

Integrating Landsat ETM+ and DEM to Support Forest Management Map in Part of Papua Province, Indonesia

Ikwan
October, 2010

Integrating Landsat ETM+ and DEM to Support Forest Management Map in Part of Papua Province, Indonesia

by

Ikwan

Thesis submitted to the Faculty of Geo-information Science and Earth Observation (ITC), University of Twente, in partial fulfilment of the requirements for the degree of Master of Science in Geo-information Science and Earth Observation in Natural Resources Management Programme and for the degree of Master in Institut Teknologi Bandung in Development Planning and Infrastructure Management.

Thesis Assessment Board

Chairman	:	Prof. Dr. V.G. (Victor) Jetten	(Department Earth Systems Analysis, ITC)
Examiner	:	Dr. Y.A. (Yousif) Hussin	(Department Natural Resources, ITC)
External Examiner	:	Drs. T.M. (Tom) Loran	(Course Director Earth Systems Analysis, ITC)

Supervisor	:	Dr. Y.A. (Yousif) Hussin	(Department Natural Resources, ITC)
	:	Dr. Ross Akbar	(Department of Urban and Regional Planning, ITB)



**Faculty of Geo-Information Science
and Earth Observation
University of Twente**



**Development Planning and Infrastructure
Management
Institut Teknologi Bandung**

Disclaimer

This document describes work undertaken as part of a programme of study at the Faculty of Geo-information Science and Earth Observation, University of Twente. All views and opinions expressed therein remain the sole responsibility of the author, and do not necessarily represent those of the faculty.

Abstract

There is a big challenge in the integration between land to conserve and land to develop in regional planning. In some areas with the lack of high spatial resolution information, due to the scale problem, landscape approach using remote sensing and GIS can contribute as an input in regional spatial planning. The aim of this study was to test the capabilities of Neural Network Classification, using Landsat ETM+ and DEM, to produce useful information with sufficient accuracy. Spatial planning maps of Jayapura City and Cycloop Nature Reserve, were used to define the gap of management that emerge. ASTER GDEM and SRTM DEM compared to select the appropriate DEM sources to derived morphometric elements in the study area. Several combinations of Neural Network Classifications were done to combine Landsat ETM+ and DEM for deriving the morphometric element in the study area. Further, the study compared Maximum Likelihood and Neural Network Classification. Thus, the study finished with detailing land cover information in the gap area. Using cross section (profile) and minimum curvature, the study shows that SRTM DEM give more accurate information of elevation. Neural Network classifier using Landsat ETM+ and extra information of elevation and classes of elevation can improve the overall accuracy by 10 % compared to standard statistical classifier (i.e. maximum likelihood). Elevation information from ASTER GDEM were unreliable because of the stacking processes in ASTER GDEM. To further improve the classification results, Neural Network classifier need more extra information which are closely related with the land cover types to classify them.

Acknowledgements

First of all, i thank to the Almighty Allah SWT for His unlimited blessing on me during all the time at ITC and also on my family.

I would like to express my gratitude to all those who gave me the possibility to complete this thesis.

Thanks to my supervisor, Yousif Hussin, for his guidance, support, comments and suggestion during this research. I gratefully acknowledge the contribution of Willem Nieuwenhuis for his help on Neural Network application.

Thanks to Dr. Michael Weir, the NRM Course Director, and all Natural Resources Department ITC staff who be helpful and encouraging.

Thanks to all my colleagues in DD ITB – ITC 2008-2010, and all my colleagues in NRM course 2009, thanks for the discussion and sharing thoughts.

Thanks to all Indonesian students in ITC, our togetherness made my study period here full with experiences.

Thanks to my mother and father for their endless praying, to my lovely wife, Anna Tosiani, for her patient, praying, and taking care of my daughter, Kenes. You were keeping me in spirit for this study.

Enschede, September 2010

Ikwan

Table of contents

1.	Introduction	7
1.1.	Background	7
1.1.1.	Spatial Planning and Natural Resources.....	7
1.1.2.	Forestry Planning and Decentralised.....	7
1.1.3.	Regional Spatial Planning and Data in Papua	9
1.1.4.	Cycloops Nature Reserve and Jayapura City	9
1.1.5.	Remote Sensing and GIS	10
1.2.	Conceptual Framework	10
1.3.	Problem Statement	11
1.4.	Research Objectives	12
1.4.1.	General Objectives	12
1.4.2.	Specific Objectives	12
1.5.	Research Question.....	12
1.6.	Hypothesis.....	12
2.	Concept and Definition	13
2.1.	Spatial Planning	13
2.1.1.	Regional Planning.....	13
2.1.2.	Protection Area and Nature Reserve	13
2.2.	Spatial data and data required	14
2.2.1.	Landsat ETM+	14
2.2.2.	DEM	14
2.3.	Geospatial Analysis.....	15
2.3.1.	Landform and Landscape	15
2.4.	Image Classification	17
2.4.1.	Maximum likelihood Classification	18
2.4.2.	Artificial Neural Network Classification	18
3.	Study Area, Materials and Method	21
3.1.	Study Area.....	21
3.1.1.	Jayapura City	21
3.1.2.	Cycloops Nature Reserve	23
3.2.	Materials.....	24
3.2.1.	Data Used:	24
3.2.2.	Software Used.....	27
3.3.	METHOD.....	27
3.3.1.	Mapping the gap area of Cycloops Nature Reserve and Regional Planning of Jayapura city. 27	
3.3.2.	Spatial information of the gap area	27
3.3.3.	Research Method Flowchart.....	30
4.	Result and Discusses	32
4.1.	Result.....	32
4.1.1.	Mapping the gap area of Cycloops Nature Reserve and Regional Planning of Jayapura city. 32	

4.1.2.	Detailing spatial information of the gap area	33
4.1.3.	Maximum Likelihood and Neural Network Classification	36
4.1.4.	Accuracy Assessment	40
4.1.5.	Landcovers In The Gap Area	43
4.2.	Discusses	44
4.2.1.	Mapping the gap area of Cycloops Nature Reserve and Regional Planning of Jayapura city.	44
4.2.2.	Detailing spatial information of the gap area	45
4.2.3.	Neural Network Classification	47
4.2.4.	Accuracy Assessment	49
4.2.5.	Landcover In The Gap Area	50
4.3.	Limitation	51
5.	Conclusion and Recomendation.....	52
5.1.	Conclusions	52
5.2.	Recomendations.	53
References	55
Appendices	57
Appendix A :	Learning rate process in the Neural Network classification	57
Appendix B :	The sources image in the stacking process	63

List of figures

Figure 1-1 : Conceptual Framework.....	11
Figure 2-1 : Morphometric features <i>sources : (Wood, 1996)</i>	16
Figure 2-2 : Morphological element from DEM <i>Sources :(de Smith et al., 2009)</i>	17
Figure 2-3 : Spectral Reflectance curve of 3 land covers.....	17
Figure 2-4 : A simple NN architecture (Jellema, 1997)	19
Figure 3-1 : Maximum and minimum temperature in Jayapura for 2005 <i>sources : (BPS, 2005)</i>	21
Figure 3-2 : Rainfall in Jayapura 2005 (in mm/month) <i>sources : (BPS, 2005)</i>	22
Figure 3-3 : Population in Jayapura for each district and city 2005 <i>sources : (BPS, 2005)</i>	22
Figure 3-4: Location of the study area <i>Resources : Google maps</i>	23
Figure 3-5 : Soil map.....	25
Figure 3-6 : Geology map	25
Figure 3-7 : Class elevation map derived from SRTM	26
Figure 3-8 : windows of NN parameters in NeuralNet for ENVI	29
Figure 3-9 : Flowchart of Research Method	31
Figure 4-1 : Map of the gap area.....	32
Figure 4-2 : The morphometric properties of ASTER DEM and SRTM DEM	34
Figure 4-3 : Cross section (profile) from ASTER GDEM and SRTM DEM.....	34
Figure 4-4 :Topographic Maps.	35
Figure 4-5 : Topographic feature map from SRTM	35
Figure 4-6 : Land cover classification maps.	38
Figure 4-7 : Land use map using neural network classification	39
Figure 4-8 : Summary of the accuracy assessment of all 7 maps	43
Figure 4-9 : Landuse on gap area	44
Figure 4-10 : Population 1971 – 2000 Figure 4-11 : Jayapura City and its expansion.....	45
Figure 4-12 : Jayapura City in google earth 3D	45
Figure 4-13 : Comparison of different area in resulted maps.....	48
Figure 4-14 : Pie chart of land cover in the gap area	50
Figure 4-15 : Accuracy for three major classes in the gap area.....	51

List of tables

Table 1-1 : The different policies responsibility	9
Table 3-1 : List of ancillary data used in this research work	26
Table 3-2 : Morphometric features classification criteria sources: (Wood, 1996)	27
Table 3-3 : Seven different types of Classifications used in this research.....	29
Table 4-1 : Seven classification maps resulted from different input combinations.....	37
Table 4-2 : Area of land cover for each classification map (in ha).....	39
Table 4-3 : Error matrix for Map 1 (Landsat ETM+)	40
Table 4-4 : Error matrix for Map 2 (Landsat ETM+, mf, srtm)	40
Table 4-5 : Error matrix for Map 3 (Landsat ETM+, srtm).....	41
Table 4-6 : Error matrix for Map 4 (Landsat ETM+, mf).....	41
Table 4-7 : Error matrix for Map 5 (Landsat ETM+, class elevation).....	42
Table 4-8 : Error matrix for Map 6 (Landsat ETM+, geology, soil type)	42
Table 4-9 : Error matrix for Map 7(Landsat ETM+, geology)	42
Table 4-10 : Accuracy assessment of classification maps	43
Table 4-11 : area of landuse in gap area (ha).....	44

1. Introduction

1.1. Background

“Spatial planning is concerned with the coordination and integration of the spatial dimension of sectoral policies through a territorially-based strategy” (Cullingworth and Nadin, 2006). Moreover, by creating more constant and expected condition for investment and development, spatial planning will increase the benefit for economic, environmental and social sectors. However, spatial planning is different from simple land-use regulation. Spatial planning is important to solve the problems and different policies among sectors. Such as conflicts different policies among economic, environmental and social sectors. At last, spatial planning also should make benefit for the community by encourage wise use of land and natural resources (UN, 2008). Therefore spatial planning differs greatly from one country to another, depend on their resources.

1.1.1. Spatial Planning and Natural Resources

Indonesian natural resources is the second highest biodiversity in the world (after Brazil), out of which forest cover approximately 60 % of the country's area. Primary and secondary tropical rainforests dominate large parts of Indonesia (Barber et.al, 1995). Indonesian forest planning was started to manage forest as one of the country's resources to increase the economic development. Since new order regime in 1966, big part of forest areas in Indonesia have been utilized and managed as timber production forests. This was done using the system of holding concession. This means that forest were given to forest concession holders (i.e. private and semi-government forest companies) (Nugroho, 2006). Forestry sector becomes the leading income sector, which lead to raising the economic growth in last 50 years. Increasing in economic development also means increase the others sector. The need of land is not limited only for forestry sector. Other sector such as industrial and agriculture also need area to develop. Therefore, from 1981, the Directorate general of forestry, supervised by Ministry of Agriculture develop a map called Forest Land Use Consensus (TGHK). This map is classified land use for the allocation of sectoral interests based on land use functions (Soetarto et.al, 2001)

1.1.2. Forestry Planning and Decentralised.

In 1982, Ministry of forestry of Indonesia released the forest land use planning for all provinces in Indonesia, known as TGHK (Tata Guna Hutan Kesepakatan/ Forest Planning Agreement) in the scale of 1 : 250,000. This map is basically zoning map of forest area using rainfall intensity, soil types, slope classes, altitude, forest boundary and other information about biodiversity and wildlife (Nugroho, 2006). In the 1990's, Ministry of Public Work also release the spatial planning in national scale for all province (Rencana Tata Ruang Wilayah Provinsi/RTRWP map). These two maps then integrated and harmonized to make a new forest planning map. This new forest planning map is determined by the Minister of Forestry in the format of Ministerial Decree (MD) on the Designation of Provincial Forest Area and Inland Water, Coastal and Marine Ecosystem. The release date for each

provincial is different, depend on the process. For Irian Jaya Province (Then named Papua Province in the decentralized era), this map have released in 1999 by MD number 891/KptsII/1999.

Base on the maps from the mentioned planning process, forest area is categorized as Conservation Forest, Protection Forest and Production Forest, defined as the following:

- Conservation Forest is a forest area having specific characteristic established for the purposes of conservation of animal and plant species and their ecosystem.
- Protection Forest is a forest area designated to serve life support system, maintain hydrological system, prevent of flood, erosion control, seawater intrusion, and maintain soil fertility.
- Production forest is a forest area designated mainly to promote sustainable forest production. Production forest is classified as permanent production forest, limited production forest, and conversion production forest.

Unfortunately the input data / maps are varies in quality for each region. For java and Sumatra islands, the base map and thematic map to generate the forest planning map have detail scale information (up to 1:25,000). But for the Irian Jaya Province, the base map and thematic map to generate the forest planning map are in the general scale (less than 1:250,000). As an illustration, for Irian Jaya Province which have 43 million ha area, covered only by 17 meteorological station (bps, 2008 and www.bmg.go.id) to generate rainfall intensity map. The soil type map only available in the general scale (1:500,000).

While the process of integrating and harmonizing TGHK and RTRWP still in the process, the economic crisis of 1997 and the new era of political reform have generated changes in the structure and policies of the Indonesian government. This political reform changes from centralise to decentralise policy which indicated by the passing of law on regional autonomy (Act No.22/1999) and intergovernmental fiscal balance (Act No.25/1999). The name of Irian Jaya Province then changed become Papua Province. In order to maintain the issues of disintegration of Papua province from Indonesia, The central government release the law of special autonomy for Papua Province (Act No 21/2001). These three legislations designed to transferring the authority to the provincial and district governments, allowing provincial and district government with rich resources to take larger share of the fiscal revenues which is generate within their regions (Soetarto et al, 2001). The euphoria of decentralised reform in Papua Province marked by the increasing number of regency, from 11 becomes 31 regencies. The special autonomy of Papua tends to raise the development in Papua, such as road network to connect all regencies, new public facilities for the new regencies etc. This also support by the increasing in fiscal revenue share up to 26% each year (BPS, 2008) for Papua Province. However, the human resources capacity in Papua was not enough to support the development. 66% of population in Papua is only graduated from elementary school. While only 1.8% graduated from bachelor degree (BPS, 2003). To fulfil the need of educated human resources, employer from other islands (mostly from Java, Sumatra and Sulawesi) comes to Papua. This urbanisation process increased the population in Papua. As the development process continues, the population in the

Papua also increase derived by urbanisation from other islands. Increasing in population also means increasing the need of area for settlement and public facilities (Tokede, 2005)

1.1.3. Regional Spatial Planning and Data in Papua

Papua is the biggest province in Indonesia, with an area of more than 31 million hectares. Most of the province area is covered by forests, ranges from low land forests to swamp forests to high mountain forests. High population are found in big cities such as Jayapura, Timika, Merauke and other sub-regional cities in remote area, which cannot be reach by the roads. Most of the cities and areas in Papua can only be reached by small air plane. With population density of 6.31 /km² in 2005 (compare to Java Island which has population density of 979/km² in the same year), Papua has the lowest population density in Indonesia (BPS, 2005). The lack of the intensive or high density information and data of soil type, rainfall and slope make the zoning map of forest planning and management map, inaccurate when compared with the real condition. The change from centralized to decentralized government policy, gives more power to local government to plan their own region. The above mentioned problem of forest planning map in Papua province becomes more serious when compared with the regional spatial planning. One of the locations that have a serious problem is the area of Cycloops Nature Reserve (CNR).

1.1.4. Cycloops Nature Reserve and Jayapura City

The process of the establishment of cycloops as a nature reserve start from 1974, with a lot of biodiversities research, studies and boundary survey by FAO/UNDP (by request of the government), Ministry of forestry, WWF, and local government (Petocz, 1989). These activities finished in 1987, when the Ministry of Forestry Enactment Decree number 56/1987 about the establishment of the Cycloops nature reserve, was issued. This nature reserve is located close to Jayapura, the capital city of Papua province. When the CNR establish in 1987, Jayapura was a small city, but now after the change from centralized to decentralized policy in Indonesia from 1998, Jayapura grows into a developed city. In centralized policy, central government (Ministry of Public Work and National Planning Board /Bappenas) was the board that has responsibilities in spatial planning. The regional government only as the implementer of the policy and regulation in spatial planning. (table 1.1)

Table 1-1 : The different policies reponsibility

Era	Central Government	Regional Government
Centralized (before 1998)	Policy, Decision making, Regulator.	Implementer
Decentraliced (after 1998)	Regulator	Decision making, policy, implementer

Sources : Modified from the Law no27/2006

In the decentralized policy, the regional government have capacity to make their own regional planning. The regional planning of Jayapura city released in 2006 showing the need to build public services area. Part of the CNR (based on forest planning map) now plan to be developed area based on regional spatial planning. This area based on CNR is an area as protected forest area but on the other hand, the government of Jayapura city plan to develop this area. This gap of management emerges between the management of CNR under ministry of forestry and local government for

Jayapura city. The problem between area for nature reserve and for build up area emerges. Gap area is the area that there is a conflict of management.

Alternative should be made to adjust and propose modification for the gap of different management purposes area of the Cycloops nature reserve and regional planning of Jayapura City.

1.1.5. Remote Sensing and GIS

“The quality of the spatial planning is mostly depend on the quality of the gathered data and the quality of ecological evaluation methods applied” (Schaal, 2000), and remote sensing and GIS can provide the recent information with sufficient data quality. Therefore remote sensing and GIS can support planning in processing, visualizing and implementing of the plan. Recent technology and tools for mapping give a lot of new ways to extract landscape information in more details. The availability of digital elevation model (DEM) from SRTM (Shuttle Radar Topography Mission) and ASTER GDEM (Global Digital Elevation Model) improves elevation data resources for all tropical regions (Hofman *et al.*, 2006) therefore a DEM is often the primary data for deriving terrain variables related to landuse/landcover (Miller and Franklin, 2002). Many researches try to combine the elevation information to increase the accuracy in image classification.

Remote sensing and GIS have developed new method and application to analyze the landscape. In earth science, Artificial Neural Networks (ANN) classifier can be used for classifying remotely sensed imagery combined with DEM. Something that a classification like maximum likelihood cannot do. ANN has developed rapidly, mainly because it is believed to improve the classification result from standard statistical classifiers such as maximum likelihood. ANN can identify and learn correlated pattern between input data and corresponding target values. The lack of assumptions about data distribution is another factor that makes ANN more attractive than statistical classifiers (Tso and Mather, 2009) and (Lek and Guégan, 1999). ANN also can integrated data from different sources, such as from different sensor types (e.g. optical and non optical) and different data types (raster, vector) (Ardo *et al.*, 1997).

Integrating satellite image and DEM using ANN classifier can increasing the accuracy of the classification results (Miller and Franklin, 2002, Lek and Guégan, 1999, Ardo *et al.*, 1997). DEM can be derived into some information such as relief aspect, morphometric properties, slope and class elevation. This research try to integrate Landsat ETM+ with Derived information from DEM. Implementing this classification in the area that need detail information (the lack of data and information for the study area) will contribute to regional spatial planning.

1.2. Conceptual Framework

From the background mention above, we make a conceptual framework of this research. Remote sensing and GIS as tools to obtain the more detail in scale and up to date for the landcover information in Cycloops Nature reserve and regional planning of Jayapura city (Figure 1).

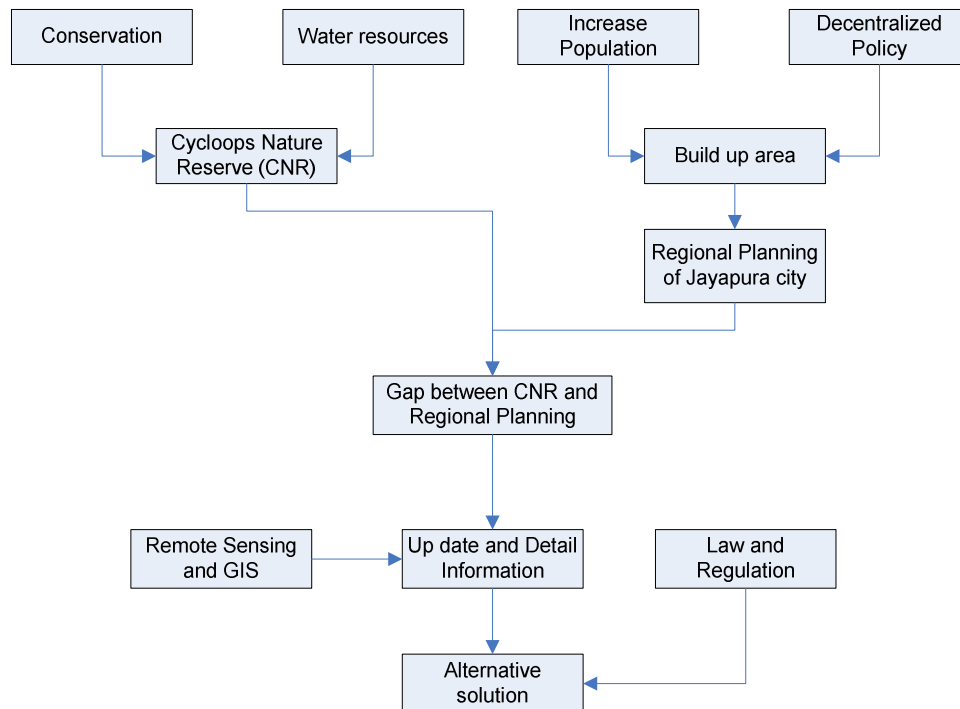


Figure 1-1 : Conceptual Framework

1.3. Problem Statement

In regional planning there is a big challenge of the integration between land to conserve and land to develop. Based on the introduction mention above, some problem in planning process in CNR and Jayapura City, can be pointed as:

- Change from centralized to decentralized policy.
- Different sectors in planning process.
- Lack of intensive data.

The Problem in Jayapura city is the lack of the detail land cover. The need of land cover information in Jayapura city to support the planning process is high. However, the available data of land cover for this area not detail enough to use as input in planning process. The available data still using manual interpretation in their process to derived landcover information. The more detail landcover information is needed. Nevertheless, NN classification believed can improve the accuracy in image processing with adding extra information in their classification processes. Thus, integrating Landsat ETM+ and derived information from DEM (morphometric properties, elevation and class elevation) to make landuse/landcover map using Neural Network (NN) Classification will be tested for their capabilities to produce useful information.

1.4. Research Objectives

1.4.1. General Objectives

The research objectives is to assess the ability of integrated Landsat ETM+ and DEM data using Neural Network Classification to detailing the scale information of land cover in part of Jayapura city in Papua province, Indonesia.

1.4.2. Specific Objectives

- a) Locating the gap area between Cycloops Nature Reserve and regional spatial planning of Jayapura city.
- b) Integrate Landsat-ETM+ and DEM to derive landscape element using morphometric properties,
- c) Compare effectiveness and accuracy of two different DEM resources (SRTM and ASTER GDEM) to derive morphometric properties,
- d) Assess the ability of Neural Network Classification to accurately classify the integrated Landsat ETM+ and DEM,

1.5. Research Question

- a) Where is the location of the gap area between Cycloops Nature Reserve and regional spatial planning of Jayapura city?
- b) How to integrate Landsat ETM+ and DEM to derive landscape element using morphometric properties?
- c) Which DEM source SRTM or Aster GDEM more effective and accurate in deriving morphometric properties?
- d) How accurate can Neural Network Classification be in classify landscape element from integrated Landsat-ETM+ and DEM ?

1.6. Hypothesis

- a) The integration of Landsat ETM+ and DEM using Neural Network Classification can significantly increasing the accuracy of landcover map compared to the standard statistical classification (maximum likelihood)
- b) Aster GDEM is more accurate in deriving morphometric properties.
- c) The method proposed by this research is effective in detailing the information of the gap area of Cycloops Nature Reserve and Regional Planning.

2. Concept and Definition

2.1. Spatial Planning

“Spatial planning is a function to influence the future spatial distribution of activities. It aims to create a territorial organization of land uses and the linkages between them, to balanced demand for development with need to protect the environment, and to achieve social and economic objectives” (UN 2008). The main challenge in the spatial planning is to make the balance between developments and protect the environment. In many spatial planning it was carried out by making a clear boundary between the development area, and the protection area. Indonesian spatial planning laws number 27/2007 used this approach. The development area is the areas that have human activities or plan to be human activities area based on the condition and the resources. On the other hand the protection area is the area that used to protect the sustainability of the environment. Spatial planning is therefore an important level for promoting sustainable development and improving the quality of life.

Spatial planning must operate in conjunction with land registration, since it involves measures that create new subdivisions of the land and new pattern use. Failure to identify existing patterns and right ownership, frequently leads to delays or even failure in development programmes. Base on the spatial planning laws 26/2007, the issue of land ownership also refer to ownership of the development area and the protection area.

2.1.1. Regional Planning

The order of spatial planning usually divided by national and regional level. Regions is vary in size, but according to UN (2008) it will usually cover large territories of relatively consistent character such as “ travel to work areas”, development corridors and river catchments in an effort to deal with functional spatial development relationships in a constant way. In Indonesia the order of spatial planning divided based on administration structure, such as national, provincial, and regency or city level.

The main task at the regional level is to interpret and adapt national policies based on their priorities and regional conditions. Different condition for each region can be a strengthening factor to the region itself. In Indonesia, the situation for each region is very different from western part, and eastern part. The decentralized policies in 1998’s give effort to eastern part of Indonesia to developing faster.

2.1.2. Protection Area and Nature Reserve

Nature reserve is a protection area because of its natural condition that has a specific characteristic of plants, animals, and ecosystems or particular ecosystems that need protection and development which take place naturally (Law number 5/1990). In the nature reserve utilization of potential activities and development facilities is not allowed, unless the activities and / or development of facilities and infrastructure that can support the activities of monitoring and protection. These

activities can only be done in a nature reserve, such as: for educational activities, research and supporting the provision of germplasm for aquaculture. Utilization activities should be conducted in such a way that does not reduce the total area, does not interfere with the function of the region, and does not include plant or animal species that are not in situ species. The nature reserve also sometimes considered as the protected area for water supply, and because of the potential hazard if that area is not well protected.

2.2. Spatial data and data required

Spatial data is data related to the location/position (ITC, 2009). It can be point, line or area. Spatial planning always related with spatial data. Spatial data/information can be used and manipulated to make a decision about spatial planning. Spatial data such as relief, soil, rainfall and land cover are basic information for spatial distribution activities. Other important data like transportation network, river, population distribution and potential hazard area, also needed to describe and give impression about the area that will be plan. The detail scale of map is dependent on the level of the planning, from national level (general scale) to local level (detail scale). Based on Regulation number 10/2000 about detail information for the spatial planning, for regional level (regency/city) the detail map must be at minimum scale of 1: 100,000.

Recent technology in remote sensing provides spatial information which is vary in detail and scale, from global information (MeteoSat/SEVIRI, NOAA/AVHRR), to regional information (Landsat TM, SPOT, ASTER) to very high detail information (GeoEye, Ikonos, QuickBird). Relief information also can be derived from this technology, such as SRTM, and ASTER GDEM. This type of information gives a lot of application as input in spatial planning.

2.2.1. Landsat ETM+

Although from the end of May 2003 this satellite has a problem, but the archive image is publicly provided via internet. With 30 meters spatial resolution, this image can represent data in detail scale up to 1:100,000. Six bands of multispectral, 1 band thermal, and 1 panchromatic band, is sufficient enough to manipulate into land cover information.

2.2.2. DEM

“Digital Elevation Model is a representation of a surface in terms of elevation values that change with position” (ITC, 2009). This model can represent the three dimension information, with elevation as the third dimension. From this model, topographic information such as slope, relief can be derived, which are also important in spatial planning.

ASTER GDEM

The Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) Global Digital Elevation Model (GDEM) was developed jointly by the Ministry of Economy, Trade, and Industry

(METI) of Japan and the United States National Aeronautics and Space Administration (NASA). The ASTER instrument was built by METI and launched onboard NASA's Terra spacecraft in December 1999 and again in Aqua spacecraft in 2002. It has an along-track stereoscopic capability using its near infrared spectral band and its nadir-viewing and backward-viewing telescopes to acquire stereo image data. *ASTER GDEM* distribution started on June 29, 2009. The ASTER GDEM covers land surfaces between 83°N and 83°S. The ASTER GDEM is in GeoTIFF format with geographic lat/long coordinates and a 1 arcsecond (approximately 30 m) grid (METI and NASA, 2009).

SRTM

On 11 February 2000, the space shuttle Endeavour with the Shuttle Radar Topography Mission (SRTM) payload on board was launched. A single technique, synthetic aperture radar (SAR) interferometry, was used for producing a consistent DEM covering between 60°N and 57°S. The 3 arc sec. (90 m spatial resolution) SRTM data are publicly available at <http://seamless.usgs.gov>.

2.3. Geospatial Analysis

2.3.1. Landform and Landscape

"Landform as physical constituent of landscape may be extracted from digital elevation data using many approaches such as classification of morphometric parameters" (Dehn *et al.*, 2001). DEM can be derived from contour lines or other sources like the Shuttle Radar Topography Mission (SRTM). With adding the off nadir sensor on its satellite, ASTER image also can be used to derived digital elevation model (DEM). The Advanced Space borne Thermal Emission and Reflection Radiometer (ASTER) Global Digital Elevation Model (GDEM) was developed jointly by the Ministry of Economy, Trade, and Industry (METI) of Japan and the United States National Aeronautics and Space Administration (NASA). The availability of SRTM and ASTER GDEM improves elevation data resources for all tropical regions (Hofton *et al.*, 2006). A DEM is often the primary data for deriving terrain variables related to landuse/landcover (Miller and Franklin, 2002).

Describing the shape of surface feature on earth using a set of numerical measures (derivatives) such as profile curvature, plan convexity, slope, cross sectional curvature, minimum and maximum curvatures from DEMs is known as morphometry (Ehsani and Quiel, 2009). Integrating land surface form (morphometric features) with spectral information from remotely sensed data contributes to the explanation of relationship between landscape component process on one hand and delimiting boundaries of homogenous landscape element on the other hand. Fauzi *et al.*, (2005) have improved NN classification accuracy when integrating DEM with Landsat ETM+, to detect logged-over tropical rain forest in East Kalimantan, Indonesia.

In geomorphic studies of landscapes, the first and second order derivatives of DEM are the basic component for this research. Slope, is the first order, while cross sectional curvature, maximum and minimum curvature are the second order. They are unique properties to identify morphometric features (Wood 1996). A local window is passed over the DEM and change in gradient of a central

point in relation to the neighbours. From these four basic components, then we can determine the morphometric features are: Peak, Ridge, Pass, Plane, Chanel and Pit (Figure 2.1).

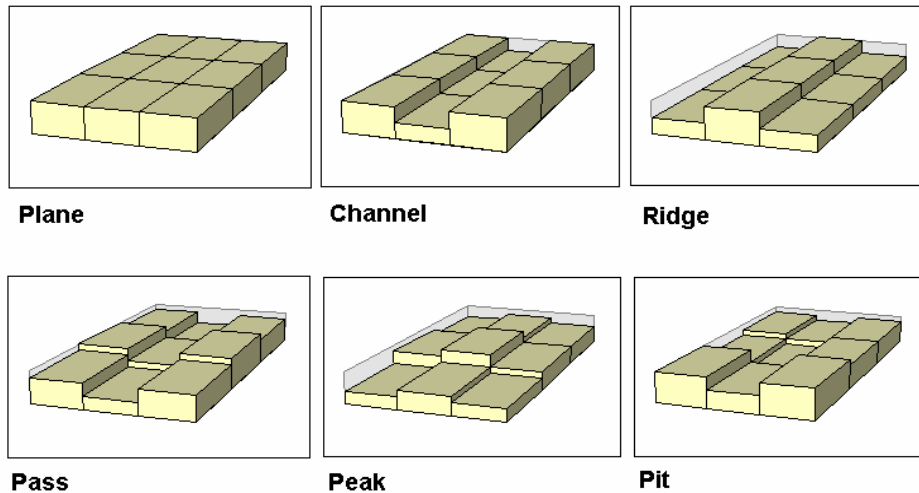


Figure 2-1 : Morphometric features

sources : (Wood, 1996)

Slope

Slope is one of the most widely used elements of surface attributes. It is define as the magnitude or size of the gradient. This parameter can be extracted from DEM by taking the partial first order derivative. Slope value is usually represented in degrees (Wood, 1996) (Figure2.2).

Cross sectional curvature

Cross-sectional curvature is used to characterise the second derivative as this is the convexity measure that is most closely related to geomorphological process. It is define as intersecting plane of the normal slope and perpendicular aspect direction (Wood, 1996; de Smith *et al.*, 2009) (Figure 2.2).

Maximum and minimum curvature

Maximum and minimum curvature used to determine the morphometric features if the slope and the cross sectional curvature is undefined. It is defined as the difference between the plan and profile curvature (Young 1978 after Woods 1996, (de Smith *et al.*, 2009)) (Figure 2.2).

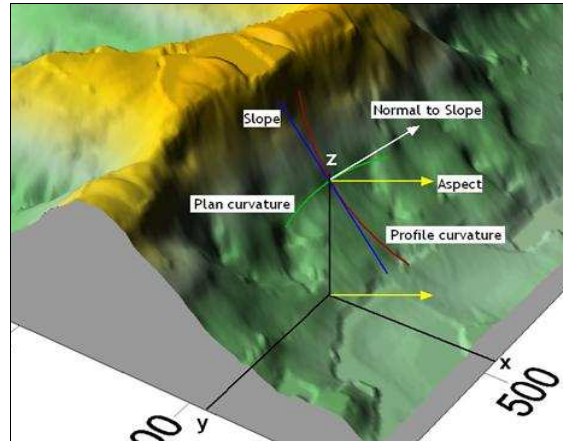


Figure 2-2 : Morphological element from DEM Sources : (de Smith et al., 2009)

Together, slope, cross sectional curve, maximum and minimum curvatures determine the morphometric features based on Woods work. (Woods, 1996) (de Smith et al., 2007).

2.4. Image Classification

The purpose of the classification process is to categorize all pixels in a digital image into one of several land cover classes, or "*themes*". This categorized data may then be used to produce thematic maps of the land cover present in an image. Normally, multispectral data are used to perform the classification and, indeed, the spectral pattern present within the data for each pixel is used as the numerical basis for categorization (Lillesand and Kiefer, 1994). The objective of image classification is to identify and portray, as a unique gray level (or color), the features occurring in an image in terms of the object or type of land cover these features actually represent on the ground.

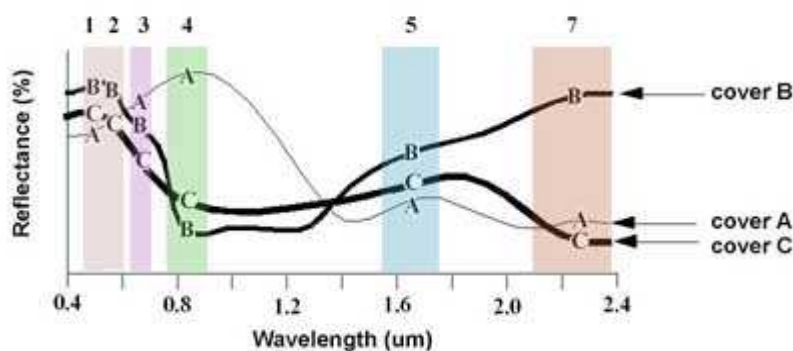


Figure 2-3 : Spectral Reflectance curve of 3 land covers

Image classification is perhaps the most important part of digital image analysis. It is very nice to have a "*pretty picture*" or an image, showing a magnitude of colors illustrating various features of the underlying terrain, but it is quite useless unless to know what the colors mean. (Lillesand and Kiefer, 1994).

In the image, each pixel has its own value. This value is calculated in classification process. One assigns meaning to each class of information. Each class contain within it one or more features.

Features are pixels which fall within a certain statistical intensity range and/or have a spatial consistency (forming a line, a square etc.). For instance, in multi spectral images a feature band signifies one of the spectral bands. An image containing a combination of different bands, contains statistical and spatial features. Finding the features belonging to a class one classifies the information in an image. The most commonly used method is statistical feature extraction in feature space.

2.4.1. Maximum likelihood Classification

The most common statistical classifier is maximum likelihood. This classifier used equi-probability lines around the mean of the feature class, using its statistical parameters (Jelema 1997). If the position of a point in feature space lies within two overlapping feature classes, it is assigned to the feature class with the highest probability line closest to that point. Maximum likelihood Classification is a statistical decision criterion to assist in the classification of overlapping signatures; pixels are assigned to the class of highest probability. Maximum Likelihood is the most powerful classifier in common (Lillesand and Kiefer, 1994). Based on statistics (mean; variance/covariance), a probability function is calculated from the inputs for classes established from training sites. Each pixel is then judged as to the class to which it most probably belongs.

2.4.2. Artificial Neural Network Classification

Combination between human eye and human brain is the most efficient to detect pattern recognition. This led to consider that computer system with simple model of the brain can be more effective than standard statistical classification method (Tso and Mather, 2009). ANN imitates the learning process of the combination of human eye and brain. The use of ANN does not require any assumption about the statistical distribution of the data. That is why ANN are generally describes as non parametric (Lek and Guégan, 1999).

Various types of ANN then developed by many researchers, depend on its suitability to solve different kinds of problems; images pre-processing, images compression, segmentation, object recognition and image understanding (Egmont-Petersen *et al.*, 2002). Many researchers have successfully applied ANN to solve the mentioned problems, but some researchers have found that ANN classifier did not significantly improve the classification compared to standard statistical classification method. ANN problem is due to the “black box” approach (Lek and Guégan, 1999; Egmont-Petersen *et al.*, 2002; Fauzi *et al.*, 2005).

Tso and Mather, (2009) explained that there are 5 kinds of fundamental neural network architectures in classification methods for remotely sensed data:

- a) Multilayer perceptron with back-error propagation.
- b) The self organized feature map (SOM)
- c) Counter propagation network
- d) Hopfield networks, and
- e) Adaptive Resonance Theory (ART) systems.

All of these different types of networks can be used for classifying remotely sensed images. Nevertheless, Egmont-Petersen (2001) reviewing several kinds of architectures in ANN, has concluded that Self Organized feature Map (SOM) classification is an interesting alternative to supervised technique.

A neural network is an interconnection of simple processing elements, units or nodes, which imitate on the animal neuron. The processing ability of the network is stored in the inter-unit connection strengths, or weights, obtained by a process of adaptation to, or learning from, a set of training patterns (Jellema 1997).

Nodes

The basic element in a neural network, called nodes, units or neurons, contain the following elements: an input scalar or vector, a weighting scalar or vector, a bias, a transfer functions of the type function (Picton 2000). The definition of the transfer function depends on the problem to be solved. The transfer function transforms an input range into a output range, according to desired behaviour.

Architecture

ANN consists of multiple neurons interconnected in some way. In this research used NN architectures without feedback (feedforward NN), because in this architecture, the output will independent of a previous input feature (Jellema 1997). In this case, a NN exist of an input layer (on the left), followed by one or more NN layer and finally an output layer (on the right).

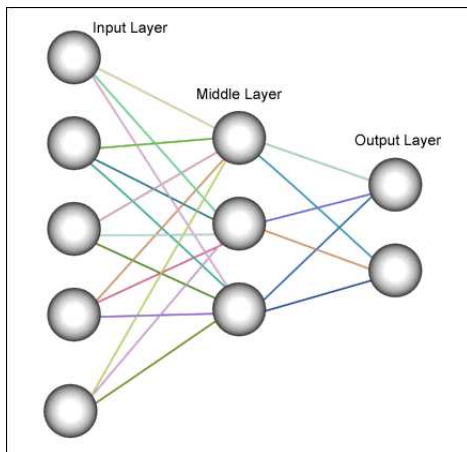


Figure 2-4 : A simple NN architecture (Jellema, 1997)

Each grey circle corresponds to a neuron. Custom and interpretation clarity dictate that only one type of transfer used per layer. The combination of different layer with different transfer function, different number of neurons and different connections allow for solutions for a broad spectrum of problems. There are two processes in the Neural Network for classification. Training the network, and classify based on the training result (picton 2000).

Training network.

Training a NN is necessary to behave correctly. Training a NN basically consists adjusting the weighting vectors w and the bias b , according to the difference between the expected output and simulated output, given a known input. To get the best result, the training process can be done by

adjusting the learning rate and maximum iteracy, to find the best minimum squared error. After the learning process have the best minimum squared error, the classification process next to be done.

Classify based on the training result

The classifying an image using neural network is the absence of a null-class. When presented with an input feature, a neural network trained to recognize several classes, always classifies that input feature into one of those classes. Even when that input feature belongs to a class the neural network was not trained to recognize (Jellema 1997)

3. Study Area, Materials and Method

3.1. Study Area.

3.1.1. Jayapura City

Jayapura is the capital city of Papua Province, Indonesia located on the Island of New Guinea. It is situated on the eastern part of Indonesia. Compared with other cities in Indonesia, Jayapura is a small city. The distance from Jakarta (the capital of Indonesia) to Jayapura is about 3.700 km (equal Madrid – Moscow). Because Indonesia is an archipelago country (many islands), the transportation from and to Jayapura is mostly using ship or airplane. This is also the reason why Jayapura city is not growing as fast as other provincial city in Indonesia. The change from centralized to decentralized government policy in Indonesia in 1998, make the growth of Jayapura city faster. In the decentralized policy, the local government get more budgets allocation to develop, based on their resources. The budget allocation for development of the city is increasing about 26 % for each year (BPS, 2008).

Climate

According to the Meteorology and Geophysical Agency of Papua Province, temperature in Jayapura is between 21.2°C for minimum temperature, and 32.2°C for maximum temperature (Figure 3.1).

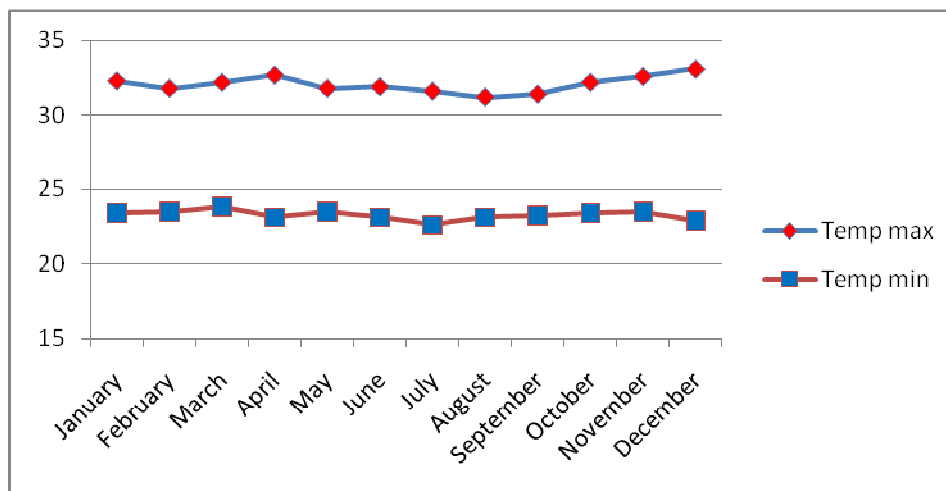


Figure 3-1 : Maximum and minimum temperature in Jayapura for 2005 sources : (BPS, 2005)

Rainfall

The study area is characterized as normal tropical condition with high amount of rainfall. The amount of rainfall in Jayapura is between 1192 mm/year to 2400 mm/year (Figure 3.2), with about 125 to 217 rainfall days per year.

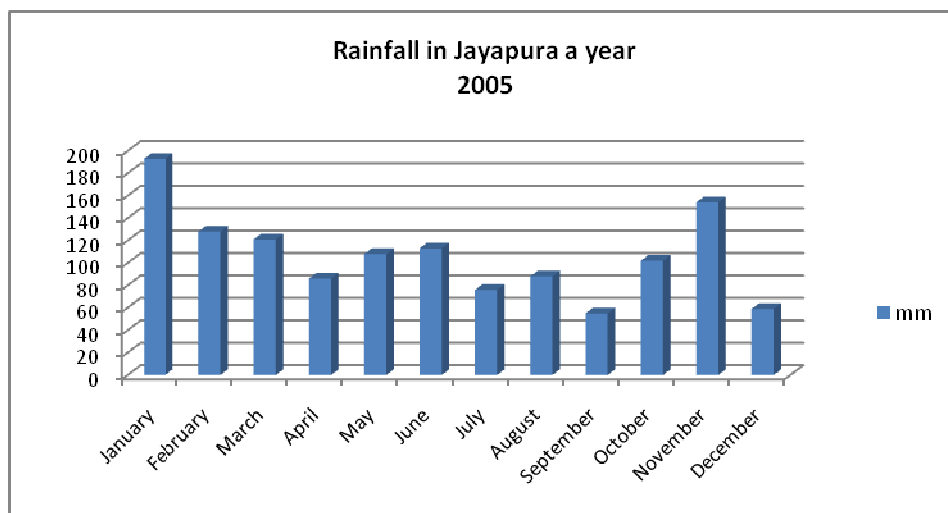


Figure 3-2 : Rainfall in Jayapura 2005 (in mm/month)

sources : (BPS, 2005)

Population

Increasing number of population in Jayapura is influenced by the number of immigration and migration. Start from 45,786 in 1970's, and double 8 times in 2000, become 341,365. In the period 1998 – 2000 a big conflict related to decentralization, push a big number of people move out from Jayapura. The number of population then increase after the condition was getting better later (Figure 5).

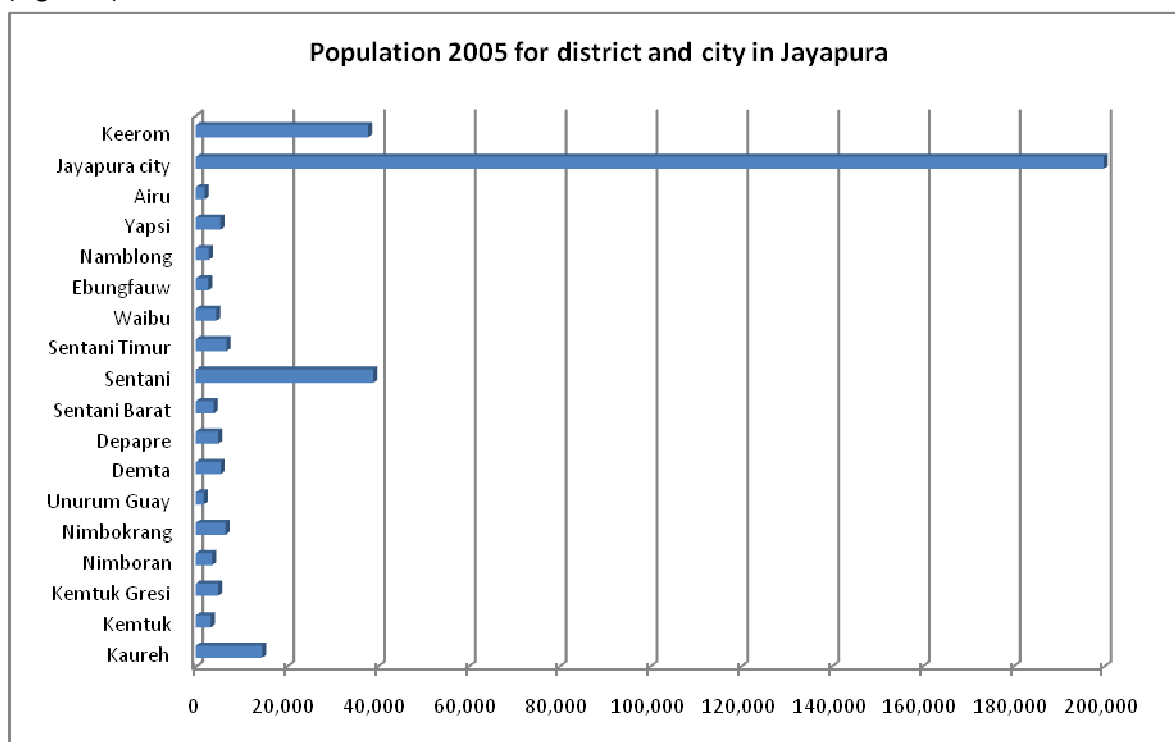


Figure 3-3 : Population in Jayapura for each district and city 2005

sources : (BPS, 2005)

Land use

Forest is still a dominant land cover in this area. But for each year the area of forest is decreased because of deforestation and forest degradation activities taken place. These activities are related

to the increase of population, the area for settlement, gardening, and cultivation activities each year. Some areas are in high risk of landslide and flood because of deforestation and forest degradation.

3.1.2. Cycloops Nature Reserve

The selected study area to implement this research works is Cycloops Nature Reserve. The area is located near Jayapura. It was established in 1987 as nature reserve by the enactment of Ministry of Forestry decree number 56/1987. Cycloops Natural Reserve is a mountainous area protected for water resources for Jayapura city and its surrounding. This area becomes vulnerable because of the human settlement and cultivation. It is located in between 2° 21' to 2° 36' S and 140° 18' to 140° 46' E (Figure 3.4). This area also deforested because of the mining resources inside the area. This area also is the main water supply for Sentani lake.

This area is selected, because the it is under high pressure from human settlement and cultivation. However, the deforestation and forest degradation in this area also give negative impact in affecting surrounding areas through landslide, flood, and lack of water resources.

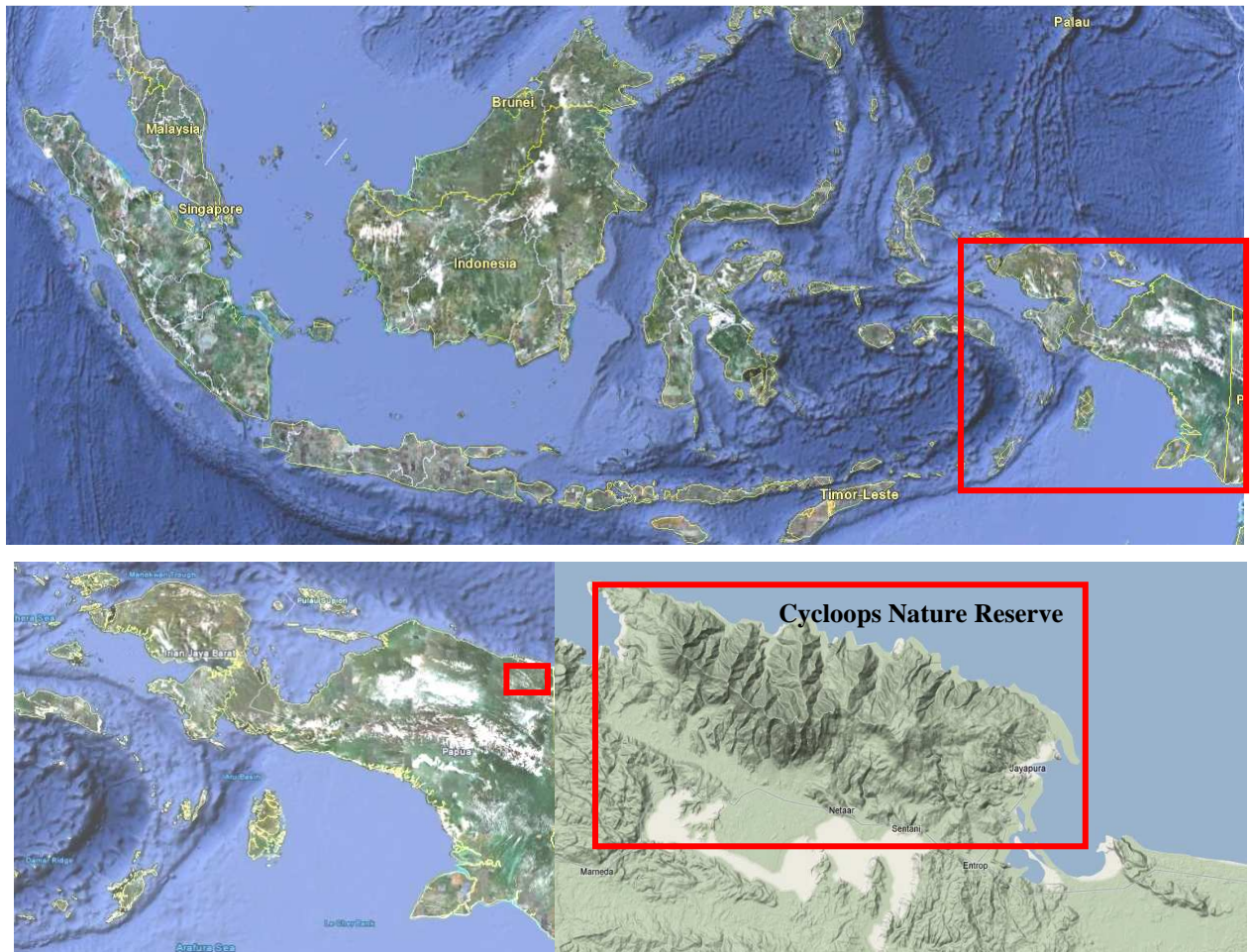


Figure 3-4: Location of the study area

Resources : Google maps

3.2. Materials

3.2.1. Data Used:

To define the gap area, two maps were needed. The first one is the regional planning map of Jayapura city, released in 2006, declared by the legislative board of Jayapura city. The format of the digital maps is in AutoCad software format.

The second map of Cycloops Nature Reserve was released by the Ministry of Forestry in 1987 after closing the boundary. This map is in ArcInfo format.

Two DEM datasets were used and compared in this research. They are SRTM and ASTER GDEM. The two datasets of DEM and one image (i.e. Landsat ETM+) data, used in this research, were publicly available through the internet. These datasets were sufficient to extract topographic data because this study area did not have sufficient topographic information.

a) SRTM

On 11 February 2000, the space shuttle Endeavour with the Shuttle Radar Topography Mission (SRTM) payload on board was launched. A single technique, synthetic aperture radar (SAR) interferometry, was used for producing a consistent DEM covering between 60°N and 57°S. The 3 arc sec. (90 m spatial resolution) SRTM data are publicly available at <http://seamless.usgs.gov>.

In this research, the study area covered by SRTM data path 101 row 62. In this data the minimum value is -2, and the maximum value is 3986 (after cropped to the study area).

b) ASTER GDEM

The Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) Global Digital Elevation Model (GDEM) was developed jointly by the Ministry of Economy, Trade, and Industry (METI) of Japan and the United States National Aeronautics and Space Administration (NASA). The ASTER instrument was built by METI and launched onboard NASA's Terra spacecraft in December 1999. It has an along-track stereoscopic capability using its near infrared spectral band and its nadir-viewing and backward-viewing telescopes to acquire stereo image data. *ASTER GDEM* distribution started on June 29, 2009. The ASTER GDEM covers land surfaces between 83°N and 83°S. The ASTER GDEM is in GeoTIFF format with geographic lat/long coordinates and a 1 arcsecond (approximately 30 m) grid (METI and NASA, 2009).

In this research the data covered by ASTER GDEM S03/E140, downloaded in February 2010. In this data the minimum value is 0 and the maximum value is 4988 (after cropped to the study area).

c) Landsat ETM+

This image was collected on 6 February 2003, and downloaded in the TIFF file format from <http://glcfapp.umiaccs.umd.edu:8080/esdi/index.jsp>. The cloud cover is about 30 % of the image, but in the research area, the cloud is much less, except in the high area of CNR. The format of the image is Band Sequential (BSQ). This means each band of the image is saved in a separate file. The image was already geometrically corrected. Stacking the image into one file was done to make it work for the next process in the ENVI 4.5 image processing software.

d) Soil map

Soil map for the study area available in the digital shape file format. The sources data for this map derived from scale 1 : 500,000,

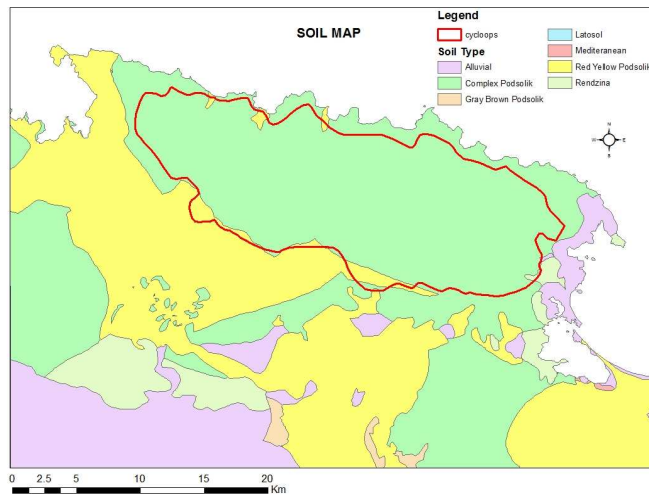


Figure 3-5 : Soil map

In the study area there are seven of soil classes. Most of the CNR (Inside the red line) is complex podzolic soil. Podzolic soil usually forming in a broadleaf forest and characterized by moderate leaching, which produces an accumulation of clay and, to some degree, iron that have been transported (eluviated) from another area by water. The humus formed produces a textural horizon (layer) that is less than 50 cm from the surface (FitzPatrick, 1980). And most of the area of Jayapura city is Alluvial soil class.

e) Geology map

Geology map for the study area digitized from the geology map of Jayapura. The sources of the geology map in the scale of 1 : 500,000.

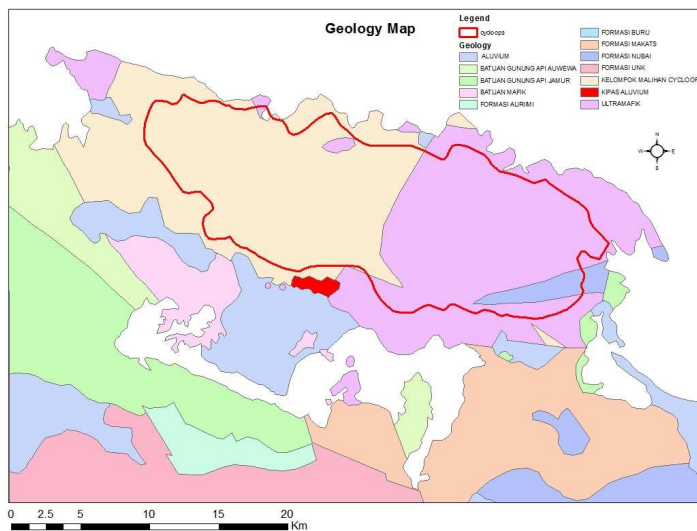


Figure 3-6 : Geology map

Based on this map, CNR consist of two classes of geology; Cycloops metamorf rock and ultramafic rock. And for Jayapura city have alluvium and ultramafic for the geology class.

f) Class elevation Map.

In this research, class elevation map used as input in one of Neural Network classifications, as the extra information. The class of elevation derived from DEM information. The class of elevation modify to relate with the land cover. Figure 3-7 show the map of class elevation derived SRTM

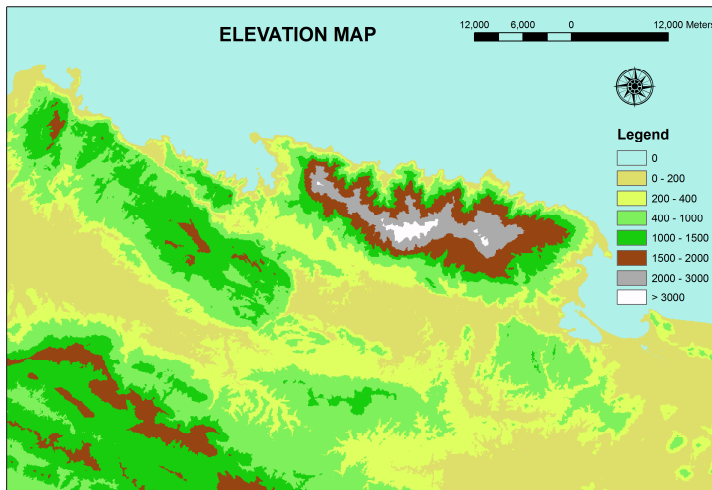


Figure 3-7 : Class elevation map derived from SRTM

g) Training sample and test sample

Other ancillary data used in this research are listed in Table 3.1. In this research, there is no field work to collect the training sample and test sample in the classification processes. However, to get the training samples and test sample in this research done by using available land use map of the area (from ministry of forestry) in the scale of 1 : 100.000, and support by google earth image for the detail information. Moreover the image for the location from the google earth has a high spatial resolution. These data used to compare and as information sources in the assign the training sample and test sample in the classification process.

Table 3-1 : List of ancillary data used in this research work

Theme	Description	Source	Year
Landuse map	Map (shape file)	Baplan, Ministry of Forestry, Indonesia	2003
TGHK map	Map (Shape file)	Baplan, Ministry of Forestry, Indonesia	1999
Road networks map	Map (shape file)	Baplan, Ministry of Forestry, Indonesia	2003
Administrative boundary map	Map (shape file)	Local government of Papua province	2006
Google earth	Interactive map	Google	2010

3.2.2. Software Used

- Erdas
- Arc GIS 9.3.1
- ENVI

3.3. METHOD

3.3.1. Mapping the gap area of Cycloops Nature Reserve and Regional Planning of Jayapura city.

Intersecting between maps of Cycloops Nature Reserve area and regional planning of Jayapura city was done to define the gap area. This gap area actually is an area of CNR that also manage by government of Jayapura city and have the different in planning purposes. In one hand the management of CNR plan that area to be protection area, but on the other hand, local government of Jayapura City plan that area as build up area. ArcGIS 9.3 used in this process. First, intersecting the boundary of CNR and the administration boundary of Jayapura City. This process is to define the area of CNR which inside Jayapura city. Then overlaying this area with the regional planning of Jayapura city. In this process the area of CNR which also plan as a protected forest define as the area that have the same purposes management area. The gap area is the area that belong to CNR but plan as developed area in the regional planning (figure 4.1)

3.3.2. Spatial information of the gap area

Morphometric deriving

In this part, two DEM sources (SRTM and ASTER GDEM) were used to derive morphometric elements using their morphometric properties using ENVI 4.5 software since it has the module of topographic features under topographic module.

Together, slope, cross sectional curve, maximum and minimum curvatures determine the morphometric features (Figure 2.2) based on the rule in the Table 3.2 (Woods, 1996) (de Smith *et al.*, 2007).

Table 3-2 : Morphometric features classification criteria

sources: (Wood, 1996)

Morphometric features	1 st and 2 nd derivates of DEM as Basic component			
	Slope	Cross sectional curvature	Maximum curvature	Minimum curvature
Peak	0	#	+va	+va
ridge	0 +va	# +va	+va *	0 *
Pass	0	#	+va	-va
Plane	0 +va	# 0	0 *	0 *
Channel	0 +va	# -va	0 *	-va *
Pit	0	#	-va	-va

Va: derivatives value, #: undefined value, *: not part of selection criteria. For features with positive (+) value for slope, cross-sectional curvature should be considered but for features with zero value for slope (0), cross-section curvature is undefined (#) so maximum and minimum curvatures are main criteria.

The calculation for deriving the following information is based on the works of Woods, (1996):

$$\text{slope} = \text{atan}(\sqrt{d*d + e*e})$$

$$\text{cros} = n*g*(b*d*d + a*e*e - c*d*e)/(d*d + e*e)$$

$$\text{maxic} = n*g*(-a-b+\sqrt{(a-b)*(a-b) + c*c})$$

$$\text{minic} = n*g*(-a-b-\sqrt{(a-b)*(a-b) + c*c})$$

After making the 2 morphometric feature maps from 2 different sources of DEM data, then a visual comparison of the two maps was done. Cross section profile also used to see the different information of elevation between these two DEM data. Thus, based on the information derived from the two maps, a selection of which one of them will be more accurate in deriving morphometric elements will be chosen for this research. ENVI 4.3 was used in this process.

Classifications

Maximum likelihood classification was done using Landsat ETM+ as the input image, to derived landcover map. The resulted map of maximum likelihood then compared with the result map of Neural Network classification. ANN consists of multiple neurons interconnected in some way. In this research used NN architectures without feedback (feedforward NN), because in this architecture, the output will independent of a previous input feature (Jellema 1997). In this case, a NN exist of an input layer (on the left), followed by one or more NN layer and finally an output layer (on the right). The morphometric properties of the best DEM source resulted from the previous process combined with Landsat ETM+ image were classified using Neural Network classification. The information from Landsat ETM+, geology and soil were also used in this processes. Based on the different input of topographic features and other information (i.e. geology and soil), six different types of classification were done (Table 3.3). The basis to make 6 different types of Neural Network classification is based on the capability of Neural Network to combine several types of data (i.e. DEM and vector data). The land cover types (i.e. classes) used for the classification was based on the classification that used by Ministry of Forestry.

A total of 229 training samples were used in all classification process. The training samples were based on the high resolution image of Google Earth and land cover maps release by Ministry of Forestry in 2003. Advanced tools called Neural Net (NRS) which are added to ENVI 4.3 in Neural Network classification process were used in this research. In this tools, the NN classification done in two important processes. First is training the network, and second is Classify based on the training result.

Training the network

Training the network is necessary to behave correctly. In NRS tool for ENVI , this process consist of defining 5 parameters (figure 3-7)

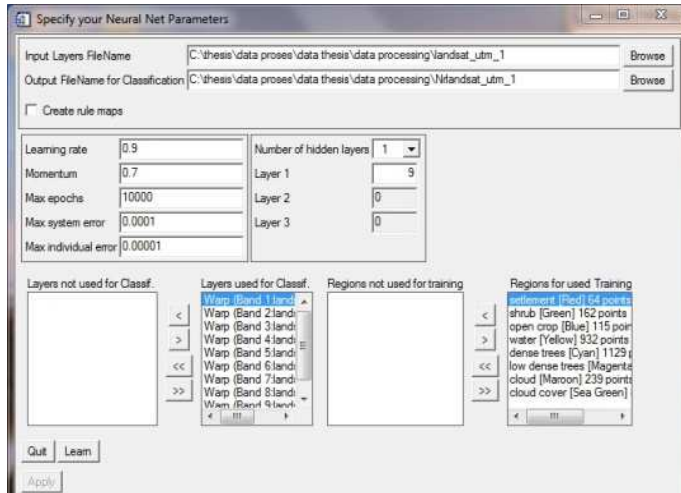


Figure 3-8 : windows of NN parameters in NeuralNet for ENVI

Learning rate and momentum are to define the decreasing function in time. In this process learning rate value is 0.9 to as the initial value, and the momentum 0.7 as the alpha function. Maximum epochs is the maximum iteration process in the learning the network. Higher the number of iteration process will affect the capacity of the learning the network, however the larger the network, also mean the more processing power required. In this process the maximum epoch is 10,000 means the learning process will be iterate 10,000 times, if the maximum system error higher than 0.0001. if the maximum system error reaching 0.0001 then the learning process will stop. The parameter used for NN classification in this research can be seen in appendix A.

Classify based on the training result

This process is to classify the images based on the weighted resulted for each node from the learning process. The number of classes depends on the number of region used in learning process. In this research 10 classes included cloud and cloud cover used classes in landcover map.

Table 3-3 : Seven different types of Classifications used in this research

Image	Method	Input
Image 1	MLC	Landsat 1,2,3,4,5,7
Image 2	NN	Landsat 1,2,3,4,5,7 and morphometric features and SRTM
Image 3	NN	Landsat 1,2,3,4,5,7 and SRTM
Image 4	NN	Landsat 1,2,3,4,5,7 and morphometric features
Image 5	NN	Landsat 1,2,3,4,5,7 and geology and soil
Image 6	NN	Landsat 1,2,3,4,5,7 and Geology
Image 7	NN	Landsat 1,2,3,4,5,7 and elevation class

Accuracy

In order to know how the neural network classification and morphometric elements can improve the classification results an accuracy assessment was done to select the best result. . A total of 277 test samples, base on high resolution image of Google Earth, were used in this accuracy assessment. A confusion matrix was constructed for the accuracy assessment to calculate the users, producers and overall accuracy. Kappa coefficient was also used to select the best image classification resulted in this process. Kappa coefficient is a statistical measure of agreement or inter-annotator agreement for qualitative (categorical) items. It is generally thought to be a more robust measure than simple percent agreement calculation since κ takes into account the agreement occurring by chance (Carletta, 1996).

3.3.3. Research Method Flowchart

Figure 3-5 (flowchart of research method). It shows the detail method of this research. First part of the method is to define the gap area using regional spatial planning map and Cycloop Nature Reserve Map. Then compare two dataset of DEM (ASTER GDEM and SRTM DEM) for deriving the morphometric element in the study area. Later compare Maximum Likelihood Classification and Neural Network Classification results. The final step is done by detailing landcover information in the gap area.

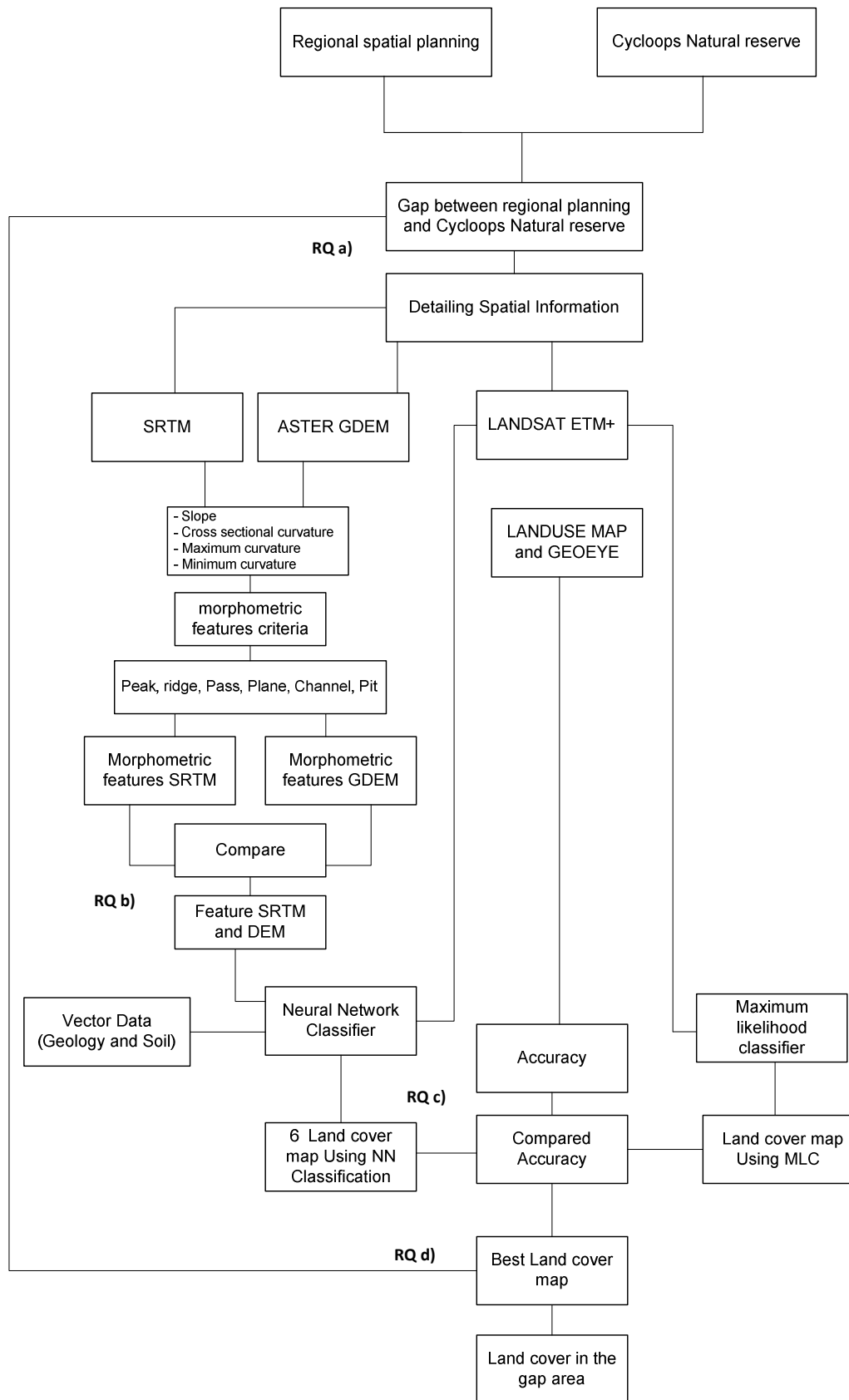


Figure 3-9. : Flowchart of Research Method

4. Result and Discusses

4.1. Result

4.1.1. Mapping the gap area of Cycloops Nature Reserve and Regional Planning of Jayapura city.

Based on TGHK map of CNR, the total area of nature reserve is 22,500ha. Administratively CNR is divided into two regions, one is Jayapura Regency and the second is Jayapura city. Out of the total area of the nature reserve, 10,200ha is part of Jayapura city. Based on the regional spatial planning map of Jayapura city, 7,790ha of CNR area which overlap with Jayapura city (i.e. 10,200ha) is planned to be a Protected Area (green colour in the figure 4.1).

The difference between 10,200ha and 7,790ha is the gap area. This area is designated by the yellow color with dot on Figure 4.1. This gap area which is part of both CNR and Jayapura city is planned to be a developing area based on regional spatial planning. There is a conflict in the management of this area. On one hand CNR consider it as part of protection area, which means there should be no human activities on it. On the other hand the Government of the City of Jayapura is considering this area as a developed one. This planning problem is happening because of scale of the available maps and lack of the detailed information on this area.

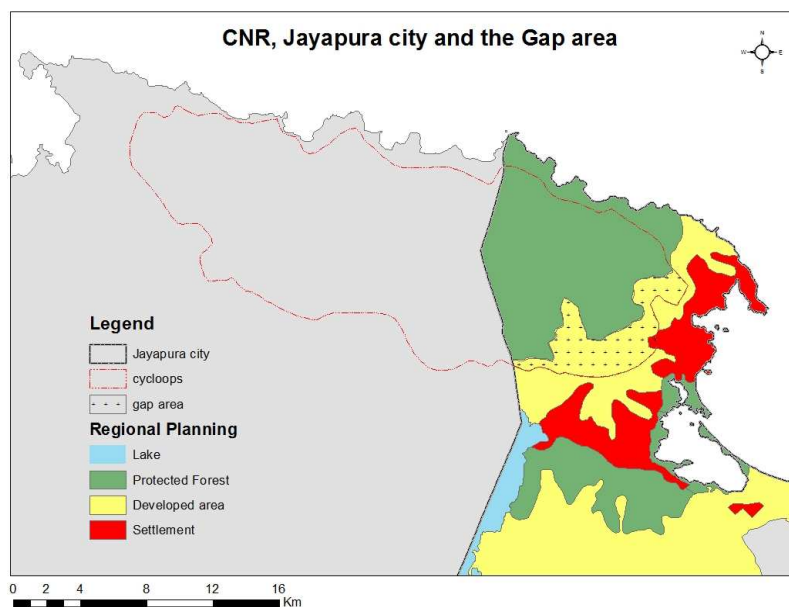


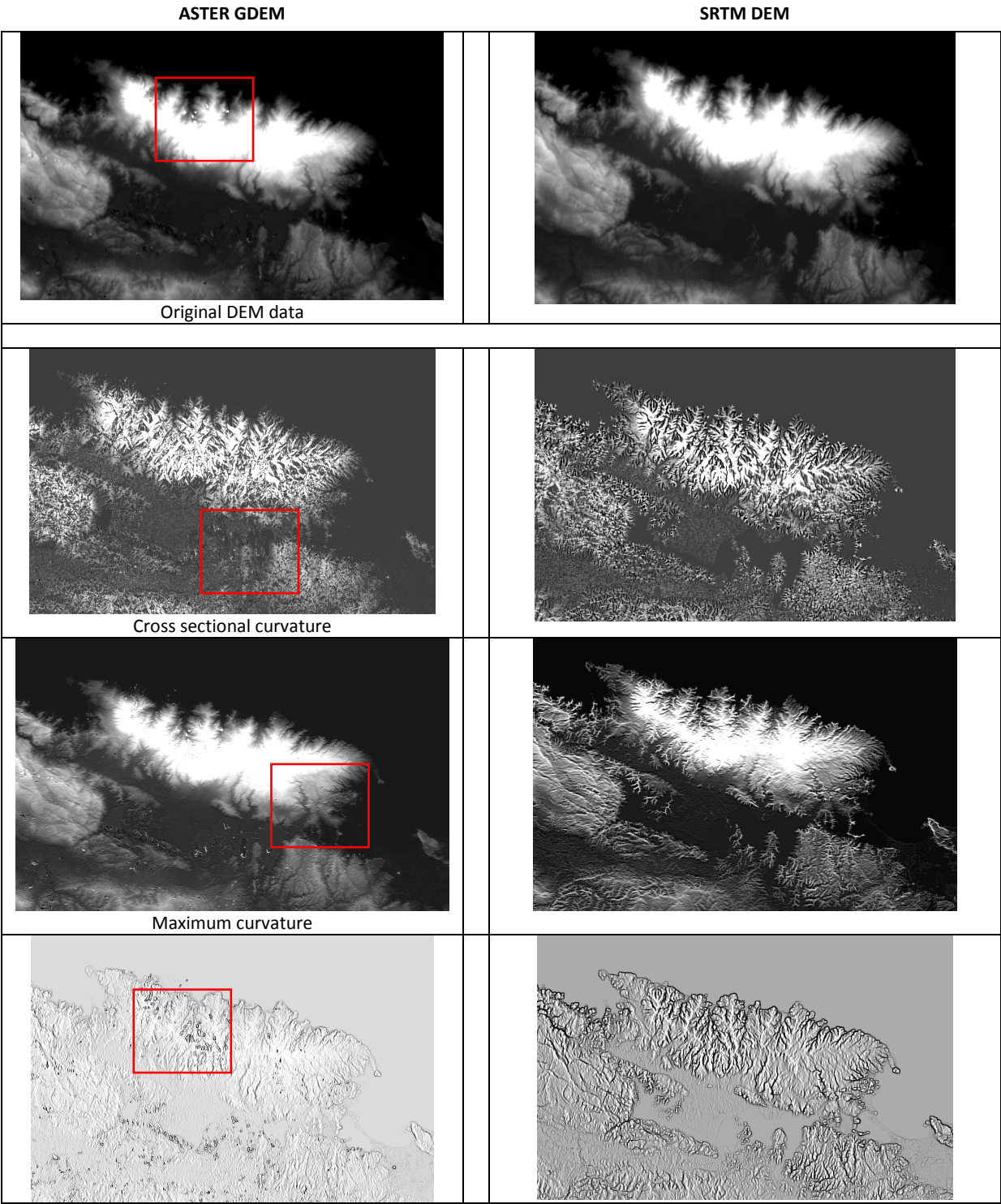
Figure 4-1 : Map of the gap area

The detail information of this area can be extracted from remotely sensed data by combining and classifying Landsat ETM+ and DEM information using NN classifier, which can provide the detail information needed to solve the planning and management conflict between the city of Jayapura and CNR.

4.1.2. Detailing spatial information of the gap area

This process used two DEM data from different sources, ASTER GDEM and SRTM DEM. From these two DEM data, the morphometric properties such as cross sectional curvature, maximum curvature, minimum curvature and slope were derived. Each map of the morphometric properties showed in the Figure 4.2.

From the Figure 4.2, for all morphometric properties, the morphometric properties derived from SRTM gives a clear boundary for the Sentani Lake (southern side of CNR), different with morphometric properties derived from ASTER GDEM that gives unclear boundary for the lake.



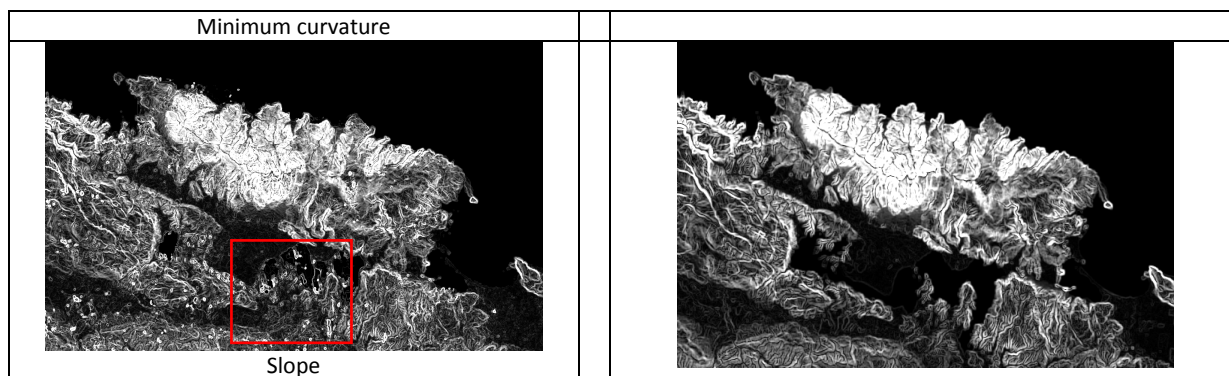


Figure 4-2 : The morphometric properties of ASTER DEM and SRTM DEM

From the maps of original DEM data (Figure 4.2), the ASTER GDEM showed some points that have high value (bright tone) in northern part of CNR (in the red box), but these points are not appearing on the SRTM. These points also can be clearly detected on the minimum curvature maps of ASTER GDEM. From the maximum curvature and minimum curvature the maps derived from SRTM gives more contrast (more clear images) than from the ASTER GDEM respectively.

The slope map derived from ASTER GDEM also showed some points that do not appear on the slope map derived from SRTM DEM. Using cross section of these areas (red boxes), the difference between these two DEM can be seen in the Figure of 4.3. In this figure the cross section shows how relief can be draw in 2 dimensions. In this 2 dimensions graph, x as the line of the cross section, and y as the elevation point. The ASTER DEM (in some points) gives a very high elevation (red circles). This should be a rare situation (unusual) in the reality. Thus it is considered as anomaly.

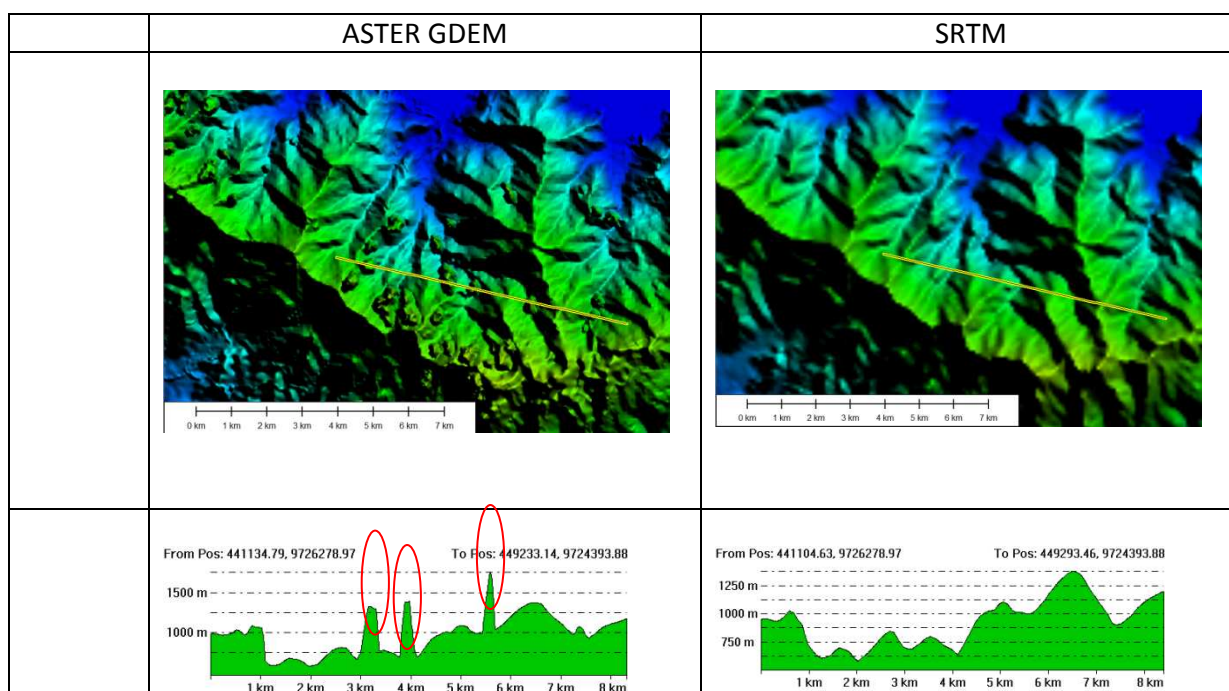


Figure 4-3 : Cross section (profile) from ASTER GDEM and SRTM DEM

Using ENVI 4.5, two topographic features maps derived from four morphometric properties for each DEM data, have been created. The maps of topographic feature showed in Figure 4.4. The maps consist of 6 classes (Plane, Ridge, Pit, Pass, Channel and Peak).

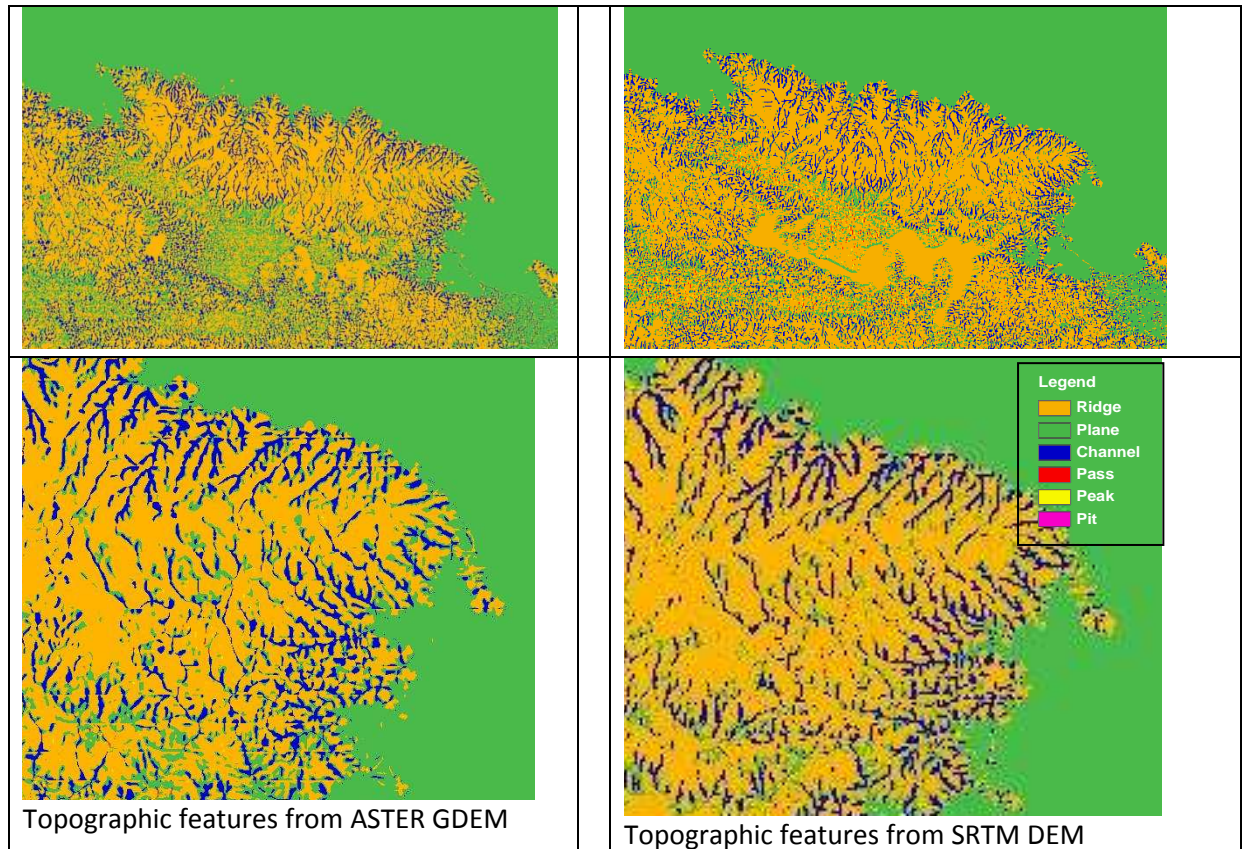


Figure 4-4 :Topographic Maps.

From the Figure 4.4, it is clear that there is a slight difference between these two features maps. This can happen because in the process of making these features maps, the moving window of the filter can makes the point of anomalies averaging with their neighbour points.

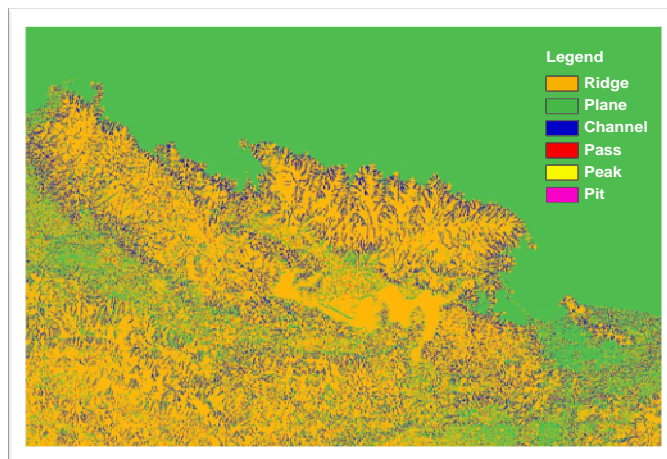


Figure 4-5 : Topographic feature map from SRTM

After deriving topographic feature information from these two DEM sources (SRTM and ASTER GDEM), SRTM was chosen (Figure 4.5) because of its DEM data gives more relevant topographic information than the other. Although the pixel size from SRTM is 90 meter, which means less details than ASTER GDEM, which has a 30 meter pixel size. However, DEM of SRTM is derived from more reliable morphometric properties.

4.1.3. Maximum Likelihood and Neural Network Classification

Using the best DEM source (i.e. SRTM) and the topographic feature map together with Landsat ETM+, Neural Network classification was used. The information from Landsat ETM+, geology and soil are used in this processes.

Seven different types of classification were done, based on the different input (Table 4.1). For all classifications in this research, the same training samples were used.

- The first classification was supervised Maximum Likelihood of the Landsat-7 ETM+ image only. This classification was done to be used as a standard one to compare with the neural network classification. The result of the classification is shown in Figure 4.6. (map 1). The map showed that all class appears in the map. Primary dryland forest is with the largest area, then secondary dryland forest and settlement, respectively. There are a lot of scattered pixels in this map. These individual scattered pixel were classified as a class different from its surrounding neighbourhood classes. The unsatisfied classification result can be seen in the class of settlement. The high reflectance of settlement (in the visible spectral band), in the periphery of cloud classified as settlement because of that area also gives the same high reflectance number.
- The second, third, fourth and fifth classifications are resulted from the Neural Network classification using the Landsat-7 ETM+ and DEM information (i.e. SRTM, morphometric feature and elevation class). These classifications process used to test the capability and contribution of the DEM information involving in classification process. The results of the classification are shown in Figures 4.6 (map2, map3, map4, and map5). Compared with map 1, all other maps showed larger area of yellow color (classified as bush and shrub). The scattered pixels in all maps were reduced, compared to the map 1. The area of primary dryland forest was also more compact. The different classification result can be seen in the cloud class. The classification using elevation class (map 5) give higher area that cover with cloud. This can be happen because of the cloud is easily form in the high area (represented by the elevation class). Classification using morphometric feature showed less cloud cover in this process.
- The sixth and seventh classifications are resulted from Neural Network classification using Landsat-7 ETM+ and vector data of the geology and soil maps. These classifications were done to test the capability of Neural Network classifiers involving soil and geology data. This was done to check whether these extra knowledge (geology or soil or topographic features) added to the spectral data of Landsat ETM would improve the

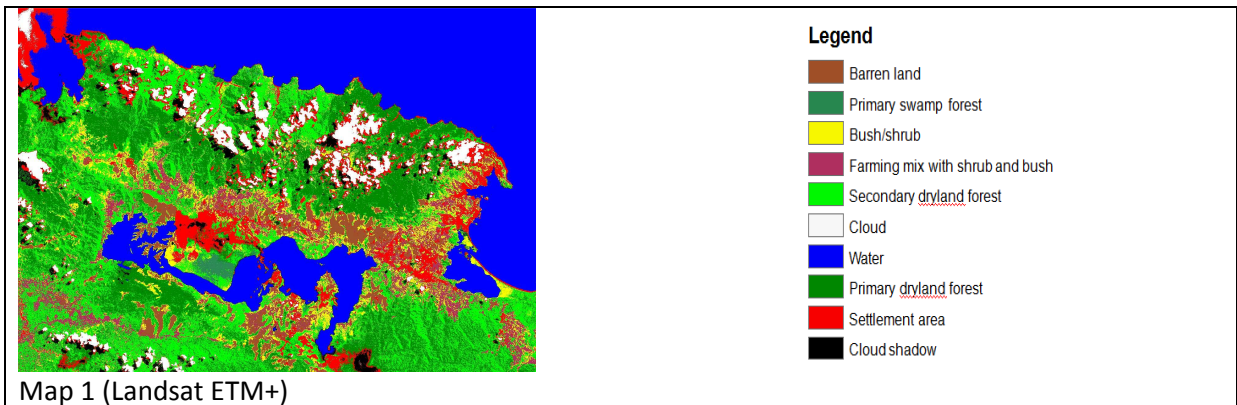
classification results or not. The result of the classification is shown in Figure 4.6. Maps 6 and 7 appeared different, from other maps. The clear boundary class, more influences by the vector data (i.e. the boundary of geology in the map 7). The class is look very homogenous, and the spatial distribution of the classes is clustered in area.

The comprehensive information about learning rate process in the Neural Network classification for map 2 – map 7, is found in Appendix A. The land cover classification was based on the classification that used by Ministry of Forestry.

Table 4-1 : Seven classification maps resulted from different input combinations

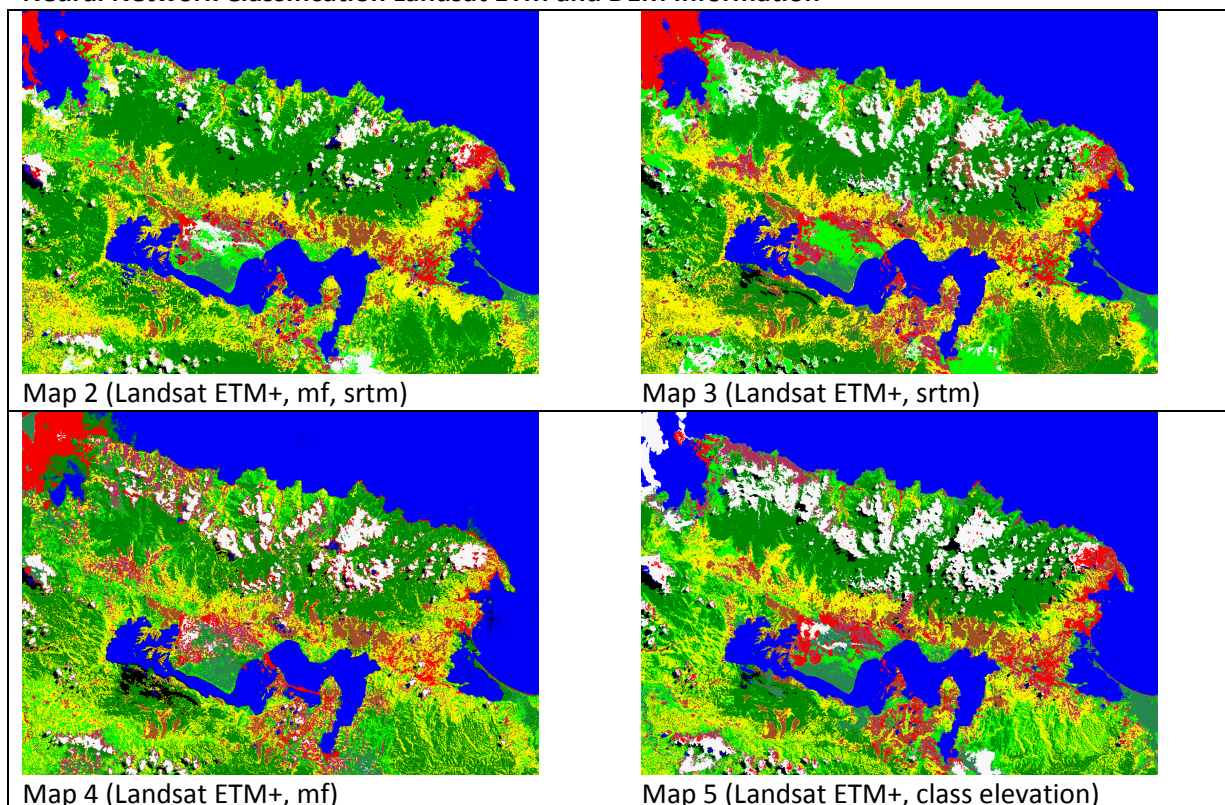
Maximum Likelihood Classification	
Map 1	Landsat 1,2,3,4,5,7
Neural Network Classification Landsat ETM and DEM Information	
Map 2	Landsat 1,2,3,4,5,7 and morphometric features(mf) and SRTM
Map 3	Landsat 1,2,3,4,5,7 and SRTM
Map 4	Landsat 1,2,3,4,5,7 and morphometric features (mf)
Map 5	Landsat 1,2,3,4,5,7 and elevation class
Neural Network Classification Landsat ETM and Vector data	
Map 6	Landsat 1,2,3,4,5,7 and geology and soil
Map 7	Landsat 1,2,3,4,5,7 and Geology

Maximum Likelihood Classification



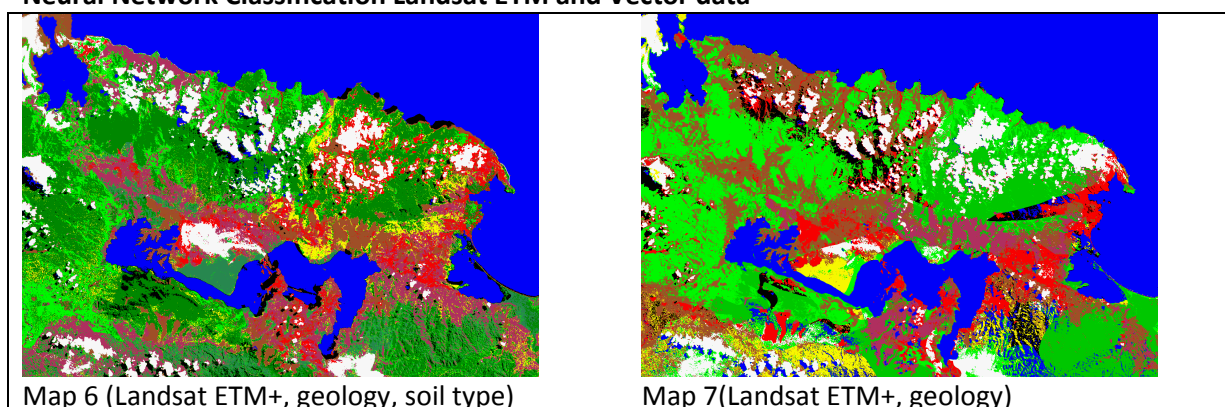
Visually, map 1 give salt and paper in between primary and secondary dryland forest. This is because maximum likelihood classification is a pixel based classification. The information derived only from the landsat ETM+ image (6 bands). Misclassification also shown in the periphery of cloud cover, classify as settlement (Red). This is because digital number almost same.

Neural Network Classification Landsat ETM and DEM Information



Maps 2 ,3,4 and 5 show less salt and paper compared to map 1. Settlement is decrease in all map. This classification can distinguish periphery of cluoud with settlement better than maximum likelihood classification (map1). The influence of morphometric features can be seen in the map 4. The channel and ridge influencing this landcover map. Using class elevation, the landcover map show the clear diferenciat class based on the elevation starting from settlement, shrub and bush, secondary dryland forest, primary dryland forest and cloud.

Neural Network Classification Landsat ETM and Vector data



The landcover in maps 6 and 7 visually slightly different compare to other maps. The border of the soil and geology can be seen clearly in the boundary of classes in the maps. The scale of the input data (1:500,000) also influencing generalized the information of the classes in this classification process.

Figure 4-6 : Land cover classification maps.

Land cover area for all classification results showed in Table 4.2. Compared to map 1, map 2,3,4,5 resulted in higher area for primary dryland forest, bush and shrub classes, and less area for secondary dryland forest and settlement classes.

Table 4-2 : Area of land cover for each classification map (in ha)

Land cover	Map 1	Map 2	Map 3	Map 4	Map 5	Map 6	Map 7
Primary dryland forest (PDF)	37,552	45,988	41,803	40,727	34,506	1,575	37,542
Secondary dryland forest (SDF)	32,989	16,350	15,445	15,023	17,348	-	16,444
Primary swamp forest (PSF)	1,099	2,976	3,100	5,541	6,515	5,609	6,956
Bush and Shrub (BS)	11,385	28,612	25,695	28,629	23,442	50,982	5,851
Bare land (BL)	5,215	4,600	6,280	5,311	6,054	4,583	9,403
Cloud (C)	6,614	8,073	11,572	8,474	14,868	10,025	13,357
Cloud shadow (CS)	3,758	1,514	2,084	2,814	3,087	6,209	5,004
Water (W)	54,539	58,187	55,124	51,733	57,008	55,458	54,300
Farming mix with bush and shrub (FBS)	10,387	6,778	9,166	11,057	9,776	41,547	22,173
Settlement (S)	14,275	4,732	7,542	8,502	5,207	1,823	6,780

From the classification resulted in this process, the advantage of the Neural Network is to combine two different data types such as Landsat ETM+ spectral images (Data value range from 0-255) and DEM which is an elevation data in meters (Data value range from any value e.g. 0-5000 meters).

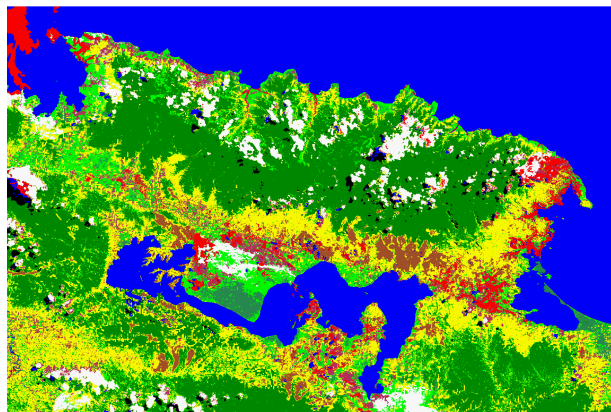


Figure 4-7 : Land use map using neural network classification

4.1.4. Accuracy Assessment

Using 277 test samples, the confusion matrices made to assess the accuracy of the result of different maps (Tables 4.3-4.9).

Table 4-3 : Error matrix for Map 1 (Landsat ETM+)

Land Cover	PDF	SDF	PSF	BS	BL	FBS	W	S	Grand Total	user accuracy	Total accuracy
PDF	30	23	3	4				2	62	48.39	58.84
SDF	8	15	2	3				2	30	50.00	
PSF	1		6	1					8	75.00	
BS		2		20	1	2		13	38	52.63	
BL				5	20	7		4	36	55.56	
FBS				7	1	35		4	47	74.47	Kappa
W							31		31	100.00	0.52
S		1		8	5	5		6	25	24.00	
Grand Total	39	41	11	48	27	49	31	31	277		
producer accuracy	76.92	36.59	54.55	41.67	74.07	71.4	100	19.35			

From the table 4.3 (error matrix for maximum likelihood classification), confusion occurs between related classes, ie., among primary and secondary dryland forest, bare land and farming mix with shrub and bush. But in settlement class, the confusion spread almost among all classes. From table above, the lowest accuracy is for the settlement class. Most of the settlement class, classified as bush and shrub (13 from 31). The Kappa coefficient is 0.52

Table 4.4 is the error matrix for NN classification using landsat ETM+, SRTM and morphometric features. The overall accuracy is lower than maximum likelihood classification (map 1). Confusion occurs between related classes primary and secondary dryland forest, bareland and farming mix with shrub and bush. There are 20 from 48 point of test sample from swamp forest classify as settlement. This misclassify is the most error affect overall accuracy.

Table 4-4 : Error matrix for Map 2 (Landsat ETM+, mf, srtm)

Land Cover	PDF	SDF	PSF	BS	BL	FBS	W	S	Grand Total	user accuracy	Total accuracy
PDF	15	13							28	53.57	54.87
SDF	18	11		6				1	36	30.56	
PSF	4	7	8	1				1	21	38.10	
BL		3	3	18	27	13		9	73	24.66	
FBS		1		3		23		1	28	82.14	
CS	1								1	-	Kappa
W							31		31	100.00	0.48
S	1	6		20		13		19	59	32.20	
Grand Total	39	41	11	48	27	49	31	31	277		
producer accuracy	38.46	26.83	72.73	37.5	100	46.9	100	61.29			

Table 4-5 : Error matrix for Map 3 (Landsat ETM+, srtm)

Land Cover	PDF	SDF	PSF	BS	BL	FBS	W	S	Grand Total	user accuracy	Total accuracy
PDF	31	10		2					43	72.09	68.23
SDF	4	22	1	2	2			2	33	66.67	
PSF	1	1	10	1				5	13	76.92	
BS	3	6		24	1	1		3	40	60.00	
BL				9	20	7		2	39	51.28	
FBS				3	1	32			38	84.21	
CS		1							1	-	0.63
W				1			31		32	96.88	
S		1		6	3	9		19	38	50.00	
Grand Total	39	41	11	48	27	49	31	31	277		
producer accuracy	79.49	53.66	90.91	50	74.07	65.3	100	61.29			

Table 4-6 : Error matrix for Map 4 (Landsat ETM+, mf)

Land Cover	PDF	SDF	PSF	BS	BL	FBS	W	S	Grand Total	user accuracy	Total accuracy
PDF	26	20	2	4					52	50.00	51.62
SDF	5	7	4	2				1	19	36.84	
PSF	1		4						5	80.00	
BS	2	6		7	1				16	43.75	
BL	1	4	1	5	21	8		7	47	44.68	
FBS				10	2	27		3	42	64.29	Kappa
CS	2	1		1					4	-	0.45
W							31		31	100.00	
S	2	3		19	3	14		20	61	32.79	
Grand Total	39	41	11	48	27	49	31	31	277		
producer accuracy	66.67	17.07	36.36	14.58	77.78	55.1	100	64.516			

Table 4.5 is the error matrix for NN classification using landsat ETM+ and SRTM (map 3). Misclassify between primary and secondary dryland forest is decrease than previous classification. Almost all class have higher accuracy than previous classification. The lowest producer accuracy is bush and shrub class (50%). In this classification accuracy also found 1 test sample for secondary dryland forest, misclassify as cloud shadow.

Table 4.6 is the error matrix for NN classification using landsat ETM+ and morphometric features. Compared with overall accuracy from map 1,2 and 3, the overall accuracy is decrease. Confusion almost occurs in all classes.

Table 4.7 is the error matrix for NN classification using landsat ETM+ and class of elevation (map 7). The overall accuracy is higher than maximum likelihood classification (map 1). Confusion occurs between related classes primary and secondary dryland forest, bareland and farming mix with shrub and bush. The accuracy is increase almost for all landcover classes, including better accuracy for settlement. The lowest accuracy happen in secondary dryland forest (53%).

Table 4-7 : Error matrix for Map 5 (Landsat ETM+, class elevation)

Land Cover	PDF	SDF	PSF	BS	BL	FBS	W	S	Grand Total	user accuracy	Total accuracy
PDF	30	4		1					35	85.71	69.67
SDF	6	22		3					31	70.97	
PSF		6	11	2				1	20	55.00	
BS	3	5		30	1	5		4	48	62.50	
BL				4	18	9			31	58.06	
FBS					3	30		5	38	78.95	Kappa
CS		1							1	-	0.65
W							31		31	100.00	
S		3		8	5	5		21	42	50.00	
Grand Total	39	41	11	48	27	49	31	31	277		
producer accuracy	76.92	53.66	100	62.5	66.67	61.2	100	67.742			

Table 4-8 : Error matrix for Map 6 (Landsat ETM+, geology, soil type)

Land Cover	PDF	SDF	PSF	BS	BL	FBS	W	S	Grand Total	user accuracy	Total accuracy
PDF	9	9	4	2				1	25	36.00	51.98
SDF	23	22		3		1		1	50	44.00	
PSF	1		6						7	85.71	
BS				10	22	13		6	51	19.61	
FBS				3	1	27		5	36	2.78	
C			1	2		1		1	5	20.00	Kappa
CS	3	1							4	-	0.50
W	1	2		2			31		36	86.11	
S	2	7		26	4	7		17	63	26.98	
Grand Total	39	41	11	48	27	49	31	31	277		
producer accuracy	23.08	53.66	54.55	20.83	81.48	55.1	100	54.839			

Table 4-9 : Error matrix for Map 7(Landsat ETM+, geology)

Row Labels	PDF	SDF	PSF	BS	BL	FBS	W	S	Grand Total	user accuracy	Total accuracy
PDF	14	13		4				1	32	43.75	53.4296
SDF	20	23	3	3		1			50	46.00	
PSF			7						7	100.00	
BS	2			6	1	5		1	15	40.00	
BL		1		8	20	7		4	40	50.00	
FBS				4	2	26		3	35	74.29	Kappa
C			1					1	2	-	0.47
CS	1								1	-	
W							31		31	100.00	
S	2	4		23	4	10		21	64	32.81	
Grand Total	39	41	11	48	27	49	31	31	277		
producer accuracy	35.9	56.1	63.64	12.5	74.07	53.1	100	67.742			

Table 4.8 and 4.9 show the error matrices for neural network classification using Landsat ETM+ merging with geology and soil map (vector file). For these two maps, the overall accuracy are less than overall accuracy from maximum likelihood classification (map 1). Misclassify almost spread in all classes. Some test sample also classify as cloud or cloud cover.

For all matrices accuracy, class of water give high accuracy. This increased overall accuracy for all tables. If the water class dropped from the accuracy table, it will decrease the overall accuracy.

Table 4-10 : Accuracy assessment of classification maps

Map	Accuracy	Kappa
Maximum Likelihood Classification		
Map 1	59	0.52
Neural Network Classification Landsat ETM and DEM Information		
Map 2	55	0.48
Map 3	69	0.63
Map 4	52	0.45
Map 5	70	0.65
Neural Network Classification Landsat ETM and Vector data		
Map 6	52	0.53
Map 7	53	0.47

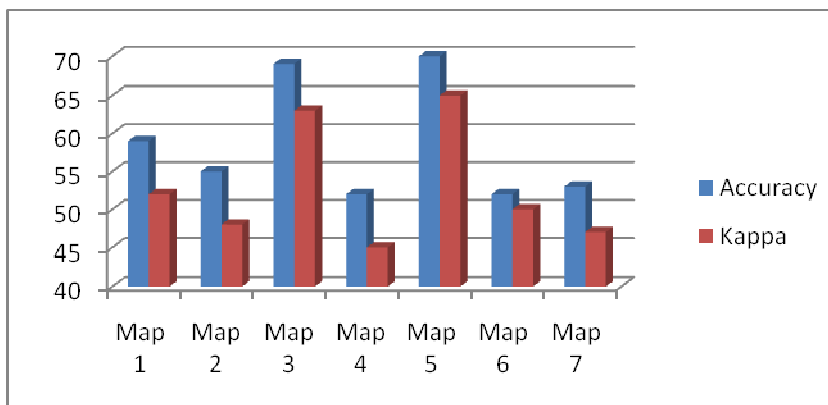
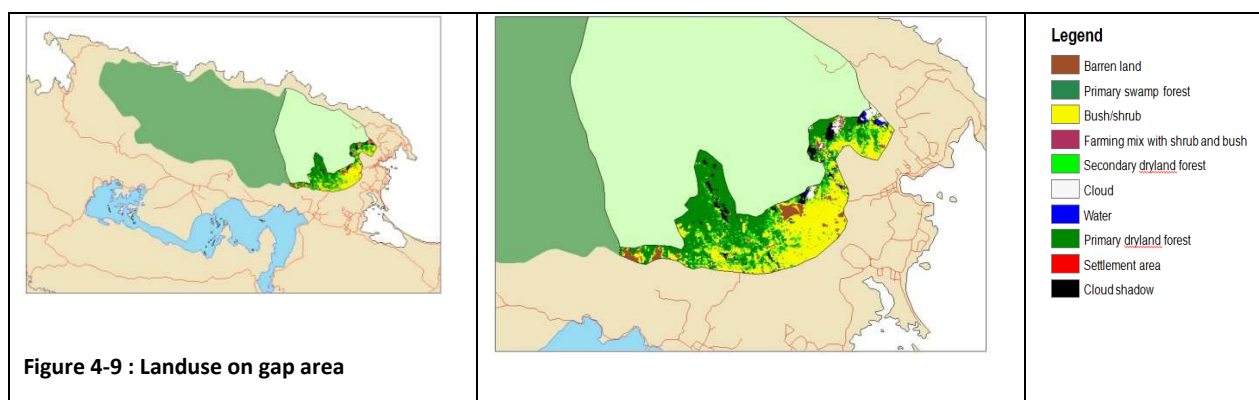


Figure 4-8 : Summary of the accuracy assessment of all 7 maps

From the accuracy assessment, the map 3 and 5, using neural network classification with Landsat ETM+ and DEM information from SRTM give higher accuracy than Map 1, which was done using maximum likelihood classification of Landsat ETM+ only. Although neural network can be used to classify different format of spatial data (i.e vector data), but the results were not good enough in accuracy, shown from the accuracy from map 6 and 7.

4.1.5. Landcovers In The Gap Area

The highest accuracy map was resulted from the neural network classification. thus the landcover of the gap area was analyzed. The landcover over the gap area based on the neural network classification shown in the Figure 4.9



The landuse in the gap area shown in the table 4.3.

Table 4-11 : area of landuse in gap area (ha)

No	Landuse	ha	%	No	Landuse	ha	%
1	Bare Land	122.94	5.12	6	Primary Swamp forest	0.36	0.02
2	Primary forest	995.76	41.50	7	Farming mix with shrub and bush	61.38	2.56
3	Bush/Shrub	599.67	24.99	8	Water	4.95	0.21
4	Secondary forest	389.16	16.22	9	Cloud	47.88	2.00
5	Settlement area	31.14	1.30	10	Shadow cloud	146.16	6.09

From Table 4.11, showed that the gap area still dominated by primary dryland forest (41%). Bush and shrub is the second largest area in the gap area with 25%. Settlements only cover 1.3 % of the gap area.

4.2. Discusses

4.2.1. Mapping the gap area of Cycloops Nature Reserve and Regional Planning of Jayapura city.

Gap area is the area on which there is a conflict of management. Two stakeholders are involved in this conflict. The first is the management of Cyclops Nature Reserve, under Ministry of Forestry and the second is the Government of Jayapura City. As to the nature reserve this area is important as a catchment area of water resources of Jayapura City. There are 8 clean water resources for Jayapura City and most of them are coming from this catchment area (Government of Jayapura City, 2006). As the background of the Jayapura City, this area also have a potential uses as settlement area (Figure 4-2). The needed of settlement is because of the increasing number of population each year in line with the development growth of Jayapura City. The population growth in Japapura City can be seen in Figure 4-1.

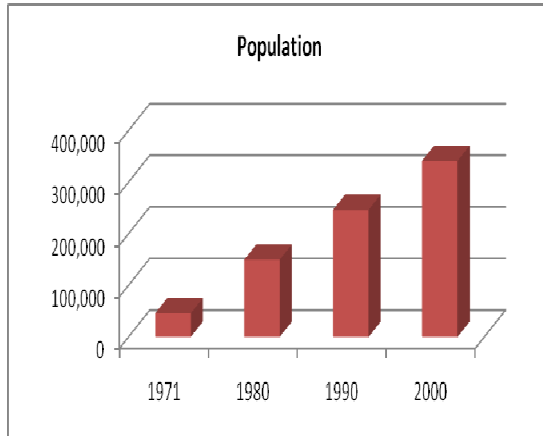


Figure 4-10 : Population 1971 – 2000



Figure 4-11 : Jayapura City and its expansion

sources : Petocz (1989) and BPS (2005)

The solution for this planning problem can be done by looking in more detail at the gap area. One of the needed information is: what are the actual uses of the area. This existing condition can describe how the planning done in this area. By overlaying the maps of Cyclops Nature Reserve and Map of regional planning of Jayapura City, the gap area can be defined (Figure 5.3) .

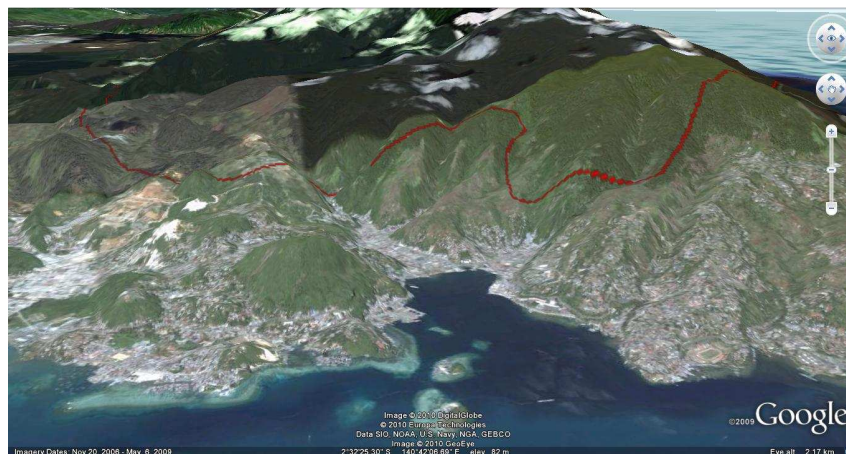


Figure 4-12 : Jayapura City in google earth 3D

4.2.2. Detailing spatial information of the gap area

Morphometric properties such as plane, pit, pass, ridge, channel and peak, describe how the surface of the earth looks like based on the concavity and convexity of neighbourhood properties for each point in the elevation data (Wood, 1996). If the point does not lie on any surface concavity or convexity, then the point will be calculated as plane. If the point lies on a local convexity in all directions (all neighbours lower), then the point will be calculated as peak.

The resulted map of morphometric properties derived from ASTER GDEM and SRTM shows that the morphometric properties of the area are mostly in ridge class. It means most of the study area is an inclined plane. The flat area (plane) only shows in a small part of the city or in swamp area.

The important part in the process of deriving the morphometric features is to define the size of the filter window. If the filter window is too small the result will cover all individual pixels, therefore

create a lot of noise pixel. On the other hand, if the filter window is too big, in consequence small feature such as peak or pit will disappear. Ehsani et al., (2009) conclude that in order to avoid artefact and effect of noise present in flat areas, filter windows size of 3x 3 that at least 3 data points from original latitude/longitude DEM in N-S and 4 points in E-W direction are included. Other way to avoid the artefact and effect of noise is divide the morphometric into 3 categories (point, line and area features).

From the results, some problems resulted from the ASTER GDEM. It is related with unreliable elevation information. Some literatures called it relief anomalies. Paul et al., (2004) found that anomalies of the ASTER DEM increase in the number of incorrectly classified region, mainly at W-E oriented mountain crests, which may block terrain in the back-looking band 3B. He used ASTER to derived DEM to make classification of glacier debris cover. He suggested an additional correction of such DEM errors prior to slope calculation may reduce such anomalies and improve the classification. However, for the gentle slopes of debris-cover glacier landscape, the ASTER DEM has a great potential to facilitate glacier mapping from a global perspective (Paul et al 2004). Jacobsen and Passini (2009) Compare two DEM (ASTER GDEM and SRTM DEM) to derived contour lines. They conclude that ASTER GDEM does not give reasonable accuracy for the contour lines, because the problem in stacking processes in ASTER GDEM.

The anomalies can be traced back to the process for deriving the elevation information. Based on the summary report of ASTER Global DEM Validation (2009), the methodology used to produce the ASTER GDEM involved in automated processing of the ASTER archive. Stereo correlation with VNIR band 3 that also acquired using a backward-looking telescope, which provides along-track stereo coverage of the earth surface. The process includes:

- a. Cloud masking to remove cloudy pixel,
- b. Stacking all scene-based DEMs,
- c. Removing residual bad values and outliers,
- d. Averaging selected data to create final pixel value,
- e. Correcting residual anomalies, and finally
- f. Partitioning data into 1 degree by 1 degree tiles.

These process are leading to some problems that may affect the ASTER GDEM elevation, such as residual cloud anomalies, steps at scene boundaries, artefacts (pits, bumps and mole runs) that makes this DEM data is not as good as SRTM. The sources image in the stacking process also can be seen in the image following the Aster GDEM, when downloaded the data, is found in Appendix B

Different than ASTER GDEM, SRTM used interferometry technique to map the elevation of the earth surface using RADAR energy. SRTM used C and X band of radar wavelengths of 5.6 cm and 3 cm respectively. The process for C data of SRTM is resulting in 1 arc resolution (30 meters). But the free data that release by NIMA derived from the C band of the Radar is in 3 arc resolution (90 meters). This research is using the free data of 90 meter resolution.

One of the advantages of using RADAR energy is the cloud free data. This wavelength can penetrate the cloud cover, thus there is no cloud cover problem like in ASTER GDEM data because ASTER is an optical sensor, its visible near IR energy cannot penetrate cloud. Sesnie et al (2008) mentioned that elevation data from SRTM-DEM and topographic features associated with soil drainage and moisture, and solar radiation were likely to regulate differences in tree species composition.

4.2.3. Neural Network Classification

As the use of digital spatial data such as DEM have been increased recently to enhance classification results, it becomes increasingly important to develop algorithms to handle both remotely sensed images and other spatial data.

For classification purposes, commonly used remote sensing algorithm such as the maximum likelihood classifier and the minimum distance classifier can only be used to deal with spatial data of certain interval and ratio scales such as image data of 0-255 DN value. Neural networks, on the other hand, are capable of handling data with any measurement scale. The advantage of NN classification is that this type of classification gives opportunity to use other spatial data of nominal or ordinal (Gong, 1996) such as elevation, soil and geology data. In his research, Gong combining satellite image with geology map.

NN classifier has been used in many applications. Fauzi (2005) used NN to detect logged-over in tropical rain forest. While Paul (2004) used NN for mapping debris-covered glaciers and Gong (1996) used NN for geological mapping.

Generally, this research used 3 classifications (maximum likelihood, NN with DEM, and NN with vector data). From the result the highest accuracy is for NN with DEM then maximum likelihood and NN with vector data respectively. Visually, the image resulted from NN with vector data (soil and geology) gives dissatisfactory result. Conversely, the resulted map from NN with DEM gives satisfactory result. It is look like that it is hard to differentiate land cover classes using soil and geology information. Other reason why the result of NN with vector data gives dissatisfactory results is the scale of geology map is too small. The sources for geology map is from 1 : 500.000. Even Gong (1996) found different result, which is the neural network generated result more compatible with the geological map made manually. The differences also can be seen by looking at the area resulted from the classification.

From Figure 4-13 we can see that the NN with geology and soil (map 6 and map 7) gives very different information compared to other results. Maps 1, 2, 3, 4 and 5 give more comparable among the area of the land cover types.

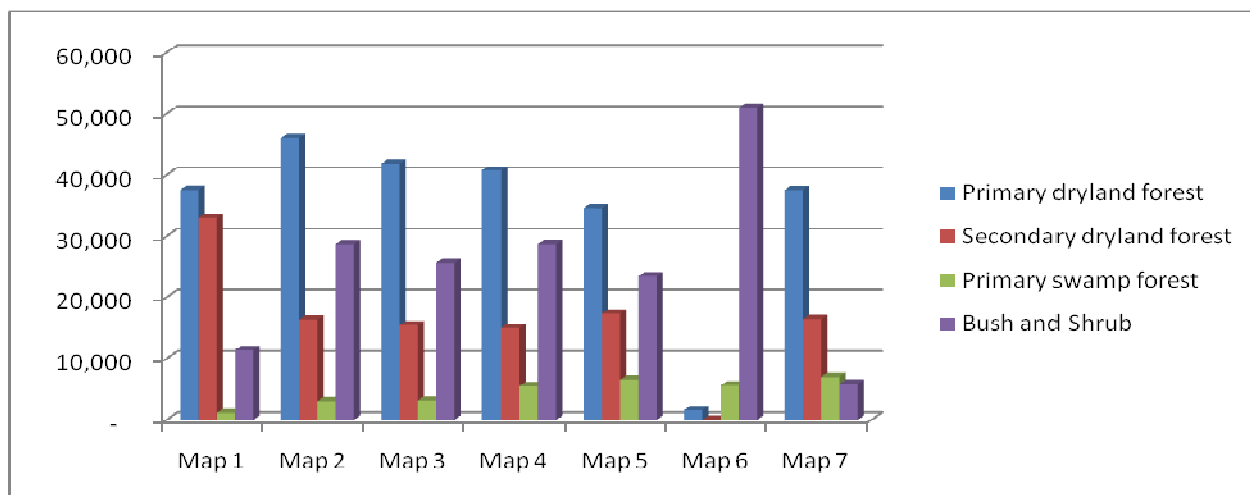


Figure 4-13 : Comparison of different area in resulted maps.

From the results of neural network classifications, two maps showed that NN can increase the accuracy. With adding the elevation information in the classification process, which cannot be done if using standard statistical classification, the accuracy increased by about 10 % (from 59 to 70), indicating that adding a DEM in the input layer significantly improves the accuracy compared to the use of spectral information alone.

From the resulted map, the neural network classification using Landsat ETM+ and elevation also can remove the noise pixel. In the standard classification, the noise pixel usually removed using filter window. But it is also generated by losing the information. With NN classifier, the reduction of noise pixel is done in the process of classification itself.

The training samples used for classification in the neural network are a little bit different with the standard classification. This is because of training samples should consider both input data (e.g. image and DEM). If class of elevation used in the classification, the training sample should consider that in classes. The problems also come out for the cloud and cloud shadows. The presence of cloud and cloud shadow in the neural network process using elevation data will create unwanted cloud and its shadow in the area that have the same elevation class. This also depends on the training sample used to define the cloud and cloud shadow. There should be different training samples for each neural network classification, depend on the data used. But to maintain the objectivity, all classifications in this research used the same training samples. It is interesting to test how training samples will influence the classification process in the neural network classification.

This research also tested the advantages of NN classification to integrate data from different data types (vector, raster). Unfortunately the accuracy by adding the vector maps show that it was lower than the standard classifier. The vector data used in this classification were geology and soil.

Neural network classification using image and DEM data in this research have applied in the area that have a big different in elevation, relief and slope. This kind of classification should be tested in flat area, to know whether it also can improve the classification or not.

4.2.4. Accuracy Assessment

The issue of accuracy in the NN classification also become interesting subject in NN since the NN believed to improve the capabilities and increase the accuracy in classification. Foody (1997) conclude that there are four factors on effecting the accuracy in the NN classification. These factors related to the dimensionality of the remotely sensed data, the neural network architecture, and the characteristic of the training samples and test samples. Variations in the dimensionality of the data sets, as well as the training and testing set characteristics have a significant effect on classification accuracy. However the number of hidden units and layers in the NN architecture did not have a significant effect on classification accuracy. Jellema (1997) also found the same conclusion about the effect of NN architecture, especially at number of hidden units and layers.

From the tables of accuracy resulted in this research (table 4-3/4.9), confusion occurs between related classes. Primary and secondary dryland forest is the related class that mostly have confused in classification. The different between these two classes is in the relative different on canopy density. Ministry of forestry in their technical guidance for manual image interpretation mention that the different between primary and secondary dryland forest is based on the human access to the forest. If there is no human access to the forest, so it classify as primary forest. But if there is human access to the forest, then it is classified as secondary forest.

Other confusion occurs between farming mix shrub class and bush class. Sometimes these two classes is hard to differentiate by digital image classification, because these two classes somehow related with human activities in that area.

Kappa coefficient also calculated in this accuracy assessment. Kappa coefficient is a statistical measure of agreement for qualitative (categorical) items. The Kappa coefficient resulted in this research varies between 0,45 – 0,65. Koch (1977) make a magnitude guidelines for kappa coefficient, <0 means no agreement, 0-0.20 as slight, 0.20-0.40 as fair, 0.40-0.60 as moderate, 0.60-0.80 as substantial, and more than 0.80 means almost perfect agreement. Based on this classes of kappa coefficient, Map 1,2,4,6 and 7 the magnitude of agreement is moderate. And the rest maps (3 and 5), the magnitude of agreement is substantial.

From the accuracy assessment, the 2 maps (3&5) from neural network classification give better accuracy than the standard statistical classification. The highest accuracy comes from NN classification using input from Landsat ETM+ and Elevation class map (70% of overall accuracy), then follow by the NN classification using input from Landsat ETM+ and SRTM DEM (69% of overall accuracy).

Even the morphometric properties describe how the surface look like, but the result of classification using NN gives low overall accuracy (55%) compared to standard statistical classification. It seems that the land covers are more related to the elevation or elevation classes than with morphometric properties (plane, ridge, pit, pass, peak and channel). For some features such as water, in the morphometric properties can be a plane or a channel. Adding the DEM information in NN classification was also done by Fauzi (2005), compared NN classifiers with maximum likelihood to detect logged-over in tropical rain forest in Indonesia. Slope, elevation and aspect maps can be derived from DEM. The NN classification increased overall accuracy by 10 % in detecting logged over and unlogged forest than the maximum likelihood classification. NN classification also gives higher

accuracy, even it is using the same data sources. Jianwen (2005) improve the overall accuracy of land use classification using ASTER data, even by not adding other types of information.

4.2.5. Landcover In The Gap Area

From the Table 4.11 and figure 4.14, the gap area is still dominated with the primary dryland forest with 41% and secondary dryland forest with 16% of the total area. Other dominated cover in this area is bush and shrub with 25%. These three classes covered 82% of the total gap area.

Even though for overall accuracy, water class increasing the number of accuracy, but if we take a look at particular classes, we can see the accuracy also increase for individual class. Figure 4.15 show the user accuracy for each class for these three major class covered in the gap area. From this figure, the user accuracy for each major classes from map 5 (Landsat ETM+ and class elevation) also showed better accuracy then other maps.

Increasing in population for jayapura city also means the need of area for settlement. The lower part of Jayapura city has already become a dense building area, where economic, government and development activities done. The need of settlement due to the increasing in population is in high demand (Gov of Jayapura, 2006). The conversion of land cover for this area should be done in careful way. The high intensity of precipitation (140 mm/year averages) increase the hazard level of flooding and landslide, as in the low stream of this area is the central of the Jayapura city. The planning to make this area as settlement should be done with pay a big attention to the landscape properties.

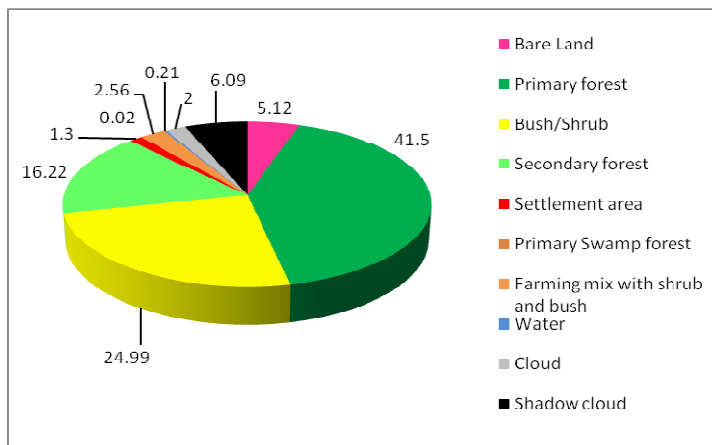


Figure 4-14 : Pie chart of land cover in the gap area

Based on the slope map derived from SRTM, this area is moderate to steep slope. In this gap area, the area of primary and secondary dryland forest covers in steep area. And bush and shrub class (which is actually also in the class of farming mix with shrub) covers the moderate steep area.

This area and the settlement cover about 1.3 % of the area. From the regional planning report (2006), this settlement actually is a military settlement camp. But in the last recent years, this area have become bigger and bigger. The settlement now also settled by non military activities. For the Government of Jayapura, this information can be used to plan the area in more detailed planning.

The bare land, bush and shrub, farming mixed with bush and shrub, can be manage as developed area, and keep the rest of primary and secondary dryland forest as it is.

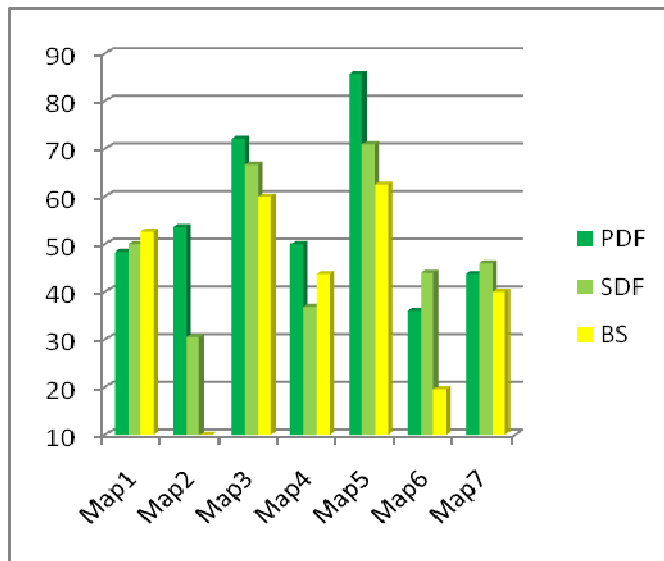


Figure 4-15 : Accuracy for three major classes in the gap area.

4.3. Limitation

There are some limitations in this research. These limitations influenced as the sources of error and accuracy in the process of classification.

a) The scale of the input map.

The scales input maps for extra information in NN classification for geology map and soil type map only available in the scale of 1 : 500,000. This can be sources of the low accuracy for the resulted maps. The result may be different if there are better scales for this extra information in NN classification.

b) The training sample and test sample.

In this research, there is no field work. The data for training sample and test sample come from available data and supported with high resolution image from google earth. This training sample and test sample may sources of error in the process of classification and can decrease the overall accuracy. However, the local knowledge is helpful to understand the description of the area for selected training sample and test sample.

c) The different date of image sources.

The sources of the image used in the classification process, and the image for training sample and test sample from google earth have different time recording. In this different time, the landcover of the area can be change. This can be the sources of the error in the accuracy assessment.

5. Conclusion and Recommendation

5.1. Conclusions

The following conclusions are presented as responses to the research questions proposed in chapter one (1) :

Research question :

- a) *Where is the location of the gap area between Cycloops Nature Reserve and regional spatial planning of Jayapura city?*

Intersecting between maps of Cycloops Nature Reserve area and regional planning of Jayapura city was done to define the gap area. Total area with 2.410ha was the gap area resulted from intersecting process.

- b) *How to integrate Landsat ETM+ and DEM (morphometric properties)?*

Neural Network Classifier can be used to integrate Landsat ETM+ and DEM. Some basic components of morphometric features, such as plane, channel, ridge, pass, peak and pit can be derived from DEM. Slope, aspect, and classes of elevation can be derived from DEM. These derived information can be used as extra information with satellite imagery (i.e Landsat ETM+) to extract the information of land cover.

- c) *Which DEM resources SRTM or Aster GDEM are more effective and accurate in deriving morphometric properties?*

Using morphometric features, visually they show that SRTM DEM give more accurate information of elevation. Some anomalies detected from ASTER GDEM which makes this extracted information from this DEM are not accurate. The anomalies also can be seen using cross section (profile) of the DEM and minimum curvature derived from the DEM.

- d) *How accurate can Neural Network Classification be in classify landscape element from integrated Landsat-ETM+ and DEM ?*

NN classifier gives higher overall accuracy than standard statistical classification (i.e. Maximum Likelihood). Extra information of elevation and class elevation together with Landsat ETM+ can improve the overall accuracy by 10%. But other extra information such as geology and soil have not improve the classification shown by the overall accuracy. As a result, the NN classifier can improve the classification but depend on which extra information is added and are more relevant to describe the landcover.

5.2. Recomendations.

- a). This study can be improve by using the different training samples, depends on the extra information that used with Landsat ETM+ to classify landcover using NN classifier.
- b). Further study should be done to compare the result if applied in flat area, and in the different of morphometric features area.

References

- Ardo, J., Pilesjo, P., Skidmore, A.K., 1997. Neural networks, multitemporal Landsat thematic mapper data and topographic data to classify forest damages in the Czech republic. In: *Canadian Journal of Remote Sensing*, 23(1997)3, pp. 217-228.
- Aster Global DEM Validation Team. 2009. Aster Global DEM Validation; Summary Report.
- Barber, Victor., Afiff, S., Purnomo, A., 1995. Tiger by the tail? : reorienting biodiversity conservation and development in Indonesia : World Resources Institute Washington, DC
- Baskent, E.Z., Keles, S., 2005. Spatial forest planning: A review. *Ecological Modelling* 188, 145-173.
- BPS, 2003. Papua in Figure 2003, Biro Pusat Statistik, Jayapura.
- BPS, 2005. Papua in Figure 2005, Biro Pusat Statistik, Jayapura.
- BPS, 2008. Papua in Figure 2008, Biro Pusat Statistik, Jayapura.
- Cullingworth, B. and Nadin, V. 2006 Town and Country Planning in the UK. Fourteenth edition. Routledge, London.
- Carletta, Jean. (1996) Assessing agreement on classification tasks: The kappa statistic. *Computational Linguistics*, 22(2), pp. 249–254
- de Smith, M.J., Goodchild, M., Longley, P., 2007. Geospatial analysis : a comprehensive independent guide to principles, techniques and software. Matador, Leicester.
- de Smith, M.J., Goodchild, M., Longley, P., 2009. Geospatial analysis : a comprehensive guide : e-book. Matador, Leicester.
- Dehn, M., Gärtner, H., Dikau, R., 2001. Principles of semantic modeling of landform structures. *Computers & Geosciences* 27, 1005-1010.
- Egmont-Petersen, M., de Ridder, D., Handels, H., 2002. Image processing with neural networks--a review. *Pattern Recognition* 35, 2279-2301.
- Ehsani, A.H., Quiel, F., 2009. A semi-automatic method for analysis of landscape elements using Shuttle Radar Topography Mission and Landsat ETM+ data. *Computers & Geosciences* 35, 373-389.
- Fauzi, A., Hussin, Y.A., Weir, M., 2005. A Comparison of Neural Networks and Maximum Likelihood Remotely Sensed Data Classifiers to Detect Logged-Over Tropical Rain Forest in Indonesia. *International Journal of Geoinformatics* 1, 1- 10.
- Gong, P., 1996. Integrated Analysis of Spatial Data from Multiple Sources: Using Evidential Reasoning and Artificial Neural Network Techniques for Geological Mapping. *Photogrametric engineering & Remote Sensing*, Vol.62, No. 5, May 1996, pp. 513-523
- Government of Jayapura City, 2006. Regional Spatial Planning Repport, Jayapura.
- Hofton, M., Dubayah, R., B., J. B., Rabine, D., 2006. Validation of SRTM elevations Over Vegetated and Non-vegetated terrain Using Medium Footprint Lidar. *Photogrametric Engineering and Remote Sensing* 72, 279 - 285.
- ITC, 2009. Principles of Remote Sensing, 4th edition, ITC Educational Textbook Series, Enschede.
- Jacobsen, K., and Passini, R., 2009. Analysis of Aster GDEM Elevation Models. *ISPRS Proceedings*, 09_03.
- Jianwen, M., Bagan, H., 2005. Land-use classification using ASTER data and self-organized neural networks. *International Journal of Applied Earth Observation and Geoinformation* 7, 183-188.

- Landis, J.R.; & Koch, G.G. (1977). "The measurement of observer agreement for categorical data". *Biometrics* **33**: 159–174
- Lek, S., Guégan, J.F., 1999. Artificial neural networks as a tool in ecological modelling, an introduction. *Ecological Modelling* 120, 65-73.
- Lillesand, T.,M., and Kiefer, R.,W., 1994. *Remote Sensing and Image Interpretation*, John Wiley & Sons, Inc, New York.
- Mathys, L., Ginzler, C., Zimmermann, N.E., Brassel, P., Wildi, O., 2006. Sensitivity assessment on continuous landscape variables to classify a discrete forest area. *Forest Ecology and Management* 229, 111-119.
- METI, NASA, 2009. ASTER Global DEM Validation Summary Report. In: Team, A.G.V. (Ed.).
- Miller, J., Franklin, J., 2002. Modeling the distribution of four vegetation alliances using generalized linear models and classification trees with spatial dependence. *Ecological Modelling* 157, 227-247.
- Nugroho, M., 2006. Integration of multi remotely sensed data and geodatabases for forestry management in Indonesia. Wageningen University, Wageningen.
- Paul, F., Huggel, C., Kaab,A., 2004. Combining Sattellite Multispectral data and Digital Elevation Model for Mapping Debris-covered Glaciers. *Remote Sensing of Environment* 89 (2004) 510-518
- Petocz, R.G., 1989. *Conservation and Development in Irian Jaya: a Strategy for Rational Resource Utilization*, Leiden.
- Schaal, P., 2000. *Landscape Planning and GIS-based Data Management*, <http://www.iuw.uni-vechta.de/personal/schaal/index.html>
- Sesnie, S.,E., Gessler, P.,E., Finegan, B., Thessler, S. 2008. Integrating Landsat TM and SRTM-DEM derived variables with Decision Tree for Habitat Classification and Change Detection in Complex Neotropical Environments. *Remote Sensing & Environment*, 112 (2008) pp 2145-2159
- Soetarto, E., Sitorus,M.T.F, Napiri, M.Y. 2001; *Decentralisation of Administration, Policy Making and Forest Management in Ketapang District, West Kalimantan*, CIFOR, Bogor.
- Tokede, M.J, Wiliam, D., Widodo, Gandhi,Y., Imburi,C., Patriahadi, Marwa,J., Yufuai, M.Ch.; 2005, *Dampak Otonomi Khusus di Sektor Kehutanan Papua; Pemberdayaan Masyarakat Hukum Adat dalam Pengusahaan Hutan di Kabupaten Manokwari*; UNIPA, CIFOR Bogor.
- Tso, B., Mather, P.M., 2009. *Classification methods for remotely sensed data*. CRC, Boca Raton.
- UN 2008, *Spatial Planning; Key Instrument for Development and Effective Governance with Special Reference to Countries in Transition*, Economic Commission for Europe, Geneva.
- Wood, J., 1996. *The Geomorphological Characterisation of Digital Elevation Model*. Department of Geography University of Leicester, Leicester LE1 7RH, p. 185.

Appendices

Appendix A : Learning rate process in the Neural Network classification

Map 2

Learning Performance in file C:\thesis\reprocess\landsat_srtm_feature_clip.rep

number of inputnodes : 8

number hiddenlayers : 2

nodes hidden layer 1 : 7

nodes hidden layer 2 : 8

nodes per hiddenlayers

parameters

Learning rate : 0.900000

Momentum : 0.700000

Maximum system error : 0.0001

results

learning time : 409.92300 seconds

number of epochs spent: 5000

normalized system error 0.00362767

Size of training set : 229

Training pixels correctly classified 79%

Confusion Matrix: Groundtruth\calculated											
map	samples points training set										
classnames	0	1	2	3	4	5	6	7	8	9	

2001 [Gree	39	7	0	1	0	0	0	0	0	0	
2002 [Gree	0	15	0	3	0	0	0	0	6	0	
2005 [Sea	0	0	13	1	0	0	0	0	0	0	
2007 [Yell	2	7	1	29	3	0	0	0	14	0	
2014 [Sien	0	0	0	0	28	0	0	0	1	0	
2500 [Whit	0	0	0	0	0	10	0	0	0	0	
2501 [Blac	0	0	0	0	0	0	7	0	0	0	
5001 [Blue	0	0	0	0	0	0	0	13	0	0	
20092 [Mar	0	0	0	1	0	0	0	0	8	0	
2012 [Red]	0	0	0	0	0	0	0	0	0	20	

% class OK	95	51	92	82	90	100	100	100	27	100	
------------	----	----	----	----	----	-----	-----	-----	----	-----	--

Map 3

Learning Performance in file C:\thesis\reprocess\landsat_srtm_feature_clip.rep

number of inputnodes : 7

number hiddenlayers : 1

nodes hidden layer 1 : 7

nodes per hiddenlayers

parameters

Learning rate : 0.900000

Momentum : 0.700000

Maximum system error : 0.0001

results

learning time : 312.42600 seconds

number of epochs spent: 5000

normalized system error 0.00246819

Size of training set : 229

Training pixels correctly classified 83%

| Confusion Matrix: Groundtruth\calculated

map | samples points training set

classnames| 0 1 2 3 4 5 6 7 8 9

2001 [Gree| 41 4 0 1 0 0 0 0 0 0

2002 [Gree| 0 15 2 3 0 0 0 0 0 0

2005 [Sea | 0 1 12 0 0 0 0 0 0 0

2007 [Yell| 0 7 0 30 1 0 0 0 12 0

2014 [Sien| 0 0 0 0 29 0 0 0 0 0

2500 [Whit| 0 1 0 0 0 10 0 0 1 0

2501 [Blac| 0 0 0 0 0 0 7 0 0 0

5001 [Blue| 0 0 0 1 0 0 0 13 0 0

20092 [Mar| 0 1 0 0 1 0 0 0 15 0

2012 [Red]| 0 0 0 0 0 0 0 0 1 20

% class OK| 100 51 85 85 93 100 100 100 51 100

Map 4

Learning Performance in file C:\thesis\reprocess\landsat_srtm_feature_clip.rep

number of inputnodes : 7

number hiddenlayers : 1

nodes hidden layer 1 : 8

nodes per hiddenlayers

parameters

Learning rate : 0.900000

Momentum : 0.700000

Maximum system error : 0.0001

results

learning time : 313.28500 seconds

number of epochs spent: 5000

normalized system error 0.00319254

Size of training set : 229

Training pixels correctly classified 77%

Confusion Matrix: Groundtruth\calculated										
map	samples points training set									
classnames	0	1	2	3	4	5	6	7	8	9
<hr/>										
2001 [Gree	38	6	2	2	0	0	0	0	1	0
2002 [Gree	1	13	0	8	0	0	0	0	0	0
2005 [Sea	2	1	12	0	0	0	0	0	0	0
2007 [Yell	0	8	0	24	1	0	0	0	14	0
2014 [Sien	0	0	0	0	29	0	0	0	0	1
2500 [Whit	0	0	0	0	0	10	0	0	0	0
2501 [Blac	0	0	0	0	0	0	7	0	0	0
5001 [Blue	0	0	0	0	0	0	0	13	0	0
20092 [Mar	0	1	0	1	1	0	0	0	13	0
2012 [Red]	0	0	0	0	0	0	0	0	1	19
<hr/>										
% class OK	92	44	85	68	93	100	100	100	44	9

Map 5

Learning Performance in file C:\thesis\reprocess\landsat_elev.rep

number of inputnodes : 7

number hiddenlayers : 1

nodes hidden layer 1 : 7

nodes per hiddenlayers

parameters

Learning rate : 0.900000

Momentum : 0.700000

Maximum system error : 0.0001

results

learning time : 314.07100 seconds

number of epochs spent: 5000

normalized system error 0.00265646

Size of training set : 229

Training pixels correctly classified 82%

| Confusion Matrix: Groundtruth\calculated

map | samples points training set

classnames| 0 1 2 3 4 5 6 7 8 9

2001 [Gree]	40	5	0	1	1	0	0	0	0	0
2002 [Gree]	1	16	0	5	0	0	0	0	3	0
2005 [Sea]	0	1	14	0	0	0	0	0	0	0
2007 [Yell]	0	6	0	28	0	0	0	0	13	0
2014 [Sien]	0	0	0	0	30	0	0	0	0	1
2500 [Whit]	0	0	0	0	0	10	0	0	0	0
2501 [Blac]	0	0	0	0	0	0	7	0	0	0
5001 [Blue]	0	0	0	0	0	0	0	13	0	0
20092 [Mar]	0	1	0	1	0	0	0	0	13	0
2012 [Red]	0	0	0	0	0	0	0	0	0	19

% class OK	97	55	100	80	96	100	100	100	44	95
------------	----	----	-----	----	----	-----	-----	-----	----	----

Map 6

Learning Performance in file C:\thesis\reprocess\landsat_geo_soil.rep

number of inputnodes : 8
number hiddenlayers : 2
nodes hidden layer 1 : 7
nodes hidden layer 2 : 8
nodes per hiddenlayers
parameters
Learning rate : 0.900000
Momentum : 0.700000
Maximum system error : 0.0001
results
learning time : 456.31000 seconds
number of epochs spent: 5000
normalized system error 0.00594695
Size of training set : 229
Training pixels correctly classified 53%

Confusion Matrix: Groundtruth\calculated										
map	samples points training set									
classnames	0	1	2	3	4	5	6	7	8	9
<hr/>										
2001 [Gree	0	0	0	0	0	0	0	0	0	0
2002 [Gree	0	0	0	0	0	0	0	0	0	0
2005 [Sea	0	0	7	0	0	0	0	0	0	0
2007 [Yell	18	16	6	33	7	0	0	0	11	3
2014 [Sien	0	0	0	0	23	0	0	0	1	1
2500 [Whit	0	0	0	0	0	10	0	0	0	0
2501 [Blac	0	0	0	0	0	0	5	0	0	0
5001 [Blue	0	0	0	0	0	0	2	13	0	0
20092 [Mar	23	13	1	2	1	0	0	0	17	1
2012 [Red]	0	0	0	0	0	0	0	0	0	15
<hr/>										
% class OK	0	0	50	94	74	100	71	100	58	75

Map 7

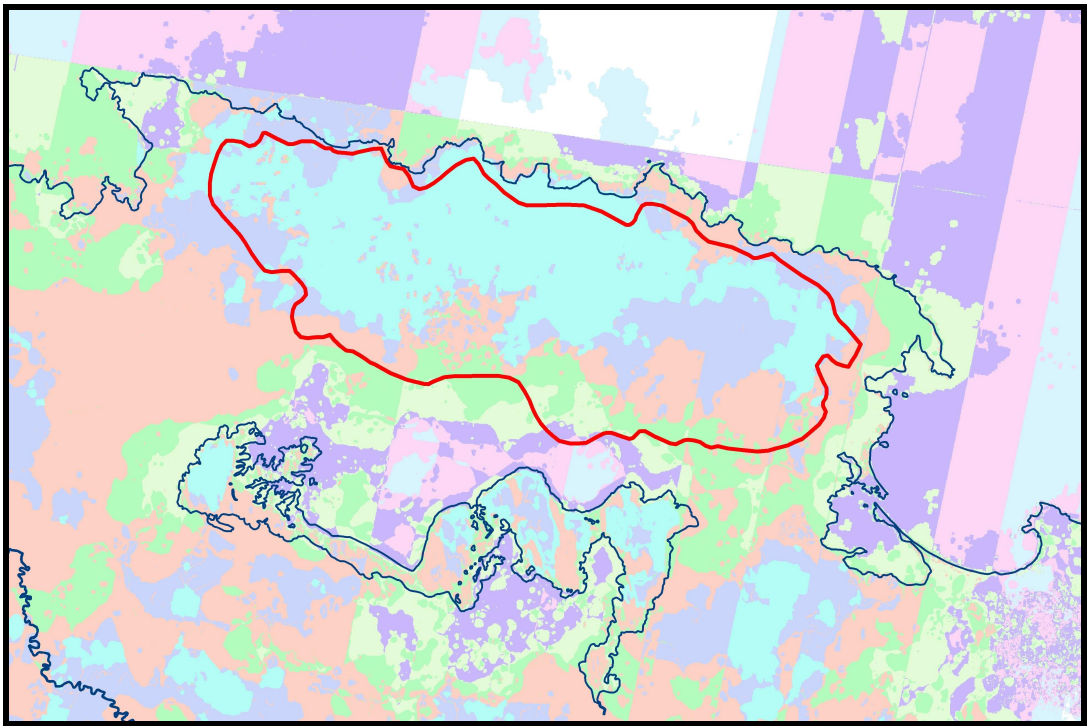
Learning Performance in file C:\thesis\reprocess\landsat_geo_soil.rep

number of inputnodes : 7
number hiddenlayers : 1
nodes hidden layer 1 : 7
nodes per hiddenlayers
parameters
Learning rate : 0.900000
Momentum : 0.700000
Maximum system error : 0.0001
results
learning time : 350.98900 seconds
number of epochs spent: 5000
normalized system error 0.00343865
Size of training set : 229
Training pixels correctly classified 78%











Confusion Matrix: Groundtruth\calculated										
map	samples points training set									
classnames	0	1	2	3	4	5	6	7	8	9
<hr/>										
2001 [Gree	40	8	1	0	0	0	0	0	0	0
2002 [Gree	1	10	0	3	0	0	0	0	2	0
2005 [Sea	0	0	12	2	0	0	0	0	0	0
2007 [Yell	0	8	0	20	0	0	0	0	2	0
2014 [Sien	0	0	0	2	29	0	0	0	2	1
2500 [Whit	0	0	1	0	0	10	0	0	0	0
2501 [Blac	0	1	0	0	0	0	7	0	0	0
5001 [Blue	0	0	0	0	0	0	0	13	0	0
20092 [Mar	0	1	0	7	0	0	0	0	20	0
2012 [Red]	0	1	0	1	2	0	0	0	3	19
<hr/>										
% class OK	97	34	85	57	93	100	100	100	68	95

Appendix B : The sources image in the stacking process

Sources of Images in stacking processes of Aster GDEM, in the study area.



Legend

-  Boundary of Cycloops Nature Reserve
-  SRTM V2
-  SRTM V3
-  Aster scene 1
-  Aster scene 2
-  Aster scene 3
-  Aster scene 4
-  Aster scene 5
-  Aster scene 6
-  Aster scene 7