THREE-TIER DETECTION AND MULTI-LEVEL SYNERGY FOR COASTAL MIXED-LAND ZONE CLASSIFICATION

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A thesis submitted in partial fulfillment of the
requirements for the award of the degree of
Master of Science (Computer Science)

Faculty of Computing
Universiti Teknologi Malaysia

MAY 2013

All praises to Allah the Almighty for
the strengths and His blessing in completing this thesis.

Specially dedicated to;
my beloved parents Mohd Pouzi bin Hamzah and Murni binti Ghani
my precious siblings Muhamad Afiq and Adlina Najihah
my most helpful friend Ismaliza binti Ismail

ACKNOWLEDGEMENT

I would like to express my gratitude to my supervisor, Dr. Muhamad Razib bin Othman, my co-supervisor, Dr. Hishammuddin bin Asmuni as well as Dr. Rohayanti binti Hassan for their patience, guidance, encouragement, invaluable comments, and advice that made this research possible and completed. I would like to thank all members of the Laboratory of Computational Intelligence and Biotechnology (LCIB) for their continuous support in many aspects of this research.

My deepest appreciation also goes to my parents as they were the ones who encouraged me to pursue my MSc. My father, who is a lecturer, shared his valuable experience in research including the ethics and skills while my mother has been continuously giving her greatest support. The strength to withstand the hardships that were encountered along this road came from their aspirations that live in me, for it will inspire me to achieve more great things in life ahead. With God's willing.

The datasets used in this study are the courtesy of Geographic Information System (GIS) solution provider and Malaysian Remote Sensing Agency (ARSM). Last but not least, I would like to acknowledge the funding from GATES BIOTECH Solution Sdn. Bhd. (GBIT) under GATES Scholars Foundation (GSF) scheme (LTR/GSF/2011-06) and MyMaster Scholarship of Ministry of Higher Education Malaysia as well as the research opportunity provided by the Faculty of Computing, Universiti Teknologi Malaysia.

ABSTRACT

Vegetation, urban terrain and water are considered as the problematic segments in land use and land cover classifications because of confusion factors. These segments are vulnerable to high misclassification level. In addressing these problems, several fundamental issues shall be emphasized: ineffective stand-alone data classification, high investment for data fusions and the need for high frequency of data collection. Thus, this research proposes a classification method consisting of two important components: Three-tier Detection (TTD) and Multi-level Synergy (MLS) after evaluating LiDAR point cloud, aerial photography, Quickbird and Landsat 7 ETM+ images. TTD which is a hierarchical and priority-based data fusion method is used to solve the vegetation and urban terrain classification while MLS, which is a synergy strategy by the utilization of single data and robust learning algorithms is used for water classification. The creation of TTD that has managed to outperform the stand-alone data classification made it a worthwhile investment while for MLS, the usage of single data is capable of meeting the high data collection demand. Both methods started with data processing such as image filtering followed by the comparison of several existing techniques for each data (rank) to identify their potentials and limitations. Next, multi-level data fusions and multi-level synergy are conducted for TTD and MLS, respectively. The dataset employed is Bukit Kanada, Sarawak which exemplifies a coastal mixed-land zone. The performance is then measured using statistical indices include overall accuracy and Kappa Index of Agreement. Both TTD and MLS outperformed recent works such as Normalized Digital Surface Model, Edge Detection technique and Support Vector Machine. Based on the success rates, TTD is suitable to be applied in planning and development sectors, management and detection of land use changes while MLS is suitable for creating maps, charts, and also in monitoring national coastline.

ABSTRAK

Cabaran utama dalam pengklasifikasian penggunaan dan penutupan tanah adalah kekeliruan yang berlaku pada segmen-segmen yang bermasalah seperti tumbuh-tumbuhan, kawasan bandar dan air. Segmen-segmen ini terdedah kepada tahap keterlepasan pengklasifikasian yang tinggi. Bagi menangani permasalahan ini, beberapa isu asas perlu dititikberatkan iaitu pengklasifikasian data tunggal yang tidak berkesan manakala paduan data melibatkan pelaburan yang tinggi serta kebergantungan kepada frekuensi pengumpulan data yang tinggi. Oleh yang demikian, kajian ini telah memperkenalkan satu kaedah pengklasifikasian yang terdiri daripada dua komponen penting iaitu *Three-tier Detection* (TTD) dan *Multi-level Synergy* (MLS) setelah menilai beberapa data. TTD merupakan kaedah paduan data yang berasaskan kepada hierarki dan keutamaan yang digunakan untuk pengklasifikasian tumbuh-tumbuhan dan kawasan bandar manakala MLS yang merupakan strategi sinergi berdasarkan kepada data tunggal dan algoritma-algoritma pembelajaran digunakan untuk pengklasifikasian air. Pencapaian TTD yang telah berjaya mengatasi pengklasifikasian data tunggal menjadikannya suatu pelaburan yang berbaloi manakala MLS yang dioperasikan berdasarkan data tunggal dilihat mampu memenuhi kebergantungan kepada frekuensi pengumpulan data yang tinggi. Kedua-dua kaedah ini bermula dengan pemprosesan data seperti penapisan imej dan diikuti dengan perbandingan beberapa teknik yang sedia ada untuk setiap data bagi mengenal pasti potensi dan kelemahannya. Seterusnya, pelbagai peringkat paduan data dan sinergi diuji bagi TTD dan MLS. Lokasi kajian ini ialah Bukit Kanada, Sarawak yang merupakan zon tanah bercampur di kawasan pantai. Berdasarkan indeks-indeks statistik termasuk ketepatan keseluruhan dan *Kappa Index of Agreement*, TTD dan MLS telah berjaya mengatasi kerja-kerja baru seperti *Normalized Digital Surface Model*, teknik *Edge Detection* dan *Support Vector Machine*. Dengan pencapaian ini, TTD sesuai untuk diaplikasikan dalam sektor perancangan dan pembangunan, pengurusan dan pengesanan perubahan penggunaan tanah manakala MLS sesuai untuk mewujudkan peta, carta dan juga memantau perairan kebangsaan.

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AB	-	AdaBoost
AP	-	Aerial photography
AOI	-	Area-of-interests
ANN	-	Artificial Neural Networks
BB	-	Bagging and Boosting
B_f	-	Branching factor
C_e	-	Commission error
C_m	-	Completeness
Ct	-	Computational technique
C_r	-	Correctness
DS	-	Dempster-Shafer
DEM	-	Digital Elevation Model
DSM	-	Digital Surface Model
DTM	-	Digital Terrain Model
ED	-	Edge Detection
ELF	-	Enhanced Lee Filtering
FN	-	False Negative
FP	-	False Positive
FS	-	Fuzzy Sets
GIS	-	Geographical Remote Sensing
Gr	-	Green
GCP	-	Ground control point
htnDSM	-	Height threshold of nDSM
ICP	-	Image control points

J48 DT	-	J48 Decision Tree
KIA	-	Kappa Index of Agreement
kNN	-	k-Nearest Neighbor
LC	-	Land Cover
LU	-	Land Use
LDST	-	Landsat 7 ETM+
LPC	-	LiDAR point cloud
ARSM	-	Malaysian Remote Sensing Agency
ML	-	Maximum Likelihood
M	-	Methods
MIR	-	Middle infrared band
MD	-	Minimum Distance
M_f	-	Miss factor
MODIS	-	Moderate-resolution Imaging Spectroradiometer
MNDWI	-	Modified Normalized Difference Water Index
MLP	-	Multi-layer Perceptron
MLPNN	-	Multi-layer Perceptron Neural Network
MLS	-	Multi-level Synergy
Multi	-	Multiple
MCS	-	Multiple classifier system
NB	-	Naïve Bayes
NIR	-	Near-infrared
NN	-	Neural Network
NDVI	-	Normalized Difference Vegetation Index
nDSM	-	Normalized Digital Surface Model
O_e	-	Omission error
O_{ac}	-	Overall accuracy
PP	-	Parallelepiped
PC	-	Personal Computer
Q	-	Quality
QB	-	Quickbird
RBF	-	Radial Basis Function
RAM	-	Random Access Memory

RF	-	Random Forest
R	-	Rank
RGB	-	Red, green and blue
Rsd	-	Remote sensing data
S	-	Sample
SOI	-	Segment-of-interest
SOM	-	Self-Organizing Map
SRTM	-	Shuttle Radar Topography Mission
Si	-	Single
SAM	-	Spectral Angle Mapper
SVM	-	Support Vector Machine
SAR	-	Synthetic Aperture Radar
TS	-	Test scenes
TTD	-	Three-tier Detection
TIN	-	Triangulated Irregular Network
TN	-	True Negative
TP	-	True Positive
UTM	-	Universal Transverse Mercator

CHAPTER 1

INTRODUCTION

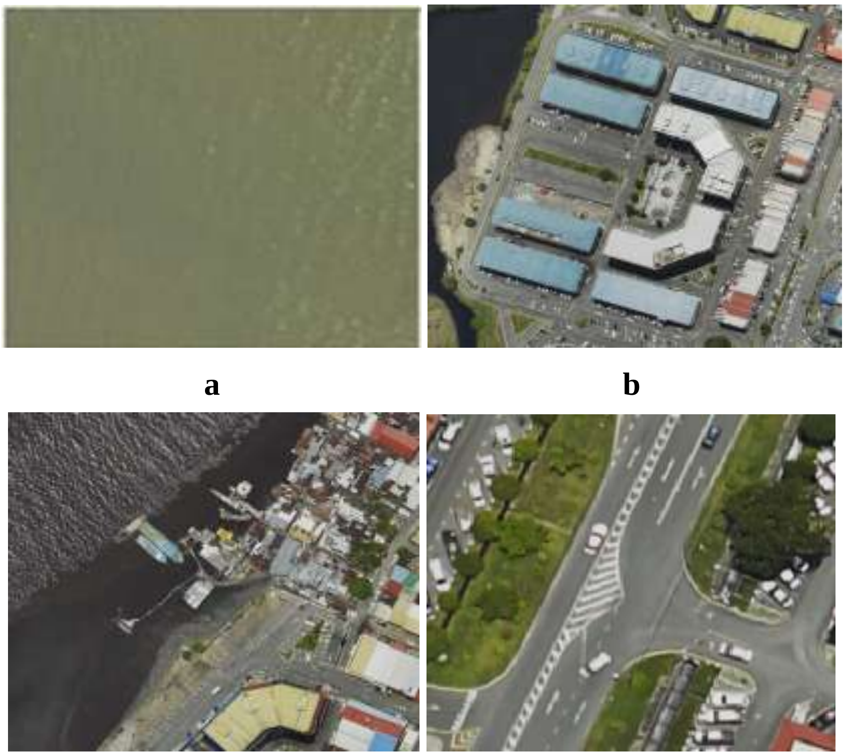
1.1 Background

In Geographical Remote Sensing (GIS) perspective, Earth can be categorized into two categories: (i) Land Use (LU) which describes the human use of land that involves management or modification of natural environment or wilderness into built environment such as residential and industrial area; and (ii) Land Cover (LC) which describes physical materials at the surface of Earth such as vegetation, urban terrain and water segments. The main difference between LU and LC is that LU concerns on the changes that are made to the Earth's surface while LC includes the changed area and natural area. Among the important aspects related to LU and LC is the classification that also depends on the efficiency of data procurement. The traditional ways involve physical contact with the objects, high cost, time-consuming and some areas are not easy to be reached such as volcanic, landslides and remote areas. These limitations have been successfully overcome by the enhanced remote sensing technology by using plane, unmanned aerial vehicle and satellite which do not involve physical contact, low cost, fast and high reach capabilities. As well as the data, the capabilities increase from time to time and each of them carries particular advantages in which some are unique. LiDAR point cloud (LPC), aerial photography (AP), Quickbird (QB) and Landsat 7 ETM+ (LDST) images are examples of remote sensing data types used for the classification.

The classification task takes place in two types of area-of-interests (AOI: see Figure 1.1) which are: (i) mixed-land zones (Garcia-Gutierrez *et al*., 2011); and (ii) urban areas (Awrangjeb *et al*., 2010). A mixed-land zone is an area that is comprised of land uses in a variety of ways such as industrial areas, port facilities, roads and natural areas in the same space (Garcia-Gutierrez *et al*., 2011; see Figure 1.2). It usually consists of low and medium-sized buildings and large area vegetation segments. These characteristics exist in almost all countries in the world. However, in a coastal mixed-land zone, seawater is included besides freshwater. Meanwhile, an urban area consists mainly of high buildings and smaller vegetation areas. Besides, an urban area may consist of more modern and sophisticated structures. Among the obvious examples are Petronas Twin Towers and KL Tower in Kuala Lumpur as well as Taming Sari Tower in Melaka. The basic criteria used to differentiate these two AOIs are building density and total area of vegetation in which a coastal mixed-land zone commonly has lower building density and larger total area of vegetation compared to the urban areas.

a **b**

Figure 1.1 Comparisons between a coastal mixed-land zone and urban area; (a) a coastal mixed-land zone and (b) urban area.



a b

c d

Figure 1.2 Several characteristics of a coastal mixed-land zone; (a) seawater, (b) industrial areas, (c) port facilities, and (d) roads.

1.2 Challenges of Land Use and Land Cover Classification

The existence of many types of data with various capabilities accompanied by advances in computer field provides wider options in LULC classification in order to improve the classification accuracy. These options include Normalized Digital Surface Model (nDSM) application presented by Demir *et al*. (2008), the height threshold of nDSM (htnDSM) application by Hermosilla *et al*. (2011) and the Edge Detection (ED) technique by Babykalpana and Thanushkodi (2011). The nDSM, htnDSM and ED technique were reported to produce good classification accuracy together with certain limitations. This is where the first challenge belongs. Due to the experiments demonstrated by the previous researchers that are incomparable from each other since many parameters are different such as: (i) dataset; (ii) method; and segment-of-interest (SOI), these inconstancies made the comparison difficult while it is crucial to recognize the advantages and disadvantages of each remote sensing data, techniques and the proposed methods to provide better solution for particular problems.

Several works such as by Sohn and Dowman (2007) and Awrangjeb *et al*. (2010) have suggested data fusion as a new option for LULC classification. It enables the collection of useful information from different sensors (Campos *et al*., 2010) which is reported to outperform stand-alone data classification. A number of researchers such as Rottensteiner *et al*. (2005) and Hyde *et al*. (2006) have proved the potential of data fusions as new alternative in LULC classification. In order to consider the data fusion options, the second challenge must be tackled. This challenge concerns the data fusion methods used to solve the classification problem since current results were not in satisfactory level. As example, the method by Campos *et al*. (2010) which employs data fusion of LPC data with QB data achieved Kappa Index of Agreement (KIA) value of 0.78 which is in the range of “Good” based on Kappa strength of agreement. The achievement is below the “Very good” range. Awrangjeb *et al*. (2010) fused various products of LPC with QB. Low completeness and correctness level in particular test scenes as well as low quality level were reported. To date, Pérez-Hoyos *et al*. (2012) created a synergetic land-cover map by using four types of data. However, some issues arose such as the reproducibility of the method, availability and price of the data. In short, the key of tackling the second challenge relies on the handling of the first challenge.

In contrast with vegetation and urban terrain segments, the water segment possessed many factors which rapidly affect the condition of this segment such as daily human activity, natural phenomena and pollution. Hence, frequent classification works are needed to fulfill the purposes of water classification such as to monitor the national coastline. Since this task requires high frequency of data collection, the investment in preparing the data must be minimized. Such circumstance requires forcing good results from a single data which lead to the consideration of learning algorithms and water index utilization, where the third challenge stemmed from. Multiple classifier system (MCS) is an advanced approach of learning algorithms which has been proven by Du *et al*. (2012) to outperform single classifier while Modified Normalized Difference Water Index (MNDWI) is a well-known water index which was explored by Ho *et al*. (2010). This method is capable of classifying water bodies due to the sensitivity of LDST data. However, several issues aroused such as the classifiers that will be chosen which affect the effectiveness and time consumption of the MCS and the identification of the superior method for water classification.

1.3 Current Methods in Land Use and Land Cover Classification

Generally, current methods for LULC classification can be categorized into two: stand-alone data and data fusions:

(i) Stand-alone data - utilizes a single dataset for the classification task by exploiting the benefits of each data type. For LPC, nDSM (Brennan and Webster, 2006; Demir *et al*., 2008), ED (Babykalpana and Thanushkodi , 2011) and LPC with intelligent techniques (Garcia-Gutierrez *et al*., 2011). For imagery data, the application of single learning algorithm (Foody *et al*., 2007; Perumal and Bhaskaran, 2010; Szuster *et al*., 2011) while the fusion of the learning algorithms was implemented by Du *et al*. (2012). Lee and Yeh (2009) utilized the near-infrared band of QB images by Normalized Difference Vegetation Index (NDVI) which is a well-known vegetation index.

(ii) Data fusions - utilize more than one dataset for the classification task whereby many schemes have been observed. Amarsaikhan *et al*. (2010) fused the nDSM of LPC data with Support Vector Machine (SVM) application on imagery data. Khoshelham *et al*. (2010) fused the htnDSM with MCS that consists of SVM and Maximum Likelihood (ML). Guan *et al*. (2012) fused Triangulated Irregular

Network (TIN) and nDSM with SVM. Elghazali (2011) and Campos *et al*. (2010) fused LPC with QB data.

1.4 Problem Statement

The accuracy of LULC classification is a general problem because LULC does not only consist of vegetation, urban terrain and water segments. In such confused environment, the method of reducing the misclassification levels by using large amount of data has not been adequately investigated. In order to solve this problem, various classification schemes have been observed with single data application, data fusions and learning algorithms are among the options. However, for some purposes, the classification results are highly demanded over a period of time such as water classification (the details are presented in Chapter 6). Hence, the investment in preparing the data and the dependency on frequent data collection need to be addressed. Since the results by different researchers are incomparable due to various experimental configurations, therefore, the classification problems to be solved in this study can be described as follows:

> "Given a number of remote sensing data with particular capabilities and exploitation methods with their barely known advantages and disadvantages, the main problem is to produce an accurate classification level by reducing the misclassification levels namely False Negative (FN) and False Positive (FP) caused by the presence of confusion factors in the study area in order to achieve higher overall accuracy (O_{ac}) and Kappa Index of Agreement (KIA). While current data fusions seem to be insufficiently effective, particular purposes urge to force good results from a single data. The investment to prepare the data and the dependency on frequent data collection are taken into account."

Based on the above challenges, some factors need to be addressed by the possible solution. The first factor is related to insufficient knowledge on the advantages and disadvantages of particular methods in classifying a coastal mixed-land zone caused by the different experiment settings. Thus, the results are incomparable and the actual potential of the methods remains questionable. Thus, this study aims to investigate a number of selected methods to recognize their capabilities in terms of accuracy level and identify the contributors of the misclassifications.

The second factor is the unsatisfactory performance of current data fusion techniques which may lead to waste of investment. This condition is mainly caused by the inability of the data fusions to fully utilize the potential of the data in order to manage the misclassification factors that exist in a coastal mixed-land zone. Realising these facts, after the advantages and disadvantages of the data and methods have been identified, this study aims to properly utilize them in order to reduce the FN and FP levels by considering several options of data fusion techniques. The third factor is the urge to reduce the investment in preparing the data based on the demand of high frequency of data collection. Forcing good results from a single data lead to the use of learning algorithms which is among the considerable options. While current MCS is at unsatisfactory level and consists of too many classifiers, this study aims to produce a method based on MCS by decreasing the number of classifiers involved, which is able to reduce time consumption as well as producing good results.

1.5 Objectives of the Study

The goal of this study is to develop a method that can produce high classification levels for vegetation, urban terrain and water segments in the presence of various confusion factors. This can be objectified into:

(i) To perform a comparative study which investigates the potential of each selected data and method in terms of classifying vegetation, urban terrain and water segments in coastal mixed-land zone.

(ii) To develop a method that utilizes the capabilities of the data for vegetation and urban terrain which is able to manage the misclassification factors that exist in coastal-mixed land zone.

(iii) To establish a method based on MCS that is able to separate various water types in a coastal mixed-land zone from other segments as well as reducing the number of classifier combinations.

1.6 Scope and Significance of the Study

In this study, the remote sensing data used are LPC, AP, QB and LDST images obtained from GIS solution provider and Malaysian Remote Sensing Agency (ARSM: http://www.remotesensing.gov.my/). The proposed method consists of two components: Three-tier Detection (TTD) and Multi-level Synergy (MLS). TTD is used to solve the issues of vegetation and urban terrain classification while MLS is for water classification. The proposed method is conducted in a coastal mixed-land zone exemplified by Bukit Kanada in Sarawak. The performance is then measured using reliable statistical indices which are completeness (C_m), correctness (C_r), omission error (O_e), commission error (C_e), branching factor (B_f), miss factor (M_f), quality (Q), O_{ac}, KIA, and McNemar's test. The scope of this study is simplified in Figure 1.3.

The significance of this study can be branched according to the SOI: (i) vegetation and urban terrain; and (ii) water. For vegetation and urban terrain, the proposed method can be served in management, planning and development sectors such as estate, oil palm plantations, city and housing. In other aspects, it can also be used for detection of land use changes such as soil erosion and deforestation and natural disaster management such as flood. The end results of water classification are

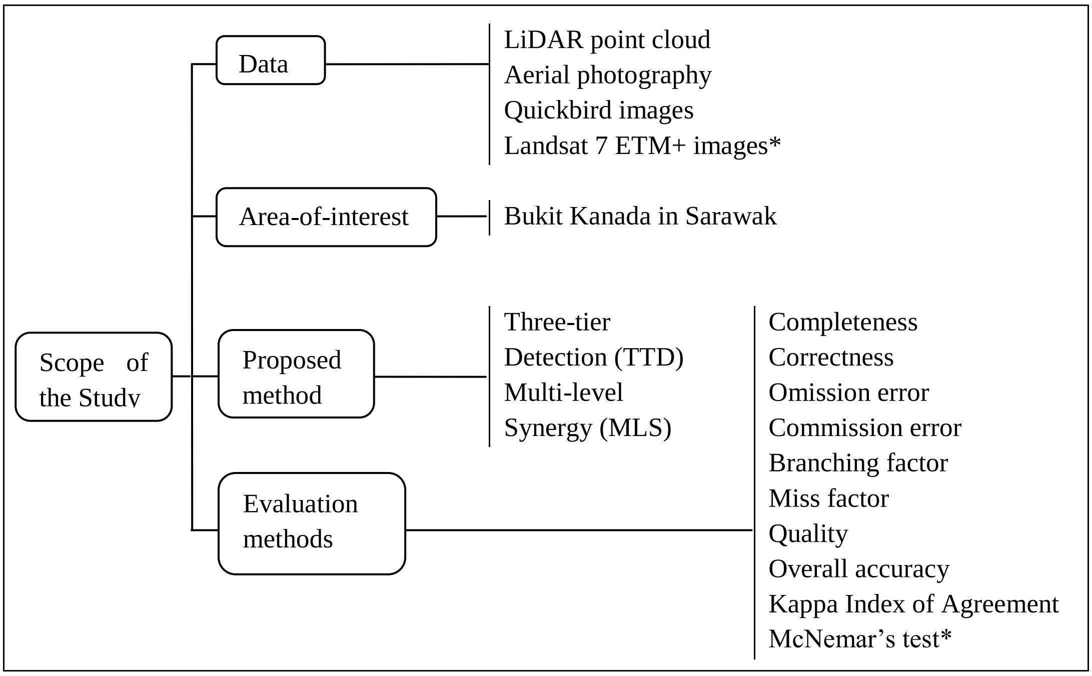


Figure 1.3 Scope of the study. Note that "*" indicates the involvement in water classification only.

also substantial. Other than mapping the river, lake and reservoirs, the mapping of coastal area is very important for many countries to define and monitor large national coastline, create maps and charts, and monitor environmental change. Nautical charts which are among the coastal mapping products are fundamental tools to mariners in planning voyages and navigating ships using the shortest, safest, and the most economical routes. Besides, coastal mapping is performed for coastal change assessment which is to determine the changing rate of the coast, which can help with future planning. It is conducted by measuring the differences in the past and present shoreline locations. The 'before' and 'after' comparison is one way of how the scientists determine shoreline change.

1.7 Organization of the Thesis

This thesis is organized into seven chapters. A brief description on the content of each chapter is given below:

(i) Chapter 1 defines the challenges, problems, current methods, objectives, scope and significance of the study.

(ii) Chapter 2 reviews the main subjects of interest which are coastal mixed-land zone classification, remote sensing data, data fusions and the application of remote sensing data with learning algorithm(s).

(iii) Chapter 3 provides the design of the computational method that supports the objectives of the study. This includes research framework, data sources, instrumentation and analysis of results.

(iv) Chapter 4 presents the comparative study of stand-alone data application whereby several existing techniques were evaluated using several statistical indices. The objectives are to produce comparable results between the techniques and identify the contributors of FN and FP.

(v) Chapter 5 describes the proposed TTD which is the data fusions used to reduce the FN and FP levels for vegetation and urban terrain classification in coastal mixed-land zone.

(vi) Chapter 6 describes another component of the proposed method namely MLS. MLS synergizes single remote sensing data with the fusions of learning algorithms used to solve the issues of water classification. MLS fulfils the requirements of high frequency of data collection.

(vii) Chapter 7 draws general conclusions of the accomplished results and presents the contributions of the study as well as suggests several ideas for related future works.

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