_148	Rafah	Rafah	78666.836	80053.049
Abu Zohri Well	P_138	Rafah	Rafah	78773.000	79764.000
El-Hashash Well	P_145	Rafah	Rafah	79368.232	79856.165
Shuka Well	Shuka	Rafah	Shuka	80266.000	80177.000
Naser 02 Well	Naser2	Rafah	Nasser	79891.000	80302.000

Appendix 2 – Chloride Dataset

Appendix 2.1 - Chloride Dataset in 2001

S/N	Well_ID	Well_Name	X	Y	Chloride Concentration in mg/l
1	C_128	Abu Gazalah	106477.556	104891.263	**247.65**
2	C_79A	Al Awqaf well	105350.281	105094.134	**479.07**
3	C_76	Industrial Area Well	104667.093	104336.570	**578.90**
4	A_185	Mashro Well	102529.950	106252.123	**95.56**
5	E_06	Shawa Well	103012.159	105333.978	**98.50**
6	A_180	Gabin Well	102459.196	107033.005	**88.46**
7	D_67	Atatra Well	101715.425	107217.505	**35.40**
8	D_73	Salateen Well	101036.182	106827.164	**70.75**
9	E_01	Abu Hasira Well	103273.717	104897.703	**112.57**
10	E_04	Bahtimi Well	103034.144	105064.223	**73.73**
11	E_156	Abu Talal Well	102067.198	104589.246	**150.90**
12	E_90	Hawooz Well (Paris)	101280.226	104587.480	**158.15**
13	D_20	Abu Sharikh Eastern Well	101379.650	105027.493	**154.45**
14	D_60	Abu Sharikh Western Well	101286.467	105111.237	**120.50**
15	D_74	Amer Well (17 Well)	100503.704	106104.088	**73.65**
16	D_71	Sheikh Radwan No. 15	101457.632	106193.151	**84.93**
17	D_72	Sheikh Radwan No. 16	101739.331	106462.512	**74.32**
18	D_70	Sheikh Radwan No. 12	101440.342	105833.464	**99.05**
19	D_69	Sheikh Radwan No. 11	100836.179	105464.148	**102.82**
20	D_68	Sheikh Radwan No. 10	100513.384	105180.887	**130.90**
21	E_154	Sheikh Radwan No. 8	99329.682	105051.664	**539.63**
22	R_162H	Sheikh Radwan No. 7	99056.143	103668.501	**506.90**
23	R_162HA	Sheikh Radwan No. 7-A	99048.735	103698.189	**506.95**
24	R_162LA	Sheikh Radwan No. 1-A	98480.709	104045.751	**451.80**
25	R_162CA	Sheikh Radwan No. 4	98867.347	104589.998	**280.00**
26	R_162BA	Sheikh Radwan No. 3	98727.630	104412.150	**506.05**
27	E_157	Sheikh Radwan No. 9	100156.242	104670.263	**173.35**
28	R_162D	Sheikh Radwan No. 5	98640.251	104992.751	**562.40**
29	R_162EA	Sheikh Radwan No. 2	98247.667	104479.677	**364.70**
30	R_162G	Sheikh Radwan No. 13	99166.221	103951.902	**521.10**
31	R_112	Sheikh Ejleen No. 1	96061.301	102651.012	**869.13**
32	R_277	Sheikh Ejleen No. 5	96236.996	101529.748	**169.40**
33	R_270	Maslahk Well	96230.000	99750.000	**362.53**
34	R_254	Sheikh Ejleen No. 2	96540.877	102055.549	**407.65**
35	R_113	Sheikh Ejleen No. 4	96532.492	102589.653	**308.40**
36	R_265	Sheikh Ejleen No. 3	95808.755	101707.838	**183.60**
37	R_75	Shijaia No. 2 (Abu Abali Well)	100416.471	101298.121	**733.30**
38	Q_68	Safa-05 (Zimmo Well)	102220.996	103530.894	**176.50**
39	R_25B	Safa-01	100777.863	102527.824	**545.90**
40	R_25A	Safa-02	100758.643	102581.703	**477.15**
41	R_25C	Safa-03	100775.793	102454.926	**937.45**
42	R_25D	Safa-04	100820.083	102495.564	**711.05**

S/N	Well_ID	Well_Name	X	Y	Chloride Concentration in mg/l
43	J_146	Abo Naser Well	91199.807	90460.942	**577.30**
44	S_69	Abu Merwan Well	91769.916	90702.258	**466.00**
45	T_46	Abu Hamam Well	91983.766	90273.159	**519.50**
46	K_21	El-Berka No. 1	85915.694	89758.346	**188.00**
47	K_20	El-Berka No. 2	86265.407	89777.531	**187.80**
48	G_49	Nusirat New Well (Municipal Well)	91378.528	96449.254	**1,022.00**
49	H_60	Fallet Well	91380.000	94950.000	**1,022.00**
50	G_30	Hertani Well	91478.840	95975.570	**973.70**
51	G_50	Al-Zahra Well	93154.175	98410.772	**140.00**
52	S_71	Magazi Well No. S-71	92674.599	91699.851	**503.50**
53	L_41	Mahata Eastern Well	84345.622	83160.595	**989.25**
54	L_286	Abu Rashwan Well No. "B"	81564.289	82410.458	**118.24**
55	L_184	Abu Rashwan Well No. "A"	81608.000	82519.000	**121.70**
56	L_43	Aia Well	83063.193	83461.450	**705.15**
57	L_159A	Al-Amal New Well	82680.000	85080.000	**281.05**
58	L_159	Al-Amal Old Well	82607.000	85049.000	**492.90**
59	L_87	El-Sa'ada Well	83040.000	84200.000	**933.25**
60	L_127	El-Ahrash Well	82852.000	83935.000	**680.65**
61	L_176	El-Sha'er Well / Old Southern Well	82187.000	83276.000	**779.05**
62	L_187	El-Satar Well	84364.000	86335.000	**1,175.75**
63	K_19	AL Matahen Well	86461.000	88592.000	**112.85**
64	L_179	Western well	85572.000	87460.000	**650.00**
65	L_181	EV01 - Eastern Village No. 1	81358.761	82404.408	**98.15**
66	P_146	EV02 - Eastern Village No. 2	80949.000	81865.000	**160.00**
67	P_15	Hejazi Well (Zu'rub)	77925.638	78903.921	**708.45**
68	P_124	Western Abu Hashem Well	77599.000	79414.000	**433.55**
69	P_144A	Canada Well	78314.071	80366.603	**264.30**
70	P_138	Abu Zohri Well	78773.000	79764.000	**128.60**
71	P_145	El-Hashash Well	79368.232	79856.165	**264.30**

Appendix 2.2 - Chloride Dataset in 2003

S/N	Well_ID	Well_Name	X	Y	Chloride Concentration in mg/l
1	C_128	Abu Gazalah	106477.556	104891.263	**238.80**
2	C_79A	Al Awqaf well	105350.281	105094.134	**477.70**
3	C_76	Industrial Area Well	104667.093	104336.570	**620.30**
4	C_127A	Ezba New Well	104785.023	106154.679	**57.20**
5	C_137	Nada Well	104987.959	106485.517	**29.32**
6	A_185	Mashro Well	102529.950	106252.123	**114.05**
7	A_205	Sheikh Zaid East Well	103497.357	105126.104	**51.99**
8	E_06	Shawa Well	103012.159	105333.978	**95.11**
9	A_180	Gabin Well	102459.196	107033.005	**106.55**
10	D_67	Atatra Well	101715.425	107217.505	**46.30**
11	D_73	Salateen Well	101036.182	106827.164	**67.75**
12	E_01	Abu Hasira Well	103273.717	104897.703	**124.75**
13	E_04	Bahtimi Well	103034.144	105064.223	**90.00**
14	E_156	Abu Talal Well	102067.198	104589.246	**160.45**
15	E_90	Hawooz Well (Paris)	101280.226	104587.480	**192.55**
16	D_20	Abu Sharikh Eastern Well	101379.650	105027.493	**149.60**
17	Q_40C	Nammar / Edara Well	102773.848	103960.567	**184.60**
18	Q_72	El - Hissi Well	102528.930	103933.565	**124.88**
19	D_60	Abu Sharikh Western Well	101286.467	105111.237	**139.00**
20	D_74	Amer Well (17 Well)	100503.704	106104.088	**88.40**
21	D_71	Sheikh Radwan No. 15	101457.632	106193.151	**85.50**
22	D_72	Sheikh Radwan No. 16	101739.331	106462.512	**78.40**
23	D_70	Sheikh Radwan No. 12	101440.342	105833.464	**103.15**
24	D_69	Sheikh Radwan No. 11	100836.179	105464.148	**106.70**
25	D_68	Sheikh Radwan No. 10	100513.384	105180.887	**142.30**
26	E_154	Sheikh Radwan No. 8	99329.682	105051.664	**938.80**
27	R_162H	Sheikh Radwan No. 7	99056.143	103668.501	**519.30**
28	R_162HA	Sheikh Radwan No. 7-A	99048.735	103698.189	**515.85**
29	R_162LA	Sheikh Radwan No. 1-A	98480.709	104045.751	**766.80**
30	R_162CA	Sheikh Radwan No. 4	98867.347	104589.998	**322.00**
31	R_162BA	Sheikh Radwan No. 3	98727.630	104412.150	**780.25**
32	E_157	Sheikh Radwan No. 9	100156.242	104670.263	**186.95**
33	R_162D	Sheikh Radwan No. 5	98640.251	104992.751	**2,009.65**
34	R_162EA	Sheikh Radwan No. 2	98247.667	104479.677	**762.00**
35	R_162G	Sheikh Radwan No. 13	99166.221	103951.902	**547.90**
36	R_112	Sheikh Ejleen No. 1	96061.301	102651.012	**820.40**
37	R_277	Sheikh Ejleen No. 5	96236.996	101529.748	**199.00**
38	R_270	Maslahk Well	96230.000	99750.000	**443.05**
39	R_254	Sheikh Ejleen No. 2	96540.877	102055.549	**366.40**
40	R_113	Sheikh Ejleen No. 4	96532.492	102589.653	**330.85**
41	R_265	Sheikh Ejleen No. 3	95808.755	101707.838	**199.20**
42	R_280	Sheikh Ejleen No. 6	95760.876	101154.530	**60.49**
43	R_75	Shijaia No. 2 (Abu Abali Well)	100416.471	101298.121	**659.10**
44	R_74	Shijaia No. 3(Abu Lafi)	100659.744	101542.207	**745.50**

S/N	Well_ID	Well_Name	X	Y	Chloride Concentration in mg/l
45	Q_68	Safa-05 (Zimmo Well)	102220.996	103530.894	**174.35**
46	R_25B	Safa-01	100777.863	102527.824	**526.50**
47	R_25A	Safa-02	100758.643	102581.703	**490.90**
48	R_25C	Safa-03	100775.793	102454.926	**953.50**
49	R_25D	Safa-04	100820.083	102495.564	**736.25**
50	H_95	Zawaida New Well	89462.115	92752.927	**630.00**
51	J_146	Abo Naser Well	91199.807	90460.942	**607.80**
52	S_69	Abu Merwan Well	91769.916	90702.258	**436.00**
53	T_46	Abu Hamam Well	91983.766	90273.159	**508.00**
54	K_21	El-Berka No. 1	85915.694	89758.346	**228.80**
55	K_20	El-Berka No. 2	86265.407	89777.531	**293.20**
56	G_49	Nusirat New Well (Municipal Well)	91378.528	96449.254	**1,041.00**
57	H_60	Fallet Well	91380.000	94950.000	**994.50**
58	G_30	Hertani Well	91478.840	95975.570	**923.00**
59	F_205	Wadi Gaza Well	97083.010	96337.176	**207.74**
60	G_50	Al-Zahra Well	93154.175	98410.772	**257.80**
61	F_203	Moghraqa Well No. 3	93719.685	97945.334	**261.98**
62	F_192	Moghraqa Well No. 2 - JC	95405.166	98642.566	**293.00**
63	F_191	Moghraqa Well No. 1 - JC	94959.667	98953.183	**300.30**
64	S_71	Magazi Well No. S-71	92674.599	91699.851	**525.40**
65	S_72	Karaj Well	93199.944	93513.760	**1,023.60**
66	L_41	Mahata Eastern Well	84345.622	83160.595	**970.30**
67	Ma'an	Ma'an Eastern Well	84544.985	82616.927	**1,024.00**
68	MadenaRiyadia	Al Madena Al Riyadia	83496.769	81790.166	**479.80**
69	Rashwan_C	Abu Rashwan Well No. "C"	81953.889	82385.253	**526.25**
70	L_286	Abu Rashwan Well No. "B"	81564.289	82410.458	**157.50**
71	L_184	Abu Rashwan Well No. "A"	81608.000	82519.000	**199.25**
72	L_43	Aia Well	83063.193	83461.450	**744.60**
73	L_159A	Al-Amal New Well	82680.000	85080.000	**311.50**
74	L_159	Al-Amal Old Well	82607.000	85049.000	**472.60**
75	L_87	El-Sa'ada Well	83040.000	84200.000	**946.00**
76	L_127	El-Ahrash Well	82852.000	83935.000	**715.75**
77	L_176	El-Sha'er Well / Old Southern Well	82187.000	83276.000	**860.50**
78	L_187	El-Satar Well	84364.000	86335.000	**1,285.50**
79	K_19	AL Matahen Well	86461.000	88592.000	**198.80**
80	L_179	Western well	85572.000	87460.000	**404.70**
81	L_181	EV01 - Eastern Village No. 1	81358.761	82404.408	**100.90**
82	P_146	EV02 - Eastern Village No. 2	80949.000	81865.000	**118.90**
83	P_15	Hejazi Well (Zu'rub)	77925.638	78903.921	**579.95**
84	P_124	Western Abu Hashem Well	77599.000	79414.000	**458.20**
85	P_153	El-Iskan Well	77736.215	80519.752	**114.60**
86	P_144A	Canada Well	78314.071	80366.603	**293.60**
87	P_138	Abu Zohri Well	78773.000	79764.000	**179.00**
88	P_145	El-Hashash Well	79368.232	79856.165	**286.40**

Appendix 2.3 - Chloride Dataset in 2005

S/N	Well_ID	Well_Name	X	Y	Chloride Concentration in mg/l
1	C_20	Aida Abu Gazalah	106738.419	104856.817	**214.70**
2	C_128	Abu Gazalah	106477.556	104891.263	**249.35**
3	C_76	Industrial Area Well	104667.093	104336.570	**713.20**
4	C_127A	Ezba New Well	104785.023	106154.679	**97.60**
5	C_137	Nada Well	104987.959	106485.517	**56.62**
6	A_210	Om El-Naser Well	104434.599	106243.541	**43.06**
7	A_185	Mashro Well	102529.950	106252.123	**129.40**
8	A_211	Shekh Zaid West Well	103328.602	105390.978	**52.47**
9	A_205	Sheikh Zaid East Well	103497.357	105126.104	**101.80**
10	E_06	Shawa Well	103012.159	105333.978	**105.10**
11	A_180	Gabin Well	102459.196	107033.005	**137.75**
12	D_67	Atatra Well	101715.425	107217.505	**48.30**
13	D_73	Salateen Well	101036.182	106827.164	**70.10**
14	E_01	Abu Hasira Well	103273.717	104897.703	**119.70**
15	E_04	Bahtimi Well	103034.144	105064.223	**81.82**
16	E_156	Abu Talal Well	102067.198	104589.246	**161.50**
17	E_90	Hawooz Well (Paris)	101280.226	104587.480	**208.80**
18	D_20	Abu Sharikh Eastern Well	101379.650	105027.493	**150.50**
19	Q_40C	Nammar / Edara Well	102773.848	103960.567	**201.00**
20	Q_72	El - Hissi Well	102528.930	103933.565	**159.30**
21	D_60	Abu Sharikh Western Well	101286.467	105111.237	**166.00**
22	D_74	Amer Well (17 Well)	100503.704	106104.088	**98.58**
23	D_75	Zohour Well	101085.391	105814.549	**96.25**
24	D_71	Sheikh Radwan No. 15	101457.632	106193.151	**96.69**
25	D_72	Sheikh Radwan No. 16	101739.331	106462.512	**77.10**
26	D_70	Sheikh Radwan No. 12	101440.342	105833.464	**112.40**
27	D_69	Sheikh Radwan No. 11	100836.179	105464.148	**124.30**
28	D_68	Sheikh Radwan No. 10	100513.384	105180.887	**116.90**
29	E_154	Sheikh Radwan No. 8	99329.682	105051.664	**1,946.00**
30	R_162H	Sheikh Radwan No. 7	99056.143	103668.501	**477.70**
31	R_162HA	Sheikh Radwan No. 7-A	99048.735	103698.189	**528.50**
32	R_162LA	Sheikh Radwan No. 1-A	98480.709	104045.751	**1,207.50**
33	R_162CA	Sheikh Radwan No. 4	98867.347	104589.998	**833.60**
34	R_162BA	Sheikh Radwan No. 3	98727.630	104412.150	**791.10**
35	E_157	Sheikh Radwan No. 9	100156.242	104670.263	**189.50**
36	R_162EA	Sheikh Radwan No. 2	98247.667	104479.677	**1,329.50**
37	R_162G	Sheikh Radwan No. 13	99166.221	103951.902	**628.30**
38	R_112	Sheikh Ejleen No. 1	96061.301	102651.012	**2,031.00**
39	R_277	Sheikh Ejleen No. 5	96236.996	101529.748	**219.95**
40	R_270	Maslahk Well	96230.000	99750.000	**491.45**
41	R_254	Sheikh Ejleen No. 2	96540.877	102055.549	**325.70**
42	R_113	Sheikh Ejleen No. 4	96532.492	102589.653	**351.50**
43	R_265	Sheikh Ejleen No. 3	95808.755	101707.838	**245.10**
44	R_293	Sheikh Ejleen No. 7	96713.479	101394.692	**381.30**

S/N	Well_ID	Well_Name	X	Y	Chloride Concentration in mg/l
45	R_280	Sheikh Ejleen No. 6	95760.876	101154.530	**107.49**
46	R_75	Shijaia No. 2 (Abu Abali Well)	100416.471	101298.121	**806.20**
47	R_74	Shijaia No. 3(Abu Lafi)	100659.744	101542.207	**682.70**
48	Q_68	Safa-05 (Zimmo Well)	102220.996	103530.894	**197.50**
49	R_25B	Safa-01	100777.863	102527.824	**510.20**
50	R_25A	Safa-02	100758.643	102581.703	**742.00**
51	R_25C	Safa-03	100775.793	102454.926	**994.20**
52	R_25D	Safa-04	100820.083	102495.564	**627.15**
53	H_95	Zawaida New Well	89462.115	92752.927	**717.55**
54	J_146	Abo Naser Well	91199.807	90460.942	**640.60**
55	S_69	Abu Merwan Well	91769.916	90702.258	**461.10**
56	T_46	Abu Hamam Well	91983.766	90273.159	**603.60**
57	K_21	El-Berka No. 1	85915.694	89758.346	**247.30**
58	J_2	El-Sahel No. 2	86073.590	90006.285	**508.00**
59	K_20	El-Berka No. 2	86265.407	89777.531	**357.70**
60	T_52	Wadi El-Salga Well	89412.942	87720.219	**545.21**
61	G_49	Nusirat New Well (Municipal Well)	91378.528	96449.254	**1,093.00**
62	H_60	Fallet Well	91380.000	94950.000	**1,154.00**
63	G_30	Hertani Well	91478.840	95975.570	**943.70**
64	G_45	Abu Ereban Well	91853.380	95529.720	**874.10**
65	F_208	Nusirat F-208 (Zahra'a Well)	93493.157	97839.178	**273.60**
66	F_205	Wadi Gaza Well	97083.010	96337.176	**777.75**
67	G_50	Al-Zahra Well	93154.175	98410.772	**353.70**
68	F_203	Moghraqa Well No. 3	93719.685	97945.334	**272.60**
69	F_192	Moghraqa Well No. 2 - JC	95405.166	98642.566	**268.70**
70	F_191	Moghraqa Well No. 1 - JC	94959.667	98953.183	**306.30**
71	S_80	Magazi Well No. S-80	93117.838	91923.243	**496.00**
72	S_71	Magazi Well No. S-71	92674.599	91699.851	**550.25**
73	S_72	Karaj Well	93199.944	93513.760	**1,051.50**
74	L_41	Mahata Eastern Well	84345.622	83160.595	**957.80**
75	Ma'an	Ma'an Eastern Well	84544.985	82616.927	**1,066.00**
76	MadenaRiyadia	Al Madena Al Riyadia	83496.769	81790.166	**576.40**
77	Rashwan_C	Abu Rashwan Well No. "C"	81953.889	82385.253	**1,045.00**
78	L_286	Abu Rashwan Well No. "B"	81564.289	82410.458	**224.10**
79	L_184	Abu Rashwan Well No. "A"	81608.000	82519.000	**194.00**
80	L_189A	Tahadi Well	81832.000	82693.000	**454.00**
81	L_182	New Southern Well	81858.000	82927.000	**493.00**
82	Al_Najar	Al-Najar Well	82430.000	82100.000	**670.10**
83	L_43	Aia Well	83063.193	83461.450	**754.20**
84	L_159A	Al-Amal New Well	82680.000	85080.000	**324.30**
85	L_159	Al-Amal Old Well	82607.000	85049.000	**514.20**
86	L_87	El-Sa'ada Well	83040.000	84200.000	**917.30**
87	L_127	El-Ahrash Well	82852.000	83935.000	**672.00**
88	L_176	El-Sha'er Well / Old Southern Well	82187.000	83276.000	**634.20**
89	L_187	El-Satar Well	84364.000	86335.000	**1,233.00**
90	L_190	El-Satar New Well (Northern)	85758.000	87281.000	**1,385.00**
91	K_19	AL Matahen Well	86461.000	88592.000	**320.70**
92	L_179	Western well	85572.000	87460.000	**694.70**
93	L_181	EV01 - Eastern Village No. 1	81358.761	82404.408	**100.90**

S/N	Well_ID	Well_Name	X	Y	Chloride Concentration in mg/l
94	P_146	EV02 - Eastern Village No. 2	80949.000	81865.000	**158.35**
95	P_154	EV03 - Eastern Village No. 3	80847.000	81468.000	**179.60**
96	P_15	Hejazi Well (Zu'rub)	77925.638	78903.921	**649.10**
97	P_124	Western Abu Hashem Well	77599.000	79414.000	**452.40**
98	P_139	Al Bahar Well	77165.000	82011.000	**334.30**
99	P_153	El-Iskan Well	77736.215	80519.752	**122.45**
100	P_144A	Canada Well	78314.071	80366.603	**307.80**
101	P_148	Tal Al Sultan -PWA	78666.836	80053.049	**116.30**
102	P_138	Abu Zohri Well	78773.000	79764.000	**239.70**
103	P_145	El-Hashash Well	79368.232	79856.165	**348.65**
104	Shuka	Shuka Well	80266.000	80177.000	**232.40**

Appendix 2.4 - Chloride Dataset in 2007

S/N	Well_ID	Well_Name	X	Y	Chloride Concentration in mg/l
1	C_20	Aida Abu Gazalah	106738.419	104856.817	**247.40**
2	C_128	Abu Gazalah	106477.556	104891.263	**252.45**
3	C_155	Khadija	106857.426	105351.288	**270.00**
4	C_79A	Al Awqaf well	105350.281	105094.134	**502.00**
5	C_76	Industrial Area Well	104667.093	104336.570	**709.90**
6	C_127A	Ezba New Well	104785.023	106154.679	**100.40**
7	C_137	Nada Well	104987.959	106485.517	**60.96**
8	A_210	Om El-Naser Well	104434.599	106243.541	**35.14**
9	A_185	Mashro Well	102529.950	106252.123	**147.45**
10	A_211	Shekh Zaid West Well	103328.602	105390.978	**86.05**
11	A_205	Sheikh Zaid East Well	103497.357	105126.104	**115.30**
12	E_06	Shawa Well	103012.159	105333.978	**124.70**
13	A_180	Gabin Well	102459.196	107033.005	**179.10**
14	D_67	Atatra Well	101715.425	107217.505	**53.86**
15	D_73	Salateen Well	101036.182	106827.164	**68.49**
16	E_01	Abu Hasira Well	103273.717	104897.703	**128.85**
17	E_04	Bahtimi Well	103034.144	105064.223	**95.09**
18	E_156	Abu Talal Well	102067.198	104589.246	**170.55**
19	E_90	Hawooz Well (Paris)	101280.226	104587.480	**228.20**
20	D_20	Abu Sharikh Eastern Well	101379.650	105027.493	**158.35**
21	Q_40C	Nammar / Edara Well	102773.848	103960.567	**214.85**
22	Q_72	El - Hissi Well	102528.930	103933.565	**181.25**
23	D_60	Abu Sharikh Western Well	101286.467	105111.237	**205.95**
24	D_74	Amer Well (17 Well)	100503.704	106104.088	**183.30**
25	D_75	Zohour Well	101085.391	105814.549	**100.61**
26	D_71	Sheikh Radwan No. 15	101457.632	106193.151	**93.22**
27	D_72	Sheikh Radwan No. 16	101739.331	106462.512	**86.70**
28	D_70	Sheikh Radwan No. 12	101440.342	105833.464	**121.90**
29	D_69	Sheikh Radwan No. 11	100836.179	105464.148	**121.90**
30	D_68	Sheikh Radwan No. 10	100513.384	105180.887	**150.60**
31	E_154	Sheikh Radwan No. 8	99329.682	105051.664	**2,077.00**
32	E_154A	Sheikh Radwan No. 8-A	99336.835	105056.140	**1,387.00**
33	R_162H	Sheikh Radwan No. 7	99056.143	103668.501	**493.70**
34	R_162HA	Sheikh Radwan No. 7-A	99048.735	103698.189	**563.25**
35	R_162LB	Sheikh Radwan No. 1-B	98453.297	104044.530	**495.20**
36	R_162LA	Sheikh Radwan No. 1-A	98480.709	104045.751	**2,028.50**
37	R_162CA	Sheikh Radwan No. 4	98867.347	104589.998	**446.20**
38	R_162BA	Sheikh Radwan No. 3	98727.630	104412.150	**671.00**
39	E_157	Sheikh Radwan No. 9	100156.242	104670.263	**204.10**
40	R_162EA	Sheikh Radwan No. 2	98247.667	104479.677	**1,988.00**
41	R_162G	Sheikh Radwan No. 13	99166.221	103951.902	**693.70**
42	R_277	Sheikh Ejleen No. 5	96236.996	101529.748	**273.65**
43	R_270	Maslahk Well	96230.000	99750.000	**530.70**
44	R_254	Sheikh Ejleen No. 2	96540.877	102055.549	**407.20**

S/N	Well_ID	Well_Name	X	Y	Chloride Concentration in mg/l
45	R_113A	Sheikh Ejleen No. 4	96532.492	102589.653	**382.80**
46	R_265	Sheikh Ejleen No. 3	95808.755	101707.838	**280.75**
47	R_293	Sheikh Ejleen No. 7	96713.479	101394.692	**503.35**
48	R_280	Sheikh Ejleen No. 6	95760.876	101154.530	**145.10**
49	R_312	Al Shijaia No. 6 (Al Montar)	100004.184	100005.239	**769.35**
50	R_75	Shijaia No. 2 (Abu Abali Well)	100416.471	101298.121	**878.45**
51	R_74	Shijaia No. 3(Abu Lafi)	100659.744	101542.207	**781.60**
52	Q_68	Safa-05 (Zimmo Well)	102220.996	103530.894	**223.20**
53	R_25B	Safa-01	100777.863	102527.824	**533.00**
54	R_25A	Safa-02	100758.643	102581.703	**511.70**
55	R_25C	Safa-03	100775.793	102454.926	**1,012.00**
56	R_25D	Safa-04	100820.083	102495.564	**742.70**
57	R_314	Remal No.2 (Kamal Naser)	99164.439	104391.099	**177.65**
58	R_313	Remal-01 (Al Jundi Garden - Well)	97563.923	103022.306	**362.30**
59	R_307	Sabra-02 (Dairi Well)	97602.376	101510.214	**329.30**
60	R_308	Sabra-03 (Sh'haiber Well)	98262.823	101598.399	**549.70**
61	R_305	Zaiton-02 (Om El-Laymon-Abu Khosa)	97547.626	100274.629	**502.40**
62	R_310	Zaiton-01	97415.859	100282.770	**247.49**
63	R_311	Daraj-01(Basha Well)	99287.488	101643.335	**712.35**
64	R_306	Sabra-01 (Dogmosh Well)	97075.516	101805.570	**261.52**
65	R_309	Sheja'ia No.5 -Soq Al Halal	99687.000	99203.000	**1,109.00**
66	H_95	Zawaida New Well	89462.115	92752.927	**1,109.00**
67	Aisha	Aisha Well	89518.317	92949.763	**638.25**
68	J_146	Abo Naser Well	91199.807	90460.942	**717.10**
69	S_69	Abu Merwan Well	91769.916	90702.258	**512.70**
70	T_46	Abu Hamam Well	91983.766	90273.159	**674.10**
71	J_3	El-Sahel No. 3	85589.714	89657.360	**437.45**
72	J_4	El-Sahel No. 4	85253.031	89308.798	**251.00**
73	J_5	El-Sahel No. 5	84876.365	89043.249	**229.50**
74	K_21	El-Berka No. 1	85915.694	89758.346	**355.00**
75	J_2	El-Sahel No. 2	86073.590	90006.285	**921.50**
76	K_20	El-Berka No. 2	86265.407	89777.531	**433.85**
77	T_52	Wadi El-Salga Well	89412.942	87720.219	**623.20**
78	G_49	Nusirat New Well (Municipal Well)	91378.528	96449.254	**1,129.50**
79	H_60	Fallet Well	91380.000	94950.000	**1,276.50**
80	G_30	Hertani Well	91478.840	95975.570	**1,004.00**
81	G_45	Abu Ereban Well	91853.380	95529.720	**1,212.00**
82	F_208	Nusirat F-208 (Zahra'a Well)	93493.157	97839.178	**473.30**
83	F_205	Wadi Gaza Well	97083.010	96337.176	**839.00**
84	G_50	Al-Zahra Well	93154.175	98410.772	**480.50**
85	F_203	Moghraqa Well No. 3	93719.685	97945.334	**390.85**
86	F_192	Moghraqa Well No. 2 - JC	95405.166	98642.566	**254.60**
87	F_191	Moghraqa Well No. 1 - JC	94959.667	98953.183	**250.30**
88	S_80	Magazi Well No. S-80	93117.838	91923.243	**717.10**
89	S_71	Magazi Well No. S-71	92674.599	91699.851	**588.95**
90	S_82	Magazi Well No. S-82	93117.838	91923.243	**213.40**
91	Makbola	Makbola Well	93108.102	92454.610	**344.20**
92	S_72	Karaj Well	93199.944	93513.760	**1,083.00**
93	Musadar	Musadar Well (Yusif Thabet Well)	91874.427	90945.884	**415.90**

S/N	Well_ID	Well_Name	X	Y	Chloride Concentration in mg/l
94	L_41	Mahata Eastern Well	84345.622	83160.595	**1,047.00**
95	Ma'an	Ma'an Eastern Well	84544.985	82616.927	**1,124.00**
96	MadenaRiyadia	Al Madena Al Riyadia	83496.769	81790.166	**714.30**
97	L_198	Cultural Center Well	83462.388	81977.159	**659.70**
98	Rashwan_C	Abu Rashwan Well No. "C"	81953.889	82385.253	**2,004.00**
99	L_286	Abu Rashwan Well No. "B"	81564.289	82410.458	**735.05**
100	L_184	Abu Rashwan Well No. "A"	81608.000	82519.000	**425.10**
101	L_189A	Tahadi Well	81832.000	82693.000	**541.40**
102	L_182	New Southern Well	81858.000	82927.000	**668.90**
103	Al_Najar	Al-Najar Well	82430.000	82100.000	**1,322.50**
104	L_43	Aia Well	83063.193	83461.450	**823.50**
105	L_159A	Al-Amal New Well	82680.000	85080.000	**484.05**
106	L_159	Al-Amal Old Well	82607.000	85049.000	**580.85**
107	L_87	El-Sa'ada Well	83040.000	84200.000	**489.42**
108	L_127	El-Ahrash Well	82852.000	83935.000	**669.40**
109	L_176	El-Sha'er Well / Old Southern Well	82187.000	83276.000	**589.65**
110	L_187	El-Satar Well	84364.000	86335.000	**1,291.00**
111	L_190	El-Satar New Well (Northern)	85758.000	87281.000	**1,292.50**
112	K_19	AL Matahen Well	86461.000	88592.000	**169.90**
113	L_179	Western well	85572.000	87460.000	**410.00**
114	L_181	EV01 - Eastern Village No. 1	81358.761	82404.408	**179.30**
115	P_146	EV02 - Eastern Village No. 2	80949.000	81865.000	**177.55**
116	P_154	EV03 - Eastern Village No. 3	80847.000	81468.000	**173.25**
117	M_12	An-Najar Well	85384.000	83299.000	**956.10**
118	M_11	Abu-Shahla Well	85100.000	83358.000	**467.10**
119	P_159	El-Fakhari Well (Khazzan well)	80359.000	79965.000	**358.60**
120	P_15	Hejazi Well (Zu'rub)	77925.638	78903.921	**773.75**
121	P_124	Western Abu Hashem Well	77599.000	79414.000	**519.90**
122	P_139	Al Bahar Well	77165.000	82011.000	**174.23**
123	P_153	El-Iskan Well	77736.215	80519.752	**126.20**
124	P_144A	Canada Well	78314.071	80366.603	**444.60**
125	P_148	Tal Al Sultan -PWA	78666.836	80053.049	**198.25**
126	P_138	Abu Zohri Well	78773.000	79764.000	**486.15**
127	P_145	El-Hashash Well	79368.232	79856.165	**431.00**
128	Shuka	Shuka Well	80266.000	80177.000	**358.60**
129	Naser2	Naser 02 Well	79891.000	80302.000	**93.22**

Appendix 3 – Water Level Dataset

Appendix 3.1 – Water Level Dataset in 2001

S_N	Well_ID	Well_Type	X	Y	Water Level in m
1	A_102	Monitoring	100161.23	1007597.87	-0.713
2	A_107	Monitoring	101217.80	107481.63	-2.060
3	A_115	Monitoring	102171.49	108994.26	-0.782
4	A_21	Monitoring	103204.89	105475.68	-2.181
5	A_31	Monitoring	102773.03	106051.71	-2.600
6	A_47	Monitoring	103101.61	107074.25	-1.391
7	A_53	Monitoring	102191.45	106917.00	-2.735
8	A_64	Monitoring	103330.19	108096.81	-0.937
9	B_5	Monitoring	106654.85	106876.39	-0.179
10	BLBH_2D	Monitoring	104000.00	107150.00	0.928
11	BLBH_9	Monitoring	104740.00	107070.00	0.040
12	C_104	Monitoring	105892.23	106624.21	-0.228
13	C_126	Monitoring	104656.34	106017.71	-0.635
14	C_12A	Monitoring	107410.08	105174.85	0.845
15	C_27	Monitoring	107692.25	104563.90	1.233
16	C_30	Monitoring	106603.78	104470.95	0.395
17	C_3C	Monitoring	107626.36	105585.48	0.946
18	C_48	Monitoring	106501.02	105842.88	0.478
19	C_49	Monitoring	1060028.19	105244.83	-0.327
20	C_61	Monitoring	105983.62	104039.88	0.154
21	C_78	Monitoring	104930.74	104934.26	-0.671
22	D_34	Monitoring	100920.63	106287.79	-4.027
23	D_6	Monitoring	101151.15	105633.94	-4.455
24	E_116	Monitoring	100647.40	103487.42	-3.175
25	E_12	Monitoring	101589.48	104297.70	-0.902
26	E_32	Monitoring	99053.10	106224.66	-0.669
27	E_45	Monitoring	99823.26	105405.00	-2.938
28	F_121	Monitoring	96218.37	95434.80	1.632
29	F_21	Monitoring	94056.24	95964.45	0.881
30	F_43	Monitoring	94145.38	97593.92	1.361
31	F_68B	Monitoring	94998.25	96627.40	1.051
32	F_84	Monitoring	96191.52	97993.86	1.789
33	G_10	Monitoring	91189.24	96148.81	0.605
34	G_13	Monitoring	91928.02	96099.75	0.633
35	G_24B	Monitoring	92376.56	98908.88	0.379
36	G_26	Monitoring	91922.37	94938.84	1.147

S_N	Well_ID	Well_Type	X	Y	Water Level in m
37	H_11	Monitoring	90660.32	92785.02	0.132
38	H_23	Monitoring	91010.01	94331.68	0.642
39	H_5	Monitoring	89613.29	92965.11	0.083
40	J_103	Monitoring	88733.24	92930.49	0.042
41	J_68	Monitoring	85988.38	90847.67	-1.074
42	L_18	Monitoring	85277.44	85821.60	-0.465
43	L_36	Monitoring	85175.85	82635.94	1.450
44	L_47	Monitoring	82610.31	82589.34	-2.464
45	L_57	Monitoring	84368.98	81663.11	-1.053
46	L_61	Monitoring	83310.37	78719.78	-1.366
47	L_66	Monitoring	82716.30	79914.50	-2.786
48	L_8	Monitoring	86254.41	86212.13	-0.563
49	L_86	Monitoring	82244.33	84658.55	3.026
50	M_10	Monitoring	85967.49	84740.36	-0.331
51	M_8	Monitoring	86607.72	84009.51	-0.066
52	N_12	Monitoring	88701.25	80356.73	8.974
53	N_16	Monitoring	88941.39	81122.74	7.289
54	N_23	Monitoring	86899.19	81550.77	1.644
55	N_6	Monitoring	88197.68	83204.82	1.262
56	N_7	Monitoring	89262.95	83502.88	1.688
57	O_2	Monitoring	89521.75	80087.64	12.885
58	P_10	Monitoring	78612.96	77038.70	-1.616
59	P_48A	Monitoring	80066.99	79696.06	-6.469
60	P_50	Monitoring	81167.09	80838.04	-4.470
61	P_61	Monitoring	81112.54	79150.07	-5.872
62	P_66	Monitoring	82373.98	77844.19	-1.333
63	P_94	Monitoring	80941.85	76960.21	-0.713
64	P_99	Monitoring	78681.04	78385.32	-3.960
65	Piezo_10A	Piezometer	81957.76	80909.10	-3.364
66	Piezo_23	Piezometer	88781.37	94162.61	0.493
67	Piezo_24	Piezometer	99269.13	107327.29	-0.012
68	Piezo_25A	Piezometer	99919.88	106651.14	-1.867
69	Piezo_25B	Piezometer	99919.86	106650.92	-1.852
70	Piezo_26B	Piezometer	100549.36	108580.11	-0.213
71	Piezo_27	Piezometer	100870.10	107857.73	-1.273
72	Piezo_29	Piezometer	102387.47	109386.95	-0.310
73	Piezo_2C	Piezometer	98328.83	105798.25	-0.110
74	Piezo_2D	Piezometer	98330.18	105799.51	0.045
75	Piezo_36A	Piezometer	98978.74	105215.04	-1.747
76	Piezo_36B	Piezometer	98978.74	105215.09	-2.429
77	Piezo_3B	Piezometer	93621.26	95543.60	2.475
78	Piezo_8A	Piezometer	95579.28	98225.43	1.949

S_N	Well_ID	Well_Type	X	Y	Water Level in m
79	Piezo_8B	Piezometer	95575.02	98224.43	1.814
80	Q_12	Monitoring	104914.33	101957.73	0.716
81	Q_2	Monitoring	103785.41	104376.19	-1.983
82	Q_20	Monitoring	103759.84	102767.27	0.068
83	Q_31	Monitoring	103838.98	103994.35	-1.483
84	Q_56	Monitoring	103382.35	101363.77	0.302
85	Q_7	Monitoring	104903.87	103530.61	-0.229
86	R_108 illegal	Monitoring	93373.59	100136.32	0.804
87	R_133	Monitoring	96773.31	101064.29	1.115
88	R_161	Monitoring	97636.71	104909.35	-0.039
89	R_171	Monitoring	100289.40	102543.40	-2.055
90	R_210	Monitoring	94911.14	101914.04	0.677
91	R_216	Monitoring	101523.17	101059.39	-0.885
92	R_24	Monitoring	100613.70	102462.92	-3.836
93	R_38	Monitoring	102027.16	101782.87	-0.971
94	R_60	Monitoring	101060.99	99498.47	1.071
95	R_84	Monitoring	99419.28	98987.91	0.949
96	R_96	Monitoring	99424.86	100463.55	2.108
97	R-I-10	Monitoring	96683.63	99338.61	2.487
98	R-I-69	Monitoring	96681.20	100107.03	1.923
99	R-I-92	Monitoring	95839.85	99669.81	2.329
100	S_11	Monitoring	94970.19	93542.62	2.007
101	S_15	Monitoring	94278.40	94366.74	1.503
102	S_28	Monitoring	93307.07	92855.66	0.914
103	S_50	Monitoring	91341.80	90667.80	-1.234
104	S_60	Monitoring	93656.94	91961.27	1.592
105	T_1	Monitoring	89693.01	89349.75	-1.829
106	T_15	Monitoring	87279.12	87444.48	-0.262
107	T_22	Monitoring	88337.98	85643.53	-0.036
108	T_26	Monitoring	87080.51	85663.61	-0.237
109	T_6	Monitoring	88321.99	88116.69	0.045
110	T_9	Monitoring	88757.26	87070.02	-0.147
111	Y_4	Monitoring	88757.26	77842.93	0.128

Appendix 3.2 – Water Level Dataset in 2003

S_N	Well_ID	Well_Type	X	Y	Water Level in m
1	A_102	Monitoring	100161.23	1007597.87	-0.316
2	A_107	Monitoring	101217.80	107481.63	-1.579
3	A_21	Monitoring	103204.89	105475.68	-2.164
4	A_31	Monitoring	102773.03	106051.71	-2.514
5	A_47	Monitoring	103101.61	107074.25	-0.959
6	A_53	Monitoring	102191.45	106917.00	-2.489
7	A_64	Monitoring	103330.19	108096.81	-0.299
8	B_5	Monitoring	106654.85	106876.39	-0.277
9	C_104	Monitoring	105892.23	106624.21	-0.320
10	C_126	Monitoring	104656.34	106017.71	-0.434
11	C_12A	Monitoring	107410.08	105174.85	0.346
12	C_27	Monitoring	107692.25	104563.90	0.666
13	C_30	Monitoring	106603.78	104470.95	-0.056
14	C_3C	Monitoring	107626.36	105585.48	0.214
15	C_48	Monitoring	106501.02	105842.88	-0.340
16	C_49	Monitoring	1060028.19	105244.83	-0.557
17	C_61	Monitoring	105983.62	104039.88	-0.063
18	C_78	Monitoring	104930.74	104934.26	-0.715
19	D_34	Monitoring	100920.63	106287.79	-3.773
20	D_6	Monitoring	101151.15	105633.94	-3.816
21	E_116	Monitoring	100647.40	103487.42	-3.186
22	E_12	Monitoring	101589.48	104297.70	-0.795
23	E_32	Monitoring	99053.10	106224.66	-0.471
24	E_45	Monitoring	99823.26	105405.00	-2.949
25	F_121	Monitoring	96218.37	95434.80	2.117
26	F_21	Monitoring	94056.24	95964.45	1.300
27	F_43	Monitoring	94145.38	97593.92	1.759
28	F_68B	Monitoring	94998.25	96627.40	1.193
29	F_84	Monitoring	96191.52	97993.86	1.846
30	G_10	Monitoring	91189.24	96148.81	0.391
31	G_13	Monitoring	91928.02	96099.75	0.971
32	G_24B	Monitoring	92376.56	98908.88	0.407
33	G_26	Monitoring	91922.37	94938.84	1.298
34	H_11	Monitoring	90660.32	92785.02	0.181
35	H_23	Monitoring	91010.01	94331.68	0.885
36	H_5	Monitoring	89613.29	92965.11	-0.090
37	J_103	Monitoring	88733.24	92930.49	-0.185
38	J_68	Monitoring	85988.38	90847.67	-1.165

S_N	Well_ID	Well_Type	X	Y	Water Level in m
39	L_18	Monitoring	85277.44	85821.60	-0.502
40	L_47	Monitoring	82610.31	82589.34	-3.731
41	L_57	Monitoring	84368.98	81663.11	-1.841
42	L_61	Monitoring	83310.37	78719.78	-2.287
43	L_66	Monitoring	82716.30	79914.50	-3.962
44	L_8	Monitoring	86254.41	86212.13	-0.481
45	L_86	Monitoring	82244.33	84658.55	2.872
46	M_10	Monitoring	85967.49	84740.36	-0.470
47	M_8	Monitoring	86607.72	84009.51	-0.240
48	N_12	Monitoring	88701.25	80356.73	9.601
49	N_16	Monitoring	88941.39	81122.74	7.996
50	N_23	Monitoring	86899.19	81550.77	1.579
51	N_6	Monitoring	88197.68	83204.82	1.350
52	N_7	Monitoring	89262.95	83502.88	1.882
53	P_10	Monitoring	78612.96	77038.70	-2.289
54	P_34	Monitoring	78686.10	79538.76	-7.692
55	P_48A	Monitoring	80066.99	79696.06	-8.173
56	P_50	Monitoring	81167.09	80838.04	-5.911
57	P_61	Monitoring	81112.54	79150.07	-8.032
58	P_68	Monitoring	81350.19	77748.05	-3.348
59	P_94	Monitoring	80941.85	76960.21	-1.421
60	P_99	Monitoring	78681.04	78385.32	-4.909
61	Piezo_10A	Piezometer	81957.76	80909.10	-4.888
62	Piezo_23	Piezometer	88781.37	94162.61	0.974
63	Piezo_24	Piezometer	99269.13	107327.29	0.204
64	Piezo_25A	Piezometer	99919.88	106651.14	-1.533
65	Piezo_25B	Piezometer	99919.86	106650.92	-1.672
66	Piezo_26A	Piezometer	100549.15	108580.10	0.040
67	Piezo_26B	Piezometer	100549.36	108580.11	0.198
68	Piezo_27	Piezometer	100870.10	107857.73	-0.798
69	Piezo_2C	Piezometer	98328.83	105798.25	-0.143
70	Piezo_36A	Piezometer	98978.74	105215.04	-1.703
71	Piezo_36B	Piezometer	98978.74	105215.09	-2.467
72	Piezo_3B	Piezometer	93621.26	95543.60	2.953
73	Piezo_8A	Piezometer	95579.28	98225.43	2.172
74	Piezo_8B	Piezometer	95575.02	98224.43	2.006
75	Q_2	Monitoring	103785.41	104376.19	-1.908
76	Q_20	Monitoring	103759.84	102767.27	-0.244
77	Q_56	Monitoring	103382.35	101363.77	0.107
78	Q_7	Monitoring	104903.87	103530.61	-0.415
79	R_108 illegal	Monitoring	93373.59	100136.32	-0.711
80	R_133	Monitoring	96773.31	101064.29	1.176

S_N	Well_ID	Well_Type	X	Y	Water Level in m
81	R_161	Monitoring	97636.71	104909.35	0.349
82	R_171	Monitoring	100289.40	102543.40	-2.079
83	R_210	Monitoring	94911.14	101914.04	0.806
84	R_216	Monitoring	101523.17	101059.39	-0.610
85	R_38	Monitoring	102027.16	101782.87	-0.872
86	R_60	Monitoring	101060.99	99498.47	1.255
87	R_84	Monitoring	99419.28	98987.91	-4.918
88	R-I-10	Monitoring	96683.63	99338.61	2.868
89	R-I-69	Monitoring	96681.20	100107.03	2.140
90	R-I-92	Monitoring	95839.85	99669.81	2.380
91	S_11	Monitoring	94970.19	93542.62	2.335
92	S_15	Monitoring	94278.40	94366.74	1.792
93	S_28	Monitoring	93307.07	92855.66	1.128
94	S_50	Monitoring	91341.80	90667.80	-1.045
95	S_60	Monitoring	93656.94	91961.27	1.875
96	T_1	Monitoring	89693.01	89349.75	-1.483
97	T_15	Monitoring	87279.12	87444.48	-0.077
98	T_22	Monitoring	88337.98	85643.53	0.186
99	T_26	Monitoring	87080.51	85663.61	-0.180
100	T_6	Monitoring	88321.99	88116.69	0.327
101	T_9	Monitoring	88757.26	87070.02	0.112
102	Y_4	Monitoring	88757.26	77842.93	0.157

Appendix 3.3 – Water Level Dataset in 2005

S_N	Well_ID	Well_Type	X	Y	Water Level in m
1	A_107	Monitoring	101217.80	107481.63	-2.650
2	A_31	Monitoring	102773.03	106051.71	-2.917
3	A_47	Monitoring	103101.61	107074.25	-1.381
4	A_53	Monitoring	102191.45	106917.00	-3.048
5	A_64	Monitoring	103330.19	108096.81	6.315
6	C_104	Monitoring	105892.23	106624.21	0.989
7	C_126	Monitoring	104656.34	106017.71	-0.138
8	C_12A	Monitoring	107410.08	105174.85	1.802
9	C_27	Monitoring	107692.25	104563.90	2.136
10	C_30	Monitoring	106603.78	104470.95	1.008
11	C_3C	Monitoring	107626.36	105585.48	1.996
12	C_48	Monitoring	106501.02	105842.88	1.115
13	C_49	Monitoring	1060028.19	105244.83	0.581
14	C_61	Monitoring	105983.62	104039.88	0.792
15	C_78	Monitoring	104930.74	104934.26	-0.127
16	CAMP_11	Piezometer	85223.90	84556.53	-0.566
17	CAMP_12	Piezometer	96338.07	100535.29	1.281
18	CAMP_13	Piezometer	92593.99	97657.87	1.674
19	CAMP_14	Piezometer	93107.16	91999.06	0.881
20	CAMP_1A	Piezometer	103593.63	107122.60	0.019
21	CAMP_1B	Piezometer	103596.30	107123.63	-0.003
22	CAMP_2	Piezometer	104577.63	105088.15	-0.328
23	CAMP_3A	Piezometer	98491.00	104402.57	-2.664
24	CAMP_3B	Piezometer	98493.17	104400.13	-2.995
25	CAMP_4	Piezometer	97737.69	96579.02	2.195
26	CAMP_7A	Piezometer	77355.65	79846.45	-4.508
27	CAMP_7B	Piezometer	77353.32	79846.22	-5.831
28	CAMP_8	Piezometer	86858.81	79606.83	6.361
29	CAMP_9	Piezometer	81041.06	75604.56	0.495
30	D_34	Monitoring	100920.63	106287.79	-4.240
31	E_116	Monitoring	100647.40	103487.42	-3.799
32	E_12	Monitoring	101589.48	104297.70	-4.021
33	E_32	Monitoring	99053.10	106224.66	-0.871
34	E_45	Monitoring	99823.26	105405.00	-3.376
35	F_121	Monitoring	96218.37	95434.80	1.910
36	F_21	Monitoring	94056.24	95964.45	1.240
37	F_43	Monitoring	94145.38	97593.92	1.612
38	F_68B	Monitoring	94998.25	96627.40	1.019

S_N	Well_ID	Well_Type	X	Y	Water Level in m
39	F_84	Monitoring	96191.52	97993.86	1.489
40	G_10	Monitoring	91189.24	96148.81	-0.062
41	G_24B	Monitoring	92376.56	98908.88	0.238
42	G_26	Monitoring	91922.37	94938.84	0.464
43	H_11	Monitoring	90660.32	92785.02	-0.451
44	H_5	Monitoring	89613.29	92965.11	-0.787
45	J_103	Monitoring	88733.24	92930.49	-0.785
46	J_68	Monitoring	85988.38	90847.67	-1.307
47	L_18	Monitoring	85277.44	85821.60	-0.674
48	L_47	Monitoring	82610.31	82589.34	-4.720
49	L_57	Monitoring	84368.98	81663.11	-2.947
50	L_61	Monitoring	83310.37	78719.78	-2.950
51	L_8	Monitoring	86254.41	86212.13	-0.725
52	L_86	Monitoring	82244.33	84658.55	3.335
53	M_10	Monitoring	85967.49	84740.36	-0.861
54	M_8	Monitoring	86607.72	84009.51	-0.646
55	N_12	Monitoring	88701.25	80356.73	10.058
56	N_16	Monitoring	88941.39	81122.74	8.299
57	N_6	Monitoring	88197.68	83204.82	1.653
58	N_7	Monitoring	89262.95	83502.88	1.732
59	P_10	Monitoring	78612.96	77038.70	-3.264
60	P_34	Monitoring	78686.10	79538.76	-8.822
61	P_48A	Monitoring	80066.99	79696.06	-10.055
62	P_61	Monitoring	81112.54	79150.07	-9.045
63	P_68	Monitoring	81350.19	77748.05	-3.944
64	P_94	Monitoring	80941.85	76960.21	-2.125
65	P_99	Monitoring	78681.04	78385.32	-5.881
66	Piezo_23	Piezometer	88781.37	94162.61	0.395
67	Piezo_24	Piezometer	99269.13	107327.29	-0.171
68	Piezo_25A	Piezometer	99919.88	106651.14	-1.974
69	Piezo_25B	Piezometer	99919.86	106650.92	-1.990
70	Piezo_26A	Piezometer	100549.15	108580.10	-0.190
71	Piezo_26B	Piezometer	100549.36	108580.11	-0.160
72	Piezo_27	Piezometer	100870.10	107857.73	-1.533
73	Piezo_2A	Piezometer	98330.20	105799.52	-1.169
74	Piezo_2B	Piezometer	98330.31	105799.51	-0.279
75	Piezo_2C	Piezometer	98328.83	105798.25	-0.406
76	Piezo_2D	Piezometer	98330.18	105799.51	-2.925
77	Piezo_2E	Piezometer	98329.09	105798.14	-1.651
78	Piezo_2F	Piezometer	98328.97	105798.09	-0.062
79	Piezo_36A	Piezometer	98978.74	105215.04	-1.956
80	Piezo_36B	Piezometer	98978.74	105215.09	-2.881

S_N	Well_ID	Well_Type	X	Y	Water Level in m
81	Piezo_3A	Piezometer	93621.17	95543.62	1.186
82	Piezo_3B	Piezometer	93621.26	95543.60	1.219
83	Piezo_7	Piezometer	84108.97	77899.19	0.682
84	Piezo_8A	Piezometer	95579.28	98225.43	1.759
85	Piezo_8B	Piezometer	95575.02	98224.43	1.576
86	Q_2	Monitoring	103785.41	104376.19	-1.776
87	Q_20	Monitoring	103759.84	102767.27	-0.474
88	R_133	Monitoring	96773.31	101064.29	0.655
89	R_161	Monitoring	97636.71	104909.35	-0.237
90	R_210	Monitoring	94911.14	101914.04	0.609
91	R_216	Monitoring	101523.17	101059.39	-0.961
92	R_38	Monitoring	102027.16	101782.87	-1.102
93	R_84	Monitoring	99419.28	98987.91	1.076
94	R-I-69	Monitoring	96681.20	100107.03	1.520
95	S_11	Monitoring	94970.19	93542.62	2.053
96	S_15	Monitoring	94278.40	94366.74	1.400
97	S_28	Monitoring	93307.07	92855.66	0.558
98	S_50	Monitoring	91341.80	90667.80	-1.412
99	T_1	Monitoring	89693.01	89349.75	-1.839
100	T_15	Monitoring	87279.12	87444.48	-0.297
101	T_22	Monitoring	88337.98	85643.53	-0.090
102	T_26	Monitoring	87080.51	85663.61	-0.436
103	T_6	Monitoring	88321.99	88116.69	-0.001
104	T_9	Monitoring	88757.26	87070.02	-0.089
105	Y_4	Monitoring	88757.26	77842.93	0.046

Appendix 3.4 – Water Level Dataset in 2007

S_N	Well_ID	Well_Type	X	Y	Water Level in m
1	A_31	Monitoring	102773.03	106051.71	-3.050
2	A_47	Monitoring	103101.61	107074.25	-1.547
3	A_53	Monitoring	102191.45	106917.00	-3.048
4	A_64	Monitoring	103330.19	108096.81	6.229
5	C_104	Monitoring	105892.23	106624.21	0.913
6	C_126	Monitoring	104656.34	106017.71	-0.248
7	C_12A	Monitoring	107410.08	105174.85	1.992
8	C_27	Monitoring	107692.25	104563.90	2.180
9	C_30	Monitoring	106603.78	104470.95	1.201
10	C_48	Monitoring	106501.02	105842.88	1.238
11	C_49	Monitoring	1060028.19	105244.83	0.427
12	C_61	Monitoring	105983.62	104039.88	0.824
13	C_78	Monitoring	104930.74	104934.26	-0.438
14	CAMP_12	Piezometer	96338.07	100535.29	0.015
15	CAMP_13	Piezometer	92593.99	97657.87	1.097
16	CAMP_1A	Piezometer	103593.63	107122.60	-0.514
17	CAMP_1B	Piezometer	103596.30	107123.63	-0.418
18	CAMP_2	Piezometer	104577.63	105088.15	-0.606
19	CAMP_3A	Piezometer	98491.00	104402.57	-3.001
20	CAMP_3B	Piezometer	98493.17	104400.13	-3.294
21	CAMP_4	Piezometer	97737.69	96579.02	1.457
22	CAMP_7A	Piezometer	77355.65	79846.45	-6.335
23	CAMP_7B	Piezometer	77353.32	79846.22	-8.056
24	CAMP_8	Piezometer	86858.81	79606.83	7.059
25	CAMP_9	Piezometer	81041.06	75604.56	0.286
26	D_34	Monitoring	100920.63	106287.79	-3.975
27	E_116	Monitoring	100647.40	103487.42	-4.198
28	E_12	Monitoring	101589.48	104297.70	-4.875
29	E_32	Monitoring	99053.10	106224.66	-0.965
30	E_45	Monitoring	99823.26	105405.00	-3.259
31	F_21	Monitoring	94056.24	95964.45	0.137
32	F_43	Monitoring	94145.38	97593.92	0.087
33	F_68B	Monitoring	94998.25	96627.40	0.002
34	F_84	Monitoring	96191.52	97993.86	-0.014
35	G_10	Monitoring	91189.24	96148.81	-0.460
36	G_13	Monitoring	91928.02	96099.75	2.403
37	G_24B	Monitoring	92376.56	98908.88	0.114

S_N	Well_ID	Well_Type	X	Y	Water Level in m
38	G_26	Monitoring	91922.37	94938.84	0.267
39	H_11	Monitoring	90660.32	92785.02	-0.898
40	H_5	Monitoring	89613.29	92965.11	-1.544
41	J_103	Monitoring	88733.24	92930.49	-1.310
42	J_68	Monitoring	85988.38	90847.67	-2.045
43	L_101	Monitoring	84805.69	89100.40	-0.313
44	L_18	Monitoring	85277.44	85821.60	-1.426
45	L_47	Monitoring	82610.31	82589.34	-6.007
46	L_57	Monitoring	84368.98	81663.11	-3.623
47	L_66	Monitoring	82716.30	79914.50	-6.063
48	L_8	Monitoring	86254.41	86212.13	-1.202
49	L_86	Monitoring	82244.33	84658.55	3.068
50	L_88	Monitoring	81404.30	86783.97	-0.107
51	L_94	Monitoring	83065.87	88152.41	-0.684
52	M_10	Monitoring	85967.49	84740.36	-1.370
53	M_8	Monitoring	86607.72	84009.51	-1.076
54	N_12	Monitoring	88701.25	80356.73	10.453
55	N_16	Monitoring	88941.39	81122.74	8.942
56	P_10	Monitoring	78612.96	77038.70	-4.048
57	P_24	Monitoring	77319.38	82292.30	1.340
58	P_34	Monitoring	78686.10	79538.76	-10.925
59	P_48A	Monitoring	80066.99	79696.06	-12.797
60	P_61	Monitoring	81112.54	79150.07	-10.890
61	P_94	Monitoring	80941.85	76960.21	-2.491
62	P_99	Monitoring	78681.04	78385.32	-7.341
63	Piezo_12	Piezometer	84407.95	88962.82	0.781
64	Piezo_22A	Piezometer	86304.18	89542.85	-1.743
65	Piezo_22B	Piezometer	86304.05	89542.79	-1.751
66	Piezo_23	Piezometer	88781.37	94162.61	0.189
67	Piezo_24	Piezometer	99269.13	107327.29	-0.262
68	Piezo_26A	Piezometer	100549.15	108580.10	-0.239
69	Piezo_26B	Piezometer	100549.36	108580.11	-0.262
70	Piezo_27	Piezometer	100870.10	107857.73	-1.538
71	Piezo_2A	Piezometer	98330.20	105799.52	-1.315
72	Piezo_2B	Piezometer	98330.31	105799.51	-0.314
73	Piezo_2C	Piezometer	98328.83	105798.25	-0.521
74	Piezo_2D	Piezometer	98330.18	105799.51	-2.941
75	Piezo_2E	Piezometer	98329.09	105798.14	-1.705
76	Piezo_2F	Piezometer	98328.97	105798.09	-0.182
77	Piezo_36A	Piezometer	98978.74	105215.04	-2.139
78	Piezo_36B	Piezometer	98978.74	105215.09	-3.083
79	Piezo_3A	Piezometer	93621.17	95543.62	0.501

S_N	Well_ID	Well_Type	X	Y	Water Level in m
80	**Piezo_3B**	**Piezometer**	93621.26	95543.60	**0.541**
81	**Piezo_7**	**Piezometer**	84108.97	77899.19	**0.667**
82	**Piezo_8A**	**Piezometer**	95579.28	98225.43	**0.342**
83	**Piezo_8B**	**Piezometer**	95575.02	98224.43	**0.339**
84	**R_108 illegal**	**Monitoring**	93373.59	100136.32	**0.653**
85	**R_133**	**Monitoring**	96773.31	101064.29	**-0.234**
86	**R_161**	**Monitoring**	97636.71	104909.35	**-0.665**
87	**R_210**	**Monitoring**	94911.14	101914.04	**0.417**
88	**R_216**	**Monitoring**	101523.17	101059.39	**-1.654**
89	**R_38**	**Monitoring**	102027.16	101782.87	**-1.267**
90	**R-I-69**	**Monitoring**	96681.20	100107.03	**0.074**
91	**S_11**	**Monitoring**	94970.19	93542.62	**1.763**
92	**S_15**	**Monitoring**	94278.40	94366.74	**0.776**
93	**S_28**	**Monitoring**	93307.07	92855.66	**0.269**
94	**T_1**	**Monitoring**	89693.01	89349.75	**-1.635**
95	**T_15**	**Monitoring**	87279.12	87444.48	**-0.938**
96	**T_22**	**Monitoring**	88337.98	85643.53	**-0.257**
97	**T_26**	**Monitoring**	87080.51	85663.61	**-0.848**
98	**T_6**	**Monitoring**	88321.99	88116.69	**-0.530**
99	**Y_4**	**Monitoring**	88757.26	77842.93	**-0.100**

Appendix 4 – Rainfall Dataset

Appendix 4.1 – Rainfall Dataset in 2000/01

Station_Name	Station_Location	X	Y	Rainfall_in_mm
Beit Hanoun	BH	106420	105740	**497.50**
Beit Lahia	BL	99750	108280	**490.40**
Jabalia	JB	99850	105100	**540.00**
Shati	SHATI	99500	105320	**478.90**
Gaza City	REMAL	97140	103300	**511.90**
Tuffah	TUFFAH	100500	101700	**533.40**
Gaza South	MOGHR	95380	98000	**563.60**
Nusseirat	NUSS.	91950	94080	**558.30**
Deir Al Balah	DB	88550	91600	**550.50**
Khan Younis	KY	84240	83880	**381.00**
Khuzaa	KHUZ.	83700	76350	**284.30**
Rafah	RF	79060	75940	**308.00**

Appendix 4.2 – Rainfall Dataset in 2002/03

Station_Name	Station_Location	X	Y	Rainfall_in_mm
Beit Hanoun	BH	106420	105740	**801.50**
Beit Lahia	BL	99750	108280	**724.00**
Jabalia	JB	99850	105100	**692.60**
Shati	SHATI	99500	105320	**627.00**
Gaza City	REMAL	97140	103300	**599.00**
Tuffah	TUFFAH	100500	101700	**653.50**
Gaza South	MOGHR	95380	98000	**790.70**
Nusseirat	NUSS.	91950	94080	**446.20**
Deir Al Balah	DB	88550	91600	**372.60**
Khan Younis	KY	84240	83880	**298.00**
Khuzaa	KHUZ.	83700	76350	**261.20**
Rafah	RF	79060	75940	**220.80**

Appendix 4.3 – Rainfall Dataset in 2004/05

Station_Name	Station_Location	X	Y	Rainfall_in_mm
Beit Hanoun	BH	106420	105740	**358.70**
Beit Lahia	BL	99750	108280	**320.60**
Jabalia	JB	99850	105100	**345.50**
Shati	SHATI	99500	105320	**296.60**
Gaza City	REMAL	97140	103300	**316.00**
Tuffah	TUFFAH	100500	101700	**345.40**
Gaza South	MOGHR	95380	98000	**323.60**
Nusseirat	NUSS.	91950	94080	**405.00**
Deir Al Balah	DB	88550	91600	**345.50**
Khan Younis	KY	84240	83880	**373.00**
Khuzaa	KHUZ.	83700	76350	**367.70**
Rafah	RF	79060	75940	**360.20**

Appendix 4.4 – Rainfall Dataset in 2006/07

Station_Name	Station_Location	X	Y	Rainfall_in_mm
Beit Hanoun	BH	106420	105740	**509.90**
Beit Lahia	BL	99750	108280	**530.30**
Jabalia	JB	99850	105100	**536.70**
Shati	SHATI	99500	105320	**469.00**
Gaza City	REMAL	97140	103300	**501.20**
Tuffah	TUFFAH	100500	101700	**545.50**
Gaza South	MOGHR	95380	98000	**388.20**
Nusseirat	NUSS.	91950	94080	**403.00**
Deir Al Balah	DB	88550	91600	**418.00**
Khan Younis	KY	84240	83880	**252.00**
Khuzaa	KHUZ.	83700	76350	**256.10**
Rafah	RF	79060	75940	**225.00**

Appendix 5 – Chloride Modeling Dataset

Appendix 5.1 - Chloride Modeling Dataset in 2001

S/N	Well_ID	Well_Name	X	Y	Cl_01
1	C_128	Abu_Gazalah	106477.556	104891.263	**247.65**
2	C_79A	Al_Awqaf_well	105350.281	105094.134	**479.07**
3	A_185	Mashro_Well	102529.950	106252.123	**95.56**
4	E_06	Shawa_Well	103012.159	105333.978	**98.50**
5	A_180	Gabin_Well	102459.196	107033.005	**88.46**
6	D_67	Atatra_Well	101715.425	107217.505	**35.40**
7	E_01	Abu_Hasira_Well	103273.717	104897.703	**112.57**
8	E_04	Bahtimi_Well	103034.144	105064.223	**73.73**
9	E_156	Abu_Talal_Well	102067.198	104589.246	**150.90**
10	E_90	Hawooz_Well_(Paris)	101280.226	104587.480	**158.15**
11	D_20	Abu_Sharikh_Eastern_Well	101379.650	105027.493	**154.45**
12	D_60	Abu_Sharikh_Western_Well	101286.467	105111.237	**120.50**
13	D_74	Amer_Well_(17_Well)	100503.704	106104.088	**73.65**
14	D_71	Sheikh_Radwan_No._15	101457.632	106193.151	**84.93**
15	D_72	Sheikh_Radwan_No._16	101739.331	106462.512	**74.32**
16	D_69	Sheikh_Radwan_No._11	100836.179	105464.148	**102.82**
17	D_68	Sheikh_Radwan_No._10	100513.384	105180.887	**130.90**
18	E_154	Sheikh_Radwan_No._8	99329.682	105051.664	**539.63**
19	R_162H	Sheikh_Radwan_No._7	99056.143	103668.501	**506.90**
20	R_162HA	Sheikh_Radwan_No._7_A	99048.735	103698.189	**506.95**
21	R_162LA	Sheikh_Radwan_No._1_A	98480.709	104045.751	**451.80**
22	R_162BA	Sheikh_Radwan_No._3	98727.630	104412.150	**506.05**
23	E_157	Sheikh_Radwan_No._9	100156.242	104670.263	**173.35**
24	R_162D	Sheikh_Radwan_No._5	98640.251	104992.751	**562.40**
25	R_162EA	Sheikh_Radwan_No._2	98247.667	104479.677	**364.70**
26	R_162G	Sheikh_Radwan_No._13	99166.221	103951.902	**521.10**
27	R_112	Sheikh_Ejleen_No._1	96061.301	102651.012	**869.13**
28	R_277	Sheikh_Ejleen_No._5	96236.996	101529.748	**169.40**
29	R_270	Maslahk_Well	96230.000	99750.000	**362.53**
30	R_113	Sheikh_Ejleen_No._4	96532.492	102589.653	**308.40**
31	R_265	Sheikh_Ejleen_No._3	95808.755	101707.838	**183.60**
32	R_75	Shijaia_No._2_(Abu_Abali_Well)	100416.471	101298.121	**733.30**
33	Q_68	Safa_05_(Zimmo_Well)	102220.996	103530.894	**176.50**
34	R_25B	Safa_01	100777.863	102527.824	**545.90**
35	R_25A	Safa_02	100758.643	102581.703	**477.15**
36	R_25C	Safa_03	100775.793	102454.926	**937.45**
37	R_25D	Safa_04	100820.083	102495.564	**711.05**
38	J_146	Abo_Naser_Well	91199.807	90460.942	**577.30**
39	T_46	Abu_Hamam_Well	91983.766	90273.159	**519.50**
40	K_21	El_Berka_No._1	85915.694	89758.346	**188.00**
41	K_20	El_Berka_No._2	86265.407	89777.531	**187.80**
42	G_49	Nusirat_New_Well_(Municipal_Well)	91378.528	96449.254	**1,022.00**
43	H_60	Fallet_Well	91380.000	94950.000	**1,022.00**

S/N	Well_ID	Well_Name	X	Y	Cl_01
44	G_50	Al_Zahra_Well	93154.175	98410.772	**140.00**
45	S_71	Magazi_Well_No._S_71	92674.599	91699.851	**503.50**
46	L_41	Mahata_Eastern_Well	84345.622	83160.595	**989.25**
47	L_286	Abu_Rashwan_Well_No._"B"	81564.289	82410.458	**118.24**
48	L_184	Abu_Rashwan_Well_No._"A"	81608.000	82519.000	**121.70**
49	L_43	Aia_Well	83063.193	83461.450	**705.15**
50	L_159A	Al_Amal_New_Well	82680.000	85080.000	**281.05**
51	L_159	Al_Amal_Old_Well	82607.000	85049.000	**492.90**
52	L_87	El_Sa'ada_Well	83040.000	84200.000	**933.25**
53	L_127	El_Ahrash_Well	82852.000	83935.000	**680.65**
54	L_187	El_Satar_Well	84364.000	86335.000	**1,175.75**
55	K_19	AL_Matahen_Well	86461.000	88592.000	**112.85**
56	L_181	EV01___Eastern_Village_No._1	81358.761	82404.408	**98.15**
57	P_146	EV02___Eastern_Village_No._2	80949.000	81865.000	**160.00**
58	P_15	Hejazi_Well_(Zu'rub)	77925.638	78903.921	**708.45**
59	P_124	Western_Abu_Hashem_Well	77599.000	79414.000	**433.55**
60	P_144A	Canada_Well	78314.071	80366.603	**264.30**
61	P_145	El_Hashash_Well	79368.232	79856.165	**264.30**

Appendix 5.2 - Chloride Modeling Dataset in 2003

S/N	Well_ID	Well_Name	X	Y	Cl_03
1	C_128	Abu Gazalah	106477.556	104891.263	**238.80**
2	C_79A	Al Awqaf well	105350.281	105094.134	**477.70**
3	C_76	Industrial Area Well	104667.093	104336.570	**620.30**
4	C_137	Nada Well	104987.959	106485.517	**29.32**
5	A_185	Mashro Well	102529.950	106252.123	**114.05**
6	E_06	Shawa Well	103012.159	105333.978	**95.11**
7	A_180	Gabin Well	102459.196	107033.005	**106.55**
8	D_67	Atatra Well	101715.425	107217.505	**46.30**
9	D_73	Salateen Well	101036.182	106827.164	**67.75**
10	E_01	Abu Hasira Well	103273.717	104897.703	**124.75**
11	E_04	Bahtimi Well	103034.144	105064.223	**90.00**
12	E_156	Abu Talal Well	102067.198	104589.246	**160.45**
13	E_90	Hawooz Well (Paris)	101280.226	104587.480	**192.55**
14	D_20	Abu Sharikh Eastern Well	101379.650	105027.493	**149.60**
15	Q_40C	Nammar / Edara Well	102773.848	103960.567	**184.60**
16	Q_72	El - Hissi Well	102528.930	103933.565	**124.88**
17	D_60	Abu Sharikh Western Well	101286.467	105111.237	**139.00**
18	D_74	Amer Well (17 Well)	100503.704	106104.088	**88.40**
19	D_71	Sheikh Radwan No. 15	101457.632	106193.151	**85.50**
20	D_70	Sheikh Radwan No. 12	101440.342	105833.464	**103.15**
21	D_69	Sheikh Radwan No. 11	100836.179	105464.148	**106.70**
22	D_68	Sheikh Radwan No. 10	100513.384	105180.887	**142.30**
23	E_154	Sheikh Radwan No. 8	99329.682	105051.664	**938.80**
24	R_162H	Sheikh Radwan No. 7	99056.143	103668.501	**519.30**
25	R_162HA	Sheikh Radwan No. 7-A	99048.735	103698.189	**515.85**
26	R_162CA	Sheikh Radwan No. 4	98867.347	104589.998	**322.00**
27	R_162BA	Sheikh Radwan No. 3	98727.630	104412.150	**780.25**
28	E_157	Sheikh Radwan No. 9	100156.242	104670.263	**186.95**
29	R_162D	Sheikh Radwan No. 5	98640.251	104992.751	**2,009.65**
30	R_162EA	Sheikh Radwan No. 2	98247.667	104479.677	**762.00**
31	R_162G	Sheikh Radwan No. 13	99166.221	103951.902	**547.90**
32	R_112	Sheikh Ejleen No. 1	96061.301	102651.012	**820.40**
33	R_277	Sheikh Ejleen No. 5	96236.996	101529.748	**199.00**
34	R_254	Sheikh Ejleen No. 2	96540.877	102055.549	**366.40**
35	R_113	Sheikh Ejleen No. 4	96532.492	102589.653	**330.85**
36	R_265	Sheikh Ejleen No. 3	95808.755	101707.838	**199.20**
37	R_75	Shijaia No. 2 (Abu Abali Well)	100416.471	101298.121	**659.10**
38	R_74	Shijaia No. 3(Abu Lafi)	100659.744	101542.207	**745.50**
39	Q_68	Safa-05 (Zimmo Well)	102220.996	103530.894	**174.35**
40	R_25B	Safa-01	100777.863	102527.824	**526.50**
41	R_25C	Safa-03	100775.793	102454.926	**953.50**
42	R_25D	Safa-04	100820.083	102495.564	**736.25**
43	H_95	Zawaida New Well	89462.115	92752.927	**630.00**
44	J_146	Abo Naser Well	91199.807	90460.942	**607.80**

S/N	Well_ID	Well_Name	X	Y	Cl_03
45	T_46	Abu Hamam Well	91983.766	90273.159	**508.00**
46	K_21	El-Berka No. 1	85915.694	89758.346	**228.80**
47	G_30	Hertani Well	91478.840	95975.570	**923.00**
48	F_205	Wadi Gaza Well	97083.010	96337.176	**207.74**
49	G_50	Al-Zahra Well	93154.175	98410.772	**257.80**
50	F_203	Moghraqa Well No. 3	93719.685	97945.334	**261.98**
51	F_192	Moghraqa Well No. 2 - JC	95405.166	98642.566	**293.00**
52	F_191	Moghraqa Well No. 1 - JC	94959.667	98953.183	**300.30**
53	S_71	Magazi Well No. S-71	92674.599	91699.851	**525.40**
54	S_72	Karaj Well	93199.944	93513.760	**1,023.60**
55	L_41	Mahata Eastern Well	84345.622	83160.595	**970.30**
56	Ma'an	Ma'an Eastern Well	84544.985	82616.927	**1,024.00**
57	MadenaRiyadia	Al Madena Al Riyadia	83496.769	81790.166	**479.80**
58	Rashwan_C	Abu Rashwan Well No. "C"	81953.889	82385.253	**526.25**
59	L_286	Abu Rashwan Well No. "B"	81564.289	82410.458	**157.50**
60	L_184	Abu Rashwan Well No. "A"	81608.000	82519.000	**199.25**
61	L_159A	Al-Amal New Well	82680.000	85080.000	**311.50**
62	L_159	Al-Amal Old Well	82607.000	85049.000	**472.60**
63	L_87	El-Sa'ada Well	83040.000	84200.000	**946.00**
64	L_127	El-Ahrash Well	82852.000	83935.000	**715.75**
65	L_176	El-Sha'er Well / Old Southern Well	82187.000	83276.000	**860.50**
66	K_19	AL Matahen Well	86461.000	88592.000	**198.80**
67	L_181	EV01 - Eastern Village No. 1	81358.761	82404.408	**100.90**
68	P_146	EV02 - Eastern Village No. 2	80949.000	81865.000	**118.90**
69	P_15	Hejazi Well (Zu'rub)	77925.638	78903.921	**579.95**
70	P_124	Western Abu Hashem Well	77599.000	79414.000	**458.20**
71	P_153	El-Iskan Well	77736.215	80519.752	**114.60**
72	P_144A	Canada Well	78314.071	80366.603	**293.60**
73	P_145	El-Hashash Well	79368.232	79856.165	**286.40**

Appendix 5.3 - Chloride Modeling Dataset in 2005

S/N	Well_ID	Well_Name	X	Y	Cl_05
1	C_20	Aida Abu Gazalah	106738.419	104856.817	**214.70**
2	C_127A	Ezba New Well	104785.023	106154.679	**97.60**
3	C_137	Nada Well	104987.959	106485.517	**56.62**
4	A_210	Om El-Naser Well	104434.599	106243.541	**43.06**
5	A_185	Mashro Well	102529.950	106252.123	**129.40**
6	A_205	Sheikh Zaid East Well	103497.357	105126.104	**101.80**
7	E_06	Shawa Well	103012.159	105333.978	**105.10**
8	A_180	Gabin Well	102459.196	107033.005	**137.75**
9	D_67	Atatra Well	101715.425	107217.505	**48.30**
10	E_01	Abu Hasira Well	103273.717	104897.703	**119.70**
11	E_04	Bahtimi Well	103034.144	105064.223	**81.82**
12	E_156	Abu Talal Well	102067.198	104589.246	**161.50**
13	D_20	Abu Sharikh Eastern Well	101379.650	105027.493	**150.50**
14	Q_40C	Nammar / Edara Well	102773.848	103960.567	**201.00**
15	Q_72	El - Hissi Well	102528.930	103933.565	**159.30**
16	D_60	Abu Sharikh Western Well	101286.467	105111.237	**166.00**
17	D_74	Amer Well (17 Well)	100503.704	106104.088	**98.58**
18	D_75	Zohour Well	101085.391	105814.549	**96.25**
19	D_71	Sheikh Radwan No. 15	101457.632	106193.151	**96.69**
20	D_72	Sheikh Radwan No. 16	101739.331	106462.512	**77.10**
21	D_70	Sheikh Radwan No. 12	101440.342	105833.464	**112.40**
22	D_69	Sheikh Radwan No. 11	100836.179	105464.148	**124.30**
23	D_68	Sheikh Radwan No. 10	100513.384	105180.887	**116.90**
24	E_154	Sheikh Radwan No. 8	99329.682	105051.664	**1,946.00**
25	R_162H	Sheikh Radwan No. 7	99056.143	103668.501	**477.70**
26	R_162HA	Sheikh Radwan No. 7-A	99048.735	103698.189	**528.50**
27	R_162LA	Sheikh Radwan No. 1-A	98480.709	104045.751	**1,207.50**
28	R_162BA	Sheikh Radwan No. 3	98727.630	104412.150	**791.10**
29	E_157	Sheikh Radwan No. 9	100156.242	104670.263	**189.50**
30	R_162D	Sheikh Radwan No. 5	98640.251	104992.751	**2,865.50**
31	R_162EA	Sheikh Radwan No. 2	98247.667	104479.677	**1,329.50**
32	R_162G	Sheikh Radwan No. 13	99166.221	103951.902	**628.30**
33	R_112	Sheikh Ejleen No. 1	96061.301	102651.012	**2,031.00**
34	R_277	Sheikh Ejleen No. 5	96236.996	101529.748	**219.95**
35	R_270	Maslahk Well	96230.000	99750.000	**491.45**
36	R_254	Sheikh Ejleen No. 2	96540.877	102055.549	**325.70**
37	R_113	Sheikh Ejleen No. 4	96532.492	102589.653	**351.50**
38	R_265	Sheikh Ejleen No. 3	95808.755	101707.838	**245.10**
39	R_293	Sheikh Ejleen No. 7	96713.479	101394.692	**381.30**
40	R_75	Shijaia No. 2 (Abu Abali Well)	100416.471	101298.121	**806.20**
41	R_74	Shijaia No. 3(Abu Lafi)	100659.744	101542.207	**682.70**
42	Q_68	Safa-05 (Zimmo Well)	102220.996	103530.894	**197.50**
43	R_25B	Safa-01	100777.863	102527.824	**510.20**
44	R_25A	Safa-02	100758.643	102581.703	**742.00**

S/N	Well_ID	Well_Name	X	Y	Cl_05
45	R_25D	Safa-04	100820.083	102495.564	**627.15**
46	H_95	Zawaida New Well	89462.115	92752.927	**717.55**
47	S_69	Abu Merwan Well	91769.916	90702.258	**461.10**
48	T_46	Abu Hamam Well	91983.766	90273.159	**603.60**
49	K_21	El-Berka No. 1	85915.694	89758.346	**247.30**
50	J_2	El-Sahel No. 2	86073.590	90006.285	**508.00**
51	T_52	Wadi El-Salga Well	89412.942	87720.219	**545.21**
52	H_60	Fallet Well	91380.000	94950.000	**1,154.00**
53	G_30	Hertani Well	91478.840	95975.570	**943.70**
54	G_45	Abu Ereban Well	91853.380	95529.720	**874.10**
55	F_208	Nusirat F-208 (Zahra'a Well)	93493.157	97839.178	**273.60**
56	F_205	Wadi Gaza Well	97083.010	96337.176	**777.75**
57	G_50	Al-Zahra Well	93154.175	98410.772	**353.70**
58	F_192	Moghraqa Well No. 2 - JC	95405.166	98642.566	**268.70**
59	S_80	Magazi Well No. S-80	93117.838	91923.243	**496.00**
60	S_71	Magazi Well No. S-71	92674.599	91699.851	**550.25**
61	S_72	Karaj Well	93199.944	93513.760	**1,051.50**
62	Ma'an	Ma'an Eastern Well	84544.985	82616.927	**1,066.00**
63	MadenaRiyadia	Al Madena Al Riyadia	83496.769	81790.166	**576.40**
64	Rashwan_C	Abu Rashwan Well No. "C"	81953.889	82385.253	**1,045.00**
65	L_286	Abu Rashwan Well No. "B"	81564.289	82410.458	**224.10**
66	L_184	Abu Rashwan Well No. "A"	81608.000	82519.000	**194.00**
67	L_182	New Southern Well	81858.000	82927.000	**493.00**
68	Al_Najar	Al-Najar Well	82430.000	82100.000	**670.10**
69	L_43	Aia Well	83063.193	83461.450	**754.20**
70	L_87	El-Sa'ada Well	83040.000	84200.000	**917.30**
71	L_127	El-Ahrash Well	82852.000	83935.000	**672.00**
72	L_176	El-Sha'er Well / Old Southern Well	82187.000	83276.000	**634.20**
73	L_187	El-Satar Well	84364.000	86335.000	**1,233.00**
74	K_19	AL Matahen Well	86461.000	88592.000	**320.70**
75	L_179	Western well	85572.000	87460.000	**694.70**
76	L_181	EV01 - Eastern Village No. 1	81358.761	82404.408	**100.90**
77	P_146	EV02 - Eastern Village No. 2	80949.000	81865.000	**158.35**
78	P_154	EV03 - Eastern Village No. 3	80847.000	81468.000	**179.60**
79	P_15	Hejazi Well (Zu'rub)	77925.638	78903.921	**649.10**
80	P_124	Western Abu Hashem Well	77599.000	79414.000	**452.40**
81	P_139	Al Bahar Well	77165.000	82011.000	**334.30**
82	P_153	El-Iskan Well	77736.215	80519.752	**122.45**
83	P_148	Tal Al Sultan -PWA	78666.836	80053.049	**116.30**
84	P_138	Abu Zohri Well	78773.000	79764.000	**239.70**
85	P_145	El-Hashash Well	79368.232	79856.165	**348.65**

Appendix 5.4 - Chloride Modeling Dataset in 2007

S/N	Well_ID	Well_Name	X	Y	Cl_07
1	C_20	Aida Abu Gazalah	106738.419	104856.817	**247.40**
2	C_128	Abu Gazalah	106477.556	104891.263	**252.45**
3	C_155	Khadija	106857.426	105351.288	**270.00**
4	C_79A	Al Awqaf well	105350.281	105094.134	**502.00**
5	C_76	Industrial Area Well	104667.093	104336.570	**709.90**
6	C_127A	Ezba New Well	104785.023	106154.679	**100.40**
7	A_210	Om El-Naser Well	104434.599	106243.541	**35.14**
8	A_185	Mashro Well	102529.950	106252.123	**147.45**
9	A_205	Sheikh Zaid East Well	103497.357	105126.104	**115.30**
10	E_06	Shawa Well	103012.159	105333.978	**124.70**
11	A_180	Gabin Well	102459.196	107033.005	**179.10**
12	D_67	Atatra Well	101715.425	107217.505	**53.86**
13	D_73	Salateen Well	101036.182	106827.164	**68.49**
14	E_01	Abu Hasira Well	103273.717	104897.703	**128.85**
15	E_04	Bahtimi Well	103034.144	105064.223	**95.09**
16	E_90	Hawooz Well (Paris)	101280.226	104587.480	**228.20**
17	D_20	Abu Sharikh Eastern Well	101379.650	105027.493	**158.35**
18	Q_40C	Nammar / Edara Well	102773.848	103960.567	**214.85**
19	Q_72	El - Hissi Well	102528.930	103933.565	**181.25**
20	D_60	Abu Sharikh Western Well	101286.467	105111.237	**205.95**
21	D_74	Amer Well (17 Well)	100503.704	106104.088	**183.30**
22	D_75	Zohour Well	101085.391	105814.549	**100.61**
23	D_71	Sheikh Radwan No. 15	101457.632	106193.151	**93.22**
24	D_70	Sheikh Radwan No. 12	101440.342	105833.464	**121.90**
25	D_69	Sheikh Radwan No. 11	100836.179	105464.148	**121.90**
26	D_68	Sheikh Radwan No. 10	100513.384	105180.887	**150.60**
27	E_154	Sheikh Radwan No. 8	99329.682	105051.664	**2,077.00**
28	E_154A	Sheikh Radwan No. 8-A	99336.835	105056.140	**1,387.00**
29	R_162H	Sheikh Radwan No. 7	99056.143	103668.501	**493.70**
30	R_162HA	Sheikh Radwan No. 7-A	99048.735	103698.189	**563.25**
31	R_162LB	Sheikh Radwan No. 1-B	98453.297	104044.530	**495.20**
32	R_162LA	Sheikh Radwan No. 1-A	98480.709	104045.751	**2,028.50**
33	R_162CA	Sheikh Radwan No. 4	98867.347	104589.998	**446.20**
34	R_162BA	Sheikh Radwan No. 3	98727.630	104412.150	**671.00**
35	E_157	Sheikh Radwan No. 9	100156.242	104670.263	**204.10**
36	R_162D	Sheikh Radwan No. 5	98640.251	104992.751	**4,098.50**
37	R_162EA	Sheikh Radwan No. 2	98247.667	104479.677	**1,988.00**
38	R_162G	Sheikh Radwan No. 13	99166.221	103951.902	**693.70**
39	R_112	Sheikh Ejleen No. 1	96061.301	102651.012	**2,674.50**
40	R_277	Sheikh Ejleen No. 5	96236.996	101529.748	**273.65**
41	R_254	Sheikh Ejleen No. 2	96540.877	102055.549	**407.20**
42	R_113A	Sheikh Ejleen No. 4	96532.492	102589.653	**382.80**
43	R_265	Sheikh Ejleen No. 3	95808.755	101707.838	**280.75**
44	R_293	Sheikh Ejleen No. 7	96713.479	101394.692	**503.35**

S/N	Well_ID	Well_Name	X	Y	Cl_07
45	R_280	Sheikh Ejleen No. 6	95760.876	101154.530	**145.10**
46	R_312	Al Shijaia No. 6 (Al Montar)	100004.184	100005.239	**769.35**
47	R_74	Shijaia No. 3(Abu Lafi)	100659.744	101542.207	**781.60**
48	Q_68	Safa-05 (Zimmo Well)	102220.996	103530.894	**223.20**
49	R_25B	Safa-01	100777.863	102527.824	**533.00**
50	R_25A	Safa-02	100758.643	102581.703	**511.70**
51	R_25C	Safa-03	100775.793	102454.926	**1,012.00**
52	R_25D	Safa-04	100820.083	102495.564	**742.70**
53	R_313	Remal-01 (Al Jundi Garden - Well)	97563.923	103022.306	**362.30**
54	R_307	Sabra-02 (Dairi Well)	97602.376	101510.214	**329.30**
55	R_308	Sabra-03 (Sh'haiber Well)	98262.823	101598.399	**549.70**
56	R_305	Zaiton-02 (Om El-Laymon-Abu Khosa)	97547.626	100274.629	**502.40**
57	R_310	Zaiton-01	97415.859	100282.770	**247.49**
58	R_311	Daraj-01(Basha Well)	99287.488	101643.335	**712.35**
59	R_309	Sheja'ia No.5 -Soq Al Halal	99687.000	99203.000	**1,109.00**
60	Aisha	Aisha Well	89518.317	92949.763	**638.25**
61	J_146	Abo Naser Well	91199.807	90460.942	**717.10**
62	S_69	Abu Merwan Well	91769.916	90702.258	**512.70**
63	J_3	El-Sahel No. 3	85589.714	89657.360	**437.45**
64	J_4	El-Sahel No. 4	85253.031	89308.798	**251.00**
65	J_5	El-Sahel No. 5	84876.365	89043.249	**229.50**
66	K_21	El-Berka No. 1	85915.694	89758.346	**355.00**
67	J_2	El-Sahel No. 2	86073.590	90006.285	**921.50**
68	G_49	Nusirat New Well (Municipal Well)	91378.528	96449.254	**1,129.50**
69	H_60	Fallet Well	91380.000	94950.000	**1,276.50**
70	G_45	Abu Ereban Well	91853.380	95529.720	**1,212.00**
71	F_208	Nusirat F-208 (Zahra'a Well)	93493.157	97839.178	**473.30**
72	F_205	Wadi Gaza Well	97083.010	96337.176	**839.00**
73	G_50	Al-Zahra Well	93154.175	98410.772	**480.50**
74	F_203	Moghraqa Well No. 3	93719.685	97945.334	**390.85**
75	F_192	Moghraqa Well No. 2 - JC	95405.166	98642.566	**254.60**
76	F_191	Moghraqa Well No. 1 - JC	94959.667	98953.183	**250.30**
77	S_71	Magazi Well No. S-71	92674.599	91699.851	**588.95**
78	S_82	Magazi Well No. S-82	93117.838	91923.243	**213.40**
79	Makbola	Makbola Well	93108.102	92454.610	**344.20**
80	Musadar	Musadar Well (Yusif Thabet Well)	91874.427	90945.884	**415.90**
81	L_41	Mahata Eastern Well	84345.622	83160.595	**1,047.00**
82	Ma'an	Ma'an Eastern Well	84544.985	82616.927	**1,124.00**
83	MadenaRiyadia	Al Madena Al Riyadia	83496.769	81790.166	**714.30**
84	L_286	Abu Rashwan Well No. "B"	81564.289	82410.458	**735.05**
85	L_189A	Tahadi Well	81832.000	82693.000	**541.40**
86	L_182	New Southern Well	81858.000	82927.000	**668.90**
87	Al_Najar	Al-Najar Well	82430.000	82100.000	**1,322.50**
88	L_43	Aia Well	83063.193	83461.450	**823.50**
89	L_159A	Al-Amal New Well	82680.000	85080.000	**484.05**
90	L_87	El-Sa'ada Well	83040.000	84200.000	**489.42**
91	L_127	El-Ahrash Well	82852.000	83935.000	**669.40**
92	L_176	El-Sha'er Well / Old Southern Well	82187.000	83276.000	**589.65**
93	L_187	El-Satar Well	84364.000	86335.000	**1,291.00**
94	L_190	El-Satar New Well (Northern)	85758.000	87281.000	**1,292.50**

S/N	Well_ID	Well_Name	X	Y	Cl_07
95	K_19	AL Matahen Well	86461.000	88592.000	**169.90**
96	L_181	EV01 - Eastern Village No. 1	81358.761	82404.408	**179.30**
97	P_146	EV02 - Eastern Village No. 2	80949.000	81865.000	**177.55**
98	P_154	EV03 - Eastern Village No. 3	80847.000	81468.000	**173.25**
99	P_159	El-Fakhari Well (Khazzan well)	80359.000	79965.000	**358.60**
100	P_15	Hejazi Well (Zu'rub)	77925.638	78903.921	**773.75**
101	P_124	Western Abu Hashem Well	77599.000	79414.000	**519.90**
102	P_139	Al Bahar Well	77165.000	82011.000	**174.23**
103	P_153	El-Iskan Well	77736.215	80519.752	**126.20**
104	P_148	Tal Al Sultan -PWA	78666.836	80053.049	**198.25**
105	P_138	Abu Zohri Well	78773.000	79764.000	**486.15**
106	Naser2	Naser 02 Well	79891.000	80302.000	**93.22**

Appendix 6 – Water Level Modeling Dataset

Appendix 6.1 – Water Level Modeling Dataset in 2001

S_N	Well_ID	Well_Type	X	Y	WL_01
1	A_102	Monitoring	100161.23	100759.78	-0.713
2	A_107	Monitoring	101217.80	107481.63	-2.060
3	A_115	Monitoring	102171.49	108994.26	-0.782
4	A_21	Monitoring	103204.89	105475.68	-2.181
5	A_31	Monitoring	102773.03	106051.71	-2.600
6	A_47	Monitoring	103101.61	107074.25	-1.391
7	A_53	Monitoring	102191.45	106917.00	-2.735
8	B_5	Monitoring	106654.85	106876.39	-0.179
9	BLBH_2D	Monitoring	104000.00	107150.00	0.928
10	BLBH_9	Monitoring	104740.00	107070.00	0.040
11	C_104	Monitoring	105892.23	106624.21	-0.228
12	C_126	Monitoring	104656.34	106017.71	-0.635
13	C_12A	Monitoring	107410.08	105174.85	0.845
14	C_27	Monitoring	107692.25	104563.90	1.233
15	C_30	Monitoring	106603.78	104470.95	0.395
16	C_3C	Monitoring	107626.36	105585.48	0.946
17	C_48	Monitoring	106501.02	105842.88	0.478
18	C_61	Monitoring	105983.62	104039.88	0.154
19	C_78	Monitoring	104930.74	104934.26	-0.671
20	D_34	Monitoring	100920.63	106287.79	-4.027
21	D_6	Monitoring	101151.15	105633.94	-4.455
22	E_116	Monitoring	100647.40	103487.42	-3.175
23	E_12	Monitoring	101589.48	104297.70	-0.902
24	E_32	Monitoring	99053.10	106224.66	-0.669
25	E_45	Monitoring	99823.26	105405.00	-2.938
26	F_121	Monitoring	96218.37	95434.80	1.632
27	F_21	Monitoring	94056.24	95964.45	0.881
28	F_43	Monitoring	94145.38	97593.92	1.361
29	F_68B	Monitoring	94998.25	96627.40	1.051
30	F_84	Monitoring	96191.52	97993.86	1.789
31	G_10	Monitoring	91189.24	96148.81	0.605
32	G_13	Monitoring	91928.02	96099.75	0.633
33	G_26	Monitoring	91922.37	94938.84	1.147
34	H_11	Monitoring	90660.32	92785.02	0.132
35	H_23	Monitoring	91010.01	94331.68	0.642

S_N	Well_ID	Well_Type	X	Y	WL_01
36	J_103	Monitoring	88733.24	92930.49	0.042
37	J_68	Monitoring	85988.38	90847.67	-1.074
38	L_18	Monitoring	85277.44	85821.60	-0.465
39	L_36	Monitoring	85175.85	82635.94	1.450
40	L_47	Monitoring	82610.31	82589.34	-2.464
41	L_57	Monitoring	84368.98	81663.11	-1.053
42	L_61	Monitoring	83310.37	78719.78	-1.366
43	L_66	Monitoring	82716.30	79914.50	-2.786
44	L_8	Monitoring	86254.41	86212.13	-0.563
45	M_10	Monitoring	85967.49	84740.36	-0.331
46	M_8	Monitoring	86607.72	84009.51	-0.066
47	N_12	Monitoring	88701.25	80356.73	8.974
48	N_16	Monitoring	88941.39	81122.74	7.289
49	N_23	Monitoring	86899.19	81550.77	1.644
50	N_6	Monitoring	88197.68	83204.82	1.262
51	N_7	Monitoring	89262.95	83502.88	1.688
52	O_2	Monitoring	89521.75	80087.64	12.885
53	P_10	Monitoring	78612.96	77038.70	-1.616
54	P_48A	Monitoring	80066.99	79696.06	-6.469
55	P_50	Monitoring	81167.09	80838.04	-4.470
56	P_61	Monitoring	81112.54	79150.07	-5.872
57	P_66	Monitoring	82373.98	77844.19	-1.333
58	P_99	Monitoring	78681.04	78385.32	-3.960
59	Piezo_10A	Piezometer	81957.76	80909.10	-3.364
60	Piezo_23	Piezometer	88781.37	94162.61	0.493
61	Piezo_24	Piezometer	99269.13	107327.29	-0.012
62	Piezo_25A	Piezometer	99919.88	106651.14	-1.867
63	Piezo_25B	Piezometer	99919.86	106650.92	-1.852
64	Piezo_26B	Piezometer	100549.36	108580.11	-0.213
65	Piezo_29	Piezometer	102387.47	109386.95	-0.310
66	Piezo_2C	Piezometer	98328.83	105798.25	-0.110
67	Piezo_2D	Piezometer	98330.18	105799.51	0.045
68	Piezo_36B	Piezometer	98978.74	105215.09	-2.429
69	Piezo_3B	Piezometer	93621.26	95543.60	2.475
70	Piezo_8A	Piezometer	95579.28	98225.43	1.949
71	Piezo_8B	Piezometer	95575.02	98224.43	1.814
72	Q_12	Monitoring	104914.33	101957.73	0.716
73	Q_2	Monitoring	103785.41	104376.19	-1.983
74	Q_20	Monitoring	103759.84	102767.27	0.068
75	Q_31	Monitoring	103838.98	103994.35	-1.483
76	Q_56	Monitoring	103382.35	101363.77	0.302
77	Q_7	Monitoring	104903.87	103530.61	-0.229

S_N	Well_ID	Well_Type	X	Y	WL_01
78	R_108 illegal	Monitoring	93373.59	100136.32	0.804
79	R_133	Monitoring	96773.31	101064.29	1.115
80	R_161	Monitoring	97636.71	104909.35	-0.039
81	R_171	Monitoring	100289.40	102543.40	-2.055
82	R_210	Monitoring	94911.14	101914.04	0.677
83	R_216	Monitoring	101523.17	101059.39	-0.885
84	R_24	Monitoring	100613.70	102462.92	-3.836
85	R_38	Monitoring	102027.16	101782.87	-0.971
86	R_60	Monitoring	101060.99	99498.47	1.071
87	R_84	Monitoring	99419.28	98987.91	0.949
88	R_96	Monitoring	99424.86	100463.55	2.108
89	R-I-10	Monitoring	96683.63	99338.61	2.487
90	R-I-69	Monitoring	96681.20	100107.03	1.923
91	R-I-92	Monitoring	95839.85	99669.81	2.329
92	S_11	Monitoring	94970.19	93542.62	2.007
93	S_28	Monitoring	93307.07	92855.66	0.914
94	S_50	Monitoring	91341.80	90667.80	-1.234
95	S_60	Monitoring	93656.94	91961.27	1.592
96	T_1	Monitoring	89693.01	89349.75	-1.829
97	T_22	Monitoring	88337.98	85643.53	-0.036
98	T_26	Monitoring	87080.51	85663.61	-0.237
99	T_6	Monitoring	88321.99	88116.69	0.045
100	T_9	Monitoring	88757.26	87070.02	-0.147
101	Y_4	Monitoring	88757.26	77842.93	0.128

Appendix 6.2 – Water Level Modeling Dataset in 2003

S_N	Well_ID	Well_Type	X	Y	WL_03
1	A_102	Monitoring	100161.23	100759.78	-0.316
2	A_107	Monitoring	101217.80	107481.63	-1.579
3	A_21	Monitoring	103204.89	105475.68	-2.164
4	A_31	Monitoring	102773.03	106051.71	-2.514
5	A_47	Monitoring	103101.61	107074.25	-0.959
6	A_53	Monitoring	102191.45	106917.00	-2.489
7	B_5	Monitoring	106654.85	106876.39	-0.277
8	C_104	Monitoring	105892.23	106624.21	-0.320
9	C_126	Monitoring	104656.34	106017.71	-0.434
10	C_12A	Monitoring	107410.08	105174.85	0.346
11	C_27	Monitoring	107692.25	104563.90	0.666
12	C_30	Monitoring	106603.78	104470.95	-0.056
13	C_3C	Monitoring	107626.36	105585.48	0.214
14	C_48	Monitoring	106501.02	105842.88	-0.340
15	C_61	Monitoring	105983.62	104039.88	-0.063
16	C_78	Monitoring	104930.74	104934.26	-0.715
17	D_34	Monitoring	100920.63	106287.79	-3.773
18	D_6	Monitoring	101151.15	105633.94	-3.816
19	E_116	Monitoring	100647.40	103487.42	-3.186
20	E_12	Monitoring	101589.48	104297.70	-0.795
21	E_32	Monitoring	99053.10	106224.66	-0.471
22	E_45	Monitoring	99823.26	105405.00	-2.949
23	F_121	Monitoring	96218.37	95434.80	2.117
24	F_21	Monitoring	94056.24	95964.45	1.300
25	F_43	Monitoring	94145.38	97593.92	1.759
26	F_68B	Monitoring	94998.25	96627.40	1.193
27	F_84	Monitoring	96191.52	97993.86	1.846
28	G_10	Monitoring	91189.24	96148.81	0.391
29	G_13	Monitoring	91928.02	96099.75	0.971
30	G_26	Monitoring	91922.37	94938.84	1.298
31	H_11	Monitoring	90660.32	92785.02	0.181
32	H_23	Monitoring	91010.01	94331.68	0.885
33	J_103	Monitoring	88733.24	92930.49	-0.185
34	J_68	Monitoring	85988.38	90847.67	-1.165
35	L_18	Monitoring	85277.44	85821.60	-0.502
36	L_47	Monitoring	82610.31	82589.34	-3.731
37	L_57	Monitoring	84368.98	81663.11	-1.841
38	L_61	Monitoring	83310.37	78719.78	-2.287

S_N	Well_ID	Well_Type	X	Y	WL_03
39	L_66	Monitoring	82716.30	79914.50	-3.962
40	L_8	Monitoring	86254.41	86212.13	-0.481
41	L_86	Monitoring	82244.33	84658.55	2.872
42	M_10	Monitoring	85967.49	84740.36	-0.470
43	M_8	Monitoring	86607.72	84009.51	-0.240
44	N_12	Monitoring	88701.25	80356.73	9.601
45	N_16	Monitoring	88941.39	81122.74	7.996
46	N_23	Monitoring	86899.19	81550.77	1.579
47	N_6	Monitoring	88197.68	83204.82	1.350
48	N_7	Monitoring	89262.95	83502.88	1.882
49	P_10	Monitoring	78612.96	77038.70	-2.289
50	P_34	Monitoring	78686.10	79538.76	-7.692
51	P_48A	Monitoring	80066.99	79696.06	-8.173
52	P_50	Monitoring	81167.09	80838.04	-5.911
53	P_61	Monitoring	81112.54	79150.07	-8.032
54	P_68	Monitoring	81350.19	77748.05	-3.348
55	P_99	Monitoring	78681.04	78385.32	-4.909
56	Piezo_10A	Piezometer	81957.76	80909.10	-4.888
57	Piezo_23	Piezometer	88781.37	94162.61	0.974
58	Piezo_24	Piezometer	99269.13	107327.29	0.204
59	Piezo_25A	Piezometer	99919.88	106651.14	-1.533
60	Piezo_25B	Piezometer	99919.86	106650.92	-1.672
61	Piezo_26A	Piezometer	100549.15	108580.10	0.040
62	Piezo_26B	Piezometer	100549.36	108580.11	0.198
63	Piezo_2C	Piezometer	98328.83	105798.25	-0.143
64	Piezo_36B	Piezometer	98978.74	105215.09	-2.467
65	Piezo_3B	Piezometer	93621.26	95543.60	2.953
66	Piezo_8A	Piezometer	95579.28	98225.43	2.172
67	Piezo_8B	Piezometer	95575.02	98224.43	2.006
68	Q_2	Monitoring	103785.41	104376.19	-1.908
69	Q_20	Monitoring	103759.84	102767.27	-0.244
70	Q_56	Monitoring	103382.35	101363.77	0.107
71	Q_7	Monitoring	104903.87	103530.61	-0.415
72	R_108 illegal	Monitoring	93373.59	100136.32	-0.711
73	R_161	Monitoring	97636.71	104909.35	0.349
74	R_171	Monitoring	100289.40	102543.40	-2.079
75	R_210	Monitoring	94911.14	101914.04	0.806
76	R_216	Monitoring	101523.17	101059.39	-0.610
77	R_38	Monitoring	102027.16	101782.87	-0.872
78	R_60	Monitoring	101060.99	99498.47	1.255
79	R_84	Monitoring	99419.28	98987.91	-4.918

S_N	Well_ID	Well_Type	X	Y	WL_03
80	R-I-10	Monitoring	96683.63	99338.61	2.868
81	R-I-69	Monitoring	96681.20	100107.03	2.140
82	R-I-92	Monitoring	95839.85	99669.81	2.380
83	S_11	Monitoring	94970.19	93542.62	2.335
84	S_28	Monitoring	93307.07	92855.66	1.128
85	S_50	Monitoring	91341.80	90667.80	-1.045
86	S_60	Monitoring	93656.94	91961.27	1.875
87	T_1	Monitoring	89693.01	89349.75	-1.483
88	T_22	Monitoring	88337.98	85643.53	0.186
89	T_26	Monitoring	87080.51	85663.61	-0.180
90	T_6	Monitoring	88321.99	88116.69	0.327
91	T_9	Monitoring	88757.26	87070.02	0.112
92	Y_4	Monitoring	88757.26	77842.93	0.157

Appendix 6.3 – Water Level Modeling Dataset in 2005

S_N	Well_ID	Well_Type	X	Y	WL_05
1	A_107	Monitoring	101217.80	107481.63	-2.650
2	A_31	Monitoring	102773.03	106051.71	-2.917
3	A_47	Monitoring	103101.61	107074.25	-1.381
4	A_53	Monitoring	102191.45	106917.00	-3.048
5	C_104	Monitoring	105892.23	106624.21	0.989
6	C_126	Monitoring	104656.34	106017.71	-0.138
7	C_12A	Monitoring	107410.08	105174.85	1.802
8	C_27	Monitoring	107692.25	104563.90	2.136
9	C_30	Monitoring	106603.78	104470.95	1.008
10	C_3C	Monitoring	107626.36	105585.48	1.996
11	C_48	Monitoring	106501.02	105842.88	1.115
12	C_61	Monitoring	105983.62	104039.88	0.792
13	C_78	Monitoring	104930.74	104934.26	-0.127
14	CAMP_11	Piezometer	85223.90	84556.53	-0.566
15	CAMP_12	Piezometer	96338.07	100535.29	1.281
16	CAMP_13	Piezometer	92593.99	97657.87	1.674
17	CAMP_14	Piezometer	93107.16	91999.06	0.881
18	CAMP_1A	Piezometer	103593.63	107122.60	0.019
19	CAMP_1B	Piezometer	103596.30	107123.63	-0.003
20	CAMP_2	Piezometer	104577.63	105088.15	-0.328
21	CAMP_3A	Piezometer	98491.00	104402.57	-2.664
22	CAMP_3B	Piezometer	98493.17	104400.13	-2.995
23	CAMP_4	Piezometer	97737.69	96579.02	2.195
24	CAMP_7A	Piezometer	77355.65	79846.45	-4.508
25	CAMP_7B	Piezometer	77353.32	79846.22	-5.831
26	CAMP_8	Piezometer	86858.81	79606.83	6.361
27	CAMP_9	Piezometer	81041.06	75604.56	0.495
28	D_34	Monitoring	100920.63	106287.79	-4.240
29	E_116	Monitoring	100647.40	103487.42	-3.799
30	E_12	Monitoring	101589.48	104297.70	-4.021
31	E_32	Monitoring	99053.10	106224.66	-0.871
32	E_45	Monitoring	99823.26	105405.00	-3.376
33	F_121	Monitoring	96218.37	95434.80	1.910
34	F_21	Monitoring	94056.24	95964.45	1.240
35	F_43	Monitoring	94145.38	97593.92	1.612
36	F_68B	Monitoring	94998.25	96627.40	1.019
37	F_84	Monitoring	96191.52	97993.86	1.489

S_N	Well_ID	Well_Type	X	Y	WL_05
38	G_10	Monitoring	91189.24	96148.81	-0.062
39	G_26	Monitoring	91922.37	94938.84	0.464
40	H_11	Monitoring	90660.32	92785.02	-0.451
41	J_103	Monitoring	88733.24	92930.49	-0.785
42	J_68	Monitoring	85988.38	90847.67	-1.307
43	L_18	Monitoring	85277.44	85821.60	-0.674
44	L_47	Monitoring	82610.31	82589.34	-4.720
45	L_57	Monitoring	84368.98	81663.11	-2.947
46	L_61	Monitoring	83310.37	78719.78	-2.950
47	L_8	Monitoring	86254.41	86212.13	-0.725
48	M_10	Monitoring	85967.49	84740.36	-0.861
49	M_8	Monitoring	86607.72	84009.51	-0.646
50	N_12	Monitoring	88701.25	80356.73	10.058
51	N_16	Monitoring	88941.39	81122.74	8.299
52	N_6	Monitoring	88197.68	83204.82	1.653
53	N_7	Monitoring	89262.95	83502.88	1.732
54	P_10	Monitoring	78612.96	77038.70	-3.264
55	P_34	Monitoring	78686.10	79538.76	-8.822
56	P_48A	Monitoring	80066.99	79696.06	-10.055
57	P_61	Monitoring	81112.54	79150.07	-9.045
58	P_68	Monitoring	81350.19	77748.05	-3.944
59	P_99	Monitoring	78681.04	78385.32	-5.881
60	Piezo_23	Piezometer	88781.37	94162.61	0.395
61	Piezo_24	Piezometer	99269.13	107327.29	-0.171
62	Piezo_25A	Piezometer	99919.88	106651.14	-1.974
63	Piezo_25B	Piezometer	99919.86	106650.92	-1.990
64	Piezo_26A	Piezometer	100549.15	108580.10	-0.190
65	Piezo_27	Piezometer	100870.10	107857.73	-1.533
66	Piezo_2A	Piezometer	98330.20	105799.52	-1.169
67	Piezo_2B	Piezometer	98330.31	105799.51	-0.279
68	Piezo_2C	Piezometer	98328.83	105798.25	-0.406
69	Piezo_2D	Piezometer	98330.18	105799.51	-2.925
70	Piezo_2E	Piezometer	98329.09	105798.14	-1.651
71	Piezo_2F	Piezometer	98328.97	105798.09	-0.062
72	Piezo_36B	Piezometer	98978.74	105215.09	-2.881
73	Piezo_3A	Piezometer	93621.17	95543.62	1.186
74	Piezo_3B	Piezometer	93621.26	95543.60	1.219
75	Piezo_7	Piezometer	84108.97	77899.19	0.682
76	Piezo_8A	Piezometer	95579.28	98225.43	1.759
77	Piezo_8B	Piezometer	95575.02	98224.43	1.576
78	Q_2	Monitoring	103785.41	104376.19	-1.776
79	Q_20	Monitoring	103759.84	102767.27	-0.474

S_N	Well_ID	Well_Type	X	Y	WL_05
80	R_161	Monitoring	97636.71	104909.35	-0.237
81	R_210	Monitoring	94911.14	101914.04	0.609
82	R_216	Monitoring	101523.17	101059.39	-0.961
83	R_38	Monitoring	102027.16	101782.87	-1.102
84	R_84	Monitoring	99419.28	98987.91	1.076
85	R-I-69	Monitoring	96681.20	100107.03	1.520
86	S_11	Monitoring	94970.19	93542.62	2.053
87	S_28	Monitoring	93307.07	92855.66	0.558
88	S_50	Monitoring	91341.80	90667.80	-1.412
89	T_1	Monitoring	89693.01	89349.75	-1.839
90	T_22	Monitoring	88337.98	85643.53	-0.090
91	T_26	Monitoring	87080.51	85663.61	-0.436
92	T_6	Monitoring	88321.99	88116.69	-0.001
93	T_9	Monitoring	88757.26	87070.02	-0.089
94	Y_4	Monitoring	88757.26	77842.93	0.046

Appendix 6.4 – Water Level Modeling Dataset in 2007

S_N	Well_ID	Well_Type	X	Y	WL_07
1	A_31	Monitoring	102773.03	106051.71	-3.050
2	A_47	Monitoring	103101.61	107074.25	-1.547
3	A_53	Monitoring	102191.45	106917.00	-3.048
4	C_104	Monitoring	105892.23	106624.21	0.913
5	C_126	Monitoring	104656.34	106017.71	-0.248
6	C_12A	Monitoring	107410.08	105174.85	1.992
7	C_27	Monitoring	107692.25	104563.90	2.180
8	C_30	Monitoring	106603.78	104470.95	1.201
9	C_48	Monitoring	106501.02	105842.88	1.238
10	C_61	Monitoring	105983.62	104039.88	0.824
11	C_78	Monitoring	104930.74	104934.26	-0.438
12	CAMP_12	Piezometer	96338.07	100535.29	0.015
13	CAMP_13	Piezometer	92593.99	97657.87	1.097
14	CAMP_1A	Piezometer	103593.63	107122.60	-0.514
15	CAMP_1B	Piezometer	103596.30	107123.63	-0.418
16	CAMP_2	Piezometer	104577.63	105088.15	-0.606
17	CAMP_3A	Piezometer	98491.00	104402.57	-3.001
18	CAMP_3B	Piezometer	98493.17	104400.13	-3.294
19	CAMP_4	Piezometer	97737.69	96579.02	1.457
20	CAMP_7A	Piezometer	77355.65	79846.45	-6.335
21	CAMP_7B	Piezometer	77353.32	79846.22	-8.056
22	CAMP_8	Piezometer	86858.81	79606.83	7.059
23	CAMP_9	Piezometer	81041.06	75604.56	0.286
24	D_34	Monitoring	100920.63	106287.79	-3.975
25	E_116	Monitoring	100647.40	103487.42	-4.198
26	E_12	Monitoring	101589.48	104297.70	-4.875
27	E_32	Monitoring	99053.10	106224.66	-0.965
28	E_45	Monitoring	99823.26	105405.00	-3.259
29	F_21	Monitoring	94056.24	95964.45	0.137
30	F_43	Monitoring	94145.38	97593.92	0.087
31	F_68B	Monitoring	94998.25	96627.40	0.002
32	F_84	Monitoring	96191.52	97993.86	-0.014
33	G_10	Monitoring	91189.24	96148.81	-0.460
34	G_13	Monitoring	91928.02	96099.75	2.403
35	G_26	Monitoring	91922.37	94938.84	0.267
36	H_11	Monitoring	90660.32	92785.02	-0.898
37	J_103	Monitoring	88733.24	92930.49	-1.310

S_N	Well_ID	Well_Type	X	Y	WL_07
38	J_68	Monitoring	85988.38	90847.67	-2.045
39	L_101	Monitoring	84805.69	89100.40	-0.313
40	L_18	Monitoring	85277.44	85821.60	-1.426
41	L_47	Monitoring	82610.31	82589.34	-6.007
42	L_57	Monitoring	84368.98	81663.11	-3.623
43	L_66	Monitoring	82716.30	79914.50	-6.063
44	L_8	Monitoring	86254.41	86212.13	-1.202
45	L_88	Monitoring	81404.30	86783.97	-0.107
46	L_94	Monitoring	83065.87	88152.41	-0.684
47	M_10	Monitoring	85967.49	84740.36	-1.370
48	M_8	Monitoring	86607.72	84009.51	-1.076
49	N_12	Monitoring	88701.25	80356.73	10.453
50	N_16	Monitoring	88941.39	81122.74	8.942
51	P_10	Monitoring	78612.96	77038.70	-4.048
52	P_24	Monitoring	77319.38	82292.30	1.340
53	P_34	Monitoring	78686.10	79538.76	-10.925
54	P_48A	Monitoring	80066.99	79696.06	-12.797
55	P_61	Monitoring	81112.54	79150.07	-10.890
56	P_99	Monitoring	78681.04	78385.32	-7.341
57	Piezo_12	Piezometer	84407.95	88962.82	0.781
58	Piezo_22A	Piezometer	86304.18	89542.85	-1.743
59	Piezo_22B	Piezometer	86304.05	89542.79	-1.751
60	Piezo_23	Piezometer	88781.37	94162.61	0.189
61	Piezo_24	Piezometer	99269.13	107327.29	-0.262
62	Piezo_26A	Piezometer	100549.15	108580.10	-0.239
63	Piezo_26B	Piezometer	100549.36	108580.11	-0.262
64	Piezo_2A	Piezometer	98330.20	105799.52	-1.315
65	Piezo_2B	Piezometer	98330.31	105799.51	-0.314
66	Piezo_2C	Piezometer	98328.83	105798.25	-0.521
67	Piezo_2D	Piezometer	98330.18	105799.51	-2.941
68	Piezo_2E	Piezometer	98329.09	105798.14	-1.705
69	Piezo_2F	Piezometer	98328.97	105798.09	-0.182
70	Piezo_36B	Piezometer	98978.74	105215.09	-3.083
71	Piezo_3A	Piezometer	93621.17	95543.62	0.501
72	Piezo_3B	Piezometer	93621.26	95543.60	0.541
73	Piezo_7	Piezometer	84108.97	77899.19	0.667
74	Piezo_8A	Piezometer	95579.28	98225.43	0.342
75	Piezo_8B	Piezometer	95575.02	98224.43	0.339
76	R_108 illegal	Monitoring	93373.59	100136.32	0.653
77	R_161	Monitoring	97636.71	104909.35	-0.665
78	R_210	Monitoring	94911.14	101914.04	0.417

S_N	Well_ID	Well_Type	X	Y	WL_07
79	R_38	Monitoring	102027.16	101782.87	-1.267
80	R-I-69	Monitoring	96681.20	100107.03	0.074
81	S_11	Monitoring	94970.19	93542.62	1.763
82	S_28	Monitoring	93307.07	92855.66	0.269
83	T_1	Monitoring	89693.01	89349.75	-1.635
84	T_22	Monitoring	88337.98	85643.53	-0.257
85	T_26	Monitoring	87080.51	85663.61	-0.848
86	T_6	Monitoring	88321.99	88116.69	-0.530
87	Y_4	Monitoring	88757.26	77842.93	-0.100

Appendix 7 – Rainfall Modeling Dataset

Appendix 7.1 – Rainfall Modeling Dataset in 2001

S/N	Station_Name	Station_Location	X	Y	Rainfall_in_mm
1	Beit Hanoun	BH	106420	105740	**497.50**
2	Beit Lahia	BL	99750	108280	**490.40**
3	Shati	SHATI	99500	105320	**478.90**
4	Gaza City	REMAL	97140	103300	**511.90**
5	Tuffah	TUFFAH	100500	101700	**533.40**
6	Gaza South	MOGHR	95380	98000	**563.60**
7	Nusseirat	NUSS.	91950	94080	**558.30**
8	Deir Al Balah	DB	88550	91600	**550.50**
9	Khan Younis	KY	84240	83880	**381.00**
10	Rafah	RF	79060	75940	**308.00**

Appendix 7.2 – Rainfall Modeling Dataset in 2003

S/N	Station_Name	Station_Location	X	Y	Rainfall_in_mm
1	Beit Hanoun	BH	106420	105740	**801.50**
2	Beit Lahia	BL	99750	108280	**724.00**
3	Shati	SHATI	99500	105320	**627.00**
4	Gaza City	REMAL	97140	103300	**599.00**
5	Tuffah	TUFFAH	100500	101700	**653.50**
6	Gaza South	MOGHR	95380	98000	**790.70**
7	Nusseirat	NUSS.	91950	94080	**446.20**
8	Deir Al Balah	DB	88550	91600	**372.60**
9	Khan Younis	KY	84240	83880	**298.00**
10	Rafah	RF	79060	75940	**220.80**

Appendix 7.3 – Rainfall Modeling Dataset in 2005

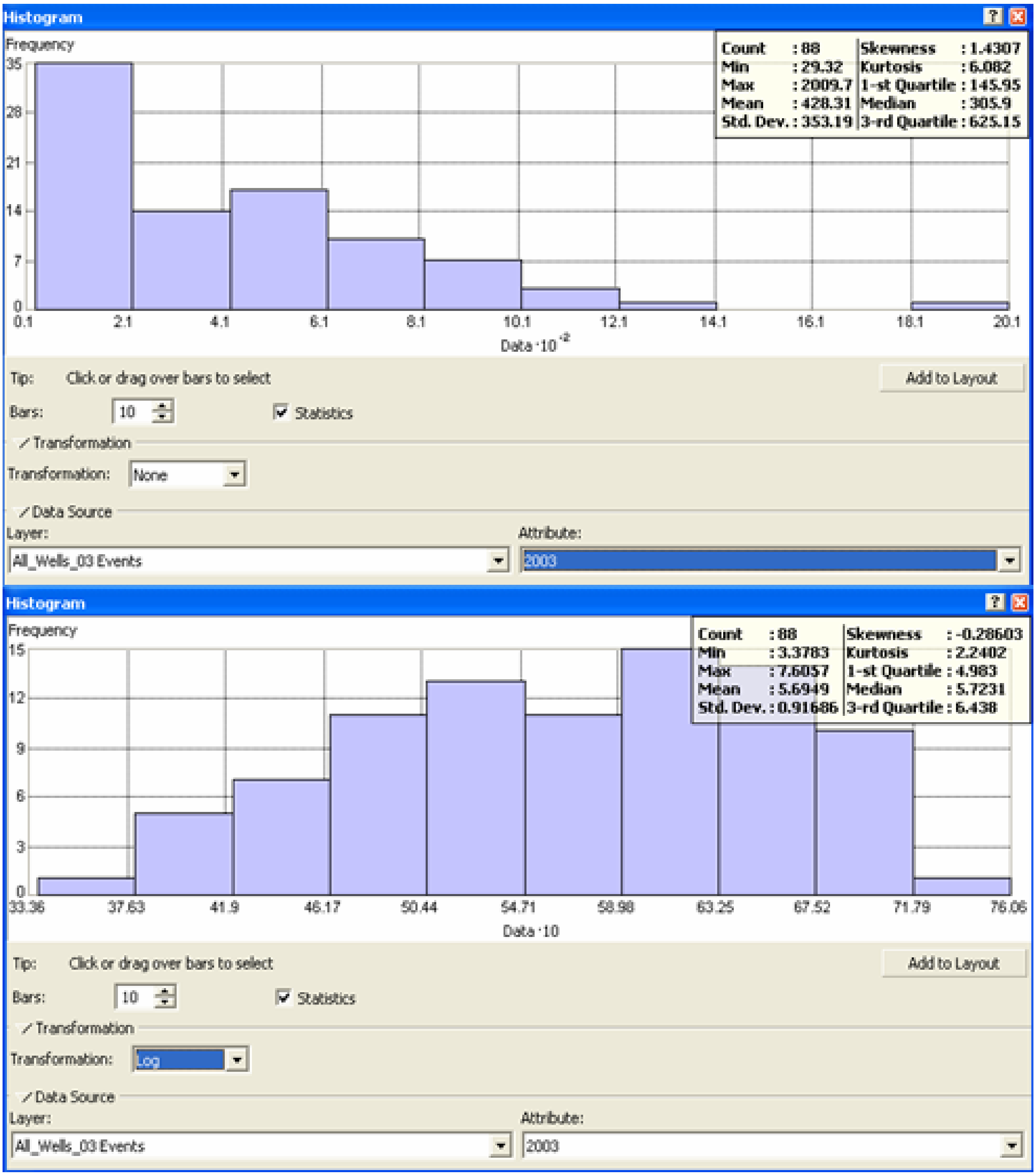
S/N	Station_Name	Station_Location	X	Y	Rainfall_in_mm
1	Beit Hanoun	BH	106420	105740	**358.70**
2	Beit Lahia	BL	99750	108280	**320.60**
3	Shati	SHATI	99500	105320	**296.60**
4	Gaza City	REMAL	97140	103300	**316.00**
5	Tuffah	TUFFAH	100500	101700	**345.40**
6	Gaza South	MOGHR	95380	98000	**323.60**
7	Nusseirat	NUSS.	91950	94080	**405.00**
8	Deir Al Balah	DB	88550	91600	**345.50**
9	Khan Younis	KY	84240	83880	**373.00**
10	Rafah	RF	79060	75940	**360.20**

Appendix 7.4 – Rainfall Modeling Dataset in 2007

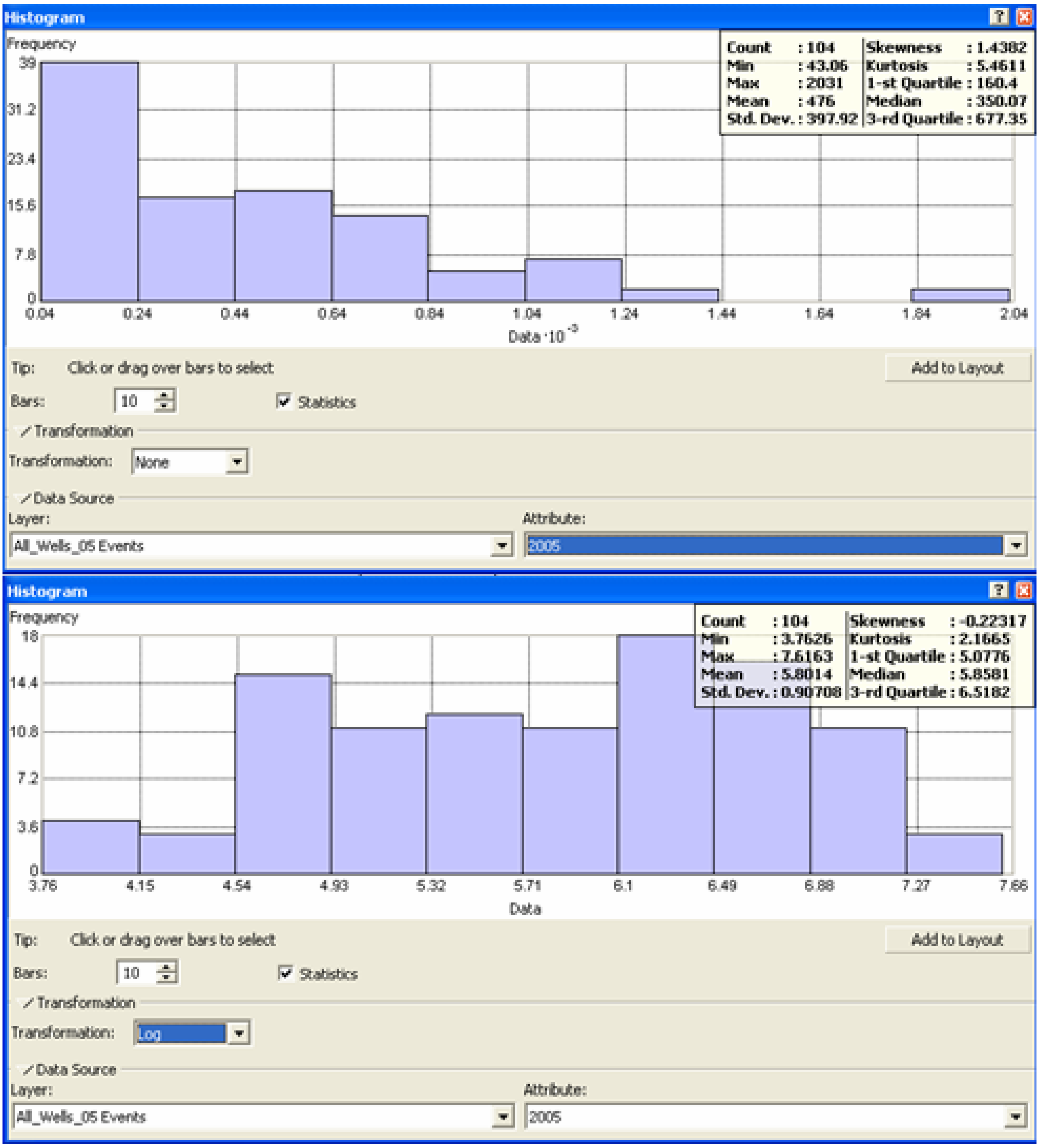
S/N	Station_Name	Station_Location	X	Y	Rainfall_in_mm
1	Beit Hanoun	BH	106420	105740	**509.90**
2	Beit Lahia	BL	99750	108280	**530.30**
3	Shati	SHATI	99500	105320	**469.00**
4	Gaza City	REMAL	97140	103300	**501.20**
5	Tuffah	TUFFAH	100500	101700	**545.50**
6	Gaza South	MOGHR	95380	98000	**388.20**
7	Nusseirat	NUSS.	91950	94080	**403.00**
8	Deir Al Balah	DB	88550	91600	**418.00**
9	Khan Younis	KY	84240	83880	**252.00**
10	Rafah	RF	79060	75940	**225.00**

Appendix 8 – Chloride Dataset Histogram & Normalization for years 2001, 2003, 2005, & 2007

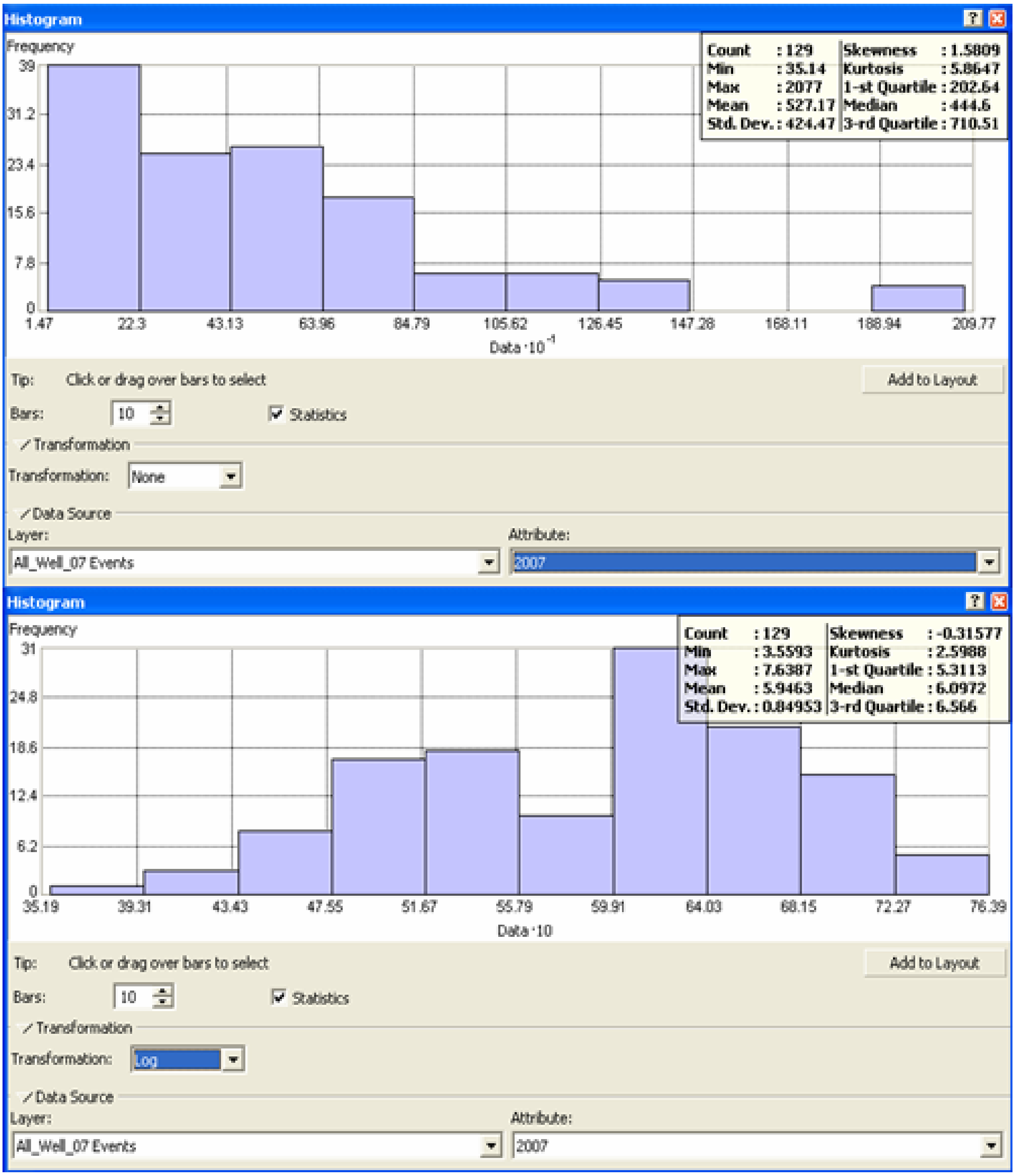
Histogram Graph for Chloride in year 2001 before and after log transformation and normalization process



Histogram Graph for Chloride in year 2003 before and after log transformation and normalization process.

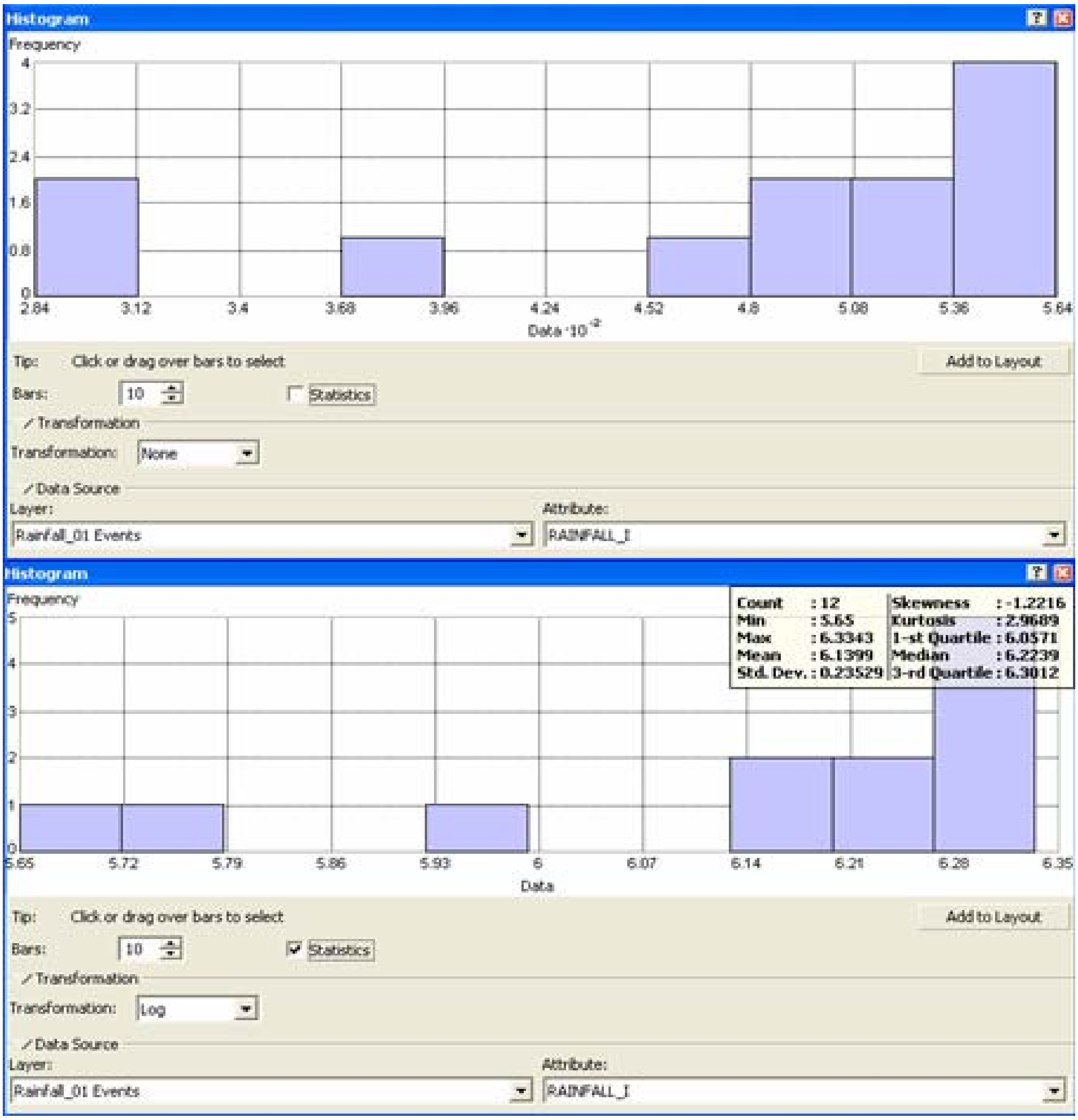


Histogram Graph for Chloride in year 2005 before and after log transformation and normalization process

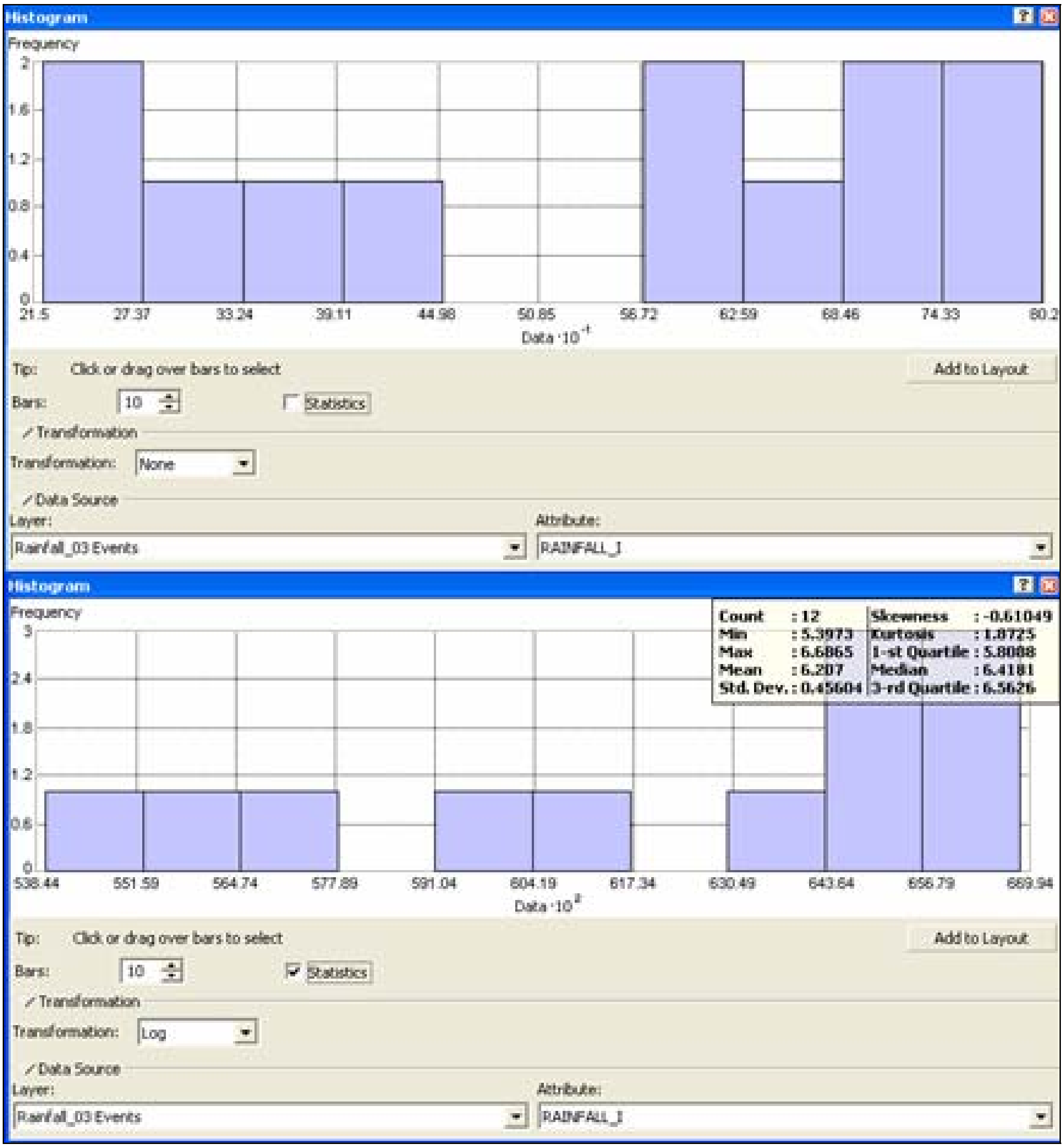


Histogram Graph for Chloride in year 2007 before and after log transformation and normalization process

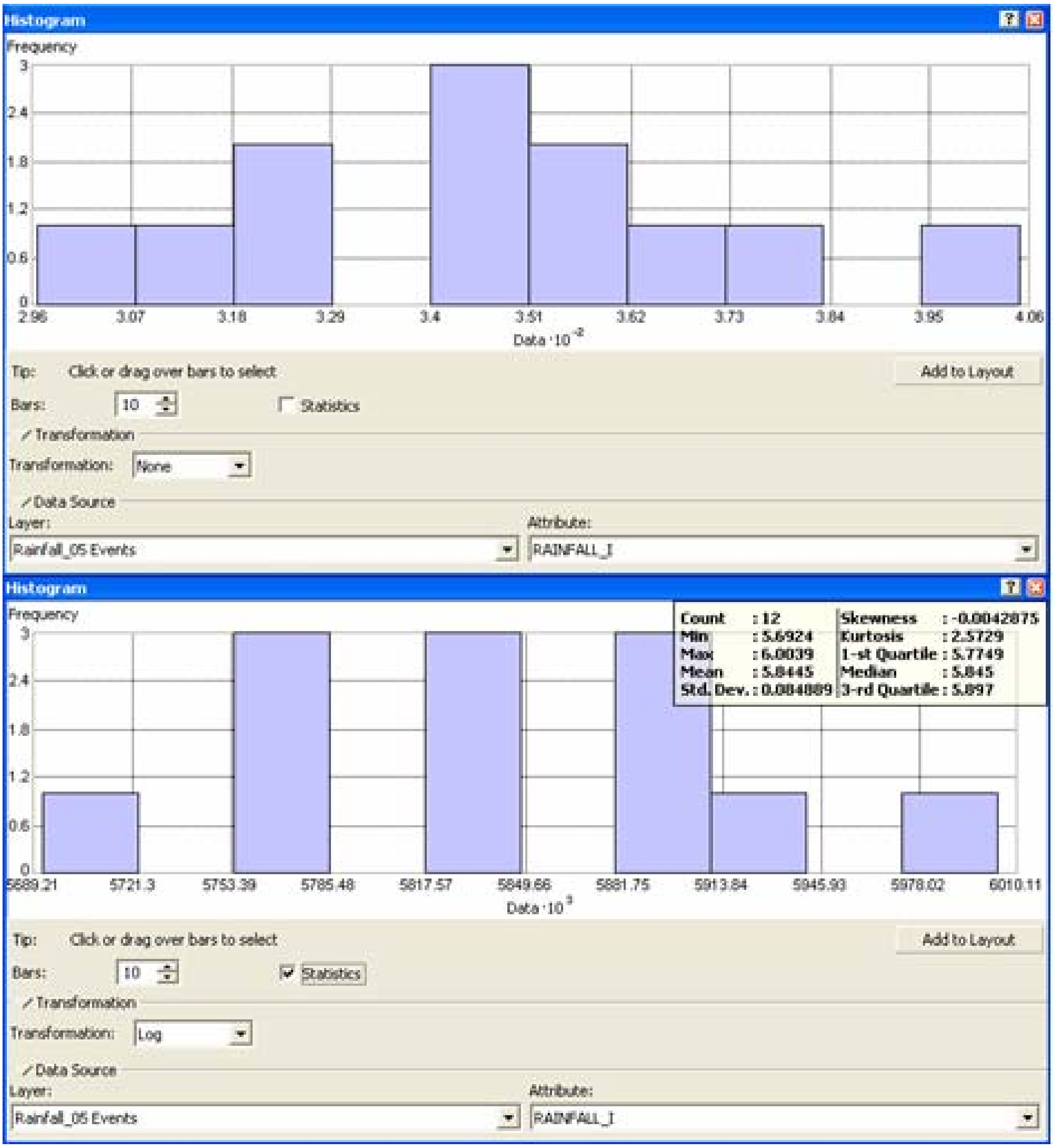
Appendix 9 – Rainfall Dataset Histogram & Normalization for years 2001, 2003, 2005, & 2007



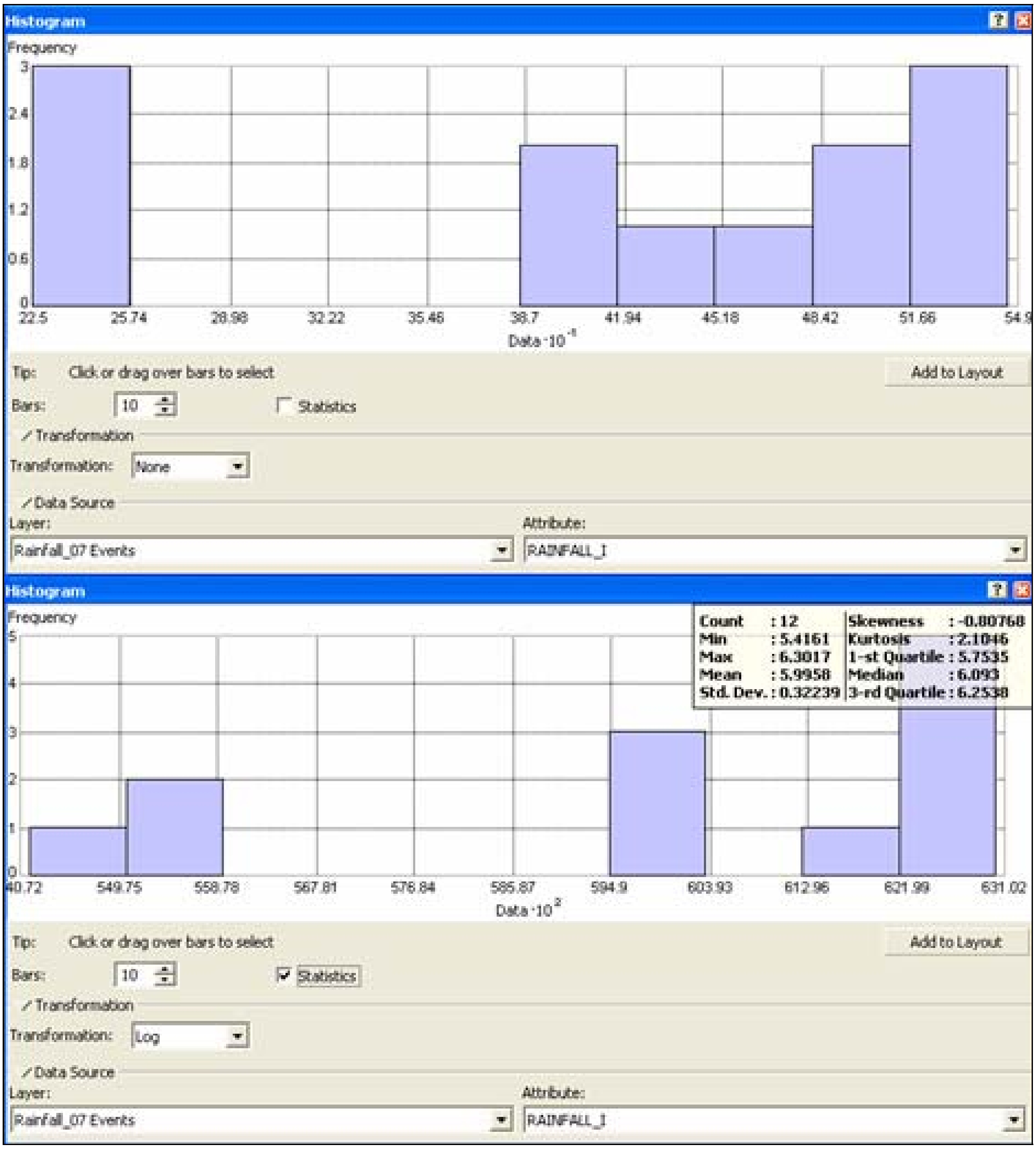
Histogram Graph for Rainfall in year 2001 before and after log transformation and normalization process.



Histogram Graph for Rainfall in year 2003 before and after log transformation and normalization process.



Histogram Graph for Rainfall in year 2005 before and after log transformation and normalization process.



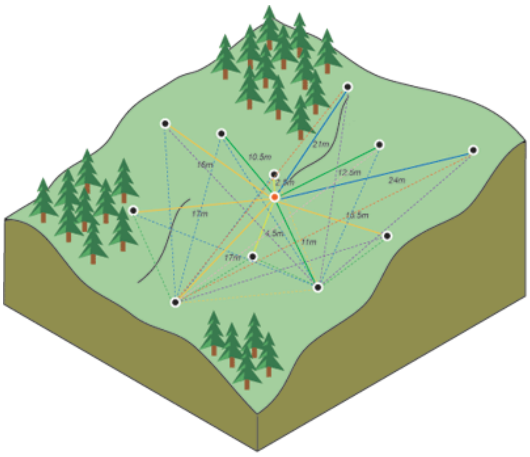
Histogram Graph for Rainfall in year 2007 before and after log transformation and normalization process.

Appendix 10 – Kriging Interpolation Method and its Techniques

Variogram Models

A variogram is a Geostatistical technique which can be used to examine the spatial continuity of a regionalized variable and how this continuity changes as a function of distance and direction. The variogram is an essential step on the way to determining optimal weights for interpolation **(Burrough & McDonnell, 1998).**

In spatial modeling of the structure of the measured points, you begin with a graph of the empirical semivariogram, computed as: **Semivariogram (distance h) = 0.5 * average [(value at location i – value at location j)^2]** for all pairs of locations separated by distance h. The formula involves calculating the difference squared between the values of the paired locations. The image below shows the pairing of one point (the red point) with all other measured locations. This process continues for each measured point.



Five measured points (neighbors) will be used when predicting a value for the location without a measurement.
(http://www.gis.com/whatisgis/index.cfm)

The most commonly used variogram models are spherical, exponential, and Gaussian **(Sunila & Kollo 2005).**

The empirical semivariogram provides information on the spatial autocorrelation of datasets. However, it does not provide information for all possible directions and distances. For this reason, and to ensure that Kriging predictions have positive Kriging variances, it is necessary to fit a model - that is, a continuous function or curve - to the empirical semivariogram. Abstractly, this is similar to regression analysis, in which a continuous line or curve is fitted to the data points (ArcGIS desktop).

The semivariogram and model fitting - The semivariogram is an essential step for determining the spatial variation in the sampled variable. It provides useful

information for interpolation, sampling density, determining spatial patterns, and spatial simulation.
The semivariogram is of the form:

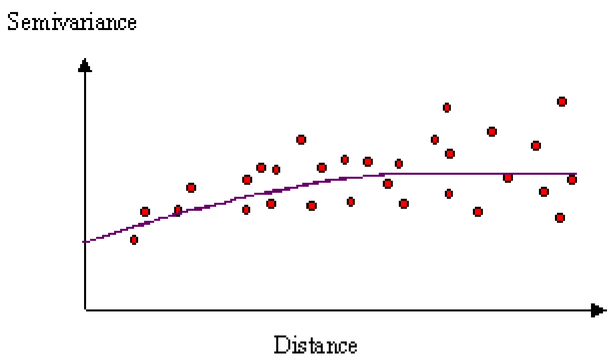
$$\gamma(h) = \frac{1}{2}\mathrm{E}(y(x) - y(x+h))^2$$

Where:
γ (h) = semivariogram, dependent on lag or distance h
(x,x+h) = pair of points with distance vector h
y(x) = regionalized variable y at point x
y(x)-y(x+h) = difference of the variable at two points separated by h
E = mathematical expectation

The Spherical Model

The spherical function is one of the most frequently used models in geostatistics **(Webster & Oliver, 2001).** The spherical model is good choice when the nugget variance is important but not too large, and there is a clear range and sill **(Burrough & McDonnell, 1998).**

Figure 20 shows a progressive decrease of spatial autocorrelation (equivalently, an increase of semivariance) until some distance, beyond which autocorrelation is zero. The spherical model is one of the most commonly used models.



Illustrative model of spatial spherical model autocorrelation process.

the formula can be drawn as following:

$$\gamma(h) = \begin{cases} c_o + c_1\left\{\dfrac{3h}{2a} - \dfrac{1}{2}\left(\dfrac{h}{a}\right)^3\right\} & \textit{for } 0 < h < a \\ \\ c_o + c_1 & \end{cases}$$

$$\gamma(0) = 0 \qquad \textit{for } h \geq a$$

Where,

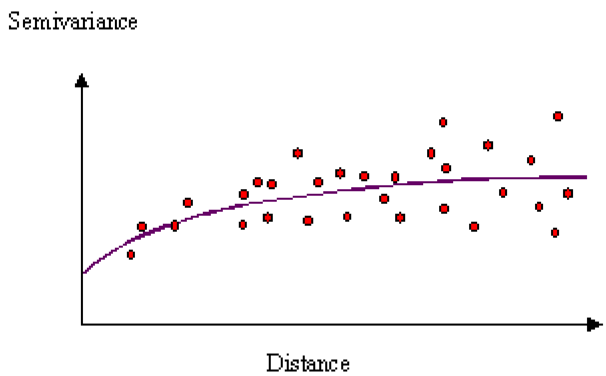
$\gamma(h)$ = semivariance
h = lag
a = range
c_0 = nugget variance
$c_0 + c_1$ = sill

The Exponential model

The exponential model is a good choice when there is a clear nugget and sill, but only a gradual approach to the range **(Sunila & Kollo 2005).**

$$\gamma(h) = c_o + c_1\left\{1 - \exp\left(-\frac{h}{a}\right)\right\}$$

This model is applied when spatial autocorrelation decreases exponentially with increasing distance. Here the autocorrelation disappears completely only at an infinite distance. The exponential model is also a commonly used model. The choice of which model to use is based on the spatial autocorrelation of the data and on prior knowledge of the phenomenon.



Illustrative model of spatial exponential model autocorrelation process.

The Gaussian model

If the variance is very smooth and the nugget variance is very small compared to the spatially dependent random variation, then the variogram can often best fitted with Gaussian model **(Burrough & McDonnell, 1998).**

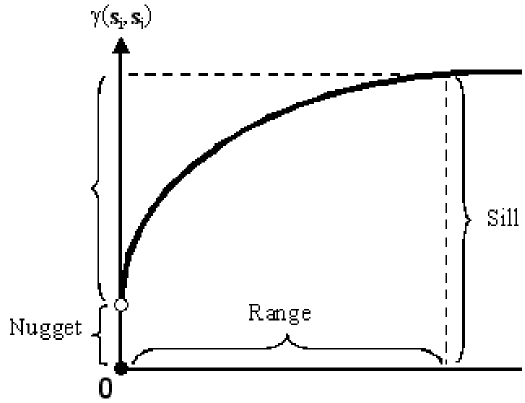
Where we can see that:

$$\gamma(h) = c_o + c_1\left\{1 - \exp\left(-\frac{h^2}{a^2}\right)\right\}$$

Range, sill, and nugget

As previously discussed, the semivariogram depicts the spatial autocorrelation of the measured sample points. Because of a basic principle of geography (things that are closer are more alike), measured points that are close will generally have a smaller difference squared than those farther apart. Once each pair of locations is plotted after being binned, a model is fit through them. Range, sill, and nugget are commonly used to describe these models.

The distance where the model first flattens is known as the range. Sample locations separated by distances closer than the range are spatially autocorrelated, whereas locations farther apart than the range are not. The value at which the semivariogram model attains the range (the value on the y-axis) is called the sill. A partial sill is the sill minus the nugget (see the following section). Theoretically, the nugget value at zero separation distance (for example, lag = 0), the semivariogram value is zero. If for example the semivariogram model intercepts the y-axis at 2, then the nugget is 2.



Illustrative model of nugget, sill, & range relationship

Appendix 11 Validation and Modeling for Chloride

Appendix 11.1 Validation Trials and Results for Chloride in year 2001

Method	Spline (RBF)	
	Regularized Spline	Spline with Tension
Parameter Optimized	0.016212	0.005019
Mean (ME):	-17.03	-15.82
Root-Mean-Square (RMSE):	211.7	206.2
		OK

Method	IDW				
Power	2	2	3.2273	3.2273	10
smooth (0-1)	0.5	1	0.5	1	1
Cross Validation statistics					
Mean (ME):	-21.53	-15.56	-11.16	-10.99	-8.231
Root-Mean-Square (RMSE):	196	194.2	187.6	187.5	205.7
				OK	

Method	**Kriging/Ordinary**
Geostatisitcal Method/Output	**Prediction Map**
Transformation	**log**

Semivariogram parameters	Spherical				Expo.			
Partial sill	0.93551	0.93551	0.8442	1.0926	1.1225	0.88253	0.96802	0.84165
Nugget	0	0	0	0	0	0	0	0
Lag Size	774.81	774.81	1000	500	774.81	1000	500	1200
Smooth	0.5	1	1	1	0.5	1	1	1
Cross Validation statistics								
Mean (ME):	6.613	1.936	-2.076	7.512	6.431	0.982	7.524	0.01636
Root-Mean-Square (RMSE):	214.4	194.6	193.5	198.7	204.8	195.8	195.8	195.7
		OK						

Appendix 11.2 Validation Trials and Results for Chloride in year 2003

Method	Spline (RBF)	
	Regularized Spline	Spline with Tension
Parameter Optimized	0.019769	0.012102
Mean (ME):	-8.972	-8.951
Root-Mean-Square (RMSE):	258.2	258.4
		OK

Method	IDW				
Power	2	2	3.1965	3.1965	10
smooth (0-1)	0.5	1	0.5	1	1
Cross Validation statistics					
Mean (ME):	-27.91	-19.56	-31.01	-28.95	-33.98
Root-Mean-Square (RMSE):	251.7	253.6	245.7	245.9	264.4
				OK	

Method	Kriging/Ordinary								
Geostatisitcal Method/Output	Prediction Map								
Transformation	log								
Semivariogram parameters	Spherical				Expo.				
Partial sill	1.036	1.036	0.8492	0.8325	1.1631	1.1631	0.8314	0.7554	0.7395
Nugget	0	0	0	0	0	0	0	0.0145	0.0430
Lag Size	635.36	635.36	1000	1500	635.36	635.36	1500	2300	2400
Smooth	0.5	1	0.5	1	0.5	1	1	1	1
Cross Validation statistics									
Mean (ME):	10.11	13.56	8.093	7.261	17.4	17.84	11.93	8.164	11.13
Root-Mean-Square (RMSE):	266.2	268.6	269.1	267.7	264.6	264.2	260.9	259	257.1
								OK	

Appendix 11.3 Validation Trials and Results for Chloride in year 2005

Method	Spline (RBF)	
	Regularized Spline	Spline with Tension
Parameter Optimized	0.0056453	0.001735
Mean (ME):	-27.17	-30.44
Root-Mean-Square (RMSE):	340.1	333.4
		OK

Method	IDW			
Power	2	2	10	1
smooth (0-1)	0.5	1	1	1
Cross Validation statistics				
Mean (ME):	-50.01	-44.32	-63.04	-17.58
Root-Mean-Square (RMSE):	349.5	358.6	364.9	406.1
	OK			

Method	**Kriging/Ordinary**							
Geostatisitcal Method/Output	**Prediction Map**							
Transformation	**log**							
Semivariogram parameters	**Spherical**				**Expo.**			
Partial sill	0.94891	1.1934	0.95041	0.91038	0.99974	1.1631	0.92099	1.1366
Nugget	0.033329	0.057465	0	0.009812	0	0	0	0
Lag Size	983.43	500	1500	1200	983.43	635.36	1200	500
Smooth	0.5	1	1	1	0.5	1	1	1
Cross Validation statistics								
Mean (ME):	-10.28	4.655	-10.31	-8.78	3.237	4.796	3.864	12.02
Root-Mean-Square (RMSE):	332.2	332.8	333.8	332.4	336.7	337	338.9	336.6
				OK				

Appendix 11.4 Validation Trials and Results for Chloride in year 2007

Method	**Spline (RBF)**	
	Regularized Spline	Spline with Tension
Parameter Optimized	1.0696	1.5406
Mean (ME):	-16.84	-17.26
Root-Mean-Square (RMSE):	505.4	505
		OK

Method	**IDW**					
Power	2	2	2.6853	2.3946	2.3946	10
smooth (0-1)	0.5	1	0.5	0.5	1	1
Cross Validation statistics						
Mean (ME):	-26.17	-26.91	-42.73	-36.97	-37.35	-67.47
Root-Mean-Square (RMSE):	514.3	513.9	510.5	511.1	511	555.1
				OK		

Method	**Kriging/Ordinary**						
Geostatisitcal Method/Output	**Prediction Map**						
Transformation	**log**						
Semivariogram parameters	**Spherical**				**Expo.**		
Partial sill	0.85736	0.85736	0.97391	0.77707	0.99424	0.88696	1.1055
Nugget	0.11035	0.11035	0.12336	0.10771	0	0	0.01933
Lag Size	746.65	746.65	500	1000	746.65	1000	500
Smooth	0.5	1	1	1	0.5	1	1
Cross Validation statistics							
Mean (ME):	-9.362	-3.944	0.8896	-13.22	-7.787	-6.427	0.8638
Root-Mean-Square (RMSE):	473.1	474.3	474.5	471	489.5	492.2	485.6
			OK				

Appendix 12 Validation and Modeling for Water Level

Appendix 12.1 Validation Trials and Results for Water Level in year 2001

Method	**Spline (RBF)**	
	Regularized Spline	Spline with Tension
Parameter Optimized	0.018213	0.004366
Mean (ME):	-0.000608	0.008238
Root-Mean-Square (RMSE):	1.293	1.2
		OK

Method	**IDW**					
Power	2	2	10	2.3103	2.5008	2.5306
smooth (0-1)	0.5	1	0.5	0.5	1	0.8
Cross Validation statistics						
Mean (ME):	0.0100	0.0099	0.0743	0.0222	0.0325	0.0327
Root-Mean-Square (RMSE):	1.243	1.267	1.534	1.222	1.221	1.219
						OK

Method	**Kriging/Ordinary**						
Geostatisitcal Method/Output	**Prediction Map**						
Transformation	**None**						
Semivariogram parameters	**Spherical**				**Expo.**		
Partial sill	8.6411	8.6411	6.0051	7.9131	9.5694	9.5694	6.5553	3.8288
Nugget	1.8618	1.8618	0.066472	2.1801	0.52827	0.52827	0	0
Lag Size	2695.7	2695.7	2000	3000	2695.7	2695.7	1000	500
Smooth	0.5	1	0.5	0.5	1	0.5	1	1
Cross Validation statistics								
Mean (ME):	0.001763	0.007969	0.04789	-0.00275	0.03106	0.02917	0.02901	0.01743
Root-Mean-Square (RMSE):	1.426	1.418	1.282	1.459	1.266	1.282	1.167	1.116
								OK

Appendix 12.2 Validation Trials and Results for Water Level in year 2003

Method	**Spline (RBF)**	
	Regularized Spline	Spline with Tension
Parameter Optimized	0.031901	0.007482
Mean (ME):	-0.005668	0.006603
Root-Mean-Square (RMSE):	1.53	1.444
		OK

Method	**IDW**				
Power	2	2	2.4874	2.4874	10
smooth (0-1)	0.5	1	0.5	1	1
Cross Validation statistics					
Mean (ME):	0.000874	0.001147	0.01483	0.01618	-0.01239
Root-Mean-Square (RMSE):	1.423	1.417	1.362	1.37	1.732
			OK		

Method	**Kriging/Ordinary**							
Geostatisitcal Method/Output	**Prediction Map**							
Transformation	**None**							
Semivariogram parameters	**Spherical**				**Expo.**			
Partial sill	7.9273	7.9273	7.3337	7.8863	9.7464	9.7464	9.7039	9.7362
Nugget	0	0	0	0	0	0	0	0
Lag Size	2628.5	2628.5	2000	2500	2628.5	2628.5	2500	3000
Smooth	0.5	1	0.5	1	0.5	1	1	1
Cross Validation statistics								
Mean (ME):	0.04171	0.03238	0.03655	0.03229	0.02894	0.02501	0.02497	0.02502
Root-Mean-Square (RMSE):	1.479	1.464	1.486	1.463	1.443	1.422	1.421	1.422
							OK	

Appendix 12.3 Validation Trials and Results for Water Level in year 2005

Method	**Spline (RBF)**	
	Regularized Spline	Spline with Tension
Parameter Optimized	30.661	0.51753
Mean (ME):	0.003301	0.1222
Root-Mean-Square (RMSE):	1.778	1.677
		OK

Method	**IDW**				
Power	2	2	2.8772	2.8772	10
smooth (0-1)	0.5	1	0.5	1	1
Cross Validation statistics					
Mean (ME):	0.02121	0.001312	0.05608	0.05502	0.03546
Root-Mean-Square (RMSE):	1.414	1.499	1.35	1.372	1.569
			OK		

Method	**Kriging/Ordinary**							
Geostatisitcal Method/Output	**Prediction Map**							
Transformation	**None**							
Semivariogram parameters	**Spherical**				**Expo.**			
Partial sill	10.505	10.505	7.963	8.6882	11.263	11.263	8.471	7.1874
Nugget	2.4871	2.4871	0	0	0	0	0	0
Lag Size	2748	2748	2000	750	2748	2748	2000	750
Smooth	0.5	1	1	1	0.5	1	1	1
Cross Validation statistics								
Mean (ME):	-0.004681	-0.003879	0.03001	0.0134	0.04238	0.02455	0.01679	0.007288
Root-Mean-Square (RMSE):	1.519	1.517	1.104	1.067	1.133	1.113	1.077	1.064
								OK

Appendix 12.4 Validation Trials and Results for Water Level in year 2007

Method	Spline (RBF)	
	Regularized Spline	Spline with Tension
Parameter Optimized	24.823	0.29112
Mean (ME):	-0.1475	0.03052
Root-Mean-Square (RMSE):	2.369	2.218
		OK

Method	IDW				
Power	2	2	2.6643	2.6643	10
smooth (0-1)	0.5	1	1	0.5	1
Cross Validation statistics					
Mean (ME):	-0.1474	-0.1209	-0.1036	-0.1032	-0.1732
Root-Mean-Square (RMSE):	1.898	1.926	1.852	1.848	2.06
				OK	

Method	Kriging/Ordinary						
Geostatisitcal Method/Output	Prediction Map						
Transformation	None						
Semivariogram parameters	Spherical				Expo.			
Partial sill	12.267	12.267	10.62	10.707	13.7	13.7	11.27	10.707
Nugget	3.8724	3.8724	0	0	0	0	0	0
Lag Size	2748	2748	2000	1600	2748	2748	2000	1600
Smooth	0.5	1	1	1	0.5	1	1	0.5
Cross Validation statistics								
Mean (ME):	-0.02023	-0.06515	-0.08456	-0.08758	-0.06127	-0.08617	-0.06432	-0.06504
Root-Mean-Square (RMSE):	2.083	2.108	1.577	1.535	1.61	1.594	1.557	1.542
								OK

Appendix 13 Validation and Modeling for Rainfall

Appendix 13.1 Validation Trials and Results for Rainfall in year 2001

Method	**Spline (RBF)**	
	Regularized Spline	Spline with Tension
Parameter Optimized	0.0004537	0.000193
Mean (ME):	7.087	5.274
Root-Mean-Square (RMSE):	44.1	36.6
		OK

Method	IDW				
Power	2	2	6.7128	6.7128	10
smooth (0-1)	0.5	1	0.5	1	0.5
Cross Validation statistics					
Mean (ME):	16.01	9.83	9.308	9.21	9.2230
Root-Mean-Square (RMSE):	60.3	38.23	39.46	39.31	40.91
			OK		

Method	**Kriging/Ordinary**							
Geostatisitcal Method/Output	**Prediction Map**							
Transformation	**log**							
Semivariogram parameters	**Spherical**				**Expo.**			
Partial sill	0.038164	0.038164	0.027514	0.014292	0.034475	0.013191	0.01137	0.007833
Nugget	0	0	0	0	0	0	0	0
Lag Size	2695	2695	2000	1500	2695.7	1500	1200	1000
Smooth	0.5	1	0.5	1	0.5	1	0.5	1
Cross Validation statistics								
Mean (ME):	5.289	8.584	5.513	7.078	7.102	7.507	7.45	7.143
Root-Mean-Square (RMSE):	38.19	33.83	40.44	33.45	51.89	34.05	34.24	34.68
		OK						

Appendix 13.2 Validation Trials and Results for Rainfall in year 2003

Method	Spline (RBF)	
	Regularized Spline	Spline with Tension
Parameter Optimized	0.0004462	1.35E-05
Mean (ME):	0.103	-14.41
Root-Mean-Square (RMSE):	111	102.1
		OK

Method	IDW				
Power	2	2	5.1879	5.1879	10
smooth (0-1)	0.5	1	0.5	1	0.5
Cross Validation statistics					
Mean (ME):	16.88	-5.38	-20.88	-23.83	-32.54
Root-Mean-Square (RMSE):	131.8	105.6	106	105.5	111.6
		OK			

Method	Kriging/Ordinary							
Geostatisitcal Method/Output	Prediction Map							
Transformation	log							
Semivariogram parameters	Spherical				Expo.			
Partial sill	0.19871	0.19871	0.1313	0.2352	0.17708	0.17708	0.1183	0.2089
Nugget	0	0	0	0	0	0	0	0
Lag Size	2695	2695	2000	3000	2695	2695	2000	3000
Smooth	0.5	1	0.5	1	0.5	1	1	1
Cross Validation statistics								
Mean (ME):	-1.723	-1.359	-4.254	0.521	2.339	2.377	-1.094	4.295
Root-Mean-Square (RMSE):	104	102.2	103.4	101.9	103.3	101.9	102.6	101.9
				OK				

Appendix 13.3 Validation Trials and Results for Rainfall in year 2005

Method	**Spline (RBF)**	
	Regularized Spline	Spline with Tension
Parameter Optimized	0.0030383	0.004376
Mean (ME):	-1.849	-1.607
Root-Mean-Square (RMSE):	29.720	29.4
		OK

Method	**IDW**				
Power	2	2	1	1	10
smooth (0-1)	0.5	1	0.5	1	0.5
Cross Validation statistics					
Mean (ME):	-5.628	-4.097	-3.43	-3.19	-32.54
Root-Mean-Square (RMSE):	31.24	33.77	32.51	32.13	111.6
				OK	

Method	**Kriging/Ordinary**							
Geostatisitcal Method/Output	**Prediction Map**							
Transformation	**log**							
Semivariogram parameters	**Spherical**				**Expo.**			
Partial sill	0.00561	0.00561	0.004739	0.005338	0.007021	0.007021	0.005701	0.00749
Nugget	0.0041087	0.0041087	0.004612	0.00424	0.002833	0.002833	0.003641	0.002128
Lag Size	2695	2695	3000	2000	2695	2695	3000	2000
Smooth	0.5	1	1	1	0.5	1	1	1
Cross Validation statistics								
Mean (ME):	-1.442	-2.314	-2.301	-2.313	-0.6931	-2.542	-2.498	-2.631
Root-Mean-Square (RMSE):	29.1	33.02	32.82	32.96	29.02	32.71	32.49	32.69
					OK			

Appendix 13.4 Validation Trials and Results for Rainfall in year 2007

Method	Spline (RBF)	
	Regularized Spline	Spline with Tension
Parameter Optimized	0.0017835	0.001022
Mean (ME):	7.021	6.995
Root-Mean-Square (RMSE):	71.91	70.67
		OK

Method	IDW				
Power	2	2	7.7733	7.7733	10
smooth (0-1)	0.5	1	0.5	1	0.5
Cross Validation statistics					
Mean (ME):	20.22	10.15	9.789	9.817	9.432
Root-Mean-Square (RMSE):	68.67	50.76	50.03	50.33	50.91
			OK		

Method	**Kriging/Ordinary**							
Geostatisitcal Method/Output	**Prediction Map**							
Transformation	**log**							
Semivariogram parameters	**Spherical**				**Expo.**			
Partial sill	0.09088	0.09088	0.004739	0.00533	0.08149	0.08149	0.1008	0.05178
Nugget	0	0	0.004612	0.0042	0	0	0	0
Lag Size	2695	2695	3000	2000	2695	2695	3000	2000
Smooth	0.5	1	0.5	1	0.5	1	1	1
Cross Validation statistics								
Mean (ME):	0.8529	8.197	-2.201	-2.313	3.574	9.053	10.25	7.219
Root-Mean-Square (RMSE):	56.51	57.71	58.18	62.96	61.94	51.53	51.89	51.03
	OK							