LAND USE LAND COVER CHANGE ANALYSIS USING MULTI SPATIAL DATA FOR SUNGAI RAYA CATCHMENT

by

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LIST OF ABBREVIATIONS

AOI	Area of Interest
ARSM	Malaysian Remote Sensing Agency
ASTER	Advance Spaceborne Thermal Emmision and Reflection Radiometer
BSQ	Band Sequential
CBERS	China-Brazil Earth Resources Satellite
CCD	Charged Coupled Device
CGIAR	Consultative Group on International Agricultural Research
CGIAR-CSI	CGIAR Consortium for Spatial Information
CNES	French Centre National d'Etudes Spatiales
DEM	Digital Elevation Model
DNs	Digital Numbers
DOA	Department of Agriculture Malaysia
DRT	Draft Rancangan Tempatan
DTED	Digital Terrain Elevation Data
EOS	Earth Observation Satellite
ERDAS	Earth Resources Data Analysis Systems
ESDI	Earth Science Data Interface
ESRI	Economic and Social Research Institute
ETM+	Enhanced TM Plus
FTP	File Transfer Protocol
GCPs	Ground Control Points
GDEM	Global Digital Elevation Model
GeoTIFF	Geostationary Earth Orbit Tagged Image File Format
GIS	Geographical Information System

GLCF	Global Land Cover Facility
GLS	Global Land Survey
GPS	Global Positioning System
HEC	Hydrologic Engineering Center's
IRS	India Remote Sensing Satellite
JPBD	Malaysia Town and Rural Planning Department
JUPEM	Malaysia Jabatan Ukur and Pemetaan
Landsat	Land Satellite
LDCM	Landsat Data Continuity Mission
LoG	Laplacian of Gaussian
LULC	Land Use Land Cover
MACRES	Malaysia Centre for Remote Sensing
MDGLS	Mid-Decadal Global Land Survey
METI	Japan Ministry of Economy, Trade and Industry
MSS	Multi-Spectral Scanner
NASA	National Aeronautics and Space Administration
NSLRSDA	U.S. National Satellite Land Remote Sensing Data Archive
OIF	Optimum Index Factor
PC	Principle Component
PCA	Principle Component Analysis
RMSE	Root Mean Square Error
RSO	Rectified Skew Orthomorphic
SPOT	Systéme Probatoired' Observation de la Terre
SRTM	Shuttle Radar Topography Mission
SWIR	Shortwaye Infrared

TIFF	Tagged Image File Format
TM	Thematic Mapper
USGS	United States Geological Survey
USGS EROS	USGS Earth Resources Observation and Science
UTM	Universal Transverse Mercator

ANALISIS PERUBAHAN GUNA TANAH MENGGUNAKAN PELBAGAI DATA SPATIAL UNTUK TADAHAN SUNGAI RAYA

ABSTRAK

Sumber air adalah salah satu kepentingan kritikal dalam kehidupan manusia. Pembangunan pesat, pertumbuhan penduduk, penghijrahan dan pembandaran menyebabkan krisis air, dalam kuantiti dan kualiti. Kawasan tadahan Sungai Raya adalah sub kawasan tadahan Sungai Kinta negeri Perak. Kawasan tadahan ini berkedudukan di pinggir bandar Ipoh yang mana, sebahagian daripadanya dimasukkan ke dalam Draft Rancangan Tempatan (DRT) Ipoh 2020. Pengawalan process pertumbuhan kawasan pingir bandar sementara menjamin bekalan sumber air, pegawai undang-undang, perancang negeri dan kerajaan tempatan memerlukan maklumat pengunaan tanah dan perubahan tanah (LULC) dalam menentukan dasar polisi yang lebih baik. Analisis pengunaan tanah dan perubahan tanah (LULC) untuk penilaian kawasan tadahan air Sungai Raya telah dijalankan dari 1990 hingga 2010, melalui integrasi Model Ketinggian Digital (DEM), dataset satelit dan Sistem Maklumat Geografi (GIS). Kajian dijalankan menggunakan teknik perbandingan pasca pengkelasan dan Sistem Maklumat Geografi (GIS), dengan pengesanan rangkaian, teknik pengkelasan asas pixel atau teknik pengkelasan asas objek. Keputusan analisis pengkelasan menunjukkan teknik pengkelasan asas objek adalah lebih baik dalam mengkelaskan kawasan membangun dan tanah lapang. Bagaimanapun, asas piksel adalah lebih tepat dalam mengkelaskan kelas tumbuhtumbuhan. Maka teknik pengkelasan asas pixel adalah teknik yang sesuai bagi kawasan kajian kerana tingginya litupan tumbuh-tumbuhan. Pengunaan tanah kawasan kajian menunjukkan proses pembangunan yang rendah dalam tempoh 1990 hinga 2000 dengan perubahan daripada 1.587% kepada 1.8737%. Tempoh 2000 hingga 2005, pembangunan pengunaan tanah lebih tertumpu bidang pertanian. Ditunjukkan dari proses pembukaan hutan dan peningkatan kawasan rumput dari 5.949% kepada 11.030%. Aktiviti pembangunan tanah tertumpu pada pembangunan penempatan manusia dalam tempoh 2005 hingga 2010 dengan perubahan dari 2.047% kepada 3.769%.

LAND USE LAND COVER CHANGE ANALYSIS USING MULTI SPATIAL DATA FOR SUNGAI RAYA CATCHMENT

ABSTRACT

Water resources are one of the critical importance's in human life. The rapid development, population growth, migration and urbanization cause water crisis, in quantity and quality. Sungai Raya catchment is a sub-catchment of Sungai Kinta catchment in Perak state. Catchment area is located at the edge of the Ipoh city and part of it is included in the Ipoh Plan 2020. In controlling the suburbanisation process while securing water resource, officials of legislators, planners, state and local governmental required Land Use Land Cover (LULC) information in determining the suitable policy. The temporal Land Use Land Cover (LULC) change analysis for Sungai Raya watershed evaluation is conducted from 1990 to 2010, by integrating Digital Elevation Model (DEM), satellite dataset and Geographic Information System (GIS). Study conducted utilizing post-classification comparison and GIS approach, with network detection, pixel base classification and object base classification technique. The classification analysis results showed that object-base classification method are better in classifying the buildup and bareland. However, pixel base are more accurate in classifying the vegetation class. Hence the pixel base classification technique is suitable technique for study area since high vegetation cover. Study area land use show low development process in period 1990 to 2000, with changes from 1.587% to 1.8737%. In the period of 2000 to 2005, the land developments are concentrated on agriculture area through indicator of open forest area and increment of grassland area from 5.949% to 11.030%. The land development activity is concentrated on human settlement in period 2005 to 2010 with changes from 2.047% to 3.769%.

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CHAPTER ONE

1.1 Introduction

The rapid growth of the world population is a recent phenomenon, with the world population estimation 7 billion by 31 October 2011 (UNFPA Information and External Relations Division, 2011). The unprecedented rates of population growth have sparked alarm about impact on the global environment and future prospects, with the intense modern debate over relationship between numbers of people and use of available land in both Thomas Malthus's hypothesis and its critics (US National Academy of Science et al., 2001).

As reported by National Research Council (2005), the human influences on the natural environment were understood to occur through two main processes: land use land cover (LULC) change and industrial metabolism which is the transformation of materials and energy for industrial production and economic consumption. LULC classification data is one of the critical valuable information data for the knowledge of the present distribution and area of such agricultural, recreational and urban lands as well as information on their changing proportions.

In the evaluation of LULC change, remote sensing imagery and geographical information system (GIS) can be used. The use of remote sensing image has more benefit when compared to traditional approach such as aerial photo interpretation (Amin et al., 2012). Land use types can be mapped from digital satellite imagery faster and often with lower costs, even updating of land use map products is fast and

inexpensive. The digital forms of satellite imagery data and satellite images also cover large geographic areas.

GIS can be briefly defined as an assemblage of hardware, software, data and organizational structure for collecting, storing, manipulating and analysing spatially referenced data (Wolf and Dewitt, 2000). As reported by National Research Council (2003), many in-house GIS with satellite remote sensing data processing capabilities can be utilized in conjunction with available spatial digital data for local authority / agency to improve of environmental ecosystem modelling in 2-Dimensional. The role played by remote sensing data and GIS has been used in lot of applications, e.g. urbanization (Gluch, 2002, Amin et al., 2012), agriculture (Warner and Steinmaus, 2005, Kass et al., 2011), forest (Sirén and Brondizio, 2009, Nandy et al., 2011), wetland (Rebelo et al., 2009, Zhang et al., 2011), health management (Herbreteau et al., 2007, Liu and Weng, 2012), hydrology and climate (Rango and Shalaby, 1998, Pietroniro and Prowse, 2002, Boyd, 2009).

The present project focuses in evaluating the LULC information data for the land surface and basin hydrology resource management using multi spatial data (SRTM DEM data, Aster GDEM data, Landsat data and SPOT data) with postclassification technique and GIS techniques.

1.2 Problem Statement

Land surface is an important control for both the water and energy balance, as it is the primary influence in the surface water budget and it is almost always a required input in both hydrological and atmospheric models (Pietroniro and Leconte, 2005). Particularly in suburbanisation process, the LULC information is important information required by legislators, planners, and state and local governmental officials to determine the better LULC policy, in projecting water resource inventory, flood control, water supply planning, wastewater treatment, water demand in identify future development pressure points and areas, and to implement effective plans for regional development (Anderson et al., 1976, Rango and Shalaby, 1998, Gluch, 2002).

According to Lu et al. (2004), in order to have high accuracy of change detection analysis, many factor had to be considered. Part of factors is geometrical rectification, precise image registration, change detection methods and complexity of landscape. Traditionally the topographic map is the most valuable data in the process of geometrical rectification and precise image registration. However, most of the topographic map is published past decade and the elevation model data are less accurate (Rango and Shalaby, 1998, Jarvis et al., 2004). Alternative to the topographic map are the orthorectified satellite data and DEM data. However, DEM data might contains anomalies and artifacts that will impede the data effectiveness, therefore the accuracy assessment and preprocessing are required (Tachikawa et al., 2011).

In consideration, significance change detection method in producing quality LULC change detection information. A variety of change detection techniques have been developed and many have been summarized and revised (Lu et al., 2004, Lu et al., 2005, Afify, 2011, Chen et al., 2011). According to Lu et al. (2004) and Chen et al. (2011), post-classification comparison is the suitable implemented method with capability in providing matrix of change information and reducing external impact from atmospheric and environmental difference between the multi-temporal images. Meanwhile the GIS techniques are helpful in change detection of multi-source data (Lu et al., 2004).

Conventionally pixel-based classification techniques such as maximum likelihood classification method and the minimum distance classification method have been extensively employed in the thematic information extraction since 1980s (Ziyu et al., 2004). The classification techniques that is overwhelmingly focused on spectral or brightness values (Warner and Steinmaus, 2005, Gao, 2009), that lead to a variety of errors because lack of the spatial characteristics (Ziyu et al., 2004, Gao, 2009). Particularly areas that covered with complex scenes that coexistence of forest area, clearing area, mining, industrial, agriculture, waterbodies, residential area, and etc.

In order to characterize this complex scenes study area, it was proposed to conduct the incorporating analysis of the spatial information in producing LULC information. Utilizing segmentation classification of object based classification technique, that spatially aggregating neighbouring pixels with similar spatial or spectral characteristics (Gao, 2009).

1.3 Research Aim and Objective

The aim of this study is to evaluate the temporal LULC change analysis for Sungai Raya watershed from 1990 to 2010. To achieve the aim of the research, an integrated approach of remote sensing and GIS is employed and the following objectives are drawn up i.e.:

6.2.1. To evaluate the AsterGDEM with SRTM and GPS.

6.2.2. To determine Sungai Raya basin delineation using automated delineation.

- 6.2.3. To evaluate the difference between the pixel-base classification and object-base classification method.
- 6.2.4. To identify the LULC at state level classifications.
- 6.2.5. To evaluate the LULC change analysis for areas of mixed LULC classes.
- 6.2.6. To determine major driving factors and the trend of LULC change.

1.4 Layout of Thesis

This thesis is organized into the six chapters. Chapter 1 provides an overview of the research and the important predefinition of the LULC, remote sensing and GIS. In Chapter 2, a comprehensive literature review of the remote sensing and GIS in the LULC change analysis, categories of change detection techniques and the current trend classification method. Chapter 3 presents the detail of the study area geographical and biophysical, also the data source and its description. In the Chapter 4, the methodology section describing each methodology step. Chapter 5, result and discussion section showing the results and their related interpretation. In the last section, Chapter 6 comprises some general conclusion and recommendations.

CHAPTER TWO LITERATURE REVIEW

2.1 Introduction

LULC change is geographical information, the interpreted and meaningful information that are generated from geographical data (i.e. facts, observation results, field data, remote sensing data, GPS, analog maps, census figures and statistical data and etc.). Meanwhile, the remote sensing and GIS are tools in obtaining data and generating the valuable geographical information.

Land use can be defined as the degree of human activities that are directly related to land and making use of its resource usage in order to obtain an impact on the critical intersection of economy and environment (Veldkamp and Fresco, 1996, Fischer and Sun, 2001). Meanwhile, land cover describes the physical state of the earth's surface and immediate subsurface in terms of the natural environment (such as vegetation, soils, and surfaces and groundwater) and manmade structures (Malczewski, 2004). According to Veldkamp and Fresco (1996), the determination of LULC are based on an interaction in space and time of biophysical factors (soils, climate, topography and etc.) and human factors (population, technology, economic conditions and etc.).

Thus LULC changes are information which are important in identifying the direct and indirect process of land degradation, biodiversity loss, climate change and natural disaster that are not only affected in local scale but also even at the global scale (Zhang et al., 2011). Particularly, the human factor of population and migration that made the human interaction is unplanned and uncontrolled in changing land

cover. According to UNFPA Information and External Relations Division (2011), the rapid growth of the world population since 1950, with reductions in mortality in the less developed regions, resulting in an estimated population of 6.1 billion in the year 2000, nearly two-and-a-half times the population in 1950. Through resourceful land use land cover information, enables access of current state of knowledge, help set research priorities, explore possible alternative futures, and test the potential effect of policies in environmental sustainability and future planning (National Research Council, 2005).

2.2 Land Use Land Cover in Water Resource Management

In water resource management on catchment scale, the effects of atmosphere, lakes, rivers, and groundwater towards the availability of fresh water focuses to critical reservoirs (Potter and Colman, 2003). With the occurrence of global climate change and the possibility of increased frequency of floods or droughts, responsible hydrologic management will be key to achieving sustainable water resources through continuous progress in understanding the various components of the catchment hydrologic cycle (Potter and Colman, 2003).

LULC information is used in hydrologic modelling to estimate surface roughness or friction values, since it affects the surface streamflow, a particular important process at the catchment scale that can recharge reservoirs and replenish rivers (Potter and Colman, 2003, Garen et al., 2006). Groundwater modelling, land use information coupled with the hydrologic characteristics of land surface soils, can provide measures of expected percolation and water holding capacity (Johnson, 2008, Lerner and Harris, 2009). Utilization of land use data in calculation of impervious surface, enables the analysis of initial conditions of flood forecasting, and

monitoring flooded areas (Potter and Colman, 2003). Monitoring and / or prediction of soil erosion can be computed using the Universal Soil Loss Equation (USLE) which can be done by integrating GIS with LULC factors (Potter and Colman, 2003, Pradhan et al., 2012).

Likewise, shifts in certain water quality constituents may be caused by agriculture activities such as sudden changes in the use of certain types of pesticides (Potter and Colman, 2003, Seeboonruang, 2012). According to Potter and Colman (2003), changes in land use and the development of reservoirs and diversion structures may also cause trends and shifts in streamflow series and groundwater. Last but not least, LULC information used in water supply and irrigation system planning with water demand forecasting, which associate land use data with customer billing meter data, system meter data, zoning, population and etc. (Johnson, 2008).

2.3 Remote Sensing

Remote sensing is the information acquisition of an object, area or phenomenon, by the use of recording real-time sensing device without physical contact (Gibson, 2000). Remote Sensing also provides synoptic, objective and homogeneous data, which can be geographically and temporally registered in providing standard and high quality information (Kass et al., 2011). The large collections of remote sensing imagery have provided a solid foundation for spatial temporal analysis of the environment and the impact of human activities (Qian et al., 2007). According to Potter and Colman (2003), there are two general areas where remote sensing can be used in hydrologic modelling: (1) determining watershed geometry, drainage network, and other map type information for distributed

hydrologic models and for empirical flood peak, annual runoff, or low-flow equations; and (2) providing input data such as snow cover or precipitation, diagnostic variables such as soil moisture or surface temperature, or model parameters such as delineated land-use classes used to define runoff coefficient. Remote sensing sensors are data scanners of the electromagnetic energy that interacts with materials on the earth's surface that hold the chemical composition information of the materials activities. Ryerson (1999), have specify the extensive study of electromagnetic energy respond toward the chemical composition of the materials, that have enable us to indicate the specific spectral characteristics of the earth surface feature.

However, the electromagnetic energy are affected by the atmospheric absorption and scattering of the electromagnetic energy. The atmospheric absorption results in the effective loss of energy to atmospheric constituents of water vapour, carbon dioxide and ozone as describe in Figure 2.1(a) and the atmospheric scattering causes unpredictable diffusion of radiation by atmospheric constituents that produce haze and etc. in data (Ryerson, 1999, Gibson, 2000). Figure 2.2, describes overall process of electromagnetic radiation interaction with atmosphere. With this limitation, only small part of the electromagnetic energy can pass the atmosphere that can be recorded by the remote sensing sensor as we describe as atmospheric windows as show in Figure 2.1(b).



Figure 2.1: (a) Absorption characteristics of gaseous components of the atmosphere.(b) Transmission through the atmosphere as a function of wavelength and the location of atmospheric window. (Source: Gibson 2000)



Figure 2.2: Interaction of electromagnetic radiation with the atmosphere and small radiation part is measured by remote sensing sensors (Source: Gibson 2000)

The beginning of the 21st century promised to be a period of technological innovation, with remote sensing identified as one of 21 technologies well placed to meet contemporary issues and challenges facing society. More than hundred satellite sensors have been launched, numerous airborne and terrestrial sensors manufactured (Boyd, 2009). Recently, rectified analysis of the Landsat scenes for the globe, spanning the time period from the 1972 – 2005, approximately two million exist in the U.S. National Satellite Land Remote Sensing Data Archive (NSLRSDA) at the USGS EROS facility in Sioux Falls, South Dakota (Goward, 2007).

The analysis is continuously expanded with the cooperation of the Landsat International co-operators in rectifying the Landsat scenes not in the NSLRSDA. Boyd (2009), state there are intention of creating international consortia that coincidentally operate several satellites, such as Landsat Data Continuity Mission (LDCM), Sentinel 2 (European), China-Brazil Earth Resources Satellite (CBERS), India Remote Sensing satellite (IRS) and others, to provide a global observatory system that systematically monitors the Earth's land areas a primary source of global change.

2.4 Geographic Information System (GIS)

The GIS term were introduced on mid-1960s, with development of Canada Geographic Information System as a computerized map measuring system (Longley et al., 2001). Since then, there are many definitions of GIS have been suggested in term of different perspective or disciplinary origin. A common definition of GIS is described as a technology system that contains a set of procedures that facilitate the data input, data storage and management, data manipulation and analysis, and data output for both spatial and non-spatial data into information about some portion of the earth (Collins et al., 2001, Malczewski, 2004).

During late 1980 and early 1990s, the dynamic and multi-dimensional GIS have been emphasized, spurred by US Vice-President Al Gore speech in 1998 "The Digital Earth: Understanding Our Planet in the 21st Century", where three key issues as mention; 1) the multi-resolution representation of the Earth, 2) three dimension representation of the Earth and 3) issues related to how to embed vast amounts of geo-referenced data (Bergougnoux, 2000). One of the spur effect of Al Gore speech is that few topics became priority list of the Association of Geographic Information Laboratory in Europe: the three dimensional and four dimensional modelling, cartographic generalization, change detection / modelling, dynamic process, spatiotemporal models, and etc. (Bergougnoux, 2000).

Irrespective of its precise definition, GIS plays a critical role in digital image analysis related closely in at least two areas: (1) it provides a framework for preparing the data for analysis and for undertaking change detection analysis; and (2) it is able to supply a huge amount of non-satellite data in knowledge-based image analysis (Gao, 2009). GIS techniques manipulate DEM data to derive watershed characteristics such as drainage network structure, delineate watershed boundaries and in conjunction with remotely sensed product, a realistic perspective views of a watershed that aid visualization and understanding of spatial and temporal variability of hydrological parameters (Potter and Colman, 2003). A particular GIS technique is the overlay analysis can be used to show spatial correlation among different variables, revealing any cause effect relationship, or modifying the database or study area, and detecting changes in land cover (Gao, 2009).

2.5 Land Use Land Cover Change Detection Methods

According to Lu et al. (2004), a good change detection should provide information of area change and change rate, spatial distribution of changed types, change trajectories of land cover types and accuracy assessment of change detection results. Lu et al. (2005), have highlighted several factors of change detection accuracy results are depended on:

- 1. Precise geometric registration between multi-temporal images
- 2. Calibration or normalization between multi-temporal images
- 3. Availability of quality ground truth data

- 4. Complexity of landscape and environments of the study area
- 5. Change detection methods or algorithms used
- 6. Classification and change detection schemes
- 7. Analyst's skills and experience
- 8. Knowledge and familiarity of the study area
- 9. Time and cost restrictions.

Lu et al. (2004), Liu et al. (2004), and Coppin et al. (2004) have reviewed many change detection methods. Lu et al. (2004) also categorize the methods used such as algebra, transformation, classification, advanced models, GIS approaches, visual analysis, and other approaches. Liu et al. (2004) tested the change detection technique from mathematical perspective using image differencing, image ratioing, image regression and principle component analysis (PCA), concluded that standardized PCA was the most accurate procedure. Meanwhile Afify (2011), evaluation summarize that post-classification comparison was higher accuracy compared than image differencing, image ratioing and PCA technique in monitoring land cover changes.

Post-classification comparison approach is the most often used to detect detailed "from-to" change trajectory, whereas image differencing, image ratioing, vegetation index differencing, and PCA are often used to detect binary change and non-change information (Lu et al., 2004, Lu et al., 2005). According to Lu et al. (2004), post-classification is separately classifies multi-temporal images into thematic maps, then implements comparison of the classified images pixel by pixel, minimizes impacts of atmospheric, sensor and environmental differences between multi-temporal images, while provides a complete matrix of change information. Our inability to monitor land cover changes in a consistent way over the longterm is a serious limitation in our capacity to understand the driving forces and processes controlling these changes (Petit and Lambin, 2001). According to Petit and Lambin (2001), incorporation of multi-source data (e.g. aerial photographs, SPOT XS and previous thematic maps) has become an important method for LULC change detection especially when the change detection involved long period intervals associated with different data sources, formats and accuracies or multi-scale land cover change analysis. Utilizing the overlay technique of GIS layers, an aid of satellite imagery data interpretation, analysis and ability to directly update land use information in GIS different data quality from various sources (Lu et al., 2004).

2.6 Land Use Land Cover Classification System

Image classification refers to the extraction of differentiated classes or themes, usually LULC categories, from raw remotely sensed digital satellite data (Qian et al., 2007). LULC classification system is based on the Town and Rural Planning Department (JPBD) land use classification system, the Malaysia Department that provides existing land use and proposed zoning land use information for Malaysia in all the development plans prepared under Town and Country Planning Act 1976 (Act 172) including Malaysia National Physical Plan, Structure Plan and Local Plan (JPBD 2012). Table2.1 describe the JPBD classification and land use code V.8A amendment in December 2008. The classification system on Level II and Level III meets the needs at state and district general interest at scale less than 1:80,000 and more than 1:20,000 (Anderson et al., 1976). Based on Anderson et al. (1976), a LULC classification system can effectively employ remote sensing data and should meet certain following criteria:

- 1. The minimum level of interpretation accuracy of land use and land cover categories should be at least 85 percent.
- 2. The accuracy of interpretation for the several categories should be a about equal.
- 3. Repeatable or repetitive result should be obtained from one interpreter to another and from one time of sensing to another.
- 4. The classification system should be applicable over extensive areas.
- 5. The categorization should permit vegetation and other types of land cover to be used as surrogates for activity.
- 6. The classification system should be suitable for use with remote sensing data obtained at different times of the year.
- Effective use of subcategories that can be obtained from ground surveys or from the use of larger scale or enhanced remote sensing data should be possible.
- 8. Aggregation of categories must be possible.
- 9. Comparison with future land use data should be possible.
- 10. Multiple use of land should be recognized when possible.

I and I (Country)	Level II (State)	Lovel III (District)	Level IV (District)
Level I (Country)	Level II (State)	Level III (District)	
		Residential (TRM)	 Planned Housing Non-Planned Housing
			Planned Industry
	Sha na si shaka	Industrial (TIN)	Non-Planned Industry
			Pit/Quarry
		Commercial and	Planned Commercial
		Services (TPD)	Non-Planned Commercial Education
		12-2 - 14 - 2 - 2 - 1 - 2 - 1 - 2	Health
			Religious
	Built. In (and	Institution and	• Cemetery
	Dune op cante	Society Facility (TIS)	Security
			Welfare Home Government Lise / Statutory
			Body
			Other Society Facility
Built-Up Land			Open Ground
		Open Ground and	Sports Facilities and
		Recreation (ILR)	Recreational Green Area
		The second second second	Natural
		Vacant Land (TTK)	Artificial
	Transportation, Infrastructure and Utilities	Transportation (IPG)	Road
			• Rail
		Infrastructure and Utilities (IFU)	Transportation Facility
			Gas Supply
			Water Supply
			Irrigation and Drainage
			Telecommunications
			Solid Wasteland
	a service and the service of the ser		I oxic Wasteland Sewerage
			Rubber
		A grieulturel land	Palm oil
		(PT)	Paddy
Agricultural Land (P	T)		Other type Agriculture
		Pasture and	Pasture
		Aquaculture (PA)	Aquaculture
Forest Land (HT)			Inland Forest
		Forest Land (HT)	Wetland Forest
		rorest Lanu (HT)	Peat Forest
			Cleaned Forest
Water Bodies		Water Bodies (BA)	Artificial
		Deschor (DNI)	Natural
		Beaches (PN)	• Canceman

Table 2.1: JPBD Classification and Land Use Code V.8A Amendment in December 2008

2.7 Land Use Land Cover Classification Method

The accuracy of post-classification comparison is highly dependent on the LULC classification results at each date (Coppin et al., 2004). By its very nature, land cover classification from satellite imagery inherently possesses various classification errors caused by factors such as noise in satellite observations, spectral confusion among different land cover classes, and limitations of classification algorithms (Liu and Cai, 2011). In conducting classification of remotely sensed data, the spectral pattern, spatial pattern and temporal pattern information can be used. Spectral pattern is the combination of digital numbers (DNs) for different feature types, spatial pattern refers to the spatial relationship of the pixels, such as image texture, pixel proximity, feature size, and shape and temporal pattern refers to temporal characteristics of the features (Qian et al., 2007).

2.7.1. Network Detection

Edge detection technique is one many network detection method that was reported applied in road network (Wang et al., 2006, Sirmacek and Unsalan, 2010, Hauptfleish, 2010) and geologic features (Argialas and Mavrantza, 2004, Sefercik and Gülegen, 2004, Ping et al., 2010). Edge detection technique is the mathematical identification of abrupt pixel intensity change in an image (Maini and Aggarwal, 2009).

Figure 2.3(a), show the signal at the ramp edge and line, with an edge shown by the jump in intensity function g(x). As gradient of this signal, the 1st derivative, $\frac{\partial g}{\partial x}$ with respect to x, we get the curve as shown in Figure 2.3(b) and the 2nd derivative $\frac{\partial^2 g}{\partial x^2}$ with respect to x, we get the curve as shown in Figure 2.3(c). From the derivative

figure, show changes located at the centre of the edge in the original signal. The sobel and prewitt edge detection filter is the 1^{st} spatial derivative and the Laplacian is a 2^{nd} spatial derivative. Table 2.2 describing the advantages and disadvantages of the 1^{st} and 2^{nd} spatial derivatives.



Figure 2.3: Edge and Line Derivatives (Erdas, 2010)

Table 2.2: Advantage and disadvantages of edge detectors (Maini and Aggarwal,2009)

Operator	Advantages	Disadvantages
Classical	Simplicity, detection of edges	Sensitivity to noise, Inaccurate
(Sobel, prewitt)	and their orientations	Zero
Crossing	Detection of edges and their	Responding to some of the
(Laplacian)	orientations. Having fixed	existing edges, Sensitivity to
(Lapiacian)	characteristics in all directions	noise
Laplacian of Gaussian (LoG) (Marr-Hildreth)	Finding the correct places of edges, Testing wider area around the pixel	Malfunctioning at the corners, curves and where the gray level intensity function varies. Not finding the orientation of edge because of using the Laplacian filter
Gaussian (Canny)	Using probability for finding error rate, Localization and response. Improving signal to noise ratio, Better detection specially in noise conditions	Complex Computations, False zero crossing, Time consuming

2.7.1.1. Laplacian Edge Detection

The Laplacian is more convenient than the previous 1^{st} spatial derivative operator, on utilizing a more isotropic single kernel and effective in detecting lines or spots distinctively from ramp edges (Bourne, 2010). The Laplacian L(x,y) of an image with pixel intensity values I(x,y) is given by Eqn 2.1.

$$L[f(x,y)] = \frac{\partial^2 f(x,y)}{\partial x^2} + \frac{\partial^2 f(x,y)}{\partial y^2}$$
 (Eqn 2.1)

2.7.1.2. Laplacian of Gaussian (LoG) Edge Detection

However, Laplacian kernels are very sensitive to noise. In order to reduce the high frequency noise effect prior to the differentiation step, Gaussian smoothed is applied before the Laplacian filter. Rather than dual kernel filter process, Gaussian and Laplacian function is combined to single LoG kernel filter with function Eqn 2.2 as given in by Marr-Hildreth:

$$LoG(x,y) = -\frac{1}{\pi\sigma^4} \left[1 - \frac{x^2 + y^2}{2\sigma^2} \right] e^{-\frac{x^2 + y^2}{2\sigma^2}}$$
(Eqn 2.2)

Noted that, contrariwise of the Gaussian smoothing reduces noise, the laplacian enhancement effect becomes less. As the Gaussian is made increasingly narrow ($\sigma < 0.5$ pixels), the LoG kernel turning to Laplacian kernels, since smoothing effect is negligible (Maini and Aggarwal, 2009).

2.7.2. Pixel Base Classification

Historically, methods of producing a cover type map from remotely sensed data are conducted solely on the spectral pattern (Matinfar et al., 2007, Raines et al., 2008). There are two broad type categories of pixel based classification methods, unsupervised and supervised. Unsupervised classification assigns pixels to classes by comparing them to one another, producing a specified number of clusters, each of which must be combined and relabel to the informational categories designated by the analyst to produce meaningful cover type classes (Raines et al., 2008). However, unsupervised classification are merely spectral clustering classification that do not necessarily correspond to information classes on the ground with exception the scene has rather simplistic structure or the information class of interest has its own unique spectral properties (Gao, 2009), and it believed that supervised classifications traditionally produce more accurate results (Raines et al., 2008).

Supervised classification technique are involved training stage and classification stage. Training stage is the spectral statistical estimation calculation process that representing each ground cover type of interest spectral attributes, that require trainer studying aerial photographs, high resolution satellite imagery or field studies (Matinfar et al., 2007, Raines et al., 2008). Classification stage, the ground cover spectral attributes are partitioned into class-specific domain using correlation pattern recognition that base on either parametric rule that use parametric rule (minimum distance to mean and maximum likehood) or non-parametric rule (parallelepiped) in classifying the pixels (Richards and Jia, 2005, Gao, 2009), as shown in Figure2.4.

The maximum likelihood classification, is the most widely used method (Qian et al., 2007), by theoretically comparing the maximum likehood classifier which utilizes more statistical parameters for training and the most complex than other supervised classifiers (Gao, 2009). The maximum likehood classification technique, pixel is classed based on pixel probability toward a ground cover class using multivariate normal distribution, therefore the effectiveness of this method depends upon reasonably accurate estimation of the mean vector and the covariance matrix for each spectral class (Richards and Jia, 2005). By estimating the mean sufficient number and quality of training pixels for each class is important in perform the maximum likelihood classifier(Gao, 2009).





Figure 2.4: Supervised Classification Technique (source: Lillesand & Kiefer 1994)

Object-Base Classification 2.7.3.

Pixel-based classification methods is argued to be limited by utilizing only spectral information without considering texture and contextual information, although the techniques are well developed and many successful applications have been reported, however it suffers from ignoring the spatial pattern in classification (Qian et al., 2007). Particularly in areas forms a complex scene of land covers (Emerson et al., 2005, Gao, 2008, Gao, 2009), resulting the classification product to very general land cover information, or else detailed land cover information with limited accuracies (Gao, 2008) and the product are normally suffer from a "salt and pepper" effect (Meinel et al., 2001, Gao, 2008). However, with the adding of other spatial image elements to the multispectral bands are helpful in resolving complex land cover scene classification problem through the object-oriented classification.

Object-oriented classification approach utilizes spectral information, texture information and context information in the satellite data (Oruc et al., 2004, Matinfar et al., 2007). This approach classifying groups of like pixels together or classifying a single pixel based on that pixel's relationship to surrounding pixels, accounting for spatial properties as well as spectral properties inherent within satellite data (Raines et al., 2008). In return of the classification homogenous group / region of pixels of different classes eliminate "salt and pepper" classification effect. The object-oriented approach consists of two steps; i.e. segmentation satellite data into regions object and classification of regions object.

2.7.3.1. Segmentation

Image segmentation is the process subdivision of a digital image into homogeneous sites / small separated regions and hence abstracting raster cells into regions (Liu and Du, 2010). This greatly reduces the number of image elements for classification and significantly reduces the volume of data (Meinel et al., 2001). Software SPRING use segmentation algorithm region growing, techniques that are widely used for remote sensing applications and they guarantee creating closed regions (Espindola et al., 2006). Region growing algorithm is a multi-resolution or hierarchical segmentation (Baatz and Schäpe, 2000), an algorithm that group pixels or sub regions into larger regions, starting from suitable initial pixels (seeds) by iteratively augmenting them with neighbouring pixels that satisfy a chosen homogeneity criteria (Baatz and Schäpe, 2000, Gao, 2008). SPRING uses region growing segmentation method. It has two parameters in guiding the segmentation procedure:

- "Similarity" is a threshold value that determines if two neighbouring pixels (objects) are grouped. According to Espindola et al. (2006), high values of similarity threshold force the union of spectrally distinct regions, resulting in under-segmentation.
- 2. "Area" threshold is used to filter out the objects smaller than this value by merging them with its most similar neighbour. In keeping with Espindola et al. (2006), low values of area threshold result in excessive partitioning, producing a confusing visual picture of the regions.

Usually the competent identified land cover objects in remotely sensed data have different scales, with multi-resolution or hierarchical segmentation algorithm offers new opportunities, not only for analysis of the remote sensed data at several different scales consecutively, but also for working with hierarchical structures, by setting objects in relation to sub-objects or super-objects (Kass et al., 2011). However, several segmentation tests with different parameters need to be conducted, in order to achieve the best segmentation for a given image, before the region classification process (Meinel et al., 2001, Oruc et al., 2004).

2.7.3.2. Segmentation Optimization

Espindola et al. (2006) proposed an objective function for SPRING software that aims at maximizing homogeneity within segments and separability between neighbouring segments. Since the segmentation result has a direct effect on the classification accuracy, and the objective function are not solely work on single band