LAND USE LAND COVER MODELING IN A PART OF BRAHMAPUTRA BASIN USING GEOINFORMATICS

A THESIS

Submitted in partial fulfilment of the requirements for the award of the degree

of

DOCTOR OF PHILOSOPHY

by

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CANDIDATE'S DECLARATION

I hereby certify that the work which is being presented in the thesis entitled "**Land Use Land Cover Modeling in a Part of Brahmaputra Basin using Geoinformatics**" in partial fulfilment of the requirements for the award of the Degree of Doctor of Philosophy and submitted in the Department of Water Resources Development and Management of Indian Institute of Technology, Roorkee, Roorkee is an authentic record of my own work carried out during a period from January of 2007 to December of 2011 under the supervision of Dr. Nayan Sharma, Professor, Department of Water Resources Development and Management & Dr. P. K. Garg, Professor, Department of Civil (Geomatics) Engineering, Indian Institute of Technology, Roorkee, Roorkee and Dr. Martin Kappas, Professor, Dept. of Cartography, GIS and Remote Sensing, Institute of Geography, Georg August University of Göttingen, Göttingen, Germany.

The matter presented in the thesis has not been submitted by me for the award of any other degree of this or any other Institute.

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This is to certify that the above statement made by the candidate is correct to the best of our knowledge.

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The Ph.D. Viva-Voce Examination of **Mr. Md. Surabuddin Mondal**, Research Scholar, has been held on

Signature of Supervisor(s) **Signature of Chairman (SRC)** **Signature of External Examiner**

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ABSTRACT

The land use and land cover change (LULCC) plays an important role in global environmental change. Projections of future land use and land cover (LULC) patterns are needed to emulate the implications of human actions for the sustainable ecosystem. Models of land use and land cover changes have been developed by various researchers to address which, where and why land use and land cover changes occur.

This study aims at to predict future land use and land cover scenario in a developing region using empirical data and analysing their effects of different modeling parameters into the predicting results. The main objectives of this study are; (i) Analysis of different satellite images on the basis of their land use and land cover classes (ii) Quantification of land use and land cover changes using change detection method and (iii) Simulation of land use and land cover changes using Cellular Automata Markov (CA Markov) chain based land use and land cover changes model for projecting the future land use and land cover scenario. To fulfil the above mentioned objectives, some research questions are posed, which include (i) What kind of changes occur in the study area? (ii) What types of transition are going on within changes? (iii) What will be the future LULC? (iv) Do different sizes of neibourhood (3x3, 5x5, and 7 x 7 cellular automata) have an impact on CA Markov prediction results? (v) Which LULC parameter(s) have highest or lowest influence on predicted results? (vi) Are predicted results statistically independent or not? and (vii) Whether different time steps have any impact on CA Markov model predicted results?

To describe the above mentioned objectives and to answer the above mentioned questions, a study has been made to identify and review remote sensing GIS based LULCC models. Critical assessment and comparative analysis of identified reviewed models and background of remote sensing and GIS based LULCC modeling are described in this study. About 29 models are short-listed on the basis of their importance. It was also found that land use and land cover change is poorly understood and LULCC modeling for specific region, especially in developing regions, needs to be continuing.

Therefore, an attempt has been made to evaluate Cellular Automata (CA) Markov model to predict the future land use and land cover scenario in a Kamrup Metropolitan district of Assam State of India, using land use and land cover maps derived from multi-temporal satellite images. For this purpose, land use and land cover maps of the study area have been extracted from multi temporal satellite images of LANDSAT - 5 TM image acquired on December 26, 1987, IRS-1C LISS III image acquired on March 5, 1997, IRS-P6 LISS III image acquired on 14th December of 2007 digitally classified for land use and land cover mapping. Dynamics of LULC critically analysed for the two time periods 1987 & 1997 and 1997 & 2007.

Land use and land cover maps derived from satellite images of 1987 and 1997 were used to predict future land use and land cover of 2007. The number of iteration was based on the time steps i.e., iterations 10 for predicting LULC for 2007. The net effects of different contiguity filters i.e., 3x3, 5x5 and 7x7 on prediction results as the action of cellular automata component onto CA MARKOV model were also evaluated. The 5x5 contiguity filter produced slightly better geographically spatial distributed results although quantifiably the area statistics of predicted LULC of 2007 were same when using 3x3, 5x5, 7x7 CA contiguity filters. Kappa indices of agreements and related statistics also proved that when 5x5 contiguity filter is used it produces most effective results with $K_{standard}$ for 5x5 filter as 0.7928, whereas $K_{standard}$ for 3x3 filters is 0.7857 and for 7x7 filters it is 0.7777.

In this study, the spatio-temporal CA Markov model of landscape change using multi-temporal LANDSAT TM and IRS LISS III imagery has been used which enabled to predict future land use and land cover for Kamrup Metropolitan district of Assam state in India. The CA model, coupled with the Markov transition probability, has indicated the capability of trend projection for landscape change. This spatio-temporal model provided not only the quantitative description of change in the past but also the direction and magnitude of change in the future. This study shows that by incorporating more spatial algorithms into the prediction of landscape change, more accurate long-term landscape changes can be reproduced in the future.

This study establishes the validity of the CA Markov process for describing and projecting future land use and land cover changes in the study area by examining statistical independence and variations on the Kappa index of agreement. Statistical test of independence (K^2) is performed and Markovian suitability has been checked by using hypothesis of goodness of fit (Xc^2). The hypothesis of statistical independence is rejected which proves that the change trends are dependent on previous development of land. The hypothesis of goodness of fit (Xc^2) proved that actual transition probability of matrix is fitted with expected transition probability prepared using Markov chain method. The validation calculates various Kappa Index of Agreement (KIA or $K_{standard}$) and related statistical variations on the KIA. The statistics indicate K_{no} as 0.8347, $K_{location}$ as 0.8591, $K_{locationStrata}$ as 0.8591 and $K_{standard}$ as 0.7928.

Sensitivity analysis has been carried out to identify the parameter(s), which have the highest, lowest or intermediate influence on predicted results. The results shows that the land with or without scrub appeared to be most sensitive parameter as it has highest influences on predicted results of LULC of 2007. The second most sensitive parameter was lakes / reservoirs / ponds to predict LULC of 2007, followed by river, agricultural crop land, plantation, open land, marshy / swampy, sandy area, aquatic vegetation, built up land, dense forest, degraded forest, waterlogged area and agricultural fallow land. The least sensitive parameter is agricultural fallow land, which has minimum influence on predicted results of LULC of 2007.

An attempt has also been made to verify different time steps impacts on CA Markov prediction model results. For this purpose, 1987 and 1997 images are used in CA Markov model to predict land use and land cover of 2007. Images of 1997 and 2007 were also calibrated in CA Markov model to predict land use and land cover of 2017, 2027 and 2050. The number of iteration is based on the time steps i.e., iterations are 10 to predict LULC for 2007; iterations are 20 to predict LULC for 2017; iterations are 30 for 2027; iterations are 53 for 2050 when using 1987 and 1997 image to predict future. The number of iteration was based on the time steps i.e., iterations are 10 to predict LULC for 2017; iterations are 20 to

2027; iterations are 43 for 2050 when using 1997 and 2007 image to predict future. The net effects of different time steps iterations on CA Markov prediction results are evaluated. The predicting quantity change and location change has been analysed and statistically evaluated. The analysis proved that although there have been nearly no effects of time steps on quantitative prediction results but there have been impact of time steps on spatial distribution of predicted land use and land cover results. The results also indicate that less time steps produces spatially more accurate results, whereas more time steps produce spatially less accurate results.

Future work may be devoted to explore emerging techniques like robust technique ANN - Artificial Neural Network to train the non-linear relationship of CA Markov modeling dynamic process. The socio-economic parameters of the land use and land cover change model deserve additional attention given their importance in governing the model. The future research could also include some dynamic as well as static variables in CA Markov model to explore the potentiality of explanatory of driving forces (dynamic or static variables). Further research may carry out with using more multi-temporal (10 times) satellite images. Further research may carry out with using multi-temporal high resolution satellite images for more accurate results.

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Lastly, and most importantly, I wish to thank my parents and to them I dedicate this thesis.

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LIST OF ABBREVIATIONS

Symbols	Description
ANN	: Artificial Neural Network
BN	: Belief Networks
CA	: Cellular Automata
CA Markov	: Cellular Automata Markov
CLUE	: Conversion of Land Use and its Effects
CLUE-CR	: Conversion of Land Use and its Effects - Costa Rica
CLUE-S	: Conversion of Land Use and its Effects - Santa Barbara
CUF	: California Urban Futures
CURBA	: California Urban and Biodiversity Analysis Model
CVA	: Change Vector Analysis
EOT	: Empirical Orthogonal Tele-connection
ERTS	: Earth Resources Technology Satellite
ESDI	: Earth Science Data Interface
ESRC	: Economic and Social Research Council
ETM	: Earth Trends Modeler
FASOM	: Forest and Agriculture Sector Optimization Model
GCP	: Ground Control Points
GEM	: General Ecosystem Model
GIS	: Geographical Information Sciences
GLCF	: Global Land Cover Facility
GMC	: Guwahati Municipal Corporation
GMDA	: Guwahati Metropolitan Development Authority
IPCC	: Intergovernmental Panel on Climate Change
IRS	: Indian Remote Sensing Satellite
KIA	: Kappa Index of Agreement
$K_{location}$	: Kappa for grid-cell level location
$K_{locationStrata}$	: Kappa for stratum-level location
K_{no}	: Kappa for no information
LCM	: Land Change Modeler – for Ecological Sustainability

LISS	: Linear Imaging Self Scanner
LTM	: Land Transformation Model
LUCAS	: Land Use Change Analysis System
LULCC	: Land Use and Land Cover Change
LULC	: Land Use and Land Cover
MABEL	: Multi Agent-Based Economic Landscape Model
MDP	: Markov-Decision Problem
MEC	: Multi-Criteria Evaluation
MOLA	: Multi-Objective Land Allocation
MSS	: Multispectral Scanner
NASA	: National Aeronautic and Space Agency
NELUP	: NERC/ESRC Land Use Programme
NERC	: Natural Environment Research Council
NIC	: National Informatics Centre
NIR	: Near Infra-Red
NRCS	: Natural Resources Conservation Service
NRSC	: National remote Sensing Centre
PCA	: Principal Component Analysis
PLM	: Patuxent Landscape Model
RESAC	: Mid-Atlantic Regional Earth Science Applications Centre
SELUTH	: Slope, Exclusion, Land use, Urban extent, Transportation, Hill Shade
SOI	: Survey of India
SVI	: Spectral Vegetation Index
SWIR	: Short Wave Infra-Red
TD	: Transformed Divergence
TM	: Thematic Mapper
TOA	: Top-of-Atmosphere
USDA	: United State Department of Agriculture
USGS	: United States Geological Survey
UTM	: Universal Transverse Mercator projection
WCRP	: World Climate Research Programme
WGS	: World Geo-coordinate System
WRS	: Worldwide Reference System

LIST OF NOTATIONS *

* Symbols having a common meaning are defined here. Other locally used symbols are defined wherever they occur

Symbols	Description
$\hat{K}$	: Kappa coefficient
A_{ik}	: Actual value of data from category in I to category in k
E_{ij}	: Number of transition from category i to j during the period 1987-1997
E_{ik}	: Expected value under Markov hypothesis
E_j	: Number of cells in category j in 1987
E_{jk}	: Number of transition from category j to k during the period 1997-2007
H (m)	: Agreement due to location at the stratified level
i, j	: Land use / land cover type of the first and second time period
K (m)	: Disagreement due to location at the grid cell level
K^2	: Statistical Independence Test
M (m)	: Agreement due to location at the grid cell level
N	: Number of observations
N (m)	: Agreement due to quantity
N (n)	: Agreement due to chance
O_{ik}	: Observed transition probability data from 1987-1997
P	: Markov transition matrix P
P (m)	: Disagreement due to location at the stratified level
P (p)	: Disagreement due to quantity
Pij	: Probability from land use / land cover type i to land type j
r	: Number of rows in the matrix
x_{i+} and x_{+i}	: Marginal totals of row r and column i, respectively
x_{ii}	: Number of observations in row i and column $_i$ (the $_i$ th diagonal elements)
x(t)	: Land cover at time t is thus represented by the state vector
Xc^2	: Goodness of fit test
x_t	: Initial condition of the map (i.e., its state at the first time or t_o)
$x_{t+1}=x_{tP}$	: State vector post-multiplied by the transition matrix

Chapter - 1

INTRODUCTION, OBJECTIVES OF STUDY AND RESEARCH QUESTIONS

1.1. BACKGROUND

In the last three decades, remote sensing and GIS have emerged as powerful tools to create spatial inventory on natural resources and the state of environment. Remote sensing and GIS, and process-based modeling play crucial roles in spatial and dynamic assessment of an area. Remote sensing methods have great advantages in observation of actual conditions, since such information can be obtained on remote (synoptic view), wide area, non-destructive, and/or real time bases. Furthermore, thanks to the sensor technologies, non-visible signals such as in near infrared, thermal-infrared and microwave wavelength domains can be observed. The GIS is a powerful tool for integration of data and information, for their spatial analysis, and for visual presentations. Some advantages of remote sensing in land use and land cover mapping are; (i) Remote sensing techniques provide reliable, accurate, baseline information for land use and land cover (LULC) mapping, generalized land use and land cover classification for large areas, their delineation and spatial distribution categories, are possible by satellite imagery, because of its synoptic coverage of large areas; (ii) Study on the structure and dynamics of land use is possible because of repetitive coverage of the same area; (iii) Monitoring the land use for optimal use on long term basis is possible by remote sensing techniques; multispectral multi-temporal imagery enhances land use information; (iv) Land use mapping both by visual interpretation and computer based digital image processing analysis is possible by remote sensing technique; (v) Land use maps can be prepared more speedily, accurately and economically by remote sensing techniques; and (vi) Land use maps thus prepared will form a basic input in planning and management decisions. Some significances of land use and land cover mapping are; (i) To form and implement land and policies regarding existing and future land use, (ii) Planning, management and monitoring of natural resources, and (iii) LULC is an input parameter in many fields as geology, hydrology, demography, environment etc..

The land use and land cover change (LULCC) plays an important role in global environmental change. It contributes significantly to earth-atmosphere interactions and biodiversity loss, and is a major factor in sustainable development and human responses to global change. Inventory and monitoring of land use and land cover changes are indispensable aspects of further understanding of change mechanism and modeling the impact of change on environment and associated eco-systems at different scales (Turner et al., 1995; William et al., 1994; Meyer and Turner, 1994).

The LULCC research activities ultimately contributes to (i) methodological advancement in the design and implementation of LULCC case studies and case study protocols; the means to interpolate and extrapolate from LULCC sample data across space and time scales, and the structure and functioning of integrated LULCC models, (ii) analytical advancement in a suite of integrated LULCC models ranging from the household and farm to the globe, and (iii) empirically-derived inventories of geographically specific land use and land cover changes and analytically-derived projections thereof across specific time scales. The understanding gained from the results of a LULCC project/programme will be of use to a wide range of researchers, policy planners, and other decision makers requiring improved means of projecting LULCC in terms of its implications for (i) global environmental change, (ii) local-to-regional sustainability issues, and (iii) the assessment of responses to local and environmental change. Land use and land cover change has the potential to integrate research on the natural and human dimensions of global environmental change, and the understanding gained from this integration contributes to other research and policy initiatives, such as those of the World Climate Research Programme (WCRP, 1990) and the Intergovernmental Panel on Climate Change (IPCC, 1990).

1.2. SIGNIFICANCE OF LAND USE AND LAND COVER (LULC) CHANGE

LULCC is a locally pervasive and globally significant ecological trend (Agarwal et al., 2001). Vitousek (1994) notes that "three of the well-documented global changes are increasing concentrations of carbon dioxide in the atmosphere; alterations in the biochemistry of the global nitrogen cycle; and on- going land use and land cover change." In the case of United States of America, for example, 121,000 km^2 of non-federal lands were converted to urban developments over a 15-year interval between 1982 and 1997 (NRCS/USDA, 1999). On a global scale, nearly 1.2 million km² of forest and woodland and 5.6 million km² of grassland and pasture have been converted to other uses during the last three centuries, according to Ramankutty and Foley (1999). During the same time period, cropland has increased by 12 million km². Currently, humans have transformed significant portions of the Earth's land surface: 10 to 15 percent is dominated by agricultural row crop or urban- industrial areas, and 6 to 8 percent is pasture (Vitousek et al., 1997).

1.3. MODELING ASPECTS OF LAND USE AND LAND COVER CHANGE (LULCC)

Models on land use and land cover changes are powerful tools that can be used to understand and analyse the important linkage between socio-economic processes associated with land development, agricultural activities and natural resource management strategies and the ways that these changes affect the structure and function of ecosystems (Roy and Tomar, 2001). Long term understanding on LULC needs to propose a more dynamic framework that explicitly links, what is often divided into separate natural and human systems into a more integrated model. In developing countries like India, likely land use and land cover are often semantically equivalent i.e., land use activities associated with logging leads to a deforested land cover (Lambin, 1997). Therefore, satellite images can often be used to detect land use changes through observations of the biophysical characteristics of the lands. Contrastingly, developed countries, like United States of America (USA) and Europe, LULC are less likely to be equivalent. Although, forestry can be modeled as a land use activity that responds to economic, social and demographic drivers such drivers do not provide direct predictors for understanding and modeling the amount and locations of forests and tree cover in all parts of a landscape (Mauldin et al., 1999; Geist and Lambin, 2002).

1.4. STATEMENT OF PROBLEM

Several empirical models have been developed to address the LULC conversion process. Transition probability models have been extensively used for analysis and stochastic modeling of land use and land cover changes (Bell, 1974; Turner, 1987; Muller and Middleton, 1994). Markov chain models represent a suite of such models. The central mechanism of a Markov chain is a probability function which refers to the likelihood of transition from one cover to another cover. The probability function can be static over time or can be adjusted at specific intervals to account for changes in the stationary of the processes controlling the transition sequences. The probability function and transition sequences can be derived from direct observations using satellite data. The primary limitations of Markov transition probability-based models for LULCC analysis are: (1) the assumption of stationary in the transition matrix i.e. that it is constant in time and space; (2) the assumption spatial independence of transitions; and (3) the difficulty of ascribing causality within the model, i.e. the transition probabilities are often derived empirically from multi-temporal maps with no description of the process (Baker, 1989). The third limitation assumes greater significance in the context of land cover change studies from remotely-sensed images, and when those changes are driven by economic and social processes. To address the limitations 1 and 3 as above, Baker (1989) suggested setting state transition probabilities as a function of exogenous or endogenous variables, which vary in space and time. These models have been used in various case studies to account for changes in the rate of LULC conversion under constraints.

Whereas Markov transition probabilities provide a convenient analytical framework for simulating land use and land cover change using observed transitions, e.g., from remote sensing, alternate approaches are used for modeling the influence of social and economic drivers on land use and land cover change. The alternative model structures are designed to introduce a better representation of causative factors into the models by relating change to either exogenous driving variables, spatial interaction process or both. The spatial-transition-based models are exemplified by a spatial-temporal expansion of the Markov transition models referred to as cellular automata (CA) (Deadman et al., 1993; Clarke et al., 1997). This model uses spatially variable transition probabilities to account for the effects of exogenous variables on the transition process (Baker, 1989; Brown et al., 2000). This model is usually calibrated using maps of observed change. This model has been developed in recent years as a response to the availability of remote sensing, geographic information systems, and multivariate-multitemporal mathematical models. The use of satellite imagery would create an opportunity for improved analysis. Moreover, the Markov models have been mostly employed for studies around a city or a slightly larger area, with a regional concentration. The application of stochastic models to simulate dynamic systems, such as land use and land cover changes in a developing nation, like India, is rare. Clearly, much work needs to be done in order to develop an operational procedure that integrates the techniques of satellite remote sensing, GIS, and Markov modeling for monitoring and modeling land use and land cover changes for developing country.

1.5. STUDY OBJECTIVES AND RESEARCH QUESTIONS

The general objective in this dissertation is to combine remote sensing, GIS and landscape models to critically analyse the landscape pattern and predict the future patterns and also compare the technical issue, different sizes of neibourhood i.e., 3x3, 5x5, and 7 x 7 CA and varying time steps iterations which may have impact on CA Markov prediction results.

The study is undertaken with the following objectives:

1. Analysis of different satellite images on the basis of their LULC classes.
2. Quantification of land use and land cover change using change detection method.
3. Simulation of land use and land cover change using CA Markov chain based LULCC model for projecting the future LULC scenario.

The research will focus on critical research questions:

(i) What kinds of changes occur in the study area? Which are the area changes very fast, slow/no changes?

(ii) What types of transition are going on within changes?

(iii) What are the futures LULC in study area?

(iv) Do different sizes of neibourhood (3x3, 5x5, and 7x7 CA) have any impact on CA Markov prediction results?

(v) Which LULC parameter(s) have highest or lowest influences on predicted results?

(vi) Are prediction results statistically independent or not?

(vii) Whether different time steps have any impact on CA Markov model predicted results?

The general framework in this research is five fold. First, a multi-temporal landscape classification will be carried out with satellite imageries for LULC mapping. With that information, an in-depth analysis of land use and land cover changes will be performed. The future LULC of the study area will be predicted, the impact of different sizes of neigbourhood (3x3, 5x5, and 7 x 7 CA) on CA Markov prediction results will be addressed. Sensitivity analysis will be carried out to address which LULC parameter(s) have highest or lowest influences on predicted results. Hypothesis test, statistical independence test and validation of the prediction results will be done. Lastly, the impact of different time steps on CA Markov model prediction results will be addressed.

1.6. ORGANIZATION OF THE THESIS

The goal of this doctoral research is to explore CA Markov model to predict the future LULC and to explore comprehensive comparison of different CA size impacts on prediction results as well as comprehensive comparison of different time steps impacts on prediction results using the extracted geospatial information from the satellite imagery. This study is structured to build a bridge between the Geoinformatics (Remote sensing, GIS etc.) research, LULC pattern characterization, modeling of spatial processes and techniques. Although LULCC study is a very popular topic, the integrative perspective and methodology make this research unique since relatively little work has been reported in the literature to exploit in the study area situated in a developing country (India) using both the remote sensing data, spatial analysis method, and landscape model.

First chapter of this doctoral research introduced the general background of this study, objective and related research questions. Remote sensing, GIS based LULCC models identified and reviewed in chapter 2. Critical assessment and comparative analysis for identified reviewed models and background of remote sensing and GIS based LULCC modeling also described in chapter 2. The description about study area, data used for this study and methodology adopted for this study is given in chapter 3.

To evaluate CA Markov model to predict the future LULC scenario in a developing region, Kamrup Metropolitan district of Assam state of India LULC map of the study area derived from satellite images. Choosing well-suited imagery and methods for land use and land cover change research is significant. The data requirements in the remote sensing application, as well as the classification methods and LULC mapping are discussed in chapter 4. Landsat - 5 TM image of 1987, IRS-1C LISS III image of 1997, IRS-P6 LISS III image of 2007 digitally classified for LULC mapping and dynamics of land use and land cover critically analysed for the two time periods in between 1987 & 1997 and in between 1997 & 2007. The critical assessments of land use and land cover changes have been discussed in chapter 5.

After the image classification and the land use and land cover change pattern analysis, we developed a CA Markov model to monitor and predict the future spatial pattern for the study area in chapter 6. The CA Markov model simulated for an especial study area which covered a large proportion by urban landscape surrounding by others 13 classes of LULC. Chapter 6 describes about the process, calibration and results of LULC CA Markov modeling using satellite images of 1987 and 1997 to predict future LULC of 2007. The net effects of different contiguity filter i.e., 3x3, 5x5 and 7x7 filters on the prediction results as the action of CA component onto CA Markov prediction model were also evaluated in this chapter. The 5x5 contiguity filters produce slightly better geographically spatial distributed effective results although quantifiably the area statistics of predicted LULC of 2007 are same when using 3x3, 5x5, 7x7 CA contiguity filter. Kappa indices of agreements and related statistics also proved that when used 5x5 contiguity filter produce most effective results with $K_{standard}$ for 5x5 filters is 0.7928 whereas $K_{standard}$ for 3x3 filters is 0.7857 and for 7x7 filters is 0.7777. Chapter 6 also describes the sensitivity analysis to identify the parameter(s), which have highest, lowest or intermediate influence on predicted results. The results have shown that the land with or without scrub appeared to be most sensitive parameter, which have highest influence on predicted results of LULC of 2007. The agricultural fallow land is the least sensitive parameter, which have lowest influence on predicted results of LULC of 2007. The followings are the parameter(s), arranged in ascending order, i.e., lakes / reservoirs / ponds, river, agricultural crop land, plantation, open land, marshy / swampy, sandy area, aquatic vegetation, built up land, dense forest, degraded forest, waterlogged area, which haves the intermediate influence on predicted results.

Chapter 7 describes the validity of the CA Markov process for projecting future land use and cover changes in the study area by examining statistical independence test and the Kappa index of agreement. In chapter 7, the prediction results are statistically independence or not, have been tested. The hypothesis of statistical independence (K^2) was rejected proved that the land use and land cover change trends are dependent on previous development of land. With acceptance of the hypothesis of goodness of fit (Xc^2) proved that actual transition probability of matrix is fitted with expected transition probability prepared using Markov chain method. The validation calculates various Kappa Index of Agreement (KIA or $K_{standard}$) and related statistical variations on the KIA. The statistics indicate K_{no} is 0.8347, $K_{location}$ is 0.8591, $K_{location\ Strata}$ is 0.8591 and $K_{standard}$ is 0.7928.

Chapter 8 verified different time steps impacts on CA Markov prediction model results. The net effects of different time steps iterations on CA Markov prediction results were evaluated for this purpose. The predicting quantity change and predicting location change has been analysed and statistically evaluated and analysis proved that although there have nearly no effects of time steps on quantitative prediction results but there have impacts of time steps on spatial distribution of predicted LULC results. The result also indicates that less time steps produce spatially more accurate results, whereas more time steps produce spatially less accurate results.

Finally, chapter 9 describes the summary-conclusions and future scope of this study.

1.7. SUMMARY

In this chapter, first of all, the general background of this research study and the statement of problems are described. The aim objective and research questions of the study are also clearly presented in this chapter. Finally, organization of this thesis is described in this chapter.

Chapter - 2

LITERATURE REVIEW

2.1. REMOTE SENSING AND GIS BASED LAND USE AND LAND COVER CHANGE (LULCC) MODELING

With the availability of aerial photographs and development of photo-interpretation techniques in the 1920's, their use for LULC mapping began in the mid-1930s (Rust, 1978). Several studies on land use and land cover mapping and change detection have been subsequently carried out using aerial photographs (Avery, 1968; Sahai et al., 1977; Quirk and Scarpace, 1982). Though the Gemini and Apollo space photographs were used for mapping LULC in the late 1960's and early seventies (Mcphail and Campbell, 1970), the operational use of space-borne multispectral data began only after the launch of the Earth Resources Technology Satellite (ERTS-I), later renamed as Landsat-1, in July 1972. Synoptic view of a fairly large area at regular intervals provided by Landsat Multispectral Scanner (MSS) was exploited for mapping and monitoring land use land cover following the United States Geological Survey (Anderson et al., 1971) LULC classification system (Sharma, 1980).

There has been a growing trend in the development of change detection techniques using remote sensing data. The change detection techniques, thus developed, could be grouped into two general categories; (i) those based on spectral classification of input data, such as post-classification comparison (Mas, 1999) and direct two-date classification (Li and Yeh, 1997), and (ii) those based on radiometric change between acquisition dates, including (a) image algebra method, such as band differencing (Weismiller et al., 1977), ratioing (Howarth and Wickware, 1981) and vegetation indices (Nelson, 1983), (b) regression analysis (Singh, 1986), (c) principal component analysis (Byrne et al., 1980; Gong, 1993), and (d) change-vector analysis (CVA) (Malila, 1980). In addition, hybrid approaches involving a mixture of categorical and radiometric change information have also been proposed and evaluated (Colwell and Weber, 1981).

Some attempts have been made to evaluate the reliability of various change detection techniques in order to suggest a particular technique for land use and land cover change detection. For instance, while evaluating the automated methods for change detection for identifying an optimum algorithm for forest change detection, Singh (1986 and 1989) observed that the regression method using Landsat MSS band 2 produced the highest change detection accuracy followed by image ratioing and image differencing.

Projections of future LULC patterns are needed to emulate the implications of human action for the sustainability of ecosystem (Turner et al., 1995). Models of land use and land cover change have been developed by various authors to address which, where and why land use changes occur (Riebsame et al., 1994; Lambin, 1997; Theobald and Hobbs, 1998). These models are very useful tools that can be used to understand and analyse the important linkage between socio-economic processes associated with land development, agricultural activities, and natural resources management strategies, and the ways that these changes affect the structure and function of ecosystems (Turner and Meyer, 1991). They usually involve empirically fitting the models to some historical pattern of change, and then extending these patterns for the future prediction. These models present a range of outcomes that reflect the current and recent trends that can serve as useful benchmarks against which more process-oriented models can be compared. To be useful, predictive models need to represent with reference to current and recent trends, (i) amount of land use and land cover changes, (ii) location of future changes, and (iii) spatial patterns of those changes. Although several models exist to address the first two of these conditions (Veldkamp, and Fresco, 1996; Landis and Zhang, 1998), few models exist that specifically aim to reproduce the spatial patterns of land cover changes.

Two primary types of LULC causal change models, namely regression type models and spatial transition-based models have been used for land cover change analysis (Theobald and Hobbs, 1998). The first types of models establish functional relationships between a set of spatial predictor variables that are used to predict the location of change on the landscape. The regression models utilize a system of observation in conjunction with ancillary variables, such as socio-economic data, to identify explicitly the causes of land use and land cover change. These types of models attempt to relate rates of cover conversion to data expressing the various hypothesized driving forces or proximate causes of land use and land cover changes. Regression analyses can be conducted in two ways: by cross-sectional analysis (i.e., at one point in time across a large number of specific locations), or by panel analysis (by relating change in cover during an interval of time to changes in other variables during the same interval across a large number of specific locations). Included in this category are logistic regression models (Landis, 1994), hedonic price models (Alig, 1986; Geoghegan et al., 1997), and artificial neural networks (Pijanowski et al., 2000).

To estimate probabilities of land use transition, land use change is typically modeled as a function of variables describing biophysical land quality (i.e. soils and terrain), and location relative to for example, jobs, markets and amenities (Landis and Zhang, 1998). This approach consists of analysing LULC conversion in relation to geographically referenced data on natural and cultural landscape variables. Both types of models, namely regression and spatial transition-based models could be used to include geographic site and situation variables in modeling changes.

In essence, these classes of models form a constellation of approaches which, when taken together, can be used to analyse when (Markov and logistic), why (regression) and where (spatial statistical) LULC conversion (or modification) processes operate. The suite of empirical models can serve as a foundation upon which system's dynamic models can be built; the essential feature being the use of direct observations of spatial phenomena.

Modelers have used linear statistical models, such as logistic regression (Wear and Bolstad, 1998; Schneider and Pontius, 2001), and non-linear approaches, like artificial neural networks, because the relationships between the predictor variables and land use and land cover change are not always linear. Generalized Additive Model (GAM) offers a non-linear statistical alternative to logistic regression (Hastie and Tibshirani, 1990). For the estimation of land cover patterns in Glacier National Park (USA), Brown (1994) implemented GAMs, and found significant non-linear relationships with topographic and disturbance variables. Besides, theory of evidence (Dempster-Shafer theory) has also been used for modeling LULC changes (Hubert-Moy et al., 2001). The Dempster-Shafer theory introduces uncertainty in modeling, and allows the expression of ignorance in the body of knowledge. It states that belief in a hypothesis is not necessarily the compliment of its negation.

2.2. PREVIOUS MODELS

Summarizing a large number of case studies, Agarwal et al., (2001) finds that land use and land cover change is driven by a combination of fundamental high level causes such as resource scarcity leading to an increase in the pressure of production on resources, changing opportunities created by markets, outside policy intervention, loss of adaptive capacity and increased vulnerability and changes in social organization, in resource access and in attitudes. Agarwal et al., (2001) highlight as many as 19 LULCC models for their spatial, temporal and human decision-making characteristics for comparing and reviewing land use change models (Figure 2.1).

1. General Ecosystem Model (GEM) (Fitz et al., 1996)
2. Patuxent Landscape Model (PLM) (Voinov et al., 1999)
3. CLUE Model (Conversion of Land Use and its Effects) (Veldkamp and Fresco, 1996)
4. CLUE-CR (Conversion of Land Use and its Effects – Costa Rica) (Veldkamp and Fresco, 1996)
5. Area base model (Hardie and Parks, 1997)
6. Univariate spatial models (Mertens and Lambin, 1997)
7. Econometric (multinomial logit) model (Chomitz and Gray, 1996)
8. Spatial dynamic model (Gilruth et al., 1995)
9. Spatial Markov model (Wood et al., 1997)
10. CUF (California Urban Futures) (Landis, 1994, Landis and Zhang, 1998)
11. LUCAS (Land Use Change Analysis System) (Berry et al., 1996)
12. Simple log weights (Wear et al., 1998)
13. Logit model (Wear et al., 1999)
14. Dynamic model (Swallow et al., 1997)
15. NELUP (Natural Environment Research Council (NERC)–Economic and Social Research Council (ESRC): NERC/ESRC Land Use Programme (NELUP) (O'Callaghan, 1995)
16. NELUP - Extension, (Oglethorpe and O'Callaghan, 1995)
17. FASOM (Forest and Agriculture Sector Optimization Model) (Adams et al., 1996)
18. CURBA (California Urban and Biodiversity Analysis Model) (Landis et al., 1998)
19. CA model (Clarke et al., 1997, Kirtland et al. 2000)

Figures 2.2 & 2.3 are the examples of the framework with the three dimensions represented together with a few general models, including other types that were reviewed by Agarwal et al. 2001. Various modeling approaches would vary in their placement along these three dimensions of complexity since the location of a LULCC model reflects its technical structure as well as its sophistication and application. The analysis that follows attempts to characterize existing LULCs models on each modeling dimension. Models are assigned a level in the human decision-making dimension, and their ability in the spatial and temporal dimensions are estimated as well. In addition, document and compare models across several other factors including: the model type, dependent or explanatory variables if any, modules, and independent variables (Agarwal et al., 2001).

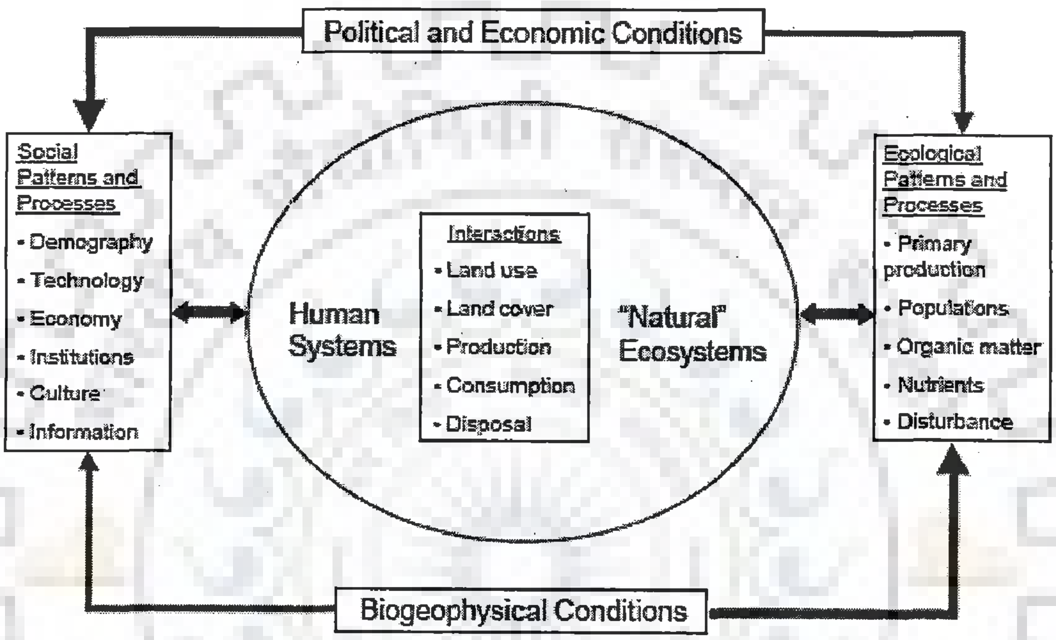


Figure 2.1: Conceptual framework for investigating human ecosystems (Sources: Agarwal et al., 2001)

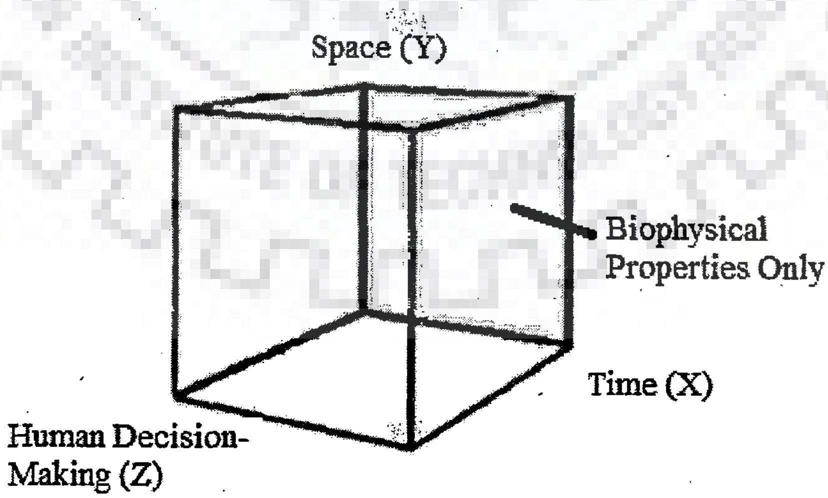


Figure 2.2: A three-dimensional framework for reviewing and assessing land use change models (Sources: Agarwal et al., 2001)

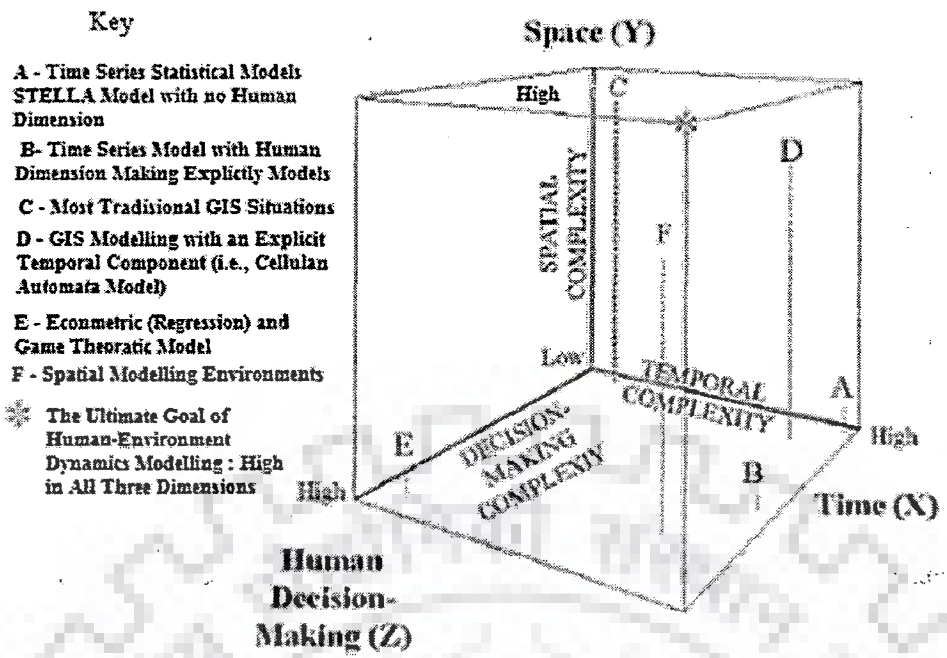


Figure 2.3: Model complexity and a three-dimensional framework for reviewing and assessing land use change models (Sources: Agarwal et al., 2001)

2.3. RECENTLY DEVELOPED MODEL

The models surveyed are taken from a series of recent papers, reports and workshops which have been carried out by members of LULCC and other research community (Turner et al., 1995; Moran, 2000; Pijanowski et al., 2000; Laurance et al., 2001; McConnell and Moran, 2001; Nepstad et al., 2001; Pontius et al., 2001, 2004; Vander Veen and Rotmans, 2001; Veldkamp and Lambin, 2001; Alves, 2002; Geist and Lambin, 2002b; Soares-Filho et al., 2002, 2004; Leemans et al., 2003; Pontius and Batchu, 2003; de Nijs et al., 2004; Engelen et al., 2003; Verburg et al. 2004; Verburg and Veldkamp, 2004; McConnell et al., 2004; Pontius et al., 2002, 2004; Pontius and Malanson, 2005; Pontius and Spencer, 2005; Batty and Torrens, 2005; Brown et al., 2005; Castella et al., 2005; Pijanowski et al., 2005; Koomen et al., 2005; Kasper et al., 2001; Pontius and Cheuk, 2006; Pontius and Lippitt, 2006; IDRISI (Clark Labs) Focus Paper 2007, 2008; Konstantinos et al., 2009). These can be summarized as:

1. GEOMOD & GEOMOD 2 (Pontius et al., 2001)
2. LTM (Land Transformation Model) (Pijanowski et al., 2001)
3. SELUTH (Slope, Land use, Exclusion, Urban extent, Transportation, Hill shade) (Clarke et al., 2003)
4. Environment Explorer (de Nijs, de Niet, and Crommentuijn, 2004)

5. CLUE-S (2005) (Verburg and Veldkamp, 2005)
6. Land Use Scanner (Koomen et al., 2005)
7. SAMBA (Castella et al., 2005)
8. Land Change Modeler – for Ecological Sustainability (Clark Labs., 2006)
9. Earth Trends Modeler (Clark Labs., 2007)
10. Multi Agent-Based Economic Landscape (MABEL) Model (Konstantinos, Alexandridis, Pijanowski and Zhen, 2008)

Pontius Jr. et al. (2001) modeled the spatial pattern of land use change for Costa Rica using GEOMOD 2 model. GEOMOD is a LULCC model designed to simulate a one-way transition from one category to one other category (Pontius et al., 2001; Pontius and Malanson 2005; Pontius and Spencer 2005). The model quantities factors associated with land use, and simulate the spatial pattern of land use forward and backward in time. Schneider and Pontius Jr. (2001) modeled the land use change in the Ipswich watershed, Massachusetts, USA using logistic regression, multi-criteria analysis and spatial filters.

For visualizing alternate future scenario of the Washington, DC – Baltimore region, Clarke and Gaydos (1998) used SLEUTH (Slope, Land use, Exclusion, Urban extent, Transportation, Hill shade) – one of the CA class of models. SLEUTH is a shareware CA model of urban growth and land use change, which was calibrated using four different methods: the traditional brute force method (Silva and Clarke, 2002), a full resolution brute force method (Dietzel and Clarke, 2004), a genetic algorithm (Goldstein, 2004), and a randomized parameter search.

Pijanowski et al. 2000, 2002 and 2005 used artificial neural networks to simulate land change. The neural net trains on an input-output relationship until it obtain a satisfactory fit between the data concerning urban growth and the independent variables. The LTM obtains a relationship between the independent variables and urban growth.

Koomen et al., (2005) uses Land Use Scanner model, which is a GIS-based model that uses a logit model and expert opinion to simulate future land use patterns (Koomen et al. 2005; Hilferink and Rietveld 1999; Schotten et al. 2001). The expected quantities of changes are based on a linear extrapolation of the national trend in land use statistics from two time data. The regional demand for each land use is allocated to individual pixels based on suitability. Suitability maps are generated for all different land uses based on physical properties, operative policies, relations to nearby land use functions, and expert judgment. The model uses data in which each pixel possesses a specific proportion of 36 possible categories.

de Nijs, et al., (2004) uses Environment Explorer which is a dynamic CA model, which consists of three spatial levels (de Nijs et al., 2004; Engelen et al., 2003; Verburg et al., 2004). At the national level, the model combines countrywide economic and demographic scenarios, and distributes them at the regional level. The regional level uses a dynamic spatial interaction model to calculate the number of inhabitants and number of jobs over forty regions, and then proceeds to model the land use demands. Allocation of the land use demands on the 500 meter grid is determined by a weighted sum of the maps of zoning, suitability, accessibility, and neighborhood potential.

Castella et al., (2005) modeled SAMBA, which is an agent-based modeling framework. "SAM" is the French mountain name and "BA" means "three" in Vietnamese. The SAMBA team developed a number of scenarios that were discussed by scientists and local stakeholders as part of a negotiation platform on natural resources management through a participatory process combining role-play gaming and agent-based modeling (Boissau and Castella 2003; Castella et al., 2005 a; Castella et al., 2005 b). The model is parameterized according to local specificities, e.g. soil, climate, livestock, population, ethnicity, and gender.

Verburg et al., (2005) developed CLUE-S (2005), which is a fundamentally revised version of the model called Conversion of Land Use and its Effects (CLUE 1996). CLUE-S (2005) is a spatially-explicit, multi-scale model that projects land use change (Kok et al., 2001; Veldkamp and Fresco 1996; Verburg et al. 1999). CLUE (1996) is the predecessor of CLUE-S, so the two models share many common philosophical approaches and computational features. The CLUE (1996) model structure is based on systems theory to allow the integrated analysis of land use change in relation to socio-economic and biophysical driving factors. Verburg et al. (2002) developed a dynamic, spatially explicit land use change model – CLUE (Conversion of Land Use and its Effects) for the regional scale. CLUE-S is designed to work with fine resolution data where each pixel represents a single dominant land use, rather than a heterogeneous mix of various categories as in the original CLUE model (Verburg et al., 2002; Verburg and Veldkamp, 2004). CLUE-S consists of two main components. The first component supports a multi-scale spatially-explicit methodology to quantify empirical relationships between land use patterns and their driving forces. The second component uses the results from the first component in a dynamic simulation technique to explore changes in land use under various scenarios. A combination of expert knowledge and empirical analysis usually serve for calibration. A user of CLUE-S can specify any quantity of land change based on various sectoral models.

Clark Labs (2006) developed the Land Change Modeler (LCM) for ecological sustainability is a software solution designed to address the pressing problem of accelerated land conversion and the very specific analytical needs of biodiversity conservation. Land Change Modeler provides tools for the assessment and projection of land cover change, and the implications for species habitat and biodiversity.

Clark Labs (2007) developed Earth Trends Modeler is a new vertical application focused on the analysis of trends and the dynamic characteristics of these phenomena as evident in image time series. Earth trends modeler allows to view animations of series in a space-time cube format, analyze variability across varying temporal scales, extract profiles of values over time, and analyze long-term trends with a variety of tecniques for trend analysis. Tools are included to examine trends in seasonality, such as phenological change in plant species, with a newly developed procedure for seasonal trend analysis, utilize principal components analysis for the decomposition of a series into its underlying constituents, uncover characteristic patterns of variability over space-time with the empirical orthogonal teleconnection (EOT) method, explore for the presence of cycles in the series utilizing Fourier-PCA, and examine relationships between series using a linear modeling (multiple regression) tool.

Konstantinos et al., (2009) developed MABEL model uses sequential decision-making process simulations for base agents in multi-agent based economic landscape. The sequential decision-making process described here is a data-driven Markov-Decision Problem (MDP) integrated with stochastic properties. Utility acquisition attributes in our model are generated for each time step of the simulation. The basic components of such a process in MABEL are illustrated, with respect to land use change. How Geographic Information Systems (GIS), socio-economic data, a knowledge base, and a market model are integrated into MABEL? A rule-based maximum expected utility acquisition is used to as a constraint optimization problem. The optimal policy of base-agents' decision making in MABEL is one that maximizes the differences between expected utility and average expected rewards of agent actions. Finally, a procedural representation of extracting optimal agent policies from socio-economic data is presented using Belief Networks (BN's) (Konstantinos et al., 2009).

2.4. PROBLEM WITH LAND USE AND LAND COVER (LULC) MODELING

Initial knowledge on extrinsic and intrinsic factors operating at different spatial and temporal scales is urgently required to be developed for quantifying LULC changes. In the past few decades, there are substantial changes observed in LULC, because of expansion of mining areas, increment in construction of dams, industrialization, urbanization etc., to name a few, which affect the areas as an external factors. Internal changes includes shifting cultivation areas, selective logging due to human pressure on forest resources and habitat loss of wildlife due to reduction in the forests. Land use and land cover change is, however, poorly understood. The long-term global character, extent, and rates of changes in land cover and some land uses are known in rough outline. Uncertainty and error remain relatively high (Meyer and Turner, 1994), yet the advent of more precise and geographically referenced data on cover and use has created opportunities for improved analysis. Modeling the dynamics of land use and land cover change, however, has been hindered by the large variation in those dynamics across physical and social settings. Global aggregate assessments based on simple assumptions miss the target for large sections of the world, while local and regional assessments are too specific to be extrapolated to wider scales. Much work remains to be done to fill these increasingly critical gaps in understanding.

2.5. SUMMARY

Within reviewed models, no single model was available, which will fulfil all needs of LULC change analyst community. Each and every model has some merit and demerits. Some models technical limitations (i.e., spatial interaction, temporal complexity etc.), some models considered limited human decision making or socio-economic factors, some model considered limited biophysical factors. It is also observed that one single model cannot be sufficient for LULCC modeling that is suitable worldwide. It is due to regional variation of human dimension and biophysical factors. Much modeling work remains to be done to understand land use and land cover changes. LULCC modeling for developing regions with considering regional factorial specification requires to be developed in future.

Chapter - 3

STUDY AREA, DATA AND METHODOLOGY USED

3.1. STUDY AREA

The study area comprises part of Brahmaputra River basin spreading over an area about 413.94 km². The area lies in parts of (Azara, Guwahati, New Guwahati and Dispur revenue circles) of Kamrup Metropolitan district in the state of Assam, India. Geographically, it is located between 26° 02' 04" to 26° 14' 27" north latitudes and 91° 33' 01" to 91° 51' 41" east longitudes. The principal river in the area is the Brahmaputra River (Figure 3.1). It is located on Survey of India topographical maps 72N/12 and 72N/16 at 1:50,000 scale, covering banks of Brahmaputra River and foothill zone of lower Meghalaya Hills with elevation ranging from 49.5 m to 638 m above the mean sea level. But average altitude of the Guwahati city area is 54 m (above MSL).

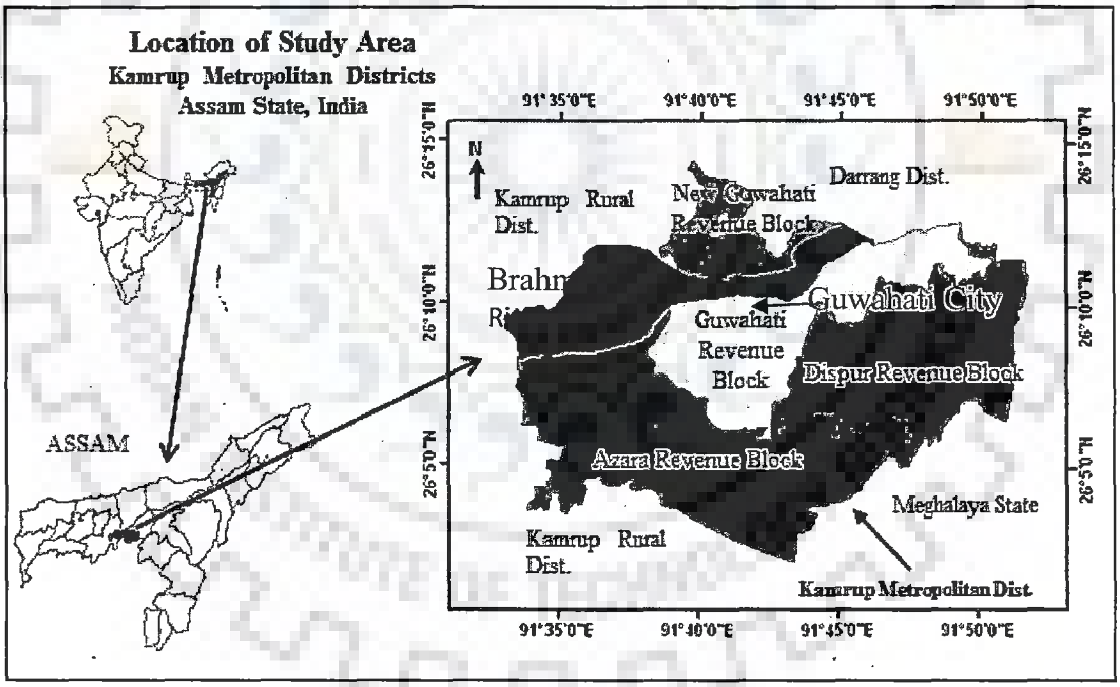


Figure - 3.1: Location of study area

3.1.1. Climates of Study Area

Climate of the study area is sub-tropical with semi-dry summer & cold in winter. Annual rainfall ranges between 1500 mm to 2600 mm. Average humidity is 75%, maximum and minimum temperatures are 38.5°C and 7°C, respectively (Source: National Informatics Centre - Kamrup Districts). The major natural calamity is flood, which occurs generally in the low lying areas of the district during May to August every year. Late flood during the later part of September & October also occurs. The occurrence of flood in the district is due to the river Brahmaputra and its tributaries. During rainy days the city of Guwahati also witnesses localised flood due to poor drainage system of the city.

3.2. DATA USED FOR THE STUDY

Digital satellite data of Landsat - 5 TM image acquired on Dec. 26, 1987, IRS-1C LISS III image acquired on March 5, 1997, IRS-P6 LISS III image acquired on Dec.14, 2007 has been used for this study. Properties of the satellite data used in the study shows in Table 3.1 and Figure 3.2. Other than satellite data, Survey of India (SOI) topographic sheet No. 72N/12 & 72N/16 at 1:50,000 scales along with master plan prepared by Guwahati Metropolitan Development Authority (GMDA) also have been used for this study. Data from Guwahati Metropolitan Development Authority (GMDA), Guwahati Municipal Corporation (GMC), Kamrup Metropolitan District - National Informatics Centre (NIC) have been also used (Table 3.2).

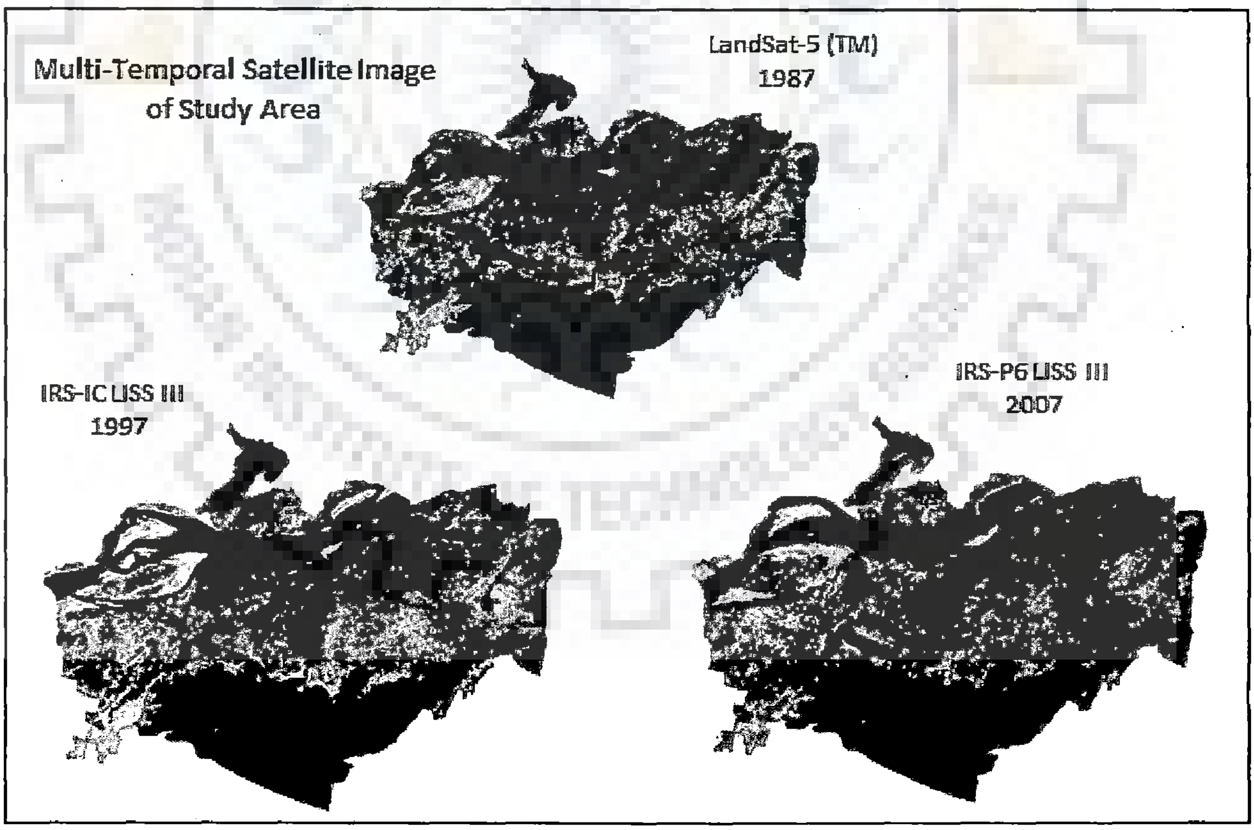


Figure – 3.2: Satellite images of study area

Table - 3.1: Details of satellite data used in the study

Satellite	Sensor	Path / Row	Data Acquired	Spatial Resolution (m)	Spectral Band	Data Sources
LANDSAT - 5	TM	136/042 (WRS-2 footprints)	26-12-1987	30 (120 m – thermal (B 6))	B 1 (blue): 0.45-0.52 µm B 2 (green) : 0.52-0.60 µm B 3 (red): 0.63-0.69 µm B 4 (NIR): 0.76-0.90 µm B 5 (SWIR): 1.55-1.75 µm B 6 (thermal IR):10.4-12.5 µm B 7 (Mid-Infrared) : 2.08-2.35 µm	GLCF*-Earth Science Data Interface
IRS-1C	LISS-III	110/53	05-03-1997	23.5 (70 m - B5 (SWIR))	B 2 (green) : 0.52 – 0.59 µm B 3 (red): 0.62 – 0.68 µm B 4 (NIR): 0.77 – 0.86 µm B 5 (SWIR): 1.55 – 1.70 µm	NRSC
IRS-P6 (Resourcesat-1)	LISS-III	110/53	14-12-2007	23.5	B 2 (green) : 0.52 – 0.59 µm B 3 (red): 0.62 – 0.68 µm B 4 (NIR): 0.77 – 0.86 µm B 5 (SWIR): 1.55 – 1.70 µm	NRSC

*The *Global Land Cover Facility* (*GLCF*) is a NASA-funded member of the Earth Science Information Partnership at the University of Maryland, providing free satellite images to users all over world.

Table – 3.2: Others data used in the study

Data	Data Sources	Scale
Topographic Sheet No. 72N/12 & 72N/16	Survey of India (SOI)	1:50,000
Master Plan of Guwahati	Guwahati Metropolitan Development Authority (GMDA)	1: 25,000
Maps	- Guwahati Metropolitan Development Authority (GMDA) - Guwahati Municipal Corporation (GMC) - Kamrup Metropolitan District - National Informatics Centre (NIC)	at various scale
IKONOS, QUICKBIRD Satellite Images	www.earth.google.com	

3.3. METHODOLOGY USED FOR THIS RESEARCH

The methodology used for this study is shows in Figure 3.3. It involves the following phases: classification of multi temporal satellite images and accuracy assessment of classification; critical analysis of LULC changes; CA Markov modeling to predict LULC of 2007 using classified 1987 and 1997 images; validation of predicted results; cellular automata (CA) contiguity filters impacts on modeling results; sensitivity analysis to identify sensitive LULC parameter(s); statistical independence test of predicted results; prediction of LULC of 2017, 2027 and 2050 using 1987 & 1997, 1997 & 2007 and 1987 & 2007 LULC images, analysis of time steps effects on predicted results of 2017, 2027 and 2050. Further details are given in subsequent chapters.

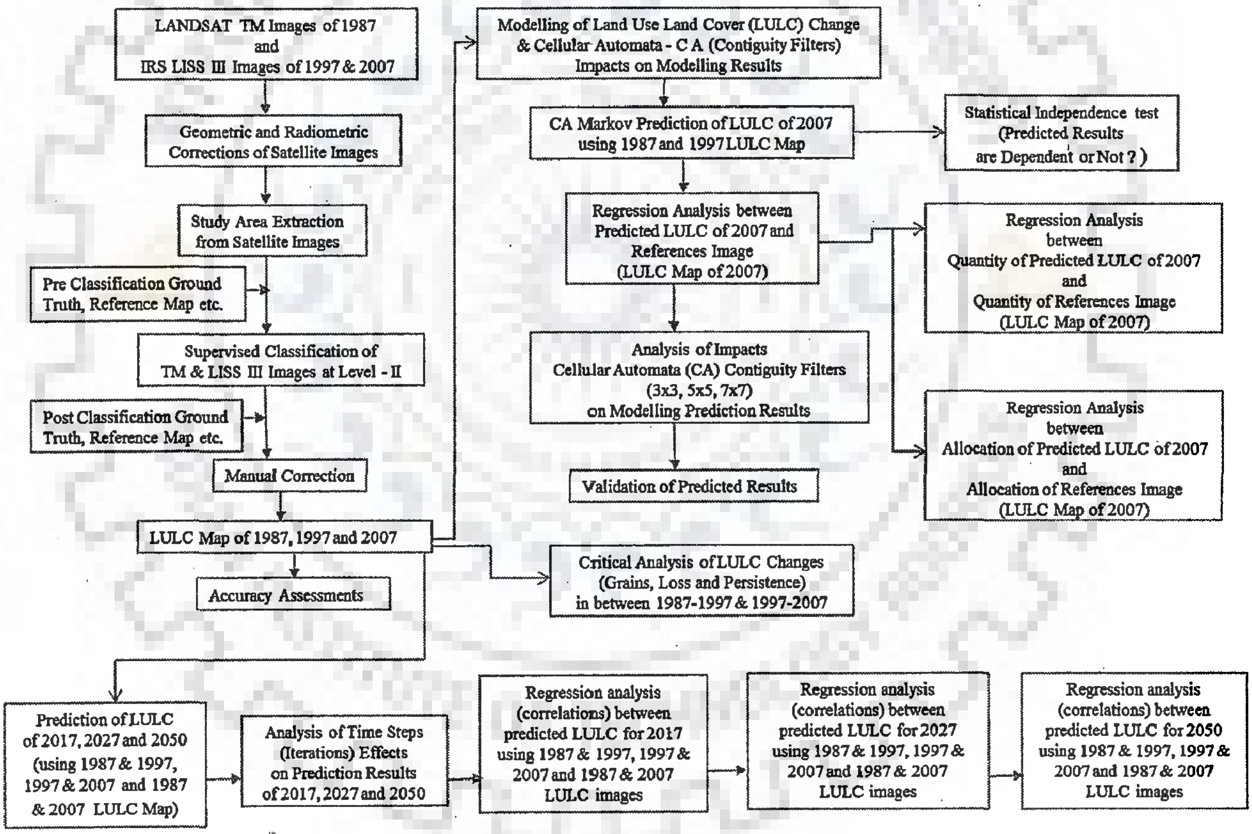


Figure - 3.3: The overall methodology adopted for this research

Chapter - 4

LAND USE AND LAND COVER (LULC) MAPPING

4.1. METHODOLOGY FOR LAND USE AND LAND COVER (LULC) MAPPING

The methodology adopted in this study involves following phases: pre-processing of satellite images, development of a classification scheme, formation of training dataset, spectral separability analysis, satellite images classification and accuracy assessment (Figure 4.1).

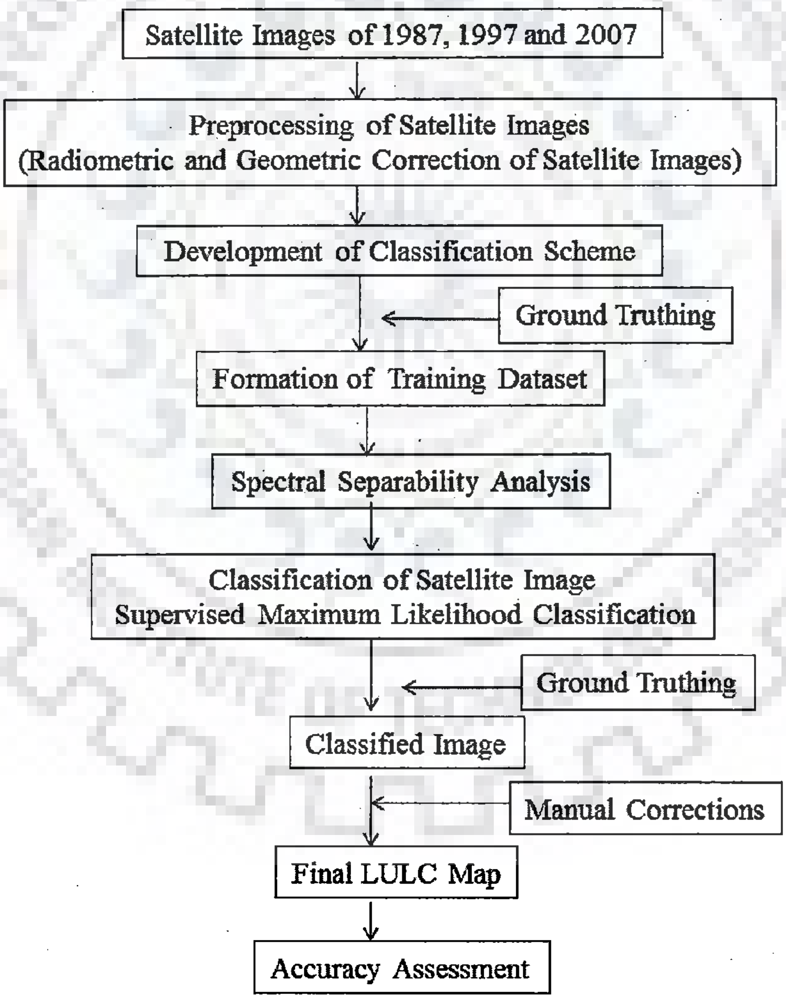


Figure 4.1: Flowchart shows methodology adopted for LULC mapping

4.1.1. Preprocessing of Satellite Images

4.1.1.1. Radiometric correction of satellite images

The image dataset used in this study consists of Landsat-5 TM images of December 1987, IRS -1C images of March 1997 and IRS-P6 images of December 2007. Only images acquired in December and March months (winter season) were considered. The available images were selected based on the absence of cloud cover. When multi-date images from different sources are used, different atmospheric and terrain conditions may cause variations in data. Therefore, radiometric corrections including atmospheric correction were applied in this study. After carefully checking with all the acquired images over the study area, it was found that the atmospheric effects were mainly caused by the variation of illumination and haze. Therefore, an atmospheric correction method incorporated in ERDAS Imagine 9.0 - was applied to all images used in the study. The process considers atmospheric properties, sensor characteristics, elevation and solar zenith angles in calculating reflectance values, also called Top-of-Atmosphere (TOA) reflectance calibration. The TOA calibration is to correct the reflectance differences caused by the solar distance and angle. The sun zenith and azimuth angles for each pixel and the distance from the scene centre to the sun are calculated. The reflectance correction is then calculated for each band, as described by Vermote et al., (1997). Top-of-Atmosphere (TOA) reflectance is also removed from IRS series data.

4.1.1.2. Geometric correction of satellite images

After radiometric correction, geometric correction was applied to the images. The 1987 Landsat image from Global Land Cover Facility (GLCF) was chosen which has been orthorectified by the United States Geological Survey (USGS). For accurate change detection and modelling of LULCC especially for future prediction of LULC, an accurate geometric registration is needed. The IRS-1C images of 1997 and IRS-P6 images of 2007 were rectified (geometrically corrected) with reference to the orthorectified Landsat satellite image of 1987. A two-order polynomial transformation model was used and, furthermore, the recommended number of ground control points (GCPs), was increased by 14 more points (mainly road junctions, refer to Figure 4.2) to further improve the georeferencing accuracy. All images were resampled using Nearest Neighbor resampling method with a root mean square error of less than ± 0.5 pixels per image to a 23.5 m resolution with the UTM coordinate system (zone 46, WGS 84 datum system).

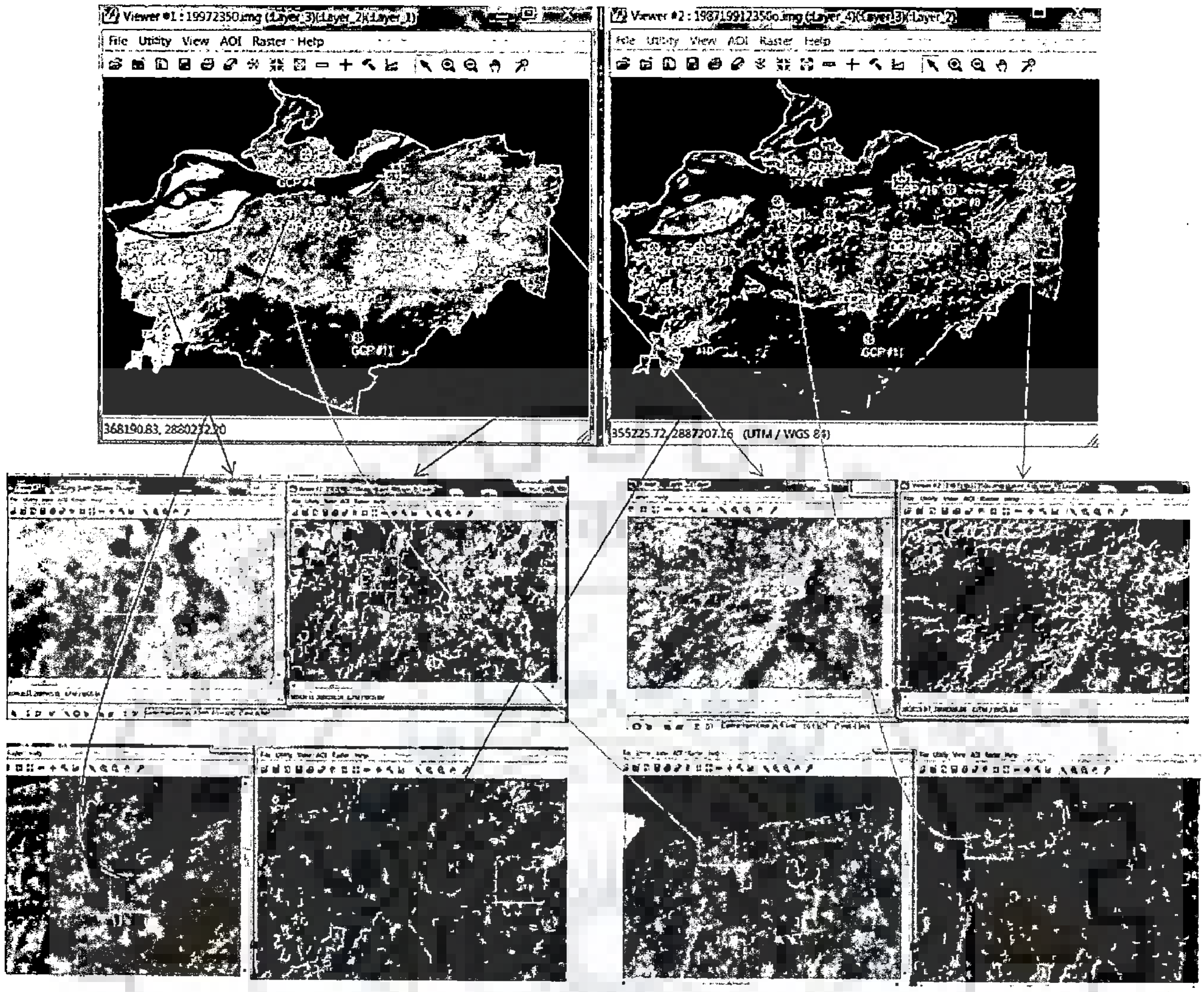


Figure 4.2: Ground Control Points (GCPs) collected in entire images (mainly road junctions or in bridges) for geometric correction of satellite images

4.1.2. Development of a Classification Scheme

To classify satellite images, first of all a suitable classification scheme for the study area is needed. There are different perspectives in the classification process, and the process itself tends to be subjective, even when an objective numerical approach is used. Each classification is made to suit the needs of the user, and few users will be satisfied with an inventory that does not meet most of their needs (Anderson, 1971). Therefore, for this study modified (modified from NRSA classification system for India and classification scheme adopted for European Commission sponsored Brahmatwin projects) classification scheme (level II) is adopted for different categories of LULC (Table 4.1 & Table 4.2). The principal data source for Level II classification scheme data at the present time is high-altitude, color-infrared photography. Scales smaller than 1:80,000 are characteristics of high-altitude photographs, but scales from 1: 24,000 to 1: 250,000 generally have been used for the final map products. Similarly, several Level II categories have been interpreted from Landsat data supported with 1: 50,000 scale Survey of India topographical sheets along with secondary map (i.e., Master Plan) as well as very high resolution Google Earth images and maps.

Table - 4.1: Levels and LULC classes considered for classification

Level I	Level II
1. Built Up Land	1.1. Built Up Land
2. Agricultural land	2.1. Agricultural Crop Land
	2.2. Agricultural Fallow Land
	2.3. Plantations
3.Forest	3.1. Dense Forest
	3.2. Degraded Forest
4.Waste Land	4.1. Land with or without Scrub
	4.2. Marshy / Swampy
	4.3. Waterlogged Area
	4.4. Sandy Area (River Bed)
5. Water Bodies	5.1. River / Stream
	5.2. Lake/Reservoir/Pond/Tank
6. Others	6.1. Open Land
	6.2. Aquatic Vegetation

Table - 4.2: Description of different land use and land cover classes

LULC Classes	Description
1. Built-up Land	It is defined as an area of human habitation developed due to non-agricultural use and that which has a cover of buildings, transport, and communication, utilities in association with water, vegetation and vacant lands.
2. Agricultural Land	It is defined as the land primarily used for farming and for production of food, fiber, and other commercial and horticultural crops. It includes crop land, fallow and agricultural plantations.
2.1. Agriculture Crop land	It includes those lands with standing crop as on the date of the satellite imagery. The crops grown either in kharif or rabi or double crop (Kharif + Rabi) seasons. The kharif season satellite imageries were used to identify the cropland under kharif season. At the time of field validation the major kharif crop identified.
2.2. Agriculture Fallow Land	It is described as agricultural land, which is taken up for cultivation but is temporarily allowed to rest, un-cropped for one or more seasons. These lands are particularly those, which are seen devoid of crops at the time when the imagery is taken of both seasons.
2.3. Plantation	It is described as an area of trees of species of forestry importance and raised on notified forestlands. This sub-class consists mainly of Eucalyptus plantations as observed during field visit.

3. Forest	It is an area (within the notified forest boundary) bearing an association of pre-dominantly of trees and other vegetation types capable of producing timber and other forest produce. This class is distributed in north-west, west, south and south-western parts of study area. The sub-classes under this class have been identified and described.
3.1.Dense Forest	Forest land includes all forested areas like moist deciduous, dry deciduous and tropical thorn forest species. The low spatial resolution and the heterogeneous nature of the forest cover allowed only a generalized classification. Further, the satellite data had been acquired during the leaf fall season (December & March). Most of the trees had shed their leaves exposing the ground in different degrees.
3.2. Degraded Forest	In this sub-class, the vegetative density is still less than 20% of the canopy cover and gradually under degraded stage. This is also the result of both biotic and abiotic influences.
4. Wasteland	Wastelands may be described as degraded land which can be brought under vegetative cover with reasonable effort and which is currently under unutilized land. This land is deteriorating due to lack of appropriate water and soil management or on account of natural causes. Wastelands can result from inherent/imposed constraints such as by location, environment, chemical and physical properties of the soil or financial or management constraints. This class includes land with or without scrub, Marshy / Swampy, Water Logged Area, Sandy Area (River Bed).
4.1. Land With or Without Scrub	This sub-class is found usually at relatively higher topography like uplands or high grounds with scrub or without scrub. These lands are generally prone to degradation or erosion.
4.2. Marshy / Swampy	Predominately wetland or marsh features associated with water and also indicative of upland wetland features or forested wetland vegetation
4.3. Waterlogged Area	The rise of water table beyond a critical limit or surface ponding results in water logging condition.
4.4. Sandy Area (River Bed)	Sandy areas mostly occur in this study this category found in river bed and river flood plains area.
5. Water Body	Water as defined, includes all areas within the land mass of the earth that persistently are water covered. Water body is an area of impounded water, aerial in extent and often with a regulated flow of water. It includes man-made lakes / tanks besides natural lakes, rivers and streams. Satellite data is found reliable in locating surface water and multispectral band shows the contrast between water and other surfaces on the ground so clearly that water bodies were identified in the study area.
5.1. River / Stream	These are the natural course of flowing water on the land along definite channels. It includes from a small stream to a big river and its branches. These may be perennial or non-perennial. The study area is drained by important perennial river system named Brahmaputra.
5.2. Lake/Reservoir/Pond/Tank	Lakes are the natural or man-made enclosed water body with a regulated flow of water. These features are medium/smaller in aerial extent when compared to reservoirs with limited use. For this study we found lake (beel) and ponds only.
6.1. Open Land	In this category barren lands and sands have been put. Barren land is a land of limited ability to support life. In general it is thin soil.
6.2.Aquatic Vegetation	Aquatic vegetation is plants that have adapted to living within aquatic environments. They are also referred to as hydrophytes or aquatic macrophytes. These plants require special adaptations for living submerged in water or at the water's surface. Aquatic plants can only grow in water or in soil that is permanently saturated with water. In this study aquatic vegetation we found mostly in Beel (Lake) areas.

4.1.3. Formation of Training Datasets

As supervised classification technique will be used for this study, it requires a priori knowledge of the number of classes, as well as knowledge concerning statistical aspects of the classes. In supervised training, the user relies on her / his own pattern recognition skills and priori knowledge of the data to help the system determine the statistical criteria (signatures) for data classification. These are called "training sites". To select reliable training samples, the users should know some information-either spatial or spectral-about the pixels that they want to classify. The location of a specific characteristic, such as a land cover type, may be known through ground truthing. Ground truthing refers to the acquisition of knowledge about the study area from field work, analysis or aerial photography, personal experience, etc. Global positioning system receivers are useful tools to conduct ground truth studies and collect training sets. Training samples are sets of pixels that represent what is recognized as a discernible pattern, or potential class. The system will calculate statistics from the sample pixels to create a parametric signature for the class.

Areas of visually homogeneous spectral response were chosen (10-12 training set for per class) well distributed all over images as AOI (area of interest) and added to the spectral signature editor (Figure 4.3). Limited pre-classification ground truth helped to select the training samples. The pre-classification ground truth was conducted on 14th Dec., 2007, the same date when satellite collected the images for the study area (Figure 4.4). After the base training sets are established, each training set 'signature' is scrutinized by looking at the brightness count histogram for each band of each set. The histogram exhibited a unimodal distribution in each band. A bimodal distribution would indicate that the training area had two distinct classes of pixels instead of one classification (i.e., a region being picked to train pixels of agricultural region may include some forested area also). The spectral characteristics of signatures of training samples marked on satellite images of 1987, 1997 and 2007 are shows in Figure 4.5a, 4.5b and 4.5c, respectively.

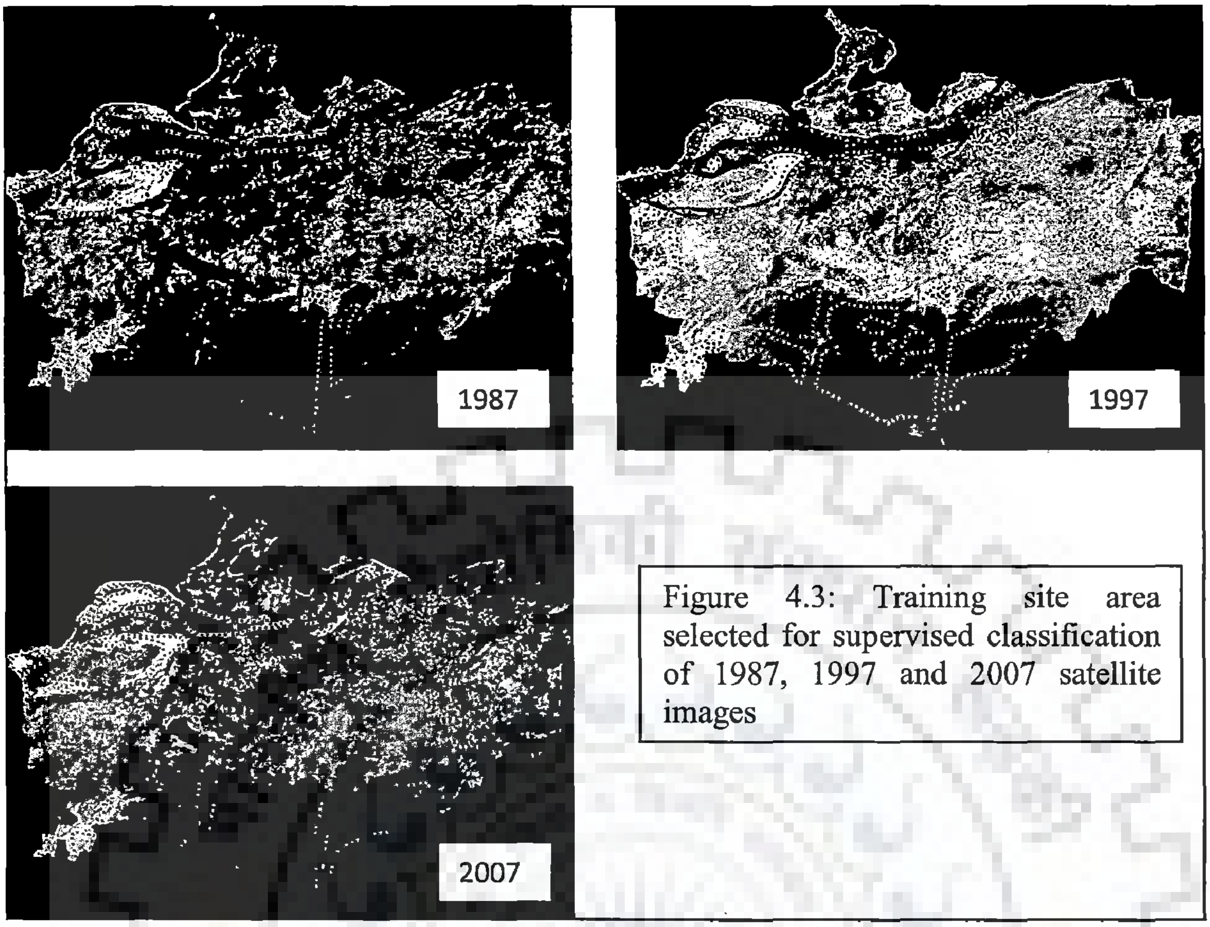


Figure 4.3: Training site area selected for supervised classification of 1987, 1997 and 2007 satellite images

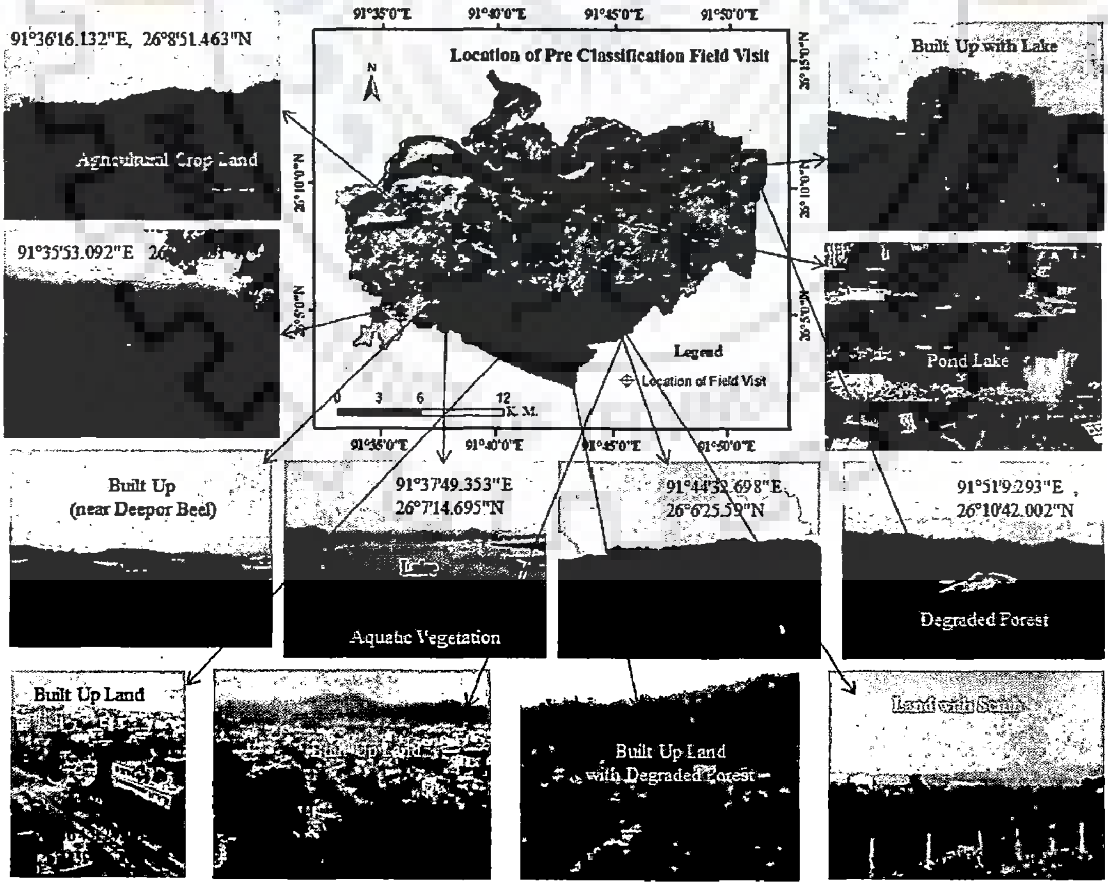


Figure 4.4: Location of pre-classification field visit and photographs

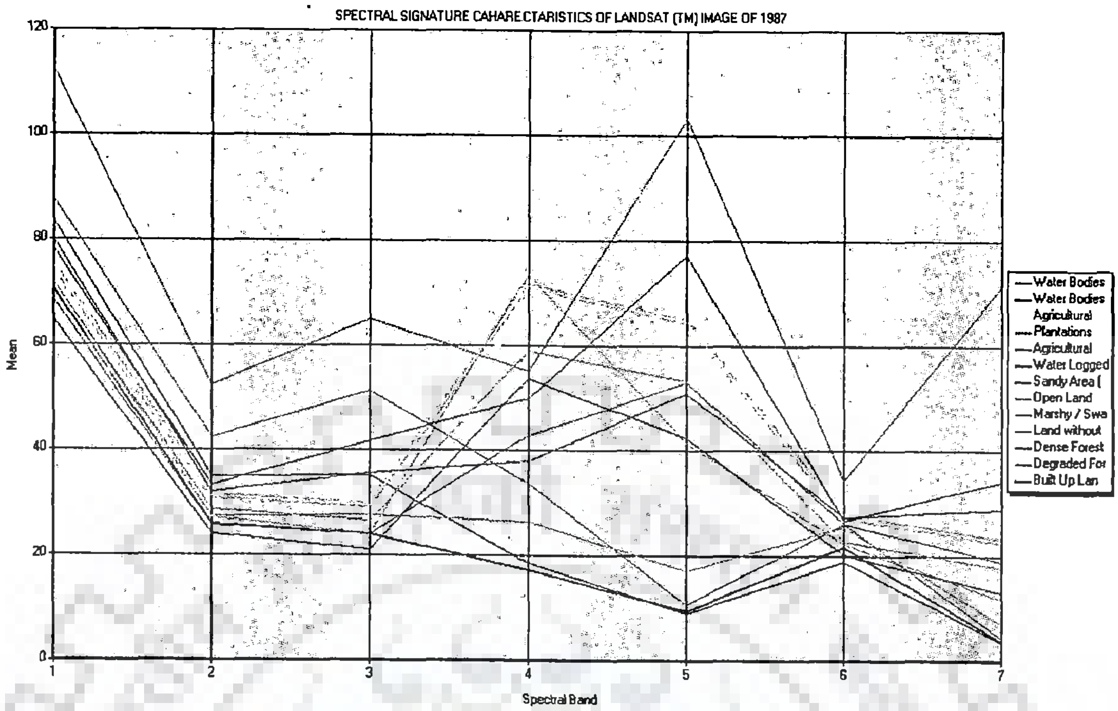


Figure 4.5a: Spectral characteristics of signatures of training samples for satellite images of 1987

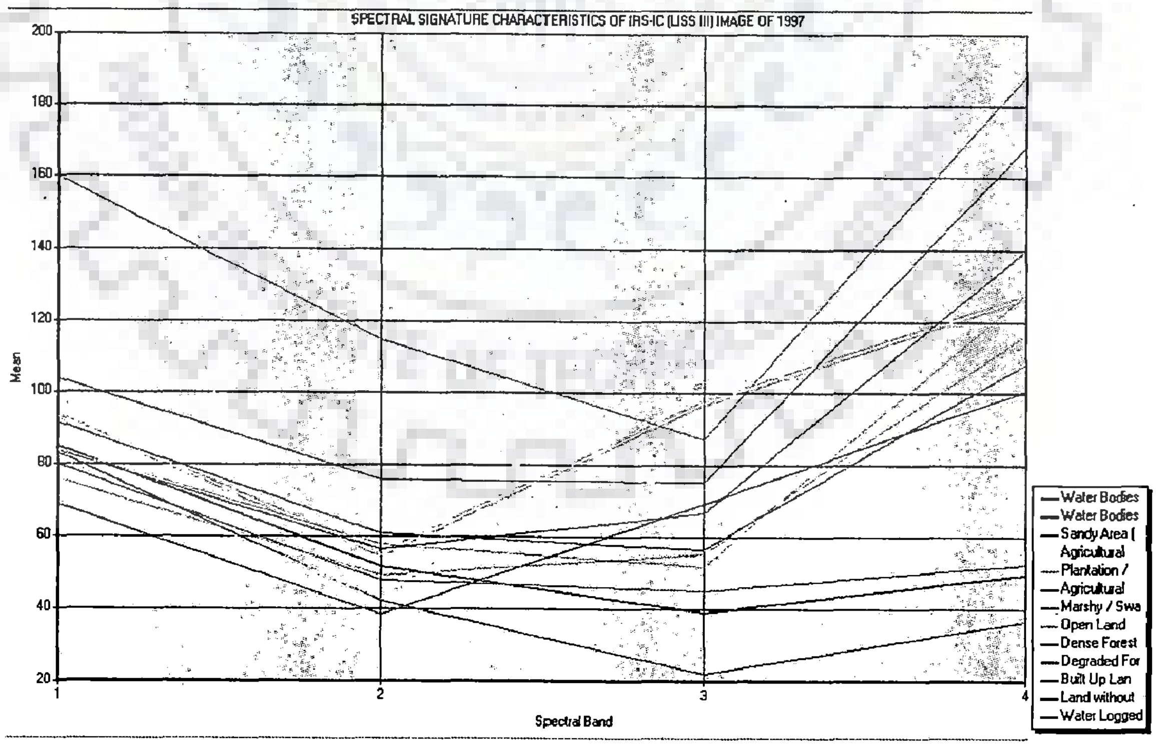


Figure 4.5b: Spectral characteristics of signatures of training samples for satellite images of 1997

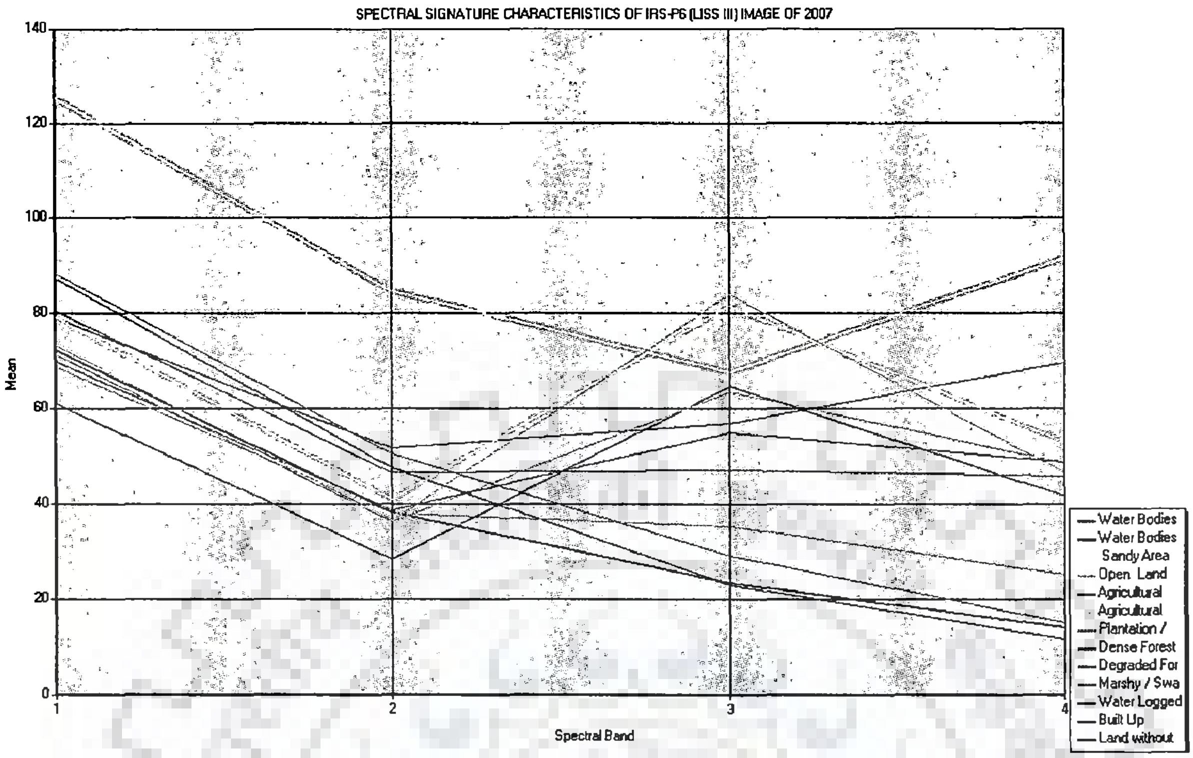


Figure 4.5c: Spectral characteristics of signatures of training samples for satellite images of 2007

4.1.4. Spectral Separability Analysis

In the classification, the signature separability functions were used to examine the quality of training sites and class signature, before performing the classification. Seperability helps refining the digital accuracy of classification (Dwivedi et. al., 2001). A separability listing is a report of computed divergence for every class pair and one band combination. The listing contains every divergence value for the bands studied for every possible pair of signatures. The separability listing also contains the average divergence and the minimum divergence for the band set. These numbers can be compared to other separability listings (for other band combinations) to determine which set of bands is the most useful for classification (Campbell, 2007). Class separability analysis was carried out by computing the transformed divergence (TD) values. Transformed divergence (TD) has upper and lower bounds between 0 and 2000. If the calculated divergence is equal to the appropriate upper bound, then the signatures can be said to be totally separable in the bands being studied. A calculated divergence of zero means that the signatures are inseparable. The separability cell array presents the results of one of the classifications for Landsat data of 1987, with range of values (from 1931.08 to 2000, where the average divergence is 1965.54) in the band combinations of band 2 (green: 0.52-0.60 μm), band 3 (red: 0.63-0.69 μm), band 4 (NIR: 0.76-0.90 μm) combination. IRS-1C LISS III of 1997 show the range of divergence values from 1903.02 to 2000 in the band 2 (green: 0.52 – 0.59 μm), band 3 (red: 0.62 – 0.68 μm), band 4 (NIR: 0.77 – 0.86 μm) combination. IRS-P6 LISS III of 2007 shows the range of divergence values from 1922.02 to 2000 in the band 2 (green: 0.52 – 0.59 μm), band 3 (red: 0.62 – 0.68 μm), band 4 (NIR: 0.77 – 0.86 μm) combination. Therefore, combination of band 2 (green), band 3 (red) and band 4 (near infra-red) was the most useful for classification purposes for the time series data (i.e., 1987, 1997, and 2007). As all separability figures are above 1900, it shows very good separability between the different classes implying that our results of the final classification are good. The results would require ground-truth as a final accuracy check.

4.1.5. Classification of Satellite Images

For this study, supervised maximum likelihood classifier is used to classify of all satellite images. As we know, supervised classification is usually appropriate when relatively few classes are to be identified, or when training sites have been selected that can be verified with ground truth data, or when distinct, homogeneous regions are identified that represent each class. Maximum likelihood classification method uses the training data as a means of estimating means and variances of the classes, which are then used to estimate probabilities. Maximum likelihood classification considers not only the mean or average values in assigning classification, but also the variability of brightness values in each class. It is the most powerful classification methods as long as accurate training data are provided. Therefore, this method requires excellent training data. An advantage of this method is that it provides an estimate of overlap areas based on statistics. The maximum likelihood decision rule is based on the probability that a pixel belongs to a particular class is more. The basic equation assumes that these probabilities are equal for all classes, and that the input bands have normal distributions. The maximum likelihood algorithm assumes that the histograms of the bands of data have normal distributions (Campbell, 2007).

4.1.6. Accuracy Assessment

Accuracy assessment is an important step in the classification process. The goal is to quantitatively determine how effectively pixels were grouped into the correct feature classes in the area under investigation. The land use and land cover types derived from digital image classification validate with data obtained from limited post-classification ground verification and using high resolution Google earth images (Figure 4.6). For quantitative estimates of the classification accuracy of classified images samples were selected randomly (Congalton et al, 1983). Accuracy estimation in terms of overall accuracy, errors of omission and errors of commission, and Kappa coefficient ($\hat{K}$) was subsequently made after generating confusion matrix. The Kappa coefficient ($\hat{K}$) was computed as follows (Bishop et al., 1975):

$$\hat{K} = \frac{N\sum_{i=1}^{r} x_{ii} - \sum_{i=1}^{r}(x_{i+} * x_{+i})}{N^2 - \sum_{i=1}^{r}(x_{i+} * x_{+i})} \quad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots(4.1)$$

where, r is the number of rows in the matrix, x_{ii} is the number of observations in row i and column $_i$ (the $_i$ th diagonal elements), x_{i+} and x_{+i} are the marginal totals of row r and column i, respectively, and N is the number of observations. The Kappa coefficient lies typically at a scale between 0 and 1, where the latter indicates complete agreement, and is often multiplied by 100 to give a percentage measure of classification accuracy. Kappa values are also characterized into 3 groupings: a value greater than 0.80 (80%) represents a strong agreement, a value between 0.40 and 0.80 (40 to 80%) represents a moderate agreement and a value below 0.40 (40%) represents a poor agreement (Congalton, 1996).

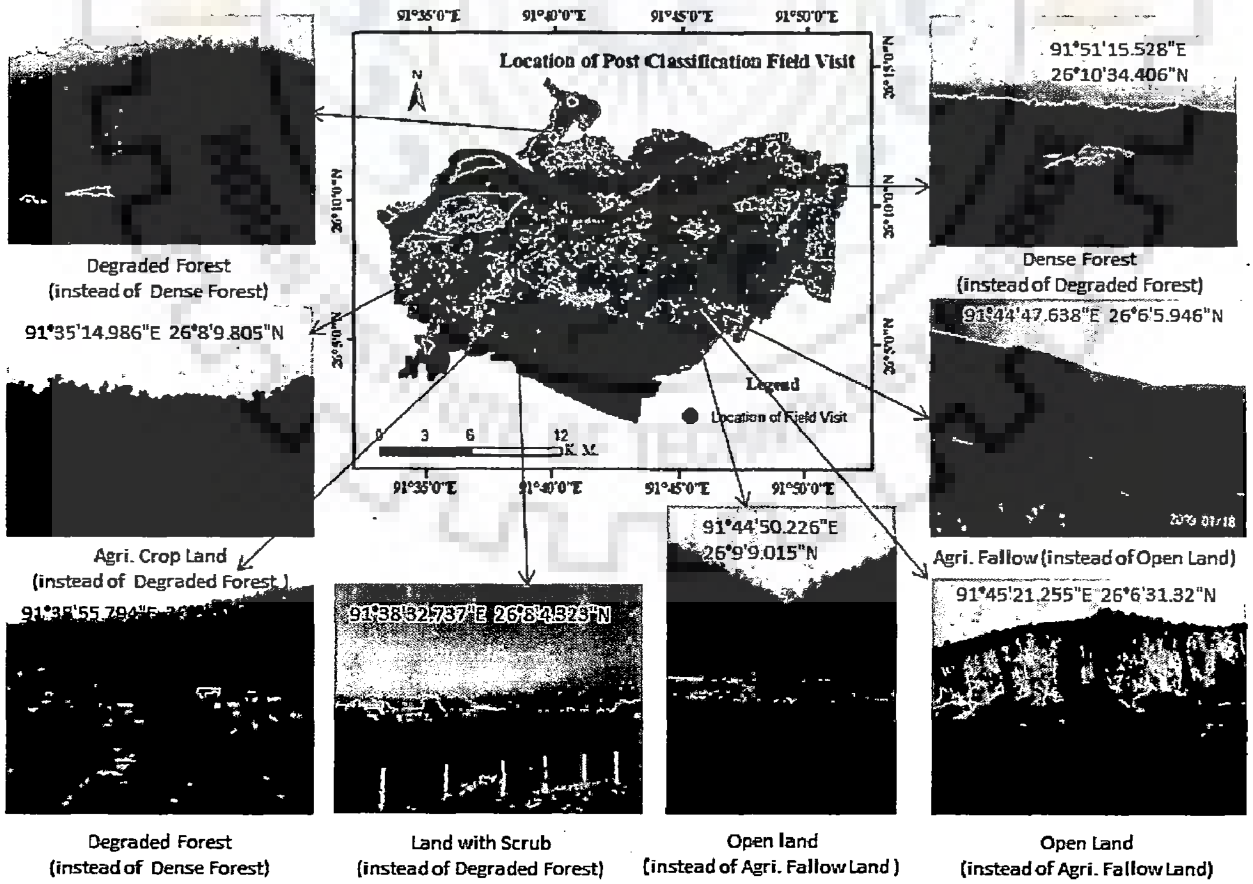


Figure 4.6: Location of post-classification field visit and photographs

4.2. CLASSIFICATION RESULTS AND DISCUSSIONS

4.2.1. Quantity of Land Use and Land Cover (LULC)

The quantitative results of land use and land cover assessment based on digital classification of satellite images for three different years 1987, 1997 and 2007 are shows in Table 4.3. Each LULC map (1987, 1997 and 2007) contains 14 LULC classes i.e., built up land, agricultural crop land, agricultural fallow land, plantation, dense forest land, degraded forest land, land with or without scrub, marshy / swampy land, waterlogged area, sandy area, river, lakes/reservoirs/ponds, open land, aquatic vegetation area. The total study area is about 413.98 km^2 and LULC map of 1987 shows that nearly 86.26 km^2 (20.84%) of the study area is covered by dense forest followed by degraded forest 83.48 km^2 (20.17%), built up land 60.59 km^2 (14.63%), agricultural fallow land 48.27 km^2 (11.66%), river / stream 37.27 km^2 (9.00%), agricultural crop land 25.91 km^2 (6.26%). In 1987 forest land (dense forest and degraded forest) 169.74 km^2 (41.01%) dominant in the study area followed by agricultural land (if we combined agricultural cropland and agricultural fallow land) 74.18 km^2 (17.92%) and then built up area 60.51 km^2 (14.62 %).

LULC map of 1997 shows that nearly 102.4 km^2 (24.73%) of the study area is covered by built up land followed by dense forest 80.56 km^2 (19.46%), degraded forest 76.95 km^2 (18.59%), agricultural fallow land 34.08 km^2 (8.23%), river / stream 32.51km^2 (7.85%), land with or without scrub 24.82 km^2 (6%). If we look carefully at built up area, it is the highest area occupied class in 1997 dense forest 80.56 km^2 (19.46%) followed by degraded forest 76.95 km^2 (18.59%). But if we look carefully combined dense forest and degraded forest as forest land, it is 157.51 km^2 (38.05%) and is the dominant LULC in the study area in 1997 followed by built up area 80.56 km^2 (19.46%) and agricultural land (agricultural cropland and agricultural fallow land) 40.07 km^2 (9.68%).

The classified LULC map of 2007 shows 141.35 km^2 (34.14%) of the study area is occupied by built up land followed by dense forest 74.84 km^2 (18.08%), degraded forest 60.31 km^2 (14.57%), river / stream 33.42 km^2 (8.07%), agricultural fallow land 25.12 km^2 (6.07%), land with or without scrub 23.78 km^2 (5.74%). LULC map of 1997 also shows built up land as dominant an individual LULC class among the all LULC classes followed by dense forest 74.84 km^2 (18.08%), degraded forest 60.31 km^2 (14.57%). The major LULC classes in 1987, 1997 and 2007 are shows in Table 4.4. Ranking of all LULC in three time points (1987, 1997 and 2007) are shows in Table 4.5.

Table 4.3: Area statistics of LULC

Sl. No.	Class Name	1987 Area (km²)	1987 % of Area	1997 Area (km²)	1997 % of Area	2007 Area (km²)	2007 % of Area
1.	Built Up Land	60.54	14.63	102.4	24.73	141.35	34.14
2.	Agricultural Crop Land	25.91	6.26	5.99	1.45	7.17	1.73
3.	Agricultural Fallow Land	48.27	11.66	34.08	8.23	25.12	6.07
4.	Plantations	1.38	0.33	3.68	0.89	3.35	0.81
5.	Dense Forest	86.26	20.84	80.56	19.46	74.84	18.08
6.	Degraded Forest	83.48	20.17	76.95	18.59	60.31	14.57
7.	Land with or without Scrub	9.48	2.29	24.82	6	23.78	5.74
8.	Marshy / Swampy	13.42	3.24	10.26	2.48	6.82	1.65
9.	Water Logged Area	3.57	0.86	1.86	0.45	1.52	0.37
10.	Sandy Area (River Bed)	14.83	3.58	16.08	3.88	15.92	3.85
11.	River / Stream	37.27	9	32.51	7.85	33.42	8.07
12.	Lake/Reservoir/Pond/Tank	7.99	1.93	6.05	1.46	6.59	1.59
13.	Open Land	13.8	3.33	7.28	1.76	6.97	1.68
14.	Aquatic Vegetation	7.78	1.88	11.46	2.77	6.82	1.65
	Total	413.98	100.00	413.98	100.00	413.98	100.00

4.2.2. Allocation of Land Use and Land Cover (LULC)

The spatial distribution (allocation) of land use and land cover based on digital classification of satellite images for three different years between 1987, 1997 and 2007 are shows in Figure 4.7. The built up land mainly lies at south bank of Brahmaputra River, within the twin township of Guwahati and Dispur - the capital of Assam state, India. Forests occupy about 20.84 %, 19.46 % and 18.08 % of study area in 1987, 1997, and 2007 respectively, and are mainly concentrated in the hills and Piedmont zone. The majority of mapped forest area lies within the reserve forest boundaries. Degraded forest mainly mapped in the adjacent area of forest and near the built up area. LULC map shows land used for agricultural purposes mainly found in outskirt of built up land. The fallow land also mainly confined in the near agricultural crop land. The plantation mainly within the city constitutes. Land with or without Scrub mainly confined in near degraded forest. The Brahmaputra River flowing through middle of the study area, occupied nearly 9%, 7.85%, 8.07% of study area respectively in three years. Sandy areas are found mainly within the river channel. The main lake (Deepor Beel) situated in middle of study area just outside of city or built up area. Marshy / swampy land mainly demarcated in lake area and also in south-east and south-west part of study area. Aquatic vegetation concentrated mainly within near the lake area.

Table 4.4: Major LULC classes in 1987, 1997 and 2007

LULC 1987	Area (km²)	%	LULC 1997	Area (km²)	%	LULC 2007	Area (km²)	%
Dense Forest	86.26	20.84	Built Up Land	102.4	24.73	Built Up Land	141.35	34.14
Degraded Forest	83.48	20.17	Dense Forest	80.56	19.46	Dense Forest	74.84	18.08
Built Up Land	60.54	14.63	Degraded Forest	76.95	18.59	Degraded Forest	60.31	14.57
Agricultural Fallow Land	48.27	11.66	Agricultural Fallow Land	34.08	8.23	River / Stream	33.42	8.07
River / Stream	37.27	9	River / Stream	32.51	7.85	Agricultural Fallow Land	25.12	6.07
Agricultural Crop Land	25.91	6.26	Land with or without Scrub	24.82	6	Land with or without Scrub	23.78	5.74

Table 4.5: Ranking of area statistics of LULC in three time points (1987, 1997 and 2007)

LULC 1987	Area (km²)	%	LULC 1997	Area (km²)	%	LULC 2007	Area (km²)	%
Dense Forest	86.26	20.84	Built Up Land	102.4	24.73	Built Up Land	141.35	34.14
Degraded Forest	83.48	20.17	Dense Forest	80.56	19.46	Dense Forest	74.84	18.08
Built Up Land	60.54	14.63	Degraded Forest	76.95	18.59	Degraded Forest	60.31	14.57
Agricultural Fallow Land	48.27	11.66	Agricultural Fallow Land	34.08	8.23	River / Stream	33.42	8.07
River / Stream	37.27	9	River / Stream	32.51	7.85	Agricultural Fallow Land	25.12	6.07
Agricultural Crop Land	25.91	6.26	Land with or without Scrub	24.82	6	Land with or without Scrub	23.78	5.74
Sandy Area (River Bed)	14.83	3.58	Sandy Area (River Bed)	16.08	3.88	Sandy Area (River Bed)	15.92	3.85
Open Land	13.8	3.33	Aquatic Vegetation	11.46	2.77	Agricultural Crop Land	7.17	1.73
Marshy / Swampy	13.42	3.24	Marshy / Swampy	10.26	2.48	Open Land	6.97	1.68
Land with or without Scrub	9.48	2.29	Open Land	7.28	1.76	Marshy / Swampy	6.82	1.65
Lake/Reservoir/Pond/Tank	7.99	1.93	Lake/Reservoir/Pond/Tank	6.05	1.46	Aquatic Vegetation	6.82	1.65
Aquatic Vegetation	7.78	1.88	Agricultural Crop Land	5.99	1.45	Lake/Reservoir/Pond/Tank	6.59	1.59
Waterlogged Area	3.57	0.86	Plantations	3.68	0.89	Plantations	3.35	0.81
Plantations	1.38	0.33	Waterlogged Area	1.86	0.45	Waterlogged Area	1.52	0.37
Total	413.98	100	Total	413.98	100	Total	413.98	100

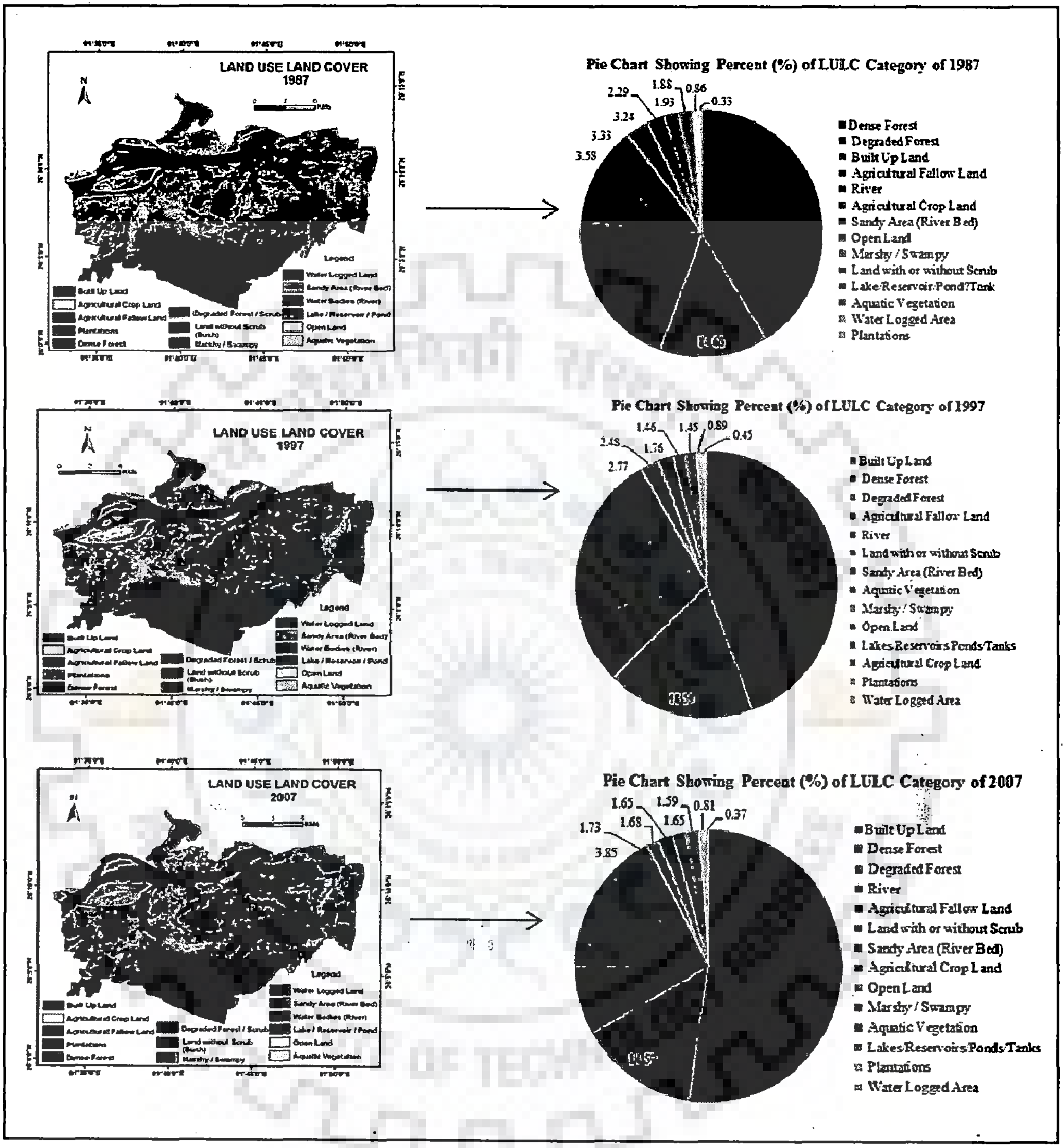


Figure 4.7: Allocation of LULC and percent (%) of LULC of 1987, 1997 and 2007

4.3. ACCURACY ASSESSMENT OF CLASSIFICATION

One of the most common means of accuracy assessment is the preparation of a classification error matrix (Congalton, 1991; Lillesand and Kiefer, 2004; Jensen, 2005).

An error matrix is an effective way to show the relationship between ground truth and the classification results (Lillesand and Kiefer, 2004). In this study, overall accuracy, producer's accuracy, user's accuracy and Kappa statistic are calculated to show the classification performance. For quantitative estimates of the classification accuracy of classified images, samples were selected randomly. Table 4.6 shows producer's accuracy, user's accuracy for different LULC classes. The overall accuracy and overall Kappa statistics are also shows in Table 4.6. The overall accuracy of the LULC maps of 1987, 1997 and 2007 are 84.77%, 85.55% and 87.50%, respectively at a confidence level of 95%. Overall Kappa statistics for 1987, 1997 and 2007 are 0.8011, 0.8111 and 0.8363, respectively. Among the fourteen LULC classes, it was most difficult to improve classification accuracy of aquatic vegetation. Due to their similar spectral characteristics, aquatic vegetation could not be adequately separated from forest (dense and degraded), agricultural crop land and scrub land in the classification using low spatial and spectral resolution images in the study area. It was found that about half of the reference pixels for aquatic vegetation were classified as forests in classifications of Landsat images from 1987 and 2007. Therefore, the producer accuracies of aquatic vegetation were only 47%, 53% and 55% from images of 1987, 1997 and 2007, respectively.

Table 4.6: Classification accuracy of different LULC

Sl. No.	Class Name	1987		1997		2007	
		Producers Accuracy %	**Users Accuracy %**	**Producers Accuracy %**	**Users Accuracy %**	**Producers Accuracy %**	**Users Accuracy %**
1.	Built Up Land	100.00	94.43	100.00	98.31	100.00	100.00
2.	Agricultural Crop Land	77.00	92.00	79.89	98.89	81.00	87.00
3.	Agricultural Fallow Land	89.00	92.00	88.89	88.89	100.00	85.00
4.	Plantations	63.33	79.00	69.00	81.00	75.00	85.00
5.	Dense Forest	74.07	74.07	78.26	66.67	75.00	77.78
6.	Degraded Forest	57.69	68.18	69.23	81.82	66.67	72.73
7.	Land with or without Scrub	93.00	62.50	87.50	87.50	100.00	87.50
8.	Marshy / Swampy	65.45	79.33	75.56	88.33	75.56	87.33
9.	Waterlogged Area	69.45	86.33	55.56	89.33	55.56	91.33
10.	Sandy Area (River Bed)	65.45	83.33	55.56	83.33	55.56	83.33
11.	River / Stream	97.00	83.33	100.00	83.33	100.00	83.33
12.	Lake/Reservoir/Pond/Tank	87.00	92.00	89.89	88.89	100.00	85.00
13.	Open Land	65.00	89.00	14.29	50.00	28.57	100.0
14.	Aquatic Vegetation	47.00	59.00	53.00	59.00	55.00	67.00
Overall Accuracy		84.77		85.55		87.50	
Overall Kappa Statistics		0.8011		0.8111		0.8363	

4.4. SUMMARY

The status of LULC in the study area as evaluated by digital image processing of satellite data which indicates that majority of areas are built up land, dense forest, degraded forest, agricultural land (crop and fallow), waste land (land with or without scrub, marshy / swampy), river and river bed. Built up land is occupied as 14.63% in 1987, 19.46% in 1997 and 34.14% in 2007. The hilly region consists of dense forest (20.84% in 1987, 18.08% in 1997 and 19.46% in 2007) and degraded forest (20.17%, 18.59% and 14.57% area in 1987, 1997 and 2007, respectively). This study reiterated that the remote sensing with its multispectral, multi-temporal and synoptic view has the potential to provide accurate spatial and temporal information on LULC.

Chapter - 5

CRITICAL ANALYSIS OF LAND USE AND LAND COVER (LULC) CHANGE

5.1. INTRODUCTION

There has been a growing trend in the development of change detection techniques using remote sensing data. Pre-classification enhancement approaches to land cover change involve enhancing alterations in the concentration of some landscape attribute that can be continuously measured (e.g. spectral vegetation index - SVI) (Coppin et al., 2001). Various methods have been developed to compare multi-temporal signatures, and are reviewed by Singh (1989) and Jensen (2007). Post-classification comparison examines the changes over time between various thematic land cover categories (e.g. forest, grassland, agriculture) (Singh, 1989). Further, post-classification comparison permits the use of information on the types of land cover transformations. This approach has significant limitations, because the comparison of classifications for different dates does not allow the detection of subtle, low-magnitude modifications within land cover categories (Stow et al., 1980). Further, the propagation of error through post-classification comparison approaches has been documented by Stow et al., 1980; Macleod and Congalton, 1998.

5.2. METHODOLOGY

5.2.1. Quantity of Change

The quantity of LULCC for each category was analysed in terms of relative changes, gross gains, gross losses and persistence. The maps were overlaid to produce a matrix that provides the LULC areas by categorical transition between 1987 and 1997 and between 1997 and 2007. The off-diagonal entries comprise proportions of the landscape that experienced transition from one category to a different category, while the diagonal entries indicate persistence of categories. The row totals at the right denote the proportion of the landscape by LULC category in 1987 and the column totals at the bottom denote the proportion of landscape by category in time 1997. On other hand, row totals at the right denotes the proportion of the landscape by LULC category in 1997 and the column totals at the bottom denotes the proportion of landscape by category in 2007.

5.2.1.1. Relative changes

The relative changes are derived from different land use and land cover category in each period (1987-1997 and 1997-2007).

5.2.1.2. Gross gains, gross losses and persistence

The cross tabulation matrix between 1987 - 1997 and 1997 - 2007 is extended to derive the gross gains and gross losses by categories. The gross gain for each category is derived by subtracting the persistence from the column total, while the gross loss is computed by subtracting the persistence from the row total.

5.2.1.3. Net change and swap change

LULCC in terms of the net change and swap change are derived from the extended cross tabulation matrix. The total change for a category is the sum of its gross gain and gross loss. The net change for a category is the difference between the gross gain and gross loss, i.e. difference between the row total and the column total for a given category in the matrix. The swap change for a category is the total change minus the net change for the category.

5.2.2. Allocation of Change

When LULC maps of two years are overlaid, the spatial distribution of change can be visualized. The gain, loss and persistence for each category are derived to assess where the changes have taken place. The change maps with the gains; losses and persistence were laid over the map of the region in order to compute the gains, losses and persistence within the study area.

5.3. RESULTS AND DISCUSSIONS

5.3.1. Quantity of Change

The quantity of LULCC for each category was found in terms of the following relative changes, gross gains, gross losses and persistence.

5.3.1.1. Relative changes

The area statistics of LULC and relative changes of two time periods i.e., between 1987 & 1997 and 1997 & 2007 are shows in Table 5.1 and Table 5.2, respectively. Correlation between relative changes of two time periods are positive, where r = 0.799 (R^2 = 0.638)

(Figure 5.1). It established that relative changes of two time periods are positively correlated; the trends of relative changes between the time periods between 1987 & 1997 and 1997 & 2007 are slightly different from one time period to another time period.

Table 5.1: Area statistics and relative changes of each land use and land cover changes category between 1987 and 1997

Sl.	Class Name	1987		1997		Relative Change between 1987 and 1997	
		Area (km^2)	% of Area	Area (km^2)	% of Area	Area (km^2)	Area %
1.	Built Up Land	60.54	14.63	102.4	24.73	41.86	10.12
2.	Agricultural Crop Land	25.91	6.26	5.99	1.45	-19.92	-4.82
3.	Agricultural Fallow Land	48.27	11.66	34.08	8.23	-14.19	-3.42
4.	Plantations	1.38	0.33	3.68	0.89	2.3	0.55
5.	Dense Forest	86.26	20.84	80.56	19.46	-5.7	-1.33
6.	Degraded Forest	83.48	20.17	76.95	18.59	-6.53	-1.58
7.	Land with or without Scrub	9.48	2.29	24.82	6	15.34	3.7
8.	Marshy / Swampy	13.42	3.24	10.26	2.48	-3.16	-0.76
9.	Waterlogged Area	3.57	0.86	1.86	0.45	-1.71	-0.41
10.	Sandy Area (River Bed)	14.83	3.58	16.08	3.88	1.25	0.28
11.	River / Stream	37.27	9	32.51	7.85	-4.76	-1.17
12.	Lake/Reservoir/Pond/Tank	7.99	1.93	6.05	1.46	-1.94	-0.47
13.	Open Land	13.8	3.33	7.28	1.76	-6.52	-1.58
14.	Aquatic Vegetation	7.78	1.88	11.46	2.77	3.68	0.89
	Total	413.98	100.00	413.98	100.00	0.0	0.0

Table 5.2: Area statistics and relative changes of each land use and land cover changes category between 1997 and 2007

Sl.	Class Name	1997		2007		Relative Change between 1997 and 2007	
		Area (km^2)	% of Area	Area (km^2)	% of Area	Area (km^2)	Area %
1.	Built Up Land	102.4	24.73	141.35	34.14	38.95	9.41
2.	Agricultural Crop Land	5.99	1.45	7.17	1.73	1.18	0.28
3.	Agricultural Fallow Land	34.08	8.23	25.12	6.07	-8.96	-2.16
4.	Plantations	3.68	0.89	3.35	0.81	-0.33	-0.08
5.	Dense Forest	80.56	19.46	74.84	18.08	-5.72	-1.38
6.	Degraded Forest	76.95	18.59	60.31	14.57	-16.64	-3.98
7.	Land with or without Scrub	24.82	6	23.78	5.74	-1.04	-0.27
8.	Marshy / Swampy	10.26	2.48	6.82	1.65	-3.44	-0.82
9.	Waterlogged Area	1.86	0.45	1.52	0.37	-0.34	-0.08
10.	Sandy Area (River Bed)	16.08	3.88	15.92	3.85	-0.16	-0.04
11.	River / Stream	32.51	7.85	33.42	8.07	0.91	0.21
12.	Lake/Reservoir/Pond/Tank	6.05	1.46	6.59	1.59	0.54	0.11
13.	Open Land	7.28	1.76	6.97	1.68	-0.31	-0.09
14.	Aquatic Vegetation	11.46	2.77	6.82	1.65	-4.64	-1.11
	Total	413.98	100	413.98	100	0.0	0.0

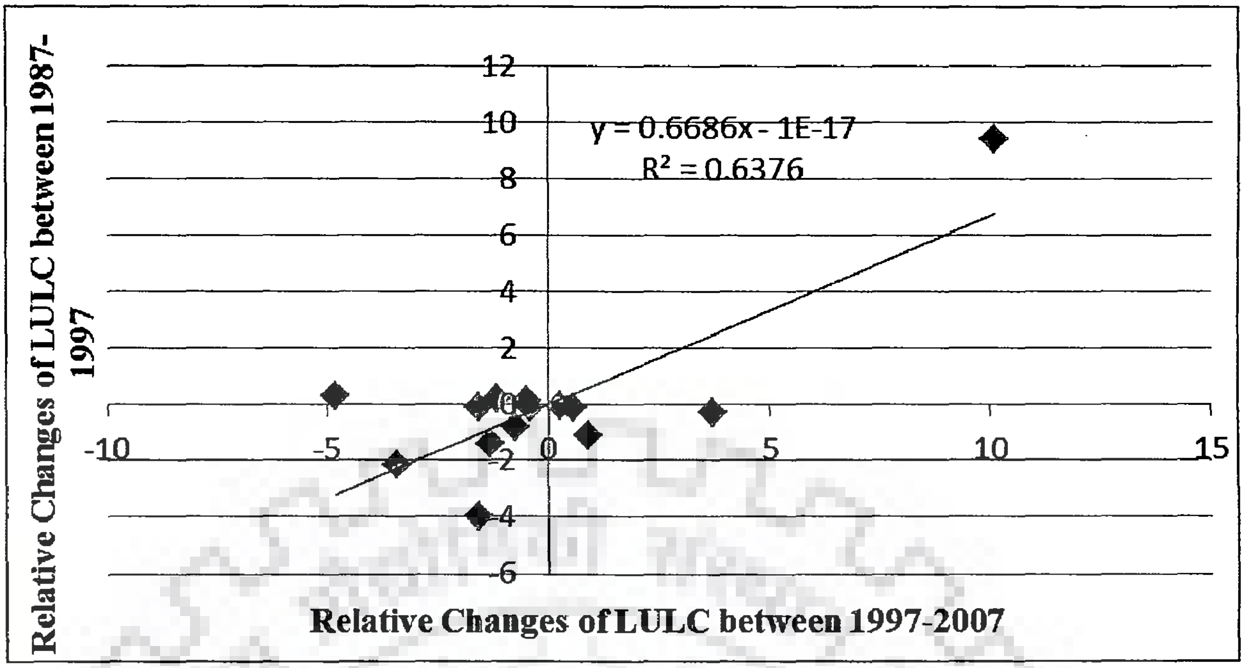


Figure 5.1: Correlation between relative changes of LULC in 1987-1997 and relative changes of LULC in 1997-2007

5.3.1.2. Gross gain, gross loss, and persistence

Table 5.1 and Table 5.2 give useful information about the quantity of each category, but they do not offer any details concerning individual transitions between different 14 categories. Therefore, overlaying the 1987 map with the 1997 map and then the 1997 map with the 2007 map produced two matrices which are respectively presented in Tables 5.3 and Table 5.4. Each matrix has a total column at the right that gives the stock of each category at the initial time, and a total row at the bottom that gives the stock of each category at the subsequent time. Furthermore, the matrix for each time interval shows the flow of each category by presenting a column of gross losses and a row of gross gains. These extended cross tabulation matrix (Pontius et al., 2008) is to show the gross gains and gross losses by category for the periods between 1987 – 1997 and 1997 – 2007.

The transition matrices of 1987-1997 and 1997-2007 LULC maps are shows in Table 5.3 and Table 5.4, wherein Table 5.3 the rows display the results of the LULC categories of 1987 and the columns display those of the categories of 1997. In Table 5.4, the rows display the results of the LULC categories of 1997 and the columns display those of the categories of 2007. The traditional transition matrix would have had only the total change without the last column (gross loss) and the last row (gross gain), while this extended

Table 5.3: Losses and gains respectively, transition matrixes of 1987-1997 LULC

LULC in 1997	LULC in 1987														Total 1987	Gross Gain
	Built Up Land	Agricultural Crop Land	Agricultural Fallow Land	Plantations	Dense Forest	Degraded Forest / Scrub	Land with or without Scrub	Marshy /Swampy	Water logged Area	Sandy Area (Riverbed)	River /Stream	Lake/ Reservoir/Pond/ Tank	Open Land	Aquatic Vegetation		
Built Up Land	14.33	1.75	2.30	0.03	0.05	3.65	0.66	0.48	0.11	0.12	0.08	0.08	0.98	0.12	24.75	10.4
Agricultural Crop Land	0.00	0.46	0.40	0.00	0.00	0.07	0.00	0.15	0.00	0.33	0.01	0.00	0.01	0.00	1.44	0.9
Agricultural Fallow Land	0.00	0.71	5.21	0.00	0.01	0.69	0.19	0.36	0.14	0.14	0.00	0.03	0.60	0.15	8.23	3.0
Plantations	0.11	0.09	0.04	0.16	0.01	0.34	0.03	0.04	0.01	0.01	0.00	0.00	0.02	0.01	0.89	0.7
Dense Forest	0.00	0.06	0.05	0.03	17.71	1.52	0.03	0.03	0.00	0.00	0.00	0.01	0.02	0.01	19.48	1.7
Degraded Forest	0.06	1.65	1.29	0.06	2.82	10.54	0.56	0.48	0.08	0.05	0.04	0.11	0.66	0.16	18.58	8.0
Land with or without Scrub	0.00	0.98	0.94	0.01	0.19	2.31	0.61	0.11	0.03	0.02	0.00	0.06	0.48	0.25	5.99	5.3
Marshy / Swampy	0.03	0.21	0.40	0.00	0.01	0.45	0.05	0.52	0.02	0.44	0.12	0.02	0.12	0.08	2.48	1.9
Waterlogged Area	0.00	0.01	0.10	0.00	0.00	0.08	0.00	0.12	0.10	0.00	0.00	0.01	0.01	0.02	0.45	0.3
Sandy Area (River Bed)	0.00	0.04	0.02	0.00	0.00	0.01	0.00	0.10	0.02	1.73	1.94	0.00	0.01	0.00	3.87	2.1
River / Stream	0.00	0.02	0.01	0.00	0.00	0.00	0.00	0.29	0.01	0.71	6.80	0.00	0.00	0.00	7.85	1.0
Lake/Reservoir/Pond/Tank	0.02	0.03	0.07	0.02	0.00	0.10	0.01	0.21	0.09	0.01	0.00	0.64	0.03	0.22	1.46	0.8
Open Land	0.05	0.12	0.70	0.00	0.01	0.16	0.05	0.16	0.12	0.02	0.01	0.03	0.29	0.03	1.76	1.4
Aquatic Vegetation	0.02	0.11	0.12	0.01	0.00	0.24	0.09	0.18	0.11	0.00	0.00	0.94	0.10	0.84	2.77	1.9
1997 Total	14.63	6.26	11.65	0.34	20.81	20.16	2.29	3.24	0.86	3.59	9.02	1.93	3.34	1.88	100.00	40.06
Gross Loss	0.30	5.80	6.44	0.18	3.10	9.62	1.68	2.72	0.76	1.86	2.22	1.29	3.05	1.04	40.06	

Note: Light sky shows persistence 1 of categories 2, while pink and ash colours shows major changes (in between 1987-1997)

Table 5.4: Losses and gains respectively, transition matrixes of 1987-1997 LULC

LULC in 2007	LULC in 1997: Built Up Land	Agricultural Crop Land	Agricultural Fallow Land	Plantations	Dense Forest	Degraded Forest	Land with or without Scrub	Marshy /Swampy	Water logged Area	Sandy Area (Riverbed)	River /Stream	Lake/Reservoir /Pond/Tank	Open Land	Aquatic Vegetation	Total 1997	Gro[ss] Gai[n]
Built Up Land	24.05	0.14	1.97	0.39	0.24	4.30	1.41	0.50	0.06	0.08	0.05	0.15	0.53	0.30	34.17	10.1
Agricultural Crop Land	0.01	0.53	0.17	0.03	0.05	0.40	0.17	0.14	0.01	0.10	0.00	0.02	0.01	0.09	1.73	1.2
Agricultural Fallow Land	0.03	0.34	3.49	0.02	0.02	0.57	0.52	0.36	0.03	0.08	0.00	0.05	0.42	0.13	6.07	2.5
Plantations	0.02	0.02	0.05	0.21	0.11	0.22	0.11	0.01	0.01	0.00	0.00	0.02	0.00	0.03	0.81	0.6
Dense Forest	0.00	0.00	0.00	0.00	16.99	1.03	0.04	0.00	0.00	0.00	0.00	0.00	0.00	0.01	18.07	1.0
Degraded Forest	0.14	0.04	0.67	0.13	1.80	9.08	2.02	0.27	0.09	0.01	0.00	0.05	0.10	0.17	14.58	5.5
Land with or without Scrub	0.07	0.05	1.07	0.07	0.16	1.93	1.25	0.26	0.13	0.02	0.00	0.16	0.27	0.29	5.73	4.4
Marshy / Swampy	0.04	0.06	0.09	0.02	0.04	0.39	0.07	0.33	0.05	0.28	0.13	0.07	0.04	0.05	1.66	1.3
Waterlogged Area	0.00	0.00	0.04	0.00	0.01	0.09	0.05	0.01	0.02	0.03	0.03	0.02	0.03	0.03	0.37	0.3
Sandy Area (River Bed)	0.01	0.11	0.06	0.00	0.00	0.02	0.01	0.28	0.00	1.88	1.45	0.01	0.01	0.00	3.84	1.9
River / Stream	0.04	0.13	0.06	0.00	0.00	0.05	0.01	0.19	0.00	1.41	6.18	0.00	0.00	0.00	8.07	1.8
Lake/Reservoir/Pond/Tank	0.02	0.00	0.04	0.00	0.01	0.08	0.03	0.02	0.01	0.00	0.00	0.63	0.03	0.70	1.57	.9
Open Land	0.31	0.02	0.45	0.01	0.02	0.25	0.15	0.08	0.01	0.00	0.00	0.03	0.26	0.08	1.67	1.4
Aquatic Vegetation	0.01	0	0.08	0.01	0.01	0.15	0.16	0.03	0.04	0	0.00	0.24	0.03	0.90	1.66	.7
2007 Total	24.76	1.45	8.23	0.89	19.45	18.56	6.00	2.48	0.45	3.88	7.86	1.46	1.76	2.77	100	34.20
Gross Loss	0.71	0.92	4.74	0.68	2.46	9.48	4.75	2.15	0.43	2.00	1.68	.83	1.50	1.87	34.20	

Note: Light sky shows persistence 1 of categories 2, while pink and ash colours shows major changes (in between 1997-2007).

transitional matrix (Pontius et. al 2010) last column indicates gross loss by category and the last row indicates gross gain by category in the landscape during the 1987 and 2007.

Statistics of landscape persistence and components (gains and losses) of change in terms of percent of study area in the time periods 1987-1997 and 1997-2007 is shows in Table 5.5 and Table 5.6, respectively. Between 1987 and 1997, the gain is highest for built up land 10.42% followed by degraded forest 8.04%. Between 1987 and 1997, loss is highest for degraded forest 9.62% followed by agricultural fallow land 6.44%, agricultural crop land 5.80%. The gain is highest in between 1997 and 2007 for built up land as 10.12% followed by degraded forest 5.5%. The loss is highest in between 1997 and 2007 for degraded forest as 9.48 %. If we look ranking gain loss matrix of 1987-1997 and 1997-2007, degraded forest experiences the largest loss in both time intervals and built up experiences the largest gain in both time intervals. Others important gain experiences by degraded forest, land with or without Scrub, agricultural fallow land, sandy area (river bed), marshy / swampy in both time periods. Others important losses experiences by agricultural fallow land followed by agricultural crop land, dense forest, open land, marshy / swampy in 1987-1997 time intervals and land with or without scrub followed by agricultural fallow land, dense forest, marshy / swampy in 1997-2007 time intervals. So, other than degraded forest agricultural land (fallow and crop), dense forest, land with or without scrub, open land and marshy-swampy are the important category which are experiences important losses in both time intervals (1987-1997 and 1997-2007).

The persistence of the landscape is 59.94% between 1987-1997 time period and 65.8% between 1997-2007 time periods. In other words, about 40.06% of the study area exhibited transition from one category to a different category during 1987-1997 and about 34.2% of the study area exhibited transition from one category to a different category during 1997-2007.

5.3.1.3. Net Change and Swap Change

The exhibited transition from one category to a different category is about 40.06% and 34.20%, respectively, during 1987-1997 and 1997-2007. Overall (total) change is more during 1987-1997 as compared to 1997-2007. The overall (total) change during 1987-1997 is 80.12% and during 1997-2007 is 68.40% (Figure 5.2).

Table 5.5: Statistics of landscape persistence and components (gains and losses) of change in terms of percent of study area in the time periods 1987-1997

Land use/land cover class	Persistence	Gain	Loss	Total change (Gain+ Loss)	value of net change (Gain-Loss)	Absolute value of net change (Gain-Loss)	Swap (Total Change - Absolute value of net change)
Built Up Land	14.33	10.42	0.30	10.72	10.12	10.12	0.60
Agricultural Crop Land	0.46	0.98	5.80	6.78	-4.82	4.82	1.96
Agricultural Fallow Land	5.21	3.02	6.44	9.46	-3.42	3.42	6.04
Plantations	0.16	0.73	0.18	0.91	0.55	0.55	0.36
Dense Forest	17.71	1.77	3.10	4.87	-1.33	1.33	3.54
Degraded Forest	10.54	8.04	9.62	17.66	-1.58	1.58	16.08
Land with or without Scrub	0.61	5.38	1.68	7.06	3.7	3.7	3.36
Marshy / Swampy	0.52	1.96	2.72	4.68	-0.76	0.76	3.92
Waterlogged Area	0.1	0.35	0.76	1.11	-0.41	0.41	0.70
Sandy Area (River Bed)	1.73	2.14	1.86	4.00	0.28	0.28	3.72
River / Stream	6.8	1.05	2.22	3.27	-1.17	1.17	2.10
Lake/Reservoir/Pond/Tank	0.64	0.82	1.29	2.11	-0.47	0.47	1.64
Open Land	0.29	1.47	3.05	4.52	-1.58	1.58	2.94
Aquatic Vegetation	0.84	1.93	1.04	2.97	0.89	0.89	2.08
Total	59.94	40.06	40.06	80.12	0.0	31.08	49.04

Table 5.6: Statistics of landscape persistence and components (gains and losses) of change in terms of percent of study area in the time periods 1997-2007

Land use/land cover class	Persistence	Gain	Loss	Total change (Gain+ Loss)	value of net change (Gain-Loss)	Absolute value of net change (Gain-Loss)	Swap (Total Change - Absolute value of net change)
Built Up Land	24.05	10.12	0.71	10.83	9.41	9.41	1.42
Agricultural Crop Land	0.53	1.2	0.92	2.12	0.28	0.28	1.84
Agricultural Fallow Land	3.49	2.58	4.74	7.32	-2.16	2.16	5.16
Plantations	0.21	0.6	0.68	1.28	-0.08	0.08	1.2
Dense Forest	16.99	1.08	2.46	3.54	-1.38	1.38	2.16
Degraded Forest	9.08	5.5	9.48	14.98	-3.98	3.98	11
Land with or without Scrub	1.25	4.48	4.75	9.23	-0.27	0.27	8.96
Marshy / Swampy	0.33	1.33	2.15	3.48	-0.82	0.82	2.66
Waterlogged Area	0.02	0.35	0.43	0.78	-0.08	0.08	0.7
Sandy Area (River Bed)	1.88	1.96	2	3.96	-0.04	0.04	3.92
River / Stream	6.18	1.89	1.68	3.57	0.21	0.21	3.36
Lake/Reservoir/Pond/Tank	0.63	0.94	0.83	1.77	0.11	0.11	1.66
Open Land	0.26	1.41	1.5	2.91	-0.09	0.09	2.82
Aquatic Vegetation	0.9	0.76	1.87	2.63	-1.11	1.11	1.52
Total	65.8	34.2	34.2	68.4	0.0	20.02	48.38

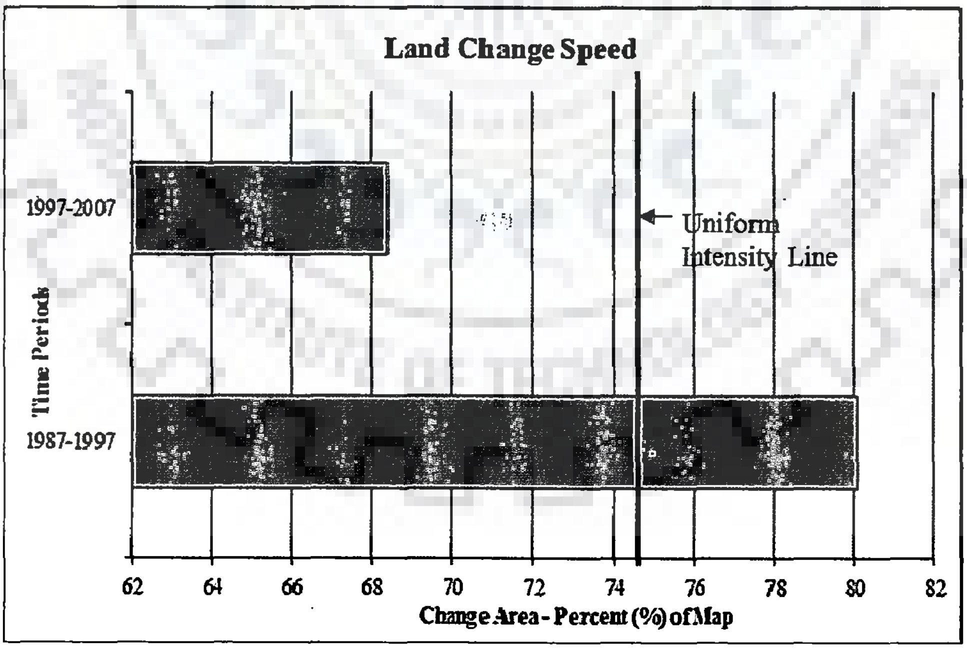


Figure 5.2: Land change speed (rate of change) in between 1987 & 1997 and 1997 & 2007

A gross gain of one category is always accompanied by a gross loss of another category, so the total gross gain is equivalent to the total gross loss in a landscape, which is 40.06% in 1987 -1997 time period and 34.2% in between 1997-2007. Between 1987-1997, degraded forest is the most highest category in terms of total gross gains and gross losses (17.66%) , since it accounts for 8.04% points of the total gross gain and for 5.21% points of the total gross losses, followed by agricultural fallow land since it accounts for 3.02% points of the total gross gain and for 9.62% points of the total gross losses and total grain and loss 9.46%. while built up land is the highest gained LULC since it accounts for 10.42% points of the total gross gain and for only 0.30% points of the total gross losses, but there is a high proportion (10.72%) of total gain loss components of change for built up land ,we considered only the net change, the bulk of change in built up land would have been overlooked, which could have led to the wrong conclusion that built up is one of the more dynamic categories after degraded forest. Thus both swap and net changes are important to understand the total change in a landscape. This is in agreement with the finding of Pontius et al. (2004) who stated that accounting for only net change could lead to a bias of dramatically underestimating the total change. While the sum of gross gain and gross loss indicates the total change, the difference between the gross gain and gross loss for a category is the net change for the given category. The difference between the total change and net change is the amount of swap change (Table 5.7 & Table 5.8). Figure 5.3 shows the intensity of gross gain and gross loss of each LULC category between 1987 and 1997 and Figure 5.4 shows the intensity of gross gain and gross loss of each LULC category between 1987 and 1997.

According to swap change (Table 5.9) between 1987-1997, degraded forest exhibits net change on 17.66% of the study area and swapping change on about 16.08% of the study area clearly indicating most dynamic LULC in 1987-1997, followed by agricultural fallow land (6.04% swapping). According to swap change (Table 5.9) in 1997-2007 time periods, degraded forest (11%) is also most dynamic LULC followed land with or without scrub (8.96%). Degraded forest is the most dynamic category in terms of swap change followed by agricultural fallow land, land with or without scrub, marshy / swampy, open land, sandy area (river bed), river / stream of the study area in last 20 years accounting period in both time points (1987-1997 and 1997-2007).

Table 5.7: Ranking, % of gains, losses and persistence's of LULC category between 1987 and 1997

Land use/land cover class	Gain	Land use/land cover class	Loss	Land use/land cover class	Total change (Gain+ Loss)	Land use/land cover class	Persistence
Built Up Land	10.42	Degraded Forest	9.62	Degraded Forest	17.66	Dense Forest	17.71
Degraded Forest	8.04	Agricultural Fallow Land	6.44	Built Up Land	10.72	Built Up Land	14.33
Land with or without Scrub	5.38	Agricultural Crop Land	5.8	Agricultural Fallow Land	9.46	Degraded Forest	10.54
Agricultural Fallow Land	3.02	Dense Forest	3.1	Land with or without Scrub	7.06	River / Stream	6.8
Sandy Area (River Bed)	2.14	Open Land	3.05	Agricultural Crop Land	6.78	Agricultural Fallow Land	5.21
Marshy / Swampy	1.96	Marshy / Swampy	2.72	Dense Forest	4.87	Sandy Area (River Bed)	1.73
Aquatic Vegetation	1.93	River / Stream	2.22	Marshy / Swampy	4.68	Aquatic Vegetation	0.84
Dense Forest	1.77	Sandy Area (River Bed)	1.86	Open Land	4.52	Lake/Reservoir/Pond/Tank	0.64
Open Land	1.47	Land with or without Scrub	1.68	Sandy Area (River Bed)	4	Land with or without Scrub	0.61
River / Stream	1.05	Lake/Reservoir/Pond/Tank	1.29	River / Stream	3.27	Marshy / Swampy	0.52
Agricultural Crop Land	0.98	Aquatic Vegetation	1.04	Aquatic Vegetation	2.97	Agricultural Crop Land	0.46
Lake/Reservoir/Pond/Tank	0.82	Waterlogged Area	0.76	Lake/Reservoir/Pond/Tank	2.11	Open Land	0.29
Plantations	0.73	Built Up Land	0.3	Waterlogged Area	1.11	Plantations	0.16
Waterlogged Area	0.35	Plantations	0.18	Plantations	0.91	Waterlogged Area	0.1
Total	40.06		40.06		80.12		59.94

Table 5.8: Ranking, % gains, losses and persistence's of LULC category between 1997 and 2007

Land use/land cover class	Gain	Land use/land cover class	Loss	Land use/land cover class	Total change (Gain+ Loss)	Land use/land cover class	Persistence
Built Up Land	10.12	Degraded Forest	9.48	Degraded Forest	14.98	Built Up Land	24.05
Degraded Forest	5.5	Land with or without Scrub	4.75	Built Up Land	10.83	Dense Forest	16.99
Land with or without Scrub	4.48	Agricultural Fallow Land	4.74	Land with or without Scrub	9.23	Degraded Forest	9.08
Agricultural Fallow Land	2.58	Dense Forest	2.46	Agricultural Fallow Land	7.32	River / Stream	6.18
Sandy Area (River Bed)	1.96	Marshy / Swampy	2.15	Sandy Area (River Bed)	3.96	Agricultural Fallow Land	3.49
River / Stream	1.89	Sandy Area (River Bed)	2	River / Stream	3.57	Sandy Area (River Bed)	1.88
Open Land	1.41	Aquatic Vegetation	1.87	Dense Forest	3.54	Land with or without Scrub	1.25
Marshy / Swampy	1.33	River / Stream	1.68	Marshy / Swampy	3.48	Aquatic Vegetation	0.9
Agricultural Crop Land	1.2	Open Land	1.5	Open Land	2.91	Lake/Reservoir/Pond/Tank	0.63
Dense Forest	1.08	Agricultural Crop Land	0.92	Aquatic Vegetation	2.63	Agricultural Crop Land	0.53
Lake/Reservoir/Pond/Tank	0.94	Lake/Reservoir/Pond/Tank	0.83	Agricultural Crop Land	2.12	Marshy / Swampy	0.33
Aquatic Vegetation	0.76	Built Up Land	0.71	Lake/Reservoir/Pond/Tank	1.77	Open Land	0.26
Plantations	0.6	Plantations	0.68	Plantations	1.28	Plantations	0.21
Waterlogged Area	0.35	Waterlogged Area	0.43	Waterlogged Area	0.78	Waterlogged Area	0.02
Total	34.2	--	34.2		68.4		65.8

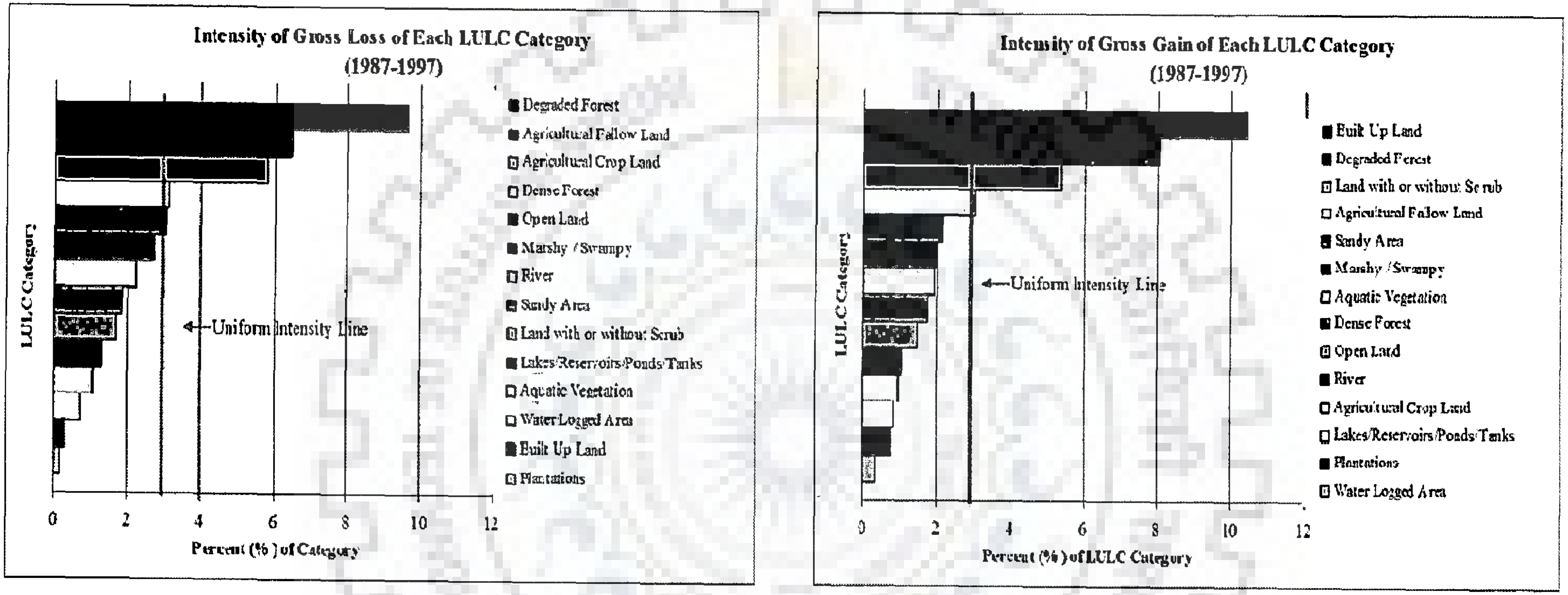


Figure 5.3: Intensity of gross gain and gross loss of each LULC category in between 1987 and 1997

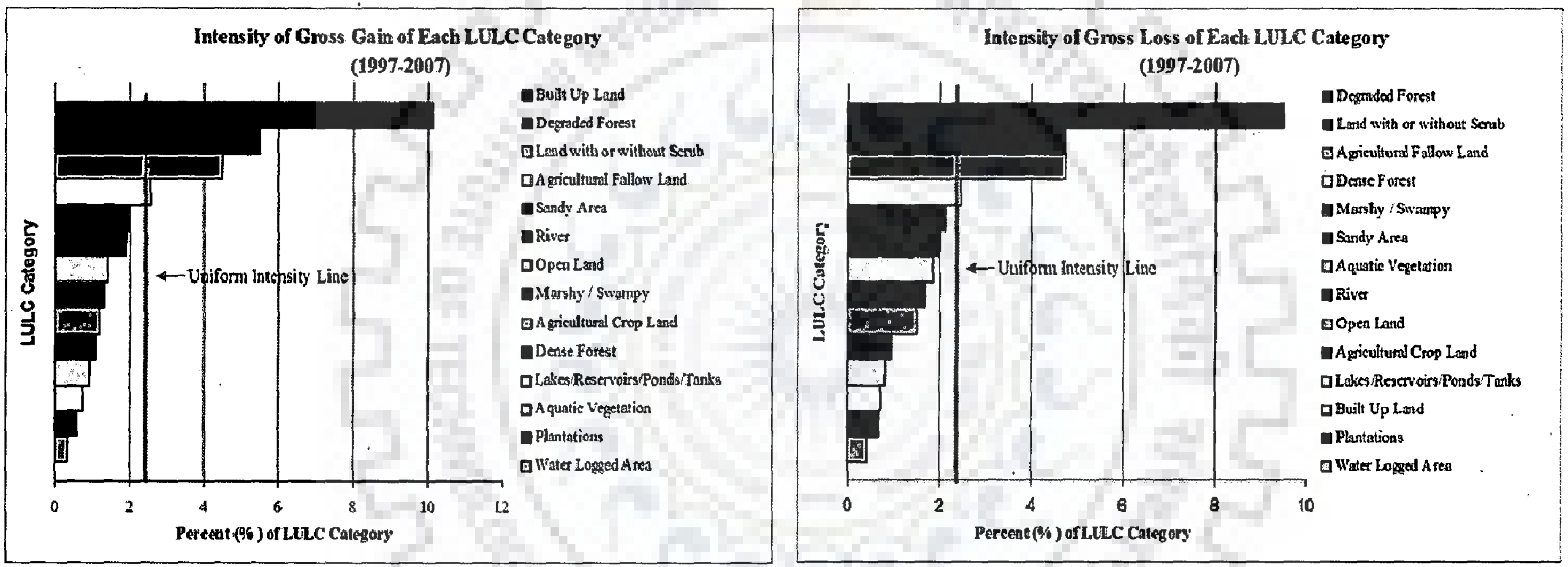


Figure 5.4: Intensity of gross gain and gross loss of each LULC category in between 1997 and 2007

Table - 5.9: Ranking of swap rate between different time periods

Swap Ranking between 1987 and 1997		Swap Ranking between 1997 and 2007	
Swap	LULC class	LULC class	Swap
16.08	Degraded Forest	Degraded Forest	11
6.04	Agricultural Fallow Land	Land with or without Scrub	8.96
3.92	Marshy / Swampy	Agricultural Fallow Land	5.16
3.72	Sandy Area (River Bed)	Sandy Area (River Bed)	3.92
3.54	Dense Forest	River / Stream	3.36
3.36	Land with or without Scrub	Open Land	2.82
2.94	Open Land	Marshy / Swampy	2.66
2.1	River / Stream	Dense Forest	2.16
2.08	Aquatic Vegetation	Agricultural Crop Land	1.84
1.96	Agricultural Crop Land	Lake/Reservoir/Pond/Tank	1.66
1.64	Lake/Reservoir/Pond/Tank	Aquatic Vegetation	1.52
0.7	Waterlogged Area	Built Up Land	1.42
0.6	Built Up Land	Plantations	1.2
0.36	Plantations	Waterlogged Area	0.7

As expected the built up expansion is mainly in the outskirts of the existing built-up i.e. expansion of Guwahati city and other built up areas for both time periods due to mainly rapid urbanization in Guwahati Metropolitan areas. The gain of built up land within surrounding the existing built up land is mainly in degraded forest, agricultural land and land with or without scrub area. The gain in built-up is more than the loss in all over the study area for both time periods. It has happened due to rapid conversion of degraded forest land, agricultural land and land with or without scrub to built up land within the study area between 1987 to 2007. Degraded forest land decrease due to transformation to built up land and land with or without scrub. Interestingly, agricultural land and land with or without scrub also finally converted to built up land due to rapid increased of population in Guwahati city and surrounding areas. Local Lake-Reservoir-Pond-Tank, open land has also been converted to built up land. Lake (Deepor beel) and marshy or swampy land (i.e., near Deepor beel protected land) converted to built up land also. Forest land is mainly converted to degraded forest, and then degraded forest is converted to land with or without scrub and agricultural land, then land with or without scrub and agricultural land converted to built up land. The substantial exchanges of areas and allocation of change in both time periods (1987-1997 and 1997 -2007) are nearly similar as above. Another major transition is found river-stream to sandy area or in river bed (1.94%) between 1987-2007. The river stream is slightly decreased by 1.94% area mainly occupied by sandy area caused by deposition of river. Plantation land somehow increased due to awareness of advocacy of the concept of social forestry by government. Persistence & changes of LULC between 1987 and 1997 are shows in Figure 5.5, while persistence & changes of LULC between 1997 and 2007 are shows in Figure 5.6. Figure 5.7 and Figure 5.8 show gross loss of each LULC category during 1987 & 1997 and 1997 & 2007, respectively. Figure 5.9 and Figure 5.10 show gross gain of each LULC category during 1987 & 1997 and 1997 & 2007, respectively. Figure 5.11 shows gains, losses and persistence of each LULC category during 1987 - 1997. Figure 5.12 also shows gains, losses and persistence of each LULC category during 1997 - 2007.

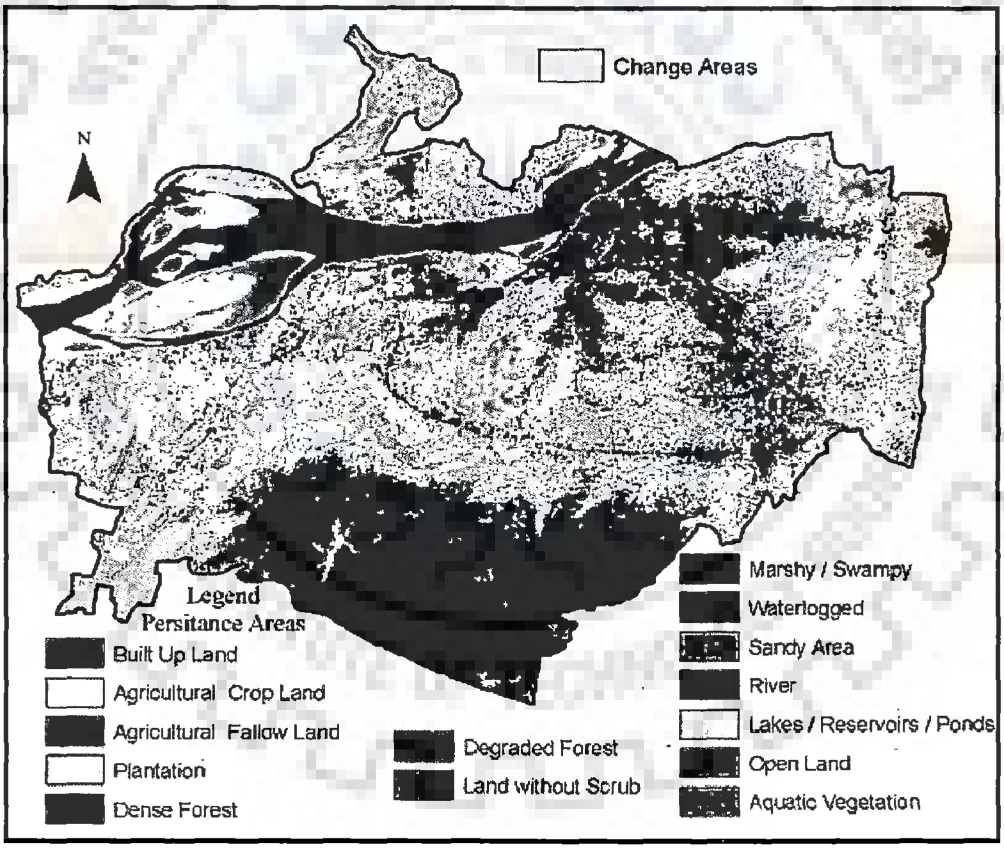


Figure 5.5: Persistence and change areas between 1987 and 1997

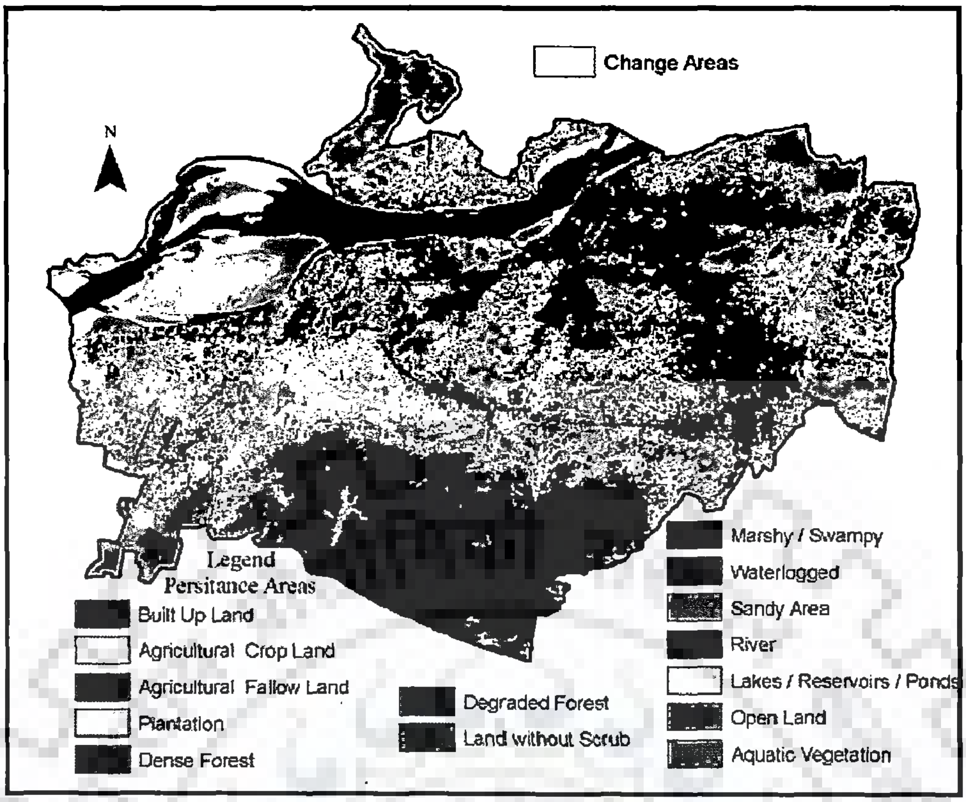


Figure 5.6: Persistence and change areas between 1997 and 2007

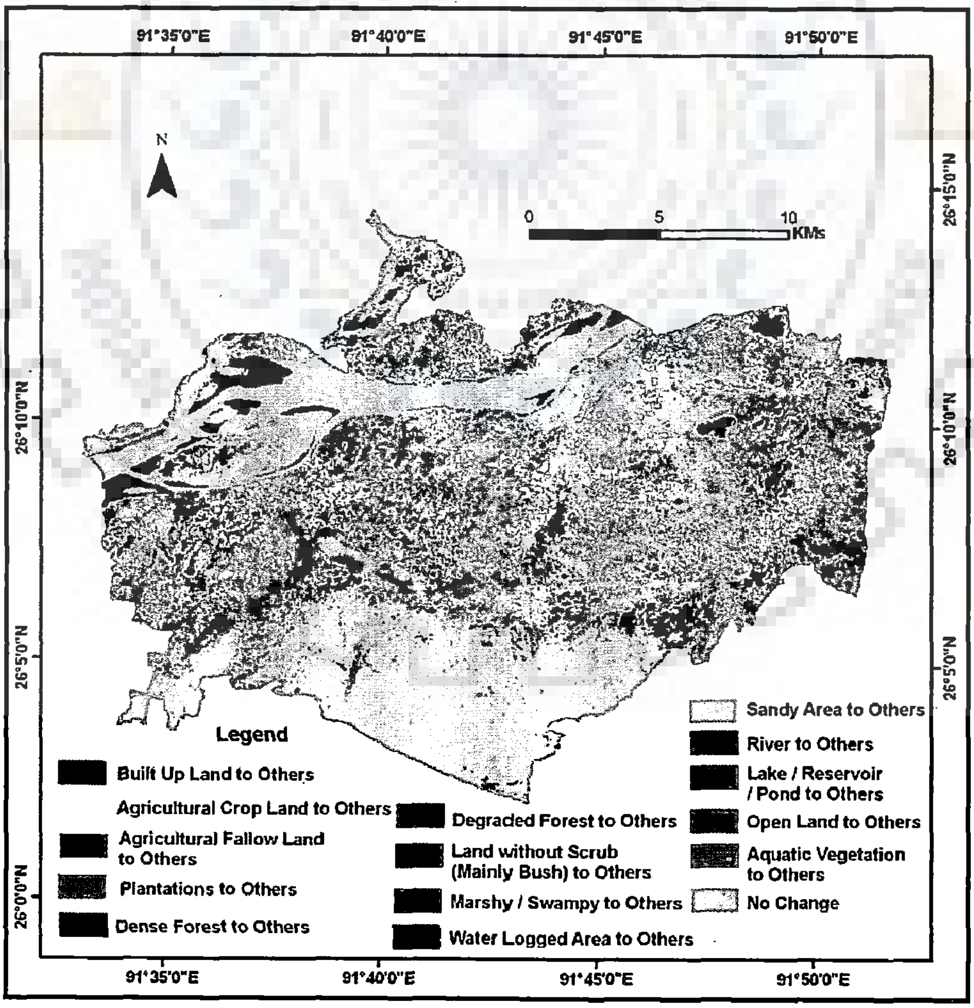


Figure 5.7: Gross loss of each LULC category during 1987 and 1997

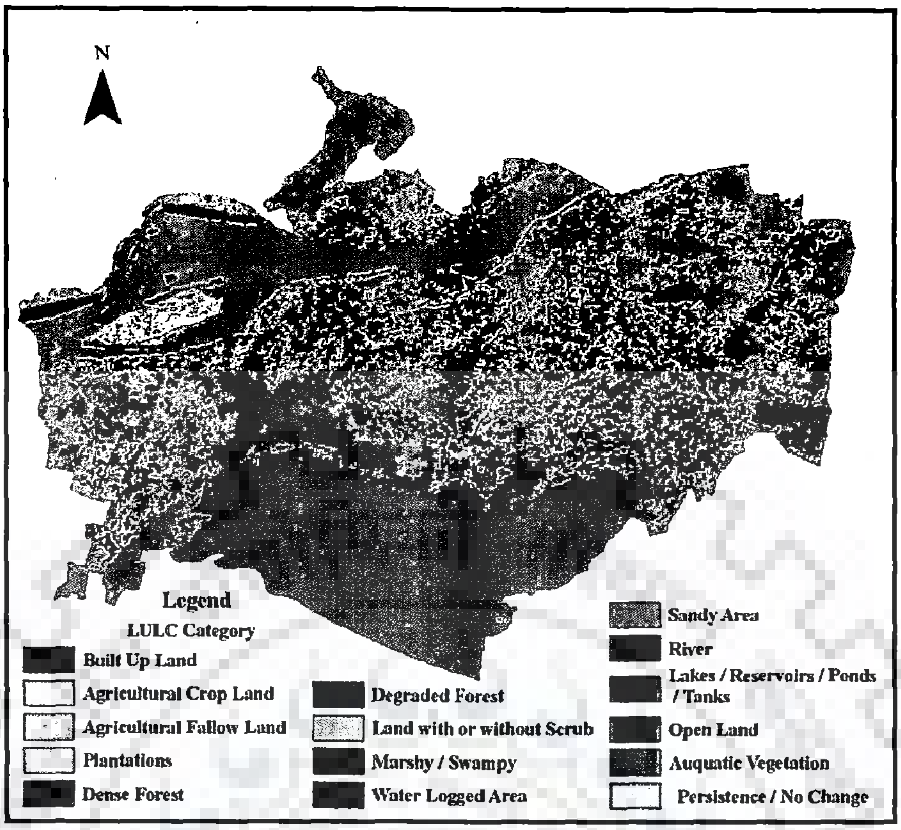


Figure 5.8: Gross gain of each LULC category during 1987 and 1997

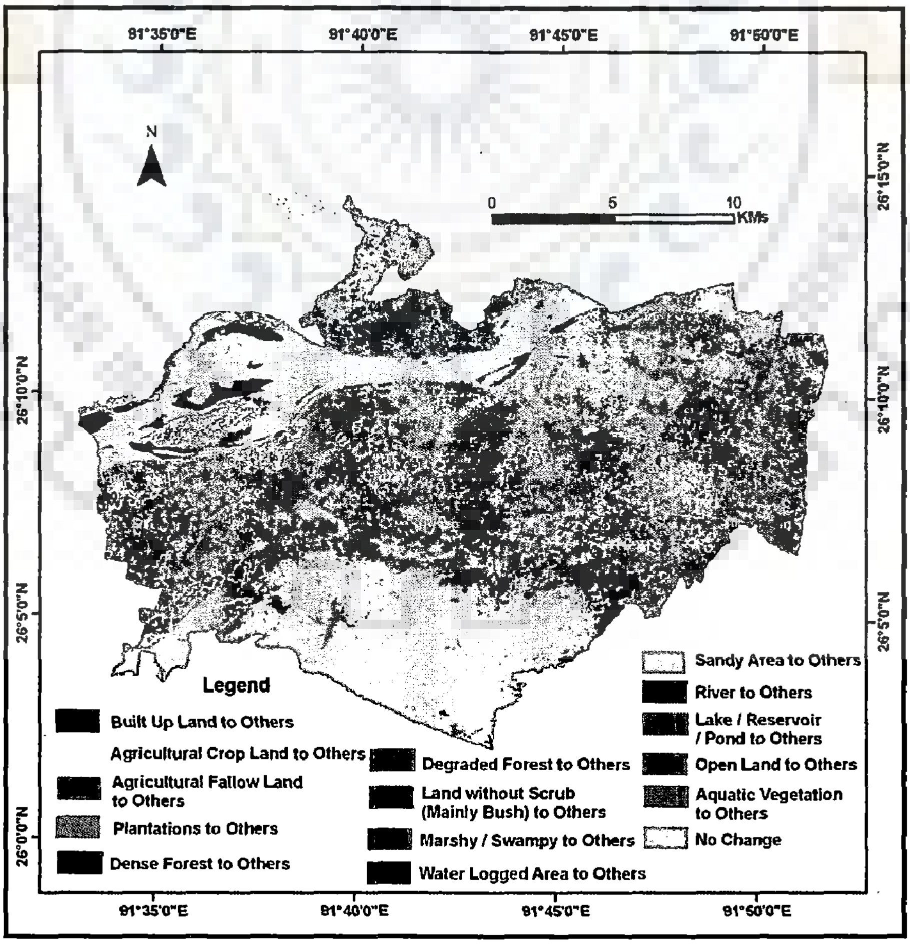


Figure 5.9: Gross loss of each LULC category during 1997 and 2007

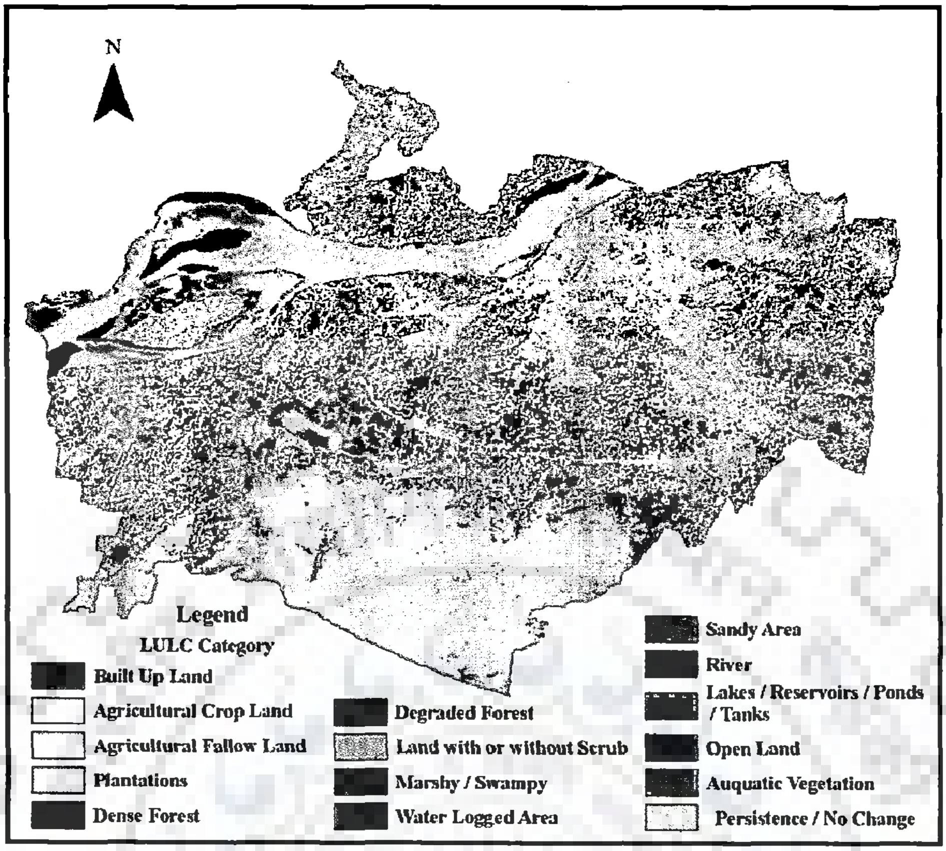


Figure 5.10: Gross gain of each LULC category during 1997 and 2007

There are substantial exchanges of areas during 1987-1997 between degraded forests and built up land; agricultural crop land as well as agricultural fallow land and built up land; dense forest and degraded forest. The prominent transitions are from degraded forest to built up land (3.65%). These are followed by both agricultural crop and agricultural fallow land converting to built up land (1.75% and 2.30%, respectively). The other prominent transitions are from dense forest to degraded forest (2.82%) and degraded forest to land with or without scrub (2.31%). Another major transition was found in river / stream during 1987-97 to sandy area or in river bed (1.94%). Similarly between 1987 -1997 time periods, there are substantial exchanges of areas during 1997-2007 between degraded forests and built up land; agriculture fallow land and built up land; dense forest and degraded forest. Others substantial exchanges of areas during 1997-2007 found between land with scrub and built up land; agricultural fallow land and land with or without scrub. The prominent transitions are from degraded forest to built up land (4.30%). These are followed by both agricultural fallow land and land with scrub converting to built up land (1.97% and 1.41%, respectively). The other prominent transitions are from dense forest to degraded forest (1.80%); degraded forest and agricultural fallow land to land with or without scrub (1.93% and 1.07%, respectively).

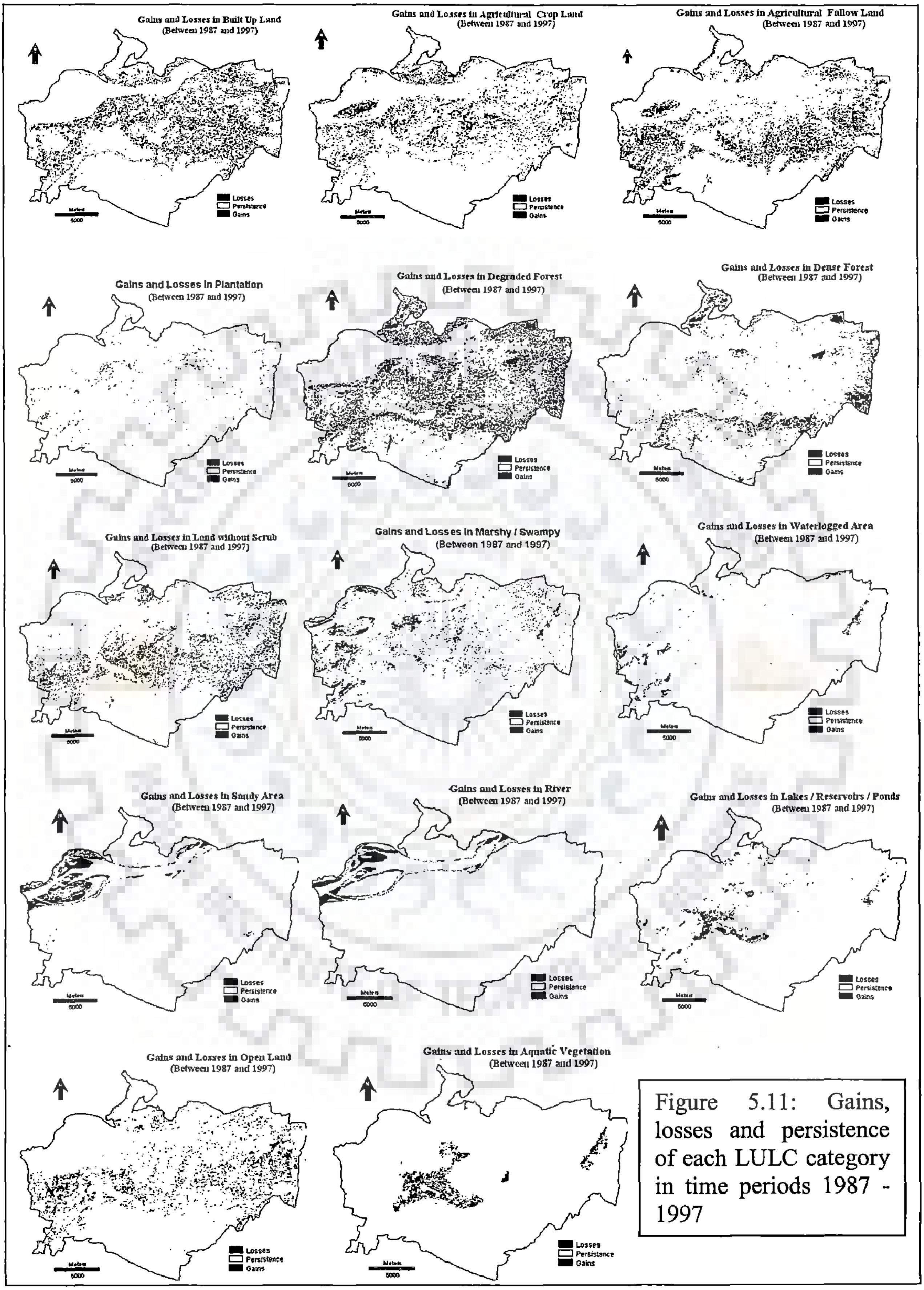


Figure 5.11: Gains, losses and persistence of each LULC category in time periods 1987 - 1997

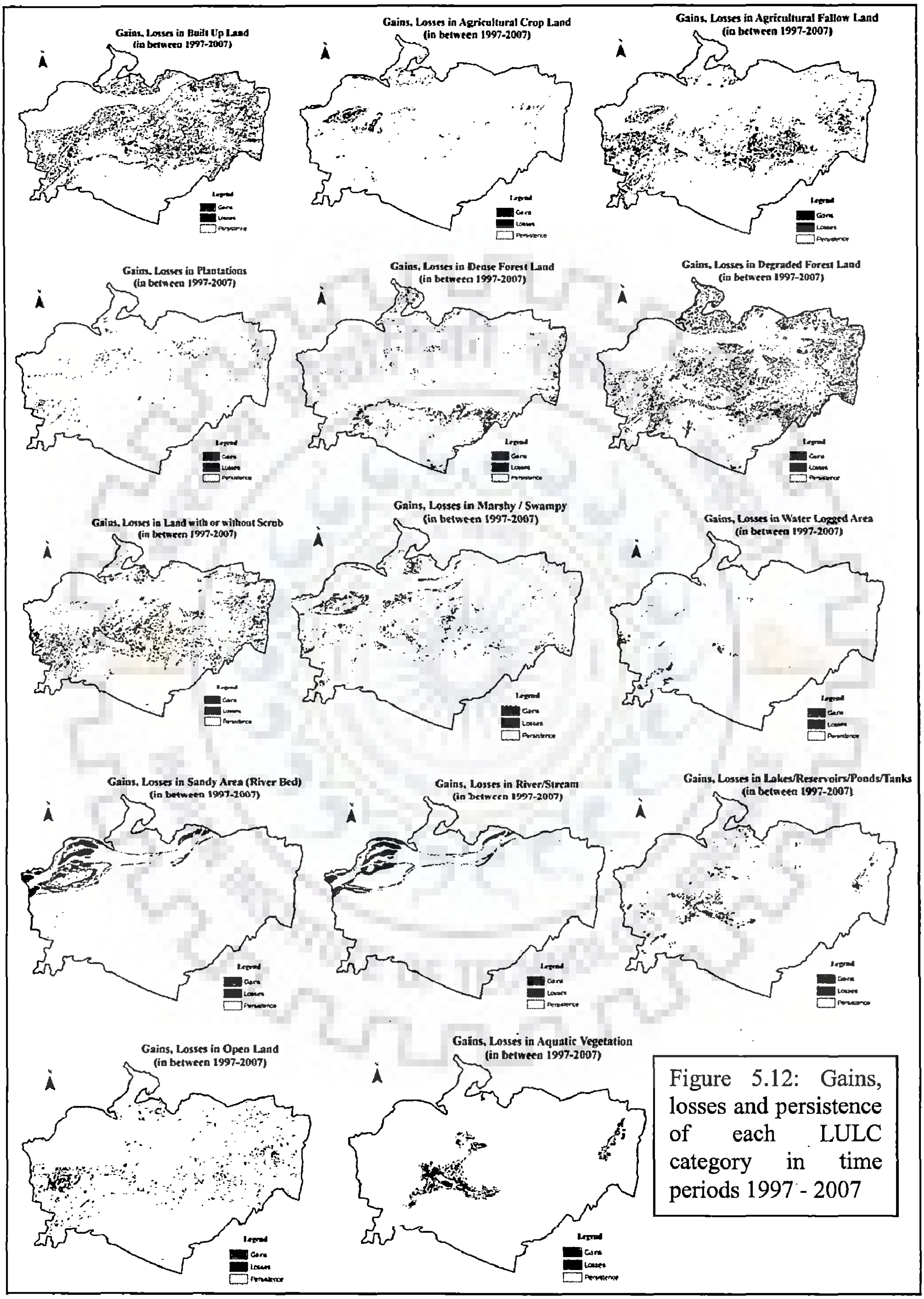


Figure 5.12: Gains, losses and persistence of each LULC category in time periods 1997 - 2007

Another major transition we found in 1997-2007 is river / stream to sandy area or in river bed and vice versa (1.41% and 1.45%, respectively). Therefore, exchanges of areas in both periods (1987-1997 and 1997 -2007) are nearly similar. In other words, the trends of major exchanges between LULC categories are nearly similar. Table 5.10 and Figure 5.13 & Figure 5.14 clearly show major substantial exchanges between LULC categories during (1987-1997 and 1997 -2007). Degraded forest experienced the greatest amount of gross loss to land with or without scrub between 1987 and 1997 compare to between 1997 and 2007. Land with or without scrub experienced the greatest amount of gross loss to built up land after 1997. However, it was found that there are small transitions between other LULC categories in both time periods.

Table 5.10: Substantial exchanges / prominent transitions between LULC categories

LULC		**Time Periods**	
Change from	Change to	1987-1997 (%)	1997-2007 (%)
Degraded Forest	Built up	3.65	4.30
Agricultural fallow land	Built up	2.30	1.97
Agricultural Crop land	Built up	1.75	0.14
Dense	Degraded	2.82	1.80
Degraded Forest	Land with or without scrub	2.31	0.16
Land with or without scrub	Built up	0.66	1.41
River	River bed	1.94	1.45
River bed (Sandy Area)	River	-	1.41
Agricultural fallow land	Land with or without scrub	-	1.07

5.4. SUMMARY

The dynamics of LULC analysis was done for the study area. The salient findings are:

(i) About 40.06% (during 1987-1997) and 34.20% (during 1997-2007) of the study area exhibited transition from one category to a different category. The total change during (1987-1997) is 80.12% and during (1997-2007) is 68.40%.

(ii) This study examined changes among several categories between 1987-1997 and 1997-2007 in the study area. Results show that the annual speed of change was slower during 1997-2007 than during 1987-1997.

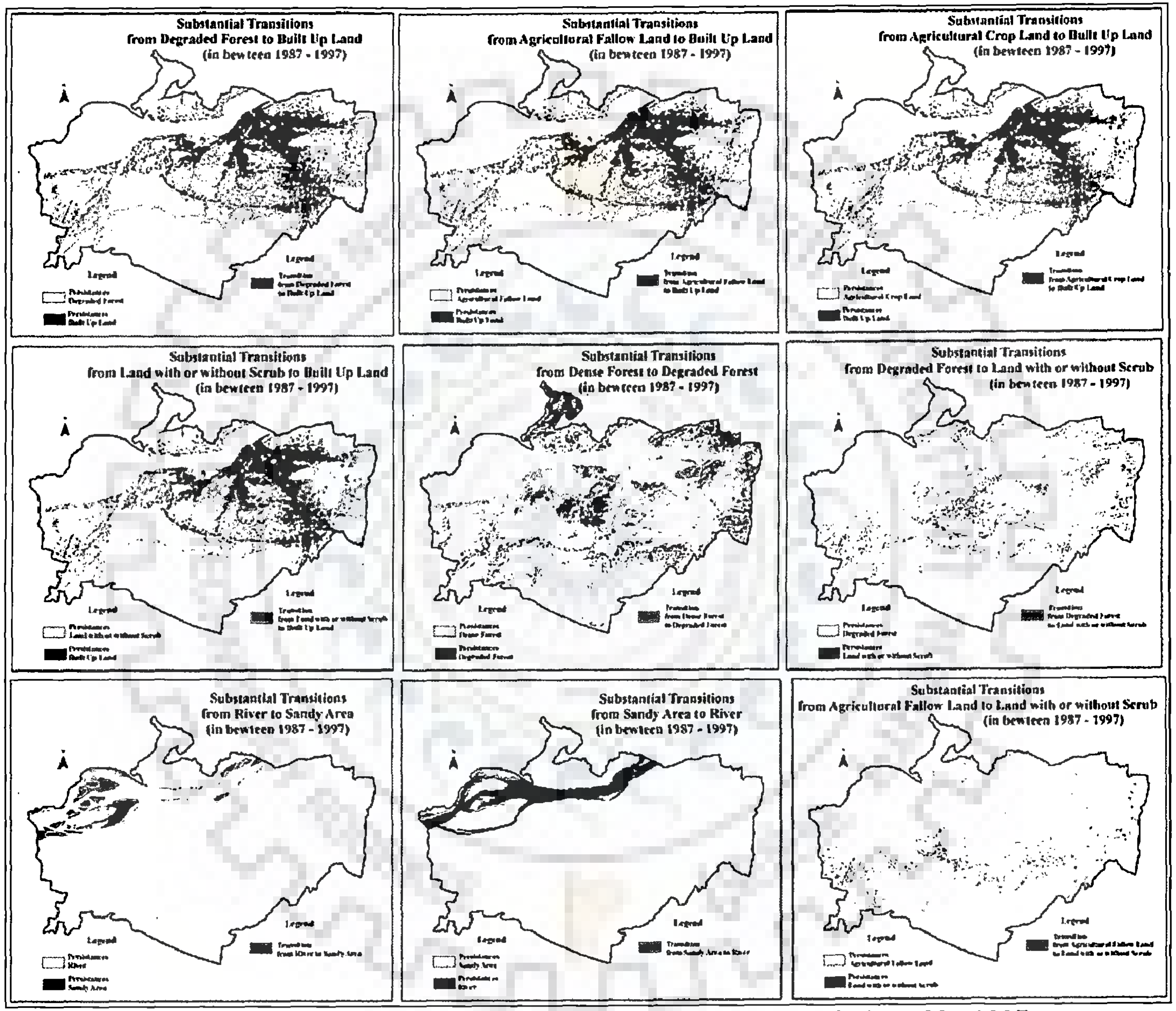


Figure 5.13: Substantial transitions between different LULC during 1987-1997

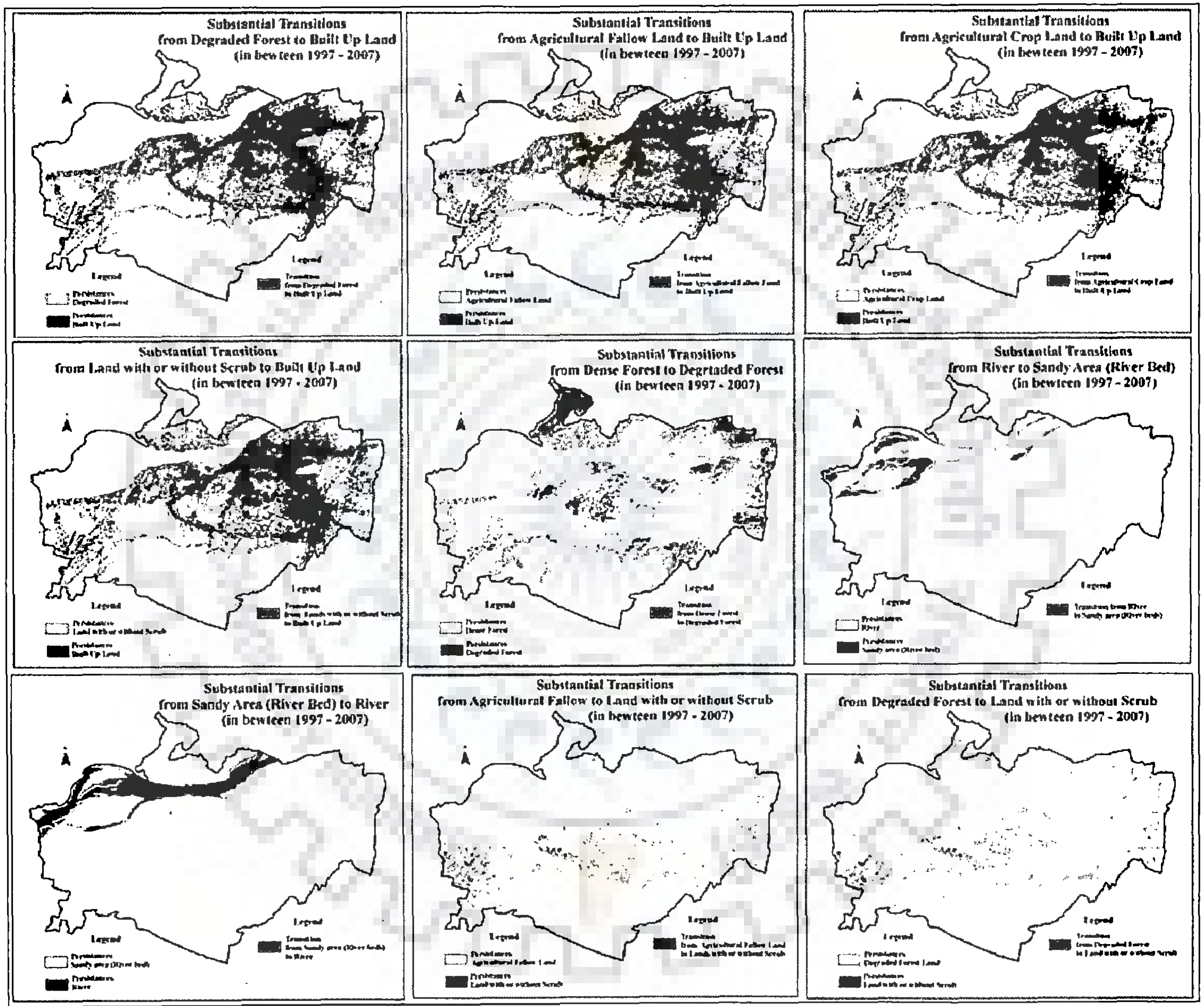


Figure 5.14: Substantial transitions between different LULC during 1997-2007

(iii) Since 1987 the amount of landscape change in the study area has greatly increased during each period.

(iv) Exchanges of areas is degraded forest and built up land. The other prominent transitions are dense forest to degraded forest. The dominant systematic transitions are: degraded forest to built up land; dense forest to degraded forest; agricultural land to built up; degraded forest to land with or without scrub; land with or without scrub to built up; and in between river and sandy area. These transitions are probably due to increased land values caused by the growing socio-economic activities and population growth in the capital city Guwahati-Dispur.

(v) During both the periods, degraded forest has the highest total gains and gross losses means most dynamic LULC categories followed by agricultural fallow land, land with or without scrub, sandy area (river bed), river / stream, dense forest, open land, marshy / swampy. Interestingly, built up is nearly lowest category in terms of total gross gains and gross losses because its gains more area compare to gross losses.

(vi) The largest transitions are exchanges between degraded forests and built up land followed by dense forest to degraded forest. Other major transitions are in between agricultural land (crop as well as fallow) to built up; degraded forest to land with or without scrub; land with or without scrub to built up; river (stream) to sandy area (river bed); agricultural fallow land to land with or without scrub.

(vii) Built-up gain occurs mainly in the outskirt of existing built up land in degraded forests, agricultural (crop as well as fallow) land and land with or without scrub. Dense forest loss is occurring mainly in degraded forest.

(viii) Built-up experiences a consistently large intensity of gains since 1987 in all time periods, built-up has expanded into degraded forests, agricultural area; but since 1997 built-up has also expanded into land with or without scrub.

The overarching conclusion in this study is that when only the net changes are used, the bulk of changes accruing from swap changes would have missed. Additionally, when analysis is done based on the traditional transitional matrix, we would have focused only on the larger categories and missed the systematic transitions in the landscape. Thus, in-depth analysis has enabled the visualization of the major transitions of LULC categories, which in turn have provided some insights to the nature and processes (either random or systematic) of LULC transitions. It is inferred that LULC patterns in the area are generally controlled by agro-climatic conditions, ground water potential and hosts of other factors like irrigation facilities, soil characteristics, socio-economic status and demography. Deeper explanation of the driving factors of LULC dynamics will be the subject of future study. Finally, it can be suggested that the transformation from forest to built up land especially built-up area constitutes a large percentage of the total landscape, but it contributes a substantial ecological footprint and thus increase in built-up areas needs to be considered in the realm of environmental monitoring and sustainability.

Chapter - 6

MODELING OF LULC CHANGE, CELLULAR AUTOMATA (CA) CONTIGUITY FILTERS IMPACTS ON MODELING RESULTS AND SENSITIVITY ANALYSIS TO IDENTIFY SENSITIVE PARAMETER(S)

6.1. INTRODUCTION

The central mechanism of a Markov chain is a probability function which refers to the likelihood of transition from one cover to another cover. The probability function can be static over time or can be adjusted at specific intervals to account for changes in the stationary of the processes controlling the transition sequences. The probability function and transition sequences can be derived from direct observations using satellite data. The primary limitations of Markov transition probability-based models for land use and land cover change analysis are: (1) the assumption of stationary in the transition matrix i.e., that it is constant in time and space; (2) the assumption spatial independence of transitions; and (3) the difficulty of ascribing causality within the model, i.e. the transition probabilities are often derived empirically from multi-temporal maps with no description of the process (Baker, 1989). The third limitation assumes greater significance in the context of land cover change studies from remotely-sensed images, and when those changes are driven by economic and social processes. To address the above limitations 1 and 3, Baker (1999) suggested setting state transition probabilities as a function of exogenous or endogenous variables, which vary in space and time. These models have been used in various case studies to account for changes in the rate of LULC conversion under constraints.

6.2. MARKOV CHAIN ANALYSIS

Markov chain analysis is a convenient tool for modeling land use and land cover change when changes and processing in the LULC are difficult to describe. A Markovian process is simply one in which the future state of a system can be modeled purely on the basis of the immediately preceding state. Markov chain analysis will describe LULC from one period to another and will use this as the basis to project future changes. This is accomplished by developing a transition probability matrix of land use and land cover change from time one to time two, which will be the basis for projecting to a later time periods.

Markov chain is a series of random values whose probabilities at a time interval depend on the value of the number at the previous time. A given parcel of land theoretically may change from one category of land use, to any other, at any time. Markovian analysis uses matrices that represent all the multi-directional LULC changes between all the mutually exclusive LULC categories. One way to summarize landscape change is to simply tally all the instances, on a cell-by-cell basis, in which a cell (pixel) changed LULC types over that time interval. A concise way of summarizing these tallies is the so-called tally matrix, which for N cover types is an N x N matrix, the elements n_{ij} of which tally the number of cells that changed from type i to type j over the time interval. This tally matrix reflects the size of the images, of course, and so it is better to convert the tally numbers into proportions instead (gets rid of size bias). This is done by dividing each of the elements by the row total, which generates a transition matrix, P. Change is represented in a matrix of transition probabilities (transition matrix), P, with elements, p_{ij}, which summarize the proportion of cells of each LULC type that changed into each other LULC type during that time interval. The diagonal elements of this matrix, p_{ii}, are the proportions of cells that did not change.

The key of using this model is to obtain *P*, the initial transition probability matrix for the purpose of reciprocal transformation among different land use types. The mathematical expression of *P* is as follows:

$$P = (p_{ij}) = \begin{vmatrix} P_{11} & P_{12} & \cdots & P_{1n} \\ P_{21} & P_{22} & \cdots & P_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ P_{n1} & P_{n2} & \cdots & P_{nn} \end{vmatrix}, \quad \sum_{j=1}^{n} p_{ij} = 1 \qquad \text{.................................... (6.1)}$$

Where, P is the Markov transition matrix P,

i,j is the land use land cover type of the first and second time period,

and P_{ij} is the probability from land use and land cover type i to land type j

In this expression, n is the number of land use and land cover types in the target area, and is the probability of transition of type i into that of type j from the initiation to the end. In the transition matrix, it requests that each rate is a non-minus quantity, and each line factor plus to 1. The estimate of Markov chain is the relative frequency of transitions observed over the entire time period. The results of the estimation would use for prediction.

The same basic data used to build the transition matrix P can also be used to summarize the state of the landscape in each time period. This summary takes the form of a state vector x, the elements of which (x_i) tally the number of cells in each cover type i at each time period:

$$x_t = [x_1, x_2, x_3, \ldots\ldots] \quad \text{for} \quad i = 1, 2, \ldots\ldots\ldots \text{ N patch types.} \qquad (6.2)$$

Land cover at time t is thus represented by the state vector, x(t). As with the transition matrix, it is customary to relativize this state vector into proportions of the landscape, by dividing each element by the number of cells in the landscape map.

To project changes in land cover from time t to t+1, use the equation x(t+1)=Px(t). Writing the state of the system as the vector x, the future state of the system can be projected:

$x_{t+1} = x_{tP}$ that is, the state vector post-multiplied by the transition matrix. The next projection for time t+2 is continued:

$$x_{t+2} = x_{t+1}P = x_{tP}\, P = x_{tP2} \qquad (6.3)$$

and in general, the state of the system at time t=t+k is given by:

$$x_{t+k} = x_t P^k \qquad (6.4)$$

where, x_t is the initial condition of the map (i.e., its state at the first time or t_o). Thus, the model can be projected into the future simply by iterating through the matrix operation.

Although, the transition probabilities are accurate on a per category basis, there is no knowledge of the spatial distribution of the occurrences within each category i.e., there is no spatial components in the outcome. The Markov model alone lacks knowledge of spatial dependence. CA Markov gives more spatially dependence results. CA can add spatial characteristics to the model. In other words, the main problem of Markov analysis is that it is insensitive to space and it provides no sense of geography. Although the transition probabilities may be accurate for a particular class as a whole, there is no spatial element to the modeling process. CA adds a spatial dimension to the model.

6.3. CELLULAR AUTOMATA (CA)

By definition, a Cellular Automation is an agent or object that 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 neighbors. A CA filter is used to develop a spatially explicit contiguity weighting factor to change the state of cells based on its neighbors, thus giving geography more importance in the solution. CA was firstly used by Von Neumann (1966) for self-reproducible systems. In CA, Von Neumann neighborhood comprises of four cells orthogonally surrounding a central cell on a two-dimensional square lattice (Figure 6.1a). The neighborhood is named after John von Neumann, who used it for his pioneering CA including the Universal Constructor. It is one of the two most commonly used neighborhood types, the other one being the 8-cell Moore neighborhood. It is similar to the notion of 4-connected pixels in computer graphics (Figure 6.1b).

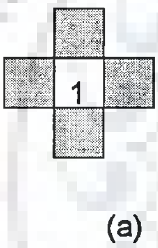


Figure 6.1a:
The Von Neumann neighbor of cell '1'

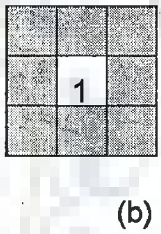


Figure 6.1b:
The Moore neighbor of cell '1'

Since the evolution of CA, it is being used in many disciplines ranging from sciences to commercial fields. Because of its capabilities to address the complex patterns with the help of very simple transition rules it has been accepted in many fields of research. In comparison with traditional approaches based on differential or difference equations the CA has several advantages. CA can incorporate spatial component, and it addresses, dynamism with simple rules, which increases computational efficiency. Since computational efficiency translates into better handling of dynamism, CA becomes favorites to many modelers. The construction of model is simple and easy. It has an ability to perform spatial dynamics, and time explicitly. After analyzing the similarities and capabilities of CA, it was proposed by Wagner (1997) that CA can be considered as analytical engine of GIS. Raster GIS with map algebra can be integrated with enhanced capabilities. CA is considered to have a "natural affinity" with raster data. It has similarities with GIS, such as both represents attribute information in a layered fashion, and manipulate that information with operators (Overlay in GIS, Transitional rules in CA). The focal sum or focal mean functions of GIS has direct analogous with neighborhood functions.

Having a natural affinity with the GIS, it was obvious to have adopted by geographers as a tool for modeling spatial dynamics. Here an attempt was made to integrate non-spatial information with spatial information using GIS (Kumar, 2003). A CA filter is used to generate a spatial explicit contiguity-weighting factor to change the state of cells based on its neighbors. The filter is integral to the action of the CA component. Its purpose is to down-weight the suitability's 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. The 3x3, 5x5 and 7x7 contiguity filters have the following kernel:

3X3

0	1	0
1	1	1
0	1	0

5x5

0	0	1	0	0
0	1	1	1	0
1	1	1	1	1
0	1	1	1	0
0	0	1	0	0

7x7

0	0	0	1	0	0	0
0	0	1	1	1	0	0
0	1	1	1	1	1	0
1	1	1	1	1	1	1
0	1	1	1	1	1	0
0	0	1	1	1	0	0
0	0	0	1	0	0	0

6.4. CELLULAR AUTOMATA (CA) MARKOV MODEL

CA Markov model combines both the concept of a CA filter and Markov chain procedure. Markov chain and CA both is the discrete dynamic model in time and state. The transition probabilities may be accurate on per category basis, but there is no knowledge of the spatial distribution of occurrences within each LULC category. CA will add spatial character to the model. CA is a discrete dynamic system in which the state of each cell at time t+1 is determined by the stated of its neighboring cells at time according the pre-defined transition rules. CA as a method with temporal-spatial dynamics can simulate the evolution of things in two dimensions.

Using the outputs from the Markov chain analysis, the transition matrix, CA Markov will apply a contiguity filter to 'grow out' LULC from the time two to a later time periods. CA Markov will use the transition areas tables and the conditional probability images to predict land use and land cover changes over the periods specified in Markov chain analysis. In essence, the CA will develop a spatially explicit weighting factor which will be applied to each of the suitability, weighting more heavily areas that proximate to existing LULC. This will ensure that land use and land cover change occur proximate to existing, like LULC classes and not wholly random. CA Markov will produce much better results geographically using the contiguity filter; those areas likely to change will do so proximity to existing LULC classes.

6.5. ASSUMPTIONS OF CA MARKOV MODEL

Markov chain models have the following assumption of stationarity. It means that the change predict what the landscape might look like in the future if the nature of development stays the same (stationarity). In the study area, there is a static situation; no major economic, social, and biophysical changes are there. Transition probabilities are assumed to be constant (stay same over time) - that is, to predict the state of the system at time t+1. As land use and land cover change reflects the dynamics and interplay of economic, social, and biophysical factors over time, it would be impossible to expect stationarity in LULC data. However, it might be practical to regard land use and land cover change to be reasonably stationary, if the time span is not too large.

6.6. BENEFITS OF CA MARKOV MODEL AND ITS LIMITATION

If land cover change does not fit in with the above assumptions, attempts to project future land cover exactly using a Markov approach are usually unsuccessful. That does not mean that the Markov approach is worthless, however; instead, the Markov approach represents a possibility of future landscape status. The interpretation from transition matrix can be used as an indicator of magnitude and direction of change in land use in the future and Markov with CA (CA Markov) has enormous capabilities to show the trend projection as well as describe future spatial distribution of LULC.

The limitation of this study is that the potential power of explanatory variables has not been explored. Variables can be added to the model either as static or dynamic components. Static variables express aspects of basic suitability for the transition under consideration, and show no change over time. Dynamic variables are time dependent drivers, such as proximity to existing development or infrastructure and are re-calculated over time during the course of a prediction.

6.7. STRUCTURE/PROCESS OF CA MARKOV MODEL

CA Markov is a combined CA, Markov Chain, Multi-Criteria Evaluation (MCE), Multi-Objective Land Allocation (MOLA) LULC prediction procedure that adds an element of spatial contiguity as well as knowledge of the likely spatial distribution of transitions to Markov chain analysis. CA Markov uses CA procedures in combination with Markov Chain analysis and MCE and MOLA routines. This works as follows:

(i) The transition probability matrix from a Markov Chain analysis of two prior LULC maps establishes the quantity of expected land use and land cover change from each existing category to each other category in the next time period.

(ii) The basic LULC image [the later (second) land cover image of two time periods used in the Markov Chain analysis] is used as the starting point for change simulation.

(iii) Suitability maps (here, evidence likelihood map) for each land cover establish the inherent suitability of each pixel for each land cover type. However, a contiguity filter down-weights the suitability of pixels far from existing areas of that class (as of that iteration), thus giving preference to contiguous suitable areas.

(iv) The number of iterations chosen establishes the number of time steps that will be used in the simulation.

(v) 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 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.

(vi) The results of each MOLA operation are overlaid to produce a new LULC map at the end of each iteration.

(vii) The filter is integral to the action of CA component. Its purpose is to down-weight the suitability of pixels that are distant from existing instances of LULC type under consideration. The net effect is that to be a likely choice for LULC conversion, the pixel must be both inherently suitable and near to existing areas of that class.

(viii) CA Markov automatically normalizes the filter kernel to force the values to sum to 1 (thus the values ultimately vary from 0 to 0.0076). This filter is passed over a Boolean image for each class from the current land cover image within each iteration. Following this, a value of 0.1111 is added to the filtered results to produce a set of weight images. These are multiplied by the original suitability maps to down-weight suitabilities distant from existing areas of each class. The results are then stretched back to a byte (0-255) range. The net effect is that down-weighted suitabilities never exceed a down-weighting in excess of 90% of their original value. This ensures that suitable areas can be found if none are available in proximate areas (Eastman et al., 2009).

6.8. LULC MAPS USED FOR PREDICTION

The CA Markov model is calibrated using the LULC raster image/map series generated from the classification of the Landsat MSS image of 1987, Landsat TM image of 1997 and LULC map of the same area derived from IRS-P6 LISS III image of 2007 used as reference map. Each LULC map (1987, 1997 and 2007) contains 14 LULC classes; having average accuracy of classification around 85%.

6.9. MARKOV CHAIN – TRANSITION PROBABILITY MATRIX

The transition probability matrix has been calculated for the time period of 1987-1997 for the prediction LULC of 2007. The expected probability of transition of LULC category is displayed in Table 6.1. The transition probability matrix is the cross tabulation of the two images (1987 and 1997), that each LULC category will change to every other category. The transition probability areas matrix records the number of pixels that are expected to change over the specified of time. Here, the row represents the 1987 LULC categories and the columns represent the 1997 categories.

6.10. PREPARATION OF SUITABILITY MAP (EVIDENCE LIKELIHOOD MAP)

According to the underlying land use and land cover change dynamics between years 1987 and 1997, a series of suitability maps (evidence likelihood map) consisting of built up land suitability, agricultural crop land suitability, agricultural fallow land suitability, plantation suitability, dense forest land suitability, degraded forest land suitability, land with or without scrub suitability, marshy/swampy land suitability, waterlogged area suitability, sandy area suitability, river suitability, lakes/reservoirs/ponds suitability, open land suitability, aquatic vegetation land suitability were standardized between 0 and 255 (Figure 6.2). The production of these images although empirically derived, follows the same procedures of decision making exercise of multi-criteria evaluation (MCE). It was created by determining the relative frequency with which different LULC categories occurred within the areas from 1987 to 1997. The number thus expresses the likelihood of finding the LULC at the pixel in question, if this lies in transition area. These images (evidence likelihood maps) are calculated as projections from the later date image (1997) of two input LULC images (before image 1987 and later image 1997). The output images are the conditional probability images. This conditional probability images report the probability that each LULC type would be found at each pixel in future after the specified time. The procedure looks at the relative frequency of pixels belonging to the different categories of that variable within areas of change. In effect, it asks the question of each category of the variable, "How likely is it that you would have a value like this if you was an area that would experience change?"(Eastman et al., 2009).

6.11. CALIBRATION OF THE CA MARKOV MODEL

To project land use and land cover change for next 10 year using known LULC of 1987 and 1997, probability statistics for land use and land cover change for 2007 has been generated through cross tabulation of two LULC maps. Thus, CA Markov model combines both the concepts of Markov chain procedure and CA filters, after getting Markov transition probability, CA Markov used the transition probability matrix and probability images (here, suitability / evidence likelihood map) to predict the LULC over a 10 years period i.e., 2007. The total numbers of iterations are based on the number of time steps, for 10 years model will choose to complete run in 10 iterations. With each pass, LULC suitability image is re-weighted as a result of the contiguity filter on each existing LULC. Once re-weighted the revised suitability maps are the run through MOLA

Table 6.1: Transition probability matrix of 1987 and 1997 LULC

	Built Up Land	Agricultural Crop Land	Agricultural Fallow Land	Plantations	Dense Forest	Degraded Forest	Land with or without Scrub	Marshy / Swampy	Water logged Area	Sandy Area (River Bed)	River / Stream	Lake /Reservoir /Pond /Tank	Open Land	Aquatic Vegetation
Built Up Land	0.9799	0	0	0.0078	0	0.0047	0	0.0019	0	0	0.0003	0.0012	0.0037	0.0014
Agricultural Crop Land	0.2812	0.0736	0.1141	0.0149	0.0098	0.2637	0.1569	0.0342	0.0016	0.006	0.0033	0.005	0.019	0.0172
Agricultural Fallow Land	0.1998	0.0343	0.4459	0.0031	0.0045	0.1109	0.0801	0.0343	0.0084	0.0016	0.0007	0.0061	0.0602	0.0103
Plantations	0.0821	0.0056	0.0111	0.4736	0.0984	0.1829	0.044	0.002	0.0004	0	0	0.0595	0.0052	0.0353
Dense Forest	0.0055	0	0.0002	0.0004	0.8486	0.1349	0.0093	0.0005	0	0	0.0001	0.0001	0.0003	0
Degraded Forest	0.1827	0.0032	0.0343	0.017	0.0751	0.5218	0.1143	0.0221	0.0038	0.0005	0.0001	0.0049	0.0078	0.0121
Land with or without Scrub	0.2883	0.0015	0.0837	0.0112	0.0137	0.243	0.2666	0.0215	0.0019	0.0001	0	0.0054	0.0227	0.0406
Marshy / Swampy	0.1491	0.0472	0.1102	0.0135	0.0083	0.1487	0.0336	0.1599	0.0369	0.0316	0.0904	0.066	0.0499	0.0546
Waterlogged Area	0.1301	0.0008	0.1624	0.0159	0.0017	0.0946	0.036	0.0259	0.1196	0.0259	0.0102	0.1072	0.1379	0.132
Sandy Area (River Bed)	0.0334	0.0928	0.039	0.002	0.0001	0.0132	0.0063	0.1235	0	0.4823	0.1981	0.0026	0.0067	0
River / Stream	0.0092	0.0009	0.0003	0.0003	0	0.005	0	0.0137	0.0001	0.2156	0.7537	0.0002	0.0009	0
Lake/Reservoir/Pond /Tank	0.0442	0.0018	0.0133	0.0026	0.0067	0.0585	0.0287	0.0097	0.0028	0.0008	0.0014	0.3293	0.0158	0.4845
Open Land	0.2967	0.0032	0.1786	0.0056	0.0067	0.1966	0.1448	0.0369	0.0032	0.0023	0.0007	0.0102	0.0861	0.0293
Aquatic Vegetation	0.0639	0	0.0774	0.0077	0.005	0.0872	0.1318	0.0400	0.0091	0.0001	0	0.1151	0.0155	0.4473

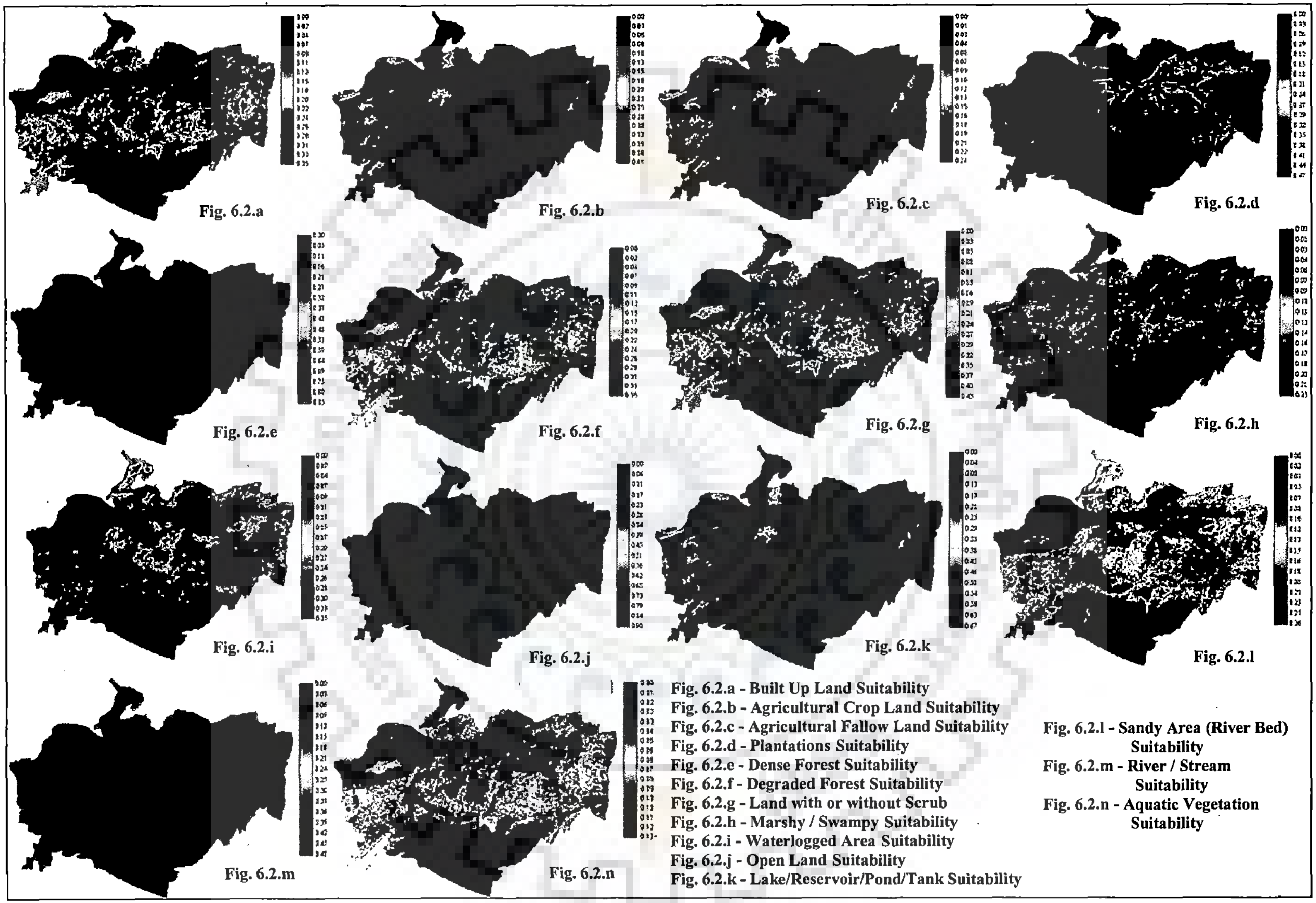


Figure 6.2: Suitability (evidence likelihood) map used to predict future LULC

(Multi Objective Land Allocation), to allocate 1/10 of the required land in first run and 2/10 in second run and so on until the full allocation of land for each LULC category is obtained.

The transition probability matrix will determine how much land is allocated to each LULC category over 10 year period. Within each iteration, every LULC class typically loses some of its land to one or more other categories (and at the same time it may also gain land from others). Thus within the consideration of each host within each iteration, claimant classes select land from the host based on the suitability map for the claimant class. Since there will commonly be competition for specific land parcels, this process of land allocation is undertaken using a MOLA. The CA component arises in part from the iterative process of land allocation, and in part from a filtering stage with each iteration that reduces the suitabilities of land away from exiting areas of that type. By filtering a Boolean mask of the class being considered, the mean filter yields a value of 1 when it is entirely within the existing class and when it is entirely outside. However, when it crosses the boundary, it will yield values that quickly transition from 1 to 0. This result is then multiplied by the suitability image to that class. Note that class is defined at each step to incorporate new area of growth, and 3x3, 5x5 and 7x7 CA contiguity filters are evaluated to predict LULC in 2007 using 1987 and 1997 LULC maps. CA Markov is computationally intensive - a typical run involved several thousand GIS operations. The net results of this iterative process are that land use and land cover change develops as a high suitability proximate to existing areas.

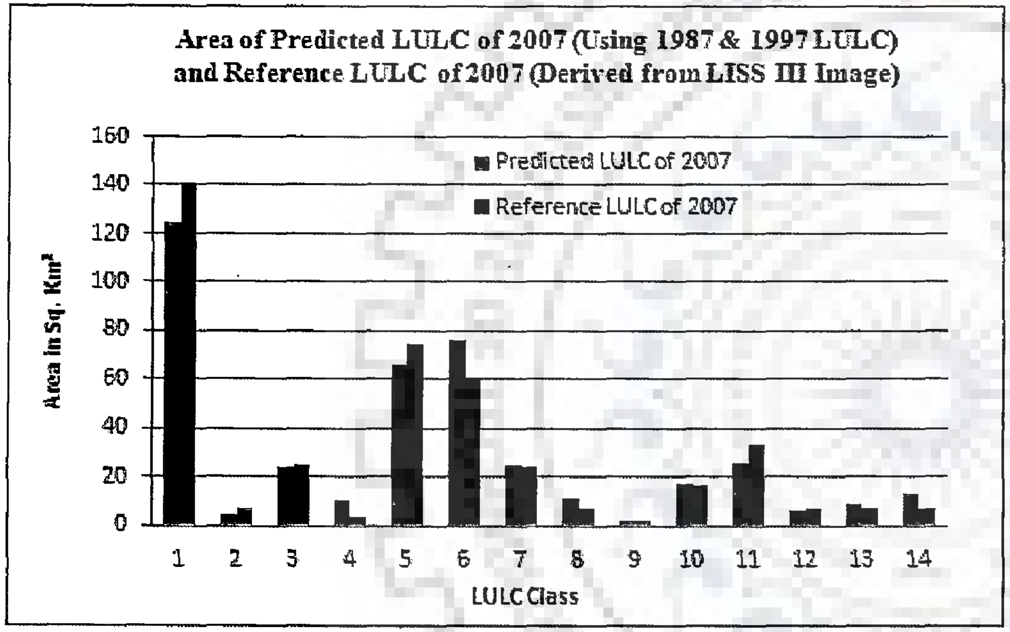
6.12. SIMULATED RESULTS AND EFFECT OF CONTIGUITY FILTERS ON SIMULATED RESULTS

6.12.1. Predicting Quantity

Fourteen LULC classes are used to compute Markov transition probabilities and to predict the future LULC. The quantitative results are shows in Table 6.2 and Figure 6.3. Analysing from the quantitative figures of simulated-forecasted, predicted 14 scenarios are slightly different from LULC derived from LISS III image of 2007. Relative difference in predicted LULC of 2007 and LULC derived from LISS III image of 2007 ranges between (+) 15.88 km² and (-) 16.26 km² only. This difference is small, ± 1.34 km² per year in a study area of 413.98 km². Correlation between predicted two LULC classes are strong, where $r = 0.983$ and $R^2 = 0.967$ (Figure 6.4). It is established that predicted LULC of 2007 and LULC derived from LISS III Image of 2007 are strongly correlated; they are slightly different to each-other.

Table - 6.2: Area statistics of predicted LULC of 2007 using 1987 & 1997 LULC image and LULC derived from LISS III image of 2007

LULC Class	**Area (in Km²)**				
	Predicted LULC 2007 (Using 1987 & 1997 LULC Image)				
	3x3 CA Contiguity Filter	**5x5 CA Contiguity Filter**	**7x7 CA Contiguity Filter**	**LULC 2007 (Derived from LISS III Image of 2007)**	**Differences**
Built Up Land	125.09	125.09	125.09	141.35	-16.26
Agricultural Crop Land	4.32	4.32	4.32	7.17	-2.85
Agricultural Fallow Land	23.62	23.62	23.62	25.12	-1.50
Plantation	10.57	10.57	10.57	3.35	+7.22
Dense Forest	66.26	66.26	66.26	74.84	-8.58
Degraded Forest	76.19	76.19	76.19	60.31	+15.88
Land with or without Scrub	24.95	24.95	24.95	23.78	+1.17
Marshy / Swampy	10.91	10.91	10.91	6.82	+4.09
Waterlogged	1.46	1.46	1.46	1.52	-0.06
Sandy Area	17.39	17.39	17.39	15.92	+1.47
River	25.72	25.72	25.72	33.42	-7.70
Lakes / Reservoirs / Ponds	6.31	6.31	6.31	6.59	-0.28
Open Land	8.67	8.67	8.67	6.97	+1.70
Aquatic Vegetation	12.52	12.52	12.52	6.82	+5.70
Total	413.98	413.98	413.98	413.98	



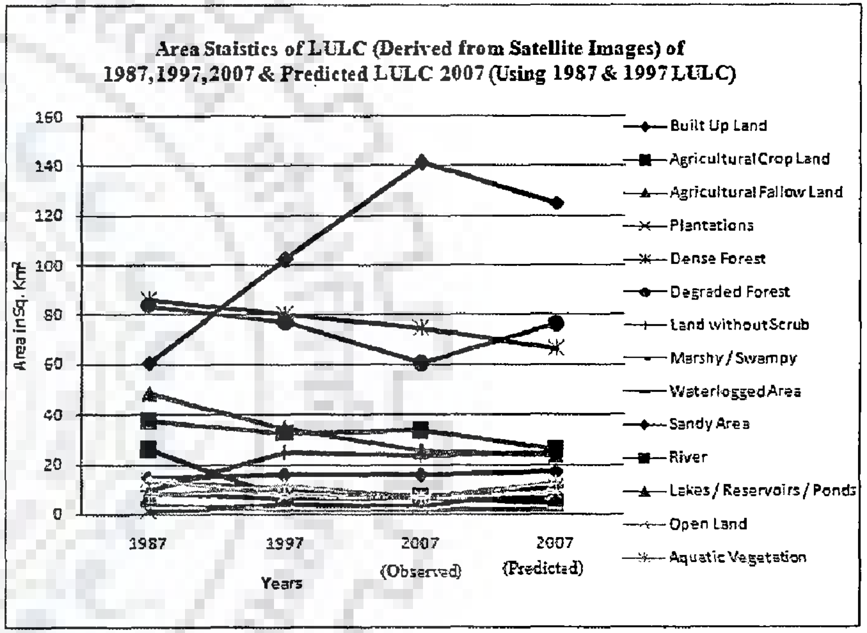


Figure 6.3: Area statistics of predicted LULC of 2007 using 1987 & 1997 LULC image and LULC derived from LISS III image of 2007

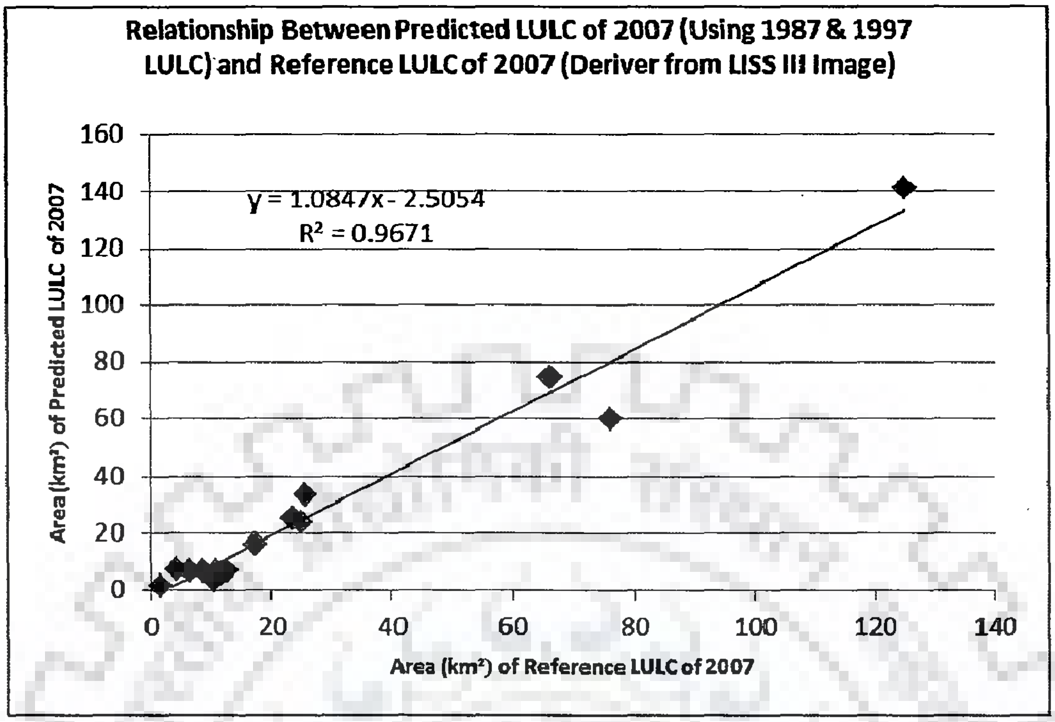


Figure 6.4: Relationship between predicted LULC of 2007 (using 1987 & 1997 LULC image) and LULC derived from LISS III image of 2007

6.12.2. Predicting Locations

The predicted results of LULC, (using 1987 and 1997 LULC maps) by using 3x3, 5x5 and 7x7 CA contiguity filters in CA Markov model are shows in Figure 6.5, Figure 6.6 and Figure 6.7, respectively. When we look at the quantity of predicted LULC of 2007 area statistics derived by using 3x3, 5x5 and 7x7 CA contiguity filters, the predicted area statistics are the same. But when we look the area statistics of LULC derived from LISS III images of 2007 and predicted LULC of predicted LULC derived by using 3x3, 5x5 and 7x7 CA contiguity filter, these are slightly different as mentioned in previous paragraph. The spatial difference between predicted LULC of 2007 and LULC derived from LISS III images of 2007 is evaluated and they are found to be slightly different. Regression analysis of three pairs of images (predicted LULC of 2007 using 3x3 filter and LULC derived from LISS III images of 2007; predicted LULC of 2007 using 5x5 filter and LULC derived from LISS III images of 2007; predicted LULC of 2007 using 7x7 filter and LULC derived from LISS III images of 2007) established the spatial relationship amongst them. The linear equations derived from the regression analysis give us an idea about how much are these spatially related. Correlation coefficient between predicted LULC classes using 3x3 CA filters and LULC derived from LISS III image of 2007 is r = 0.7906 (Figure 6.8.a) where Correlation between predicted LULC classes using 5x5 CA filters and LULC derived from LISS III Image of 2007 is r = 0.7929 (Figure 6.8.b) and correlation coefficient (r) between predicted LULC classes using 7x7 CA filters and LULC derived from LISS III image of 2007 is r = 0.7927 (Figure 6.8.c). Therefore, the 5x5 contiguity filters (correlation coefficient (r) when using 5x5 filters is highest among 3x3, 5x5, and 7 x 7 filters) produce most geographically / spatially distributed effective results, although the differences between them are very small.

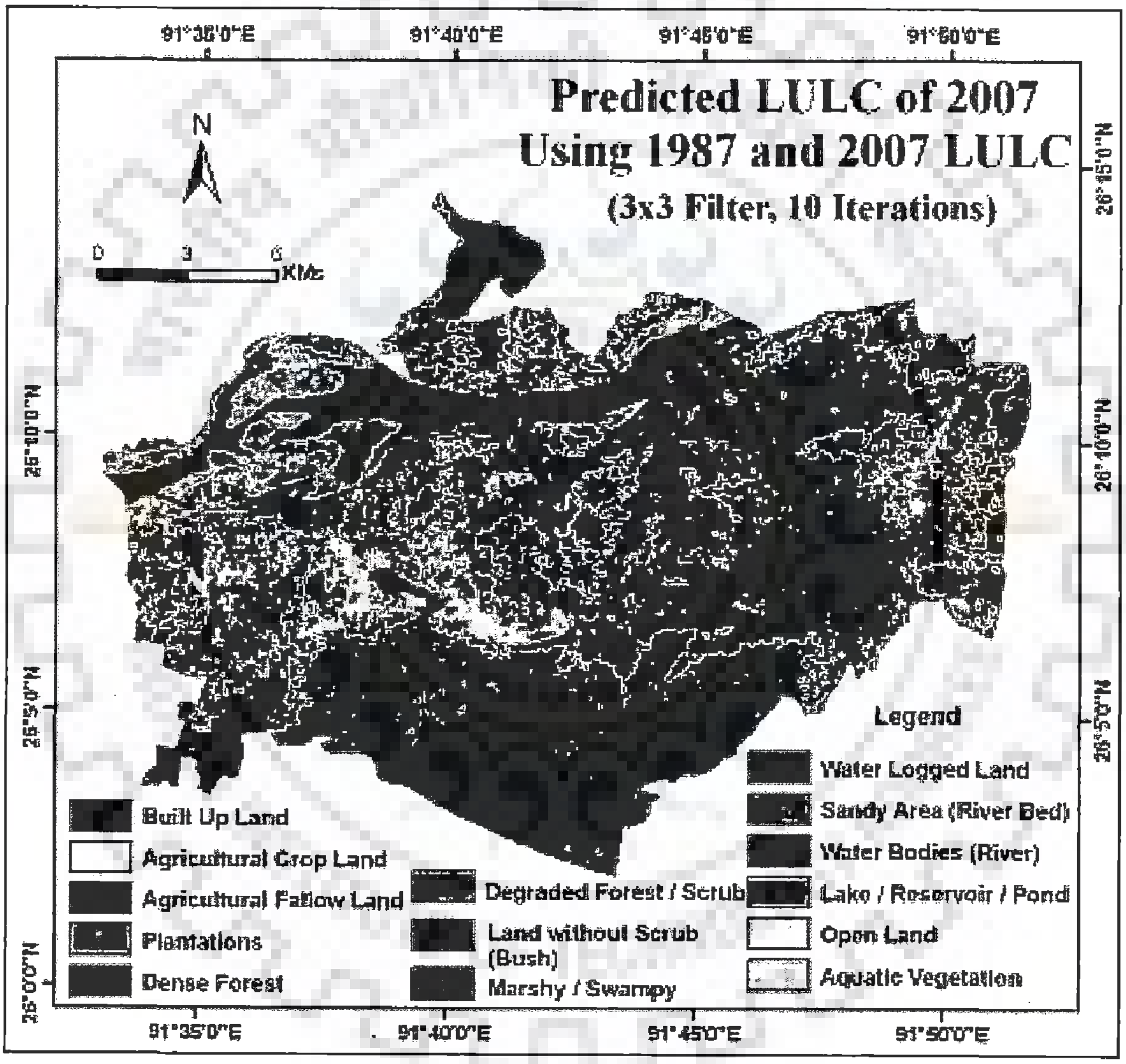


Figure 6.5: Predicted LULC of 2007 using 1987 & 1997 LULC image

(3x3 contiguity filter, 10 iterations)

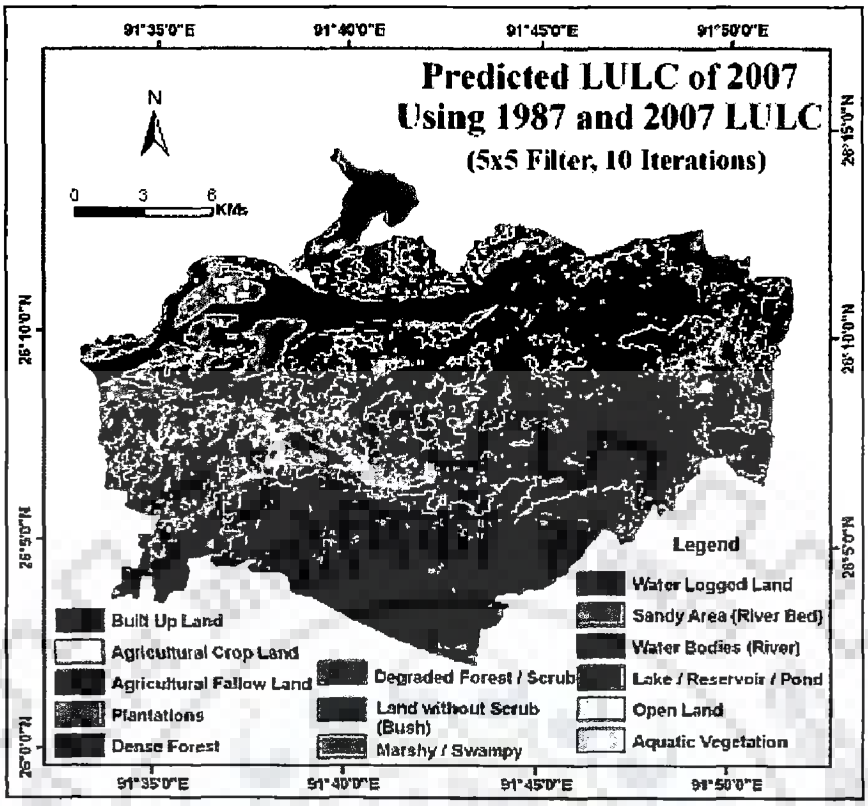


Figure 6.6: Predicted LULC of 2007 using 1987 & 1997 LULC image (5x5 contiguity filter, 10 iterations)

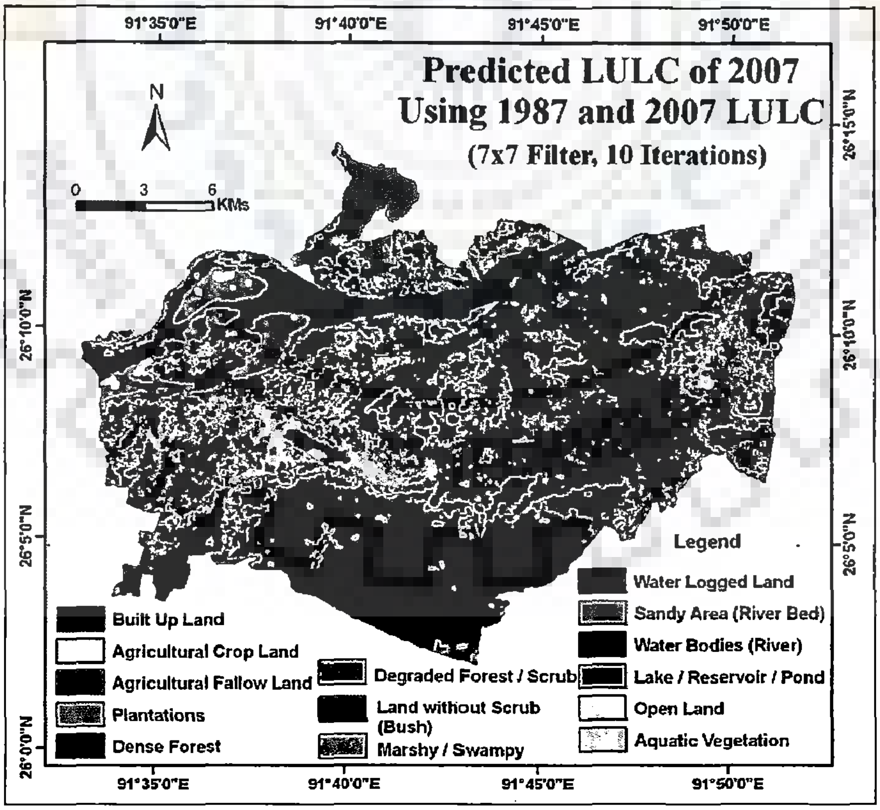


Figure 6.7: Predicted LULC of 2007 using 1987 & 1997 LULC image (7x7 contiguity filter, 10 iterations)

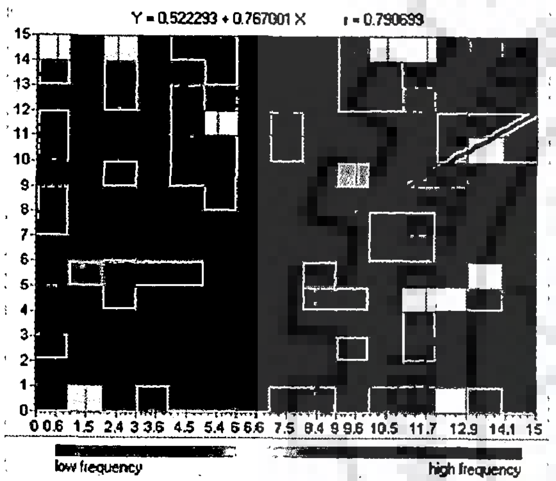


Figure - 6.8.a
(3x3 contiguity filter and references)

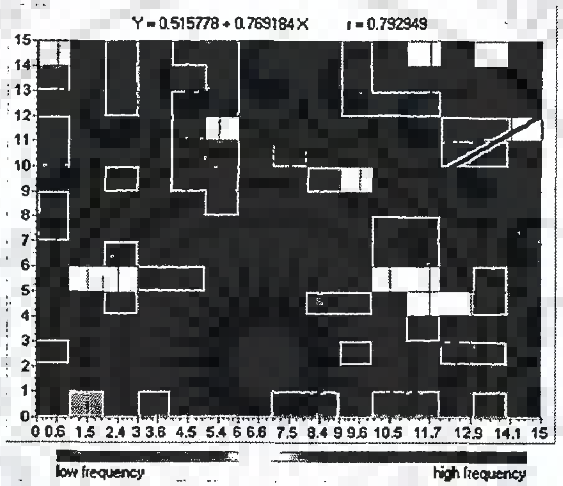


Figure - 6.8.b
(5x5 contiguity filter and references)

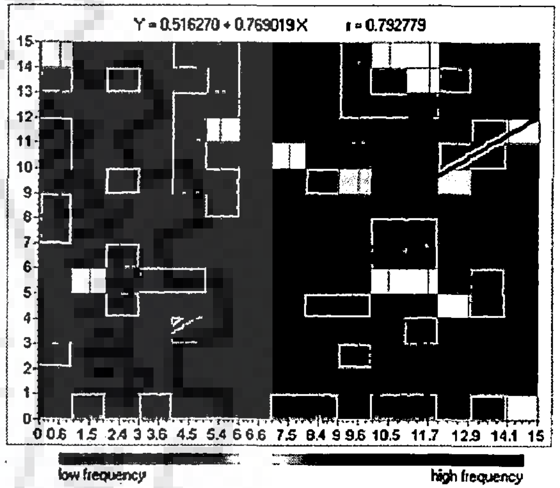


Figure - 6.8.c
(7x7 contiguity filter and references)

Figure 6.8: Spatial relationship between predicted LULC of 2007 (using 3x3, 5x5, 7x7 contiguity filter) and LULC derived from LISS III image of 2007 (references image)

6.13. SENSITIVITY ANALYSIS TO IDENTIFY SENSITIVE PARAMETER(S)

Sensitivity analysis is the act of determining the changes in model behaviour due to a predetermined adjustment of model parameters. A sensitivity analysis was carried out to find out which parameters had the largest influence on the model prediction results and vice-versa. Sensitivity analysis was performed on the differences between the predicted LULC of 2007 (using 1987 & 1997 LULC image) and LULC derived from LISS III image of 2007, to identify the most sensitive parameters of the model. Jetten et al., (1998) showed that the sensitivity to certain parameters might depend on the level of other parameters. Thus model sensitivity can be more completely evaluated by changing the combinations of parameters. Nonetheless, a simple sensitivity analysis in which only one parameter value is changed at a time is the easiest way to determine which individual parameter will be most important (Hessel, 2002). Therefore, in this study, simulations were carried out by uniformly excluding one parameter from all the parameters.

6.13.1. Predictions and Sensitivity Analysis

Sensitivity analysis can identify the parameter(s), which have most to least influences on land use and land cover prediction results. According to the underlying land use and land cover change dynamics between years 1987 and 1997, a series of maps (evidence likelihood map) consisting of built up land suitability, agricultural crop land suitability, agricultural fallow land suitability, plantation suitability, dense forest land suitability, degraded forest land suitability, land with or without scrub suitability, marshy / swampy land suitability, waterlogged area suitability, sandy area suitability, river suitability, lakes/reservoirs/ponds suitability, open land suitability, aquatic vegetation land suitability maps were used to predict 2007 land use and land cover. The output suitability maps actually are the conditional probability images that report the probability that each LULC type is found at each pixel in predicted map. The transition probability matrix of 1987-1997 and probability images (here, suitability / evidence likelihood map) were used in CA Markov model to predict the LULC over a 10 years period i.e., 2007 (Table 6.1 & Figure 6.2). This transition probability matrix will determine how much land is allocated to each LULC category over a 10 year period. To predict LULC of 2007, all 14 suitability / evidence likelihood maps (probability images) were used to calibrate the CA Markov model. But to identify the sensitivity of above parameters (those used in CA Markov model), the CA Markov model calibrated 14 times for 14 parameters, and in every calibration one parameter (one suitability / evidence likelihood map) has been excluded in CA Markov model calibration to identify the sensitivity of a particular parameter to predict the results. For example, the CA Markov model was calibrated without built up land sensitivity map to identify the sensitivity of built up land. Similarly, the CA Markov model was calibrated without agricultural crop land suitability map to identify the sensitivity of agricultural crop land. This procedure was followed for every other parameter (i.e., agricultural fallow land, plantation, dense forest land, degraded forest land, land with or without scrub, marshy / swampy land, waterlogged area, sandy area, river, lakes/reservoirs/ponds, open land, aquatic vegetation land) (Table 6.3). These predicted LULC of 2007 were correlated with predicted LULC of 2007 using all parameters / suitability or evidence likelihood maps and the correlation coefficient (r) value arranged in descending order. The least and most 'r' values determine the most and least sensitive parameter(s), respectively.

Table 6.3: Description of predicted LULC of 2007 using all parameters except any one parameter

Scenario	Descriptions
A	Predicted LULC of 2007 using all parameters except built up land
B	Predicted LULC of 2007 using all parameters except agricultural crop land
C	Predicted LULC of 2007 using all parameters except agricultural fallow land
D	Predicted LULC of 2007 using all parameters except plantation
E	Predicted LULC of 2007 using all parameters except dense forest land
F	Predicted LULC of 2007 using all parameters except degraded forest land
G	Predicted LULC of 2007 using all parameters except land with or without scrub
H	Predicted LULC of 2007 using all parameters except marshy / swampy land
I	Predicted LULC of 2007 using all parameters except waterlogged area
J	Predicted LULC of 2007 using all parameters except sandy area
K	Predicted LULC of 2007 using all parameters except river
L	Predicted LULC of 2007 using all parameters except lakes/reservoirs/ponds
M	Predicted LULC of 2007 using all parameters except open land
N	Predicted LULC of 2007 using all parameters except aquatic vegetation land

6.13.2. Sensitivity of Different Parameter(s)

6.13.2.1. Sensitivity of different parameter(s) in predicting quantity

The area statistics of predicted LULC results of 2007 using all parameters & area of predicted LULC of 2007 using all parameters except one parameter (i.e., Scenario A, B, C, D, E, F, G, H, I, J, K, L, M, N) are shows in Table 6.4. When we look at the predicted LULC of 2007 area statistics derived by using all parameters and using all parameters except any one parameter, the predicted area statistics are more or less same because the same transition probability matrix of 1987-1997 is determined how much land is allocated to each LULC category over 10 year's period in every calibration of CA Markov model for all parameters. Relative difference in predicted LULC of 2007 using all parameters and predicted LULC of 2007 using all parameters except any one parameter ranges between (+) 10.23 km^2 and (-) 0.07 km^2 only (Table 6.5).

The correlation between predicted LULC of 2007 using all parameters except any one parameter and predicted LULC of 2007 using all parameters is strong, where $r = 0.994$ and $R^2 = 0.988$ (Figure 6.9). As expected, that predicted LULC of 2007 using all parameters and predicted LULC of 2007 using all parameters except any one parameter are strongly correlated.

6.13.2.2. Sensitivity of different parameter(s) in predicting locations

Predicting locations of LULC of 2007 using all parameters are shows in Figure 6.10 and predicted locations of LULC of 2007 using Scenario A, B, C, D, E, F, G, H, I, J, K, L, M, N are shows in Figure 6.11.a, Figure 6.11.b, Figure 6.11.c, Figure 6.11.d, Figure 6.11.e, Figure 6.11.f, Figure 6.11.g, Figure 6.11.h, Figure 6.11.i, Figure 6.11.j, Figure 6.11.k, Figure 6.11.l, Figure 6.11.m and Figure 6.11.n, respectively.

Table 6.4: Area statistics of predicted LULC of 2007 using all parameters & predicted LULC of 2007 using all parameters except any one parameter

LULC Class	Area (in Km²)														
	Predicted LULC of 2007 Using all Parameters	Predicted LULC of 2007 Using all Parameters except													
		Built Up Land	Agricultural Crop Land	Agricultural Fallow Land	Plantation	Dense Forest	Degraded Forest	Land with or without Scrub	Marshy / Swampy	Waterlogged	Sandy Area	River	Lakes / Reservoirs / Ponds	Open Land	Aquatic Vegetation
Built Up Land	125.09	135.32	135.32	135.32	135.32	135.32	135.32	135.32	135.32	135.32	135.32	135.32	135.32	135.32	135.32
Agricultural Crop Land	4.32	4.08	4.08	4.08	4.08	4.08	4.08	4.08	4.08	4.08	4.08	4.08	4.08	4.08	4.08
Agricultural Fallow Land	23.62	24.55	24.55	24.55	24.55	24.55	24.55	24.55	24.55	24.55	24.55	24.55	24.55	24.55	24.55
Plantation	10.57	4.74	4.74	4.74	4.74	4.74	4.74	4.74	4.74	4.74	4.74	4.74	4.74	4.74	4.74
Dense Forest	66.26	75.45	75.45	75.45	75.45	75.45	75.45	75.45	75.45	75.45	75.45	75.45	75.45	75.45	75.45
Degraded Forest	76.19	68.52	68.52	68.52	68.52	68.52	68.52	68.52	68.52	68.52	68.52	68.52	68.52	68.52	68.52
Land with or without Scrub	24.95	22.74	22.74	22.74	22.74	22.74	22.74	22.74	22.74	22.74	22.74	22.74	22.74	22.74	22.74
Marshy / Swampy	10.91	8.86	8.86	8.86	8.86	8.86	8.86	8.86	8.86	8.86	8.86	8.86	8.86	8.86	8.86
Waterlogged	1.46	1.53	1.53	1.53	1.53	1.53	1.53	1.53	1.53	1.53	1.53	1.53	1.53	1.53	1.53
Sandy Area	17.39	15.44	15.44	15.44	15.44	15.44	15.44	15.44	15.44	15.44	15.44	15.44	15.44	15.44	15.44
River	25.72	28.76	28.76	28.76	28.76	28.76	28.76	28.76	28.76	28.76	28.76	28.76	28.76	28.76	28.76
Lakes / Reservoirs / Ponds	6.31	7.01	7.01	7.01	7.01	7.01	7.01	7.01	7.01	7.01	7.01	7.01	7.01	7.01	7.01
Open Land	8.67	5.61	5.61	5.61	5.61	5.61	5.61	5.61	5.61	5.61	5.61	5.61	5.61	5.61	5.61
Aquatic Vegetation	12.52	11.37	11.37	11.37	11.37	11.37	11.37	11.37	11.37	11.37	11.37	11.37	11.37	11.37	11.37
Total	413.98	413.98	413.98	413.98	413.98	413.98	413.98	413.98	413.98	413.98	413.98	413.98	413.98	413.98	413.98

Table 6.5: Relative differences between predicted LULC of 2007 using all parameters and predicted LULC of 2007 using all parameters except any one parameter

LULC Class	Area (in km²)		
	Predicted LULC of 2007 using all parameters	Predicted LULC of 2007 using all parameters except any one parameter	Differences
Built Up Land	125.09	135.32	+10.23
Agricultural Crop Land	4.32	4.08	-0.24
Agricultural Fallow Land	23.62	24.55	+0.93
Plantation	10.57	4.74	-5.83
Dense Forest	66.26	75.45	+9.19
Degraded Forest	76.19	68.52	-7.67
Land with or without Scrub	24.95	22.74	-2.21
Marshy / Swampy	10.91	8.86	-2.05
Waterlogged Area	1.46	1.53	+0.07
Sandy Area	17.39	15.44	-1.95
River	25.72	28.76	+3.04
Lakes / Reservoirs / Ponds	6.31	7.01	+0.7
Open Land	8.67	5.61	-3.06
Aquatic Vegetation	12.52	11.37	-1.15
Total	413.98	413.98	

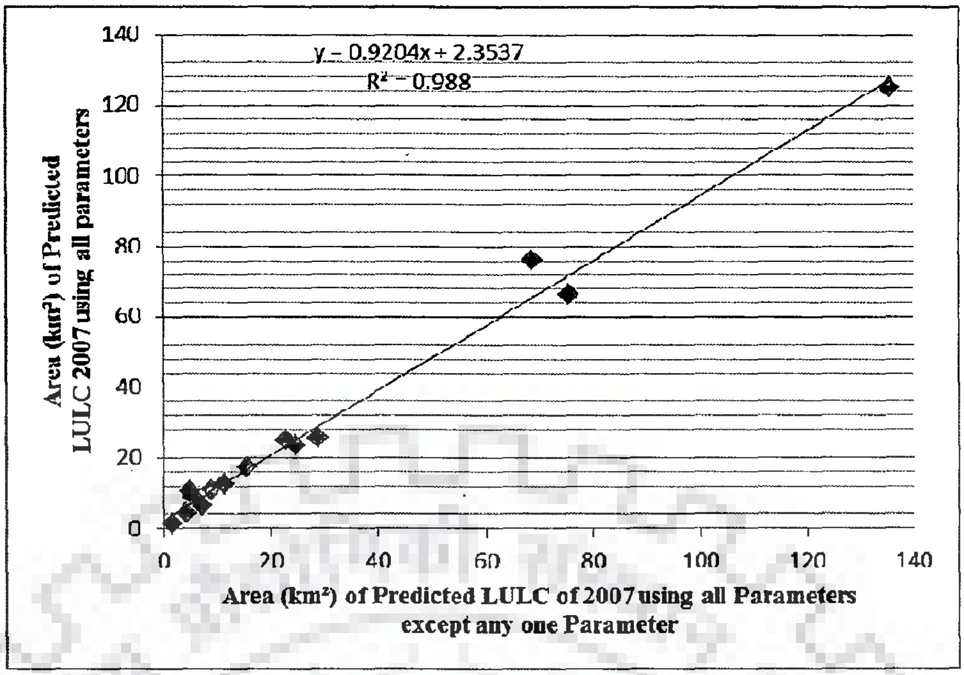


Figure 6.9: Relationships between predicted LULC of 2007 using all parameters and predicted LULC of 2007 using all parameters except any one parameter

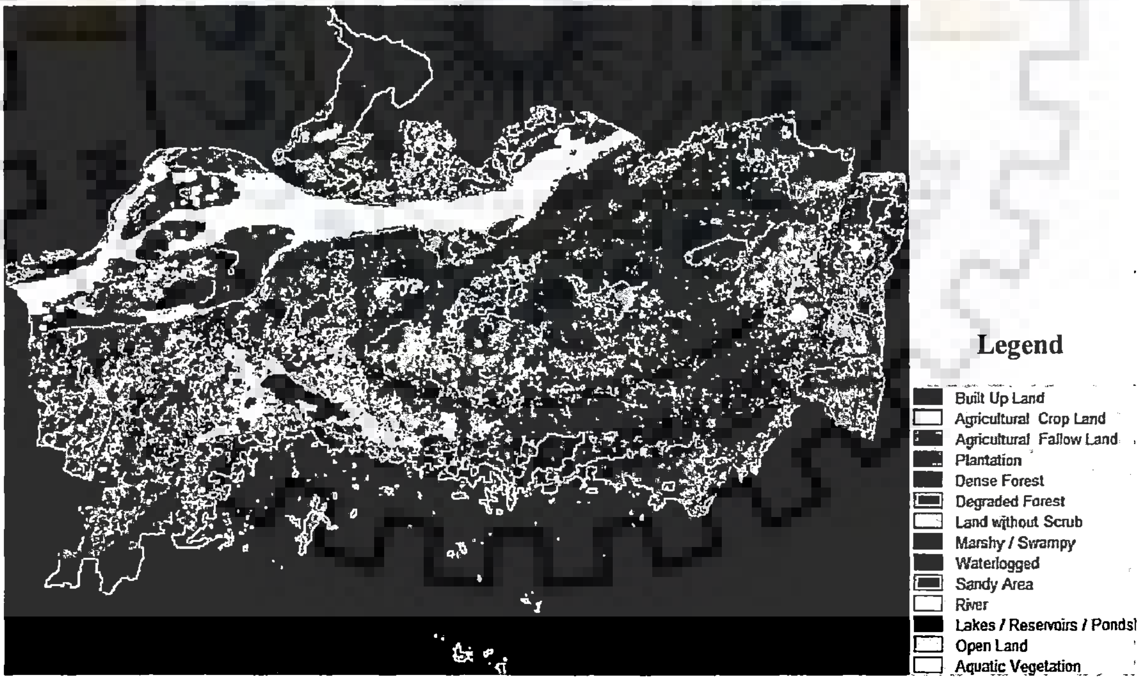


Figure 6.10: Predicted LULC of 2007 using all parameters / all suitibility maps

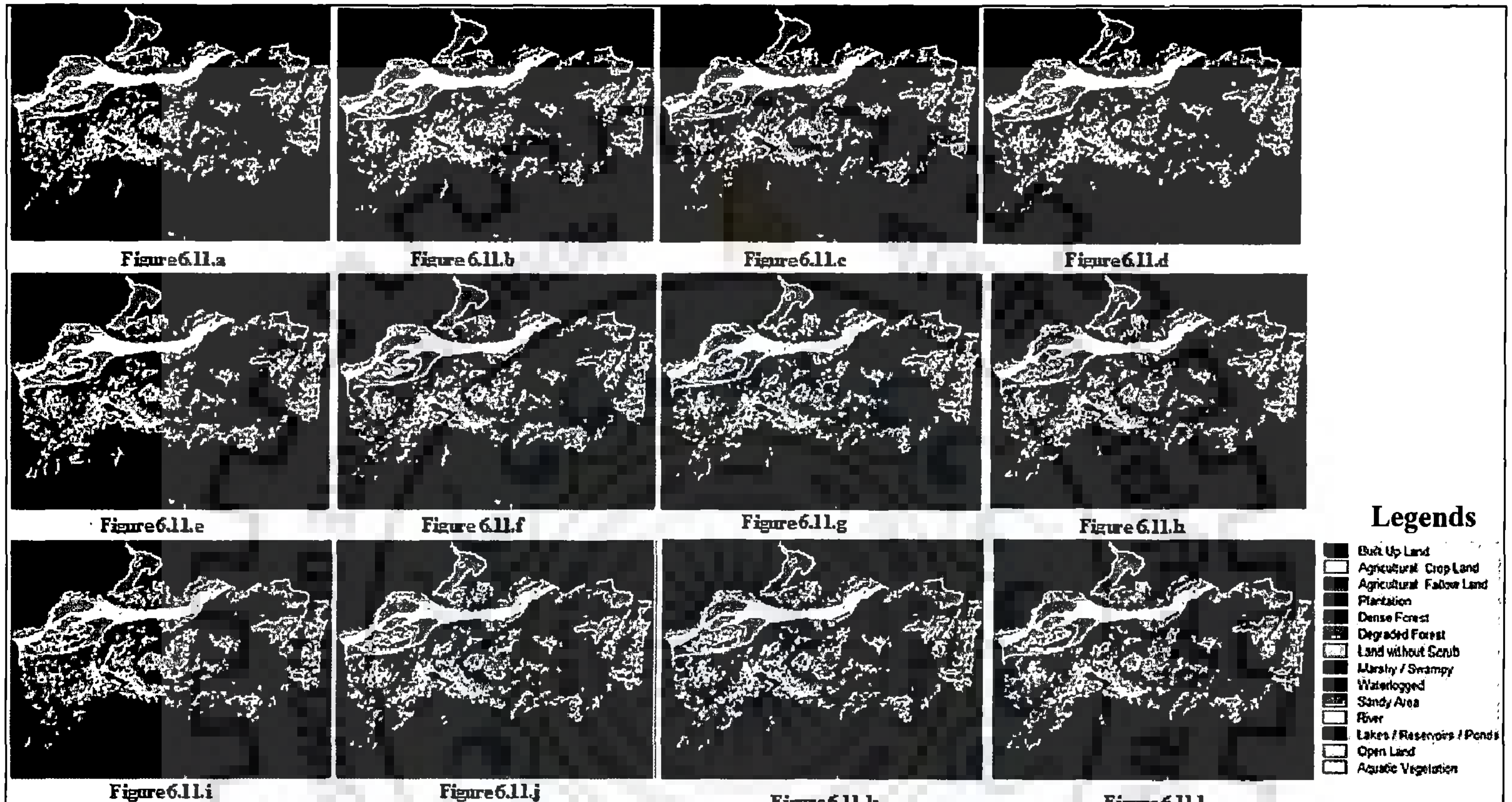


Fig. 6.11.a - Predicted LULC using all Parameters except Built Up Land
Fig. 6.11.b - Predicted LULC using all Parameters except Agricultural Crop Land
Fig. 6.11.c - Predicted LULC using all Parameters except Agricultural Fallow Land
Fig. 6.11.d - Predicted LULC using all Parameters except Plantations
Fig. 6.11.e - Predicted LULC using all Parameters except Dense Forest
Fig. 6.11.f - Predicted LULC using all Parameters except Degraded Forest
Fig. 6.11.g - Predicted LULC using all Parameters except Land with or without Scrub
Fig. 6.11.h - Predicted LULC using all Parameters except Marshy / Swampy
Fig. 6.11.i - Predicted LULC using all Parameters except Water Logged Area
Fig. 6.11.j - Predicted LULC using all Parameters except Open Land
Fig. 6.11.k - Predicted LULC using all Parameters except Lake/Reservoir/Pond/Tank
Fig. 6.11.l - Predicted LULC using all Parameters except Sandy Area (River Bed)
Fig. 6.11.m - Predicted LULC using all Parameters except River / Stream
Fig. 6.11.n - Predicted LULC using all Parameters except Aquatic Vegetation

Figure 6.11: Predicted LULC of 2007 using all parameters except any one parameter

Regression analysis of 14 pairs of images (Combination A, B, C, D, E, F, G, H, I, J, K, L, M, N) was carried out for the establishment of spatial relationship amongst them (Table 6.6). These relationships are shows in Figure 6.12. Correlation coefficient (r) and coefficient of determination (R^2) between predicted LULC of 2007 using all parameters and predicted LULC of 2007 using all parameters except any one parameter are shows in Table 6.7.

When we look at the area statistics of predicted LULC of 2007 simulated using all suitability maps and predicted LULC of 2007 simulated using all parameters except any one parameter (any one suitability map), these are more or less the same (Table 7.2). But, spatially these are different. The correlation between predicted LULC of 2007 using all parameters and predicted location of LULC of 2007 using all parameters except any one parameter established that they are spatially different.

Table 6.6: 14 pairs of images

Sl no.	Combination	Images
1	A	Predicted LULC of 2007 using all parameters and predicted LULC of 2007 using all parameters except built up land
2	B	Predicted LULC of 2007 using all parameters and predicted LULC of 2007 using all parameters except agricultural crop land
3	C	Predicted LULC of 2007 using all parameters and predicted LULC of 2007 using all parameters except agricultural fallow land;
4	D	Predicted LULC of 2007 using all parameters and predicted LULC of 2007 using all parameters except plantation
5	E	Predicted LULC of 2007 using all parameters and predicted LULC of 2007 using all parameters except dense forest land;
6	F	Predicted LULC of 2007 using all parameters and predicted LULC of 2007 using all parameters except degraded forest land;
7	G	Predicted LULC of 2007 using all parameters and predicted LULC of 2007 using all parameters except land with or without scrub;
8	H	Predicted LULC of 2007 using all parameters and predicted LULC of 2007 using all parameters except marshy / swampy land;
9	I	Predicted LULC of 2007 using all parameters and predicted LULC of 2007 using all parameters except waterlogged area
10	J	Predicted LULC of 2007 using all parameters and predicted LULC of 2007 using all parameters except sandy area
11	K	Predicted LULC of 2007 using all parameters and predicted LULC of 2007 using all parameters except river
12	L	Predicted LULC of 2007 using all parameters and predicted LULC of 2007 using all parameters except lakes/reservoirs/ponds
13	M	Predicted LULC of 2007 using all parameters and predicted LULC of 2007 using all parameters except open land;
14	N	Predicted LULC of 2007 using all parameters and predicted LULC of 2007 using all parameters except aquatic vegetation land

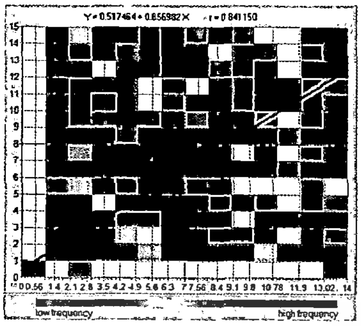


Figure 6.12.a: Combination A

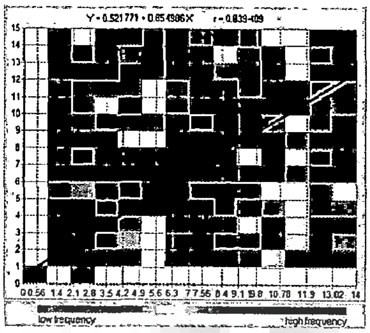


Figure 6.12.b: Combination B

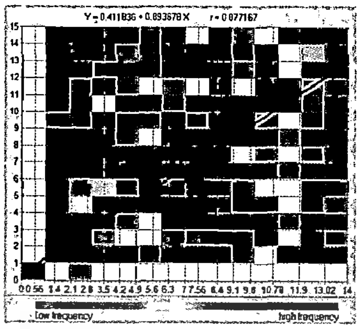


Figure 6.12.c: Combination C

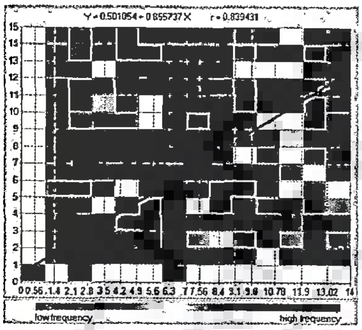


Figure 6.12.d: Combination D

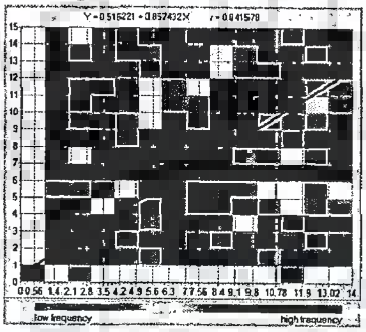


Figure 6.12.e: Combination E

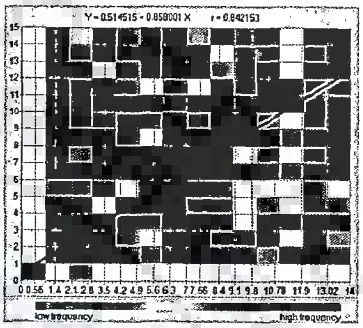


Figure 6.12.f: Combination F

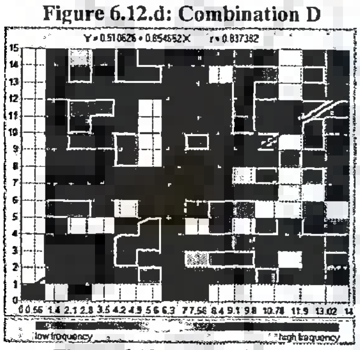


Figure 6.12.g: Combination G

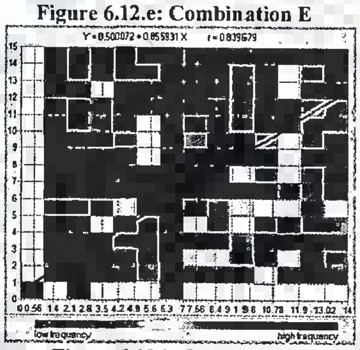


Figure 6.12.j: Combination J

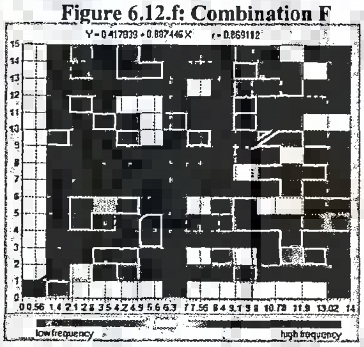


Figure 6.12.i: Combination I

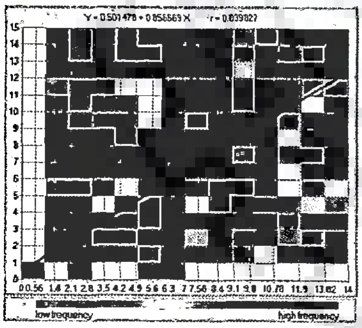


Figure 6.12.j: Combination J

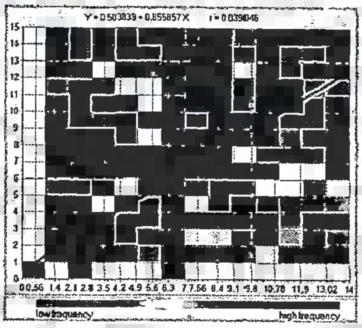


Figure 6.12.k: Combination K

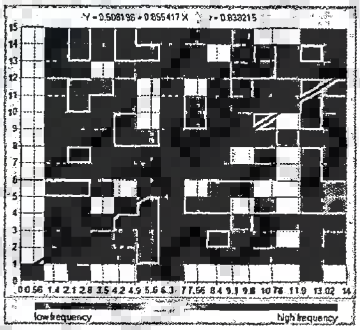


Figure 6.12.l: Combination L

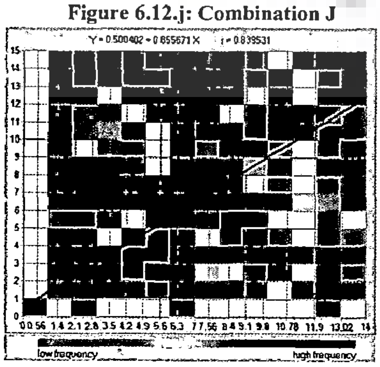


Figure 6.12.m: Combination M

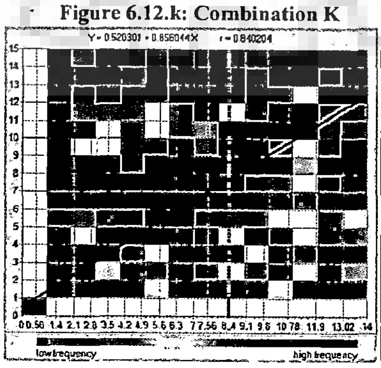


Figure 6.12.n: Combination N

Figure 6.12: Spatial relationships between predicted LULC of 2007 (using all parameters) and predicted LULC of 2007 (using all parameters except one parameter)

Table 6.7: Relationship between predicted LULC of 2007 using all parameters & predicted LULC of 2007 using all parameters except any one parameter

Sl. no.	Combination	Image Pairs	r	R^2
1	A	Predicted LULC of 2007 using all parameters and Predicted LULC of 2007 using all parameters except built up land	0.8412	0.7075
2	B	Predicted LULC of 2007 using all parameters and Predicted LULC of 2007 using all parameters except agricultural crop land	0.8394	0.7046
3	C	Predicted LULC of 2007 using all parameters and Predicted LULC of 2007 using all parameters except agricultural fallow land;	0.8772	0.7694
4	D	Predicted LULC of 2007 using all parameters and predicted LULC of 2007 using all parameters except plantation	0.8394	0.7046
5	E	Predicted LULC of 2007 using all parameters and Predicted LULC of 2007 using all parameters except dense forest land;	0.8416	0.7083
6	F	Predicted LULC of 2007 using all parameters and Predicted LULC of 2007 using all parameters except degraded forest land;	0.8422	0.7092
7	G	Predicted LULC of 2007 using all parameters and Predicted LULC of 2007 using all parameters except land with or without scrub;	0.8374	0.7012
8	H	Predicted LULC of 2007 using all parameters and Predicted LULC of 2007 using all parameters except marshy / swampy land;	0.8397	0.7051
9	I	Predicted LULC of 2007 using all parameters and Predicted LULC of 2007 using all parameters except waterlogged area	0.8691	0.7554
10	J	Predicted LULC of 2007 using all parameters and Predicted LULC of 2007 using all parameters except sandy area	0.8398	0.7053
11	K	Predicted LULC of 2007 using all parameters and Predicted LULC of 2007 using all parameters except river	0.8390	0.7040
12	L	Predicted LULC of 2007 using all parameters and Predicted LULC of 2007 using all parameters except lakes/reservoirs/ponds	0.8382	0.7026
13	M	Predicted LULC of 2007 using all parameters and Predicted LULC of 2007 using all parameters except open land;	0.8395	0.7048
14	N	Predicted LULC of 2007 using all parameters and Predicted LULC of 2007 using all parameters except aquatic vegetation land	0.8402	0.7059

The linear equations derived from the regression analysis give us an idea about how much are they spatially related. Ascending/descending order of relationship (correlation coefficient) also gives an idea about the sensitivity of different parameters (Table 6.8). One-tailed probability-value (at the hypothesized population mean) of a z-test for the data set (r values) is also calculated for improvement the error statistics (Table 6.8). The least correlation coefficient value determines the most sensitive parameter while most correlation coefficient value determines the least sensitive parameter. The results of linear equations on all parameters indicate that the most sensitive parameter are land with or without scrub is (r is 0.8374, where P-value of a z-test for r is 0.0145) which has highest influences among different suitability map to predict LULC of 2007. The second most sensitive parameter is lakes / reservoirs / ponds (where r is 0.8382, where P-value of a z-test for r is 0.0262) which has second highest influence to predicted LULC of 2007 when different suitability map are using for predictions. The third most sensitive parameter is river (r is 0.8390, where P-value of a z-test for r is 0.0450), followed by agricultural crop land (r is 0.8394, where P-value of a z-test for r is 0.0578), plantation (r is 0.8394, where P-value of a z-test for r is 0.0578), open land (r is 0.8395, where P-value of a z-test for r is 0.0614), marshy / swampy (r is 0.8397, where P-value of a z-test for r is 0.0691), sandy area (r is 0.8398, where P-value of a z-test for r is 0.0733), aquatic vegetation (r is 0.8402, where P-value of a z-test for r is 0.0918), built up land (r is 0.8412, where P-value of a z-test for r is 0.1526), dense forest (r is 0.8416, where P-value of a z-test for r is 0.1832), degraded forest (r is 0.8422, where P-value of a z-test for r is 0.2356), waterlogged area (r is 0.8691, where P-value of a z-test for r is 1). As per r value, the least sensitive parameter is agricultural fallow land (r is 0.8772, where P-value of a z-test for r is 1), which has least influence to predicted LULC of 2007 when different suitability maps are used for predictions. But as per, z-test of r values the least sensitive parameters are the waterlogged area and agricultural fallow land (where P-value of a z-test for both are 1), which haves least influence to predicted LULC of 2007.

Table 6.8: Ranking (descending order) of relationship between predicted LULC of 2007 using all parameters and predicted LULC of 2007 using all parameters except any one parameter

Sl no.	Image Pairs	r	One-tailed P-value of a z-test (for r value)	R^2	One-tailed P-value of a z-test (for R^2 value)
1	Predicted LULC of 2007 using all parameters and Predicted LULC of 2007 using all parameters except **land with or without scrub**	0.8374	0.0145	0.7012	0.0149
2	Predicted LULC of 2007 using all parameters and Predicted LULC of 2007 using all parameters except **lakes / reservoirs / ponds**	0.8382	0.0262	0.7026	0.0271
3	Predicted LULC of 2007 using all parameters and predicted LULC of 2007 using all parameters except **river**	0.8390	0.0450	0.7040	0.0469
4	Predicted LULC of 2007 using all parameters and Predicted LULC of 2007 using all parameters except **agricultural crop land**	0.8394	0.0578	0.7046	0.0583
5	Predicted LULC of 2007 using all parameters and Predicted LULC of 2007 using all parameters except **plantation**	0.8394	0.0578	0.7046	0.0583
6	Predicted LULC of 2007 using all parameters and Predicted LULC of 2007 using all parameters except **open land**	0.8395	0.0614	0.7048	0.0626
7	Predicted LULC of 2007 using all parameters and Predicted LULC of 2007 using all parameters except **marshy / swampy**	0.8397	0.0691	0.7051	0.0694
8	Predicted LULC of 2007 using all parameters and Predicted LULC of 2007 using all parameters except **sandy area**	0.8398	0.0733	0.7053	0.0743
9	Predicted LULC of 2007 using all parameters and Predicted LULC of 2007 using all parameters except **aquatic vegetation**	0.8402	0.0918	0.7059	0.0905
10	Predicted LULC of 2007 using all parameters and Predicted LULC of 2007 using all parameters except **built up land**	0.8412	0.1526	0.7075	0.1461
11	Predicted LULC of 2007 using all parameters and Predicted LULC of 2007 using all parameters except **dense forest**	0.8416	0.1832	0.7083	0.1811
12	Predicted LULC of 2007 using all parameters and Predicted LULC of 2007 using all parameters except **degraded forest**	0.8422	0.2356	0.7092	0.2264
13	Predicted LULC of 2007 using all parameters and Predicted LULC of 2007 using all parameters except **waterlogged area**	0.8691	1	0.7554	1
14	Predicted LULC of 2007 using all parameters and Predicted LULC of 2007 using all parameters except **agricultural fallow land**	0.8772	1	0.7694	1

6.14. SUMMARY

CA Markov LULCC simulation and forecast model is a meaningful exploration by combining of the process of CA and Markov chain analysis, which takes the complexity of combination CA, Markov chain, multi-criteria evaluation (MCE), and multi-objective land allocation (MOLA) into land use and land cover change account. The spatial simulation accuracy of CA Markov model is also good, not only quantitatively as well as spatially. Quantitatively it's near reality. Spatially also, it's also near reality. After getting suitable parameters (drivers variables), we can get the results that is close to the reality. The results of simulation are not just a kind of probability, as well as spatial expression has great meanings for revealing LULCC dynamic mechanism, exploring the simulate and forecast the spatio-temporal pattern and distribution of LULCC in the future in different scenarios.

On the other hand, the results of sensitivity analysis of all parameters indicate that land with or without scrub appeared to be most important sensitive parameter, which has highest influence on predicted results of LULC of 2007 and the agricultural fallow land came out to be the least sensitive parameter, which has least influence on predicted results of LULC of 2007. The lowest correlation coefficient (r) value is 0.8374 (land with or without scrub) and the highest correlation coefficient (r) value is 0.8772 (agricultural fallow land). Whereas, one-tailed probability-value of a z-test for the data indicating that waterlogged area and agricultural fallow land are the least sensitive parameters (where P-value of a z-test for both are 1), which haves least influence to predicted LULC of 2007. This study also established that a simple sensitivity analysis in which only one parameter value is changed at a time is the easiest way to determine which individual parameter will be most important or which individual parameter will be least important.

Chapter - 7

STATISTICAL INDEPENDENCE TEST AND VALIDATION OF CA MARKOV LULCC MODEL

7.1. STATISTICAL INDEPENDENCE TEST

Markov model considers that LULC as stochastic process, and different categories of LULC as the states of chain. A chain is defined as stochastic process having the conditional probability distribution of the process at time n+1, X_{n+1} depends upon only value of X_n, and is not dependent on all other previous value X_{n-1}, X_{n-2} ....X_0. It can be explained as:

$$P\,[X_{n+1} = X_{n+1} \mid X_n = X_n, \ldots\ldots\ldots\ldots X_0 = x_0$$

$$P\,[X_{n+1} = xn{+}1 \mid Xn = xn] \quad \ldots\ldots (7.1)$$

This can also be expressed as

$$P_{ij} = P\,[X_{n+1} = j \mid Xn = i] \quad \ldots\ldots (7.2)$$

$$ij = 0,1,2,\ldots\ldots\ldots\ldots$$

Here P_{ij} is transition probability of one step, which can be analysed as the conditional probability at time n when the process in state 1 and at time n+1 the process is in state j. Two step transition probabilities are defined with generalization of Chapman-Kolmogorov equation.

$$P_{ij}^{\,2} = P\,[X_{n+2} = j \mid X_n = i] = \sum P\,[X_{n+2} = j \mid X_{n+i} = k]\; P\,[X_n = k \mid X_n = i] \quad \ldots\ldots (7.3)$$

This is equivalent to $(P)_{m+n} = (P)_n * (P)_m$ .... (7.4)

7.2. HYPOTHESIS TEST FOR STATISTICAL INDEPENDENCE

To follow the hypothesis of statistical independence involves a process of comparing the actual data with expected data of land use adopting following formula:

$$K^2 = \sum_i \sum_k (A_{ik} - E_{ik})^2 / E_{ik} \quad \ldots\ldots (7.5)$$

where,

E_{ik} = expected value under Markov hypothesis

A_{ik} = actual value of data from category in i to category in k

If the value of K^2 is greater than the tabulated value on the critical region 0.05 with degree of freedom $(D.F. - 1)^2$ the hypothesis will be rejected. Expected value calculated with the use of Chapman-Kolmogorov equation following the Markov method. For calculation of transition probability matrix for the period 1987-2007 can be obtained by multiplying the 1987-1997 matrices (Table 7.1) and 1997-2007 matrices (Table 7.2). The expected value is calculated by following formula:

$$E_{ik} = E(E_{ij})\,(E_{jk})/E_j \quad \text{.......(7.6)}$$

where,

E_{ij} = the transition from category i to j during the period 1987-1997

E_{jk} = the transition from category j to k during the period 1997-2007

E_j = the number of cells in category j in 1987

7.3. TEST OF GOODNESS OF FIT

Chi square test of goodness of fit is used to test order Markovian suitability with the data. This test analysed that a particular distribution has been adequately described or not. By making comparison between actual observed probability and expected probability.

$$X_c^2 = \sum \sum (O_{ik} - E_{ik})^2/E_{ik} \quad \text{.......(7.7)}$$

where,

O_{ik} = observed transition probability (matrix) of 1987-1997

E_{ik} = expected transition probability (matrix) of 1987-2007

If the X_c^2 is less than the table value of X_{1-a} on the 0.05 critical regions then the hypothesis is accepted.

7.4. RESULTS OF STATISTICAL INDEPENDENCE

The transition probability matrix has been calculated between 1987-1997 for prediction of LULC of 2007 (Table 7.3). The excepted probability of transition of LULC category is displayed in Table 7.4. The transition probability matrix is the cross tabulation of the two images (images of 1987 and 1997).

Table 7.1: Transition matrix of 1987-1997

LULC Classes	Built Up Land	Agricultural Crop Land	Agricultural Fallow Land	Plantations	Dense Forest	Degraded Forest	Land with or without Scrub	Marshy / Swampy	Water logged Area	Sandy Area (River Bed)	River / Stream	Lake /Reservoir /Pond /Tank	Open Land	Aquatic Vegetation
Built Up Land	0.0001	0.083	0.0101	0.0133	0.0002	0.0003	0.0212	0.0038	0.0028	0.0006	0.0007	0.0005	0.0005	0.0057
Agricultural Crop Land	0	0	0.0027	0.0023	0	0	0.0004	0	0.0009	0	0.0019	0	0	0.0001
Agricultural Fallow Land	0.0001	0	0.0041	0.0302	0	0	0.004	0.0011	0.0021	0.0008	0.0008	0	0.0001	0.0035
Plantations	0	0.0007	0.0005	0.0002	0.0009	0.0001	0.002	0.0001	0.0003	0.0001	0	0	0	0.0001
Dense Forest	0.0001	0	0.0004	0.0003	0.0002	0.1025	0.0088	0.0002	0.0002	0	0	0	0.0001	0.0001
Degraded Forest	0.0002	0.0004	0.0096	0.0075	0.0004	0.0163	0.061	0.0032	0.0028	0.0005	0.0003	0.0003	0.0007	0.0038
Land with or without Scrub	0	0	0.0057	0.0054	0.0001	0.0011	0.0134	0.0035	0.0006	0.0002	0.0001	0	0.0003	0.0028
Marshy / Swampy	0	0.0002	0.0012	0.0023	0	0.0001	0.0026	0.0003	0.003	0.0001	0.0026	0.0007	0.0001	0.0007
Waterlogged Area	0	0	0.0001	0.0006	0	0	0.0004	0	0.0007	0.0006	0	0	0	0.0001
Sandy Area (River Bed)	0.0001	0	0.0002	0.0001	0	0	0.0001	0	0.0006	0.0001	0.01	0.0113	0	0
River / Stream	0.0001	0	0.0001	0	0	0	0	0	0.0017	0.0001	0.0041	0.0394	0	0
Lake/Reservoir/Pond /Tank	0	0.0001	0.0002	0.0004	0.0001	0	0.0006	0.0001	0.0012	0.0005	0.0001	0	0.0037	0.0002
Open Land	0	0.0003	0.0007	0.0041	0	0	0.0009	0.0003	0.0009	0.0007	0.0001	0	0.0002	0.0017
Aquatic Vegetation	0	0.0001	0.0006	0.0007	0.0001	0	0.0014	0.0005	0.001	0.0007	0	0	0.0054	0.0006

Table 7.2: Transition matrix of 1997-2007

LULC Classes	Built Up Land	Agricultural Crop Land	Agricultural Fallow Land	Plantations	Dense Forest	Degraded Forest	Land with or without Scrub	Marshy / Swampy	Water logged Area	Sandy Area (River Bed)	River / Stream	Lake /Reservoir /Pond /Tank	Open Land	Aquatic Vegetation
Built Up Land	0.0001	0.1393	0.0008	0.0114	0.0022	0.0014	0.0249	0.0082	0.0029	0.0004	0.0005	0.0003	0.0009	0.0031
Agricultural Crop Land	0	0.0001	0.0031	0.001	0.0002	0.0003	0.0023	0.001	0.0008	0	0.0006	0	0.0001	0.0001
Agricultural Fallow Land	0.0001	0.0002	0.002	0.0202	0.0001	0.0001	0.0033	0.003	0.0021	0.0002	0.0005	0	0.0003	0.0025
Plantations	0	0.0001	0.0001	0.0003	0.0012	0.0006	0.0013	0.0006	0	0	0	0	0.0001	0
Dense Forest	0.0001	0	0	0	0	0.0984	0.006	0.0003	0	0	0	0	0	0
Degraded Forest	0.0001	0.0008	0.0002	0.0039	0.0007	0.0104	0.0526	0.0117	0.0016	0.0005	0	0	0.0003	0.0006
Land with or without Scrub	0.0001	0.0004	0.0003	0.0062	0.0004	0.0009	0.0112	0.0072	0.0015	0.0007	0.0001	0	0.0009	0.0016
Marshy / Swampy	0	0.0002	0.0003	0.0005	0.0001	0.0002	0.0023	0.0004	0.0019	0.0003	0.0016	0.0008	0.0004	0.0003
Waterlogged Area	0	0	0	0.0002	0	0	0.0005	0.0003	0.0001	0.0001	0.0002	0.0002	0.0001	0.0002
Sandy Area (River Bed)	0.0001	0	0.0007	0.0003	0	0	0.0001	0	0.0016	0	0.0109	0.0084	0.0001	0.0001
River / Stream	0	0.0002	0.0008	0.0003	0	0	0.0003	0.0001	0.0011	0	0.0082	0.0358	0	0
Lake/Reservoir/Pond /Tank	0	0.0001	0	0.0002	0	0	0.0005	0.0002	0.0001	0.0001	0	0	0.0037	0.0002
Open Land	0	0.0018	0.0001	0.0026	0.0001	0.0001	0.0014	0.0009	0.0005	0.0001	0	0	0.0002	0.0015
Aquatic Vegetation	0	0.0001	0	0.0005	0	0.0001	0.0009	0.0009	0.0002	0.0002	0	0	0.0014	0.0002

Table 7.3: Transition probability of prepared LULC data for 1987-2007

LULC Classes	Built Up Land	Agricultural Crop Land	Agricultural Fallow Land	Plantations	Dense Forest	Degraded Forest	Land with or without Scrub	Marshy / Swampy	Water logged Area	Sandy Area (River Bed)	River / Stream	Lake /Reservoir /Pond /Tank	Open Land	Aquatic Vegetation
Built Up Land	0.4190	0.0001	0.0001	0.0002	0	0.0004	0.0003	0	0	0	0	0	0	0
Agricultural Crop Land	0.0002	0.0821	0.0178	0.0264	0.0006	0.0011	0.0415	0.0066	0.0052	0.0013	0.0009	0.0009	0.0011	0.0105
Agricultural Fallow Land	0	0	0.0024	0.0016	0	0.0004	0.0021	0.0001	0.0009	0.0002	0.0017	0	0.0001	0.0002
Plantations	0.0001	0.0001	0.0026	0.0223	0	0.0001	0.0033	0.0009	0.0011	0.0005	0.001	0	0.0001	0.002
Dense Forest	0	0.0001	0.0005	0.0003	0.0009	0.0005	0.0016	0.0002	0.0002	0.0001	0	0	0.0001	0.0001
Degraded Forest	0.0001	0	0	0.0001	0.0001	0.1005	0.0039	0	0.0001	0	0	0	0	0
Land with or without Scrub	0.0002	0.0005	0.0076	0.0048	0.0002	0.0157	0.0481	0.0019	0.0018	0.0003	0.0001	0	0.0004	0.0023
Marshy / Swampy	0.0001	0.0003	0.0031	0.007	0	0.0012	0.0114	0.0022	0.0024	0.0016	0.0002	0	0.0005	0.0021
Waterlogged Area	0	0.0002	0.0004	0.001	0	0.0006	0.0018	0.0002	0.0019	0.0001	0.0017	0.001	0.0001	0.0001
Sandy Area (River Bed)	0	0	0.0001	0.0002	0	0.0002	0.0003	0.0003	0.0002	0.0001	0.0002	0.0002	0.0001	0.0001
River / Stream	0.0001	0	0.0003	0.0001	0	0	0	0	0.0016	0.0001	0.0105	0.0094	0	0
Lake/Reservoir/Pond /Tank	0.0001	0	0.0001	0	0	0	0	0	0.0016	0	0.0043	0.0406	0	0
Open Land	0	0	0.0001	0.0003	0.0001	0	0.0004	0.0001	0.0002	0.0001	0	0	0.006	0.0001
Aquatic Vegetation	0	0.0014	0.001	0.0026	0	0.0001	0.0015	0.0003	0.0009	0.0001	0.0001	0	0.0001	0.0013

Table 7.4: Transition probability of LULC from 1987 to 2007 under Markov hypothesis

LULC Classes	Built Up Land	Agricultural Crop Land	Agricultural Fallow Land	Plantations	Dense Forest	Degraded Forest	Land with or without Scrub	Marshy / Swampy	Water logged Area	Sandy Area (River Bed)	River / Stream	Lake /Reservoir /Pond /Tank	Open Land	Aquatic Vegetation
Built Up Land	0.9799	0	0	0.0078	0	0.0047	0	0.0019	0	0	0.0003	0.0012	0.0037	0.0014
Agricultural Crop Land	0.2812	0.0736	0.1141	0.0149	0.0098	0.2637	0.1569	0.0342	0.0016	0.006	0.0033	0.005	0.019	0.0172
Agricultural Fallow Land	0.1998	0.0343	0.4459	0.0031	0.0045	0.1109	0.0801	0.0343	0.0084	0.0016	0.0007	0.0061	0.0602	0.0103
Plantations	0.0821	0.0056	0.0111	0.4736	0.0984	0.1829	0.044	0.002	0.0004	0	0	0.0595	0.0052	0.0353
Dense Forest	0.0055	0	0.0002	0.0004	0.8486	0.1349	0.0093	0.0005	0	0	0.0001	0.0001	0.0003	0
Degraded Forest	0.1827	0.0032	0.0343	0.017	0.0751	0.5218	0.1143	0.0221	0.0038	0.0005	0.0001	0.0049	0.0078	0.0121
Land with or without Scrub	0.2883	0.0015	0.0837	0.0112	0.0137	0.243	0.2666	0.0215	0.0019	0.0001	0	0.0054	0.0227	0.0406
Marshy / Swampy	0.1491	0.0472	0.1102	0.0135	0.0083	0.1487	0.0336	0.1599	0.0369	0.0316	0.0904	0.066	0.0499	0.0546
Waterlogged Area	0.1301	0.0008	0.1624	0.0159	0.0017	0.0946	0.036	0.0259	0.1196	0.0259	0.0102	0.1072	0.1379	0.132
Sandy Area (River Bed)	0.0334	0.0928	0.039	0.002	0.0001	0.0132	0.0063	0.1235	0	0.4823	0.1981	0.0026	0.0067	0
River / Stream	0.0092	0.0009	0.0003	0.0003	0	0.005	0	0.0137	0.0001	0.2156	0.7537	0.0002	0.0009	0
Lake/Reservoir/Pond /Tank	0.0442	0.0018	0.0133	0.0026	0.0067	0.0585	0.0287	0.0097	0.0028	0.0008	0.0014	0.3293	0.0158	0.4845
Open Land	0.2967	0.0032	0.1786	0.0056	0.0067	0.1966	0.1448	0.0369	0.0032	0.0023	0.0007	0.0102	0.0861	0.0293
Aquatic Vegetation	0.0639	0	0.0774	0.0077	0.005	0.0872	0.1318	0.0400	0.0091	0.0001	0	0.1151	0.0155	0.4473

The statistical test (Table 7.5) of independence is used to understand whether the changes in LULC are dependent or not. This statistical test of independence, (K^2) is performed on LULC data. The results of K^2 is 497.12, which is more than the significance 201.1 on critical region 0.05 with degree of freedom $(14 - 1)^2$. So the hypothesis of statistical independence is rejected. Therefore, the changes in LULC are dependent. One can say that the land use and land cover change trends are dependent on previous development of land.

The Markovian suitability has been checked by using hypothesis of goodness of fit. In this test, actual LULC from 1987 to 2007 has been compared with expected data (LULC), which were calculated using Markov model. This hypothesis is accepted for these data. The calculated value of Xc^2 is 0.52 and it is very less then significance 22.4 on critical region 0.05 with 13 degree of freedom (Table 7.5). With acceptance of the hypothesis one can say that actual transition probability of matrix from 1987-2007 is fitted with expected transition probability prepared using Markov method.

Table 7.5: Statistical results of data

Test Perform	Calculated Value	chi^2 Table Value on .05 Critical Region
Statistical Independence Test (K^2)	497.12	201.1
Goodness of Fit Test (Xc^2)	0.52	22.4

7.5. KAPPA INDICES OF AGREEMENT AND DISAGREEMENT

The international scientific community has called for research into land cover change, specifically models that predict spatial patterns of future change (Turner et al., 1995; Lambin, 1997). Modelers are satisfying this need with a variety of approaches (Wilkie and Finn, 1988; Baker, 1989; Lambin, 1994, 1997; Hall et al., 1995; Veldkamp and Fresco, 1996; Geoghegan et al., 1997; Mertens and Lambin, 1997; Liverman et al., 1998; Wu and Webster, 1998: Pontius et al., 2004). In most cases, the models are connected to a raster-based GIS. Scientists are required to must develop statistical methods to validate such model, because it is essential to know its prediction accuracy (Pontius, 2002). For validation, a map of simulated future change is compared to a map of recent real land cover change. For appropriate validation, the map of reality used for validation should not be used in calibration (Pontius et al., 2001). Therefore, land use and land cover change data derived from satellite images for describing and projecting land use and cover changes establishes the validity of the predicted results of the CA Markov process in this study. The methods are validated using statistical independence, variations on the Kappa Index of agreement. Here, LULC of 2007 is predicted using LULC maps of 1987 and 1997, derived from Landsat and IRS-P6 satellite images, respectively. As the map of reality, LULC map derived from LISS III image of IRS P6 satellite is used.

The methods used for validation of predicted LULC have been developed at Clark University, U. S. A. by Pontius et al., (2004) who have suggested the use of measurements of both – the quantity and the location of land categories for prediction over several decades at multiple resolutions. They also suggested the use of Kappa statistics for testing accuracy in terms of location (Kappa for location) and quantity of correct cells (Kappa for quantity). This provides a method to measure agreement between two categorical images, a "comparison" map (here the predicted LULC of 2007) and a "reference" map (LULC map derived from IRS-P6 LISS III image of 2007). The comparison map is the result of CA Markov model simulation results, whose validity is to be assessed against a reference map that depicts reality. The validation offers one comprehensive statistical analysis that answers simultaneously two important questions:

(i) How well do a pair of maps agree in terms of the quantity of cells in each category?

(ii) How well do a pair of maps agree in terms of the location of cells in each category?

The validation calculates various Kappa Indices of Agreement and related statistics to answer these questions. The statistics indicate how well the comparison map agrees with the reference map. The analysis separates agreement and disagreement between the two images into the following components:

i) Agreement due to chance - N (n)

ii) Agreement due to quantity - N (m)

iii) Agreement due to location at the stratified level - H (m)

iv) Agreement due to location at the grid cell level - M (m)

v) Disagreement due to location at the grid cell level - K (m)

vi) Disagreement due to location at the stratified level - P (m)

vii) Disagreement due to quantity - P (p)

In the notation of each expression, the argument in bold represents three possible levels of information of quantity: n means no information, m means medium information and p means perfect information. Similarly, the function denoted by the capital letter indicates one of five possible levels of information of location: N(x) means no information, H(x) means medium stratum-level information, M(x) means medium grid cell-level information, K(x) means perfect grid cell-level information given imperfect stratum-level information, and P(x) means perfect grid cell-level information across the landscape (Pontius et al. 2005).

The seven components of agreement and disagreement as expressed in terms of those points are given below in Table 7.6.

Table 7.6: Seven components of agreement and disagreement of Kappa Indices

Sl No.	Name of Component	Definition
1	Disagreement due to quantity	P(p)-P(m)
2	Disagreement at stratum level	P(m)-K(m)
3	Disagreement at grid cell level	K(m)-M(m)
4	Agreement at grid cell level	MAX [M(m)-H(m), 0]
5	Agreement at stratum level	MAX [H(m)-N(m), 0]
6	Agreement due to quantity	If MIN [N(n), N(m), H(m), M(m)]=N(n), then MIN [N(m)-N(n), H(m)-N(n), M(m)-N(n)], else 0
7	Agreement due to chance	MIN [N(n), N(m), H(m), M(m)]

When considered as a set, these seven mathematical expressions constitute a sequence of measures of agreement between the reference map and the modified comparison maps that have increasingly accurate information. Therefore, usually $0 < N(n) < N(m) < H(m) < M(m) < K(m) < P(m) < P(p) = 1$. This sequence partitions the interval [0, 1] into components of the agreement and disagreement between the reference map and the comparison map. M(m) is the total proportion correct, thus 1 - M(m) is the total proportion of disagreement between the reference map and the comparison map. The sequence of N(n), N(m), H(m) and M(m) defines components of agreement, and the sequence of M(m), K(m), P(m) and P(p) defines components of disagreement (Pontius et al., 2005).

The Kappa for Location ($K_{location}$) statistic measures the goodness-of-fit between two images based on the grid cell-level location of categories, given that the category quantities are specified. The validation methods give also the traditional Kappa Index of Agreement (KIA) and some more useful variations on the KIA. KIA is denoted also by $K_{standard}$. Both the percent correct and the standard KIA confound disagreement of quantity with disagreement of location. Thus, in addition to calculating the standard KIA, Validate offers three more statistics: (i) Kappa for no information (denoted K_{no}), (ii) Kappa for grid-cell level location (denoted $K_{location}$), and (iii) Kappa for stratum-level location (denoted $K_{locationStrata}$). All of these statistics are linear functions of points in the Validate output. Specifically,

$$K_{no} = \{M(m)-N(n)\}/\{P(p)-N(n)\} \quad \text{.......(7.8)}$$

$$K_{location} = \{M(m)-N(m)\}/\{P(m)-N(m)\} \quad \text{.......(7.9)}$$

$$K_{locationStrata} = \{M(m)-H(m)\}/\{K(m)-H(m)\} \quad \text{.......(7.10)}$$

where, $K_{location}$ indicates how well the grid cells are located on the landscape. $K_{locationStrata}$ indicates how well the grid cells are located within the strata. A $K_{location}$ value of 0 means that a spatial model's ability to specify the grid cell-level location of future change is equal to random. A $K_{location}$ of 1 means that a model's ability to specify the grid cell-level location of future change is perfect.

7.6. RESULTS - KAPPA FOR QUANTITY AND LOCATION

Pontius et al. (2002) suggested how to use measurements of both - the quantity and the location of land categories for prediction over several decades at multiple resolutions and also suggested the use Kappa statistics for testing the accuracy in terms of location (Kappa for location) and quantity of correct cells (Kappa for quantity). This provides a method to measure agreement between two categorical images, a "comparison" map here the predicted LULC of 2007 and a "reference" map i.e., LULC map derived from IRS-P6 LISS III image of 2007. The comparison map is the result of CA Markov model simulation results, whose validity is being assessed against a reference map that depicts reality. The validation offers one comprehensive statistical analysis for 3x3, 5x5, 7x7 contiguity filters that answered that the quantity (Table 7.7) is same for 3x3, 5x5 and 7x7 filters but spatially (Kappa for location) slightly different. The $K_{standard}$ for 5x5 filters is 0.7928 whereas $K_{standard}$ for 3x3 filters is 0.7857 and for 7x7 filters is 0.7777 (Table 7.8.).

Now a statement will be made about its acceptance in the CA Markov model's 2007 landscape prediction. The statistical methods separate error and agreement by components due to specification of quantity and location. The simulated map of 2007 is compared to the reference map of 2007, a Kappa for quantity and location statistic is derived. The statistics for location shows K_{no} is 0.8347, $K_{location}$ is 0.8591, $K_{locationStrata}$ is 0.8591 and $K_{standard}$ is 0.7928 (Table 7.8). The results indicate that CA Markov model's ability to specify grid cell level location of future change is nearly perfect (here $K_{location}$ value is 0.859, where $K_{location}$ value of 1 is perfect).

Table 7.7.a : Agreement/disagreement according to ability to specify accurately quantity and location to predict 2007 LULC using 3x3 contiguity filter and 10 (step times) iteration

Sl. No.	Information of Location	Information of Quality		
		No[n]	Medium[m]	Perfect[p]
1.	Perfect[P(x)]	P(n) = 0.4592	P(m) = 0.9478	P(p) = 1.0000
2.	PerfectStratum[K(x)]	K(n) = 0.4592	K(m) = 0.9478	K(p) = 1.0000
3.	MediumGrid[M(x)]	M(n) = 0.4397	M(m) = 0.8599	M(p) = 0.8890
4.	MediumStratum[H(x)]	H(n) = 0.1522	H(m) = 0.3235	H(p) = 0.3261
5.	No[N(x)]	N(n) = 0.1522	N(m) = 0.3235	N(p) = 0.3261

Agreement Chance	0.1522
Agreement Quantity	0.1713
Agreement Strata	0.0000
Agreement Grid cell	0.5363
Disagree Grid cell	0.0880
Disagree Strata	0.0000
Disagree Quantity	0.0522

Table 7.7.b: Agreement/disagreement according to ability to specify accurately quantity and location to predict 2007 LULC using 5x5 contiguity filter and 10 (step times) iteration

Sl. No.	Information of Location	Information of Quality		
		No[n]	**Medium[m]**	**Perfect[p]**
1.	Perfect[P(x)]	P(n) = 0.4592	P(m) = 0.9478	P(p) = 1.0000
2.	PerfectStratum[K(x)]	K(n) = 0.4592	K(m) = 0.9478	K(p) = 1.0000
3.	MediumGrid[M(x)]	M(n) = 0.4398	M(m) = 0.8550	M(p) = 0.8856
4.	MediumStratum[H(x)]	H(n) = 0.1522	H(m) = 0.3235	H(p) = 0.3261
5.	No[N(x)]	N(n) = 0.1522	N(m) = 0.3235	N(p) = 0.3261

Agreement Chance	0.1522
Agreement Quantity	0.1713
Agreement Strata	0.0000
Agreement Grid cell	0.5315
Disagree Grid cell	0.0928
Disagree Strata	0.0000
Disagree Quantity	0.0522

Table 7.7.c: Agreement/disagreement according to ability to specify accurately quantity and location to predict 2007 LULC using 7x7 contiguity filter and 10 (step times) iteration

Sl. No.	Information of Location	Information of Quality		
		No[n]	**Medium[m]**	**Perfect[p]**
1.	Perfect[P(x)]	P(n) = 0.4592	P(m) = 0.9478	P(p) = 1.0000
2.	PerfectStratum[K(x)]	K(n) = 0.4592	K(m) = 0.9478	K(p) = 1.0000
3.	MediumGrid[M(x)]	M(n) = 0.4391	M(m) = 0.8496	M(p) = 0.8820
4.	MediumStratum[H(x)]	H(n) = 0.1522	H(m) = 0.3235	H(p) = 0.3261
5.	No[N(x)]	N(n) = 0.1522	N(m) = 0.3235	N(p) = 0.3261

Agreement Chance	0.1522
Agreement Quantity	0.1713
Agreement Strata	0.0000
Agreement Grid cell	0.5261
Disagree Grid cell	0.0982
Disagree Strata	0.0000
Disagree Quantity	0.0522

Table 7.8: Kappa Index of Agreement to ability to specify accurately quantity and location to predict 2007 LULC using 3x3, 5x5, 7x7 contiguity filter and 10 (step times) iteration

	3x3 Contiguity Filter	5x5 Contiguity Filter	7x7 Contiguity Filter
K_{no}	0.8290	0.8347	0.8226
$K_{location}$	0.8513	0.8591	0.8427
$K_{locationStrata}$	0.8513	0.8591	0.8427
$K_{standard}$	0.7857	0.7928	0.7777

7.7. SUMMARY

Currently, land-change modelers are not being held accountable for their prediction of future landscapes. Most land-change modelers fail to validate models and fail to state the uncertainty in future prediction. Consequently, policy makers and the general public develop opinions based on misleading research that fails to give them the appropriate interpretations required to make informed decisions. Validation efforts to a known point in time are necessary to make an estimate of the uncertainty for the extrapolation to an unknown point in time. This study concludes that use of statistical independence test, Kappa indices are potentially useful techniques for purposes of validation of modelling results.

Chapter - 8

MODELING AND ANALYSES OF LULC CHANGE WITH EFFECT OF NUMERICAL ITERATIONS & IMAGE INTERVAL ON RESULTS

8.1. INTRODUCTION

CA Markov is a combined of CA and Markov chain LULC prediction procedure that adds an element of spatial contiguity as well as knowledge of the likely spatial distribution of transition to Markov change analysis. Markov analyses two qualitative land cover images from different dates and produces a transition matrix and CA adds the spatial distribution of the transition. Within CA Markov model, the transition areas file from a Markov Chain analysis of two prior LULC maps establishes the quantity of expected land use and land cover change from each existing category to each other category in the next time period. The basic LULC image (the later land cover image used in the Markov Chain analysis) is used as the starting point for change simulation.

Suitability maps (here, evidence likelihood map) establish the inherent suitability of each pixel for each land cover type. However, a contiguity filter down-weights the suitabilities of pixels far from existing areas of that class (as of that iteration), thus giving preference to contiguous suitable areas. The number of iterations chosen establishes the number of time steps that will be used in the simulation. 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 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 LULC map at the end of each iteration.

CA Markov automatically normalizes the filter kernel to force the values to sum equal to 1. This filter is passed over a Boolean image for each class from the current land cover image within each iteration. First, the transition areas file from a Markov chain analysis of two prior LULC maps establishes the quantity of expected land use and land cover change from each existing category to each other category in the next time period, and then finally number of iterations chosen establishes the number of time steps that will be used in the simulation. In this study, future LULC has been predicted for 2017, 2027 and 2050 using 1987 & 1997 and 1997 & 2007 LULC images. Future LULC has been also predicted for 2017, 2027 & 2050 using 1987 & 2007 LULC image. The period between the first and second images is 10 years and the period to project forward from the second image is 20 years to predict LULC in 2017, 30 years to predict LULC in 2027 and 53 years to predict LULC in 2050 when using 1987 & 1997 LULC image. The number of time periods between the first and second images is 10 years and the number of time periods to project forward from the second image is 10 years to predict LULC in 2017, 20 years to predict LULC in 2027 and 43 years to predict LULC in 2050 when using 1997 & 2007 LULC image to predict future LULC. The period between the first and second images is 20 years and the period to project forward from the second image is 10 years to predict LULC in 2017, 20 years to predict LULC in 2027 and 43 years to predict LULC in 2050 when using 1987 & 2007 LULC.

8.2. CALIBRATION

8.2.1. Calibration to Predict LULC in 2017, 2027, 2050 using 1987 & 1997 LULC Image

First of all, the model used to predict the LULC of 2017, 2027, 2050 using 1987 & 1997 LULC image where 1997 LULC is the later (second) image and 1987 LULC image is the previous data. The transition probabilities matrix were generated using classified LULC image of 1987 as first (earlier) image and LULC image of 1997 as later (second) image by using Markov transition estimator to predict LULC of 2017, 2027 and 2050 (Appendix I, Appendix II, Appendix III). This, transition probabilities matrix between LULC of 1987 & LULC of 1997 is used as an input to CA Markov model. Transition suitability image collection (i.e., built up land suitability, agricultural crop land suitability, agricultural fallow land suitability, plantation suitability, dense forest land suitability, degraded forest land suitability, land with or without scrub suitability, marshy/swampy land suitability, waterlogged area suitability, sandy area suitability, river suitability, lakes/reservoirs/ponds suitability, open land suitability, aquatic vegetation land suitability) are also used as input to the model (Figure 8.1). For this, the number of time interval (periods) between the first and second images is 10 years and the numbers of time steps to project forward from the second image are 20 years to predict LULC in 2017, 30 years to predict LULC in 2027 and 53 years to predict LULC in 2050 (Table 8.1). The number of iteration was based on the time steps i.e., iterations 20 to predict LULC for 2017 (prediction from 1997 to 2017); iterations 30 for 2027 (prediction from 1997 to 2027); iterations 53 for 2050 (prediction from 1997 to 2050). The number of iterations is determined by the time steps to project forward from second image and effectively equals to the time step; therefore, here the two terms are referred together. For iterations 20, MOLA (Multi Objective Land Allocation) will run to allocate 1/20 of the required land in the first run, and 2/20 the second run, and so on until the 20/20, the full allocation of land for each land use and land cover classes is obtained. Standard 5x5 CA contiguity filter was used to predict LULC by using classified (LULC) images of 1987 & 1997 and compared the predicted LULC results.

8.2.2. Calibration to Predict LULC for 2017, 2027, 2050 using 1997 & 2007 LULC Image

The best performed/resultant CA contiguity filter (5x5) is used for LULC prediction of 2017, 2027, and 2050 from 2007 and 1997 (previous/earlier image) using the CA Markov model. The CA Markov model calibrated to predict LULC in 2017 from classified image of 2007 and 1997. Here 1997 data is the earlier or previous land cover image and 2007 data is later LULC image to predict future LULC. The transition probabilities matrix has been generated using classified LULC image of 1997 as first (earlier) image and LULC image of 2007 as latter (second) image to predict future LULC of 2017, 2027 and 2050 (Appendix IV, Appendix V, Appendix VI). Transition probabilities matrix of LULC of 1997 and LULC of 2007, and transition suitability image collection (i.e., built up land suitability, agricultural crop land suitability, agricultural fallow land suitability, plantation suitability, dense forest land suitability, degraded forest land suitability, land with or without scrub suitability, marshy / swampy land suitability, waterlogged area suitability, sandy area suitability, river suitability, lakes/reservoirs/ponds suitability, open land suitability, aquatic vegetation land suitability) are used as an input to CA Markov model (Figure 8.2). The number of time interval (periods) between the first and second images is

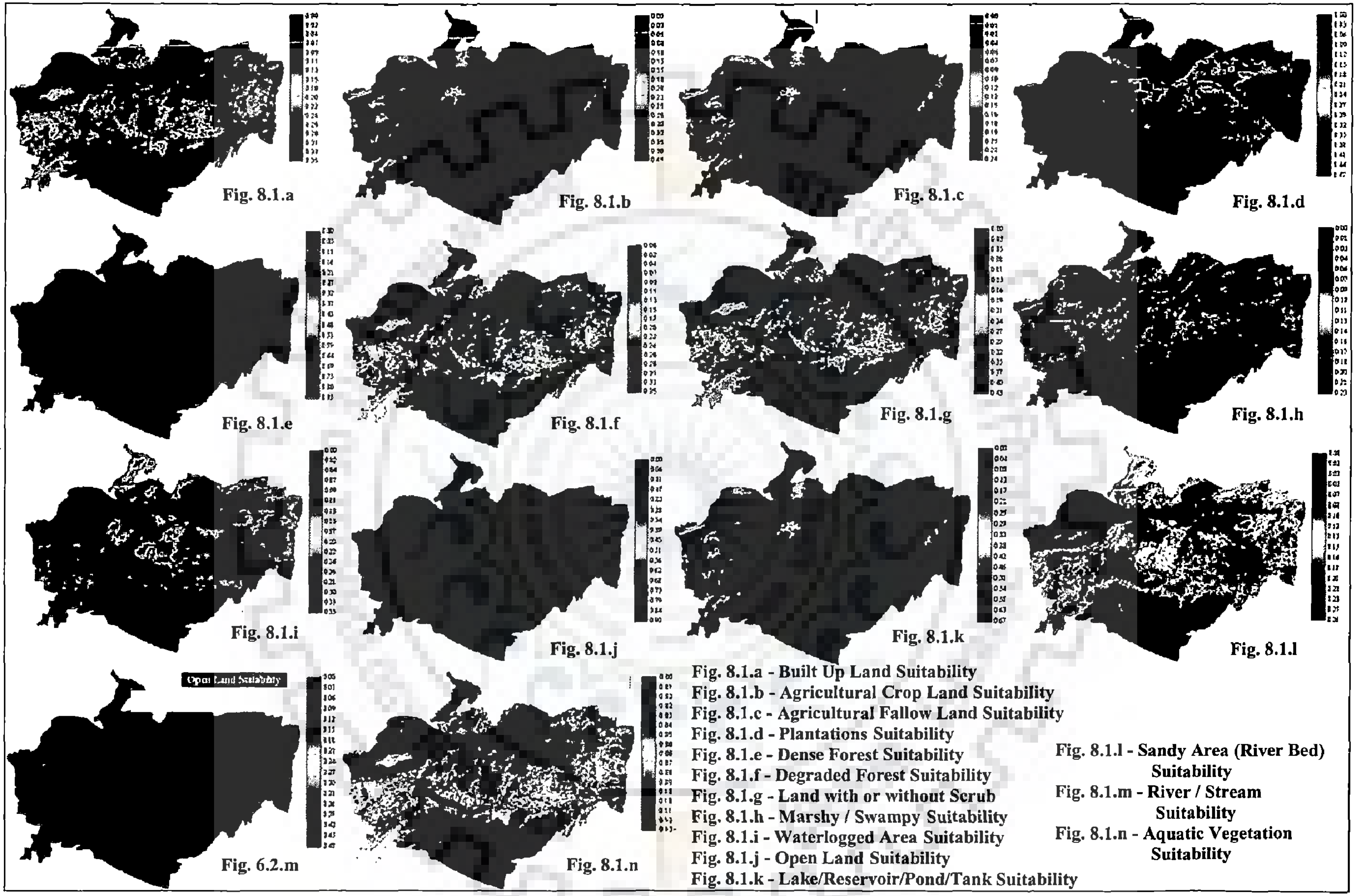


Figure 8.1: Suitability (evidence likelihood) map used to predict future LULC of 2017, 2027, 2050 using 1987 & 1997 LULC image

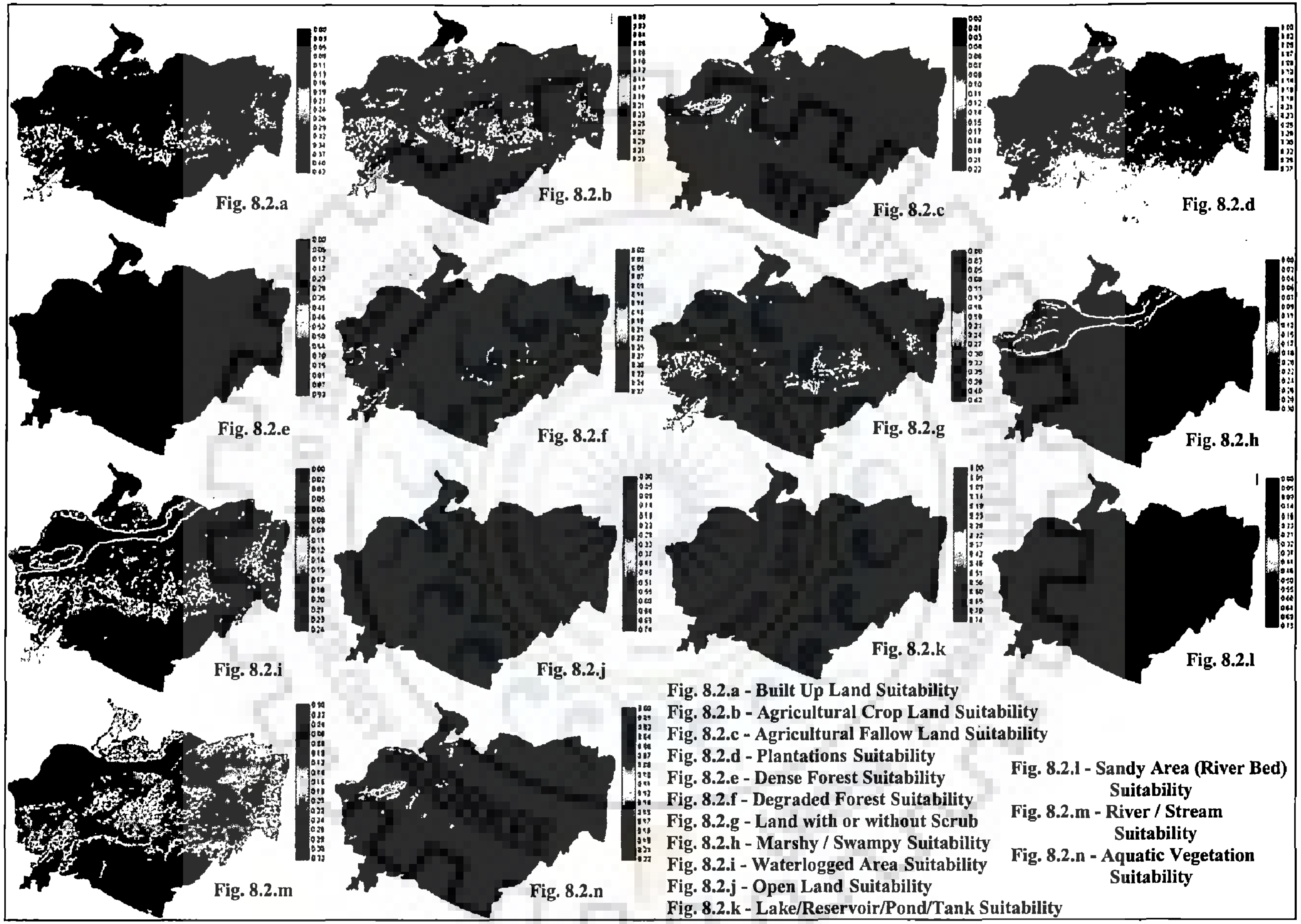


Figure 8.2: Suitability (evidence likelihood) map used to predict future LULC of 2017, 2027, 2050 using 1997 & 2007 LULC image

10 (years) and the number of time steps to project forward from the second image is 10 (years) to predict LULC in 2017, 20 (years) to predict LULC in 2027 and 43 (years) to predict LULC in 2050, (Table 8.1). Therefore, the number of iteration was based on the time steps i.e., iterations 10 to predict LULC for 2017 (prediction from 2007 to 2017); iterations 20 for 2027 (prediction from 2007 to 2027); iterations 43 for 2050 (prediction from 2007 to 2050). Standard 5x5 CA contiguity filter was also used to predict future LULC and compared the predicted LULC results.

8.2.3. Calibration to Predict LULC in 2017, 2027, 2050 using 1987 & 2007 LULC Image

The CA Markov model also calibrated with 5x5 cellular automata contiguity filter to predict LULC in 2017, 2027 and 2050 from classified image of 1987(classified earlier LULC image) and 2007 (classified later LULC Image). The transition probabilities matrix has been generated using classified LULC image of 1987 as first (earlier) image and LULC image of 2007 as latter (second) image. The number of time interval (periods) between the first and second images is 20 (years) and the number of time steps to project forward from the second image is 10 (years) to predict LULC in 2017, 20 (years) to predict LULC in 2027 and 43 (years) to predict LULC in 2050. Transition probability matrix between LULC of 1987 & LULC of 2007 (Appendix VII, Appendix VIII, Appendix IX) and transition suitability image collection (i.e., built up land suitability, agricultural crop land suitability, agricultural fallow land suitability, plantation suitability, dense forest land suitability, degraded forest land suitability, land with or without scrub suitability, marshy / swampy land suitability, waterlogged area suitability, sandy area suitability, river suitability, lakes/reservoirs/ponds suitability, open land suitability, aquatic vegetation land suitability) for all LULC classes are used as an input to CA Markov model (Figure 8.3). The number of iteration was based on the time steps for all cases i.e., iterations 10 to predict LULC for 2017; iterations 20 for 2027; iterations 43 for 2050 (Table 8.1). Standard 5x5 CA contiguity filter was also used to predict future LULC and compared the predicted LULC results.

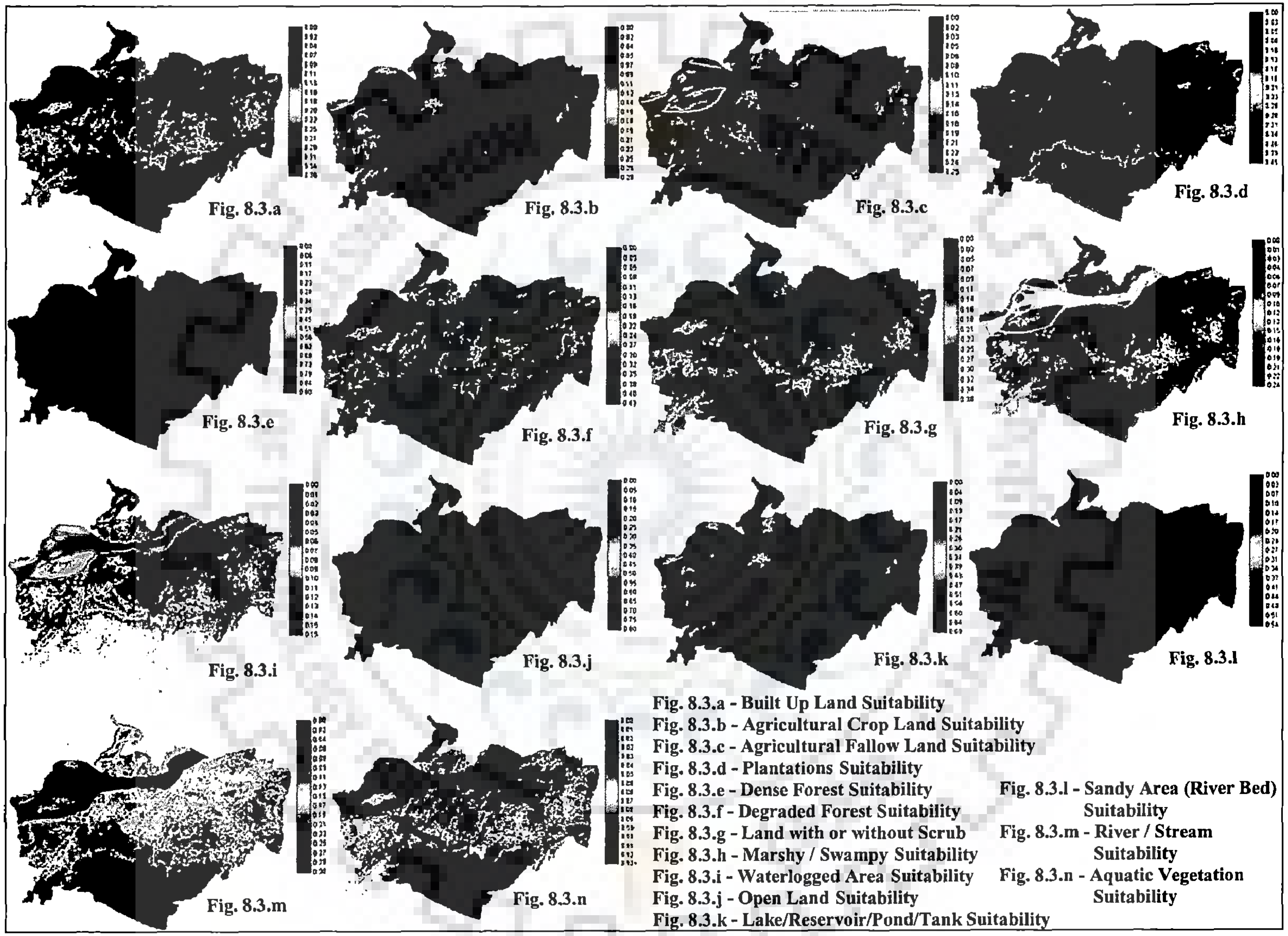


Figure 8.3: Suitability (evidence likelihood) map used to predict future LULC of 2017, 2027, 2050 using 1987 & 2007 LULC image

Table 8.1: Prediction years, data used, time interval (between the first and second images) and different time steps / iterations

Prediction for Year	Data Used	Interval between the first and second images (1987 – 1997) (Year)	Time Steps (Year) / Iteration	Data Used	Interval between the first and second images (1997 – 2007) (Year)	Time Steps (Year) / Iteration	Data Used	Interval between the first and second images (1987 – 2007) (Year)	Time Steps (Year) / Iteration
2017	1987 & 1997 LULC Map	10	20	1997 & 2007 LULC Map	10	10	1987 & 2007 LULC Map	20	10
2027	1987 & 1997 LULC Map	10	30	1997 & 2007 LULC Map	10	20	1987 & 2007 LULC Map	20	20
2050	1987 & 1997 LULC Map	10	53	1997 & 2007 LULC Map	10	43	1987 & 2007 LULC Map	20	43

Finally, a comparative analysis and qualitative and quantitative assessment of all above LULC predictions was done. Relationships (correlations) between predicted quantities of all above LULC predictions have been established. Relationships (correlations) between predicted locations of all above LULC predictions have been also established.

8.3. RESULTS AND ANALYSIS

8.3.1. Quantity of Prediction

8.3.1.1. Quantity of predicted LULC of 2017, 2027, 2050 using 1987 & 1997, 1997 & 2007 & 1987 & 2007 LULC images

Table 8.2 shows the area statistics of predicted LULC of 2017, 2027, 2050 using 1987 & 1997, 1997 & 2007 and 1987 & 2007 LULC images. Figures 8.4 show graphical representation for area statistics of predicted LULC of 2017, 2027, 2050 using 1987 & 1997, 1997 & 2007 and 1987 & 2007 LULC images. Figure 8.5 shows a comparative graphical presentation of overall (total) area statistics of predicted LULC of 2017, 2027, 2050 using 1987 & 1997, 1997 & 2007 and 1987 & 2007 LULC images. Figure 8.6 also shows a comparative graphical presentation of overall (total) area statistics of the observed LULC of 1987, 1997 and 2007 as well as predicted LULC of 2017, 2027, 2050 using 1987 & 1997, 1997 & 2007, and 1987 & 2007 LULC images.

The areas of predicted LULC of 2017 using 1987 & 1997, 1997 & 2007 and 1987 & 2007 LULC images are slightly different from each other. Here, the differences of predicted LULC range between 0.29 to 16.03 km^2 only, with average value as 6.15 km^2. The areas of predicted LULC of 2027 using 1987 & 1997, 1997 & 2007 and 1987 & 2007 are slightly different from each other, which range between 0.47 to 17.66 km^2 only, with average value as 6.53 km^2. The areas of predicted LULC of 2050 using LULC images of 1987 & 1997, 1997 & 2007 and 1987 & 2007 are slightly different from each other. Here, the differences of predicted LULC range between 0.71 to 21.65 km^2 only and average is 7.49 km^2. These differences are small (0.29 to 16.03 km^2, 0.47 to 17.66 km^2, 0.71 to 21.65 km^2) in a study area of 413.98 km^2.

Table - 8.2: Area statistics of predicted LULC of 2017, 2027, 2050

LULC Class	Area (km^2)											
	Predicted LULC 2017				Predicted LULC 2027				Predicted LULC 2050			
	Using 1987 & 1997 LULC Image	Using 1997 & 2007 LULC Image	Using 1987 & 2007 LULC Image	Maximum Differences	Using 1987 & 1997 LULC Image	Using 1997 & 2007 LULC Image	Using 1987 & 2007 LULC Image	Maximum Differences	Using 1987 & 1997 LULC Image	Using 1997 & 2007 LULC Image	Using 1987 & 2007 LULC Image	Maximum Differences
uilt Up Land	153.49	155.52	154.25	2.03	174.55	179.89	173.73	6.16	208.65	219.87	213.73	11.
gricultural Crop Land	3.71	7.22	6.79	3.51	3.27	6.69	5.94	0.75	2.51	5.30	4.63	2.
gricultural Fallow and	19.78	20.32	11.05	9.27	17.18	19.18	11.25	7.93	13.28	15.64	11.90	3.
antation	9.88	3.83	4.45	6.05	9.35	3.22	4.63	6.13	8.48	2.40	4.46	6.
ense Forest	62.95	59.77	72.31	12.54	62.04	55.11	70.57	15.46	62.49	45.58	63.54	17.
egraded Forest	67.76	57.29	51.73	16.03	60.81	49.27	43.15	17.66	48.81	37.24	27.16	21.
and with or without crub	22.42	23.26	23.97	1.57	19.87	20.34	22.16	0.47	15.67	15.50	17.06	1.
arshy / Swampy	9.31	7.77	8.66	1.54	8.18	6.88	8.03	1.3	6.48	5.58	6.27	[illegible]
aterlogged	1.26	1.59	2.19	0.93	1.15	1.46	2.02	0.87	0.86	1.21	1.57	0.
andy Area	15.53	17.18	16.02	0.49	13.74	17.01	15.13	3.27	10.38	16.13	12.07	5.
iver	23.12	33.13	28.35	10.01	20.99	33.03	28.26	0.48	16.92	32.77	28.76	15.
akes / Reservoirs / onds	5.95	5.92	5.66	0.29	5.55	5.07	5.43	11.81	4.71	3.79	4.74	0.
pen Land	6.57	15.73	21.54	14.97	5.55	12.20	17.36	7.1	4.40	9.51	12.90	[illegible]
quatic Vegetation	12.27	5.45	7.01	6.82	11.74	4.64	6.32	12.04	10.34	3.45	5.19	6.
Total	413.98	413.98	413.98	Minimum - 0.29 Max. - 16.03 Average - 6.15	413.98	413.98	413.98	Minimum - 0.47 Max. - 17.06 Average- 6.53	413.98	413.98	413.98	Minimum - 0.7 Max. - 21.65 Average -7.49

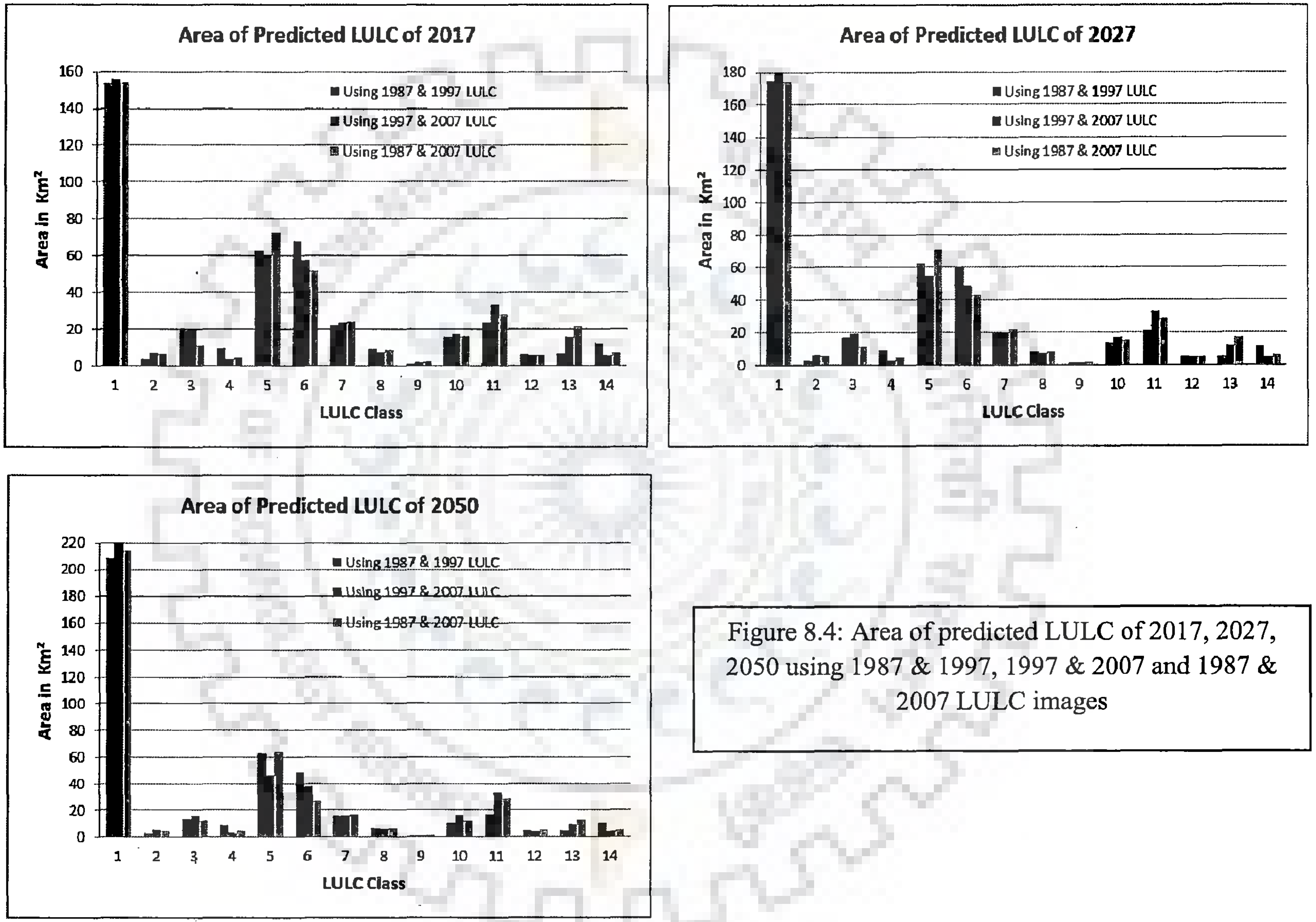
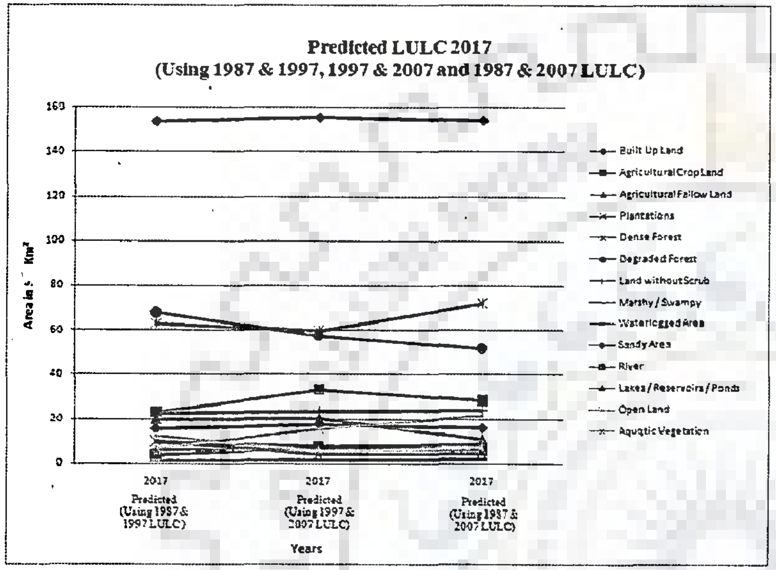
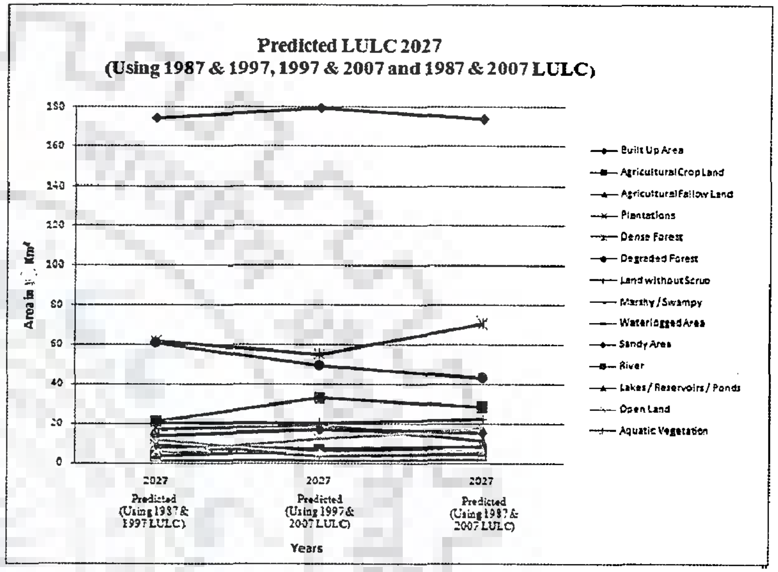


Figure 8.4: Area of predicted LULC of 2017, 2027, 2050 using 1987 & 1997, 1997 & 2007 and 1987 & 2007 LULC images





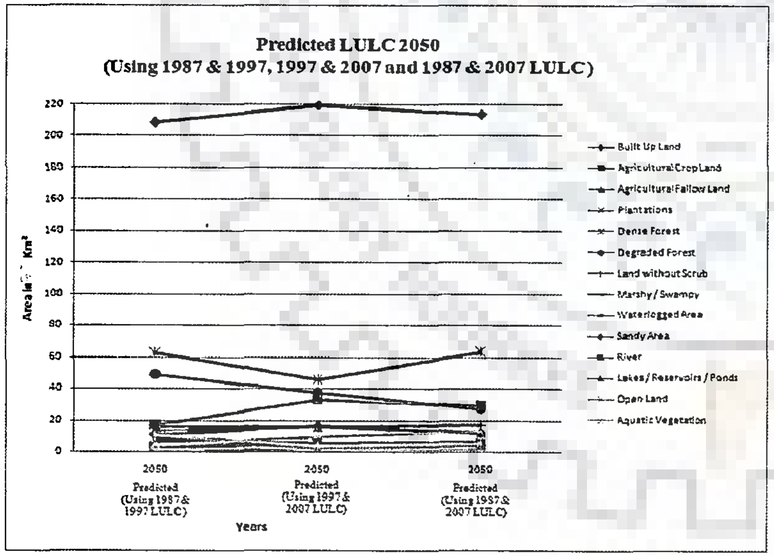
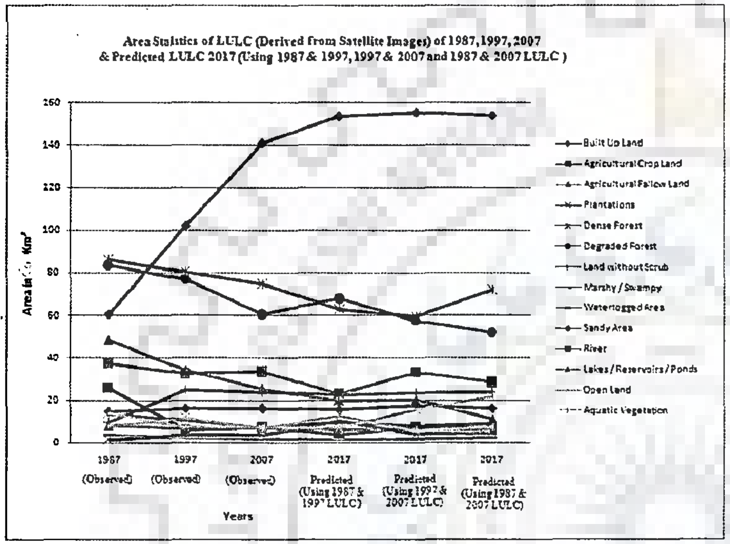
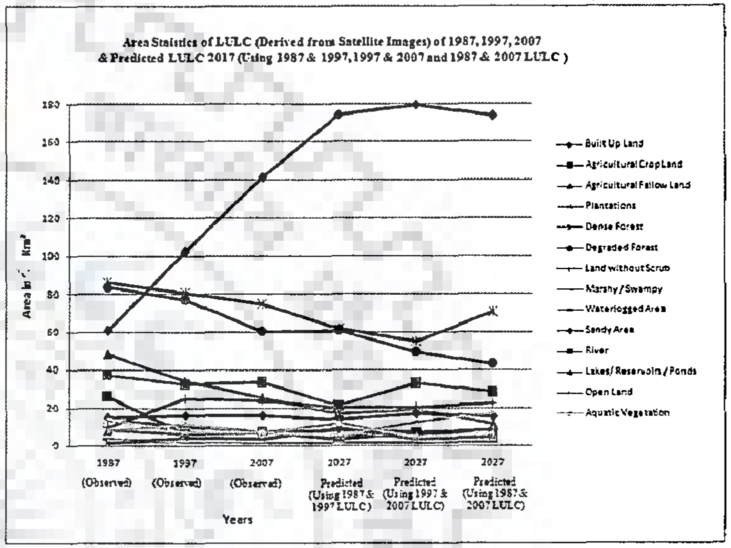


Figure 8.5: Area of predicted LULC of 2017, 2027, 2050 using 1987 & 1997, 1997 & 2007 and 1987 & 2007 LULC images





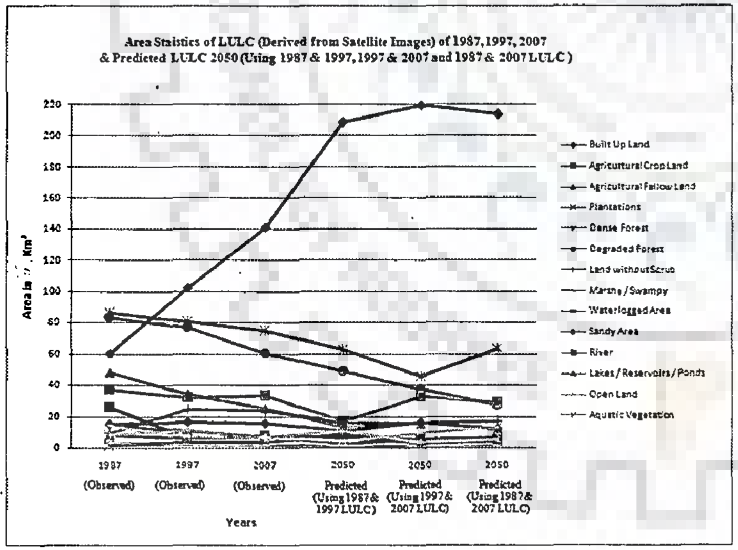


Figure 8.6: Area of the observed LULC of 1987, 1997 & 2007 as well as predicted LULC of 2017, 2027, 2050 using 1987 & 1997, 1997 & 2007 and 1987 & 2007 LULC images

8.3.2. Correlations between Predicted Quantities

8.3.2.1. Correlations between area of predicted LULC of 2017 using LULC images of 1987 & 1997, 1997 & 2007 and 1987 & 2007

The correlation between area of predicted LULC of 2017 using 1987 & 1997 and 1997 & 2007 LULC images is strong, where r is 0.991 and one-tailed probability-value (at the hypothesized population mean) of a z-test for the data set (r values) is also calculated for improvement the error statistics, where P-value of a z-test for r is 0.7937. Correlation between area of predicted LULC of 2017 using 1997 & 2007 and 1987 & 2007 LULC images is also strong, where r is 0.992 and where P-value of a z-test for r is 0.8791. The correlation between area of predicted LULC of 2017 using 1987 & 1997 and 1987 & 2007 LULC images is strong, where r is 0.983 and where P-value of a z-test for r is 0.0233 (Table 8.3 & Figure 8.7).

8.3.2.2. Correlations between area of predicted LULC of 2027 using LULC images of 1987 & 1997, 1997 & 2007 and 1987 & 2007

The correlation between area of predicted LULC of 2027 using 1987 & 1997 & 1997 & 2007 LULC images is strong, where r is 0.991 and one-tailed probability-value (at the hypothesized population mean) of a z-test for the data set (r values) is also calculated for improvement the error statistics, where P-value of a z-test for r is 0.6473. Correlation between area of predicted LULC of 2027 using 1997 & 2007 and 1987 & 2007 LULC images is also strong, where r is 0.993 and where P-value of a z-test for r is 0.9347. The Correlation between area of predicted LULC of 2027 using 1987 & 1997 and 1987 & 2007 LULC images is strong, where r is 0.987 and where P-value of a z-test for r is 0.0294 (Table 8.3 & Figure 8.8).

8.3.2.3. Correlations between area of predicted LULC of 2050 using LULC images of 1987 & 1997, 1997 & 2007 and 1987 & 2007

The correlation between area of predicted LULC of 2050 using LULC images of 1987 & 1997 and 1997 & 2007 is strong, where r is 0.988 and one-tailed probability-value (at the hypothesized population mean) of a z-test for the data set (r values) is also calculated for improvement the error statistics, where P-value of a z-test for r is 0.0541. Correlation between area of predicted LULC of 2050 using 1997 & 2007 and 1987 & 2007 LULC images is also strong, where r is 0.993 and where P-value of a z-test for r is 0.9668. The correlation between area of predicted LULC of 2050 using 1987 & 1997 and 1987 & 2007 LULC images is strong, where r is 0.990 and where P-value of a z-test for r is 0.4093 (Table 8.3 & Figure 8.9).

Differences within the area of predicted LULC of 2017, 2027 & 2050 are small (0.29 to 16.03 km^2, 0.47 to 17.66 km^2, 0.71 to 21.65 km^2), in a study area of 413.98 km^2. The average differences are 6.15 km^2 for 2017, 6.53 km^2 for 2027 and 7.49 km^2 only for 2050. The areas of predicted LULC of 2017, 2027 & 2050 using 1987 & 1997, 1997 & 2007 and 1987 & 2007 LULC images, all cases shows strong r values (0.981, 0.984, 0.966, 0.975, 0.977, 0.987, and 0.980). It is established that quantitatively they have positive relationship. It is established that there is almost no effect in quantity of prediction results when different time steps images are used to predict future LULC.

Table 8.3: Correlations of between area of predicted LULC using 1987 & 1997, 1997 & 2007 & 1987 & 2007 LULC images

Correlation between area of predicted LULC	**Correlation Coefficient (r) for 2017**	**one-tailed P-value of a z-test (for r value)**	**Correlation Coefficient (r) for 2027**	**one-tailed P-value of a z-test (for r value)**	**Correlation Coefficient (r) for 2050**	**one-tailed P-value of a z-test (for r value)**
Using 1987 & 1997 LULC Image and Using 1997 & 2007 LULC images	0.991	0.7937	0.991	0.6473	0.988	0.0541
Using 1997& 2007 LULC Image and Using 1987& 2007 LULC images	0.992	0.8791	0.993	0.9347	0.993	0.9668
Using 1987 & 1997 LULC Image and Using 1987 & 2007 LULC images	0.983	0.0233	0.987	0.0294	0.990	0.4093

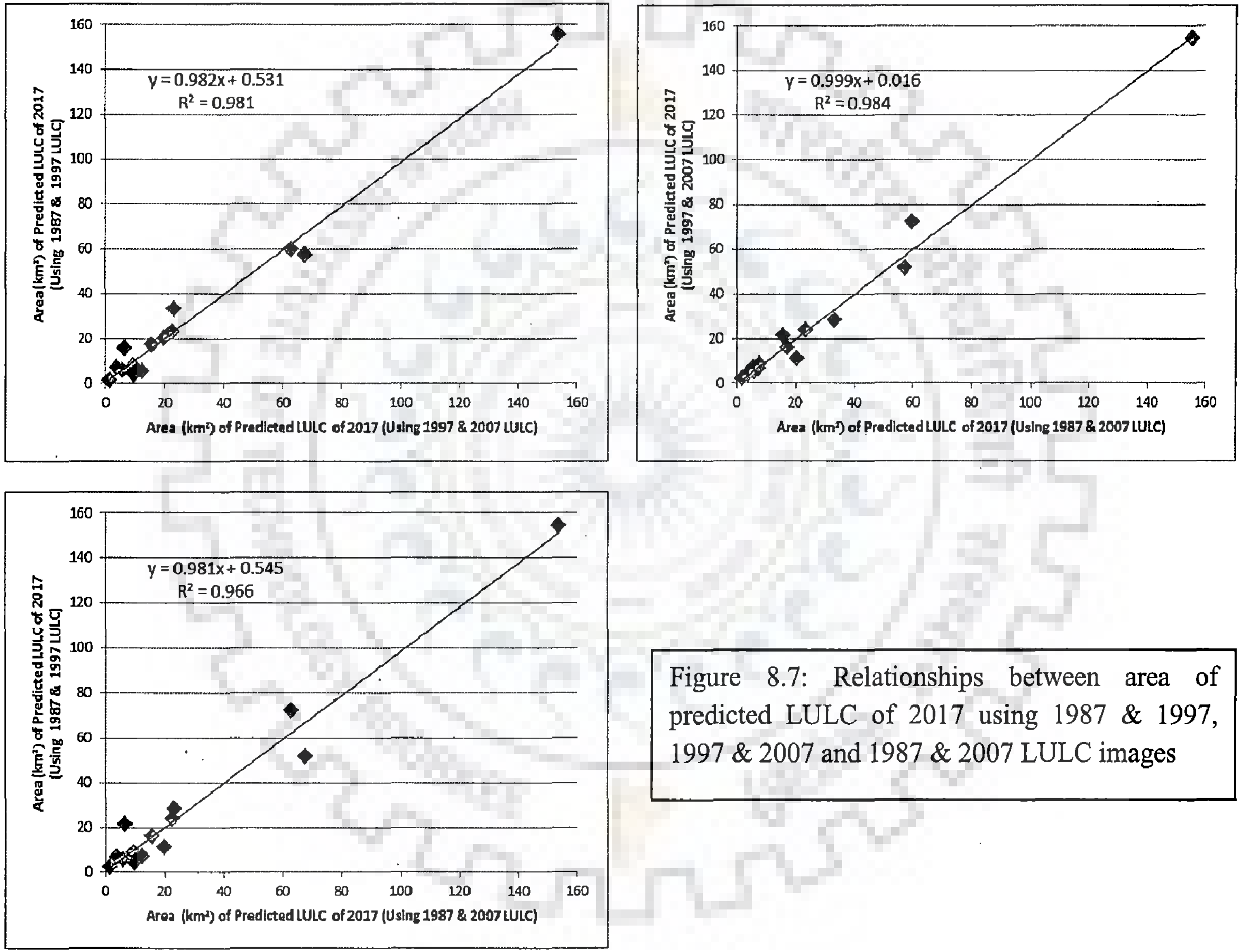


Figure 8.7: Relationships between area of predicted LULC of 2017 using 1987 & 1997, 1997 & 2007 and 1987 & 2007 LULC images

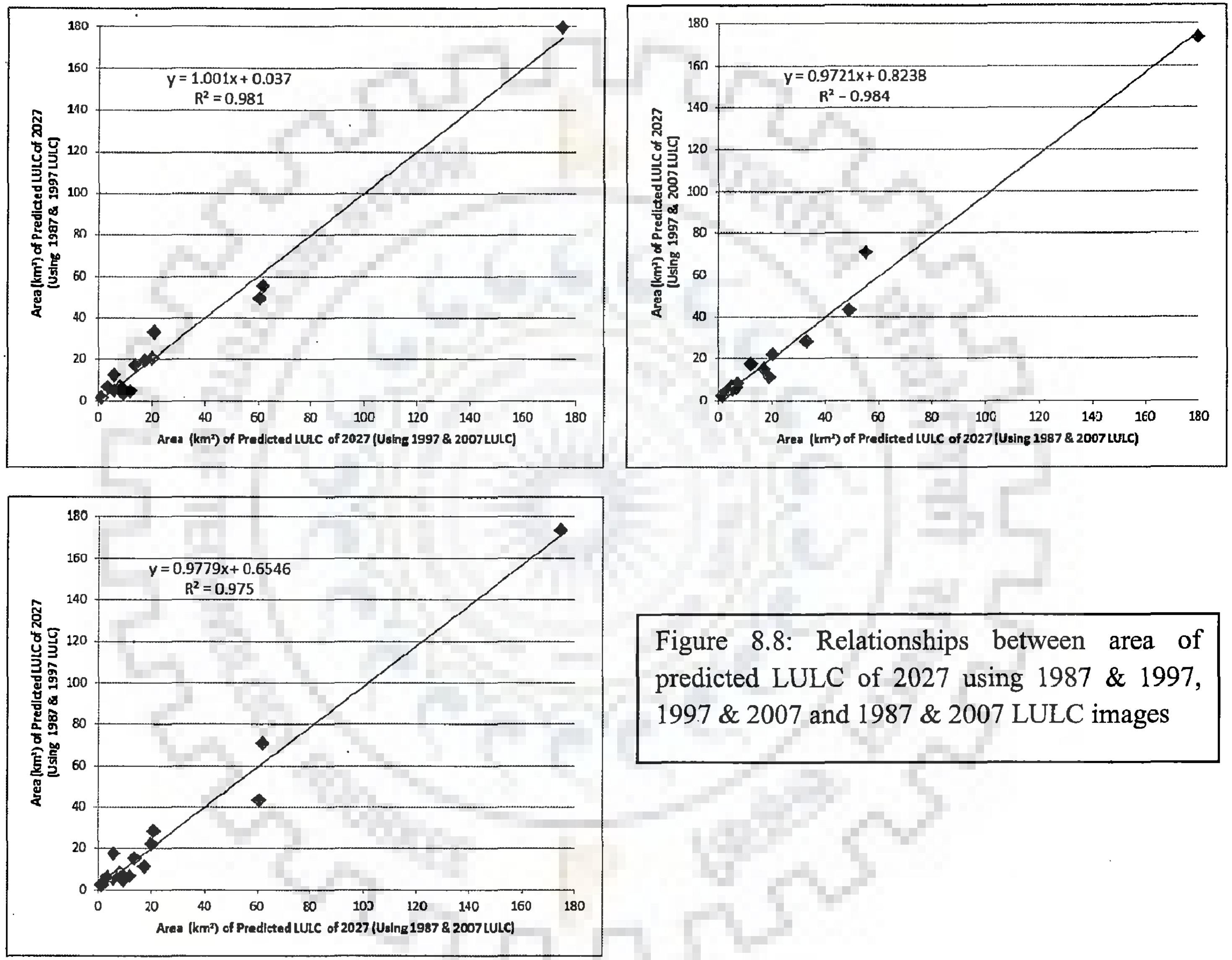


Figure 8.8: Relationships between area of predicted LULC of 2027 using 1987 & 1997, 1997 & 2007 and 1987 & 2007 LULC images

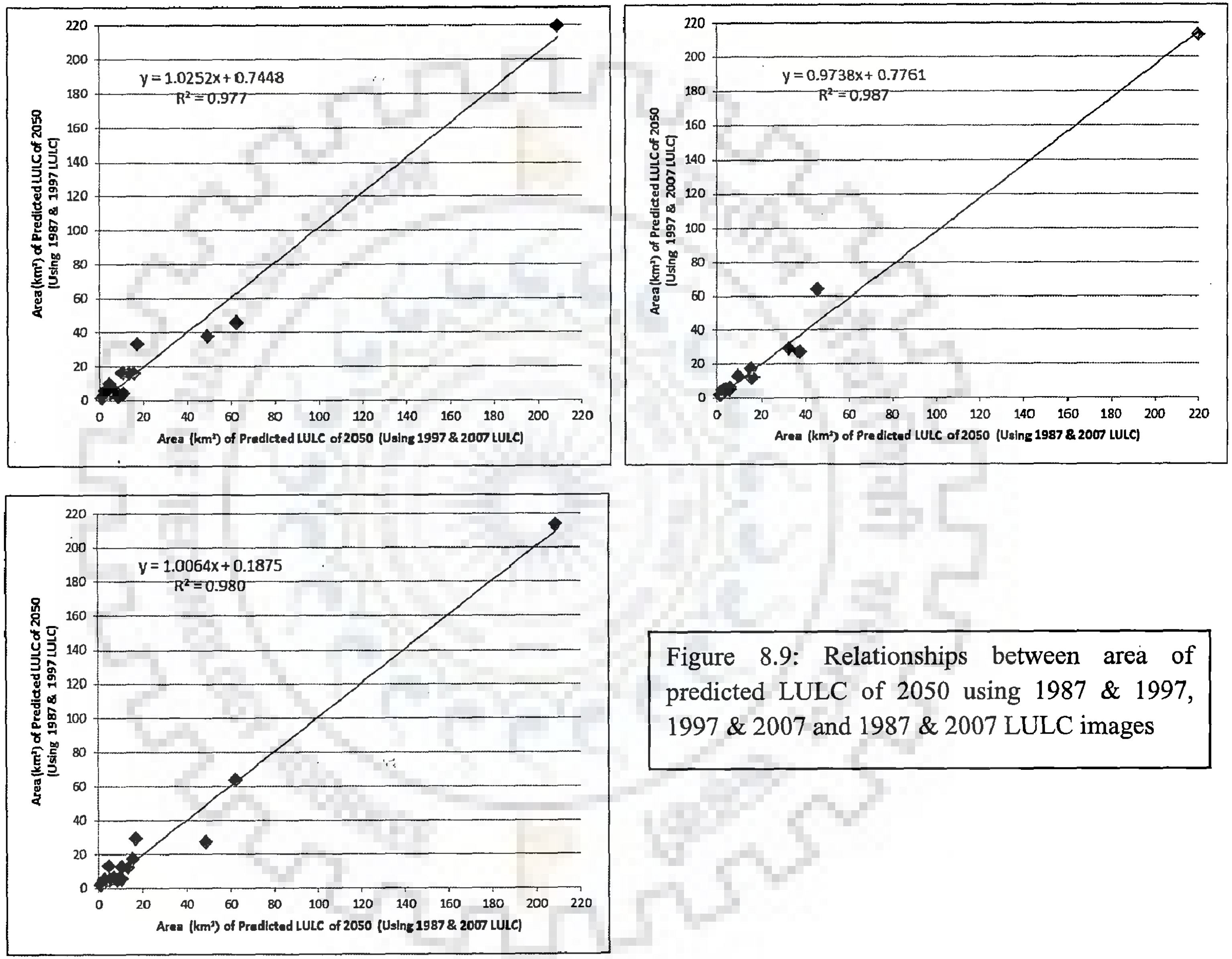


Figure 8.9: Relationships between area of predicted LULC of 2050 using 1987 & 1997, 1997 & 2007 and 1987 & 2007 LULC images

8.3.3. Allocation of Prediction

8.3.3.1. Allocation of predicted LULC of 2017, 2027, 2050 using 1987 & 1997, 1997 & 2007 and 1987 & 2007 LULC images

Figure 8.10 shows allocations of predicted LULC of 2017 using 1987 & 1997, 1997 & 2007 and 1987 & 2007 LULC images. Figure 8.11 shows allocations of predicted LULC of 2027 using 1987 & 1997, 1997 & 2007 and 1987 & 2007 LULC images. Figure 8.12 shows allocations of predicted LULC of 2050 using 1987 & 1997, 1997 & 2007 and 1987 & 2007 LULC images.

8.3.4. Correlations between Predicted Locations

8.3.4.1. Correlations between location of predicted LULC of 2017 using 1987 & 1997, 1997 & 2007 and 1987 & 2007 LULC images

The area statistics of different predicted LULC of 2017, 2027 & 2050 (using LULC images of 1987 & 1997, 1997 & 2007 and 1987 & 2007 LULC) shows that there are not much of differences as mentioned in previous paragraph. But the spatial differences between predicted LULC of 2017 using 1987 & 1997, 1997 & 2007 and 1987 & 2007 LULC images are found different. Regression analysis of three pairs of images (predicted LULC of 2017 using 1987 & 1997 and 1997 & 2007 LULC images; using 1997 & 2007 and 1987 & 2007 LULC images; using 1987 & 1997 and 1987 & 2007 LULC images) established that they are spatially different. One-tailed probability-value (at the hypothesized population mean) of a z-test for the data set (r values) is also calculated for improvement the error statistics. Spatial correlation coefficient (r) is 0.728 between predicted LULC class of 2017 using 1987 & 1997 and 1997 & 2007 LULC images, where P-value of a z-test for r is 0.4093. The correlation coefficient (r) is 0.758 between predicted LULC class of 2017 using 1997 & 2007 and 1987 & 2007 LULC images, where P-value of a z-test for r is 0.9668. The correlation coefficient (r) is 0.708 between predicted LULC class of 2017 using 1987 & 1997 and 1987 & 2007 LULC images, where P-value of a z-test for r is 0.0541. All the three cases show positive but weak correlation as 0.728, 0.758, and 0.708, respectively (Figure 8.13.a, Figure 8.13.b, and Figure 8.13.c). It is established that spatially they have some differences. It is established that there have some effects in spatial distribution of predicted LULC of 2017 when different time steps images are used to predict future LULC.

8.3.4.2. Correlations between location of predicted LULC of 2027 using 1987 & 1997, 1997 & 2007 and 1987 & 2007 LULC images

The spatial differences between predicted LULC of 2027 using LULC images of 1987 & 1997, 1997 & 2007 and 1987 & 2007 are found different. Regression analysis of three pairs of images (predicted LULC of 2027 using 1987 & 1997 and 1997 & 2007 LULC images; predicted LULC of 2027 using 1997 & 2007 and 1987 & 2007 LULC images; predicted LULC of 2027 using 1987 & 1997 and 1987 & 2007 LULC images) established that they are spatially different. One-tailed probability-value (at the hypothesized population mean) of a z-test for the data set (r values) is also calculated for improvement the error statistics. Spatial regressions correlation coefficient (r) is 0.696 between predicted LULC class of 2027 using 1987 & 1997 and 1997 & 2007 LULC images, where P-value of a z-test for r is 0.2916. The correlation coefficient (r) is 0.761between predicted LULC class of 2027 using 1997 & 2007 and 1987 & 2007 LULC images, where P-value of a z-test for r is 0.9738. The correlation coefficient (r) is 0.674 between predicted LULC class of 2027 using 1987 & 1997 and 1987 & 2007 LULC images, where P-value of a z-test for r is 0.0821. All the three cases show positive but weak correlation as 0.696, 0.761, and 0.674, respectively (Figure 8.14.a, Figure 8.14.b, and Figure 8.14.c). It is also established that spatially they have some differences. It is established that there have some effects in spatial distribution of predicted LULC of 2027 when different time steps images are used to predict future LULC.

8.3.4.3. Correlations between location of predicted LULC of 2050 using 1987 & 1997, 1997 & 2007 and 1987 & 2007 LULC images

The spatial differences between predicted LULC of 2050 using LULC images of 1987 & 1997, 1997 & 2007 and using 1987 & 2007 LULC are found different. Regression analysis of three pairs of images (predicted LULC of 2050 using 1987 & 1997 and 1997 & 2007 LULC images; predicted LULC of 2050 using 1997 & 2007 and 1987 & 2007 LULC images; predicted LULC of 2050 using 1987 & 1997 and 1987 & 2007 LULC images) established that they are spatially different. One-tailed probability-value (at the hypothesized population mean) of a z-test for the data set (r values) is also calculated for improvement the error statistics. Spatial regressions correlation coefficient (r) is 0.599 between predicted LULC class of 2050 using 1987 & 1997 and 1997 & 2007 LULC images, where P-value of a z-test for r is 0.2382. The correlation coefficient (r) is 0.721 between predicted LULC class of 2050 using 1997 & 2007 and 1987 & 2007 LULC images, where P-value of a z-test for r is 0.9758. The correlation coefficient (r) is 0.574 between predicted LULC class of 2050 using 1987 & 1997 and 1987 & 2007 LULC images, where P-value of a z-test for r is 0.1034. All the three cases show positive but weak correlation as 0.599, 0.721, and 0.574, respectively (Figure 8.15.a, Figure 8.15.b, and Figure 8.15.c). It is also established that spatially they have some differences. It is established that there have some effects in spatial distribution of predicted LULC of 2050 when different time steps images are used to predict future LULC.

In all the above three cases i.e., location predicted LULC of 2017, 2027, 2050 show positive but weak correlation (Table 8.4). It is also established that spatially they have some differences. It is established that there have some effects in spatial distribution of predicted LULC of 2017, 2027, 2050 when different time steps and time intervals images are used to predict future LULC.

Table 8.4: Correlations between location of predicted LULC for 2017, 2027 & 2050 using 1987 & 1997, 1997 & 2007 and 1987 & 2007 LULC images

Correlation between area of predicted LULC	**Correlation Coefficient (r) for 2017**	**One-tailed P-value of a z-test (for r value)**	**Correlation Coefficient (r) for 2027**	**One-tailed P-value of a z-test (for r value)**	**Correlation Coefficient (r) for 2050**	**One-tailed P-value of a z-test (for r value)**
Using 1987 & 1997 LULC Image and Using 1997 & 2007 LULC images	0.728	0.4093	0.696	0.2916	0.599	0.2382
Using 1997& 2007 LULC Image and Using 1987& 2007 LULC images	0.758	0.9668	0.761	0.9738	0.721	0.9758
Using 1987 & 1997 LULC Image and Using 1987 & 2007 LULC images	0.708	0.0541	0.674	0.0821	0.574	0.1034

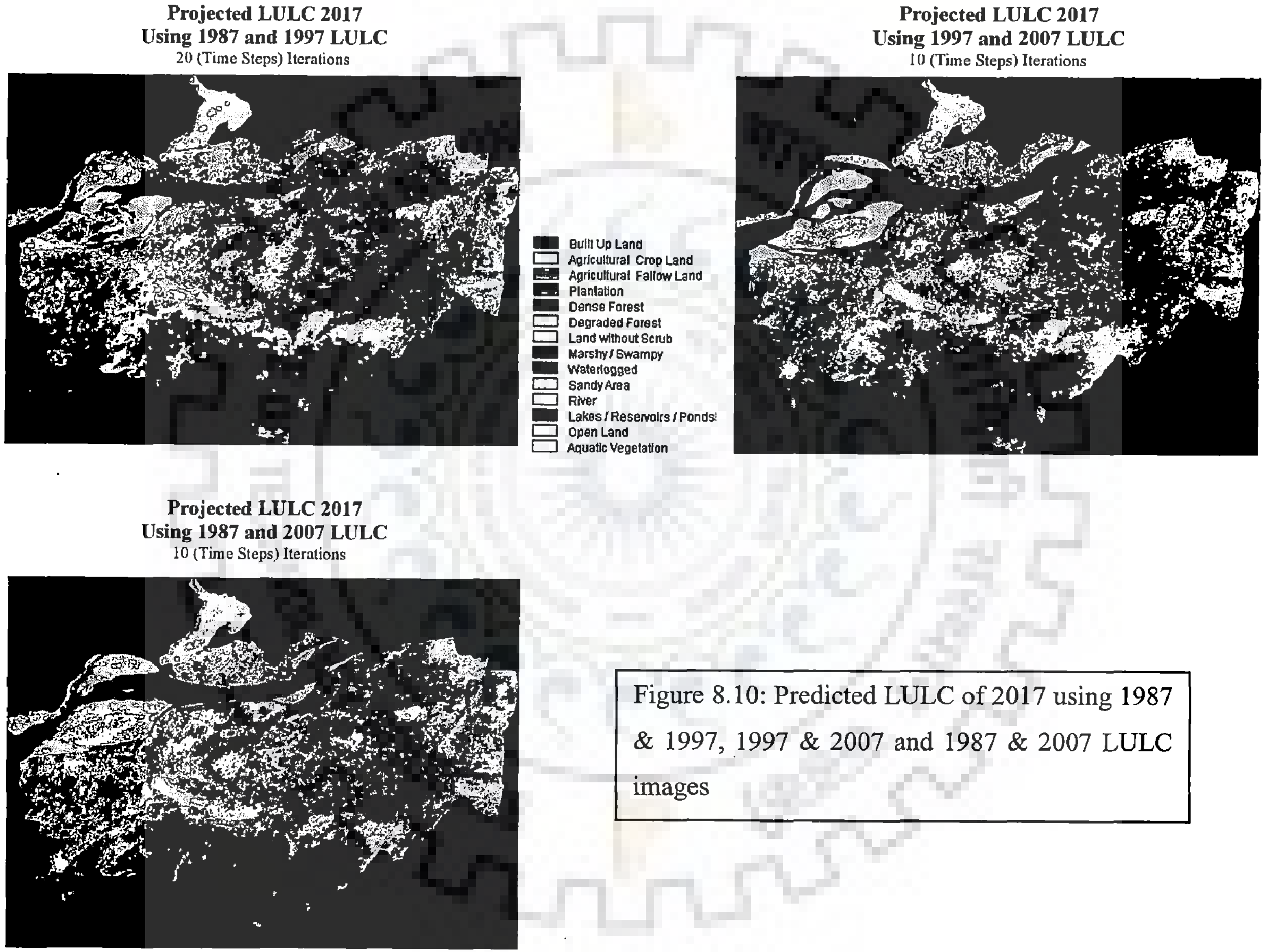


Figure 8.10: Predicted LULC of 2017 using 1987 & 1997, 1997 & 2007 and 1987 & 2007 LULC images

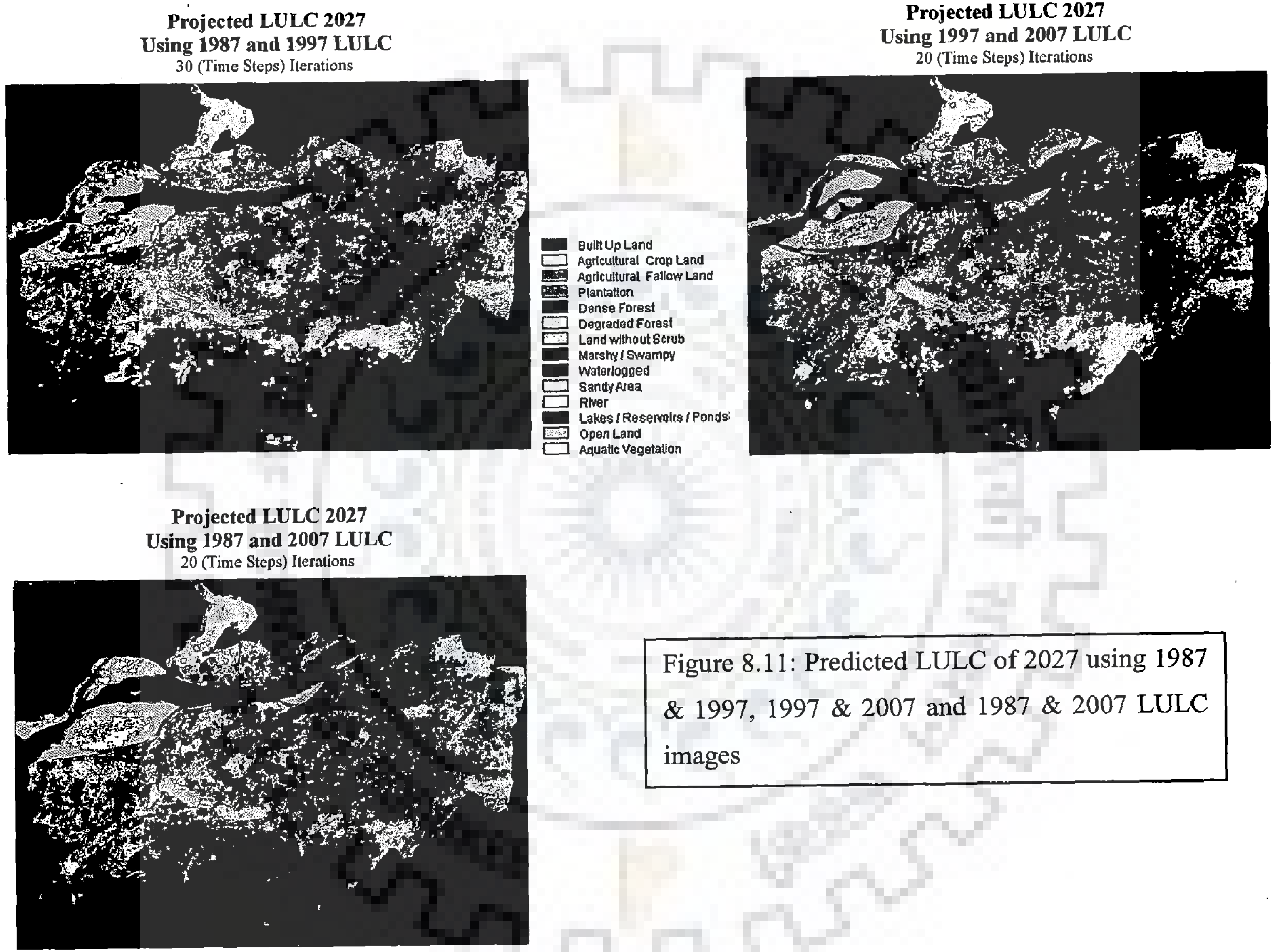


Figure 8.11: Predicted LULC of 2027 using 1987 & 1997, 1997 & 2007 and 1987 & 2007 LULC images

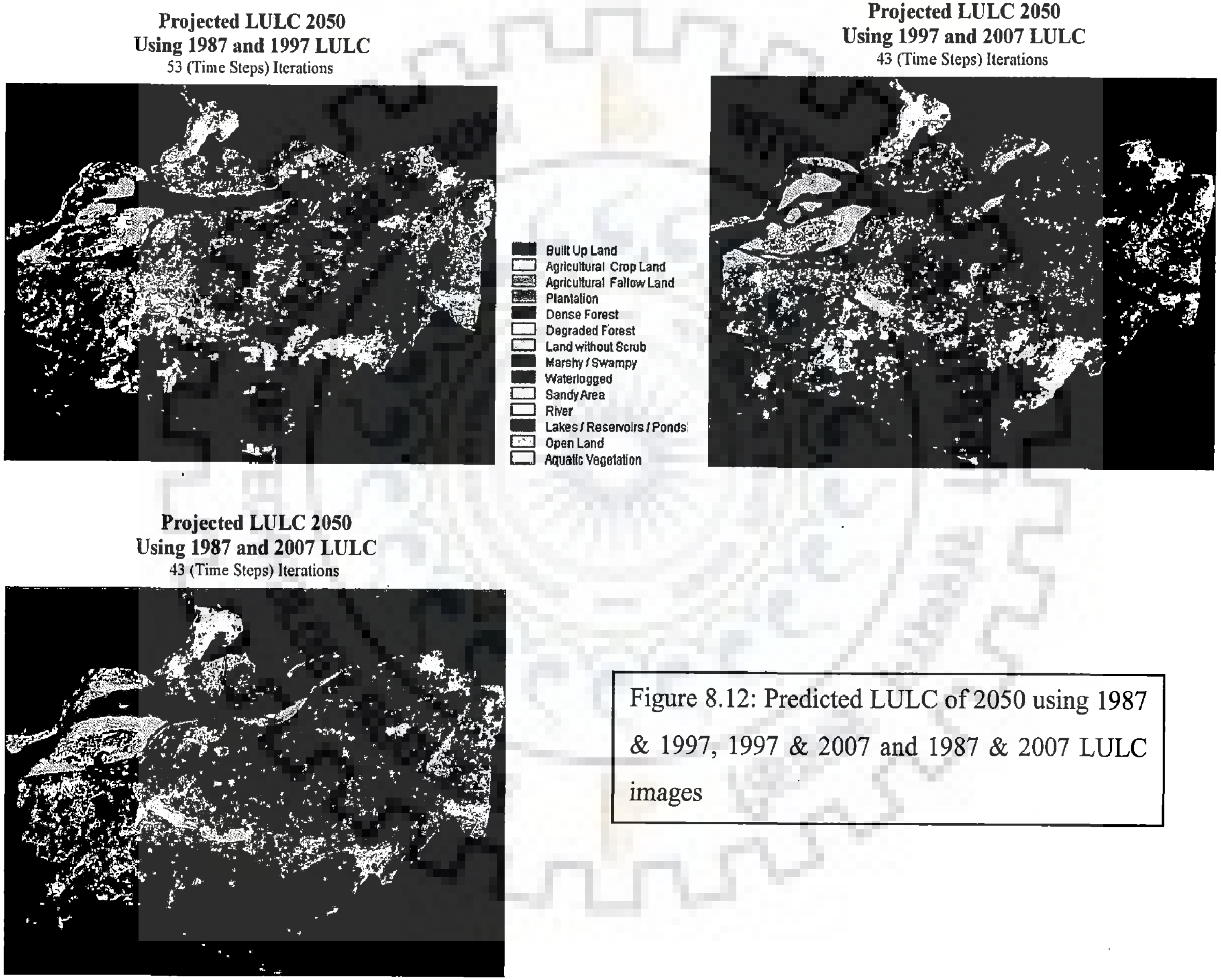


Figure 8.12: Predicted LULC of 2050 using 1987 & 1997, 1997 & 2007 and 1987 & 2007 LULC images

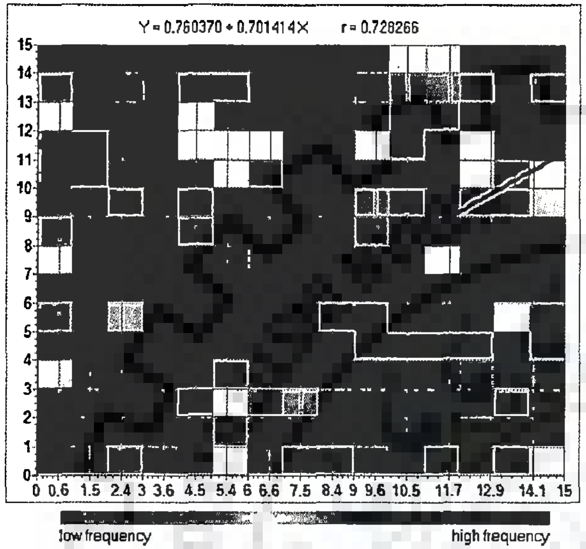


Figure: 8.13.a

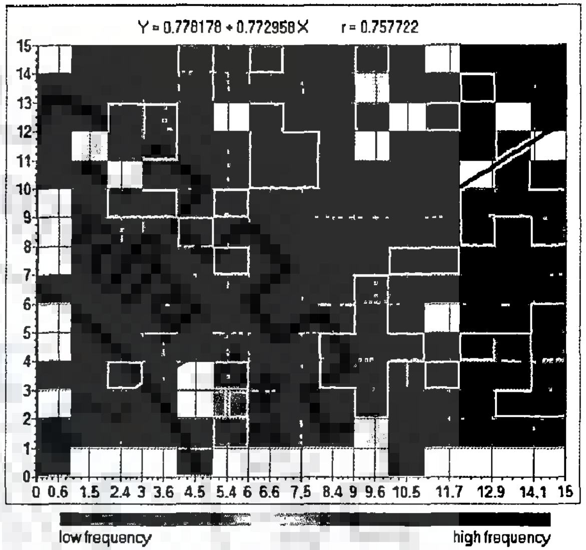


Figure: 8.13.b

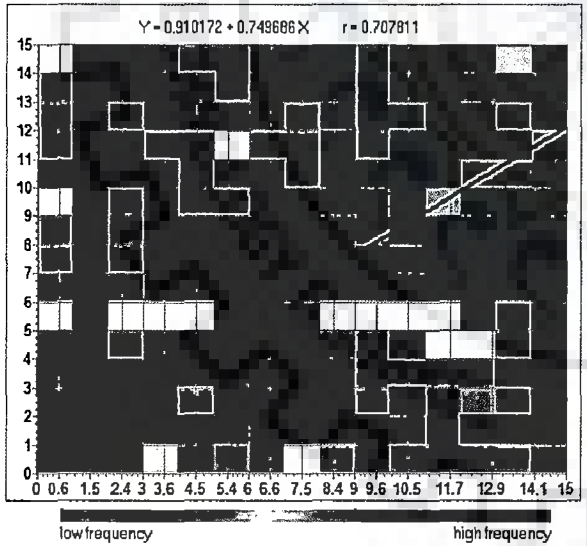


Figure: 8.13.c

Figure 8.13.a: Relationships between predicted LULC of 2017 using 1987 & 1997 and 1997 & 2007 LULC images

Figure 8.13.b: Relationships between predicted LULC of 2017 using 1997 & 2007 and 1987 & 2007 LULC images

Figure 8.13.c: Relationships between predicted LULC of 2017 using 1987 & 1997 and 1987 & 2007 LULC images

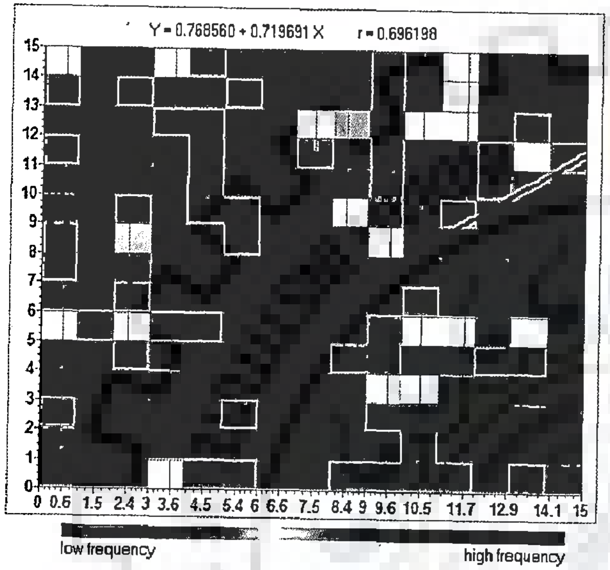


Figure: 8.14.a

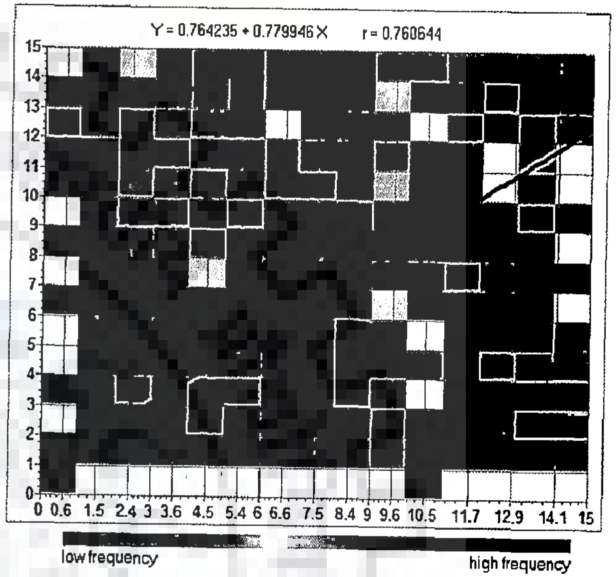


Figure: 8.14.b

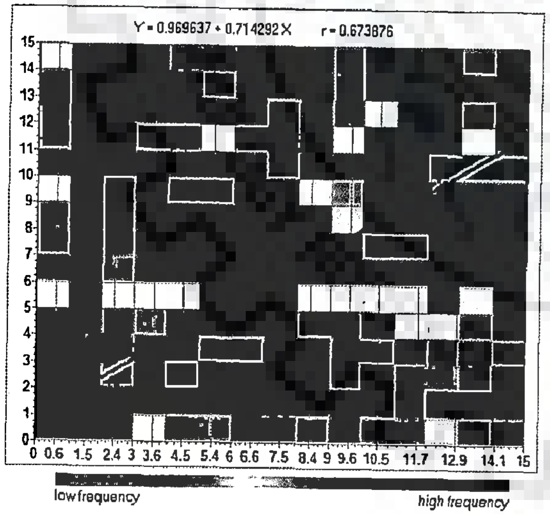


Figure: 8.14.c

Figure 8.14.a: Relationships between predicted LULC of 2027 using 1987 & 1997 and 1997 & 2007 LULC images

Figure 8.14.b: Relationships between predicted LULC of 2027 using 1997 & 2007 and 1987 & 2007 LULC images

Figure 8.14.c: Relationships between predicted LULC of 2027 using 1987 & 1997 and 1987 & 2007 LULC images

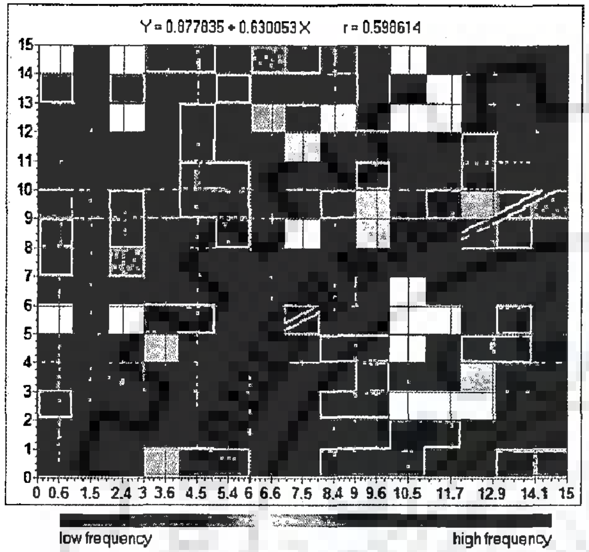


Figure: 8.15.a

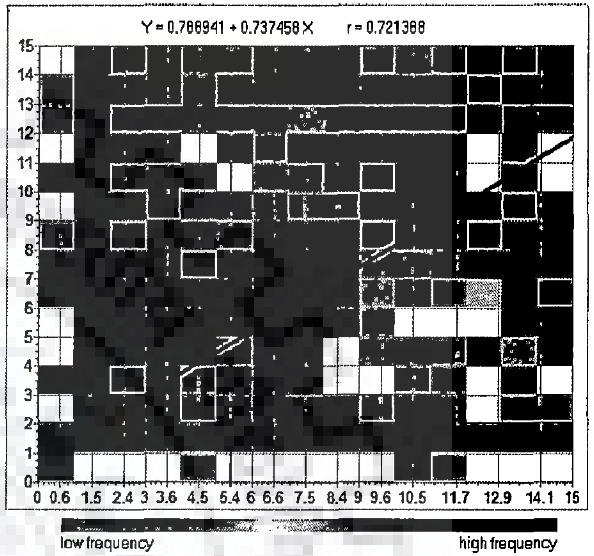


Figure: 8.15.b

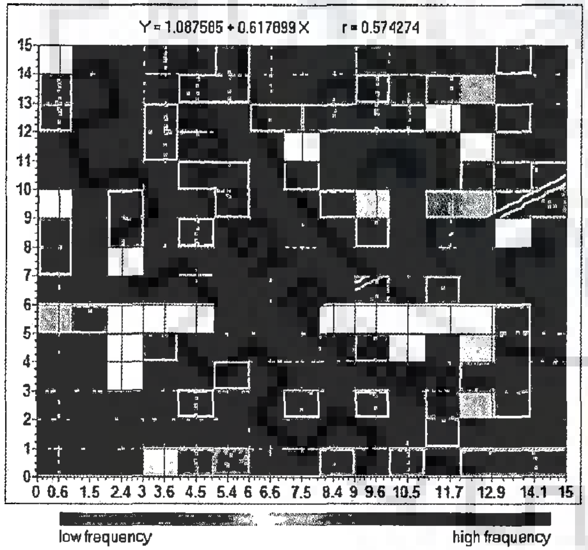


Figure: 8.15.c

Figure 8.15.a: Relationships between predicted LULC of 2050 using 1987 & 1997 and 1997 & 2007 LULC images

Figure 8.15.b: Relationships between predicted LULC of 2050 using 1997 & 2007 and 1987 & 2007 LULC images

Figure 8.15.c: Relationships between predicted LULC of 2050 using 1987 & 1997 and 1987 & 2007 LULC images

8.4. SUMMARY

This approach presented in this chapter examines if there is any effect in LULC prediction results when different time interval and time steps are used. When the quantity of predicted LULC of 2017, 2017 & 2050 (using 1987 & 1997, 1997 & 2007 and 1987 & 2007 LULC images) changes are analyzed, they are found to have also strong positive correlation for three time periods (i.e., 0.991, 0.992, 0.983 for 2017; 0.991, 0.993, 0.987 for 2027; 0.988, 0.993, and 0.990 for 2050). Initially, these strong correlations established that there is almost no effect in quantity of prediction results different time steps images and time intervals used to predict future LULC. Secondly, the location of predicted LULC of 2017, 2027 & 2050 for the three cases shows positive correlation (0.728, 0.758 and 0.708 for 2017 - when relatively less time steps used; 0.696, 0.761 and 0.674 for 2027 - when using medium time steps used; 0.599, 0.721, 0.574 for 2050 – when using more time steps used). It proves that there have some effects in spatial distribution of predicted LULC when different time steps images are used to predict future LULC. The results also indicate that relatively less time steps produced spatially more accurate results. Whereas, more time steps produce spatially less accurate results. The results also indicate less time intervals produced spatially more accurate results; whereas, more time intervals produce spatially less accurate results. The results also indicate that combination of less time steps and less time intervals produced spatially most accurate results. Overall from the present study results, it is found that there is nearly no effect in quantity of prediction results when different time steps and time intervals images are used to predict future LULC but there have some effect in spatial distribution of predicted LULC when we use different time steps and time intervals images to predict future LULC. Overall, the analysis proved that although there is nearly no effect on quantitative prediction results but have small impact of time steps and time intervals on spatial distribution of predicted LULC results.

Chapter - 9
SUMMARY, CONCLUSIONS AND SCOPE OF FUTURE WORKS

9.1. SUMMARY AND CONCLUSIONS

The goal of this doctoral research is to explore CA Markov model to predict the future LULC and to study the comparison of impact of different CA size as well as comprehensive comparison of different time steps on prediction results using the geospatial information extracted from the satellite imagery. This study is structured to build a bridge between the Geoinformatics (Remote Sensing, GIS etc.) research, LULC pattern characterization, modeling of spatial processes and techniques. Although the study of land use and land cover change is a very popular topic, the integrative perspective and methodology make this research unique since relatively little work has been reported in the literature to use CA and Markov.

First chapter of this doctoral research introduced the general background of this study, objective and related research questions. Remote sensing and GIS based LULCC models identified and reviewed for this study. Critical assessment & comparative analysis for reviewed models and background of remote sensing & GIS based LULCC modeling approach helped in selection of appropriate model for the study. About the study area, data used and methodology adopted for this study are described in chapter 3.

LANDSAT - 5 TM image of 1987, IRS-1C LISS III image of 1997, IRS-P6 LISS III image of 2007 were digitally classified for LULC mapping and assessing the changes in between 1987 & 1997 and in between 1997 & 2007.

After the image classification and analysis of land use and land cover change pattern, a CA Markov model has been developed to monitor and predict the future spatial pattern for the study area. The CA Markov model simulated for the study area covered a large proportion by urban landscape surrounded by other 13 classes of LULC. The present work describes about the process, calibration and results of LULC CA Markov modeling using satellite images of

1987 and 1997 to predict LULC of 2007. The net effect of different contiguity filters i.e., 3x3, 5x5 and 7x7 size on the prediction results as the action of CA component onto CA Markov prediction model were also evaluated. The 5x5 contiguity filter produces slightly better results although quantifiably the area statistics of predicted LULC of 2007 is same when 3x3, 5x5, 7x7 CA contiguity filters are used. Kappa indices of agreement and related statistics also proved that 5x5 contiguity filter produces most effective results with $K_{standard}$ as 0.7928 whereas $K_{standard}$ for 3x3 filter is 0.7857 and for 7x7 filter is 0.7777.

The study describes the validity of the CA Markov process for projecting future land use and land cover changes in the study area by examining statistical independence test and the Kappa index of agreement. The prediction results are tested for statistical independence. The hypothesis of statistical independence (K^2) proved that the land use and land cover change trends are dependent on previous development of land. The hypothesis of goodness of fit (Xc^2) proved that actual transition probability of matrix is fitted with expected transition probability prepared using Markov chain method. The validation calculates various KIA or $K_{standard}$ and related statistical variations on the KIA. The statistics indicate that K_{no} is 0.8347, $K_{location}$ is 0.8591, $K_{locationStrata}$ is 0.8591 and $K_{standard}$ is 0.7928.

The study also analysed sensitivity of different LULC parameters to identify the parameter(s), which have the highest, lowest or intermediate influence on predicted results. The results have shown that the land with or without scrub appeared to be most sensitive parameter and agricultural fallow land is least sensitive parameter which have maximum and minimum influences on predicted results of LULC of 2007, respectively. The others LULC parameter(s), which have the intermediate influence on predicted results are lakes / reservoirs / ponds, river, agricultural crop land, plantation, open land, marshy / swampy, sandy area, aquatic vegetation, built up land, dense forest, degraded forest, waterlogged area.

The study also evaluated the impact of different time steps on CA Markov prediction model results. The net effect of different time steps on CA Markov prediction results were evaluated for this purpose. The change in predicting quantity and location has been analysed and statistically evaluated. The analysis proved that although there is nearly no effect of time steps on quantitative prediction results but there is impact of time steps on spatial distribution of predicted LULC results. The results also indicate that less time steps produce spatially more accurate results, whereas more time steps have produced spatially less accurate results.

A systematic analysis of process, calibration, results and validations of CA Markov land use and land cover change model has been done in this doctoral research. The validity of the CA Markov process for projecting future land use and cover changes in the study area by examining statistical independence test (K^2), goodness of fit (Xc^2) and the Kappa index of agreement. Sensitivity analysis has been carried out to identify the parameter(s), which have the highest or lowest influence on predicted results. This study also explored a unique comprehensive comparison of different CA sizes impact on prediction results as well as comprehensive comparison of different time steps impact on prediction results. The study area experienced a remarkable change in the last two decades and possible change trend is assessed for the future. The proposed methodology for land use and land cover change analysis and modeling is not only applicable to the urban LULC, but also to the others different LULC surroundings by urban landscape.

9.2. CONTRIBUTION AND SIGNIFICANCE OF THIS RESEARCH

This dissertation is a systematic study of modeling of land use and land cover dynamics in a metropolitan district (included 14 LULC class and about 413.18 km^2 area) of India. The study area, Kamrup metropolitan district of Assam state of India is mostly covered by urban landscape (around 14% in 1987, 24% in 1997 and around 34% area in 2007) as well as other thirteen LULC classes. This is a study where not only urban landscape dynamic modeling has been studied; CA Markov model calibrated with a total of 14 LULC classes at a single framework together to predict future LULC classes. This involves multi-class LULC category to predict multi class LULC category, in connection with a developing region in a developing country i.e., in India. Spatio-temporal dynamics modeling of fourteen LULC classes (included urban landscapes) have been studied by using CA Markov model to predict future LULC for the study area.

The direct beneficiaries of this research will include two distinct groups: (1) resource managers at the local, regional and state levels of government, and (2) regional as well as urban planners who want better urban planning in broader social and economic settings. The primary significance of this research falls into four aspects:

- This research is a systematic description of LULC landscape dynamics for a study area in a developing country. The present research will provide a better understanding of the land use and land cover change pattern and future LULC pattern.
- It provides a geographically referenced model using the evidence likelihood map in development and calibration of model. This will provide a bridge study between the advanced remote sensing techniques and landscape process model.
- The present research also attempts to standardize methodology for validation of prediction results. Statistical independence test and Kappa validation has been standardized for these purposes, as demonstrated by their gainful applications.
- This research also attempts to identify the sensitive parameter(s), which have the highest, lowest or intermediate influence on predicted results of CA Markov model.
- More significantly, this research addresses the answers of two technical issues within CA Markov model future prediction model, namely relating to impact of different size of neibourhood (3x3, 5x5, and 7x7 CA) on CA Markov prediction results and impact on CA Markov model prediction results due to different time steps and time intervals.

9.3. FUTURE WORKS

Future work may be devoted to attempt an advanced robust Artificial Neural Network technique to train the non-linear relationship of CA Markov modeling dynamic process. The socio-economic parameters of the LULCC model deserve additional attention. Future research could include some dynamic as well as static variables in CA Markov model to explore the potentiality of explanatory of driving forces (dynamic or static variables). Further research may carry out with using more multi-temporal (10 times) satellite images. Further research may carry out with using multi-temporal high resolution satellite images for more accurate results.

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APPENDIX

Appendix – I: Transition probability matrix to predict 2017 LULC using 1987 & 1997 LULC

LULC Class	Built Up Land	Agricultural Crop Land	Agricultural Fallow Land	Plantations	Dense Forest	Degraded Forest	Land with or without Scrub	Marshy /Swampy	Water Logged Area	Sandy Area (River Bed)	River / Stream	Lake /Reservoir /Pond /Tank	Open Land	Aquatic Vegetation
Built Up Land	0.8183	0.0008	0.0059	0.0562	0.0056	0.0435	0.008	0.0116	0.0006	0.0006	0.0026	0.0114	0.02	0.0151
Agricultural Crop Land	0.4248	0.0108	0.0911	0.0178	0.0336	0.2251	0.1003	0.024	0.0041	0.0055	0.0072	0.0108	0.019	0.0258
Agricultural Fallow Land	0.3763	0.0213	0.1966	0.0091	0.0175	0.1646	0.0913	0.0311	0.0073	0.0035	0.0048	0.0118	0.0412	0.0236
Plantations	0.1822	0.0045	0.0268	0.1953	0.1522	0.2273	0.0664	0.0096	0.0018	0.0003	0.0004	0.0559	0.0084	0.0691
Dense Forest	0.0456	0.0007	0.0083	0.0043	0.6244	0.2666	0.0368	0.0053	0.0008	0.0001	0.0003	0.0012	0.0023	0.0031
Degraded Forest	0.3449	0.0048	0.0526	0.0219	0.115	0.2775	0.1061	0.0217	0.0042	0.0015	0.0026	0.0103	0.0131	0.0237
Land with or without Scrub	0.4419	0.0054	0.08	0.0161	0.0364	0.2229	0.0988	0.0211	0.0037	0.0011	0.0022	0.0127	0.0185	0.0392
Marshy / Swampy	0.2704	0.0189	0.1026	0.0154	0.0236	0.163	0.0668	0.0393	0.013	0.0419	0.0905	0.0464	0.03	0.0781
Water Logged Area	0.261	0.0105	0.1396	0.0155	0.0142	0.1415	0.0806	0.0309	0.0162	0.0194	0.0169	0.0697	0.0458	0.1382
Sandy Area (River Bed)	0.1146	0.0625	0.0664	0.0061	0.0038	0.0689	0.031	0.0926	0.0055	0.2381	0.2716	0.012	0.0156	0.0114
River / Stream	0.0322	0.0266	0.0133	0.0014	0.0007	0.0146	0.0034	0.0487	0.0008	0.3305	0.5206	0.0022	0.0037	0.0012
Lake/Reservoir/Pond /Tank	0.1202	0.0021	0.0586	0.008	0.0161	0.1107	0.0947	0.0283	0.0067	0.0015	0.0028	0.1413	0.0176	0.3915
Open Land	0.4382	0.0096	0.1223	0.0119	0.0251	0.1889	0.0949	0.0252	0.0049	0.0032	0.0047	0.014	0.0231	0.034
Aquatic Vegetation	0.1872	0.0056	0.0987	0.0125	0.0182	0.1521	0.1244	0.0356	0.0087	0.002	0.0042	0.1006	0.0232	0.2272

Appendix - II: Transition probability matrix to predict 2027 LULC using 1987 & 1997 LULC

LULC Class	Built Up Land	Agricultural Crop Land	Agricultural Fallow Land	Plantations	Dense Forest	Degraded Forest	Land with or without Scrub	Marshy /Swampy	Water Logged Area	Sandy Area (River Bed)	River / Stream	Lake /Reservoir /Pond /Tank	Open Land	Aquatic Vegetation
Built Up Land	0.8061	0.0011	0.0091	0.0499	0.0108	0.0493	0.0122	0.0104	0.0008	0.001	0.0032	0.0121	0.0163	0.0178
Agricultural Crop Land	0.5205	0.0058	0.0676	0.0179	0.0497	0.1757	0.0704	0.0181	0.0036	0.0054	0.009	0.0126	0.0155	0.0284
Agricultural Fallow Land	0.4884	0.0123	0.1123	0.0129	0.0308	0.1592	0.0756	0.0231	0.0052	0.0045	0.0074	0.0135	0.0259	0.029
Plantations	0.2695	0.0039	0.0366	0.0984	0.168	0.2118	0.0692	0.0133	0.0026	0.0008	0.0014	0.0424	0.0101	0.0718
Dense Forest	0.0988	0.0014	0.0159	0.0072	0.5441	0.2621	0.0465	0.0078	0.0013	0.0004	0.0008	0.0028	0.0041	0.0067
Degraded Forest	0.4434	0.0047	0.0513	0.0206	0.1252	0.1949	0.0795	0.0176	0.0035	0.0023	0.0044	0.0122	0.0128	0.0275
Land with or without Scrub	0.5341	0.0053	0.0631	0.0172	0.0515	0.1754	0.0621	0.0172	0.0034	0.0021	0.004	0.0143	0.0149	0.0352
Marshy / Swampy	0.3661	0.012	0.0801	0.0153	0.0367	0.1492	0.0667	0.0242	0.0059	0.0419	0.081	0.0322	0.0194	0.0694
Water Logged Area	0.3688	0.0098	0.1023	0.0155	0.0278	0.1493	0.0799	0.0265	0.0059	0.015	0.0199	0.0467	0.0241	0.1085
Sandy Area (River Bed)	0.193	0.0386	0.067	0.0085	0.0112	0.0919	0.04	0.062	0.0052	0.1648	0.2666	0.0144	0.0159	0.021
River / Stream	0.0672	0.034	0.0274	0.003	0.0026	0.0318	0.0117	0.0574	0.0021	0.3048	0.4407	0.0053	0.007	0.0052
Lake/Reservoir/Pond /Tank	0.218	0.0045	0.0773	0.0118	0.0276	0.1428	0.1025	0.0294	0.007	0.0027	0.0053	0.0877	0.0195	0.2641
Open Land	0.5333	0.0073	0.0816	0.0148	0.0393	0.1586	0.0688	0.0187	0.0039	0.0039	0.0068	0.0144	0.0152	0.0334
Aquatic Vegetation	0.2981	0.0065	0.0913	0.0146	0.0322	0.1654	0.1028	0.0287	0.0068	0.0035	0.007	0.0706	0.0213	0.151

Appendix III: Transition probability matrix to predict 2050 LULC using 1987 & 1997 LULC

LULC Class	Built Up Land	Agricultural Crop Land	Agricultural Fallow Land	Plantations	Dense Forest	Degraded Forest	Land with or without Scrub	Marshy /Swampy	Water Logged Area	Sandy Area (River Bed)	River / Stream	Lake /Reservoir /Pond /Tank	Open Land	Aquatic Vegetation
Built Up Land	0.7846	0.0015	0.0133	0.0409	0.0214	0.0575	0.0173	0.0096	0.001	0.0018	0.0043	0.0125	0.0133	0.021
Agricultural Crop Land	0.6534	0.0032	0.0367	0.0165	0.0652	0.1083	0.0402	0.0116	0.0021	0.0055	0.0101	0.0116	0.0101	0.0255
Agricultural Fallow Land	0.645	0.0048	0.0419	0.0157	0.0508	0.1134	0.0453	0.0133	0.0026	0.0053	0.0097	0.0124	0.0123	0.0276
Plantations	0.4388	0.0036	0.0404	0.0265	0.1657	0.1617	0.0566	0.0136	0.0028	0.0022	0.0041	0.023	0.0106	0.0506
Dense Forest	0.2334	0.0024	0.026	0.0111	0.4051	0.2285	0.0514	0.0101	0.0019	0.0013	0.0024	0.006	0.0067	0.0137
Degraded Forest	0.5887	0.0035	0.0367	0.0171	0.1231	0.113	0.0461	0.0119	0.0023	0.0035	0.0065	0.0117	0.01	0.026
Land with or without Scrub	0.6627	0.0034	0.0362	0.0165	0.0661	0.1084	0.0342	0.0113	0.0021	0.0033	0.0062	0.0122	0.0101	0.0273
Marshy / Swampy	0.5244	0.008	0.0478	0.015	0.0545	0.1141	0.0475	0.0165	0.003	0.0345	0.0624	0.0183	0.0121	0.0421
Water Logged Area	0.5481	0.0058	0.0551	0.0158	0.0503	0.1241	0.0553	0.0172	0.0028	0.0115	0.0203	0.0236	0.0136	0.0565
Sandy Area (River Bed)	0.3477	0.0199	0.0516	0.0111	0.0284	0.0962	0.04	0.0361	0.0034	0.1018	0.211	0.0137	0.0125	0.0266
River / Stream	0.1792	0.0307	0.0443	0.0067	0.0116	0.0656	0.027	0.052	0.0032	0.2254	0.3177	0.0101	0.0108	0.0156
Lake/Reservoir/Pond Tank	0.4319	0.0056	0.0682	0.0155	0.0524	0.148	0.0757	0.0212	0.0047	0.0051	0.0095	0.0367	0.0164	0.1092
Open Land	0.6657	0.0038	0.039	0.0159	0.0559	0.1044	0.0402	0.0117	0.0022	0.0046	0.0085	0.0121	0.0089	0.027
Aquatic Vegetation	0.4982	0.0054	0.062	0.0162	0.0564	0.1416	0.0667	0.0187	0.004	0.0055	0.0103	0.0326	0.015	0.0675

Appendix IV: Transition probability matrix to predict 2017 LULC using 1997 & 2007 LULC

LULC Class	Built Up Land	Agricultural Crop Land	Agricultural Fallow Land	Plantations	Dense Forest	Degraded Forest	Land with or without Scrub	Marshy /Swampy	Water Logged Area	Sandy Area (River Bed)	River / Stream	Lake /Reservoir /Pond /Tank	Open Land	Aquatic Vegetation
Built Up Land	0.8257	0.0035	0.0082	0.0045	0	0.0342	0.018	0.0093	0.0007	0.0018	0.0088	0.0052	0.0769	0.0032
Agricultural Crop Land	0.1063	0.3115	0.253	0.0169	0.0001	0.031	0.0357	0.0445	0.0024	0.0854	0.0984	0.0017	0.013	0
Agricultural Fallow Land	0.2651	0.0229	0.3599	0.007	0.0002	0.0899	0.1448	0.0124	0.0054	0.0078	0.0077	0.005	0.0608	0.0111
Plantations	0.4544	0.0358	0.0189	0.1968	0.0013	0.1507	0.0878	0.02	0.0036	0.0009	0.0036	0.0046	0.0124	0.0093
Dense Forest	0.0251	0.0056	0.0024	0.0114	0.7422	0.1878	0.0166	0.004	0.0007	0	0	0.0009	0.0021	0.0013
Degraded Forest	0.2648	0.0245	0.0351	0.0137	0.0636	0.4156	0.1191	0.0241	0.0052	0.0013	0.0032	0.0052	0.0154	0.0091
Land with or without Scrub	0.2451	0.0288	0.0897	0.0188	0.0077	0.3501	0.1775	0.0116	0.008	0.0015	0.0021	0.0052	0.0264	0.0276
Marshy / Swampy	0.2058	0.0592	0.1474	0.0029	0.0002	0.1125	0.1072	0.1117	0.0045	0.1153	0.0785	0.0101	0.0334	0.0114
Water Logged Area	0.1439	0.0159	0.0637	0.0114	0.0021	0.193	0.2887	0.1008	0.0354	0.0012	0.0006	0.0242	0.0284	0.0907
Sandy Area (River Bed)	0.0237	0.0281	0.023	0.0004	0	0.0023	0.0045	0.0811	0.0095	0.4114	0.4143	0.0005	0.0012	0
River / Stream	0.0089	0.0003	0.001	0	0	0.0004	0.0005	0.0267	0.0063	0.2867	0.6687	0.0005	0	0
Lake/Reservoir/Pond /Tank	0.117	0.0141	0.0355	0.0167	0.0011	0.0418	0.124	0.0524	0.0165	0.0066	0.0015	0.3693	0.0234	0.18
Open Land	0.3091	0.0077	0.2483	0.0023	0.0007	0.0607	0.1571	0.0256	0.0196	0.0078	0.0012	0.0169	0.1277	0.0152
Aquatic Vegetation	0.1152	0.0342	0.0497	0.0121	0.0035	0.0643	0.1113	0.02	0.012	0.0001	0	0.2723	0.0295	0.2758

Appendix -V: Transition probability matrix to predict 2027 LULC using 1997 & 2007 LULC

LULC Class	Built Up Land	Agricultural Crop Land	Agricultural Fallow Land	Plantations	Dense Forest	Degraded Forest	Land with or without Scrub	Marshy /Swampy	Water Logged Area	Sandy Area (River Bed)	River / Stream	Lake /Reservoir /Pond /Tank	Open Land	Aquatic Vegetation
Built Up Land	0.808	0.0048	0.0225	0.0042	0.0014	0.0405	0.0257	0.009	0.0018	0.004	0.0111	0.0062	0.0563	0.0045
Agricultural Crop Land	0.2277	0.1238	0.2037	0.0123	0.0021	0.0646	0.0627	0.033	0.004	0.0924	0.1416	0.0036	0.0237	0.0048
Agricultural Fallow Land	0.4252	0.0246	0.1821	0.0087	0.006	0.132	0.1097	0.0141	0.0053	0.0118	0.0152	0.0092	0.0417	0.0144
Plantations	0.5987	0.0284	0.0388	0.0494	0.0101	0.1426	0.0636	0.0144	0.003	0.0068	0.0099	0.0073	0.0167	0.0102
Dense Forest	0.0746	0.0089	0.0096	0.0113	0.6525	0.1945	0.0296	0.0065	0.0013	0.0009	0.0011	0.0019	0.0044	0.0029
Degraded Forest	0.4121	0.0258	0.0528	0.0126	0.0813	0.2465	0.0918	0.0185	0.0043	0.0066	0.0089	0.0082	0.0185	0.0121
Land with or without Scrub	0.4089	0.0281	0.0831	0.014	0.0274	0.2577	0.0882	0.0162	0.0051	0.0062	0.008	0.0132	0.0237	0.0203
Marshy / Swampy	0.3308	0.0411	0.1182	0.0067	0.0073	0.1231	0.0781	0.0309	0.0051	0.0903	0.1192	0.0111	0.0254	0.0129
Water Logged Area	0.3197	0.0295	0.0905	0.0131	0.0151	0.2258	0.129	0.03	0.0064	0.0148	0.0119	0.0386	0.0272	0.0484
Sandy Area (River Bed)	0.0609	0.0276	0.0381	0.0013	0.0002	0.0164	0.0178	0.0557	0.0068	0.2648	0.5012	0.0017	0.0054	0.0021
River / Stream	0.0243	0.0078	0.0097	0.0003	0	0.0048	0.0056	0.039	0.0066	0.3146	0.5842	0.001	0.0013	0.0008
Lake/Reservoir/Pond /Tank	0.2437	0.0247	0.0646	0.0158	0.005	0.1012	0.1157	0.037	0.0113	0.0132	0.0098	0.1972	0.0265	0.1342
Open Land	0.4616	0.0174	0.1633	0.0069	0.0053	0.12	0.1063	0.0171	0.007	0.0107	0.0092	0.0167	0.0396	0.019
Aquatic Vegetation	0.2434	0.0332	0.0733	0.0142	0.0085	0.1092	0.1105	0.0276	0.0102	0.0072	0.0058	0.2001	0.0279	0.1289

Appendix -VI: Transition probability matrix to predict 2050 LULC using 1997 & 2007 LULC

LULC Class	Built Up Land	Agricultural Crop Land	Agricultural Fallow Land	Plantations	Dense Forest	Degraded Forest	Land with or without Scrub	Marshy /Swampy	Water Logged Area	Sandy Area (River Bed)	River / Stream	Lake /Reservoir /Pond /Tank	Open Land	Aquatic Vegetation
Built Up Land	0.7806	0.007	0.0311	0.0043	0.0054	0.051	0.0301	0.0088	0.002	0.0078	0.0174	0.0074	0.041	0.0061
Agricultural Crop Land	0.4378	0.0238	0.0822	0.0061	0.0114	0.083	0.0497	0.0198	0.0039	0.0791	0.1683	0.0072	0.0192	0.0084
Agricultural Fallow Land	0.6376	0.0168	0.0577	0.0065	0.0209	0.1041	0.0533	0.0114	0.003	0.016	0.029	0.0109	0.0216	0.0112
Plantations	0.732	0.0129	0.0366	0.0051	0.0228	0.0787	0.0351	0.0087	0.002	0.0117	0.0216	0.0078	0.0173	0.0076
Dense Forest	0.2085	0.0125	0.0227	0.0101	0.4913	0.1772	0.0392	0.0085	0.0019	0.004	0.0059	0.0042	0.0085	0.0054
Degraded Forest	0.6062	0.0165	0.0463	0.0072	0.0861	0.1043	0.0486	0.0111	0.0027	0.0123	0.0215	0.0095	0.0178	0.0099
Land with or without Scrub	0.6234	0.0172	0.0526	0.0071	0.046	0.1191	0.043	0.0114	0.0028	0.0126	0.0216	0.0122	0.0191	0.0118
Marshy / Swampy	0.511	0.0184	0.0566	0.0055	0.02	0.0861	0.0438	0.0145	0.0035	0.0648	0.1394	0.0098	0.0173	0.0096
Water Logged Area	0.5667	0.0197	0.0603	0.0079	0.0361	0.125	0.0581	0.0138	0.003	0.0179	0.0309	0.0221	0.0201	0.0184
Sandy Area (River Bed)	0.154	0.0187	0.0384	0.0023	0.0032	0.0336	0.0229	0.0342	0.0053	0.1774	0.4945	0.0037	0.0078	0.004
River / Stream	0.085	0.0162	0.0273	0.0013	0.0012	0.0197	0.0156	0.0413	0.0063	0.286	0.49	0.0025	0.0049	0.0026
Lake/Reservoir/Pond /Tank	0.4893	0.0228	0.0665	0.0099	0.0195	0.117	0.073	0.0192	0.0054	0.0188	0.0291	0.0594	0.0225	0.0479
Open Land	0.6587	0.0153	0.0604	0.0061	0.0196	0.0972	0.0495	0.0108	0.0028	0.0136	0.0236	0.0128	0.0176	0.012
Aquatic Vegetation	0.4933	0.0232	0.0678	0.0098	0.0227	0.1179	0.0725	0.0184	0.0052	0.0162	0.0238	0.0674	0.0225	0.0392

Appendix -VII: Transition probability matrix to predict 2017 LULC using 1987 & 2007 LULC

LULC Class	Built Up Land	Agricultural Crop Land	Agricultural Fallow Land	Plantations	Dense Forest	Degraded Forest	Land with or without Scrub	Marshy /Swampy	Water Logged Area	Sandy Area (River Bed)	River / Stream	Lake /Reservoir /Pond /Tank	Open Land	Aquatic Vegetation
Built Up Land	0.8326	0.001	0	0.0063	0	0.0174	0.007	0.014	0.0012	0	0.0009	0.0016	0.1179	0
Agricultural Crop Land	0.3695	0.0938	0.0879	0.0144	0	0.265	0.1069	0.011	0.0006	0.0101	0.0011	0.0008	0.034	0.005
Agricultural Fallow Land	0.2638	0.0344	0.4102	0.0029	0	0.0616	0.1416	0.0201	0.0006	0.0003	0	0.0022	0.0521	0.0101
Plantations	0.2042	0.0274	0	0.5236	0.037	0.1244	0.012	0.004	0.0033	0	0	0.0412	0.0229	0
Dense Forest	0	0.0023	0	0.0045	0.7737	0.2101	0.0005	0.0068	0.0021	0	0	0	0	0
Degraded Forest	0.2486	0.0266	0.0263	0.0141	0.0304	0.4787	0.1366	0.0214	0.0014	0	0	0.0015	0.0108	0.0037
Land with or without Scrub	0.3904	0.0083	0.0832	0.0158	0	0.1751	0.2005	0.0207	0.0363	0	0	0.0052	0.0306	0.0338
Marshy / Swampy	0.1429	0.068	0.0582	0.0107	0.0004	0.089	0.1704	0.1396	0.0114	0.101	0.0786	0.0043	0.0684	0.0573
Water Logged Area	0.0665	0.0428	0.1073	0.0161	0	0.0221	0.4962	0.0224	0.0289	0.0246	0.0065	0.0107	0.0323	0.1237
Sandy Area (River Bed)	0	0.1089	0.0477	0.0001	0.0001	0	0	0.1109	0.0116	0.5527	0.1681	0	0	0
River / Stream	0.0175	0	0	0	0.0001	0.0011	0	0.016	0.0056	0.2287	0.7308	0.0002	0	0
Lake/Reservoir/Pond Tank	0.0412	0.0092	0	0.0039	0	0.0167	0.0319	0.0131	0.0128	0.0008	0	0.5761	0.0093	0.2851
Open Land	0.4325	0.0149	0.1403	0.0042	0	0.137	0.1507	0.0061	0.0036	0.0006	0.0005	0.0028	0.0872	0.0197
Aquatic Vegetation	0.0329	0.0267	0.1001	0.0015	0.0032	0.0513	0.1395	0.0314	0.0247	0	0	0.1834	0.0367	0.3686

Appendix -VIII: Transition probability matrix to predict 2027 LULC using 1987 & 2007 LULC

LULC Class	Built Up Land	Agricultural Crop Land	Agricultural Fallow Land	Plantations	Dense Forest	Degraded Forest	Land with or without Scrub	Marshy /Swampy	Water Logged Area	Sandy Area (River Bed)	River / Stream	Lake /Reservoir /Pond /Tank	Open Land	Aquatic Vegetation
Built Up Land	0.8239	0.0026	0.0051	0.0077	0	0.0313	0.018	0.0121	0.0016	0.0003	0.0021	0.0026	0.0914	0.0014
Agricultural Crop Land	0.4971	0.0562	0.0715	0.0142	0.0007	0.2108	0.0869	0.011	0.0021	0.0088	0.0028	0.0029	0.028	0.0071
Agricultural Fallow Land	0.4197	0.0253	0.2812	0.0054	0.0018	0.0757	0.1121	0.0165	0.0026	0.0016	0.0003	0.0047	0.041	0.0123
Plantations	0.3287	0.0214	0.0031	0.3766	0.0486	0.1262	0.0227	0.0054	0.0031	0	0	0.0415	0.0205	0.0022
Dense Forest	0.0166	0.0052	0.002	0.0076	0.7095	0.2287	0.0181	0.0083	0.0023	0	0	0.0005	0.0012	0
Degraded Forest	0.3934	0.0203	0.0311	0.015	0.0368	0.3503	0.1077	0.0173	0.003	0.0005	0	0.0037	0.0142	0.0069
Land with or without Scrub	0.514	0.0095	0.0703	0.0152	0.0005	0.1487	0.1378	0.0164	0.0225	0.0002	0	0.0091	0.0269	0.0289
Marshy / Swampy	0.2793	0.0476	0.06	0.0115	0.0028	0.0963	0.1274	0.0868	0.0097	0.0892	0.0865	0.0102	0.0477	0.045
Water Logged Area	0.2569	0.0307	0.0978	0.0166	0.0002	0.0649	0.3191	0.0203	0.0206	0.0208	0.0096	0.0211	0.0297	0.0919
Sandy Area (River Bed)	0.0519	0.0924	0.0578	0.0023	0	0.0054	0.0094	0.0961	0.0104	0.4307	0.2384	0.0006	0.0045	0
River / Stream	0.0255	0.0014	0.0008	0	0	0.0009	0.0006	0.0294	0.0062	0.2746	0.6603	0.0003	0	0
Lake/Reservoir/Pond /Tank	0.1193	0.0121	0.0132	0.0059	0.001	0.0389	0.0542	0.0155	0.013	0.0019	0.0004	0.4557	0.0147	0.2543
Open Land	0.5503	0.0125	0.1063	0.0061	0.001	0.1203	0.1103	0.0076	0.0041	0.0011	0.001	0.0055	0.0563	0.0176
Aquatic Vegetation	0.1673	0.0228	0.0937	0.0048	0.0052	0.0735	0.1231	0.0259	0.019	0.0001	0	0.1714	0.0323	0.261

Appendix - IX: Transition probability matrix to predict 2050 LULC using 1987 & 2007 LULC

LULC Class	Built Up Land	Agricultural Crop Land	Agricultural Fallow Land	Plantations	Dense Forest	Degraded Forest	Land with or without Scrub	Marshy /Swampy	Water Logged Area	Sandy Area (River Bed)	River / Stream	Lake /Reservoir /Pond /Tank	Open Land	Aquatic Vegetation
uilt Up Land	0.808	0.0041	0.0153	0.009	0.0011	0.0443	0.027	0.0103	0.0019	0.0016	0.0036	0.0039	0.0658	0.0041
gricultural Crop and	0.7127	0.0081	0.0393	0.0124	0.0101	0.1083	0.0488	0.0093	0.0033	0.0064	0.0059	0.0064	0.0194	0.0095
gricultural Fallow ,and	0.6804	0.0116	0.0776	0.0086	0.0055	0.0858	0.0625	0.0105	0.004	0.0034	0.0026	0.0087	0.0246	0.014
lantations	0.5412	0.0123	0.0141	0.1303	0.0646	0.1183	0.0357	0.0072	0.003	0.001	0.0007	0.0388	0.0177	0.015
ense Forest	0.105	0.008	0.0099	0.0109	0.5787	0.2288	0.0365	0.0095	0.0025	0.0008	0.0006	0.0016	0.0047	0.0024
egraded Forest	0.6375	0.011	0.0343	0.0151	0.0455	0.139	0.0619	0.0109	0.0039	0.0025	0.0021	0.0071	0.0184	0.0108
and with or ithout Scrub	0.72	0.0087	0.0422	0.0126	0.0076	0.0937	0.0441	0.0092	0.0042	0.0026	0.0022	0.0143	0.0205	0.0181
larshy / Swampy	0.5189	0.018	0.0515	0.0115	0.0076	0.0909	0.0573	0.0174	0.0057	0.0652	0.095	0.0179	0.0195	0.0234
'ater Logged Area	0.5796	0.0135	0.0657	0.0151	0.005	0.1033	0.0741	0.014	0.0058	0.0142	0.0149	0.0331	0.0228	0.0389
ındy Area liver Bed)	0.1917	0.0473	0.0588	0.0056	0.0006	0.0458	0.0385	0.0533	0.0072	0.225	0.3025	0.0029	0.0132	0.0079
iver / Stream	0.0564	0.0245	0.0169	0.001	0	0.0051	0.0085	0.0435	0.0066	0.3048	0.5271	0.0007	0.0031	0.0018
ıke/Reservoir/Pond 'ank	0.28	0.0152	0.0473	0.009	0.0041	0.0726	0.0803	0.0176	0.0123	0.0039	0.0025	0.2441	0.0217	0.1894
pen Land	0.748	0.0079	0.0458	0.0085	0.0065	0.0815	0.0463	0.0081	0.0033	0.0022	0.0022	0.0094	0.0175	0.0128
ıquatic Vegetation	0.4187	0.0154	0.0733	0.0098	0.0093	0.0987	0.087	0.0164	0.0099	0.004	0.003	0.1351	0.0245	0.095

LIST OF PUBLICATIONS

List of Manuscript prepared based on the content of this thesis

Paper Accepted in Journal

Mondal M. S., N. Sharma, M. Kappas, P. K. Garg. Modeling of Spatio-Temporal Dynamics of LULC - A Review and Assessment, Journal of Environmental Science and Engineering, ISSN 1934-8932, USA, Accepted: December 22, 2010.

Mondal M. S., N. Sharma, M. Kappas, P. K. Garg. Modelling of spatio-temporal dynamics of land use and land cover in a part of Brahmaputra Basin River using Geoinformatics techniques, in the "Geographical Applications of Remote Sensing" special issue of Geocarto International (Published by Taylor & Francis).

Paper Submitted in Journal

Mondal M. S., Nayan Sharma, P. K. Garg, Martin Kappas. Critical Assessment of dynamics of land use land cover using multi-temporal satellite images in Kamrup metropolitan district of Assam state, India. (Submitted to Italian Journal of Remote Sensing).

Paper Presented at International Conferences (Peer Reviewed)

*Mondal M. S., N. Sharma, M. Kappas, P. K. Garg, 2011, Statistical independence test and validation of land use land cover prediction results when using CA Markov LUCC model. Paper presented in the Annual International Conferences of Remote Sensing & Photogrammetry Society, RSPSoc 2011, 13-15 September 2011, University of Bournemouth, Bournemouth, U. K..

*As per recommendation of RSPSoc 2011, this paper now submitted in International Journal of Remote Sensing, the official journal of Remote Sensing & Photogrammetry Society for publication.

Paper Accepted for International Conferences (Peer Reviewed)

Mondal M. S., Nayan Sharma, P. K. Garg, Martin Kappas. Critical assessment and modeling of dynamics of land use land cover using multi-temporal satellite images. Accepted (reference 0082) for poster presentation in International Conference on Climate Change, Deforestation and the Future of African Rainforests, 4-6 January 2012, Environmental Change Institute, School of Geography and the Environment, University of Oxford, U. K..

Mondal M. S., N. Sharma, M. Kappas, P. K. Garg. Modeling of Spatio-Temporal Dynamics of Land Use and Land Cover Using Geoinformatics Techniques. Paper accepted for AAG annual meeting and selected for as Chair of the session, February 24-28, 2012, New York, USA.

Mondal M. S., Nayan Sharma, P. K. Garg, Martin Kappas. Modelling of spatio-temporal dynamics of land use and land cover using multi-temporal satellite images and GIS. Accepted for presentation at the ASPRS 2012 Annual Conference, March 19-23, 2012 to be held at the Sacramento Convention Center in Sacramento, California, USA.

Paper to be Submitted Shortly in Journal

Mondal M. S., N. Sharma, P. K. Garg, M. Kappas. CA Markov modeling of dynamics of land use land cover and time steps effects on predicted results.

Mondal M. S., N. Sharma, P. K. Garg, M. Kappas. CA Markov modeling of dynamics of land use land cover and sensitivity analysis to identify sensitive parameter(s).

Title of Thesis: "**Land Use Land Cover Modeling in a Part of Brahmaputra Basin Using Geoinformatics**"

Name of the Student: **Md. SurabuddinMondal**

I revised thoroughly the comments of the thesis submitted earlier incorporating all the observation of the examiners to the best of my ability. Point wise replies to the observations of the examiners are given bellow.

S. Mondal. 08/12/201

(Md. Surabuddin Mondal)

ANSWERS TO THE QUERIES OF REVIEWER 1

Chapter 3

Sl No.	Comments & References	Answer to Comments	Present References
1	Page 20, Figure 3.1, show the "Brahmaputra River" and "Guwahati City" in figure	"Brahmaputra River" and "Guwahati City" inserted in Figure 3.1	Page 20, Figure 3.1
2	Page 24, insert supporting text to explain methodology	Supporting text has been included to explain the methodology	Page 23, Para: 1,lines 1-16

Chapter 4

Sl No.	Comments & References	Answer to Comments	Present References
1	Page 35, explain about "kappa specific values"	Some sentences added in text to explain "kappa specific values"	Page 34, lines 9 - 14

Chapter 5

Sl No.	Comments & References	Answer to Comments	Present References
1	Page 42, 46, 47. Table 5.3 & Table 5.4, Are the years correct?	The year is wrongs, 1987 is replaced by 1997 in row total, 1997 replaced by 2007 in column total	Page 45, 46. Table 5.3 & Table 5.4
2	Page 61 and 62, Figure 5.11 and 5.11, different format and background colour	Different format and background colour have been changed	Page 60 and 61, Figure 5.11 and 5.11
3	Page 63, last line, "1987-97slower than1997-07"	It was a mistake, now changed as "1997-07 slower than 1987-97"	Page 62, last line

Chapter 6

Sl No.	Comments & References	Answer to Comments	Present References
1	Page 69, three lines from bottom, P_{ij}should be inserted between "and" and "is"	"and" and "is" inserted	Page 68, three lines from bottom
2	Page 75, Eastman et al. 2010; page 94, Lambin (1994), Pontius (1994); page 140, Lambin (1997), correspondence between the references in the text and in the references should be checked	" Eastman et al. 2010", it is "Eastman et al. 2009", references now carefully checked, replaced wherever missing and deleted where unnecessary appeared	Page 74
3	Page 78, Figure 6.1 and later similar diagrams. The individual titles are barely legible?	Backgrounds of the title / title style have been changed.	Page 70, Figure 6.1; Page 114, Figure 8.1; Page 115, Figure 8.2; Page 117, Figure 8.3
4	Pages 74, 75; Section 6.7 and Section 6.9, the link is not clear, perhaps some references and explanation would be helpful	Now Section 6.7 and Section 6.9 are properly linked, some text and references have been added for this purposes	Pages 73, Section 6.7 Para: 3, line 1; Pages 74, Section 6.9, Para: 4, line 6, and Page 147, Para: 5, line 1

Chapter 7

Sl No.	Comments & References	Answer to Comments	Present References
1	Page 89, The mathematical developments on page 89 is not entirely clear and requires some guesswork	The sentences (Page 89, Para: 2, lines 3, 4 and Page 89, Para: 4, lines 3, 4) related to the mathematical development have been changed. It is now clear and meaningful.	Page 89, Para: 2, lines 3,4 and Page 89, Para: 4, lines 3,4

Chapter 8

Sl No.	Comments & References	Answer to Comments	Present References
1	Page 120, the figure numbers references 8.10, 8.11 and 8.12 should be 8.11, 8.12 and 8.13	It was a mistake. Figure 8.5 has been deleted as per the suggestion of another Reviewer / Examiner. So, figure numbers are now correct.	Pages 132. 133, 134

ANSWERS TO THE QUERIES OF REVIEWER 2

ABSTRACT

Sl No.	Comments & References	Answer to Comments	Present References
1	Page i, line 1, change “LUCC” to “LULCC”	The word “LUCC” has been replaced by “LULCC”	Page i, line 1
2	Page i, line 2, insert “and” between “land use” and “land cover”	The word “and” has been inserted between “land use” and “land cover”	Page i, line 2
3	Page i, line 3, insert “and” between “land use” and “land cover”	The word “and” has been inserted between “land use” and “land cover”	Page i, line 3
5	Page ii, line 1, insert “(” before CA “)” after CA	Inserted “(” before CA “)” after CA	Page ii, line 1
6	Page iii, Para: 2, line 9, delete the line “ when using 1997 and 2007 image to predict future”	Deleted the line “ when using 1997 and 2007 image to predict future” as it had appeared twice	Line deleted

ACKNOWLEDGEMENTS

Sl No.	Comments & References	Answer to Comments	Present References
1	Page v, Para: 3, lines 6, 7, 8; replaced “Netherlands” instead of “ Nederlands”	The Dutch word “Nederlands” replaced by English word “Netherlands”	Page v, Para: 3, lines 6, 7, 8
2	Page vi, Para: 4, lines 2; replaced “Netherlands” instead of “ Nederlands”	The Dutch word “Nederlands” replaced by English word “Netherlands”	Page vi, Para: 4, line 2

ANSWERS TO THE COMMENTS OF REVIEWER 2

General

Comments 1

Due to large number of mistakes in the thesis, overall I could not able to enjoy while reading it. Moreover, the thesis was checked by two eminent professors from IIT Roorkee and one from Germany. It was a very hard time for me to correct the entire thesis as far as possible. It was supposed to be the responsibilities of the student and his three advisors to submit an error free thesis.

Answer:

Thesis has been carefully checked now and mistakes removed.

General

Comments 2

The tools and techniques applied in the thesis are very standard and a good number of similar researches have been undertaken in other river basin/catchments of the country and abroad. According to me there is little contribution of the thesis to the development of the science.

Answer:

Markov CA model has not been applied much in Indian conditions especially for LULCC in a fast developing semi-urban setting in the Brahmaputra river flood plains. Cellular Automata technique provides better simulation of predicted results. The approach proposed used minimum number of satellite images for the prediction of future LULC, which highlighted its advantageous application for computing the dynamics of LULCC in a rapidly developing urban area.

Chapter 6 & 8

Query

I realized as the thickness of the thesis in some chapters was unnecessarily increased. For example, one can give either table or figure in the thesis, not both. Table 6.2 and Fig. 6.2/6.3; Table 8.2 and Fig. 8.2-8.7 are few examples. The tables and figures are not quoted in text but presented in the thesis. Special care is imperative to prepare figures and tables, particularly the units. Hardly the tables and figure are explained in the text about its trend with scientific reasoning's/justifications.

Answer:

Some similar kinds of figures have been deleted from the thesis (i.e., Figure 6.2, Figure 8.5). Missing tables and figures are now quoted in the text. As per suggestions given by the examiner, the figures and tables have been improved. These tables and figures are now explained in the text.

Chapter 8

Query

The R^2 (coefficient of determination) and r (correlation coefficient) are two different statistical parameters with different meaning. The student has used both the parameters interchangeably in the thesis (Example: Table 8.3)

Answer:

Now, R^2 (coefficient of determination) and r (correlation coefficient), both have been used separately and not interchangeably.

Chapter 8

Query

Between observed and predicted values, there are few more error statistics, which should be tried in the revised thesis (R^2/r does not represent true picture between observed and simulated results). The student should try to improve "r" in Table 8.4 or any other error statistics, which will be his one of the major contributions. He should do sensitivity analysis to identify the sensitive parameter(s), which may further improve the predicted results and error statistics.

Answer:

As per suggestion, a z-test for the data set (r value) is also calculated for improvement the error statistics and included in paragraph & sub para of 8.3.2. and paragraph & sub para of 8.3.3. (Page 124, Para: 1 & 2, lines 2,3,4,6,8; Page 124, Para: 3, lines 2, 3, 4; Page 125, Para: 1, lines 1, 3 & Table 8.3; Page 129, Para: 2, lines 8,9,10,12,14,16, Page 130, Para: 2, lines 6,7,8, 10,12,14, Page 130, Para: 3, lines 6,7; Page 131, Para: 1, lines 1, 3, 5, 7 & Table 8.4). Sensitivity analysis to identify the sensitive parameter(s) has been carried out and included in Chapter 6.

REPLY TO THE REPORT OF THE EXAMINERS

This is to certify that **Mr. Md. Surabuddin Mondal**, Research Scholar, Dept. of W R D & M has revised his thesis entitled **"Land Use Land Cover Modeling in a Part of Brahmaputra Basin Using Geoinformatics"**, in the light of the comments and suggestions made by the thesis examiners. Further all the revision suggested by the thesis examiners have been incorporated in the revised thesis by Mr. Md. Surabuddin Mondal. A separate sheet, which includes the point wise answers to all the questions raised by the thesis examiners, has been enclosed with the revised Ph.D. thesis.

Date: 08/12/2011

Yours sincerely,

P.K.Garg
8/12/2011

Prof. P. K. Garg
Dept. of Civil Engineering
(Supervisor)

08/12/2011

Prof. Nayan Sharma
Dept. of W R D & M
(Supervisor)

ANSWERS TO THE COMMENTS OF REVIEWER 1

Chapter 1

Query:

How should the work be taken further? There is only a limited suggestion in the thesis.

Answer:

Further research may carry out with using more multi-temporal (10 times) satellite images. Further research may carry out with using multi-temporal high resolution satellite images for more accurate results. Further research may carry out with more frequently real time field visit.

Chapter 4

Query:

The conclusions on page 56, about the expansion of built-up land at the expense of degraded forest and others lands, can be deduced by eye from Table 4.3 on page 37. Therefore, what additional information does the analysis between pages 37 and 56 provide?

Answer:

The area statistics (area in km^2) is shown in Table 4.3 on page 37 and the swap changes (area in km^2) is given in Table 5.9 on page 56. The locations of different LULC are described in text on page 37 whereas the changes of location of different LULC are described in text on page 59. Therefore, information given on these two pages is different.

Chapter 5

Query

The correlation diagram (Figure 5.1) on page 45 skewed by the single point for built-up land. Would the correlation be as good without that point?

Answer:

If we excluded the single point for built up land the correlation coefficient (r) comes out to be 0.176 ($R^2 = 0.031$) in order. We have not taken all this data to establish the linear equation and compute correlation coefficient (r), it is come out to be poor.

Chapter 8

Query

The use of terms "iterations" and "time step" in section 8 is confusing. It seems that the number of iterations is determined by the time step and effectively equals the time step. The two terms are then referred together. The candidate should therefore give precise definitions of the two terms and explain the significance of the terms for the simulations.

Answer:

The number of iterations is determined by the time step and effectively equals the time step. For example, the number of time interval (periods) between the first and second images is 10 years and the numbers of time steps to project forward from the second image are 20 years to predict LULC in 2017, 30 years to predict LULC in 2027 and 53 years to predict LULC in 2050. Here, the number of iteration was based on the time steps i.e., iterations 20 to predict LULC for 2017 (prediction from 1997 to 2017); iterations 30 for 2027 (prediction from 1997 to 2027); iterations 53 for 2050 (prediction from 1997 to 2050). Therefore, here the two terms are referred together. For iterations 20, MOLA (Multi Objective Land Allocation) will run to allocate 1/20 of the required land in the first run, and 2/20 the second run, and so on until the 20/20, the full allocation of land for each land use and land cover classes is obtained. All though unnecessary (two word together) "time steps (iterations)" has been deleted. Precise definitions of the two terms have been given and explained the significance of the terms for the simulations in section 8 (Page113, Para: 1, lines 7 - 12).

Publications

Query

What are the candidate's plans for publishing his work? The examination panel should establish that there is sufficient publishable material in the thesis.

Answer:

Sufficient publishable material is there, from the thesis work; 2 papers are accepted for publication in peer reviewed journal; one paper (peer reviewed) presented in international conference in the U. K. and published; 2 papers accepted in international conference and will be presented in U.S.A. and U.K.; 2 papers will be submitted shortly in journals. (Kindly see list of publications, page 171-172 in thesis for details).

Acknowledgements

Query

The student does not know the spelling of a European country where he has spent considerable time to learn geoinformatics tools under Nuffic Scholarships.

Answer:

"Nederland" is the Dutch name/word for "Netherlands", now changed it to "Netherlands".

Chapter 2 (Literature Review)

Query

This chapter and in other chapters, the quoted references in the text are missing in the REFERENCES or vice-versa. Other common mistaken are spelling of the author(s) and year of publication. The student does not know how to write a reference, if there are two or more than two authors. It seems as if nobody has checked the Literature Review chapter. As far as possible, I have pointed out the mistakes on the body of the thesis.

Answer:

References have been carefully checked and rewritten. Missing references included, spelling of the author(s) corrected, and years of publication corrected as per suggestions given by examiners.

Chapter 3 (Study area)

Query

In page 21, it was unnecessary to write two-third of a page about Guwahati city, its history, importance and connectivity.

Answer:

As per examiner suggestions, the extra description for study area has been removed.

References

Query

The student does not know how to write references, the first reference in the list is a clear example. Let him maintain a uniform style of writing the references, with volume, issue, and page numbers.

Answer:

References are carefully checked and the mistakes are removed. Uniform style of writing has been adopted for entire references.

List of Publications

Query

Normally, when any manuscript is submitted for publication to any journal, the manuscript is either under review or accepted or in press. I have not come across any such terminology "tentatively for possible publication", which has been mentioned against four manuscripts. Status of papers out of the Ph.D. thesis should be clearly mentioned.

Answer:

As per examiners suggestion, the terminology has been changed in list of publications.

Chapter 1

Sl No.	Comments & References	Answer to Comments	Present References
1	Page 2, Para: 1, line 7; insert "." after "al"	inserted "." after al	Page 2, Para: 1, line 7
2	Page 2, Para: 2, lines 16,17; insert "," after "WRCP" and "IPCC"	inserted "," after "WRCP" and "IPCC"	Page 2, Para: 2, lines 16,17
3	Page 2, Para: 2, lines 16,17; references "WCRP,1990" and "IPCC,1990" is missing	It was missing, now incorporated in references. "IPCC, 1990" inserted on Page 149, Para: 7, line 1 and "WCRP,1990" inserted on Page160, Para: 2, line 1	Page 149. Para: 7, line 1; Page160, Para: 2, line 1
4	Page 2, Para: 3, line 1; Agarwal et al., 2000 or Agarwal et al., 2001	It is Agarwal et al., 2001, corrected as 2001 instead of 2000	Page 2, Para: 3, lines 1
5.	Page 2, Para: 1, line 1; insert word "of America" after United States	Inserted word "of America" after United States	Page 2, Para: 1, lines 1
6	Page 3, Para: 1, line 8; insert "," after "Vitousek et al."	Inserted "," after "Vitousek et al."	Page 3, Para: 1, lines 8
7	Page 3, Para:2,line 4; insert "," after "Roy et al."	Actually it is " Roy and Tomar, 2001"	Page 3, Para: 2, line 4
8	Page 3, Para: 2, line 4; references "Roy et al., 2005" is missing	Actually it is " Roy and Tomar, 2001", Inserted "Roy and Tomar, 2001" in text and as well as references	Page 3, Para: 2, line 4 and Page 156, Para: 3, line 1
9	Page 3, Para: 2, line 15; references "Mauldin et al., 1999" is missing	Inserted "Mauldin et al., 1999" in references	Page 152, Para: 8, line 1
10	Page 4, Para: 1, line 13; references "Baker (1999)" is missing	It is corrected as "Baker (1989)" not "Baker (1999)"	Page 4, Para: 1, line 13 and Page 144, Para: 2, line 1
11	Page 4, Para: 2, line 10; references "Baker (1999)" is missing	It is corrected as "Baker (1989)" not "Baker (1999)"	Page 4, Para: 2, line 10 and Page 144, Para: 2, line 1
12	Page 5, Para: 3, line 4; "if situation is static in the study area", why not dynamic?	The line "if situation is static in the study area "is deleted because situation may be static or it may be dynamic or may be both whatever it is we have to find out the futures of LULC for the study area	Page 5, Para: 3, line 4
13	Page 7, Para: 2, line 13; replace "Kstandars" to "Kstandard"	"Kstandars" has been replaced by "Kstandard"	Page 7, Para: 2, line 13

Sl No.	Comments & References	Answer to Comments	Present References
1	Page 9, Para: 1, line 2; reference "Rust, 1978" is missing	Inserted "Rust, 1978" in references	Page 1, Para: 1, line 2 and Page 154, Para: 4, line 1
2	Page 9, Para: 1, line 6; check spelling " McPhail"	Spelling checked, it is ok	Page 1, Para: 1, line 6
3	Page 9, Para: 1, line 11; references is "Andersons et al., 1976"	Changed as "Andersons et al., 1971"	Page 1, Para: 1, line 11 and Page 143, Para: 6, line 1
4	Page 9, Para: 1, line 12; references "Sharma, 1980" is missing	Inserted "Sharma, 1980" in references	Page 2, Para: 3, lines 1 and Page 156, Para: 8, line 1
5	Page 9, Para: 2, lines 4, 5; references "Li and Yeh, 1998" is missing	Actually it is "Yeh and Li",therefore, corrected in text and inserted in references also	Page 1, Para: 2, lines 4, 5and Page 161, Para: 3, line 1
6	Page 9, Para: 2, line 6; references "Weismiller et al., 1977" is missing	Inserted "Weismiller et al., 1977" in references	Page 1, Para: 2, lines 6 and Page 160, Para: 6, line 1
7	Page 9, Para: 2, line 7; "Howwarth and Wickware, 1987", check the year 1987	It has been checked, it is 1981, therefore, corrected in text as well as in references	Page 1, Para: 2, line 7 and Page 149, Para: 5, line 1
8	Page 9, Para: 2, line 11; references "Colwell and Weber, 1981" is missing	Inserted "Colwell and Weber, 1981" in references	Page 9, Para: 2, line 11 anc Page 146, Para: 4, line 1
9	Page 9, Para: 3, line 4; references "Singh (1984)" is missing	Actually it is "1989", therefore, corrected in text and inserted in references also	Page 9, Para: 3, line 4 and Page 157, Para: 2, line 1
10	Page 10, Para: 2, line 4; check spelling "Lambin"	Spelling checked, it is correct	Page 10, Para: 2, line 4
11	Page 10, Para: 2, line 8; check spelling "Meyer"	Spelling checked, it is correct	Page 10, Para: 2, line 8
12	Page 11, Para: 1, line 2; check spelling "Pijanowsky"	Spelling checked, it is "Pijanowski", therefore changed in text as well as in references	Page 11, Para: 1, line 2 anc Page 154, Para: 4, line 1
13	Page 11, Para: 2, line 3; check the year "Landis	Actually it is "1998",therefore, corrected in text and inserted in	Page 11, Para: 2, line 3 anc

	and Zhang,1996”	references also	Page 151, Para: 8, line 1
14	Page 11, Para: 3, line 1; references is written “Wear et al., 1998” , check it	Actually it is “Wear and Bolstad, 1998”,therefore, corrected in text and inserted in references also	Page 11, Para: 3, line 1 and Page 160, Para: 3, line 1
15	Page 11, Para: 3, line 5; check spelling “Hasite”	Spelling checked, it is “Hastie”, therefore changed in text as well as in references	Page 11, Para: 3, line 5 and Page 149, Para: 1, line 1
16	Page 11, Para: 3, line 4; references “Brown 1994” is missing	Inserted “Brown 1994” in references	Page 9, Para: 3, line 4 and Page 144, Para: 8, line 1
17	Page 11, Para: 4, line 1; it is Agarwal et al., 2000?	No, it is Agarwal et al., 2001	Page 11, Para: 4, line 1
18	Page 12, Para: 1, line 2; it is Agarwal et al., 2000?	No, it is Agarwal et al., 2001	Page 12, Para: 1, line 2
19	Page 12, Para: 2, line 1; insert “,” after “Fitz et al.”	Inserted “,” after “Fitz et al.”	Page 12, Para: 2, line 1
20	Page 12, Para: 2, line 2; insert “,” after “Voinov et al.”	Inserted “,” after “Voinov et al.”	Page 12, Para: 2, line 2
21	Page 12, Para: 2, line3 ; insert “,” after “Veldkamp and Fresco”	Inserted “,” after “Veldkamp and Fresco”	Page 12, Para: 2, line 3
22	Page 12, Para: 2, line 5; insert “,” after “Veldkamp and Fresco”	Inserted “,” after “Veldkamp and Fresco”	Page 12, Para: 2, line 5
23	Page 12, Para: 2, line 6; insert “,” after “Hardie and Parks”	Inserted “,” after “Hardie and Parks”	Page 12, Para: 2, line 6
24	Page 12, Para: 2, line 7; insert “,” after “Mertens and Lambin”	Inserted “,” after “Mertens and Lambin”	Page 12, Para: 2, line 7
25	Page 12, Para: 2, line 8; insert “,” after “Chomitz and Gray”	Inserted “,” after “Chomitz and Gray”	Page 12, Para: 2, line 8
26	Page 11, Para: 2, line 8; references “Chomitz and Gray, 1996” is missing	Inserted “Chomitz and Gray, 1996” in references	Page 9, Para: 3, line 4 and Page 145, Para: 6, line 1
27	Page 12, Para: 2, line 10; insert “,” after “Gilruth et al.”	Inserted “,” after “Gilruth et al.”	Page 12, Para: 2, line 10
28	Page 12, Para: 2, line 11; insert “,” after “Wood et al.”	Inserted “,” after “Wood et al.”	Page 12, Para: 2, line 11
29	Page 12, Para: 2, line 12; insert “,” after	Inserted “,”after “Landis” and “Landis et al.”, actually it is “Landis	Page 12, Para: 2, line 12

	"Landis" and "Landis et al."	and Zhang", corrected in text as well as in references and inserted "," after "Landis and Zhang".	and Page 151, Para: 8, line 1
30	Page 12, Para: 2, line 13; insert "," after "Berry et al."	Inserted "," after "Berry et al."	Page 12, Para: 2, line 13
31	Page 12, Para: 2, line 14; insert "," after "Wear et al."	Inserted "," after "Wear et al."	Page 12, Para: 2, line 14
32	Page 12, Para: 2, line 14; references "Wear et al." is missing	Inserted "Wear et al." in references	Page 12, Para: 2, line 14and Page 160, Para: 5, line 1
33	Page 12, Para: 2, line 15; insert "," after "Wear et al."	Inserted "," after "Wear et al."	Page 12, Para: 2, line 15
34	Page 12, Para: 2, line 16; insert "," after "Shallow et al."	Inserted "," after "Shallow et al."	Page 12, Para: 2, line 16
35	Page 12, Para: 2, line 19; references "O'Callaghan, 1995" is missing	Inserted "O'Callaghan, 1995" in references	Page 12, Para: 2, line 19 and Page 153, Para: 9, line 1
36	Page 12, Para: 2, line 20; insert "," after "Oglethorpe and O'Callaghan"	Inserted "," after "Oglethorpe and O'Callaghan"	Page 12, Para: 2, line 20
37	Page 12, Para: 2, line 21; insert "," after "Adams et al."	Inserted "," after "Adams et al."	Page 12, Para: 2, line 21 and Page 143, Para: 1, line 1
38	Page 12, Para: 2, line 22; insert "," after "Landis et al."	Inserted "," after "Landis et al."	Page 12, Para: 2, line 22
39	Page 12, Para: 2, line 22; references "Landis et al., 1998" is missing	Inserted "Landis et al., 1998" in references	Page 12, Para: 2, line 22 and Page 151, Para: 6, line 1
40	Page 12, Para: 2, line 24; insert "," after "Clarke et al." and "Kirtland et al."	Inserted "," after "Clarke et al.", and after "Kirtland et al."	Page 12, Para: 2, line 24
41	Page 12, Para: 2, line 24; it is Clarke et al., 1998, is it 1998?	No, it is 1997, therefore changed in text as well as in references	Page 12, Para: 2, line 24 and Page 146, Para: 3, line 1
42	Page 12, Para: 2, line 24; references "Kirtland	Inserted "Kirtland et al., 2000" in references	Page 12, Para: 2, line 24

	et al., 2000" is missing		and Page 150, Para: 6, line 1
43	Page 12, Para: 3, line 3; is it Agarwal et al., 2000?	No, it is Agarwal et al., 2001, itself	Page 12, Para: 3, line 3
44	Page 13, Para: 1, line 5; is it Agarwal et al., 2000?	No, it is Agarwal et al., 2001, itself	Page 13, Para: 1, line 5
45	Page 13, Figure 2.1(title), line 2; is it Agarwal et al., 2000?	It is Agarwal et al., 2001, therefore, corrected in text	Page 13, Figure 2.1(title), line 2
46	Page 13, Figure 2.2(title), line 2; is it Agarwal et al., 2000?	It is Agarwal et al., 2001, therefore, corrected in text	Page 13, Figure 2.2(title), line 2
47	Page 14, Para: 1, lines 4, 5; references "Vander Veen and Rotmans, 2001" is missing	Inserted "Vander Veen and Rotmans, 2001" in references	Page 14, Para: 1, lines 4, 5 and Page 158, Para: 5, line 1
48	Page 14, Para: 1, line 6; references "Soares-Filhoet al., 2002, 2004" is missing	Inserted "Soares-Filhoet al., 2002, 2004" in references	Page 14, Para: 1, line 6 and Page 157, Para: 3 and 4, lines 1
49	Page 14, Para: 1, line 7; references "Verburg and Veldkamp, 2004" is missing	Inserted "Verburg and Veldkamp, 2004" in references	Page 14, Para: 1, line 7 and Page 159, Para: 1 and 4, lines 1
50	Page 14, Para: 1, line 8; references "Pontius et al.,2004" was repeated	"Pontius et al.,2004" is deleted from the text as it was a repeat	Page 14, Para: 1, line 8
51	Page 14, Para: 1, lines 8, 9; references "Pontius and Malanson, 2005" is missing	Inserted "Pontius and Malanson, 2005" in references	Page 14, Para: 1, line 8 and Page 154, Para: 7, line 1
52	Page 14, Para: 1, line 7; references "Verburg and Veldkamp, 2004" is missing	Inserted "Verburg and Veldkamp, 2004" in references	Page 14, Para: 1, line 7 and Page 157, Para: 1 and 4, lines 1
53	Page 14, Para: 1, line 9, 11; references "Pontius and Spencer, 2005" was repeated in text	"Pontius et al.,2004"is deleted from text (Page 14, Para: 1, line 9), as it was a repeat	Page 14, Para: 1, line 11
54	Page 14, Para: 1, line 11; is it Kasper et al., 2006	Kasper et al., 2006, corrected in text	Page 14, Para: 1, line 9, 11
55	Page 14, Para: 1, lines 11,12; references	Inserted "Pontius and Cheuk, 2006" and "Pontius and Lippitt,	Page 14, Para: 1, line 11

	"Pontius and Cheuk, 2006" and "Pontius and Lippitt, 2006" are missing	2006"in references	and Page 154, Para: 5 and 6, lines 1
56	Page 15, Para: 1, line 2; references " K C Clarke et al., (2003)" is missing	It was a mistake, actually the correct references is "Clarke and Gaydos (1998)" instead of " K C Clarke et al., (2003), now inserted "Clarke and Gaydos (1998)" in references	Page 15, Para: 1, line 2 and Page 146, Para: 2, line 1
57	Page 15, Para: 1, lines 5, 6; references "Silva and Clarke, 2002" is missing	now inserted "Silva and Clarke, 2002" in references	Page 15, Para: 1, lines 5 and Page 156, Para: 8, line 1
58	Page 15, Para: 1, lines 6; references "Dietzel and Clarke, 2004" is missing	now inserted "Dietzel and Clarke, 2004" in references	Page 15, Para: 1, lines 6 and Page 145, Para: 3, line 1
59	Page 15, Para: 2, lines 1,2; references "Pijanowski et al., 2001" is missing	Actually it is "Pijanowski et al. 2000, 2002 and 2005", now corrected in text and in references and deleted "Pijanowski et al. 2000, Pijanowski et al. 2002 and Pijanowski et al. 2005" onPage 15, Para: 2, line 2	Page 15, Para: 2, line 1 and Page 152, Para: 2, 3 and 4, line1
60	Page 16, Para: 2, line 1; references "de Nijs, et al., (2004)" is missing	now corrected and inserted "de Nijs, et al., (2004)" in references	Page 16, Para: 2, line 1 and Page 147, Para: 1, line 1
61	Page 16, Para: 2, line 3; insert "," after "Verburg et al."	Inserted "," after "Verburg et al."	Page 16, Para: 2, lines 3,4
62	Page 16, Para: 3, line 1; full form of the term " SAMBA" is missing	Now the full form of "SAMBA" is explained in text	Page 16, Para: 3, line 2
63	Page 16, Para: 3, line 5; it was "Castella, trung and Boissau, 2005"	Now corrected as "Castella et al., 2005"	Page 16, Para: 3, line 5
64	Page 16, Para: 3, line 5; insert "," after "Castella et al."	Inserted "," after "Castella et al.,"	Page 16, Para: 3, line 5
65	Page 16, Para: 4, line 4; it was "kok and veldkamp 2001"	Now corrected as "Kok et al., 2001"	Page 16, Para: 4, line 54
66	Page 16, Para: 4, line 8; references "Verburg et al., (2004)" is missing	Now inserted "Verburg et al., (2004) in references	Page 16, Para: 4, line 8 and Page 157, Para: 2, line 1
67	Page 17, Para: 1, line 5; references "Verburg et al., 2004" is missing	Deleted"Verburg et al., 2002" in text	Page 17, Para: 1, line 5
68	Page 17, Para: 1, line 5; references	"Verburg and Veldkamp, 2004" is correct	Page 17, Para: 1, line 5

	"Verburgand veldkamp, 2004", the year is 2005?		
69	Page 17, Para: 2, line 1; references "Clark Labs (2006)" is missing	inserted "Clark Labs (2006)" in references	Page 17, Para: 3, line 1
70	Page 17, Para: 3, line 1; references "Clark Labs (2006)" is missing	inserted "Clark Labs (2006)" in references	Page 17, Para: 3, line 1
71	Page 17, Para: 4, line 1; references in text was "Konstantinos, Alexandridis, pijanowski and Zen (2008)"	Now changed as "Konstantinos et al., (2009)"	Page 17, Para: 4, line 1 and Page 150, Para: 8 and , lines 1
72	Page 18, Para: 1, line 5; put "?" after word "MARBEL"	"?" inserted after word "MARBEL"	Page 18, Para: 1, line 5

Chapter 3

Sl No.	Comments & References	Answer to Comments	Present References
1	Page 20, Para: 1, line 1; put "," after word "area"	","inserted after word "area"	Page 20, Para: 1, line 1
2	Page 20, Para: 1, line 8; put "the" after word "above"	"the" inserted after word "above"	Page 20, Para: 1, line 8
3	Page 21, Para: 1 – 3.1.1., what is the use of describing Guwahati city	Para 3.3.1., deleted	Page 20, Para: 2, lines 1,2, 3. 4 and Page 21, Para: 1, pages 1, 2
4	Page 21, Para: 2, line 2; delete "mm" after 1500	deleted "mm" after 1500	Page 21, Para: 2, line 2
5	Page 21, Para: 2, line 3; add "s" with word "temperature" and write "are' instead of "is' after word "temperature"	added "s" with word "temperature" and replaced "are' instead of "is' after word "temperature"	Page 21, Para: 2, line 3
6	Page 21, Para: 2, line 4; put "," after word "flood"	","inserted after word "flood"	Page 21, Para: 2, line 4
7	Page 21, Para: 2, line 6; add "s" with word	added "s" with word "part"	Page 21, Para: 2, line 6

	"part"		
8	Page 21, Para: 3 - 3.1.3., unnecessary	Para 3.3.3. has been deleted	deleted
9	Page 22, in Table 3.1. , replace "meters" by "m"	"meters" replaced by "m"	Page 22, in Table 3.1.
10	Page 24, in Figure 3.3. , what connections?	First 'Ground truths" replaced by " Pre-classification Ground truths" and second 'Ground truths" replaced by " Post-classification Ground truths"	Page 23, in Figure 3.3.

Chapter 4

Sl No.	Comments & References	Answer to Comments	Present References
1	Page 26, Para: 1, line 16; references "Vermote et al., 1994", the year is 1997?	"1994" is replaced by "1997"	Page 25, Para: 1, line 16
2	Page 27, Para: 1, line 5; references "Anderson, 1976", the year is 1971?	"1976" is replaced by "1971"	Page 26, Para: 1, line 5
3	Page 28, in Table 4.1. , merge "water" and "Logged"	Merged "water" and "Logged" now it is "waterlogged"	Page 27, in table 4.1.
4	Page 28, in Table 4.2. , missing description of about "2.3. plantations"	Replaced description of "2.3. plantations" from next page to here	Page 27, in table 4.2.
5	Page 29, in Table 4.2. , merge "water" and "Logged"	Merged "water" and "Logged" now it is "waterlogged"	Page 28, in Table 4.2.
6	Page 33, Para: 1, line 9; references "Campbell, 2011" is missing	inserted "Campbell, 2011" in references	Page 32, Para: 1, line 9 and Page 142, Para: 3, line 1
7	Page 34, Para: 2, line 15; references "Campbell, 2011" is missing	inserted "Campbell, 2011" in references	Page 33, Para: 1, line 15 and Page 142, Para: 3, line 1
8	Page 35, Para: 1, line 5; references "Bishop et al., 1975" is missing	inserted "Bishop et al., 1975" in references	Page 34, Para: 1, line 5 and Page 144, Para: 5, line 1
9	Page 36, Para: 1,2 and 3; remove gap between numeric and "%" and rewrite all LULC	removed gap between numeric and "%" and rewritten all LULC parameters name in small word	Page 35, Para: 1,2 and 3

	parameters name in small word not in capital		
10	Page 37, Para: 1, lines 3,4; delete the sentence "The built up land………bank of Brahmaputra River"	deleted the sentence "The built up land………bank of Brahmaputra River"	deleted the sentence
11	Page 38, in Table 4.4. and 4.5 , replace "Km^2" by "km^2"	"Km^2" replaced by "km^2"	Page 37, in Table 4.4. and 4.5
12	Page 39, Para: 1, line 2; references "Congalton, 1991" is missing	inserted "Congalton, 1991" in references	Page 38, Para: 1, line 2 and Page 146, Para: 5, line 1
13	Page 39, Para: 1, line 2; references " Lillesand and Kiefer, 2004" is missing	inserted " Lillesand and Kiefer, 2004" in references	Page 38, Para: 1, line 2 and Page 152, Para: 2, line 1
14	Page 40, Para: 1, line 2; references " Lillesand and Kiefer, 2004" is missing	inserted " Lillesand and Kiefer, 2004" in references	Page 39, Para: 1, line 2 and Page 152, Para: 2, line 1
15	Page 40, Para: 1, line 7; add word "overall" next to word "the" and delete "ing" in the word "accuracing"	added "overall" next to word "the" and deleted "ing" in the word "accuracing"	Page 39, Para: 1, line 7
16	Page 40, in Table 4.6., delete "%" after all numeric	Deleted "%" after all numeric values in the table	Page 39, in Table 4.6.
17	Page 41, Para: 1; remove all gap between all numeric and all "%"	removed all gap between all numeric and all "%" in Para 1	Page 40, Para: 1
18	Page 41, Para: 1, line 7; add word "respectively " next to word "2007"	added word "respectively " next to word "2007"	Page 40, Para: 1, line 7

Chapter 5

Sl No.	Comments & References	Answer to Comments	Present References
1	Page 42, Para: 1, line 6; references "Jensen, 1996", is missing	It is "Jensen, 2007", inserted "Jensen, 2007" in text and in references	Page 41, Para: 1, line 6 and Page 150, Para: 2, line 1
2	Page 44, Para: 1, line 1, relatively strong correlated??	"relatively strong" is replaced by "positively"	Page 43, Para: 1, line 1
3	Page 44, in Table 5.1. and 5.2. , replace "Km^2"	"Km^2" replaced by "km^2"	Page 43, in Table 5.1. and

	by “km^2”		5.2.
4	Page 45, Para: 1, lines 1,2; delete the sentence “The area statistics of …………and 1997-2007)”, as already mentioned	deleted the sentence “The area statistics of …………and 1997-2007)”	Page 44, Para: 1, lines 1,2
5	Page 45, Para: 1, line 11; references “Pontius et al., 2010” is missing	It is “Pontius et al., 2008”, inserted “Pontius et al., 2008” in references	Page 44, Para: 1, line 11 and Page 155, Para: 5, line 1
6	Page 46, in Table 5.3., change title	Title of the table has been changed	Page 45, in Table 5.3.,
7	Page 47, in Table 5.4., change title	Title of the table has been changed	Page 46, in Table 5.4.
8	Page 48, Para: 1, line 1; references “Pontius et al., 2010” is missing	It is “Pontius et al., 2008”, inserted “Pontius et al., 2008” in references	Page 47, Para: 1, line 1 and Page 155, Para: 5, line 1
9	Page 48, Para: 1,2 and 3; remove all gap between all numeric and all “%” and rewrite all LULC parameters name in small word, not in capital	removed all gap between all numeric and all “%” and rewritten all LULC parameters name in small word	Page 47, Para: 1,2 and 3
10	Page 51, Para: 1,2; remove all gap between all numeric and all “%” and rewrite all LULC parameters name in small word not in capital	removed all gap between all numeric and all “%” and rewritten all LULC parameters name in small word	Page 50, Para: 1,2
11	Page 56, Para: 1, lines 1, 5; replace “Built-up” by “built-up”	“Built-up” is replaced by “built-up”	Page 55, Para: 1, lines 1, 5
12	Page 57, in Figure 5.5., remove title from figure	title “persistence and change areas in between 1987 and 1997” removed from figure	Page 56, in Figure 5.5.
13	Page 58, in Figure 5.6. and 5.7., remove title from figure	Title “persistence and change areas in between 1987 and 1997” and “gross loss of land use land cover category (1987-1997)” removed from figure 5.6. and 5.7., respectively	Page 57, in Figure 5.6. and 5.7.
14	Page 59, in figure 5.8. and 5.9., remove title from figure	Title “gross gain of land use land cover category (1987-1997)” and “gross loss of land use land cover category (1997-2007)” removed from figure 5.6. and 5.7., respectively	Page 58, in Figure 5.8. and 5.9.,
15	Page 60, in Figure 5.10, remove title from figure	Title “gross gain of land use land cover category (1997-2007)” removed from figure 5.6. and 5.7., respectively	Page 59, in Figure 5.10
16	Page 63, Para: 1; remove all gap between all numeric and all “%”	removed all gap between all numeric and all “%”	Page 62, Para: 1,2

17	Page 63, in Table 5.10., delete "%" after all numeric	Deleted "%" after all numeric in the table	Page 62, in Table 5.10
18	Page 63, Para: 1,2; remove all gap between all numeric and all "%"	removed all gap between all numeric values and all "%"	Page 62, Para: 1
19	Page 66, Para: 3; rewrite all LULC parameters name in small word not in capital	rewritten all LULC parameters name in small word	Page 65, Para: 3

Chapter 6

Sl No.	Comments & References	Answer to Comments	Present References
1	Page 71, Para: 1, line 5, insert "(" before 1966 ")" after 1996	Inserted "(" before 1966 ")" after 1966	Page 70, Para: 1, line 5
2	Page 71, Para: 1, line 7, rewrite "figure" as "Figure"	rewritten "figure" as "Figure"	Page 70, Para: 1, line 7
3	Page 71, Para: 1, line 21, insert year of references	Inserted the year of references – Wagner (1997)	Page 70, Para: 1, line 21
4	Page 75, Para: 2, line 10; references "Eastman et al., 2010" is missing	It is "Eastman et al., 2009", inserted "Eastman et al., 2009" in references	Page 74, Para: 1, line 20 and Page 147, Para: 5, line 1
5	Page 81, Figure 6.2, bar and line graph shown similar things	Line graph has been deleted	Page 80
6	Page 83, in Figure 6.4, from x and y axis titles "in sq." should remove	"in sq." has been deleted from x and y axis titles	Page 81, in Figure 6.3
7	Page 84, how to improve "r" value?	Now "r" (correlation coefficient) as well as "R^2"(coefficient of determination) incorporated in text	Page 82

Sl No.	Comments & References	Answer to Comments	Present References
1	Page 88, in last line, replace "i" instead of "I"	replaced "i" instead of"I"	Page 98, in last line
2	Page 89, Para: 2, line 8, insert word "table" after "less than the"	word "table" inserted after "less than the"	Page 99, Para: 2, line 8
3	Page 93, in Table 7.4., merge "water" and "Logged"	Merged "water" and "Logged", now it is "waterlogged"	Page 103, in Table 7.4
4	Page 94, Para: 1, line 2, delete word "for"	word "for" deleted	Page 104, Para: 1, line 2
5	Page 94, Para: 1, line 3, replace word "significance" to "table value"	word "significance" replaced by "table value"	Page 104, Para: 1, line 3
6	Page 94, Para: 2, line 4, replace word "significance" to "table value"	word "significance" replaced by "table value"	Page 104, Para: 2, line 4
7	Page 94, Para: 2, line 2; references "Lambin et al., 1999" is missing	It is "Lambin, 1997", inserted "Lambin, 1997" in references	Page 104, Para: 2, line 2 and Page 151, Para: 5, line 1
8	Page 94, Para: 3, line 4; references "Pontius, 1994" is missing	It is "Pontius et al., 2004", inserted "Pontius et al., 2004" in references	Page 104, Para: 3, line 6 and Page 155, Para: 3, line 1
9	Page 94, Para: 3, line 8; references "Pontius, 2001" is missing	It is "Pontius et al.,, 2001", inserted "Pontius, 2002" in references	Page 104, Para: 3, line 2 and Page 155, Para: 4, line 1
10	Page 95, Para: 1, line 1; references "Pontius, 2001" is missing	It is "Pontius et al.,, 2001", inserted "Pontius et al.,, 2001" in references	Page 105, Para: 1, line 1and Page 155, Para: 1, line 1
11	Page 95, Para: 2, line 2; references "Pontius,	It is "Pontius et al., 2004", inserted "Pontius et al., 2004" in	Page 105, Para: 2, line 2

	1994" is missing	references	and Page 155, Para: 2, line 1
12	Page 97, Para: 1, line 4; insert "," after "Pontius et al."	Inserted "," after "Pontius et al."	Page 107, Para: 1, line 4
13	Page 97, Para: 5, line 1; references "Pontius et al., 2002" is missing	It is "Pontius, 2002", inserted "Pontius, 2002" in references	Page 107, Para: 5, line 1and Page 155, Para: 5, line 1
14	Page 100, Table 7.8. not mentioned in text	Table 7.8. mentioned in the text on page 108, Para: 1, line 7	page 108, Para: 1, line 7

Chapter 8

Sl No.	Comments & References	Answer to Comments	Present References
1	Page 102, Para: 1, line 3; delete "LULC image" and add "s" to word "image"	delete "LULC image" and added "s" to word "image"	Page 112, Para: 1, line 4
2	Page 102, Para: 2, line 7; maintain gap between "(iterations)" and "to"	maintained gap between "(iterations)" and "to"	Page 112, Para: 2, line 7
	Page 106, Para: 2, line 8; maintain gap between "43" and "(years)"	maintained gap between "43" and "(years)"	Page 116, Para: 1, line 8
3	Page 106, Para: 1, line 9; replace word "probabilities" to "probability"	word "probabilities" replaced by "probability"	Page 116, Para: 1, line 9
4	Page 106, Para: 1, line 11; replace word "Transition" to "transition"	word "Transition" replaced by "transition"	Page 116, Para: 1, line 11
5	Page 106, Para: 1, line 17; replace word "for" to "to"	word "for" replaced by "to"	Page 116, Para: 1, line 17
6	Page 108, in Table 8.1, add word "year" to row 1 and column 2,3,5,6,8,9	added word "year" to row 1	Page 118, in Table 8.1
7	Page 109, heading, Para: 1, 2; delete sentences, words, add "," etc.	Rewritten (deleted sentences, words, added ",", etc.) as per suggestion	Page 119, heading, Para: 1, 2
8	Page 110, in Table 8.2, row 1; replace word	replaced word "Km^2" to "km^2"	Page 120, in Table 8.2

	"Km^2" to "km^2"		
9	Page 111, in Figure 8.4, change figure title	changed figure title	Page 121, in Figure 8.4
10	Page 111, in Figure 8.4, from y axis title "in sq." should remove	"in sq." has been deleted from y axis title	Page 121, in Figure 8.4
11	Page 112, Figure 8.5, delete figure	deleted figure 8.5	deleted figure 8.5
12	Page 113, in Figure 8.6, change figure title	changed figure title	Page 122, in Figure 8.5
13	Page 113, in Figure 8.6, from y axis title "in sq." should remove	"in sq." has been deleted from y axis title	Page 122, in Figure 8.5
14	Page 114, in Figure 8.7, change figure title	changed figure title	Page 123, in Figure 8.6
15	Page 114, in Figure 8.7, from y axis title "in sq." should remove	"in sq." has been deleted from y axis title	Page 123, in Figure 8.6
16	Page 115, headings, Para: 1, 2, 3; delete sentences, words, add "," etc.	Rewritten (deleted sentences, words, added ",", etc.) as per suggestion	Page 124, headings, Para: 1, 2, 3
17	Page 116, in Table 8.3, change table title	changed table title as per suggestion	Page 125, in Table 8.3
18	Page 116, in Table 8.3, change R^2 as Coefficient of determination	Rewritten the table as per suggestion's, now "R^2" (Coefficient of determination) as well as "r" (correlation coefficient) added	Page 125, in Table 8.3
19	Page 116, Para: 2, delete km^2 in lines 1, 2 after "0.29", "0.47", "0.71"	deleted km^2 in lines 1, 2 after "0.29", "0.47", "0.71"	Page 125, Para: 2, lines 1, 2
20	Page 116, Para: 2, lines 4, 5, 6; rewrite the sentences "The area of predicted………………and 0.980)"	As per suggestion, the sentences "The area of predicted………………and 0.980)" is rewritten.	Page 125, Para: 2, lines 4, 5, 6
21	Page 117, in Figure 8.8, in y axis title add "km^2"	"km^2" has been added in y axis title	Page 126, in Figure 8.7
22	Page 117, in Figure 8.8, change figure title	changed figure title	Page 126, in Figure 8.7
23	Page 118, in Figure 8.9, in y axis title add "km^2"	"km^2" has been added in y axis title	Page 127, in Figure 8.8
24	Page 118, in Figure 8.9, change figure title	changed figure title	Page 127, in Figure 8.8
25	Page 119, in Figure 8.10, in y axis title add "km^2"	"km^2" has been added in y axis title	Page 128, in Figure 8.9
26	Page 119, in Figure 8.10, change figure title	change figure title	Page 128, in Figure 8.9
27	Page 120, headings, Para: 1, 2; delete	Rewritten (deleted sentences, words, added ",", etc.) as per	Page 129, headings, Para:

	sentences, words, add "," etc.	suggestion	1, 2
28	Page 120, whether "R^2" is the only error statistics	As per suggestion, a z-test for the data set (r value) is also calculated for improvement the error statistics and included in paragraph & sub para of 8.3.2. and paragraph & sub para of 8.3.3.	Page 124, Para: 1 & 2, lines 2,3,4,6,8; Page 124, Para: 3, lines 2, 3, 4; Page 125, Para: 1, lines 1, 3 & Table 8.3; Page 129, Para: 2, lines 8,9,10,12,14,16, Page 130, Para: 2, lines 6,7,8, 10,12,14, Page 130, Para: 3, lines 6, 7; Page 131, Para: 1, lines 1, 3, 5, 7 & Table 8.4
29	Page 121, similarly Para 1and 2 of page 120 may be corrected	Rewritten/corrected similar page 120, Para 1, 2 (deleted sentences, words, added ",", etc.) as per suggestion	Page 130, headings, Para: 1, 2
30	Page 122, in Table 8.4, change table title	table title has been changed	Page 131, in Table 8.4
31	Page 122, in Table 8.4, how to improve "r" value	Now "r" as well as "R^2" included in table 8.4	Page 131, in Table 8.4
32	Page 123, in Figure 8.11, change figure title	figure title has been changed	Page 132, in Figure 8.10
33	Page 124, in Figure 8.12, change figure title	figure title has been changed	Page 133, in Figure 8.11
34	Page 125, in Figure 8.13, change figure title	figure title has been changed	Page 134, in Figure 8.12
35	Page 126, in Figure 8.14, change figure title	figure title has been changed	Page 135, in Figure 8.13
36	Page 127, in Figure 8.15, change figure title	figure title has been changed	Page 136, in Figure 8.14
37	Page 128, in Figure 8.16, change figure title	figure title has been changed	Page 137, in Figure 8.15
38	Page 129, Para: 1, lines 2, 3, 4, 5; correct the sentences	As per suggestion, the sentences has been corrected	Page 138, Para: 1, lines 2, 3, 4, 5
39	Page 129, Para: 1, lines 6 ; replace word "Firstly" with word " Initially"	replace the word "Firstly" replaced by word " Initially"	Page 138, Para: 1, lines 6
40	Page 129, Para: 1, lines 6 ; add word "at" in between " results" and " different"	Added word "at" in between " results" and " different"	Page 138, Para: 1, lines 6
41	Page 129, Para: 1, lines 6 ; delete word "predicting"	deleted word "predicting"	Page 138, Para: 1, lines 6

Chapter 9

Sl No.	Comments & References	Answer to Comments	Present References
1	Page 130, Para: 2, lines 5 ; add word “the” in between “ about” and “study”	added word “the” in between “ about” and “study”	Page 139, Para: 2, lines 5
2	Page 130, Para: 4, line 3; put “,” after word “area”	“,” inserted after word “area”	Page 139, Para: 4, line 3

REFERENCES

Sl No.	Comments & References	Answer to Comments	Present References
1	Page 134 to 149, delete /add words, add pp., put “,” correct years, correct authors name etc.	References checked carefully and rewritten as per suggestions given	Page 143 to 161

LIST OF PUBLICATIONS

Sl No.	Comments & References	Answer to Comments	Present References
1	Page159, rearrange authors name “ M. S. Mondal” as “ Mondal M. S.” and write either as (i) paper accepted or (ii) Paper submitted	Rearranged authors name “ M. S. Mondal” as “ Mondal M. S.” and list of publication reorganized as (i) paper accepted or (ii) Paper submitted	Pages 171, 172