ESTIMATION OF SALINITY AND HEAVY METALS OVER MARSHLADS BASED ON LANDSAT-8 DATA

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Dedicated to my beloved family,

to the most precious persons in my life, my mother, my wife and

my handsome son.

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ABSTRACT

Marshes are the provider of habitat for several types of living creatures. Their preservation are prioritized for sustainable environment and eco-friendliness. Iraqi marshland is the largest wetland with an area of 15,000-20,000 km^2 in the Middle East and Western Eurasia and has a significant impact on the ecosystem. The salinity in the Tigris and Euphrates Rivers near their discharge point at the marsh ranges from 0.5 to 2ppt (parts per thousand). This thesis focuses on Al-Hawizeh marsh, which is one of the major marshes with an area of 2,500-3,000 km^2 in Iraq and considered as an enriched resource of fishing and irrigation. Of this mashland, 74% of it's agricultural land suffers from high degree of salination that need to be overcomed. Several man-made activities and post-war related events have caused radical deterioration of water quality in this marshland. The aim of this study is to monitor and assess the water quality parameters of this marsh. The optical remote sensing dataset (bands B6, B7, and B11) from Landsat-8 (OLI/TIRS) are synergistically integrated to the proposed salinity index (SI) and soil moisture index (SMI) model. By using the newly developed algorithms, the optimum water quality parameters in terms of salinity and minerals contents which comprised of iron, lead, zinc, nickel, calcium carbonate and sulphate are determined. This creative integration between remote sensing data and developed algorithms is established to successfully map the spatial variation of salinity and minerals distributions within Al-Hawizeh marsh during four seasons in the year 2013. The results of this study show that SMI model achieved better accuracy in retrieving the water quality parameters than the SI model. The average of the concentrations values for (salinity, SO_4, $CaCO_3$, Fe, Pb, Ni and Zn) by using SMI model are found to be minimal in winter as (746, 121, 84, 0.59, 0.49, 0.04 and 0.036) mg respectively and maximum in autumn as (1956, 202, 172, 0.64, 0.53, 0.08 and 0.05) mg respectively. The decision tree (DT) classification that uses single band outperformed the support vector machine (SVM) classification when combined with SMI model. This study also found that the change of value for salinity and mineral are minimum between winter and spring but maximum between summer and autumn. In conclusion, the developed systematic and generic approach may constitute a basis for determining the water quality parameters in the marshland worldwide.

ABSTRAK

Paya menjadi pembekal habitat untuk beberapa jenis hidupan. Pemeliharaan mereka diutamakan untuk mengekalkan kelastarian alam sekitar dan mesra alam. Tanah paya Iraq merupakan paya terbesar dengan keluasan 15,000-20,000 km^2 di Timur Tengah dan Barat Eurasia dan mempunyai kesan yang signifikan terhadap ekosistem. Kemasinan Sungai Tigris dan Euphrates berhampiran titik aliran mereka di kawasan paya adalah di antara 0.5-2ppt (bahagian per ribu). Tesis ini memberi tumpuan kepada tanah paya Al-Hawizeh yang merupakan salah satu daripada paya yang terbesar dengan keluasan kawasan 2,500-3,000 km^2 di Iraq dan dianggap sebagai sumber terkaya untuk perikanan dan pengairan. Bagi tanah paya ini, 74% daripada tanah paya ini adalah tanah pertanian yang mengalami tahap kemasinan tinggi yang perlu diatasi. Beberapa aktiviti buatan manusia dan peristiwa berkaitan pasca perang telah menyebabkan kemerosotan secara radikal terhadap kualiti air dalam tanah paya ini. Tujuan kajian ini adalah untuk memantau dan menilai parameter kualiti air paya ini. Set data penderiaan jauh optik (jalur B6, B7, dan B11) daripada Landsat-8 (OLI/TIRS) diintegrasikan secara sinergi dalam model indeks kemasinan (SI) dan indeks kelembapan tanah (SMI). Dengan menggunakan algoritma baru yang dibangunkan, parameter optimum kualiti air dari segi kemasinan dan kandungan mineral yang terdiri daripada besi, plumbum, zink, nikel, kalsium karbonat dan sulpid dapat ditentukan. Integrasi kreatif di antara data penderiaan jauh dan algoritma yang dibangunkan telah berjaya untuk memetakan variasi spatial kemasinan dan taburan mineral di dalam paya Al-Hawizeh sepanjang empat musim dalam tahun 2013. Hasil kajian ini menunjukkan bahawa model SMI mencapai ketepatan yang lebih baik bagi mendapatkan semula parameter kualiti air berbanding dengan model SI. Purata nilai kepekatan untuk kemasinan SO_4, $CaCO_3$, Fe, Pb, Ni dan Zn dengan menggunakan model SMI didapati adalah minimum pada musim sejuk iaitu masing masing adalah 746, 121, 84, 0.59, 0.49, 0.04 dan 0.036 mg dan maksimum pada musim luruh iaitu 1956, 202, 172, 0.64, 0.53, 0.08 dan 0.05 mg. Pengelasan keputusan pokok (DT) menggunakan jalur tunggal mengatasi pengelasan mesin vektor sokongan (SVM) apabila digabungkan dengan model SMI. Kajian ini juga mendapati bahawa nilai perubahan kemasinan dan mineral adalah minimum di antara musim sejuk dan musim bunga tetapi maksimum di antara musim panas dan musim luruh. Kesimpulannya, pendekatan yang sistematik dan generik yang dibangunkan boleh menyumbang kepada asas penentuan parameter kualiti air di tanah paya di seluruh dunia.

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LIST OF ABBREVIATIONS

AGNPS	-	Agriculture Non Point Source Pollution
ALI	-	Advanced Land Imager
ANN	-	Artificial Neural Network
ASI	-	Aster Salinity Index
ASTER	-	Advanced Space borne Thermal Emission and Reflection Radiometer
BI	-	Brightness Index
BM	-	Band Math
BOD	-	Biochemical Oxygen Demand
CAD	-	Computer Aided Design
CASI	-	Compact Airborne Spectrographic Imager
CDOM	-	Colored Dissolved Organic Matter
Ch1	-	Chlorophyll-a
CLEQM	-	Central Laboratories For Environmental Quality Monitoring
CM	-	Clay Mineral
CN	-	Color Normalized
COD	-	Chemical Oxygen Demand
CPAs	-	Color Producing Agents
CRIM	-	Center for the Restoration of Iraq's Ministry
DN	-	Digital Numbers
DO	-	Dissolved Oxygen
DOC	-	Dissolved Organic Carbon
DOS	-	Dark Object Subtraction
DSS	-	Decision Support System
DT	-	Decision Tree

EC	-	Electric Conductivity
EFs	-	Enrichment Factors
EMR	-	Electromagnetic Radiation
ETM	-	Enhanced Thematic Mapper
FLAASH	-	Fast Line of sight Atmospheric Analysis of Spectral Hypercubes
GA	-	Genetic Algorithm
GB	-	Green Bio-volume
GDSHW	-	General Directorate Of State Hydraulic Works
GDVI	-	Generalized Difference Vegetation Index
GIS	-	Geographic Information System
GMM	-	General Mineral Model
GPS	-	Global Position System
GUAC	-	Quick Atmospheric Correction
GWR	-	Geographically Weighted Regression
HBI	-	Hilsenhoff Biotic Index
HIS	-	Hyperspectral Imaging System
HIS	-	Hue-Saturation-Intensity
HRV	-	High Resolution Visible
HSPF	-	Hydrologic Simulation Program Fortran
HSV	-	Hue Saturation Value
IAR	-	Internal Average Reflectance
ICP-OES	-	Inductively Coupled Plasma Optical Emission Spectrometry
IDL	-	Interactive Data Language
IOPs	-	Inherent Optical Properties
LST	-	Land Surface Temperature
MD	-	Minimum Distance
MERIS	-	Medium Resolution Imaging Spectrometer
MIS	-	Multispectral Imaging System
ML	-	Maximum Likelihood
MNDWI	-	Modified Normalized Difference Water Index
MOEE	-	Ministry of Environment and Energy
MOS	-	Modular Optical Scanner

MS	-	Multispectral Scanner
MWR	-	Ministry Water Resources
NDII	-	Normalized Difference Infrared Index
NDSI	-	Normalized Difference Salinity Index
NDVI	-	Normalized Difference Vegetation Index
NDWI	-	Normalized Difference Water Index
NIR	-	Near Infrared
NRMSE	-	Normalized Root Mean Squared Error
NPOC	-	Non-Purged Organic Carbon
NTD	-	Normalized Trough Depth
OCTS	-	Ocean Color and Temperature
OLI	-	Operational Land Imager
PC	-	Principal Components
PCA	-	Principal Components Analysis
PRZM	-	Pesticide Root Zone Model
RBF	-	Radial Basis Function
RMSE	-	Root Mean Square Error
ROI	-	Region of Interest
RS	-	Remote Sensing
SE	-	Standard Error
SI	-	Salinity Index
SIM	-	Salinity Index Modified
SMS	-	Suspended Minerals
SM	-	Salinity Model
SMI	-	Soil Moisture Index
SPIM	-	Suspended Particulate Inorganic Material
SRO	-	Salinity Ratio
SR	-	Surface Reflectance
SS	-	Suspended Sediments
SSSI	-	Soil Salinity and Sodicity Index
SVM	-	Support Vector Machine
SWM	-	Stanford Watershed Model
SWNIR	-	Short Wave Near-Infrared

TDS	-	Total Dissolved Soilds
TIRS	-	Thermal Infrared Sensor
TLID	-	Transmitted Light Intensity Depth
TM	-	Thematic Mapper
ToA	-	Top of Atmosphere
TSM	-	Total Suspended Matters
TSS	-	Total Suspended Soilds
WQM	-	Water Quality Model
WQMISW	-	Water Quality Management Information System
WRI	-	Water Ratio Index

LIST OF SYMBOLS

Ca	-	Calcium
$CaCO_3$	-	Calcium Carbonate
Cd	-	Cadmium
Cr	-	Chromium
Fe	-	Iron
Hg	-	Mercury
Mg	-	Magnesium
N	-	Nitrogen
Ni	-	Nickel
Pb	-	Lead
PPT	-	Parts per Thousand
SO_4	-	Sulphate
T	-	Temperature (ºC)
Th	-	Thallium
TN	-	Total Nitrogen
TP	-	Total Phosphorus
Zn	-	Zinc

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CHAPTER 1

INTRODUCTION

1.1 Background of the Study

Marshes being the provider of habitat for several types of plants, animals, and insects often form a transition between the aquatic and terrestrial ecosystems. Prediction of marshes water quality by developing an accurate model and its subsequent remediation of water pollutants is prerequisite for sustainable development and ecological balance. Presently, many environmental problems such as pollution, frequent earth quake, tsunami, global warming, ozone hole, etc. certainly posed severe threat to humankind and nature (Abdul Jabbar, 2010). Literature hinted that some of these environmental crises are manmade, however the actual reasons still to be clarified.

A large portion of earth's landscape is covered by marshes so called wetland, which is one of the most important habitats that support more life than any other type of habitat. They are also essential to keep our environment clean. Thus, proper restoration of marshes and effective maintenance of their water quality is mandatory for environmental sustainability and human safety in terms of health and hygiene. Marshes being ubiquitous all over the Earth surface, the landscape of Iraq is not an exception. Actually, a large part of Iraq is covered by marshes where keeping the environmental affability to protect the communities from harsh weather conditions, supporting breeding grounds for commercially valuable fishes, and offering recreational opportunities are significant. Controlling the marshes water quality by detecting the presence of heavy metals including mercury (Hg), cadmium (Cd), arsenic (As), chromium (Cr), thallium (Th) and lead (Pb) and subsequently remediating them is an essential requirement to preserve such habitat for sustainability. Definitely, clean water is an essential requirement for aquatic life and human survival (Wu *et al*., 2014).

Categorically, several environmentally destructive development and human non-ethical activities such as water pollutions, inadequately discharges of sewage and industrial waste waters, poor agricultural practices, and lack of integrated watersheds management created major problems. Consequently, the water quality in rivers, lakes, and marshes are severely affected. These indicators posed a serious concern to the ecosystem, water resources degradation, public health risks and watersheds especially prone to water quality problems (Azab, 2012). Therefore, the quality of surface water is rapidly deteriorating. This is categorized as point sources involving the discrete flows of polluted water that enters the watersheds through a channel or pipe such as the effluent from a sewage treatment plants. They are often associated with municipalities or industries. Conversely, the non-point sources are usually associated with the widely covered land usage including forest management practices, agricultural cultivation, and livestock grazing. Generally, these pollution sources enter watersheds area through groundwater flow, overland flow or flow from small tributaries (Wu *et al*., 2013).

The surface water quality of watersheds such as marshes, lakes and reservoirs often vary depending on natural of hydrological, biological, chemical, morphological and sedimentation processes. Salinity, heavy metals, and pathogens such as parasites, bacteria and viruses being the waste materials are most dangerous environmental pollutants (Azab, 2012; Kerekes and Baum, 2005; Mather and Koch, 2011; Ongley, 2000; Ustin, 2004; Zacharias and Gianni, 2008). Supply of poor water quality severely affects the sanitation and causes soil erosions (Ustin, 2004) unless inhibited. Globally, approximately 25,000 deaths occur daily due to the water borne diseases (Amel Mustafa, 2012; Mujumdar, 2001; Ongley, 2000). Over the years, aerial or space sensor technologies so called remote sensing are intensively used to detect and classify marshes on Earth, which played a significant role towards natural resource management. It is worth mentioning that the water quality of rivers, streams, lakes and marshes in Iraq (Schwarte, 2003; Ustin, 2004) became questionable due to American-Iraq war related activities during 1991 and 2003 and proliferation of chemicals.

In the past few decades the problems regarding water quality is greatly cropped up in Iraq. Water pollutions in the form of discharges of sewage and industrial waste waters, poor agricultural practices, and lack of integrated watersheds management intensified the soil erosion and sedimentation. Furthermore, the poor public awareness on the water resources protection threatened the ecosystems, endangered the public health and degraded the water quality in Iraq (Kerekes and Baum, 2005; Schwarte, 2003; Ustin, 2004). Thus, proper management, assessment, monitoring and solving the problems of surface water quality require an in-depth analyses of watersheds, where an integrated catchment approach is believed to play a major role (Amel Moustafa, 2012; Haith and Tubbs, 1981).

The watershed database and modeling tools coupled GIS is prospective to simulate hydrological processes on a daily time step including surface water quality, runoff, evapotranspiration, soil erosion and agricultural pollutant transport (Quilbé and Rousseau, 2007). The mathematical modeling of water quality is essential for developing management plans for watersheds. The integration between GIS, different computer technologies, remote sensing techniques, and water quality models act as a powerful tool for water quality management, especially with complicated surface networks in watersheds. Moreover, GIS assist to collect, store, analyze, manipulate and display data that can be used easily to construct models for water quality management (Azab, 2012; Goodchild *et al*., 1996). The integrated model with the spatial capabilities of GIS together with spatial and temporal capacities of remote sensing can provide a powerful tool for management and assessment the surface water quality problems (Ammenberg *et al*., 2002; Amel Moustafa, 2012). In this view, the present thesis takes an attempt to model the marshes water quality accurately based on optical remote sensing information acquisition.

It is needless to mention that remote sensing is highly useful for monitoring and mapping the water quality on earth's surface (Ammenberg *et al*., 2002; Ustin, 2004). It is greatly potential for estimating, monitoring and mapping various parameters relating water quality. Recent advancement in remote sensing towards data acquisition and integration of spatial and temporal water quality models provided a renewed prospect for managing and evaluating the surface water quality problems in the marshes zone of southern Iraq. This study proposes some novel mathematical algorithms to retrieve numerous water quality parameters using Landsat-8 Operational Land Imager (OLI) and Thermal Infrared Sensor (TIRS) data acquired for four seasons in 2013. The developed model is implemented to assess and map these water quality parameters distributions in the context of marshland situated in Al-Hawizeh (southern Iraq).

1.2 Problem Statement

The over-exploitation, political reprisals against the inhabitants, and lack of coordinated management caused several problems connecting the Iraqi water quality over the past fifteen years. Thus, the primary water resources in Iraq including the marshes are contaminated, in which the marshlands water quality is declined and appeared very much harmful for human consumption. The repeated construction of dams due to acute water storage in Turkey and Syria which is the major reason for water quality deterioration in the Iraqi marshlands needs further clarification. Besides, the domestic industrial pollution and hydroelectric power generation along the Euphrates and Tigris rivers also declined the marshland water quality in Iraq (Khattab and Merkel, 2014; Abdul Jabbar, 2010; Nicholson and Clark, 2003; Sun *et al*., 2014; Ustin, 2004; Wu *et al*., 2013; Wu *et al*., 2014). Despite the necessity, research is seldom carried out to model the Iraqi marshlands water quality for effective remediation of pollutants.

Wars related destructive manmade events added extra impulses towards environmental crises, in which the natural water recourses are the greatest victim. The unforgettable Gulf war's over past three decades that majorly deteriorated the Iraqi marsh resources and caused irreparable environmental damage in the Arabian Gulf coastal waters need to be assessed. During Gulf War, million tons of oil that are spilled in the Arabian Gulf is eventually affected the water quality of rivers, streams, lakes and marshes in Iraq (Schwarte, 2003; Ustin, 2004). In addition, scantily treated sewage, poor land use practices, industrial wastewaters discharges, excessive use of fertilizers, and a lack of integrated watershed management are other factors that impacted the marshland water quality in Iraq (Ustin, 2004). Yet, no comprehensive study is made to determine their influence on marshlands water quality declination.

The water resources degradation being threatening to the ecosystems and public health requires special attention in term of remediation. A mathematical model enclosing all these negative effects such as environmentally destructive development, lack of information regarding water quality, poor public awareness and education on the protection of water resources, rapid deterioration of marshland water quality, etc. are far from being achieved (Kerekes and Baum, 2005; Schwarte, 2003; Sun *et al*., 2014; Ustin, 2004; Wu *et al*., 2013; Wu *et al*., 2014). Advancement of such model on marshland water quality prediction, monitoring and assessment may be advantageous to solve several socio-economic problems especially health, hygiene and food security.

With modernization and rapid industrialization, the ever-increasing water and soil salinity appears detrimental unless overcome. For instance, salinity in the Tigris and Euphrates rivers near their discharge point at the marsh ranges from 0.5 to 2 parts per thousand (PPT). Thus, 74% of irrigated land that is suffering from certain degree of salination needs remediation (Wu *et al*., 2013; Wu *et al*., 2014). In fact, salinity being the key parameter to understanding the water quality in marshland zones requires accurate measurement methods. Marshland salinity is a vital index for all living creatures including vegetations, species, microorganisms, animals, birds, insects, and plants. Thus, salinity monitoring, predicting, modelling, and simulation are crucial in the evaluation of ecological resources in Iraqi marshland zones.

Better management and assessment of marshes water quality requires the identification of diverse components of watershed, the land categories usage, and the interaction among various connected water bodies. By determining the salinity, heavy metals, hydrodynamics of the water bodies and their various affecting factors, one develops better understanding of the marshes water quality problems. This truly reflects the requirements of effective tools for water quality management. By synergistically combining the existing tools for the surface water quality management one can develop a better approach to determine the appropriate solutions connecting water pollution problems. Water quality models are considered as key tools in understanding such problems. They also act as main components in management and decision support systems. Accurate interpretation of aquatic environment water quality in terms of salinity and existence of heavy metals require comprehensive models describing the detailed parameters. Using such models, much authentic data can be produced in an efficient manner. This introduces the integration of information technology tools with modeling and remote sensing that can be readily designed to support the marshland water quality management and assessment process.

The advances made in water quality modeling using remote sensing data and information systems coupled to decision support systems in the management process are increasingly being recognized. This thesis combines the optical remote sensing data with water quality modeling to develop and support system concerning surface water quality management in marshes. It also explores the development in these tools to solve particular water quality problems. The main scope of the integration is to clearly understand the water quality of different types of connected water bodies in marshes. This integration is expected to provide a precise assessment of the water quality problems and to develop remedial management actions for environmental protection in the future.

1.3 Aim and Objectives of Study

The aim of this study is to monitor and assess the parameters governing the water quality such as salinity and heavy metals (SO_4, $CaCO_3$, Fe, Pb, Ni and Zn) in Al-Hawizeh Marsh (Iraq) by developing a model based on optical Remote Sensing (RS) data. Based on the problem statement the following objectives are set:

1. To develop a mathematical model based on Landsat-8 (OLI) and (TIRS) data for determining marshland water quality parameters including salinity and heavy metals (SO_4, $CaCO_3$, Fe, Pb, Ni and Zn).
2. To determine the spatial distributions of the salinity and metals in marshland water using data fusion techniques for monitoring and assessment.
3. To classify the marshland water quality parameters by using Support Vector machine (SVM) and Decision Tree (DT) classification depending on the mathematical models for optimization.

1.4 Research Questions

Based on the problem statement and cited objectives the following research questions are set:

1. Is it possible to retrieve the water quality parameters by developing a model based on Landsat-8 data?

2. How data fusion techniques can assess and monitor the water quality parameters?
3. Can Decision Tree effectively classify the water quality parameters?
4. How to optimize the developed model for achieving the results closer to the reality?

1.5 Significance of Study

Marshes are considered as an important water source for the humans and the agricultural areas south of Iraq. The environmental pollution such as the domestic, agricultural and industrial activities as well as the remnants wars and the heavy or toxic metals are considering as significant effects on marshes water quality parameters. Thus effects have both direct and indirect impacts on the economic wealth, natural resources and human activities of all the regions around marshes.

This study discovered the surface water quality problems and derived a computational framework for assessing salinity and numbers of minerals in Al-Hawizeh. The assessment of surface water quality on a watershed in Al-Hawizeh Marsh southern Iraq, involves the examination of all activities in the watershed for their possible effects on the existing water bodies. Agricultural irrigated watersheds are of complex physical nature because they include interacting irrigation and drainage networks which may be connected to marshes. Studying surface water quality problems in such watersheds of marsh zone for better management practices calls for a reassessment and integration of information technology tools designed to support the management process. Therefore, the integration between mathematical modeling and remote sensing applications could provide a powerful tool for management and decision making process related to the solution of surface water quality problems. The present research aims to contribute to the field of surface water quality management through integrating water quality mathematical models with the spatial and temporal capabilities of remote sensing.

New models are developed and integrated with the optical remote sensing data such as Landsat-8 for retrieving, monitoring and assessment of spatiotemporal changes and mapping the spatial distributions patterns for water quality parameters such as salinity and heavy metals (SO_4, $CaCO_3$, Fe, Pb, Ni, Zn) in Al-Hawizeh Marsh southern Iraq during four seasons in 2013. This study distinguishes to be unique for retrieving water quality parameters depending on Landsat-8 images. Thus, an attempt is made to develop an integrated water quality management information system that is applicable to watersheds of Al-Hawizeh Marsh. The developed models of this study are generic and can be applied to other marshes of local and international regions with similar conditions.

1.6 Scope of Study

This study focuses on Al-Hawizeh Marsh, which is the largest wetland ecosystem in the southern Iraq. This marshland is facing a declination in recent decades. The monitoring and assessment of spatiotemporal changes of water quality in Al-Hawizeh marsh is the main focus. The dataset used in this study comprise of satellite data (Landsat-8) acquired for four different seasons in 2013. These data are obtained from Iraq's ministry of water resources (MWR) and center for the restoration of Iraq's marshlands (CRIM). Landsat-8 data is greatly authentic because it has multi-spectral band images. In addition, the hyper-spectral imaging system that refers to high resolution (1-30m) imaging of the surface water is included. This study depends on the bands of B1 to B11. Additional topographical survey data is also used in the study. The software used for data processing includes ERDAS 2011 and ArcGIS10.1 coupled to ENVI 5.1. In order to reach the first objective of this research, the study considers the water quality modeling technical approaches to retrieve the water quality from Landsat-8 data. New algorithms are developed and integrated with remote sensing data for monitoring and assessing the water quality parameters such as heavy metals and salinity. ENVI techniques are used to map and assess water quality distribution patterns seasonally in Al-Hawizeh Marsh in southern Iraq.

1.7 Thesis Outline

This chapter provides a brief background to justify the importance of undertaken research on marshland water quality modeling based on optical remote sensing. The existing problems are highlighted as problem statement. To bridge the gap, a set of objectives are set with appropriate research questions. The significance and the scope of this research for developing an accurate water quality model are emphasized. Furthermore, the feasibility assessing and monitoring the water quality parameters using the satellite data in Al-Hawizeh Marsh of southern Iraq is underscored.

Chapter two provides a comprehensive literature review in terms of theories and applications regarding this study. Existing relevant literatures are critically evaluated to obtain useful information on remote sensing (RS) and appropriate parameters for water quality models (WQM).

Chapter three describes in detail the research methodology. It covers the procedures of data collection and data processing. It evaluates the accuracy and capability of water quality modeling to assess and monitor water quality parameters.

Chapter four presents the results and analyses for accomplishing the stated objectives, where the implementation of the developed model is demonstrated.

Chapter five discusses the results and interprets those using different mechanisms.

Chapter six concludes the thesis together with useful suggestions and recommendations for pursuing future research.

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