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A thesis submitted as a partial fulfillment to the admission of the degree of Master in surveying

A Comparison of Depth Interpolation by Using GIS & Neural Networks

مقارنة إستكمال الأعماق بإستخدام نظم المعلومات الجغرافية والشبكات العصبية

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khalid M. abdalla

المستخلص

قياس الأعماق يعتبر الهدف الأول في المسح الهيدروغرافي و يعتمد علي تقنيات وأجهزة مختلفة ، وهي الطريقة الأكثر تكلفة ومع ذلك استخدمت بعض النماذج الرياضية لتكثيف الأعماق مع تكلفة منخفضة نسبيًا.

ظهرت الشبكات العصبية الاصطناعية واستخدمت في تطبيقات عديدة بغرض:-

التنبؤ ، و التصنيفات ومشاكل الدوال التقريبية ، فهي سريعة وذكية وسهلة الاستخدام.

الهدف من هذا البحث هو اختبار إمكانية استخدام هذه الطريقة للتنبؤ بالأعماق مع مقارنة مع نموذج من نظم المعلومات الجغرافية.

وجد أن الشبكات العصبية الاصطناعية يمكن أن تعطي نتائج أفضل إحصائيا.

Abstract

Depth measurement is Considered as a first goal in hydrographic survey, it depends on different techniques and instruments, it’s most costly procedures. However; some mathematical models are used for condensing depths with a relatively low cost.

Artificial neural networks appears and in many applications used to solve real-world forecasting, classification and function approximation problems. It is fast, intelligent and easy to use Neuro Intelligence supports all stages of neural network application.

The objective of this research is to test the possibility of using such a method for depth prediction, and comparing with the geographical information system models.

It is found that artificial neural networks statistically give abetter results.

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CHAPTER ONE

INTRODUCTION

1.1 General review

Lead line and sounding pole were the earliest methods used for directly measuring water depth.Their easy principles of operation ensured their continued use over many centuries.

During the last decade, hydrographic surveying has experienced a conceptual change in depth measurement technology and methodology, Single beam acoustic depth sounding is by far the most widely used depth measurement technique in hydrographic survey.

In this thesis used single beam echo sounder to collect the data in the form of cross sections .

A new technique suggested for interpolation is the Artificial Neural Network (ANN). It is based on the structure and the performance of our biological neural network. (ANN) consists of units called neurons. These units are subdivided into three connected layers with an activation functions (initial functions) .The output (predicted values) referring to its input value (known values). It also contains learning laws and training algorithms.

In previous study, for example, use artificial neural networks for sediment load forecasting of talkherood river mouth in Iran to solve it.

1.2 Problem Statement

The process of depth measurement is more complex and expensive ,and must take caution during the work , necessary to discover solve of this problem by software techniques .

1.3 Thesis Objectives

The main objective of this study is to use the artificial neural network technique for estimate the depth value considering a particular law of algorithms and compare it with GIS model, also to avoid double work, high cost, different technical standards and different coding which minimize effort, cost and errors.

1.4 Thesis layout

This research consists of six chapters including this introductory chapter , chapter two expose depth measurement techniques, chapter three is about the artificial neural networks, chapter four explains the Geograpich Information Systems, chapter five illustrate the Methodology and results, finally, conclusion and recommendations are presented in chapter six.

CHAPTER TWO

DEPTH DETERMINATION

2.1 Introduction

Hydrography is that branch of physical oceanography dealing with the measurement and definition of the configuration of the bottoms and adjacent land areas of oceans, lakes, rivers, harbors, and other water forms on Earth.

The navigation of commercial vessels requires increasingly accurate and reliable knowledge of the water depth in order to exploit maximum cargo capabilities safely. It is imperative that depth accuracy standards in critical areas, particularly in areas of marginal under-keel clearance and where the possibility of obstructions exists, are more stringent than those established in the past and that the issue of adequate bottom search is addressed.

Depth determination is a fundamental task for a hydrographer, which requires specific knowledge of the medium, of underwater acoustics, of the plethora of devices available for depth measurement, of complementary sensors for attitude and heave measurement and proper procedures to achieve and meet the internationally recommended standards for accuracy and coverage as articulated in International Hydrographic Organization (IHO) publication S-44 5th Edition.

Lead line and sounding pole were the earliest methods used for directly measuring water depth.Their easy principles of operation ensured their continued use over many centuries.

Single beam echo sounders, derived from military sonar's, were a major development and have been used in hydrographic surveying since the mid 1900s.

Echo sounders can be divided into single beam and multi beam. Single Beam Echo Sounders (SBES) may have transducers either with a single transducer piece or an array. Multi Beam Echo Sounders (MBES) have transducer arrays built up from several elements. As mentioned before, this is a result of the need for beam forming in multiple directions and, sometimes, beam steering to compensate for platform attitude.

State of the art of the depth measurement equipment was evaluated as follows:

2.2 Single beam echo sounders

Single beams require only a transducer, for both transmission and reception, but a transducer array may be used particularly when stabilization is required, knowledge of roll and pitch angles are needed for beam stabilization.

Beam width is a function of the transducer dimensions and acoustic wave length.

The higher the frequency and the larger the transducer is, the narrower the beam will be. Thus to have a narrow beam in low frequencies, a large transducer is required.

The transducer selected for (SBES) may have a narrow beam when high directivity is required or a wide beam when directivity is not the main concern but the detection of minimum depths or obstacles on the seafloor is the priority.

Wide beams have the capacity to detect echoes with in a large solid angle, which is useful for the detection of hazards to navigation requiring further investigation.

These beams are usually not stabilized, for common sea conditions the attitude of the transducer does not impact on the measurements.

On the other hand, narrow beams, typically 2º to 5º, are usually required for high resolution mapping . These beams might be stabilized in order to measure the depth vertically below the transducer have reached a sub-decimeter accuracy in shallow water.

The market offers a variety of equipment with different frequencies, pulse rates etc. and it is possible to satisfy most users' and, in particular, the hydrographers' needs.

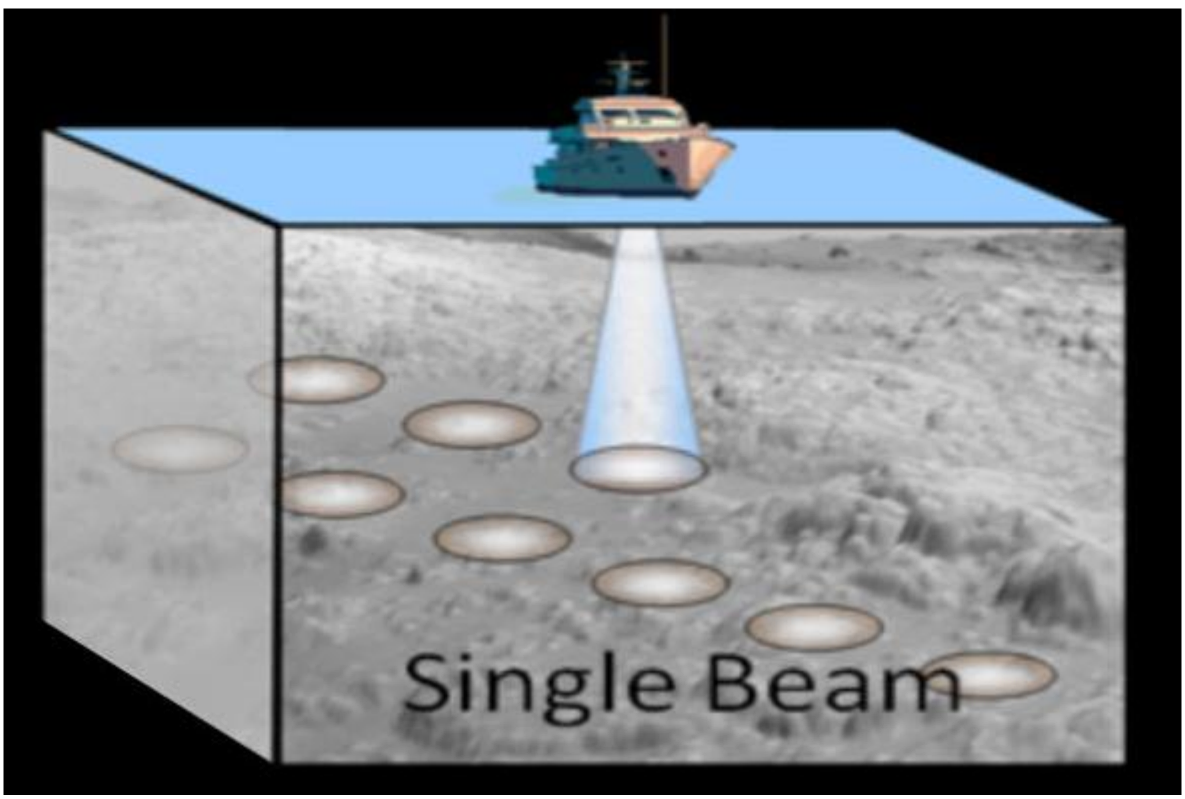

Figure 2.1 : Single beam echo sounder(www.noaa.com)

2.3 Multi beam echo sounder

MBES usually have separated transducer arrays for transmission and reception, i.e. one projector and one hydrophone, where the first is oriented longitudinally and the second is oriented transversally to the vessel’s bow. The most common is to have only one transmitted beam with a fan shape, narrow along track and broad across track.

The reception transducer forms several beams, in predefined directions, narrow across track and broad along track, guaranteeing, regardless of the attitude of the surveying platform, intersection between the transmission and the reception beams.

The reduction of side lobes is essential for correct depth measurement and positioning of (MBES).

Technology is developing rapidly and offers great potential for accurate and total seafloor search if used with proper procedures and provided that the resolution of the system is adequate for proper detection of navigational hazards.

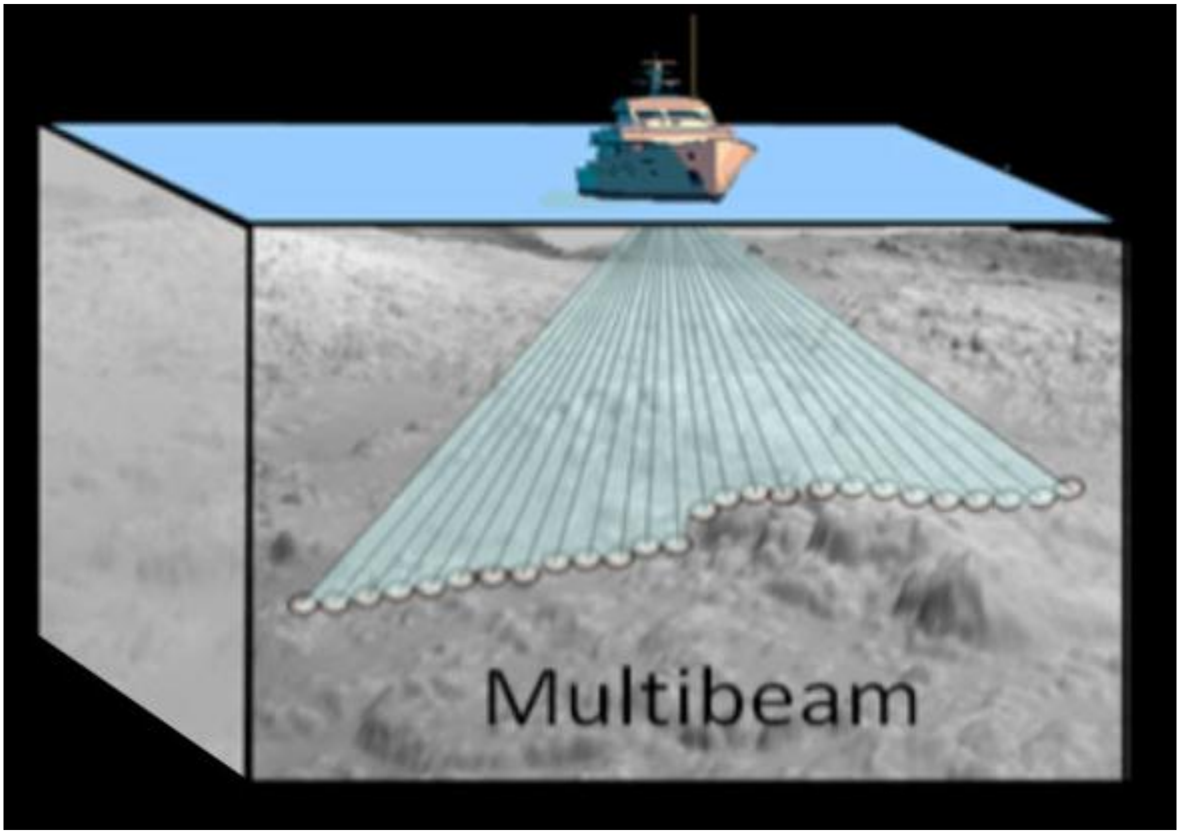

Figure 2.2 : Multi beam echo sounder(www.noaa.com)

2.4 Airborne laser sounding

Is a new technology which can offer substantial productivity gains for surveys in shallow, clear water? Airborne laser systems are capable of measuring depths to 50 m or more.

Despite these new technologies, single beam echo sounders (SBES) still remain, for the present, the traditional equipment used on hydrographic surveys worldwide. These echo sounders have also evolved from analogue to digital recording, with greater precisions and higher accuracies and with specific features which allow a wider variety of purposes to be met. The use of digital echo sounders along with motion sensors, satellite positioning systems (such as GPS) and software for data acquisition have combined to optimize productivity with corresponding reductions in personnel for survey operations.

(MBES) have become a valuable tool for depth determination when full seafloor personification is required. An increasing number of National Hydrographic Offices (NHO) has adopted multi beam technology as the methodology of choice for the collection of bathymetric data for new chart production. The acceptance of Multi beam data for use in published nautical charts is a sign of growing confidence in the technology.

Not with standing their impressive capabilities, it is vital that planners, operators and checkers have in depth knowledge of MBES operating principles, as well as practice in data interpretation and validation.

Airborne laser sounding systems are being used by a few (NHO); these systems have, by far, the highest data acquisition rates and are particularly suited to near shore and shallow water areas. However, the high costs for the assets involved in data collection and their operation do not currently allow a more general use.

Figure 2.3: Bathymetric lidar (WWW.OZ COASTS MAPPING)

CHAPTER THREE

ARTIFICIAL NEURAL NETWORKS

3.1 Introduction

Artificial Neural Networks (ANN) are mathematical models based on the structure and the performance of our Biological Neural Networks (BNN) used to perform pattern recognition tasks.

Just like the biological neural networks the artificial neural networks models consist of unites called the neurons. It can also display some of the features of the biological network. However these models are not expected to reach the performance of the BNN for two reasons:

(i) We are not fully understand the operation of the (BNN) and their interaction.

(ii) Their operation in the neutral asynchronous is not known.

3.2 Historical background

The first model was proposed by Warren McClloch and Walter Pittes in 1943. They called it McCulloch Pittes neurons, the proposed model uses the weighted sum of the input followed by a threshold logic operation. The main drawback of this model of computation is that the weight are fixed and hence the model could not learn by itself.

Six years later (in 1949) Donald Hebb proposed a learning law for adjusting a connection weight based on pre and post synaptic values of the variables. Hebb's law become fundamental learning rule of the neural networks.

In 1958 Rosenblatt proposed a perceptron network and a perceptron learning law. The network itself is a supervised network (based on prior knowledge). The learning law was chosen in a way that it covers the problem of patterns classification which are linearly separable in the feature space. It was shown that a multilayer perceptron could be used to perform any pattern classification task. However, there was no systematic learning algorithm to adjust the weights realizing the classification task.

Ten years later the limitation of the perceptron models was demonstrated by Minsky and Papert through several illustrative examples.

In the 1960s Widrow and his group proposed an Adaline model, which is an adaptive threshold logic element. It uses a Least Mean Square learning algorithm (LMS) to adjust the weights of an Adaline model. The algorithm was successfully used for an adaptive single processing situation.

Lack in suitable learning law for multilayer perceptron network had put brakes on the development of the neural networks models for pattern recognition tasks for nearly 15 years till 1984.

Actually the increase of the interest in artificial neural network is due to two keys development in early 1980s. The first one is the energy analysis of feedback neural networks by John Hopfield. The analysis has shown the existence of a stable equilibrium state in feedback network, provided that the network has symmetric weights and that the state update is made asynchronously. Also, in 1986 Rumelhart, and others, have shown that it is possible to adjust the weight of a multilayer feed forward neural network in a systematic way to learn the implicit mapping in a set of input-output pattern, the learning law has been called the generalization delta rule or error back propagation learning low (Rumelhart et al 1986).

At the same time Ackley Hinton and Sejnowski proposed the Boltzmann machine, which had included the hidden unites. These unites were used to make a given pattern problem re presentable in feedback networks. Several learning laws were also developed; the prominent among them being the reinforcement learning or learning with critic.

3.3 Network architecture

Generally, neural networks can be categorized into two main types: namely supervised networks and unsupervised networks. The way the network architecture is designed depends on the ability of its training algorithm. In most newly proposed network topologies, the design of the corresponding training algorithm are deemed essential. Apparently, a successful network architecture must be supported by an effective and simple enough training algorithm.

3.3.1 Supervised neural networks

Supervised neural networks are the mainstream of neural network development. The differentiable characteristic of the supervised neural network lies in the inclusion of a teacher on their learning process. The basic block diagram of the supervised learning for all neural network models can be described through figure (3.1). For learning process, the network needs training data examples consisting of a number of input-output pairs. The desired output vector in the training data set serves as a teacher for the network learning. In the training process error signals are constructed from the difference between the desired output and the system output. Through an iterative training procedure the network's weights are adjusted by the error signal in a way that the neural network output tries to follow the desired output as close as possible. The training procedure is repeated until the error signal is close to zero or below a predefined value. The sum of the errors over all the training samples can be considered as a network performance measure, which is a function of the free parameters of the system. Such function can be visualized a multidimensional error surface where network free parameters serve as coordinates. During the course of learning the system gradually moves to a minimum point along an error surface. The error surface is determined by the network architecture and the cost function. In the coming sections, some example of supervised neural network models are presented.

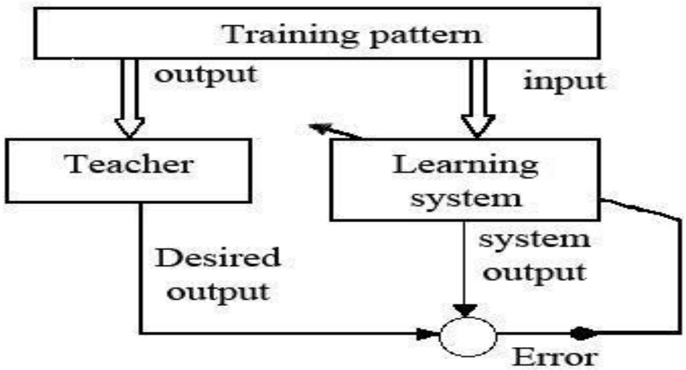

Figure (3.1) Overview of the supervised learning

3.3.1.1 McCulloch-Pitts (MP) model

In McCulloch-Pitts model (Figure (3.2)) the activation (x) is given by a weighted sum of its M inputs values (a s) and a bias term (θ). The output signal *(s)* is typically a nonlinear function, $f(x)$, of an activation function value(x).

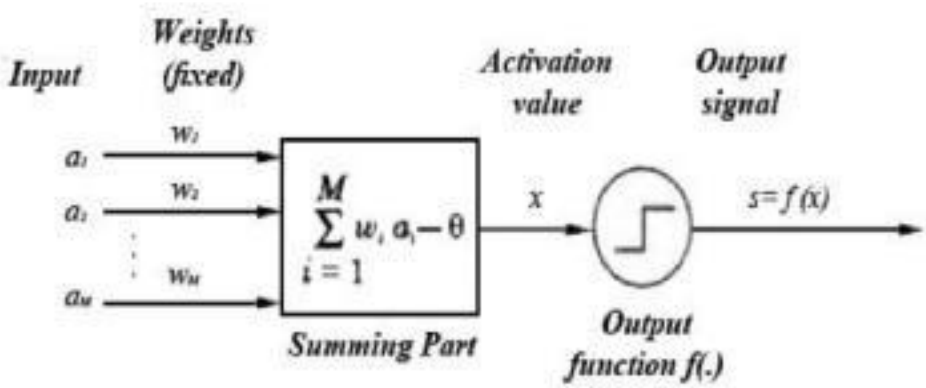

Figure (3.2) McCulloch-Pitts model

The following equations describe the operation of the MP model:

Activation: $x = \sum_{i=1}^{M} w_i a_i - \theta$ **(3.1)**

Output signal: $s = f(x)$ **(3.2)**

There are three commonly non-linear functions : binary, ramp, and sigmoid are shown in Figure (3.2). However only binary function was used in the original multi-preceptron (MP) model.

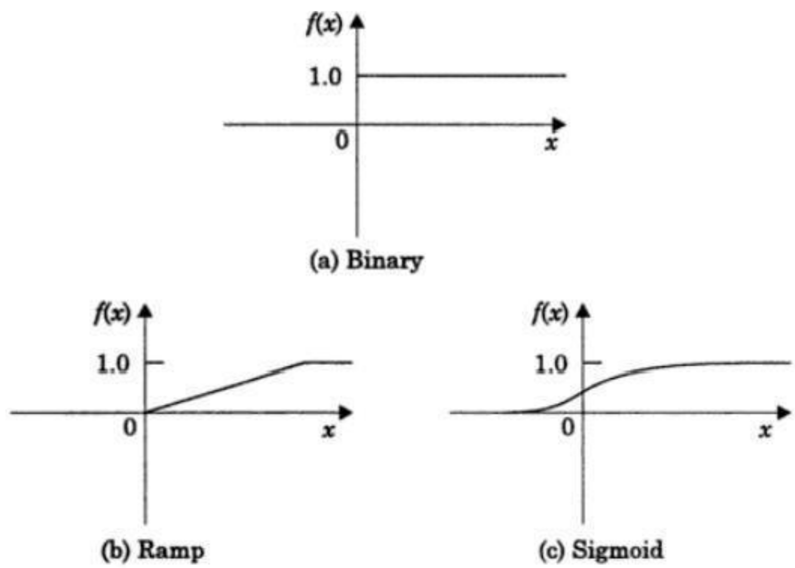

Figure (3.3) Some non-linear functions

In MP model the weights are fixed. But a network using this mode doesn't have the capability of learning. Moreover the original model allows only binary output states operating at descried time steps.

3.3.1.2 Rosenblatt Perceptron model

The Rosenblatt perceptron model figure (3.4) is an artificial neural network consisting of outputs from sensory units to a fixed set of association unites, which are fed to a MP neuron.

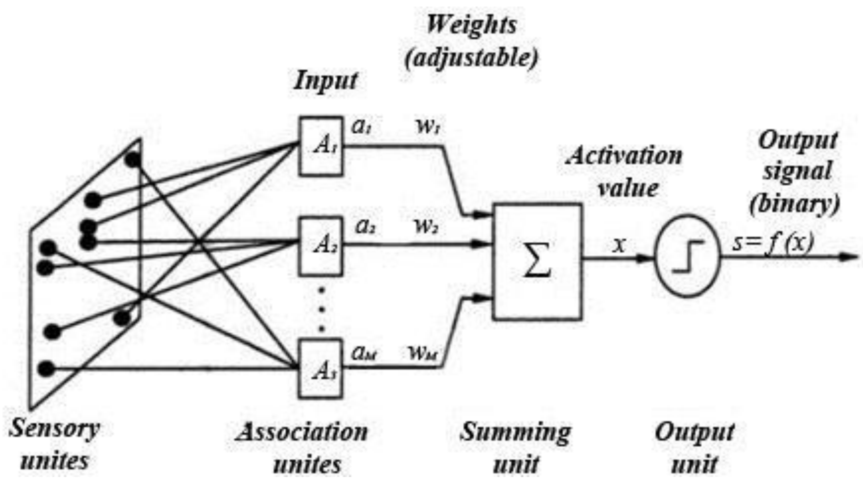

Figure (3.4) Rosenblatt perceptron model of neurons

The association unites perform predetermined manipulation on their units. The main deviation from the MP model is that learning (i.e. adjustment of weights) is incorporated in the operation of the units. The desired, or target output, (b) is compared with the actual binary output (s) and the error (δ) is used to adjust the weight. The following equations describe the operation of the perceptron model of a neuron:

Activation $\quad x = \sum_{i=1}^{M} w_i a_i - \theta$ **(3.3)**

Output signal $\quad s = f(x)$ **(3.4)**

Error $\quad \delta = \boldsymbol{b} - \boldsymbol{s}$ **(3.5)**

Weight change $\quad \Delta\omega_i = \eta\ \delta a_i$ **(3.6)**

where η is the learning rate

There are perceptron learning laws that give a step-by-step procedure for adjusting the weight. The converges or non convergence of the adjustment depend on the nature of input-output pairs to be represented by the model. The perceptron convergence theorem enables us to determine whether the given pattern pairs are represent able or not. If the weight values converge, the corresponding problem is said to be represent able by perceptron network.

3.3.1.3 Adeline

ADAptive LINear Element (ADALINE) is another computing model proposed by Widrow in. In the Adaline model the activation value (x) is compared with the target output (b). In other words the output is a linear function of the activation value (x). The equations that describes the operation of an (Adaline) are as follows:

$$x = \sum_{i=1}^{M} w_i a_i - \theta \qquad \textbf{(3.7)}$$

$$s = f(x) = x \qquad \textbf{(3.8)}$$

$$\delta = b - s = b - x \qquad \textbf{(3.9)}$$

$$\Delta\omega_i = \eta\ \delta a_i \qquad \textbf{(3.10)}$$

All the variables as defined as before. This weight role minimizes the mean squared error (δ^2) averaged over all inputs.

Hence it is called Least Mean Squire (LMS) error learning law. This law is derived using the negative gradient of the error surface in the weighted space. Hence it is also known as a gradient descent algorithm.

3.3.1.4 Multilayer feed forward neural networks

In a simple form a feed forward network consists of an input layer and a single layer of neurons. Such a single layer feed forward network is not capable of classifying nonlinear separable pattern. Multilayer feed forward network has become the major and most widely used for the architecture of the neural network. In the feed forward networks all the connections are acyclic or in directed from the input to the output layer.

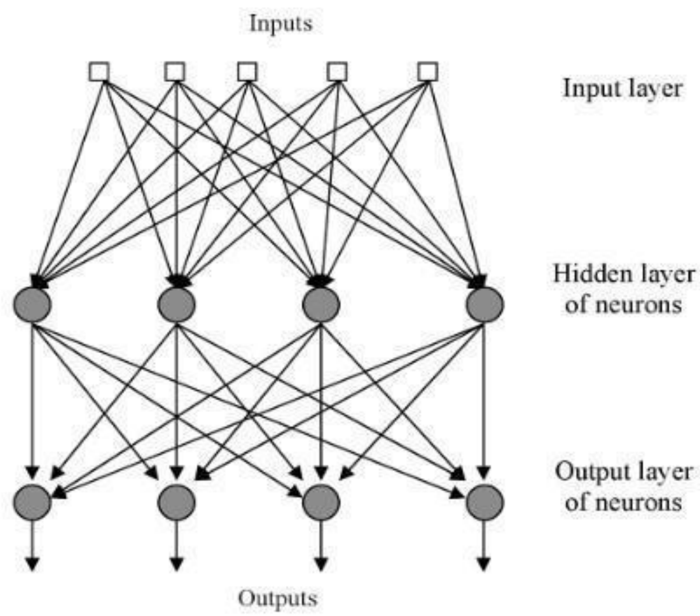

Figure (3.5) Multilayer feed forward neural network with one hidden layer

Multilayer network in figure (3.5) consist of one or more layers of neurons between input and output layer, called the hidden layer. The neurons in the hidden layers are called hidden neurons. The network is called fully connected when every the neurons in one layer is connected to every neuron in the next layer.

3.3.1.5 Recurrent neural network

A recurrent network is a special form of neural networks. It can be a single layer or a multiple hidden layer neural network. The basic difference between this network and feed forward network is that it has one or more feedback loops as shown in Figure (3.6). The feedback loops can appear in many forms between any two neurons or layers. It typically involve unites delay elements denoted by (z^{-1}). Recurrent neural networks exhibit complex dynamics because of the large number of feed forward feedback connections. This characteristic provides them extra advantages in handling time series related and dynamical problems over feed forward networks. Recurrent networks are also useful for processing special data such as graph structure data. A recurrent small size network with size may be equivalent to complicated type of feed forward network.

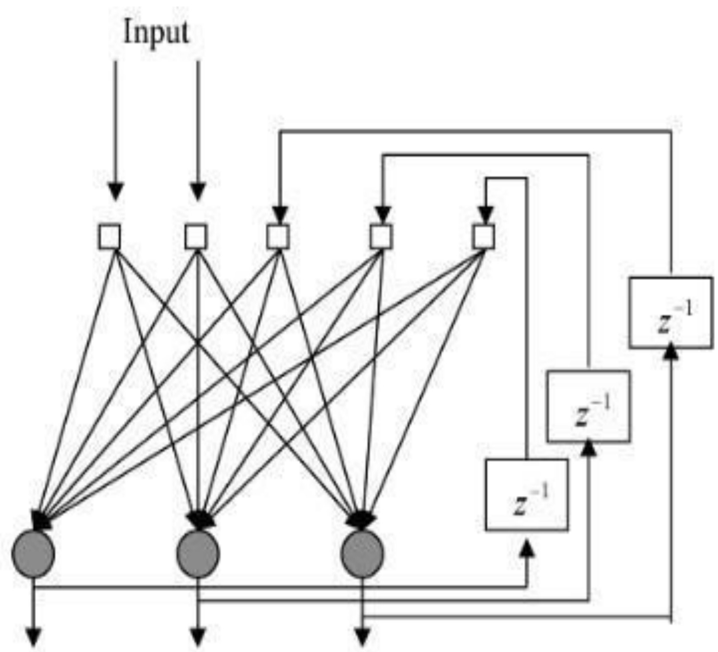

Figure (3.6) Recurrent neural

3.3.2 Unsupervised neural networks

Unlike the supervised networks, unsupervised networks do not have a teacher in the training data set. The learning process of unsupervised neural network is carried out from the self-organizing behavior. In the course of training, no extra factor is used to affect the weights adjustment of the network.

The correct outputs are not available during the course of training. For instance, a typical unsupervised network consists of an input layer and a competitive layer. Through competitive learning the network output automatically reflects some statistical characteristics of input data such as cluster, topological ordering etc.

One of the most widely used unsupervised neural network is Self-Organizing Map (SOM) represented by Figure (3.7). As shown in the figure all neurons arranged on a fixed grid of output layer, containing a weight vector similar to the input dimension. After training, each neuron becomes representative of different data sets. One of the most important characteristics of SOM lies in its topological ordering which means that the neurons that have similar weights (in the input dimension) are also close to each other in the SOM output map. This type of (SOM) map is useful in many applications including visualization, quantization, and retrieval clustering.

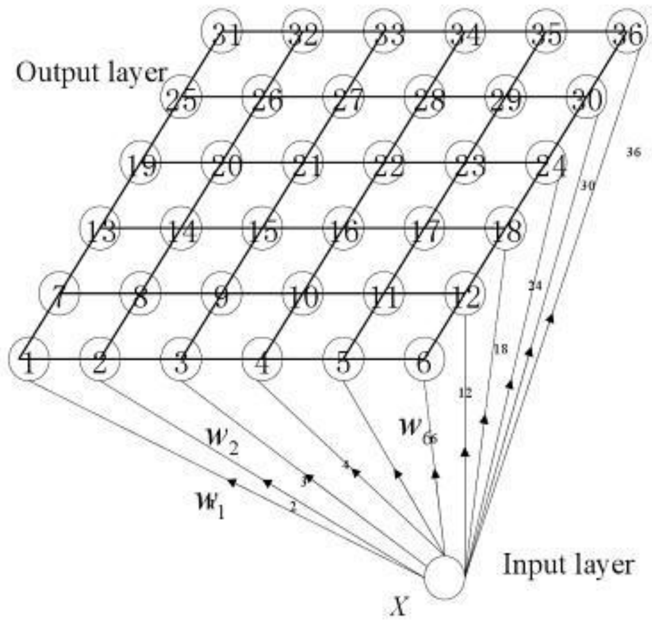

Figure (3.7) SOM network architecture

3.4 Training algorithms

Many training algorithms had been developed since the 1950's, Here are some examples for these algorithms:

3.4.1 Conjugate gradient descent

The conjugate gradient-descent optimization technique was developed by (Hestenes and Stiefel) (Tommy W S Chow, Siu Yeung Cho (2007)). As an optimization technique, the conjugate gradient descent can be the applied to neural network training by adopting weights as was in back propagation. In addition, the conjugate gradient descent has the ability to work with a large number of weights Conjugate gradient descent performs a series of line searches across the error surface.

It determines the direction of the steepest descent and projects a line in that direction to locate the minimum, after which it update in the weights once per epoch. Another search is then preformed along a conjugate direction from that point. This direction is been chosen to insure that all direction that have been minimized stay minimized. It does this in the assumption that the error surface is quadratic. If the quadratic assumption was wrong and the chosen slope direction doesn't slope downwards, it will then calculate a line of steepest descent and search that direction. Each epoch involves searching in specific direction these results in a search that doesn't generally follow the steepest descent, but it often produces a faster convergence than a search along the steepest decent direction because it is only searches one direction at a time. As the algorithm moves closer to the minimum point the quadratic assumption is more likely to be true and the minimum is then located quickly.

3.4.2 Back propagation

Since 1989, learning by back propagation has become the most popular method of training neural networks. The reason for this popularity is the underlying simplicity and the relevant power of the algorithm. Its power derives from the fact that, unlike its precursors, the perceptron learning rule and the Widrow-Hoff learning rule can be employed for training nonlinear networks of arbitrary connectivity. Since such networks are often required for real world application, such a learning procedure is critical. Nearly as important as its power in explaining its popularity is its simplicity. The basic idea is old and simple, namely define an error function and use a gradient descent to find a set of weights which optimize performance of particular task. This algorithm is to a degree that simple so it can be implemented in few lines of code.

3.4.3 Quick propagation

The quick propagation algorithm is a variation of the standard back-propagation algorithm developed by Scott Fahlman in 1989. It assumes that the local is quadratic and employs an approximation to the second order derivatives of the quadratic to make weight changes. The algorithm is generally not fast but has shown that to be faster than back-propagation for some applications, but is not generally faster. It can also get trapped in local minima or become unstable in a manner similar to back-propagation. For these reasons it is not considered a general purpose method for training feed forward networks, but can treated as specialized technique that can sometimes, produce rapid training.

3.4.4 Quasi-Newton

The Quasi-Newton method is a popular algorithm for nonlinear optimization. It uses second order derivatives to find an optimal solution. They generally converge faster than first order techniques such as the gradient method used in back-propagation. However, its memory requirements and computation complexity scale as the squire of the number and weights. For these reasons it is generally not suited for training networks with many weights.

3.4.5 Levenderg-Marquardt

This is another nonlinear optimization algorithm based on second neural networks.

It is however more restrict than back-propagation. Like quasi-newton method, the memory requirements for the (LM) algorithm scales as a function of the squire of numbers and weights, and their for restricted to smaller networks, typically, on the order of few hundred weights. It works only with summed squire error functions.

CHAPTER FOUR

GEOGRAPHIC INFORMATION SYSTEMS

Geographic information systems are an important product of the revolution of information technology. Which allow us to use and analyze spatial information in conjunction with connected socio-economic information, and therefore it's an ideal basis for the planning and management. There are many definitions for GIS depending on its components and functions. The U.S Federal Interagency Coordinating Committee (1988) definition stated that a GIS is a system of computer hardware, software, and procedures designed to support the capture, management, manipulation, analysis, modularity and display of spatially referenced data for solving complex planning and management problems. Shoba and Ra sappan (2013: 1) also describe GIS as: A computer tool for capturing, storing, querying, analyzing and displaying spatial data from the real world for a particular set of purposes. GIS has capability of efficient storage, retrieval, integration, manipulation, updating and changing, managing and exchanging, combining, analyzing, and presenting of geographical and non-geographical information. GIS technology can be used for scientific investigations, resources management, asset management, environmental impact assessment, urban planning, cartography, criminology, history, sales, marketing, and logistics, etc.

4.1 Components of GIS

Actually GIS is quoting its power and comprehensiveness from its strong components, mainly have five components, which are: hardware, software, data, people, and procedures.

4.1.1 Hardware

GIS needs many types of hardware to satisfy some of its main functions such as data collection, storage, manipulation, and presentation. The heart of GIS is the computer which can be a personal computer (PC) or a workstation depending on the volume of the GIS projects and the organization. Input units mainly the keyboard and the mouse, the output units such as the monitor. Many types of devices are attached to the computer as input devices such as scanners, cameras, digitizers, and many others. Also printers and plotters of different sizes are attached to the computer as output devices. Networks hardwares, such as modems, cables, hubs, bridges and other networks devices, are utilized in GIS to share data, software, and hardware.

4.1.2 Software

Several comprehensive software systems are developed and fully support GIS applications. GIS has benefited greatly from the rapid, continuous development in the software systems, Many organizations and companies concerned with GIS had developed softwares to satisfy different functions of GIS such as those developed by The Environmental Systems Research Institute (ESRI): Arcview, Arcinfo and ArcGis. ArcGis is composed of many modules such as ArcMap, ArcCatalogue, ArcToolbox, ArcReader, ArcGlobe, and ArcScene. These modules are functioning in a integrating manner for capturing, managing, manipulating, displaying, and analyzing spatial data. There are many other GIS softwares such as Geographic Resources Analysis Support System (GRASS) which had been developed by U.S Army Construction Engineering Research Laboratories (USACERL). Also Intergraph's Modular GIS Environment (MGE) and many other systems.

4.1.3 Data

The efficiency of any GIS scheme depends on the quantity and the quality of data.The expected results of analysis are affected directly by the availability, accessibility, reliability, validity, integrity, and completeness of data. Data must be classified in several classes and all data of a particular level of classification, such as roads or vegetation type are grouped into layers or coverages. Layers can be combined to each other in various ways to create new layers that are a function of individual ones. Data collection and processing is the most expensive part of GIS. There are two main types of GIS data: spatial or geographical data and non-spatial data or attributes.

4.1.3.1 Spatial Data

Spatial data describes the absolute or relative location of geographic features, it is the graphical representation of the geographic locations in a digital form, and it can be classified into two basic data models: raster data model and vector data model. Raster data model, known also as a grid model is a mathematical model. It is a set of grid of uniform, regular cells. The cell is called pixel which refers to a picture element usually it is rectangular or square but it may be triangular or hexagonal. The main sources of raster data models are satellite imageries, aerial photographs and digital image scan of existed maps. Vector data model is: representation of the geographical phenomena in terms of the spatial components, consisting of points, lines, areas, surfaces and volumes and each layer in the vector data model must be composed of only one component. The point is an object of zero dimensions called node or vertex. Line is the link between two points which has one dimension called link or arc, while area has two dimensions and composed of at least two arcs called polygon or face. The geometrical relationships and connections between objects are controlled by Topology independent of their coordinates. Topology model is based on mathematical graph theory that deals with the geometrical properties and employs nodes and links.

4.1.3.2 Attributes

Attributes are non-graphic data that describe properties of the geographic features or elements represented on the map. Attributes are stored in a table in a manner that each record or row in the table corresponds to geographic object on the map, whereas each property is stored in a column or a field. Each object must have an identity (ID) or access key. The number of columns representing the properties is not limited, but is optionally selected due to the available attributes. The number of columns may be extended by joining several tables automatically using a common field. The first line or row in the attributes table contains the name of the field which must not exceed ten characters, the data of each field must be of the same type of characters and the type can be short integer, long integer, float, double, text and date.

4.1.4 People

Different levels of people from different disciplines are involved to establish GIS project or organization. People involved in GIS team depend on the capacity of the organization and the nature of the GIS project, GIS team may include GIS experts, who advise and solve problems for end users, cartographers, system analysts, computer specialists and people specialized in the field of the project in question e.g. geologists, agriculturists, engineers. GIS team also include end users, who seek problem solutions and see final products only in the form of maps and reports, GIS operators of low level of experience who understand the functions of specific system so as to manipulate data and data compilers, who understand the data but not the system.

4.1.5 Procedures

Procedures include how the data will be retrieved, input into the system, stored, managed, transformed, analyzed, and finally presented in a final output. The procedures are the step taken to answer the question needs to be resolved. The ability of a GIS to perform spatial analysis and answer these questions is what differentiates this type of system from any other information systems. The transformation processes includes such tasks as adjusting the coordinate system, setting a projection, correcting any digitized errors in a data set, and converting data from vector to raster or raster to vector (Carver, 1998).

4.2 Functionalities of GIS

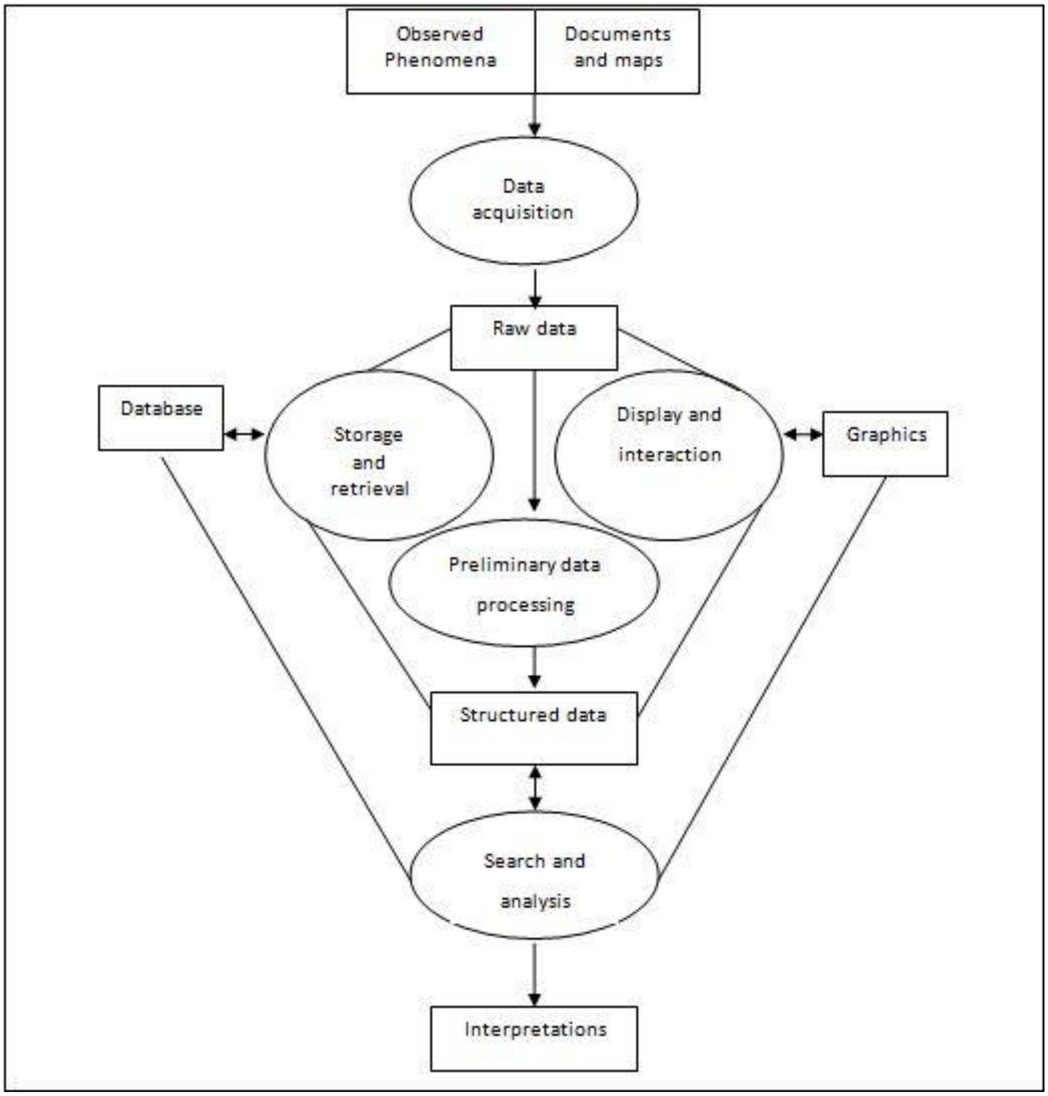

Figure 4.1: Relationship between GIS functions

(Christopher B. Johns 1988)

4.3 Model builder

Model Builder is an application use to create, edit, and manage models. Models are workflows that string together sequences of geo processing tools, feeding the output of one tool into another tool as input. Model Builder can also be thought of as a visual programming language for building workflows. Design of workflow of planning process with fixed tools and variable data.

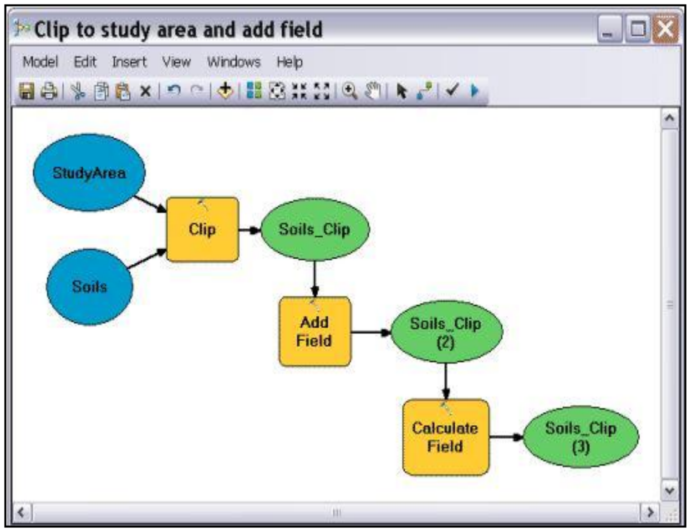

Figure 4.2: Simple model builder

While Model Builder is very useful for constructing and executing simple workflows, it also provides advanced methods for extending Arc GIS functionality by creation and sharing the models as tool. Model Builder can even be used to integrate Arc GIS with other applications. An example is Figure(4.3) .

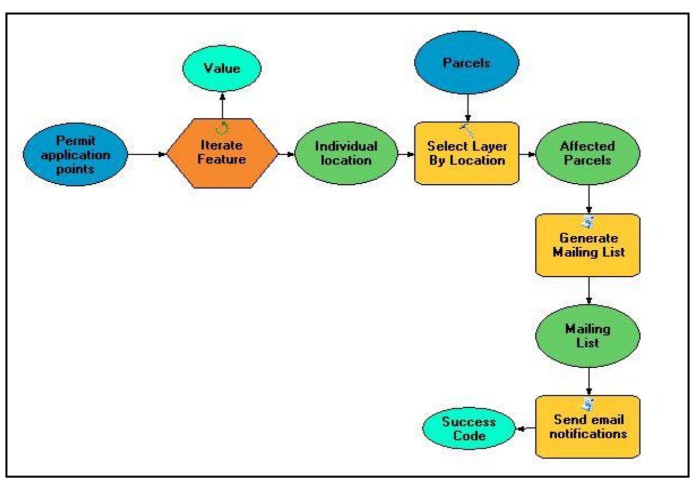

Figure 4.3: Advanced model builder

4.3.1 Benefits of model Builder

The benefits of Model Builder can be summarized as follows:

- Model Builder is an easy-to-use application for creating and running workflows containing a sequence of tools.
- You can create your own tools with Model Builder. Tools you create with Model Builder can be used in Python scripting and other models.
- Model Builder, along with scripting, is a way for you to integrate Arc GIS with other applications.

4.3.2 Model elements

Model elements are the basic building blocks of models. There are three types:

4.3.2.1 Tools: Geo processing tools are the basic building blocks of workflows in a model. Tools perform various operations on geographic or tabular data. When tools are added to a model, they become model elements.

4.3.2.2 Variables: Variables are elements in a model that hold a value or a reference to data stored on disk. There are two types of variables:

- **Data:** Data variables are model elements that contain descriptive information about data stored on disk. Properties of data that are described in a data variable include field information, spatial reference, and path.

- **Values:** Value variables are values such as strings, numbers, Booleans (true/false values), spatial references, linear units, or extents. Value variables contain anything but references to data stored on disk.

4.3.2.3 Connectors: Connectors connect data and values to tools. The connector arrows show the direction of processing. There are four types of connectors:

- **Data:** Data connectors connect data and value variables to tools.

- **Environment:** Environment connectors connect a variable containing an environment setting (data or value) to a tool. When the tool is executed, it will use the environment setting.

- **Precondition:** Precondition connectors connect a variable to a tool. The tool will execute only after the contents of the precondition variable are created.

- **Feedback:** Feedback connectors connect the output of a tool back into the same tool as input.

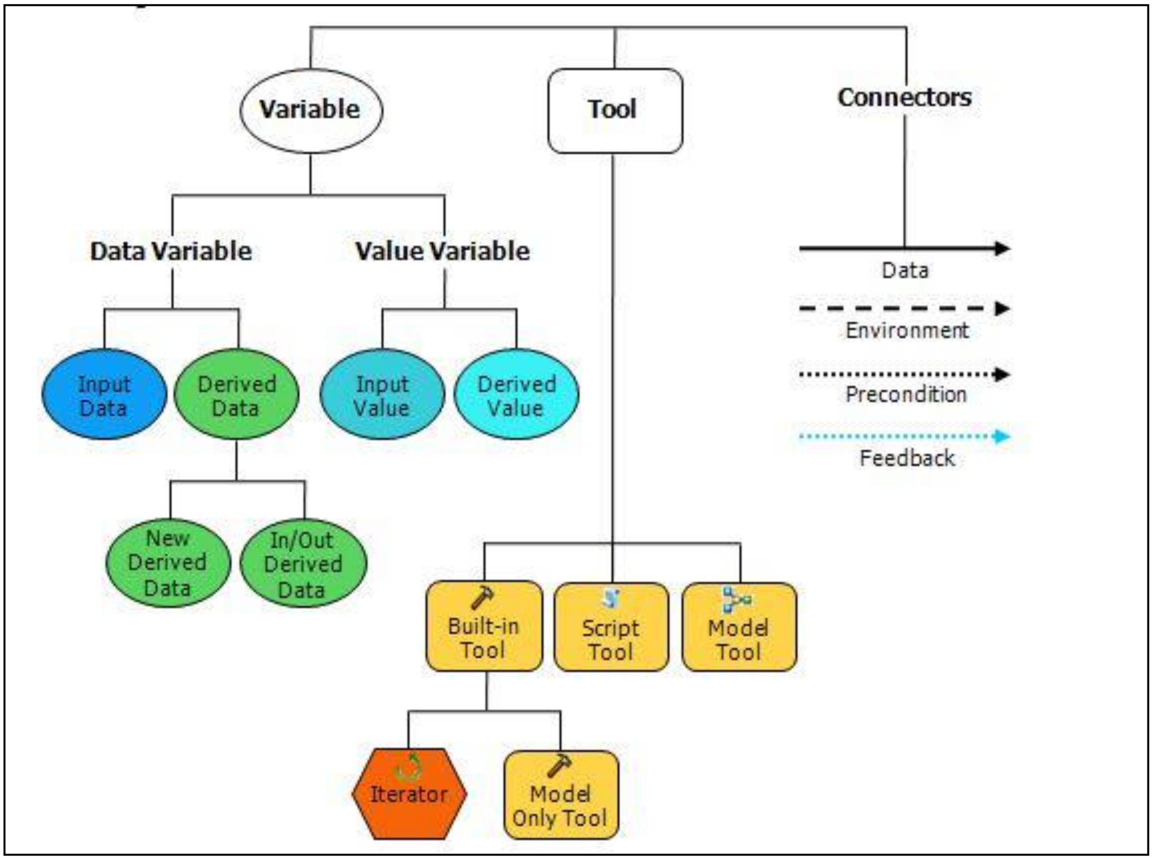

Figure 4.4: How model elements are classified in Model Builder

CHAPTER FIVE

METHODOLOGY AND RESULS

5.1 Study area

The study area is Merowe reservoir, which is located North of Khartoum State in Northern State , located between latitude(19° 30' 29.26"& 19° 16' 26.30")**N** and longitude (33° 7' 45.40"& 32° 43' 44.33")**E** .

Figure 5.1 : Study area

The geodetic reference points on the right bank of Merowe dam (had been established by Dam Implementation Unit (DIU) in 2007) were used as a reference points. Leica GPS system 1200 and Navisound were used to define the coordinate and the depth on the boat.

5.2 Data collection

The echo sounder and GPS were used to collect data , and thereafter AHYPACK software was used for data processing. The survey work from Abohamed to south west of Abohamed along twelve kilometers(entrance of the Merowe reservoir).

The total number of the cross-sections which had been measured in this survey is twelve cross-section during two different years (2011) &(2012).

Table(5.1) : List of control point(Adindan Sudan Zone 36N)

PT	E(m)	N(m)	Height(m)
1	511970.710	2160602.915	315.960
2	506934.433	2159976.375	313.317
3	502157.775	2158891.189	316.072
4	499289.598	2154855.035	311.395

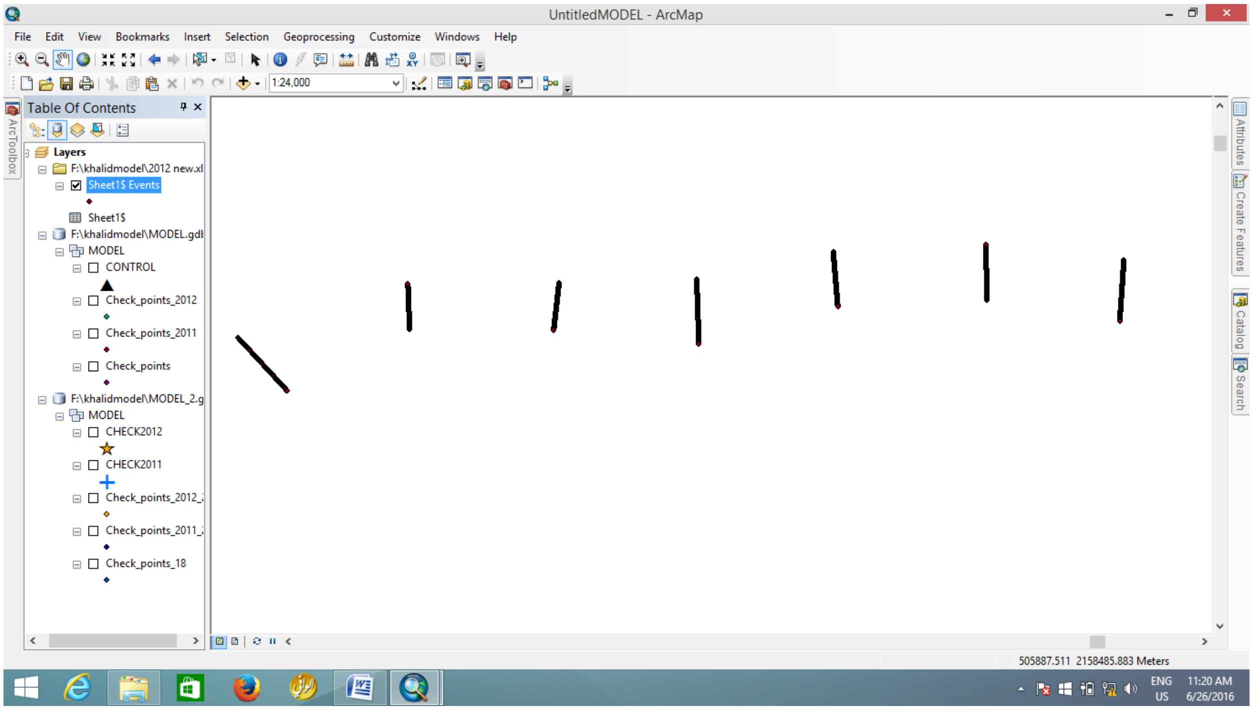

Figure 5.2 : Sample of measured points(cross -section)

5.3 Bathymetric survey team

The following equipment were used to collect data:-

1- Field Laptop

2- License of HYPACK software

3- Navisound 210

4- Leica RTK GPS system1200

5- Garmin Navigator GPS

6- Zodiac Boat with 40 HP Engine

7- Two cars

5.4 Methodology of Survey Work

A geodetic network had been established in around Merowe reservoir on both sides in 2007 by (DIU). Only the control points on the right bank of Merowe reservoir were used in the bathymetric survey. The control points had been established with five Km spacing. This network had been used as a reference for the survey work.

5.4.1 Coordinate system

The local coordinate system Adindan Sudan had been used in the survey.

5.5 Echo Sounder Test and Calibration

Standard check test and calibration had been carried out for the above echo sounder before starting the bathymetric survey.

The main objective of this calibration had been to eliminate the error in depth measurement due to:

1. Variation of sound velocity in water column.
2. The index error.

The sound velocity is variable; it is a function of, temperature, salinity and pressure. These three factors (mainly density) vary with the depth through the water column..

In rivers, where the water column, is not deep, the water is well mixed. Therefore there is a very little chance for sound variation error in the river. The main error here is believed to be an index error.

The Eco-sounder had been calibrated using steel rod which indicated an index error 5cm about.

Correction of sound speed according to the water temperature had been done in the HYPACK software during the processing.

5.6 Bathymetric survey

The whole bathymetric survey work had been carried out using inflatable zodiac boat. The boat has a very small draft, so it can navigate in the shallow water close to the shores. The survey boat had been equipped with one unit of Leica GPS system 1200 working as Rover. The GPS receives correction from another Leica GPS system 1200 working as Station installed on the control point on the right bank of the reservoir. The communication of the units is done through a radio system. The GPS on the boat (Rover) had been received the correction and sended the corrected coordinate to the computer through RS232 connection.

The eco-sounder (Navisound) had been attached to the left side of the boat . The eco-sounder measures the raw depth and sends it to the computer.

The boat had been equipped with a tough field Laptop receiving the data from the GPS and the eco-sounder through two serial boards.

5.7 Data acquiring

HYPACK version 6.2b had been installed on the laptop and had been used in acquiring the data during the survey. The software had been collected and synchronized the data from the GPS and the eco-sounder. The software also offers the orientation of the boat on the predefined cross-section during the survey. A very high skilled boat driver had been encharged to insure keeping the boat on the planned lines.

The software had been stored the surveyed cross-sections on a raw data files. The raw data files had been checked day by day to make sure that all the cross-sections had been properly measured.(3773 points had been measured in (2011)) & (4036 points in 2012).

5.8 Bias display

The processing of the survey data had been done in the same software (HYPACK). For final production of the profiles and the following steps had been done:

- Screening the raw data and removing the biased data acquired by the eco-sounder to the GPS and applying the sound correction. Calculating the final elevation of the river bed. The edited cross-sections in this step are stored in a new folder called (edit).

Figure 5.3: Bias display

- The stored data during the survey is of a large a mount. More that three points per second had been stored. To reduce the amount of data and make it flexible the editing of the cross-section the edited data had been sorted with one meter distance between the sounding. The software stores the sorted data in xyz formal.
- The sorted data had been remapped on the planned lines. The remapped data is stored in the edited folder.

To have the final data projected on the planned lines the remapped data had been snapped on the planned lines.

Water level has been measured and calculate reduce level of river bed depend on the depth measurement .

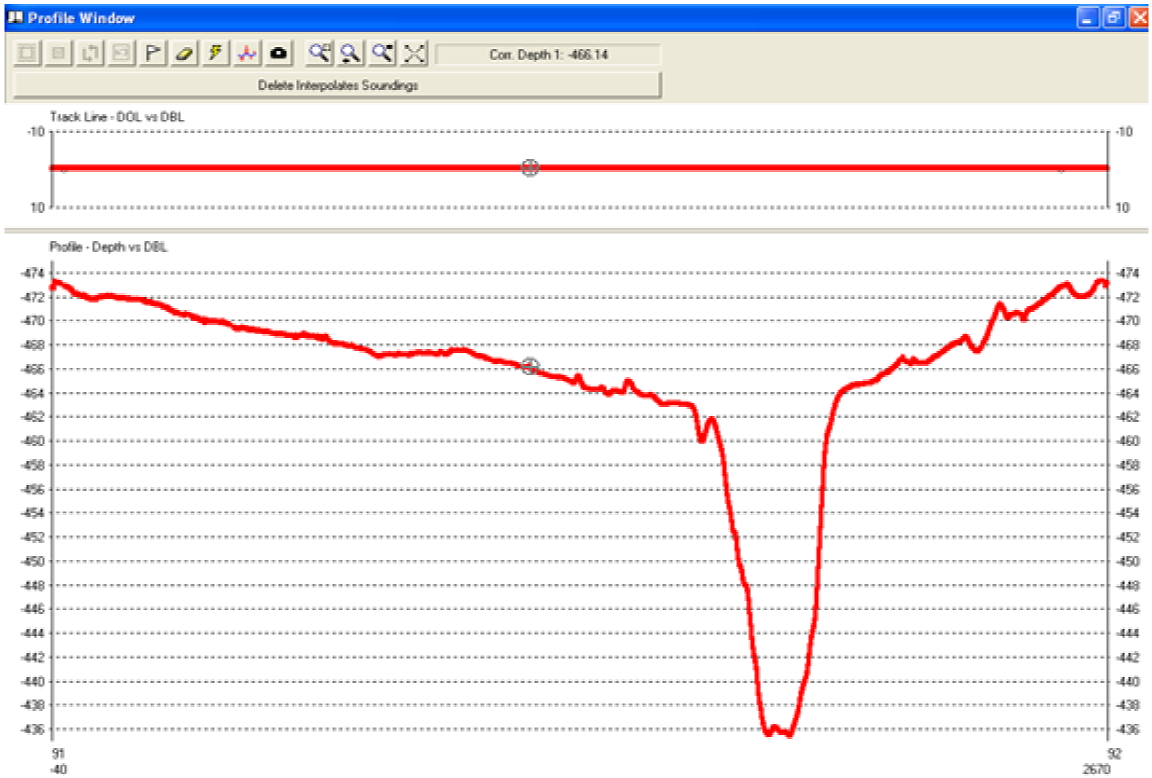

Figure 5.4: Sample of cross-section after final editing

- Finally the cross-sections had been exported from the remapped and snapped data. The profile had been exported in (E,N,H) format.
- Two data(E,N,H) sets had been obtained in (2011 &2012).

5.9 Modelling

Two models were prepared from the data at hand to test the possibility of interpolation ,instead of this amount of field work, together with carrying statistical tests for comparison.

5.9.1 Geographic Information System Modelling

Three linear interpolation equations had been used to estimate the depth value and to establish the model .

Taken apart of data in (2011) because it had large amount of data as follow: The value of depth had given as follow calculated depth (D _cal) and the difference with observed depth(DIFF) on table (5.2):

Table (5.2):The calculation of depth(D_CAL) used GIS model and the different(DIFF) between it and observed depth (D)

OBJECTI	SHAPE	E	N	D	D_CAL	DIFF
1	Point	59622.44	2158823.68	287.35	301.124	13.774
2	Point	509624.6	2158574.16	292.22	301.335	9.115
3	Point	508606.67	2158865.32	287.41	300.872	13.462
4	Point	508590.3	2158623.4	288.85	301.072	12.222
5	Point	507653.96	2158976.09	289.03	300.575	11.545
6	Point	507660.18	2158762.16	289.11	300.756	11.646
7	Point	506596.7	2158948.27	285.2	300.372	15.172
8	Point	506615.6	2158721.45	288.55	300.567	12.017
9	Point	505642.25	2158758.59	289.39	300.327	10.937
10	Point	505652.07	2158474.57	288.43	300.568	12.138
11	Point	504675.54	2158756.45	287.78	300.122	12.342
12	Point	504648.45	2158519.43	287.45	300.315	12.865
13	Point	503630.46	2158768.62	280.02	299.888	19.868
14	Point	503639.19	2158535.7	287.63	300.086	12.456
15	Point	502471.91	2158401.4	288.78	299.949	11.169
16	Point	502726.09	2158127.36	294.4	300.233	5.833
17	Point	501996.2	2157520.49	276.54	300.587	24.047
18	Point	502146.39	2157441.45	276.96	300.686	23.726
19	Point	500975.15	2155820.11	275.41	301.798	26.388
20	Point	500979.23	2155816.99	274.22	301.801	27.581
21	Point	499591.49	2154412.21	278.57	302.685	24.115
22	Point	499593.73	2154411.62	278.72	302.686	23.966
23	Point	499152.75	2152461.07	286.17	304.231	18.061
24	Point	499275.75	2152418.55	289.1	304.293	15.193

The standard deviation of the difference = 6.065 m

The value of depth had given as follow calculated depth (D_cal1) and the difference between depth (DIFF1) on table (5.3):

Table (5.3): The calculation of depth(D_CAL1) used GIS model and the different(DIFF1) between it and observed depth (D)

OBJECTI	SHAPE *	E	N	D	D_CAL1	DIFF1
1	Point	509622.44	2158823.68	287.35	300.509	13.159
2	Point	509624.6	38574.16	292.22	300.648	8.428
3	Point	508606.67	2158865.32	287.41	300.486	13.076
4	Point	58590.3	2158623.4	288.85	300.62	11.77
5	Point	507653.96	2158976.09	289.03	300.424	11.394
6	Point	507660.18	2158762.16	289.11	300.543	11.433
7	Point	506596.7	2158948.27	285.2	300.439	15.239
8	Point	506615.6	2158721.45	288.55	300.566	12.016
9	Point	505642.25	2158758.59	289.39	300.545	11.155
10	Point	505652.07	2158474.57	288.43	300.703	12.273
11	Point	504675.54	2158756.45	287.78	300.546	12.766
12	Point	504648.45	2158519.43	287.45	300.678	13.228
13	Point	503630.46	2158768.62	280.02	300.539	20.519
14	Point	503639.19	2158535.7	287.63	300.669	13.039
15	Point	502471.91	2158401.4	288.78	300.744	11.964
16	Point	502726.09	2158127.36	294.4	300.896	6.496
17	Point	501996.2	2157520.49	276.54	301.234	24.694
18	Point	502146.39	2157441.45	276.96	301.278	24.318
19	Point	500975.15	2155820.11	275.41	302.18	26.77
20	Point	500979.23	2155816.99	274.22	302.182	27.962
21	Point	499591.49	2154412.21	278.57	302.963	24.393
22	Point	499593.73	2154411.62	278.72	302.963	24.243
23	Point	499152.75	2152461.07	286.17	304.049	17.879
24	Point	499275.75	2152418.55	289.1	304.072	14.972

The standard deviation = 6.215 m

The value of depth had given as follow calculated depth (D_cal2) and the difference between observed depth (DIFF2) on table (5.4):

Table (5.4): The calculation of depth(D_CAL2) used GIS model and the different(DIFF2) between it and observed depth (D)

OBJECTI	SHAPE *	E	N	D	D_CAL2	DIFF2
1	Point	509622.44	2158823.68	287.35	301.669	14.319
2	Point	509624.6	2158574.16	292.22	300.848	8.628
3	Point	508606.67	2158865.32	287.41	301.594	14.184
4	Point	508590.3	2158623.4	288.85	300.893	12.043
5	Point	507653.96	2158976.09	289.03	301.674	12.644
6	Point	507660.18	2158762.16	289.11	301.137	12.027
7	Point	506596.7	2158948.27	285.2	301.349	16.149
8	Point	506615.6	2158721.45	288.55	300.876	12.326
9	Point	505642.25	2158758.59	289.39	300.792	11.402
10	Point	505652.07	2158474.57	288.43	300.304	11.874
11	Point	504675.54	2158756.45	287.78	300.629	12.849
12	Point	504648.45	2158519.43	287.45	300.309	12.859
13	Point	503630.46	2158768.62	280.02	300.467	20.447
14	Point	503639.19	2158535.7	287.63	300.251	12.621
15	Point	502471.91	2158401.4	288.78	300.096	11.316
16	Point	502726.09	2158127.36	294.4	299.946	5.546
17	Point	501996.2	2157520.49	276.54	299.833	23.293
18	Point	502146.39	2157441.45	276.96	299.757	22.797
19	Point	500975.15	2155820.11	275.41	300.36	24.95
20	Point	500979.23	2155816.99	274.22	300.357	26.137
21	Point	499591.49	2154412.21	278.57	302.665	24.095
22	Point	499593.73	2154411.62	278.72	302.662	23.942
23	Point	499152.75	2152461.07	286.17	304.974	18.804
24	Point	499275.75	2152418.55	289.1	304.723	15.623

The standard deviation =5.731 m

The same steps had been followed in 2012 the values shown on table(5.5) as follows:

Table (5.5): The calculation of depth(D_CAL) used GIS model and the different(DIFF) between it and observed depth (D) (2012)

OBJECTI	SHAPE *	E	N	D	D_CAL	DIFF
1	Point	509622.41	2158823.68	287.71	313.739	26.029
2	Point	509624.59	2158574.16	291.71	313.503	21.793
3	Point	508606.36	2158865.32	287.4	313.93	26.53
4	Point	508589.15	2158623.4	289.73	313.704	23.974
5	Point	507653.92	2158976.09	288.72	314.177	25.457
6	Point	507658.75	2158827.22	285.3	314.035	28.735
7	Point	506596.93	2158575.91	285.97	313.956	27.986
8	Point	506615.51	2158860.77	288.91	314.222	25.312
9	Point	505641.76	2158606.43	289.91	314.127	24.217
10	Point	505653.26	2158440.27	290.2	313.969	23.769
11	Point	504673.07	2158734.91	287.47	314.393	26.923
12	Point	504653.4	2158562.8	278.08	314.233	36.153
13	Point	503632.05	2158726.23	284.12	314.54	30.42
14	Point	503638.77	2158546.9	287.36	314.369	27.009
15	Point	502476.34	2158396.62	286.4	314.401	28.001
16	Point	502710.75	2158143.9	294.18	314.127	19.947
17	Point	502024.62	2157505.53	284.87	313.627	28.757
18	Point	502072.75	2157480.2	272.94	313.595	40.655
19	Point	500877.77	2155896.46	284.67	312.278	27.608
20	Point	500996.75	2155800.62	273.8	312.17	38.37
21	Point	499557.1	2154421.35	277.96	311.082	33.122
22	Point	499636.54	2154401	282.44	311.051	28.611
23	Point	499036.12	2152518.21	288.72	309.362	20.642
24	Point	499237.56	2152447.56	287.47	309.266	21.796

The standard deviation =5.233 m

Table (5.6): The calculation of depth(D_CAL1) used GIS model and the different(DIFF1) between it and observed depth (D) (2012)

OBJECTI	SHAPE *	E	N	D	D_CAL1	DIFF1
1	Point	509622.41	2158823.68	287.71	314.348	26.638
2	Point	509624.59	2158574.16	291.71	314.181	22.471
3	Point	508606.36	2158865.32	287.4	314.375	26.975
4	Point	508589.15	2158623.4	289.73	314.214	24.484
5	Point	507653.92	2158976.09	288.72	314.449	25.729
6	Point	507658.75	2158827.22	285.3	314.35	29.05
7	Point	506596.93	2158575.91	285.97	314.182	28.212
8	Point	506615.51	2158860.77	288.91	314.372	25.462
9	Point	505641.76	2158606.43	289.91	314.203	24.293
10	Point	505653.26	2158440.27	290.2	314.092	23.892
11	Point	504673.07	2158734.91	287.47	314.288	26.818
12	Point	504653.4	2158562.8	278.08	314.174	36.094
13	Point	503632.05	2158726.23	284.12	314.283	30.163
14	Point	503638.77	2158546.9	287.36	314.163	26.803
15	Point	502476.34	2158396.62	286.4	314.063	27.663
16	Point	502710.75	2158143.9	294.18	313.894	19.714
17	Point	502024.62	2157505.53	284.87	313.468	28.598
18	Point	502072.75	2157480.2	272.94	313.451	40.511
19	Point	500877.77	2155896.46	284.67	312.394	27.724
20	Point	500996.75	2155800.62	273.8	312.33	38.53
21	Point	499557.1	2154421.35	277.96	311.409	33.449
22	Point	499636.54	2154401	282.44	311.396	28.956
23	Point	499036.12	2152518.21	288.72	310.139	21.419
24	Point	499237.56	2152447.56	287.47	310.092	22.622

The standard deviation =5.108 m

Table(5.7): The calculation of depth(D_CAL2) used GIS model and the different(DIFF2) between it and observed depth (D) (2012)

OBJECTI	SHAPE *	E	N	D	D_CAL2	DIFF2
1	Point	509622.41	2158823.68	287.71	281.219	-6.491
2	Point	509624.59	2158574.16	291.71	275.823	-15.887
3	Point	508606.36	2158865.32	287.4	286.696	-0.704
4	Point	508589.15	2158623.4	289.73	281.969	-7.761
5	Point	507653.92	2158976.09	288.72	293.014	4.294
6	Point	507658.75	2158827.22	285.3	290.268	4.968
7	Point	506596.93	2158575.91	285.97	290.966	4.996
8	Point	506615.51	2158860.77	288.91	295.591	6.681
9	Point	505641.76	2158606.43	289.91	296.187	6.277
10	Point	505653.26	2158440.27	290.2	293.646	3.446
11	Point	504673.07	2158734.91	287.47	302.682	15.212
12	Point	504653.4	2158562.8	278.08	300.489	22.409
13	Point	503632.05	2158726.23	284.12	307.499	23.379
14	Point	503638.77	2158546.9	287.36	305.389	18.029
15	Point	502476.34	2158396.62	286.4	309.795	23.395
16	Point	502710.75	2158143.9	294.18	306.018	11.838
17	Point	502024.62	2157505.53	284.87	304.258	19.388
18	Point	502072.75	2157480.2	272.94	303.705	30.765
19	Point	500877.77	2155896.46	284.67	300.801	16.131
20	Point	500996.75	2155800.62	273.8	298.987	25.187
21	Point	499557.1	2154421.35	277.96	306.258	28.298
22	Point	499636.54	2154401	282.44	305.211	22.771
23	Point	499036.12	2152518.21	288.72	305.043	16.323
24	Point	499237.56	2152447.56	287.47	301.701	14.231

The standard deviation =12.109 m

5.9.2 Mat lab model

Use artificial neural network technique in mat lab to compare with model which had been created by GIS.

Input and output had been selected in program :

input = input

target= output

then selected percentages of training and validation and testing:

training= 70%

validation= 15%

testing=15%

after that running processing

in 2011 the result is:

Table (5.8):The calculated of depth and the different between it and the observed depth in artificial neural network by mat lab software (2011)

PT	E(m)	N(m)	Depth(observed) (m)	Depth(calculated) (m)	Diff(m)
1	509622.44	2158823.68	287.350	287.291	0.058
2	509624.6	2158574.16	292.220	292.202	0.017
3	508606.67	2158865.32	287.410	286.859	0.550
4	508590.3	2158623.4	288.850	287.439	1.410
5	507653.96	2158976.09	289.030	287.627	1.402
6	507660.18	2158762.16	289.110	289.260	-0.150
7	506596.7	2158948.27	285.200	286.056	-0.856
8	506615.6	2158721.45	288.550	288.542	0.007
9	505642.25	2158758.59	289.390	289.294	0.095
10	505652.07	2158474.57	288.430	293.217	-4.787

11	504675.54	2158756.45	287.780	288.207	-0.427
12	504648.45	2158519.43	287.450	287.864	-0.414
13	503630.46	2158768.62	280.020	280.356	-0.336
14	503639.19	2158535.7	287.630	287.738	-0.108
15	502471.91	2158401.4	288.780	284.652	4.127
16	502726.09	2158127.36	294.400	294.335	0.064
17	501996.2	2157520.49	276.540	276.529	0.010
18	502146.39	2157441.45	276.960	277.009	-0.049
19	500975.12	2155820.11	275.410	274.094	1.315
20	500979.23	2155816.99	274.220	274.297	-0.077
21	499591.49	2154412.21	278.570	278.125	0.444
22	499593.73	2154411.62	278.720	278.252	0.467
23	499152.75	2152461.07	286.170	286.145	0.024
24	499275.75	2152418.55	289.100	289.058	0.041

The standard deviation = 1.433 m

In 2012 the result is:

Table (5.9):The calculated depth and the different between it and the observed depth in artificial neural network by mat lab software (2012)

PT	E(m)	N(m)	Depth(observed) (m)	Depth(calculated) (m)	Diff(m)
1	509622.41	2158827.22	287.710	288.427	-0.717
2	509624.59	2158575.91	291.710	292.734	-1.024
3	508606.36	2158860.77	287.400	287.771	-0.371
4	508589.15	2158606.43	289.730	290.143	-0.413
5	507653.92	2158977.55	288.720	287.493	1.226
6	507658.75	2158811.19	285.300	288.160	-2.860

7	506596.93	2158945.5	285.970	287.030	-1.060
8	506615.51	2158722.51	288.910	287.855	1.054
9	505641.76	2158772.77	289.910	286.296	3.613
10	505653.26	2158440.27	290.200	288.292	1.907
11	504673.07	2158734.91	287.470	283.498	3.971
12	504653.4	2158562.8	278.080	284.679	-6.599
13	503632.05	2158726.23	284.120	284.640	-0.520
14	503638.77	2158546.9	287.360	286.492	0.867
15	502476.34	2158396.62	286.400	282.683	3.716
16	502710.75	2158143.9	294.180	290.074	4.105
17	502024.62	2157505.53	284.870	272.725	12.144
18	502072.75	2157480.2	272.940	274.744	-1.804
19	500877.77	2155896.46	284.670	284.440	0.229
20	500996.75	2155800.62	273.800	286.465	-12.665
21	499557.1	2154421.35	277.960	282.255	-4.295
22	499636.54	2154401	282.440	282.850	-0.410
23	499036.12	2152518.91	288.720	288.017	0.702
24	499237.56	2152447.56	287.470	288.198	-0.728

The standard deviation = 4.434 m

5.10 Results

The root mean square error (RMSE) was used for comparing and the following results were obtained:

Table (5.10): Standard deviation of (2011) data using different percentages (Training& Validation& Testing)

Training	Validation	Testing	Standard deviation (m)
70%	10%	20%	**1.451**
70%	20%	10%	**1.606**
70%	15%	15%	**1.610**
75%	10%	15%	**1.619**
75%	15%	10%	**1.845**
80%	10%	10%	**2.064**
60%	20%	20%	**1.796**

The value in percentage (training70% & validation10% & testing 20%) = **1.451 m** is the best one.

Table (5.11): Standard deviation of (2012)data using different percentages (Training& Validation& Testing)

Training	Validation	Testing	Standard deviation (m)
70%	10%	20%	**1.360**
70%	20%	10%	**0.801**
70%	15%	15%	**1.334**
75%	10%	15%	**1.112**
75%	15%	10%	**1.428**
80%	10%	10%	**1.457**
60%	20%	20%	**1.159**

The value in percentage (training 70% & validation 20% & testing 10%) = **0.801 m** is the best one.

CHAPTER SIX

CONCLUSION AND RECOMMENDATIONS

6.1 Conclusion

After analyzing data at hand with the comparison the following can be calculated :

- The best value for standard deviation in geographic information system model is = 5.731 m (in 2011 year).
- The best value for standard deviation in geographic information system model is = 5.108 m (in 2012 year).
- The best value for standard deviation in Artificial neural networks under mat lab software is = 1.451m (in 2011 year).
- The best value for standard deviation in Artificial neural networks used by mat lab software is = 0.801m (in 2012 year).
- It's found that artificial neural networks gives better results for the height estimation .
- Random seed values have the major effect on the networks' precision.
- Precision results obtained from artificial neural networks it depend on:

- Percentages of(training& validation& testing).

- Selection of percentages of(training& validation& testing) based on surface.

- number of iterations .

- High precision results could be obtained by increasing the size of the random seed and the number of iterations.

- The software has two problems ,The first is the complexity and the second is there is no three dimensional representation for the surfaces.

6.2 Recommendations

- Use separate software for artificial neural networks for example (Alyuda Neuro Intelligence).
- For surveyors the three dimensional representation to make the software more suitable.

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