

EVALUATION OF REMOTE SENSING BASED LAKE BATHYMETRY
FOR SEDIMENT YIELD ESTIMATION: THE CASE STUDY OF LAKE
HAWASSA.

By

Abdi Tadesse Gute



A Thesis Submitted to the Department of Geomatics Engineering, School of
Civil Engineering and Architecture

Presented in Partial Fulfillment of the Requirements for the Degree of
Master's in Geo-Informatics Engineering

Office of Graduate Studies

Adama Science and Technology University

Adama, Ethiopia
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APPROVAL OF BOARD OF EXAMINERS

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ACKNOWLEDGMENT

First and foremost, I want to praise, and thanks to Almighty God, the Lord of everything, who is credited with all of the completion of this Thesis work.

This work wouldn't be completed without the assistance of several persons and organizations, all of whom I grateful acknowledgement. I would like to express my sincerest thanks and appreciation to my advisors who indeed contributed to the complement of this study. I would like to deeply acknowledge My Main Advisor Dr. Getachew Brhanemeskel and Co-Advisor Dr. Daniel Alemayehu for their supervision, support, guidance, helping me overcoming the obstacles, and answering all my questions during the time of my Thesis work.

Special thanks to Adama Science and Technology University (ASTU) and Wachemo University for financial support to pursue my studies and related research activities to achieve my research objectives.

I would love to thank also Dr. Yonas Girma (Assistant Professor in Water Resources Engineering and Management at Ethiopian Institute of Water Resources, Addis Ababa University) for sharing to me the bathymetric field survey data of Lake Hawassa of 2011 collected for his Ph.D. Dissertation and Ethiopian Construction Design and Supervision Works Corporation for their kindness and collaboration in providing me the required data for my Thesis work.

Last but not least, with all love and respect I would like to thank my parents, course instructors and friends for their thoughtful encouragement all the time during my thesis work in this difficult time of COVID-19.

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LIST OF ACRONYMS AND ABBREVIATIONS

2D	Two Dimension
3D	Three Dimension
ACRON	Atmospheric CORection NOW
AHDA	Aswan High Dam Authority
ATCOR	Atmospheric CORection
BIL	Band-Interleaved-By-Line
BIP	Band-Interleaved-By –pixel
DBM	Digital Bathymetry Model
DN	Digital Number
DOP	Depth of Penetration
DOS	Dark Object Subtraction
EBK	Empirical Bayesian Kriging
ECDSWC	Ethiopian Construction Design and Supervision Works Corporation
EMR	Electromagnetic Radiation
ENVI	Environment for Visualizing Images
ETM+	Enhanced Thematic Mapper Plus
FLAASH	Fast Line-of-sight Atmospheric Analysis of Spectral Hypercubes
GIS	Geographic Information System
GPS	Global Positioning System
HS	Hyper-Spectral
IDL	Interactive Data Language
IDW	Inverse Distance Weighting
LiDAR	Light Detection and Ranging
LLHM	Localized Linear Histogram Match
LN	Lake Nubia
m.a.s.l	meter above sea level
MAE	Mean Absolute Error
MIR	Middle Infrared
MLR	Multiple Linear Regression
MNDWI	Modified Normalized Difference Water Index
MODTRAN	MODerate resolution atmospheric TRANsmission
MS	Multi-Spectral

NIR	Near Infrared
NDWI	Normalized Difference Water Index
RBF	Radial Basis Function
RS	Remote Sensing
RMSE	Root Mean Square Error
SAR	Synthetic Aperture Radar
SGA	Stratified Genetic Algorithm
SLC	Scan-Line Corrector
SONAR	Sound Navigation and Ranging
TIN	Triangulated Irregular Network
TM	Thematic Mapper
TOA	Top of Atmosphere reflectance
WV-2	WorldView-2
WWDSE	Water Works Design and Supervision Enterprise

ABSTRACT

Sedimentation in Lake Hawassa is a major problem for lake level rise and reduction in storage capacity. To overcome this problem sediment yield estimation plays an important role. In order to estimate the amount of sediment yield, it needs an accurate and continuous bathymetry survey. Moreover, the lack of a continuous bathymetry survey of the lake is a major factor for managing and studying morphometries of the lake. Nowadays, Remote sensing technology had led to overcome this problem if used for depth estimation and applied to sediment yield estimation. However, remote sensing was not implemented before in retrieving the bathymetry of Lake Hawassa. So, the aim of this study was to evaluate the accuracy of depth estimated from remote sensing data and applying to sediment yield estimation. Landsat 7 ETM+ with a resolution of 30 m data was used for depth estimation. While Lyzenga or linear band model were used for depth estimation. Preprocessing activities were made on secondary data to obtain corrected surface reflectance. Corrected reflectance values were log-transformed and Multiple linear regression is carried out by using an input 70% of in-situ measurement and corresponding reflectance values to get depth estimating model parameters for construction. The model performance and accuracy in estimating depth were assessed and validated by quantifying the error between 30% of the in-situ field measured depth not used in model construction and corresponding estimated depths. The result indicates that the correlation coefficient ($R = 0.7$), Mean Absolute Error (MAE = 3.06) and Root Mean Square Error (RMSE = 3.69 m) for testing data set (30% of in-situ depth). The result showed Lyzenga or linear model has less performance in estimating depth less than 5 m and depth greater than 20 m. Moreover, the result was statistically unsatisfactory when the model is calibrated for the whole area at once. Relying on the estimated depths, 3D bed surface of 2011 and for the year 1999 based on generated bed elevation from bed surface topographic maps by three interpolation methods using 50% of bed elevation. The result of statistical indicators for Empirical Bayesian Kriging was (Mean Absolute Error = 0.027 m and Root Mean Square Error = 0.096 m) for the year 1999 and (Mean Absolute Error = 1.069 m and Root Mean Square Error = 1.403 m) for the year 2011 respectively lower than the Inverse Distance Weighting and Radial Basis Function method of interpolation. The result showed Empirical Bayesian Kriging has better performance in generating 3D bed surface of Lake Hawass. Using the two generated 3D bed surface by Empirical Bayesian Kriging, a map of bed changes were created to estimate sediment yield between the years 1999 and 2011. The result of sediment yield estimated between 1999-2011 were 94.1 million m^3 . The sediment yield by the present approach were compared with the in-situ based depth 3D bed surface of the lake. The result showed that the estimated sediment yield relying on the estimated depth by the present approach (from remote sensing data) overestimated the result by 24.1 million m^3 compared to the result derived from the generated 3D bed surface of the lake based on the field measurements. Therefore, the study concludes estimating depth from remote sensing data by applying a linear model for the whole area at once and applying the estimated depth for sediment yield estimation overestimates and gives unsatisfactory result. Finally, the study recommends Lyzenga or linear model could not be used for depth estimation and applied for sediment yield estimation. Additionally, Empirical Bayesian Kriging can yield better accuracy in the generation of the 3D bed surface of Lake Hawassa and can be used in the future.

Key Words: Bathymetry, Lake Hawassa, Lyzenga Model, Remote Sensing, Regression, Sediment Yield.

CHAPTER ONE: INTRODUCTION

1.1. Background of the study

Bathymetry is a method of quantifying depths to study the topography of water bodies, including oceans, seas, rivers, streams, and lakes. Accurate determination of water depth is important both for the purposes of monitoring underwater topography and movement of deposited sediments and for producing nautical charts in support of navigation. Such information is also critical to port facility management, dredging operations, and to predicting channel infill and sediment budgets (Jawak *et al.*, 2015). Until recently, bathymetric surveying of water bodies has been mainly based on conventional ship-borne echo sounding operations. However, this technique demands cost and time, particularly in shallow waters, where a dense network of measured points is required (Doxani *et al.*, 2012). On the other hand, Remote Sensing (RS) data has led to overcoming this depth measurement problem and to be used for a sediment yield estimation.

Drying-up of some lakes in Ethiopia, such as Lake Haromaya in the Eastern part (Tamiru *et al.*, 2007) and Lake Cheleleka in the upstream of Lake Hawassa are among the live examples of the impact of sedimentation on the reduction of storage capacities and then the disappearance of the entire lakes. The problem for the peoples of Hawassa town in the Hawassa watershed is the water level rise of Lake Hawassa, causing parts of the town to flood regularly. One of the main causes of this water level rise is siltation due to gully erosion (Hoogenboom, 2013). On the other hand, recent siltation of Lake Hawassa has been perceived as one of the environmental dangers threatening the lake that can lead to changes in its morphology-which may decrease the water storage capacity that in turn contribute to the rise of the water level. The annual reduction in storage capacity due to the siltation of Lake Hawassa is about 0.08% (Belete, 2013). To overcome the problems created by sediment accumulation in lakes, it has the utmost importance to estimate the sediment yield and its distribution in the lakes. This estimation of the sediment yield needs accurate depth determination. But achieving this task based on field measurements consumes time, money, and effort.

Despite its importance, the in-lake sedimentation of Lake Hawassa has never been monitored because of some perceived reasons such as cost, little awareness about the degree of the problem, and probably due to the absence of an explicitly responsible organization for such activities (Belete, 2013). Moreover, monitoring changes in major

Ethiopian lakes that require frequent bathymetric surveys have always been a challenge due to cost and technology-related limitations. These limitations resulted in fewer researchers dedicated to studying morphometry (Yonas *et al.*, 2018). There is also no bathymetry survey made at a good spatial resolution to better understand the bed topography in previous studies. Additionally, it is observed there is a lack of continuous bathymetry survey data of Lake Hawassa. In some of the previous studies (Belete, 2013; Yonas *et al.*, 2018) bathymetry survey was made at 500 m spacing to prepare bathymetry maps and estimate sediment yield in Lake Hawassa. However, a bathymetry map prepared at 500m spacing may not provide significant insight to study bed topography and estimate sediment amount. On the other hand, remote sensing data had led to overcome this problem if used in sediment yield estimation and verified by field measurements. Optical remote sensing enables one to determine water depth directly from the radiometric properties of the captured image. But it was not implemented on Lake Hawassa to derive bathymetry and applied to estimate sediment yield. And, also the accuracy of deriving bathymetry from RS data and its result on sediment yield estimation is unknown.

During the last decades remotely sensed data have provided a cost- and time-effective solution to sufficiently accurate depth estimation (Lyzenga, 1985; Stumpf *et al.*, 2003; Su *et al.*, 2008). With the advent of Landsat images, the methods of monitoring seafloor were increased, so as to be efficiently applied on optical satellite images (Lyzenga, 1981; Spitzer & Dirks, 1987; Philpot, 1989; Van Hengel & Spitzer, 1991; Doxani *et al.*, 2012). A wide variety of empirical models has been proposed and evaluated for bathymetric estimations by establishing the statistical relationship between image pixel values and field measured water depth values. The actual estimation of bathymetry based on empirical modeling requires proper selection of the sensing wavelength band(s), model construction and validation. The most popular approach of the empirical model was proposed by Lyzenga (1978, 1981, 1985) and was based on the fact that the bottom-reflected reflectance is approximately a linear function of the bottom reflectance and an exponential function of the water depth (Doxani *et al.*, 2012). To account for water quality heterogeneity and depth-independent variability in reflectance values between bands, this algorithm is updated by Lyzenga *et al.*, (2006). The implementation and the accuracy of this process is hindered by different factors such as; the appearance of clouds, sun-glint, the predominant atmospheric conditions and the existence of several kinds of spectral noise.

The aim of this study was to estimate depth using an empirical model updated by Lyzenga *et al.*, (2006) from Landsat 7 ETM+ multispectral bands and evaluating its accuracy and applying it for sediment yield estimation via generating 3D bed surfaces. Particularly, three critical issues were undergone; a) pre-processing topographic maps to generate bed surface elevation for the year 1999 and satellite imagery to remove the effect of the atmosphere, SLC-off gap, and sun-glitter from satellite imagery; b) taking advantage of the multiplicity of the imagery bands to overcome the confrontation of the bottom reflectance variations effects on the bathymetry model; c) depth estimation model construction and performance assessment. Finally, the accuracy of estimated depth by the linear model is evaluated, 3D bed surface was predicted, and sediment yield between the years 1999 and 2011 was estimated by the present approach and compared with sediment yield based on in-situ measurement.

1.2. Statement of the Problem

The problem for the people or dwellers of Hawassa town in the Hawassa watershed is the water level rise of Lake Hawassa, causing parts of the town to flood regularly. One of the main causes of this water level rise is siltation due to gully erosion (Hoogenboom, 2013). On the other hand, recent siltation of Lake Hawassa has been perceived as one of the environmental dangers threatening the lake that can lead to changes in its morphology-which may decrease the water storage capacity that in turn contribute to the rise of the water level. Additionally, sedimentation has undesirable impacts on water quality, storage capacity, recreational value, and natural lake bed habitat of natural and/or artificial lakes. The annual reduction in storage capacity due to the siltation of Lake Hawassa is about 0.08% (Belete, 2013). To overcome the problems created by sediment accumulation in lakes, it has the utmost importance to estimate the sediment yield and its distribution in the lakes. This estimation of the sediment yield needs accurate depth determination. Moreover, repeated bathymetric surveys can provide significant insight into the nature of sedimentation within a reservoir/Lake. Changes in reservoir/Lake bottom topography can be monitored over time to provide an overall estimate of the sediment accumulation rate and spatially explicit representation of sediment accumulation (DeNoyelles and Jakubauskas, 2008) as cited in (Belete, 2013).

Despite its importance, the in-lake sedimentation of Lake Hawassa has never been monitored because of some perceived reasons such as cost, little awareness about the degree of the problem, and probably due to the absence of an explicitly responsible

organization for such activities (Belete, 2013). Moreover, monitoring changes in major Ethiopian lakes that require frequent bathymetric surveys have always been a challenge due to cost and technology-related limitations. These limitations resulted in fewer researchers dedicated to studying morphometries (Yonas *et al.*, 2018). There is also no bathymetry survey made at a good spatial resolution to better understand the bed topography in previous studies. Additionally, it is observed there is a lack of continuous bathymetry survey data of Lake Hawassa. In some of the previous studies (Belete, 2013; Yonas *et al.*, 2018), a bathymetry survey was made at 500 m spacing to prepare a bathymetry map and estimate sediment yield amount in Lake Hawassa. However, the bathymetry map prepared at 500m spacing may not provide significant insight to study bed topography. On the other hand, remote sensing data enables one to determine water depth directly from the radiometric properties of the captured image. This shows Remote Sensing (RS) data has led to overcoming depth measurement problems and can be used for a sediment yield estimation. But it is identified as a gap for the present study that, remote sensing was not implemented previously on Lake Hawassa for depth estimation and the accuracy of estimating depth from RS data by existing empirical models is unknown. Therefore, it is intended to fill this gap by estimating depth from optical remote sensing data using an empirical linear model, evaluating its accuracy, and applying it for sediment yield estimation.

Bathymetry survey through field measurements is constrained by its inefficiency in shallow water and very high operating logistic cost. In comparison, remote sensing technologies present an efficient, faster, and cost-effective means of mapping bathymetry over remote and broad areas. Nowadays, the freely available remote sensing data at spatial resolution from several meters to 30 meters (such as; Landsat) enables us to estimate the depth at good spatial resolution and have significant in-sight to study bed topography. This means, depth can be estimated from RS data at a maximum interval or distance of 30 m, which is labor-intensive and expensive to do by field measurement. This in turn enables us to have better knowledge about bed topography and monitoring the morphometry of the lake with a better result than the previously made field bathymetry survey. Therefore, in order to estimate sediment yield using extracted depth from remote sensing data it needs to know the accuracy and performance of available depth estimation models.

1.3. Objectives

1.3.1. General Objective

To evaluate remote sensing-based Lake Bathymetry for sediment yield estimation, the case study of Lake Hawassa.

1.3.2. Specific Objectives

- To evaluate the accuracy of estimated depth from reflectance values.
- To generate a 3D bed surface of the years 1999 and 2011.
- To estimate sediment yield between 1999 and 2011 based on the generated 3D bed surfaces.

1.4. Research Questions

- What is the accuracy of estimated depths from remote sensing data?
- Which interpolation method is better in the prediction of the 3D bed surface?
- How much is the sediment yield of Lake Hawassa between periods of 1999 and 2011?

1.5. Significance of the study

The final output of this study will provide information for different stakeholders in a way that;

Management sector of the Lake: it will provide the details of retrieving bathymetric information by the present approach (estimation of depth by linear model) and its effect on estimating the sediment yield of the Lake. Moreover, it recommends the interpolation method to generate a 3D profile of the Lake with better performance and accuracy. This may help the management sector to generate a navigational chart of the Lake, Lake Profile, Lake level rise, predict channel infill and sediment budget, monitoring of underground topography and movement of deposited sediment.

Further Researcher: the study provides the fundamental scientific approach of bathymetric mapping, information on the performance of linear or Lyzenga model to retrieve bathymetry of Lake Hawassa and its effect on applying the estimated depth or bathymetry by the present approach in sediment yield estimation. Additionally, it recommends the interpolation method that is better for prediction of 3D bed surface of the lake for those who study; assessment of sedimentation, storage capacity and effect of sedimentation on the storage capacity of the Lake.

1.6. Delimitations and Limitations of the study

The present research was conducted on Lake Hawassa, the southern part of Ethiopia using the 2011 satellite imagery of the area to retrieve bathymetry from remote sensing data and evaluate its accuracy. Statistical analysis was made on estimated depth from reflectance values of Landsat 7 ETM+ multispectral bands to evaluate the performance and accuracy of the empirical model used in this study. Relying on the estimated depth of 2011 and generated bed elevation of 1999, 3D bed surfaces were predicted. The created 3D bed surfaces are used in creating a map of changes in bed levels to estimate sediment yield between 1999 and 2011. To achieve these objectives, this study attempted to see all significant factors that have contributed to retrieving the bathymetry of the lake from remote sensing, evaluating its accuracy, generation of the 3D bed surface and applying it for sediment yield estimation by integrating all possible efforts in acquiring required inputs in the form of secondary data collection, analysis and interpretation of the results, conclude and recommend for further researchers.

However, the study has encountered certain limitations. One of the limitations was the lack of in-situ bathymetry data of the year 1999, which enables to generation 3D bed surface. This limitation was solved by using topographic maps existing in blueprint hardcopy on four A1 paper. The topographic map was line data and was converted into a continuous surface in a raster format that represents bed elevation using ArcGIS Environment.

1.7. Thesis Organization

This thesis is presented into five chapters. The first chapter introduces the proposed topic, remote sensing-based bathymetry retrieval and effect of sediment on Lake Hawassa. It also includes the problem statements, research questions, significances of the study, objectives, delimitations and limitations of the study. The second chapter is literature review. This includes the theoretical framework on the retrieving bathymetry from remote sensing, such as definition, methods and empirical framework which includes previous studies related to this study. Afterwards, chapter 3 has a closer look to the materials and methods. This chapter gives an overview of description of the study area, materials used, data analysis methods and conceptual framework of the study. Results obtained from the data analysis to achieve the objectives of the study follow in chapter 4, together with interpretation of results and discussion. Chapter 5 is the conclusion and recommendations for future studies based on the result of the study.

CHAPTER TWO: LITERATURE REVIEW

A literature review was performed on different methods of bathymetric mapping and estimation of sediment yield. This chapter contains two main parts; theoretical framework and empirical review. Theoretical framework explains about the relevant literature reviewed focusing on the different methods of bathymetric mapping and extraction of bathymetric information from satellite imagery. The choice of these frameworks is based on the notion that theories are fundamental tools in research problems, which facilitate the choice of methodological approaches to be used in studies as well as interpreting the findings (Elvik, 2002). The second part is empirical review concerning the previously made study on detection of bathymetry from satellite imagery and studies that have estimated sediment yield by utilizing remotely detected bathymetry.

2.1. Theoretical Framework

2.1.1. Bathymetry and Bathymetric Mapping

Bathymetry is a method of quantifying depths to study the topography of water bodies, including oceans, seas, rivers, streams, and lakes. Bathymetric information plays an essential role in all branches of oceanography, paleoclimate studies, and marine geology (Jawak *et al.*, 2015).

Bathymetric mapping is the process of making bathymetric maps based upon the depth data. Bathymetric maps represent the water body depth as a function of geographical coordinates, similar to topographic maps representing the altitude of Earth's surface at different geographic coordinates. The most popular type of bathymetric maps is represented by lines of equal depths called isobaths (Clay, 1998).

Accurate determination of water depth is important both for the purposes of monitoring under water topography and movement of deposited sediments, and for producing nautical charts in support of navigation. Such information is also critical to port facility management, dredging operations, and to predicting channel infill and sediment budgets (Gao, 2009).

2.1.2. Methods of Bathymetric Mapping

Bathymetry data are collected in different forms. Traditionally, ocean floor data are collected by measuring the time taken by the laser light, or an acoustic sonar pulse, to travel through the water column to the ocean floor and back, based on the speed of sound in water, sensor characteristics, time, and other variables. Spatial resolution, coverage,

temporal resolution and data type vary among the different bathymetry acquisition systems (Kearns *et al.*, 2010). Nowadays, bathymetry is mapped using echo sounders and the depth datasets are processed to compile nautical charts, shaded relief maps, and digital terrain/bathymetric models. Bathymetric data are generally used to generate navigational charts, 3D models, and seafloor profiles (Jawak *et al.*, 2015).

Bathymetry has been conventionally mapped using vessel-based acoustic echo sounding. This method is able to generate accurate point measurements or depth profiles along transects, but is constrained by inefficiency, expense and inaccessibility. Environmental conditions and technological restraints prevent its applicability to near shore waters (Tronvig, 2005) as shallow coastal waters are hazardous to navigate, especially at low tides. An alternative is to combine shipboard and satellite data to improve bathymetric prediction (Sichoix & Bonneville, 1996). In this 2-D spectral method, bathymetry is predicted from a compensation model with two layers for the crust. This method is disadvantaged by its coarse horizontal resolution of 8 km and poor accuracy of < 300 m. By comparison, the remote sensing method is faster and applicable to various environments, including shallow coastal waters, clear rivers, and the relatively clean riverine reaches in the upper parts of estuaries (Roberts & Anderson, 1999).

2.1.3. Remote Sensing Based Bathymetry

Remote sensing of bathymetry takes several forms, each having its own detection depth, accuracy, strengths, limitations and best application settings. These forms fall into two broad categories: non-imaging and imaging (Table 2.1). The non-imaging method as exemplified by light detection and ranging (LiDAR) detects the distance between the sensor and the water surface/sea floor using a single wave or double waves. It is the lapse of the returned radiation pulses from the target at the sensed spots that are used to generate bathymetric information. By comparison, imaging methods base the estimation of water depth on the pixel values of an image. They make use of the visible light and microwave radiation. On microwave imagery, radar backscatter captures variations in sea surface roughness's that are caused by modulations in the wave spectrum related to surface current velocity. Variations in the current velocity at the sea surface manifest interactions between tidal flow and bottom topography. Although this method is not subject to cloud cover, it is rather complex as numerical instead of analytical inversion is used to derive bathymetry from speckle-infested radar imagery. In addition, its accuracy is rather low as a result of its

vulnerability to wind influences (Table 2.1). Consequently, it has found limited applications in shallow seas and open waters (Gao, 2009).

Unlike microwave sensing, optical imaging is able to determine water depth directly from the radiometric properties of the captured image. One particular form of the imaging methods is video imaging that provides continuous data recording automatically in nearshore waters. It is best deployed in the intertidal zone to map beach bathymetry, and to survey shoreline elevations less than 15 cm. A successful example of the video-based method is the subtidal beach mapper method for estimating nearshore bathymetry (Aarninkhof *et al.*, 2005). As such, it is incapable of applications in offshore waters (Table 2.1). A variant of this method is remote sensing imagery integrated with open-channel flow principles. Such a hydraulically assisted bathymetry technique is suitable for estimating the depth of rivers without the need for in situ depth information at the time of flight (Fonstad & Marcus, 2005).

Airborne optical sensing of bathymetry is by far the most frequently used for a wide range of water bodies, including inland lakes, shallow estuaries, coastal areas, and open seas. This method can be implemented either analytically or empirically. Each implementation has its own strengths and limitations (Gao, 2009).

By comparison with the traditional method, RS method is faster and applicable to various environments, including shallow coastal waters, and clear rivers (Roberts & Anderson, 1999). RS allows modeling of bathymetry at spatial scales that are impossible to achieve with traditional methods. Bathymetry can be estimated using RS by using several techniques, each having its own depth detection capability, accuracy/error/precision, strengths/advantages, drawbacks and best application environment (Gao, 2009). The two broad categories used in remote sensing for deriving bathymetry information are active RS methods and passive RS methods (Jawak *et al.*, 2015). Passive RS methods employ passive sensors, which measure energy that is naturally available, e.g. multispectral or optical satellite sensors. Passive sensors record electromagnetic radiation (EMR) that is reflected (e.g., blue, green, red, and near-infrared light) or emitted (e.g., thermal infrared energy) from the surface of the Earth. However, the use of passive remote sensing for modeling water depth in fluvial environments remains a challenge (Flener *et al.*, 2012).

Table 2.1 Types of non-imaging and imaging systems with their strengths and limitations.

(Source: Jawak *et al.*, (2015))

Method	Sensor	Type	Accuracy	Controlling Factors	Advantages	Drawbacks	Scope of Application
Imaging	Microwave or SAR sensor	Active	Relatively low	Image resolution, slicks, waves, fronts, weather condition	- Applicable over large areas - Unaffected by cloud cover	- Relative low accuracy	Bathymetry derivation from open oceanic waters
Non-imaging	Radar Altimetry	Active	Very low accuracy	Elastic thickness of the lithosphere and/or crustal thickness, sediments	Global coverage, needs only simple altimetry with no iono/tropo-sphere measurement	Possible over a limited wavelength band	Coarse bathymetry derivation for oceans
Non-imaging	LIDAR	Active	≈15 cm	Water clarity or turbidity, bed material, surface state	Wide depth range; concurrent measurement not essential	- Expensive - Limited swath width	Varied aquatic environments of narrow range
Imaging	Optical (analytical)	Passive	Relatively high	Water quality (clarity or turbidity), cloud cover, atmospheric conditions	- Based on physical process - Relatively higher accuracy	- Complex execution as input parameters are required - Real-time <i>in-situ</i> data essential	Turbid and shallow inland waters, estuaries, river channels
Imaging	Optical (empirical)	Passive	Varying accuracy	Atmospheric calibration, water turbidity, bottom reflectance	- Simple to execute - Accurate at definite depth	- Limited depth - Accuracy lower at a larger depth - Real-time ground truth essential	Near shore and coastal waters, open waters
Imaging	Video	Passive	Relatively high	Image resolution	- Capable to produce minor bathymetric change	Restricted area Bathymetry along profiles	Intertidal zone and estuaries

Active sensors, on the other hand, transmit pulses of electromagnetic energy and record the origin and strength of the backscatter received from objects within the system's field of view, e.g. synthetic aperture radar (SAR), and light detection and ranging (LIDAR). Advantages for active sensors include the ability to acquire measurements in all-weather and day and night conditions. Active sensors can be used for examining wavelengths that are not sufficiently provided by the sun, such as microwaves, or to better control the way a target is illuminated. Methods for derivation of bathymetry can also be categorized as non-imaging methods and imaging methods (Table 2.1) (Jawak *et al.*, 2015).

LIDAR and satellite altimetry are the two major non-imaging methods used for bathymetry derivation. LIDAR is elucidated as light detection and ranging, which measures the distance between the sensor and the water surface or an ocean floor using a single wave pulse or double waves. It is the time drift of the returned radiation pulses from the object at the sensed spots, which is eventually used to produce bathymetric information. However, this method is limited by the coarse bathymetric sampling interval and high cost. The conceptual approach employs the sparse depth sounding measurements to restrict the long wavelength depth while the shorter-wavelength topography is envisaged from the downward continued satellite gravity measurements (Smith & Sandwell, 1997).

On the other hand, imaging methods approximate the water depth based on the pixel values or digital numbers (DN) of an image. Imaging methods make use of the visible and/or near infrared (NIR) light and microwave radiation. Radio detection and ranging (radars) are imaging sensors whilst radar altimeters and scatterometers are non-imaging sensors used for bathymetry derivation. Radar satellites use short pulses of electromagnetic radiation (EMR) in the microwave range (10 s or 100 s of GHz), therefore they do not depend on daylight and are unaffected by wind, fog, dust, clouds, and bad weather conditions. These satellites measure the radar pulses reflected from the ground surface, evaluate the signal strength or intensity to recover information on the structure of the earth's surface, and identify the elapsed time between pulse emission and return. In case of microwave imagery, radar observes the backscattered variations from the sea surface, e.g. roughness caused by modulations in the wave spectrum with respect to the surface current (Jawak *et al.*, 2015). Such variations in the current velocity at the ocean surface can be recognized because of interactions between tidal flow and bed topography. Although imaging method using microwave data is not subject to

cloud cover, it is rather complicated because numerical inversion in place of analytical inversion is employed to derive bathymetry from speckle infested radar imagery. Additionally, its accuracy is rather low as a result of its vulnerability to wind influences (Calkoen *et al.*, 2001).

2.1.4. Bathymetric Measurements Using Optical Remote Sensing

Optical RS-based bathymetry is derived from the principle that the total amount of radioactive energy reflected from a water column is a function of water depth. Optical RS takes advantage of shortwave radiation in the blue and green spectrum that has strong penetration capabilities. As the incident solar radiation propagates through the water, it is scattered and absorbed by water molecules and in-water constituents, leaving varied energy to be emitted and recorded in RS imagery. The energy received by the sensor is inversely proportional to the water depth after removing atmospheric corrections and water column effects. Therefore, the intensity of the returned signal is indicative of the depth at which the solar radiation has penetrated. Optical RS can be implemented for bathymetry derivation using two methods; analytical modeling and empirical modeling (Jawak *et al.*, 2015).

A. Analytical modeling

Analytical modeling of bathymetry is based on the characteristics of propagation of light in the water column. An analytical model is based on number of optical properties of water, such as the attenuation coefficient and backscattering are required as input parameter (Gao, 2009). The flow radiative transfer model is a commonly used analytical model and it requires the input of the spectral signatures of suspended and dissolved materials, and bottom reflectance (Jawak *et al.*, 2015).

B. Empirical Modeling

In case of empirical models, the mathematical relationship between the remotely sensed radiance of a water body and the depth at few sampled locations (ground truth) is established empirically independent of the characteristics of light transmittance in water. A strong correlation exists between water depth and the single band radiance for waters of uniform optical properties and bottom reflectance. Lyzenga, (1998) suggested the use of multiple spectral bands to overcome the problem of varying optical properties of the water column. The establishment of this empirical model requires a set of in-situ measurements that may include

water and bottom reflectance, the vertically averaged diffuse attenuation coefficient, and the concentrations of suspended inorganic constituents, chlorophyll, and dissolved organic carbon. The field measured spectral reflectance over a wide range of wavelength is helpful to understand the most suitable band(s) for sensing bathymetry. This is especially significant in conditions of spatially varying turbidity and water qualities. In addition, other in-situ measurements may include a collection of water samples and determination of water depth at the sampling locations (determined by the GPS) using echo sounder (Figure 2.1).

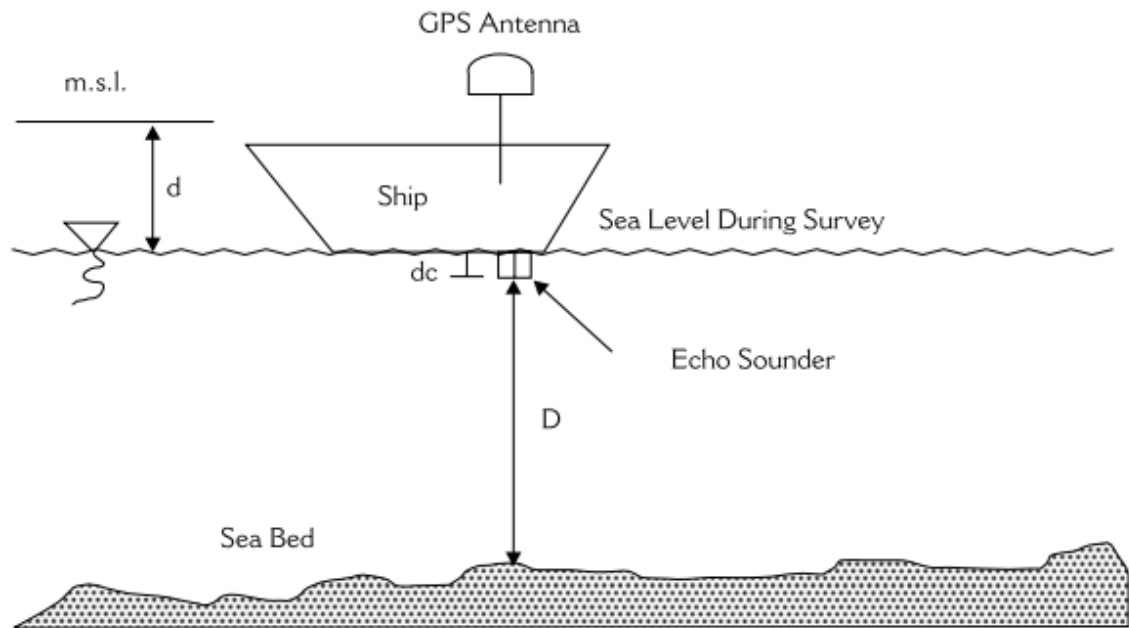


Figure 2.1. Collection of in situ water depth using a GPS-enabled echo sounder in constructing Empirical Model

(Source: Gao, 2009)

The least square regression analysis is used to formulate this empirical model. Regression of the observed water depth against the spectral reflectance in the most sensitive spectral band (s) is capable to yield an efficient empirical model for water depth. Applications of this model to the entire satellite image results in the generation of a bathymetric map. The empirical modeling method is valid given that the total water reflectance is related essentially to water depth, and to water turbidity (Lafon *et al.*, 2002). This claim has been backed by (Ji *et al.*, 1992), who concluded that water column scattering dominates the exit radiance from the water except if it is very shallow and transparent water bottom (Gao, 2009).

Both implementations of the optical method are very efficient for mapping bathymetry over a large area. They are able to yield finer resolution depth information than the LiDAR method, even though the range of detectable depths is reduced. Under optimum conditions, the discernible depth rarely exceeds 20 m and uncertainties can be worse than 4–5 m. Usually, sea-truth data must be collected concurrently for model construction. Both types of methods are limited in that it is very difficult to calibrate the detected depth (Gao, 2009).

All analytical models require radiometric calibration to account for the atmospheric effect irrespective of their specific format (Table 2.1). The analytical implementation is more accurate, but very complex, and requires the input of more parameters related to the water and even the atmosphere. Thus, it is highly complicated, but can yield highly accurate bathymetric information. By comparison, empirical modelling is much simpler and easy to use. This regression-based model is able to take into account the local set of conditions of the study area, and the atmospheric effects on the electromagnetic waves path in its structure. Therefore, it is not always vital to calibrate the remote sensing imagery radiometrically (Gao, 2009).

Optical RS methods are potentially used for derivation of bathymetry from space-borne or airborne multispectral (MS) and hyperspectral (HS) imageries (Jawak *et al.*, 2015).

i. Bathymetric Measurements Using Multi-Spectral Imagery

Coastlines, lakes, shoals and reefs are some of the most continuously varying dynamic regions of the Earth. Monitoring and measuring spatial changes are critical for understanding the environment. According to (Jawak *et al.*, 2015), near-shore bathymetry can be estimated using MS satellite imagery MS/HS imagery provides bathymetry measurements which are not reliable enough to be used for navigation purposes. However, MS/HS imagery based method is a cost effective option for bathymetry over large areas. These bathymetric products are suitable for a range of environmental and scientific applications. Imagery derived bathymetry is not directly measured, it is inferred, and as such the bathymetry is estimated, with a lower accuracy than LIDAR or multi-beam echo sounders. The depth to which the imagery is useful is limited by light attenuation. Depending on water clarity, depths derived from aerial or satellite imagery are limited to 25 - 30 m because of light penetration issues (Collet *et al.*, 2000). There are two recognized techniques for deriving bathymetry using MS satellite imagery: 1) radiometric approach and 2) photogrammetric approach (Khoury & Ellis, 2009).

1) Radiometric approach for deriving bathymetry: The radiometric approach exploits the fact that different wavelengths of light are attenuated to different degrees by water, with red light being attenuated much more quickly than blue light. RS technologies have exceeded the capability of existing MS satellite to detect light in the blue (450 - 510 nm), green (510 - 580 nm) and red bands (630 - 690 nm) to achieve superior estimates of depth, in water up to 15 meters deep. In addition, with the help of sound navigation and ranging (SONAR) based in-situ measurements, it is possible to achieve vertical and horizontal accuracies of less than 1 meter. Currently, airborne or space-borne high-resolution MS platforms are employed in order to improve bathymetric measurements, e.g. WorldView-2 (WV-2). These sensors are capable to detect light between 400 and 450 nm wavelengths – the EMR spectrum that provides the deepest penetration of clear water. Several studies using these datasets have shown that accurate and precise bathymetric quantification can be achieved up to 20 meters and deeper. According to (Jawak *et al.*, 2015), WV-2 is the first industrial high-resolution satellite to provide 1.84 m resolution MS imagery, plus a coastal blue spectral band focused on the 400 - 450 nm range, which can be used for bathymetric measurements with substantially improved depth and accuracy. Large synoptic collections, enabled by WV-2 agility and rapid retargeting capabilities, allow to evaluate the differing absorption of the blue, coastal blue, and green spectral bands, and to calibrate their bathymetric measurements using a few in situ points, and then consistently extend the model across the entire study area (Jawak *et al.*, 2015).

2) Photogrammetric approach using digital elevation model (DEM) for deriving bathymetry: In this method, stereoscopic images can be collected over the target area (Jawak & Luis, 2012) or digital bathymetry model (DBM) of the shallow ocean floor can be produced from the imagery. Early studies with both satellite imagery and digital photography appeared promising, and reveal that this method can be used to generate accurate bathymetric models of shallow environments without in situ data. However, the method has not been widely studied because of the limitations in the capabilities of current sensors. The challenge in collecting stereoscopic imagery of the shallow ocean floor is to understand the interaction of light with the air/water interface. At high angles of incidence, the light is entirely reflected off the surface of the water, preventing any observation of sub-aquatic features. Present multispectral satellite sensors are not capable to collect enough high-resolution stereoscopic imagery within the narrow angle needed to penetrate the sea surface. In addition, none of them is capable to

provide shorter wavelength blue light necessary for maximum depth penetration. WV-2 can be used for implementing this new method for measuring bathymetry. The Coastal Blue band can deliver maximum water penetration and WV-2's enhanced agility enables the acquisition of enormous amounts of high-resolution in-track stereo imagery at the ideal angle for water penetration. The advantage of this approach is that numerous images can be co-registered using tie points that are visible on land and water, and the resulting stereo composite can be used to calculate the water depth without relying on in situ measurements (Jawak *et al.*, 2015).

2.1.5. Derivation of Bathymetry Using Optical Remote Sensing Models

Following are the most commonly used algorithms for calculating the bathymetry from multispectral and hyperspectral imageries (Jawak *et al.*, 2015).

i. Stumpf Model/Linear Ratio Model

Stumpf *et al.*, (2003) proposed a “Ratio method” to overcome the drawbacks of changing substrate albedo in deriving bathymetry information. The model is based on the theory of light attenuating exponentially with depth, and proposed that the effects of substrate albedo are minimized using two bands to derive the depth. This principle is explained mathematically as follows:

$$Z = g^{-1}[\ln(A_d - R_\infty) - \ln(R_w - R_\infty)] \quad \text{Equation 2.1}$$

where Z is depth, g is a function of the diffuse attenuation coefficients for both down welling and upwelling light, A_d is the bottom albedo, R_∞ is the water column reflectance if the water were optically deep, and R_w is observed reflectance. The ratio model addresses the drawback by comparing the attenuation of two spectral bands against each other rather than using albedo as a variable in depth derivation. Different spectral bands attenuate at different rates. Therefore, the ratio between two spectral bands will vary with depth. The modification in the bottom albedo should affect both spectral bands equally, but the modification in attenuation with depth will be greater than the alteration attributable to bottom albedo so that the ratio between two bands should remain comparable over different substrates at the similar depth. This can be illustrated mathematically as follows:

$$Z = m_1 \frac{\ln(nR_w(\lambda_i))}{n(nR_w(\lambda_j))} - m_0 \quad \text{Equation 2.2}$$

Where, Z is depth, m_1 is a tunable constant to scale the ratio to depth, n is a constant to ensure the ratio remains positive under all values, R_w is observed reflectance, and m_0 is the offset for a

depth of m_0 . The ratio transform method addresses several issues that have substantial significance to use passive MS imagery to map shallow-water bathymetry. First, 1) it does not require subtraction of dark water pixels, 2) the ratio transform method has fewer empirical coefficients required for the solution, which makes the method easier to use and more stable over broad geographic areas, and 3) the ratio method can be tuned using available reliable depth soundings (Jawak *et al.*, 2015).

ii. Lyzenga Model or Linear Band Model

Satellite RS data is the amount of light reflected, which is affected by the atmosphere, water clarity, depth attenuation, bottom reflectance, scattered suspended material and so on (Baban, 1993). Campbell, (1996) described that the sunlight spectrum has different penetrability, bottom reflectance and suspended material scattering. Therefore, to advance the accuracy of water-depth estimation, the RS data can be classified using multiband radiance. In ideal conditions, under the assumptions of a homogeneous atmosphere, similar wave situation, similar water property, and homogeneous bottom property, the water depth can be retrieved from a satellite. After penetrating the water column, the satellite sensor detects the visible light reflected from the bottom. In the water column, the light is attenuated exponentially with depth by Beer's Law and the relationship of observed reflectance to depth and bottom albedo could be described as (Stumpf *et al.*, 2003; Lyzenga, 1998);

$$R = (A_b - R_\infty) \exp(-gz) + R_w \quad \text{Equation 2.3}$$

Where R_∞ is the water column reflectance, if the water is optically deep, A_b is the bottom albedo, z is the depth, and g is a function of the diffuse attenuation coefficients for both downwelling and upwelling light. However, the derivation of depth from a single band is dependent on the albedo A_b , with a decline in albedo resulting in amplification in the estimated depth. Lyzenga (1985) proposed a linear solution of correction for albedo with two bands as;

$$Z = a_0 + a_1 X_i + a_2 X_j \quad \text{Equation 2.4}$$

Where $X_1 = \ln[R(\lambda) - R_\infty(\lambda_1)]$ and λ is the wavelength. The algorithm corrects for a range of variations in both water attenuation and bottom reflectance using a linear combination of the log-transformed radiances in the blue and green channels. Lyzenga model has essentially

attempted to account for unpredictability in bottom type by using multiple spectral bands. A variable, X_j , was defined for each of the N bands as:

$$X_j = \ln(L_j - L_{wj}) \quad \text{Equation 2.4.1}$$

Where, L_j = above-surface reflectance in band j and L_{wj} = averaged deep-water reflectance. The reflectance values were log-transformed to create a linear relationship between input reflectance and depth. Deep-water reflectance was used to account for reflection because of surface effects and volume scattering in the water column and was assumed to result mostly from external water reflection, including sun-glint effects, and atmospheric scattering. However, the effect of deep water radiance was almost negligible in shallow water bodies. To account for water quality heterogeneity and depth-independent variability in reflectance values between bands this algorithm was updated by (Lyzenga, 1985), and again (Lyzenga *et al.*, 2006). This produced $(N + 1)$ depth-independent variables that could be used as indices of bottom type, and finally modeled depth as:

$$h = h_0 + \sum_{j=1}^N h_j X_j \quad \text{Equation 2.5}$$

Where, h_0 and each h_j are constants defining a linear relationship between X_j and depth. h_0 and all of h_1 to h_j are determined through multiple linear regression between a set of known depths and the log-transformed reflectance values found at those depths. The method increases operational flexibility since wavelength bands are not restricted by the algorithm.

iii. Jupp's Model or Depth of Penetration Zone (DOP) Model

A model that finds large usage in literature to reconstruct the bathymetry in coastal zones from MS imagery is the depth of penetration zone (DOP) method proposed by (Jupp, 1988). There are two parts to Jupp's method: 1) the computation of DOP zones, and 2) the interpolation of depths within DOP zones. The method (Jupp, 1988) has three critical assumptions: 1) attenuation of light is an exponential function of depth, 2) water quality does not vary within an image, and 3) reflective properties of the substrate are constant. The second and third assumptions are the weakness of this model because in some cases water and seabed properties fluctuate, as the satellite image normally covers a very large area. Considering a bunch of monochromatic light, the relative loss of radiant flux is proportional to the size of the

path, to less of a coefficient of proportionality (extinction coefficient). Jupp's model can be mathematically expressed as:

$$L_e = (e^{-2k})L_b + (1 - e^{-2k})L_w \quad \text{Equation 2.6}$$

Where L_e is measured at-sensor radiance, L_b is the emergent radiance from the seabed, L_w is the emergent radiance from different layers of water, z is depth, k is the coefficient of absorption. If the term L_w is hypothesized as negligible and is directly related to the quality of the water (suspended sediments) and small changes in the seabed, then, among the depth of the water column and the logarithm of the measured at-sensor radiance, there will be a linear relationship. Under these conditions, rearranging Equation (2.6) lead to the classical DOP equation for the water depth determination:

$$Z = \sum_{i=1}^N \ln \frac{(L_e)_i}{-2k_{iN}} - \sum_{i=1}^N \ln \frac{(L_b)_i}{-2k_{iN}} \quad \text{Equation 2.7}$$

Where N is the number of spectral bands. In practice, to guarantee homogeneity, the DOP model assumes constant coefficient of absorption, which is the main cause of the failure of the DOP algorithm in some cases, where the spatial lack of homogeneity is very high.

2.1.6. Estimating the Sediment Yield of a Lake

There are many problems associated with sediment deposition in lakes. For instance, sediment accumulations in lakes resulting in decreasing the lake storage capacity, navigation problems and other water quality and environmental problem. To overcome the problems created by sediment accumulation in lakes and also to get use of this sediment, it is of outmost important to estimate the sediment capacity (amount) and its distribution in these lakes (Negm *et al.*, 2018). Estimating the sediment yield amount in the lakes is an essential task for the managers and decision makers of water management sector. Achieving this task based on the field measurements consumes time, money and effort. On the other hand, detecting bathymetric data (depths) using Remote Sensing (RS) data has led to overcome such problems if used in estimating the sediment yield and verified by field measurements (Elsahabi *et al.*, 2018b).

2.2. Empirical Review

2.2.1. Bathymetry of Lake Hawassa

Bathymetry of Lake Hawassa were observed in previous project report and studies for the year 1999, 2010 and 2011 through field measurement of depth. For the year 1999, bathymetry map

was prepared by Water Works Design and Supervision Enterprise to study the Lake Level Rise. Bathymetric map of the lake with scale 1:10,000 and contour interval of 2m has been done by conducting bathymetry survey of the lake water body. Instruments used for bathymetry survey were echo sounder, total stations with reflector; boat equipped with depth counter, GPS and Motorola radio communicators (WWDSE, 2001).

The other bathymetry map was prepared by (Belete, 2013) through field measurement to study the effect of sedimentation on the storage capacity of Lake Hawassa. The bathymetry survey was made on December 2010 using Sonarmite echosounder depth measuring device and 337 points gridded with 500 x 500m spacing were observed for the whole area. The bathymetry map of Lake for the year 1999 prepared by Water Works Design and Supervision Enterprise was first pre-processed and topographic differencing between the two bathymetry maps were done. And, the result of topographic differencing shows the average sediment thickness between 1999 and 2010 was to the magnitude of $14 \pm 5\text{cm}$ (Belete, 2013). Yonas *et al.*, (2018), have also prepared the bathymetry map of Lake Hawassa to study Morphometric Change Detection of Lake Hawassa in the Ethiopian Rift Valley. Bathymetry was measured in field through rapid bathymetric surveying using the SonarMite echo-sounder (Bonn, Germany) (235 kHz frequency, 0.3–75 m depth capacity and $\pm 0.025\text{ m}$ accuracy), eTrex Venture Garmin (Garmin Corporation, Taipei County, Taiwan) geographic positioning system (GPS) and a motorized boat to measure lake depth at uniform grid points, and a leveling survey to determine the lake level elevation in January 2011. Water depth measurements from 396 grid points and several shoreline points were collected. To develop a geo-statistical bathymetric model for Lake Hawassa in 2011, sounding depth data were converted to elevation data by subtracting the measured depth from the lake level elevation at the grid locations resulting in point bed elevation data. The delineated and GPS verified shoreline result of the modified NDWI analysis on the 2011 Landsat image was converted to point data having the same elevation with the Lake Hawassa level. Relying on the bathymetry survey data, the bed surface is finally predicted using kriging interpolation (Yonas *et al.*, 2018).

Generally, there is a lack of continuous bathymetric survey of the Lake and there is no previous bathymetry made at good spatial resolution to better study the lake. Moreover, the currently evolving RS technology is not implemented before on Lake Hawassa and the capability of retrieving bathymetry of the lake by existing models is also unknown.

2.2.2. Measurement of Bathymetry Using Satellite Imagery

The measurement of bathymetry using satellite imagery is one of the fundamental researches in the field of remote sensing (RS) of the marine environment, which has numerous practical applications to the coastal environment and its monitoring. Accurate determination of water depth is essential for various purposes such as monitoring underwater topography, movement of deposited sediments, and producing maritime charts for navigation. Such information is also vital for port facility management, dredging operations, and to predict channel infill and sediment budget. Case studies that have utilized various satellite datasets and methods for bathymetry derivation are summarized in Table 2.2.

Table 2.2. Summary of case studies utilizing various satellite datasets and methods for bathymetry derivation.

(Source: Jawak *et al.*, (2015)).

Study Area (Satellite Data) [Ref.]	Method Used	Significant Conclusion	Comments
Larsemann Hills, Antarctic. (WV-2) [Jawak and Luis, (2015)]	1. Lyzenga model 2. Stumpf model	Lyzenga model yielded better results than Stumpf model	The coastal band in the WV-2 plays an essential role in bathymetry
Coastal region near Mumbai, India. (RISAT-1 SAR) [Mishra, M.K. <i>et al.</i> , 2014]	1. Wave-tracing method 2. Linear dispersion relation	Using wave tracing method, the swell wavelength has been found to be in the range of 80 - 210 m. Using the Linear dispersion method the maximum swell wavelength was 210 m.	The wavelength decreases as the wave moves closer to the coast.
The lagoon of Venice. (QuickBird) [Gianinetto and Lechi, 2013]	Stratified genetic algorithm (SGA).	A very high correlation $R^2 = 0.96$ was obtained with respect to in-situ data	SGA performs better than generic Jupp's model
Wales, Alaska. (WV-2) [Smith, J.R., <i>et al.</i> , 2013]	Relative Water Depth in ENVI software.	A linear regression between measured and derived values of absolute depths resulted in R^2 of 0.7221.	Locations with potentially high suspended sediments were found to cause discrepancies between in-situ and derived depth values.
Thessaloniki, Greece. (WV-2) [Doxani, G., <i>et al.</i> , 2012]	Lyzenga model	Water depths measured: - Area with seagrass 2 - 6 m, - Area mixed with seagrass 2.4 - 6m, - Seagrass free area 6 - 15 m.	In all areas the majority of the estimated depths (73% - 76%), differed adequately from the soundings.
Strait southwest of the Singapore main island. (WV-2) [Liew, S.C., <i>et al.</i> , 2012]	Shallow Water Remote Sensing Reflectance Model	For water with a dark seabed, the Green band has the most depth sensitivity for depth up to about 5 m. In case of a bright seabed, the Red and Yellow bands are the most sensitive.	In cases where the depth sensitivity is low, the spectral bands are still useful for the derivation of water optical parameters.
The Southern coast of	Jupp Method	Comparison of the two images being	A satisfactory correlation between

the island of Sardinia, Italy. (WV-2) [Deidda and Sanna, 2012)]	a) IDL b) ENVI	different in geometry and quality, the results coincide to a precision of 0.6 m.	in situ and derived depths was observed
Aquitaine, France. (SPOT-5) [Lafon, V. <i>et al.</i> , 2002]	1. Empirical calibration based on ground truth data 2. Semi-analytical model.	Semi-analytical model: The accuracy is satisfying (0.5 m) and not depth-dependent. Empirical model: The computed depths are under-estimated when water depth exceeds 2.5 m. The accuracy is depth dependent getting worse with larger water depths.	Empirical fitting is time-efficient, but Requires simultaneous high-density soundings. The semi-analytical approach can be implemented in any place without any ground truth data.
Kaneohe Bay, Oahu, Hawaii. (IKONOS, LIDAR) [Hochberg, E.J. <i>et al.</i> , 2011]	Lyzenga model	Water depths > 20 m were obtained using Multi-beam SONAR. Water depths < 20 m were derived from an IKONOS image using Lyzenga method.	The most accurate method was simple, empirical multiple linear regression against known depths.
Eastern Banks, Moreton Bay. (QuickBird) [Lyons, M., <i>et al.</i> , 2011]	1. Lyzenga model 2. Stumpf model	Lyzenga algorithm was effectively used to map Water depth over the sand substrate type. An algorithm based on reflectance band ratios (Stumpf) was also tested separately on sand and seagrass substrate types.	Lyzenga algorithm could not be used to derive depth over seagrass substrate types. Stumpf algorithm was not able to effectively derive water depth on either substrate type.
Naozhou Island in Guangdong, China. (SPOT-5) [Liu, S., <i>et al.</i> , 2009]	1. Optical RS inversion technique for depth. 2. Depth inversion	The mean relative error of the depth segment ranges from 0 - 5 m. The dual-band model is the best of all the models used, its mean relative error is 22%, and its mean square error is 1.87 m. The model worked relatively well in the shallow water.	The multi-spectral image of SPOT-5 has the ability to inverse water depth, and its high resolution can describe more detail topographic information under water.
South China Sea. (WV-2, QuickBird) [Ho, C.R., <i>et al.</i> , 2009]	Lyzenga Model	Using Lyzenga model the error of water depth from QuickBird image is found to be about 9.7%.	The coastal blue band in WV may retrieve more information.
Cancun and Hawaii, USA. (IKONOS,	Lyzenga Model	A single set of coefficients derived from a set of the IKONOS images gives good	The algorithm corrects for a range of variations in both water attenuation

SHOALS LIDAR) [Lyzenga, D.R., <i>et al.</i> , 2006]		performance over a variety of conditions, with an aggregate RMS of 2.3 m over all of the data sets.	and bottom reflectance using a linear combination of the log-transformed radiances in the blue and green channels.
Cape Verde Islands, Africa. (QuickBird, IKONOS) [Pennucci, G., <i>et al.</i> , 2006]	1. Lyzenga Model 2. Jupp Model 3. Stumpf Model	The depth in coastal water (shallow water areas, depth < 30 m) with three different methodologies.	The results show that the ratio model is more robust in case of the non-homogeneous environment.
QingDaocity ShanDong province in China. (Landsat-TM) [Qing, D.W., <i>et al.</i> , 1996]	Bottom Reflection Model Based on Remote Sensing Bathymetry	The absolute values of negative linear relation coefficient -0.493425 is smaller than that derived from bottom classification.	The precision of bottom type classification using multi-spectral image information is better than single-band method.
Northwest Hawaiian Islands. (IKONOS, LIDAR) [Stumpf, R.P., <i>et al.</i> , 2003]	1. Lyzenga Model 2. Stumpf Model	Both algorithms compensate for variable bottom type and albedo (sand, pavement, algae, and coral) and retrieve bathymetry in water depths of less than 10 - 15 m.	The ratio transform is more robust than the linear transform.

Some previous studies that have utilized remotely sensed bathymetry for sediment capacity estimation are also reviewed. Elsahabi *et al*, (2018b) have made study on Lake Nasser, Egypt. The study aims to estimate the total amount of the accumulated sediment and its distribution on the bed of Lake Nasser using RS and GIS techniques (Elsahabi *et al*, 2018b). In this study, bathymetric data such as; hydrographic data and topographic maps, sediment data, satellite images (i.e., Landsat 7) and water level data are used. The study starts with extraction of water body from satellite images followed by spatial interpolation process in ArcGIS to generate 3D bed surface of the lake for the years 1964 and 2011, then map of changes for the period (1964-2011) is produced to determine sediment and erosion capacity and finally sediment distribution map is created. On the paper it is finally concluded that, the paper presents and discusses the results of the RS/GIS approach for sediment deposition assessment in Lake Nasser based on the generation of 3D bed surfaces for this lake. The results indicated that the created 3D bed surface of the year 1964 was well verified. On the other hand, the results showed that the total amount (capacity) of sediment in the study area till 2012 was about 1.194 billion m³. Also, results indicated that the present approach, which based on building 3D profiles for the study area within Lake Nasser, overestimated the sediment amount by about 2.40% from the year 1964 to 2012 compared to the results of the method used by AHDA, based on the complementary cross sections (Elsahabi *et al*, 2018b).

Negm *et al.*, (2018) have conducted a research entitled “Lake Nubia Sediment Capacity Estimation Based on Satellite Remotely Sensed Detected Bathymetry (Southern Egypt)”. The objective of this research is to estimate the sediment capacity of Lake Nubia (the Sudanese part of Aswan High Dam Lake) via the detected bathymetry using a Landsat-8 multiband combination. The remotely sensed derived bathymetry and the bathymetry derived from an old contour map of the year 1964 for the study area are then interpolated by Arc GIS software to estimate the accumulated sediment capacity in Lake Nubia (LN) till the year 2012 (Negm *et al.*, 2018). In this research, the following data's are used; hydrographic survey (field measurements) of the lake for the year 2012, and Landsat-8 collected image data in 11 spectral bands with a 30 m spatial resolution (Path/Row = 175/045). The image was captured on the same date of the field measurements. To achieve the objectives of this study, systematic steps were conducted including (i) the satellite image was filtered to discard the atmospheric interferences; (ii) water reflectance values were isolated from the land; (iii) sun specular effect

was removed to decrease noise and scattering effects on the input image; (iv) the reflectance values corresponding to the points, where there were available depth measurements, were extracted from multispectral images for usage bands and (v) correlating empirically the extracted reflectance values with the in situ measurements to predict the water depths. The estimated lake depths from RS satellite image were then used to estimate the sediment and erosion capacity in the lake using the developed 3D profile of this lake and the generated changes map using ArcGIS software. The results of using the complimentary cross-section (the traditional method adopted by Aswan High Dam Authority, AHDA) and using the 3D profile of the Lake were evaluated too, and compared with the present estimated sediment capacity based on the 3D profile of the lake that was built using the predicted depths via multiple linear regression based on the detected bathymetry from the satellite images using RS. The cross-section methods used by Aswan High Dam Authority (AHDA) was taken as a reference method when the results were compared (Negm *et al.*, 2018).

Some of Case studies reviewed for extraction of bathymetric data and estimation of sediment capacity based on remotely detected bathymetry are summarized in Table 2.3.

Table 2.2 Previous studies reviewed on remote sensing based bathymetric mapping and sediment capacity estimation

Authors	Title	Data Used	Model used for extracting bathymetry	Purpose/aim of the study and conclusion
Kelvin <i>et al.</i> , (2015)	Converting Digital Number into Bathymetric Depth: A Case Study over Coastal and Shallow Water of Langkawi Island, Malaysia	Landsat 8 satellite images	linear ratio/stumpf	- to evaluate the usability of space-borne bathymetric mapping technique and identify the appropriate spectrum channels to be used in extracting bathymetric information from Landsat 8 multispectral satellite data. - a shallow water bathymetry map has been successfully mapped via the remote sensing approach. The proposed deviation method which gauging the relative attenuation of the blue band and green band radiations were examined and verified. The results showed that the high compatibility satellite-derived bathymetric mapping was able to offer a fast, flexible, efficient and economically advantageous solution to map the seabed topography. It is also proven to be more cost-effective, less labour-intensive and time-saving method of acquiring bathymetry comparing to the conventional sonar sounding surveys as well as allows significant repetitions of bathymetry mapping over broad areas. Perhaps, the satellite-derived bathymetry can be an alternative method and reconnaissance tool in facilitating the increasingly demand of hydrographic surveying activities around the coastal and shallow water areas.
Deng, Z. <i>et al.</i> , (2008)	Mapping bathymetry from multi-source remote sensing images: a case study in the beilun estuary,	QuickBird (band 4, 3, 2) and Landsat ETM+ (band 2, 3, 4)	linear ratio/stumpf	- to build a GIS database for a long term monitoring of the coastal environment in the region. - it is important to acquire remote sensing data with compatible spatial resolutions if consistency and high precision are required in bathymetry mapping. The bathymetry mapping approach introduced in this study still needs more rigorous field verification and further improvement.

	guangxi, china			
Doxani <i>et al.</i> , (2012)	Shallow-water bathymetry over variable bottom types using multispectral worldview-2 image	The multispectral imagery (worldview-2) and echo sounding data	The linear bathymetric model/lyzenga	- To evaluate the contribution of the eight bands of Worldview-2 imagery in the estimation of sea. - Bathymetric model involving the imagery data of high spectral and spatial resolution produced fairly accurate results. However a thorough statistical analysis was required to optimize the selection of the appropriate spectral bands.
Negm <i>et al.</i> , (2018)	Lake Nubia sediment capacity estimation based on satellite remotely sensed detected bathymetry	Hydrographic survey data and Satellite remote sensing data(Landsat-8 with spatial resolution of 30m)	Multiple Linear Regression model	- to estimate the sediment capacity of Lake Nubia (LN) (the Sudanese part of Aswan High Dam Lake) till the year 2012 via generating the 3D bed surface of year 2012 from the detected bathymetry data using a Landsat-8 multiband combination and generating the 3D bed surface of year 1964 from topographic map, sediment data and hydrographic survey data. - Results showed that an error of 0.6 m is obtained in depths estimation. This accuracy may be enough when using bathymetry by remote sensing in the preliminary survey.
Elsahabi <i>et al.</i> , (2018a)	Lake Nubia bathymetry detection by satellite remote sensing	Hydrographic survey data and Landsat 8	Multiple Linear Regression model	- to propose a methodology for bathymetry detection of Lake Nubia using Landsat-8 multiband combination after removing atmosphere and sun glint effects and their logarithms as the dependent variable and in-situ measurement as the independent variable in Multiply Linear Regression (MLR). - Results showed that the errors around 1.7m can be obtained. This accuracy may be enough when using bathymetry by remote sensing in the preliminary survey.

2.2.3. Pre-processing Satellite Imagery

Satellite images are affected by a variety of environmental factors such as atmosphere and sun specular. It needs pre-corrections to avoid the influence of the inversion depth (Elsahabi *et al.*, 2018a).

A. Radiometric Calibration

Radiometric calibration is the process of converting the Digital Number (DN) in satellite images into a physical value (irradiance and Top of Atmosphere reflectance (TOA)). In order to apply atmospheric correction it needs to convert the raw image into radiance. Radiance is simply the amount of radiation coming from an area. To derive a radiance from un-calibrated image (DN), a gain and offset values must be applied to the pixel values. The digital number (DN) converted to the spectral radiance at the aperture (L_λ) is measured in (watts/ meter squared * ster * μm) using the gain and bias information of sensor bands as follows (Chander *et al.*, 2009);

$$L_\lambda = M_L * Q_{cal} + A_L \quad \text{Equation 2.8}$$

Where, M_L is Band-specific multiplicative rescaling factor (RADIANCE_MULT_BAND_x) or Rescaling gain factor (Gain) from Land-sat metadata files,
 Q_{cal} is calibrated standard product pixel values (DN) and
 A_L is Band-specific additive rescaling factor (RADIANCE_ADD_BAND_x) or Rescaling bias factor (Bias) from Land-sat metadata file.

In ENVI software, there is a radiometric calibration tool that converts digital number (DN) into radiance. Radiance is computed using the following equation (RSI, 2009);

$$L_\lambda = Gain * Pixel Value + offset \quad \text{Equation 2.9}$$

ENVI expects gains and offsets to be in units of $\text{W}/(\text{m}^2 * \text{sr} * \mu\text{m})$. If so, then radiance will be in units of $\text{W}/(\text{m}^2 * \text{sr} * \mu\text{m})$.

B. Atmospheric Correction

As name suggests, atmospheric correction is the process of removing the effects of the atmosphere on the reflectance values of remotely sensed images. The atmospheric effects may be referred to as presence of gas absorption, molecule and aerosol scattering that can influence incident and reflected radiation the atmosphere can have high impact on the reflectance values

of images (especially those are taken from space). The nature of remote sensing requires that solar radiation pass through the atmosphere before it is collected by the instrument. Because of this, remotely sensed images include information about the atmosphere and the earth's surface. For those interested in quantitative analysis of surface reflectance, removing the influence of the atmosphere is a critical pre-processing step (RSI, 2009). The importance of atmospheric correction is to get better results while it removes atmospheric noises and provides the true surface reflectance. The presence of aerosols makes it difficult to read the true surface reflectance values which hinders the accurate study of, for example, water depth.

There exist two types of atmospheric correction; relative and absolute correction. Relative correction normalizes the images and is easier to achieve because normalization makes the image directly comparable to other images rather than removing the effect of atmosphere. One of the most common relative atmospheric correction is dark object subtraction (DOS), where dark objects (objects with very low reflectance) is subtracted from image. In absolute atmospheric correction, the atmospheric profile obtained on the same day at the same location are used in conjunction with an algorithm to compensate for an atmosphere. Unavailability of this information makes it difficult to perform absolute atmospheric correction. This information is usually obtained from one of the two very robust and time-tested radiative transfer models: MODTRAN (MODerate resolution atmospheric TRANsmission) or 6s (Second Simulation of the Satellite Signal in the Solar Spectrum). These models store information of the location, time, average ground elevation, altitude of the sensor, and bandwavelength ranges. These characteristics are used for absolute atmospheric correction. The most common algorithms used to perform this correction are; Atmospheric CORrection NOW (ACRON), Fast Line-of-sight Atmospheric Analysis of Spectral Hypercubes (FLAASH), and Atmospheric CORrection (ATCOR).

FLAASH atmospheric correction is one of the most widely used algorithm in retrieving of bathymetry from remote sensing imagery. A tool that performs this algorithm exists in ENVI software. ENVI's Fast Line-of-sight Atmospheric Analysis of Spectral Hypercubes (FLAASH) module is a first-principles atmospheric correction modeling tool for retrieving spectral reflectance from hyperspectral radiance images. With FLAASH, you can accurately compensate for atmospheric effects. FLAASH corrects wavelengths in the visible through near-infrared and short-wave infrared regions, up to 3 μm . Unlike many other atmospheric

correction programs that interpolate radiation transfer properties from a pre calculated database of modeling results, FLAASH incorporates the MODTRAN4 radiation transfer code (RSI, 2009).

FLAASH starts from a standard equation for spectral radiance at a sensor pixel, L , that applies to the solar wavelength range (thermal emission is neglected) and flat, Lambertian materials or their equivalents. The equation is as follows (RSI, 2009);

$$L = \left(\frac{A\rho}{1-\rho_e S} \right) + \left(\frac{B\rho_e}{1-\rho_e S} \right) + L_a \quad \text{Equation 2.10}$$

where: ρ is the pixel surface reflectance

ρ_e is an average surface reflectance for the pixel and a surrounding region

S is the spherical albedo of the atmosphere

L_a is the radiance back scattered by the atmosphere

A and B are coefficients that depend on atmospheric and geometric conditions but not on the surface.

The first term in Equation (2.10) corresponds to radiance that is reflected from the surface and travels directly into the sensor, while the second term corresponds to radiance from the surface that is scattered by the atmosphere into the sensor. The values of A , B , S and L_a are strongly dependent on the water vapor column amount, which is generally not well known and may vary across the scene. To account for unknown and variable column water vapor, the MODTRAN4 calculations are looped over a series of different column amounts, then selected wavelength channels of the image are analyzed to retrieve an estimated amount for each pixel. The input image for FLAASH must be a radiometrically calibrated radiance image in band-interleaved-by-line (BIL) or band-interleaved-by-pixel (BIP) format (RSI, 2009).

In addition to the image file to be corrected, FLAASH also needs information on the geographical Centre location of the image and the time it was captured. The ENVI software automatically retrieve itself the center location of the scene, pixel size, and sensor altitude from the meta-data and the sensor type, time and year the image is acquired is entered by the user. Additionally, the input parameters used for atmospheric correction; ground elevation, atmospheric model, aerosol model, aerosol retrieval are entered by the user.

C. Gap-filling

On May 31, 2003, the scan-line corrector (SLC) of ETM+ failed permanently, which caused roughly 22% of the pixels to be un-scanned in any ETM+ images (referred to as SLC-off images) (Arvidson *et al.*, 2006). Nevertheless of SLC-Off mode, the ETM+ still acquires approximately 78 percent of the data for any given scene. Without the operating SLC, there are resulting gaps on images ranging as large as 14 pixels near the edges (Zhang *et al.*, 2007). Since the failure of SLC on Landsat 7, and the gaps on the bands, many methods were developed to fill the existing gaps (Potic, 2015).

Scaramuzza *et al.*, (2004) developed a technique which can be used to fill gaps in one scene with data from another Landsat scene. A linear transformation is applied to the filling image to adjust it based on the standard deviation and mean values of each band, of each scene. One of this linear transformation is Localized linear histogram match (LLHM) method. Filling the scan gap first requires precise knowledge of what pixels are valid in an image and which are to be filled. To do this a scan gap mask is created for each band that marks existing data as 1 and missing data in the scan gap and fill regions as 0. These scan gap masks are created during L1G product creation by a second pass through the same resampling algorithms used to create the L1G product. They are delivered with the product as 8-bit images having dimensions identical to the corresponding image band files, and are compressed using the gzip utility to avoid expanding the product size. Once the gaps are located, the linear histogram matching methodology attempts to find a linear transformation between one image and another (Scaramuzza *et al.*, 2004).

With a SLC-On fill scene X and a SLC-Off primary scene Y, we make the assumption that (Scaramuzza *et al.*, 2004):

$$Y \approx GX + B \quad \text{Equation 2.11}$$

Where; G = the gain used to histogram match the fill image to the primary image.

B = the bias used to histogram match the fill image to the primary image.

X = the fill (SLC-On) scene array.

Y = the primary (SLC-Off) scene array.

The gain and bias can be calculated using the standard deviation and mean of arrays X and Y:

$$G = \frac{\sigma_y}{\sigma_x} \quad \text{Equation 2.11(a)}$$

$$B = \bar{Y} - G\bar{X} \quad \text{Equation 2.11(b)}$$

Where; σ_x = the standard deviation of data in fill image X.

σ_y = the standard deviation of data in primary image Y.

X = the mean of the fill (SLC-On) scene array.

Y = the mean of the primary (SLC-Off) scene array.

D. Extraction of Water bodies

When extracting aquatic information, it is useful to eliminate all upland and terrestrial features. Thus, all upland features were masked out of the image. There are various methods for the extraction of water information from remote sensing imagery, which, according to the number of bands used, are generally divided into two categories, i.e. single-band and multi-band methods. The single-band method usually involves choosing a band from a multispectral image to extract open water information (Rundquist *et al.*, 1987). A threshold is then determined for the band to discriminate water from land. However, the subjective selection of the threshold value may lead to an over- or under-estimation of open water area and the extracted water information is often mixed with shadow noise. The multi-band method takes advantage of reflective differences of each involved band (Xu, 2006). Xu, (2006) have developed multi-band method of MNDWI to extract water bodies and it is expressed as follows:

$$MNDWI = \frac{(Green - MIR)}{(Green + MIR)} \quad \text{Equation 2.12}$$

Where; MIR is a middle infrared band such as TM band 5.

The greater enhancement of water in the MNDWI-image will result in more accurate extraction of open water features as the built-up land, soil and vegetation all negative values and thus are notably suppressed and even removed (Xu, 2006).

E. Sun-glint correction

Specular reflection of solar radiation, known as sun glint must be removed for accurate benthic habitat classification. In this study, the simple and robust removal of sun-glnt proposed by (Hedley *et al.*, 2005) is used to remove the effect of sun-glnt. The sun-glnt correction is

performed for the extracted water body. The sun-glint is corrected by the regression performed between the NIR brightness and the brightness in the visible band using a sample set of pixels, which would be homogeneous if not for the presence of sun glint (e.g. deep water) by the application of the following equation (Hedley *et al.*, 2005);

$$R'_i = R_i - b_i(R_{NIR} - MIN_{NIR}) \quad \text{Equation 2.13}$$

Which simply means: reduce the pixel value in band i (R_i) by the product of regression slope (b_i) and the difference between the pixel NIR value (R_{NIR}) and the ambient NIR level (Min_{NIR}). This gives R'_i , the sun-glint corrected pixel brightness in band i. Min_{NIR} essentially represents the NIR brightness of a pixel with no sun-glint and can be estimated by the minimum NIR found in the regression sample or alternatively as the minimum NIR value found in the whole image. The minimum sample size required is two pixels, displaying differing amounts of sun glint over similar sub-surface spectral brightness. Hedley *et al.*, (2005) recommends to select a sample area (or areas) of the image displaying a range of sun glint, but where the image would be expected to be more or less homogeneous if the sun-glint was not present (e.g. over deep water).

CHAPTER THREE: MATERIALS AND METHODS

This chapter includes description of the research study area, conceptual framework, materials and data's used, and details on methods of data analysis.

3.1. Description of the study area

3.1.1. Location and Topography

Considering the availability of data required, the magnitude of the problem due to sediment deposition, its value to Hawassa Town and surrounding people, and interest of the researcher to conduct remote sensing detected bathymetry on, Lake Hawassa is chosen for this study. Lake Hawassa watershed is located in the central North-East of the Ethiopian Rift Valley Basin. The lake catchment falls into two regions, Sidama Region (formerly in Southern Nation, Nationalities and Peoples Region) and Oromia Regional States. The city of Hawassa, named after the lake, is located at 275 km south of the capital city-Addis Ababa and is established in the very eastern shore of the lake (MoWR, 2010).

As extracted from Landsat 7 ETM+ satellite imagery of March 2011 in this study, the geographical coordinates of Lake Hawassa is between 38° 23' 20" E to 38° 29' 02" E Longitude and 06° 59' 00" N to 07° 07' 40" N Latitude and it covers total area of 92.6 km² as determined using MNDWI from the satellite imagery for the year 2011. And, also it is 16 Kilometers long in the North-South direction and 8 Kilometers width in the East-West direction. A map that depicts the location of the study area is shown in Figure 3.1.

Majority of the watershed is flat to gently undulating but bounded by steep escarpments. The altitude ranges from 1680 m.a.s.l at Lake Hawassa to 2700 m.a.s.l on the Eastern escarpment: an

altitude range of 1020 m.a.s.l. Most slopes (56%) are flat to gentle (0-8%) with a further 33% moderately sloping (8-30%) and only 5% steep to very steep (> 30%) (MoWR, 2010).

3.1.2. Climate

According to Legesse *et al.*, (2003), the watershed is characterized by three main seasons. The long rainy season in the summer from June-September is known locally as Kiremt and is primarily controlled by the seasonal migration of the inter-tropical convergence zone (ITCZ), which lies to the north of Ethiopia at this period. The wet period (locally named as Kiremt)

represents 50-70% of the mean annual total rainfall. The dry period (locally named as *baga*) extends between October and February when the ITCZ lies to the south of Ethiopia (Legesse *et al.*, 2004). During March and May, the "small rain" season (locally named as *belg*) occurs when about 20-30% of the annual rainfall falls. The climate in the area varies from dry to sub-humid according to the Thornthwaite's system of defining climate or moisture regions (Belete, 2013). As computed from the long-term (1973-2010) rainfall record of Hawassa meteorological station, the annual average magnitude is computed to be 961 mm and distributed as 50% for Kiremt (June-September); 20% for *baga* (October-February) and 30% for *belg* season (March-May) (Belete, 2013).

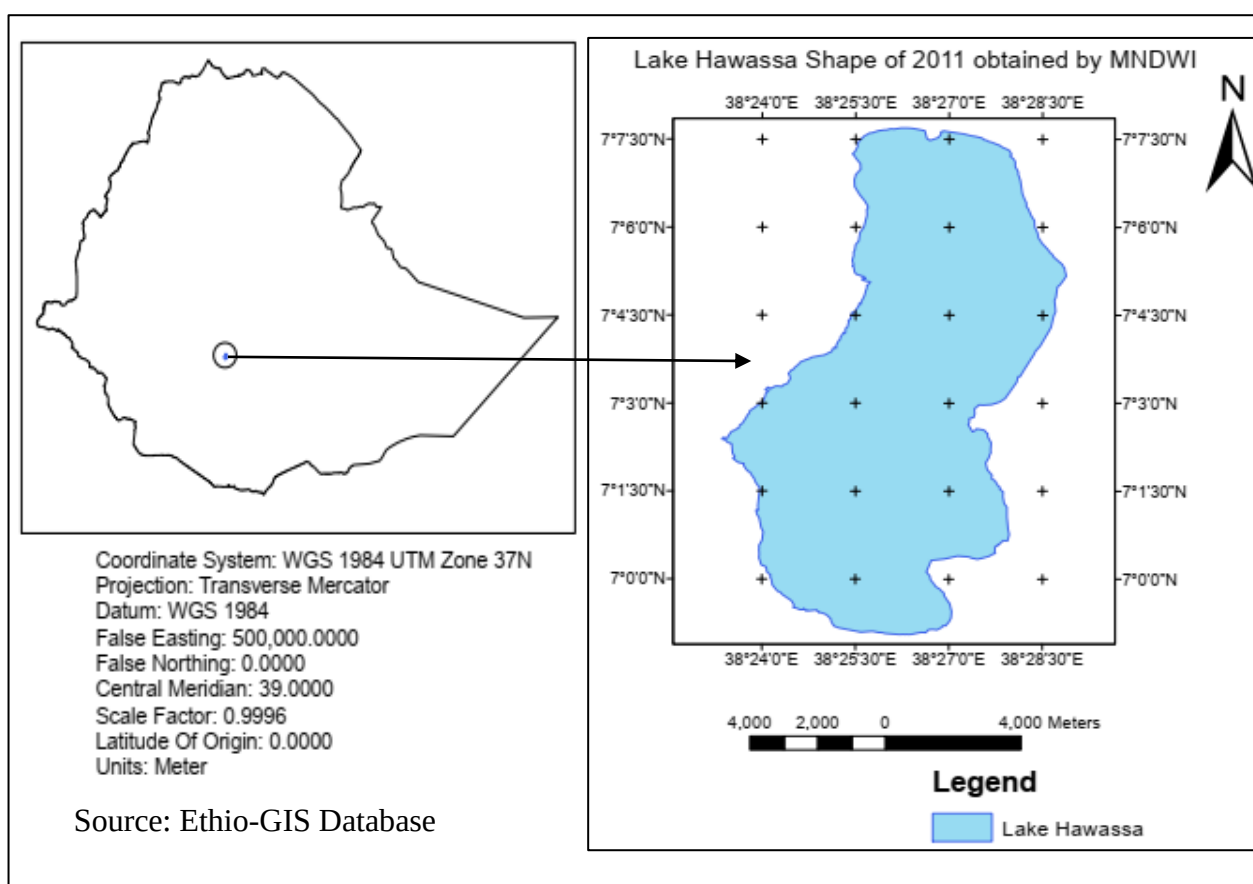


Figure 3.1 Location Map of Study Area

3.1.3. Land use/cover

According to MoWR, (2010) as cited in (Belete, 2013), land use in the watershed is dominated by cultivation which occupies 61% of the total area (or 66% of the land area) with intensive cultivation. The major land cover splits into smallholder cultivation (95%) of which 31% is

cereals and perennials (CI3) and 64% cereals only (CI4) and mechanized cultivation (5%) most of which is state owned rather than private. Intensive cultivation with perennial crops occurs in the eastern hills with cereal cultivation dominating the western, southern and northern areas.

Other important land covers include disturbed and plantation forests in the Wendo Koshe hills and around Wendo Genet comprising 3% of the area; dense and open shrubland in the Wendo Koshe hills and west of Cheleleka comprising 6%, grassland (11%) comprising open grassland in the Wendo Koshe hills (3%), in association with marshland at Cheleleka (4%), in association with moderate smallholder cultivation in the Eastern hills (3%) and wooded grassland (1%) in the eastern hills (Belete, 2013).

3.1.4. Morphology of Lake Hawassa

Lake Hawassa is the smallest and the highest in altitude among the Great Ethiopian Rift Valley lakes (1680 m.a.s.l) and located between the Ziway-Shalla lakes to the north and Lakes Chamo and Abaya to the south. The lake lies within a nested caldera complex and is predominantly underlain by highly faulted ignimbrites and other silicic pyroclastic deposits (Belete, 2013).

When the elevation of Lake Hawassa (1680 m) is compared with lake Ziway (1636 m), Langano (1585 m), Abiyata (1578 m), Shalla (1550 m) and Abaya and Chamo (~1180m), it is possible for ground water to flow from Lake Hawassa to low lying lakes when hydrogeological condition permits (Gebreegziabher, 2004; Belete, 2013).

The maximum and mean depths estimated in this study were 23.7 m and 12 m respectively for the year March 2011. According to the bathymetry survey of by (Belete, 2013), which was conducted on January 2011, the maximum depth of the lake is 23.4 m and an average depth of 13.3 m. And according to (Yonas *et al.*, 2018) based on conducted bathymetry on January 2011, maximum depth is 23.34 m and an average depth of 12.08 m.

3.2. Materials

3.2.1. Data Types and Sources

All the data used to achieve the objectives of this study were secondary data. These data and their sources are explained below in Table 3.1.

Table 3.1 List of Data types and sources used

A. Topographic Map						
S/N	Data	Data Type	Scale	Data Source	Year	Purpose
1	Boundary, Contour	Bed Surface Topographic Maps	1:10,000	ECDSWC	1999	- To generate bed elevation of Lake Hawassa for the year 1999
B. Hydrographic Survey Data						
	Data	Data Type	Grid space	Data Source	Year	Purpose
2	In-situ Depth	Point Data	500 m	Field Data	2011	- For depth estimating model construction and accuracy assessment
C. Remote Sensing Data						
	Satellite	Sensor	Resolution	Source	Year	Purpose
3	Landsat 7	- ETM+	30 m	USGS (GLOVIS) Earth Explorer	2011	- For detecting bathymetry of the lake for the year 2011.
4	Landsat 5	- TM	30 m	USGS (GLOVIS) Earth Explorer	2011	- For gap-filling the Landsat 7 ETM+ SLC-off scene using as a reference scene.

3.2.2. Software's Used

Software used in this study is selected based on the capability to work on the existing problems in achieving the predetermined objectives. The details of software's used in this study are tabulated and explained in Table 3.2 below.

Table 3.2 List of software's used

S/N	Name	Version	Purpose
1	ENVI	5.2.	- To pre-process satellite imagery.
2	Global Mapper	19.0	- To pre-process the scanned Bed surface Topographic maps
3	ArcGIS	10.3	- To digitize contour lines from the pre-processed scanned topographic map - To generate DEM and extract depth of the lake from the vector contour lines. - To extract reflectance values of pre-processed satellite images. - To generate continuous bed surfaces of the lake through interpolation. - To create map of changes to determine sediment and erosion capacity of the lake.
4	Microsoft Office Excel	2016	- To establish the relationship between in-situ depth (dependent variable) and reflectance values (independent variable) for obtaining the linear/Lyzenga model calibration/construction parameters. - To estimate/predict depth for the whole area using the calibrated model
5	Mendeley Desktop	1.14	- To insert citation and references used for the study.

2.3. Conceptual Framework

The theoretical framework presented the review of literature on different theories related to the different methods of bathymetric mapping and different models of bathymetric data extraction from satellite imagery and its role in sediment capacity estimation. In addition, the empirical review has presented bathymetry of Lake Hawassa in the previous studies, different studies

conducted before on utilizing various satellite datasets and methods for bathymetry derivation and sediment capacity estimation. Depending on the reviewed theories and empirical frameworks, to answer the questions, objectives and statement of the problem of this study the conceptual framework is developed.

The rationale for utilizing remote sensing for bathymetric data extraction in this study is that RS method is faster and applicable to various environments, including shallow coastal waters, and clear rivers. RS allows modeling of bathymetry at spatial scales that are impossible to achieve with traditional methods. Conventional approaches to bathymetry mapping rely on field surveys of water depth at sampled locations. Such approaches are however characterized as being labor-intensive and time-consuming. Moreover, it is often difficult to achieve the desired mapping accuracy just based on a limited number of sampled points. On the other hand, the state-of-the-art mapping approaches include using ship-borne underwater dragging sonar to record returned sounding signals in a fixed time interval for extensive water depth measurements. This advanced approach can accurately depict the underwater terrain and suitable for marine engineering design and construction, but its high cost makes it less accessible for generic low-budget research projects with lower accuracy requirements. Ever since the 1970s, satellite remote sensing technology has been gradually adopted as an alternative to minimize field work for clear water bathymetry mapping. The synoptic view, easy access, and dynamic nature have made the remote sensing approach a rather cost-effective way to provide quick solutions to bathymetry mapping for studies of the fast-changing coastal environment (Deng *et al.*, 2008).

The accuracy of depth estimation using linear model from remote sensing is evaluated. Optical remote sensing of deriving bathymetry using Empirical model of linear or Lyzenga model is used for this study to extraction of bathymetric data or depth estimation. This algorithm is chosen because of the following reasons; data availability and requirements of parameters, user-friendly and easy to use, software used and facility. And, finally extracted bathymetric data is applied for sediment capacity estimation of Lake Hawassa because of required data availability for the study, and Lake Hawassa is one of the Rift Valley's Lakes in Ethiopia that is more researchable area and facing problem due to siltation such as Lake level rise and reduction in storage capacity. And, also the bathymetry of the lake is not retrieved from remote sensing imagery and the accuracy of depth estimated by any empirical model from

remote sensing is not known before. Therefore, there is a need in evaluating the accuracy of depth estimation from remote sensing data using linear model and its result on estimation of sediment yield.

Generally, to achieve the objectives of this study, the following systematic steps were conducted including; (i) secondary data collection such as; in-situ bathymetry survey data, bed topography map and remote sensing data i.e. satellite imagery (ii) preprocessing of bed topographic map to generate bed elevation of the year 1999 and satellite imagery such as radiometric correction to convert digital number to top of atmosphere reflectance; atmospheric correction to remove the effect of atmosphere; SLC-off gap-filling; isolating water reflectance values from non-water features; removing sun specular effect to decrease noise and scattering effects on the input image; (iii) extracting the reflectance values from multispectral images for usage bands corresponding to the points, where there were available depth measurements, (iv) correlating empirically the extracted reflectance values with the in situ measurements to estimate the water depths; (v) statistical analysis of the model for performance assessment of the model to validate the result; (vi) generation of 3D bed surface relying on estimated depth through interpolation or prediction; (vii) creating map of changes in bed level between the two generated 3D bed surfaces; (viii) estimating the sediment yield; (ix) finally comparing the result of the present study with the in-situ measured depth based sediment yield.

The conceptual framework is presented graphically below to achieve the objectives and answer the research questions of this study. So, the following systematic steps which is involved in the flowchart shown in Figure 3.2 were conducted and performed.

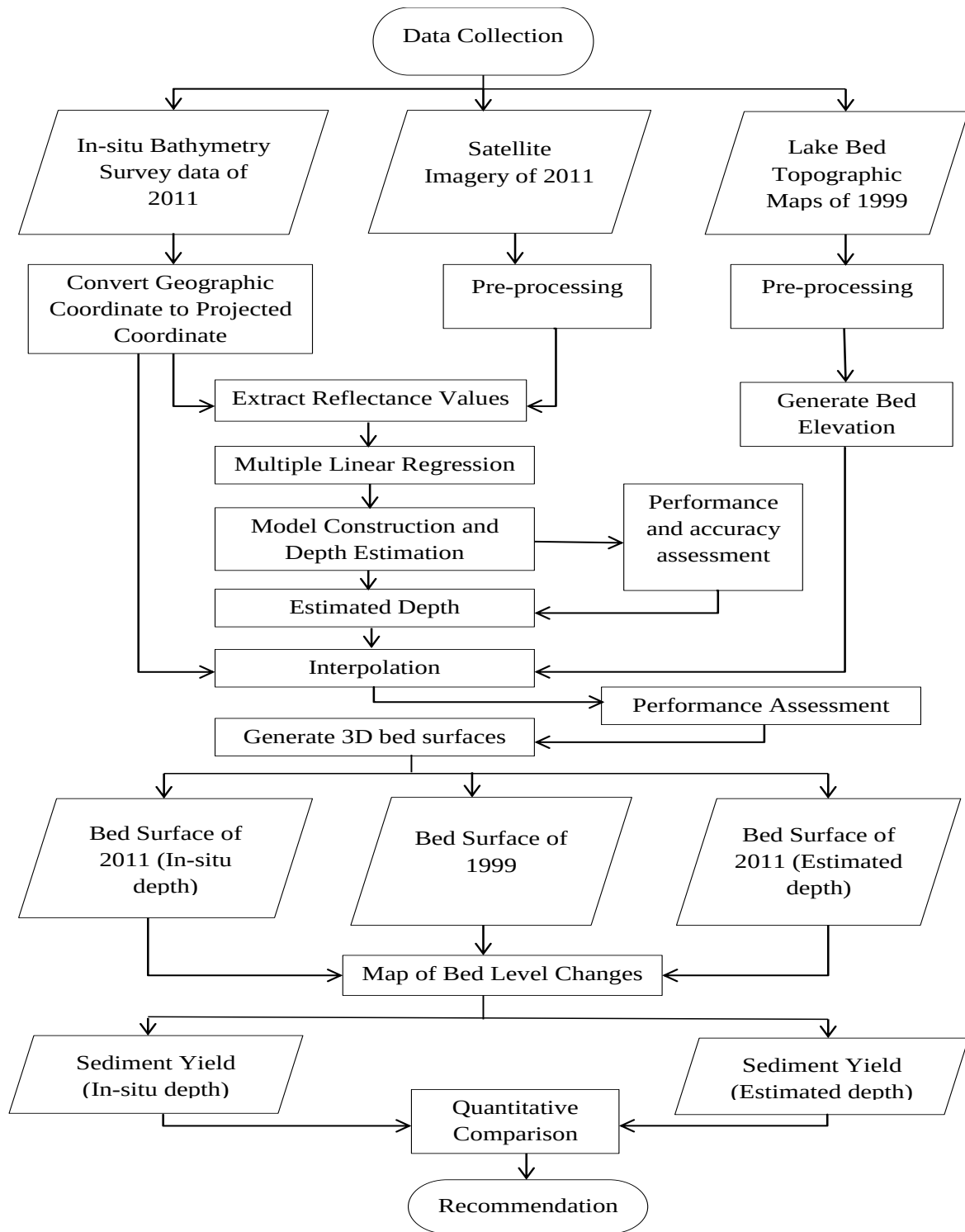


Figure 2.2. Conceptual framework flowchart of methodology adopted for the study

3.3. Methods of Data Analysis

The details of data analysis as per the conceptual framework flow chart presented in Figure 3.2 above are discussed in detail under this section.

3.3.1. Pre-processing

Pre-processing activities made was twofold; for lake bed surface topographic map and satellite imagery.

The lake bed surface topographic maps prepared from the bathymetry survey of the lake water body data with scale 1:10,000 and contour interval of 2m were collected from ECDSWC. These maps exist in hardcopy blueprint on four different A1 size papers which covers the whole lake bed. These bed topographic maps were pre-processed to generate lake bed elevation of the year 1999 and the following systematic steps were followed.

The blueprint hard copy bed surface topographic maps were first scanned using A1 scanner. These scanned bed topographic maps are then geo-referenced to Adindan UTM zone 37 N using the grid coordinates on the maps and mosaicked on Global Mapper software. To make the spatial reference of the bed surface topographic maps the same with satellite imagery it is projected to WGS84 UTM zone 37 N. The contours lines on the projected image were vectorized manually through digitization in ArcGIS software, presented in (Appendix-1). The elevations of these contours are added as an attribute. The TIN were created using elevation attribute as input and converted to raster DEM data with pixel size of 40 m, which represent the bed elevation. The elevation value of each raster pixel is extracted and prepared for generation of 3D bed surface of the year 2011 in combination with Lake Shoreline point data that represent the Lake surface elevation. These shoreline were digitized from the bed surface topographic maps that represent the boundary of the Lake.

The other pre-processing activity were done for satellite imagery. The details of these pre-processing activities are discussed in literature review section 2.3.2. The raw satellite imagery is first converted to radiance by using radiometric calibration tool in ENVI software. Using the radiance as an input, FLAASH atmospheric correction input parameters (Appendix-2) are entered and the effect of atmosphere is removed from the image in ENVI software. After applying FLAASH atmospheric correction, FLAASH produces negative minimum values and multiplies reflectance data by 10,000 to save space for output data. So, in order to remove the

negative value and rescale the reflectance values between 0 and 1 based on the theory that the reflectance value ranges between 0 and 1, the following formula is used according to (Singh, 2018) cited in (Elmorshdy, 2019) using band math tool in ENVI software;

$$(B1 \leq 0) * 0 + (B1 \geq 10000) * 1 + (B1 > 0 \text{ and } B1 < 10000) * \text{float}(b1)/10000 \quad \text{Equation 3.1}$$

Where; B1 is a channel or band which will be applied for every channel to scale the reflectance values within the range of 0 to 1, where is the 100% reflectance.

These two pre-processing activities are done for both Landsat 7 ETM+ and 5 TM multi-spectral bands.

Following rescaling the reflectance values, the gap-filling were done for Landsat 7 ETM+ using Landsat 5 TM of January 10, 2011, which is close scene in time to the Landsat 7 ETM+ and also both scene have equal wavelength multi-spectral bands, as reference scene for gap-fill. The gap-fill were made by Linear Local Histogram Matching algorithm in ENVI software gap-fill file extension. This algorithm is used since it is better than the existing gap-fill methods in the gap-fill file extension. The output of the gap-filled image is presented in Appendix-3. Following gap-fill, water body is extracted by applying MNDWI (Equation 2.12) on the gap-filled Landsat 7 ETM+ using band math tool in ENVI software. The output raster has a threshold value ranges between 0 and 1, and is then reclassified based on the threshold value using reclassify raster tool in ArcGIS environment. Threshold values are assigned as; less than 0 to non-water bodies and greater than 0 for water body (Appendix-4). The reclassified raster is converted to polygon and the shape file of Lake Hawassa is exported. Using Lake Hawassa shape file, water body is extracted from the gap-filled image.

Using the extracted water body, the technique of (Hedley *et al.*, 2005) was implemented on the ‘glint’ image bands towards the correction of sun-glint effect. Three image samples with size 50x50 pixels were carefully selected from glinted areas (deep water) at different locations on the image. Linear regression is made between NIR and Visible bands to determine regression slope. As soon as the regression slope was defined for every band combination, the Equation (2.13) was used to determine the deglinted pixel using raster calculator tool in ArcGIS environment.

Finally, for the implementation of the linear bathymetric model (Equation 2.6) the corrected reflectance values are extracted using Extract Multi-values to points in ArcGIS Environment and log-transformed to determine their natural logarithm values. The log-transformation of these corrected reflectance values were done using Microsoft Excel. And, the natural logarithms of these corrected reflectance values of bands 1, 2, 3 and 4 were determined using $\ln(x)$ function.

3.3.2. Estimation of Depth

The model used in this study for estimation of depth is Lyzenga or linear band model algorithm updated by (Lyzenga, 1985), and again (Lyzenga, *et al.*, 2006) which is described in detail in literature review section 2.2.5 (ii). This model is chosen for this study on the basis of available data required. Additionally, since the model account for water quality heterogeneity and depth-independent variability in reflectance values between bands this it is used for this study. This model has been most widely used for estimating water depths from optical multi-spectral remote sensing imagery (Su *et al.*, 2008).

In order to construct and evaluate model performance, the in-situ depth is categorized into two groups as training and test datasets, through random sampling techniques that account for all depth ranges and spatial distribution of all the study area. 70% of the data as training dataset for construction of model while 30% of the data were test data set assigned for model validation assessment. Multiple linear regressions is carried out on Microsoft Excel 2017 using an input of training datasets and corresponding log-transformed reflectance values of bands 1, 2, 3, and 4 to obtain model parameters. These multiple bands are used on the basis of contribution to overcome the problem of heterogeneous bottom types. In this study band 5 (SWIR1) and band 7 (SWIR2) were excluded as their spectral information is generally considered insignificant for bathymetry applications.

Following model construction, the statistical analysis was made for model performance and accuracy assessment using the statistical parameters; correlation coefficient (R), Mean Absolute Error (MAE) and Root Mean Square Error (RMSE). This is done using an input of the model estimated depth with the corresponding in-situ measured samples (test data sets) not used in model calibration. The value of R was determined from the correlation analysis made on Microsoft Excel, and MAE and RMSE were calculated by the following equations;

$$MAE = \frac{1}{n} \sum_{i=1}^n |O_i - E_i| \quad \text{Equation 3.2}$$

$$RMSE = \sqrt{\sum_{i=1}^n \frac{(O_i - E_i)^2}{n}} \quad \text{Equation 3.3}$$

Where, O_i is in-situ observed/measured depth and E_i is the corresponding estimated depth at location i . n is number of samples.

Finally, the linear model calibrated is applied to estimate the depth for the whole study area using an input of log-transformed reflectance values on Microsoft Excel.

3.3.3. Interpolation

In order to generate continuous bed levels of the study area, it is necessary to approximate the elevation values in areas that are not included with measurements (levels points) through interpolation. In this study, interpolation was done using these most widely used three interpolation methods namely; Inverse Distance weighting (IDW), Radial Basis Function (RBF) and Empirical Bayesian Kriging (EBK-found in a newer version of ArcGIS environment) under Geo-statistical Analyst Tool of interpolation module in ArcGIS environment. For more information on the theoretical background of these methods, those interested readers can review the help topics of ArcGIS Software.

The input data set were split-half into two; 50% for interpolation and 50% for cross-validation. Splitting of samples is done through random sampling techniques that accounts for spatial distribution of samples over the study area. One dataset (interpolation dataset) are interpolated into 3D bed surface and the other (validation dataset) is used to determine the error variance by cross-validation (Isaaks & Mohan, 1989). Predictive ability or model performance in prediction of 3D bed surface, of each methods are validated through cross-validation technique of internal validation type using validation dataset. Statistical analysis were performed to quantify the error between input and predicted data using the two statistical indicators; MAE and RMSE, to evaluate model performance in prediction of 3D bed surface. These statistical indicators were calculated using the formulas;

$$MAE = \frac{1}{n} \sum_{i=1}^n |M_i - P_i| \quad \text{Equation 3.4}$$

$$RMSE = \sqrt{\sum_{i=1}^n \frac{(M_i - P_i)^2}{n}} \quad \text{Equation 3.5}$$

Where; M_i is measured/input elevation at i and P_i is the corresponding predicted elevation at i .

n is number of samples.

3.3.4. Generation of the 3D bed surfaces

In this study, 3D bed surfaces for the year 1999 relying on the bed elevation generated from topographic maps, and for the year 2011 relying on the depth estimated by Lyzenga or linear band algorithm, are obtained using the interpolation method with the better performance, described in section 3.3.3. These 3D bed surfaces are used in creating map of changes to estimate the amount of sediment yield between the years from 1999 to 2011.

3.3.5. Creating Map of Bed Changes

The map of changes in bed level, created by overlaying the two created bed surfaces in the ArcGIS Software Environment, represents the changes zones. This map was created in order to determine the amounts of sediment yield in the study area from year 1999 to year 2011.

3.3.6. Estimation of Sediment Yield

Sediment yield between the years 1999 and 2011 were estimated relying on the the created map of bed changes, described in section 3.3.5. This was done in using the volume statistics in the attribute table of created map of bed changes. Negative values which represents fill or sediment deposition were summed up which shows the amount of sediment yield between 1999 and 2011 over the lake bed surface.

3.3.7. Comparison

Quantitative comparison of estimated sediment yield of the lake between 1999 and 2011 was made between the present approach estimates and estimation based on generating 3D bed of the lake relying on the in-situ depth measurement.

CHAPTER FOUR: RESULT AND DISCUSSION

In this chapter, the results obtained from data analysis as per the study objectives, and discussion on result are presented and described in detail.

4.1. Depth Estimation

4.1.1. Model Construction

A total of 368 bathymetric data points obtained from (Yonas *et al.*, 2018) were used in this study for retrieval of depth from satellite image. These data were collected by rapid bathymetric surveying using the SonarMite echo-sounder (Bonn, Germany) (235 kHz frequency, 0.3–75 m depth capacity and +/- 0.025 m accuracy), eTrex Venture Garmin (Garmin Corporation, Taipei County, Taiwan) geographic positioning system (GPS) and a motorized boat to measure lake depth at uniform 500 m grid points in January 2011. These in-situ data were collected at 500 m spacing and the depth ranges from 0.45 m – 23.37 m. Using a total of 258 points (training dataset) in-situ depths corresponding to the log-transformed corrected reflectance's as an input, multiple linear regression is carried out for empirical modeling or construction of a model. The result of regression statistics summary for model construction is presented in Table 4.1.

Table 4.1 Regression Statistics analysis output of Model Construction

Regression Statistics	
Multiple R	0.707
R Square	0.500
Adjusted R Square	0.492
Standard Error	3.731
Observations	258
ANOVA	
Coefficients	
Intercept	-34.895
Band1	6.656
Band2	4.158
Band3	-7.149
Band4	-16.686

Model parameters were obtained from the regression statistics coefficients (Table 4.1) and the model is constructed as follows;

$$z = -34.895 + 6.656X_1 + 4.158X_2 - 7.149X_3 - 16.686X_4 \quad \text{Equation 4.2}$$

Where; z = the estimated depth

X_1, X_2, X_3, X_4 = the natural logarithms of the corresponding pixel values of bands 1, 2, 3 and 4.

4.1.2. Model Performance Assessment

After the model is constructed (Equation 4.2) using the training dataset, the depths corresponding in-situ depth (test data set) were estimated.

The assessment of accuracy and model performance in estimating depth is made by comparing the model estimated depth with the corresponding in-situ depth of 110 points test dataset samples not used in calibration of the model. The accuracy of model in estimating depth is assessed using simple statistical models; correlation coefficient (R), mean absolute error (MAE) and root mean square error (RMSE). The results of statistical analysis on the model performance and accuracy are presented in Table 4.1.

Statistical Analysis	Correlation Coefficient (R)	Mean Absolute Error (MAE)	Root Mean Square Error (RMSE)
Values	0.7	3.06 m	3.69 m

Apart from the abovementioned statistical results, the observations are supported by establishing a scatter diagram as shown in Figure 4.1, to compare the in-situ measured depth and model estimated depth.

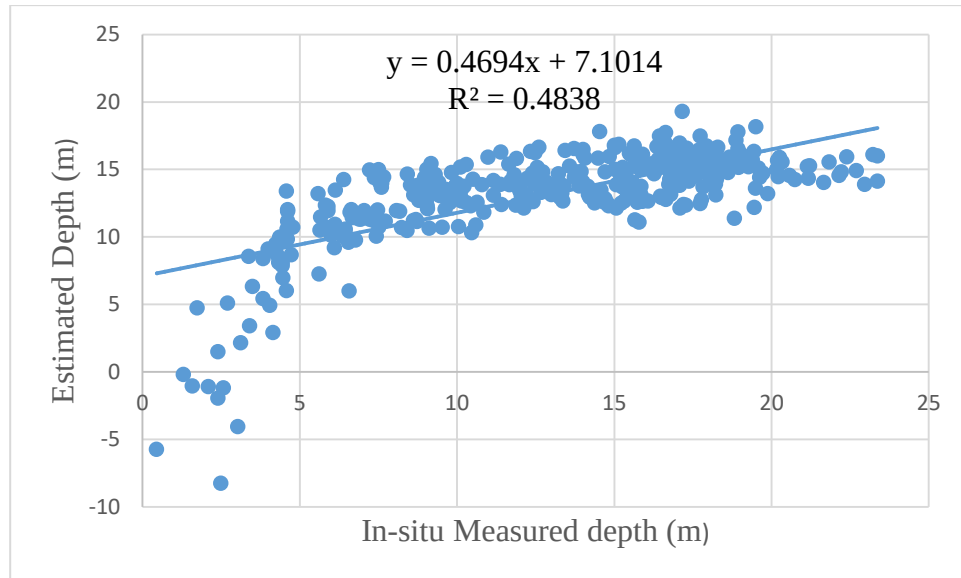


Figure 4.1 Scatter plot for estimated and in-situ measured depth of the year 2011

During model construction, the regression statistics output (Table 4.1) shows the model has Coefficient of multiple determination (R^2) of 0.5. This Coefficient of multiple determination (R^2) is the measure of variation of the dependent variable that is explained by the regression line and the independent variable. Also, it is probably the most popular measure of how well a regression model fits the data. Its values range from zero to one. A value of R^2 near zero indicates no linear relationship, while a value near one indicates a perfect linear fit. The value of R^2 (0.5) of the model (Table 4.1.) shows, 50% of the variation in the dependent variable (depth) is accounted for by the variations in the independent variables (reflectance values), while the rest of variations, 50% is unexplained. So, the model has able to account half of the depth-independent variability in reflectance values between bands.

The statistical analysis on model performance assessment and accuracy in estimating depth shows that the model performs with R, MAE and RMSE value of 0.7, 3.06 m and 3.69 m respectively. The value of correlation coefficient ($R = 0.7$) is close to 1, and it shows there is a good positive correlation between in-situ and corresponding estimated depths. But, MAE and RMSE, which quantify error, are a better indicators for evaluating model prediction performance accuracy. However, the result of mean absolute error ($MAE = 3.06$ m) and root mean square error ($RMSE = 3.69$ m) values shows the model performs with an errors of 3.06 m and 3.69 m respectively. This errors result shows the model accuracy is unsatisfactory statistically in estimating depth.

Moreover, the absolute value of estimated depth by the model corresponding to in-situ measured depth ranges from 0.5 m to 20 m. As shown in figure 4.1, the scatter diagram shows the data fits the regression line for the depth between 5 m and 20 m. By taking sample of estimated and in-situ measured it is also observed through comparison, which is presented in (Appendix-5), a model has good performance in estimating depth between 5m and 20 m. In other way, it is also observed the model has less performance in estimating depth lower than 5m and greater than 20 m. Since this depth less than 5 m is around the edge of the lake, the varying bottom surface are misleading the results. Additionally, there exist a negative values of the estimated depth by the model and they are observed spatially near the shoreline or shallow part of the lake. Around the near shoreline of the lake, the area is mostly covered by vegetations and these have led the model to perform less in estimation of depth on this region. It is noticed in previous study (Lyons *et al.*, 2011) presented in Table 2.2 of literature review, Lyzenga algorithm could not be used to derive depth over seagrass substrate types.

Additionally, in the estimated depth corresponding to the in-situ depth, a depth greater than 20 m where not obtained. This shows the model has low performance in estimating depth for the deepest part of the Lake. Despite what was said in section 3.3.2, about the multiplicity of bands that contributes to overcome the problem of heterogeneous bottom types, the calibration or construction of linear model in the whole of the study area was not statistically satisfactory. These can be overcome by dividing the study area into different sub-regions with uniform or almost uniform bottom and calibrating linear model separately for each region (Doxani *et al.*, 2012). It is noticed in previous study (Doxani *et al.*, 2012), the application of linear or Lyzenga model for the whole area have resulted unsatisfactory. So, it is preferred to divide the area into three sub-regions; the sea grass area with the shallower waters, the sandy area with the deeper waters and the mixed area with intermediate depths. Finally in the study linear model was calibrated separately for each region and the outcomes of the statistical analysis indicated that the model provided very good results for the mixed and sea grass-free area. However, during conducting this or present study there where lack of information and knowledge on bottom surface of the year 2011 during the satellite imagery is captured. Therefore, it was unable to divide the area into sub-regions based on bottom surface and calibrate the model separately to estimate depth for further accuracy assessment.

In general, as an argument observed in previous studies to estimate depth with better accuracy it needs to calibrate the model separately based on bottom surface. Also, other empirical models that are not used in this study needs to be checked. However, the accuracy of result obtained by the present study shows the remote sensing retrieved bathymetry in present study is statistically unsatisfactory for an application that needs better accuracy. But, the estimated depth will be enough for the area between 5 and 20 meter and can be used for application that needs less accuracy instead of costly field measurements.

Finally, the model is applied for the whole area at the pixel size (i.e. 30 m), the depth is estimated and prepared for 3D bed generation to determine the amount of sediment yield for the years 1999 to 2011. The absolute value of estimated depth ranges from 0.02 m to 23.7 m.

4.2. Generation of the 3D Bed Surfaces

The bed elevation obtained from the pre-processed bed surface topographic maps in combination with the elevation points of shoreline determined from the digitized boundary on the bed surface topographic maps were used to obtain the 3D bed surface of the year 1999. As of June 21st, 1999 the lake surface level assumed an elevation of 1681.70 m.a.s.l. (WWDSE, 2001). This elevation were used for shoreline points that represent the lake surface level.

The estimated depths explained in section 4.1 by Lyzenga or linear band model, were used to determine the bed elevation for the year 2011. These depth at pixel size (30 m interval) were subtracted from the Lake surface elevation 1681.05 m (Yonas *et al.*, 2018) to determine bed elevation, on Microsoft Excel. These points are combined with the shoreline points of the extracted water surfaces by the MNDI algorithm from the Landsat 7 ETM+ image, which represents the highest surface elevation. These points are imported and then exported to shape file in ArcGIS environment. The feature class is then converted to 3D feature by attribute of bed elevation using Feature to 3D by attribute module in 3D Analyst and prepared for interpolation to generate or predict continuous 3D bed surface. Interpolation was made by three methods; Empirical Bayesian Kriging (EBK), Inverse Distance Weighting (IDW) and Radial Basis Function (RBF) using an interpolation datasets, described in section 3.3.3, as input for both years 1999 and 2011 in ArcGIS software. The predicted bed elevation at unsampled points corresponding to validation datasets are extracted from the interpolated or predicted surface by the three methods. Predictive ability or model performance were made by

internal cross-validation in prediction of 3D bed surface. The statistical analysis was made to compare the performance of interpolation by quantifying the error for each methods. The result of statistical analysis and comparison matrix of methods is presented in Table 4.2.

Table 4.2 Statistical indicators of interpolation methods

Methods	Year 1999		Year 2011		Decision
	MAE (m)	RMSE (m)	MAE (m)	RMSE (m)	
EBK	0.027	0.096	1.069	1.403	First Rank
IDW	0.091	0.292	1.089	1.445	Third Rank
RBF	0.041	0.118	1.084	1.433	Second Rank

The 3D bed surfaces are generated by EBK method with minimum MAE and RMSE values. All bed elevation data's are used as an input for prediction of 3D bed surfaces of year 1999 and 2011. The results of generated 3D bed surfaces for both years are presented in Figure 4.2.

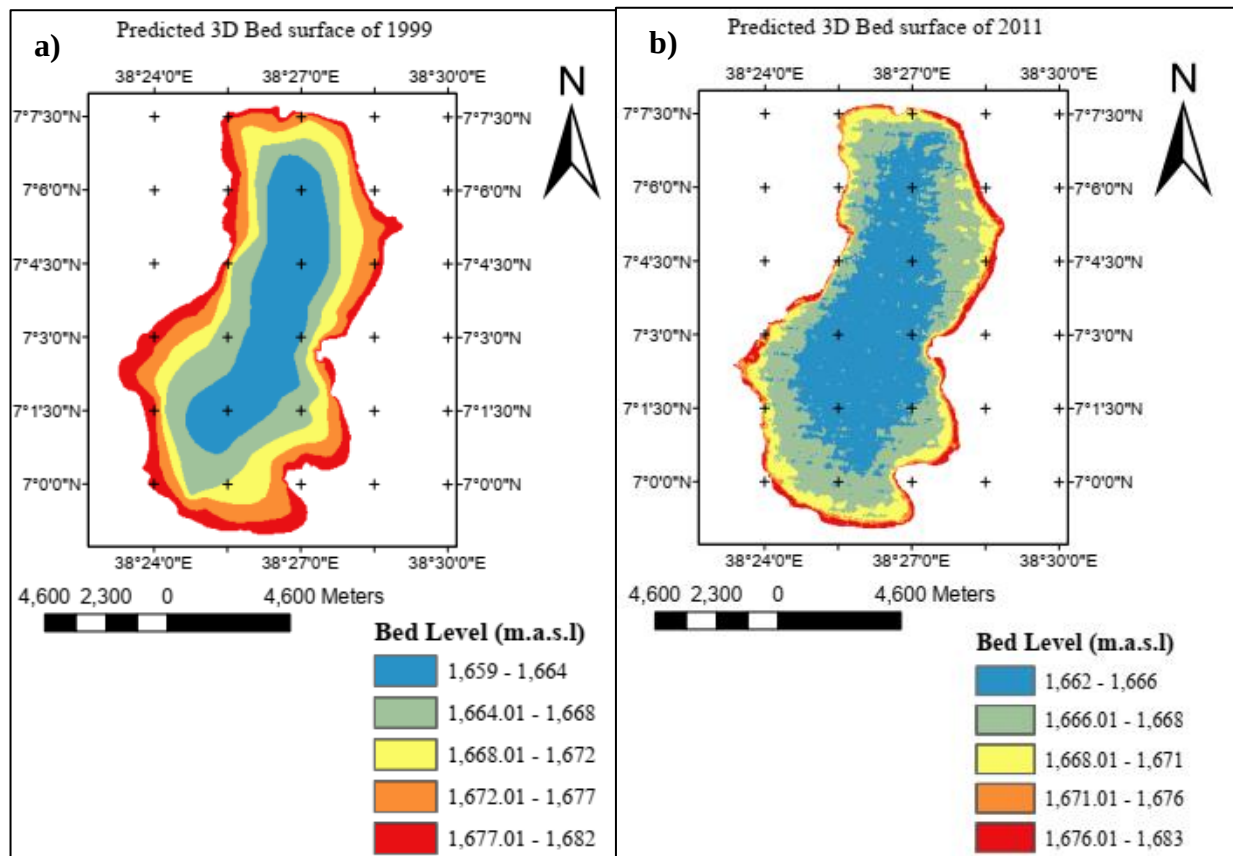


Figure 4.2 The generated 3D bed surfaces maps: (a) 1999; (b) 2011

In addition the 3D bed surface of the year 2011 relying on the in-situ depth were also generated using EBK method of interpolation. The result of generated 3D bed surface is presented in figure 4.3.

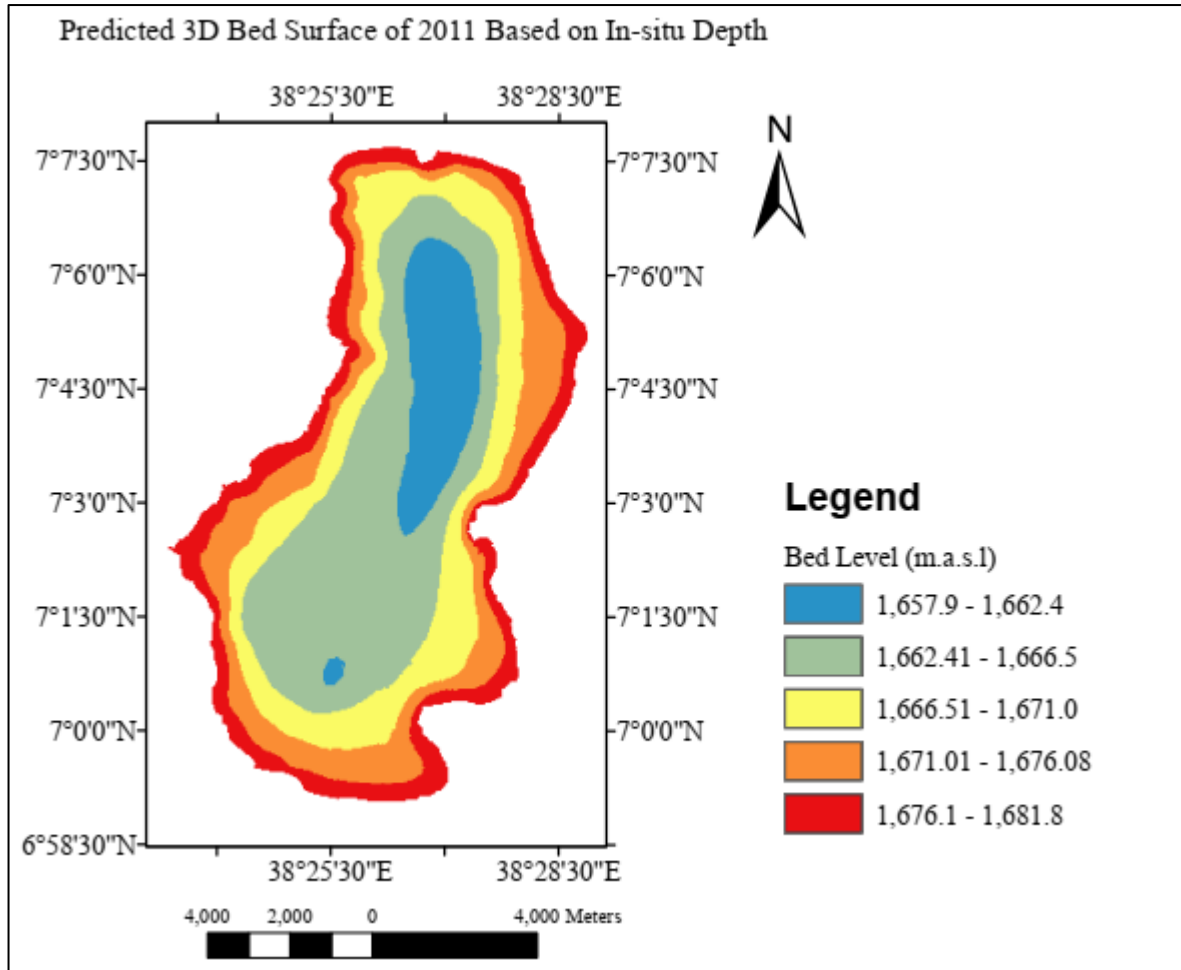


Figure 4.3. The generated 3D bed surface of 2011 based on In-situ depth

The statistical analysis based on the MAE and RMSE (Table 4.2) were made to generate 3D with the best performed method. The root mean square error (RMSE) has been used as a standard statistical metric to measure model performance. The mean absolute error (MAE) is another useful measure widely used in model evaluations (Chai & Draxler, 2014). To obtain the complete predict 3D bed surfaces of the lake by the interpolation process, the EBK method for interpolation was used as it produced the best results (the lowest values for both the MAE and the RMSE) between the other tested methods of interpolation in this study. The lowest values of MAE and RMSE close to zero shows more accurate. For EBK method, the MAE and

RMSE for the year 1999 equals 0.027 m and 0.096 m respectively, and for the year 2012 MAE and RMSE equals 1.069 m and 1.403 m respectively. This indicates, EBK has the highest accuracy of the interpolation process over the two methods (IDW and RBF) in this study. Moreover, it is observed using in-situ depth of 2011 that EBK has better accuracy in prediction of 3D bed surface of Lake Hawassa the two methods. It is noted in previous studies (Elsahabi *et al.*, 2017; Elsahabi *et al.*, 2018b) the performance assessment was done to choose the interpolation method with better performance based on MAE and RMSE value, to generate 3D bed surfaces. These interpolation methods were namely; inverse distance weighting (IDW), radial basis function (RBF) and ordinary kriging (OK). These studies have chosen the method with low values of MAE and RMSE and generated 3D bed surface. Therefore, this study concludes EBK has better performance in prediction of 3D bed surface for Lake Hawassa over IDW and RBF, and it is used to generate 3D bed surfaces for the years 1999 and 2011, presented in Figure 4.2, and in-situ based depth Figure 4.3.

4.3. Estimation of Sediment Yield

Estimation of sediment yield by the bathymetric approach in this study was based on a change in Lake Bottom elevation at two different time periods (topographic differencing technique).

In order to determine the amount of sediment yield between the years 1999 and 2011, map of changes in bed levels were created by overlaying the two created 3D bed surface of 1999 (as before) and 2011 (as after), shown in Figure 4.2(a) and (b), using cut/fill tool in 3D Analyst of ArcGIS environment. The map of change in bed level or elevation were created within the extracted waterbody by MNDWI. The result of created map of changes in bed levels for the period (1999 - 2011) were produced and presented in Figure 4.4.

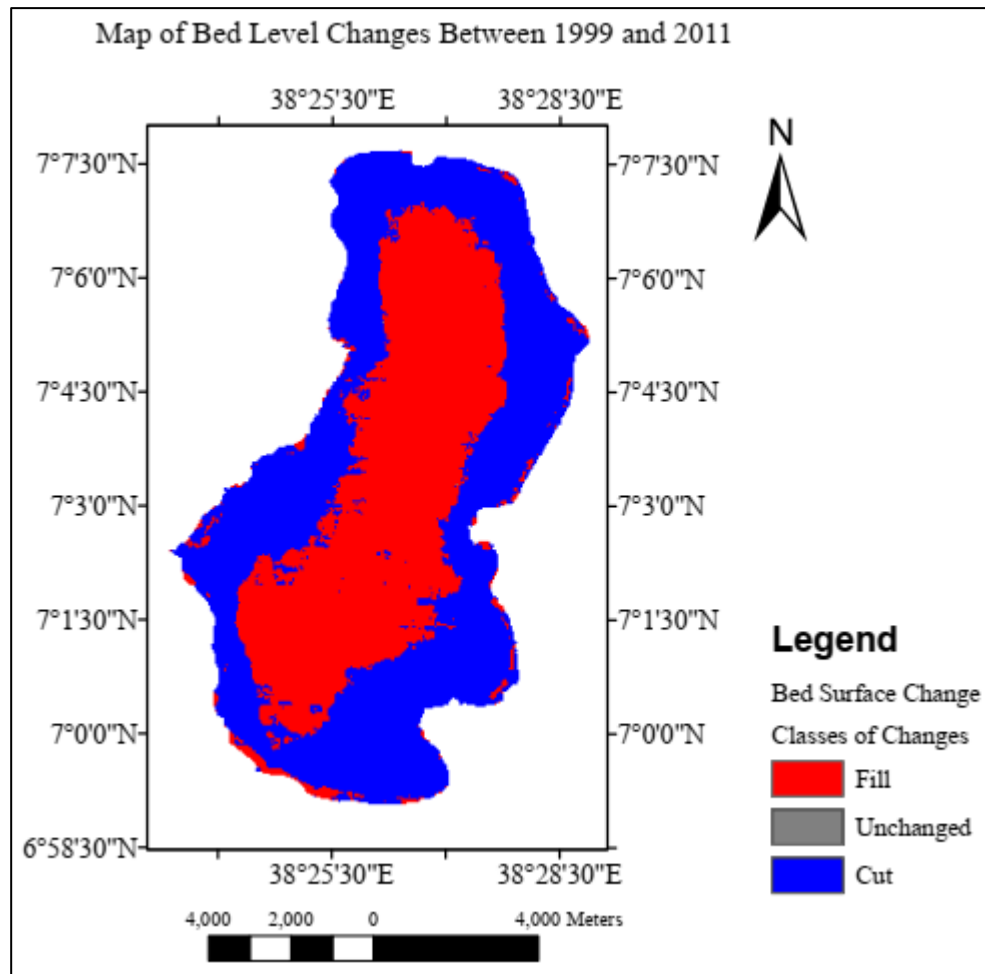


Figure 4.3 Created Map of Bed Level Changes

The changes in bed levels between the two predicted bed surfaces, shown in Figure 4.4, were generalized by three broad change categories, namely; unchanged, fill and cut. Unchanged (colored in brown on Figure 4.4) means the bed levels that have the same elevation values in the old and new bed surface. Fill (colored in red on Figure 4.3) means the old bed surface levels that were increased in the new bed surface and cut (colored in blue in Figure 4.3) means the old bed surface levels that were decreased in the new bed surface.

However, the main aim of this study was to estimate sediment yield between 1999 and 2011. So, it is focused on the class that is classified as fill (Figure 4.3). It shows, the sediment accumulation were occurred on those region colored red on Figure 4.3. When this is observed on the temporal basis, using Figure 4.2 (a) and (b), there is an increase in bed elevation from the year 1999 (Figure 4.2(a)) to 2011 (Figure 4.2 (b)) which is colored in red (Figure 4.3) for

bed level change. And, it implies the sediment deposition has taken place over those area between the year 1999 and 2011. This sediment yield between these two years in the lake were estimated.

This sediment yield between the years 1999 and 2011 were determined by the volume statistics in the attribute table of the created map of changes. Negative values indicate areas that have been filled (material added). These negative values were summed up which shows fill or sediment deposition (sediment yield). Table 4.3 shows the sediment yield on 2D surface areas and amounts in the period (1999 – 2011), which were estimated by using the statistics of the classes of changes in the generated map of changes.

Table 4.3 Sediment yield between 1999 and 2011

Bed Surface change	Sediment Yield
2D Area (km ²)	40.9
Volume/Amount (Million m ³)	94.1

The result (Table 4.3) shows the amount of sediment yield for the years 1999 to 2011 is 94.1 million m³ over 40.9 km² area. The spatial distribution or sediment delta formation is observed (Figure 4.3) mostly along the center or deep region of the lake.

The results of the present estimated sediment yield based on detected bathymetry from the RS satellite data by present approach were compared with the sediment capacity estimated by generating 3D bed surface relying on the 368 points in-situ depth of year 2011, used in this study to calibrate and validate the empirical model for depth estimation. The 3D surface of the year 2011 (Figure 4.3) were generated by EBK interpolation method with better performance than the two (IDW and RBF), using the in-situ depth and used for estimation of sediment yield. Table 4.4 presents a quantitative comparison of the two applied approaches.

Table 4.4 Comparison of sediment yield of present approach with in-situ measurement

Bed Change Category	Sediment Yield
Estimation by the present approach (Estimated Depth from RS) (Million m ³)	94.1
Estimation based on the in-situ measurements depth (Million m ³)	70

The computed amount of sediment yield using the present approach is 94.1 million m³ which is higher than the results of the result obtained based on the in-situ measurement. The results indicate that the present approach overestimates sediment amount by about 24.1 million m³ compared to the results estimated from in-situ based depth measurements.

The overestimation of sediment yield amount results from the low performance of depth estimation model. As discussed in section 4.1.2, the Lyzenga or linear band model has low performance in estimating depth, especially depth less than 5 m and greater than 20m. However, this estimated depths were used to observe its effect on estimating sediment yield through generation of 3D of the year 2011.

The overestimation of sediment amount arises from the model performance in estimation of depth at the deepest part of the lake. That is, the estimated depth at the deepest region of the lake by the model is less than the expected depth or underestimated. This shows there is an increase in generated bed surface elevation from the expected bed surface or resulted in overestimation of bed elevation. So, this results in overestimation of sediment yield in a way that, sediment accumulation estimated over the area is more than the accumulation occurred. Moreover, the estimated depth at shallow part of the lake has negative values and the model has also overestimated depth over this region. This means the bed elevation generated using this depth is lower than the expected bed elevation of the Lake. Accordingly, the estimated depth by the applied approach in the present study have given uncomfortable result. Therefore, the bathymetry retrieved in present study from multi-spectral bands 1, 2, 3 and 4 of Landsat 7 ETM by applying Lyzenga or linear band model for the whole area at once overestimates the sediment yield, and the result was unsatisfactory.

CHAPTER FIVE: CONCLUSION AND RECOMMENDATION

5.1. Conclusion

The linear model was calibrated and validated to estimate depth for the whole area at 30 m interval. The statistical analysis of R, MAE and RMSE were done to assess the model performance and accuracy in estimating depth. The values of R, MAE and RMSE were 0.70, 3.06 m and 3.69 m respectively. Results showed that an error of 3.06 and 3.69 m is obtained for depth estimation. This implication of estimating depth by linear or Lyzenga model from remote sensing data shows the model has less accuracy in estimating depth for the whole area. Especially, the model has lower performance in estimating depth at shallow and deepest part of the Lake. Moreover, it is noticed Lyzenga or linear model performs less when calibrated at once for the whole area at once. This accuracy implies that it is statistically unsatisfactory for applications that need better accuracy. Therefore, the study concludes Lyzenga or Linear model has low performance and accuracy statistically if calibrated for the whole area at once to estimate depth.

Interpolation was made by three methods; EBK, IDW, and RBF, and the ability in prediction of 3D bed surfaces was cross-validated statistically. The result of model performance shows EBK has better performance in the prediction of 3D bed surface with lesser values of MAE and RMSE for both years 1999 and 2011 over IDW and RBF methods. The values of MAE (0.027 m) and RMSE (0.096 m) for the year 1999, and MAE (1.069) and RMSE (1.403) for the year 2011, which is less than the MAE and RMSE values of IDW and RBF (Table 4.2). Additionally, it is also observed EBK performs better for prediction of 3D bed surface of the year based on in-situ measurement. This implies that EBK has better accuracy in prediction or generation of 3D bed lake Hawassa than IDW and RBF. Therefore the study concludes that EBK has better performance in the generation of 3D bed surface of Lake Hawassa and it can be used in the future for different applications such as; sediment capacity estimation, storage capacity, sediment assessment.

Moreover, the amount of sediment and erosion between the years 1999 and 2011 was estimated by creating a map of changes using the predicted 3D bed surfaces. The results indicated that the computed amount of sediment using the estimated depths from the RS data (the present approach) is 94.1 million m³. When compared with the sediment yield derived

from the generated 3D bed surface of the Lake based on the field measurements, the present approach overestimates by about 24.1 million m³. The implication of using estimated depth by Lyzenga or linear model overestimates sediment yield and results in unsatisfactory. Therefore, the study concludes the estimation of sediment yield relying on estimated depth by calibrating linear or Lyzenga model for the whole area at once from Landsat 7 ETM+ multispectral bands of bands 1, 2, 3 and 4 results unsatisfactory statistically and cannot be used for the future.

5.2. Recommendations

In order to estimate depth using optical remote sensing of multispectral bands 1, 2, 3 and 4 of Landsat 7 ETM+, the model have to be calibrated separately by dividing the area into regions based on surface material and depth to get better result of depth. Additionally, the accuracy of other empirical models such as; Stumpf and Jupp's model have to be applied for the study area and their accuracy needs to be checked.

Empirical Bayesian Kriging (EBK) method of interpolation can produce a better result than Inverse Distance Weighting (IDW) and Radial Basis Function (RBF), if used for 3D bed surface prediction for Lake Hawassa.

Depth estimation from optical remote sensing of MS imagery of Landsat 7 ETM+ bands 1, 2, 3 and 4 by applying linear or Lyzenga model for the whole area at once could overestimates sediment yield and the result is unsatisfactory. So, it could not be used for sediment yield estimation of Lake Hawassa.

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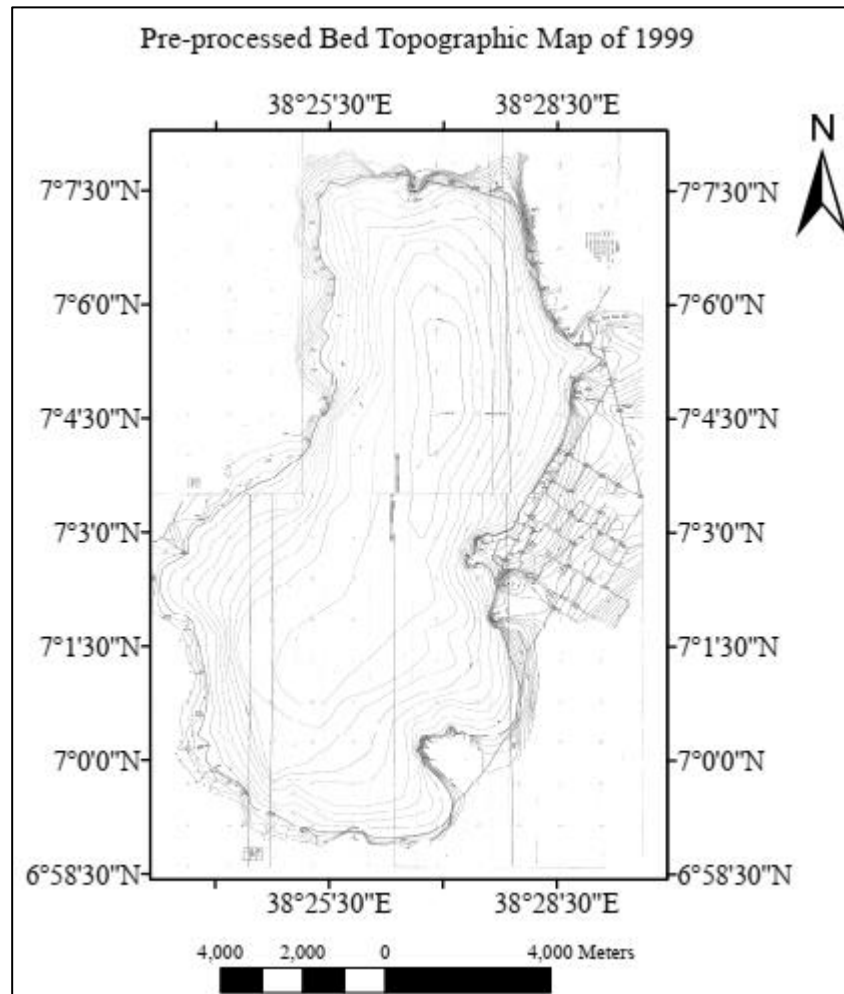
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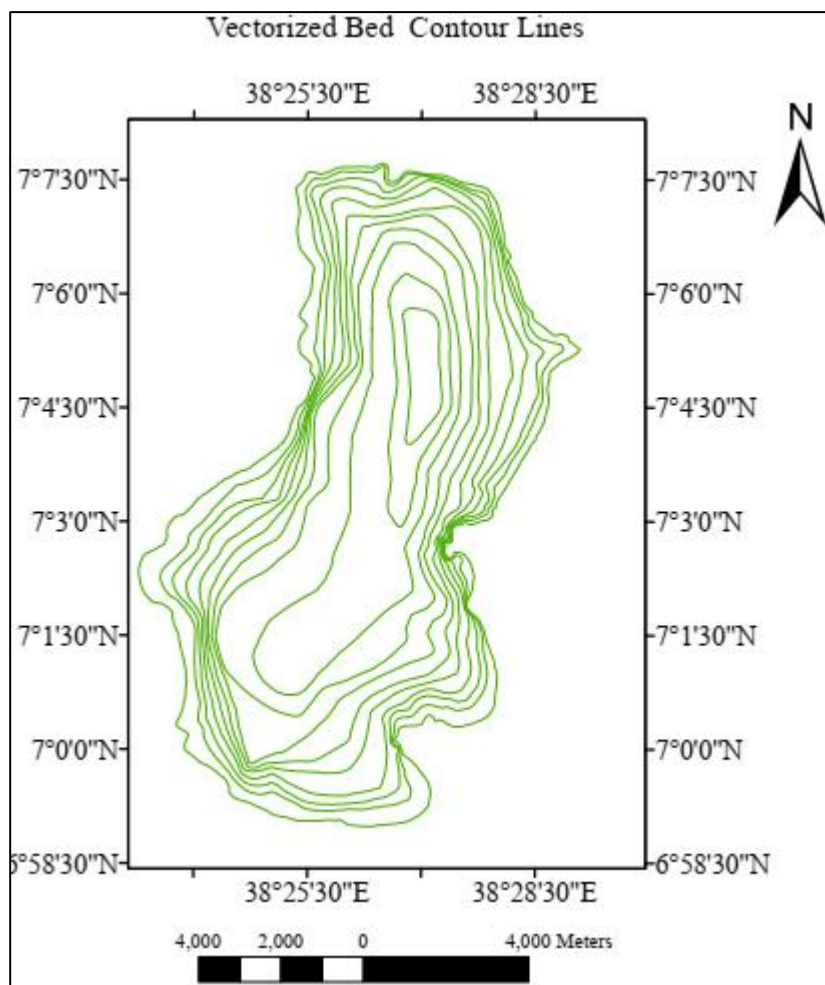
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APPENDICES

Appendix-1. Pre-processed Lake Bed Surface Topographic map



A) Scanned and Geo-referenced Bed Surface Topographic Map



B) Vectorized Contour

Appendix-2. FLAASH Atmospheric correction input parameters

FLAASH Atmospheric Correction Model Input Parameters

Input Radiance Image: C:\Users\Abdi\Documents\research data\Abdi\from GLOVIS\April 28-2020\Radiometric Calibration\Radiance-7.d

Output Reflectance File: C:\Users\Abdi\Documents\research data\Abdi\from GLOVIS\April 28-2020\FLAASH Atmospheric correction\Sur

Output Directory for FLAASH Files: C:\Users\Abdi\Documents\research data\Abdi\from GLOVIS\April 28-2020\FLAASH Atmospheric com

Rootname for FLAASH Files: FLAASH_

Scene Center Location: DD <-> DMS

Lat: 7 14 13.72

Lon: 38 56 7.98

Sensor Type: Landsat TM7

Sensor Altitude (km): 705.000

Ground Elevation (km): 1.681

Pixel Size (m): 30.000

Flight Date: Mar 23 2011

Flight Time GMT (HH:MM:SS): 07:34:20

Atmospheric Model: Tropical

Aerosol Model: Tropospheric

Water Retrieval: No

Aerosol Retrieval: 2-Band (K-T)

Water Column Multiplier: 1.00

Initial Visibility (km): 40.00

Apply Cancel Help

Multispectral Settings... Advanced Settings... Save... Restore...

Appendix-3. Gap-filling of Landsat 7 ETM+ Image by LLHM Method

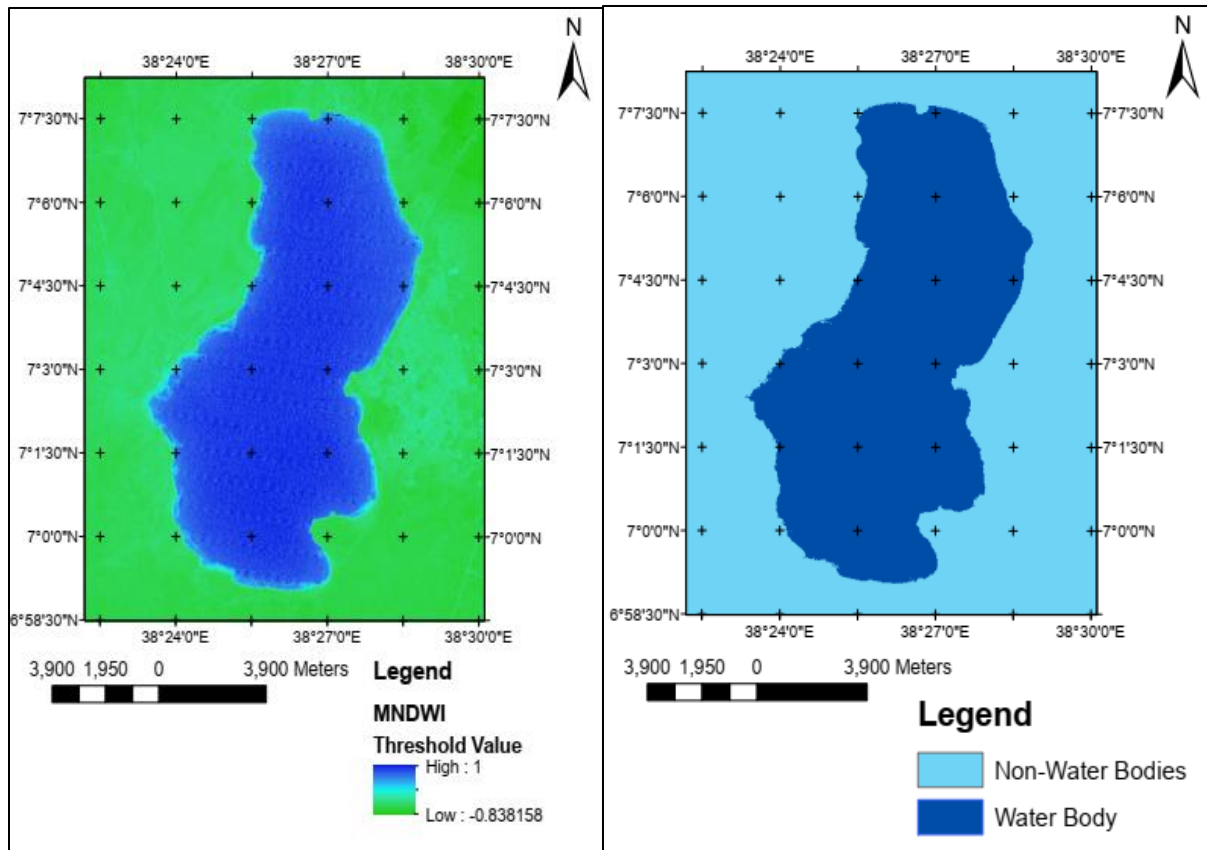


a) Before gap-fill image of Landsat 7 ETM+



b) gap-filled image of Landsat 7 ETM+

Appendix-4. Extraction of Water Body by MNDWI Algorithm



a) MNDWI output

b) Reclassified MNDWI based on Threshold value

Appendix-5. Comparison of samples of Estimated and Corresponding In-situ Measured Depth.

In-situ Depth (m)	Estimated Depth (m)	Easting UTM WGS84 (m)	Northing UTM WGS84 (m)
1.740	1.851	440495.0684	787464.6284
4.730	5.257	434010.8805	779352.0373
6.110	6.454	440509.8772	775351.7957
6.450	6.614	434010.0094	775850.7114
6.557	6.835	439830.1543	778568.3138
6.782	6.618	440010.4018	774851.8415
7.523	7.570	437010.4084	772850.8991
8.243	8.507	435509.916	779850.7212
8.413	8.646	434509.9738	774350.846
8.735	8.784	440010.3862	775349.9991
9.120	9.010	441510.2297	783352.0147
10.053	9.598	438010.304	787350.9045
10.853	10.408	441010.1609	785352.3395
11.163	11.327	435510.1371	773851.4324
11.413	11.335	437509.9429	773851.3595
11.878	11.397	435010.3893	778850.2793
12.050	12.808	437010.1198	781850.9991
12.127	11.625	439510.2886	776351.6416
12.427	12.089	439510.2779	776849.7999
12.560	13.039	434510.2526	777849.8429
12.603	12.889	434510.0529	775351.9146
12.948	12.652	437510.2084	783852.5213
13.168	13.264	437509.9495	774349.5188
13.227	14.000	437510.2419	784851.2164
13.343	13.402	437510.2601	785351.7503
13.813	13.974	438510.1397	775351.7576
14.000	14.169	440010.2785	779850.0292
14.183	12.364	437010.4493	774350.1228
15.018	15.922	436009.9027	778851.4022
15.067	14.848	440010.1842	785851.662
15.273	15.853	437509.9605	774850.0507
16.177	16.272	436010.4388	777850.3339
16.280	16.176	437510.1107	780851.6947
16.400	16.482	435510.3454	777350.4229
16.437	16.130	437010.0219	779350.7044
16.537	16.469	435010.2067	776349.9808

16.557	16.255	437010.0025	778850.1713
17.037	17.423	439510.2402	779850.6139
17.047	16.816	438010.233	784850.6084
17.090	16.977	438010.2092	783851.9141
17.100	17.302	435510.2853	776351.7276
17.697	17.575	438010.1309	780350.5572
17.850	17.858	437509.9935	776351.6458
18.110	18.213	439010.2254	785852.8452