SPATIAL ANALYSIS OF LAND USE/LAND COVER CHANGE DYNAMICS USING REMOTE SENSING AND GEOGRAPHIC INFORMATION SYTEMS:

A Case Study in the down stream and surroundings of the Ci Tarum watershed

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A thesis submitted in fulfilment of the requirements for the degree of Doctor of Philosophy

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Abstract

This study is concerned with land use/land cover change detection, identification, analysis and prediction using remote sensing and GIS techniques in the downstream of the Citarum watershed and its surroundings in West Java, Indonesia. Supervised Maximum Likelihood classification of PCA and NDVI transformed images are used to classify and identify land use/land cover categories. A post-classification comparison approach was used to detect land use/land cover changes, and a Markov Cellular automata model is then used to predict possible future land use/land cover patterns in the study area. "Leaf on" and "leaf off" phenomena of the broad leaf vegetation cover have been recognised related to dry and wet season as well as rice field (planted) and rice field (unplanted) related to growing season in the study area. Forest and plantation area were extensive in wet season and less in dry season. Rice field (planted) area was large in harvesting time and less in planting time. Settlement has increased continuously and is not influenced by season or weather. Overall, the KIA of the classification was 0.89. Settlement and rice field are the main land use/land cover types that have been changed and this is related to factors such as proximity to roads and to urban and semi-urban centres. There is an indication that land use/land cover in the study area was converted from intensive agriculture land such as rice field to settlement, rather than from less intensive uses such as open/dry land, plantation or forest. Discriminant analysis as well as overlay and simple linear analysis support factors such as proximity to roads, urban and semi-urban centres, as well as slope, as being most influential in land use/land cover change in the study area. The Markov Cellular automata model affords a powerful descriptive and predictive model for land

use/land cover change and for future land use/land cover distribution in the study area, but it needs some adjustment in order to obtain suitable results. Markov transition, as well as suitability, maps of each land use/land cover category are created.

Abbreviations and Glossary

BAKOSURTANAL	The Coordinating Agency for National Survey and Mapping
BAPPEDA	Regional Development Planning Boards
BAPPENAS	The National Development Planning Agency
BPN	The National Land Agency
BPPT	The Agency for Assessment and Application of Technology
CA	Cellular Automata
DGWRD	Directorate General of Water Resources Development
FAO	Food and Agriculture Organization
GTZ	Gesellchaft fuer Technische Zusammenarbeit.
GIS	Geographic Information Systems
IGBP	International Geosphere and Biosphere Programme
ITC	International Institute for Aerospace
JABOTABEK	Jakarta, Bogor, Tanggerang and Bekasi
Kabupaten	Regency or District
Kecamatan	Sub-district
KIA	Kappa Index Agreement
LUCC	Land use/cover Change
LUPAM	Land Use Planning and Mapping
LREP	Land Resources Evaluation and Planning
MCE	Multi Criteria Evaluation
MOA	Ministry of Agriculture
MOF	Ministry of Forestry
MOLA	Multi Objective Land Allocation
MPW	Ministry of Public Work
MREP	Marine Resources Evaluation and Planning
NDVI	Normalized Difference Vegetation Index
PCA	Principal Component Analysis
RCSA	The Research Centre of Soil and Agro-climate
RePPProt	Regional Physical Planning Program for Transmigration
SARCS	Southeast Asia Research Centre for STAR

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Declaration

This work contains no material which has been accepted for the award of any other degree or diploma in any university or any other tertiary institution, and to the best of my knowledge and belief, contains no material previously published or written by another person, except where due reference has been made in the text.

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(Asep Karsidi)

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common word coming from my son, is very much encouraging and truly a reminder that I must complete my study and gain the best ever in my life.

Chapter One

INTRODUCTION

1.1 Introduction

Accelerating changes to the earth's environment are being driven by growth in human population, the increasing level of resource consumption by human societies and by changes in technology and socio-political organization. Changes in land use and land cover are part of this transformation. Land use and land cover are closely interrelated but are not the same. The term "land use" denotes the human utilization of the land, while "land cover" denotes the physical state of the land. Baulies (1997) indicates that land use and land cover change dynamically due to demographic pressure, road construction, fire, nutrient deposition, and many other factors. Land use/land cover change may be the result of natural processes or human activities (Turner II *et al.*, 1994, Tucker *et al.*, 1991, Sage, 1994). Furthermore, technological advances and expanding population have put increasing pressure on scarce resources and have created a variety of complex land use dilemmas that affect persons at all levels of society (Sommers, 1981).

In the last decade, land use/land cover change has become a major issue at the global and regional level. International attention has focussed on it because of concern over issues such as global warming and climate change.

Many studies have been conducted regarding the land use/land cover change issue (Turner, 1991; Turner, 1994; Mayer *et al.*, 1994; Baulis, 1997; Thomas, 1997; Heilig, 1997; Rindfuss, 1998; Koning, 1999; Mc Connell, 2000; Solecki, 2001; Bicik, 2001). Some of those studies focus on understanding the process of land use/land cover change as well as developing predictive models of change at the global level (Turner, 1991; Turner, 1994; Mayer *et al.*, 1994; Baulis, 1997). There have also been numerous studies conducted at regional or country level looking at land use/land cover change (Thomas, 1997; Heilig, 1997; Koning, 1999; Mc Connell, 2000; Solecki, 2001; Bicik, 2001, Reid, 2001; Schneider, 2001; Pontius.Jr, 2001).

Land use/land cover change is also a major issue in Indonesia. Demographic pressure with an annual rate of population growth between 1990 – 2000 at the national level of 1.49 % (Central Bureau of Statistics, 2000) and an uneven population distribution has had an effect on the land use pattern in Indonesia. The 2000 National Census placed Indonesia's population at 206 million (Central Bureau of Statistics, 2000). Of this total population, 58 % live on the island of Java, and rural areas accommodated 57 % of Java's population (Central Bureau of Statistics, 2000). However between the 1990 and 2000 census, the population in rural areas slightly decreased while the urban population increased at the rate of 5.4% per year over the period of 1990-2000. There were 55.4 million urban residents in Indonesia in 1990 and 85.4 million in 2000 (Central Bureau of Statistics, 2000). Approximately one-fourth of this urban population is concentrated in the Jakarta, Bogor, Tanggerang and Bekasi (JABOTABEK) extended metropolitan region (Firman, 2002). The increase of urban population has had an impact on land use. Other land has been converted from rural to urban use, from less intensive to more intensive agriculture, or from agricultural to non-agricultural use. Nasution (1999) reported that about 20 000 ha per year of agricultural land, has been converted into non-agricultural land mainly in the areas adjoining large cities on Java Island (Nasution, 1999).

In terms of the land use and population growth relationship, Sandy (1977) produced a land use evolution model for Indonesia. People will start to cultivate an area at 25 m above sea level, which has a gentle slope and is free from flooding. When population increases, they will extend to cultivate the areas to the upper slopes and with more population growth, the area that could be conserved (such as forest in the steep slopes and wetlands or swamp forests near the coast) will be cultivated, and as a result this marginal land will deteriorate. This simplified model shows that population pressure can create ecological stress and land resources crises. Many other studies (Clark, 1977; Wolman, 1993; Haub, 1996) have revealed that where there has been a long history of population growth, there have been substantial effects on land and environment change (Wolman, 1993). The evidence suggests that the combination of a large population base, a relatively rapid rate of population growth, and rapid rates of technological change has an effect of increasing the rate of change on land and in the environment. One of the major impacts is associated with the structural economic changes producing a shift of people from rural to urban areas, leading to a greater proportion of the population living in urban centres and a greater share of land use being in urbanized areas (Hugo, 1982).

There have been numerous studies on the land use issue in Indonesia (Sandy, 1975, Sandy, 1977; Firman, 1997; Tampubolon, 1997; Nasution, 1997; Silalahi, 1999). These studies have mostly focussed on making an inventory of land use conditions and the causal relationship between social and biophysical factors. Very few studies have sought to understand the dynamics of land use/land cover change over time and space and to predict future changes. In this context, knowledge on the causes and effects, magnitude, spatial and temporal distribution of land use/land cover change dynamics, as well as change prediction in Indonesia is far from complete. One of the problems is the limited availability of spatial information regarding land use/land cover conditions.

There are a range of techniques for collecting information on land use/land cover conditions, including field surveys and mapping from aerial photography and satellite remote sensing. These techniques have various advantages and disadvantages. Field surveys can provide extremely accurate data but are very time consuming and usually impractical for large areas. Accurate mapping can be achieved from aerial photography, but it depends upon the availability of photography at an appropriate scale (Lunetta *et al.*, 1999). Satellite remote sensing with various spatial resolutions can be effectively used over large areas.

An additional advantage of satellite remote sensing is its application to multi-temporal analysis (Foster, 1985). The high frequency of satellite overpass makes it relatively easy to detect changes in land cover such as those resulting from land use changes. Various studies have been conducted regarding land use/land cover identification using remote sensing techniques (Gordon, 1986; Jadhav, 1993; Ram, 1993; Dobson, 1996;

Karsidi *et al.*, 1997; Henderson, 1997; Foody, 1999; Morisette, 1999; and Ward; 2000).

The availability of accurate spatial information of land use/land cover, integrated with vector data in a GIS, can facilitate further spatial analysis and model development. Spatial analyses of land use/land cover change, such as where and what type of land use/land cover has changed, and to what extent this change relates to social and biophysical factors including why, is important for spatial planning purposes and to ensure scarce high quality agricultural land is not taken out of production prematurely.

Geographic Information Systems (GIS) are a powerful tool to capture, manage, manipulate, analyse and display spatially referenced data (Burrough, 1986). A common approach of GIS is map overlay, which is capable of integrating many kinds of social and biophysical data layers. This approach has been widely used in many spatial analysis studies (Pathan *et al.*, 1993; Schmid *et al.*, 1995; Zeidler, 1997; Li, and Yeh, 1998; Cox, 1998; Debinski, 1999; and by Frederick *et al.*, 2001) but has been rarely done in Indonesia. However, this traditional GIS technique cannot effectively handle the dynamic processes involved in land use/land cover change. Other techniques such as Cellular Automata (CA) are a potential solution to handle dynamic process when coupled with GIS techniques (Shi and Matthew, 2000). Cellular Automata are capable of representing the spatial interaction among different systems in the real world and generating a realistic prediction of a complex spatial pattern based on simple rules. It is in these areas that this study seeks to make a contribution.

This study explores land use/land cover change dynamics in an Indonesian region using detection and spatial analysis via remote sensing and GIS techniques. It uses this as a basis to predict future land use/land cover using a GIS based Cellular Automata model in the downstream areas of the Ci Tarum watershed, West Java, Indonesia (Figure 1.1). The area includes the large-scale, multipurpose Jatiluhur reservoir. The construction of the reservoir has created a dynamic response in the land use/land cover change. Equally important, this area has been heavily influenced by the expansion of the mega-city of Jakarta and surroundings (Jakarta, Bogor, Tanggerang and Bekasi or JABOTABEK). The development of new housing and other urban land use associated with urbanization is a powerful force of change in the study area. On the eastern side of Jakarta, where the study area is located, there has been dynamic expansion of housing and industrial estate development. This is especially evident in the Bekasi kabupaten, which separates the study area from Jakarta where there are many new housing estates adjacent to industrial areas such as the Tambun industrial zone, Cikarang industrial zone and Karawang integrated industrial estate (Goldblum, 2001).

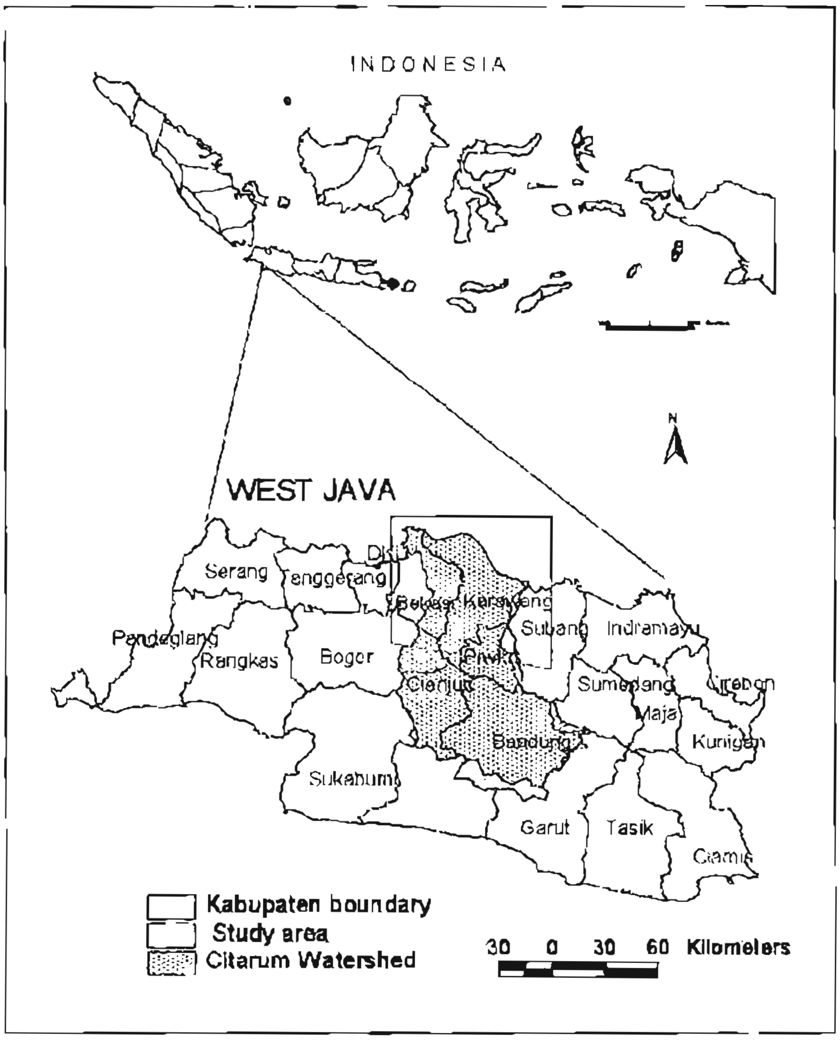


Figure 1.1. The Study area of the Ci Tarum Watershed

1.2 Aims and Objectives

The main purpose of this study is to provide an understanding of, and to predict, land use/land cover change using remote sensing and GIS techniques in Indonesia through a case study in the downstream area, and surroundings of, the Ci Tarum watershed in West Java.

The study consists of:

- *detection* of land use/land cover change over specific time intervals
- *identification* of what change occurred and where
- *analysis* of the causes and implications of the change
- *prediction* of land use/land cover change in the future.

It is hoped that by understanding more about the spatial phenomenon of land use - land cover change dynamics, and developing and applying techniques to detect and predict land use/land cover change using remote sensing and GIS, it will be possible to reduce the misallocation of resources and mismanagement of land use in this area. Finally, it is anticipated that this understanding will be of some assistance in the formulation of policies that will improve land use planning and land resources management in Indonesia more generally.

The more detailed objectives of this study are as follows:

- To detect and determine land use - land cover change dynamics using remote sensing techniques.
- To understand the inter-annual dynamics of land use - land cover changes.
- To analyse the spatial dimension of land use/land cover change dynamics associated with demographic pressure, economic and physical environment.
- To develop and apply methods that can be used to detect and predict land use–land cover change dynamics using remote sensing and GIS.
- To predict future land use/land cover.

1.3 The context of the study

The Indonesian archipelago, as one of world's most ecologically diverse ecosystems (Tomascik *et al.*, 1997), has experienced significant land use/land cover change. The issue of change becomes more critical, as the population increases, leading to the increase in the demand for space. At the 2000 Census the population of Indonesia was 206,265,000 but it was unevenly distributed between the nation's 31 provinces (Table 1.1 and Figure 1.2). Of the population about 60 % are located in Java and Bali, which together have about 9 % of Indonesia's land. The average annual population growth rate was 1.98 % 1980 – 1990 and 1.49 % between 1990-2000.

Land use/land cover change, including from deforestation, has been of significant magnitude in the last 50 years (Frederick *et al.*, 2001). Forest cover has decreased and this is related to increasing population density. In Java and Nusa Tenggara, which have high population densities, forest cover was less than 25 % of the total area, while in Kalimantan and Irian Jaya where population density is lower, forest covers more than 75 % of the total area (Figure 1.3 and Table 1.2).

Recent studies (World Bank, 2001) indicate that because of land utilization policies, coupled with the impact of climate variability, a much larger magnitude of change in forest cover has been experienced in Indonesia than elsewhere. According to a remote sensing study, estimates showed that between the years 1985-1997 the rate of forest loss was 19,700,500 hectares or 1.5 million hectare every year. It was 119,700,500 hectares in 1985 and 100,000,000 hectares in 1997 (World Bank, 2001).

Table 1.1:Distribution of Indonesian Population and Growth Rate, 1980 - 2000

No	Province	Population ('000)			Average Growth Rate (% per annum)	
		Census 1980	Census 1990	Census 2000	1980-1990	1990-2000
1	Aceh	2611	3416	3931	2.72	1.46
2	North Sumatra	8361	10256	11650	2.06	1.32
3	West Sumatra	3407	4000	4249	1.62	0.63
4	Riau	2169	3304	4958	4.30	4.35
5	Jambi	1446	2021	2414	3.40	1.84
6	South Sumatra	4630	6313	6990	3.15	2.39
7	Bengkulu	768	1179	1567	4.38	2.97
8	Lampung	4625	6018	6741	2.67	1.17
9	Kep.Bangka Belitung*)			900		0.97
10	Jakarta	6503	8259	8389	2.42	0.17
11	West Java	27455	35384	35730	2.57	2.03
12	Central Java	25373	28521	31228	1.18	0.94
13	Jogyaka	2751	2913	3122	0.57	0.72
14	East Java	29189	32503	34784	1.08	0.70
15	Banten*)			8199		3.21
16	Bali	2470	2778	3151	1.18	1.32
17	West Nusa Tenggara	2725	3370	4009	2.15	1.82
18	East Nusa Tenggara	2737	3269	3952	1.79	1.64
19	West Kalimantan	2486	3229	4034	2.65	2.29
20	Central Kalimantan	954	1396	1857	3.88	2.99
21	South Kalimantan	2065	2598	2985	2.32	1.45
22	East Kalimantan	1218	1877	2455	4.42	2.81
23	North Sulawesi	2115	2478	2012	1.60	1.33
24	Central Sulawesi	1290	1711	2218	2.87	2.57
25	South Sulawesi	6062	6982	8060	1.42	1.49
26	South East Sulawesi	942	1350	1821	3.66	3.15
27	Gorontalo*)			835		1.59
29	Maluku	1411	1858	1206	2.79	0.08
30	Maluku Utara*)			785		0.48
31	Irian Jaya (Papua)	1174	1649	2220	3.46	3.22
	INDONESIA	147490	179379	206265	1.98	1.49

*) New Province established in 1999 and 2000

Source: Central Bureau of Statistic, 2000

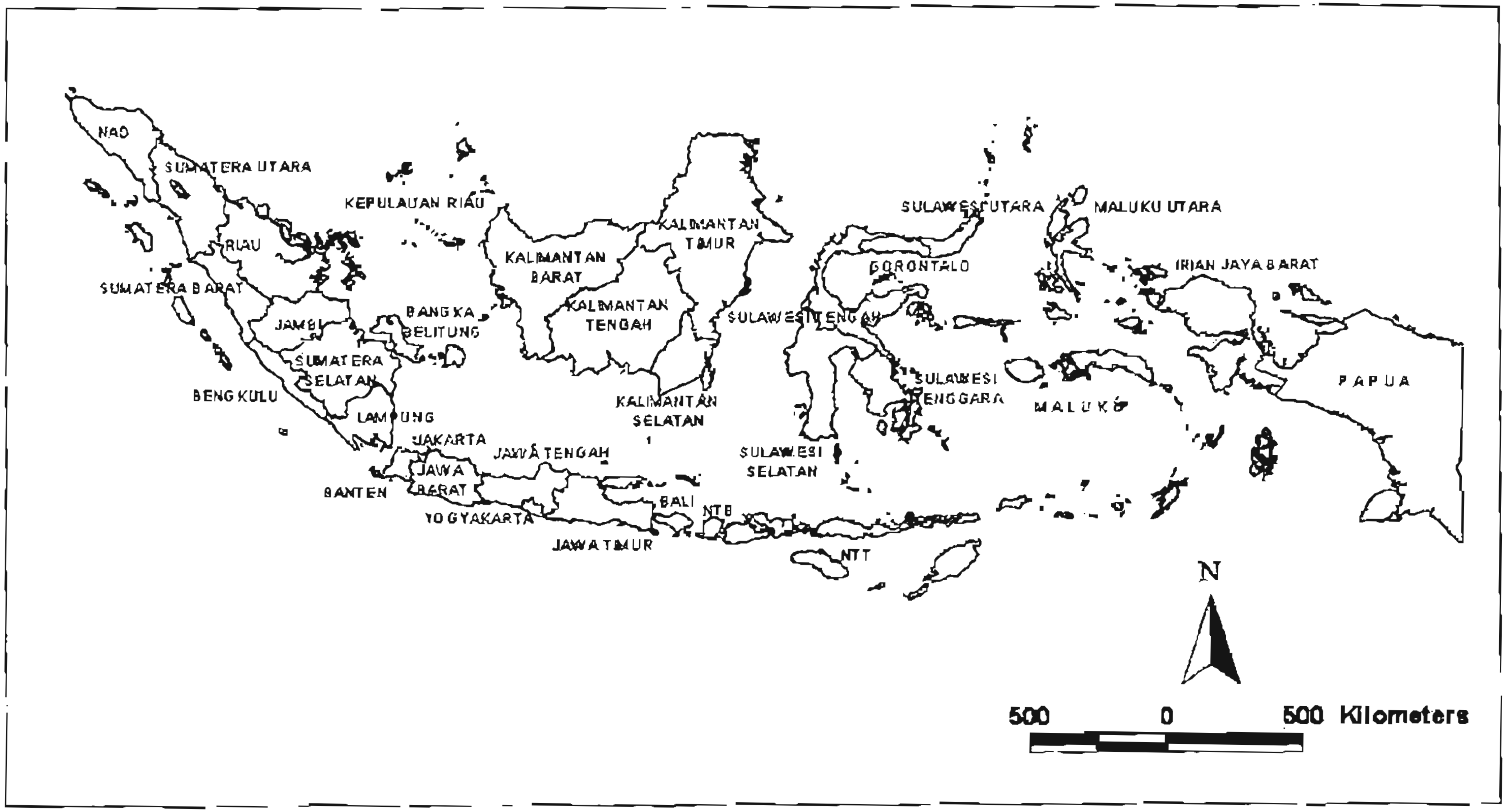


Figure 1.2. Province of the Republoc of Indonesia
Source: BAKOSURTANAL, 2000

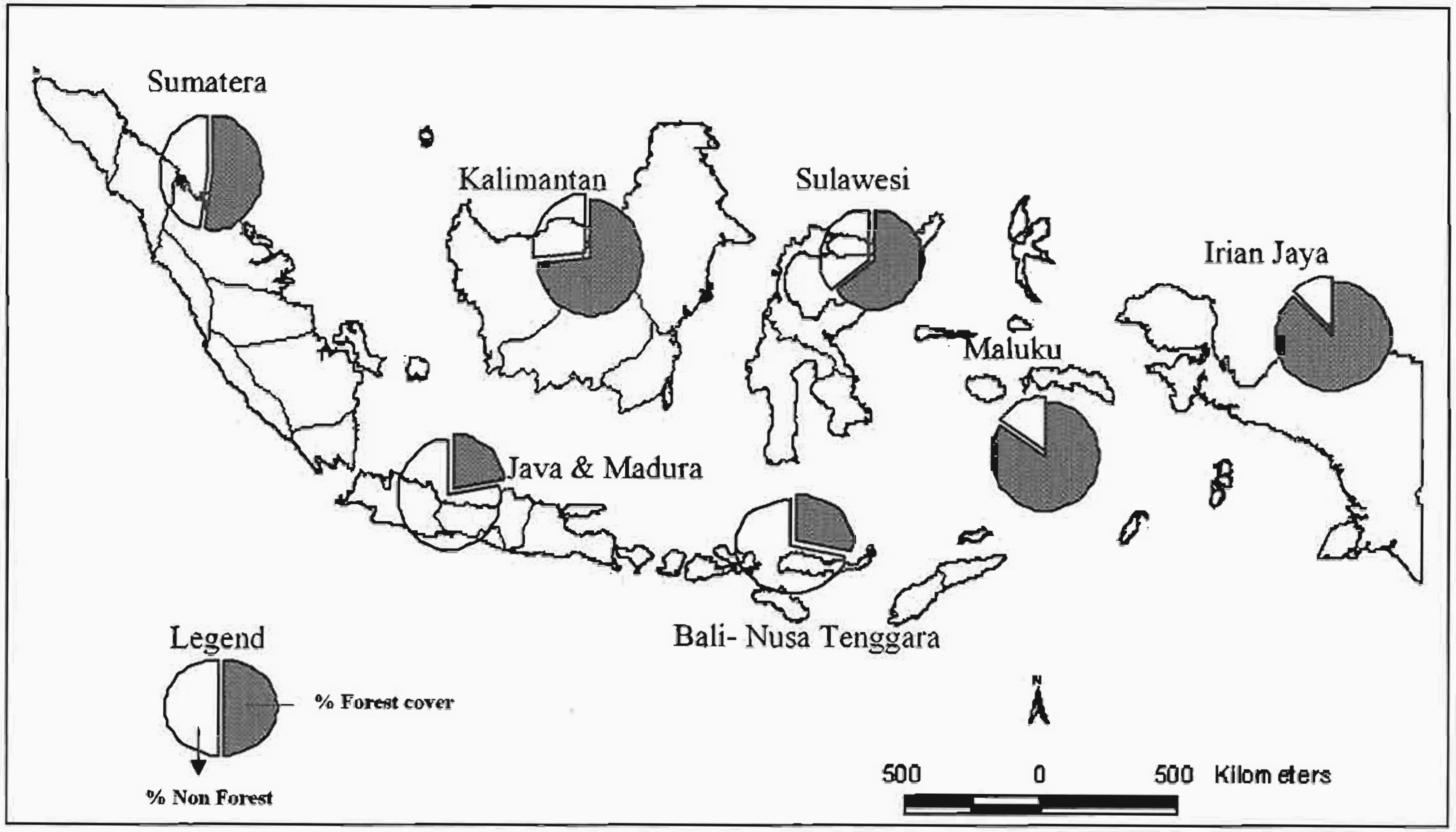


Figure1.3. Percentage of forest cover in the main island of Indonesia
Sources: Department of Forestry (Santoso, 1999)

Table 1.2: Forest cover and Population density in the main island of Indonesia
Year 1996

	Island	Total Area 1000 ha	Population density person/sqkm**)	Forest cover 1000 ha	%
1	Sumatera	47074	86	25067	53
2	Java and Madura*)	13219	868	2916	22
3	Kalimantan	53028	16	38562	73
4	Sulawesi	18412	75	11851	64
5	Maluku	7809	27	6603	85
6	Irian Jaya	40759	5	36032	88
7	Bali-Nusa Tenggara	8813	115	2494	28
	Total	189114		123525	65

Source: Department of Forestry (Harry Santoso, 1999)
*) From statistical data of Perum Perhutani
**) Calculated from Intercensal 1995 data

In the more developed islands of Java and Sumatra, land use/land cover changes because of land use conversion have been especially pronounced. Nasution (1999) estimated that between 1985 and 1995, the rate of land use conversion from rice field to non-rice field in these islands reached 20,000 hectare per year. In the islands of Java and Bali alone, more than 223,000 hectares of rice fields were converted to other uses between 1981 and 1999 (Table 1.3), with nearly 35% of this involved in conversion to settlement, industrial estate or other non-agricultural uses (Department of Agriculture and National Land Agency, 2000). Other estimates indicate that in the areas surrounding the National Capital of Jakarta, the conversion of prime rice fields to housing estates amounted to 2,000 out of 23,000 hectares in 1986 alone. Between 1989 and 2000, settlement in kabupaten Bekasi and Karawang increased, while rice fields decreased (Table 1.4). The increasing density of settlement in this area includes an increasing area of industrial estates.

Table 1.3: The change of the Agriculture area 1981 to1999 (change from rice field to other land use) in Java and Bali (ha)

No	Province	To Settlement	To Industry	To Dry Land	To Plantation	To Shrub	To Open Land	To Water	To Other	Total
1	West Java	15847.00	10771.00	8080.99	6952.00	5.00	55.00	1248.82	6809.00	49768.81
2	Central Java	19739.00	1785.00	24776.98	0.00	0.00	0.00	1329.22	8350.00	55980.20
3	Yogyakarta	2666.45	174.45	1423.30	1338.00	0.00	8.33	20.71	1650.02	281.26
4	East Java	20872.87	2870.42	14177.67	51577.00	0.00	30.23	6316.25	10626.90	106471.34
5	Bali	2626.81	677.00	2169.22	962.60	0.00	0.00	29.23	4591.14	11056.00
	Total	**61752.13**	**16277.87**	**50628.16**	**60829.60**	**5.00**	**93.56**	**8944.23**	**32027.06**	**223557.61**
	Percentage	**27.62**	**7.28**	**22.65**	**27.21**	**0.00**	**0.04**	**4.00**	**14.33**	**100**

Source: Tabulation from Directorate Extensivication of Agriculture area Dep. Of Agriculture and National Land Agency

Table 1.4: Area of rice field and settlement within kabupatens in the study area

Kabupaten	Rice field (ha)		Settlement (ha)	
	1989	2000	1989	2000
Bekasi	72677	55241	27161	41709
Karawang	100151	89791	22493	30726
Purwakarta	16813	15437	11533	13077
Subang	87321	78942	18275	25741
Total	276962	239411	79462	111253

Source: Statistical office of West Java, year 1989 and 2000.

Land use/land cover in the study area changed dramatically not just because of the influence of the expansion of the mega city of Jakarta but also the influence of the construction of Jatiluhur reservoir. The construction of the reservoir in 1962 has created a dynamic response in the land use/land cover change pattern. The flood control function of the reservoir has made more land located in the downstream area being freed from annual floods. It makes areas suitable for permanent use such as settlement. The irrigation function of the reservoir has made water more readily available all year round, making many of the downstream areas more suitable for intensive agriculture. Since Jatiluhur was constructed, rice fields with technical irrigation have increased due to the effect of the reservoir. The increase in rice fields with technical irrigation continued until 1994, but it has been decreasing slightly since then. The other categories of rice field such as rain fed, semi-technical and non-technical irrigation, have decreased since 1989 (Table 1.5). Hence the decrease of rain fed, semi-technical and non-technical irrigation are partly due to conversion into technical irrigation rice field, but since 1995 all types of rice field including technical irrigation have decreased in area due to conversion into settlement. Settlement has increased since the Jakarta-Cikampek toll way opened in 1989.

Table 1.5: Decreasing rice field and increasing settlement in West Java 1989-2000

Year	Rice field (ha)				Settlement (ha)
	Technical irrigation	Semi technical Irrigation	Non-technical irrigation	Rain fed	
2000	458240	127766	105457	225043	502540
1998	463397	123408	105357	231220	501321
1996	467414	128966	107207	232525	496638
1995	474492	126863	308110	235317	483737
1994	482787	123118	310544	249533	458869
1989	441948	135277	322807	277994	416038

Source: Central Bureau of Statistic; Compiled from West Java in Figures, 1989, 1994 1995,1996,1998, and 2000

The decrease in technical irrigation rice fields since 1994 is related to increasing industry and housing development. This is clearly seen in the kabupatens within the study area as shown in Table 1.6. The installation of hydropower plants has provided electricity supply for industrial development along the watershed. The increase of industrial development is related to an increase in the number of industry and trading companies. Table 1.6 shows that in four kabupaten within the study area, the number of national industrial and trading companies between 1989 and 2000 increased, with the highest increase in Kabupaten Bekasi (Table 1.6).

Table 1.6: Number of National Industrial and trading companies

Kabupaten	1989	2000
Subang	7260	12428
Purwakarta	1995	4087
Karawang	4777	8351
Bekasi	5699	20634
Total	19731	45500

Source: Provincial Industrial and Trade Service of West Java, year 1989 and 2000.

Industrial development has also involved establishing industrial estates such as those in Cikampek, Karawang, Cikarang, and Bekasi. From Figure 1.4 it can be seen that new developing housing and industrial estates were concentrated between Bekasi, Cikarang and Karawang along the main road of Jakarta-Purwakarta and toll way Jakarta-Cikampek. The Karawang integrated industrial estate alone covered 2000 ha, and 6234 ha of 18 industrial estate companies are located in the Bekasi integrated industrial estate (Figure 1.4 and Table 1.7).

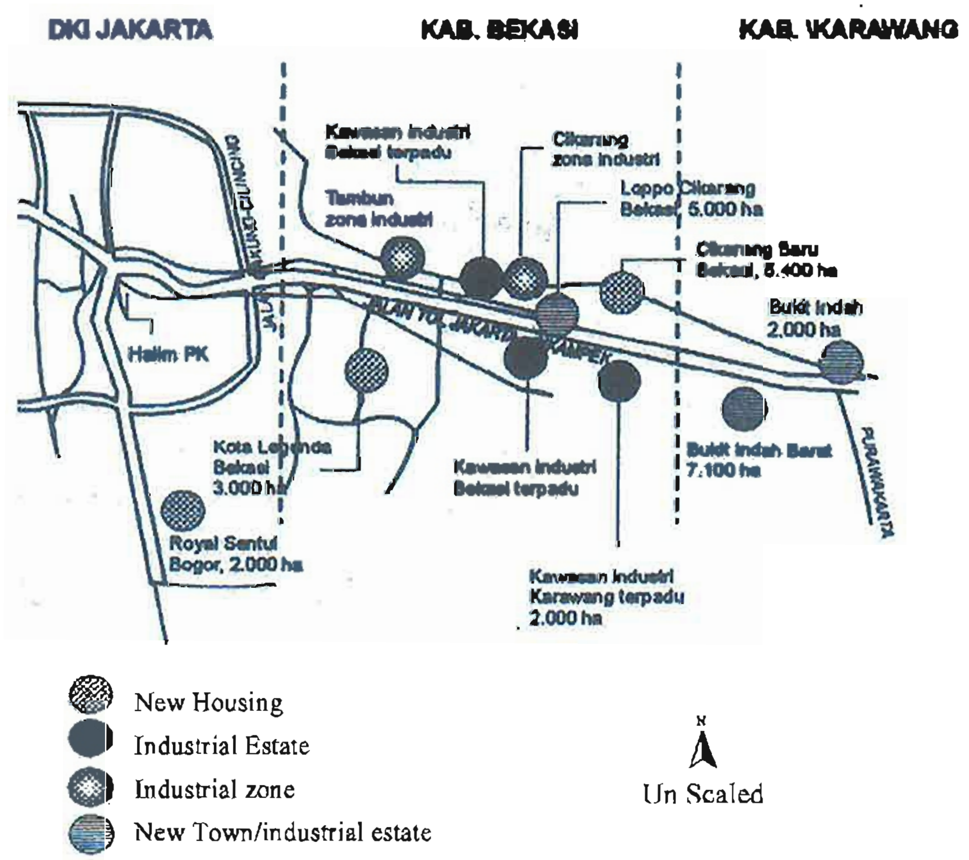


Figure1.4. Housing and Industrial estate development area in Bogor, Bekasi and Karawang (*Adopted from Jayadinata, 1999 pp.185*)

Table 1.7: Number and area of Industrial Estates in Kabupaten Bekasi year 2000

No	Name	Area (ha)
1	PT. Jababeka	1100
2	PT.Puradelta Lestari	1000
3	PT. Megapolis Manuggal Industral Estate	805
4	PT.Bekasi Fajar Industrial Estate	800
5	PT.Bekasi Matra Industrial Estate	500
6	PT.Lipo City Development	472
7	PT.East Jakarta Industrial Park (EJIP)	320,4
8	PT.Gerbang Teknologi Cikarang	240
9	PT.Indocargomas Persada	230
10	PT.Cikarang Hijau Indah	230
11	PT.Hyundai Inti Development	200
12	PT.Alinda Tama Sakti	200
13	PT.Permata Kirana Sakti	125
14	PT.Rawa Intan	100
15	PT.Gobel Dharma Nusantara	54
16	PT.Adito Mula Sakti	50
17	PT.YKK Indonesia Zipper Co.Ltd	20
18	PT.Kawasan Dharma Industri	18
	Total	6464,4

Source: Statistical office of Kabupaten Bekasi, 2000

1.4 Research Framework

The various information needs associated with land use/land cover change detection, identification, analysis and prediction include:

1) gathering, collecting, processing, documenting and describing land use/land cover change dynamics;
2) detecting and identifying the land use/land cover change; and
3) analysing the land use/land cover change and developing an appropriate method to detect and predict land use/land cover change dynamics using remote sensing and GIS.

This study includes three main elements: remote sensing, existing data collections and geographical information systems to detect, analyse and predict land use/land cover change (Figure 1.5). Figure 1.5 presents a general overview of the conceptual framework employed in this study. Remote sensing techniques are a way to detect land use/land cover change on a digital basis. The integration of remote sensing and GIS combined with existing spatial data is used to analyse land use/land cover change and the possible driver factors as well as to operationalise a land use/land cover change prediction model.

Identification and change detection of land use/land cover was based on Landsat TM image analysis. The Maximum Likelihood Classification approach was adopted to identify and make post-classification comparisons to detect changes in land use/land cover type. Landsat TM images were available from 1989 to 1997 annually. These images enable us to detect land use/land cover change on an annual basis, and the influence of weather or season variability within this time interval can be recognised.

The spatial analysis of land use/land covers change, and its relationship with the possible driver factors, was based on examining both static and dynamic driver factors. Static factors such as slope, elevation and physiography, and dynamic factors such as population density, proximity to urban and semi-urban centres, proximity to roads and proximity to toll way, were the main focus of this analysis. The relationship of these driver factors with land use/land cover was assessed in order to recognise the factors that have a strong influence on land use/land cover change in the study area.

Land use/land cover prediction is another focus in this study. Future land use/land cover information is important since it can be used to identify areas that require priority attention or to anticipate mismanagement or misarrangement of land resources. The Markov Cellular Automata (MCA) model was selected to predict future land use/land cover in the study area. This model was based on a combination of cellular automata and Markov chain models that can represent the spatial distribution of land use/land cover change in the study area.

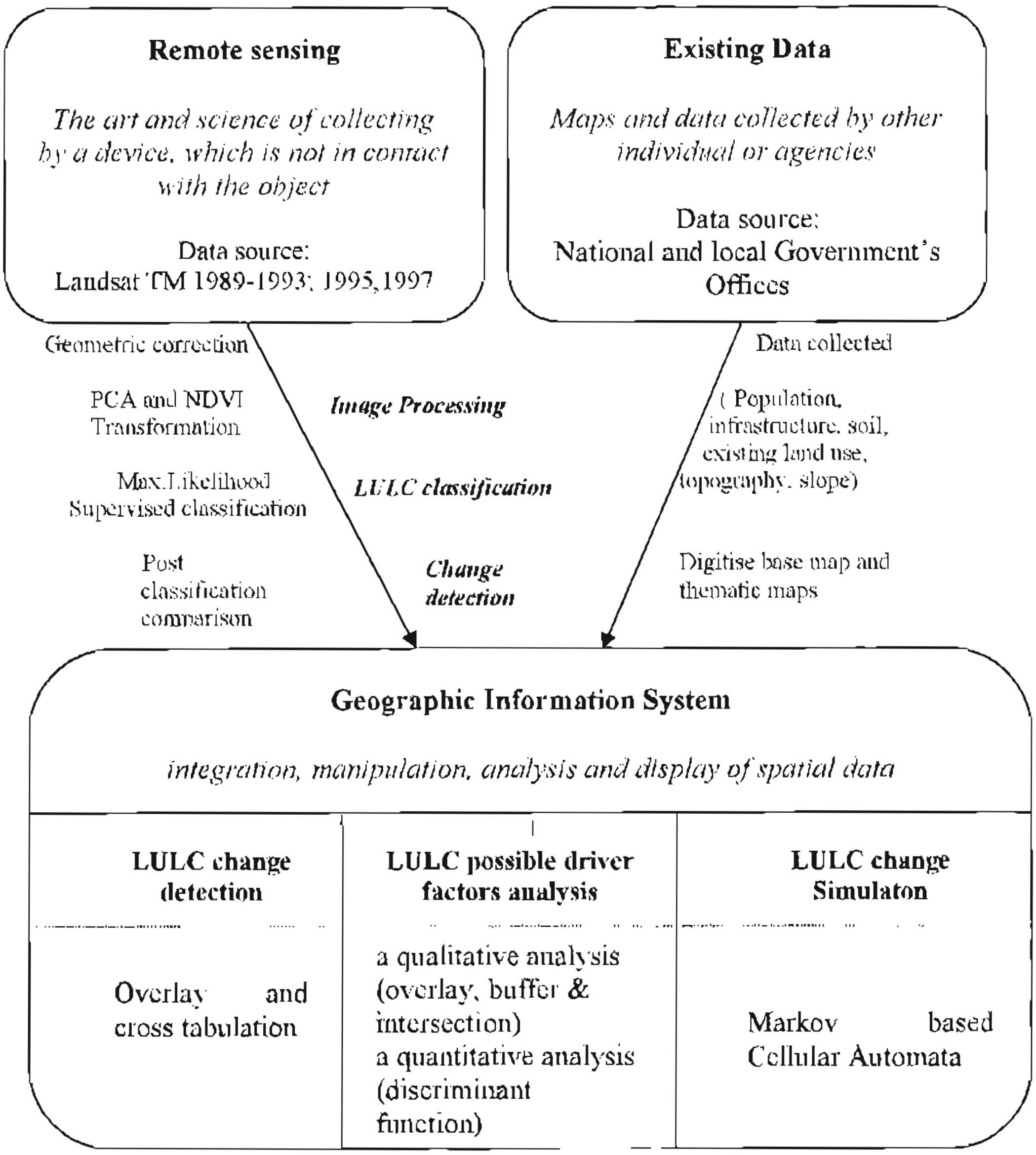


Figure 1.5. Research framework

1.5 Thesis Outline

This thesis consists of seven chapters. A general review of land use/land cover change, as well as definitions and some aspects related to land use/land cover change dynamics, are presented and discussed in Chapter 2. Chapter 3 consists of a description of the socio-economic and the biophysical characteristics of the study area and the availability of spatial data for it. This chapter provide a description of socio-economic and the physical characteristics within the fives kabupatens that cover the study area. Firstly there is a description of population growth, occupation, and land tenure as well as infrastructure, secondly, the physical characteristics of slope, physisography, soil, climate and hydrology are discussed. Chapter 4 discusses digital change detection using remote sensing and GIS. Change detection techniques are intensively reviewed in this chapter-especially detection techniques that are related to digital change detection from the satellite imagery. The dynamic change of land use/land cover related to the season and growing cycle in the study area is discussed. Chapter 5 identifies possible driver factors in land use/land cover change. Static and dynamic drivers using overlays as well as statistical analysis are discussed in this chapter. Chapter 6 is concerned with prediction. The assessment parameters of the Markov-Cellular Automata model that are available in Idris32 were conducted to get a suitable prediction result. Future land use/land cover change in the study area was predicted or simulated 10 and 20 years ahead using this model. Finally Chapter 7 presents the conclusions of the study. It includes a summary as well as some major findings and some implications for policy makers and planners in land use panning. Some recommendations for future research are put forward in the last part of this chapter.

Chapter Two

LAND USE/LAND COVER CHANGE DYNAMICS

2.1 Introduction

Human factors such as population growth and distribution, economic growth, and physical factors such as topography, slope, soil type, climate and others strongly influence land use/land cover changes (Skole and Tucker, 1993). Land use change is a matter of historical process as relating to how people use the land. Nowadays, human attachment to land is not just as habitat and living space, but also involves more complex purposes such as industry and tourism (Mather, 1986). Land use/land cover change is intricately linked to the dynamics of human activities. The dynamics of land use change is interrelated between demand and supply structure of land uses. Land use demand increases with population and elements of economic growth such as income per capita, GNP and industrialisation. On the other side, supply of land as space to be used remains static.

This chapter presents an overview of land use/land cover change dynamics, providing definition and reviews some aspects that relate to land use/land cover change.

2.2 Defining Land use/land cover change

Until recently there was no agreement worldwide, or even at national levels, on precisely what constitutes land use or land cover, or how to define them (McConnell and Emilio, 2000). There are many definitions and descriptions of land use and land cover, depending on the purpose of the application and the context of the study. It is hence necessary to define the definitions and descriptions of land use, land cover, and land use/land cover change terms that are used in this study.

In general *land cover* is the biophysical state of the earth's surface (Turner *et al.*, 1995). It may be defined as the observed physical (including the vegetation, natural or planted) and human, constructions which cover the earth's surface (Baulies, 1997). McConnell and Emilio (2000) add that water, ice, bare rock or sand and salt flats or similar un-vegetated surface, although strictly speaking part of the land (and water) itself and not its cover, are for practical reason often included in land cover. Moser (1996) notes that the term "land cover" originally referred to the type of vegetation that covered the land surface, but has broadened subsequently to include human structures, such as buildings or pavement, and other aspects of the physical environment, such as soils, surfaces and groundwater.

Land use refers to both the manner in which the biophysical attributes of the land are manipulated, and the intent underlying that manipulation or the purpose of the land used (Turner *et al.*, 1995). Moreover, *land use* involves considerations of human behaviour, with particularly crucial roles played by decision-makers, institutions, and the inter-level integration of processes at one level with those at other levels of aggregation. Therefore, land use generally represents human-induced intervention or manipulation of the land to provide food, building materials, buildings site, firewood, and clothing.

A second definition of land use is the purpose for which the land is being used (Young, 1994). This definition includes the management of land and human activities which are directly related to the land. In addition, *land use* constitutes a series of activities undertaken to produce one or more goods or services. Related to the previous definition, ITC (International Institute for Aerospace) and FAO (Food Agriculture Organization) adopted the following definition of land use: a series of operations on land, carried out by humans, with the intention to obtain products and/or benefits through using land resources (deBie *et al.*, 1996: p.5).

The term *land use/land cover* has commonly been used in association with land use, particularly in the field of remotely sensed analysis. Land use changes are a major determinant of land cover change. Land use/land cover inventories tend to be a mixture of land use and land cover. One category of land use may correspond fairly well to one class of land cover. On the other hand, a single class of land cover may consist of multiple uses. There are two categories of land use/land cover change: conversions from one land use/land cover into another, and transformations within a given land use/land cover type. Lambin *et al.* (1999: p.37) refer to the process by which land use/land cover is modified/converted as including two main components:

- *The activities (or operation) and inputs that are undertaken (or restricted) on a piece of land with significant land cover consequences; and*
- *The goals/intentions motivating these operations, including both the outputs (goods or services) that are expected, and the forces that cause land uses to occur in a certain way, at a certain time, in a certain place.*

In terms of detection or identification, land use/land cover is the observed physical cover at a given location and time, as might be seen on the ground or from remote sensing. Furthermore, land use/land cover may be determined by direct observation, whereas information on land use requires a statement of purpose from the person who controls or carries out the land use. Remotely sensed data (e.g. from satellite images) can often be used to map land use/land cover, for example, by identifying multi-spectral signatures characteristic of certain land cover types. Land use, in turn, is often related to land cover, so that land cover may be used to infer land use (Adger, 1994).

2.3 The dynamics of land use/land cover change

Land use/land cover can change due to natural or human factors. Natural factors such as flooding, drought, forest fire, and volcanic eruption result in a change of land use/land cover. Human factors such as demographic pressure, level of poverty, and the economic and institutional structures of resource use are an indirect cause of land use/land cover change. Moreover, with an increase in population and economic growth, human activities have occupied more land (Mather, 1986). Changes in the way which populations live their lives will change the function of the land, and the human factors such as population and their activities are a driving force in changes in land use/land cover. Sage and Grubler in Mayer (1994) argue that the main driving forces of land use - land cover change are population, income and technology. Robinson (1994) argues that the initial driving forces to be considered are population, income, technology and price. Hence population and their activities, such as income and technology, are forces shaping land use. But recognition of the link between human activities and land use/land cover type is not simple. Single or multiple factors may simultaneously or independently affect changes of land use/land cover.

Land use type changes from forest to agriculture or from agriculture to settlement or from agricultural to industrial or commercial, for example, are the result of changes in human activities. On the other hand, the nature of soil such as mineral content, texture, wetness and dryness as well as topography are factors that affect land use/land cover change. Therefore, the interaction of human and biophysical factors influences the dynamics of land use/land cover change. This interaction is complex and needs to be simplified and categorized in order to identify the most influential human and biophysical causes of land use/land cover change. McNeil (1994) concludes that there are four major driving forces - political, economic, demographic and environment (Table 2.1). Within these broad categories, he identifies specific attributes that strongly influence land use/land cover patterns. Land uses for settlement, for example, may be strongly influenced by demographic pressure such as population growth, education levels and income per-capita or may act together with other factors such as economic growth, policy or technology. In Indonesia, land use change is related to all these factors. The policy of privatisation of forest concession companies for example forced forest conversion in the main islands such as Kalimantan, Irian and Sumatra (World Bank, 2001). In the islands with a high-density of population such as Java, land has been converted from agricultural to settlement and industrial use. From Table 2.2 it can be seen that a high rate of conversion from agricultural to settlement and industrial areas has occurred in West Java, Central Java, East Java and Bali. This is evidence that population or demographic pressure is one of many factors that influence land use change in Indonesia.

Table 2.1: Driving forces behind land use change

Attribute	Variable	Kinds of Indicators
1. Political:		
Decision-making process Local pressure, special interest and corruption State capacity	Degree of public participation (open/closed, centralized/ decentralized) Public sector pressure/influence	Unitary of federal structure Number of special-interest Groups Public sector expenditure/ GDP Public/total land area
2.Economic:		
Vulnerability to external pressure(economic/political)	Open vs. closed economy Primary sector dependence Type of exchange rate management	Exports/GDP Partner concentration Primary sector export/ total export PEA (Population - economically active) agriculture/PEA total Real exchange rate Debt service ratio
Market allocation mechanism	State controlled, market driven	Agricultural subsidies Public sector expenditure/ GDP
Technological intensity	High-low	Energy intensity of GDP
Level and division of wealth (asset inequality)	Wealth/poverty-induce consumption	Primary sector/GDP Energy consumption/capita PEA agriculture/PEA total Percent absolute poor in total population
3.Demography:		
Population pressure on the land	High-low	Cultivated/arable land Change in population Density PEA agriculture/PEA total
4. Environment:		
Natural resource quality	Scarcity	Stock, yield, flow

Source: Adapted from McNeil (1994.p.60)

Table 2.2: Change of agriculture area to other land use between 1981-1999 in Indonesian provinces (ha)

No	Province	To Settlement	To Industry	To Dry Land	To Plantation	To Shrub	To Open Land	To Water	To Other	Total
1	Aceh	0.00	0.00	0.00	0.00	0.00	0.00	000	0.00	0.00
2	North Sumatera	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
3	West Sumatera	495.57	22.21	12.00	392.00	0.00	0.00	0.00	610.00	1531.78
4	Riau	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
5	Jambi	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
6	Bengkulu	0.00	0.00	0.00	0.00	0.00	0.00	000	0.00	0.00
7	South Sumatera	61.28	000	0.00	0.00	105.00	11.50	0.00	0.00	177.78
8	Lampung	4221.00	197.00	0.00	0.00	0.00	0.00	0.00	463.00	4881.00
9	**West Java**	**15847.00**	**10771.00**	**8080.99**	**6952.00**	**5.00**	**55.00**	**1248.82**	**6809.00**	**49768.81**
10	**Central Java**	**19739.00**	**1785.00**	**24776.98**	**0.00**	**0.00**	**0.00**	**1329.22**	**8350.00**	**55980.20**
11	Yogyakarta	2666.45	174.45	1423.30	1338.00	000	8.33	20.71	1650.02	281.26
12	**East Java**	**20872.87**	**2870.42**	**14177.67**	**51577.00**	**0.00**	**30.23**	**6316.25**	**10626.90**	**106471.34**
13	Bali	2626.81	677.00	2169.22	962.60	0.00	0.00	29.23	4591.14	11056.00
14	West Nusa Tenggara	13.72	0.00	0.00	0.00	0.00	0.00	0.00	334.00	487.72
15	East Nusa Tenggara	0.00	0.00	0.00	0.00	0.00	00C	0.00	0.00	0.00
16	West Kalimantan	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
17	East Kalimantan	0.00	0.00	0.00	0.00	0.00	0.00	000	0.00	0.00
18	South Kalimantan	4315.00	1620.00	0.00	13.00	0.00	0.00	0.00	0.00	5948.00
19	Central Kalimantan	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
20	South Sulawesi	2123.74	145.30	0.00	365.25	000	0.00	50.00	435.42	3119.71
21	Northeast Sulawesi	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
22	Central Sulawesi	11.68	0.00	0.00	0.00	0.00	1.60	10.00	15.75	39.03
23	North Sulawesi	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
24	Irian Jaya	0.00	000	0.00	0.00	0.00	0.00	0.00	0.00	0.00
25	Maluku	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Total	72994.12	18262.38	50640.16	61599.85	110.00	10666	9004.23	33885.23	239742.63
	Percentage	30.45	7.62	21.12	25.69	0.05	0.04	3.76	14.13	100

Source:Tabulation from Directorate Extensivication of Agriculture area Dep. Of Agriculture and National Land Agency

The forces driving land use/land cover change can be distinguished into two categories - direct and indirect. Direct drivers are associated with activities which directly interact with and modify the physical environment, such as deforestation, urbanization, and agricultural expansion (Turner and Meyer, 1994). The indirect drivers, or root causes, influence how individuals or groups interact with, and change land use/land cover (Blaikie *et al.*, 1994). These are generally more complex as they are built into the human system underlying a land use activity (Adger and Brown, 1994; Krummer and Tunner, 1994). An illustration of driving forces related to human systems can be seen in the demand and supply relationship of a land use change model (Figure 2.1). The demand structure of land uses is very dynamic; it means that the demands for using land for human activities increases from time to time under the influence of population growth, community structure and economy. On the supply side, structure is relatively static, the surface area is constant, and elasticity from this supply side is on the aspect of physical characteristic and function of the land. Figure 2.1 shows the mutual interaction between socio-economic activity structures, biophysical factors and the dynamics of land use change. This flowchart explains the increase of land use demand as an effect of an increase in socio-economic and welfare growth, increasing the demand for goods and services, which in turn affects the increased demand for productive land use. The flowchart also explains the opportunity of increasing on the supply side. Institutions, policy, technology and spatial distribution/variation in the natural quality of land (soil type, slope, altitude and climate) are the factors that could lead to an increase on the supply side. Institutions and policy at national, local and community level have an influence on technology and land use decisions. The technology level will affect the capability to cultivate and employ the land (Saefulhakim, 1999).

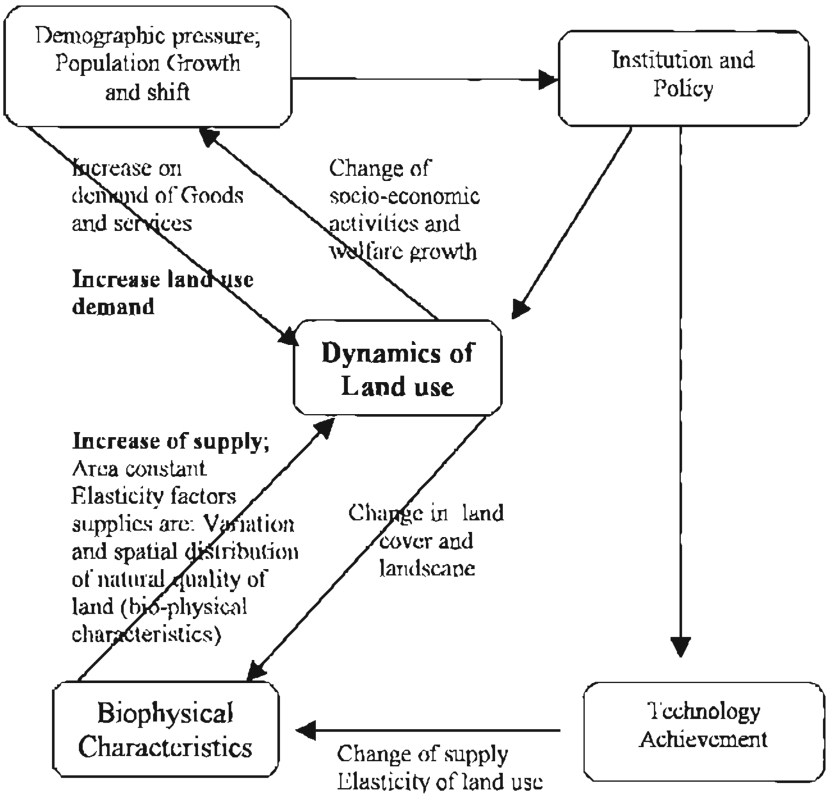


Figure 2.1. The mutual interaction of land use change dynamic. Modified from Saefulhakim (1999)

2.4 Some aspects related to land use/land cover change

2.4.1 Land use and Demographic pressure

Demographic pressure such as population growth and shift are a driving force of land use/land cover change which is unique and can be quantified (Meyer, 1992). However, population growth is not the main driving force as its importance is relative to the other forces generating land use/land cover change such as technology and social advances that improve the conditions of life. Young *et al.*(1991) did not find a significant correlation between the land use/land cover changes with increases in population density at national scale across the world. Hence increase in population density may be sufficient to cause land use change but it is not necessary. Significant correlations between population and land use/land cover change have been found when investigation is restricted to regions possessing similar socio-environmental characteristics. Comparative studies offer statistical evidence supporting the claim that population growth drives or strongly contributes to forest clearance (Meyer, 1992).

A study that analyses the interactions of population growth and land cover change (Bilborrow, 1992) concludes that population growth is an important factor, but one significantly modified by natural and institutional context. Land use/land cover change is closely associated with agriculture, but not clearly linked to population (Meyer, 1992: pp. 54). Empirical evidence highlights the complexity of factors concerning population pressure and its links with agricultural extensification and intensification. These would appear to imply that whilst the initial response to increases in population pressure may be agricultural extensification, when land becomes more difficult to access, or only very marginal areas remain, then intensification occurs. Turner *et al.* (1977) argue that population pressure increases agricultural intensity: "increases in population pressure causes increases in agriculture intensity"(Turner *et al.*, 1977 p.384). Hence land use/land cover change is usually an outcome of population growth. Moreover, population change has a direct association with change in the way people lead their lives and their activities, including agriculture activities. Population growth is argued by some to have exceeded the capacity of the biosphere, as managed by society, to sustain it (Ehrlich. I., 1990 and Ehrlich. I. 1988 cited by Meyer, 1992: pp.52). Growth in population and economic activity require land not only to fulfil the basic needs but also to ensure needs in social life and leisure activities are met. Thus, the more people, the more land needed for agriculture to produce enough food and for non-agriculture sector to build their housing, manufacturing and other activities.

2.4.2 Land use conflict and regional food security

Land as space remains static and demand to use the land rapidly increases as a result of population growth. The more people the more space that is needed for their living and other activities such as agricultural and commercial activities. In many cases population growth can bring land use conflict. Land use conflict frequently occurs between agricultural and non-agricultural uses. This conflict occurs because of the basic principle that each piece of land should be devoted to the use in which it would yield the highest rent (see Hoover and Giarratani, 1999: pp.7). Therefore demand from the non-agriculture sector is usually much stronger than from agriculture due to the much higher incomes which this sector can obtain from the same area of land. If this condition occurs in highly productive areas for agriculture it can have an effect on overall food supply. There is a significant correlation between the amount of cultivated land and food supply (Li and Hong, 2000). The conversions of agriculture area into non-agriculture area will other have an effect on regional food supply. This is because urban areas lead to be located in the most productive agriculture area. This situation is occurring in Indonesia. Indonesia was self-sufficient in rice production in 1984. After this time the rice fields began to decrease. In 1983, the area of agricultural land in Java was about 5.42 million ha, but after 10 years decreased to 4.41 million ha or decreased about 1.1 million ha (Table 2.3).

Table 2.3 Changes in Agricultural Land in Indonesia 1983-1993

Islands	**1983-Agricultural Census**	**1993-Agricultural Census**	**Change**
	Area (Million Hectare)	Area (Million Hectare)	%
Java	**5.42**	**4.41**	**-1.01**
Bali & Nusa Tenggara	1.22	1.07	-0.15
Sumatra	5.66	5.42	-0.24
Sulawesi	1.64	1.78	0.14
Kalimantan	2.23	2.19	-0.04
Maluku	0.38	0.4	0.02
Irian Jaya	0.17	0.18	0.01
Total	**16.72**	**15.45**	**-1.01**

Source: Central Bureau of Statistics

From 4.41 million ha agricultural area, Java, supported about 63% of domestic supply of rice, the remaining 38% supported by 11.04 million ha from out of Java. The decreasing of rice field in Java has an effect on decreasing rice production and rice supply at the national and regional level (Table 2.4). Therefore, to compensate the decreasing rice field in Java, the government of Indonesia has a long-term policy to open one million ha rice field in peat area in Central Kalimantan under President Decry No. 8. 26 December 1995 (Sudrajat *et al.*, 2001).

Table 2.4. The average rice productivity in Java and off Java (Ton/ha/year)

Islands	1996	1997	1998	Average
Java	**51.77**	**51.81**	**47.99**	**50.52**
Bali & Nusa Tenggara	40.88	40.91	40.48	40.76
Sumatra	38.08	38.26	37.12	37.82
Sulawesi	43.38	43.48	38.8	43.38
Kalimantan	26.36	26.38	24.1	25.61
Maluku and Irian Jaya	25.31	25.41	24.87	25.2

Source: Central Bureau of Statistics Year Book of Indonesia 1996-1998

A major factor in the decline of agricultural land in Java is the increasing industrialisation and urbanisation occurring in the island (Table 2.5). From Table 2.5 it can be seen that the highest conversion of land from rice field to settlement and industrial areas was in Java. It was 59125.32 ha change from rice field to settlement and 15600.87 ha to industrial area. While in other islands such as in Irian Jaya and Maluku there was no conversion from rice field to either settlement or industrial areas.

Table 2.5: Conversion from rice field to Settlement and Industrial areas in the main island of Indonesia 1981-1999(ha)

No	Province	Settlement	Industry
1	Sumatera	4777.85	219.21
2	**Java**	**59125.32**	**15600.87**
3	Bali	2626.81	677.00
4	Nusa Tenggara	13.72	0.00
5	Kalimantan	4315.00	1620.00
7	Sulawesi	2135.42	145.30
6	Irian Jaya	0.00	0.00
7	Maluku	0.00	0.00
	Total	72994.12	18262.38
	Percentage	30	8

Source: Dep. Of Agriculture and National Land Agency

2.4.3 Land use, Industry and Manufacturing

The demand for land by industry and other commercial purposes has strongly expanded because of the rapidity of industrial development. Many factories have been constructed and spread into the countryside in Java (Chapin, 1972; Benstein, 1994; Hidding, 2002). The number of large and medium manufacturers in Java has increased with about 80% located in Java (Table 2.6). Often industry requires more land than needed at the time to provide for subsequent growth. In effect, a lot of agriculture or rural areas have been converted into industrial or commercial area.

Table 2.6: Number of large and medium manufacturers 1997-2000

Location	1997	1998	1999	2000
Java	18024	17236	17925	17995
%	80.51	80.46	81.22	81.15
Outside java	4362	4187	4145	4179
%	19.49	19.54	18.78	18.85
Total	22386	21423	22070	22174
%	100	100	100	100

Source: Statistical office of West Java, year 1997,1998,199 and 2000

Tandy (1973) categorizes to 6 categories of industrial land use:

1. Offices and commercial building
2. Factories in urban situations
3. Factories in rural situations
4. Ancillary land use, e.g. cooling ponds, storage land, recreation
5. Special types of industry, e.g. power plant, dams or reservoirs
6. Extractive industries.

Each category has a different interrelation with land use/land cover change. Office and commercial building areas usually planned in an urban situation, therefore land allocation for this category has an effect on urban land use change (Chapin, 1972; Rhind *et al.,* 1980; Dawson, 1984; Cloke, 1989). However, in practice, there are difficulties because of competition with other purposes of land use. It is clear, nowadays, that industries look at fresh sites in the countryside to build a factory. This condition has an effect on land use/land cover change, because construction of new factories needs new roads, communications and other facilities. In Indonesia, for example, new towns are often built adjacent to industrial estates (Figure 2.2). Lippo Karawaci in Tanggerang or Lippo Cikarang in Bekasi is new towns surrounding Jakarta adjacent to industrial estates and service-oriented facilities such as hotels and offices. Development has extended beyond the administrative boundary of Jakarta Special Region, transforming the adjoining district (JABOTABEK: Jakarta, Bogor, Tanggerang and Bekasi). The development trend becomes clear when the land area used for some new town projects is considered. For instance, to the west of Jakarta in the Tanggerang district, the new towns of Serpong has taken 6000 ha and Tigaraksa 3100 ha. To the east of Jakarta in the Bekasi district, Cikarang Baru adjoining Cikarang stretches over 5400 ha, and Bekasi'2000 an area of 2000 ha. These new towns are adjacent to the industrial areas such as Bekasi integrated industrial estate, Tambun industrial zone, Cikarang industrial zone and Karawang integrated industrial estate (Djoko, 1996; Jayadinata, 1999; Goldblum, 2001).

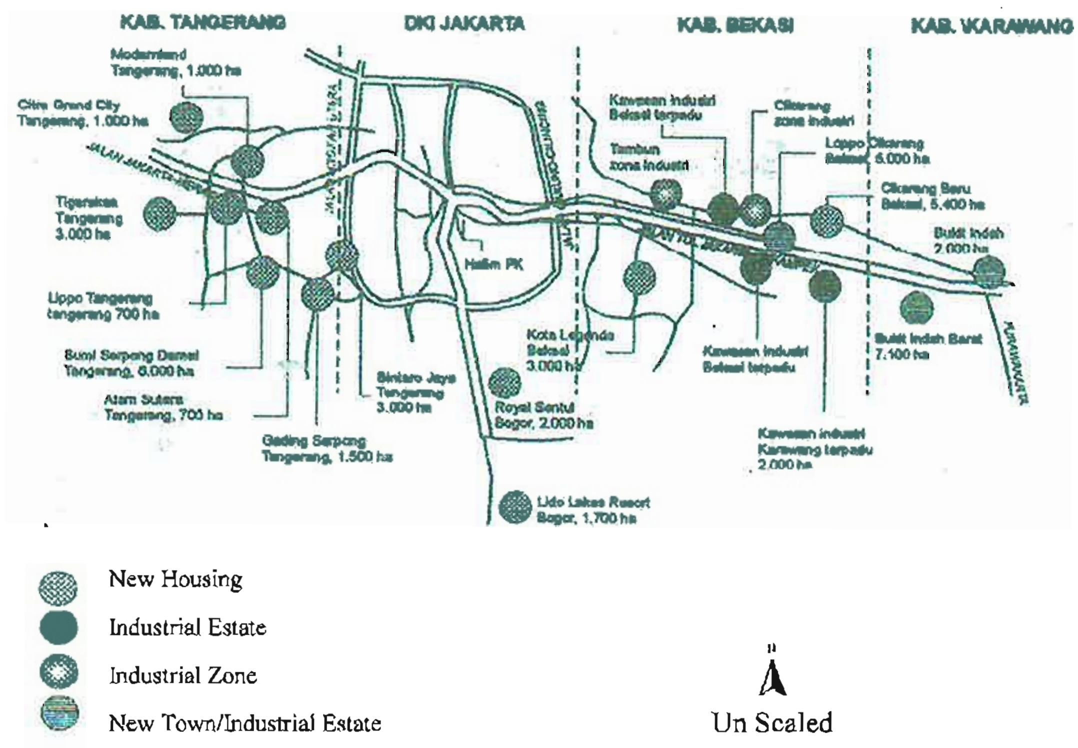


Figure2.2. Housing and Industrial estates development area in JABOTABEK and Karawang (*Adopted from Jayadinata, 1999: p.185*)

2.4.4 Land use and Agriculture

As previously mentioned, agricultural intensity is associated with population pressure; therefore the behavour of the agricultural sector with respect to demand for land from non-agricultural sectors depends on a variety of factors related to its demographic situation, such as population growth, structure of farm population, technology adaptation and others. Agricultural land use involves growth of food crops and other economically valuables crops. Food crops in Indonesia consist of paddy/rice, maize, cassava, sweet potato, peanut and soybean. Other economically valuables crops consist of tea, coffee, oil palm, tobacco and others. The extension of this agricultural land use is constrained by climate and soil factors and also depends on the agricultural market situation, changed production conditions, and government intervention such as incentives and regulation (OECD, 1976: p. 31). In the humid tropics, such as in Indonesia, intensive cropping systems occupy most of the resource-rich land, fertile soils, low slopes, and areas with adequate rainfall or irrigation. For example rice fields are mostly located in the flat areas with good irrigation and fertile soil (Figure 2.3).

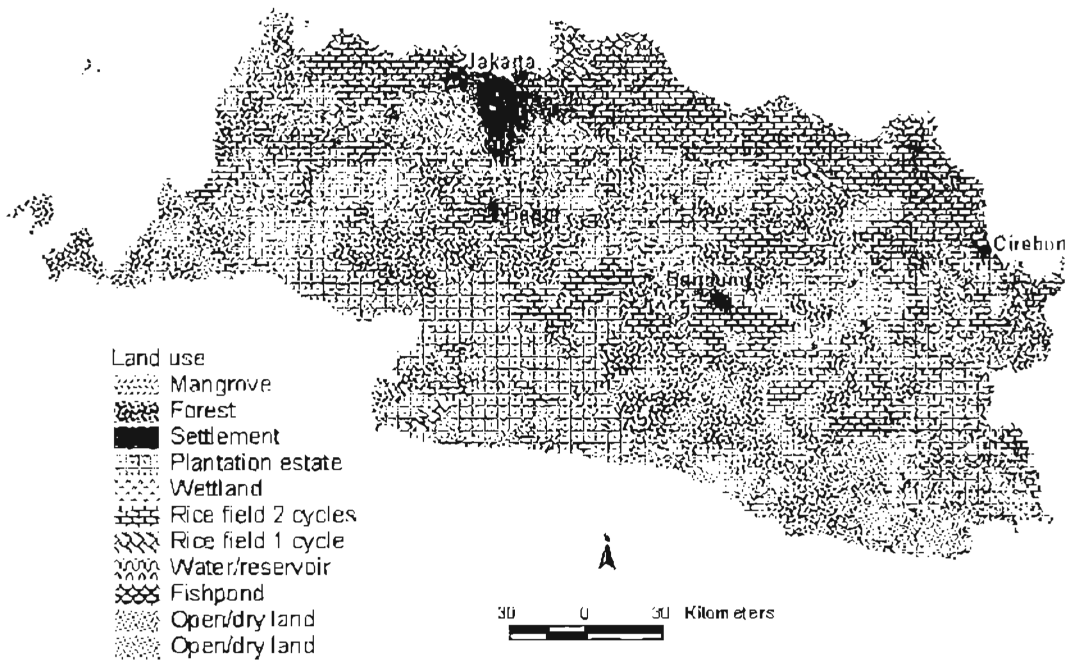


Figure 2.3. Land use in West Java 1993
Source: SARI Project BPPT, 1998.

The other economic value crops such as coffee or tea are located in areas upland of paddy fields. These crops mainly occupy fertile soil with gentle slopes at an altitude within 500 m above sea level. In many cases areas with poor soils and water resources have received far less attention in agricultural development, but increasing population and development pressures are forcing conversion of these areas into more productive and intensive land uses. These pressures continue especially in areas where there is industrial development.

2.4.5 Spatial dimension of land use/land cover change

The issue of spatial scale is important in land use/land cover change analysis. Land use/land cover change analysis at the world level, for example, is quite different from analysis at the national or local levels. Moreover, the analysis of land use/land cover change is essentially performed at the level of the land use/land cover classification systems. These systems are tied usually to a particular spatial scale. For example, at the world level, FAO distinguishes four or five major land use/land cover types (Briassoulis, 2000). At the level of nations, the number of land use/land cover types increases to around ten. At this level, each type was divided into a more detailed land use/land cover typology- Agricultural land is further subdivided according to the type of product (annual, perennial), pastures are distinguished according to ownership status into public or private.

At the national level of Indonesia, for example, the National Land Agency of Indonesia divides land use classification system into three levels: level I, II and III (Table 2.7). The level of this classification system relates also to the source of data, acquisition techniques and spatial resolution or map scale. Anderson *et al.* (1976) summarised the level of land use/land cover classification based on data source and spatial resolution into five levels (Table 2.8). Table 2.8 shows that Landsat MSS is capable of producing land use/land cover classification to level I with map scale of 1: 250 000 and smaller. Classification level I consists of the main land use/land cover

Table 2.7. The land use classification system in Indonesia

Level I Scale 1: 200 000		Level II Scale 1: 100 000 and 1: 50 000		Level III Scale 1: 25 000 and 1: 12 500			
1	Settlement	1a	Residential	1a1	Residential	6a1	Dense forest with primer wood type
2	Rice filed	1b	Cemetery	1b1	Real Cemetery	6b1	Natural shrub forest
3	Dryland Agricultur, Plantation	1c	Emplacement	1b2	Un real Cemetery	6b2	Artfisial shrub forest
	Mixe garden	2a	Rice field 2 time harvest	1c1	Permanent Emplacement	6c1	Natural homogen forest
4	Forest	2b	Rice field 1 time harvest+horticulture	1c2	Temporary Emplacement	6c2	Artifisial homogen forest
5	Bareland	2c	Rice field 1 time harvest+horticulture	2a1	Rice field 3 x at a year	6d1	Swam forest
6	Lake and wetland	2d	Rice field with can, tobacco, rosela	2a2	Rice field 2 x at a year	7a1	Marginal land with stone
7	Others		horticultur	2b1	Rice field 2 x + horticulture	7a2	Marginal land with tuff
		3a	Dryland with grass	2b2	Rice field 1 x + horticulture	7a3	Marginal land with pasir
		3b	Dryland	2c1	Rainfad rice field 1 x a year	7b1	Badland salinity intrusion
		3c	Vegetable	2c2	Swam rice Field 1 x a year	7b2	Badland, mining
		3d	Flower	2d1	Rice field with Sugarcan	7b2	Badland after query.
		4a	Rubber	2d2	Rice field with Tobaco	8a1	Grassland
		4b	Coffee	2d3	Rice field with Rosela	8a2	Alang-alang
		4c	else	3a1	Tegalan with certain crop	8b1	Shrub
		5a	Mixe plantation	3b1	Dryland 0-1 year with certain crop	8b2	Savana
		5b	Fruit crop	3b2	Dryland 1-3 year with certain crop	8b3	Bencah
		6a	Dense forest	3c1	Vegetable with certain crop	9a1	Freswater pond
		6b	Secondary forest	3d1	Flower with certain crop	9a2	Breakestwater pond
		6c	Homogen forest	4a1	Productive rubber	9a3	Salt pond
		6d	Swam forest	4a2	Pre-productive rubber	9b1	Natural lake
		7a	Marginal land	4b1	Productive coffee	9b2	Artifisial lake
		7b	Badland	4b2	Pre-productive coffee	9c1	Swam
		8a	Grassland	4c1	else	9d	Dam/Reservoir
		8b	Srhub	5a1	Mixe plantation productive	10	Primeir, Secondar and Tertier
		9a	Pond	5a2	Mixe plantation pre-productive		irigation.
		9b	Lake	5b1	Fruit plantation productive		
		9c	Swam	5c2	Fruit plantation pre-productive		
		9d	Dam/Reservoir				
		10	Irrigation				

Source: The Indonesian National Land Agency category such as built-up area, agricultural area, open/bare land and water body or wetland.

Table 2.8: Land use/land cover classification level and their sources

Classification Level	Data source	Map output scale
I	Landsat MSS and similar	1:250000 - 1: 1 Million
II	High altitude (12500m) photography; reconnaissance survey	1 : 80000 and smaller
III	Medium altitude (3000-12500m); Field survey	1 : 20000 - 1: 80000
IV	Low altitude (below 3000m); Photography; ground survey	1 : 2500 – 1 : 20000
V	Individual building or sub-building	1 : 100 - 1 : 1000

Source: Anderson *et al.* 1976

Recently, satellites can produce land use/land cover maps with more detail or higher classification level. For example, Landsat TM has a 30 m spatial resolution and can produce a map with scale of 1:80 000 or 1: 50 000. This map scale can produce land use/land cover classification at level III as in Anderson's system or level II as in the Indonesian system. New satellite such as Ikonos has a 1 m spatial resolution and can produce a map with scale up to 1: 2000. Based on this spatial resolution, land use/land cover classification system can be derived at a parcel level. At this level land use/land cover classification becomes very detailed capturing local environmental, socio-cultural, demographic, economic and other details.

These spatial scales have an influence on the level of land use/land cover change observed. For a given time interval, land use–land cover change may not be discernible at higher spatial levels while at lower levels (e.g. at the level of a settlement), very large changes may be measured. The role of the land use/land cover classification system is critical in this context, as are also the source and acquisition techniques of spatial data for the measurement of land use/land cover change.

Hence, regardless of the intended level of analysis, the results obtained and the ensuing description of land use/land cover change refers to land use/land cover change at the level of the spatial scale. The smaller the scale the broader the land use/land cover category and the more generalised the analysis.

2.4.6 The importance of land use/land cover change detection in spatial planning

In many countries there have been significant changes in land use/land cover as a consequences of development process (Scholten *et al.*, 1999). Historically, more land has been used for agricultural and urban purposes. The lack of collection of land use/land cover data or information will have implications for land use planning or spatial planning processes. Scholten *et al.*(1999) state that the need for land use/land cover change identification at national, regional or local level is increasingly important to determine the likely impact of specific projects or policies in advance of their implementation. Recently, with land use/land cover data available on a digital basis from remotely sensed data and GIS, the lack of information on land use/land cover change can be eliminated. An illustration of a model of spatial planning related to land use/land cover supported by a digital model of spatial data is shown in Figure 2.4. This figure shows that when land use/land cover data are available in digital format, they may be integrated with other data attributes to create suitability maps for each land use type and finally to support the land use allocation process for each parcel. It is a dynamic model because it deals with changes in land use taking into account the present land use pattern.

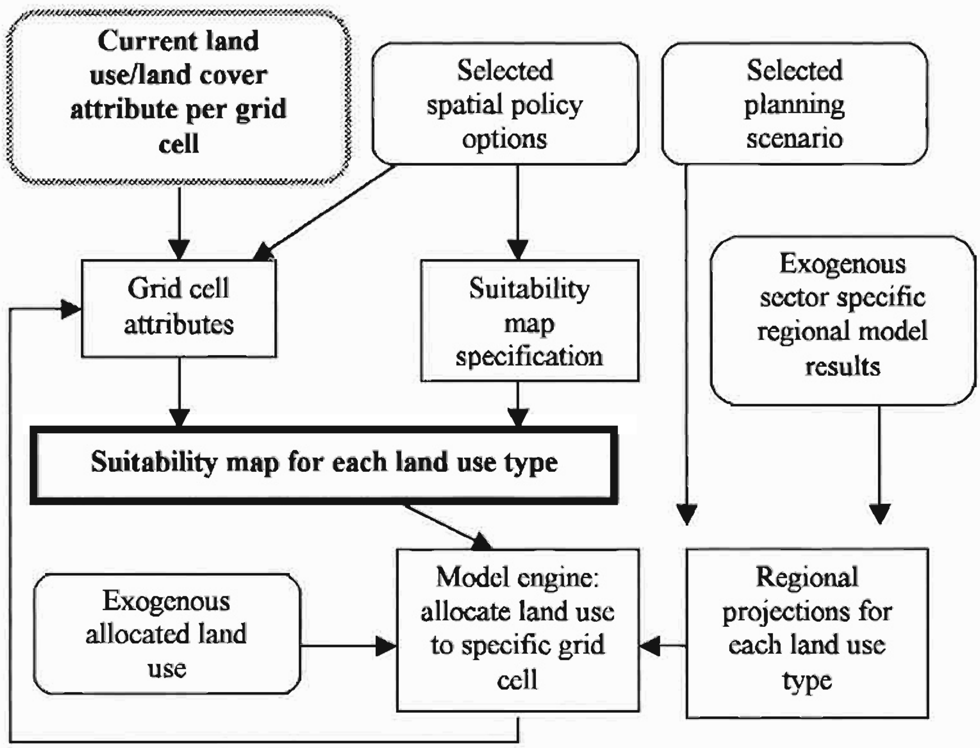


Figure 2.4. Overall model spatial planning structure related to digital data of land use/land cover. *(Adopted and modified from Scholten et al., 1999)*

2.4.7 Land use evolution and demographic pressure in Indonesia

Historically, land use inventories were initiated in 1930 when Sir Dudley Stamp for the first time undertook a land use inventory of the British Isles (Stamp, 1931). In Indonesia, systematic land use inventory started in 1960 (Sandy, 1995) as a follow-up of the Master Agrarian Act (UUPA) 1960, and land use inventory has been continually conducted since 1969 (Silalahi, 1999). Since that year, land use in all provinces in Indonesia has been mapped. The result is a land use map consisting of information of the pattern and spatial distribution of land use in all provinces in Indonesia.

Based on the spatial information of land use condition in all provinces, in 1977, Sandy (1977) produced a simplified model of land use evolution in Indonesia called the "schema of Land use Evolution in Indonesia" or "Skema Evolusi Penggunaan Tanah di Indonesia". This schema shows the evolution of land use pattern from schema A to schema I (see Figure 2.5). Schema A represents land use condition in area that humans have not settled yet, and schema I represents the land use pattern on critical condition, which is when some reserve area has been changed into marginal land.

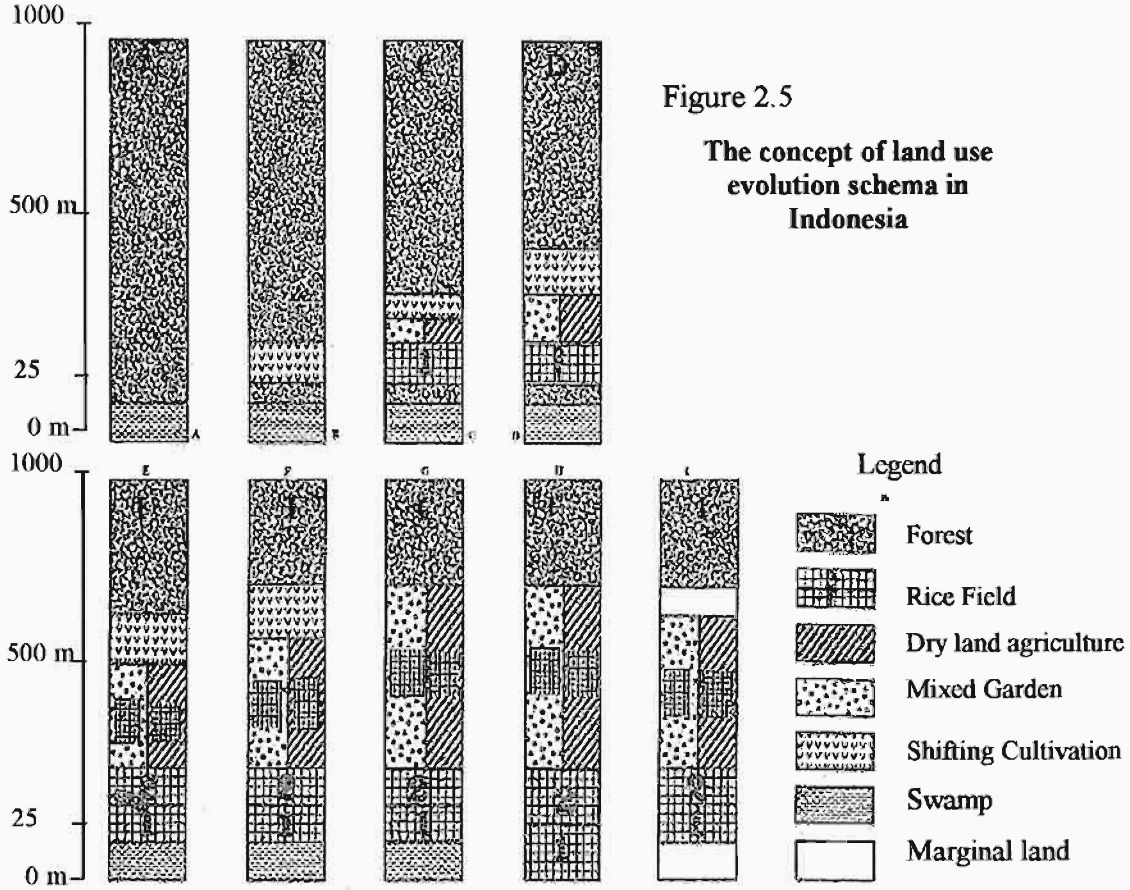


Figure 2.5

The concept of land use evolution schema in Indonesia

Source: Sandy (1977)

This land use pattern evolution is clearly recognized in Indonesia. One example can be seen in Figure 2.6 below that shows the land use evolution in the Indramayu area, West Java. Figure 2.6 (A) shows the land use condition as the same as schema D and E in 1857 when people start to develop their agricultural practices. Some dry agriculture areas have been converted into rice field and rain fed areas with 1 cycle and improved to 2 cycles rice field when supported by irrigation. Figure 2.6 (B) illustrates land use condition that has been changed similar to schema G and H by 1940. As an effect of population growth and improving agricultural practices, shifting cultivation has ceased, and some swamp areas have been drained and used for other agriculture practices. Land use condition the same as schema I is shown in figure 2.6 (C) for a depression area and Figure 2.6 (D) at high elevation area (mountain) in 1969. At this stage some marginal land present in the upper and lower areas begins to show effects of overuse.

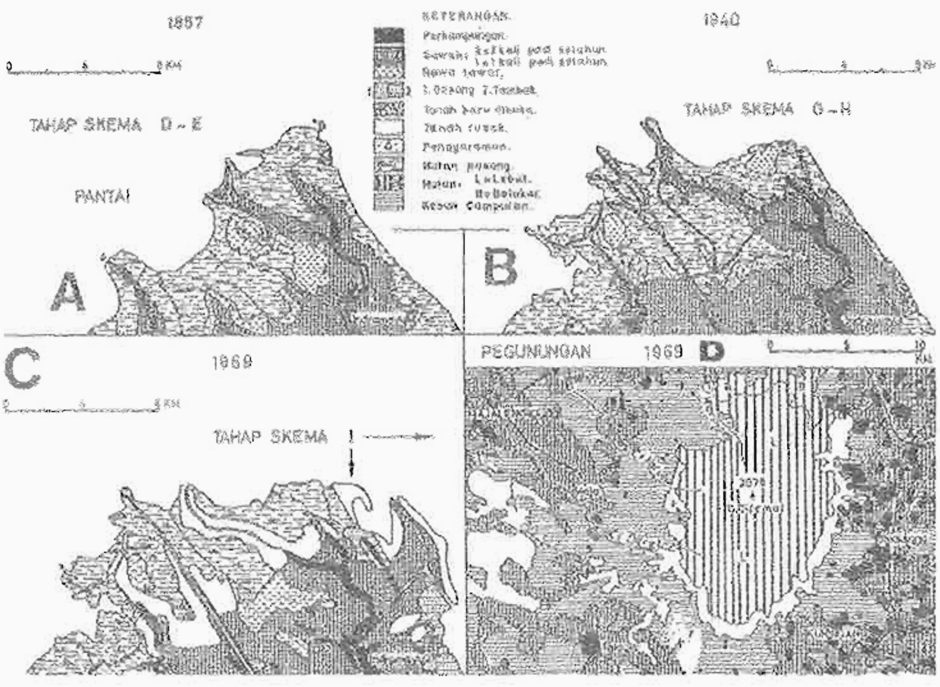


Figure 2.6 Land use evolution in Indramayu and its surrounding, West Java.
(Kartono *et al.*, 1998)

Silalahi (1999) conducted another study of land use change in Indonesia, which focuses on analytic comparison between conservation and cultivation areas. The study concludes that many factors affect land use change but the most significant factor is population, specifically the density, growth rate and the percentage of poor people. Land use changes in conservation areas are affected by population density and increases in land ownership (Silalahi, 1999).

The evolution of land use pattern that has been shown above and the study conducted by Silalahi (1999) focuses on the general scale and does not contain actual figures of land use conversion such as settlement and urban land use. The urban land use will continue to change with population growth and technological achievement. Firman (2000) conducted a study of rural to urban land conversion in Indonesia. This study concludes that the land conversion on the fringe areas of large cities in Indonesia in the 1990s has been largely due to the issuing of excessive land development permits granted by the National Land Development Agency. This conversion mainly involves land use change from agricultural into urban land use such as settlement, industrial and other commercial areas. Competition of land use in the urban areas will have an effect on land use in the countryside. The growth of Jakarta metropolitan city in Indonesia, for example, has a strong influence on land use change in other areas such as Bogor, Tanggerang, Bekasi and now through to Karawang and Cikampek as has been shown in Figure 2.2.

2.4.8 Land use/land cover change detection and spatial planning in Indonesia

Documentation of land use as well as other biophysical spatial data was conducted in Indonesia in the early 1960s (Sandy, 1995), but documentation in digital format began since the RePPProT (Regional Physiscal Planning Programme for Transmigration) project which was launched in the 1980s (Rais, 1997). Since this year several studies and a pilot project dealing with land use inventory and spatial planning on a digital basis have been conducted. Land Resources Evaluation and Planning (LREP), for example, is a project at the National-level to support spatial planning in Indonesia. This project began in 1987 and finished in 1993 and was coordinated by Bakosurtanal (The National Coordinator of Survey and Mapping Agency). Marine Resources Evaluation and Planning (MREP) is another National level project to support spatial planning, but mainly focuses on marine environments. Part of the results of these projects is providing spatial maps (base maps as well as bio-physical and land use/land cover maps) in digital format. Another pilot project that deal with spatial planning is the Land Use Planning and Mapping (LUPAM). This project, under technical aid from the German government, was implemented in the 1990s in the East Kalimantan province (GTZ, 2000). Some important information from these projects is that the land use/land cover change detection should be pursued in tandem with a streamlining of the spatial planning process. Spatial planning in Indonesian areas formerly controlled by central government (strictly a top-down approach) (UU No.24/1992) has been entangled in manifold inconsistencies with regard to competencies of different levels of government and the roles and required contributions from its stakeholders. The new paradigm in the period of Reformasi year 1999 supported by law No.22/1999 attempts to do the opposite (bottom-up planning approach) (UU No.22/1999). Through this new approach, the spatial planning process must be supported by adequate spatial data or information at appropriate scale. The government regulation No. 10/2000 supports this new spatial planning process with regards to requirement of an accurate and an appropriate map that has to be used. This law guides the office or institution responsible for spatial planning activities at any level (National, Province and District) to use maps of appropriate scales (Table 2.9).

Table 2.9: Scale map at different level of spatial planning application.

Name	Scale	Purpose
National Region Map	1:1000.000	Spatial planning at National level
Provincial region Map	1: 250.000	Spatial planning at Provincial level
	1: 100.000	Spatial planning at the provincial level
		that has small area of authority
Kabupaten/Kota madya	1: 50.000	Spatial planning at Kabupaten/Kota
(District/Municipality)		madya level
	1: 25.000 or	Spatial planning at the Kabupaten or
	1: 10.000	Kota madya that has small area of authority

Source: Government regulation No.10/2000.

As can be seen in Table 2.9, different scales are to be used for different level of spatial planning. To support spatial planning at the district level, for example, the map used required by the law, is a map with minimal scale of 1: 50.000 and for the small district/municipality a map of scale 1:25.000 or 1:10.000 must be used. This new law has implications for providing spatial data, include land use/land cover data, for spatial planning process. Figure 2.7 shows the integrated planning system for regional development in Indonesia, which uses current land use/land cover condition and other spatial and non-spatial data as a basis of this spatial planning process. Spatial planning covers physical planning and land use planning, which is closely related to, and should provide the basis for, regional or local development planning and sectoral planning as well as land resources management.

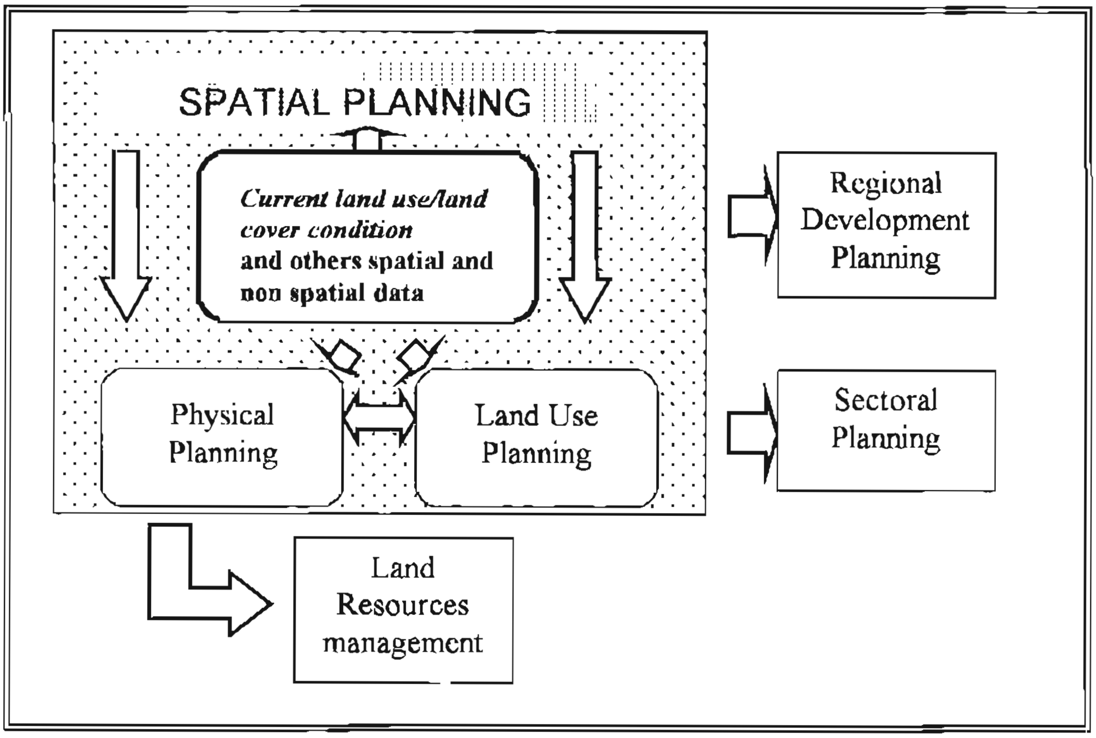


Figure 2.7 Integrated Planning Systems for Regional Development
(Adopted and modified from GTZ, 2000)

Spatial planning is the fundamental process to identify, analyse, and organise the physical requirements of a society's need and interests on a spatial and functional basis.

Physical planning is a more specific form of planning, which is the designing of the physical infrastructure of an administrative unit, such as transport facilities - roads, railway, airports and - facilities for towns and other human settlements in anticipation of population increase and socio-economic development. Physical planning is usually carried out by sectors in charge of planning and managing particular infrastructure

Land use planning is a process that facilitates the allocation of land to the uses that provide the greatest sustainable benefits (UNEP, Agenda 21, paragraph 10.5).

This schema has been introduced by GTZ to avoid the confusion of terms that indicate the differences in interrelations between the various plans and the inherent danger for overlaps and hence contradictions, between the spatial plans, development plans and land use plans in Indonesia.

2.5 Conclusion

This chapter has provided a review of land use/land cover change dynamics as well as land use/land cover definition and understanding, including some aspects related to land use/land cover change. The evolution of land use pattern in Indonesia has been presented to illustrate the relation of land use change and demographic pressure in the study area.

Land use and land cover definition depends upon the purpose of the application and the context of the study. Land use and land cover in this study has been defined as terms of "land use/land cover", which is land use representing human-induced intervention or manipulation of the land to provide food, building material, building site etc. Hence, land cover referred to the biophysical state of the earth's surface. It may incorporate the observed physical properties, including the vegetation (natural or planted) and human construction, which cover the earth's surface.

The interaction of human and biophysical factors influences the dynamics of land use/land cover change. This interaction is complex and needs to be simplified and categorized to identify the most influential human and biophysical causes of land use/land cover change. In relation to demographic pressure, land use/land cover change is associated with population growth. Population has a direct association with demand of land for their life and their activities, including agriculture activities. The initial response to increases in population pressure is agricultural extensification, when land becomes more difficult to access or only very marginal areas remain, after which intensification occurs.

The magnitude of lands use-land cover change is different at the global, national and regional level. It requires different scale maps or spatial resolutions. The more global the view the more simple is the land use/land cover category to be analysed and a smaller scale of map or lower spatial resolution required.

The spatial information of land use/land cover is the most important part of the spatial planning process. The importance of spatial data on spatial planning process in Indonesia is supported by the government regulation No.20/2000, which states that spatial planning must be supported by appropriate scale at each spatial planning level; National, Province and District.

Chapter Three

THE STUDY AREA AND SPATIAL DATA

3.1 Introduction

This study conducts an analysis of land use/land cover change in the downstream and surrounding areas of the Ci Tarum watershed. The Ci Tarum watershed is located in West Java province. Geographically, the area lies between 106 ° 57' - 107° 60' E and 5° 54' - 7°18' S. Administratively, the Ci Tarum watershed contains all or part of the districts (Kabupaten) Bandung, Sumedang, Purwakarta, Karawang, Bekasi, Bogor and Cianjur (see Figure 3.1). The upper watershed has a hilly and mountainous topography whilst the downstream area is coastal alluvial plain.

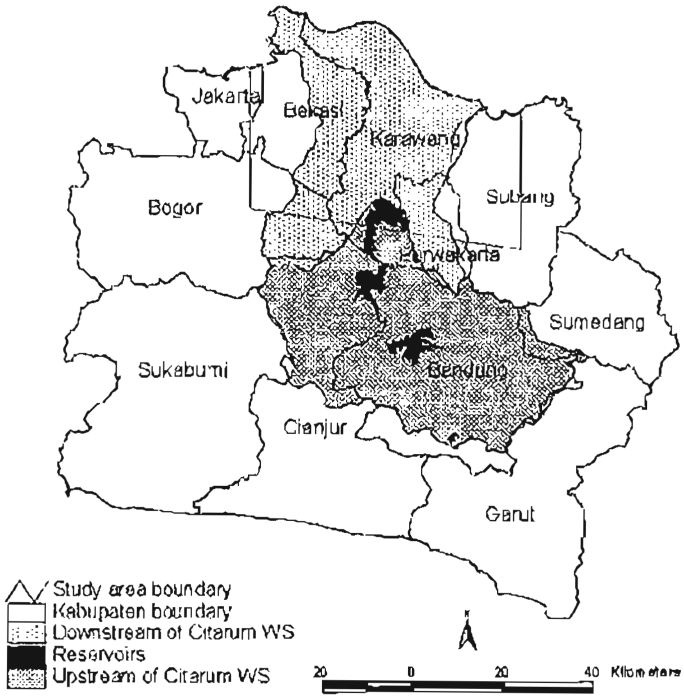


Figure 3.1. Study area as part of the Ci Tarum Watershed

This area was covered by two Landsat TM scenes 122/64 and 122/65 (path/row). Scene 122/64 covered the downstream and surrounding areas and scene 122/65 covered the upper watershed. Scene 122/64 is the only satellite data that are available for 5 consecutive years. Therefore, the area of study was focused especially in the downstream and surrounding areas of the Ci Tarum watershed consisting of all or part of the five districts (Kabupaten) Bekasi, Bogor, Karawang, Purwakarta, and Subang (Figure 3.2). This is an area of 503687 ha.

This chapter describes the social and biophysical environmental conditions in the selected study area affecting land use/land cover change and explains the availability of spatial data for the area.

3.2 Selection of Study Area

Since satellite data were not available for the whole Ci Tarum watershed, the selected area of this study is only the downstream watershed and its surroundings. The region of interest is mainly lowland, with the dominant land use/land cover being rice fields and settlement. This area has been a prime rice-producing region of Indonesia (World Bank, 1990) and also includes fast-growing industrialization and urbanization associated with the expansion of Jakarta, a city of 9 million people (Figure 3.3). Three large reservoirs have been constructed in the region; one is located in study area (namely the Jatiluhur reservoir). The other two are located in the upper Ci Tarum watershed - namely the Ci Rata and Saguling reservoirs. Jatiluhur is the largest reservoir and is a multipurpose reservoir, which supports irrigation for paddy/rice field downstream and as part of a hydroelectric power generation and supply system for the whole of Java and Bali, especially the growing mega city of Jakarta.

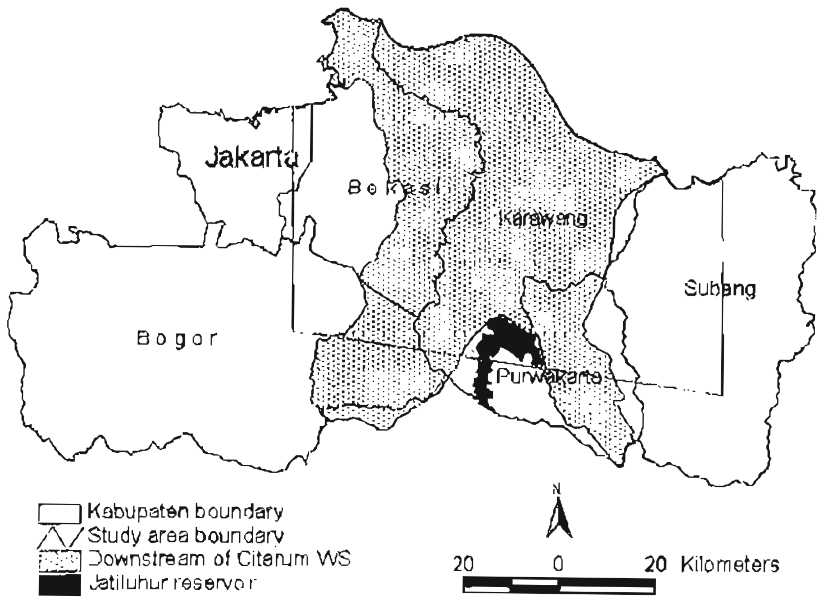


Figure 3.2 The five Kabupatens and Jakarta within the Study area

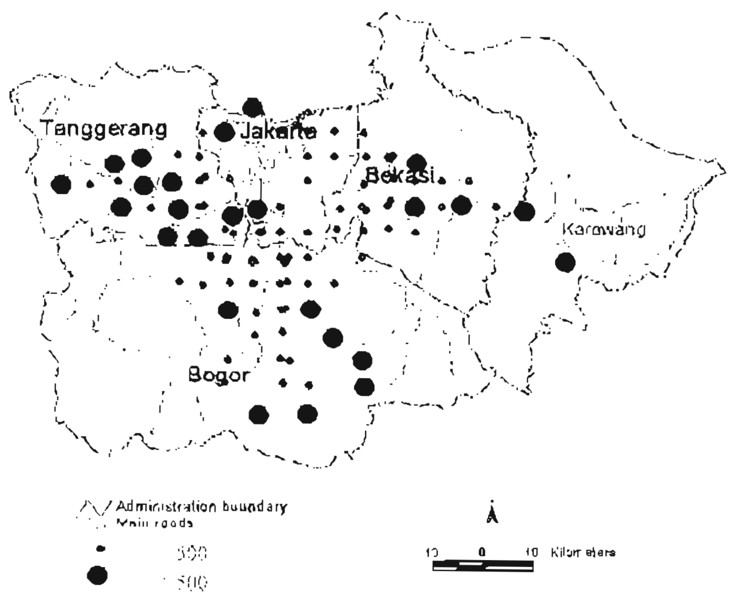


Figure 3.3. The New Town and Industrial estates development in Jakarta and surrounding areas. *(Source: adapted from Jayadinata, 1999: p 184)*

3.3 Socio-Economic Characteristics

The socio-economic and demographic conditions are generally similar in each kabupaten of the study area except kabupaten Bekasi that adjoins the special capital city district of Jakarta. The settlements are characterized by ribbon development along the roads. Currently, since the government of Indonesia constructed the Cikampek highway in mid 1985, some real estate and industrial plants, including a golf course, are located along this highway (Figure 3.4).

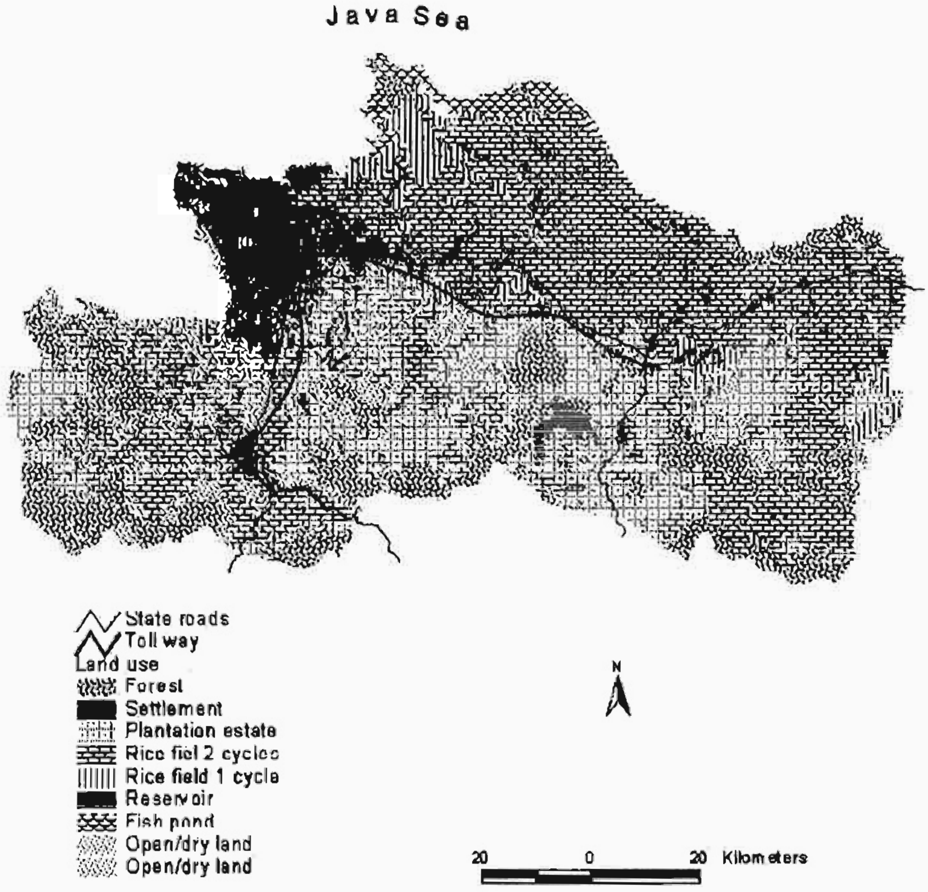


Figure 3.4. Land use of 1993 in five kabupaten within the study area and Jakarta city
Source: SARI Project BPPT, 1998.

3.3.1 Population and Demography

The total population in kabupaten Bekasi, Bogor, Karawang, Purwakarta and Subang in 1990 was 9.1 million and 11.3 million in 2000. The population growth rate in kabupaten Subang is low, 0.93%/yr during the period 1990-2000 (Table 3.1). On the other hand, population growth rates during the same period in kabupaten Bogor, Karawang, Purwakarta were high; about 1.33 – 2.40 %/yr and extremely high in kabupaten Bekasi (about 5.60 %/yr). For the whole kabupaten within study area, population growth rates during 1990– 2000 was 2.41 %/yr compared with 2.03 % in west Java and 1.4% in Indonesia.

Table: 3.1 Populations and Demographic Indicator

Indicators	Period/ Increase	Kab. Bekasi	Kab. Bogor	Kab. Karawang	Kab. Purwakarta	Kab. Subang	Total
Area (sqkm)	**1990**	1284.24	3357.92	1578.47	830.01	1864.02	8914.66
	2000	1284.24	3204.44	1578.47	830.01	1864.02	8761.18
	Change (%/Y)	0	-4.57	0	0	0	-0,13
No.of Population	**1990**	2104392	3736870	1491914	563039	1206664	9102879
	2000	3282238	4233224	1765263	698353	1319264	1129834 2
	Change (%/Y)	5.60	1.33	1.83	2.40	0.93	2.41
Population Density (per sqKm)	**1990**	1639	1113	945	678	647	1021
	2000	2556	1321	1118	841	708	1290
	Change (%/Y)	5.60	1.87	1.83	2.40	0.93	2.63
No. Of Households	**1990**	246934	708879	337229	120466	294171	1707679
	2000	864412	1029895	494158	186290	393337	2968092
	Change (%/Y)	22.73	4.11	4.23	4.96	3.06	6.71
Sex Ratio m/f	**1990**	1.00	1.03	1.00	1.02	0.98	0.98
	2000	1.01	1.03	1.01	1.02	1.00	1.01
	Change	0.01	0	0.01	0	0.02	0.03

Source: Central Bureau of Statistics; Compiled from Java in Figures, 1990, and 2000.

Table 3.1 also reveals that the number of households (one household consists of 4 to 5 persons) increases more rapidly than the population. In kabupaten Bekasi, and also in other kabupaten, the number of households increased compared to the population growth rate. In total, the number of households increased at 6.71 %/yr whereas the population growth rate was 2.41%/yr. As the number of households increases, the demand for housing units and settlement areas also increases. Thus, the trend (i.e. relative high growth rates of the number of households) signals the pressures from another forms of population dimension. This signal is the need for more spacious housing units.

3.3.2 Employment

The population aged 10 years or above in all kabupaten in year 1997 was 8.9 million, while in year 2000 it was 10 million or an increase of 12.4%. Of this part of the population, a total of 4.4 million in 1997 and 4.8 million in 2000 were in the labour force (Table 3.2). This further comes with a relatively high level of employment or employment ratio; 3.9 million working and 0.5 million seeking job in 1997 which increased in 2000 by 4.5 million working and 0.37 million seeking job.

At the kabupaten level, the role of the agriculture sector in offering employment opportunities for the ever-increasing labour force is still very significant; despite the fact that in the heart of the area near to the capital city, industrialization is progressing intensively. In kabupaten Bekasi and Bogor, located near to Jakarta, there are services, trade, hotel and restaurant (tourism), which offer considerable employment opportunities for the labour force. The role of industry (manufacturing) as the major sector offering employment opportunities can be clearly seen in the Municipality (Kotamadya) Bogor (Table 3.2). When comparing the labour force between kabupaten and municipality, it clearly recognised that labour force for industry is concentrated in the municipality. This indicates that a lot of areas have been changed to industrial or other commercial use such as for hotels, restaurants and golf. Therefore, land use condition in this area changed from agricultural to industrial area.

Table 3.2 Labour Force and Occupations in five Kabupaten and Kodya Bogor year 1997-2000

Indicators		Total in five kabupaten		Change	in Kodya Bogor		Change
		1997	2000	1997-2000	1997	2000	1997-2000
No.Of Population;=> 10 years		8878373	10052676	1174303	235638	624264	388626
Labour Force:	Working	3903838	4509838	606000	87344	258725	171381
	Seeking job	540890	373959	-166931	16218	26786	10568
	Total	4444728	4883797	439069	103562	285511	181949
Occupation by Sector;% of Working labour force:							
a. Agriculture		147,41	152,67	5,26	6,19	3,73	-2,46
b.Mining and Quarrying		6,21	3,39	-2,82	0,97	0,59	-0,38
c.Industry		87,92	76,6	-11,32	25,24	22,6	-2,64
d.Electricity,Gas & Water Supply		3,11	1,71	-1,4	0,73	0,37	-0,36
e.Construction		31,95	21,28	-10,67	8,98	6,16	-2,82
f.Trade, Hotel & Restaurants		111,41	129,27	17,86	21,48	30,98	9,5
g.Transportation		39,25	52,67	13,42	5,46	5,61	0,15
h.Bank,Financial Intermediaries		5,47	2,52	-2,95	3,16	2,14	-1,02
I.Services		66,97	59,89	-7,08	27,63	27,83	0,2
j.Others		0,3	0	-0,3	0,16	0	-0,16
	Total	100	100		100	100	

Source: West Java in Figures, 1997 and 2000.

3.3.3 The Land Tenure.

Between the two most recent agricultural censuses (i.e. 1983 and 1993) there was a substantial decrease in the area of agricultural land in Indonesia, especially in Java. However, Table 3.3 shows that there was an increase in the number of agricultural households over the same period. The reduction of agricultural land in Indonesia was 1.10-milion hectares in ten years or approximately 110,000 hectares per year. On the other hand, the number of agricultural households increased by about 2.49 million or approximately 249,000 households per year. The most important consequence of this change is in the average size of landholdings. In Indonesia, the average size of landholding per household has declined from 0.98 hectare in 1983 to 0.83 hectare in 1993; approximately a decrease of 15.31%.

Table 3.3. Changes in Agricultural Land and Households in Indonesia 1983 – 1993

ITEMS	1983-Agricultural Census	1993-Agricultural Census	Change
1. Area (Million Hectare)			
Java	**5.42**	**4.41**	**-1.01**
Bali & Nusa Tenggara	1.22	1.07	-0.15
Sumatra	5.66	5.42	-0.24
Sulawesi	1.64	1.78	0.14
Kalimantan	2.23	2.19	-0.04
Maluku	0.38	0.4	0.02
Irian Jaya	0.17	0.18	0.01
Total	16.72	15.45	-1.01
2. Number of Households (Thousand)			
Java	**11,108**	**11,593**	**488**
Indonesia	18,693	21,183	2,490

Source: Central Bureau of Statistics

In Java, the decrease of agricultural land was 1.01 million hectares, or 101 000 hectares per year, whereas the number of agricultural households increased by 448 000 over the decade. This has caused a reduction of average size of landholdings, from 0.58 hectare in 1983 to 0.47 hectare in 1993; or 18.97% decrease.

Apart from farm size, the distribution of land holdings needs to be considered. In Indonesia, in 1993, the number of households with size of land-holdings less than 0.50 hectares was 10.94 million or 51.63% of the total agricultural households. In Java, the distribution was even worse. In the same year, numbers of households with farm size less than 0.50 hectare was 8.10 million or 69.85% of total households in Java. The number of households of this category (farm size<0.50 ha) has increase by 795,000 or approximately 11% compared to that in 1983.

The type of agriculture land use is also significant since it implies productivity of the land and, thus, farm incomes to the owners and operators. One of the most productive agricultural lands is wetland or irrigated rice farms supported by irrigation facilities. Wetland rice in Java has decreased from 2.95 million hectares in 1983 to 2.51 million hectares in 1993; a reduction by 14.87% or 43,800 hectares per year. The reduction in agricultural land, particularly in Java, gives more space for the development of industrial sites, settlement, infrastructure and facilities, and other purposes (Table 3.4).

Table 3.4: The change of Agricultural land to other land use: Year 1981-1999 (Ha)

Change from Agricultural land to:	West Java	Central Java*	East Java	Indonesia
Settlement	15847.00	22405.45	20872.87	72994.12
Industry	10771.00	1959.45	2870.42	18262.38
Dry Land	8080.99	26200.28	14177.67	50640.16
Plantation	6952.00	1338.00	51577.00	61599.85
Open Land	55.00	8.33	30.23	106.66
Water	1248.82	1349.93	6316.25	9004.23
Other	6809.00	10000.02	10626.90	33885.23
Total	49763.81	63261.46	106471.34	246492.63

Source: Dep. Of Agriculture and National Land Agency
*Note: * including Yogyakarta*

In the case of wetland rice field, the developments have led to a situation where rice farming no longer is competitive, even compared to other crops such as horticulture. Near the major growth centres, wetland rices farms have given away to horticulture crops (vegetable, flowers, etc.) and for animal husbandry (especially broiler). On the other hand, industrialization does not guarantee more employment opportunities for the people.

3.3.4 Existing Land Use

Land use and land tenure are two aspects that should not be neglected in the discussion since the two are strongly related. Information on present land use in the study area can be seen in Table 3.5. The figures in Table 3.5 and Figure 3.4 reveal the decrease of the area of irrigated wetland rice field (i.e. technical, semi technical and non technical irrigation); from 349437 hectare in 1989 to 288108 hectare in 1997 and 272604 hectare in 2000; which confirms what has been discussed in land tenure. The areas of dry land farm (i.e. dry field, grassland, temporary fallow etc. except housing compound) have also decreased. The reduction of this area is due to the increase in land used for house compounds and yards. The area of housing compounds has increased from 127729 hectare in 1987 to 166761 hectare in 1997 and to 176679 in 2000.

Table 3.5 Existing Land use in the five kabupaten within study area (Ha)

Category	Type of Use	1989	1997	2000
WETLAND	Technical Irrigation	198185	196409	188580
	Semi technical Irrigation	37682	27758	25915
	Non technical Irrigation	62339	29946	20191
	Rain fed	50003	33965	37918
	Others	1228	30	0
	Total	349437	288108	272604
DRYLAND	Housing Compound and Yards	127729	166761	176679
	Garden/dry field	126015	146747	129961
	Grass land	91542	2613	2513
	Temporary fallow	4753	3218	2696
	Private wood Forest land	51696	26988	36456
	State Forest	140236	95114	96557
	Estates/Tree Crops	82453	60324	58003
	Swamps	11550	8855	17029
	Ponds	16040	26172	16564
	Others	0	66509	60158
	Total	511778	603301	596616

Source: Central Bureau of Statistics; West Java in Figures, 1989,1997 and 2000.

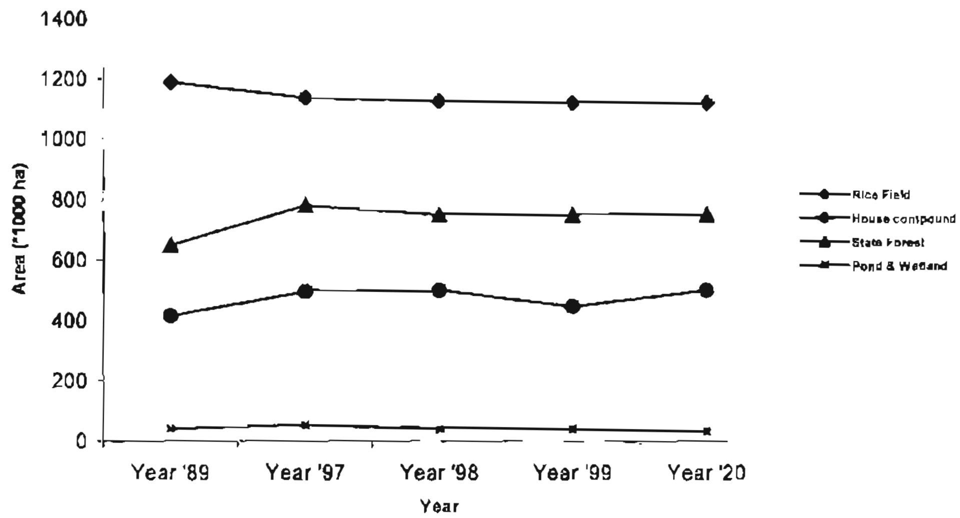


Figure 3.5 Main Land use in West Java: 1989-2000

3.3.5 Infrastructure

The provision of infrastructures (i.e. roads, electricity, water supplies) is a prerequisite for development, in particular to promote industrialization. Figure 3.6 shows the road network that passes through the study area and connects several big cities surrounding of the study area, i.e. Cirebon, Bandung Cianjur, Sukabumi and Jakarta. This road accessibility will have an influence on accelerating the development process and land use allocation.

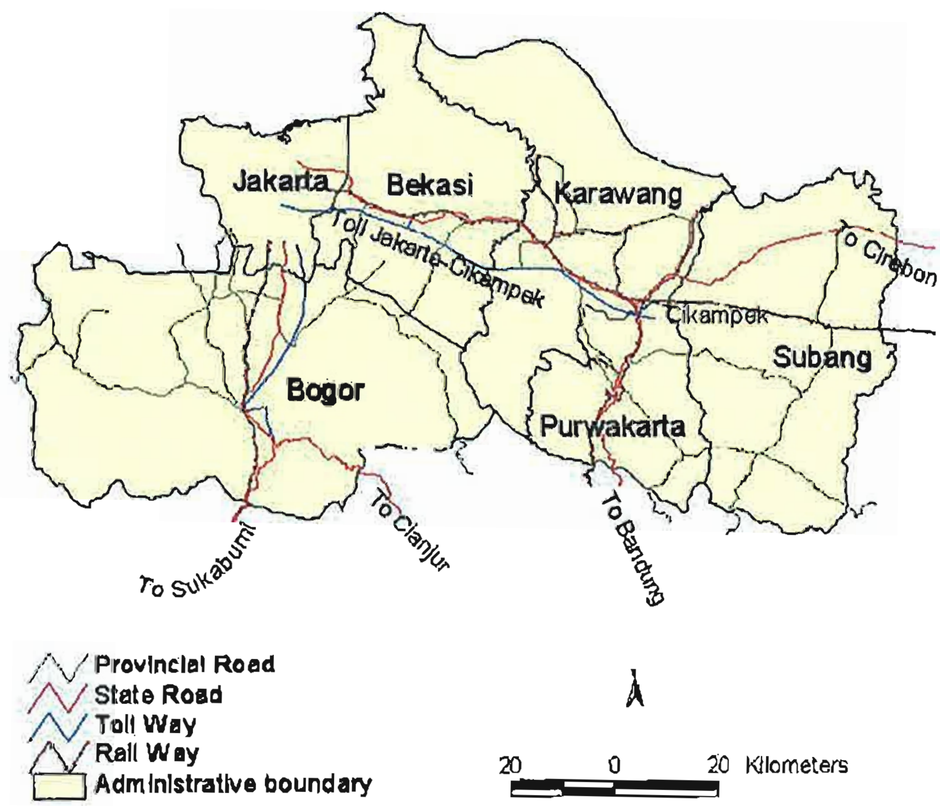


Figure 3.6. Roads networks in five kabupaten within the study area.

Table 3.6.below provides also some information on the infrastructures situation in the study area. Road length in whole area has increased by 2334.94 kilometres or 54.82 % in an eleven-year interval (West Java Statistic office). During the 1989 to 2000 time interval, there was a significant increase in road length in kabupaten Bekasi, Karawang and Subang. This increase related to construction of the Jakarta – Cikampek highway (Toll way); this had an effect on construction of connecting roads in this surrounding kabupaten.

Table: 3.6. Infrastructure in five kabupaten within the Study Area.

Infrastructures	Period	Kabupaten Bekasi	Kabupaten Bogor	Kabupaten Karawang	Kabupaten Purwakarta	Kabupaten Subang	Total
ROADS (km)							
Type of surface:							
Asphalted	**1989**	266.70	1219.00	313.45	307.32	238.41	2344.88
	2000	842.82	1288.84	768.23	330.80	722.61	3953.30
Stone/gravel's	**1989**	174.00	298.20	169.00	79.97	228.37	949.54
	2000	121.70	315.32	552.09	72.20	139.90	1201.21
Soils	**1989**	113.00	55.15	150.70	65.81	580.24	964.90
	2000	116.30	55.67	1204.48	0.00	63.30	1439.75
Condition:							
Good	**1989**	54.80	489.80	319.81	252.63	238.04	1355.08
	2000	133.96	479.45	663.41	114.70	150.66	1542.18
Moderate	**1989**	286.70	770.20	150.79	111.91	228.38	1547.98
	2000	220.06	404.11	77.83	204.06	342.25	1248.31
Damaged	**1989**	213.00	201.75	68.60	76.65	580.25	1140.25
	2000	719.65	1139.1	26.99	32.40	276.20	2194.34
Heavily damaged	**1989**	16.20	110.60	93.95	1191.00	0.00	1411.75
	2000	127.15	102.34	1756.57	51.84	257.50	2295.40
ELECTRICITY							
Power Installed (KwH)	**1997**	153791	660014	90828	109759	No data	1014392
	2000	1617586	940905	582967	389611	No data	3531069
No.Of Customers	**1997**	218795	389661	118004	184148	No data	910608
	2000	444867	513348	283183	335770	No data	1577168
Electricity sold (KwH)	**1997**	2176458	1934065	954057	1152840	No data	6217420
	2000	2679847	2191483	1607769	1276885	No data	7755984

Source: Compiled from West Java in Figures, 1989, 1997 and 2000

Rapid increases of the road length suggest rapid development of industrial and settlement areas located in the back-up area surrounding the highway (Karawang and Bekasi) where the price of land is still relatively cheap compared to areas close to Jakarta. Only with new road construction can the accessibility of those back-up areas be enhanced meaningfully.

The development of industry and services in the metropolitan area of Jakarta and other cities within the study area such as Boor, Bekasi and Karawang, also places more pressure on the demand for electricity. Factories, hotels, restaurants, resort areas, recreational facilities and places, shopping centres, education centres, etc. demand more electricity as compared to when such activities have not been intensifying. Table 3.7 shows that the number of electricity customers significantly increased in all kabupaten except kabupaten Subang (no data available) from 910608 in 1997 to 1577168 in 2000, or an increase of 73.20 % in a 3-year time interval.

3.4 Biophysical Characteristics

The physical environment conditions such as topography, physiography, soil and climate, influence the variations in land use/land cover type both temporally and spatially. Robinson (1994 pp 4) argued that physical conditions such as soil, topography and physiography are the primary constraints of agricultural expansion and other land use practices. Therefore these parameters have to be known and recognised in order to analyse land use/land cover change in the study area.

3.4.1 The Physiography and Soil type

Java consists largely of a series of east-west trending physiographic regions: a northern based coastal belt of alluvial plain, a central belt of volcanic mountains with a series of inter-mountain basins, and a southern belt of limestone hills. The study area is a part of north coastal belt of West Java. In more detail, this area can be divided into four types of physiography: "Flat", "Rolling hill", "Volcano", and "Rolling hill and Volcano". The flat area is mostly located within elevation between 0- 499 m above sea level; for the rest, elevation varies from 500 to 1499 and > 1500 m. The volcanic area is mostly located within elevation between 500 – 1499 m above sea level (Figure 3.7 and 3.8).

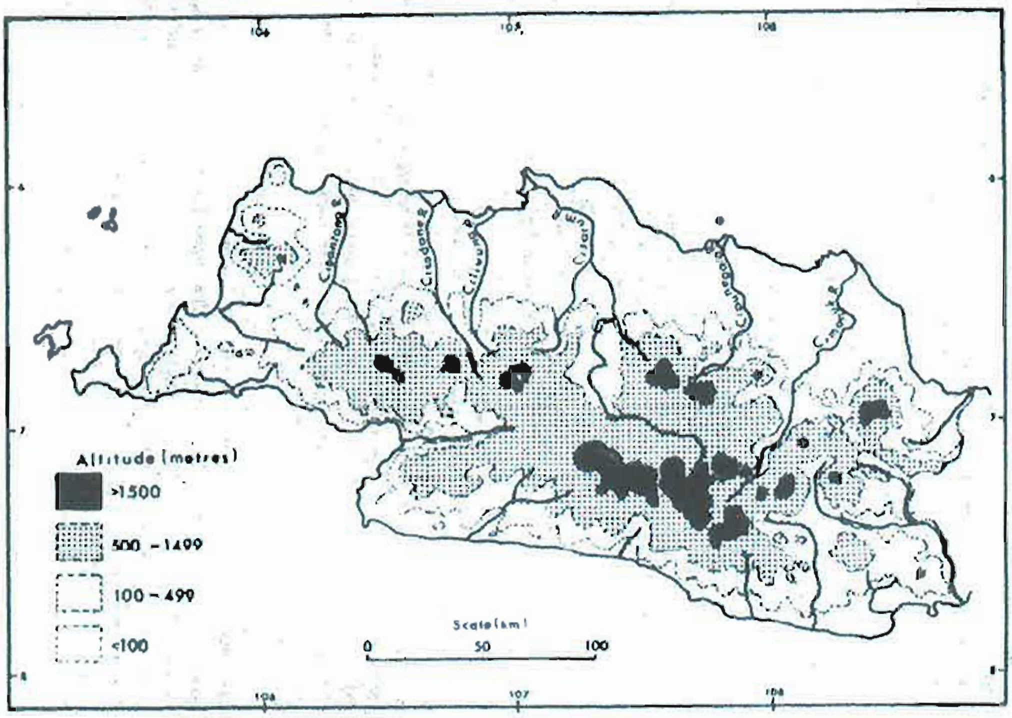


Figure 3.7. The Relief of West Java (source: adapted from Hugo, 1981: p 20)

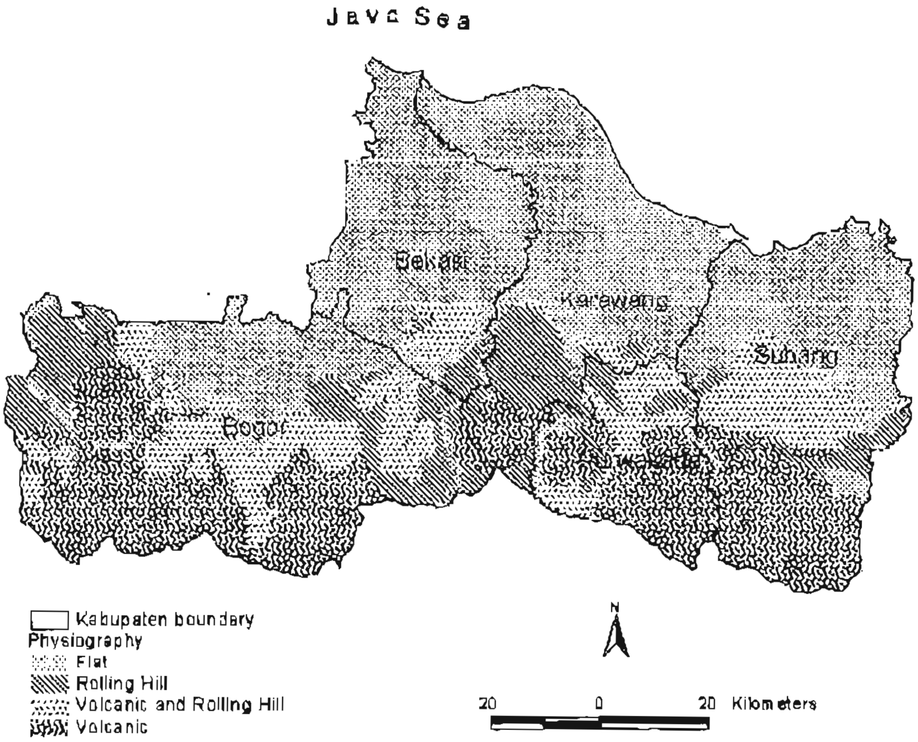


Figure 3.8. The Physiography in five kabupatens within the Study Area
(Source: BAKOSURTANAL, 1992)

Figure 3.9 shows the soil type in the five kabupaten within study area. Distribution of soil type in this area was influenced by active volcanos in the south part of study area; the type of soils are varied and underlined sedimentation of tuff volcanic. The alluvial soils mainly lay on the flat area in the north part, which was influenced by tuff volcanic sedimentation. Some andosol lay on the mountainous area in the southern part of study area, while latosol and podsolic are dominant in the central of the study area.

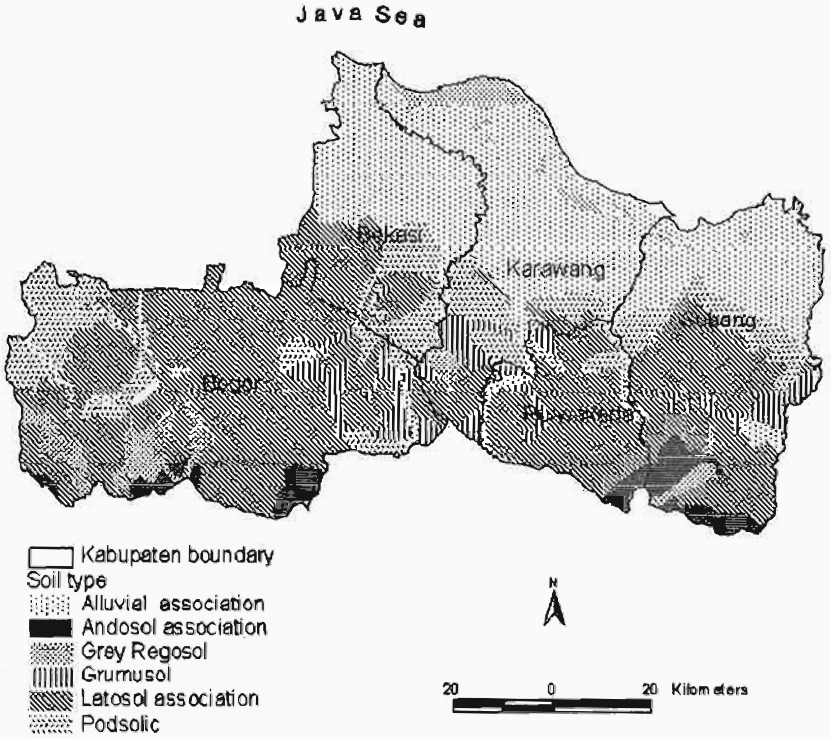


Figure 3.9. Soil type in five kabupaten within the study area
(Sources: RePPProt, 1986)

3.4.3 Climate, Irrigation and Growing season

In general, west Java receives rainfall under the influence of the West Monsoon (November to April) and East Monsoon (May to October). Due mainly to topographic effects, the rainfall is lowest along the northern coast and tends to increase as one moves inland to the more elevated areas. Figure 3.10 shows rainfall zones of the region differentiated according to the average number of dry (less than 60 mm of rainfall) and wet (more than 100 mm) months recorded (Hugo, 1981).

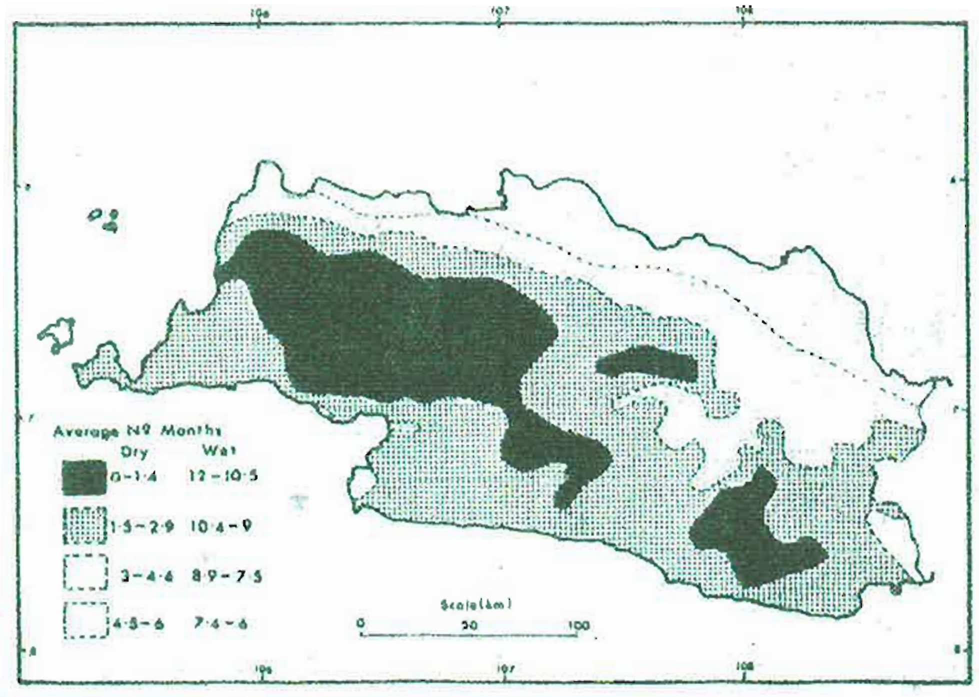


Figure 3.10. The Rainfall Regimes in West Java.
(Source: Hugo, 1981: p 21)

The rainfall distribution throughout the year is an important limiting factor to agriculture and hence density of settlement. The monthly rainfall regime throughout the year shows the dry and wet season cycle in the study area (Figure 3.11). The wet and dry season affect the growing season of rice. In the areas that are not irrigated, rice has only one growing season. The growing season cycle is improved to two cycles with the support of an irrigation system. The Jatiluhur reservoir has as its main function to irrigate the agricultural area on the northern part, which is mainly wetland rice fields, and maintains two growing cycles in this area (Table 3.7).

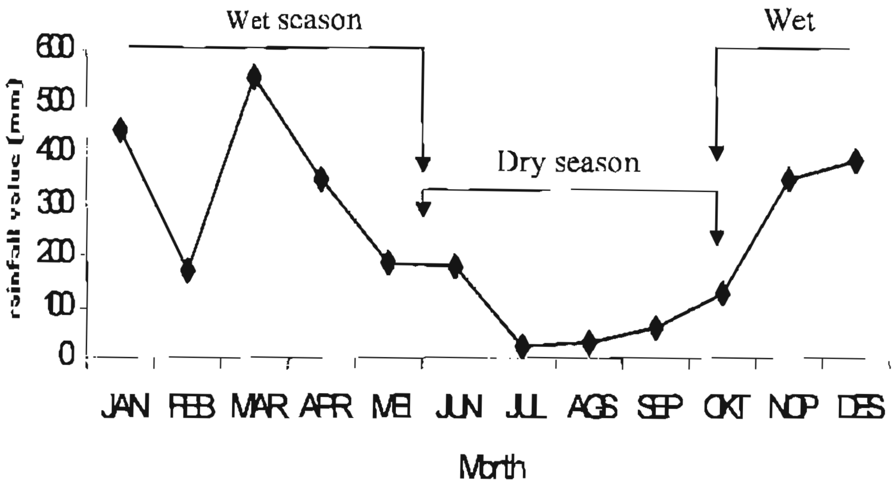


Figure 3.11. The monthly rainfall regimes in the study area
(Source: Meteorology and Geophysics Agency)

Table 3. 7. The Growing season schedule

Cycle I			
Bloc	Irrigating	Planting	Harvesting
I	October 1st	November 1st	January 1st
II	October 16st	November 16st	January 16st
III	November 1st	December 1st	February 1st
IV	November 16st	December 16st	February 16st
Cycle II			
Bloc	Irrigating	Planting	Harvesting
I	March 1st	April 1st	June1st
II	March 16st	April 16st	June 16st
III	April 1st	May 1st	July 1st
IV	April 16st	May 16st	July 16st

Source: Jatiluhur Company, 1998

There are three main irrigation systems from Jatiluhur reservoir that irrigate the rice field area in the study area. One is the east Tarum, which irrigates the eastern part of rice field area such as in Subang and Indramayu. Another is west Tarum which irrigates the western part of rice field area such as in Bekasi, as well as supplying fresh water to the Jakarta metropolitan city. The third is central Tarum that irrigates the rice field area mainly in the kabupaten Karawang (Figure 3.12).

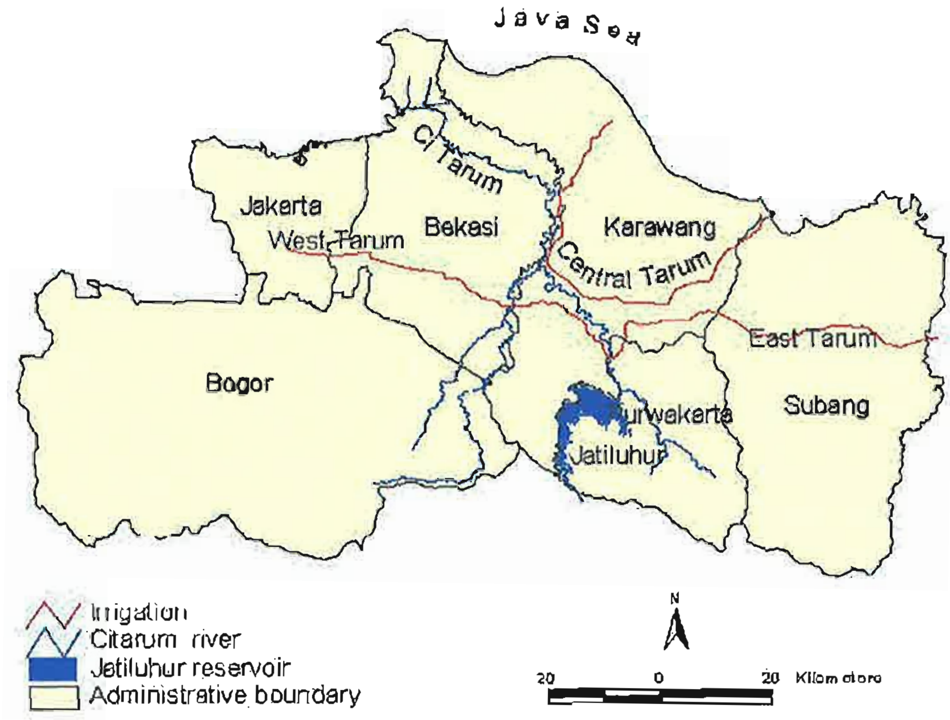


Figure 3.12. The Ci Tarum River and irrigation in the Study area

3.5 The Availability of Spatial Data

3.5.1 Existing spatial data

The main aims of this study are land use/land cover change detection, analysis and prediction by using remote sensing and GIS techniques. Spatial as well as temporal scales have an implication on the magnitude of land use/land cover change analysis. This study is concerned with land use/land cover change analysis at the spatial scale based on the resolution of Landsat TM satellite imagery. The spatial resolution of Landsat TM is 30 m. Several types of spatial data and non-spatial data were collected, constructed and converted into digital format and used as sources to construct a spatial database for further qualitative and quantitative analysis in relation to socio-economic and bio-physical driver factors of land use/land cover change.

The spatial data were available from several government agencies such as BAKOSURTANAL (The National Coordinator for Survey and Mapping Agency), Department of Forestry, BPN (National Land Agency) and Department of Mining and Energy. Each agency has its own form and content of maps. BAKOSURTANAL, which is the main agency to provide base maps, for example, Topographical maps for the whole Indonesian authority at scales 1: 250 000, 1: 100 000, and 1: 25 000. Other institution such as the Department of Forestry, the Centre of Soil and Agro-climate Research, and the Department of Mining and Energy are the institutions which provide addition spatial data such as forest cover, soil types, and geology as well as physiography. The Department of Forestry concentrates on forest mapping at scales of 1: 25 000 and 1: 50 000, while BPN creates land use maps at scales of 1: 25 000 and 1: 50 000. These maps consists of land use type which have to be updated at least every 5-year (Silalahi, 1999). Table 3.8 shows the agencies that are involved in spatial data collection.

Several spatial datasets that were used in this study consists of administrative (Kabupaten and Kecamatan) boundary, roads, rivers and irrigation of west Java sourced from BAKOSURTANAL topographical map for the year 1993 with a scale of 1: 250 000; soil type and physiographic condition maps from RePProt for the year

1986 with a scale of 1: 250 000; land use type for the year 1993 source from SARI project BPPT with a scale of 1: 250 000.

Table 3.8. Partial list of Land Resources Inventory and Mapping Agencies in Indonesia

Armed Forces Survey and Mapping Service
- Army Topographic Service (PUSURTAABRI)
- Naval Hydro-Oceanographic Service
- Air Force Aerial Photographic Service

BAKOSURTANAL (National Coordinating Agency for Surveying and Mapping)

Directorate of Geology
- Geological Mapping Division

Meteorology and Geophysics Agency

LAPAN (National Space and Aeronautics Institute)

Ministry of Agriculture
- Centre of Soil and Agro-climate Research
- Directorate General of Estates

Ministry of Forestry (MOF)
- Agency for Forest Land use Inventory

Ministry of Home affairs (MHA)
- Directorate General, Agraria
- BAPPEDAs

Ministry of Public Work (MPW)
- Directorate General for Water Resources Development (DGWRD)
- Directorate General of Human Settlement (Cipta Karya, DGCK)
- MPW Mapping Centre (PUSDATA)

Ministry of Transmigration
- Directorate General for Site Selection Planning and Programming

Pertamina (the national oil production corporation)

Source: World Bank (1990).

3.5.2 Satellite imagery

Seven Landsat TM images path/row (122/64) taken at the Dry season and the late Wet season were available for the years 1989, 1990,1991,1992,1993, 1995 and 1998 (Table 3.9). It is difficult to get imagery for the same times due to the cloud cover in this area - the acceptable cloud cover is < 10% (NRCT, 1997). These images were provided by BPPT (The Agency of the Assessment and Application of Technology) of the Government of Indonesia under Land use/land cover (LULC) Indonesia case study program (SARCS, 1997)

Table 3.9 Landsat TM data

No	Path/Row	Level	Date of acquisition	Climate condition
1	122/64	5	6-Jun-89	Dry Season
2	122/64	5	9-Jun-90	Dry Season
3	122/64	5	25-May-91	Wet Season
4	122/64	5	30-Jul-92	Dry Season
5	122/64	5	12-Apr-93	Wet Season
6	122/64	5	24-Aug-95	Dry Season
7	122/64	5	12-Jun-97	Dry Season

This satellite data were acquired at NRCT's (National Remote Sensing Centre of Thailand) receiving station in Bangkok at level 5. Level 5 means radiometrically corrected with two-dimensional re-sampling to a map projection. All images were rectified to Universal Transverse Mercator (UTM-48) coordinates using GPS data at selected sites within the study area. Landsat TM has 30x30 m spatial resolution and 16 day temporal resolution.

The satellite image for the Indonesian area can also be acquired from the LAPAN ground station in Pare-pare South Sulawesi. This ground station is capable of receiving and processing SPOT and Landsat TM data. These satellite data were useful to provide information of natural resources on spatial basis, which overpass the same area every 28 days for SPOT and 16 for Landsat satellite. The limitation of these satellite data is that the spatial resolution is less that of terrestrial mapping.

3.6 Conclusion

The aim of this chapter was to describe the social and biophysical environmental background of the study area, as well as the availability of spatial data for the purpose of the study. The selected study area is the downstream and its surroundings of the Ci Tarum watershed. This area was a prime rice-producing region and includes an area of rapid industrialization and urbanization associated with the expansion of the mega city of Jakarta. The other reason to select this area is the availability of satellite imagery on an annual basis. Only the scene 122/64 covers the study area, which is available in 5-years consecutive and free of cloud cover. The annual satellite image was needed to detect annual land use/land cover change in the study area.

The region of interest of this study is mainly lowland, with the dominant land use/land cover being rice fields and settlement. Physiographycally, this area mostly consists of a "flat" physiographic with elevations between 0 – 500 m above sea level.

Population growth is relatively high compared with population growth at the national level. Population growth in Kabupaten Bekasi was higher than in the other kabupaten. Kabupaten Bekasi was located near to Jakarta the city of 9 million people.

Several types of spatial data and non-spatial data that related to this study were collected from different agencies. The satellite images were acquired for the dry and the late wet season on annual base years: 1989,1990,1991,1992,1993, 1995,and 1997.

Chapter Four

LAND USE/LAND COVER CHANGE DETECTION; Using Remote Sensing and GIS Techniques

4.1 Introduction

Land use/land cover dynamically changes as a result of social and biophysical factors. The term land cover has commonly been used in association with land use and is often the focus of remote sensing analysis. Remote sensing provides a variable source of data from which updated land cover information can be extracted and enables the detection of land use/land cover change.

Land use/land cover change when one land use is converted to another is relatively easy to detect, in contrast to detecting land use transformations. The difficulty of detecting land use/land cover transformations is due to the mixes within land cover types. For example, it is difficult to differentiate residential and commercial areas within urban land use or between food crop plantations within agricultural land use. There are many image processing techniques (called digital change detection techniques) that are used to identify land use/land cover changes. The selection of an appropriate technique needs to take into account landscape structure, spectral signatures and radiometric corrections.

In Indonesia, which is a tropical area, land use/land cover is often dynamic and can change due to weather or climate conditions and seasonal growing cycles. Sharkov (1998, p. 175) stated that the various components of the physical environmental such as climate, soil, vegetation type, weather and relief contribute significantly to land use/land cover change. Within these conditions, land use/land cover can be difficult to detected using conventional techniques such as terrestrial mapping or surveying on short time scales. Although these techniques may achieve more detail, in terms of spatial resolution, they need more time to collect information over large areas. Land use/land cover may change significantly while the mapping is still being undertaken. Therefore, techniques that can quickly identify and detect land use/land cover, such as remote sensing analysis, can be very useful.

The spatial accuracy of land use/land cover detection is also related to the spatial resolution of the imagery used. The spatial resolution of Landsat TM imagery is 30 m, which can differentiate the detail of urban land cover from vegetation and agricultural land covers (Johnson *et al.*, 1989).

This chapter presents a review of digital change detection methods as well as the results of land use/land cover change detection in the study area. The results of the land use/land cover change are then used as an input into the land use/land cover change model described.

4.2 Land use/land cover change detection techniques

There are a number of methods for obtaining land use/land cover data, such as terrestrial surveys or mapping and remote sensing techniques. Terrestrial surveys or mapping are direct mapping techniques that have the advantage of obtaining more detailed information and can produce large-scale maps. The main disadvantage of this technique is the time required to cover large areas. Other techniques include mapping from aerial photography from aircraft or by remote sensing from airborne or satellite platforms. Aerial photography has proven to be a popular approach to the description and analysis of land use/land cover and land use/land cover change, both at a localized scale and for broader areas (Foster, 1985; Bryant *et al.*, 1986). Some disadvantages of aerial photography include timeliness, cost and comparability of photo interpretation over time when different interpreters are involved. Using remote sensing techniques, land use/land cover can be recorded over relatively large area and with reduced time between the completion of data collection and actual field conditions. However, the disadvantage of remote sensing techniques is that the spatial resolution is generally less than the result from terrestrial mapping.

In spite of its limitations, remote sensing plays an important role in the acquisition of land use/land cover data. Remote sensing techniques enable the collection of land use/land cover data in a digital format and the easy integration and analysis with other digital spatial databases. Table 4.1 shows the comparison of the terrestrial and remote sensing techniques to map land use/land cover conditions.

Table 4.1 The Comparison of the Terrestrial, Air photos and remote sensing Techniques.

	Approach	Product	Advantages	Disadvantages
Terrestrial techniques	Direct ground survey and mapping	Map analog or Digital	Detail map with high spatial resolution, good for small area	High cost and time consuming
Aerial mapping	Air photos interpretation	Map analog or Digital	Semi-detail map medium spatial resolution	High cost and time consuming
Remote Sensing techniques	Image Processing	Image and map Digital	Cover large area quick, multi tem poral acquisition easy to be pro- cess for further purposes	Less spatial resolution, need to be improved by ground truth

Source: From various literature: Jensen, 1996, Lillesand, 1987 and Lindgren, 1985.

Over the last two decades, remote sensing techniques have been increasingly developed and intensively used for natural resource inventories including land use - land cover monitoring (Weismiller *et al.,* 1977; Angelici *et al.,* 1977; Brera and Shahrokhi, 1978; Gordon, 1980; Jensen 1986; Quarmby and Cishnie, 1989; Green *et al.,* 1994; Li *et al.,* 1998). Since the first Earth Resources Technology Satellite (ERTS-1), later called Landsat 1, was launched in 1972, activities dealing with the natural resources inventory and land use/land cover change detection using remote sensing techniques have been conducted. Landsat 1 (MSS) had a spatial resolution of 80 m. With this spatial resolution, land use/land cover types smaller than 80 m x 80 m could not be recorded. Later, other natural resources satellites with finer spatial resolutions were launched. Spot 1 was launched in 1985, Spot 2 in 1990, and Spot 4 in 1998, all of which have four bands, two in the visible infrared, and one in infrared with a spatial resolution of 20 m and a broad visible infrared (panchromatic) with spatial resolution of 10 m. Landsat 5 TM was launched in 1982 and Landsat 7 TM was launched in 1999 with a 30 m spatial resolution and has eight spectral bands including thermal infrared band and panchromatic (Foster, 1985: p. 144). The resolution element (spatial and spectral) of these later systems is more comparable with the size of features requiring detection. With this improvement, land use/land cover change detection and monitoring using remote sensing can be more accurately conducted.

Many studies have been conducted regarding the application of satellite imagery data to monitoring land use/land cover change. Conventional classification methods such as Maximum Likelihood using the original Landsat TM5 band combination (4,3 and 2) has been extensively used to identify land use/land cover in the Southeast Asia region - e.g. in Indonesia, Malaysia, Philippines, and Thailand (SARCS, 1997). All of these studies result in land use - land cover change maps at the scale of 1: 100 000. Another conventional approach is Band Ratios, which have been used to assess the capabilities of Landsat TM in regional mapping in West Africa (Thenkabail, 1996). This study demonstrated that finer scale maps can be produced from Landsat TM at scales between 1: 50 000 and 1: 200 000 (Thenkabail, 1996: p. 105).

Image enhancement techniques such as Normalised Difference Vegetation Index (NDVI) and Principal Components have also been used to identify land use/land cover types (Byrne *et al.*, 1980; Fung and LeDrew, 1985; Jadhav *et al.*, 1993; Qi, 1993; Elvidge and Chen, 1995; Salem *et al.*, 1995; Lyon *et al.*, 1998; Li and Yeh, 1998; Fung and W. Siu, 2000; Zhan *et al.*, 2002; Yue *et al.*, 2002; Helmschort *et al.*, 2002; Filho *et al.*, 2002).

Table 4.2 list some of the various techniques used to identify and monitor land use/land cover using remote sensing data.

Table: 4.2. The various techniques to identify and monitor land use/land cover condition

	Techniques	Purpose	Data	Reference
1	Supervised Classification band 3,4 and 5. Texture extraction procedure B 3 and 4	Fruit Tree inventory	Landsat TM	Gordon *et al.*,1986
2	Maximum Likelihood Classification (MLC)	Grass Mapping	Landsat MSS &TM IRS-IA	Jadhav *et al.* ,1993
3	Visual interpretation of FCC band 1,2,3 and 4 combination	Monitoring Land use Change	Landsat MSS,TM IRS LISS-1	Ram, 1993
4	Vegetation Index, EVI NDVI and MLC	Detect the current land cover classes	Landsat TM	Salem, 1995
5	Unsupervised of band ratio 5/4,4/3,4/1 and combined with original band 4,3,5	Regional Agroecosystems Mapping	Landsat TM	Thenkabil *et al.*,1996
6	Photo interpretation and MCL of fcc 4,5,2 original data	To assess of environmental change	Air photos and Landsat TM	Salami, 1999
7	Post –classification and Band differencing	Land cover change and Deforestation	Landsat MSS and SPOT	Merkus *et al.*, 2000
8	MCL	Examine the differences of the TM and MSS on Wetland classification	Landsat TM and MSS	Hashiba *et al.*, 2000
9	Unsupervised Fuzzy Classification	Land cover detection	Landsat TM	Deer, 1999
10	Hierarchical unsupervised	To discriminate urban land cover types	Landsat TM	Ward *et al.*, 2000
11	Integrating spectral and texture using Neural Network	Land cover Mapping	Landsat TM	Berberoglu *et al.,2000*
12	The Vegetative cover Conversion (VCC)	Deforestation and flood detection	MODIS 250	Zhan, 2002
13	Curve theorem by using NDVI	Detecting land cover Change	Landsat TM	Yue, 2002
14	NDVI	Vegetation cover	Landsat TM	Helmschort 2002
15	PCA	Mapping and monitoring degradation area	Landsat TM	Filho, 2002

4.2.1 Digital change detection of land use/land cover

Land use/land cover change detection aims to measure different features of land use/land cover categories at two different dates. Using large-scale aerial photography at two dates of the same geographic area enables land use/land cover change to be detected, but visual interpretation has some limitations and it is difficult to undertake subsequent analysis due to the non-digital nature of the data. The digital change detection method uses digital imagery to correlate and compare two sets of images to identify changes. Four main conditions are recommended for successful change detection analysis (Jensen, 1986: p. 236). The researcher should:

- Have a prior knowledge of the study area characteristics (cultural and biophysical)
- Know the precision with which the multiple-date imagery is registered. The spectral response that is not associated with land use/land cover should be minimized
- Have an understanding of the limitations of change detection techniques.

Singh (1989: p. 990) categorizes the digital change detection techniques into two categories. The first is the independent analysis at different dates, and the second is the simultaneous analysis of multi-temporal datasets. These two categories of digital change detection are still considered the basis of digital change detection and are called pre- and post-classification approaches (Metternicht, 1999; Lunetta, 1999). All methods can be classified as one of these two approaches. In the post-classification change detection approach, two different date images are independently classified and labelled. From the result, the areas that have changed are extracted. The pre-classification spectral change detection method is based on the assumption that different spectral signatures over time represent a change in land surface conditions. This technique involves the transformation of two original images to a new single-band or multi-band image in which the areas of spectral change are highlighted (Yuan *et al.*, 1999: p. 22). The advantage of the pre-classification approach is the ability to eliminate the effect of mix-pixels, while the advantage of post-classification is overcoming difficulties in change detection associated with the analysis of images acquired at different times or by different sensors.

The disadvantage of pre-classification is the need for image co registration and the difficult in discriminating "change" and "no change" areas. Hence, the disadvantage of post-classification is highly dependent on the individual classification of each different image.

Recently, many studies have used the combination of pre-classification and post-classification approaches in a hybrid approach that complement each other in overcoming the complexity of land use/land cover change detection (e.g. Ward *et al.*, 2000; Moy *et al.*, 2001; Stefanov *et al.*, 2001; Wilson and Steven, 2002).

Table 4.3 shows the summary of digital change detection categorised by pre-classification as a simultaneous, post-classification as an independent, and Hybrid approaches. All of these techniques can include three basic approaches: pixel level approach, feature level approach and object level approach (Deep, 1999). Pixel level if detection refers to a numerical value attached to each band of each pixel in an image such as digital number (DN). Feature level refers to some transformation of pixel level values, and object level refers to symbolic or thematic labelling or classification of the data. From this point of view pre-classification can be classified as feature level or pixel level differencing, whilst most of the post-classification belongs to an object level differencing, and a hybrid approach is a combination of feature level or pixel level and object level differencing.

The common digital change detection techniques that were categorised as Pre-classification, Post-classification and Hybrid are reviewed in the following sections.

Table: 4.3. Comparison of digital detection techniques Categorized by Independently, Simultaneous and Hybrid

Categories	Method	Procedure/ Approach	Required	Advantage	Disadvantage
Independent	Post-Classification	Independently Classification Object level differencing	Accurate co-registration Atmospheric correction Select correctly the training areas	The nature of the land cover is identified	Need ground truth Many steps to be carried out Errors accumulate when combination image Accuracy of the change image is only as good as the accuracy of the land cover classification
Simultaneous	Band Differencing	Subtraction the image of one date from that another(Direct band to band subtraction) Pixel level differencing	Optimisation change/no-change Threshold level Image rectification and Radiometric Correction	Efficient method Low cost Potential for massive data processing	No 'from-to' change information Subsequent interpretation of image difference product
	Band Rationing	Rationing before band subtraction: NDVI, RVI,TNDVI,SAVI etc. Pixel level differencing	Image rectification and Radiometric Correction Optimisation change/no-change Threshold level	Efficient method Low cost Potential for massive data processing	No 'from-to' change information Subsequent interpretation of image difference product
	Principal Component	Transform the original image into a component as new image Feature level differencing	Image rectification and Radiometric Correction Optimisation change/no-change Threshold level	Efficient method Low cost Potential for massive data processing Maintaining classification accuracy without data pre-processing	No 'from-to' change information Subsequent interpretation of image difference product

Table 4.3 continues

Categories	Method	Procedure/ Approach	Required	Advantage	Disadvantage
	Direct-Multi date Classification	Single Classification of two or more dataset Class-to- class change image analysis Object level differencing	Image rectification and Radiometric correction need accurate identification of change area need normalization or transformation image	Efficient method Direct change detection	No 'from-to' change information Need large computer Spectral change cannot be easily separated
	Change vector Analysis	Vector deference (magnitude & direction) analysis of the pixel on two dates different Pixel or feature level differencing.	Image rectification and Radiometric correction Need reference for calculating change vector	Efficient method Able to monitor subtle changes within individual land cover class.	Being developed All reference to original are lost
Hybrid	Spectral Change detection and Classification	Simultaneous Spectral change identification and independently Classification Pixel and Object level differencing	Image rectification and Radiometric Select correctly the training areas	Reduce the errors of commission and provide from-to change information	Many steps to be carried out

Source: Jansen. RJ, 1996 and various Literature

4.2.1.1 Pre-classification

4.2.1.1.1 Image Differencing

In image differencing techniques, two images at different dates are spatially registered and subtracted one from the other. The corresponding pixel values are subtracted to produce a new image that represents the change between the two dates. Mathematically, this method produces a new change image with the same number of bands as the input images. Pixels presenting a significant radiance change can be expected to lie in the tails of the distributions of the different image, whereas the remaining pixels should be grouped about the mean. Images used in this technique needs to be corrected to reduce radiometric differences between the input images.

Image differencing is simple to implement and has been widely used in a variety of applications. Brera and Shahrokhi (1978) applied this technique for the analysis of desertification in the Sahara region, and Vogelmann (1988) investigated the detection of change in temperate forests. Criticism of this method comes from Riordan (1980 in Sing, 1989: p. 992). The method is sensitive to image miss-registration, to the existence of mixed pixels, and to radiometric differences between the input images. This method fails to specify the mechanism of types of information loss (Singh, 1989: p. 993). For example a forest with a radiance value of 170 in band 4 on one band and 140 on the second date shows a change of 30. This number could come from the difference between radiance values of 70 and 40 which does not represent the radiance value of the forest pixel. Thus, there is a potential loss of information with the use of simple image differencing technique. The other disadvantage is deciding the threshold boundaries between change and no-change pixels displayed in the histogram (Jansen, 1986: p.241). However, the normalized or standardized image differencing of two or more images from different dates that have been radiometrically corrected have the potential to be used for digital change detection. In a resent study, Fung (2000) was successful in monitoring the change of environment quality in Hong Kong city by using image differencing. Image differencing was also determined to provide the best results for detecting change in Long life Pine Wiregrass ecosystems (Houhouis and Micher, 1996).

4.2.1.1.2 Image Ratioing

This method calculates the ratio of the values of corresponding pixels of registered images at different dates. The basic concept of this approach is that if the intensity of reflected energy is nearly the same in each image then this indicates no change. If change occurred in a particular pixel, the ratio is expected to be either higher or lower than the ratio in the no-change areas. Similar to other techniques, the standardization of some data or radiometric correction between dates may be necessary.

This technique has not been as intensively investigated as image differencing (Nelson, 1983: p. 1304). Todd (1977) used this method to determine urban change in Atlanta, Georgia. As a result 91.4% of land cover change was correctly identified (Todd, 1977 in Nelson, 1983: p. 1304). Fung (1988) tested the accuracy of this method by comparing it with image differencing and principal components methods and found it effective in detecting change from cropland to construction with a producer's accuracy of over 90%, but it was difficult to detect change from cropland to residential (Fung, 1988: p. 1453).

Howarth (1981: p. 287) found that the use of band ratios using data from different dates produced an enhanced image of the study area. He used this technique successfully to detect flooding area in Mamawi Lake, Canada. Rachman (1997) concluded that the band ratioing technique is suitable and efficient for the study of detecting altered rocks, soil-moisture, drought, vegetation, and canopy change.

Ratios of band 3 and band 7 of Landsat TM for example, is best suited for recognizing roads or other man-made features that appear in a lighter tone due to their relatively high reflectance in the red band (band 3) and low reflectance in the mid-infrared (band7) (Lillesand, 2000: p.524). With a strong local knowledge and correct selection of the band ratio, the change detection using this method can be successfully conducted. This technique is well established and is still being used for purposes such as the pre-classification process as an aid to improving thematic and spatial accuracy (Watson *et al.*, 2001).

4.2.1.1.3 Vegetation Index Differencing

This technique also has been established for a long time and is the most common method used to identify vegetation. In the vegetation index differencing technique, the digital spectral radiance values can be analysed independently on a band-by-band basis, or in combinations of two or more bands. The most commonly used band combination techniques involve the calculation of vegetation indices. These have been developed on the basis of the strong absorption of red and strong reflectance of near-IR by vegetation. The formula of vegetation indices could be a simple combination, or band ratios, or a combination of both. It has been found that the ratio of near-IR to red reflectance is significantly correlated with green leaf biomass (Tucker, 1979). There are many vegetation indices in use (Qi, 1993; Elvidge and Chen, 1995, Salem, 1995) but the most common is the Normalized Difference Vegetation Index (NDVI) (Eastman, 2001), given by the ratio of near-IR minus red reflectance and near-IR plus red reflectance.

It is important to note that ratioing two spectral bands negates the effect of any extraneous multiplicative factors in sensor data that act equally in all bands (Lillesand and Kiefer, 1987). Singh (1989) underlined that the band ratio technique might enhance noise that is not correlated in different bands. Qi *et al.* (1993) stated that it is useful especially when satellite data are available at high temporal frequencies, with fine spatial resolution, and with atmosphere correction of data, they advocate a correction to account for first-order soil background effects when using vegetation indices. In a study on the use of vegetation indices for change detection, Lyon *et al.* (1998) found that the Normalised Difference Vegetation Index (NDVI) produced results superior to those of other vegetation indices. Nelson (1983) examined this method qualitatively in a study of gypsy moth defoliation in Pennsylvania. The result indicated that of three methods tested (i.e. image differencing, ratioing, and vegetation index difference) the vegetation index difference most accurately delineated forest canopy change. Angelici *et al.* (1977) employed the difference in the ratio between NIR and red band and the thresholding technique to delineate the change area. The disadvantage of this technique is that it's sensitive to miss-registration and the existence of mixed pixels. However, this technique could be used on land use/land cover change detection combined with other techniques (i.e. principal component techniques) to delineate other vegetation signatures. Recently, these techniques have been intensively used to identify vegetation and change detection (Ward *et al.*, 2000; Fung and Siu, 2000; Lanjeri *et al.*, 2001). Fung and Siu (2000) conclude that NDVI values were related to woodland, tall scrubland and high-density urban areas. They also found the decreasing NDVI values covered a large part of rural area revealing urban expansion. Ward (2000) found the NDVI band 5 and band 3 can successfully be used to classify vegetation cover (woody and non-woody).

2.5.1.1.4 Principal Components Analysis

Byren (1980) stated that Principal Components Analysis (PCA) is a powerful method for analyzing correlated multidimensional data. It can be used in such systems to facilitate the visual interpretation of a mass of data having uniform *a priori* significance, by reducing redundancy. Lillesand and Kiefer (1987: p. 655) also stated that PCA is a powerful data transformation method for information extraction in remote sensing. This transformation can be used either as a pre-processing operation or as an enhancement operation prior to visual interpretation of the data.

Principal components transformation is a linear transformation that defines a new, orthogonal coordinate system such that the data can be represented without correlation. Therefore the degree of correlation between bands in the original multi-spectral image can be eliminated and the redundancy of information can be reduced.

Principal Components Analysis (PCA) can also be applied to compress image datasets from two or more dates i.e. to multi-temporal image data (e.g. Byrne *et al.*, 1980: p. 175; Richards, 1984: p. 35; Ingebritsen and Lyon, 1985: p. 687; Fung and LeDrew, 1987; Ceballos and Bottino, 1997; Li and Yeh, 1998; Edge, 2001). There is a high correlation between image data for regions that have not changed significantly and a relatively low correlation between regions that have changed substantially. Richards (1984) used a principal component transformation technique to highlight regions of localized change, associated with bushfire damage and vegetation re-growth following fire burns. Singh and Harrison (1985: p. 895) compared the use of a covariance matrix and a correlation matrix. They found that there is a significant improvement in signal-to-noise ratio and image enhancement by employing the correlation matrix rather than the variance matrix. A non-standardized principal components analysis could be justified due possibly to the differences in radiometric resolution between the spectral bands of sensor. Fung and LeDrew (1987: p.1657) also examined image enhancement for change detection based on standardized versus non-standardized approaches. They stated that principal components analysis is a "scene dependent" technique and the exact nature of the principal components derived is not known without an examination of the eigenstructure and visual inspection of the image. However, it is a powerful data reducing technique, and should be used with a thorough understanding of the characteristics of the study area to avoid drawing any faulty conclusions. Ceballos and Bottino (1997) conducted a further study on the discrimination of scenes of multi-spectral imagery. They use principal component analysis to discriminate vegetated landscapes in Northeast Brazil. This approach also has been used to discriminate healthy and non-healthy corals in Fiji (Holden and LeDrew, 1998). Li and Yeh (1998) used principal component analysis to reduce over-estimation of land use/land cover change in monitoring rapid land use/land cover change and urban expansion in the Pearl River Delta. A combination of principal component analysis and linear programming methods was conducted to calculate fraction bounds of main seaweeds and inter-tidal components for mixed pixels (Bajjouk *et al.*, 1998). A recent study that has been successfully conducted is discrimination of urban and non-urban area using principal component analysis (Edge, 2001). This study has successfully discriminated urban and non-urban areas as a basis to predict urban growth in part of West Java. Principal component techniques can therefore be usefully applied to enhance images prior to image classification in order to delineate change categories.

4.2.1.1.5 Change Vector Analysis

Change vector analysis is the analysis of change based on the vector difference between the multi-band digital vectors of the pixel on two dates. A particular pixel in an image can be plotted as a point in this vector space with co-ordinates that correspond to its brightness values in the appropriate spectral components. The data values associated with each pixel thus define a vector in multi-dimensional space. If a pixel undergoes a change from time t1 to time t2, a vector describing the change can be defined by the subtraction of the vector at t1 from the vector at t2. This is called the spectral change vector. It may be calculated from either the original or transformed (e.g. PCA or NDVI) data, and using either individual pixel or clusters formed by a spectral clustering or spatial segmentation algorithm. If the magnitude of the computed spectral change vector exceeds some specified threshold criterion, it may be concluded that change has occurred. The direction of the vector contains information about the type of change. Malila (1980) introduced this method for the first time for detecting forest change in northern Idaho (Yuan, 1999: p.25). Colwell (1981) used this technique to detect forest change in the Palouse District of the Clearwater National Forest in

Idaho. He used two different strategies of digital change detection: delta-classification (post-classification) and change vector analysis (Colwell, 1981: p. 340). He concluded that using this two-change detection procedure could significantly affect the estimates of amount of change.

Lambin and Strahler (1994) used this method to detect and categorize land cover change processes. They concluded that change vector analysis combined with a PCA on the change vectors proved effective in detecting and categorizing inter-annual change between time trajectories of NDVI data. Cohen *et al.* (1999) used this technique as a multi-temporal linear transformation compared with different images techniques and composite analysis on conifer forest change detection in Pacific Northwest region. They conclude that a reference image was important for accurate characterization of forest change. If change vector analysis without a reference image was compared with image differencing techniques, the image differencing technique performed better than change vector analysis (Cohen, 1999: p. 99). The disadvantages of this method are similar to those of other methods such as the raw image differencing method, in that is that it is sensitive to miss-registration, to the existence of mixed pixels, and to radiometric differences.

4.2.1.1.6 Direct Multi-Date Classification

Direct multi-date classification uses a single analysis of a combined dataset of two or more datasets to identify areas of change. The combined data set whether, an original image or a transformed image, can be classified by a supervised or unsupervised approach. In the supervised approach, training sets pertaining to change and no-change areas are used to derive statistics to define sub-spaces of the feature (normally spectral) space. In the unsupervised approach, spectral classes are determined by cluster analysis, and subsequent inspection can reveal where changes have occurred. Hoffer and Lee (1989) used this method for forest change detection and combined it with PCA to reduce the number of bands. They were able to detect at an accuracy of 90.6% for the full 12 band, and 90.4% using 6-band after reduction by principal components analysis. Muchoney and Haack (1994) conduct a study of change detection for monitoring Forest defoliation. They conclude that by using multi-date classification under the similar condition, change areas were significantly different. A disadvantage of this method is that it needs accurate identification of the training areas for each change class. Other disadvantages are: the data need to be re-processed whenever a new image is added, it is difficult to label the change class, and there is limited information on "from-to" changes class. However, it is a simple technique because it requires only a single classification.

4.2.1.2 Post - Classification Comparison

Post - classification comparison is the most common method of detecting change. This method involves the classification of each image independently, and is followed by a comparison of the corresponding pixel signature to identify areas where change has occurred. The process of classification can be carried out separately by a supervised or unsupervised approach. It reveals that change has occurred, and also reveals the precise nature of the change, but requires an accurate rectification and classification processes. The comparison of classified images can be conducted visually or by computers. The comparison can also be undertaken using a Geographic Information System (GIS).

Joyce *et al.* (1980) concluded that post - classification comparison "appears suitable for detecting land cover change with Landsat MSS data in sites where large areas of forestland are being converted to cropland". Fisher and Pathirana (1993) found that (conventional) post - classification comparison indicated that over 40 % of the land area studied had undergone change, whereas it was known that little change had actually occurred.

Jensen *et al.* (1987) used post - classification comparison with unsupervised classification of aircraft MSS data for wetland change detection, but achieved limited success. Martin (1989) concluded post - classification comparison gave better results than either multi-date classification or principal component analysis for change detection in the rural-urban fringe. Jensen *et al.* (1995) reported on a later study also using post - classification comparison for wetland change detection. The result was that cattail and cattail mixture (sawgrass) classes could be detected. This technique is commonly used and combined with image enhancement processes to get better feature signatures in order to classify land use land cover change in what are called hybrid techniques (e.g. Deep, 1999; Ward, 2000 and Madhavan, 2000). The disadvantages of the method are: it needs ground truth information to get precise training areas, it is dependent on accuracy of individual classifications, and it requires two separate classifications. The advantages are: it reveals the area that has been changed, it provides "from-to" change class information and bypasses the difficulties associated with the analysis of images acquired at different times, in that radiometric normalization is not required.

4.2.1.3 Hybrid

The Hybrid approach combines spectral change identification methods and classification based methods in various ways to minimize errors in land cover change analysis. This method can substantially reduce the errors of commission (misidentifying no-change and change pixels). The combination between radiometrically normalized image differencing and post-classification comparison, for example, can be used in land use/land cover change detection. Radiometrical image differencing may be used to identify the area of significant spectral change, and then a post-classification comparison applied within areas where spectral change was detected to obtain class-to-class change information.

Pilon *et al.* (1988) developed this method further and applied it to the detection of changes in a northwestern Nigeria semiarid environment. They conclude that this hybrid approach can reduce commission errors. Recent studies have been conducted using new approaches to classification such as fuzzy logic and neural networks. These techniques can be used to classify land use/land cover categories on digital change detection techniques. Fuzzy logic was successful in recognizing thresholds of land use by using the fuzzy membership principle. ANN, as well as the fuzzy membership approach, was successfully used to classify land use categories when the spectral differences between classes are subtle (Berberoglu *et al.,* 2000: p.386).

Berberoglu *et al.* (2000) used hybrid methods of land cover mapping in the Mediterranean basin with the integration of spectral and textural information using neural networks. The ANN improved the accuracy of classification results compared with the maximum likelihood approach. Berberoglu concluded that when using spectral data alone and using spectral and textural data, the accuracy of ANN was greater than that of maximum likelihood. Ward *et al.* (2000) used hybrid methods as a hierarchical approach to detect urban land-use-land cover change. They combined spectral change detection to separate impervious surfaces and exposed soil by using band ratio (NDVI and Mineralogical Ratio) and post-classification by unsupervised classification. The result improved the accuracy from 75 % to 83 %. Madhavan *et al.* (2001) detected spatial growth of the Bangkok Metropolitan area using post-classification comparison techniques combined with a vegetation-impervious-soil model. The vegetation-impervious - soil model has been used to distinguish urban from non-urban morphology.

An advantage of hybrid methods is overcoming the mixed pixel problem and providing information on "from-to" change classes information. The disadvantage is that two processing steps are needed (spectral detection and post–classification comparison).

4.2.2 Selection of the appropriate detection and identification techniques

The focus on change detection in this study was to provide an approach that could be used to detect and identify land use/land cover change in the study area. Considerations taken into account in selecting an appropriate detection and identification techniques for this study were:

1. The study area is in the Tropics area that has varied physical environmental conditions such as climate, soil, vegetation type and weather as well as growing cycle.
2. Conventional change detection based on the post-classification comparison of an original band combination constrained to get correct land use/land cover due to some noise or disturbances.
3. Transformation techniques such as Principal Component Analysis (PCA) and Normalized Difference Vegetation Index (NDVI) are techniques that produce new transformed images and can be used to replace the original band image to detect land use/land cover change.

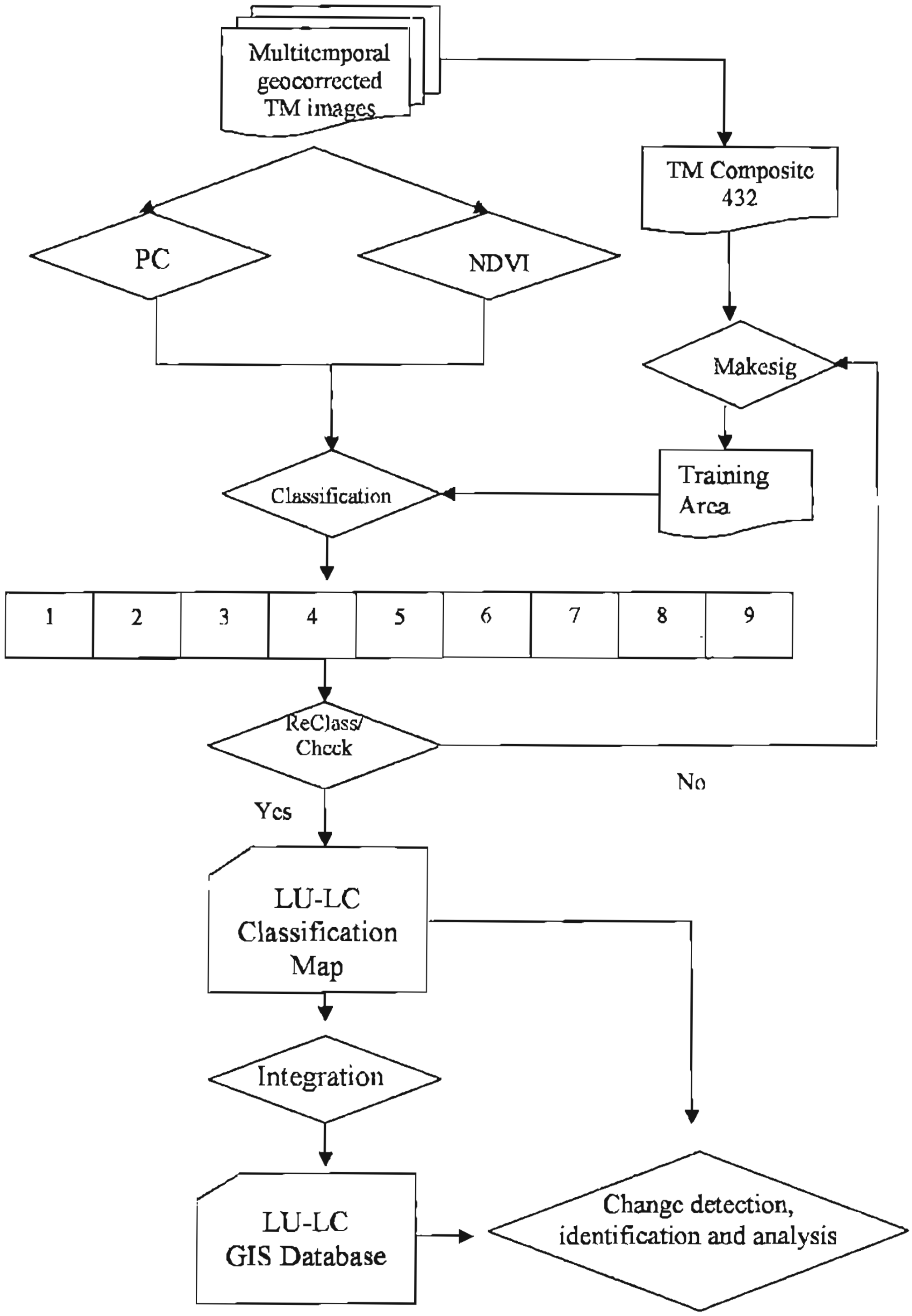
A Post-classification comparison approach was selected to detect land use/land cover change in the study area. This change detection was based on Maximum Likelihood supervised classification of transformed images principal component analysis (PCA) and NDVI.

Principal Component Analysis (PCA) transformation was selected based on the following considerations: 1) it may reduce effects of atmospheric differences (Bryne, 1980); 2) it has been successfully employed in land cover change analysis (Fung and LeDrew, 1987; Holden and LeDrew, 1998; Ceballos and Bottino, 1997; Lie and Yeh, 1998); 3) it has been successfully demonstrated to separate crop types cover without performing data pre-processing (Jiaju, 1988) and 4) it has been successfully used to recognise spectral features in order to distinguish human settlement (Edge, 2000).

NDVI transformation was the most common vegetation index that was successfully used to identify vegetation cover (Tucker, 1979, Eastman, 2001).

4.3 Methods

The main method of digital change detection using remote sensing in this study is shown in Figure 4.1. A combination of image processing, image enhancement and image classification were used to identify land use/land cover categories. Change detection was conducted through post classification comparisons. The following sections describe the integration of remote sensing and GIS operations to detect land use/land cover change in the study area.



Note:

1 = Forest	**4 = Open land**	**7 = Dry land**
2 = Plantation	**5 = Settlement**	**8 = Fishpond**
3 = Rice field	**6 = Rice field unplanted**	**9 = Water/reservoir**

Figure 4.1. The integrated model of detection, identification and analysis of land use/land cover change.

4.3.1 Digital change detection techniques

Three main processes Pre-processing, Image Enhancement and Classification are common image processing procedures to detect and identify land use/land cover from the satellite imagery. These procedures are described as follows.

4.3.1.1 Image Pre-Processing

The satellite image could not be used directly to interpret or delineate physical features. It needs to be processed, including corrections to eliminate the errors introduced during image acquisition. The ideal or perfect remote sensing system has yet to be developed (Jensen, 1986). Remote sensing devices have constraints such as spatial, spectral, temporal, and radiometric resolution. Consequently, this has an influence on data quality during data acquisition. Therefore, it is usually necessary to pre-process the remotely sensed data before analysing it in order to remove some of these errors.

Pre-processing aimed at the correction of distortions, degradations, and noise introduce during the imaging process (Moik, 1980) will produce a corrected image that is as close as possible, both geometrically and radiometrically, to the radiant energy characteristics of the original scene. Radiometric and geometric errors are the most common types of errors encountered in remotely sensed imagery.

4.3.1.1.1 Geometric Correction

Most digital satellite images have already had systematic error removed. Landsat satellite data for example, which are acquired through the EOSAT Company, have consists of spatial enhancement, radiometric enhancement and spectral enhancement. These enhancements cover image reduction and magnification, contrast enhancement and edge enhancement. Table 4.4 below shows the Image enhancement types and their function:

Table 4.4. The type of Image enhancement and function

Type of Enhancement	Algorithm	Function
Image Reduction & Magnification	Image Reduction,	To reduce the original image data set down to one or a few manageable images.
	Image Magnification	To improve the scale of display for visual interpretation purposes or occasionally to match the scale of another image.
Contrast Enhancement (CE)	Linear CE Non-linear CE Rationing Filtering	To improve the contrast of reflectance property among different material. Therefore easy to differentiate the features in the surface.
Edge Enhancement (EE)	Linear EE Non-linear EE	To enhance the edges surrounding various object or features interest.

Source: from various image processing modules (Erdas Imagine, ERMapper and Idrisi)

4.3.1.2.1 PCA and NDVI Transformation

These two transformation techniques enable one to enhance and provide new set images, which have strong spectral signatures of built-up areas or settlement and vegetation cover. Using the image-processing module in Idrisi32 that provides PCA and NDVI transformation algorithms, a new set of PCA and NDVI transformed images were created.

4.3.1.2.2 Filtering

The result of image classification produces some noise due to a scattering of individual or small groups of pixel. Filtering processes can be used to enhance the spatial features of the image. A filter creates a new image by calculating new values using a mathematical operation on the original cell value and its neighbours. The mode or focal majority filter, which assigns the most common value to the centre pixel, is commonly used to remove very small areas from a qualitative image. All of the images classified in this study were enhancing by mode filtering to remove isolated pixels.

4.3.2 Land use/land cover Classification

Multi-spectral classification is the method most often used to extract the information from remotely sensed data. This procedure assumes that imagery of a specific geographic area is collected in multiple regions of the electromagnetic spectrum and that the images have good registration (Jensen, 1996). Therefore the physical features of the earth, in particularly land use/land cover types, could be extracted through the spectral reflectance properties of those objects or features analysis.

The supervised maximum likelihood classifier was selected in this study, which has been commonly used in many studies. Three to five training areas for each land use/land cover (LULC) category in this study were selected based on the object feature of each category in the field. These categories are:

1 = Forest	4 = Open land	7 = Dry land
2 = Plantation	5 = Settlement	8 = Fishpond
3 = Rice field	6 = Rice field unplanted	9 = Water/reservoir

4.3.3 Land use/land cover change detection

This study used a post-classification comparison approach to detect land use/land cover changes in the study area. This approached is based on Maximum Likelihood classifier of the PCA and NDVI transformed images. Figure 4.2 below shows the algorithm of this approach.

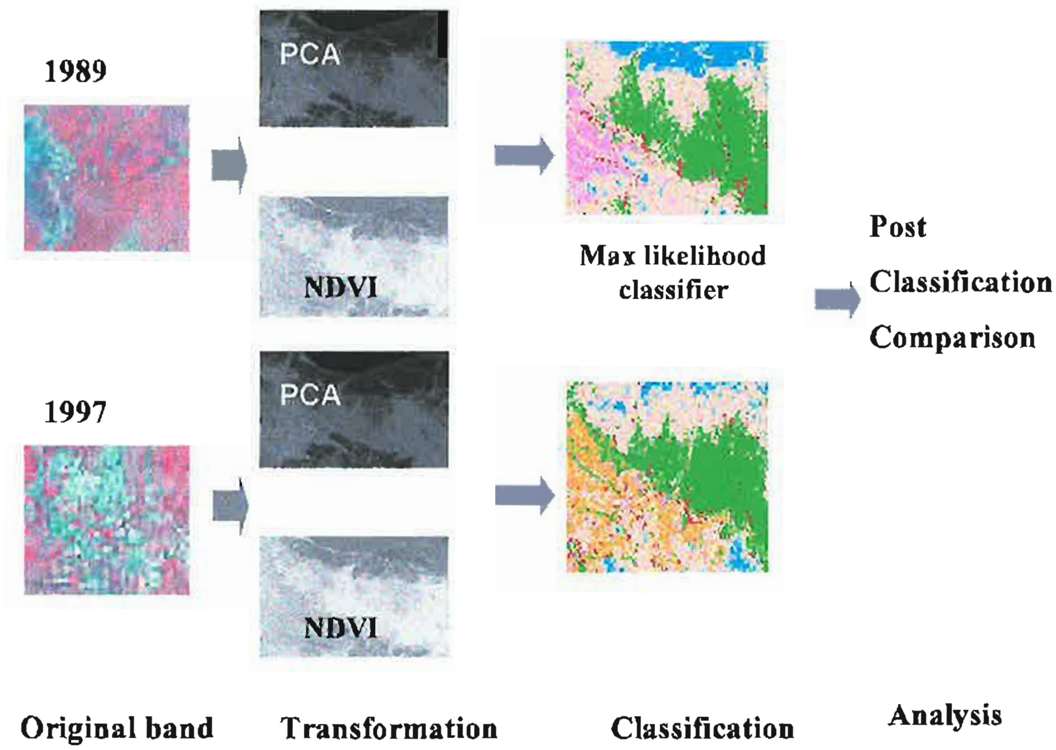


Figure 4.2. Post-classification comparison approach of land use/land cover change detection and identification

The first step is to transform the original image by using principal component (PCA) and normalized different vegetation index (NDVI). The second step is to combine these two sets of images and then classify using supervised Maximum Likelihood classification techniques. Finally, these two image representing different dates were compared with each other to detect and identify any land use/land cover change. GIS techniques, including overlaying and cross tabulation, were used to calculate the area of each land use/land cover category that has been changed.

4.3.4 Accuracy Assessment

The Kappa index of agreement (KIA) has been selected to assess the accuracy of the classification result. This method compares two images; one image contains the interpreted land cover map while the second image contains the result of ground truth investigation. It is mostly used in the post-classification assessment of land cover classifications derived from remotely sensed data (Eastman, 2001). This operation creates an error matrix that tabulates the different land cover classes to which ground truth cells have been assigned. Output also includes column and row marginal totals, errors of omission and commission, an overall error measure, confidence intervals for that figure, and a Kappa Index of Agreement (KIA), both for all classes and on a per category basis.

4.4 Result digital change detection and identification in the study area.

4.4.1 Initial recognition

Some physical characteristic of the study area have been described and displayed in the previous chapter. Physiographically, the study area is flat and consists of alluvial plain deposits. Most of the land use/land cover conditions in the study area have been modified through human settlement and agriculture practices. Population pressure has resulted in the expansion of the agriculture area, especially for wetland rice fields as well as settlements.

As a result of initial image analysis using simple original band combination (FCC TM band 4 red, TM band 3 green and TM band 2 blue), the initial identification of land cover was recognized. There were significant land cover changes as shown in Figure.4.3 a,b,c, and d).

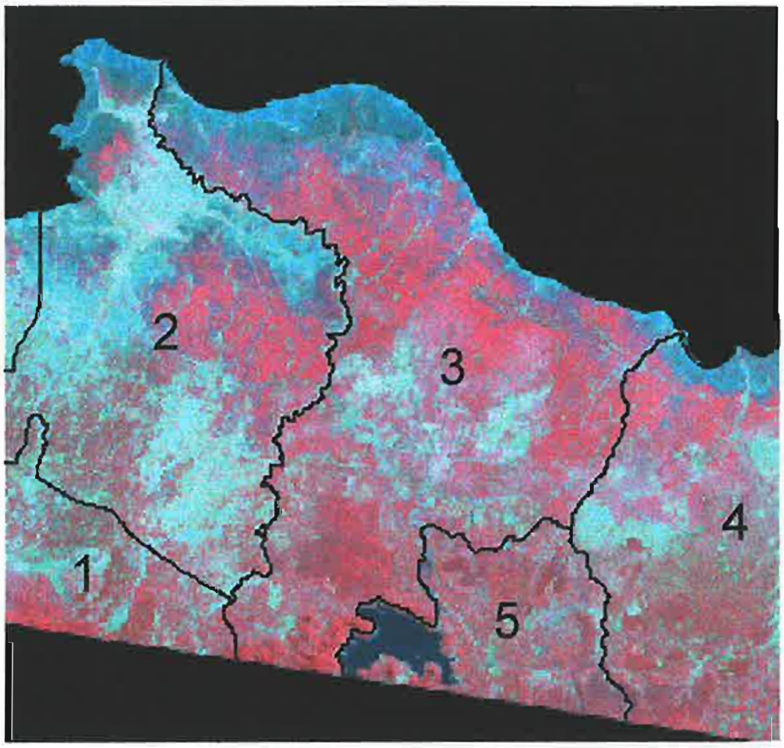


Figure 4.3a

TMComposite 432
1989

1.Kabupaten Bogor
2.Kabupaten Bekasi
3.Kabupaten Karawang
4.Kabupaten Subang
5.Kabupaten Purwakarata

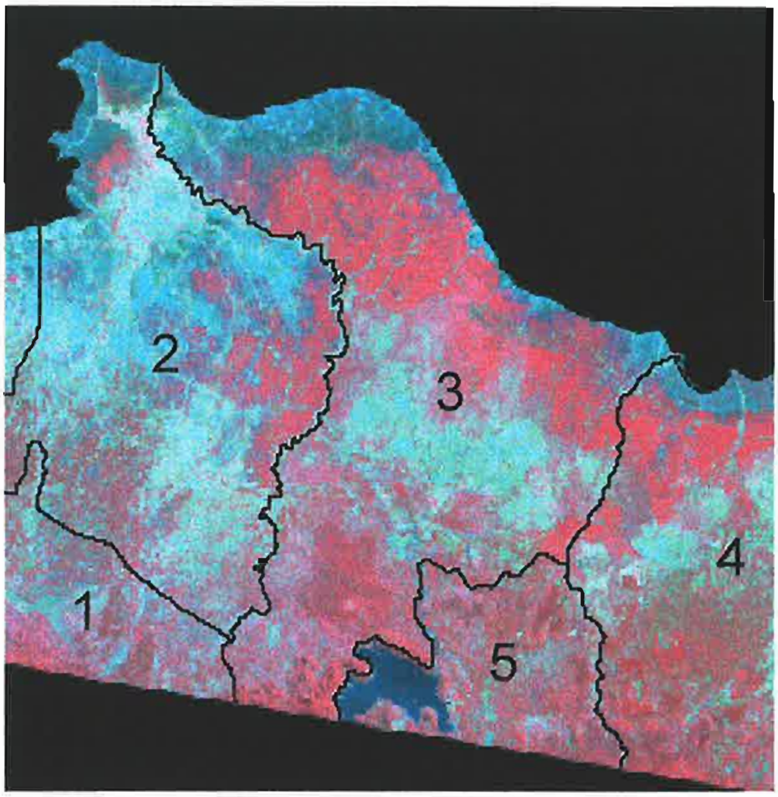


Figure 4.3b

TMComposite 432
1990
1.Kabupaten Bogor
2.Kabupaten Bekasi
3.Kabupaten Karawang
4.Kabupaten Subang
5.Kabupaten Purwakarata

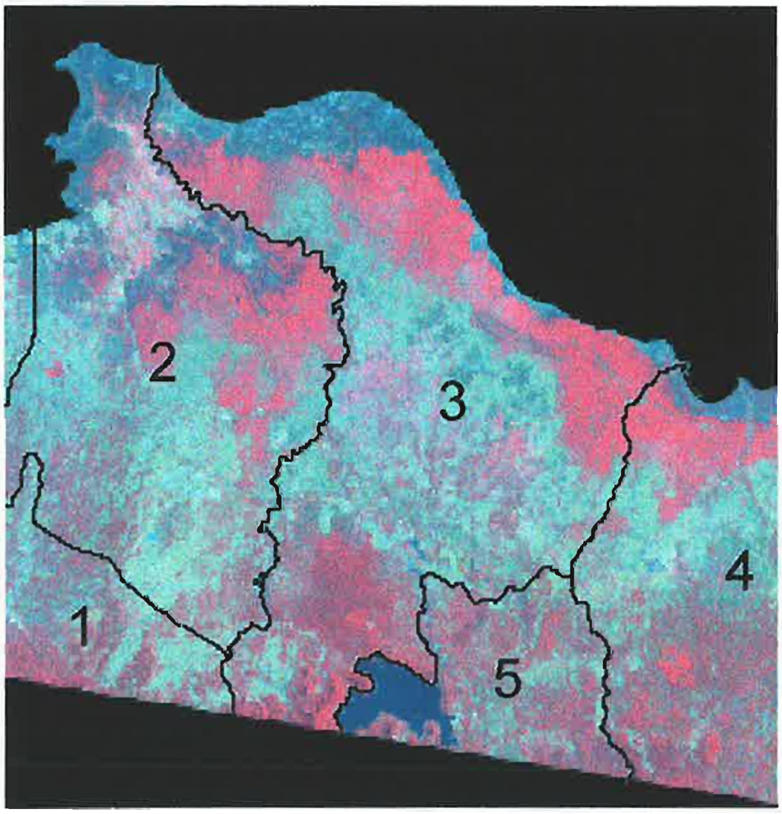


Figure 4.3c

TMComposite 432

1995
1.Kabupaten Bogor
2.Kabupaten Bekasi
3.Kabupaten Karawang
4.Kabupaten Subang
5.Kabupaten Purwakarata

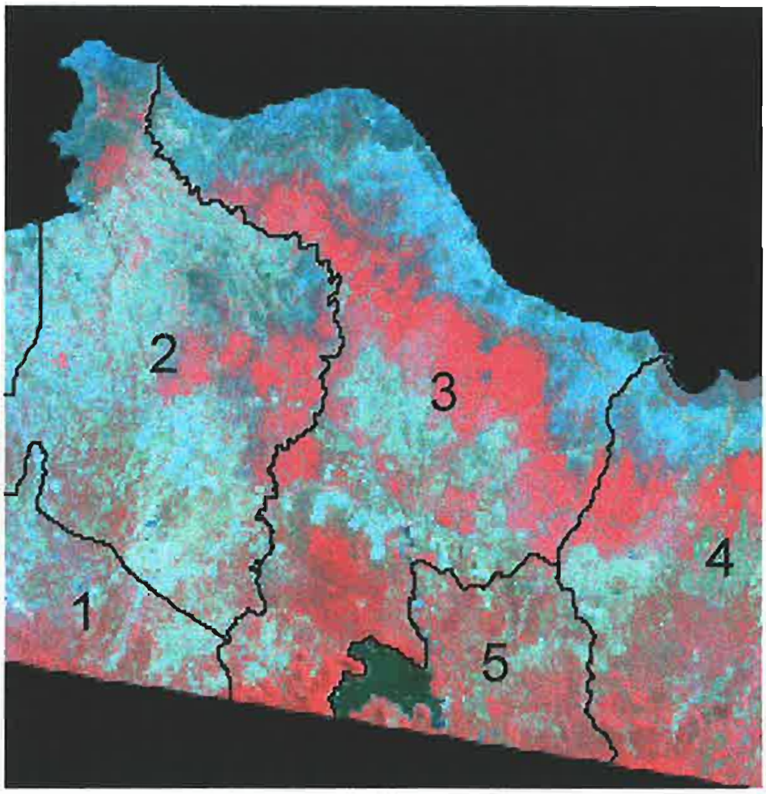


Figure 4.3d

TMComposite 432
1997
1.Kabupaten Bogor
2.Kabupaten Bekasi
3.Kabupaten Karawang
4.Kabupaten Subang
5.Kabupaten Purwakarata

Four images that have been taken for the same season (dry season): June 1989 Fig. 4.3a, June 1990 Fig. 4.3b, August 1995 Fig. 4.3c and June 1997 Fig. 4.3d show the different land use/land cover conditions in the study area. Red represents vegetative cover (mostly rice field area); light blue represents open or arable land and dark blue represents wetland and water. As seen on those images, the light blue area in 1990 is slightly larger than in 1989, indicating that open and arable land has increased. Vegetation is the dominant cover in this area in both 1989 and 1990 (see in kabupaten Karawang no. 3 and kabupaten Bekasi no. 2). This is very different when compared with conditions in years 1995 and 1997. In 1995 arable and open land (light blue area) was larger than in 1997. The other interesting feature is the vegetation (red area). This area shifts between the north and south parts of Karawang no 3. In 1995 (Figure 4.3c) vegetative area was located in the north part, while in 1997 (Figure 4.3d) vegetative area was located in the south part of Karawang. If this area is rice field, it easy to understand the shifting of this area as it could be related to the local cycle of growing season in this area.

From this initial analysis it can be seen that land cover in the study area is dynamic and changes over time. However the investigation of this change is still at a broad category level, for example, settlement areas are still not clearly recognised.

4.4.2 Image Enhancement

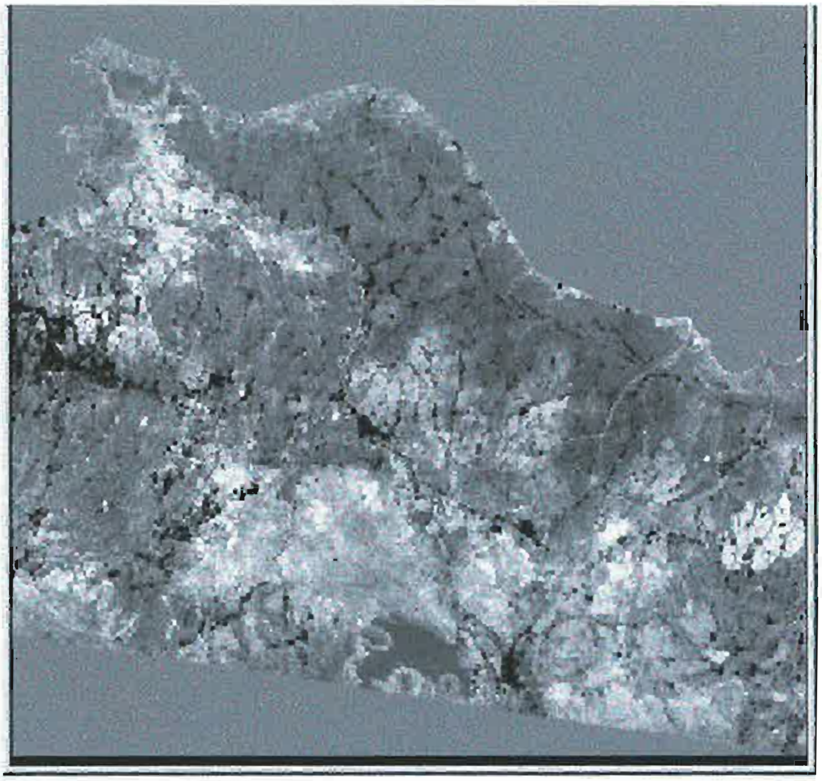
Table 4.5 shows the eigenvector matrix as well as the loading matrix from principal component transformation for 1989 (see Appendix Chapter IV for other years). The total eigenvalue indicates that the first principal component generally contains 85 – 95 per cent variance. This means the first component contains the majority of the information. On the other hand, the loading matrix expresses the degree of correlation between each component and the original bands. The highest correlation is between component 1 and TM band 4 (Table 4.5).

Table 4.5: Principal components analysis transformation TM 1989

COMPONENT	Comp 1	Comp 2	Comp 3	Comp 4	Comp 5	Comp 6
% var.	90.79	5.50	3.24	0.29	0.13	0.04
Eigen value.	2680.96	162.51	95.71	8.68	3.72	1.19
eigvec.1	0.45	0.60	-0.54	-0.38	-0.01	-0.08
eigvec.2	0.10	0.23	-0.02	0.31	0.00	0.91
eigvec.3	0.13	0.42	0.07	**0.80**	-0.01	-0.40
eigvec.4	0.64	-0.62	-0.33	0.25	0.20	0.00
eigvec.5	0.57	0.03	0.62	-0.17	-0.51	0.00
eigvec.6	0.20	0.18	0.45	-0.15	**0.84**	0.00
LOADING	**Comp 1**	**Comp 2**	**Comp 3**	**Comp 4**	**Comp 5**	**Comp 6**
TM Band 1	0.93	0.31	-0.21	-0.04	0.00	0.00
TM Band 2	0.83	0.49	-0.03	0.15	0.00	0.16
TM Band 3	0.76	0.58	0.08	0.26	0.00	-0.05
TM Band 4	**0.97**	-0.23	-0.09	0.02	0.01	0.00
TM Band 5	0.97	0.01	0.20	-0.02	-0.03	0.00
TM Band 6	0.90	0.20	0.39	-0.04	0.14	0.00

The strong correlation in this table shows that component 1 can represent the entire original band and that the most representative band is band 4. The eigenvector value within the matrix show that principal components 4 and 5 have a consistently high value and correlate with eigenvector 3 and 6 for whole year, which is related to settlement and other features that are sensitive to soil moisture content. Others principal components did not demonstrate a consistently high value except principal component 6. Principal component 6 has a high correlation with eigenvector 2, which is related to coastal sedimentation and this feature is not included in land use/land cover category in the study area.

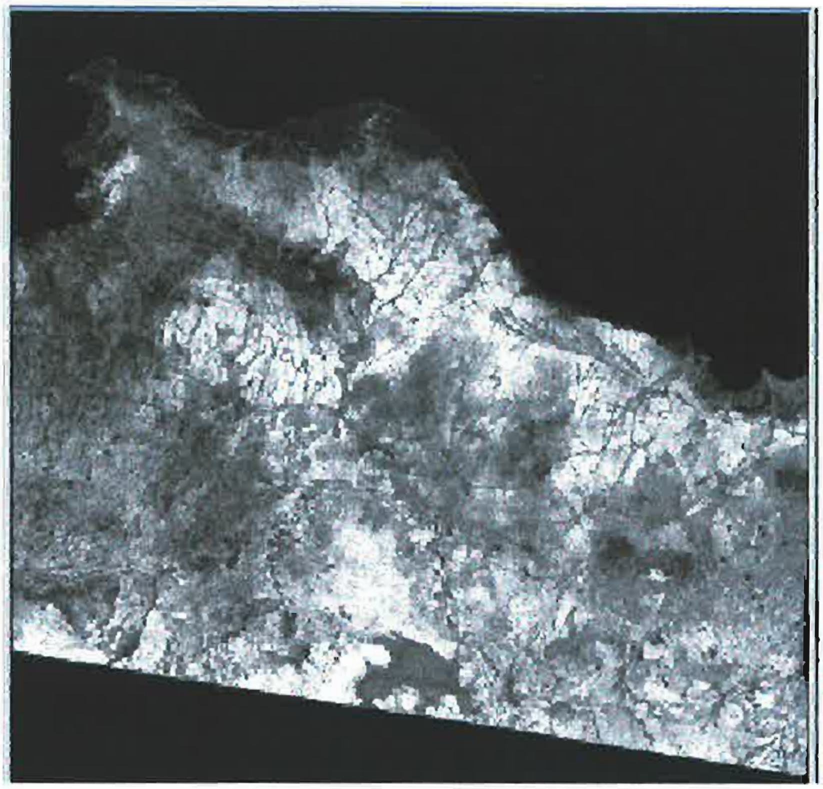
Although other components such as PC 1, PC 2 and PC 3 didn't have high values consistently correlated to a certain band, these principal components (especially PC 1 and PC 2) contain of the majority of information in the image. Therefore, all principal components, except principal component 6, were to be combined with the NDVI image to analyze land use/land cover in the study area. Figure 4.5 shows spectral features of principal component 5 (4.4 a) and spectral features of NDVI (4.4b) from TM 1989.



4.4a

Figure 4.4a. The spectral features of Principal Component 5 (PC 5)

The dark black colour in Figure. 4.4a represents settlement features and the light white colours on Figure. 4.4b represent forest and other vegetation features. Through the combination of PCA and NDVI transformed images, the settlement and vegetation types could be separately recognized.



4.4b

Figure 4.4b. The spectral features of Band Ratio NDVI (4.5b)

4.4.3 Land use/land cover Classification

The spectral signature information from the new two transformed images indicates that land use/land cover types have a strong feature signature. Nine categories of land use/land cover in the study area have been classified by using a supervised maximum likelihood classification approach. Table 4.6 shows the description of the nine categories of land use/land cover (LULC) in the study area.

Table 4.6 The Land use/land cover Classification Scheme

LULC category	Definition
1. Forest	Secondary forest mainly broadly leaf wood
2. Plantation	Plantation estate; Orange, Tea, Clove and Rubber
3. Rice field	Wet/drainage rice field (sawah) planted
4. Open land	The arable or bare land
5. Settlement	Built-up area; housing, industry and manufacturing area
6. Rice field unplanted	Wet/drainage rice field (sawah) unplanted
7. Dry land	Grass land and dry land agriculture
8. Fishpond	Pond mostly near to the coastal area
9. Water	Water body and Reservoir

The results of final classification from the image 1989 to 1997 after filtering are shown in Figures 4.5a to 4.5 g.

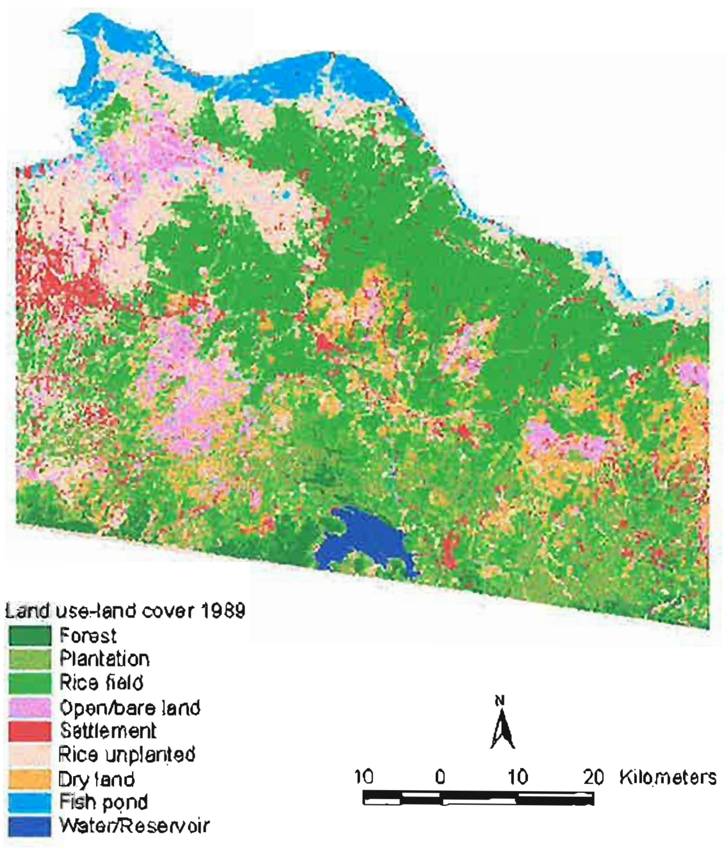


Figure 4.5a. The final classified image of land use/land cover 1989

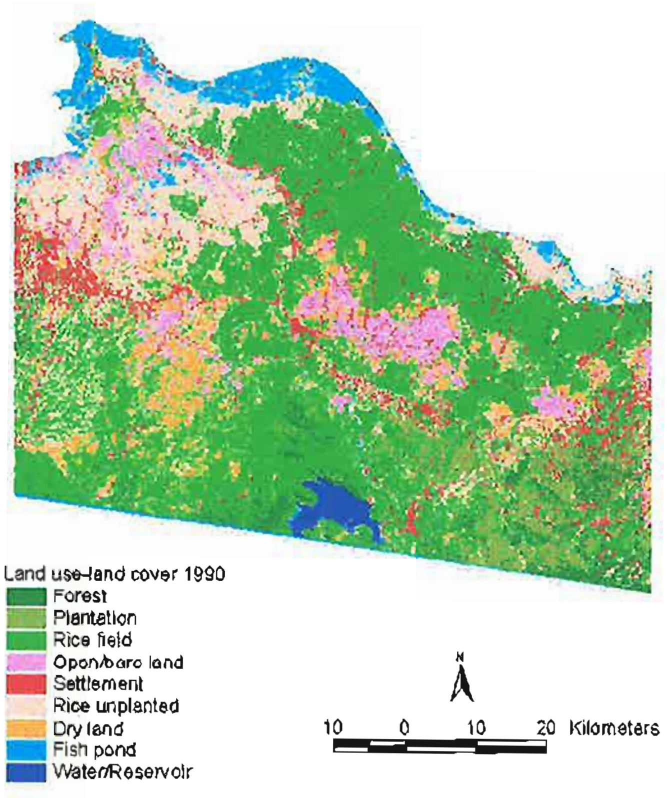


Figure 4.5b. The final classified image of land use/land cover 1990

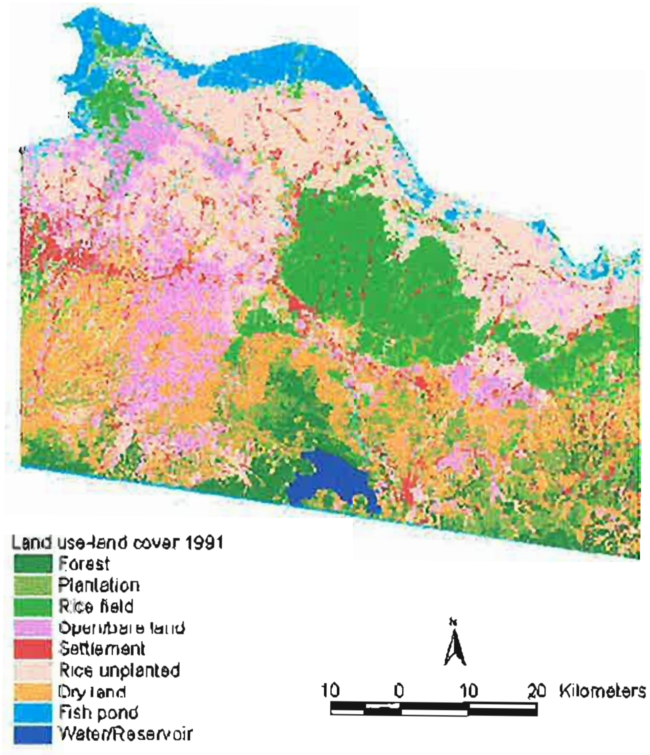


Figure 4.5c. The final classified image of land use/land cover 1991

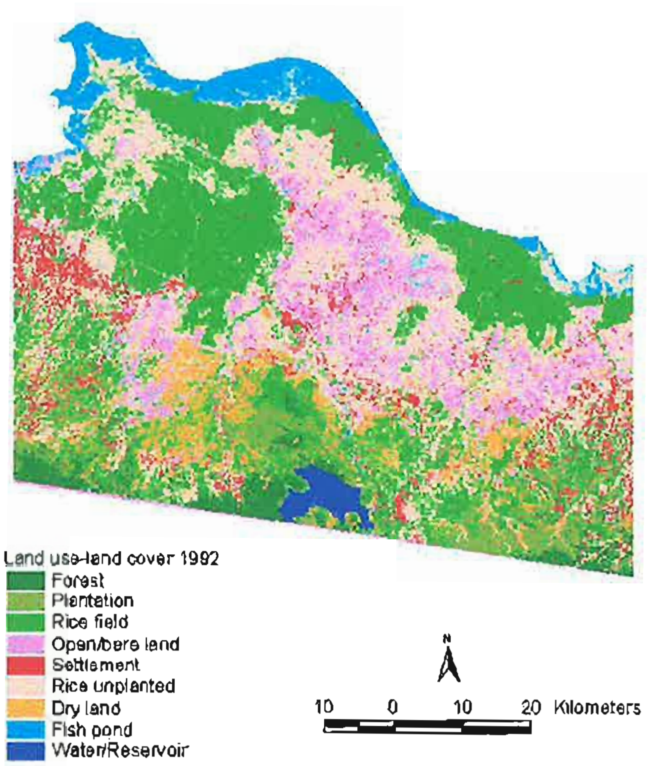


Figure 4.5d. The final classified image of land use/land cover 1992

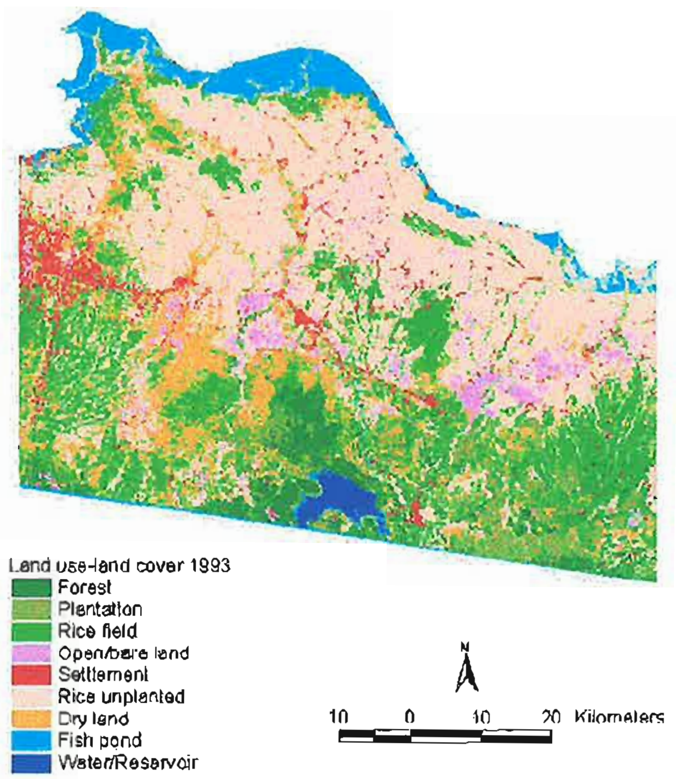


Figure 4.5e. The final classified image of land use/land cover 1993

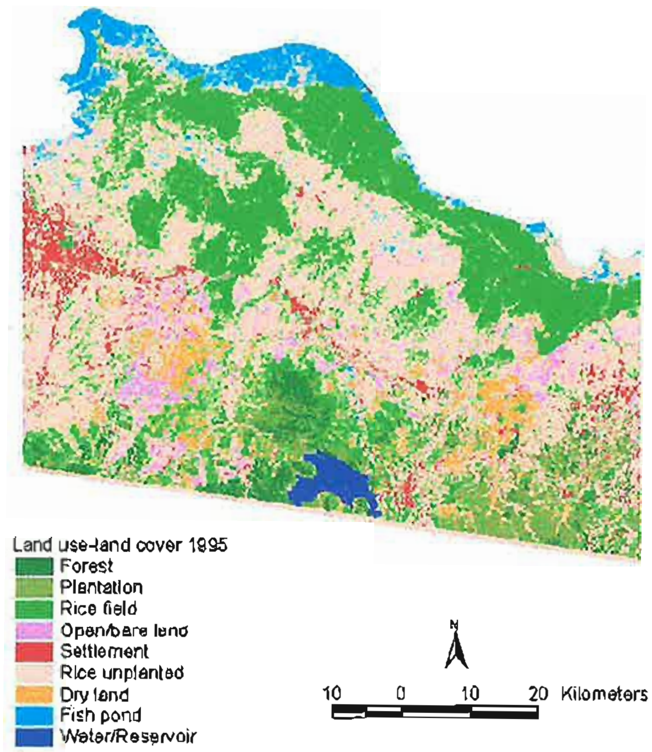


Figure 4.5f. The final classified image of land use/land cover 1995

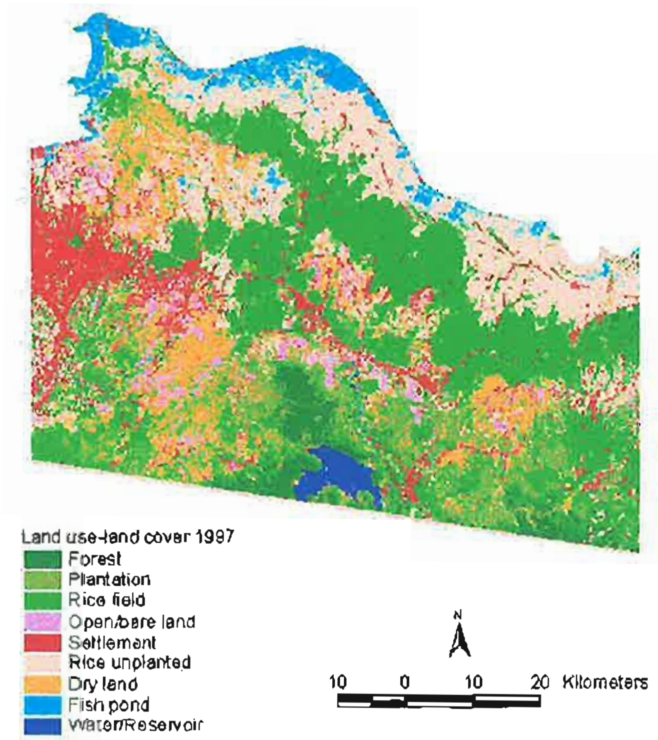


Figure 4.5g. The final classified image of land use/land cover 1997

Table 4.7 shows the accuracy assessment of years 1989 and 1997. Overall accuracy was 90 % for 1989 and 89% for 1997. From this table it can be seen that commission error (misidentifying no change and changed pixels) in 1989 was an average of 0.15 and omission (misidentifying change and no change) error was an average of 0.06. In 1997 commission error was 0.20 and omission error was 0.08. The result was an overall accuracy of 90% and 89%, which is good when compared with 85% as a standard minimum accuracy of land use/land cover classification from satellite data (Jansen, 1996).

Table 4.7: Summary of Kappa index of agreement (KIA) assessment

Class year 1989	Commission error	Omission error	Average accuracy
Forest	0.23	0.03	0.96
Plantation	0.05	0.02	0.97
Rice field	0.03	0.07	0.87
Open/bare land	0.03	0.03	0.95
Settlement	0.01	0.06	0.93
Rice unplanted	0.18	0.23	0.73
Dry land	0.73	0.05	0.94
Fishpond	0.07	0.05	0.93
Water/reservoir	0.00	0	1
Average comm. error	**0.15**		
Average om. error		**0.06**	
Overall KIA			**0.90**
Class year 1997	Commission error	Omission error	Average accuracy
Forest	0.31	0.03	0.96
Plantation	0.08	0.02	0.98
Rice field	0.01	0.06	0.89
Open/bare land	0.06	0.15	0.84
Settlement	0.51	0.10	0.90
Rice unplanted	0.07	0.28	0.70
Dry land	0.75	0.08	0.92
Fishpond	0.06	0.03	0.97
Water/reservoir	0.00	0.01	0.99
Average comm. error	**0.20**		
Average om. error		**0.08**	
Overall KIA			**0.89**

4.4.4. The land use/land cover change detection

Once the classifications have been generated, it is possible to carry out a theme comparison between two classifications. This operation is performed by cross tabulation on a pixel-by-pixel basis resulting in a complete matrix of annual changes in land use/land cover within the study area.

Figure 4.6 shows the annual fluctuation of land use/land cover in the study area. From this figure it can be seen that, in general, all land use/land cover categories fluctuate annually. Some categories increased and others are decreased. The land use/land cover category that fluctuated the most was dry land. Settlement constantly increased in the five consecutive years (1989-1993) and increased significantly between 1995 and 1997. On the other hand, rice field was tending to decrease and rice field unplanted increased but decreased significantly from 1995 to 1997; fishpond and water/reservoir remain constant.

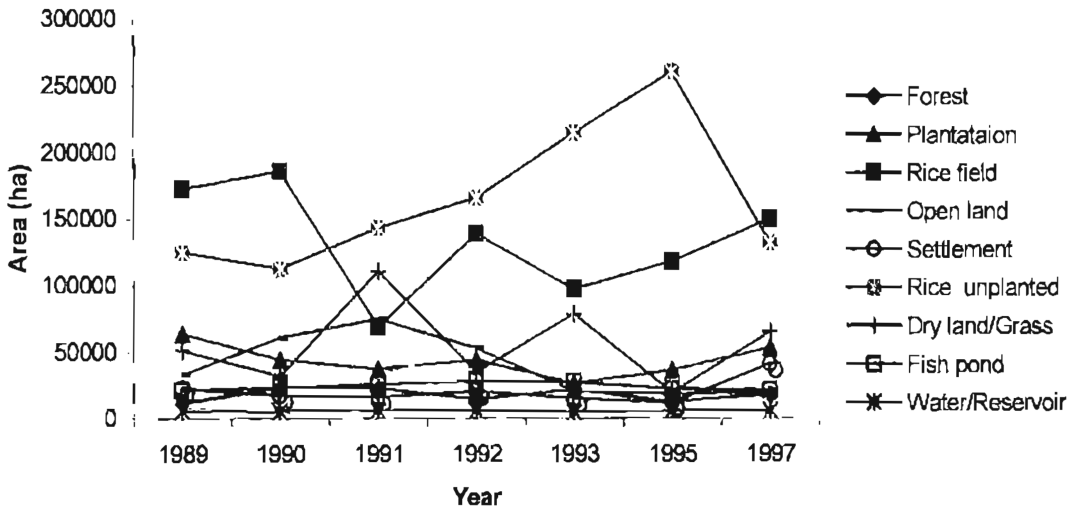


Figure 4.6. The annual land use/land cover change in the study area

More detailed analysis of land use/land cover change detection in annual 5-year consecutive (1989 to1993), 2-year time interval between 1993-1995 and 1995-1997, and 8-year time interval between 1989 and 1997 in the study area are explained and discussed as follow.

4.4.4.1 Annual Land use/land cover change from 1989 to 1993

The cross tabulation of annual land use/land cover classification generates a land use/land cover change matrix (in percentage and hectares) within the study area (Appendix Chapter IV). Tables 4.8a to 4.8d show the summary of major land use/land cover changes in the study area.

Table 4.8 a: The summary major changes in land use/land cover category 1989/1990 (dry/dry season)

Category	Change	Conversion	Shift
Open land	85% increase (27943 ha)	from rice field	Within rice field (planted) and rice field (unplanted)
Dry land	37% decrease (18954 ha)	to rice field (unplanted) and rice field (planted)	
Plantation	30% decrease (18999 ha)	to rice field (unplanted)	

From Table 4.8a it can be seen which major land use/land cover category changed between 1989 and 1990. Open land increased while dry land decreased. The increase of open land was the result of conversion from rice field (planted), and decrease of dry land and plantation was due to conversion to rice field (planted) and rice field (unplanted). Both 1989 and 1990 images were acquired in the same season (dry season at the harvesting time-Table 3.7 in Chapter 3). In the time interval 1990 to 1991 the land use/land covers that changed significantly were rice field and dry land. Rice field decreased and dry land increased (Table 4.8b).

Table 4.8b: The summary major changes in land use/land cover category 1990/1991 (dry/wet season)

Category	Change	Conversion	Shift
Rice field	63% decrease (116924 ha)	to dry land and rice field unplanted and rice field	Within rice field (unplanted)
Dry land	247% increase (78565 ha)	from rice field (unplanted) and rice field (planted)	

The decreasing of rice field (planted) and increasing of dry land in this time interval was due to the different seasons. The 1990 image was acquired in the dry season at harvesting time and the 1991 image was acquired in the wet season at planting time. In the 1990 image (harvesting time), rice fields were being planted while in 1991, rice fields have been harvested and are beginning to grow new plants (planting time). Therefore the rice field (planted) area was greater in 1990 than in 1991. Rice field (planted) in 1990 was converted to dry land and rice field (unplanted) in 1991. This phenomenon also was found when one analyzes change between 1992 and 1993; which is 1992 was dry season or harvesting time and 1993 was wet season or planting time. The change pattern in this time interval was the same as in time interval 1990 – 1991; rice field (planted) decreased and dry land increased (Table 4.8c). The decrease of rice field was due to conversion to dry land or rice field (unplanted).

Table 4.8 c: The summary major changes in land use/land cover category 1992/1993 (dry/wet season)

Category	**Change**	**Conversion**	**Shift**
Forest	48% increase (6931 ha)	from plantation	
Rice field	30% decrease (41975 ha)	to rice field (unplanted) and dry land	Within rice field (planted)
Open land	61% decrease (32093 ha)	to rice field (planted)	
Dry land	125% increase (43415ha)	from rice field (unplanted) and rice field (planted)	

In the opposite direction of the change between dry (harvesting time) to wet (planting time), is the change between 1991 and 1992 as show in Table 4.8 d.

Table 4.8 d: The summary major changes in land use/land cover category 1991/1992 (wet/dry season)

Category	**Change**	**Conversion**	**Shift**
Forest	37% decrease (8320 ha)	to plantation	
Rice field	101% increase (69991 ha)	from rice field (unplanted) and dry land	Within rice field (unplanted)
Dry land	69% decrease (75608 ha)	to rice field (unplanted) and rice field (planted)	

Rice field (planted) in wet season was less than rice field (planted) in dry season. In the wet season of 1991, most of the rice fields were under preparation to grow new plants and many rice fields were appearing as dry land or rice field (unplanted). Therefore in this time period (1992-1992), rice fields (planted) were seen larger than dry land or rice field (unplanted). The increasing and decreasing of rice field (planted) is related to decreasing and increasing of dry land and rice field (unplanted). This is the cycle of change among these categories between different growing seasons (harvesting and planting times).

The other interesting feature was the change in forest category. In the dry season, forest area was smaller than in the wet season (see Table 4.8c and 4.8d). This phenomena is related to the phenomenon of the "leaf on and leaf off" of broad leaf reflectance (Yuan *et al.,* 1999). In the dry season lots of leaves fall from broad leaf plants, so at this time the reflectance of leaf decreases, while in the wet season the reflectance increased from the leaves that have re-grown. Therefore decreasing and increasing forest does not representing deforestation in this area. It was an effect of the dry and wet seasons and could be a classification error due to a mix between forest and broad leave plantation during these seasons.

4.4.4.2 Land use/land cover change in 1993 to 1995 and 1995 to 1997

Wet and dry season phenomena of land use/land cover changes can be continually seen in the 2-year time interval (Table 4.9a). From Table 4.10a, it can be seen that forest and dry land were decreasing and rice field (planted) was increasing; this is similar to the patterns of change from wet to dry season between 1991 and 1992.

Table 4.9a: The summary major changes in land use/land cover category 1993/1995 (wet/dry season)

Category	Change	Conversion	Shift
Forest	41% decrease (8933 ha)	to plantation	Within rice field (unplanted)
Rice field	22% increase (21209 ha)	from rice field (unplanted) and dry land	
Dry land	75% decrease (58591 ha)	to rice field (unplanted) and rice field (planted)	

Another 2-year interval detection is in the dry-to-dry season between 1995 and 1997. In this time interval, the change pattern was different from the annual detection. In this time interval settlement increased, while rice field (unplanted) decreased and dry land increased. The increasing of settlement areas related to decreasing of rice field (unplanted) (Table 4.9b).

Table 4.9b: The summary major changes in land use/land cover category 1995/1997 (dry/dry season)

Category	Change	Conversion	Shift
Settlement	245% increase (28979 ha)	from rice field(unplanted)	Within rice field (unplanted)
Dry land	231% increase (45275 ha)	from rice field (unplanted) and rice field (planted)	
Rice field unplanted	50 % decrease (128877 ha)	to rice field (planted), settlement and dry land	

In dry-to-dry season between 1989 and 1990 settlement did not increase, while in dry-to-dry between 1995 and 1997 settlement was significantly increased. It means since 1995 in the study area a lot of land was converted to settlement.

4.4.4.3 Land use/land cover change in the 8-year interval 1989-1997

Table 4.11 shows a summary of land use/land cover change between 1989-1997 (the 8-year interval). The change of land use/land cover in this time interval should represent the real conversion or change of the land use/land cover in the study area after 8 years.

Table 4.10: The summary major changes in land use/land cover category 1989/1997 (dry/dry season)

Category	Change	Conversion	Shift
Open land	40% decrease (12930 ha)	to settlement and dry land	Within rice field (planted) and rice field (unplanted)
Rice field	13% decrease (21919 ha)	to rice field (unplanted) And open land	
Settlement	81% increase (18262 ha)	from rice field (unplanted) open land and dry land	
Plantation	17% decrease (11109 ha)	to forest	
Forest	57% increase (6494 ha)	from plantation	

Within the 8-year interval there are many land use/land cover categories that changed (Table 4.10). Open land and rice field (planted) decreased and settlement increased, while plantation decreased and forest increased. In this time interval it was also recognized that forest increase related to decreasing of plantations. The increasing settlement in this time interval related to the conversion from rice field (unplanted), open land and dry land, while decreasing of rice field (planted) related to conversion to rice field (unplanted). From this change trajectory, the sequence of land use/land cover change in this area can be recognized. Rice field (planted) was converted to rice field (unplanted) and open land, then rice field (unplanted) and open land was converted to settlement.

There is no change or conversion from forest to rice field or settlement. Forest change was related to plantations: if plantation decreases then forest will increase (confuse classification). The mix between forest and plantation was recognized in the field when ground truthing was conducted. In the study area, there were some broad leaf plantation areas such as rubber and teak wood plantations that 3 or 5 year later will appear as forest on the image. These plantations were located in kabupaten Karawang in the northern part of Jatiluhur reservoir.

4.4.5 Land use/land cover change identification and re-classification

The change detection of nine categories of land use/land cover in the study area has resulted in the various shifts and conversions among categories, especially in annual time intervals. Change detection on the 8-year time interval shows no annual variability except for rice field (planted) and rice field (unplanted). Rice field (planted) and rice field (unplanted) fluctuate due to different growing cycle. With this condition it was difficult to recognize the permanent change of rice field as well as open land areas. It was recognized in the field that rice field (planted) and rice field (unplanted) have the same function as rice field. Open land and dry land categories are the same as land which is unused, or under preparation for construction or for dry land agriculture. It is necessary, therefore, to regroup these two-land use/land cover categories in order to recognize the change of rice field and open/dry land within the 8-year time interval.

Figure 4.7 shows land use/land cover after reclassificationinto seven categories. Rice field (planted) and rice field (unplanted) were regrouped as rice fields. Open land and dry land were regrouped into open/dry land. From this figure it can be seen that rice field area is the largest and was the dominant land cover in whole of the study area. Settlement was seen to extend along the road corridor from the west to the east in the middle of the study area, and open/dry land was located within rice field and settlement area.

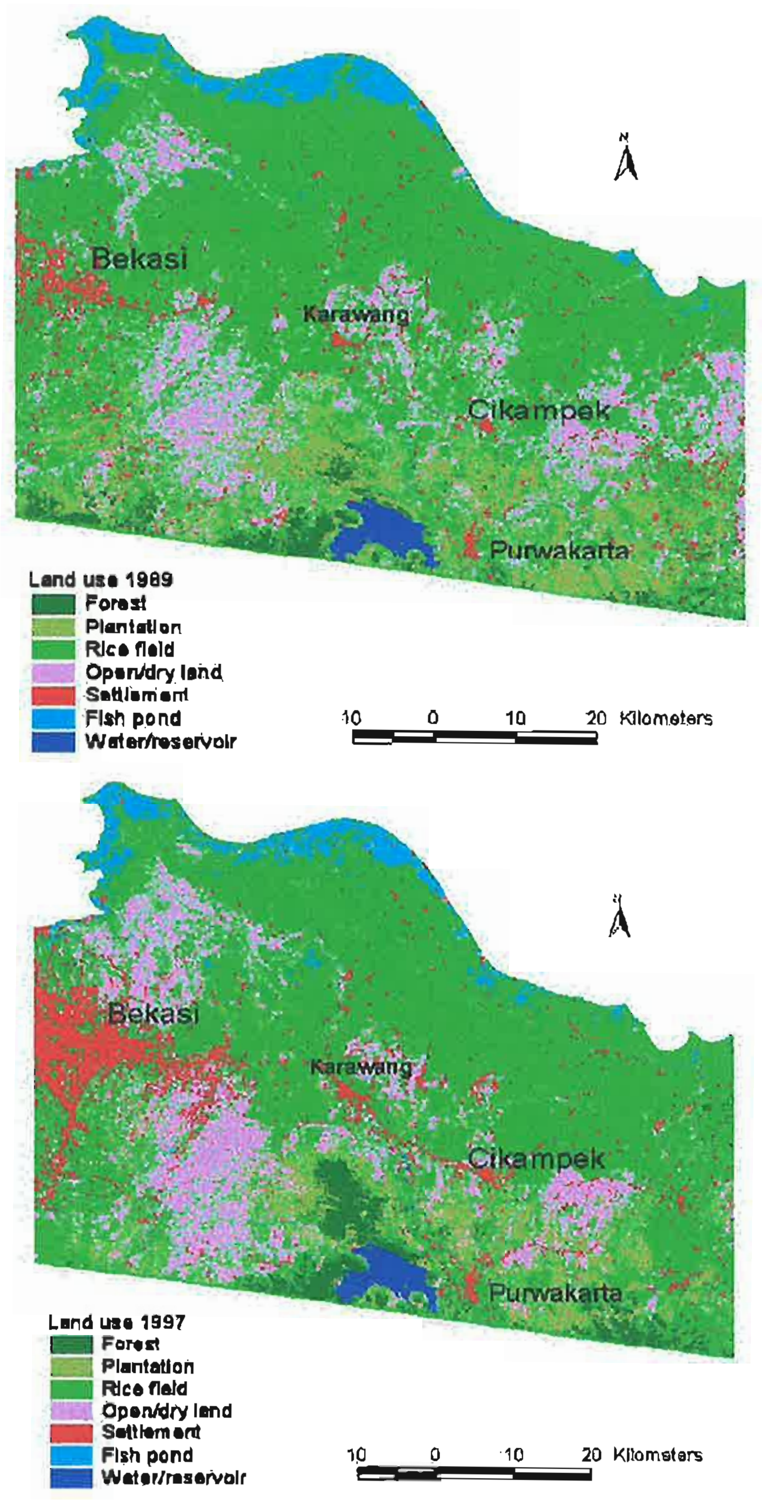


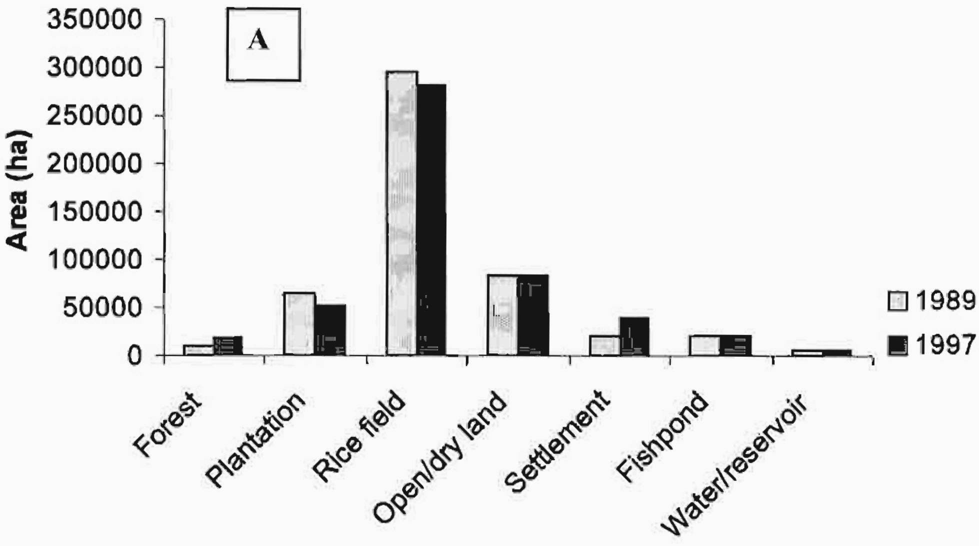
Figure 4.7. Land use/land cover in the study area 1989 and 1997

Source: LANDSAT TM Classification

Table 4.11: Land use/land cover in the study area year 1989-1997 (ha)

Types	1989	%	1997	%	Change	% Change*)
Forest	11338	2.25	17832	3.54	6494	57
Plantation	64068	12.72	52959	10.51	-11109	-17
Rice field	295732	58.71	280866	55.76	-14866	-5
Open/dry land	83407	16.56	84580	16.79	1173	0
Settlement	22535	4.47	40797	8.10	18262	81
Fishpond	21105	4.19	21185	4.21	80	0
Water/reservoir	5502	1.09	5468	1.09	-34	0
Total	503687	100	503687	100	0	0

**) Percentage of change to total area of each category in year 1989*



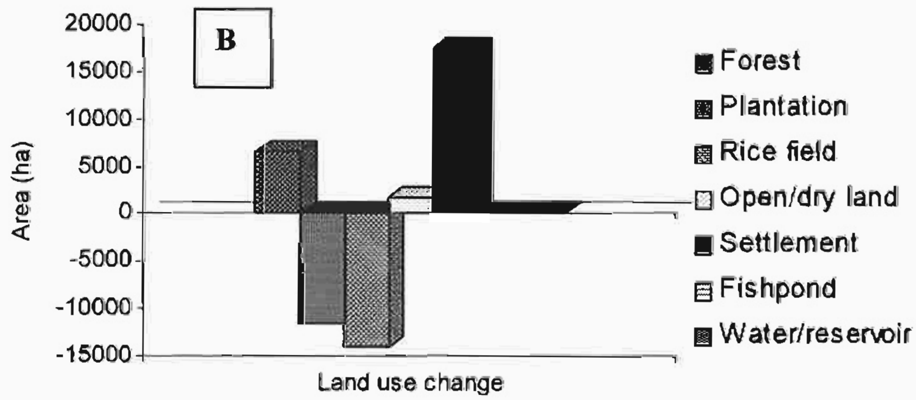


Figure 4.8. The land use/land covers change 1989-1997 in study area (a) and Total change of each category (b).

From Table 4.11 and Figure 4.8a and 4.8b. above, the change of land use/land cover among seven categories between 1989 and 1997 can be seen. Rice field decreased as well as plantation, while settlement, open/dry land, and forest increased. The decrease in rice field was related to increasing settlement and open/dry land. It is clearly shown that there was conversion from rice field into settlement. Settlement increased by 81 % or 18262 ha, while rice field decreased by 14866 ha or 5%. Plantation decreased, forest increased, and water /reservoir and fishpond was relatively constant. As has been mentioned, the increase in forest in the study area was due to the effect of "leaf on-leaf off" in the different seasons and confusion between forest and broad leaf plantation.

4.5 Discussion

The focus on change detection in this study is to recognise land use/land cover change dynamics in the study area by using image processing.

There are three common digital change detection strategies: pre-classification, post – classification and the hybrid approach. Pre-classification is the method that directly differentiates between two dates' spectral signatures. This approach was based on the assumption that different spectral signature over time represent a change in land surface conditions. Post-classification is based on images from two different dates that are independently classified or labelled. The classification process can be based on the classification of the standard/original image or a transformed image. The hybrid approach is based on the combination of pre-classification and post-classification.

From the initial recognition based on the false colour composite analysis of the study area, it was recognised that land cover in the study area is dynamic and changes over time. However, this initial recognition did not give detailed information of land cover category, due to limitations of spectral signatures on the original images of the false colour composite. The PCA and NDVI transformation was used to enhance the spectral signature of the image. PCA transformation enhanced the spectral signatures of settlement while NDVI enhanced vegetative cover. These two-transformed images were combined and used for a post-classification comparison approach to detect more detail in the land use/land cover change in the study area.

This study used post-classification comparison of two transformed (PCA and NDVI) images for the following reasons: 1) the study area has varied physical environmental conditions due to the weather/climate conditions; 2) the study area has varied land cover types; 3) the land use in study area has extensively changed due to the population and economic growth close to the Jakarta metropolitan area; 4) PCA and NDVI combination is an efficient method and has potential for data processing and maintaining classification accuracy without data pre-processing.

This approach was successful in detecting land use/land cover change in the study area. It was found that weather or season and growing cycle strongly influenced the land use/land cover conditions in the study area. In the classified image 1990 (acquired on June-the early dry season) forest cover was less than in 1991 (acquired on May - the late wet season) or within 1992 (acquired on July - dry season) and 1993 (acquired on April - wet season). Dry and wet seasons influenced the "leaf on-leaf off" phenomenon on the classified image. This phenomenon was clearly recognised in the change of plantation and forest categories. In the dry season, forest cover was less than in the wet season due to lots of leaves fall from plants ("leaf off"), while in wet season lots of leaves have re-grown ("leaf on"). Therefore in wet season, forest cover appeared to be increasing because of a lot of "leaf on" and also mixing with increasing "leaf on" of some broad leaf plantation such as rubber and teak wood The decreasing and increasing forest and plantation in this study could also be an error in classification due to mix between forest and broad leaf plantation such as ruber and teak wood.

Rice field (planted) and rice field (unplanted) were clearly recognised and changed according to growing cycles. In the harvesting time (the month of June - July), a lot of rice fields were covered by rice plantation that was ready to be harvested; therefore, in this harvesting time the identified rice field area was large. In the planting time (the month of April - May) a lot of rice fields were empty, because the land was being prepared to grow new rice. In this planting time the rice field area was less than in the month of June-July (harvest time). This phenomenon was clearly recognised in the field as well as from annual change detection.

From the summaries of annual change detection from 1989 to 1993, it can be recognised that for 1990 to 1991 the area rice fields (planted) was larger than rice field (unplanted). The 1990 image was acquired in June in the early dry season or harvesting time, while the 1991 image was acquired in May in the wet season at the planting time. Therefore, the changes of land use/land cover within this time interval dry-to-wet season were seen as conversion from rice field (planted) to rice field (unplanted) or dry land. On the other hand, change within the time interval 1991 - 1992 wet-to-dry season was seen as conversion from rice field (unplanted) to rice field (planted). The 1992 image was acquired in July at the harvesting time, when rice field areas were covered with rice plantations that were ready to be harvested.

For the long-term time interval detection (the 8-year 1989-1997) as well as the 2-year time intervals 1993 - 1995 and 1995 – 1997, seasonal variability was not an influence on land use/land cover change. In this time interval, especially in the 8- year time interval, it was recognized that some land use/land cover categories have permanently changed. Settlement was significantly increased, but rice field (planted) and rice field (unplanted) were still seen to fluctuate due to different growing cycles. Therefore, regrouping of rice field (unplanted) and rice field (planted) into rice field as well as open land and dry land into open/dry land, was necessary and resulted in more clearly recognized long-term conversion of land use/land cover change. Settlement significantly increased as a result of the conversion from rice field. Forest increased related to decreasing of plantation. The other categories such as water/reservoir (Jatiluhur reservoir) as well as fishpond remained constant.

4.6 Conclusion

Land use/land cover was clearly differentiated and could be classified into land use/land cover categories as follows: 1) Forest; 2) Plantation; 3) Rice field (planted); 4) Open land; 5) Settlement; 6) Rice field unplanted; 7) Dry land; 8) Fishpond and 9) Water/reservoir.

The trajectory of land use/land cover change in this area was recognized as follows: Rice field was converted to rice field (unplanted) and to open land, then rice field (unplanted) and open land was convert to settlement. There was no conversion from forest to rice field or settlement.

The change of forest in this study area did not represent deforestation or reforestation, it was error in classification due to mixes between broad leaf plantation and forest that related to dry and wet season ("leaf off – leaf on" phenomena). As found in the field, a lot of some broad leaf plantation (such as rubber plantation and teak wood found especially in the south part of Karawang near to the northern part of Jatiluhur reservoir), was confused with forest area.

It was necessary, for long-term detection change analysis, to reclassify or regroup the land use/land cover categories in this study area. This regrouping was important in order to recognise which land use/land cover had permanently changed. Rice field (planted) and rice field (unplanted) have the same function in the field as rice field area, and open land and dry land categories have the same function as a land which is unused or under preparation for construction or for dry land agriculture. These categories have been grouped as rice field and open/dry land.

After regrouping, the categories that really change are settlement and rice field. Settlement increased while rice field decreased. There was no change or conversion from forest to rice field or settlement.

Chapter Five

LAND USE/LAND COVER CHANGE DRIVER ANALYSIS

5.1 Introduction

Land cover in the study area changed on an annual basis related to seasonal variability or growing cycle. For example, an area may be rice field (unplanted) in one year and rice field (planted) the next year. From 8-year or long-term time interval detection, it was recognized that the land use/land covers that have permanently changed are settlement and rice field. Settlement increased while rice field decreased. The conversion of rice field to settlement increased permanently year by year, while other land use/land cover categories such as, open/dry land was changed temporarily, related to the weather or seasonal conditions. Forest and plantation was mixed related to the "leaf on and leaf off" phenomenon as an effect of weather or season condition (see Chapter 4). Moreover, the land use/land cover changes in this study area are interesting when analysed in relation to other socio-economic and biophysical factors. Factors such as population growth, economic growth (income per capita, GNP or industrialization) as well as physical factors such as topography or slope, soil and many others, are factors that could have a strong influence in the change of land use/land cover in the study area. Population density, proximity to roads as well as proximity to the city centre can represent social-economic growth as dynamic factors that influence land use/land cover change; factors such as slope, physiography and land system could represent static influence factors. The question is to what extent and which of these possible (dynamic and static) factors are the dominant or have strong influence on land use/land cover change in the study area?

This chapter presents an analysis of the possible influence factors of land use/land cover change between 1989 and 1997 in the study area. The analysis is both qualitative and quantitative. The objectives of this chapter are:

- To analyze the relationship between land use/land cover and the dynamic and static influence factors such as population density, proximity to urban and semi-urban center, proximity to roads, slope, as well as physiography and land system in spatial dimension.
- To determine the factors that have the strongest relationship on land use/land cover change in the study area.

5.2 Driver of Land use/land cover Change.

The factors that influence land use/land cover change can be divided into direct or proximate causes and indirect or underlying causes. Direct drivers are associated with activities which directly interact with and modify the physical environment, such as urbanization and agricultural expansion (Turner and Meyer, 1994). The indirect drivers influence how individuals or groups interact with, and change the land use/land cover (Blaikie *et al.,* 1994). These are generally more complex as they are built into the human system, underlying a land use activity (Adger and Brown, 1994; Krummer and Tunner, 1994).

The complexity of driving forces is highlighted by complex, interrelated influencing factors such as policy, institution, land management and climate change. Land use change does not stem solely from population growth. Several studies argue that human population affects land use change more by human actions than by sheer numbers (The National Academy of Science, 2001).

The focus of the driver or influence factors analysis in this study was divided into static and dynamic factors. Static factors were defined as factors that might never change, such as slope, elevation, or physiography, while dynamic factors were defined as factors that can be changed, such as population growth, population density, urban, and semi urban areas and transport routes, which represent impact of population, affluence and technology factors (PAT). Social and economic factors such as income per capita, GDP, industrialization and cultural structure, are also factors that can be included as dynamic drivers, but due to the difficulties and limitation of collecting this information, this analysis only includes factors such as population growth, population density, proximity to the center of urban and semi urban areas and proximity to roads.

5.2.1 Discriminant Analysis

Discriminant analysis is a technique for simultaneously examining differences between two or more groups of objects with respect to several variables (Klecka, 1980). Fisher introduced this technique for the first time in 1936 (Fisher, 1936). The concept underlying discriminant analysis is fairly simple (Marija, 1990). Linear combinations of the independent variables are formed and serve as the basis for classifying cases into one of the groups. For example, suppose we measure height in a random sample of 50 males and 50 females. Females are, on the average, not as tall as males, and this difference will be reflected in the difference in means (for the variable ***height***). Therefore, the variable ***height*** allows us to discriminate between males and females with a better than chance probability: if a person is tall, then they are likely to be male; if a person is short, then they are likely to be female (Marija, 1990).

Discriminant Analysis has been most commonly applied in medical or biological research (Rao, 1966; Reyment, 1973; Lachenbruch, 1973; Chou *at al*, 1998; Feighner *at al*, 2000; Tu *et al.*, 2003). Recently, this technique has been used for many purposes in areas such as physiology, educational research, banking, political science as well as in geography and remote sensing (Sullivan, 1980; Marija, 1990). In pattern recognition, linear discriminant analysis was successful in classifying a hyperspectral image (Du *et al.*, 2001; Du *et al.*, 2003). Du *et al.* (2001) used linear - constrained distance-based discriminant analysis (LCDA), which replaces the Fisher ratio used in linear discriminant analysis (LDA) with the ratio of inter-distance to intra-distance as a criterion for optimality. The result was that all classes of interest are forced to separate. By means of this direction, LCDA can detect and classify similar targets. Duin *et al.* (1999) used rational discriminant analysis (RDA) based on a proximity description of the data, such as similarities or the distances to a subset of the object, instead of features. They argued that formal objects might also be represented by a proximity measure (distances or similarities) to a set of prototypes or support objects. They conclude that rational discriminant analysis is a valuable pattern recognition tool for applications in which the choice of the features is uncertain.

Tappeiner, *et al.* (1998) used discriminant analysis to identify the influence of environmental parameters and human impact on the Alpine cultural landscape. This study successfully integrated discriminant analysis and GIS in modelling vegetation patterns using natural and anthropogenic influence factors. The model presented a useful tool for explaining the vegetation distribution and allowed the qualification and prediction of environmental effects on it (Tappeiner *et al.*, 1998). Sinowski *et al.* (1999) applied discriminant analysis on geological stratification. They used relief parameters such as altitude, slope and depth in discriminant analysis to stratify geological areas with different spatial variability of soil properties. They concluded that discriminant analysis could be used objectively to determine the soil depth at which geology changes.

Blackard *et al.* (1999) studied comparative accuracies of artificial neural networks and discriminant analysis in predicting forest cover types from cartographic variables. They used the cartographic variables of elevation, aspect and slope to predict forest cover type. The result was that the comparison indicated that a feed-forward artificial neural network model more accurately predicted forest cover type than did a traditional statistical model based on Gaussian discriminant analysis. Ju *et al.* (2003) improved the Gaussian discriminant analysis model with Gaussian mixture discriminant analysis to capture sub-pixel heterogeneity. They used a Gaussian mixture discriminant analysis model for inferring land cover fractions within forest stands from Landsat TM images. They conclude that the Gaussian mixture discriminant analysis model offers an attractive means for addressing the mixture-modelling problem in remote sensing.

Bertels, *et al.* (1999) conducted another comparative study; they used discriminant analysis and neural networks to evaluate company performance. They concluded that neural networks are not superior to linear discriminant analysis, except when they are given highly uncertain information. Manel *et al.* (1999) compared discriminant analysis, neural networks and logistic regression for predicting species distributions of

Himalayan river birds. They compared the performance of multiple discriminant analysis (MDA), logistic regression (LR) and artificial neural networks (ANN). The result was that MDA was preferable over LR or ANN, but where there are complex or non-linear influences on species distribution, ANN may well turn out to be advantageous.

5.3 Method

5.3.1 Overlay analysis of possible driver factors

Overlay analysis in GIS was used to analyse the relationships between static as well as dynamic factors and land use/land cover change in the study area. Static factors such as slope, physiography and land system have been created as well as dynamic factor (Table 5.1). The classes of each static factor followed the standard classification system of slope class, physiography and land system used in Indonesia (Directorate Land use and RePPProt, 1986), while dynamic factors were created by buffering a 10 km radius from the centre of urban area and semi-urban area. This radius assumes that 10 km is the longest distance people walk to work in agricultural areas. Urban and semi-urban areas were defined based on the status of the city as *a capital city*. The capital city of a kabupaten (district) was defined as urban and the capital city of kecamatan (sub-district) was defined as semi-urban. The total population at kecamatan level in which these cities were located was more then 50 000 people.

The buffer 1km from main roads (the state roads), others roads (the provincial and kabupaten roads), and toll way the proximity factor. This assumes that 1 km is the maximum distance of built up area located along the roads. This buffer area was overlayed with land use/land cover to identify the relationship between roads as an accessibility factor with land use/land cover change in the study area.

Another dynamic factor, population density, has been created based on the total population per square km area of each kecamatans (a lower level of Kabupaten). The total population data were collected from the statistical office of Kabupaten. The area of each kecamatan was calculated based on administrative boundary map that was derived from topographic maps (Chapter 3). Table 5.1 shows the method employed to create possible influence or driver factors in the study area.

Table 5.1. The Method to create area of possible influence or driver factors

Features	GIS Method	Possible influence or driver Factors
Main City	Buffer	Proximity to Urban area
Other City	Buffer	Proximity to Semi Urban area
Main roads	Buffer	Proximity to Province roads area
Other roads	Buffer	Proximity to Kabupaten roads
Toll way	Buffer	Proximity to Toll way area
Population density	Reclass	Population density area
Slope	Reclass	0 – 3 % area
		3 – 8 % area
		8 – 15 % area
		15 – 30 % area
		30 – 45 % area
		> 45 % area
Physiography	Reclass	Flat
		Rolling hill
		Volcano
		Fold hill and volcano
Land system	Reclass	Coalescent estuary area
		Coastal beach ridges area
		Hillocky plains area
		Intertidal mudflats area
		Low rounded hills area
		Minor river floodplain area
		Permanently water lodged area
		Steep hill on marls area
		Undulating to rolling
		Sedimentary plains area.
		Very steep ridges karts area

Buffering of "point" features such as main and other cities has been conducted to create an area of proximity to the urban and semi-urban as a possible dynamic influence factor. While buffering of "line" features such as main roads, toll way and other roads has been conducted to create an area of proximity to roads also as a possible dynamic influence factor, "polygon" or "area" features such as population density areas, slope class as well as physisography and land system class have been reclassified to create an influence area from this factor. These spatial data sets then were used in overlay analysis of possible influence factors and land use/land cover change in the study area.

5.3.2 Simple linear and Discriminant Analysis

The quantitative analysis undertaken here consists of simple linear regression to analyse relationships between populations and land use/land cover, and the discriminant analysis approach to determine which factors had the most influential on land use/land cover in the study area. Discriminant analysis is used to build a predictive model of group membership based on observed characteristics of each case. The procedure generates a discriminant function or a set of discriminant functions based on linear combinations of the predictor variables that provide the best discrimination between the groups.

In this study, discriminant analysis was used to analyze the predictor or independent variables of land use/land cover that provide the best discrimation between the groups. The dependent variable consists of six classes of land use/land cover (LULC) categories in the study area (forest, plantation, rice field, open/dry land, settlement and fishpond) and the independent variable consists of five variables: slope, proximity to city center (urban and semi urban), proximity to roads (province road or main road), proximity to toll way and population density. Land system is a nominal data type, therefore this static factor is not included as an independent variable in the discriminant analysis. Data for discriminant analysis must consist of an interval data type except for the dependent variable (Marija, 1990). The group membership in any given cell or pixel can be predicted based on the variables that have strong influence in discriminating land use type.

Independent variables, such as population density, proximity to the city, to main roads, to toll way, and slope as well as land use/land cover type as the dependent variable, were created on a grid system and masked with 20% of random sample grid. In this analysis, proximity to the city was created as distance to the centre of urban area (capital city of Kabupaten), and proximity to main roads was created as distance to provincial roads, this category being based on the hypothesis that only urban areas that are located along province roads have strong influence on land use/land cover change. This database was classified into 30 classes with distance intervals of 1, 5 km for roads and toll way and 2 km for proximity to the city (urban area). Another parameter is population density. This was divided into 4 classes (Class 0 no data, Class I population density 15-150 prs/sqkm, class II population density 151 – 650 prs/sqkm, and class III population density 651-1200 prs/sqkm) (Table 5.2).

Table 5.2: Variable used in the discriminant analysis

Variable	Data type	Range
Land use/land cover	Nominal	6 class
Dynamic factors		
Proximity to the city	Interval	30 class
Proximity to main roads	Interval	30 class
Proximity to Toll way	Interval	30 class
Population density	Interval	4 class
Static factor:		
Slope	Interval	6 class

This entire database was then converted into tabular format using Arc/info to obtain a database that can be used for discriminant analysis in SPSS software (Statistical Package for Social Science).

Simple linear regression analysis was conducted on the database of population at kecamatan level and land use/land cover derived from the result of image classification of years 1989 and 1997. Land use/land cover area in every kecamatan was derived from intersection of the kecamatan boundary and land use/land cover for 1989 and 1997. Based on this database, simple linear regression was conducted to identify relationships between population and land use/land cover for the years 1989 and 1997.

5.4 Results

5.4.1 Overlay analysis

5.4.1.1 Static drivers

An intersection between land use/land cover and static driver factors resulted in identification of various relationships among driver factors and land use/land cover change in the study area. Tables V.1, V.2 and V.3 (Appendix V) show the matrix of intersection between land use/land cover versus slope, physiography and land systems. From these tables it can be recognized that only four categories of land use/land cover changed significantly. These were: forest, plantation, rice field and settlement. Other categories such as open/dry land, fishpond and water/reservoir did not change significantly.

Table 5.3 shows the summary of the relationship between land use/land cover change and slope. From this table it is evident that the land use/land cover categories of forest, plantation, rice field and settlement significantly changed within all slope classes. Forest decreased mostly within slope 30-45% and > 45% and settlement increased mostly within slope 0-3%, which is where settlement predominantly is located. Plantation decreased within slope 8-15% and 15 –30%, while rice fields decreased within slope 0-3 % but increased within slope more than 3%. This change shows that land use/land cover that represents human intervention or intensive land use (settlement and rice field) is mostly located in the area within slope 0-3%.

Table 5.3: Summary of land use/land cover change versus Slope (1989-1997)

Types\Slope		0-3%	3-8%	8-15%	15-30%	30-45%	>45%
Forest	1)	6116	609	110	108	-191	-201
	2)	1.31	3.48	1.31	1.69	-8.02	-9.16
Plantation	1)	-5850	-2898	-1325	-1049	-221	-151
	2)	-1.25	-16.59	-15.85	-16.45	-9.28	-6.89
Rice field	1)	-19486	1677	1166	909	434	345
	2)	-4.16	9.60	13.94	14.25	18.23	15.71
Settlement	1)	18043	330	-18	16	-4	-3
	2)	3.85	1.89	-0.22	0.24	-0.15	-0.13

1) = unit in Ha
2)= Percentage of change area to total area of slope class

Another relationship that supports this phenomenon is also revealed by the intersection of land use/land cover and physiography (Table 5.4). Settlement and rice fields significantly changed within flat areas, while forest and plantation changed in rolling hill and volcano areas.

From both the intersection of land use/land cover with slope, as well as with physiography, it was clearly recognized that, in general, the major land use/land cover in the study area such as settlement and rice field, were predominantly located in the flat areas within slope 0-3%, followed by plantation and forest in rolling hill and volcano areas within slope 0-3% and more than 3%. This phenomenon was fitted with the schema of land use pattern in Indonesia (Chapter 2).

Table 5.4: Summary of land use/land cover change versus Physiography 1989-1997

Types		Flat	Rolling hill(RH)	RH and V	Volcano(V)
Forest	1)	1090	3785	-1085	2761
	2)	0.36	6.37	-1.02	7.37
Plantation	1)	2145	-5287	-5377	-4647
	2)	0.71	-8.90	-5.05	-12.40
Rice field	1)	-19478	-2231	-2034	1610
	2)	-6.46	-3.75	-1.91	4.30
Settlement	1)	16877	499	9967	-46
	2)	5.59	0.84	9.35	-0.12

1) = unit in Ha

2)= Percentage of change area to total area of physiography class

Further information was obtained from the result of intersection between land use/land cover and land systems. From Table 5.5 it can be recognized that land use/land cover such as rice field and settlement significantly changed in areas with land systems of coalescent estuary and undulating to rolling sedimentary plains, while forest changed in hillocky plains (Table 5.5). Land systems of coalescent estuary and undulating to rolling sedimentary plains were located in the flat area, and consist of a fertile soil and are rich with minerals from volcanic sedimentary material. Hillocky plains are located in the hill area consisting of volcanic tuff (RePPProt, 1986).

Table 5.5: Summary of land use/land cover change versus land system (1989-1997)

Land system	*Coalescent estuary*	*Coastal beach ridges*	*Hillocky plains*	*Inter-tidal Mud flats*	*Low rounded hills*	*Minor river Flood plain*	*Permanently water lodged*	*Steep hills on marls*	*Undulating to rolling sedimentary plains*	*Very steep ridges karstic*
Forest										
1)	479	0	5944	89	-405	116	0	265	-1055	1058
2)	0.25	0.00	**12.49**	0.36	-1.60	0.66	0.00	**4.20**	-0.81	**18.53**
Plantation										
1)	3537	100	-3566	334	-3030	-85	29	-630	-6799	-1472
2)	1.58	**2.67**	-7.49	1.37	**-11.94**	-0.48	0.80	**-9.99**	**-5.19**	**-25.78**
Rice field										
1)	-10796	-233	-4289	1543	3926	-1033	-1367	2	-1665	495
2)	**-4.80**	**-6.21**	**-9.01**	**6.32**	**15.45**	**-5.87**	**-37.61**	0.03	-1.27	**8.67**
Settlement										
1)	5185	43	89	243	-78	371	62	-37	11081	-3
2)	**2.32**	11.82	0.19	1.00	-0.31	**2.11**	1.71	-0.59	**8.46**	-0.05

1) = Unit in Ha

2)= Percentage of change area to total area of land system class.

5.4.1.2 Dynamic drivers

Overlay analyses of land use/land cover change with dynamic driver factors were conducted through examining the intersection between land use/land cover with population density, proximity to the center of urban and semi-urban areas, and proximity to roads. The results are presented as follows.

Population density

Table 5.6 shows the relationship between land use/land cover change and population density. It is evident that settlement has consistently increased in area with higher population density. Settlements increased gradually within areas with population density class I (increased 3374 ha by23%), while class II increased (by 3043, ha (64%), and class III increased (by 4441. ha (134%) (Figures 5.1a and 5.1b). Areas of rice field decreased with increasing population density. Rice field area decreased by 25277 ha (-11%) in areas with lowest population density (class I), while in class II it decreased by 9078 ha (-31%), and in class III it decreased by 3789. ha (-63%). There is no indication of an effect of population density on decreasing or increasing forest and plantation. Forest increased in area with population density class I and class II, while plantation area decreased in low population density (class I) and increased in area with high population (class II and III) (Table 5.6). The increasing forest and plantation in areas with high population density could be due to areas of secondary forest, as well as plantations which consists of broad leaf plantation such as rubber and teak wood which are located close to the roads and settlement.

Table 5.6: Land use/land cover and Population density Classes

	Density Class I		Density Class II		Density Class III	
LULC	Change (ha)	%Change	Change(ha)	%Change	Change(ha)	%Change
Forest	2261	**29**	642	**69**	0	0
Plantation	-10257	**-21**	2462	**61**	8	**100**
Rice field	-25277	**-11**	-9078	**-31**	-3789	**-63**
Open/dry land	25373	36	3971	78	-669	-53
Settlement	3374	**23**	3043	**64**	4441	**134**

Note: percentage change to total area of each category
Class I = 15 - 150 person/sqkm
Class II = 151 – 650 person/sqkm
Class III = 651 - 1200 person/sqkm

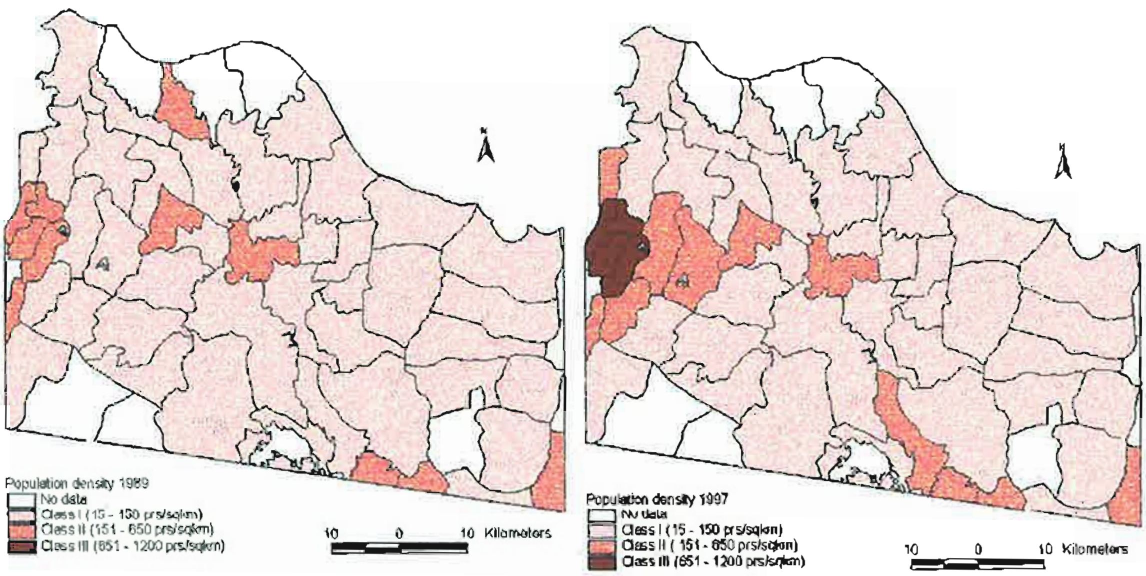


Figure 5.1a. The Classification of population density the study area

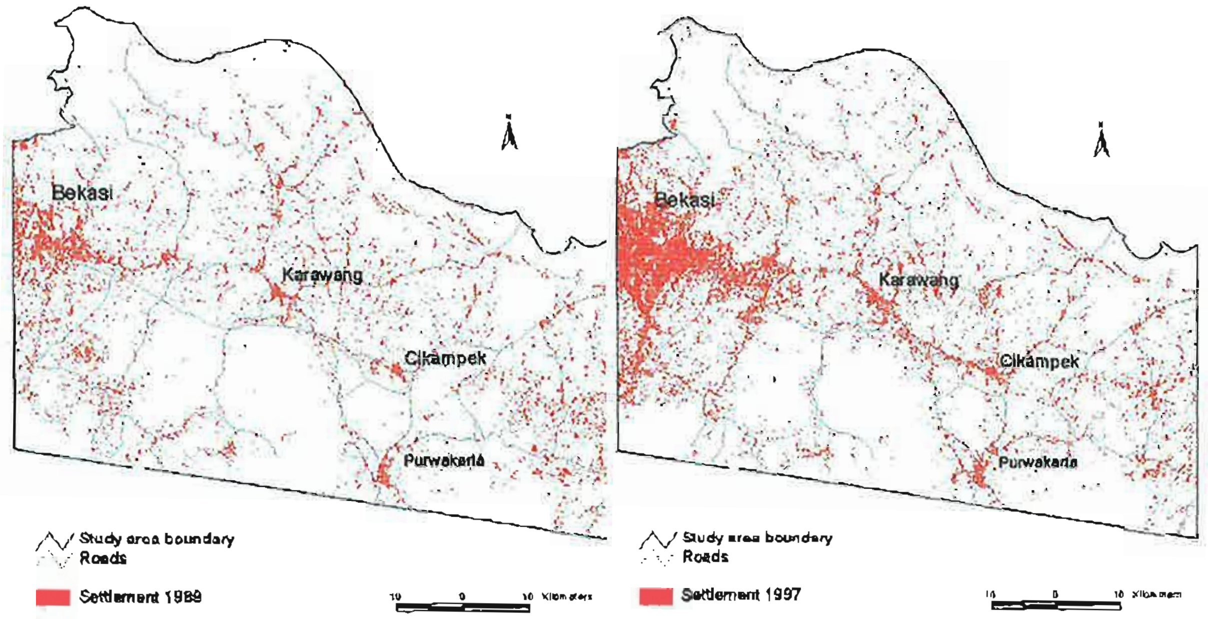


Figure 5.1b. The settlement distribution in the study area

Source: Analysis of Landsat TM 1989 and 1997

Urban and semi-urban

Rice field and settlement land use/land cover categories underwent greatest change within the 10 km radius from the urban centers (Table 5.7). This change also occurred in the area within 10 km radius from the center of semi-urban areas (Table 5.8). In this area increasing settlement was accompanied by a decrease in rice fields. The largest increase of settlement is within the area which is close to the Jakarta metropolitan area. Settlement substantially increased within 10 km of Bekasi, Babakan, Cileungsi as well as Cikarang. These areas are about 30 km from Jakarta (Table 5.9 and Figure 5.2).

Table 5.7: Land use - land cover change within10 km of urban area (Ha)

Urban	Forest	Plantation	Rice field	Open/dry land	Settlement	Fishpond
Bekasi *)	0	246	-11225	1756	9200	0
2)	0.00	0.79	**-35.91**	**5.62**	**29.43**	0.00
Karawang *)	184	866	-1781	-795	1436	90
2)	0.59	**2.77**	**-5.70**	**-2.54**	**4.59**	0.29
Purwakarta *)	724	-277	-717	-193	475	31
2)	**2.32**	-0.89	**-2.30**	-0.62	**1.52**	0.10

**) change = unit in ha*

2) Percentage of change to total area of each 10 km radius

Table 5.8: Land use -land cover change within10 km of semi-urban area (Ha)

Semi-urban	Forest	Plantation	Rice field	Open/dry land	Settlement	Fishpond
Babakan *)	0	261	-9030	8129	814	-175
2)	0.00	0.84	**-28.89**	**26.01**	**2.60**	-0.56
Cikarang *)	0	710	-5816	823	4272	0
2)	0.00	**2.27**	**-18.61**	**2.63**	**13.67**	0.00
Cileungsi *)	-77	-2791	-1201	-392	2024	0
2)	-0.37	**-13.38**	**-5.76**	**-1.88**	**9.70**	
Cikampek *)	68	852	-708	-1111	860	0
2)	0.22	**2.72**	**-2.27**	**-3.55**	**2.75**	0.00

**) change = unit in ha*

2) Percentage of change to total area of each city in segment 10 km radius

Table 5.9: Percentage of decreasing and increasing rice field and settlement within urban and semi-urban in the study area.

Urban and Sub urban	% Change of Rice field	% Change of Settlement	Distance from Jakarta (km)
Bekasi *	-36	29	15
Cikarang**	-19	14	30
Cileungsi**	-6	10	30
Karawang*	-6	5	50
Cikampek **	-2	3	75
Purwakarta*	-2	2	75

Source: Summarized from Table 5.7 and 5.8

** Urban area; ** semi-urban area.*

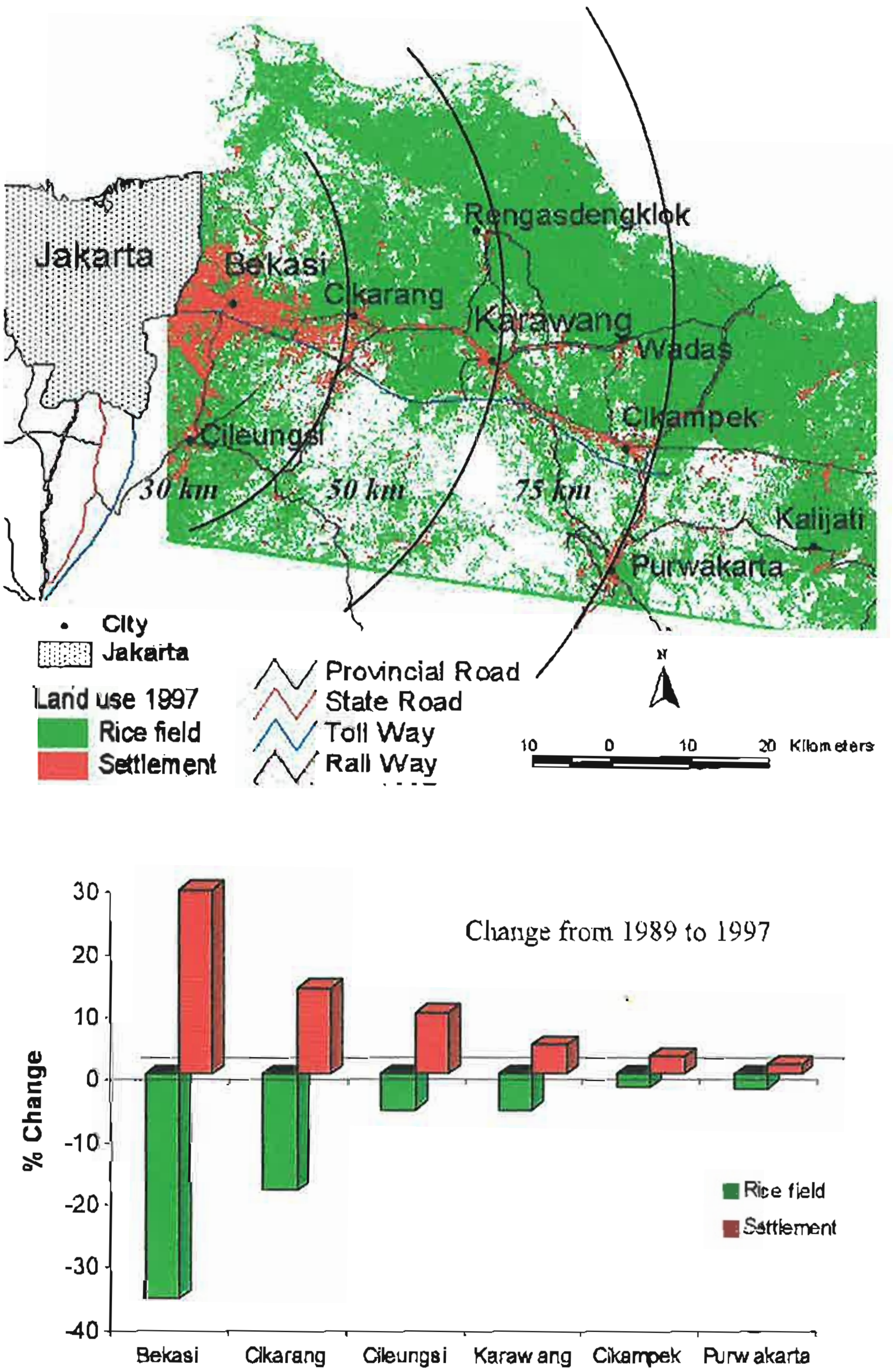


Figure 5.2. The increasing of settlement accompanied by decreasing rice field within urban and semi-urban in the study area. Sorting by distance from Jakarta city.
Source: analysis of Landsat TM 1989 and 1997

From Figure 5.2 it can be seen that the percentage increase of settlement and percentage decrease of rice field is greater for areas that are close to Jakarta than for areas that are further from Jakarta. It can also be recognized that status as a capital city of kabupaten (urban) and status as a capital city of kecamatan (semi-urban) does not necessarily relate to increasing settlement. For example, Bekasi, Karawang and Purwakarta are capital cities of kabupaten (urban areas) but the large and significant increasing area of settlement is only in Bekasi and Karawang, not in Purwakarta. However, Cikarang and Cileungsi, which are the capital cities of kecamatan (semi-urban areas), increased in their area of settlement (Table 5.9). This phenomenon supports the view that the distance from the Jakarta metropolitan area strongly influenced increasing settlement in the surrounding areas.

Another interesting feature was the increasing area of settlement in Cikampek, an area more than 75 km away from Jakarta. This increase of settlement was related to increasing industrial development in this area. Industry, manufacturing and trade in this area and surroundings increased from 4777 units of industry and manufacturing in 1989, to 6923 units in 1997 and 8354 units of industry and manufacturing in 2000 (the local Statistic office of Karawang, 2000).

Accessibility

Roads have a strategic function as a transportation connector, facilitating the flow of goods and the movement of people from one place to another. Land use/land cover along roads tends to undergo rapid change due to the accessibility of the surrounding areas.

From Tables 5.10a to 5.10c it can be seen that rice fields and settlements have undergone change along the 1 km buffer from the roads. The largest change is along the toll road. In this area, rice fields decreased by 3913 ha or -23 % and settlement increased 3810 ha or 22%. The second largest change is rice field and settlement along the state road, where settlement increased by 3552 ha or 13 % and rice field was decreased by 2135 ha or -8.02%. Along the state roads it was recognised that open land decreased by –2346 ha or –8.81%. This decrease could be some open/dry land that has been converted to settlement (housing or industrial estate) as has been found in the field. During the fieldwork in1999 it was found that in this area a lot of new housing and industrial estates have been constructed.

Table 5.10a: Land use/land cover change in 1 km buffer of Toll Road

Land use	1989 (ha)	1997 (ha)	Change (ha)	% Change
Plantation	1301	1378	77	0.46
Rice field	9517	5604	-3913	**-23.26**
Open/dry land	3774	3759	-14	-0.08
Settlement	2231	6042	3810	**22.65**

% Change = percentage of change area to total area of 1km buffer

Table 5.10b: Land use/land cover change in 1 km buffer of State Road

Land use	1989 (ha)	1997 (ha)	Change (ha)	% Change
Forest	60	293	233	0.88
Plantation	2124	2783	659	**2.48**
Rice field	15281	13146	-2135	**-8.02**
Open/dry land	4234	1887	-2346	**-8.81**
Settlement	4928	8479	3552	**13.34**

% Change = percentage of change area to total area of 1km buffer

Table 5.10c: Land use/land cover change in 1 km buffer of other Road

Land use	1989 (ha)	1997 (ha)	Change (ha)	% Change
Forest	1601	1199	-401.95	-0.40
Plantation	12767	10064	-2702.15	**-2.68**
Rice field	58969	55413	-3556.39	**-3.53**
Open/dry land	18754	19007	253.00	0.25
Settlement	7689	14131	6442.73	**6.39**

% Change = percentage of change area to total area of 1km buffer

5.4.2 Quantitative analysis (Simple linear and Discrimant analysis)

Four land use/land cover categories that had changed significantly such as settlement, rice field, forest and plantation have been analysed through simple linear regression with the total population within the study area (Figures 5.3a to 5.3d).

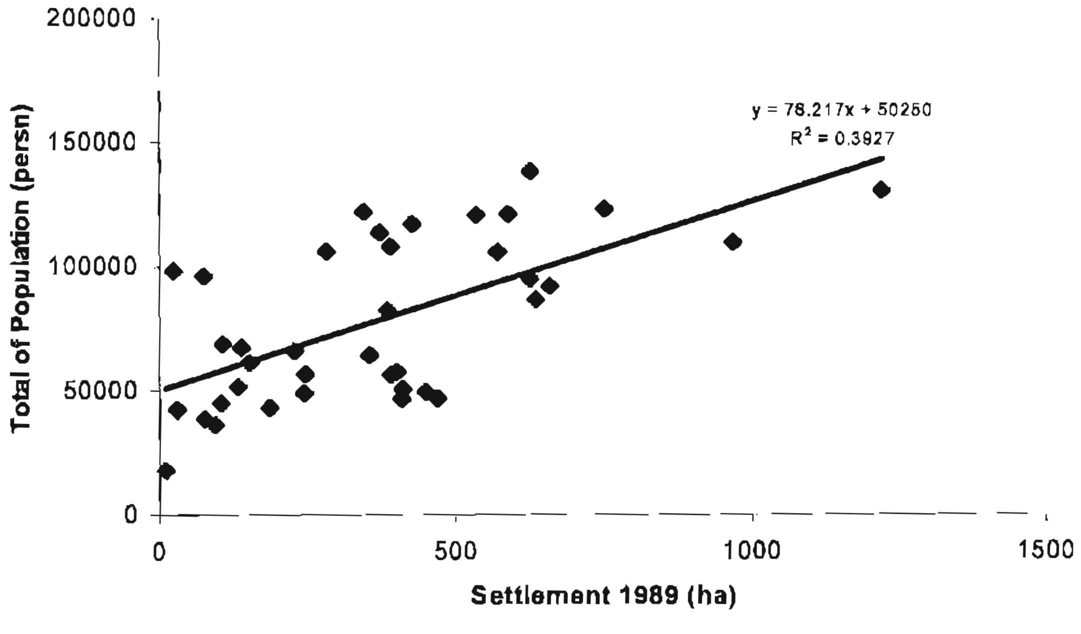


Figure 5.3a Linear regression of Total Population and Settlement 1989

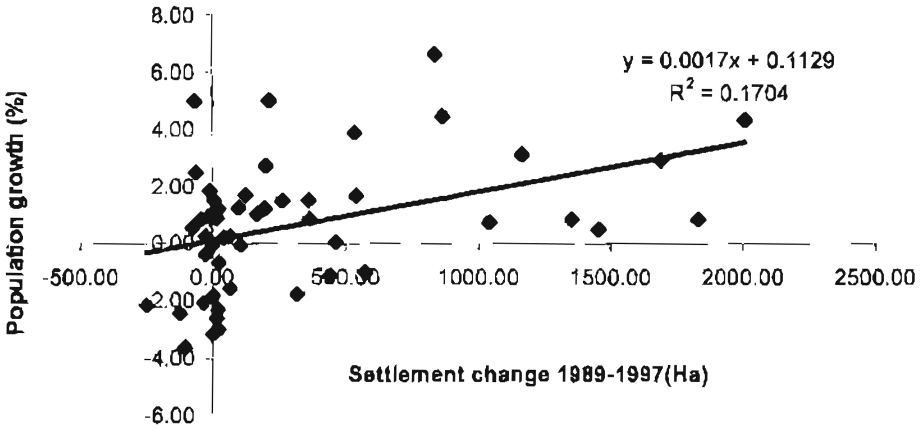


Figure 5.3d Linear regression of the Population growth and Settlement change.

From Figure 5.3 a to 5.3d it can be seen that there is positive relationship between total "population and total area of settlement", "population change and settlement change" as well as "population growth and settlement change". This means that when population increases settlement will increase, but the correlation of these relationships was low with R^2 below 0.65, and the lowest was correlation between population growth and settlement change (R^2 = 0.17,Table 5.11).

Table 5.11: R^2 of linear regression between population and land use/land cover

	Total of Population 1989	Total of Population 1997	Population growth 1989-1997
Settlement 1989	R^2 = 0.39		
Settlement 1997		R^2 = 0.66	
Settlement change 1989-1997			R^2 = 0.17
Rice field 1989	R^2 = 0.0024		
Rice field 1997		R^2 = 0.0063	
Rice field change			R^2 = 0.3477
Forest change			R^2 = 0.0013
Plantation change			R^2 = 0.1402

Relationships between population and rice field, forest and plantation shown in Figure 5.3e-5.3g, were negative. This means that when population increases rice field, forest and plantation will decrease. This relationship was poor; with most of R^2 below 0.40, and especially for forest category was very poor 0.0013 it could be due to representatives' data of forest, which is only a small part in the study area.

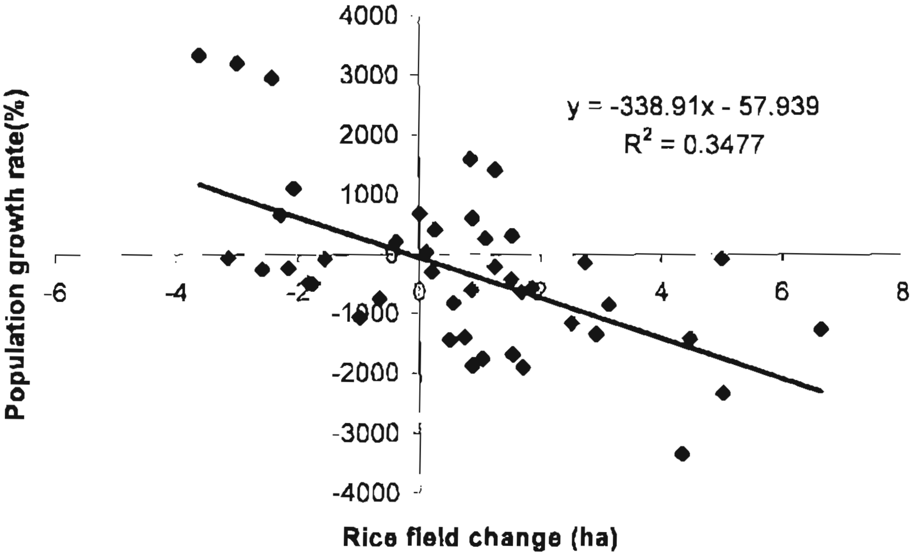


Figure 5.3e Linear regression of Population growth and Rice field change.

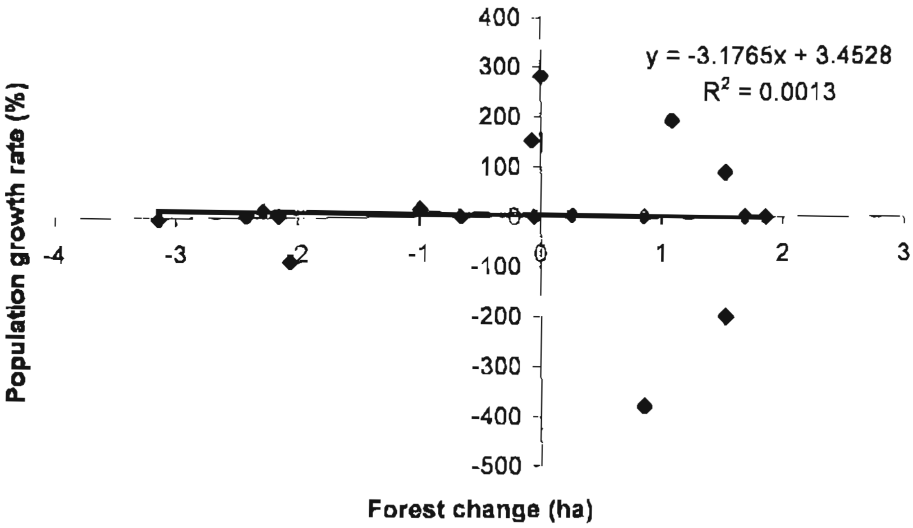


Figure 5.3f Linear regression of Population growth and Forest change.

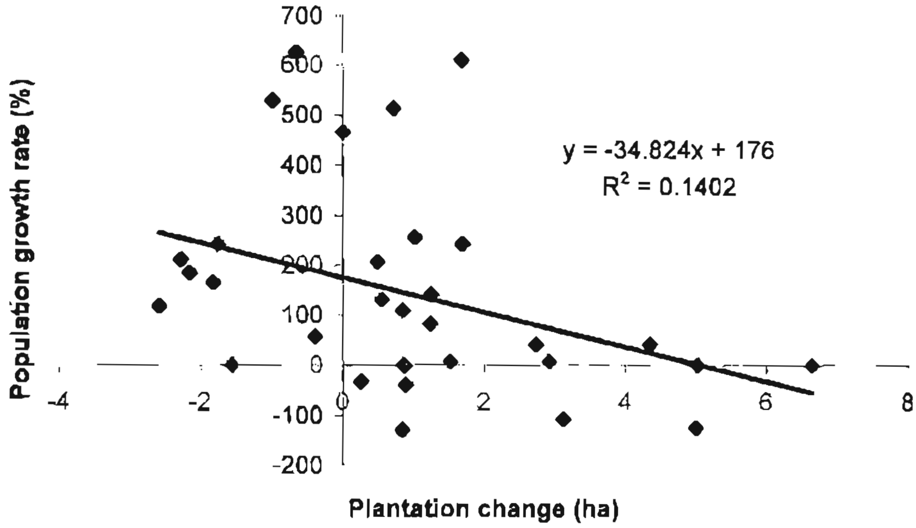


Figure 5.3g Linear regression of Population growth and Plantation change.

Discriminant function analysis results in variables that discriminate between six land use/land cover categories in the study area. Table 5.12 shows the covariance matrices for separate group. The values in this table gave some idea of how the relationship between variables changes from group to group. For example, in group 5 (Settlement), all variables have negative values except variable population density. It means these variables have negative and positive relation with settlements. Settlement areas are large in areas where population density increases (positive), and also will be small in areas when slope decreases, and proximity to urban, proximity to main road, and proximity to toll way all decrease (negative sign). This relationship makes sense, in that settlement areas are close to roads, close to urban, have little slope, and are in high population density areas. Other groups such as forest, plantation and rice field have different relationships. For example, group 1 (Forest) has a positive relation with population density and a negative relationship with slope, proximity to road and proximity to urban. It means that forest areas are large in areas with high population density and close to road and to urban. Rice fields also have positive relationship with population density, slope and proximity to urban areas, and a negative relationship with proximity to main roads and proximity to toll way. Open/dry land has the same relationship as the relationship of settlement to population density, which is a positive relationship. This is a single land use/land cover (one year 1997) analysis. Forest, plantation and rice field as well as settlement in this study area are located in areas with high population density and near to the roads. Therefore, rice field as well as forest has a positive relationship with population density and proximity to the roads. Especially for forest it could be a misinterpretation of this category due to mixes with broad leaf plantation, which is located close to settlement and main roads.

Table: 5.12. Covariance Matrices

Group	Population density	Slope	Prox. to urban	Prox. to main road	Prox. to toll way
1 = Forest	0.085	-0.033	-.2.76	-.108	0.098
2 = Plantation	0.137	0.025	-0.106	-0.068	0.122
3 = Rice field	0.169	0.007	0.098	-0.202	-0.394
4 = Open/ dry land	0.147	-0.003	-0.328	-0.348	-0.138
5 = Settlement	0.641	-0.001	-0.552	-1.252	-1.344
6 = Fish pond	0.252	0.000	1.711	0.625	-0.623

The initial statistics from the discriminant analysis are shown in Table 5.13. From this table it can be seen that the high values, occur only in four functions with an eigenvalue >0.1 or percentage of variance >15 %. This means that only of this four function that has strong relationship with land use/land cover.

Table 5.13. Eigenvalues

Function	Eigenvalue	% of Variance	Cumulative %	Canonical Correlation
1	.236[a]	35.5	35.5	.437
2	.177[a]	26.6	62.1	.388
3	.148[a]	22.2	84.2	.359
4	.105[a]	15.7	100.0	.308
5	.000	.0	100.0	.004

a First 4 canonical discriminant functions were used in the analysis.

In Table 5.14a it can be seen that all variables have a different contribution in each function. For example, the population density has a greater contribution to function 4 than the other, slope has a greater contribution to function 2, as well as proximity to main road. It means factors such as proximity to urban areas have a strong contribution in function 4, proximity to toll way has strong contribution in function 2, slope has strong contribution in functions 1 and 3, population in function 3,and proximity to main road in function 3. This relation was also supported by looking at the relationship between the dependent variable and discriminant variables in the structure matrix (Table 5.14b), which gives the canonical correlation coefficients. These values are comparable to factor loading and indicate the substantive nature of the variables. When some dependent variable has high canonical correlations while other have low, then the ones with high correlations contribute most to group separation (Bargman, 1970).

Table 5.14a. Standardized Canonical Discriminant Function Coefficients

	Function			
	1	2	3	4
Prox to urban	-.214	.567	.275	.729
Prox. to toll way	.245	-.769	-.162	.596
Slope	.660	.130	.637	-.087
Population den	-.154	-.149	.418	-.072
Prox. to main road	.576	.689	.821	.282

Table 5.14b. Structure Matrix

	Function			
	1	2	3	4
Prox to urban	.767*	.072	.627	-.066
Prox. to toll way	.734*	.387	-.485	.100
Slope	.368	-.678*	.117	.625
Population den	-.393	.392	.347	.753*
Prox. tomain road	.672	.130	.210	.044

Pooled within-groups correlations between discriminating variables and standardized canonical discriminant functions Variables ordered by absolute size of correlation within function.

* Largest absolute correlation between each variable and any discriminant function

From Table 5.14b it can be seen that proximity to urban areas, main road and toll way have a high correlation in function 1, slope in function 2, population density in function 4. If it is compared with eigenvalue in Table 5.13, it can be clearly recognized that factors such as population density, proximity to urban areas, proximity to main roads and proximity to toll way have a strong contribution. It means these factors have a strong influence on land use/land cover in the study area, similar to that found from overlay analysis.

The linear equation of the discriminant analysis is analogous with multiple regressions. The general linear equation is: **Group = a + b_1*x_1 + b_2 *x_2+......+b_m*x_m**

Table 5.15 shows the coefficients of linear equation of each group.

Table 5.15: Classification function Coefficients

	Land use/land cover category (group)					
	1	2	3	4	5	6
Population density	6.868	6.975	7.447	6.911	9.808	9.941
Slope	6.543	3.249	2.888	2.762	2.783	1.852
Proximity to urban	0.853	0.689	0.689	0.773	0.511	1.41
Proximity to main road	-0.267	-0.237	-0.306	-0.190	-0.225	-0.240
Proximity to toll way	0.759	0.656	0.928	0.553	0.675	1.041
(Constant)	-17.609	-10.708	-12.093	-10.410	-13.560	-22.673

Fisher's linear discriminant function

From Table 5.15 the linear equation of discriminant classification function can be divided into six groups as follows:

Group 1 (Forest) = -17.609+6.868*Popden+6.543*Slope+0.853*Prox.to urban-0.267 *Prox to main road + 0.759*Prox to toll way

Group 2 (Plantation) = -10.708+6.975*Popden+3.249*Slope+0.689*Prox.to urban-0.237*Prox to main road + 0.656*Prox to toll way

Group 3 (Rice field) = -12.093+7.447*Popden+2.888*Slope+0.689*Prox.to urban-0.306*Prox to main road + 0.928*Prox to toll way

Group 4 (Open/dry land) = -10.410+6.911*Popden+2.762*Slope+0.773*Prox.to urban-0.190* Prox to main road + 0.553*Prox to toll way

Group 5 (Settlement) = -13.560+9.808*Popden+2.783*Slope+0.511*Prox.to urban-0.225*Prox to main road + 0.675*Prox to toll way

Group 6 (Fishpond) = -22.673+9.941*Popden+1.852*Slope+1.41*Prox.to urban-0.240*Prox to main road + 1.041*Prox to toll way

This classification result was 43.7% of original grouped cases as well as cross-validated grouped cases correctly classified. It means the accuracy of this linear equation of discriminant classification function was 43.7 %.

5.5 Discussion

Many studies have been conducted to reveal the interplay between land use/land cover changes and the influencing factors such as growth and changing patterns of population and socio-economic factors. These studies have mainly addressed the demographic and socio-economic aspects of the non-spatial relationships between land use/land cover changes and the influencing factors, more qualitatively than quantitatively.

This study focuses on analysis of their relationships from a spatial dimension using GIS-based advanced spatial analysis techniques. The methods used in the study might shed more light on the research field of land use/land cover changes, both quantitatively and qualitatively. Such research methods and techniques can be extrapolated to a broad dimension at a regional scale.

The results from overlay analysis between land use/land cover changes and possible influencing factors in this study demonstrate that there is a close relationship between land use/land cover changes and both dynamic and static influencing factors. Slope and physiography were the static influence factors that had a strong relationship with land use/land cover. The land use/land cover types that represent human intervention (settlement, rice field, plantation) were mostly located in the flat areas with slope < 3%. The dynamic factors such as population density, proximity to the urban areas and proximity to the road also had a strong relationship with land use/land cover. Settlement increased and rice field decreased significantly with increasing population density as well as within 10 km proximity to the city and within 1 km proximity to the roads. This land use/land cover distribution conformed to the schema of land use pattern in Indonesia that has been studied by I Made Sandy (Sandy, 1997).

In urban areas such as Bekasi, Karawang and Purwakarta, decreasing rice field and increasing settlement are clearly recognized, as well as in semi-urban areas such as in Cikarang, Cileungsi and Cikampek. The increasing of settlement accompanied by decreasing rice field in the study area was related to increasing population density. Settlements increased within areas according to overall population density; class I increased 23%, class II increased 64%, and class III increased 134%. While rice field areas decreased -11% in area with lowest population density (class I), in class II it decreased -31%, and in class III it decreased -63%. This condition indicates that the increasing population density has an effect on increasing settlement and decreasing rice field in the study area. There is no indication of strong relation between population density on decreasing or increasing forest and plantation. Forest increased in areas with population density classes I and class II, while plantation area decreased in low population density (class I) and increased in areas with high population (class II and III). The increasing forest and plantation in areas that had high population density could be due to the type of forest in the study area, especially in the kabupaten Purwakarta and Karawang, where there is secondary forest as part of reforestation programs (Local Statistical Office, 1997), which are located close to the roads and settlements. Also, there are plantations which consist of broad leaf plants such as rubber and teak wood, mostly located along the roads.

Another factor that has a strong influence on increasing settlement and decreasing rice field in the study area, is the distance from the Jakarta metropolitan area. The increasing of settlement accompanied by decreasing rice field within urban and semi - urban gradually decreased with increasing distance from Jakarta. In the Bekasi area, 15 km away from Jakarta, settlement increased the greatest and rice field decreased, followed by Cileungsi and Cikarang, which are 30 km from Jakarta. This supports the view that the Jakarta metropolitan area has an influence on developing the surrounding areas.

The factor of proximity to the main roads and toll way also has a strong influence on decreasing rice field and increasing settlement. This proximity factor is easy to understand in that roads have a strategic function as a transportation connector, facilitating the flow of goods and the movement of people from one place to another. In effect, areas close to the road will have the greatest chance to be changed into settlement or other commercial areas.

From the discriminant analysis, the relationship between influence factors and land use/land cover was clearly recognized. Relationships between independent (influence factors) and dependent variables (land use/land cover types/groups) indicate that group 4 (open/dry land) and group 5 (settlement) had positive relation with population density and negative relation with, slope, proximity to urban, proximity to main road, and proximity to toll way. It means that open/dry land and settlement will increase in areas with high population density, little slope, close to urban, close to main road, and close to toll way. This relationship makes sense because most settlements are located and extended in the flat area along the road and near to the urban areas.

The other interesting feature is the positive relationship between group 1(forest) and 2 (plantation) as well as rice field with population density and its negative relationship with slope, proximity to road and proximity to urban. It means large forests in areas with high population density and close to roads and urban areas. A similar result was found from the overlay analysis in that forest and plantation areas were mostly located in the areas with high population density and close to the main roads, especially in kabupaten Purwakarta and Karawang. Rice fields had a positive relationship with population density, slope and proximity to urban, and negative relationship with proximity to main road and toll way. It represents the real condition that rice fields are mostly located in areas with high population density, near to main road and toll way and far from urban areas.

The canonical correlation on standardized canonical discriminant function coefficients and structure matrix tables indicate the contribution of relationship between dependent variable and discriminant variables. The canonical correlation is the correlation of two canonical (latent) variables, one representing a set of independent variables, the other a set of dependent variables. These values are comparable to factor loading and indicate the substantive nature of the variables. The high value of canonical correlation represents the strong contribution to group separation. Therefore, the factors population density, proximity to main road and proximity to urban are the variables that strongly contribute to separation of each group of land use/land cover in the study area.

5.6 Conclusion

This chapter has analysed the influence of land use/land cover change drivers in the study area. As the study area is mostly flat in the downstream area of the Citarum watershed, land use/land cover predominantly consists of irrigated rice fields. Static factors such as slope and physiography have a strong influence on land use/land cover in the study area. The land use/land cover types that represent human intervention (settlement, rice field, plantation) were mostly located in the region of little slope or flat areas. Dynamic factors such as population density, proximity to the urban areas and proximity to the roads also had a strong relationship with land use/land cover. This strong relationship is supported by discriminant analysis, where the factors population density, proximity to the main roads and proximity to urban were the variables that had the strongest contribution to discrimination of each group of land use/land cover in the study area. Distance to the Jakarta metropolitan area strongly influenced the increasing amount of settlement and the decreasing of rice field in the surrounding areas such as Bekasi, Cikarang and Cileungsi.

Chapter Six

LAND USE/LAND COVER CHANGE PREDICTION IN THE STUDY AREA

6.1 Introduction

Potential future spatial distribution of land use/land cover conditions is important information that can be used by planners to identify areas that require priority attention or to anticipate poor arrangement of land resources. Many researchers have developed models to simulate and explore land use/land cover changes. These models are various and relate the purpose and the scale of studies (Berry, 1996; Clarke, 1997; Verburg *et al.*, 1999; Irwin, 2001; Pontius *et al.*, 2001; Fischer, 2001 and Gobin, 2002). Pontius *et al.* (2001), for example, developed a model to simulate the location of land use/land cover change specifically for forest disturbance. They present a GIS-based model, GEOMOD2, which qualifies factors associated with land use, and simulates the spatial pattern of land use forward and backward in time. GEOMOD2 was able to classify forest cover correctly to between 84 and 86 % with Kappa about 0.34 and 0.45. Gobin *et al.* (2002) developed a model to predict the probability of private local agricultural land use. The result was a binary logistic model for estimating probabilities of private agricultural land use that correctly predicted 95.7% of the 300 sample plots. Significant progress in spatial modelling of land use/land cover change has been made when spatial data sets were available from remotely sensed data (Irwin *et al.*, 2001). Availability of digital spatial data from satellite imagery has assisted in conceptualizing the basic geographic and environmental processes associated with land use/land cover change, and developing spatial models that fit the spatial process of land use/land cover change.

Cellular automata (CA) have been used to simulate land use/land cover change (White, 1997). CA is a mathematical technique in which the behaviour of a system is generated by a set of deterministic or probabilistic rules based on the states of a cell and neighbouring cells. Cellular automata, combined with Markov chain probability principles, is a way to predict land use/land cover on a spatial basis, based on transition probability and contiguous neighbouring cells.

This chapter presents the land use/land cover change prediction as well as simulation in the study area based on Markov cellular automata models. The objectives are:

1. To use the Markov cellular automata model available in Idrisi32 to predict land use/land cover change in the study area.
2. To simulate the future land use/land cover in study area based on scenarios by using Markov cellular automata model.
3. To analyse the past and the future land use/land cover in the study area.

6.2 Land use/land cover change prediction model

Many studies have investigated land use/land cover change analysis, prediction and modelling. These vary from those that focus on the concepts of land use/land cover change to those on theorizing and modelling (Briassoulis, 2000). Models of land use/land cover change have progressed since spatial data sets from remotely sensed data have been available. Time series remotely-sensed data with multi-temporal data acquisition allow prediction of the timing of changes, opening new avenues better to link socio-economic transformation to land use changes (Kaufmann *et al.*, 2001) and to understand time lags in the response of land use to socio-economic or natural perturbations.

Serneels *et al.* (2001) assessed the driving forces of land use changes through a spatial statistical analysis. They developed spatial statistical models of the proximate causes of different processes of land use change. The descriptive spatial models developed in their study suggest some important factors driving the land use that can be related to some well-established theoretical frameworks. This study focused on understanding proximate causes of the changes. It did not address the location of land use change taking place. Pontius *et al.* (2001) studied land use/land cover changes related to location and quantity issues. This study aimed at predicting the spatial pattern, location and rate of land use/land cover change. Other models that address the location and rate of land use/land cover change include the Markov Cellular automata approach (Veldkamp *et al.*, 2001). This is a spatial model that combines the Markov transitional probability approach with cellular automata to predict land use/land cover change. Through cellular automata techniques, behavioural models of land use can be made spatially explicit (Veldkamp *et al.*, 2001).

The Markov Cellular automata model was selected in this study for three reasons. Firstly, the Markov chain principle has the simple rule that transition probability can be used to predict future land use/land cover. Secondly, cellular automata can represent the spatial dimension of the process, in this case land use/land cover states. And lastly, Markov and cellular automata approaches complement each other to predict land use/land cover change-addressing where and at what rate land use/land cover changes are likely to progress.

6.2.1 Markov chain model

Landscape change and spatial diffusion processes can be simulated using linear, stochastic techniques. A stochastic process is determined by random variables and is describable only in probabilistic terms (Lambin, 1994). Probabilistic models in general are appropriate for land use/land cover change processes given the complexity of relationships between interacting variables, and the poor understanding of the driving forces behind land use/land cover change. This approach has become common in modelling land use/land cover change.

A Markov chain is a mathematical model for describing a certain type of process that moves in a sequence of steps through a set of states. The Markov hypothesis, as applied to land use/land cover change, is that past land use/land cover is helpful in predicting future land use/land cover, given the present land use/land cover (Lambin, 1994). Bel *et al.* (1977) stated "the conditional probability of land use/land cover at any time, given all previous uses at earlier times, depends at most upon the most recent use and not upon any earlier ones". The central mechanism of a Markov chain is a probability p_{ij} which refers to the likelihood of transition or movement from state i to j in a given time interval, where i and j are either location-to model spatial diffusion processes – or locationally relevant classes – to model landscape change processes (Brown, 1970). For land use/land cover change studies, the states of the system are defined as the amount of land covered by various land use/land cover, measured as percentages of area of each land use/land cover type.

The Markov chain model will describe land use/land cover change from one period to another and than use this as the basis to project future changes. This is accomplished by developing a transition probability matrix of land use/land cover change from time (t) to time (t+1), which will be the basis for projecting to a later time period. In probabilistic terms for the sequence X (t), X (t+1) the Markov probability is expressed as follows:

$$\mathbf{P\ [X\ (t+1) = j \mid X\ (t) = i]}$$

Where i and j are indices of the Markov series of the system (Bell, 1974).

The Markov chain has been used in many studies. In the 1970s, for example, it was used for analysing the location pattern of firms, migrations, and land use change (e.g. Collin, 1973; Bell, 1974; and Bell, 1977). Aaviksoon (1995) and Howard *et al.* (1995) conducted further studies. Aaviksoon (1995) used a Markov chain model to simulate vegetation dynamics; he concluded that the development of plant cover and land use types can be modelled well both on first and second order levels. The general trends are well reproduced and the predictions are reliable to a few steps. Over longer time periods (more than three or four steps), both approximations may fail to give correct results. Howard *et al.* (1995) argued that a stationary Markov chain model allows the future consequences of a given pattern of land use changes to be studied, and can be used as an analytical tool. Logsdon *et al.* (1997) conducted another study on probability mapping of land use change. They successfully showed that the Markov chain model affords a powerful descriptive and predictive model for land use change and for future land use distribution.

In terms of prediction, the Markov chain models have the potential to provide timely projection of land use/land cover changes with minimal data requirements, but the ignorance of interactions between contiguous land areas by the Markov chain is a major limitation for broad scale application (Lambin, 1994). Another limitation is that the Markov chain model does not help to address the "Why?" question. It can predict future changes in land use/land cover-"When?" and "What?"- only as long as the stationary condition is met (Lambin, 1994).

Recently, the application of the Markov chain model has been combined with GIS (Brown *et al.*, 2000; Lopez *et al.*, 2001; Hathout, 2002; Weng, 2002). Remote sensing and GIS integration was used to provide spatial data of land use/land cover type. Weng (2002) was successful in analysing the direction, rate and spatial pattern of land use change from the integration of remote sensing and GIS. He concludes that integration of remote sensing and GIS with Markov modelling was found to be beneficial in describing and analysing land use change. The integration of GIS-based cellular automata with the Markov chain model can represent spatial dependency and can be used to predict land use change the spatial dimension.

6.2.2 Cellular automata

Spatial proximity underlies many dynamic processes in the landscape. The Game of Life, for example, is a game based on the contiguous neighbour cell. Cells will live if 3 or 4 neighbour cells are alive and will die if 3 or 4 neighbouring cells are dead. This can be very effectively modelled using a cellular automaton.

Cellular automata (CA) are dynamic models that are discrete in time, space and state (Batty, 1998). Irwin (2001) stated that a cellular automaton is a cellular entity that independently varies its state based on its previous state and that of its immediate neighbours according to specific rules. Clearly there is a similarity here to a Markovian process. The only difference is application of a transition rule that depends not only upon the previous state, but also upon the state of the local neighbourhood.

Cellular automata have been extensively used in many applications (White *et al.*, 1993; Batty, 1994; Cecchini, 1996;Xie, 1996; Batty, 1997; Wu, 1998; Besussi *et al.*, 1998; Balzter *et al.*, 1998; Candau *et al.*, 2000; Bryan, 2000; Sirakoulis, 2000). White *et al.* (1993), for example, simulate the spatial structure of urban land use using a cellular automata model. Cecchini (1996) used cellular automata to build and test urban development models, and Xie (1996) developed a generic model to simulate growth dynamics for multi-sector land use in a sub-urban area. White *et al.* (1997) conducted another study simulating the urban land use pattern using constrained cellular automata for high-resolution modelling of urban land use dynamics. Xie (1996) integrated cellular automata with GIS. He found that the integration a of cellular automata model with a GIS would be advantageous because in many cases land use data that could be used are already available in a GIS. Since that time, various studies have been conducted which are related to integration of cellular automata with GIS (Takeyama *et al.*, 1997; Wagner, 1997; Couclelis, 1997; White *et al.*, 1997; White, 1997). Takeyama and Couclelis (1997), develop a generalisation of map algebra (called "geo-algebra"), of which cellular automata is a special case, and supporting spatial database manipulations within GIS. Wu (1998) developed SimLand, to simulate land conversion through the integrated GIS and cellular automata. He uses multi-criteria evaluation (MCE) to derive behaviour-oriented rules of transition with an analytical hierarchy process method. A preliminary result of this model shows the interesting properties of cellular automata models, in particular their spatial expression of complex micro-macro dynamics. Batty *et al.* (1999) developed a model of urban dynamics through GIS based cellular automata. He presents ways in which land uses are structured through their life cycles, and ways in which urban activities spawn locations for new activities.

On the urban growth application, Ward *et al.* (2000) developed a cellular automata model integrated with a stochastic constraint to eliminate the broad scale factors of constrained urban growth within GIS. The model can potentially simulate a wide variety of urban forms depending on parameter values associated with the constraint variables. All these studies show that cellular automata provide explicit handling of dynamic spatial processes, potentially capturing in some detail the process of interaction between the human systems and the natural environment within a GIS

Recently, studies have been conducted on developing integrated cellular automata and GIS models that focus on spatial dynamics. Shi *et al.* (2000) developed extended cellular automata using Voronoi polygons to model dynamic interactions among spatial objects. The Voronoi based cellular automata can model local interactions among spatial objects to generate complex global patterns. The Voronoi spatial model offers a ready solution to handling neighbourhood relations among spatial objects dynamically. White *et al.* (2000) states that urban and regional models based on cellular automata give good representations of the spatial dynamics of land use. He developed a high-resolution integration of the spatial dynamics of urban and regional systems.

Several researchers have conducted applications of cellular automata models to spatial propagation. Bryan (2000) used cellular automata to model the propagation of land clearance. He concluded that cellular automata reveal significant ecological implications of the propagation process that are not considered by standard landscape structural metrics. Sirakoulis *et al.* (2000) used cellular automata to study the effects of population movement and vaccination on epidemic propagation. The model establishes the acceleration of the epidemic propagation because of the increment of the percentage of the moving population, or the maximum distance of population movement. Cellular automata were found to be suitable for modelling this complex non-linear problem.

The application of cellular automata in the simulation of spatial dynamic processes has continued (Li Xia *et al.*, 2001; Barredo *et al.*, 2002; de Almeida *et al.*, 2003; Arai *et*

6.2.3 Prediction based on Markov Cellular automata Model within GIS

Contemporary Geographic Information Systems (GIS) that can integrate and manage spatial data have limited abilities to model dynamic spatial processes, and are poor at modelling temporal change (Wagner, 1997). Using programming, GIS - especially those based on tessellation models (using raster data structures) - can be used to build CA models. The basic form of the CA model consists of a two-dimensional array, a set of local states, neighbourhoods and transition rules. The states of cells in the array undergo change according to transition rules. Transition rules are functions of the cell's state and the state of its neighbouring cells. This basic principle is able to extend GIS capability into dynamic process modelling.

The next state of X cell is a function of the current state of X cell and the neighbour's cells. If settlement is the state of the majority of neighbouring cells, then the X cell will change and become settlement. The algorithm used to compute the next cell state is referred to as the CA local rule. Usually, the same local rule applies to all cells of the CA. A CA is characterized by five properties (Sirakoulis *et al.*, 2000):

1. the number of spatial dimensions (n);
2. the width of each side of the array (w). w_j is the width of the *j*th side of the array, where $j = 1,2,3,\ldots n$ (number of cells) *j*
3. the width of the neighbourhood of the cell (*d*).d_j is the width of the neighbourhood along the *j*th side of the array *j*.
4. the states of the CA cells;
5. the CA rule, which is an arbitrary function F.

The state of the X cell, at time step (t=1), is computed according to F. F is a function of the state of X cell at time step (t) and the states of the cells in its neighbourhood at time step (t) (called transition rules).

The simplified figure of a two-dimensional CA (n=2), with neighbourhood width d_1 = 3 and d_2 = 3, is shown in figure 6.2 below.

i-1,j-1	i-1,j	i-1,j+1
i, j-1	(i,j)	i,j+1
i+1,j-1	i+1,j	i+1,j+1

Figure 6.1. The neighbourhood of the (i,j) cell is formed by the (i,j) cell itself and the eight adjacent cells (Sirakoulis *et al.*, 2000).

Land use/land cover change is a dynamic spatial phenomenon. It is the result of spatial interaction among socio-economic and biophysical environmental parameters. The land use/land cover type in one cell is associated with those of its neighbours. The simple rules of CA say that the state of a cell (or cells) changes according to transition rules, and the transition rules (a function of the cell's state and those of the neighbouring cells) can be applied on land use/land cover change at every cell. The future land use/land cover type (according to Markov principles) is guided by the present land use. In other words the conditional probability of land use/land cover type at any given time, given all previous uses at earlier times, depends at most upon the most recent use and not upon any earlier ones (Bell and Hinojosa, 1977). This allows the consideration of the land use/land cover category in which a parcel or cell will be classified at time (t+1) as dependent most upon its current classification at time (t). Logsdon *et al.* (1997) conclude that Markov chains afford a powerful descriptive and predictive model for land use change and for future land use distribution. Therefore, in Markov-based cellular automata models, the Markov transition probability approach is used as a transition rule of CA.

The integration of Markov based cellular automata models within GIS in order to predict land use/land cover change is relatively new. Idrisi32 ver.2 includes a Markov-based cellular automata model to predict land use/land cover change (Eastman, 2001). This model is based on Markov transition probability as a transition rule of CA and land use suitability as a constraint. In this model, the neighbouring cells that may change are constrained by the land suitability of the neighbour cells. If neighbour cells are suitable for settlement, for example, the cells will mostly likely change into settlement and if neighbour cells suitable for forest it will change into forest.

6.3 Method

The Markov based cellular automata model in Idrisi32, called CA_Markov, has been selected to model land use/land cover change in the study area. This model is based on the combination of cellular automata and Markov chain techniques. It adds an element of spatial contiguity as well as knowledge of the likely spatial distribution of transitions to Markov chain analysis.

Three data sets are required for operation of this model. Firstly, the latest land cover classification is used as a basis for land use/land cover prediction (see Chapter 4). Secondly, the Markov transition that contains the Markov transition probability matrix of land use/land cover change. Finally, the distribution of land use suitability for each land use/land cover category. The transition matrix and suitability maps will be discussed below.

6.3.1 Markov transition probability calculation

A Markovian process is one in which the state of land use/land cover at time (t+1) can be predicted by the state of the land use/land cover at time (t) given a matrix of transition probabilities from each cover class to every other cover class. The Markov module in the Idrisi3.2 can be used to create such a transition probability matrix. This matrix is a result of cross tabulation of two images adjusted by the proportional error. As input, it takes two land use/land cover maps. It then produces the following outputs: (Eastman, 2001)

- A transition probability matrix. These transition probabilities express the likelihood that a pixel of a given class will change to any other class (or stay the same) in the next time period.
- A transition areas matrix. This expresses the total (in cells) expected to change in the next time period.
- A set of conditional probability images – one for each land use/land cover class. These maps express the probability that each pixel will belong to the designated class in the next time period.

6.3.2 Multi-criteria evaluation approach to create land suitability

Change in state of cells not only depends on the Markov transition probability, but also on the inherent land use suitability of each pixcl. The suitability map was derived according to criteria such as proximity to roads, river, city and existing land use/land cover. The production of these maps follows the procedure outlined in the multi-criteria evaluation (MCE) module of Idrisi32. Thc criteria were developed empirically in relation to underlying land use/land cover change dynamics betwecn two different times (in this case between 1989 and 1997). The change of scttlement category, for example, was related to factors such as proximity to main roads, proximity to urban and semi-urban centres and mostly located in arca within slope less than 45%. Therefore in crcating the suitability for settlement, it was based on thc factors of proximity to roads and city centres as well as slopc less than 45% and existing settlement. Suitability for rice field was based on proximity to irrigation or river, slope lcss than less than 45% and existing rice fields. The factors that contribute to each land suitability analysis are listed in the Table 6.1.

Table 6.1. Land suitability factors of each category.

Suitablc for	Factor
Forest	Slope > 45 % and proximity to roads, cxisting forest
Plantation	Slope < 45% and proximity to roads, existing plantation
Ricc ficld	Slope < 45 %, proximity to roads, proximity to irrigation/river, existing rice field
Open land/dry land	All class of slope and proximity to roads, existing open land and settlement
Settlement	Slope < 45 %, Proximity to roads and proximity to city, existing settlement
Fish pond	Slope < 3 %, proximity to beach and proximity to irrigation/river

Weighting factors have also been included in order to create the suitability map. In the procedure for Multi-Criteria Evaluation using a weighted linear combination in Idrisi32 based on pairwise comparisons (Eastman, 2001), it is necessary that the weights sum to one. The consistency ratio of overall weighting value must have an acceptable value. Using the WEIGHT module in Idrisi32, the weight value of each factor for every land suitability category can be calculated.

6.3.3 Prediction process base on Markov cellular automata model

Markov cellular automata combine both the concept of a cellular automata filter and Markov model procedure. The Markov rule is that the future state can be predicted based upon the recent state, but with the Markov model alone it provides no sense of geography. The Markov transition probabilities may be accurate on a per category basis, but since there is no knowledge of the spatial distribution of occurrences within each land use/land cover category, there is no spatial component on the modelling outcome. A cellular automata (CA) model is used to add spatial characteristic to the model. The CA model has the ability to change its state based upon the application of a rule that relates the new state to its previous state and those of its neighbours. The contiguity filter was used to develop a spatially explicit contiguity-weighting factor to change the state of cells based on those of their neighbours.

The contiguity filter was applied to a series of suitability maps already identified for each land use/land cover class. The process of the Markov Cellular automata model was as follows: The first step is to create the transition probability and areas file from a Markov Chain analysis (using the MARKOV module) of two prior land use maps, establishing the quantity of expected land cover change from each existing category to each other category in the next time period. The second step was selecting the base image to use as the starting point for change simulation. The third step, to choose the number of iterations according to how many years the simulation will conducted, i.e., if 10-year simulation, then chose 10 time iterations. Within each time step, each land cover is considered in turn as a host category. All other land cover classes act as claimant classes and compete for land (only from within the host class) using the MOLA (multi-objective land allocation) procedure. The area requirements for each claimant class within each host are equal to the total established by the transition areas file divided by the number of iterations. The results of each MOLA operation are overlaid to produce a new land cover map at the end of each iteration. The cellular automaton component arises in part from the iterative process of land allocation, and in part from a filtering stage with each iteration that reduces the suitability of land away from existing areas. The filter is integral to the action of the Cellular Automata component. Its purpose is to down-weight the suitability of pixels that are distant from existing instances of the land cover type under consideration. The net effect is that to be a likely choice for land cover conversion, the pixel must be both inherently suitable and near to existing areas of that class.

This process is run for the number of iterations. Therefore, the result of prediction from this model will depend on the number of iterations and filter type as well as the basic land use/land covers data and transition probability. The filter and iteration can be adjusted to get a more suitable result.

6.4 Selecting Parameters and Testing the Model

The Markov Cellular automata prediction model used in this study in Idrisi32 is an experimental module. The operation of the Markov Cellular automata module to predict land use/land cover change depends heavily on the quality of data input, such as Markov transition probability, suitability maps and the base land use/land cover image. The number of iterations and the contiguity filter type are other factors that have to be considered. Therefore in order to perform suitable land use/land cover prediction these parameters need to be tested.

In assessing the model in this study, the latest image that was used as a base image was the 1989 classified image used to predict land use/land cover conditions for year 1997. Different time intervals of the Markov probability matrix calculation were tried, as well as different types of contiguity filters and number of iterations in order to get a suitable result of prediction or simulation. The land suitability map was also improved especially for land suitability for settlement that very clearly associated with factors of proximity to urban areas and proximity to the main roads. The best result of prediction is then compared with the classified 1997 image to examine the precision of the result. The result of test some parameters is described below.

6.4.1 Transition probability

The transition probability was calculated based on Markov Chain analysis (using the MARKOV module). Many parameters are required to create the Markov transition in this module. These options include how many years or time intervals will be used and for how long the prediction or simulation will be conducted. Table 6.2 shows the Markov transition of land use/land cover between 1989 and 1997 in the study area. It was an 8-year difference between 1989 and 1997; therefore, the time interval selected to produce this transition matrix was an 8-year time interval and an 8-year prediction time. From Table 6.2 it can be seen that the diagonal direction has the higher probability value. For example, class 1 to class1 (Forest), class 2 to class 2 (Plantation) and so on. It means that the high value of transition probability occurs between the same categories, while for a category that has no chance to be changed or low probability to change, the value was low, such as from settlement to forest or to plantation as well as to water/reservoir (Table 6.2). These low values make sense because the change of settlement to forest or to fishpond or to water/reservoir is unlikely.

Table: 6.2. The Markov transition of land use/land cover 1989-1997, 8-year interval and 8-year time to predict.

Cells in Expected transition to

LULC	Cl.1	Cl.2	Cl.3	Cl.4	Cl.5	Cl.6	Cl.7
Cl.1. Forest	57150	22300	47773	1092	116	0	26
Cl.2.Plantation	104503	234134	297490	56736	18865	142	0
Cl.3.Rice field	44330	287651	1985648	610110	271561	82092	2299
Cl.4. Open/dry land	4633	80063	405784	357597	75893	2502	185
Cl.5. Settlement	250	16424	68175	22583	141809	1052	75
Cl.6. Fishpond	47	117	79397	4406	4476	145882	23
Cl.7. Water/reservoir	122	361	7587	581	73	2329	50083

Given Probability of change to

LULC	Cl.1	Cl.2	Cl.3	Cl.4	Cl.5	Cl.6	Cl.7
Cl.1. Forest	0.4449	0.1736	0.3719	0.0085	0.0009	0	0.0002
Cl.2.Plantation	0.1468	0.3289	0.4179	0.0797	0.0265	0.0002	0
Cl.3.Rice field	0.0135	0.0876	0.6047	0.1858	0.0827	0.025	0.0007
Cl.4. Open/dry land	0.005	0.0864	0.4379	0.3859	0.0819	0.0027	0.0002
Cl.5. Settlement	0.001	0.0656	0.2723	0.0902	0.5664	0.0042	0.0003
Cl.6. Fishpond	0.0002	0.0005	0.3388	0.0188	0.0191	0.6225	0.0001
Cl.7. Water/reservoir	0.002	0.0059	0.1241	0.0095	0.0012	0.0381	0.8192

6.4.2 Land suitability of each land use/land cover category

Suitability maps are another input parameter in Markov Cellular automata. Suitability maps were developed in relation to the underlying land use/land cover change dynamics in the study area between 1989-1997. Using the Multi-Criteria Evaluation module with factors as shown in Table 6.3 and using water bodies as a constraint, produced the suitability maps. These maps were:

1. Forest suitability map
2. Plantation suitability map
3. Rice field suitability map
4. Open/dry land suitability map
5. Settlement suitability map
6. Fishpond suitability map

Table 6.3. The weight value of suitability factors

For Open land

Factors	Weight value
Existing Open land	**0.5544**
Proximity to road	**0.1556**
Existing Settlement	**0.2332**
Slope	**0.0569**

Consistency ratio = 0.04
Consistency is acceptable

For Rice field

Factors	Weight value
Existing Rice field	**0.2024**
Proximity to irrigated	**0.5434**
Slope	**0.0865**
Proximity to road	**0.0922**
Existing Settlement	**0.0756**

Consistency ratio = 0.07
Consistency is acceptable

For Plantation

Factors	Weight value
Existing Plantation	**0.5278**
Proximity to road	**0.1396**
Slope	**0.3325**

Consistency ratio = 0.05
Consistency is acceptable

For Settlement

Factors	Weight value
Existing Settlement	**0.0848**
Proximity to DKI	**0.2160**
Proximity to city	**0.2402**
Proximity to road	**0.3836**
Slope	**0.0755**

Consistency ratio = 0.08
Consistency is acceptable

For Forest

Factors	Weight value
Existing Forest	**0.4869**
Proximity to road	**0.0778**
Slope	**0.4353**

Consistency ratio = 0.01
Consistency is acceptable

Table 6.3 above shows the weight value of factors that have been selected for every land use/land cover category. For the category open land, for example, the existing open land has the highest weight value, follow by existing settlement, proximity to roads and slope. While in the settlement category, the factor proximity to road has the highest weight value, following by proximity to city and to Jakarta metropolitan area. These weighting processes were created based on the change characteristic associated with land use/land cover change dynamic between years 1989-1997. For example, settlement was mostly changed within the area close to Jakarta, urban and semi urban (city) center and the main road.

Figure 6.2a and b show the suitability map for settlement category produce by multi criteria evaluation procedure.

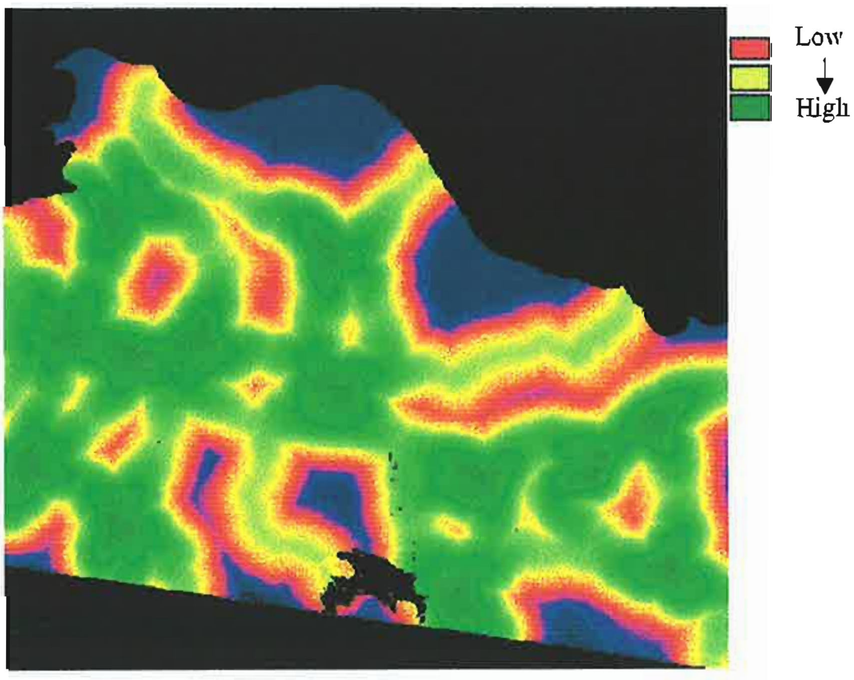


Figure 6.2a. Suitable for Settlement without factor proximity to Jakarta city

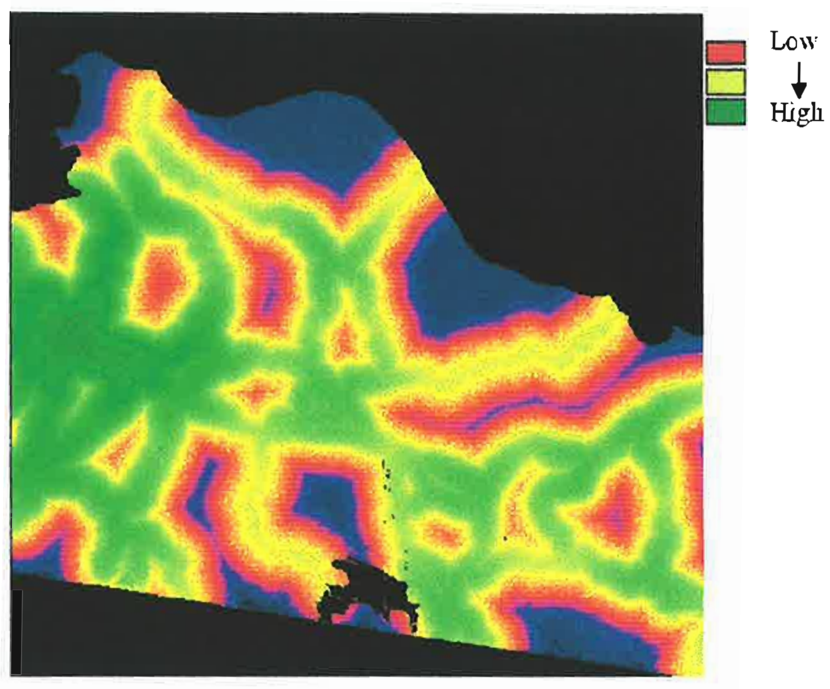


Figure 6.2b. Suitable for Settlement with factor proximity to Jakarta city

The suitability map in Figure 6.2a and 6.2b shows the gradient of land use suitability for settlement. The different colours show the gradient of suitability from unsuitable (black, red, yellow), to suitable (green) and very suitable (dark green). It can be seen that high suitability for settlement is located along the road and close to cities (Figure 6.2a) and concentrated in the area close to Jakarta (on the left side image) (Figure 6.2b). Other category suitability maps have the same colour gradient from unsuitable (black, red, yellow), suitable (green) and very suitable (dark green) (See APENDIX VI). These suitability maps were created based on examining some factors such as consistency ratio as well as underlying change characteristic of each category in the study area.

6.4.3 The result of simulation or prediction process

Once the Markov transition area and suitability maps were constructed, the Markov Cellular automata prediction model can be run. Land use/land cover for 1997 in the study area was predicted by selecting the 1989 classified image as a base image, combining it with the Markov transition and the suitability maps. In this prediction process, different parameters such as contiguity filter type as well as suitability map and Markov transition value, were tested.

Three kernel filter types (3, 5 and 7-kernel filters) were tried in order to obtain a suitable result. The 3x3 kernel filter was the best contiguity filter when compared with the 5-and 7-kernel filters. The number of iteration was 8, the same as the number of years to predict (8 years from 1989 to 1997). Different types of suitability maps have also been used, such as before and after being adjusted for proximity to Jakarta city. Figure 6.3a and 6.3c show the prediction result based on this parameter. Figure 6.3a shows the results of prediction process based on the suitability map before being adjusted and 6.3c the prediction process based on a suitability map that has been adjusted.

The result obtained when the suitability map was adjusted for proximity to Jakarta (Figure 6.3c) appears better than that for the unadjusted suitability (Figure 6.a). Settlement in areas that close to main roads and urban and semi-urban areas were improved, such as in Bekasi, Karawang, Cikampek and Purwakarta. Settlement and rice field as well as plantation, fishpond and reservoir, look appropriate as predicted except open/dry land and forest (Figure 6.3c).

Overall KIA of the predicted image before being adjusted was 56 % and after being adjusted was 67 %, an improvement of 11 % (Table 6.4a). In the image after adjustment, settlement, fishpond and water/reservoir all have a value above 56 %. Other land use/land cover category such as open/dry land and plantation as well as forest have KIA value around 41 to 46 %, while in the image before adjustment all categories were below 55 %, except fishpond and water/reservoir with 71 % and 96% respectively (Table 6.4a).

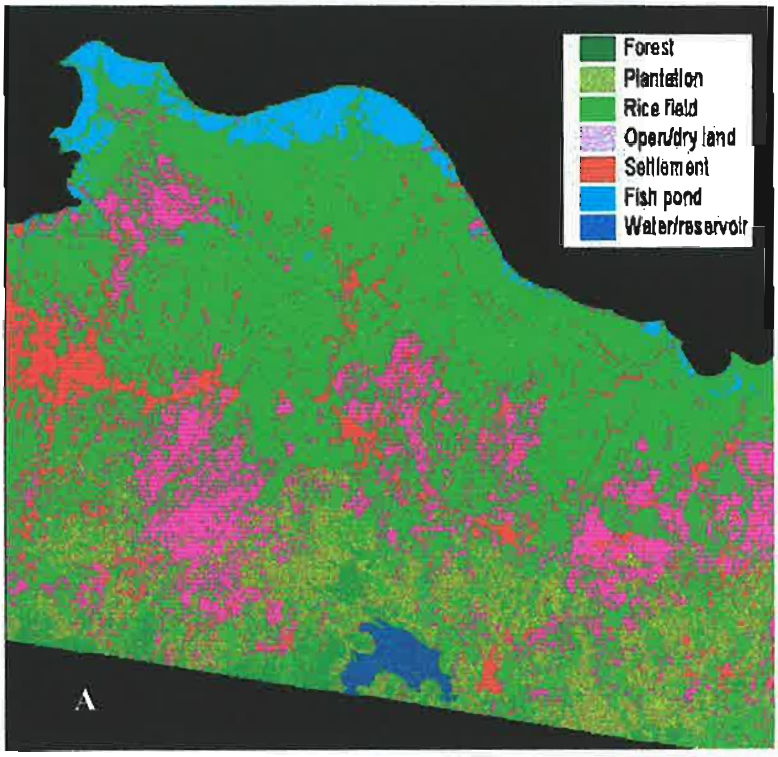


Figure 6.3. a) Prediction 1; of 8-iteration, 3-kernel filter, suitability map of settlement without proximity to Jakarta

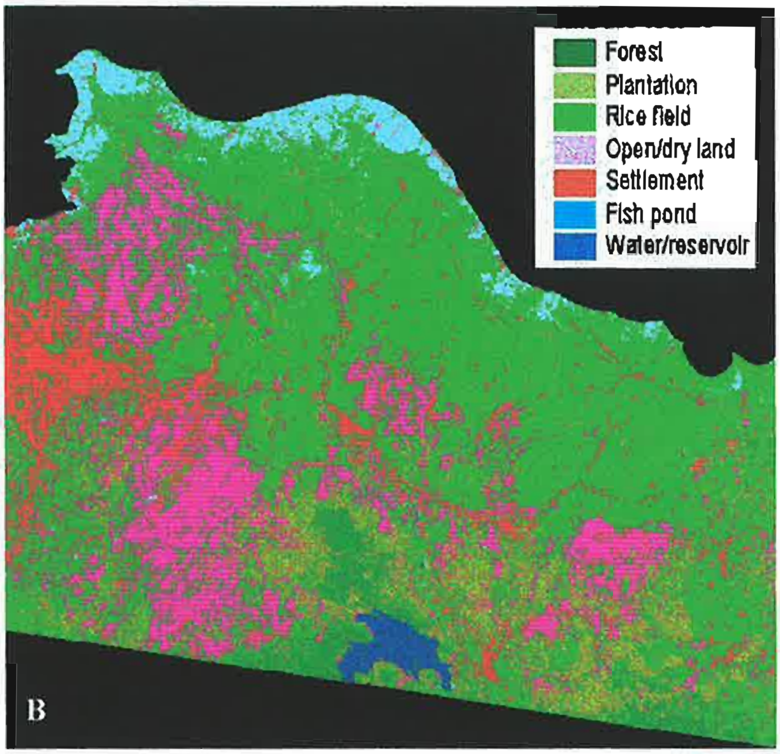


Figure 6.3. b). Original classified 1997 image

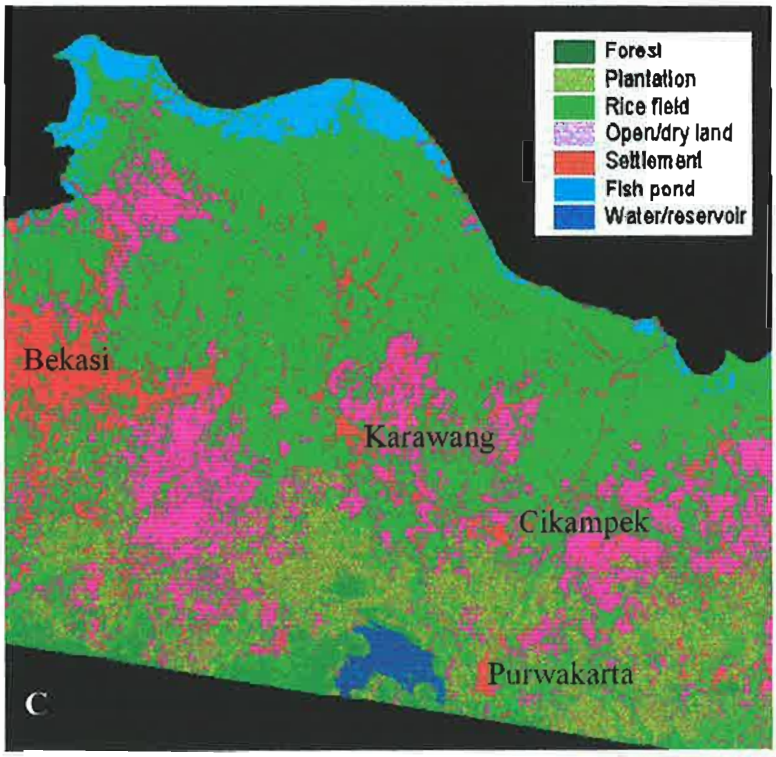


Figure 6.3c) Predicted 2; of 8-iteration, 3-kernel filter, suitability map of settlement with proximity to Jakarta city.

Table 6.4a .The Kappa Index of Agreement (KIA) value between original 1997 –1997 predicted1 and original 1997- 1997 predicted2.

LULC	KIA *)	KIA **)
Forest	0.34	0.41
Plantation	0.43	0.43
Rice field	0.55	0.56
Open/dry land	0.43	0.46
Settlement	0.48	0.67
Fishpond	0.71	0.70
Water/reservoir	0.96	0.97
Overall KIA	0.56	0.67

*) = 1997 original Image with 1997 image predicted1
**) = 1997 original Image with 1997 image predicted2

Another way to validate the prediction result is by comparing KIA of the two cross-tabulated images between the original 1989 and original 1997 images and between the original 1989 and predicted 1997 images (Table 6.4b).

Table 6.4 b. The Kappa Index of Agreement (KIA) value between 1989 original to1997 original and original 1989 to 1997 predicted image

Land use/land cover	KIA 1989 to 1997 original	KIA 1989 to 1997 predict1)	KIA 1989 to 1997 predict2)
Forest	0.32	0.79	0.63
Plantation	0.42	0.85	0.74
Rice field	**0.59**	0.80	**0.70**
Open/dry land	0.38	0.84	0.77
Settlement	**0.35**	0.95	**0.44**
Fishpond	**0.72**	096	**0.87**
Water/reservoir	**0.97**	0.99	**0.97**
Overall KIA	**0.54**	**0.88**	**0.74**

Note: predicted1 = the result based on suitability maps before being adjusted
Predicted2 = the result based on suitability maps after adjusted

The KIA value between the 1989 and 1997 original images have a low value (Table 6.4b) because land use/land covers between these two images were different. Therefore, the KIA value between the original 1989 and 1997 predicted images also should have a low value - the same or close to the KAI between the 1989-197 original was better than predicted1 which used the suitability map before it was adjusted. The KIA value of predicted2 is lower than KIA value of predicted1, and has smallest difference values with KIA value between the 1989 – 1997 original. For example, rice field, settlement, fishpond as well as water/reservoir in predicted2 have a difference value less than 0.15, and other categories such as forest, open/dry land and plantation have difference value more than 0.31. While in predicted1 all categories have difference value more than 0.35. It means in predicted2 that the prediction result is better than that in predicted1, especially for settlement and rice field categories. This condition indicates that settlement and rice field was well predicted.

Modification of the Markov transition matrix improves the amount of cells that are expected to change but did not improve the land use/land cover change on spatial distribution. An inappropriate suitability map of open/dry land category could cause the poor result on open/dry land, forest and plantation change distribution. It was no significant information to adjust the suitability map of this category. For example, there are no systematic patterns of open/dry lands. Slope and proximity to the roads as well as existing open/dry land have been selected to create suitability maps of these categories. A suitability map with or without existing land use category does not improve the prediction result of open/dry land as well as forest and plantation.

6.5 The potential outcome of future land use/land cover in the study area

The assessment of the results of the application of the Markov Cellular automata model in the study area indicates that this model was successful in simulating or predicting land use/land cover change, especially for settlement and rice field categories. Based on this outcome, the future land use/land cover in the study area was modelled. The following section presents 10 and 20-year simulation based on the classified image year 1997 as a base image. This simulation was based on two types of Markov transition matrix. One is the Markov transition based on a calculation from 1989 and 1997 images with the assumption that transition probability stays same (as Markov transition rule). The second is the Markov transition based on a scenario.

Prediction based on the transition matrix derived from the 1989-1997 images assumes that similar conditions from this period extend into the future. This is not always the case. For example in 1998 Indonesia suffered an economic crisis, which will likely influence the future rate of land use/land cover change. Therefore, to try and to incorporate the changed circumstances, two scenarios have been developed which change the transition probabilities the 1989-1997 situation. These scenarios are:

1. Scenario1 assumed urbanization will continue related to population and economic growth but not as high as rate between 1989-1997; Open/dry land will remain as idle land ("lahan tidur"), due to slow down on development housing or industrial estates; Forests have to be well protected (at least 60% could be kept to conserve Jatiluhur reservoir);

There is no change from settlement to other land use-land category as well as from rice to forest or to water/reservoir.

2. Scenario2 assumed same as scenario 1 but very low in urbanisation and high change in agricultural area.

The process and result of these simulations presented below.

6.5.1 Land use/land cover simulation 2007 (10 Year)

The time frame for simulation was ten years, and the Markov transitions for the next 10-year period from 1997 were created from the Markov module. This operation was based on the assumption that the characteristic of land use/land cover change from 1997 to 2007 is same as that between 1989 and 1997 (Markov chain rule). Other assumptions were that the rates of land use/land cover change would be slightly lower (secnario1) and much lower (scenario2) than that change between 1989-1997 due to economic crisis in 1998 as mentioned previously.

Based on this assumption a Markov transition matrix was created. Table 6.5 shows the summary of probability "expected unchanged" of each land use/land cover categories.

Table 6.5 Summary of probability expected to stay as same category
10-year scenario

LULC	From 1989-1997 Images	Scenario1	Scenario2
	Expected unchanged	Expected unchanged	Expected unchanged
Forest	36%	60%	50%
Plantation	23%	50%	45%
Rice field	56%	65%	60%
Open/dry land	29%	30%	40%
Settlement	50%	85%	90%
Fishpond	57%	55%	55%
Water/reservoir	81%	100%	100%

From Table 6.5 it can be seen that probability of "expected unchanged" are higher in both of the scenarios than that for the 1989-1997 images. This means that for the next 10 years, land use/land cover will not change as much as between 1989-1997. For example a transition probability of water/reservoir of 100 %, means there is no change to any other category from water/reservoir. Settlement also has a high probability to stay the same. Fishpond has lower value than in 1989-1997, which means it has more chance to be changed to an other category.

A more detailed composition of transition probability for each land use/land cover category can be seen in Table 6.6a and 6.6b. The composition of transition probability for each land use-land category in Table 6.6b and 6.6c represents the expected change of land use/land cover for the next 10 year from 1997.

Table 6.6a. The Markov transition of land use/land cover for 10-year prediction (1997-2007), based on 1989-1997 image.

Cells in Expected transition to

LULC	Cl. 1	Cl. 2	Cl. 3	Cl. 4	Cl. 5	Cl. 6	Cl. 7
Cl.1. Forest	70617	37349	85854	3943	277	40	59
Cl.2. Plantation	93561	136046	282742	56372	19124	588	0
Cl.3. Rice field	53052	306456	1729823	641311	298654	88941	2497
Cl.4. Open/dry land	8364	90688	471109	275542	90312	3571	188
Cl.5. Settlement	1043	33453	142653	47324	226468	2176	181
Cl.6. Fishpond	0	612	89566	6097	5155	133937	24
Cl.7. Water/reservoir	122	389	7789	650	97	2394	49318

Given Probability of change to

LULC	Cl. 1	Cl. 2	Cl. 3	Cl. 4	Cl. 5	Cl. 6	Cl. 7
Cl.1. Forest	0.36	0.19	0.43	0.02	0.00	0.00	0.00
Cl.2. Plantation	0.16	0.23	0.48	0.10	0.03	0.00	0.00
Cl.3. Rice field	0.02	0.10	0.55	0.21	0.10	0.03	0.00
Cl.4. Open/dry land	0.01	0.10	0.50	0.29	0.10	0.00	0.00
Cl.5. Settlement	0.00	0.07	0.31	0.10	0.50	0.00	0.00
Cl.6. Fishpond	0.00	0.00	0.38	0.03	0.02	0.57	0.00
Cl.7. Water/reservoir	0.00	0.01	0.13	0.01	0.00	0.04	0.81

Table 6.6b. The Markov transition of land use/land cover for 10-year (scenario 2007) assumed that changes will low

Cells in Expected transition to

LULC	Cl. 1	Cl. 2	Cl. 3	Cl. 4	Cl. 5	Cl. 6	Cl. 7
Cl.1. Forest	118884	39628	29721	9907	0	0	0
Cl.2. Plantation	147108	294217	88265	58843	0	0	0
Cl.3. Rice field	0	156037	2028478	748976	156037	31207	0
Cl.4. Open/dry land	0	93977	469887	281932	93977	0	0
Cl.5. Settlement	0	0	0	67995	385303	0	0
Cl.6. Fishpond	0	0	94156	11770	0	129465	0
Cl.7. Water/reservoir	0	0	0	0	0	0	60759

Given Probability of change to

LULC	Cl. 1	Cl. 2	Cl. 3	Cl. 4	Cl. 5	Cl. 6	Cl. 7
Cl.1. Forest	0.6	0.2	0.15	0.05	0	0	0
Cl.2. Plantation	0.25	0.5	0.15	0.1	0	0	0
Cl.3. Rice field	0	0.05	0.65	0.24	0.05	0.01	0
Cl.4. Open/dry land	0	0.1	0.5	0.3	0.1	0	0
Cl.5. Settlement	0	0	0	0.15	0.85	0	0
Cl.6. Fishpond	0	0	0.4	0.05	0	0.55	0
Cl.7. Water/reservoir	0	0	0	0	0	0	1

Table 6.6c. The Markov transition of land use/land cover for 10-year (scenario 2007) assumed that changes will very low

Cells in Expected transition to

LULC	Cl. 1	Cl. 2	Cl. 3	Cl. 4	Cl. 5	Cl. 6	Cl. 7
Cl.1. Forest	99070	59442	29721	9907	0	0	0
Cl.2. Plantation	147108	264795	88265	88265	0	0	0
Cl.3. Rice field	0	156037	1872441	873806	156037	62415	0
Cl.4. Open/dry land	0	93977	469887	375910	0	0	0
Cl.5. Settlement	0	0	0	45330	407968	0	0
Cl.6. Fishpond	0	0	94156	11770	0	129465	0
Cl.7. Water/reservoir	0	0	0	0	0	0	60759

Given Probability of change to

LULC	Cl. 1	Cl. 2	Cl. 3	Cl. 4	Cl. 5	Cl. 6	Cl. 7
Cl.1. Forest	0.5	0.3	0.15	0.05	0	0	0
Cl.2. Plantation	0.25	0.45	0.15	0.15	0	0	0
Cl.3. Rice field	0	0.05	0.6	0.28	0.05	0.02	0
Cl.4. Open/dry land	0	0.1	0.5	0.4	0	0	0
Cl.5. Settlement	0	0	0	0.1	0.9	0	0
Cl.6. Fishpond	0	0	0.4	0.05	0	0.55	0
Cl.7. Water/reservoir	0	0	0	0	0	0	1

Figure 6.4 shows the predicted land use/land cover for 2007 as a result of 10-year simulation based on the Markov transition from transition between the 1989 and 1997 images (Table 6.6a), Figure 6.5 shows land use/land cover prediction for 2007 based on scenario1 (Table 6.6b) and Figure 6.6 shows the land use/land cover prediction based on scenario2 (Table 6.6c). Figure 6.7 shows the original 1997 land use/land cover from the classified image.

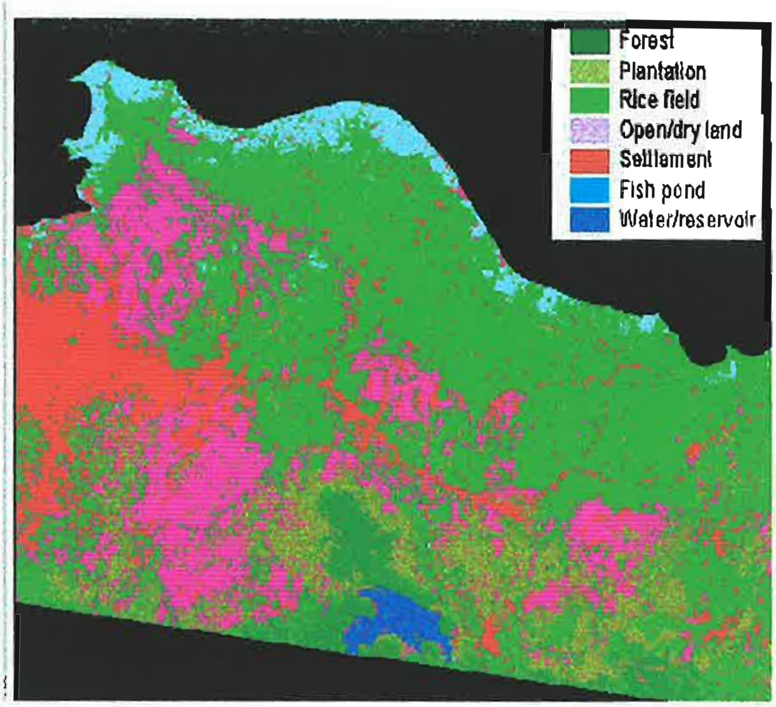


Figure 6.4. The result of land use/land cover change of 10-year simulation based on Markov calculated from 1989-1997 images (Simulation 2007)

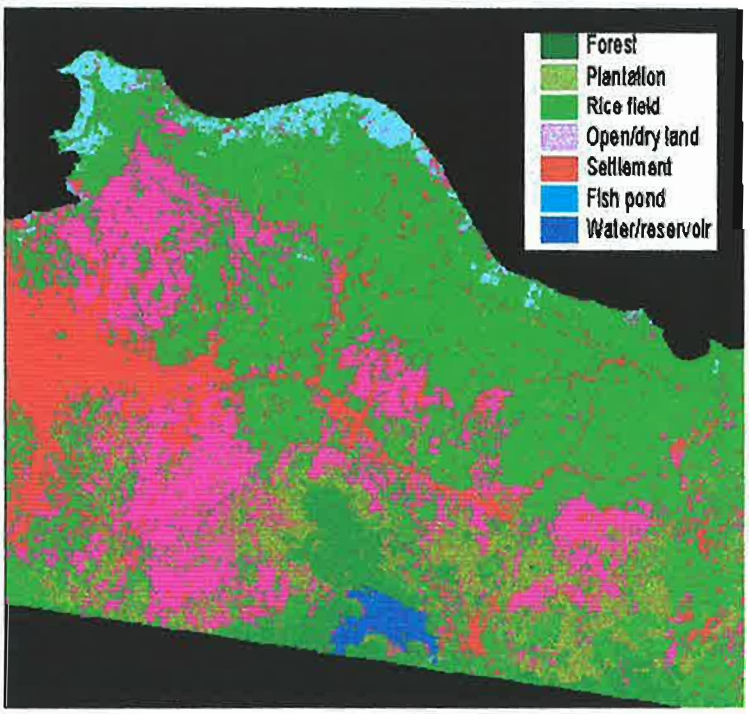


Figure 6.5. The result of land use/land cover change of 10-year simulation based on Markov scenario (Scenario1 2007).

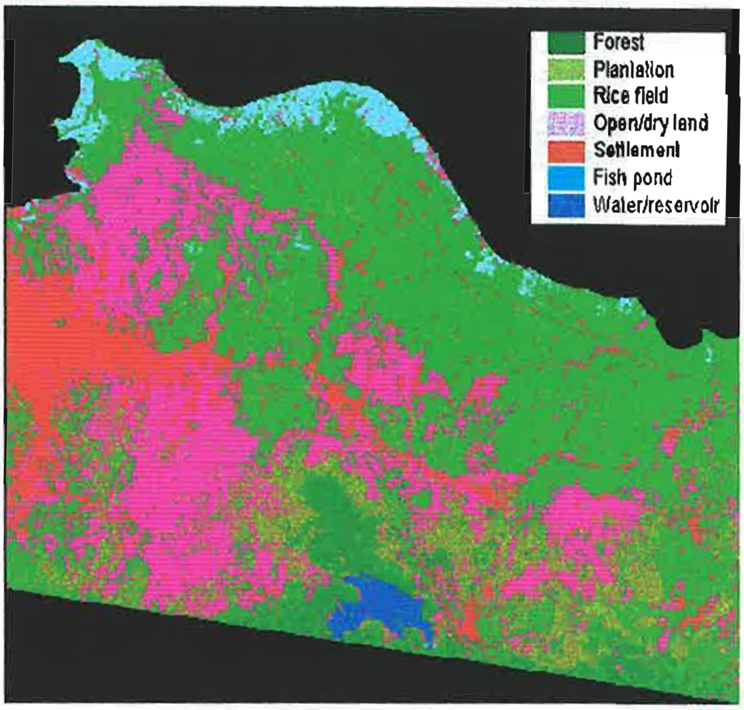


Figure 6.6. The result of land use/land cover change of 10-year simulation based on Markov scenario (Scenario2 2007).

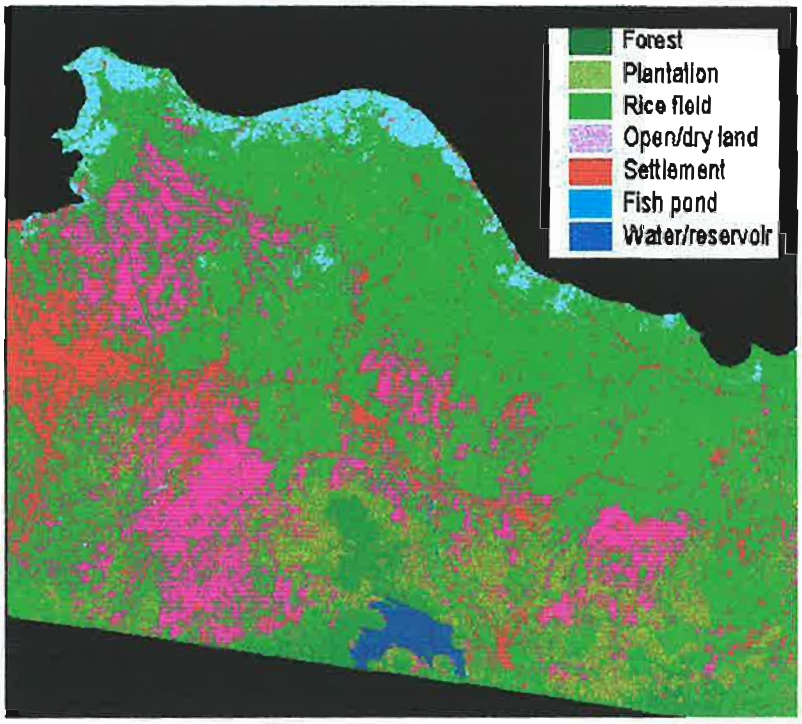


Figure 6.7. The classified 1997 image (Original)

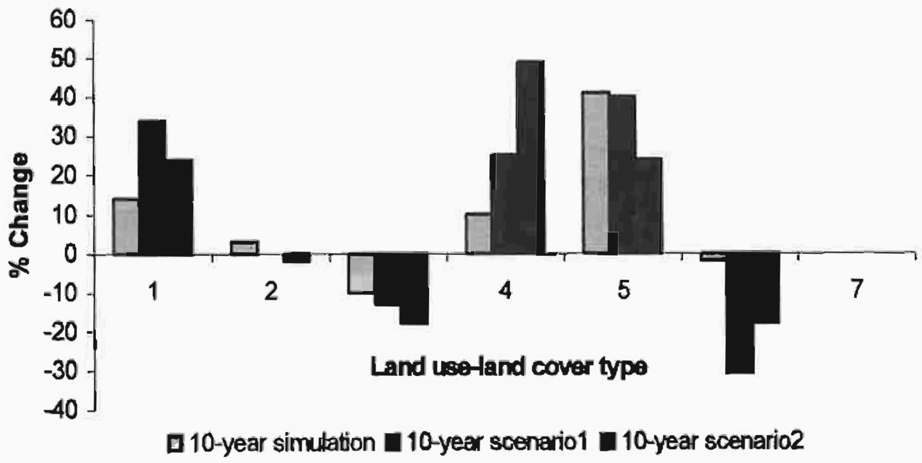
From these figures it can be seen that there are differences in land use/land cover change patterns, especially for the settlement category. As it has been assumed that land use/land cover changes for the next ten years will be low in scenario1 and very low in scenario2 compared with change between 1989-1997, the land use/land cover in scenario1 as well as in scenario2 visually was slightly different from land use/land cover simulation for 2007 (Figure 6.4). Settlement along main roads in the simulation does not show much difference from settlement in scenario1 (Figure 6.5), but higher than in scenario2 (Figure 6.6).

Different land use/land cover changes between the original simulation and the scenarios can also be seen by comparing the change characteristic between these images (Table 6.7 and Figure 6. 8). The change characteristics were calculated based on percentage change of total cells for each land use/land cover category from a cross-tabulation of 1997 original and simulation 2007 images, and cross-tabulation of 1997 original and scenario 2007 images.

From Table 6.7 and Figure 6.8 it can be seen that there are differences in the change characteristic between simulation 2007 and scenario1 2007 as well as scenario2 2007. In simulation 2007, forests increased 14 %, while in scenario1 2007 forest increased 34 % and in scenario2 increased 24%; other categories such as plantation in simulation 2007 decreased 3 %, while in scenario1 2007 decreased 1 % and in scenario2 decreased 2%. Settlement in simulation increased 41 %, while in scenario1 increased 40% and increased 24% in scenario2. These change characteristics result from the assumption that activities for construction or development of new housing or industrial estates would slow down within the ten years from 1997. For example, the increased percentage of open/dry land as well as decreasing fishpond in scenario1 and 2 represents a lot of idle land ("tanah tidur"). Slightly low settlement (1% difference) in scenario1 and very low (20% difference) in scenario2 represent low activity for the development of new housing or industry or low urbanisation.

Table 6.7. The 10-year change characteristic between Simulation and Scenario.

Land use- land cover	Change characteristic 1997 original to simulation 2007	Change characteristic 1997 original to scenario1 2007	Change characteristic 1997 original to scenario2 2007
Forest	14 % increased	34% increased	24% increased
Plantation	3% decreased	1% decreased	2% decreased
Rice field	10% decreased	13% decreased	18% decreased
Open/dry land	10 % increased	26 % increased	49 % increased
Settlement	41% increased	40% increased	24% increased
Fishpond	2% decrease	32% decreased	18% decreased
Water/reservoir	no change	No change	No change



1. Forest; 2. Plantation; 3. Rice field; 4. Open/dry land; 5. Settlement 6. Fishpond; 7. Water/reservoir.

Figure 6.8. 10-year change characteristic between simulation and scenario

6.5.2 Land use/land cover Simulation 2017 (20-Year)

In section 6.5.1 two scenarios were used which adjusted the transition probabilities from the 1989-1997 matrix. This was based on changing economic circumstances following the 1998 economic crisis. The use of these adjusted probabilities probably produced a more realistic result; however, it is not expected that these economic conditions will remain constant.

Therefore, the simulation for both scenarios was extended to 20 years. In this case the assumption were:

1. Scenario1 assumed the economic conditions was recovered and the activities of development will increase; therefore, in this scenario, land use/land cover will be increasingly changed, such as urbanisation will increase and open land will decrease.
2. Scenario2 assumed same as scenario 1 but the rate of land use/land cover change is higher than in scenario1, especially high in urbanisation.

The adjusted probabilities can be seen in Table 6.8a and 6.8b as follow.

Table.6.8a. Markov transition probability of land use/land cover for 20- year based on Scenario1

Cells in Expected transition to

LULC	Cl. 1	Cl. 2	Cl. 3	Cl. 4	Cl. 5	Cl. 6	Cl. 7
Cl.1. Forest	118884	49535	19814	9907	0	0	0
Cl.2. Plantation	73554	294217	132397	88265	0	0	0
Cl.3. Rice field	0	156037	2028478	702165	234055	0	0
Cl.4. Open/dry land	28193	93977	394705	187955	140966	93977	0
Cl.5. Settlement	0	0	0	90660	362638	0	0
Cl.6. Fishpond	0	0	58848	23539	11770	141234	0
Cl.7. Water/reservoir	0	0	0	0	0	0	60759

Given Probability of change to

LULC	Cl. 1	Cl. 2	Cl. 3	Cl. 4	Cl. 5	Cl. 6	Cl. 7
Cl.1. Forest	0.60	0.25	0.10	0.05	0.00	0.00	0.00
Cl.2. Plantation	0.12	0.50	0.22	0.15	0.00	0.00	0.00
Cl.3. Rice field	0.00	0.05	0.65	0.23	0.08	0.00	0.00
Cl.4. Open/dry land	0.03	0.10	0.42	0.20	0.15	0.10	0.00
Cl.5. Settlement	0.00	0.00	0.00	0.20	0.80	0.00	0.00
Cl.6. Fishpond	0.00	0.00	0.25	0.10	0.05	0.60	0.00
Cl.7. Water/reservoir	0.00	0.00	0.00	0.00	0.00	0.00	1.00

Table.6.8b. Markov transition probability of land use/land cover for 20- year based on Scenario2

Cells in Expected transition to

LULC	Cl. 1	Cl. 2	Cl. 3	Cl. 4	Cl. 5	Cl. 6	Cl. 7
Cl.1. Forest	148605	29721	9907	9907	0	0	0
Cl.2. Plantation	73554	294217	132397	88265	0	0	0
Cl.3. Rice field	0	0	2028478	624147	468110	0	0
Cl.4. Open/dry land	0	140966	281932	187955	281932	46989	0
Cl.5. Settlement	0	0	0	90660	362638	0	0
Cl.6. Fishpond	0	0	58848	23539	11770	141234	0
Cl.7. Water/reservoir	0	0	0	0	0	0	60759

Given Probability of change to

LULC	Cl. 1	Cl. 2	Cl. 3	Cl. 4	Cl. 5	Cl. 6	Cl. 7
Cl.1. Forest	0.75	0.15	0.05	0.05	0.00	0.00	0.00
Cl.2. Plantation	0.12	0.50	0.22	0.15	0.00	0.00	0.00
Cl.3. Rice field	0.00	0.00	0.65	0.20	0.15	0.00	0.00
Cl.4. Open/dry land	0.00	0.15	0.30	0.20	0.30	0.05	0.00
Cl.5. Settlement	0.00	0.00	0.00	0.20	0.80	0.00	0.00
Cl.6. Fishpond	0.00	0.00	0.25	0.10	0.05	0.60	0.00
Cl.7. Water/reservoir	0.00	0.00	0.00	0.00	0.00	0.00	1.00

When the simulation was run using these assumptions, the result showed that land use/land cover was changed significantly (Figure 6.9, 6.10 and 6.11). Figure 6.9 shows the result of 20-year simulation based on Markov transition from 1989-1997 (Simulation 2017), Figure 6.10 shows the result of 20-year simulation based on scenario1 and Figure 6.11 scenario2. From these figures it can be seen that land use/land cover change was quite different, especially in scenario2 where settlement increased, while rice field decreased as result of this urbanisation.

A summary of the changes can be seen in Table 6.9 and Figure 6.12. It can be clearly seen that the two scenarios produce results different from that of the original simulation.

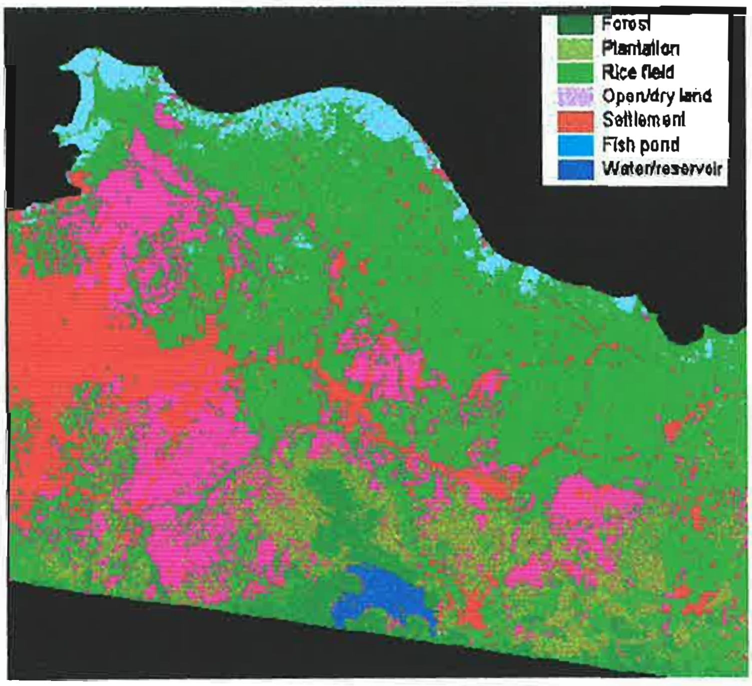


Figure 6.9. The result of land use/land cover 20-year simulation (Simulation 2017).

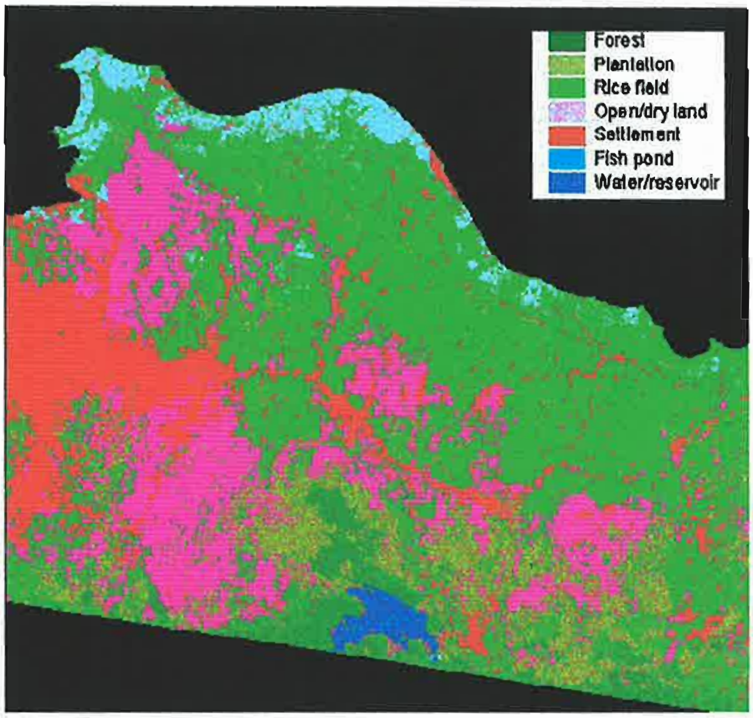


Figure 6.10 The result of land use/land cover 20-year simulation (Scenario1 2017).

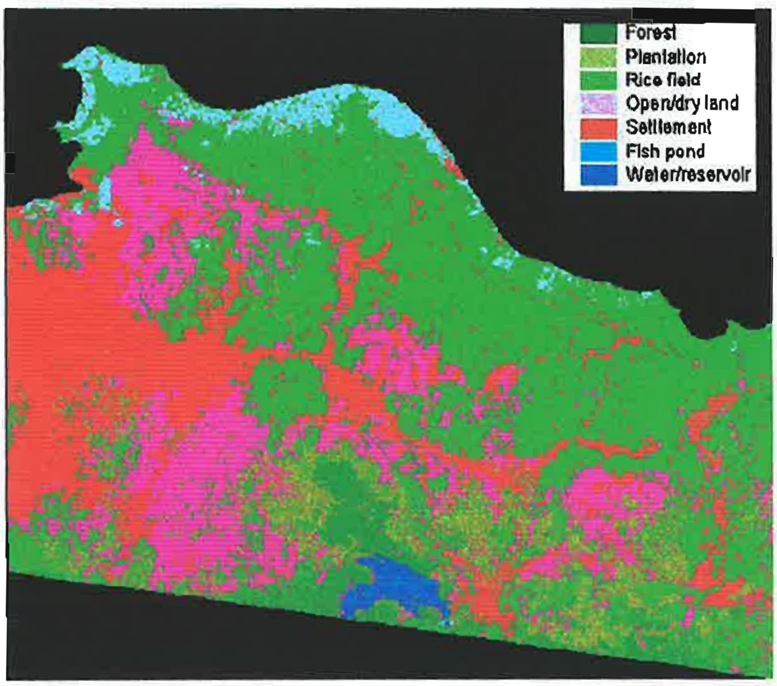
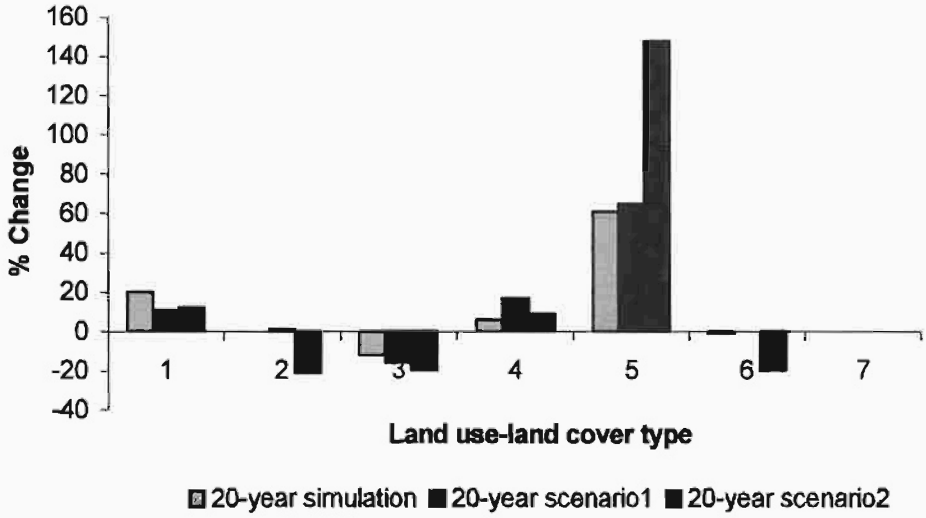


Figure 6.11. The result of land use/land cover 20-year simulation (Scenario2 2017).

Table 6.9. The 20-year change characteristic between Simulation and Scenario

Land use- land cover Category	Change characteristic 1997 original to simulation 2017	Change characteristic 1997 original to scenario1 2017	Change characteristic 1997 original to scenario2 2017
Forest	20% increased	11 % increased	12 % increased
Plantation	No change	1% decreased	21% decreased
Rice field	12% decreased	16%decreased	20%decreased
Open/dry land	6 % increased	17% increased	9 % increased
Settlement	60% increased	65% increased	148% increased
Fishpond	1% decreased	no change	no change
Water/reservoir	14% decreased	no change	no change

Figure 6.12 shows the comparison of land use/land cover change characteristics between simulation, scenario1 and 2 of 20-year prediction. It can be seen that in scenario2, land use/land cover change was higher than in scenario1 and the original simulation. For example, settlement in scenario2 increased 148% and rice field decreased 20%, while in the original simulation and scenario1 settlement increased 60% and 65%. This indicates that the assumption of high urbanisation in scenario2 resulted in high increased settlement and supports the assumption that within twenty years from 1997 the economic activity has recovered.



1. Forest; 2. Plantation; 3. Rice field; 4. Open/dry land; 5. Settlement 6. Fishpond; 7. Water/reservoir.

Figure 6.12. 20-year change characteristic between simulation, Scenario1 and scnario2.

The expansion of settlement along the roads was clearly recognised from the result of simulation both in scenario2 2007 and scenario2 2017. Figure 6.13 shows an overlaid roads network with scenario2 2007 and scenario2 2017 images. From Figure 6.13 it can be seen that settlement increased mostly along main roads and areas that are close to city centres, especially to Jakarta. In some places it is seen that open/dry land changed to settlement as well as from rice field. Forest remained unchanged.

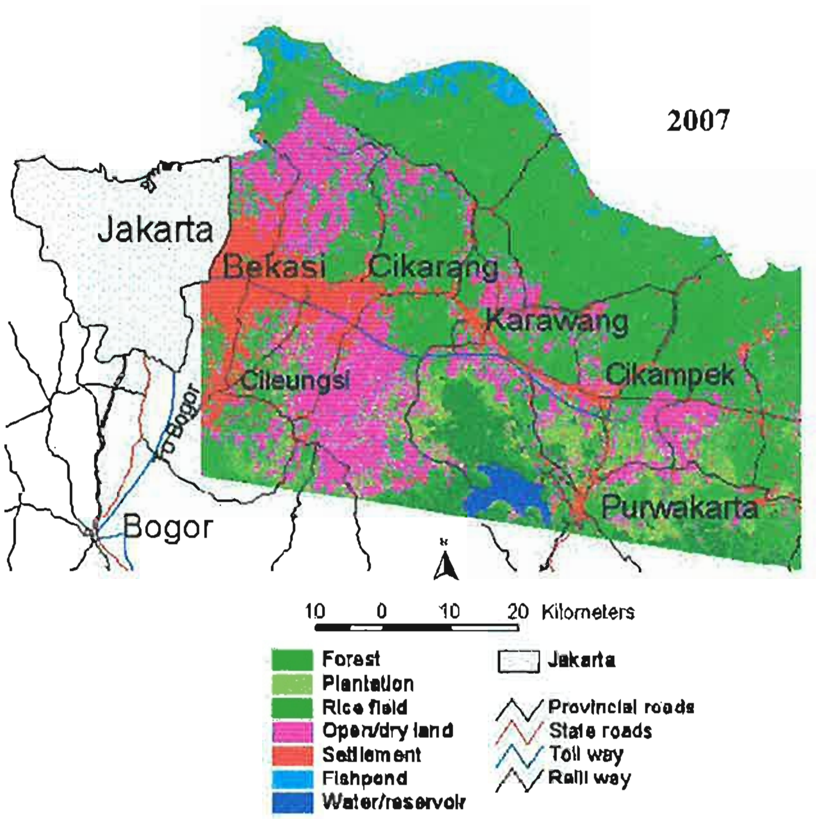


Figure 6.13a Overlay roads network with scenario2 image 2007

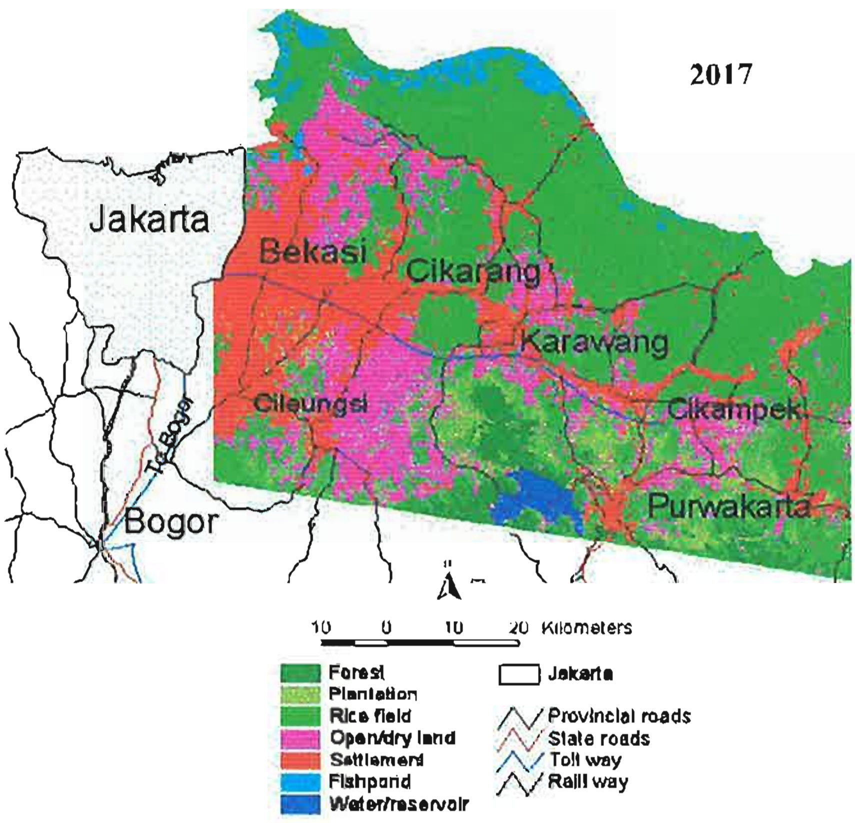


Figure 6.13b Overlay roads network with scenario2 2017 image.

6.5.3 Analysis of Land use/land cover, 1989, 1997, 2007 and 2017 in the study area.

It has previously been mentioned (Chapter V), that proximity to roads and proximity to urban and semi-urban areas are the main factors influencing land use/land cover change in the study area, especially the change of settlement and rice field categories. Therefore, spatial analysis of the future land use/land cover in this section focuses on land use/land cover within 10 km of main roads and 10 km of urban and semi-urban centres. This analysis includes the 1989, 1997 classified images, 2007 and 2017 simulation images (Scenario2).

As has been mentioned previously, scenario2 2007 was based on the assumption that land use/land cover change will slow down with very low in urbanisation due to the economic crisis in 1998. Scenario2 2017 assumed that economic activity recovered, and land use/land cover change increased with high urbanisation. Therefore, land use/land cover scenario2 year 2007 and 2017 was selected, as it is assumed that these two scenarios will represent the next 10 and 20 years of land use/land cover condition in the study area.

Table 6.10 and Figure 6.14 show land use/land cover within 10 km of main roads in 1989, 1997, 2007 and 2017.

Table 6.10. Land use/land cover within 10 km of main roads in 1989, 1997 2007 and 2017.

LULC	Area (Ha) 1989	Area (Ha) 1997	Area (Ha) 2007	Area (Ha) 2017
Forest	5899	6443	7374	6643
Plantation	29351	33659	21939	26312
Rice field	154045	136980	115090	97999
Open/dry land	57162	50811	76019	51673
Settlement	14305	32693	40760	77579
Fishpond	995	1173	575	549
Water/reservoir	2528	2528	2528	2528

Note: Year 1989 and 1997 from classified Image
Year 2007 scenario2 and 2017 scenario2 image

From Table 6.10 it can be seen that for 1989, 1997, 2007 and 2017 some land use/land cover categories in areas along the main roads decreased, such as forest, plantation, rice field, and fishpond. Settlement increased. In 1989 settlement areas were less than plantations, open/dry land and rice field, but eighteen years later settlement was more than plantation, and in 2017 settlement was more than open/dry land (Figure 6.14). This indicates that within 10 and 20 years from 1997, the agricultural areas such as plantation along the main roads will be less than settlement areas.

Other information that can be seen from Figure 6.14 and Figure 6.15 is that the increase in open/dry land in 2007 was higher than that for settlement. It indicates a lot of idle land ("lahan tidur"), due to slow down in development activity, and in 2017 settlement increased more than open/dry land. This indicated that development activities increased as it was assumed that economic activity recovered.

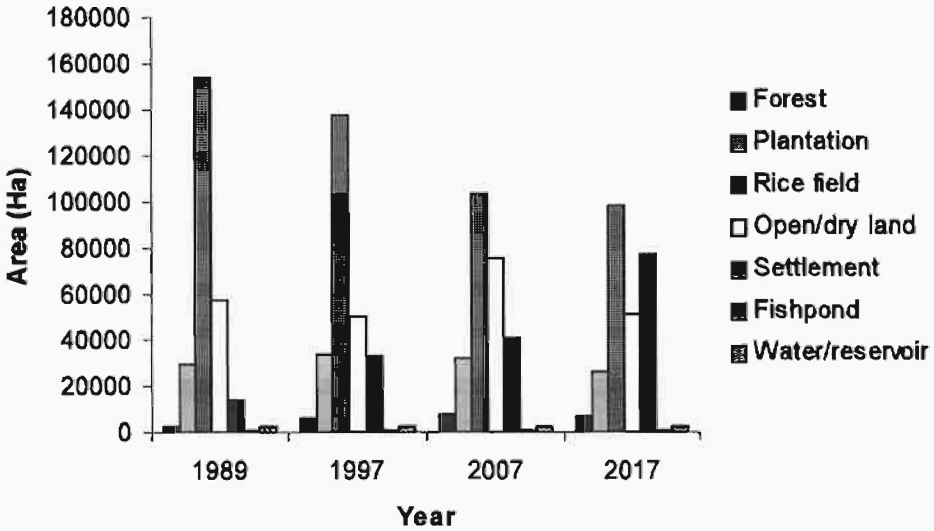


Figure 6.14. The trend of land use/land cover change within 10 km of the main roads, 1989 to 2017 (2007 and 2017 the result of scenario2)

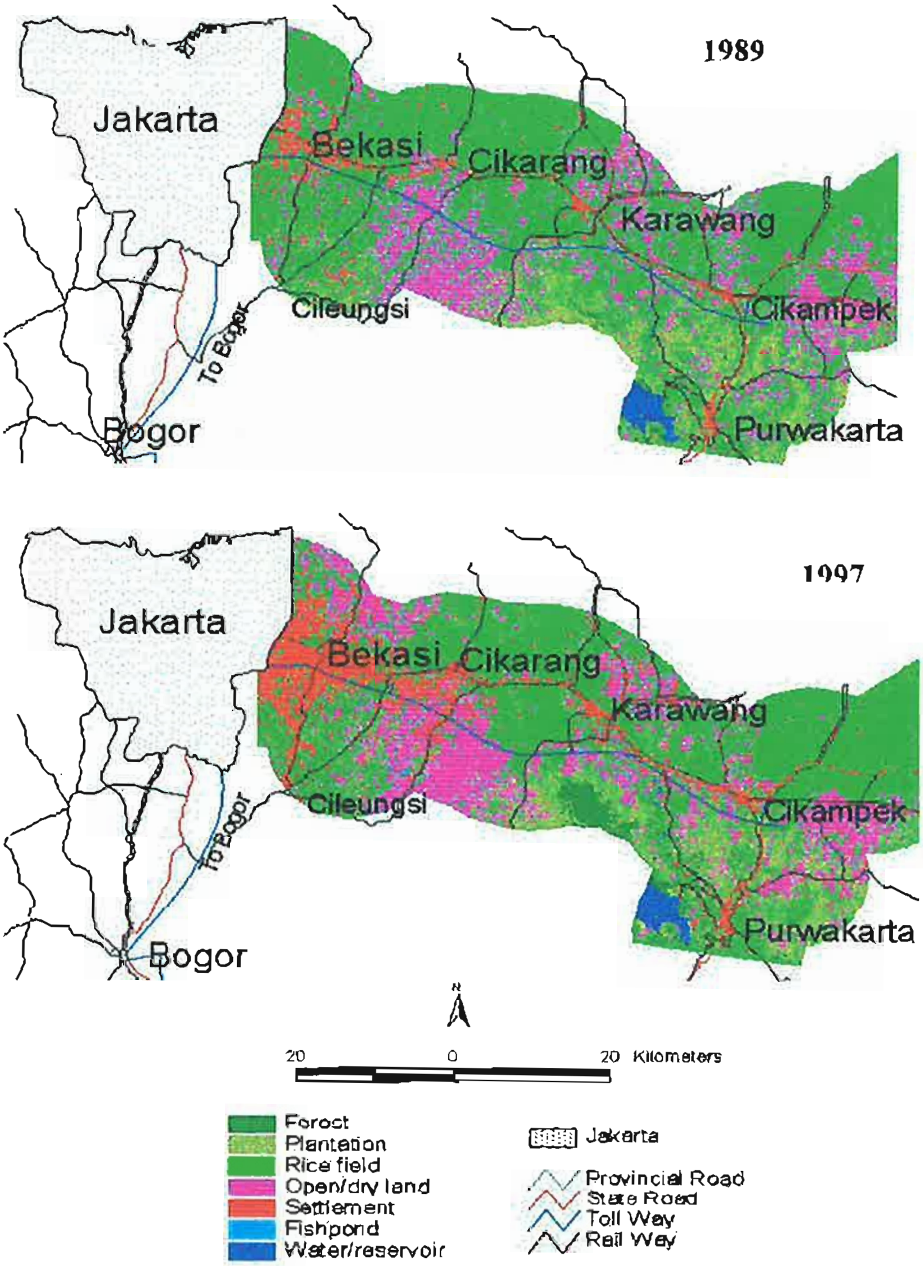


Figure 6.15a. Land use/land cover within 10 km of the main roads

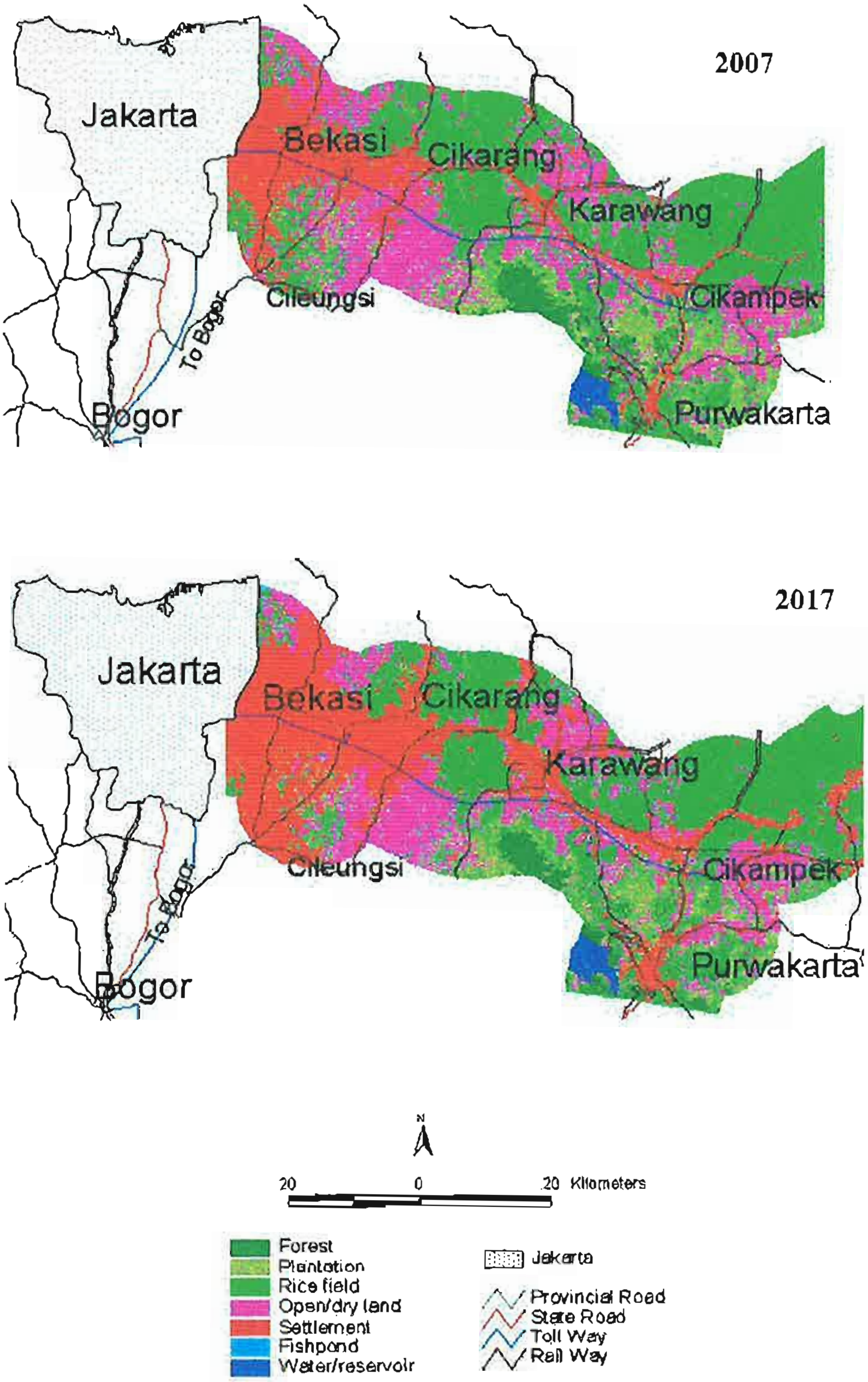


Figure 6.15b. Land use/land cover within 10 km of the main roads

Settlements continued to increase and agricultural areas to slightly decrease in the area within 10 km of the main roads. It was more drastically changed in areas within 10 km of the urban and semi-urban center (Figure 6.16 a, b and c). For example, in area within 10 km of Bekasi urban center in 1989, settlement was still less than rice field, but after 1997 settlement was greater than agricultural areas. By 2017 rice field will be nearly zero in this area as it was urbanized to adjoin the Jakarta metropolitan city. The semi-urban centers next to Bekasi are Cileungsi and Cikarang. In these two semi-urban areas, rice fields in years 1989 to 2007 was greater than settlement, but then decreased, and finally between years 2007 and 2017 settlement increased and exceeds the rice field area. In 2007 Bekasi, Cikarang and Cileungsi would become one big settlement area adjoining Jakarta city (Figure 6.17).

In other urban and semi-urban centers such as Karawang, Cikampek and Purwakarta, rice field was slightly decreased and until 2017. Rice field was still greater than settlement areas, except in Karawang, where settlement areas in 2017 were same as rice field (Figure 6.15b).

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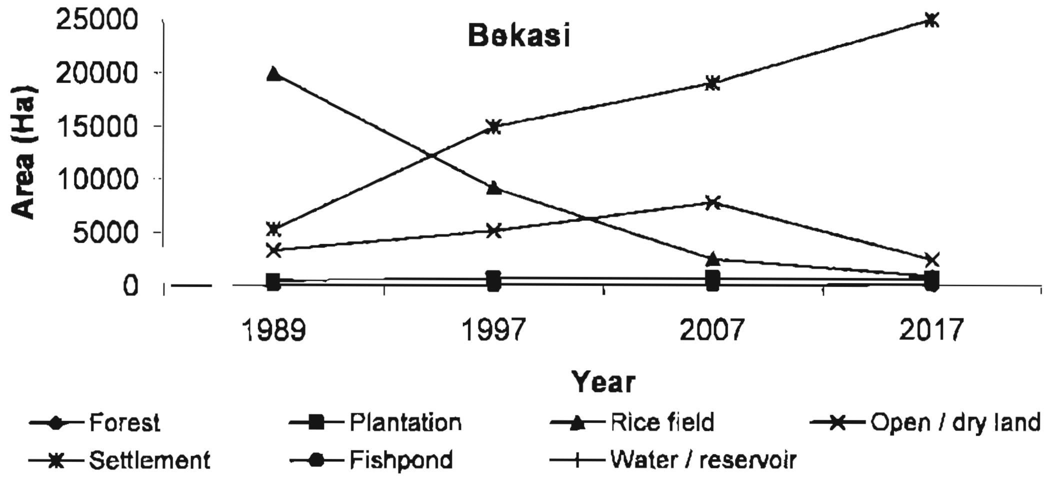


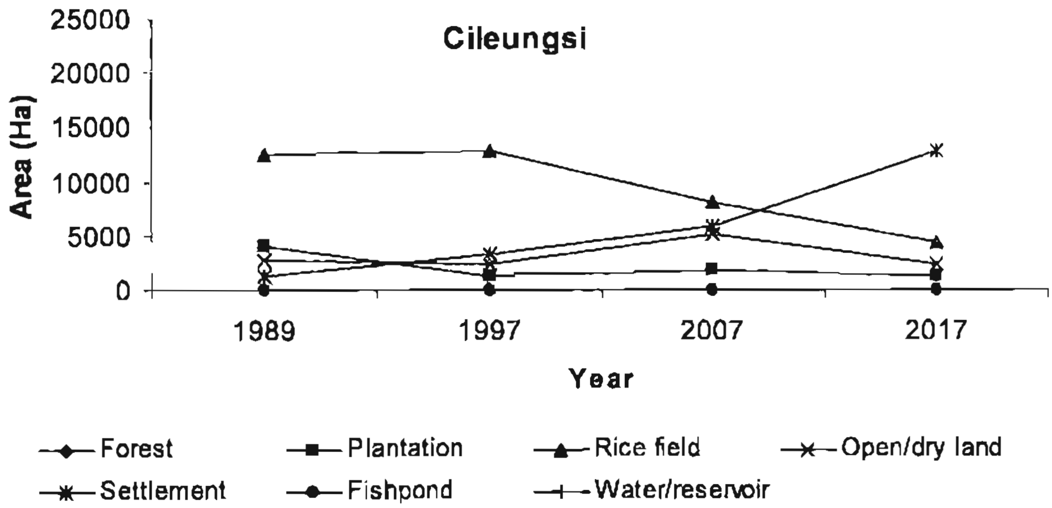
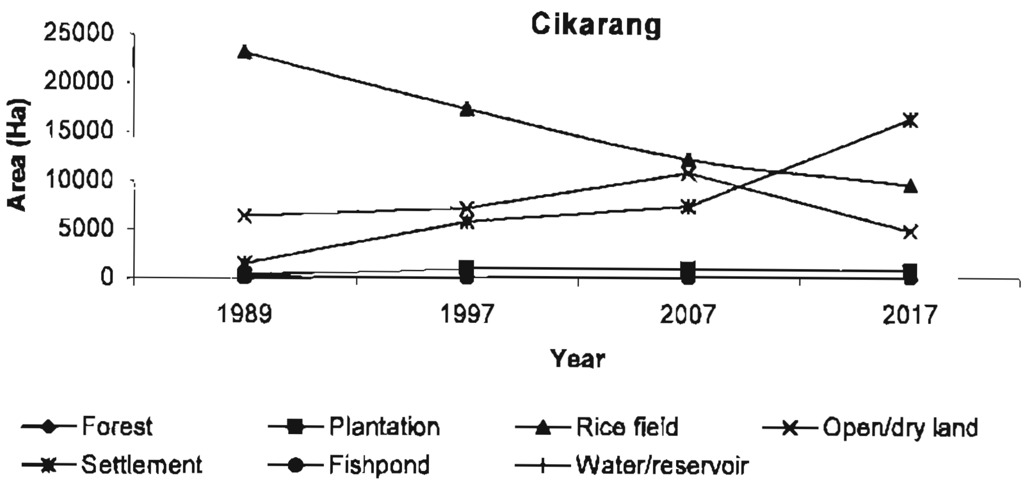


Figure 6.16a. Graphic of decreasing and increasing land use/land cover within 10 km of urban and semi-urban areas.



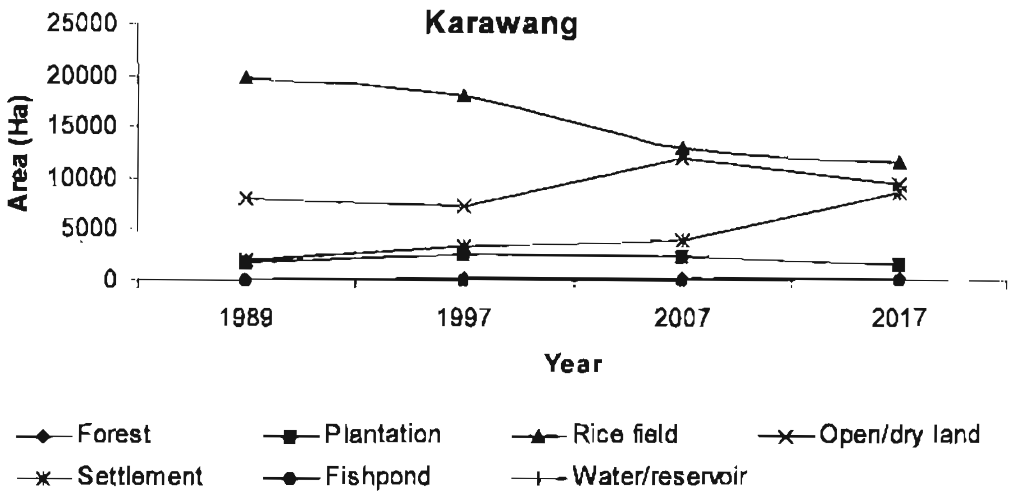
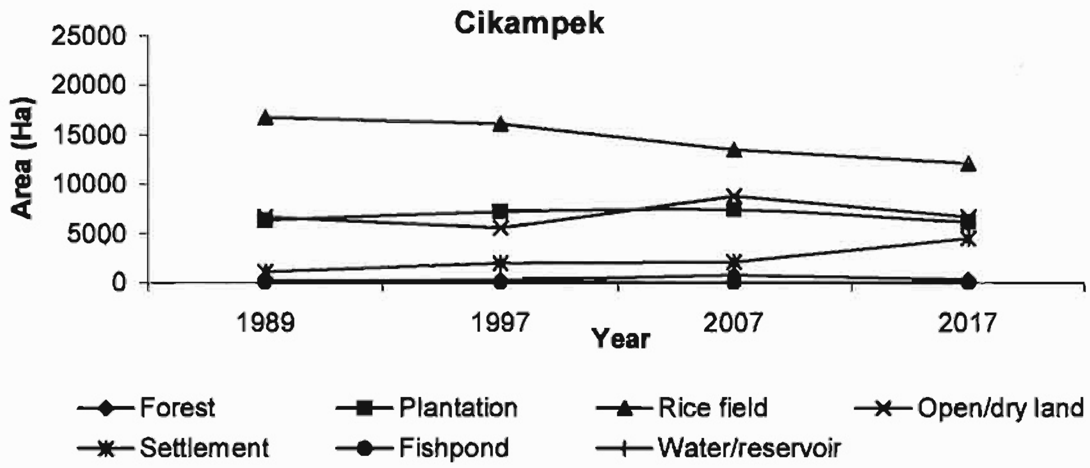


Figure 6.16b. Graphic of decreasing and increasing land use/land cover within 10 km of urban and semi-urban



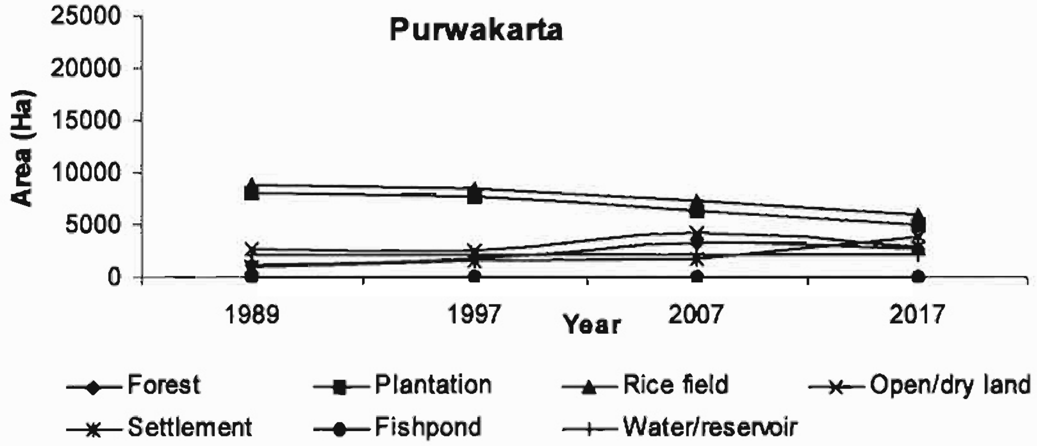


Figure 6.16c. Graphic of decreasing and increasing land use/land cover within 10 km of urban and semi-urban

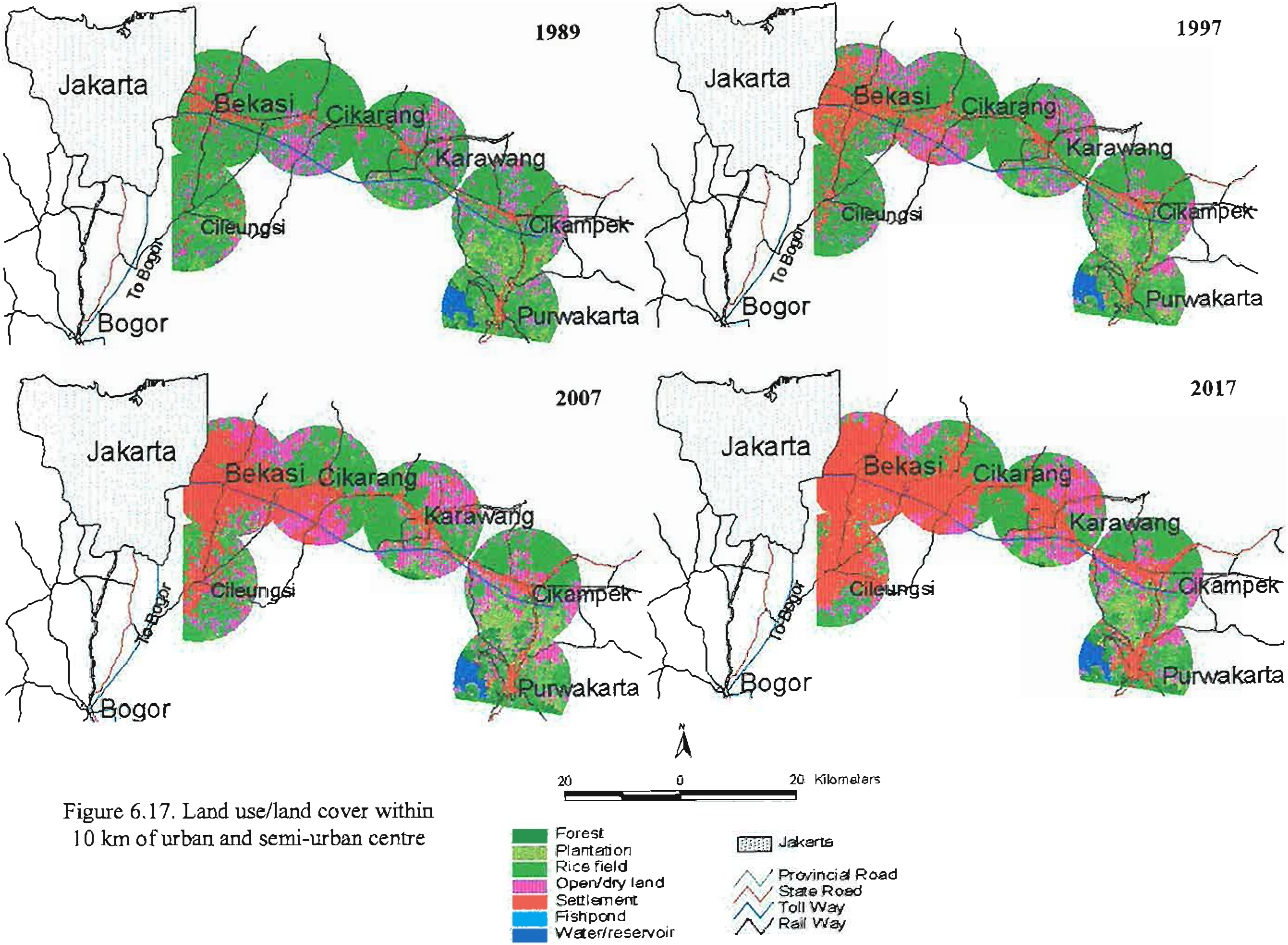


Figure 6.17. Land use/land cover within 10 km of urban and semi-urban centre

6.6 Discussion

The Markov chain model is a powerful descriptive and predictive tool for land use change and for future land use distribution. The Markov-Cellular automata model was successful in predicting land use/land cover change in the study area, especially for settlement and other categories that located close to main roads or urban centres. This model depends heavily on the quality of data input, such as Markov transition probability and suitability maps. The number of iterations and the contiguity filter type are other factors that also have to be considered.

Different combinations of filter types and number of iteration did not improve the result. Selecting different filter types shows that the groups of cells/pixels become more compact but did not improve the KIA value. The only effective way to improve the prediction results was by adjusting the suitability maps. The adjusted suitability map of settlement with added proximity factor to Jakarta and other urban areas, improved the predicted result for the settlement category. It was shown that a modified suitability map improves the spatial distribution of land use/land cover change.

Difficulty in adjusting the suitability maps of open/ dry land and other categories such as plantation and forest, resulted in poor prediction of these categories. In this case, knowledge of the background of change characteristics of each land use/land cover category in the study area needs to be considered. For example, the change characteristics of settlements was known to relate to the proximity to main roads and cities; therefore, factors such as proximity to roads and proximity to the city were appropriate factors in creating a suitability map of the settlement category. Change characteristics of open/dry land, plantation as well as forest were not clearly known. Factors such as slope and proximity to the roads that have been used in this study are not really dominant factors in the suitability maps for these categories. Further study is need with regard to obtaining more suitable prediction results for categories that still had poor predicted.

Although there were some erroneous results for some land use/land cover categories such as forest, plantation and open/dry land, good results were obtained for settlement, rice field and fishpond categories especially in areas close to main roads and urban centres. Based on this outcome, further work was undertaken to predict or simulate the future (10- and 20-year) land use/land cover change in the study area. Two Markov transition matrices for 10-year as well as 20-year simulation were created. One was from Markov transition based on transition land use/land cover change from 1989 and 1997 images, and the other one based on scenarios. A transition scenario was created that was assumed to be representative of future land use/land cover change in the study area. The economic crisis of 1998 in this country was also considered in creating the Markov transition probabilities.

A Markov Cellular automaton depends heavily on Markov transition, which assumes that the future land use/land cover change was guided by the transition from the past to the recent/present land use/land cover condition (Markov principles). The future land use/land cover change simulation based on the Markov transition from 1989-1997 was successful in simulating land use/land cover 2007 and 2017. The economic crisis in

1998 was considered as an effect in declining some economic activities such as development housing or industry. Therefore the Markov transition was adjusted in order to obtain the representative transition for the next 10-and 20-years of land use/land cover change from 1997. Two Markov transition scenarios for 10-and 20-year simulations were created based on different assumptions. Secnario1 for simulation to 2007 assumed that land use/land cover will be slightly lower and scenario2 assumes very low urbanisation and high change within agricultural area. Scenario1 of the simulation to 2017 assumed that land use/land cover change will slightly increase and there will be high level of urbanisation.

The results show that the intensive land use category in scenario1 2007, such as settlement, slightly increased while rice fields decreased. In scenario2 2007 there was very low change especially for the settlement category; it is assumed in this scenario that there will be low urbanisation. In scenario1 and scenario2 2017, it was assumed that economic activity recovered and the change of land use/land cover was higher than in 2007.

These results indicate that Markov Cellular automata model can be used to simulate the future land use/land cover change based on transition scenarios as far as the transition can represent the future land use/land cover change.

Further analysis from overlay of land use/land cover within 10km of main roads, urban and semi-urban centre has shown that land use/land cover, especially settlement and rice field, changed for the years 1989, 1997, 2007 and 2017. In an area within 10 km of main roads between Jakarta to Purwakarta, settlement increased and rice field decreased, while plantation, forest and fishpond slightly decreased. In the area within 10 km of urban and semi-urban centre that are close to Jakarta such as Bekasi, Cikarang and Cileungsi, settlement and rice field were drastically changed. In these three areas, settlement was larger than agricultural area and in 2017 these areas will become one a big settlement area adjoining Jakarta city. This phenomenon can easily be understood, since proximity to main roads as well as urban and semi-urban centres are the main factors that influence land use/land cover change, especially in settlement and rice field categories.

The present as well as the past and the future of land use/land cover information resulting from this study have implications for the spatial planning process in this area. Information such as that the future settlement area will increase at the expense of agricultural areas such as rice field, indicates that these areas will be urbanised. This information has the implication that urbanisation will have to be anticipated to eliminate future conflict in land use arrangement or land allocation as part of the spatial planning process. This would also have implications on monitoring environmental degradation such as sedimentation, flooding or decreased carrying capacity with regard to the expansion of settled areas over agricultural areas.

Other important information from this result is that settlement increased along the main roads and in areas that are close to the Jakarta metropolitan city, as the model rules stated. This indicates that the development of housing and new settlement in the fringe area of Jakarta has interaction between Jakarta, as the core metropolis, and the surroundings areas. This also indicates that new settlements surrounding Jakarta area socio-economically heavily dependent on the core, and has implication on the change of labour force, for example, from agricultural labour to non-agricultural labour.

Another implication is that exceed settlement areas the agricultural areas, for example ; or a lot of open land is idle from this simulation, shows that environmental conditions will decrease-such as increasing runoff or decreasing carrying capacity in this area.

Simulation of the future land use/land cover change based on the transition Markov principle, as well as scenarios based on justification to obtain the representative transition for the future land use/land cover change, showed that the future land use/land cover distribution could be successfully simulated. This simulation indicates that the future land use/land cover can be simulated based on some policy scenarios in order to obtain the optimal land use planning in this area, which could have a positive outcome on economic and environmental development.

The success of the Markov Cellular automata model to simulate the future land use/land cover in this study area also has a contribution on development of land use/land cover change modelling on the spatial basis.

6.7 Conclusion

This chapter has provided the results of an application of the Markov Cellular automata model to predict land use/land cover in 1997 from image 1989, as well as simulation and analysis of the future land use/land cover change in the study area. The result indicates that more appropriate suitability maps especially for forest, plantation and open/dry land category were needed.

The prediction result shows that overall KIA value is 56% before the suitability map was adjusted and 67% after it was adjusted, with KIA value of forest, plantation and open/dry land below 50%, KIA values for settlement and rice field 67% and 56 %, and KIA values of fishpond and water being 70% and 90%. The KIA of land use/land cover category with a value below 50% shows the prediction result of this category was not good enough in the categories of open/dry land, forest and plantation. Settlement and rice field categories were adequately predicted, with a KIA value over 50%. The poor prediction result on land use-land categories such as open/dry land, plantation and forest was due to limitations in the information of the background change characteristics of these categories.

The information of the distribution of land use/land cover change characteristic is important in order to select factors and criteria on creating a suitability map. The information of settlement growth along the roads and in urban and semi-urban areas, for example, was the appropriate information in order to select factors such as proximity to roads and city in creating a suitability map of settlement category.

This model was successful in simulating or predicting land use/land cover change especially for settlement and rice field categories. The future land use/land cover for years 2007 and 2017 as a result o the simulation shows that settlement was growing along the main roads and close to Jakarta metropolitan city. This simulation has an implication that there was conversion from rice field into settlement especially in area that arc close to Jakarta and along the main roads.

As a Markov transition principle, it was assumed that transition change from the past to the recent time stayed the same for the future land use/land cover change, it has weakness sincc the future may have significant change in economic conditions that could affect thc land use-land change bchaviour. Modified Markov transition with some scenarios successfully created the new simulations that could represent the future land usc/land covcr condition.

From some simulations it was found that Markov Cellular automata allow one to simulate the future land use/land cover change, based on the Markov transition created from information from the past to the recent time of land use/land cover change, and also bascd on sccnario. The appropriate background information that could have an effect on land use/land cover change is needed in order to create a suitable transition scenario that can represent the future land use/land cover change.

Chapter Seven

CONCLUSION

7.1 Summary and Findings

The main aims of this thesis were to develop a methodology effectively to detect land use/land cover change, to understand the inter-annual dynamics of land use/land cover changes and to analyse, as well as to predict, land use/land cover change dynamics using remote sensing and GIS. The Post-Classification Comparison approach was chosen because it addresses the relevant and important aspects of change: detection, identification and location. A combination of PCA and NDVI transformed images was selected instead of the original band to classify/identify land use/land cover in the study area. PCA gives a strong spectral signature of settlement or built-up area, while NDVI gives a strong spectral signature of vegetation cover. It was hypothesised that through the two transformed images, the detail of land use/land cover category in the study area could be detected and identified.

Chapter 2 reviewed and defined land use/land cover change, and described some aspects that related to land use/land cover change. It was argued that population or demographic pressure as well as economic growth and physical environmental conditions are the factors which simultaneously, or independently, affect changes of land use/land cover in the study area. The demand and supply relationship of the land use/land cover change model shows that the demand structure of land use is very dynamic; the demand for using land for human activities increases from time to time under the influence of population growth, community structure and economy. On the supply side, structure is relatively static; the surface area remains constant. The constant size of the surface area with increasing demands being placed upon it may result in land use conflict. Land use is mostly converted from less intensive uses to more intensive uses, such as from forest or open/dry land agriculture to rice field or to settlement, but it is also converted from one intensive land use to other, such as from rice field to settlement or from intensive agriculture land into non-agriculture land use, or from housing to other commercial land use. As an effect of population and economic growth, demands from the non-agriculture sector are usually much stronger than those from agriculture, due to the much higher incomes which this sector can obtain from the same area of land. In the long term, this could result in scarcity of food supply since insufficient land is available for agriculture activities. Land use allocation and management supported by the appropriate techniques such as remote sensing and GIS are required to avoid such land use conflict.

Chapter 3 describes the socio-economic and biophysical conditions in the study area. Physiographically the study area is a flat alluvial plain. Land use/land cover in the study area has changed over time as an effect of demographic pressure and economic growth, especially because the area is close to the Jakarta metropolitan area. Land use/land cover along the main roads from Jakarta to Purwakarta is very dynamic and has become more intensive over time. Within this area many rice fields have been converted into settlement or built-up areas for housing and industrial estate development.

Chapter 4 presented the analysis and results of land use/land cover change detection using image processing and GIS. The results of the Maximum Likelihood supervised classification of PCA and NDVI transformed image were successful, with a Kappa index agreement (KIA) value >85%. Land use/land cover was clearly differentiated and able to be classified into land use/land cover categories namely: 1) Forest; 2) Plantation; 3) Rice field (planted); 4) Open land; 5) Settlement; 6) Rice field (unplanted); 7) Dry land; 8) Fishpond and 9) Water/reservoir.

Post-classification comparison of this classified image was used successfully to detect land use/land cover change in the study area. At the annual interval, detection found that weather or season was related to a "leaf on and leaf off" phenomena. In the dry season, forest was less than plantation because of a lot of "leaf off" (leaf had fallen), while in the wet season forest was larger than plantation. In this time leaf leaves had regrown ("leaf on"). Therefore the change of forest area in the study area did not represent deforestation or reforestation; it was error in classification as an effect of the "leaf off – leaf on" phenomena. It was clearly recognized in the field that there are present some broad leaf plantations such as rubber plantations and teak wood, especially in the southern part of Karawang to the north of Jatiluhur reservoir, which can be confused with forest.

On the other hand, rice field (planted) and rice field (unplanted) were alternates associated with the growing cycle. It seen at harvesting time that the land was covered with rice plantation ready to be harvested, while at planting time there were no rice plantation due to the fact the land is under preparation. Therefore at harvesting time rice field (planted) was recognised to be larger than rice field (unplanted) but at planting time rice field (unplanted) was larger than rice field (planted). This phenomenon was clearly recognised in the field. Clear relationships of season or growing cycle with changes of other land use/land cover was not recognised, except the change in open land and dry land agriculture associated with dry and wet season. Settlement increased over time, fishpond and water/reservoir remain constant.

From annual detection it was recognised that rice field (planted) and rice field (unplanted) changed over time in association with the rice growing cycle. For the long-term change analysis, it was necessary to reclassify or regroup these two categories including both the open land and dry land categories. Rice field (planted) and rice field (unplanted) have the same function in the field as rice field area, and so were included as rice field. Open land and dry land categories also have the same function as land which is unused or under preparation for construction or for dry land agriculture, and so were regrouped as open/dry land. After regrouping of these land use/land cover categories it was found that settlement and rice field areas had permanently changed over time. Settlement had increased while rice field had decreased. The trajectory of land use/land cover change in this study area was recognized as follows: Rice field was converted to open/dry land or directly to settlement, and open/dry land was converted to settlement. There was no change or conversion from forest to rice field or to settlement.

Chapter 5 commences the analysis of factors influencing land use/land cover change. The large number of possible elements were simplified into static and dynamic factors.

Static factors were defined as factors that might never change, such as slope, elevation, or physiography, while dynamic factors were defined as factors that *can* change, such as population growth, population density, urban, and semi-urban areas and transport routes. Overlay analysis of these two factors with land use/land cover found that population density, proximity to urban and semi-urban centers as well as proximity to roads are the dynamic factors that have a strong relationship with land use/land cover in the study area. Settlement increased and rice field decreased significantly with increasing population density as well as within the 10 km buffer of proximity to urban and semi-urban centers and proximity to roads. As the study area is mostly a flat alluvial plain, land use/land cover types that represent human intervention (settlement and rice field) were generally located in flat areas with a slope of less than 3%.

In urban areas such as Bekasi, Karawang and Purwakarta, decreasing rice field and increasing settlement are clearly recognized as well as in semi-urban areas such as in Cikarang, Cileungsi and Cikampek. The increase of settlement accompanied by decreasing rice field area in the study area was related to increasing population density. Within an 8-year time interval (1989-1997), there was a gradual change from low population density to high population density. Settlement in the areas with a population density of 15-150 person/sqkm (class I) increased by 23%, in areas with population density of 151-650 person/sqkm (class II) increased 64%, and in areas with population density of 651-1200 person/sqkm (class III) increased of 134%. The rice field area decreased by -11% in areas with the lowest population density (class I), in class II it decreased by -31%, and in class III it decreased by -63%. This indicates that the increasing population density is an effect of increasing settlement and decreasing rice field in the study area. There is no indication of a strong relationship between increasing population density and decrease or increase in forest and plantation area. Forest increased in areas with low population density (class I and class II), while plantation decreased in areas with low population density (class I) and increased in areas with high population density (class II and III). The increasing plantation areas in areas of high population density could be due to a lot of plantations being located close to settlement areas. This is the case with rubber and teak wood plantations that are found in the study area, especially in kabupaten Purwakarta and Karawang.

Another finding is that distance from the Jakarta metropolitan area has a strong influence on increasing settlement and decreasing rice field in the study area. The increasing density of settlement accompanied by decreasing area of rice field within urban and semi – urban areas gradually decreases with increased distance from Jakarta. In the Bekasi area 15 km away from Jakarta, occurred the greatest increase in settlement density and the largest decreases in rice field, following by Cileungsi and Cikarang, which are 30 km from Jakarta. This supports the contention that the Jakarta metropolitan area exerts an influence on land use/land cover change on the surrounding areas.

A positive relationship was found between total population and settlement, while the relationship between total population and rice field, forest and plantation was negative. It was found that for an increase in total population, the area under settlement will increase and the area under rice field, forest as well as plantation will decease.

Discriminant analysis supported the strong relationship between the static and dynamic factors that influence land use/land cover. Factors such as population density, proximity to main roads, proximity to urban centre and slope are the factors that strongly influence land use/land cover change in the study area.

Chapter 6 examines, as well as applies, a Markov Cellular automata model to predict and simulate future land use/land cover change in the study area. It is shown that by selecting different filter types, the groups of cells/pixels become more compact but it did not improve the KIA value. The only effective way to improve the prediction results was by adjusting suitability maps. The adjusted suitability map of settlement which adds a proximity factor to Jakarta and other urban areas improved the predicted result for the settlement category.

The difficulty experienced in deriving an adjusted suitability map of open/ dry land and for other categories such as plantation and forest, resulted in poor prediction of these categories. In these cases, knowledge of the background of change characteristics of each land use/land cover category in the study area needs to be considered.

Markov transition probability was effective in determining the amount of area that can be expected to change, while suitability maps are effective in determining the pattern of land use/land cover change distribution. Two different Markov transitions have been used to simulate the future land use/land cover in the study area. The two Markov transitions are a Markov transition based on information that was obtained from 1989-1997 images (assuming that the future land use/land cover change transition stay the same as that transition between 1989-1997), and a Markov transition based on a scenario that was assumed to represents the future land use/land cover change transition, considering the economic crisis since 1998. It was found that the future land use-land cover change could be simulated based on the Markov transition from 1989-1997 images and the Markov transition scenario. The future land use/land cover from a simulation based on the Markov transition scenario can be more or less changed depending on the scenario assumed if comparing with the simulation based on Markov rules (transition from the past land use/land cover condition to the recent condition). It found that the trends of change which are characteristic for each land use/land cover category in the two simulation images are different. In the scenario1 2007 image as a result of simulation based on a Markov scenario that assumed the future land use/land cover will slightly change related to the economic crisis 1998, it was shown that the trend of land use/land cover change was lower than that simulation based on Markov transition 1989-1997.

Percentage of change, especially for settlement category, in a simulation 2007 based on a Markov scenario 1 and 2 was low compared with percentage change in the simulation image based on transition from 1989-1997 and high percentage in increasing open/dry land as well as decreasing fishpond. This represents a considerable amount of idle land ("tanah tidur" literally "sleeping land") within the 10 years from 1997-2007 and is assumed to be an effect of the economic crisis. While in a simulation 2017 based on scenario1 and scenario2, the percentage change increased especially for intensive land uses such as settlement, and rice field decreased, as it was assumed that within the 20 years from 1997 land use/land cover change will increase due to economic recovery from the crisis, especially after 2007.

It was found that the future land use/land cover within 10 km of main roads and urban and sub-urban centres will continue to intensify, with settlements continuing to increase and agricultural area slightly decreasing. Change was more drastic in areas within 10 km of the urban and semi-urban areas. For areas within 10 km of Bekasi urban center for example, settlement area in 1989 was less than rice field, but since 1997 settlement was more than agricultural area, and no more than rice field area in the year 2017. In two semi-urban areas next to Bekasi, Cikarang and Cileungsi, it was seen that rice field in 1989 was greater than settlement, but it continued to decrease and finally in 2007 settlement exceeded the rice field area. In 2007 Bekasi, Cikarang and Cileungsi will become one big settlement area adjoining the Jakarta metropolitan city. This area is becoming urbanized as an influence of the Jakarta metropolitan complex which has the largest urban population in Indonesia. Construction of new housing or industry in this area still continues, as well as the construction of the toll way between Cikampek-Purwakarta- Padalarang.

Finally the results of future land use/land cover change simulations found that the Markov Cellular automata model enables us to simulate the future land use/land cover change. This simulation can run based on the Markov transition that is created from information relating to past and recent land use/land cover change (Markov rules) and based on a Markov transition scenario as far as the scenario could represent future land use/land cover change. In this case, the appropriate background information and significant factors that could have an effect on the future land use/land cover change are needed in order to create suitable a Markov transition scenario.

7.2 Implications

7.2.1 Policy

Housing and industrial estate expansion has had an influence on the booming development around the big cities of Indonesia, especially in Jakarta and its adjoining areas- JABOTABEK. This pattern is being repeated around other mega city centres in Southeast Asia such as Manila, Bangkok and Ho Chi Min city. Up until July 1997 the Indonesian National Land Agency (BPN) had issued permits for development of about 121 000 hectares of land on the periphery of Jakarta (Bogor-Tanggerang-Bekasi) to private developers, of which, developers have acquired 46000 hectares (Firman, 1998). This policy has had the implication that land use/land cover in this area has changed rapidly. The recent physical development of Jakarta and its periphery is characterised by conversion of agriculture land to urban land uses. This conversion of agriculture land to urban land uses such as settlement was clearly recognised in the land use/land cover change detection in this study using satellite image for the years 1989 to 1997.

On the other hand, the future land use/land cover simulation obtained by using a Markov Cellular automata model indicates that urbanisation in this area will continue, from both a simulation based on Markov transition of land use/land cover from 1989-1997 and a Markov transition scenario which assumes that the economic crisis since 1998 will affect the rate of land use/land cover change in the study area. This urbanisation will also happen around other big cities in Indonesia such as Surabaya, Medan and Makasar.

The implications on the government policy of the results are:

1. Land use/land cover change detection using remote sensing and GIS technique is useful to obtain the recent land use/land cover condition on the spatial base.
2. Detection of land use/land cover change by using remote sensing and GIS as well as simulation of the future land use/land cover change are useful to support government policy in order to obtain optimal land use or land allocation arrangement that can eliminate land use conflict. For example, not taking productive land out of agricultural until it is necessary to do so.
3. The government has to consider that rapid land use change conversion from agricultural land to urban uses that were found in this study can be used as an input in order to arrange the land permits issued and to avoid a lot of idle land ("lahan tidur") as well as other environmental problems such as sedimentation, flood and declining carrying capacity of this area.

7.2.2 New Research

As satellite images have different levels of spatial, as well as spectral, and temporal resolution, further study is needed in order to compare the results from this study with results from studies with more detailed classes of land use/land cover categories. Soft classification using fuzzy classifiers, for example, could be used to try and obtain better land use-land cover classification within agriculture land uses or within urban land use which, in this study, was generalised to avoid mixed classification.

Markov Cellular automata model based on Markov transition from the past to the recent land use/land cover condition has a limitation on representing the future land use/land cover change if the past has significantly different condition from the future, such as declining or increasing economic conditions that could have an effect on land use/land cover change. This limitation can be eliminated by using a modified Markov transition based on consideration of some significant factors to obtain the transition that can represent the future land use/land cover change.

The further study on this simulation needs to obtain the future land use/land cover change which is simulated correctly, simulated based on the Markov transition that can represent the future land use/land cover. For example, a Markov transition scenario that was created based on the accurate and appropriate background information that could affect the future land use/land cover change, such as information of relationship between population growth or economic growth and land use/land cover change rate.

There is a pressing need to do similar studies in other mega SE Asia cities and other smaller Indonesian cities such as Surabaya, Medan and Makasar. Further research also needs to develop new factors of significance to be included in simulations of the future land use/land cover change based on the Markov Cellular automata model.

REFERENCES

Aaviksoo K. (1995). Simulating vegetation dynamics and land use in a mire landscape using a Markov model, *Landscape and Urban Planning.*, 31:129-142.

Adger W. Neil and Katrina Brown (1994). Land use and the causes of Global Warming. John Wiley, England.

Alba Ma. J.B, Flaviana.H., Anita. J., and Estella. B.J. (1997). The Philippine Land use and Landover change case study. SARCS-START-IGBP, Bangkok, Thailand.

Alomar D, C. Gallo, M. Castaneda, R. Fuchslocher (2003). Chemical and discriminant analysis of bovine meat by near infrared reflectance spectroscopy (NIRS), *Meat Science*. 63:441-450.

Anderson J.R., E.E. Hardy, J.T. Roach, and R.E.Witmer (1976). A Land Use and Land Cover Classification System for Use with Remote Sensor Data, *Profesional Paper 964*, US. Geological Survey, Reston, VA.

Angelici G.L., Brynt, N.A, and Friedman, S.Z. (1977). Techniques for Land Use Change detection using Landsat imagery. *Proceeding of the American Society of Photogrametry*, 217-228.

Arai T and Tetsuya A. (2003). Empirical analysis for estimating land use transition potential functions-case in the Tokyo metropolitan region. *Computer, Environment and Urban Systems,* (Article in Press)

Balzter H., Paul W. Braun and Wolfgang Kohler (1998). Cellular automata models for vegetation dynamics. *Ecological Modelling*, 107: 113-125.

Bargman,V. (1970). Group representations in mathematics and physic. Springer-Verlag, Berlin.

Barredo J.I, Marjo.K, Niall.McCormick, Carlo.L.(2002). Modelling dynamic spatial processes: simulation of urban future scenarios through cellular automata. *Landscape and Urban Planning,* 981:1-16.

Batty M and Kim K.S. (1992). Form follows function: reformulating urban population density function. *Urban Studies,* 29:1043-1070.

Batty .M and Y.Xie (1994). From cell to Cities. *Environment and Planning B: Planning Design,* 21: 831-848.

Batty M, H.Coucelis, M. Eichen (1997). Editorial: Urban system a cellular automata. *Environment and Planning B: Planning Design,* 24: 159-164.

Batty M, and Y. Xie (1997). Cellular Automata as the basis of integrated dynamic regional modelling. *Environment and Planning B: Planning Design,* 24: 235-246.

Batty M. (1998). Urban evolution on the desktop: Simulation with the use of extended cellular automata. *Environment and Planning, A.*30: 1943-1967.

Batty M, Yichun Xie and Zhanli Sun (1999). Modelling Urban dynamics through GIS-based cellular automata.*Computer, Environment and Urban System,* 23(3):205-233.

Baulies X. and Szejwach, G. eds. (1997), Survey of need, gaps and priorities on data for land use -land cover change research. *LUCC Data Requirements Workshop,* LUCC Report Series No.3, Barcelona, Spain.

Bajjouk T, J.Populus and B. Guillaumont (1998). Quantification of Subpixel Cover Fractions Using Principal Component Analysis and a Linier Programming Method: Application to the Coastal Zone of Roscoff (France). *Remote Sensing of Environment,* 64:153-165.

Beberoglu, C. D.Lioyd, P.M Atkinson and P.J. Curran (2000). The Integration of Spectral and Textural Information using Neural networks for Land Cover Mapping in the Mediterranean. *Computer and Geoscienc,* 26: 385-396

Bell E.J. (1974). Markov Analysis of Land Use Change an Application of Stochastic Processes to Remotely Sensed Data. *Geographical Analysis,* 28(1): 56-66.

Bell E.J. (1977). Markov analysis of Land use change: continuous time and stationary process. *Socio-Econ Planning Science,* 11:13-17.

Bell E.J and Hinojosa, R.C. (1977). Markov analysis of Land use change: continuous time and stationary processes. *Socio-Econ Planning Science.* 11:13-17.

Benstein J.D. (1994). Land use consideration in urban environmental management, Washington DC.

Bertels K, J..M. Jacques, L. Neuberg and L Gatot (1999). Qualitative company performance evaluation: Linear discriminant analysis and neural network models. *European Journal of Operational research.* 115:608-615.

Besussi E, Arnaldo.C and Enrico.R.(1998).The Diffusion City of the Italian North-East: Identification of Urban Dynamics Using Cellular Automata Urban Models. *Computer, Environment and Urban Systems,* 22(5):497-523.

Bilsborrow R.E, Okoth-Ogendo, H.W.O. (1992). Population driven changes in land use in developing countries. *Amabio,* 21:37-45.

Bicik Ivan, Leos.J., Vit.Stepanek.2001 Land use change and their Social driving forces in chechia in the 19th – 20th Centuries. *Land use Policy,* 18: 65-73

Blaikie P, Cannon.T, Davis.I and Wisner.B. (1994) At Risk: Natural Hazards, Peoples vulnerability and Disaster, London.UK.

Blackard J.A and Denis J.DDD. (1999). Comparative accuracies of artificial neural networks and discriminant analysis in predicting forest cover types from cartographic variables. *Computers and electronics in Agriculture.* 24:131-151.

Briassoulis H. (2000) Analysis of Land Use Change: Theoretical and Modellling Approaches, Regional Science.

Borak J.S., E.F.Lambin and A.H.Strahler (2000). The uses of temporal metrics for land cover change detection at coarse spatial scales. *International Journal of Remote Sensing,* 21: 1415-1432.

Brera A.M. and F. Shahrokhi (1978). Application of Landsat Data to Monitor Desert Spreadin in the Sahara Region. *Proceedings of the 12th International Symposium on Remote Sensing of Environment,* Ann Arbor, Michigan.

Bressan M, J. Vitria (2003). Nonparametric discriminant analysis and nearest neighbor classification, *Pattern Recognition Letters.* In Press.

Bruzzone L. and D. Fernandez Prieto (2000). An adaptive parcel-based technique for unsupervised change detection. *International Journal of Remote Sensing,* 21:817-822.

Bryan B. A. (2000). Modelling the propagation of land clearance using cellular automata and the implications for nature conservation. The 4th International Conference on Integrating GIS and Environmental Modelling (GIS//EM4): problem, Prospects and Research Needs, Banff, Alberta, Canada.

Brown L.A.(1970) On the Use of Markov Chains in Movement Research. *Economic Geography,* 46:393-403.

Brown .D.G, B.C.Pijanowski and J.D.Duh.(2000).Modeling the relationships between land use and land cover on private lands in the Upper Midwest, USA. *Journal of Environmental management*, 59: 247-263.

Burrough P.A. (1986). Principal of Geographical Information System for Land Resources Assessment. Oxford University Press, England. UK.

Byrne G.F., P.F. Crapper, and K.K. Mayo (1980). Monitoring Land Cover Change by Principal Component Analysis of Multitemporal Landsat Data. *Remote Sensing of Environment*, 10: 175-184.

Bryant C.R. (1986). "Agriculture and Urban development" in Pacione,M (eds.), Progress in Agricultural Geography, Bechenham,UK.

Candau .J, Steen. R, Keith C.C. (2000). A couple cellular automaton model for land use/land cover dynamics. The 4th International Conference on Integrating GIS and Environmental Modelling (GIS//EM4): problem, Prospects and Research Needs, Banff, Alberta, Canada.

Ceballos and M.J.Bottino (1997). The Discrimination of Scenes by Principal Component Analysis of Multi-Spectral Imagery. *International Journal of Remote Sensing*, 18:2437-2449.

Chapin F.S. (1972). Urban Land use planning. University of Illinois, Urbana

Charlie N, Suwit. O, Kamerun .M. (1997). The Thailand Land use and Land cover change case study. SARCS-START-IGBP, Bangkok, Thailand.

Chou Kue-Chen and David W. Elrod (1998). Using Discriminant Function for Prediction of Subcellular Location of Prokaryotic Proteins, *Biochemical and Biophysical Research Communication*. 252:63-68.

Cecchini A. (1996). Urban modelling by means of Cellular Automata: generalised urban automata with the help on-line (AUGH) model. *Environment and Planning B: Planning Design*, 23:721-732.

Cihlar J., Qinghan Xiao, J. Chen, J. Beaubien, K. Fung and R. Latifovic (1998). Classification by Progressive Generalization: a New automated Methodology for Remote Sensing Multi Channel data. *International Journal of Remote Sensing*, 19: 2685-2704.

Claramunt C, Christine Parent, Stefano Spaccapietra and Marius Theriault. (1999). Database Modelling for Environmental and Land Use Changes, in Srillwell.J, Stan Geertman and Stan Openshaw (eds.) Geographical Information and Planning. Springer-Verlag, Berlin.

Clarke K.C., Stacy Hoppen and Leonard J. Gaydos (1997). Methods and Techniques for Rigorous Calibration of a cellular automaton model of urban growth. http://www.mcgia.ucsb.edu/conf/SA..pers/clarke_keith/clrkeetal.htm1

Cloke Paul.J. (1989). Rural Land use planning in developed nation. Unwin Hyman.ltd, UK

Coucelis H. (1997). From Cellular Automata to Urban models: new principles for model development and implementation. *Environment and Planning B: Planning Design*, 24:165-174.

Cohen W.B. and Maria Fiorella (1999)." Comparison of Methods for Detecting Conifer Forest Change with Thematic Mapper Imagery". in Lunetta and Christopher D.E.(eds). Remote Sensing Change Detection: Environmental Monitoring Methods and Applications. Sleeping Bear, UK.

Coiner J.C. (1980). Using Landsat to Monitor Change in Vegetation Cover Induced by Desertification processes. *Proceedings of the 14th International Symposium on Remote Sensing of Environment,* Ann Arbor, Michigan.

Collin Clark (1977). Population growth and Land use. Macmillan. London.

Collin L. (1973). Industrial Size Distributions and Stochastic Process. *Progress in Geography,* 5:121-65.

Colwell J.E. and F.P. Weber (1981). Forest Change Detection. *Proceedings of the 15th International Symposium on Remote Sensing of Environment,* Ann Arbor, Michigan.

Dawson A.H. (1984). The Land problem in the developed Economy. Croom Helm, NSW, Australia.

deBie CA, van Leeuwen JA and Zuidema PA.(1996). The Land Use Database. A knowledge-based software programme for structured storage and retrieval of user-defined land use data set. Users' Reference Manual (vl04, DOS). ITC, Enschede; FAO, Rome: Agricultural University, Wageningen.

Deep Peter. (1999). Change Detection in Remote Sensing Using Unsupervised Fuzzy Classification. PhD dissertation University of Adelaide, Australia.

de Almeida C.M, Michael.B, Antinio.M.V.M, Gilberto.C, Britaldo.S.S.F, Gustavo.C.C, Cassio.L.P.(2003). Stochastic cellular automata modeling of urban land use dynamics: empirical development and estimation. *Computer, Environment and Urban Systems,* (Article in Press)

de Koning G.H.J, P.H. Verburg, A.Veldkamp, L.O.Fresco (1999). Multi-Scale Modelling of Land use change dynamics in Ecuador. *Agricultural Systems,* 61 : 77-93.

Djoko S. (1996). Problems and prospects of Indonesia new towns development. *Paper presented at the International Seminar Planning and Development of Satellite Towns in Southeast Asia.* Organized by LIPI-The Japan Foundation, Jakarta, 25-27 June 1996.

Dobson, M. C., Pierce, L. E. and Ulaby, F.T. 1996, Knowledge-based land cover classification using Ers-1/Jrs-1 SAR composites, *IEEE Transactions on Geoscience and Remote Sensing,* 34(1), 83-99.

Du Qian, Chein-I Chang (2001). A linear constrained distance-based discriminant analysis for hyperspectral image classification. *Pattern Recognition.*34:361-373.

Du Qian, Hsuan R (2003). Real-time constrained linear discriminant analysis to target detection and classification in hyperspectral imagery. *Pattern Recognition* .36:1-12.

Duin Robert P.W, Elzbieta P, Dick de Ridder (1999). Relational discriminant analysis. *Pattern Recognition Letters.*20:1175-1181.

Eastman. J.Ronald (2001). Tutorial Idrisi32 Release 2. Clark Labs. Clark University, USA.

Edge Dustin (2001). Urban Growth Simulation using GIS-based Cellular Automata. MSc Thesis University of Adelaide.

Ehrlich Paul.R, Anne H, Holden John P. (1977). Ecoscience. Population, resources, environment. W.H.Freeman and Company, USA.

Elvidge C.D. and Z. Chen (1995). Comparison of Broadband and Narrow-Band Red Versus Near Infra Red Vegetation Indices. *Remote Sensing of Environment,* 54: 38-48.

ERDAS. (1997). Image Manual V.8.3, 4th edn. ERDAS, Inc. 2081 Buford Highwas, NE, Atlanta, Georgia, USA.

Feighner J.P, LLLL. Sverdlov, H. Abajian, J. Hlavja, G. Nicolau (2000). Discriminant analysis to separate a study population by treatment subgroups in a pilot clinical trial with a new pontapeptide antidepressant (INN00835). *European Neuropsycho pharmacology*. 11 (3).S184.

Firman Tommy. 1997. Land Conversiton and Urban Development in the Northern Region of West Java, Indonesia. *Urban Studies*, 34(7), 1027-1046.

Firman Tommy.2000. Rural to urban land conversion in Indonesia during boom and bust periods. *Land Use Policy*, 17: 13-20.

Fisher, R.A.(1936). The use of multiple measurements in taxonomic problems, *Ann. Eugenics*, 7, 179-188.

Fischer Gunther and Laixiang Sun. (2001). Model based analysis of future land-use development in China. *Agriculture, Ecosystems and Environment*, 85: 183-176.

Fisher P.F. and S.Pathirana (1990). The Evaluation of Fuzzy Membership of Land Cover Classes in the Suburban Zone. *Remote Sensing of Environment*, 34: 121-132.

Fisher P.F. and S.Pathirana (1993). The Ordering of Fuzzy Land – Cover Information Derived from Landsat MSS Data. *Geocarto Internatioanl, 3:5*-14.

Filho R. A., Yosio E. Shimabukuro (2002). Digital processing of a Landsat-TM time series for mapping and monitoring degraded areas caused by independent gold miners, Roraima State, Brazilian Amazon. *Remote Sensing of Environment*, 79: 42-50.

Foody G.M. (2001). Monitoring the Magnitude of Land – cover change around the Southern Limits of the Sahara. *Photogrametric Engineering and Remote Sensing,* 67:841-847.

Foody G.M. (2000). Estimation of sub-pixel land cover composition in the presence of untrained classes. *Computers & Geosciences,* 26: 469-478.

Foody G.M and D.S. Boyd (1999). Detection of partial land cover change associated with the migration of inter-class transitional zones. *International Journal of Remote Sensing,* 20:2723-2740.

Foran B.D. (1987). Detection of Yearly Cover Change with Landsat MSS on Pastoral Landscapes in Central Australia. *Remote Sensing of Environment,* 23: 333-350.

Foster B.C. (1985). An examination of some problems and solution in monitoring urban areas from satellite platforms. *International Journal of Remote Sensing,* 6:139-151.

Frederick M., Iwan G., Handoko., Asep Karsidi, M. Muchlis., Andi Rahmadi., Hartanto Sanjaya., Laju Gandarum. (2001). Case Studies and Diagnostic Models of the Inter-annual Dynamics of Deforestation in Southeast Asia: Is the missing sink for Carbon in Land cover Change?. Indonesian Case Study. Final report submitted to: The United Nations Office of Project Services (UNOPS).

Fung T and W. Siu (2000). Environmental quality and its changes, an analysis using NDVI. *International Journal of Remote Sensing,* 21:1011-1024.

Fung T. and E. LeDrew (1987). The Application of Principal Component Analysis to Change Detection Using Various Accuracy Indices. *Photogrametric Engineering and Remote Sensing*, 53: 1649-1658.

Fung T. and E. LeDrew (1988). The Determination of Optimum Threshold Levels for Change Detection. *Photogrametric Engineering and Remote Sensing*, 54: 1449-1454.

Gemmell F., Jari Varjo and Mikael S. (2001). Estimating Forest cover in a boreal Forest test site using Thematic Mapper data from two dates. *Remote Sensing of Environment*, 77: 197-211.

Gobin A., P. Campling, J. Fcyen (2002). Spatial analysis of rural land ownership. *Landscape and Urban Planning*, 55: 185-194.

Goldblum C., Tai-Chee Wong (2000). Growth, crisis and spatial change: a study of haphazard urbanization in Jakarta, Indonesia. *Land Use Policy*, 17:29-37.

Gordon D.K, Warren R.P. and William D.P. (1986). Fruit Tree Inventory with Landsat Thematic Mapper Data. *Photogrametric Engineering and Remote Sensing*, 52: 1871-1876.

Gordon S. (1980). Utilizing Landsat Imagery to Monitor Land Use Change. *Remote Sensing of Environment*, 9: 189-196.

Government Regulation of the republic of Indonesia Number 10 year 2000 Concerning the Map accuracy for the Spatial Planning in Indonesia.

Green. K., Dick Kempka, and Lisa Lackey (1994). Using Remote Sensing to Detect and Monitor Land Cover and Land Use Change. *Photogrametric Engineering and Remote Sensing*, 60: 331-337.

GTZ. (2000). Final Report Private Public Partnership (PPP) Project to Promote Spatial Planning and Forest Mapping, Jakarta, Indonesia

Hashiba H., K. Kameda, S. Uesugi and S. Tanaka (2000). Land use change analysis of Tama river basin with different spatial resolution sensor data by Landsat MSS and TM. *Advance Space Research*, 26 (7): 1069-1073.

Hathout S. (2002). The use of GIS for monitoring and predicting urban growth in East and West St Paul, Winnipeg, Manitoba, Canada. *Journal of Environmental Management*, 66:229-238.

Haub Carl (1996). Future Global Population Growth, in Ramphal, Shridath and Steven W.S (eds). Population Growth and Environmental issues.Praeger Publishers. London.

Helmschrot J., Wolfgang Albert Flugel (2002). Land use characterisation and change detection analysis for hydrological model parameterisation of large scale afforested areas using remote sensing. *Physics and Chemistry of the Earth*, 27: 711-718.

Henderson, F.M. and Xia, Z.G. 1997, SAR applications in human settlement detection, population estimation and urban land use pattern analysis – a status report, *IEEE Transactions on Geoscience and Remote Sensing*, 35(1), 79-85.

Hidding M.C and Andre, T.J.T. (2002). Beyond fragmentation: new concepts for urban-rural development. *Landscape and Urban Planning*, 58: 297-308.

Heilig, G. K. 1997, Anthropogenic factors in land use change in China, *Population and Developemnt Review*, 23(1), 139 –168.

Holden H and E.LeDrew (1998). Spectral Discrimination of Healthy and Non-Healthy Corals Based on Cluster Analysis, Principal Components Analysis and Derivative Spectroscopy. *Remote Sensing of Environment*, 65:217-224.

Hoover E.M and Frank Giarratani (1999). An Introduction to Regional Economics. http://www.rri.wvu.edu/WebBook/Giarratani.

Howard D.M, P.J.A. Howard and D.C. Howard. (1995). A Markov Model Projection of Soil Organic Carbon Stores Following Land Use Changes. *Journal of Environmental management*, 45: 287-302.

Howarth P.J. and G.M. Wickware (1981). Procedures for Change Detection Using Landsat Digital Data. *International Journal of Remote Sensing*, 2: 277-291.

Huberty C.J. (1994). Applied Discriminant Analysis. John Wiley and Sons, Inc. New York.

Hugo, Graeme J. (1981). Population Mobility in West Java, Gajah Mada University Press. Yogyakarta.

Hugo, Graeme J. (1982). Evaluation of the Impact of Migration on Individuals, Households and Communities, in ESCAP, National Migration Surveys. X. Guidelines for Analyses, Comparative study on Migration, Urbanization and Development in the ESCAP Region, Survey Manuals, New York: United Nation, pp.189-215.

Ingebristsen S.E. and R.P.J. Lyon (1985). Principal Component Analysis of Multitemporal Image Pairs. *International Journal of Remote Sensing*, 6: 687-696.

Irwin E. G., Jacqueline Geoghegan (2001). Theory, data, and methods: developing spatially explicit economic models of land use change. *Agriculture Ecosystems and Environment*, 85: 7-23.

Jadhav R.N., M.M. Kimhoti and A.K.Kandya (1993). Grassland Mapping/Monitoring of Banni, Kachchh (Gujarat) using Remotely Sensed Data. *International Journal of Remote Sensing, 14*: 3093-3103.

Jayadinata J.T. (1999). Tata Guna Tanah dalam Pembangunan Pedesaan, Perkotaan dan Wilayah. ITB, Bandung.

Jensen J.R (1986) Introductory Digital Image Processing. Prentice Hall, Englewood Cliffs, New Jersey.

Jensen J.R., E.W. Ramsay, H.E.Mackey, E.J. Christensen and R.R. Sharitz (1987). Inland Wetland Change Detection Using aircraft MSS Data. *Photogrametric Engineering and Remote Sensing*, 53: 251-529.

Jensen J.R., K. Rutchey, M.S. Koch and S. Narumalani (1995). Inland Wetland Change Detection in the Everglades Water Conservation Area 2A Using a Time Series of Normalized Remotely Sensed Data. *Photogrametric Engineering and Remote Sensing*, 61: 199-209.

Jensen J.R (1996) Introductory digital image Processing: a remote sensing perspective. Prentice-Hall, USA.

Jha C.S. and N.V.M.Uni (1994). Digital Change Detection of Forest Conversion of Dry Tropical Forest Region. *International Journal of Remote Sensing*, 15: 2543-2552.

Joyce A.T., Irvey,J.H, and Burns,G.S.(1980). The use of Landsat MSS data for detecting Land use change in forestland. *Proceedings of the 154th International Symposium on Remote Sensing of Environment. Held in Costa Rica in 1982*, pp. 979-988.

Ju Junchang, eric D.Kolackzyk, Sucharita Gopal (2003). Gaussian mixture discriminant analysis and sub-pixel land cover characterization in remote sensing, Remote *Sensing of Environment.* 84:550:560.

Juppenlatz. M, Xiaofeng Tian (1996). Geographic Information Systems and remote sensing. McGraw-hill Book Company. Asutralia.

Karsidi A., SHM. Tampubolon., Moch. Muchlis, Hartanto. S. (1997). The Indonesia Land use and Land cover change case study. SARCS-START-IGBP, Bangkok, Thailand.

Karathanassi V., CH. Iossifidis and D. Rokos (2000). A Texture–based Classification method for classifying built areas according to their density. *International Journal of Remote Sensing,* 21: 1807-1823.

Kaufinann R.K., Karen C.S. (2001). Change Detection, accuracy, and bias in a sequential analysis of Landsat Imagery in the Pearl Delta, China: Econometric techniques. *Agriculture, Ecosystem and Environment,* 85:95-105.

Klecka W.R. (1980). Discriminant Analysis. In Sullivan John.L (eds). (1980). Series: Quantitative Applications in the Social Sciences. Sara Miller McCune, Sage Publication, Inc.

Krummer D and Turner II B.L.(1994). The human causes of deforestation in Southeast Asia. *Bioscience,* 44(5):323-330.

Kwarteng A.Y and P.S. Chavez, Jr. (1998). Change Detection Study of Kuwait City and environs Using Multi-temporal Landsat Thematic Mapper data. *International Journal of Remote Sensing,* 19:1651-1662.

Lachenbruch, P.A. (1973). Some Results on the multiple group discriminant problem, in T.Cacaullus (eds), 1973, Discriminnat Analysis and Application, Academic Press. New York.

Lambin E.F. and A.H. Strahler (1994). Change Vector Analysis in Multitemporal Space: a Tool to Detec and Categorise Land Cover Change Processing Using High Temporal Resolution Satellite Data. *Remote Sensing of Environment*, 48: 231-144.

Lambin E.F. (1994). Modelling Deforestation Processes. A Riview. TREES SERIES B. Research Report No.1, Luxembuourg.

Lambin E.F, Baulies X, Bockstael N, Ficcher G, Krug T, Leemans R, Moran E.F, Rinfuss R.R, Sato Y, Skole D, Turner II B.L and Vogel C. (1999). Land Use and Cover Change Implementation Strategy. IGBP Report No.48:IHDP Report No.10, Stockholm: International Geosphere-Biosphere Programme Secretariat.

Lindgren, David.T (1985). Land use planning and remote sensing. Martinus Nijhoff Publishers, Dordrecht, The Netherlands.

Liu X.H, Claes A. (2003). Assessing the impact of temporal dynamics on land –use change modeling. *Computers, Environment and Urban Systems,* Article in Press.

Li Xiubin and Hong Yang (2000). Cultivated land and food supply in China. *Land Use Policy*, 17: 73-88.

Li X., A.G.O. Yeh (1998). Principal Component Analysis of Stacked Multi-Temporal Images for the Monitoring of Rapid Urban Expansion in the Pearl River Delta. *International Journal of Remote Sensing,* 19:1501-1518.

Li Xia, and Anthon.G.O.Yeh. (2001). Modelling sustainable urban development by the integration of constrained cellular automata and GIS. *Int.J.Geographical Information Science,* 14 (2):131-152.

Li Xia, and Anthony.G.O.Yeh (2001). Calibration of cellular automata by using neural networks for the simulation of complex urban systems. *Environment and Planning.A,* 23:1445-1462.

Li Xia, and Anthony.G.O.Yeh (2001). Zoning Land for Agricultural Protection by the Integration of Remote Sensing, GIS and Cellular Automata. *Photogrametric Engineering and Remote Sensing,* 67(4):471-477.

Li Xia, and Anthony G.O.Yeh (2002). Urban simulation using Principal Components Analysis and Cellular Automata fro Land-Use Planning.*Photogrametric Engineering and Remote Sensing, 68* (4): 341-351.

Lillesand T.M. and R.W. Kicfer (1987). Remote Sensing and Image Interpretation. Wiley, USA.

Lillesand T.M. and R.W. Kiefer (2000). Remote Sensing and Image Interpretation. Wiley, USA.

Li Lin, Yohei.S, Haihong.Z. (2002). Simulating spatial urban expansion based on a physical process. *Landscape and Urban Planning,* 975:1-10.

Logsdon.M.G, Earl.J.B and Frank. V.W. (1997). Probability Mapping of Land Use Change: A GIS Interfacc for Visualizing Transition Probabilities. *Computers, Environment and Urban Systems,* 20(6): 389-398.

Lopez E., Gerardo Bocco, Manuel Mendoza, Emilio Duhau (2001). Predicting land-cover and land-use change in the urban fringe, a case in Morelia city, Mexico. *Landscape and Urban Planning,* 55: 271-285

Lunetta R.S., Cristopher D.Elvidge (1999). Remote Sensing Change Detection: Environmental Monitoring Methods and Applications. Sleeping Bear, UK.

Lyon J.G., D. Yuan, R.S. Lunetta and C.D. Evidge (1998). Change Detection Experiment Using Vegetation Indices. *Photogrametric Engineering and Remote Sensing*, 64: 143-150.

Madhavan B.B., Sachio Kubo, N.Kurisaki and T.V.L.N. Sivakumar (2001). Appraising the anatomy and spatial growth of the Bangkok Metropolitan area using a Vegetation-impervious-soil model through remote sensing. *International Journal of Remote Sensing,* 22:789-806.

Marija J.Norusis (1990). SPSS.Advanced Statistics User's Guide.SPSS Inc, Chicago.

Martin L.R.G and Howarth,P.J. (1989). Change detection accuracy assessment using Spot multispectral imagery of the rural-urban fringe. *Remote Sensing of Environment,* 30:55-66.

Malila W.A. (1980). Change vector analysis: and approach for detecting forest changes with Landsat.*Proceeding of the 6th Annual Symposium on Machine Processing of Remotely Sensed Data.* Purdue University, pp. 326-335.

Manel S, Jean-Marie D, Steve J.O. (1999). Comparing discriminant analysis, neural networks and loistic regression for predicting species distributions: a case study with a Himalayan river bird, *Ecological Modelling.* 120:337-347.

Mather A. S. (1986). *Land Use*, Longman, New York

Matsura S., Abdurahim. A., Mochtar. J. (1997). The Malaysia Land use and Land cover change case study. SARCS-START-IGBP, Bangkok, Thailand.

Meyer W. B. and B.L. Turner II. (1992). Human Population Growth and Global Land-Use / Cover Change. *Annual. Rev. Ecol. System*, 23 : 39-61.

Meyer W. B., and Turner II, B. L. (eds). (1994). *Change in Land Us and Land Cover: A Globlal Perspective*, Cambridge University Press, UK

McConnell W.J and Emilio F.M (eds.). (2000). Meeting in the Middle: The challenge of meso-level integration. LUCC Report Series No.5. LUCC Focus 1 Office.

McNeil (1994. Toward a Typology and Regionalization of Land – Cover and Land use Change: Report of Working Group B. in Meyer W. B., and Turner II, B. L. (eds). (1994). *Change in Land Us and Land Cover: A Globlal Perspective*, Cambridge University Press, UK

Metternicht G. (1999). Change Detection Assessment Using Fuzzy sets and Remotely Sensed data: an Application of Topographic map revision. *ISPRS Journal of Photogrammetry and Remote Sensing*, 54:221-233.

Morisette, J.T., Khorram, S., Mace, T. 1999, Land cover change detection enhanced with generalized linier models, *International Journal of Remote Sensing*, 20(14), 2703 – 2721.

Moser S.C. (1996). A Partial Instructional Module on Global and Regional Land use/cover change: Assessing the Data and searching for General Relationship. *Geojournal*, 39 (3). 241-250.

Moy H.L., A. Cotonnec, L. Le Du, A. Chardin and P. Perez (2001). A Comparison of Parametric Classification Procedure of Remotely Sensed Data Applied on Different Landscape Units. *Remote Sensing of Environment*, 75(2): 174 –187.

Muchoney D.M. and B.N. Haack (1994). Change detection for Monitoring Forest Deforestation. *Photogrametric Engineering and Remote Sensing*, 60: 1243-1251.

Muniyati (2000). Wetland change detection on the Kafue, Zambia, by Classification of a multitemporal Remote Sensing Image dataset. *International Journal of Remote Sensing*, 21:1787-1806

National Academic of Science (2000). Growing Population, Changing Landscapes. http://www.nap.edu/openbook/0309075548/htm/RI.html.

Nasution L.I. (1999). Kebijakan Penatagunaan Tanah di Indonesia, in Proceeding Perubahan tutupan lahan dan penggunaan tanah di Indonesia dalam kaitannya dengan study LUCC-IGBP, Karsidi,A., Hartanto,S, Laju.G (eds). Dit. TISDA-BPP Teknologi Jakarta.

Nelson R.F. (1983). Detecting Forest Canopy Change Due to Insect Activity Using Landsat MSS. *Photogrametric Engineering and Remote Sensing*, 49:1303-1314.

RePPProt (1989). Review of Phase I Results Java and Bali. Direktorat Bina Program, Departemen Transmigrasi, Jakarta.

OECD. (1976). Land use policies and agriculture. Organization for Economic Co-operation and Development, Paris.

Olson H. (1995). Reflectance Calibration of Thematic Mapper data for Forest Change Detection. *International Journal of Remote Sensing*, 16: 81-91.

Oetter D.R., Warren B.C, Mercedes B, Thomas K.M and Robert E.K. (2001). Land cover Mapping in an Agricultural setting using Multi-seasonal Thematic Mapper data. *Remote Sensing of Environment*, 76(2): 139-155.

Pastor .J and Carol.A.J. (1992). Using Simulation Models and Geographic Information System to Integrate Ecosystem and Landscape Ecology, in Naiman.

J.R (eds.). Watershed management: balancing sustainability and environmental change. Springer-Verlag, New York.

Pathan, S. K., 7 others, *et al.* 1993, Urban growth trend analysis using GIS techniques a case study of the Bombay Metropolitan, *International Journal of Remote Sensing,* 14(17), 3169 - 3179.

Pilon P.G., P.J. Howarth, R.A. Bullock and P.O. Adeniyi (1988). An Enhanced Classification Approach to Change Detection in Semi – Arid Environment. *Photogrametric Engineering and Remote Sensing*, 54: 1709- 1716.

Pontius R.G. Jr., Joseph D. Cornell, Charles A.S. Hall (2001). Modeling the spatial pattern of land-use change with GEOMOD2: application and validation for Costa Rica. *Agriculture, Ecosystems and Environment,* 85: 191-303.

Qi J., A.R. Huete, M.S. Moran, A. Chehbouni and R.D. Jackson (1993). Interpretation of Vegetation Indices Derrived from Multi-Temporal SPOT Images. *Remote Sensing of Environment*, 44: 89-101.

Quarmby N.A. and J.L. Cushnie (1989). Monitoring Urban Land Cover Changes at the Urban Fringe from Spot HRV Imagery in South - East England. *International Journal of Remote Sensing,* 10: 953-963.

Rachman.Mahbub Muhammed.(1997). Identification of Land Use and Land Cover Using Band Rationg Technique.
http://www.murraystate.edu/qacd/cos/geo/gsc641/1997/rahman/.

Rais Jacub. (1997). Planning sustainable land management at regional level: the Indonesian case, *ITC Journal.* 3:4.

Ram Balak and A. S. Kolakar. (1993). Remote sensing application in monitoring land use changes in Arid Rajasthan, *International Journal of Remote Sensing,* 14(17), 3191- 3200.

Rao, C.R.(1966). Discriminant function between composite hypotheses and related problem, *Biometrika*, 53, 339-345.

Rao K.S., Rekha Pant (2001). Land use dynamic a Landscape change pattern in a typical micro watershed in the mid elevation zone of central Himalaya, India. *Agriculture, Ecosystems and Environment,* 86:113-123.

Reyment,R.A. (1973). The discriminant function in systematic biology, in T.Cacaullus (eds), 1973, Discriminnat Analysis and Application, Academic Press. New York.

Rhind David, Ray Hudson (1980). Land Use. Mathuen, New York.

Richard J.A. (1984). Thematic Mapping from Multitemporal Image Data Using the Principal Components Transformation. *Remote Sensing of Environment*, 16: 35-46.

Rindfuss, R.R. and Stern, P.C. 1998, Lingking remote sensing and social science: the need and the challenges, in *People and Pixels*, Eds. Diana Liverman, Emilio,F.Moran., Ronald,R.Rendfuss. And Paul,C.Stern., National Academy Press ,Washington.

Reid R.S., Kruska R.L., Muthui N., Taye A., Wotton S., Wilson C.J., Mulatu W. (2000) Land use and land cover dynamics in response to changes in climatic, biological and socio-political forces: The case of south western Ethiopia. *Landscape Ecology*, 15 : 339-355.

Ridd M.K and Jiajun Liu (1998). A Comparison of Four Algorithms for Change Detection in an Urban Environment. *Remote Sensing of Environment*, 63:95-100.

Robinson C.J. (1979). A critical review of the change detection and urban classification literature. Technical Memorandum CSC/TM-79/6235, Computer Sciences Corporation, Silver Spring, MD.

Robinson J, Stephen Brush, Ian Douglas, T.E. Gradael, Dean Graetz, Winifred Hodge, Diana Liverman, Jerry Melillo, Richard Moss, Alexei Naumov, George Njirv, Joyce Penner, Peter Rogers, Vernon Ruffan, James Sturdevant.(1994). Land Use and Land Cover Projections: Report working groups C.in Changes in Land Use and Land Cover: A Global Perspective.

Saefulhakim S, Ernan.R, Dyah R.P, Dyah T.S. (1999). Pengembangan model system interaksi antar aktiffitas sosial ekonomi dengan perubahan penggunaan lahan, Lokakarya HDP-LUCC Indonesia, 16 Nopember 1999, Jakarta.

Sage Colin. 1994. Population and Income in Mayer and Turner II (eds). *Change in Land use and land cover: A Global Perspective,* Cambridge, UK: Cambridge University Press: 263-285.

Sandy I Made (1995). Tanah: Muka Bumi. PT.Indographia-FMIPA. Universitas Indonesia, Jakarta.

Sandy I Made (1977). Penggunaan Tanah (Land Use) di Indonesia. Publikasi No.75. Direktorat Tata Guna Tanah, Direktorat Jenderal Agraria, Departemen Dalam Negeri, Jakarta.

Santoso Harry (1999). Pemantauan Perubahan Penutupan dan Penggunaan Lahan Hutan di Indonesia. in Prosiding Perubahan tutupan lahan dan penggunaan tanah di Indonesia dalam kaitannya dengan study LUCC_IGBP, Karsidi,A., Hartanto,S, Laju.G (eds). Dit. TISDA-BPP Teknologi Jakarta.

Salami A.T (1999). Vegetation Dynamic on the Fringes of Lowland Tropical Rainforest of Southwestern Nigeria-an Assessment of Environmental Change with

Air Photos and Landsat TM. *International Journal of Remote Sensing,* 20:1169-1181.

Salem.B.B., A. El-Cibahy, and M.El-Raey (1995). Detection of Land Cover Classes in Agro-ecosystems of Northern Egypt by Remote Sensing. *International Journal of Remote Sensing,* 16:2581-2594.

SARCS (1997). The Final Report of LULC Case Study in the four countries: Indonesia, Malaysia, Philippinc and Thailand. SARCS Secretary Bangkok. Thailand.

Scholten H.J, Rob van de velde, Piet Rietveld and Maarten Hilferink. (1999). Spatial Information Infrastructure for Scenario Planning: Thc Development of a Land Use Planer for Holland, in Srillwell.J, Stan Geertman and Stan Openshaw (cds.). Geographical Information and Planning. Springer-Verlag, Berlin.

Sembaloni .F. (1997). An Urban and rcgional model based on cellular automata. *Environment and Planning B: Planning Design,* 24:589-612.

Semeels S, Eric F.Lambin (2001). Proximate cause of land use change in Narok District, Kenya: as spatial statistical model. Agriculture, *Ecosystems and Environment.* 85:65-81

Shi W and Matthew, Y. C.P. (2000). Development of Voronoi-base cellular automata – an integrated dynamic model for Geographic Information System, International Journal Geographic Information Science, 14(5) 455-474.

Silalahi, S.B. and Putu Suweken (1999). Tingkat Perkembangan Penggunaan Tanah. In Karsidi. A et al (eds): Prosiding Lokakarya Prubahan Tutupan Lahan dan Penggunaan Tanah di Indonesia dalam kaitannya dengan Study LULCC-IGBP. BPPT, Jakarta.

Singh A. and A.Harrison (1985). Standardized Principal Component. *International Journal of Remote Sensing,* 6: 883-896.

Singh A. (1989). Digital Change Detection Techniques Using Remotely Sensed Data. *International Journal of Remote Sensing,* 10: 989-1003.

Sinowski W, KKK. Auerswald (1999). Using relief parameters in a discriminant analysis to stratify geological areas with different spatial variability of soil properties, *Geoderma.* 89:113-128.

Sirakoulis G. Ch., I. Karafyllidis, A. Thanailakis (2000). A cellular automaton model for the effects of population movement and vaccination on epidemic propagation. *Ecological Modelling,* 133: 209-223.

Skole. D and Tucker C.(1993). Tropical deforestation and habitat fragmentation in the Amazon: satellite data from 1978 to 1998. *Science*, 260:1905-1910.

Solecki W.D. (2001). The role of Global-to local linkages in land use/land cover change in south Florida.*Ecological Economics.*37:339-356.

Sommers, L.M. 1981. The Spatial Character of Land Use. In Lounsbury, J.F.,L.M.Sommers and E.A. Fernald (eds.). *Land Use: A Spatial Approach.* Kendall/Hunt. USA.

Song C., Cutis E.W, Karen C.S, Mary P.L and Scott A.M. (2001). Classification and Change Detection Using Landsat TM Data: When and How to Correct Atmospheric Effects? *Remote Sensing of Environment*, 75:230-244.

Srillwell. J, Stan Geertman and Stan Geertman and Stan Openshaw (eds.) (1999). Geographical Information and Planning. Springer-Verlag, Berlin.

Schmidt, M. G., Schreier, H. E., Shah, P. B. 1995, A GIS evaluation of land use dynamics and forest soil fertility in a watershed in Nepal, *International Journal of Geographical Information System,* 9 (3), 317 – 327.

Srillwell. J, Stan Geertman and Stan Openshaw (1999). Developments in Geographical Information and Planning, in Srillwell.J, Stan Geertman and Stan Geertman and Stan Openshaw (eds.) Geographical Information and Planning. Springer-Verlag, Berlin.

Star. J.L, John. E.Estes, Kenneth. C. McGwire (eds) (1997). Integration of Geographic Information System and Remote Sensing. Cambridge University Press. New York.

Statsoft (2003). Discriminant function Analysis. http://www.statsoftinc.com/textbook/stdiscan.html

Stefanov W.L., Michael S.R and Philip R.C. (2001). Monitoring Urban Land cover Change. An expert system approach to land cover classification of semiarid to arid urban centers. *Remote Sensing of Environment,* 77:173-185

Stamp, L.D. (1931). The Land utilization survey in Britain. Methuen & Co Ltd. London.

Stow D.A., L.R Tinney and J.E.Estes (1980). Deriving Land use/Land Cover Change Statistics From Landsat: a Study of Prime Agricultural Land. *Proceedings of the 14h International Symposium on remote Sensing of Environment*, Ann Arbor Michigan, pp1227-1237.

Sudradjat Adjat, Apik Karya, Armen. Z, Dedih. F.R, Diana.H, Ekowati Ch., Ening.W., Gatot.P., Giyati, Gunawan.S., Mulyono, Prijanto.P., Slamet.S., Wastra, S.Y. Randha and Triyono (2001). Dasar Penerapan Kebijakan Proyek Lahan Gambut Sejuta Hektar. Program Pasca sarjana IPB, Bogor.

Sullivan John.L (eds). (1980). Series: Quantitative Applications in the Social Sciences. Sara Miller McCune, Sage Publication, Inc.

Tampubolon S.M.H. (1999). Pengaruh beberapa factor sosial-ekonomi dan kependudukan terhadap perubahan tutupan and penggunaan lahan di Indonesia, in Prosiding Perubahan tutupan lahan dan penggunaan tanah di Indonesia dalam kaitannya dengan study LUCC_IGBP, Karsidi,A., Hartanto,S, Laju.G (eds). Dit. TISDA-BPP Teknologi Jakarta.

Takeyama M, and Helen.C. (1997). Map dynamics: integrating Cellular Automata and GIS through Geo-Algebra. *Int.J.Geographical Information Science,* 11 (1) 73-91.

Tandy Clifford R.V. (1973). Industrial Land use and Dereliction, in Land use and landscape Planning, Lovejoy Derek (eds.). Leonard Hill Books. Great Britain.

Tappeiner U, Erich Tasser, Dottfried T. (1998). Modeling vegetation patterns using natural and anthropogenic influence factors: preliminary experience with a GIS based model applied to an Alpine area, *Ecological Modelling.*113: 225-237

Thenkabail P.S. and C. Note (1996). Capabilities of Landsat-5 Thematic Mapper ™ Data in Regional Mapping and Characterization of Inland Valley Agro ecosystems in West Africa. *International Journal of Remote Sensing,* 17:1505-1538.

Thomas, D.S.G., Deborah, S. (1997), Understanding the dynamic of social and environmental variability: the impacts of structural land use change on the environment and peoples of the Kalahari, Botswana, *Applied Geography,* 17(1), 11-27.

Thomascik Tomas, Amarie Janice Mah., Anugerah Nontjik., Mohamad Kasim (1997). The Ecological of Indonesian Seas. Part Onc. Periplus edition (Hk) Ltd. CV. Java Books

Todd W.J. (1977). Urban and Regional Land use change detected by using Landsat data. *Journal of Research by the US. Geological Survey,* 5:527-534.

Turner B.L., Hanham, R.O. and Portaharo, A.V. (1977). Population pressure and agricultural intensity, *Annals of the Association of American Geographers,* 6(3), 384-396.

Tu Qiang, Dafu Ding (2003). Detecting pathogcnicity islands and anomalous gene clusters by interactive discriminant analysis, *FEMS Microbiology Letters*, 221:269-275.

Turner B.L, Robert Q.Hanham and Anthony V.Prtararo (1977). Population pressure and Agricultural Intcnsity. *Annals of the Association of American Geographer,* 6: 384-396.

Turner B.L, and Meyer. W.B. (1994)."Global land use and land-cover change: an overview," in W. Meyer and B.L. Turner (eds), *Changes in Land Use and Land Cover: A Global Perspective*, Cambridgc, UK: Cambridge University Press, pp 3-10.

Turner B.L., D. Skole, S. Sanderson, G.Fischer, L. Fresco and R.Leemas (1995). Land use and land cover change: Science/Research Plan. IGBP Report No.35.HDP Report No7.IGBP and HDP Stockholm and Geneva.

Turner, B.L and W.B. Meyer. 1991. Land use and land cover in global environment change: Considerations for Study, *International Social Science Journal,* 130:669-679.

Tucker C.J. (1979). Red and Photographic Infrared Linier Combinations for Monitoring Vegetation. *Remote Sensing of Environment*, 8:127-150.

Tucker C.J, and Maxwell, E.L (1976). Sensor design for Monitoring Vegetation Canopies. *Photogrametric Engineering and Remote Sensing*, 42: 1399.
van Deusen P.C. (1994). Correcting Bias in Change Estimates from Thematic Maps. *Remote Sensing of Environment*, 50:67-73.

Tucker C.J., Dregden,H.E and Newcomb,W.W (1991). Expansion and Constaction of the Sahara Desert from 1980 to 1990. *Science*, 255: 299-301.

UU. Number 22 year 1999 regarding Regional Governance. Republic of Indonesia.

UU. Number 24 year 1992 regarding Spatial planning. Republic of Indonesia.

Volgemann J.E. (1988). Detection of Forest Change in the Green Mountains of Vermont Using Multispectral Scanner Data. *Remote Sensing of Environment*, 9:1187-1200.

Veldkamp A., E.F. Lambin (2001). Predicting Land use Change. *Agriculture, Ecosystem and Environment*, 85:1-6.

Verburg P.H., G.H.J. de Koning, K.Kok, A. Veldkamp, J. Bouma. (1999). A spatial explicit allocation procedure for modelling the pattern of land use change based upon actual land use , 116 : 45-61.

Vink A (1975). *Land Use in Advancing Agriculture*, Springer-Verlag, Berlin, Germany.

Wagner D.F. (1997). Cellular automata and geographic information systems. *Environment and Planning B: Planning Design*, 24: 219-234.

Ward D., Stuart R.P. and Alan T.M. (2000). Monitoring Growth in Rapidly Urbanizing Areas Using Remotely Sensed Data. *Professional Geographer*, 52(3): 371-386.

Watson N. and David W. (2001). Pre-classification as an Aid to Improvement of Thematic and Spatial Accuracy in Land Cover Maps Derived from Satellite Imagery. *Remote Sensing of Environment*, 75 (2): 267-278.

Weismiller R.A., S.J. Kristof, D.K.Scholz, P.EEE. Anuta and S.A. Momin (1977). Change Detection in Coastal Zone Environments. *Photogrametric Engineering and Remote Sensing*, 43: 1533-1539.

Weng Q. (2002). Land use change analysis in the Zhujiang Delta of China using satellite remote sensing, GIS and stochastic modelling. *Journal of Environmental Management*, 64:273-283.

Whitaker Jean.S. (1997). Use of Stepwise Methodology in Discriminant Analysis.http://ericae.net/ft/tamu/STEPWIS.htm

White R, Engelen G. (1992). Cellular dynamics and GIS: modelling spatial complexity. WP-9264. Research Institute for Knowledge Systems, Maastricht, The Netherlands.

White R., Engelen G. (1993). Cellular automata and fractal form: a cellular modelling approach to the evolution of urban land use patterns. *Environment and Planning A*, 25: 1175-1199.

White R. (1997). Cellular automata as the basis of integrated dynamic regional modelling. *Environment and Planning: Planning and Design*, 24: 235-246.

White R, and G.Engele.I.U. (1997). The use of constrained cellular automata for igh-resolution modelling of urban land-use dynamics. *Environment and Planning B: Planning Design,* 24:323-347.

White R., G. Engelen (2000). High-resolution integrated modelling of the spatial dynamics of urban and regional systems. Computers, *Environment and Urban Systems,* 24: 383–400.

World Bank (1990). A World Bank Country Study. Indonesia: Sustainable, Development of Forest, Land, and water. The World Bank Washington D.C.

World Bank (1999). Indonesia-Jatiluhur Water Resources Management. The World Bank Washington D.C.

World Bank (2001). Indonesian Environment and Natural Resource Management in a Time Transition. http://eap.worldbank.org/indonesia/environment.

Wilsson E.H, and Steven,A.S.(2002). Detection of forest harvest type using multiple dates of Landsat TM imagery. *Remote Sensing of Environment,* 80:385-396.

Wolman M Gordon (1993). Population, Land Use, and Environment: A Long History in Jolly Carole.L and Barbara Boyle Torrey (eds) Population and Land Use in Developing Countries. National Academy Press. Washington, D.C.

Wu F. (1998). An experiment on the generic polycentricity of Urban Growth in a cellular automatic city. *Environment and Planning B: Planning Design*, 25: 731-753.

Wu F. (1998). Simulating urban encroachment on rural land with fuzzy-logic-controlled cellular automata in a GIS. *Journal of Environmental Management, 53*: 293-308.

Wu F and C.J.Webster (1998). Simulation of Land development through the integration of cellular automata and multi criteria evaluation. *Environment and Planning B: Planning Design*, 25: 103-126.

Wu Fulong. (1998). SimLand: a prototype to simulate land conversion through the integrated GIS and cellular automata with AHP-derived transition rules. *Int.J.Geographical Information Science,* 12 (1): 63-82.

Wu Fulong, and Christopher.J.W. (2000). Simulating artificial cities in a GIS environment: Urban Growth under alternative regulation regimes. *Int.J.Geographical Information Science*, 14 (7): 625-648.

Xie Yichum. (1996). A Generalized Model for cellular Urban Dynamics. *Geographical Analysis,* 28 (14): 350-373.

Yeh A.G.O, and Xia Li (1998). Sustainable land development model for rapid growth areas using GIS. *Int.J.Geographical Information Science,* 12 (2): 169-189.

Yeh A.G.O, and Xia Li (2000). A cellular automata model to simulate development density for urban planning *Environment and Planning B: Planning Design,* 29: 431-450.

Yeh A.G.O, and Xia Li (2001). A constrained cellular automata model for the simulation and planning of suitable urban form by using GIS. *Environment and Planning B: Planning Design,* 28: 733-753.

Yuan Ding, Christopher D.Elvidge and Ross S.Lunetta .(1999). Survey of Multispcetral Methods for Land Cover Change analysis, in Ross S.Lunetta and Christopher D.Elvidge (eds). Remote Sensinf Change detection Environmental Monitoring Methods and Applications. Taylor & Francis.Ltd. Londodn.

Young S.S, Benyamin,P., Jokisch,B., Ogneva,Y., and Grrcn,A.(1991). Global Land use/cover: Assessment of data and some general relationships. Apendixt 1 of *The Report of the Ad-hoc Working group on Global Land Use Change,* Committee for Research on Global Environmental Change, Social Science Research Counsil.

Young S.S and Anyamba,A. (1999) Comparison of NOAA/NASA PAL and NOAA GVI data for vegetation change studies over China. *Photogrametric Engineering and Remote Sensing,* 65:679-688.

Young S.S. and C.Y.Wang (2001). Land cover change analysis of China using global-scale Pathfinder AVHRR Land cover (PAL) data, 1982-1992. *International Journal of Remote Sensing,* 21: 1457-1477.

Yuan D, Christopher D. Elvidge and Ross S. Lunetta (1999)." Survey of Multispectral Methods for Land Cover Change Analysis". in Lunetta and Christopher D.E. (eds). Remote Sensing Change Detection: Environmental Monitoring Methods and Applications. Sleeping Bear, UK.

Yuan D, and Chris Elvidge (1998). NACL Land Cover Change Detection Pilot Study: Washington D.C. Area Experiments *Remote Sensing of Environment,* 66: 166-18.

Yue T. X., Ji Yuan Liu, Sven Erik Jorgensen, Qin Hua Ye (2003). Landscape change detection of the newly created wetland in Yellow River Delta. *Ecological Modelling,* 3225: 1-11.

Zhan X., R.A.Sohlberg, J.R.G.Townshend, C.DiMiceli, M.L.Carroll, J.C.Eastman, M.C. Hansen, R.S. DeFries (2002). Detection of land cover changes using MODIS 250 m data. *Remote Sensing of Environment,* 83: 336-350.

APENDIX IV

Table1 : Principal components analysis transformation TM 1990

COMPONENT	Comp 1	Comp 2	Comp 3	Comp 4	Comp 5	Comp 6
% var.	89.12	7.83	2.69	0.17	0.13	0.07
Eigen value.	1895.66	166.53	57.32	3.52	2.68	1.40
eigvec.1	0.15	0.30	0.49	0.06	-0.55	-0.59
eigvec.2	0.11	0.21	0.36	0.04	-0.39	0.81
eigvec.3	0.17	0.46	0.47	0.03	0.73	0.00
eigvec.4	0.68	-0.65	0.29	-0.16	0.08	-0.01
eigvec.5	0.65	0.34	-0.51	0.45	-0.05	0.00
eigvec.6	0.22	0.34	-0.25	-0.88	-0.07	0.00
LOADING	**Comp 1**	**Comp 2**	**Comp 3**	**Comp 4**	**Comp 5**	**Comp 6**
TM Band 1	0.75	0.46	0.44	0.01	-0.10	-0.08
TM Band 2	0.79	0.44	0.44	0.01	-0.10	0.15
TM Band 3	0.72	0.59	0.35	0.00	0.12	0.00
TM Band 4	0.96	-0.27	0.07	-0.01	0.00	0.00
TM Band 5	0.98	0.15	-0.13	0.03	0.00	0.00
TM Band 6	0.89	0.40	-0.17	-0.15	-0.01	0.00

Table2: Principal components analysis transformation TM 1991

COMPONENT	Comp 1	Comp 2	Comp 3	Comp 4	Comp 5	Comp 6
% var.	85.90	8.83	4.76	0.20	0.18	0.12
Eigen value.	2505.61	257.68	138.77	5.82	5.33	3.58
eigvec.1	0.18	0.37	-0.36	-0.38	-0.01	0.74
eigvec.2	0.24	0.28	-0.45	-0.47	-0.04	-0.66
eigvec.3	0.19	0.51	-0.31	0.78	-0.06	-0.06
eigvec.4	0.62	-0.65	-0.36	0.15	0.18	0.08
eigvec.5	0.65	0.16	0.57	-0.08	-0.46	0.00
eigvec.6	0.25	0.27	0.33	-0.04	0.86	-0.05
LOADING	**Comp 1**	**Comp 2**	**Comp 3**	**Comp 4**	**Comp 5**	**Comp 6**
TM Band 1	0.76	0.50	-0.36	-0.08	0.00	0.12
TM Band 2	0.87	0.32	-0.38	-0.08	-0.01	-0.09
TM Band 3	0.73	0.61	-0.27	0.14	-0.01	-0.01
TM Band 4	0.94	-0.32	-0.13	0.01	0.01	0.00
TM Band 5	0.98	0.08	0.20	-0.01	-0.03	0.00
TM Band 6	0.89	0.31	0.28	-0.01	0.14	-0.01

Table3 : Principal components analysis transformation TM 1992

COMPONENT	Comp 1	Comp 2	Comp 3	Comp 4	Comp 5	Comp 6
% var.	91.22	4.85	3.65	0.15	0.12	0.02
Eigen value.	4471.12	237.69	178.69	7.20	5.85	1.10
eigvec.1	0.58	-0.27	-0.57	-0.44	0.01	-0.27
eigvec.2	0.24	-0.03	-0.25	0.09	-0.05	0.93
eigvec.3	0.28	0.19	-0.32	0.83	-0.19	-0.24
eigvec.4	0.46	-0.60	0.56	0.25	0.24	0.00
eigvec.5	0.52	0.53	0.44	-0.23	-0.45	0.00
eigvec.6	0.22	0.50	0.00	0.00	0.84	0.00
LOADING	**Comp 1**	**Comp 2**	**Comp 3**	**Comp 4**	**Comp 5**	**Comp 6**
TM Band 1	0.98	-0.11	-0.19	-0.03	0.00	-0.01
TM Band 2	0.97	-0.03	-0.20	0.01	-0.01	0.06
TM Band 3	0.95	0.14	-0.22	0.11	-0.02	-0.01
TM Band 4	0.93	-0.28	0.23	0.02	0.02	0.00
TM Band 5	0.95	0.22	0.16	-0.02	-0.03	0.00
TM Band 6	0.89	0.46	0.00	0.00	0.12	0.00

Table4 : Principal components analysis transformation TM 1993

COMPONENT	Comp 1	Comp 2	Comp 3	Comp 4	Comp 5	Comp 6
% var.	92.55	4.57	1.71	0.98	0.16	0.03
Eigen value.	7325.56	361.61	134.99	77.69	12.60	2.41
eigvec.1	0.70	-0.30	-0.03	-0.52	-0.02	-0.39
eigvec.2	0.49	-0.29	-0.16	0.26	-0.05	0.77
eigvec.3	0.20	-0.21	-0.22	0.78	-0.06	-0.51
eigvec.4	0.36	0.34	0.81	0.24	0.20	0.00
eigvec.5	0.31	0.78	-0.35	0.00	-0.42	0.00
eigvec.6	0.12	0.26	-0.38	0.00	0.88	0.00
LOADING	**Comp 1**	**Comp 2**	**Comp 3**	**Comp 4**	**Comp 5**	**Comp 6**
TM Band 1	0.99	-0.09	-0.01	-0.08	0.00	-0.01
TM Band 2	0.99	-0.13	-0.04	0.05	0.00	0.03
TM Band 3	0.91	-0.21	-0.13	0.37	-0.01	-0.04
TM Band 4	0.94	0.19	0.29	0.06	0.02	0.00
TM Band 5	0.85	0.48	-0.13	0.00	-0.05	0.00
TM Band 6	0.80	0.41	-0.36	0.00	0.25	0.00

Table 5: Principal components analysis transformation TM 1995

COMPONENT	Comp 1	Comp 2	Comp 3	Comp 4	Comp 5	Comp 6
% var.	90.09	5.43	4.10	0.22	0.14	0.03
Eigen value.	4187.64	252.23	190.53	10.16	6.32	1.32
eigvec.1	0.56	0.05	-0.66	-0.43	0.02	-0.27
eigvec.2	0.24	-0.07	-0.25	0.09	-0.04	0.93
eigvec.3	0.27	-0.32	-0.23	0.82	-0.19	-0.25
eigvec.4	0.46	0.77	0.28	0.27	0.21	0.00
eigvec.5	0.54	-0.32	0.58	-0.25	-0.46	0.00
eigvec.6	0.24	-0.44	0.20	0.00	0.84	0.00
LOADING	**Comp 1**	**Comp 2**	**Comp 3**	**Comp 4**	**Comp 5**	**Comp 6**
TM Band 1	0.97	0.02	-0.24	-0.04	0.00	-0.01
TM Band 2	0.97	-0.07	-0.22	0.02	-0.01	0.07
TM Band 3	0.94	-0.27	-0.17	0.14	-0.03	-0.02
TM Band 4	0.92	0.38	0.12	0.03	0.02	0.00
TM Band 5	0.96	-0.14	0.22	-0.02	-0.03	0.00
TM Band 6	0.90	-0.41	0.16	0.00	0.12	0.00

Table 6: Principal components analysis transformation TM 1997

COMPONENT	Comp 1	Comp 2	Comp 3	Comp 4	Comp 5	Comp 6
% var.	86.41	8.76	4.34	0.25	0.17	0.07
Eigen value.	2279.39	230.96	114.49	6.55	4.59	1.97
eigvec.1	0.22	0.26	0.55	0.03	0.58	-0.49
eigvec.2	0.12	0.14	0.31	0.02	0.33	0.87
eigvec.3	0.25	0.35	0.51	0.14	-0.73	0.00
eigvec.4	0.52	-0.79	0.25	-0.21	-0.07	0.00
eigvec.5	0.70	0.18	-0.48	0.48	0.09	0.00
eigvec.6	0.33	0.37	-0.23	-0.84	-0.02	0.00
LOADING	**Comp 1**	**Comp 2**	**Comp 3**	**Comp 4**	**Comp 5**	**Comp 6**
TM Band 1	0.82	0.31	0.47	0.01	0.10	-0.05
TM Band 2	0.81	0.31	0.47	0.01	0.10	0.17
TM Band 3	0.84	0.37	0.38	0.02	-0.11	0.00
TM Band 4	0.90	-0.43	0.09	-0.02	-0.01	0.00
TM Band 5	0.98	0.08	-0.15	0.04	0.01	0.00
TM Band 6	0.92	0.33	-0.14	-0.13	0.00	0.00

Table7: Change matrix of Land use/Land cover categories 1989 vs. 1990

	1	2	3	4	5	6	7	8	9	Total 1990
1. Forest 1)	5907	5417	8588	29	219	2808	298	21	24	23312
2)	1.17	1.08	1.71	0.01	0.04	0.56	0.06	0.00	0.00	4.64
2. Plantation 1)	677	25469	8130	202	1293	4190	4202	2	4	44169
2)	0.13	5.07	1.62	0.04	0.26	0.83	0.84	0.00	0.00	8.78
3. Rice field 1)	4466	25909	107979	2921	2176	22244	18939	98	32	184764
2)	0.89	5.15	21.48	0.58	0.43	4.42	3.77	0.02	0.01	36.75
4. Open land 1)	8	472	8891	17514	3500	21948	7058	1273	18	60684
2)	0.00	0.09	1.77	3.48	0.70	4.37	1.40	0.25	0.00	12.07
5. Settlement 1)	26	611	1775	409	9858	2562	1895	53	1	17191
2)	0.01	0.12	0.35	0.08	1.96	0.51	0.38	0.01	0.00	3.42
6. Rice unplanted 1)	229	4502	27610	4687	4630	57444	10943	2331	56	112432
2)	0.05	0.90	5.49	0.93	0.92	11.43	2.18	0.46	0.01	22.36
7. Dry land/Grass 1)	11	752	8261	6743	714	7896	7307	28	0	31712
2)	0.00	0.15	1.64	1.34	0.14	1.57	1.45	0.01	0.00	6.31
8. Fish pond 1)	14	27	140	234	144	5113	23	17288	288	23271
2)	0.00	0.01	0.03	0.05	0.03	1.02	0.00	3.44	0.06	4.63
9. Water/Reservoir 1)	0	10	16	2	1	138	1	11	5077	5254
2)	0.00	0.00	0.00	0.00	0.00	0.03	0.00	0.00	1.01	1.05
Total 1989 1)	11338	63168	171389	32741	22535	124343	50686	21105	5502	502788
2)	2.26	12.56	34.09	6.51	4.48	24.73	10.08	4.20	1.09	100.00

1) unit = Hectare

2) percentage of that category in the study area

Table8: Change matrix of Land use/Land cover categories 1990 vs. 1991

		1	2	3	4	5	6	7	8	9	Total 1991
1. Forest	1)	9821	3287	8735	248	126	380	53	17	1	22668
	2)	1.95	0.65	1.73	0.05	0.03	0.08	0.01	0.00	0.00	4.50
2. Plantation	1)	2704	18053	14061	268	173	1466	274	14	5	37016
	2)	0.54	3.58	2.79	0.05	0.03	0.29	0.05	0.00	0.00	7.35
3. Rice field	1)	1353	1275	29970	16834	1304	10008	7853	137	7	68740
	2)	0.27	0.25	5.95	3.34	0.26	1.99	1.56	0.03	0.00	13.65
4. Open land	1)	422	587	17158	24975	1777	17770	11294	524	0	74506
	2)	0.08	0.12	3.41	4.96	0.35	3.53	2.24	0.10	0.00	14.79
5. Settlement	1)	226	801	1652	1259	7794	3937	274	38	0	15980
	2)	0.04	0.16	0.33	0.25	1.55	0.78	0.05	0.01	0.00	3.17
6. Rice unplanted	1)	4695	2197	68852	9173	2247	47669	4020	4168	1	143021
	2)	0.93	0.44	13.67	1.82	0.45	9.46	0.80	0.83	0.00	28.39
7. Dry land/Grass	1)	3837	17934	43619	6083	3664	27152	7858	122	8	110277
	2)	0.76	3.56	8.66	1.21	0.73	5.39	1.56	0.02	0.00	21.89
8. Fish pond	1)	218	28	1562	1793	98	3923	80	17813	27	25542
	2)	0.04	0.01	0.31	0.36	0.02	0.78	0.02	3.54	0.01	5.07
9. Water/Reservoir	1)	37	8	54	51	8	128	5	439	5206	5937
	2)	0.01	0.00	0.01	0.01	0.00	0.03	0.00	0.09	1.03	1.18
Total 1990	1)	23312	44169	185664	60684	17191	112432	31712	23271	5254	503688
	2)	4.63	8.77	36.86	12.05	3.41	22.32	6.30	4.62	1.04	100.00

1) unit = Hectare

2) percentage of that category in the study area

Table9: Change matrix of Land use/Land cover categories 1991 vs. 1992

		1	2	3	4	5	6	7	8	9	Total 1992
1. Forest	1)	10819	1569	262	41	20	172	1442	18	5	14348
	2)	2.15	0.31	0.05	0.01	0.00	0.03	0.29	0.00	0.00	2.85
2. Plantation	1)	5371	22017	668	218	137	1034	14304	23	22	43794
	2)	1.07	4.37	0.13	0.04	0.03	0.21	2.84	0.00	0.00	8.70
3. Rice field	1)	5202	8713	6958	19971	1281	68811	26199	1494	11	138641
	2)	1.03	1.73	1.38	3.97	0.25	13.66	5.20	0.30	0.00	27.53
4. Open land	1)	42	245	24129	13460	297	9940	4054	294	0	52461
	2)	0.01	0.05	4.79	2.67	0.06	1.97	0.80	0.06	0.00	10.42
5. Settlement	1)	168	357	1635	2882	7914	2882	4481	58	3	20379
	2)	0.03	0.07	0.32	0.57	1.57	0.57	0.89	0.01	0.00	4.05
6. Rice unplanted	1)	869	1970	33920	29018	6116	52436	39115	2128	69	165641
	2)	0.17	0.39	6.74	5.76	1.21	10.41	7.77	0.42	0.01	32.89
7. Dry land/Grass	1)	188	2141	366	8665	201	2494	20580	20	14	34669
	2)	0.04	0.43	0.07	1.72	0.04	0.50	4.09	0.00	0.00	6.88
8. Fish pond	1)	2	2	708	251	15	5249	96	21479	141	27943
	2)	0.00	0.00	0.14	0.05	0.00	1.04	0.02	4.27	0.03	5.55
9. Water/Reservoir	1)	8	2	4	0	0	2	5	30	5672	5722
	2)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	1.13	1.14
Total 1991	1)	22668	37016	68650	74506	15980	143021	110277	25542	5937	503598
	2)	4.50	7.35	13.63	14.79	3.17	28.40	21.90	5.07	1.18	100.00

1) unit = Hectare

2) percentage of that category in the study area

Table 10: Change matrix of Land use/Land cover categories 1992 vs. 1993

		1	2	3	4	5	6	7	8	9	Total 1993
1. Forest	1)	8690	5080	6756	10	41	459	224	3	15	21279
	2)	1.73	1.01	1.34	0.00	0.01	0.09	0.04	0.00	0.00	4.22
2. Plantation	1)	1088	17108	5691	34	32	985	979	1	0	25917
	2)	0.22	3.40	1.13	0.01	0.01	0.20	0.19	0.00	0.00	5.15
3. Rice field	1)	3164	14190	26037	4612	4217	36479	7700	264	5	96666
	2)	0.63	2.82	5.17	0.92	0.84	7.24	1.53	0.05	0.00	19.19
4. Open land	1)	549	171	1189	7713	446	9234	973	182	0	20458
	2)	0.11	0.03	0.24	1.53	0.09	1.83	0.19	0.04	0.00	4.06
5. Settlement	1)	62	32	178	1420	8795	4282	25	94	0	14888
	2)	0.01	0.01	0.04	0.28	1.75	0.85	0.00	0.02	0.00	2.96
6. Rice unplanted	1)	260	1422	84355	33586	4414	81723	6048	2822	4	214635
	2)	0.05	0.28	16.75	6.67	0.88	16.23	1.20	0.56	0.00	42.61
7. Dry land/Grass	1)	516	5759	14400	4987	2374	31312	18705	30	0	78084
	2)	0.10	1.14	2.86	0.99	0.47	6.22	3.71	0.01	0.00	15.50
8. Fish pond	1)	19	33	36	188	60	1165	15	24520	985	27020
	2)	0.00	0.01	0.01	0.04	0.01	0.23	0.00	4.87	0.20	5.36
9. Water/Reservoir	1)	0	0	0	0	0	1	0	27	4714	4742
	2)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.01	0.94	0.94
Total 1992	1)	14348	43794	138641	52551	20379	165641	34669	27943	5722	503688
	2)	2.85	8.69	27.53	10.43	4.05	32.89	6.88	5.55	1.14	100.00

1) unit = Hectare

2) percentage of that category in the study area

Table11: Change matrix of Land use/Land cover categories 1993 vs. 1995

		1	2	3	4	5	6	7	8	9	Total 1995
1. Forest	1)	7282	1468	2926	239	37	150	240	4	0	12346
	2)	1.45	0.29	0.58	0.05	0.01	0.03	0.05	0.00	0.00	2.45
2. Plantation	1)	8657	14974	9401	386	43	396	2251	13	0	36121
	2)	1.72	2.97	1.87	0.08	0.01	0.08	0.45	0.00	0.00	7.17
3. Rice field	1)	2581	3037	15107	2494	126	78208	16263	60	0	117875
	2)	0.51	0.60	3.00	0.50	0.02	15.53	3.23	0.01	0.00	23.40
4. Open land	1)	39	47	2805	2919	495	8108	3664	30	0	18106
	2)	0.01	0.01	0.56	0.58	0.10	1.61	0.73	0.01	0.00	3.59
5. Settlement	1)	35	40	1295	347	7339	1728	977	56	0	11818
	2)	0.01	0.01	0.26	0.07	1.46	0.34	0.19	0.01	0.00	2.35
6. Rice unplanted	1)	2532	5993	61681	12740	6789	118451	45682	6346	60	260273
	2)	0.50	1.19	12.25	2.53	1.35	23.52	9.07	1.26	0.01	51.67
7. Dry land/Grass	1)	130	356	2989	1235	10	5795	8970	8	0	19493
	2)	0.03	0.07	0.59	0.25	0.00	1.15	1.78	0.00	0.00	3.87
8. Fish pond	1)	4	0	461	97	49	1781	36	19606	6	22040
	2)	0.00	0.00	0.09	0.02	0.01	0.35	0.01	3.89	0.00	4.38
9. Water/Reservoir	1)	20	1	2	2	0	18	1	896	4677	5616
	2)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.18	0.93	1.12
Total 1993	1)	21279	25917	96666	20458	14888	214635	78084	27020	4742	503688
	2)	4.22	5.15	19.19	4.06	2.96	42.61	15.50	5.36	0.94	100.00

1) unit = Hectare

2) percentage of that category in the study area

Table 12: Change matrix of Land use/Land cover categories 1995 vs. 1997

		1	2	3	4	5	6	7	8	9	Total 1997
1. Forest	1)	6581	8445	745	43	2	1996	8	2	9	17833
	2)	1.31	1.68	0.15	0.01	0.00	0.40	0.00	0.00	0.00	3.54
2. Plantation	1)	2230	14060	7793	79	61	26653	2050	17	17	52959
	2)	0.44	2.79	1.55	0.02	0.01	5.29	0.41	0.00	0.00	10.51
3. Rice field	1)	3222	12797	32028	5578	243	93053	1982	561	6	149470
	2)	0.64	2.54	6.36	1.11	0.05	18.47	0.39	0.11	0.00	29.68
4. Open land	1)	19	31	1683	6507	253	9036	2087	191	4	19811
	2)	0.00	0.01	0.33	1.29	0.05	1.79	0.41	0.04	0.00	3.93
5. Settlement	1)	12	37	1384	1119	9845	27952	142	303	2	40797
	2)	0.00	0.01	0.27	0.22	1.95	5.55	0.03	0.06	0.00	8.10
6. Rice unplanted	1)	187	413	60752	1088	952	62119	937	4760	188	131396
	2)	0.04	0.08	12.06	0.22	0.19	12.33	0.19	0.95	0.04	26.09
7. Dry land/Grass	1)	93	338	10985	3664	435	36764	12287	171	32	64768
	2)	0.02	0.07	2.18	0.73	0.09	7.30	2.44	0.03	0.01	12.86
8. Fish pond	1)	1	0	2501	27	27	2609	1	15964	55	21185
	2)	0.00	0.00	0.50	0.01	0.01	0.52	0.00	3.17	0.01	4.21
9. Water/Reservoir	1)	0	0	3	0	0	91	0	70	5304	5468
	2)	0.00	0.00	0.00	0.00	0.00	0.02	0.00	0.01	1.05	1.09
Total 1995	1)	12346	36121	117875	18106	11818	260273	19493	22040	5616	503688
	2)	2.45	7.17	23.40	3.59	2.35	51.67	3.87	4.38	1.12	100.00

1) unit = Hectare

2) percentage of that category in the study area

Table13: Change matrix of Land use/Land cover seven categories 1989 vs. 1997

		1	2	3	4	5	6	7	Total 1997
1. Forest	*1)*	5934.87	8591.4	2913.66	370.62	17.37	2.43	2.16	17832.51
	2)	1.18	1.71	0.58	0.07	0.00	0.00	0.00	3.54
2. Plantation	*1)*	1689.93	24786.9	18920.7	6410.34	1137.06	7.47	6.48	52958.88
	2)	0.34	4.92	3.76	1.27	0.23	0.00	0.00	10.51
3. Rice field	*1)*	3619.98	24458.94	210381.6	32476.59	4721.49	5070.69	136.89	280866.2
	2)	0.72	4.86	41.77	6.45	0.94	1.01	0.03	55.76
4. Open / dry land	*1)*	82.35	4668.57	40107.96	37864.08	1564.92	281.43	10.44	84579.75
	2)	0.02	0.93	7.96	7.52	0.31	0.06	0.00	16.79
5. Settlement	*1)*	9.09	1549.44	17860.5	6074.55	15015.51	286.29	1.53	40796.91
	2)	0.00	0.31	3.55	1.21	2.98	0.06	0.00	8.10
6. Fish pond	*1)*	0.09	12.06	5406.39	197.55	72.54	15454.53	42.03	21185.19
	2)	0.00	0.00	1.07	0.04	0.01	3.07	0.01	4.21
7. Water/Reservoir	*1)*	2.07	0.99	141.21	13.59	5.94	1.71	5302.8	5468.31
	2)	0.00	0.00	0.03	0.00	0.00	0.00	1.05	1.09
Total 1989	*1)*	11338.38	64068.3	295732	83407.32	22534.83	21104.55	5502.33	503687.7
	2)	2.25	12.72	58.71	16.56	4.47	4.19	1.09	100.00

1) Unit = hectare

2) Percentage of that category in the study area

APENDIX
CHAPTER V

Table V.1: Land use/Land cover versus Slope

1989						
Types\Slope	0-3%	3-8%	8-15%	15-30%	30-45%	>45%
Forest 1)	3306	1962	1701	2378	1263	620
2)	0.65	0.39	0.34	0.47	0.25	0.12
Plantation 1)	**51380**	**6591**	3404	2030	377	192
2)	**10.17**	**1.30**	0.67	0.40	0.07	0.04
Rice field 1)	**286696**	**5566**	2473	1714	710	1375
2)	**56.75**	**1.10**	0.49	0.34	0.14	0.27
Open/dry land 1)	**80300**	**1801**	563	187	24	7
2)	**15.90**	**0.36**	0.11	0.04	0.00	0.00
Settlement 1)	**21280**	**532**	115	35	4	4
2)	**4.21**	**0.11**	0.02	0.01	0.00	0.00
Fishpond 1)	**21021**	**0**	0	0	0	0
2)	4.16	0.00	0.00	0.00	0.00	0.00

1997						
Types\Slope	0-3%	3-8%	8-15%	15-30%	30-45%	>45%
Forest 1)	9422	2570	1811	2486	1072	418
2)	1.87	0.51	0.36	0.49	0.21	0.08
Plantation 1)	**45529**	**3693**	2078	981	156	40
2)	**9.01**	**0.73**	0.41	0.19	0.03	0.01
Rice field 1)	**267210**	**7243**	3639	2622	1144	1721
2)	**52.90**	**1.43**	0.72	0.52	0.23	0.34
Open/dry land 1)	**81473**	**2082**	640	219	5	17
2)	**16.13**	**0.41**	0.13	0.04	0.00	0.00
Settlement 1)	**39323**	**862**	976	50	1	2
2)	**7.78**	**0.17**	0.02	0.01	0.00	0.00
Fishpond 1)	**21026**	**4**	0	0	0	0
2)	4.16	0.00	0.00	0.00	0.00	0.00

1) = unit in Ha
2)= Percentage of each category to total study area

Table V.2: Land use/Land cover versus Phsyography (1989-1997)

1989				
Types	Flat	Rolling hill(RH)	Volcano(V)	RH and V
Forest	42	3431	6037	1722
Plantation	9857	17735	13369	23016
Rice field	214006	19578	12762	52199
Open/dry land	47458	11782	3121	20523
Settlement	11346	926	635	9064
Fishpond	20976	23	5	44
1997				
Types	Flat	Fold hill(FL)	Volcano(V)	FL and V
Forest	1132	7216	8798	636
Plantation	9669	16448	8722	17638
Rice field	201709	17348	14372	50165
Open/dry land	47090	14988	3439	18923
Settlement	19289	1425	589	19031
Fishpond	20797	68	32	159

Table V.3: Land use/Land cover change versus Land system

Coalescent estuary

Land use types	1989 (ha)	1997 (ha)	Change (ha)	% change
Forest	0	479	479	0.09
Plantation	1294	4830	3537	0.70
Rice field	**179302**	**168506**	-10796	-2.14
Open/dry land	31193	30804	-390	-0.08
Settlement	**8779**	**13963**	5185	1.03
Fish pond	3079	5065	1986	0.39

Inter-tidal mudflats

Land use types	1989 (ha)	1997 (ha)	Change (ha)	% change
Forest	0	89	89	0.02
Plantation	0	334	334	0.07
Rice field	8614	10157	1543	0.31
Open/dry land	158	218	61	0.01
Settlement	122	365	243	0.05
Fish pond	15517	13250	-2268	-0.45

Coastal beach ridges

Land use types	1989 (ha)	1997 (ha)	Change (ha)	% change
Forest	0	0	0	0.00
Plantation	1	101	100	0.02
Rice field	3343	3110	-233	-0.05
Open/dry land	22	18	-3	0.00
Settlement	383	426	43	0.01
Fish pond	1	95	93	0.02

Low rounded hills

Land use types	1989 (ha)	1997 (ha)	Change (ha)	% change
Forest	5588	5183	-405	-0.08
Plantation	10197	7167	-3030	-0.60
Rice field	7410	11336	3926	0.78
Open/dry land	1942	1525	-418	-0.08
Settlement	231	152	-78	-0.02
Fish pond	0	0	0	0.00

Hillocky plains

Land use types	1989 (ha)	1997 (ha)	Change (ha)	% change
Forest	1551	7495	5944	1.18
Plantation	18267	14701	-3566	-0.71
Rice field	15152	10863	-4289	-0.85
Open/dry land	12238	14051	1813	0.36
Settlement	358	447	89	0.02
Fish pond	8	15	7	0.00

Minor river floodplain

Land use types	1989 (ha)	1997 (ha)	Change (ha)	% change
Forest	51	167	116	0.02
Plantation	1825	1740	-85	-0.02
Rice field	9001	7968	-1033	-0.20
Open/dry land	5960	6498	539	0.11
Settlement	635	1006	371	0.07
Fish pond	115	164	50	0.01

Table V.3 : Land use/Land cover change versus Land system

Permanently water lodging

Land use types	1989 (ha)	1997 (ha)	Change (ha)	% change
Forest	0	0	0	0.00
Plantation	0	29	29	0.01
Rice field	2681	1314	-1367	-0.27
Open/dry land	936	2223	1288	0.25
Settlement	7	69	62	0.01
Fish pond	11	0	-11	0.00

Undulating to rolling sedimentary plains

Land use types	1989 (ha)	1997 (ha)	Change (ha)	% change
Forest	2085	1030	-1055	-0.21
Plantation	26834	20036	-6799	-1.35
Rice field	63092	61427	-1665	-0.33
Open/dry land	29203	27488	-1715	-0.34
Settlement	9802	20883	11081	2.19
Fish pond	26	176	150	0.03

Steep hills on marls

Land use types	1989 (ha)	1997 (ha)	Change (ha)	% change
Forest	528	792	265	0.05
Plantation	2659	2029	-630	-0.12
Rice field	2447	2449	2	0.00
Open/dry land	566	961	395	0.08
Settlement	102	64	-37	-0.01
Fish pond	0	0	0	0.00

Very steep ridges karstic

Land use types	1989 (ha)	1997 (ha)	Change (ha)	% change
Forest	1385	2443	1058	0.21
Plantation	2804	1332	-1472	-0.29
Rice field	1314	1809	495	0.10
Open/dry land	173	95	-78	-0.02
Settlement	31	28	-3	0.00
Fish pond	0	0	0	0.00

Table V.4: Land use/Land cover and Population density Classes

LULC	Density Class I		Density Class II		Density Class III	
	1989 (ha)	1997 (ha)	1989 (ha)	1997 (ha)	1989 (ha)	1997 (ha)
Forest	7700	9961	933	1074	0	0
Plantation	48331	38075	4032	6494	8	16
Rice field	239792	214515	29459	20372	6058	2269
Open/dry land	70117	95490	5117	9088	1260	591
Settlement	14605	19979	4765	7707	3302	7743
Fishpond	9595	11238	354	412	4	12

Note:

Class I = 15 - 150 person/sqkm

Class II = 151 - 650 person/sqkm

Class III = 651 - 1200 person/sqkm

APENDIX VI

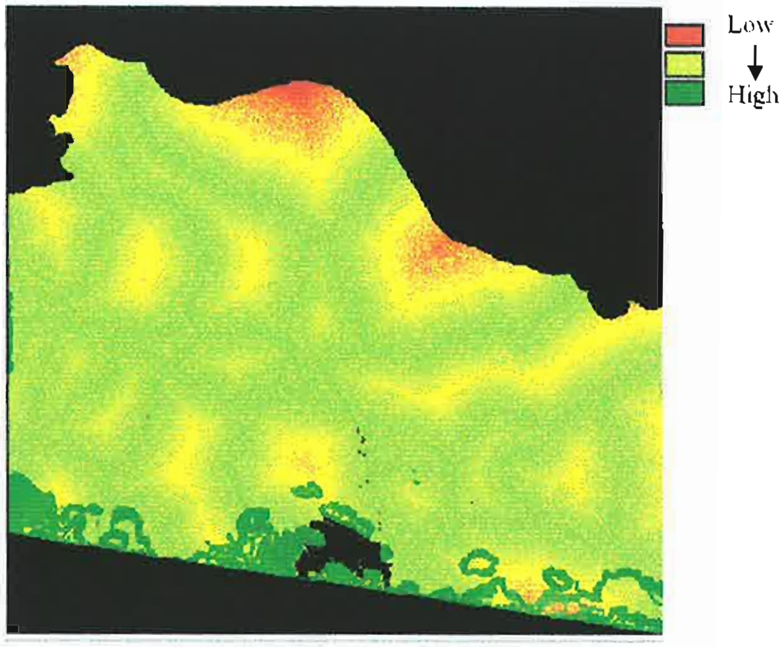


Figure 1. Suitable for Forest

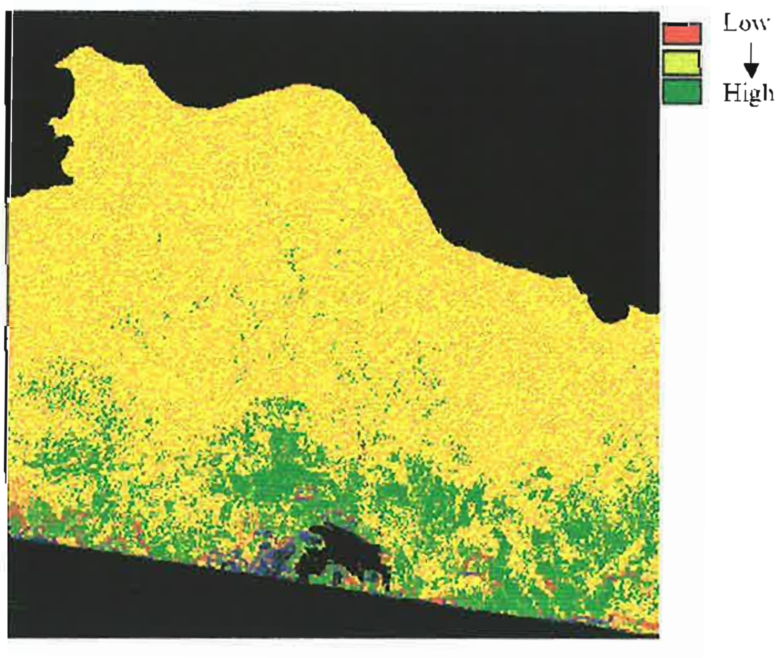


Figure2. Suitable for Plantation

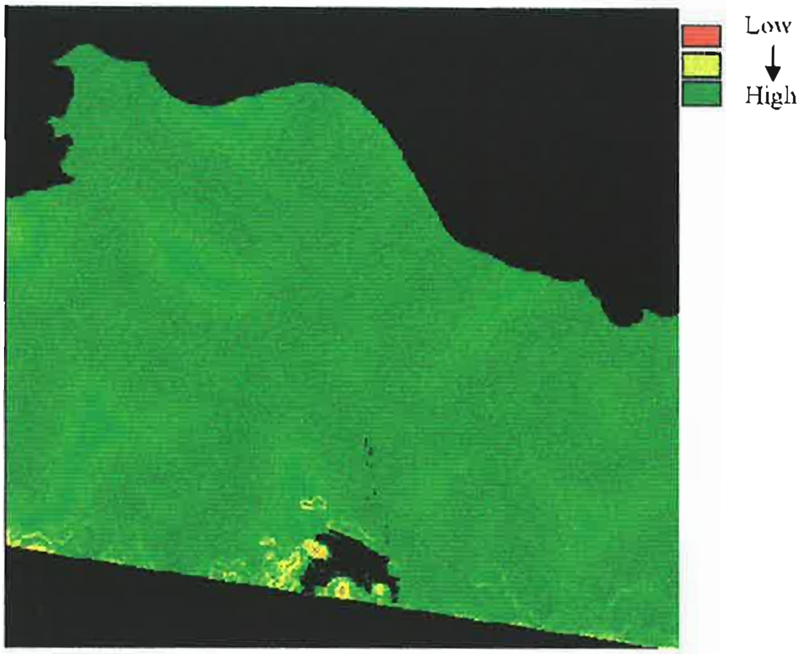


Figure 3. Suitable for Rice field

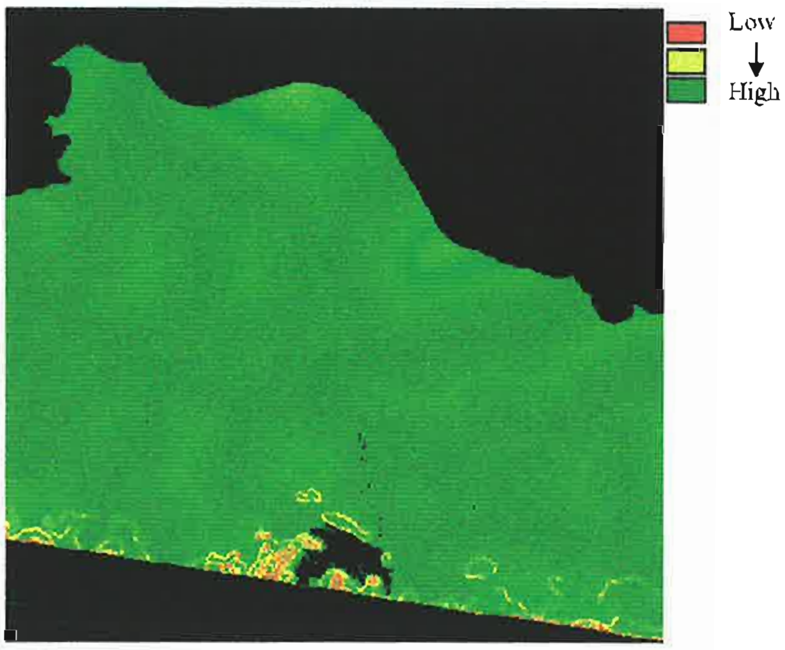


Figure 4. Suitable for Open/dry land

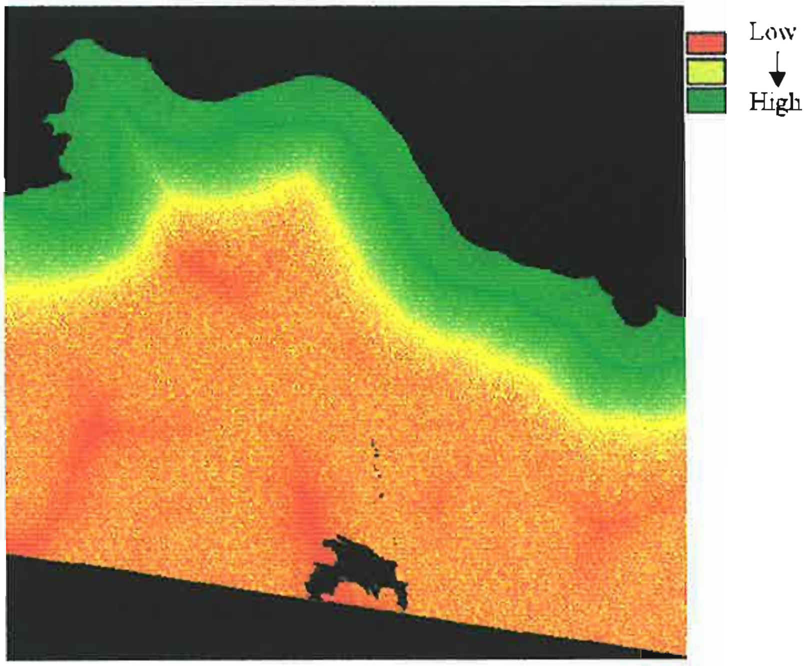


Figure 5. Suitable for Fishpond

Table: Land use/Land cover within 10 km of urban and semi urban (Ha)

Urban and semi-urban	Year	Forest	Plantation	Rice field	Open / dry land	Settlement	Fishpond	Water / eservoir
Bekasi	1989	0	409	19921	3316	5326	6	0
	1997	0	649	9206	5121	14936	30	0
	Scenario2. 2007	0	696	2930	5400	20926	5	0
	Scenario2. 2017	0	593	858	2397	26098	9	0
Cikarang		Forest	Plantation	Rice field	Open/dry land	Settlement	Fishpond	Water/reservoir
	1989	0	308	23085	6333	1530	1	0
	1997	0	1006	17328	7131	5780	12	0
	Scenario2. 2007	0	995	12903	7802	9556	2	0
	Scenario2. 2017	0	722	9497	4765	16269	3	0
Cileungsi		Forest	Plantation	Rice field	Open/dry land	Settlement	Fishpond	Water/reservoir
	1989	77	4127	12456	2839	1336	7	0
	1997	0	1301	12788	2390	3344	44	0
	Scenario2. 2007	0	1831	9258	3707	6172	16	0
	Scenario2. 2017	0	1260	4457	2380	12885	0	0
Karawang		Forest	Plantation	Rice field	Open/dry land	Settlement	Fishpond	Water/reservoir
	1989	3	1734	19685	7974	1861	0	0
	1997	187	2595	17953	7157	3276	90	0
	Scenario2. 2007	325	2477	14283	9800	4372	1	0
	Scenario2. 2017	202	1556	11597	9373	8527	2	0
Cikampek		Forest	Plantation	Rice field	Open/dry land	Settlement	Fishpond	Water/reservoir
	1989	210	6374	16798	6719	1114	40	26
	1997	272	7227	16131	5588	1958	55	26
	Scenario2. 2007	933	7651	13500	7090	2422	11	26
	Scenario2. 2017	338	6153	13124	6730	4486	22	26
Purwakarta		Forest	Plantation	Rice field	Open/dry land	Settlement	Fishpond	Water/reservoir
	1989	1090	8008	8862	2655	1042	15	2070
	1997	1803	7754	8530	2441	1500	46	2070
	Scenario2. 2007	3578	6228	7756	3252	1879	27	2070
	Scenario2. 2017	2603	5002	7254	2909	3907	44	2070

APENDIX VI-2

Markov transition matrix 8-year interval, 8 year to predict
1989 to 1997

Cells in Expected transition to

LULC	Class 1	Class 2	Class 3	Class 4	Class 5	Class 6	Class 7	Total 1989	% Change
Class 1	57150	22300	47773	1092	116	0	26	128456	0.64
Class 2	104503	234134	297490	56736	18865	142	0	711870	-0.10
Class 3	44330	287651	1985648	610110	271561	82092	2299	3283691	-0.12
Class 4	4633	80063	405784	357597	75893	2502	185	926658	0.14
Class 5	250	16424	68175	22583	141809	1052	75	250369	1.05
Class 6	47	117	79397	4406	4476	145882	23	234349	0.00
Class 7	122	361	7587	581	73	2329	50083	61137	-0.14
Total expected	211035	641051	2891855	1053105	512793	234000	52692	5596530	

Given Probability of change to

LULC	Class 1	Class 2	Class 3	Class 4	Class 5	Class 6	Class 7	Total
Class 1	0.4449	0.1736	0.3719	0.0085	0.0009	0	0.0002	1
Class 2	0.1468	0.3289	0.4179	0.0797	0.0265	0.0002	0	1
Class 3	0.0135	0.0876	0.6047	0.1858	0.0827	0.025	0.0007	1
Class 4	0.005	0.0864	0.4379	0.3859	0.0819	0.0027	0.0002	1
Class 5	0.001	0.0656	0.2723	0.0902	0.5664	0.0042	0.0003	1
Class 6	0.0002	0.0005	0.3388	0.0188	0.0191	0.6225	0.0001	1
Class 7	0.002	0.0059	0.1241	0.0095	0.0012	0.0381	0.8192	1
Total	0.6134	0.7485	2.5676	0.7784	0.7787	0.6927	0.8207	7

Markov transition matrix 8-year interval, 8 year to predict
1989 to 1997 (after rationalisation)

Cells in Expected transition to

LULC	Class 1	Class 2	Class 3	Class 4	Class 5	Class 6	Class 7	Total 1989	% Change
Class 1	57150	22326	47773	1092	116	0	0	128456	0.53
Class 2	104503	234134	297490	56736	19007	0	0	711870	-0.12
Class 3	30538	287651	2065113	610110	208186	82092	0	3283691	-0.10
Class 4	4633	80063	405784	360099	76079	0	0	926658	0.16
Class 5	0	1377	43139	37605	168248	0	0	250369	0.90
Class 6	0	0	79397	4406	4453	146093	0	234349	-0.02
Class 7	0	0	251	581	0	501	59804	61137	-0.02
Total expected	196824	625551	2938947	1070629	476088	228687	59804	5596530	

Given Probability of change to

LULC	Class 1	Class 2	Class 3	Class 4	Class 5	Class 6	Class 7	Total
Class 1	0.4449	0.1738	0.3719	0.0085	0.0009	0	0	1
Class 2	0.1468	0.3289	0.4179	0.0797	0.0267	0	0	1
Class 3	0.0093	0.0876	0.6289	0.1858	0.0634	0.025	0	1
Class 4	0.005	0.0864	0.4379	0.3886	0.0821	0	0	1
Class 5	0	0.0055	0.1723	0.1502	0.672	0	0	1
Class 6	0	0	0.3388	0.0188	0.019	0.6234	0	1
Class 7	0	0	0.0041	0.0095	0	0.0082	0.9782	1
Total	0.606	0.6822	2.3718	0.8411	0.8641	0.6566	0.9782	7

Markov transition matrix 8-year interval, 20 year to predict
From 1997

Cells in Expected transition to

LULC	Class 1	Class 2	Class 3	Class 4	Class 5	Class 6	Class 7	Total 1997	% Change
Class 1	37548	30890	101903	17932	7827	1922	119	198140	0.19
Class 2	68023	78026	315341	79085	40955	6767	235	588433	0.00
Class 3	97991	339536	1521046	645056	401639	111722	3745	3120735	-0.12
Class 4	24152	94917	513117	177617	115592	13815	564	939774	0.06
Class 5	7389	39120	189705	61739	149452	5576	317	453298	0.61
Class 6	1224	7109	104584	17772	11981	92626	94	235391	0.00
Class 7	213	723	8385	1349	547	2455	47088	60759	-0.14
Total expected	236539	590321	2754082	1000550	727993	234883	52163	5596530	

Given Probability of change to

LULC	Class 1	Class 2	Class 3	Class 4	Class 5	Class 6	Class 7	Total
Class 1	0.1895	0.1559	0.5143	0.0905	0.0395	0.0097	0.0006	1
Class 2	0.1156	0.1326	0.5359	0.1344	0.0696	0.0115	0.0004	1
Class 3	0.0314	0.1088	0.4874	0.2067	0.1287	0.0358	0.0012	1
Class 4	0.0257	0.101	0.546	0.189	0.123	0.0147	0.0006	1
Class 5	0.0163	0.0863	0.4185	0.1362	0.3297	0.0123	0.0007	1
Class 6	0.0052	0.0302	0.4443	0.0755	0.0509	0.3935	0.0004	1
Class 7	0.0035	0.0119	0.138	0.0222	0.009	0.0404	0.775	1
Total	0.3872	0.6267	3.0844	0.8545	0.7504	0.5179	0.7789	7

Markov transition matrix 8-year interval, 20 year to predict
From 1997 (Scenario)

LULC	Class 1	Class 2	Class 3	Class 4	Class 5	Class 6	Class 7	Total 1997	% Change
Class 1	148605	29721	9907	9907	0	0	0	198140	12
Class 2	73554	294217	132397	88265	0	0	0	588433	-21
Class 3	0	0	2028478	624147	468110	0	0	3120735	-20
Class 4	0	140966	281932	187955	281932	46989	0	939774	9
Class 5	0	0	0	90660	362638	0	0	453298	148
Class 6	0	0	58848	23539	11770	141234	0	235391	-20
Class 7	0	0	0	0	0	0	60759	60759	0
Total expected	222159	464904	2511562	1024472	1124451	188223	60759	5596530	

Given Probability of change to

LULC	Class 1	Class 2	Class 3	Class 4	Class 5	Class 6	Class 7	Total
Class 1	0.75	0.15	0.05	0.05	0.00	0.00	0.00	1
Class 2	0.12	0.50	0.22	0.15	0.00	0.00	0.00	1
Class 3	0.00	0.00	0.65	0.20	0.15	0.00	0.00	1
Class 4	0.00	0.15	0.30	0.20	0.30	0.05	0.00	1
Class 5	0.00	0.00	0.00	0.20	0.80	0.00	0.00	1
Class 6	0.00	0.00	0.25	0.10	0.05	0.60	0.00	1
Class 7	0.00	0.00	0.00	0.00	0.00	0.00	1.00	1
Total	0.87	0.80	1.47	0.90	1.30	0.65	1.0000	7

Cross-tabulation LULC 1997 original and 2007 simulation based on Markov transition 1989-1997

LULC	Forest	Plantation	Rice field	Open/dry land	Settlement	Fishpond	Water/reservoir	Total 2007	% Change
Forest	163154	47388	10436	4833	924	2	0	226737	14
Plantation	2633	460897	90860	36538	13843	190	0	604961	03
Rice field	32195	66309	2654640	20753	12303	16679	0	2802879	-10
Open/dry land	73	9651	180557	834987	3287	2529	0	1031084	10
Settlement	49	4051	167601	42540	422618	3298	0	640157	41
Fishpond	34	136	16447	124	319	212692	0	229752	-2
Water/reservoir	1	0	194	0	5	1	60759	60960	0
Total 1997	198139	588432	3120735	939775	453299	235391	60759	5596530	

Cross-tabulation LULC 1997 original and 2017 simulation based on Markov transition 1989-1997

LULC	Forest	Plantation	Rice field	Open/dry land	Settlement	Fishpond	Water/reservoir	Total 2017	% Change
Forest	159321	38481	31558	7181	576	38	0	237155	20
Plantation	8942	475788	77237	22052	5730	483	0	590232	0
Rice field	27791	50989	2603342	39380	13731	12601	0	2747834	-12
Open/dry land	384	11556	159049	818520	6669	3811	0	999989	6
Settlement	1118	11091	230649	52482	426180	6429	0	727949	61
Fishpond	583	527	18794	155	413	211983	0	232455	-1
Water/reservoir	0	0	106	5	0	46	60759	60916	0
Total 1997	198139	588432	3120735	939775	453299	235391	60759	5596530	

Cross-tabulation Lu 1997 original and 2007 simulation based on Markov scenario

LULC	Forest	Plantation	Rice field	Open/dry land	Settlement	Fishpond	Water/reservoir	Total 2007	% Change
Forest	169866	86682	8380	1060	1	0	0	265989	34
Plantation	1176	464889	85103	32538	153	13	0	583872	0
Rice field	21133	23168	2596366	7235	8	62585	0	2710495	-13
Open/dry land	5870	13146	269651	869979	8106	12673	0	1179425	25
Settlement	94	547	160261	28963	445031	423	0	635319	40
Fishpond	0	0	974	0	0	159697	0	160671	-31
Water/reservoir	0	0	0	0	0	0	60759	60759	0
Total 1997	198139	588432	3120735	939775	453299	235391	60759	5596530	

Cross-tabulation Lu 1997 original and 2017 simulation based on Markov scenario

LULC	Forest	Plantation	Rice field	Open/dry land	Settlement	Fishpond	Water/reservoir	Total 2017	% Change
Forest	178356	43472	12	339	0	0	0	222179	12
Plantation	6018	409499	10997	38347	31	0	0	464892	-21
Rice field	8423	106791	2332954	10644	0	52743	0	2511555	-20
Open/dry land	4315	15601	276523	726617	443	956	0	1024455	9
Settlement	1027	13053	495790	151673	452823	10093	0	1124459	148
Fishpond	0	16	4459	12155	2	171599	0	188231	-20
Water/reservoir	0	0	0	0	0	0	60759	60759	0
Total 1997	198139	588432	3120735	939775	453299	235391	60759	5596530	