6-1-2012

Management of Land Use Land Cover Through the Application of Remote Sensing, Geographic Information Systems and Simulation

Praveen Jha
University of Massachusetts Boston

MANAGEMENT OF LAND USE LAND COVER THROUGH THE APPLICATION OF REMOTE SENSING, GEOGRAPHIC INFORMATION SYSTEMS AND SIMULATION

A Dissertation Presented

by

PRAVEEN JHA

Submitted to the Office of Graduate Studies,
University of Massachusetts Boston,
in partial fulfillment of the requirements for the degree of

DOCTOR OF PHILOSOPHY

June 2012

Environmental Studies Program

MANAGEMENT OF LAND USE LAND COVER

THROUGH THE APPLICATION OF REMOTE SENSING,

GEOGRAPHIC INFORMATION SYSTEMS AND SIMULATION

A Dissertation Presented

by

PRAVEEN JHA

Approved as to style and content by:

____

Kamaljit S. Bawa, Distinguished Professor
Chairperson of Committee

____

Garrison Wilkes, Professor
Member

____

Zong-Guo Xia, Vice Provost for Research and Strategic Initiatives, Office of the Provost
Member

____

Robert D. Stevenson, Associate Professor
Member

____

Michael P. Shiaris, Program Director
Department of Biology

____

Rick V. Kesseli, Chairperson
Department of Biology

ABSTRACT

MANAGEMENT OF LAND USE LAND COVER

THROUGH THE APPLICATION OF REMOTE SENSING,

GEOGRAPHIC INFORMATION SYSTEMS AND SIMULATION

June 2012

Praveen Jha, B. Sc., Ranchi University, Ranchi, India
M. S., Indira Gandhi National Forest Academy, Dehradun, India
Ph.D., University of Massachusetts Boston

Directed by Distinguished Professor Kamaljit S. Bawa

Deforestation and degradation of forest areas, including those in the Protected Areas (PAs), are major concerns in India. There were 2 broad objectives of the study: the technological objective pertained to the development of state-of-art programs that could serve as Decision Support Systems while finalizing plans and policy interventions, while the other objective aimed at generating geo-spatial data in 2 PAs.

A part of the Eastern Himalaya biodiversity hotspot, Manas Tiger Reserve (MTR), Assam, India having an area of 2837.12 sq km and an important part of Rajajiï Corbett Tiger Conservation Unit, Rajaji National Park (RNP), Uttarakhand, India, having an area of 820.42 sq km, were taken for the assessment of land use and land cover (LULC)

change during 1990-2004. Simulation was undertaken in a smaller area of 1.2 km * 1.2 km right on the fringe of RNP. Three advanced geo-spatial programs - Multi-Algorithm Automation Program (MAAP), Data Automatic Modification Program (DAMP) and Multi-Stage Simulation Program (MUSSIP) - developed by the author were used extensively. Based on the satellite data, MAAP was used for the rapid assessments of LULC of 2004 and 1990; DAMP was used for the spectral modification of the satellite data of the adjacent scenes of 2004 and of 1990; and MUSSIP was used to simulate LULC maps for the future periods (till 2018).

These programs produced very high accuracy levels: 91.12% in 2004 and 89.67% in 1990 were obtained for MTR; and 94.87% in 2004 and 94.10% in 1990 were obtained for RNP; 93.40% pixel-to-pixel accuracy and 0.7904 for kappa were achieved for simulation. The annual rate of loss of forests (0.41% in MTR and 1.20% in RNP) and loss of water (1.79% in MTR and 1.69% in RNP) during 1990-2004 is a matter of serious concern. The scenario analysis in the study area for simulation revealed that the deforestation rate of 1.27% per year during 2004-2018 would increase to 2.04% if the human population growth rate is enhanced by 10%. Hence these PAs need urgent restoration measures and effective conservation planning to address the problems of deforestation, severe degradation and immense loss of water.

ACKNOWLEDGMENTS

Whatever has happened is sheer Godôs blessings. I would like to thank my family who has supported me during this long journey. I thank my wife, Neha, and my daughter, Navya, for all their support and patience. Neha - you have been the sole motivator in my undertaking this challenge. Thanks Navya for playing with me and providing me the refreshing zeal. I would like to express my sincere thanks to Professor Kamaljit Bawa for his guidance and support. Thank you for all your help and favor. I would like to express my sincere thanks to Professor Rick Kesseli, Vice Provost for Research and Strategic Initiatives, Office of the Provost, Zong-Guo Xia and Professor Rob Stevenson for their help. I would like to express my sincere thanks to Professor Yong Tian for his guidance and trust in me. I would like to express my sincere thanks to Professor Sugumaran for his help. I would like to express my sincere thanks to the Biology Department, especially Maria and Alexa, for getting me out of deep trouble so many times.

TABLE OF CONTENTS

CHAPTER Page

LIST OF TABLES

LIST OF FIGURES

Figure Page

LIST OF ABBREVIATIONS

Abbreviation

1. ABM - Agent Based Modeling

2. BR - Biosphere Reserve

3. CA - Cellular Automation

4. CA - Cellular Automation

5. CSC - Classes/Sub-Classes

6. DAMP - Data Automatic Modification Program

7. DEM - Digital Elevation Model

8. DF - Dense Forest

9. DIP - Digital Image Processing

10. DN - Digital Number

11. DSS - Decision Support System

12. FSI - Forest Survey of India

13. GEOMOD - Geographical Modeling

14. GIS - Geographic Information Systems

15. GL ï Grassland

16. HI - Human Inhabitation

17. ICAMM - Independent component analysis mixture model

18. ICAMM - Independent component analysis

19. IRS - Indian Remote Sensing

20. IUCN - World Conservation Union

21. LIDAR - Land Use Dynamics Simulator
22. LISS - Linear Imaging Self Scanning
23. LULC - land use and land cover
24. MAAP - Multi-Algorithm Automation Program
25. MAS - Multi-Agent simulation
26. MLA - Machine learning algorithms
27. MTR - Manas Tiger Reserve
28. MUSSIP - Multi-Stage Simulation Program
29. NF - Non-Forest
30. OF - Open Forest
31. PA - Protected Area
32. PCA - Principal Components Analysis
33. RCTCU - Rajajiï Corbett Tiger Conservation Unit
34. RNP - Rajaji National Park
35. RS - Remote Sensing
36. SLEUTH - Slope, Landuse, Exclusion, Urban extent, Transportation and Hillshade
37. TDF - Total Dense Forest
38. TFA - Total Forest Area
39. TGA - Total Green Area
40. TM - Thematic Mapper
41. TNFA - Total Non-Forest Area

42. TNGA - Total Non-Green Area

43. TR - Tiger Reserves

44. TR - Reserved Forest

45. VDF - Very Dense Forest

46. WA - Water

CHAPTER 1

INTRODUCTION

Background

Unplanned land use and land cover (LULC) change triggered by a development paradigm that lacks adequate environmental safeguards is unsustainable and is likely to have serious consequences for natural ecosystems and biodiversity. Globally, LULC has changed significantly over the last 300 years (from 1700 to 1990); forests and grasslands have decreased by 16% and 31% respectively, whereas croplands and pastures have increased substantially by 371% and 611% respectively (1). Forests have been under tremendous pressures in the recent times. Globally, the rate of forest loss was 7.3 million hectares per year during the period 2000-2005 (2). Similar forest losses have been witnessed in the earlier decades: 8.9 and 8.6 million hectares were lost per year in the 1990s and the 1980s respectively (2, 3). Deforestation is the most significant LULC change. The deforestation rate during the period 2000-2005 was as high as 13 million hectares per year (2). Significant drivers - like urbanization, conversion of land to agriculture and for developmental activities - induce LULC change (4). More than 70% of the forest loss has been attributed agriculture alone (4).

India, too, has witnessed changes in LULC, especially in the forest areas. The Ministry of Environment and Forests, Government of India has estimated that since independence in 1947, huge areas of forests have been converted to non-forest areas due to various drivers: 4.37, 0.52, 0.14, 0.07 and 0.06 million hectare of forests have been converted due to cultivation, river valley projects, industries and townships, encroachment and, transmission lines and roads respectively (5). In India, forests have decreased from 67.47 million hectares in 1980-1981 (6) to 63.73 million hectares in 1997 (7) and there after have increased to 69.09 million hectares in 2006 (8). Total forest has increased at the rate of 29,000 hectares per year during the period 2000-2005 (2). There has been deterioration in forests in the recent years: total dense forest having canopy cover greater than 30% has decreased by 89,800 hectares during the short span of 2004-2006 (8).

Change in LULC, has serious effects on biodiversity. Globally the number of species is dwindling and many face heightened level of threat. Out of 1.75 million species reported globally (9), the Red List of the World Conservation Union (IUCN) contains 44,838 species, 16,928 of which have been categorized as threatened (10). Approximately 20 to 30% of the plant and animal species face risk of extinction (11). Global projections for 2100 have shown that the loss of biodiversity would be affected most by LULC changes (12). LULC change is expected to be the most important driver of biodiversity loss in the tropics (12). It has been estimated that the rate of destruction in the tropical forests is approximately 1800 populations per hour or 16 million populations

per annum (13). In the tropics and subtropics, plantations and industrial crops are replacing species-rich forest ecosystems. Chaco thorn forests of Argentina and Bolivia and Dypterocarp forest of Borneo are being replaced by soybean cultivation and oil palm plantations respectively (14). India supports approximately 8% of the global biodiversity although it occupies only 2.4% of the worldôs land area (15). In India, one of the 17 mega diverse countries of the world, more than 136,000 species have been so far described; of what nearly 10.8% are threatened and 18.4 % are endemic (16). The Red List of the IUCN has categorized 659 species as threatened in this country (17).

LULC is also the most significant direct driver of deterioration in ecosystem and ecosystem services (4). Globally, LULC affects water, soil and ecosystem functioning. The altered ecosystem functioning in turn leads to long term decline in human welfare (18). The productive function of forest ecosystems has also fallen as a result of LULC. Contribution of forests to Gross Domestic Product has declined from 1.4% to 1.0% whereas employment in forestry has decreased from 5.4 million to 3.9 million during the period 1990-2006 (19). Freshwater ecosystems, too, have deteriorated both in terms of quantity as well as quality. Globally, over the last 40 years, more than 50% of the natural wetlands have vanished and per capita water availability has gone down nearly 50% (4). Over the next 30 years around 30% of Asia's coral reefs are likely to be lost (16). Per capita groundwater recharge has decreased from 1723 cu m to 1703 cu m during the period 2006-2007 (20). Agricultural production has been affected by the degraded services of pollinators, especially bees, and soil has degraded (18).

India, which harbors a variety of ecosystems, is facing similar deterioration. There is a great diversity of ecosystems in India: like mountains, plateaus, rivers, forests, deserts, wetlands, lakes, mangroves, coral reefs, coasts and islands (16). Growing stock of the forests has decreased from 4,781 million cu m to 4499 million cu m during the period 2002-2006 (8, 21). The tropical dry deciduous forests have fragmented in the Vindhyan highlands (22). In the subtropical evergreen to tropical moist deciduous forests of Arunachal Pradesh and Assam, 344 sq km of forests were lost during the period 1994-2002 (23). The mangrove cover increased 399 sq km across India during the period 1985-2004, while there was significant increase of 196 sq km during the period 2004-2006 (8). The tropical dry forests and seasonal forests are likely to replace the moist and dry Savannahs (16). The fresh water resources are depleting and soil is becoming degraded. It has been observed that the loss of underground water for the 4 northern states of Rajasthan, Punjab, Haryana and Delhi has been as high as 17.76 cu km per year during the period 2002-2008. (24). Nearly 146.82 million hectares in India suffers from land degradation due to factors like water, wind erosion etc and more than 90% of the area in Rajasthan and Gujarat are affected by desertification (16). Shifting cultivation, practiced in the northeastern hill states, Orissa and the Eastern Ghats with forest area of about 4.35 m ha, is contributing significantly towards forest land degradation (25).

Protected Areas (PAs) too are facing similar situation. Globally there are 102,102 PAs covering 18.8 million sq km which is 3.4% of the planetôs surface (26). The number

of PAs has increased by 111% and the area under the PAs has increased 52.87% during the period 1992-2003 (27). The adverse impacts on the PAs have resulted from LULC change such as agricultural conversion, human settlements and other developmental factors (26). Encroachment and logging are the most critical immediate threats according to a study done in 200 PAs around the world (26). Such change in LULC has adverse effects on air quality that seriously affects the biodiversity. In the PAs in Europe, it has been observed that 1300 species have been impacted negatively due to atmospheric pollution and globally 25% of the negative impacts on PAs due to atmospheric carbon dioxide have been attributed to LULC change, especially to deforestation (26).

Similar changes within PAs have also been seen in India. In India, there are altogether 668 PAs - 99 National Parks, 523 Wildlife Sanctuaries, 43 Conservation Reserves and 3 Community Reserves - occupying 158,745 sq km which is 4.83% of the total geographic area of the country and 22.98% of the total forest cover (16). There are 29 Tiger Reserves (TRs) having an area of 38,620 sq km which is 1.17% of the total geographical area of the country. The forest cover in the 28 TRs decreased by 94 sq km or 0.31% during the period 1997-2002; out of these, 11 reserves have shown decrease, 6 reserves have shown marginal increase while the remaining reserves have shown no change in the forest cover (28). There are 15 Biosphere Reserves (BRs) and several Reserved Forests (RFs). The study regarding forest cover in the 6 BRs revealed that the forest cover decreased 172 sq km or 1.6% during the period 1991-1999 (29). Other studies also have confirmed habitat

loss in PAs. The annual rate of deforestation was 1.38% during the period 1994-2002 for Kameng and Sonitpur Elephant Reserves in the northeastern India (23).

There are several difficulties while monitoring and documenting LULC change. Remote Sensing (RS) technique offers a quick way for assessment of LULC, but the accuracy and scale of application have to be taken into consideration. Resolution of satellite data has improved significantly over the last few decades, from medium to very high, which is now even less than a meter, but the cost enhances significantly as the resolution improves (30). Similarly, the time consumed for undertaking Digital Image Processing (DIP) increases with increase in the resolution of satellite data. Accurate assessment of species composition, desertification (1) etc are extremely difficult even today. Different schemes of LULC classification make comparison of data across regions and periods either extremely difficult or impossible. Similar difficulty is observed with predicted data because the applied models have different approaches and methodologies.

Objectives of the study

There are 2 broad objectives of the study: the technological objective pertains to the development of state-of-art programs that could serve as Decision Support Systems (DSSs) while finalizing plans and policy interventions while the other objective aims at generating geo-spatial data on PAs. Each of these is further elaborated below:

Technological objectives

The objective of these studies is to generate technological pathways, through the application of the state-of-art geo-spatial programs, for providing solution to the loads of problems related to land in most scientific, objective and effective manner so that management prescriptions incorporating policy interventions for conservation and sustainable development may prove to be highly successful. The objectives have been listed below:

- Developing state-of-art program for rapid assessment of LULC of the present period
- Developing state-of-art program for rapid assessment of LULC of the present period
- Developing state-of-art program for rapid assessment of LULC for other periods and for adjacent areas and developing methodology for providing metrics for the accuracy assessment
- Developing state-of-art program for simulation of LULC for the future periods

The last objective is aimed at providing solution to the following questions:

- How much would be the change in LULC in the future period?
- Where would those changes in LULC take place?
- How much adverse impacts, emanating from these agents of change, could be controlled consequent upon appropriate policy interventions?

Objectives related to generation of data

The following issues are the centerpiece objectives regarding the scientific studies in Manas Tiger Reserve (MTR), Assam, India and Rajaji National Park (RNP), Uttarakhand, India while developing geo-spatial data:

- Rapid assessment of LULC of the present period
- Rapid assessment of LULC of the past period
- Rapid assessment of change in LULC for the intervening period

These objectives primarily emanate from the quest for providing better management strategy for forest which is under tremendous pressure never witnessed before, and is undergoing rapid change.

Organization

This dissertation is organized into the following chapters:

Chapter 1: Introduction

The chapter provides the basic understanding of and rationale for such studies along with crisp summary of all the chapters that follow later on. Contained in this chapter are the background of the studies, the status and trends in LULC, especially in the forests, and the impacts of LULC change on biodiversity and ecosystems, especially in the PAs. This logically leads to defining the objectives in most unambiguous manner. Brief

narration on the forthcoming chapters has been included to summarily glance at their contents. The chapter ends up with the highlights of the conclusions.

Chapter 2: Generation of geo-spatial programs for Digital Image Processing and simulation

Transition of land among various LULC classes is dynamic in nature due to various factors, which makes assessment of LULC on suitable temporal scale mandatory from the planning perspective. With advances in science and improvement in computing power, newer technologies, methodologies and algorithms are being successfully utilized for the assessment of LULC for one point of time, for the LULC change detection and for the simulation of LULC. Equipped with artificial intelligence, 3 state-of-art geo-spatial programs, developed by the author to address the pertinent issues of conservation and sustainability from the landscape perspective are: Multi-Algorithm Automation Program (MAAP), Data Automatic Modification Program (DAMP) and Multi-Stage Simulation Program (MUSSIP). Structure of these programs is so advanced that, from millions of algorithms, they automatically select the best one leading to incredible accuracy and precision level.

Based on satellite data of the present period, MAAP does rapid assessment of LULC for repeated coverage with good accuracy. Since complex reflectance patterns emerging from ground due to biophysical characteristics pose a serious challenge on the accurate classification with remotely sensed data, MAAP, essentially based on per-pixel based

hybrid approach, aims at generating unique set of optimum MAAP algorithms for different field conditions that suit the classification process best. Depending upon the class overlap and class separation of the MAAP class values, the LULC classification is done in stages by sequentially segregating LULC classes. In this approach, emphasis has been laid not only on achieving accuracy but also on simplifying the procedure itself.

DAMP in conjunction with MAAP produces the LULC maps of different periods as well as of the adjacent areas by suitably modifying the Digital Number (DN) values of the corresponding satellite data so that the same set of MAAP algorithms, generated by MAAP, could be used for generating the LULC map. DAMP is useful for undertaking DIP of satellite data for the present period of the adjacent areas, for the past periods of the same area and in the future time of the same area. This approach also provides metric to assess the accuracy of these LULC maps, including those related to the past periods.

Taking various drivers of change for the 2 time periods into account, MUSSIP generates simulated LULC maps for the future periods. Under scenario analysis, the trends in various agents of change are incrementally changed and the consequent simulated geo-spatial data for the future periods are generated through the application of MUSSIP. The simulated geo-spatial data obtained by the scenario analysis proves to be an excellent DSS that could help in finalizing management prescriptions incorporating policy interventions in a very effective manner.

Chapter 3: Assessment of LULC and LULC change in Manas Tiger Reserve, Assam, India

The study was done in MTR in Assam, India, which falls within an Eastern Himalaya biodiversity hotspot. Deforestation, degradation and fragmentation have been a major concern in the reserve - having an area of area of 2837.12 sq km and situated in Assam district of India - which has a special status due to rich biodiversity and high endimicity along with a high level of threats. There is dearth of data regarding LULC for PAs in India, especially in the north-eastern regions. The small number of studies done in this tiger reserve does not match with the number of conservation programs that have been going on over the years.

The objectives related to the assessment of LULC for the present and the past periods were addressed in this chapter through the application of advanced technologies. For the rapid assessment of the LULC and LULC change, 2 state-of-art geo-spatial programs, MAAP and DAMP, developed by the author were used.

Based on multi-spectral satellite data having medium resolution, MAAP was used to generate the LULC map of 2004 for the tiger reserve. The entire tiger reserve was covered by 3 scenes of the satellite data. Altogether 8 MAAP algorithms were automatically generated through the application of MAAP for DIP of scene 1. Based on

the different sets of 4 DAMP algorithms, generated through the application of DAMP, one for each of the 4 bands, the satellite data were modified for rest of the 2 scenes. These modified satellite data were classified using the same MAAP algorithms generated earlier for scene 1 through the application of MAAP. Sub-classes were clubbed together to generate the final LULC map for the present period. For classification purpose altogether 6 LULC classes were taken into account. Apart from Grassland, Water and Non-Forest, 3 classes of forest were taken into consideration based on the canopy density.

For the assessment of LULC of 1990, the same methodology was adopted as explained in the previous paragraph. Adequate attention was paid on extracting the common areas of the scenes of the past and the present periods. Scenes of the present period were not mosaiced for the purpose of masking out the common areas. Choice of selecting the scene of the present period was based purely on the amount of overlap between the present and the past scenes.

The LULC change map was generated by overlaying the LULC maps of 2004 and 1990, which were generated earlier as explained above. The change map for the period 1990-2004 revealed that due to anthropogenic pressure the total green cover, including forests and Grassland, decreased 4.32%, from 1907.57 sq km to 1825.09 sq km; the total forest deceased 5.78%, from 1588.79 sq km to 1497.01 sq km; and Water decreased substantially (23.72%) from 50.01 sq km to 38.15 sq km, where as Grassland increased

2.92%, from 318.78 sq km to 328.08 sq km, primarily at the expense of forests. This approach at landscape level could facilitate in finalizing the planning process and mitigation measures promptly, especially since the changes in LULC are occurring at a rapid pace.

Chapter 4: Assessment of LULC and LULC change in Rajaji National Park, Uttarakhand, India and simulation in Uttarakhand

Similar study was done for RNP in Uttarakhand, India. This national park is abode of rich wildlife and is an important tourist place. Of late, immense anthropogenic pressure has not only affected fauna and flora of the region, but also has witnessed heightened incidences of man-animal conflict.

In the previous chapter, only those issues related to the LULC assessments of LULC for the present and the past periods, and the change in LULC for the intervening period were addressed, where as in this chapter, all the issues as listed out earlier, including those related to simulation, was addressed. Although plethora of studies has been conducted in this national park, no high end technology based on geo-spatial programming has ever been applied so far. Many vital information have not been generated in this park so far that could help manage the park in a better manner.

The generation of LULC maps was done by adopting the same methodology as applied in MTR. The classification scheme and the data period were also the same. The

entire national park was covered by just one scene of the satellite data. Altogether 13 LULC algorithms and 4 spectral algorithms were generated through the application of MAAP and DAMP respectively. The change map for the period 1990-2004 was also generated in same manner. The change map for the period 1990-2004 revealed that due to anthropogenic pressure the total green cover, including forests and Grassland, decreased a whopping 19.54%, from 488.80 sq km to 393.31 sq km; the total forest deceased 16.82%, from 581.45 sq km to 483.65 sq km; and Water decreased substantially (25.00%) from 5.84 sq km to 4.38 sq km, where as grassland increased 47.20%, from 136.88 sq km to 201.49 sq km, primarily at the expense of forests.

Answers to the pertinent issues regarding predictive modeling were also addressed through the application of MUSSIP based on simulation technique. Since geo-spatial simulation is a very time intensive process, a small area of 50*50 pixels was taken right on the boundary of RNP for study. Physical variables like road, Digital Elevation Model (DEM) and slope, biological variable like human population and legal variable like national park boundary were taken as agents of change apart from LULC itself. The classification scheme of LULC was modified for the purpose of simulation. Classes like Very Dense Forest (having canopy density more than 70%) and Water were clubbed with Dense Forest (having canopy density between 40-70%) and Non-Forest respectively. A separate class of Human Inhabitation was generated from with in Non-Forest through the application of MAAP and DAMP for the present and the past periods. So, there were altogether 5 modified LULC classes representing 5 states of cellular automata.

Simulation of LULC, based on Cellular Automation (CA), was done for the year 2018. Simulated LULC map revealed that forest cover would further decrease during 2004-2018, where as Grassland would keep on increasing and Human Inhabitations would occupy all the Non-Forest areas by 2018.

The simulation technique adopted in MUSSIP was unique because simulation was done in stages by forming groups by clubbing different LULC classes at any stage. In subsequent stages, any particular group was bifurcated before carrying out simulation. This process was repeated until each group was represented by individual LULC classes. All the combinations of group formation were compared to obtain the best result.

Under the scenario analysis, the trends in 2 of the agents of change were incrementally changed and the consequent simulated LULC map for the future periods were generated through the application of MUSSIP. These simulated data could serve as DSS for recommending management prescriptions. It was observed that by controlling human population positive effects on LULC could be realized.

Chapter 5: Applications of the advanced technologies

The new methodologies and tools regarding assessment, monitoring and simulation of LULC, as explained in chapter 2, enable us to manage LULC, especially the forest areas, in India in a scientific and effective manner. India has a very long history of forestry, but advances in technology have not been fully utilized for management purpose. Although

remote sensing has been used over the last three decades to generate spatial data for all of India, these data have never been practically integrated in the management plans. The present chapter focuses on the application of the programs, MAAP, DAMP and MUSSIP, for the management of forests from both, retrospective and prospective, perspectives.

Chapter 6: Conclusion

The research reported here was undertaken primarily from the 2 perspectives ï development of mathematical geo-spatial programs that could address the technological limitations and circumvent the financial constraints, even in a limited manner, and demonstrate the effectiveness of these programs in developing robust database and their use as Decision Support System (DSS) from the planning perspective by undertaking various studies in the tropical forests of India. Globally the scientific community has been trying hard to find any plausible management strategy that could help our planet. These studies could be seen as an honest attempt in the same direction. Transition of land among various LULC classes is dynamic in nature due to various factors, which makes assessment of LULC on suitable temporal scale mandatory from the planning perspective. In absence of any appropriate long term monitoring plan, no scientific management plan can be conceived. All the outcomes of these studies have been critically examined in light of the objectives defined earlier and the distinct advantages of the geo-spatial programs developed by the author have been discussed.

Three state-of-art geo-spatial programs developed by the author to address the pertinent issues of conservation and sustainability are: Multi-Algorithm Automation Program (MAAP), Data Automatic Modification Program (DAMP) and Multi-Stage Simulation Program (MUSSIP). Based on satellite data MAAP produces LULC map of the present period, MAAP in conjunction with DAMP produces LULC maps of the past periods as well as of the adjacent areas whereas MUSSIP produces simulated data of the future periods. Fitted with artificial intelligence, all of these programs are really expert systems and are very advanced, truly automated and cost effective apart from other unique features. No Digital Image Processing or Geographic Information Systems (GIS) professional is required, since these programs are fully expert systems as LULC maps and detailed analysis are generated automatically. Taking into account various drivers of change into account, the simulated geo-spatial data, obtained by simulation and scenario analysis through the application of MUSSIP, could serve as DSS for adopting appropriate policy interventions regarding different agents of change for optimally managing any area in an integrated, scientific, objective and effective manner. The LULC change maps generated through the application of MAAP and DAMP, and analysis of the trends therein among various LULC classes could help in developing mitigation plans.

Studies in the 2 Protected Areas, Manas Tiger Reserve and Rajaji National Park, were undertaken to generate data on LULC and to demonstrate the immense use of relevant information from the planning perspective. The LULC change map, generated by the post-classification comparison method, was done for both the Protected Areas, while

simulation was carried out in a smaller area right on the boundary of Rajaji National Park. The studies, regarding assessment of LULC for the present and the past period and the change in LULC for the intervening period (1990-2004), revealed alarming conditions in Manas Tiger Reserve and Rajaji National Park: Total Green Area, comprising of forests and Grassland, decreased 4.32% and 4.62% respectively; forests, having canopy density more than 30% decreased 9.16% and 19.54 % respectively; Water, including rivers, deceased 23.72% and 25.00% respectively; and Non-Forest, in turn, increased 10.73% and 36.01% respectively. The study regarding simulation revealed that Total Forest Area would decrease by 17.82%, 28.51% and 10.91% during 2004-2018 with the normal rate, with the accelerated rate (10% more than the normal rate) and with the decelerated rate (10% less than the normal rate) of human population growth respectively. Since the studies clearly point out that ecosystem services were severely impaired with the decrease in forests and the trends in forests were either likely to continue or may even worsen in future, proper remedial actions are warranted at the earliest before the resilience of the forest ecosystems is breached precipitating the point of no-return.

It was vividly demonstrated that based on these advanced technologies, through the application of these cutting edge mathematical programs, robust data on LULC over the temporal horizon could be generated, which could help in monitoring and in decision making processes regarding policy interventions and various other planning aspects. The assessment of LULC and change in LULC, through the application of MAAP and

DAMP, could be extremely rapid and accurate, and could be immensely cost effective. The scarce resources saved could be utilized in social sectors benefiting country in a huge way, especially in the developing countries. Success of various plans, which have bearing on LULC, and their implementation, could be easily assessed by having such a monitoring system in place. Such approach could be very useful in primary sector for monitoring natural resources like forests, grasslands, rivers and other water bodies etc, in secondary sector for monitoring agriculture, urban development, mining etc and in tertiary sector for monitoring factors, like environmental amenities, that influence tourism etc. Adverse impacts of various drivers of change could be effectively controlled by simulation through the application of MUSSIP. Appropriate policy interventions could be developed scientifically for developmental activities like mining, dam construction, communication networks etc. From the environmental perspective, these programs could be equally effective in generating optimum scenario of LULC by optimizing solution for Green House Gas emissions. Since future Green House Gas emissions could be accurately simulated for the future periods through the application of MUSSIP, precise management prescriptions could be generated for meeting the challenges of adhering to the obligations under international treaties and for Reducing Emissions from Deforestation and Degradation.

CHAPTER 2

GENERATION OF GEO-SPATIAL PROGRAMS FOR DIGITAL IMAGE PROCESSING AND SIMULATION

Abstract

The transition of land parcels among various land use/land cover (LULC) classes is dynamic. With advances in land classification theories and improvement in computing power, newer technologies, methodologies and algorithms are being successfully utilized for the assessment of LULC, for the LULC change detection and for the simulation of LULC dynamics. The per-pixel based supervised and unsupervised approaches for LULC assessment, and approaches like Post-Classification, Image Differencing, Image Ratioing etc for change detection have now being gradually taken over by new approaches like soft classification, Machine Learning Algorithms, neural network, decision tree etc. Three state-of-art geo-spatial programs were developed for each of these three categories of analysis: A Multi-Algorithm Automation Program (MAAP) for LULC assessment, Data Automatic Modification Program (DAMP) to detect change and Multi-Stage Simulation Program (MUSSIP) to model LULC through time. Common to each of these programs, which aims at improving the classification accuracy, is the use of artificial intelligence, through automated decisions during the training phase of the programs, so

that the ñbestò algorithms of analysis are automatically selected from among millions of potential algorithms. Based on satellite data of the present period, MAAP does rapid assessment of LULC for repeated coverage with good accuracy. Since complex reflectance patterns emerging from ground due to biophysical characteristics pose a serious challenge to the accurate classification with remotely sensed data, MAAP, essentially based on per-pixel based hybrid approach, aims at generating unique set of optimum MAAP algorithms for different field conditions that suit the classification process best. Depending upon the class overlap and class separation of the MAAP class values, LULC classification is done in stages by sequentially segregating the LULC classes. DAMP in conjunction with MAAP produces the LULC maps of different periods as well as of the adjacent areas by suitably modifying the DN values of the corresponding satellite data so that the same set of MAAP algorithms generated by MAAP can be used for generating the LULC map. This approach also provides metric to assess the accuracy of the LULC map of the past periods. Taking various drivers of change for the two time periods into account, MUSSIP generates simulated LULC maps for the future periods. Under scenario analysis, the trends in various agents of change are incrementally changed and the consequent simulated geo-spatial data for the future time periods are generated through the application of MUSSIP. The simulated geo-spatial data obtained by scenario analysis proves to be an excellent Decision Support System that can help us in finalizing management prescriptions incorporating policy interventions in a very effective manner.

Background

Transition of land among various LULC classes is dynamic in nature due to various factors, which makes assessment of LULC on suitable temporal scale mandatory from the planning perspective (31). Decisions related to land, which depend hugely on the information regarding LULC of the past, the present and the future periods, might have different perspectives. Monitoring of LULC change for ecosystem management is quite prevalent (32, 33). Ecological models of species associations within LULC classes, such as conifer and hardwood, have also been used (34). There has been growing recognition of the fact that forest ecosystems can be managed better by identifying the drivers of deforestation, fragmentation and LULC change (31, 35). Geo-spatial information regarding future forest disturbance through the application of simulation could help conservationists to focus on areas having the maximum LULC change (36). Various scenarios of management alternatives may be judged by the simulated LULC pattern on the basis of a set of landscape characteristics for managing ecosystem (37). From the perspective of reducing emissions from deforestation and degradation (REDD) intervention, optimal areas may be identified through simulation for reducing green house gases (GHG) emission (38). Management of urban areas by modeling urbanization and pattern of LULC change has gained lots of interest (39, 40). Integration of social aspects and ecological economics in modeling provides a comprehensive view for ecology management (41). Accurate knowledge of LULC enhances success of any policy intervention (42).

Remotely sensed data, generated by passive and active sensing systems, have been used to quantify LULC for over a century. Aeroplane based aerial photograph started in 1908, while remote sensing from space began in 1946 (43). Multi-Spectral Scanner (MSS) systems on board Earth Resources Satellite (ERTS) launched in 1972 heralded a significant step in remote sensing (44, 45). It has four spectral bands in the visible and near-infrared regions. Vegetative mapping by active systems like RADAR (radio detection and ranging) started in 1965, while LIDAR (Laser Airborne Profile Recorder) started being in 1982 (44). Multi-spectral and panchromatic satellite data having various resolutions have been utilized for various purposes and objectives. Hyper-spectral and very high resolution satellite data are of relatively recent origins. High resolution satellite data were first gathered in 1998 with the Space Information-2 (SPIN-2) project (43), a four-phase Russian mission, capable of providing 2-m resolution panchromatic imagery with 40 km X 160 km image area and 10-m multi-spectral imagery with 200 km X 300 km image area. Later on, other high resolution satellite data, like Quickbird, EROS-B, Ikonos, Cartosat-1, SPOT-5 etc, became available having panchromatic resolution of 0.6, 0.7, 0.8, 2.5 and 2.5 m respectively. Hyper-spectral data came in use after the launch of MODIS (Moderate Resolution Imaging Spectroradiometer) onboard Terra (EOS AM) and Aqua (EOS PM) satellites, having 36 bands, in 2002 (46). With revisit period of 1-2 days the resolution of this satellite data is 250 m for the bands 1and 2, 500 m for the bands 3 to 7 and 1000 m for the bands 8 to 36.

There are a variety of issues related to the use of satellite data. The basic purpose of satellite data is to create maps so that they exactly represent features on ground (63). Exact representation of 3-dimensional features onto a 2-dimensional space on map is really a challenging job (63, 64). The ógoodnessô of representativeness can be quantitatively measured by various indices of accuracy (33, 65, 66). There is no unanimity over the best index for accuracy assessment. In the present development paradigm, changes in LULC are quite rapid and deforestation rates are high (2, 3, 55). Monitoring of rapidly changing LULC may require frequent and repetitive assessments. So, rapid assessment of LULC is desirable, which may even require automation of image processing. Satellite data, especially of the high resolution and multi-spectral ones, which could be more appropriate for specific purposes, are quite expensive. Image processing procedures are complicated. Even small errors in procedures like spectral and atmospheric correction, geo-referencing etc, could lead to generation of inaccurate maps. Many algorithms fail to produce the desired maps if the pixels do not have Gaussian distribution (58). *Apriori* knowledge of the emerging pattern of LULC based on these maps also needs to be addressed for better management of land (38). Single pixel may also get influenced by a number of LULC classes on ground (76). This problem increases with decrease in spatial resolution.

The older approaches for LULC assessment suffered from several limitations and constraints. Partitioning of spectral image into different LULC classes depends on individual expertise and judgment in k-means clustering algorithm and NDVI under the

unsupervised approach of LULC classification (51). Best results are obtained by K-means algorithm when the clusters are spherical in shape having same variance (58). Under supervised approach, parametric classifiers like Maximum likelihood Classifier (MLC) and Linear Discriminant Analysis, work only for Gaussian distribution (33, 42, 51). MLC is not very appropriate when multi-source data are used for classification and it is difficult to integrate non-statistical information, and spatial and contextual attributes (51). Minimum Distance Classifier has the problem of accuracy when variance with LULC class is high (51), while Principal Component Analysis suffers from the problem of data reduction (45).

The conventional approaches for LULC change detection had procedural difficulties and problems of inaccuracy. The common Post-Classification approach suffers from ósalt and pepperô effect (32, 51, 52, 59), it is not capable of detecting subtle changes and the accuracy depends on the individual accuracies of the LULC maps of the 2 periods (52). Techniques based on algebra for LULC change like Image Differencing and Image Ratioing do not provide detailed change matrix and they depend on selection of thresholds, which is prone to bias and errors (52). Class labeling is a real challenge in Multi-Date clustering since the temporal as well as spectral features have equal status in the clustered dataset of the 2 periods (44). Parametric classifiers are restricted from use in Univatiate Image Rationing since the ratio has non-Gaussian distribution (32, 44, 52). This approach may increase noise in classification (32, 44). For the same LULC class, Vegetative Index Difference may produce entirely different result (44) and it enhances

random noise (52). Compared to the new approaches for LULC change detection, the accuracy of the conventional ones is 10-20% less (45).

Simulation, LULC change detection and analysis of trends in LULC provide insights regarding LULC that could serve as DSS (32, 47, 48, 49, 50, 51, 52). Changes in LULC and their trends facilitate mitigation measures (32, 44, 53, 54, 55; whereas simulation significantly enhances the ability to take appropriate measures, control agents of change and model the emerging scenarios consequent upon the implementation of the policy interventions (31, 35, 37). Simulation is more complex, dependent on so many variables and extremely time intensive (31, 37, 49, 50, 56) when compared with one time LULC assessment and change detection techniques (32, 51, 57).

However the advances in science and improvement in computing power have ushered an era in which emerging technologies can successfully utilize remotely sensed data for generating solutions regarding user defined goals related to LULC in more objective, accurate and scientific manner (49, 60). Several methodologies and newer algorithms are being developed and used to generate information on LULC (45, 61, 62). These are applied for the assessment of LULC for one point of time, for the LULC change detection and for the future prediction of LULC (38, 51, 57).

Objectives

The objective of this study is to provide better algorithms for assessment of LULC of historical and recent time periods and for simulation of LULC for future time periods.

The first objective is aimed at providing solution to the following questions:

- How can ógoodô LULC assessment be done for the present periods?
- How can ógoodô LULC assessment be done for the past periods?
- How can ógoodô LULC assessment be done in the future periods?
- How can LULC assessment be done at a rapid pace and in an automated but simple manner?
- How can real/near near time monitoring of LULC be done?
- How can accuracy assessment of the LULC maps be done without any ground truthing?

The second objective is aimed at providing solution to the following questions:

- How much would be the change in LULC in the future periods?
- Where would those changes in LULC take place?
- How much adverse impacts, emanating from these agents of change, could be controlled consequent upon appropriate policy interventions?

Development of geo-spatial programs

Three state-of-art geo-spatial programs developed by the author to address the pertinent issues of conservation and sustainability from the landscape perspective are: MAAP, DAMP and MUSSIP. Based on satellite data, MAAP produces LULC map of the present period; MAAP, in conjunction with DAMP, produces LULC maps of the past periods as well as of the adjacent areas. Taking various drivers of change for the two time periods into account, MUSSIP generates simulated LULC maps for the future periods. Structure of these programs is so advanced that, from millions of algorithms, they automatically select the best one leading to incredible accuracy and precision level. No DIP or GIS professional is required, since these programs are fully expert systems as the LULC maps and the detailed analysis are generated automatically. All these have been discussed in the following sections elaborately:

Rapid assessment of LULC for the present period

Introduction

Rapid assessment of LULC for repeated coverage with good accuracy is needed for adopting plans and mitigation measures (57). Accurate assessment of LULC and generation of the corresponding map is the first step in developing a science based policy intervention or management strategy. This helps in monitoring process and serves as one of the most important inputs in simulation. High level of accuracy for the LULC maps is most desirable as simulation is dependent on these maps.

Remote sensing data is used to create thematic information on 2-dimensional space corresponding to the actual LULC on ground (63, 64). This obviously requires LULC on ground to be compartmentalized into different classes under hard classification approach. Each pixel on ground is represented by a separate LULC class in thematic map. There has been considerable debate among scientific community about the best or the most accurate way of this representation. Based on error matrix, several accuracy indices are in vogue like óoverall accuracyô, óProducerôs accuracyô, óUserôs accuracyô, Cohenôs kappa coefficient or ók-statisticô that account for chance factor too in the classification process (33, 65, 66). More than two third of the authors use overall accuracy (66), some use both overall accuracy and k-statistic (62), some include mean class accuracies (67), while accuracy adjusted for the misclassification costs may also be used (68). Overall accuracy of 85% and 70% accuracy for each class has cited by G. M. Foody (66). For the present study both, k-statistic and overall accuracy, has been produced, but k-statistic has been fundamentally used for optimization of the LULC maps generated through the application of MAAP.

In unsupervised approach pixels are segregated into various LULC classes taking into account the natural groupings existing in the data set (43, 44). This approach evolved to include clustering and k-means algorithms (51, 58). More recently supervised approach has developed, where classification is based on training data sets that includes the desired groups or classes (44, 69). Among supervised classification, minimum distance-to-mean

classifier, parallelepiped classifier and maximum likelihood classifier are the most common ones (42, 51, 70).

Various techniques have been applied by different authors for assessment of change in LULC over a period of time (71). There are not many studies on comparative evaluation of these techniques that have conclusive account on accuracy (44). Even reviews on LULC change detection, like the one by Coppin in 2004 and D. LU in 2003, have refrained from making any quantitative comparison of different techniques (32, 52). These techniques include post-classification comparison (51), image differencing (33), image ratioing (71), image regression (44), vegetation index differencing (57), normalized vegetation index differencing (71), principal components analysis (PCA) (52), direct multi-date classification (53), background subtraction (52), image smoothing (32), thresholding (44) etc. In his study J. F. Mas compared several methodologies and obtained the best accuracy (86.87% overall accuracy) with the post-classification comparison approach (57), which was cited by A. Singh in 1984 and 1986 as the worst with 51.33% overall accuracy (44, 53). Singh, on the other hand, applied so many techniques like image differencing, vegetation index differencing, principal components analysis (PCA), post-classification comparison, direct multi-date classification and found enhancement procedure such as image regression the most accurate with 72.66% overall accuracy. Coppin (2004) concluded that image differencing and linear transformations perform better especially compared with other bi-temporal change detection methods (32). Despite problems of ósalt and pepperô effect (51) and difficulty in generating LULC

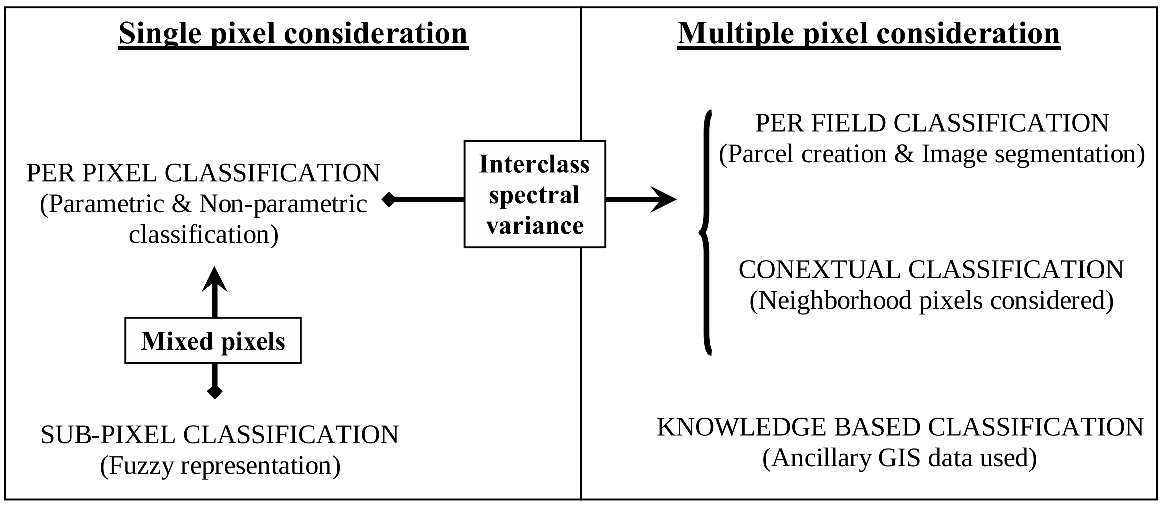
maps of the past period (52), post-classification comparison method has remained the most popular (66). The problem of radiometric calibration is minimized with post-classification comparison since the imageries pertaining to different periods are classified separately (32). Although there is no unanimity about the best technique in terms of accuracy, post-classification comparison has been used for change detection in this study.

Complex reflectance patterns emerging from ground due to biophysical characteristics pose a serious challenge on the accurate classification with remotely sensed data (57, 72). Probability of misclassification increases as the overlap in DN values increases. Problems also arise when multiple LULC classes simultaneously influence the DN values of any pixel. Accuracy of the LULC classification in the tropical regions has remained poor despite several attempts in the last few decades (42).

The actual ground condition and complexity of reflectance pattern influence the choice of the most suitable classification method from among a variety of approaches (51). Per pixel and sub-pixel classification approaches are based on the information predominantly from one single pixel, while per field, contextual and knowledge based classification approaches include information from many other pixels. Parametric and non-parametric algorithms are used in per pixel approach, which is the most common one (33). Single pixel exhibiting a composite of multiple reflectances emanating from different LULC classes, whose probability increases with decrease in spatial resolution of the satellite data, often require fuzzy representation technique while adopting sub-pixel

approach (73). Occurrence of high intra-class spectral variance may be tackled effectively by per field approach by creating parcels or by image segmentation as done in Object Oriented Classification (74). Information from neighboring pixels are considered in Contextual approach to deal with the problem of intra-class spectral variance (64, 67). Knowledge based approach uses ancillary data like communication network, population, DEM etc in GIS domain for LULC classification (63, 75).

Figure 2.1. Diagrammatic representation of classification approaches



The challenge of achieving higher accuracy for the LULC assessment is being addressed by suitable classification methods and choice of classifiers (51, 59). Approaches like sub-pixel classification, especially spectral mixing, have been utilized by many authors (59). Soft and fuzzy approaches have been applied at sub-pixel level (76).

Apart from per-pixel and sub-pixel algorithms, per-field algorithms based on the object oriented approach have also been used (32).

Many new techniques incorporating state-of-art classifiers have been attempted to enhance the classification procedure, particularly during the last couple of decades. Artificial intelligence or knowledge based expert systems have been tried to overcome the limitations of traditional statistical classifiers (32). Machine learning algorithms (MLA) have been used to address these issues (77). Expert systems, like MaxExpert, in conjunction with other classifiers, like maximum likelihood classifier, may be used to produce better classification (42). Non-parametric classifiers like neural networks can be utilized either for general classification purposes or for more difficult jobs like spectral mixture analysis (34).

Non-parametric classifiers like decision tree, stratified and layered classifiers have also emerged as new areas of research (51, 59). Decision tree approach has been tried for enhancing accuracy (70, 78, 79, 80, 81). Model tree based algorithms have shown its robustness in dealing with noisy data (79). Approaches like óbraggingô and óboostingô are being used to further enhance the accuracy level (68, 82). Independent component analysis mixture model (ICAMM) algorithm for supervised classification, based on Independent component analysis (ICA) approach, works in the non-Gaussian probability density function too (58).

Expert systems having artificial intelligence have gained much attention in recent years (32). MLAs either alone or along with other traditional classifiers have been used for increasing the accuracy of LULC assessment (45). Among them, Artificial Neural Network (ANN) and Decision Tree (DT) classifiers have been used by many authors for image classification (51) and automated knowledge generation (61). Univariate DT algorithm through the application of C4.5 software was used by Huang (61), Pal and Mather (70) and Rogan et al (77). Pal and Mather (71) also used See5.3 for univariate DT algorithm and QUEST for multivariate DT algorithm, whereas the C5.0 was used by DeFries (68) for the standard DT algorithm apart from óbraggingô and óboosting (68, 70). S-plus statistical software has been used for DT algorithm in the past by several authors like Rogan (77, 81), while Zambon (80) used it for Classification Tree Analysis (CTA) (77, 80, 81). Pal (79) used M5 model tree algorithm, a tree based regression model, and Nangendo (42) used expert system along with traditional classifiers for producing better results (42, 79). Friedl compared results obtained from univariate DT algorithm, multivariate DT algorithm and hybrid DT algorithm (78). ANN (ARTMAP) was applied by Carpenter and Rogan (34, 77).

Scientific community should constantly engage into alternate ways to overcome the shortcomings of the current advanced classification approaches. Machine Learning Algorithms (MLAs) like Artificial Neural Network (ANN) and Decision Tree (DT) suffer from the problem of long training period, ANN suffers more than DT (51, 67, 70). Overfitting in the training model can adversely affect the performance of DT (78) and

ANN (77). MLAs are sensitive to variations and changes in training set data (68, 77, 81). Size of training set also affects their performance. Performance of DT goes down with increase in dimension of data as it has problem of handling large number of features (70, 78). On the other hand, accuracy of ANN decreases as dimensionality is reduced (51). The overall accuracy is optimized in DT at the cost of class accuracies with smaller datasets in the respective classes (78). DT is not efficient in handling noisy datasets (77). These approaches are not fully automated as they have specific requirements. In ANN, configuration of network architecture and the values of a number of parameters have to be specified (70). In DT, appropriate pruning method has to be specified (70, 80). These approaches are not helpful in overcoming the drawbacks of the training set that severely impairs their performance.

Multi-Algorithm Automation Program (MAAP)

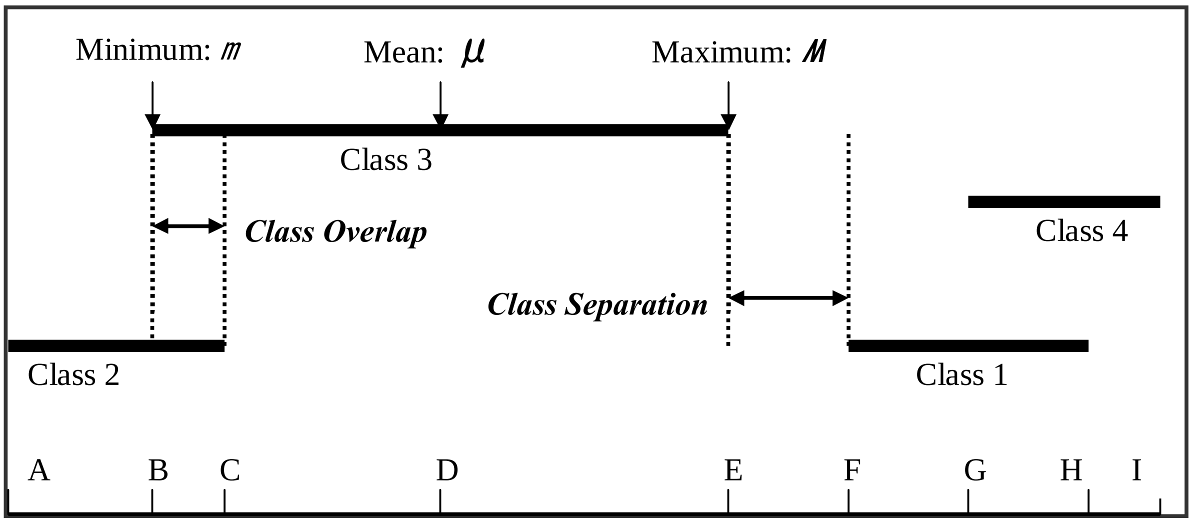
MAAP is essentially per-pixel based hybrid approach, having both the parametric and non-parametric features, with artificial intelligence that aims at generating unique algorithms, for different field conditions or features on ground, that suit the classification process. This is really a challenging job as automated classification algorithms are not easy to generate (82). The program, MAAP, is basically a mathematical model that generates a set of optimum algorithms (say MAAP algorithms) for the LULC classification. The program takes care of each field condition and uniquely generates the best set of algorithms, thereby enhancing the accuracy (Kappa statistic) of classification.

In this approach, emphasis has been laid not only on achieving accuracy but also on simplifying the procedure itself. No spectral enhancement technique or radiometric correction is required. Most of the algorithms use DN values of the selected bands so that the LULC classification gains efficiency. This is tantamount to a tendency that makes the unused bands redundant from the classification perspective. Generally Principal or Cannonical component transformations are applied to reduce dimensionality, i.e. the number of layers where the information of satellite data is contained. Dimensionality of satellite data is also not reduced here since no transformation is done; rather raw data is preferred unlike many other approaches. Rather than selecting the best bands that may be used for the MAAP algorithm development, all the bands are taken into consideration. MAAP automatically figures out the best ones and leaves out others if redundant. This process of algorithm development may take extremely long time if all the bands are considered, especially while dealing with hyper-spectral data. In such cases reducing dimensionality of the satellite data may be considered by selecting a few bands to save time.

Considering the likelihood of occurrence of spectral inseparatibility of different classes in the training set data in different bands, this program aims at generating MAAP algorithm value separatibility, which has been further explained and illustrated with example in the subsequent paragraphs. The pixels of the training set classes may be conceived as ópixel cloudsô in an n-dimensional space. Letôs define óMAAP algorithm valueô as the value of the MAAP algorithm obtained by putting the DN values of any

pixel for different bands. These MAAP algorithm values have just one dimension that can be plotted quite easily as shown in figure 2.2.

Figure 2.2. One-dimensional arrangement of MAAP algorithm values

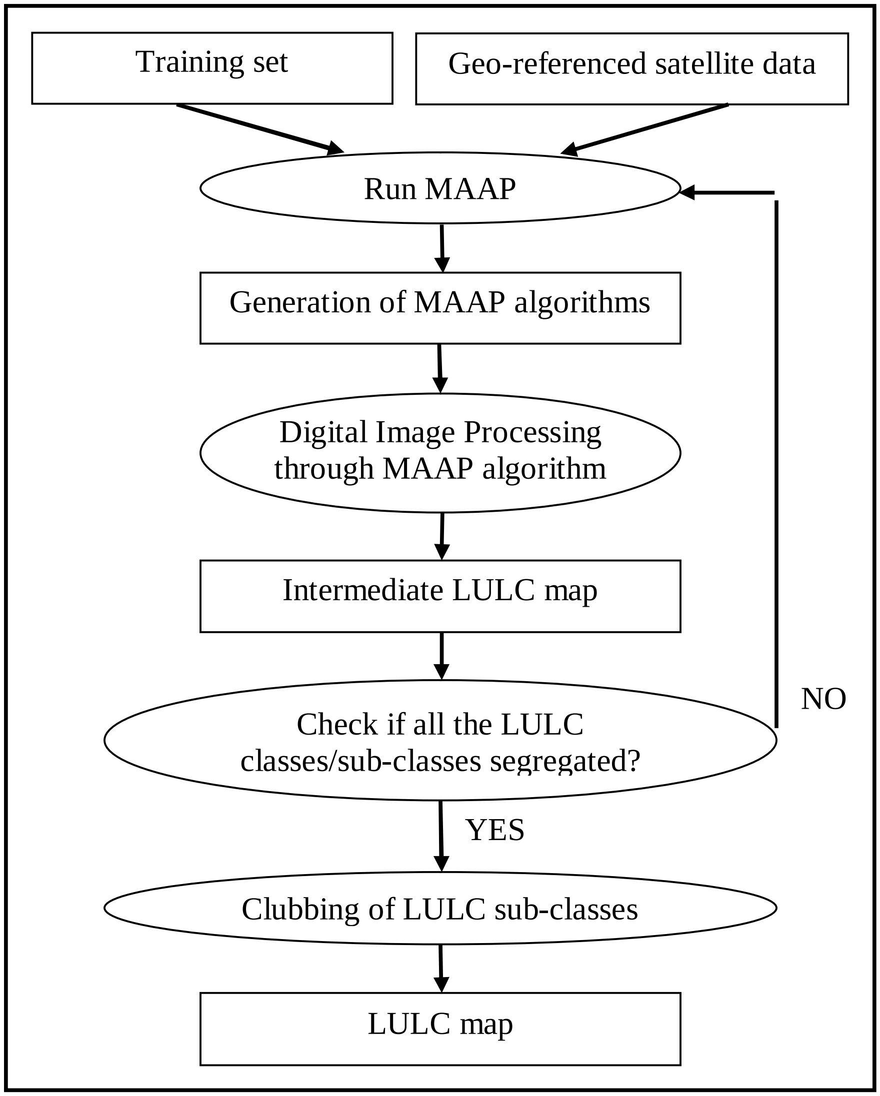


The regions of óclass overlapô and óclass separationô have been illustrated with example as shown in figure 2.2. The entire range of MAAP algorithm values of all the pixels in the training set classes stretch from point A to I. Altogether 4 LULC classes have been shown. MAAP class values for LULC classes 2, 3, 1 and 4 extend from point A to C, B to E, F to H and G to I respectively. Although the lines AC, BE, FH and GI lie on the x-axis, for visual clarity these been slightly shifted from the x-axis to make the corresponding MAAP class values distinct. The minimum, mean and maximum values of all of the LULC classes exist as has been shown for the LULC class 3. Since the minimum of the LULC class 3 (point B) is less than the maximum of the LULC class 2

(point C), MAAP algorithm values between B and C are overlapping each other for the LULC classes 2 and 3. This is called the region of class overlap for the LULC classes 2 and 3. On the other hand since the minimum of the LULC class 1 (point F) is more than the maximum of the LULC class 3 (point E), MAAP algorithm values between E and F are not overlapping each other for the LULC classes 1 and 3. This is called the region of class separation for the LULC classes 1 and 3.

Generation of optimum set of MAAP algorithms is based on creating separation between different LULC classes by utilizing the arrangement of one-dimensional MAAP algorithm values. Letôs call MAAP algorithm values within a LULC class as óMAAP class valuesô. Arrangement of MAAP class values on one dimensional scale produces conditions of óclass overlapô and óclass separationô depending upon the range of class values of each LULC class. Complex reflectance pattern, more often than not, produces conditions of inseparatibility or class overlap. MAAP generates optimum MAAP algorithms that reduces class overlap (region B to C for LULC classes 2 and 3) and increases class separation (region E to F for LULC classes 1 and 3) (figure 2.2).

Figure 2.3. Flow diagram of MAAP LULC classification



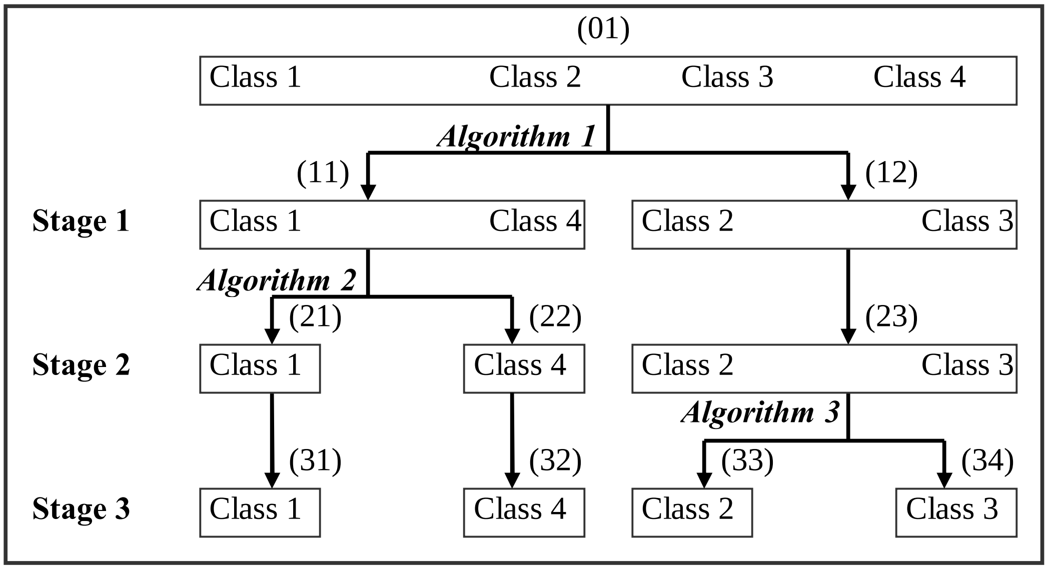
The LULC classification is done in stages depending upon the class overlap and class separation of the MAAP class values. All the LULC classes may be segregated by achieving class separations among themselves by generating just one MAAP algorithm i.e. during the stage 1, especially if the LULC classes are quite distinct and have spectral separations among different bands. When conditions of spectral overlap exist, especially

in the tropics, this approach of optimizing class separation is adopted in stages that sequentially segregate the LULC classes. During stage 1, MAAP algorithm 1 segregates LULC classes in 2 or more groups of the LULC classes. During the next stage, one of these groups having multiple LULC classes is chosen and the same process is repeated. A new MAAP algorithm is generated that segregates this chosen group. This process is repeated sequentially till the time all the LULC classes are segregated as shown in figure 2.3. Any LULC class, consisting of distinctly separate spectral ranges, may be divided into 2 or more LULC sub-classes. The process of formation of sub-classes has been elaborated in the section óTraining setô. In case there are sub-classes also, the process as explained above is repeated sequentially till the time all the LULC classes\sub-classes are segregated. All the LULC sub-classes are clubbed (or grouped) together so that separate LULC sub-classes are shown as the LULC class of what they originally consisted of.

The stages of segregation have been explained through an illustration with the help of figure 2.4. It can be seen that there is class separation between LULC classes 3 and 1. During the stage 1, MAAP algorithm 1 segregates all the 4 LULC classes (group 01) into 2 groups. The first group (group 11) contains LULC classes 1 and 4 and the second group (group 12) contains LULC classes 2 and 3. During stage 2, MAAP algorithm 2 is generated that picks up either of these groups. Letôs assume that this is the group 11. The condition of class separatability is attained through optimum MAAP algorithm 2, which segregates the LULC classes 1 and 4 (of group 11). The rest of the 2 LULC classes (of group 12) are segregated during the stage 3 through the generation of the MAAP

algorithm 3. The maximum number of stages and hence the maximum number of MAAP algorithms is one less than the number of LULC classes.

Figure 2.4. Flow diagram of LULC class segregation



Note: Group numbers are within brackets.

Based on the MAAP algorithm values and the statistical parameters, all the pixels of the imagery are classified into different LULC classes. While assigning pixels to different LULC classes, 3 scenarios may emerge depending upon the position of the MAAP algorithm value of any particular pixel and the arrangement of MAAP class values.

1. MAAP algorithm value neither in class overlap nor in class separation

The simplest case occurs when the MAAP algorithm value of any pixel falls with in any particular class value range and this class is in the position of class separation with all

other classes, then that pixel is easily classified as that LULC class. The condition of class separatability has to be considered only on that flank where the MAAP algorithm value is situated with respect to the mean of the class values (figure 2.2). All the pixels having MAAP algorithm values between points C and E can be easily classified as LULC class 3, as this region is outside the class overlap region (B and C) as well as outside class separation region (E to F).

2. MAAP algorithm value in class separation

In this situation, when the MAAP algorithm value of any pixel falls outside all the class values and with in any class separation, then that pixel is classified based on statistical parameter (figure 2.2). All pixels having MAAP algorithm values between points E and F (excusive of both the points) can be classified by this methodology. Based on the statistical parameter, which is compared with a standard threshold, the pixel is classified during stage 1 and included in group 12 or group 11. The elaborate discussion on the statistical parameter used in this methodology has been produced as a separate section later.

3. MAAP algorithm value in class overlap

In this situation, when the MAAP algorithm value of any pixel falls with in any class overlap, modification in training set is desirable before attempting any classification, which is described further in the following section. If that approach fails, classification of the pixels may be forced based on statistical parameter. All the pixels having MAAP

algorithm values between points B and C (figure 2.2; inclusive of both the points) can be classified by this methodology. Based on the statistical parameter, which is compared with a standard threshold, the pixel is classified during stage 3 and included in group 33 or group 34. The methodology has been elaborated in a separate section later.

Mathematical treatise on image processing

Letôs define the following terms and symbols used for the mathematic model used for image processing.

Mean (μ_N) as the mean of the MAAP algorithm class values of the N^{th} LULC class

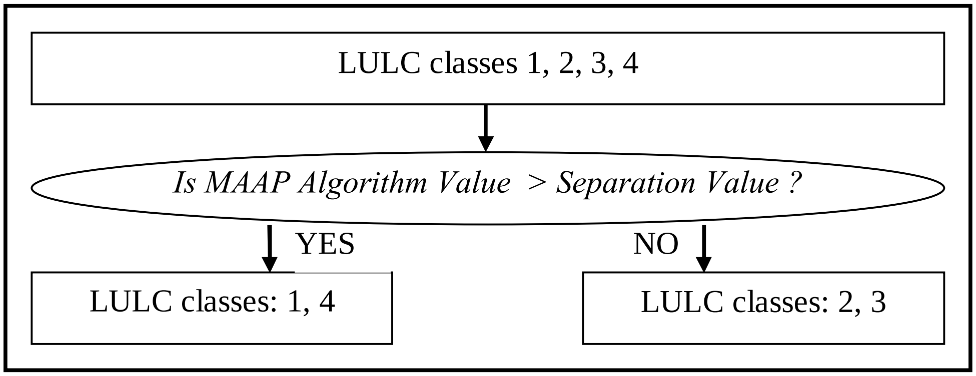
Min (m_N) as the minimum value of the MAAP algorithm class values of the N^{th} LULC class

Max (M_N) as the maximum value of the MAAP algorithm class values of the N^{th} LULC class

St Dev ($\mathring{u}_N$) as the standard deviation of the MAAP algorithm class values of the N^{th} LULC class

Separation Value = $[(M_{N+1} * \mathring{u}_N) + (m_N * \mathring{u}_{N+1})] / (\mathring{u}_N + \mathring{u}_{N+1})$ (2.1)

Figure 2.5. Flow diagram for classification of pixels in Class Separation



With reference to the figure 2.2, LULC class 4, 1, 3 and 2 may be taken as the 1st, 2nd, 3rd and 4th class respectively. Let us consider LULC class 1 as the Nth class. So LULC class 3 is the N+1th class. For pixels whose MAAP algorithm value is in the class separation between points E and F, the following comparison is used as the basis of classification:

Is MAAP Algorithm Value > Separation Value? (2.2)

If the above statement is true then the pixel is placed in the group 11 (having LULC classes 1 and 4) else it is placed in group 12 (having LULC classes 2 and 3) (see fig 2.4).

This approach is applicable in all types of distribution. Some algorithms needs Gaussian distribution for training set classes, while some others works with bivariate

Gaussian distribution only. This limitation is overcome by adopting the above methodology which makes application of MAAP universal.

Training set

Training set data should be compact and distinct. The pixels within any particular class of the training set should be close to each other and training set clouds of different classes should be well separated from each other. Apart from these, the training set should have the essential properties of completeness, representativeness and non-redundancy. Generation of such a training set is an art where stricter norms are adopted for obtaining good results.

To overcome the practical difficulties associated with the adherence to strict norms for the training set development, the statistical parameter related with class separation, acting as the artificial intelligence of MAAP, provides the necessary feedback while developing the training set. Separation upper has been defined as a function of the difference between the maximum of the LULC class and the minimum of higher LULC class values. Similarly separation lower has also been defined. Despite figuring out the optimum MAAP algorithm that minimizes the class overlap, if the separation indices (upper and lower) remains negative, then training set classes, for which the class overlap persists, should be fragmented. Either of the adjacent training set classes or both of them may be fragmented. These fragmented training set classes would represent sub-classes of the parent LULC class. Fragmentation of one of the adjacent training set classes should

be attempted first before opting for fragmenting both. This may happen during any stage of LULC class segregation. Once the class segregation is achieved, consequent upon the fragmentation of the training set classes, the image processing moves on to the next stage. The process of optimization of MAAP algorithms and fragmentation of training set classes continue till the time condition of class separation is achieved for all the training set classes. All the problems are rectified sequentially after getting feedback from MAAP, and the training set classes are modified, which leads to the generation of a set of optimum MAAP algorithms.

There are some critical issues, albeit simple ones, which require caution while developing training set and processing the image. Even if perfect class separation exists between adjacent training set classes, the pixels from both the adjacent training set classes, whose MAAP algorithm values are close to the class separation region, should be rechecked whether they really fall in the desired LULC class or not. If turned on, the inbuilt feature of MAAP can easily generate the classified map for these pixels. Caution is also desirable when class separation is too huge. This situation may point towards some LULC classes/sub-classes totally missing in the training set. Training set can be rechecked the same way as explained earlier through the generation of the classified map for those pixels whose MAAP algorithm value falls on the class separation region. Training set data may be modified if needed in both these cases.

Redundancy is not as big a problem as non-representativeness as non-representation may severely affect the accuracy level, while redundant data simply protracts the image processing time. Rather than aiming at achieving class separation among the training set classes, which may be plagued with the problem of non-representativeness, one should start with a complete and representative training set that might be a bit redundant leading to a condition of multiple overlaps. It is always safe to move from the condition of class overlap to class separation by proper modification in the training set classes.

Although the output LULC map has high accuracy level, this approach is time intensive, especially if the training set is not generated considering all the above aspects. Refinement of training set consumes much time, but classification of pixels requires no time once the set of optimum algorithms have been generated. Classification of pixels, having MAAP algorithm value in the class overlap region, may be forced if there is paucity of time or if optimum MAAP algorithm is unable to produce the condition of class separation despite its best effort, which is quite unlikely.

Rapid assessment of LULC for other periods and for adjacent areas

Introduction

Rapid assessment of LULC is required for regular monitoring, especially as the developmental activities are more pervasive and quick now-a-days. Repetitive LULC assessment gains importance for monitoring the effects of the policy interventions

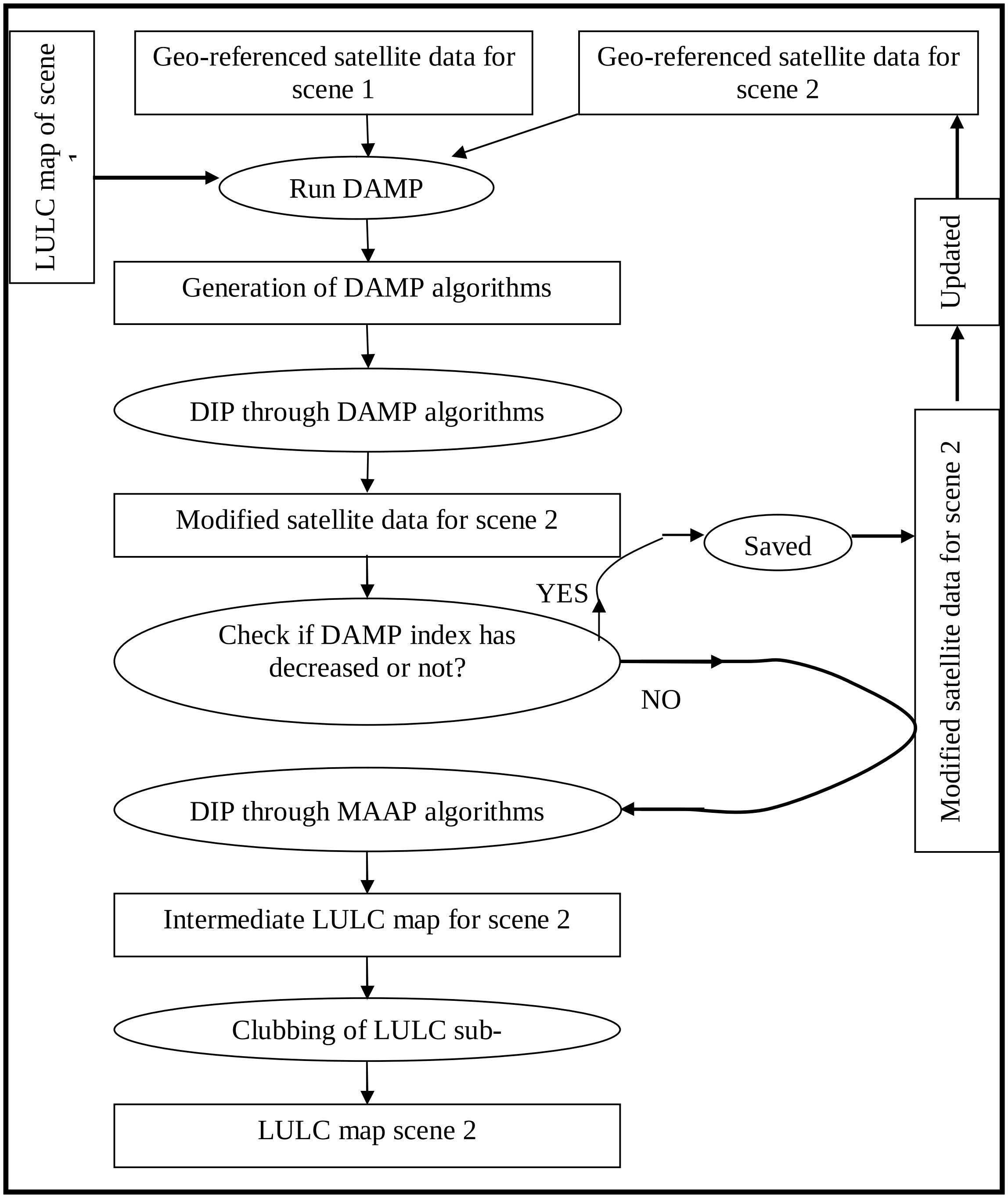
consequent upon adoption of mitigation measures and other plans. High accuracy of such assessments at short intervals through the application of remote sensing is desirable (57). Even if the traditional approaches for LULC assessment may be accurate, these are not suitable for this quick assessment since these are not automated and hence time consuming.

Accurate assessment of LULC of the past periods may be quite difficult for many reasons (52). Accuracy assessment of the LULC maps of the past period is extremely difficult since ground verification is not possible. Absence of adequate data of the past period may pose problems in verifying the accuracy of the LULC maps. Problems regarding absence of proper reference maps are being faced in most of the parts of the world. Many studies, that have used the LULC maps of the past period, have experienced similar constraints. Thus many authors have expressed concern over this issue (52, 83).

Data Automatic Modification Program (DAMP)

DAMP has been developed primarily to address the issues outline in the previous paragraphs and simplify the image processing technique. Generally radiometric and atmospheric corrections are applied before image processing. Methods like relative calibration and dark object subtraction may be applied for this purpose (52, 84). Solving the problem of radiometric calibration is not needed for post classification comparison (32).

Figure 2.6. Flow diagram of DAMP spectral modification and LULC classification



LULC classification can be partially automated for the past period through the application of DAMP. The DN values of different bands of satellite data are modified by DAMP in such a manner that the set of MAAP algorithms, developed earlier for the present period, may be used for the classification purpose. Development of a set of MAAP algorithms through the application of MAAP is based on the training set whose generation and modification is quite rigorous and time consuming. Since algorithms for the classification are not generated in this approach, all the rigors of development of the training set for the past period are avoided, which helps in rapid assessment.

DAMP is useful for undertaking DIP of satellite data under the following 3 scenarios:

1. For DIP for the present period for the adjacent areas.
2. For DIP for the past periods for the same area.
3. For DIP in future for the same area.

DAMP, in conjunction with MAAP, produces the LULC map of different periods or of the adjacent areas. This program suitably modifies the satellite data of the past periods or of the adjacent areas so that the same set of MAAP algorithms generated earlier can be used for generating the LULC map with nearly the same accuracy level. The figure 2.6 explains the process of spectral modification and LULC classification by this method. After the DIP of the satellite data of the present period or scene 1 (say sd1) is done, the satellite data for the past period or of the adjacent area or scene 2 (say sd2) is spectrally modified through the application of DAMP. DAMP takes sd1 and LULC map (say LULC

map 1) developed earlier for scene 1 as inputs apart from sd2. DAMP algorithms are generated through the application of DAMP, which is used to modify sd2. The metric ôDAMP error, as expressed in equation 2.4, is used to optimize DAMP algorithms. Till the time optimization is reached, the modified sd2 is iteratively used as input, along with sd1 and LULC map 1, to produce the next modified sd2. Taking the modified sd2, the LULC map is generated by the same set of MAAP algorithms developed earlier through the application of MAAP. Sub-classes are clubbed to generate the final LULC map 2 corresponding to scene 2.

For the spectral modification, stratified random samples of pixels are generated from both the scenes of the present and the past periods. Each LULC class is taken as a stratum. The extent of each LULC class defines the entire population of pixels of that stratum. Pixels from this stratum are chosen randomly. Pixels from all other strata are chosen in similar manner.

Accurate geo-referencing of satellite data are highly desirable. Since DAMP is designed to modify DN values of all the bands taking into account the DN values of all the sample pixels of the past period and the corresponding pixels of the present period, extreme caution is expected so that both these pixels represent the same place on ground. The DN value modification would be erroneous if both the satellite data are not properly geo-referenced. Comparative geo-processing of the scene 2 may be done with respect to the scene 1 to overcome this difficulty.

To circumvent the problems of attaining high accuracy of geo-referencing, since it depends heavily on human skill and availability of accurate ground control points, sampling may be done in a constrained manner. Only those pixels are considered where neighboring pixels have the same LULC class. All the pixels of the moore neighborhood have the same LULC class as the one situated at the center. For this methodology 5*5, 3*3 and 1*1 moore neighbor can be taken. If there are not enough pixels in the 5*5 moore neighborhood, the program automatically selects the pixels having 3*3 moore neighborhood for the sampling process. The total number of pixels may be fixed for the sampling for each LULC class. The shortfall in the number of pixels in the 5*5 moore neighborhood may be taken up from the 3*3 moore neighborhood. Further shortfall can be addressed by taking subsequent moore neighborhoods having lesser neighbors.

The timing of the satellite data chosen for monitoring in regular manner has a strong bearing on the accuracy, especially in the tropics. This approach is premised on the fact that pixels would have the same DN values in any particular band over different periods if the times of satellite data capture are the same. The reflectance pattern from ground is composite of the reflectance from all the objects on ground. Apart from species, reflectance from vegetation is also dependent upon the timing of satellite data. Deciduous forests do not behave the same way as non-deciduous forests over the year. Since this approach modifies the spectral signatures that are used for the classification based on the MAAP algorithm, the difference in the reflectance due to the different timings over any

year is not accounted for. Hence the timings (eg month) of the satellite data for different periods (years) should be the same. This is extremely important especially in the tropics.

Atmospheric and radiometric corrections are not undertaken in this approach. DAMP produces algorithms that automatically take care of the difference in atmosphere, sun angle etc. The approach is based on the relative atmospheric or radiometric correction of the scene 2 with respect to scene 1.

The DAMP algorithm of each band is of single order and it modifies the DN values of pixels based on the means and the standard deviations of the DN values of pixels of both the satellite data corresponding to that particular band. Two statistical parameters, defined as óDAMP errorô and óDAMP error bandô, have been used to optimize the accuracy level of the spectral modification through the application of DAMP. DAMP produces DAMP algorithms that minimize the DAMP indices. DAMP error band is based on the variance of the difference between the DN values of both the reference satellite data and the spectrally modified satellite data for each band.

DAMP error band$_j$ = × × (ã variance$_{i, j, n}$) / ů$_{n, j}$ (2.3)

n i

DAMP error = (× DAMP error band$_j$) / n (2.4)

j

Where variance is taken for the i^{th} pixel of the j^{th} band corresponding to the n^{th} LULC class and ů is the standard deviation is for the j^{th} band corresponding to the n^{th} LULC class of the reference satellite data whose LULC map is already available. Altogether n DAMP algorithms are produced depending based on their respective optimum DAMP error bands.

The extreme sample pixels, in terms of their DN values, from each LULC class are excluded from the set of sample pixels based on the DAMP error bands. This is primarily done to address situation where any pixel due to actual change in LULC class for different time periods is not included in the spectral modification mechanism.

This mathematical program, an expert system, is extremely useful for repetitive assessments. DAMP produces the LULC maps at a rapid pace in an automated manner, since neither any training set is developed nor any radiometric correction is carried. The approach not only saves time but also saves resources since all the rigors of traditional approaches of image processing are totally avoided. This approach could be extremely useful for large areas.

The entire procedure is processed in a number of iterations. The modified satellite data, consequent upon the first iteration of DAMP, is taken as the input data for the next iteration. The second iteration of DAMP takes into account the first modified satellite data apart from the satellite data and the LULC map of the present period. This procedure

is recursively applied till the time the optimum level of accuracy is achieved. So, each optimum DAMP algorithm minimizes the DAMP error band of the corresponding band.

Full representation of all the LULC classes/sub-classes is desirable in generating the optimum DAMP algorithms. Since common overlapping areas are taken up from the LULC map 1, scene 1 and scene 2, such situations can not be ruled out where some LULC sub-class might not be either adequately represented. The accuracy of the spectral modification decreases with the decrease in the LULC sub-classes representation; but this strategy is robust and works even if some of the LULC sub-classes are not represented.

The entire approach is equally applicable for the image processing of the satellite data of the adjacent areas. All the 8 scenes adjacent to the central one can be classified by this methodology there by saving time and resources since all the procedures like development of training set and radiometric correction are totally avoided. This helps in rapid assessment of LULC.

Metrics for accuracy assessment

An entirely new approach has been developed to provide mechanism for the accuracy assessment of the LULC maps for the adjacent areas of the present period and for the same area of different periods. A new term, "DAMP accuracy", is used to assess the accuracy of the LULC maps. This may be illustrated by defining the following terms:

LULC 1 as the LULC map of the present period generated through the application of MAAP

accuracy 1 as the actual accuracy of LULC 1 based on ground verification

LULC 2 as the LULC map of the present period for an adjacent area generated through the application of MAAP and DAMP

accuracy 2 as the actual accuracy of LULC 2 based on ground verification

relative accuracy 21 as the accuracy of LULC 2 with respect to LULC 1 within the common area

minimum DAMP accuracy 2 as the minimum accuracy of LULC 2

LULC 3 as the LULC map of the past period of the same area generated through the application of MAAP and DAMP

DAMP accuracy 3 as the accuracy of LULC 3 generated mathematically

relative accuracy 31 as the accuracy of LULC 3 with respect to LULC 1 within the common areas

minimum DAMP accuracy 3 as the minimum accuracy for LULC 3

Ŭas the accuracy factor. This essentially measures how correctly the parameter, minimum DAMP accuracy, could represent the actual accuracy of the LULC map.

minimum DAMP accuracy 2 = accuracy 1 * relative accuracy 21 (2.5)

accuracy 2 = Ŭ* minimum DAMP accuracy 2 (2.6)

So, accuracy 2 = Ŭ* accuracy 1 * relative accuracy 21 (2.7)

minimum DAMP accuracy 3= accuracy 1 * relative accuracy 31 (2.8)

DAMP accuracy 3 = Ŭ* minimum DAMP accuracy 3 (2.9)

So, DAMP accuracy 3 = Ŭ* accuracy 1 * relative accuracy 31 (2.10)

So, DAMP accuracy 3 = (accuracy 2 / relative accuracy 21) * relative accuracy 31 (2.11)

The parameter, DAMP accuracy provides a good mechanism to assess the accuracy of the LULC maps. This is very helpful under those situations where ground verification can not be undertaken. These include the LULC maps of the past periods and for the adjacent areas that are inaccessible. The DAMP accuracy could be used for other areas if there is resource constraint or if accuracy assessment has to be done rapidly. This could also help in monitoring LULC.

DAMP is useful under the following 3 scenarios:

1. For DIP of satellite data for the present period for the adjacent areas: DAMP and MAAP may be used in conjunction and accuracy may be found either by undertaking the actual ground verification or by generating the DAMP accuracy. DAMP accuracy could be helpful in these areas, especially the inaccessible ones.

2. For DIP of satellite data for the past periods for the same area: DAMP and MAAP may be used in conjunction. DAMP accuracy could be extremely helpful in these areas, especially if there is no other reliable source of data for referencing.

3. For DIP of satellite data in future for the same area: DAMP and MAAP may be used in conjunction and accuracy may be found either by undertaking actual ground verification in future or by generating the DAMP accuracy. This could be very helpful for rapid monitoring of repetitive nature.

Simulation of LULC

Introduction

Although plans for managing LULC from the landscape perspective may be based on various parameters, those based on simulation technique could be the most appropriate and scientific. One point LULC map of the present period may be taken for the planning purpose, which may be the most simplistic case. Plans and mitigation measures may also be developed based on the trends in various LULC classes over a period of time. Trend could be established on the LULC maps of 2 or more periods. These methods might be simple but not very scientific in nature. Plans developed through the application of simulation technique, based on the LULC maps of the past and the present periods, are the most scientific ones. Several simulation techniques have been in use in the past (49, 86, 88).

Primarily these techniques are based on Cellular Automation (CA), Agent Based Modeling (ABM) and Multi-Agent simulation (MAS). Software like Geographical Modeling (GEOMOD), GEOMOD2 and SLEUTH (Slope, Landuse, Exclusion, Urban extent, Transportation and Hillshade), an urban simulation model, are based on CA (35, 36, 39, 47, 83, 85, 86). Variants of CA like constrained CA working independently (87) and countervailing CA working along with SLEUTH (40) have also been successfully applied. ABM has been applied by several authors (41), so has been MAS (49, 88).

Software like Land Use Dynamics Simulator (LIDAS) and LANDIS are based on MAS (37, 89).

Geospatial simulation techniques offers immense scope in developing such a model that can have forecasting ability based on which LULC could be optimally utilized. This could lead to scientific management so that optimum resources may be harnessed in future on sustainable basis. Simulating the emerging patterns of LULC can address this issue in most scientific manner, so that appropriate management strategies and policy interventions may be taken in time.

From the planning perspective, simulation may be used for managing various other aspects apart from LULC. Several studies have been undertaken for understanding the LULC dynamics (36, 48, 86). This technique has been applied in forestry (47) and urban areas (39). Many studies have focused on issues such as forest management (35) and shifting cultivation (87). Of late, there has been strong focus on ecosystem (37, 90), ecology (40) and environment (89). Social aspects too have been studied through the application of this technique (38, 41, 50, 60, 88).

Simulated LULC map and other related details could be the basis of scientific plan. Simulation technique can produce LULC maps of the future periods. A priori knowledge of the extent and location of different LULC classes for the future periods helps immensely in the decision making process. Information on the details related to the

impending loss of forests could help in taking appropriate measures in these areas. Information on the agents of change and their impacts helps in developing appropriate scientific plans in controlling the impacts.

All the agents of change that influence LULC should be taken into account while simulating LULC over time. Different agents of change have different potentials to change LULC. These may influence different LULC classes in positive or negative fashion. Agents of change, like human population, cattle population, tourism etc, have adverse impact on forests; where as forests have positive impact. Agents of change may be static or dynamic in nature. Agents like DEM, slope and aspect are static in nature, while human population and forest are dynamic.

The exact impact of all these agents of change may be precisely quantified from the landscape perspective through óscenario analysisö. Generally simulated LULC map for the future periods is generated by simulating the LULC maps of the present period assuming that the present trends in various agents of change continue in future too. Under scenario analysis, the trends in various agents of change are incrementally changed and the consequent simulated data for future periods is generated.

Scenario analysis proves to be such a Decision Support System (DSS) that helps in finalizing the policy interventions in a very effective manner. The agents of change may be ranked in terms of the severity of adverse impacts based on the scenario analysis.

Similarly, the agents of change may also be ranked according to the positive impacts. Prioritization of policy interventions may be done quite easily once the agents of change are ranked appropriately.

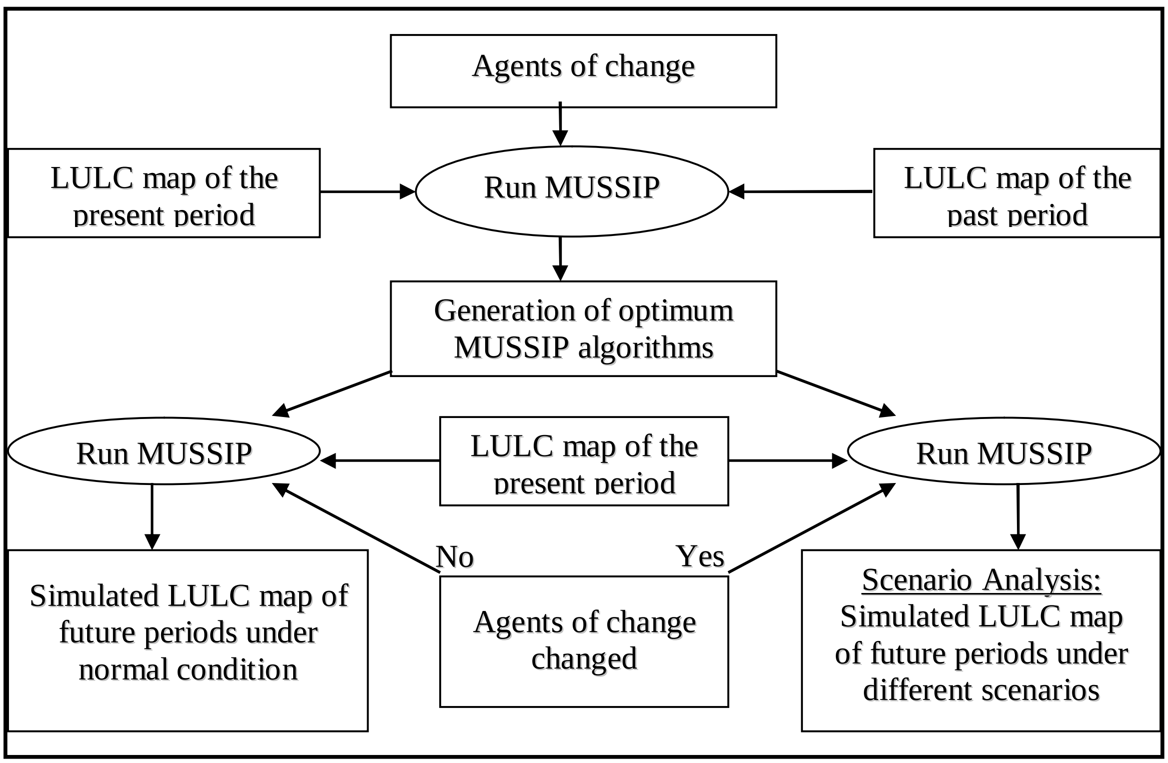
The simulated LULC maps, consequent upon the implementation of a set of policy interventions, could help develop precise goals through the application of scenario analysis. Agents of change may be effectively influenced, by adopting proper policy interventions, which in turn would influence LULC in the desired direction and extent. Such simulated LULC maps help immensely in quantifying the objectives for the planning purposes. Such bench marking also helps in monitoring process and evaluation of the plan implementation.

Multi-Stage Simulation Program (MUSSIP)

To address the issues related to simulation, as detailed above, MUSSIP, a mathematical program, has been developed to simulate LULC over time taking various agents of change into account. For simulation, LULC map containing different classes are taken corresponding to two time periods (say a base period and final period). Letôs call these base LULC and final LULC. Simulation on base LULC map over any time interval (final period ï base period) gives simulated LULC map that imitates the final LULC map.

MUSSIP generates a set of optimum algorithms (say MUSSIP algorithms) for different states of LULC. The algorithms contain a set of expressions for each attribute. The potential impact that each attribute may induce on the ecosystem is the fundamental building block of each expression, what is termed as potential. Expressions, incorporating these potentials, are used to produce the algorithms, which are the most significant step towards generating the model.

Figure 2.7. Flow diagram showing methodology of simulation



All the important agents of change that affect LULC should be taken into account while simulating LULC. The quantum of LULC change depends on the severity and type of agents of change. All the agents do not affect the ecosystem with equal force; but some

may be more harmful than others, while others may have positive effects too. Biotic factors like human population, cattle population etc; physical factors like slope, aspect etc; and environmental factors like forest cover, grasslands, water bodies etc, play important role in determining changes in LULC.

The following aspects are taken into account while simulating LULC.

Number of stages

The simulation technique adopted in MUSSIP is unique because simulation is done in stages by forming groups by grouping different LULC classes at different stages. At any stage, MUSSIP automatically forms different groups of classes and simulation is done for these groups rather than for classes. During the stage 1, 2 groups are formed by bifurcating the entire LULC classes for which the optimum solution is generated. After obtaining the optimum solution and the corresponding MUSSIP algorithm for this stage, one of these groups is automatically selected for the stage 2 and grouping of classes is done within that selected group by bifurcation. Again the optimum solution, along with the corresponding MUSSIP algorithm, is found for this stage. This process of group formation for the subsequent stages based on bifurcation of the selected group is repeated until each group is represented by an individual LULC class. Results from all the possible combinations of group formations are compared to figure out the best simulation and the corresponding set of optimum MUSSIP algorithms.

Number of iterations

The total time period, for which simulation has to be undertaken, is divided into a number of smaller time intervals called the number of iterations. Each simulation is undertaken for a given time interval. Simulation on the base LULC data for the number of iterations generates the final LULC data.The number of iterations can be mathematically expressed as

Number of iterations = Total time period / Time interval (2.12)

Decrease in time interval closely follows the natural phenomena which is desirable, but that immensely increases the time consumed for undertaking simulation. So a proper balance is always desirable. MUSSIP has the flexibility to choose the time interval.

Validation

In this approach there is hardly any calibration, rather MUSSIP takes into account all the possible MUSSIP algorithms that could have the best simulation result. The inbuilt mechanism helps in automatically rejecting inferior algorithms in the initial steps only, there by saving time.

The following 3 indices have been used for the validation of the simulated LULC maps.

1. Pixel-to-pixel accuracy

2. Kappa statistic

3. index_mussim_prelim (or index_mp), a new index created by the author, has been defined below:

index_mussim_prelim (or index_mp) =

[× (total pixels classified correctly as class k in the simulated LULC map/

total pixels classified as class k in the reference LULC map)]/number of classes (2.13)

A new index, index_mussip, has been created as shown below:

index_mussip = (index_mussim_prelim + pixel-to-pixel accuracy + kappa)/3 (2.14)

This index, index_mussip, is used to generate the optimum simulation.

Generation of the simulated LULC data

The simulated LULC data for the future periods may be generated by simulating the LULC map of the present period based on the optimum MUSSIP algorithms generated through the application of MUSSIP (see fig 2.6). The underlying assumption behind such a simulation process is the acceptance of the view that the past trends in various agents of change would continue in future too. The simulated data would have higher probability of capturing the real world situation or the emerging LULC data in future periods if index_mussip is high.

These simulated LULC data could serve as an effective DSS while finalizing the management strategies. Once the information regarding the geo-spatial changes in the LULC and the quantum of changes is generated, the most appropriate policy interventions may be devised accordingly. These policy interventions could prove to be the most effective and scientific.

Scenario analysis

Under scenario analysis, the trends in the agents of change are incrementally changed and the consequent simulated LULC data for the future periods are generated through the application of MUSSIP. Under normal circumstances, its assumed that the past trends in various agents of change would continue in future too. This assumption might not be true in the real world situation and the trends may change in future. This opens up innumerable possibilities about how the agents of change might behave in the future. There would be different LULC maps emerging in future corresponding to each such scenario.

These simulated data could serve as an effective DSS for recommending management prescriptions. Different policy interventions could influence the agents of change in different ways. This, in turn, would change the trends in the agents of change, which would, consequently generate the corresponding simulated LULC data. The policy intervention for influencing any particular agent of change that would have the desired effect on LULC in the future periods is preferred over the others. Similar policy

interventions for other agents of change may also be determined. This would lead to a set of policy interventions for all the agents of change that could generate the optimum simulated LULC data in an integrated manner.

Conclusion

The programs developed to address issues regarding the changes in the LULC over temporal horizon are unique regarding the following aspects:

1. All the programs are expert systems having artificial intelligence. All of these automatically generate a set of optimum algorithms that is best suited for the desired objectives. Multi-Algorithm Automation Program (MAAP) also provides the facility of prompting hints - when and how - to modify the training set so that the accuracy may be enhanced.

2. These programs are versatile so far as workability with different input data is concerned. MAAP and Data Automatic Modification Program (DAMP) work equally well with different number of bands and with different types of satellite data having similar, if not the same, resolution. The redundant bands are automatically left out during DIP if the number of bands or the specific bands is predefined by the user. Similarly, the type and number of input layers may also be varied while working with Multi-Stage Simulation Program (MUSSIP); the redundant layers are left out during simulation.

3. Purposely MAAP and DAMP have been developed to work in rapid, simple and cost effective manner. The preprocessing procedure is totally done away with. Development of the training set is just one time affair. This approach suits the monitoring of LULC, especially when it is repetitive in nature. All these programs are layered and generate algorithms sequentially one after another. The path of simulation (ie the sequencing of bifurcation of LULC classes) may also be predefined by the user while working with MUSSIP.

4. Many path breaking concepts have been incorporated in these programs. For the LULC maps of all the periods, except for the present ones, DAMP, in conjunction with MAAP, provides a metric for the accuracy assessment. This is extremely helpful for the past periods since there is no way to verify the ground conditions, as well as for the future periods where ground verification may be totally done away with saving time and resources. A new metric, based on a combination of indices, has been generated for the validation of the simulated LULC data.

CHAPTER 3

ASSESSMENT OF LULC AND LULC CHANGE IN MANAS TIGER RESERVE, ASSAM, INDIA

Abstract

Deforestation, degradation and fragmentation have been major concerns in the Manas Tiger Reserve, an area of 2837.12 sq km, situated in Assam district of India. The Manas Tiger Reserve is a part of the Eastern Himalaya biodiversity hotspot, and an UNESCO World Biodiversity Heritage Site. I assessed land cover and land use change using new two state-of-art geo-spatial programs that I developed to determine the extent of deforestation and changes in various types of land classes.. Based on satellite data, Multi-Algorithm Automation Program (MAAP) was used to produce the LULC map of 2004; MAAP in conjunction with Data Automatic Modification Program (DAMP) was used to produce the LULC maps of 1990 as well as for the adjacent scenes of 2004. Altogether 8 MAAP algorithms were generated for the LULC classification by MAAP for the scene 1 and 4 DAMP algorithms, one each for the 4 bands, were generated by DAMP for rest of the 2 scenes. The change map for the period 1990-2004 revealed that due to anthropogenic pressure the total green cover, including forests and Grassland, decreased 4.32%, from 1907.57 sq km to 1825.09 sq km; the total forest deceased 5.78%,

from 1588.79 sq km to 1497.01 sq km; and water decreased substantially (23.72%) from 50.01 sq km to 38.15 sq km, where as Grassland increased 2.92%, from 318.78 sq km to 328.08 sq km, primarily at the expense of forests. This approach at landscape level could facilitate conservation planning and mitigation measures in the face of rapid LULC changes.

Introduction

Over the last 300 years (from 1700 to 1990), land use and land cover has changed significantly (1). In the recent times, forests in particular have come under tremendous pressure (54, 55, 91). Globally the rate of forest loss was 7.3 million hectare per year during the period 2000-2005 (2). Similarly the forest loss in the earlier decades was 8.9 and 8.6 million hectares per year in the 1990s and 1980s respectively (2, 3). Urbanization, development, conversion of land to agriculture, invasive species, and ultimately misguided policies and poor governance are significant drivers of LULC change (4). India, too, has seen widespread changes in LULC, especially in the forest areas. The Ministry of Environment and Forests, Government of India has estimated that huge areas of forests have been converted to non-forest areas: 4.37, 0.52, 0.14, 0.07 and 0.06 million hectare of forests have been lost due to cultivation, river valley projects, industries and townships, encroachment, and transmission lines and roads respectively since Indian independence in 1947 (5). Although the forests in India have shown net increase of 728 sq km during the period 2004-2006, significant decrease of 936 sq km in very dense forests is testimony to the extensive degradation of forests (8, 92). Significant

losses in forests have taken place in Nagaland, Andhra Pradesh, Arunanchal Pradesh, Tripura and Assam, and forests have increased significantly in Mizoram, Manipur, Jharkhand, Meghalaya and Orissa (8).

Protected areas, that have increased more than 110% in number and 53% in area from 1992 to 2003, have failed to provide much immunity from such vulnerability to changes in LULC (26). Devoid of proper infrastructure and resources, these ópaper parksô have continued to be adversely affected by agricultural conversion, human settlements and other developmental factors (26). Encroachment and logging have been the most critical immediate threats according to a study done in 200 PAs around the world (26). For example, within the Gunung Palung National Park in West Kalimantan, Indonesia, the annual rate of deforestation has risen to 9.5% since 1999, and deforestation has claimed almost 75% of the buffer (55).

There have also been changes in LULC within PAs in India, but these have not been properly documented and analyzed. In India, there are altogether 668 PAs - 99 National Parks, 523 Wildlife Sanctuaries, 43 Conservation Reserves and 3 Community Reserves - occupying 158,745 sq km which is 4.83% of the total geographic area of the country and 22.98% of the total forest cover (16). Additionally there are 39 tiger reserves, 15 Biosphere Reserves and several Reserved Forests. The study done in 28 tiger reserves showed that the forests decreased by 0.31% or 94 sq km during the period 1997-2000; out of these, 11 reserves have shown decrease in forest cover, 6 reserves have shown

marginal increase while there was no change in the other reserves (28). A study of forest cover in the 6 BRs revealed that the forests decreased by 172 sq km or 1.6% during the period 1991-1999 (29).

The north-eastern region in India has exceptionally high biodiversity and endemicity, but as compared to other parts of India, the rate of deforestation is also high; Nagaland and Tripura had 81.21% and 76.99% of their respective geographic areas under forest, and their respective rates of deforestation was 0.74% and 0.61% per year during 2004-2006 (8). However, there are limited data on LULC change in the PAs in the north-eastern region (93). During 1990-1998, the forests decreased by 6.91% or 196 sq km in Manas Biosphere Reserve (29) and during 1977-2006, forests and grasslands decreased 7.86% and 4.13% respectively in Manas National Park (94). The annual rate of deforestation was 1.38% during the period 1994-2002 for Kameng and Sonitpur Elephant Reserves in the north-eastern India (23).

The present study undertaken in MTR is more exhaustive and systematic, and is aimed at overcoming the limitations of the previous studies. The entire study has been done using new programs that have proved to be extremely efficient, accurate and cost-effective. Not only has the accuracy level increased, but the metrics used for ascertaining accuracy of the LULC maps is also extremely helpful for the past period and for the inaccessible areas of MTR, which really prohibit any ground verification. Two studies done by the Forest Survey of India (FSI), Dehradun, India for the periods 1990-1998 and

1997-2002 did not assess either water or grassland. The possibility of grassland being classified by FSI as forest or as Non-Forest can not be ruled out. Another study confined to the core area for 1998-2006 did not assess forests into different canopy density classes. Appropriate restoration and conservation plans for the reserve could only be made by generating robust database by undertaking studies like the present one that addresses all the issues of deforestation, degradation and change in grasslands, water and other non-forest areas for the whole tiger reserve.

Objectives

The following are the objectives of the study in MTR:

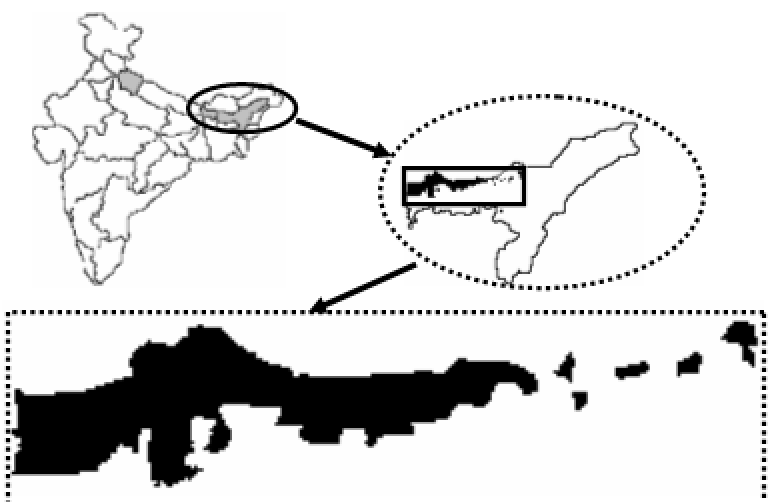
- Use of new method for rapid assessment of LULC of the present period (2004)
- Use of new method for rapid assessment of LULC of the past period (1990) by using LULC of the present period
- Assessment of change in LULC for the given time interval (1990-2004)

Study area

MTR, a part of the Eastern Himalaya biodiversity hotspot, has a special status in Indiaŝ protected are network because the area is designated as a UNESCO World Biodiversity Heritage Site due to rich biodiversity and high endimicity. The northern boundary of the park is contiguous with Royal Manas National Park of Bhutan. Reserve forests flank both the eastern and western sides. The area across the southern boundary is degraded and merges into lands that are cultivated for agriculture and tea.

Situated in Assam, a north-eastern state in India, MTR is also a biosphere reserve. MTR has total geographic area of 2837.12 sq km comprising of 519.77 sq km of core area and 2317.35 sq km of buffer area. The site lies between latitude 26° 29′ N and 26° 55′ N and longitude 89°51′ E to 91° 56′E. It is the core area that has the status of national park, the core zone of Chirang Ripu Elephant Reserve, and the UNESCO World Biodiversity Heritage Site. The reserve derives its name from river Manas, which flows into the reserve from the hills of Bhutan.

Figure 3.1. Location map of Manas Tiger Reserve, Assam, India



Altogether 513 species of plants have been recorded in the tiger reserve and 21 species of mammals, many of which are endangered (95). Forests are dense with thick under story. Grasslands, interspersed among forests, comprise 46.44% of the national park (93). Grasslands and the eco-tone with the forests are very important for the survival

of wildlife, especially the tigers, since these provide excellent conditions for habitat and food availability.

Methodology

Details regarding the satellite data used and the methodology adopted for rapid assessment of LULC are described below:

Satellite data

Multi-spectral Indian Remote Sensing (IRS), Linear Imaging Self Scanning (LISS) satellite data, IRS P6 - LISS 3, with a resolution of 23.5 m was used for the LULC classification for the present period (2004). All the 4 bands were taken into consideration during DIP. Multi-spectral LANDSAT, Thematic Mapper (TM) satellite data with a resolution of 30 m was used for the LULC classification for the past period (1990). Source of this data was the Global Land Cover Facility (http://glcf.umiacs.umd.edu). For carrying out DIP, bands 2, 3, 4 and 5 were stacked and resampled so that the resolution becomes the same as that of IRS-LISS data. Except accurate geo-referencing, no other preprocessing operation was undertaken for the satellite data. Table 3.1 details the scenes of satellite data used in this study.

Table 3.1. Details regarding satellite data for 2004 and 1990 for MTR

Period	Scene no	Path/Row	Date
Present	1	109/053	Nov 06, 2004
	2	110/052	Dec 29, 2004
	3	110/053	Dec 29, 2004
Past	1	137/041	Nov 07, 1990
	2	138/041	Nov 14, 1990
	3	138/042	Nov 14, 1990
	4	137/042	Nov 26, 1990

Classification scheme

The LULC maps, designed to be generated in this study would comprise of LULC classes like Forests, Grassland (GL), Water (WA) and Non-Forest (NF; excluding water). Forests would be further classified into Very Dense Forest (VDF; having canopy density more than 70%), Dense Forest (DF; having canopy density between 40% - 70%) and Open Forest (OF; having canopy density between 10% - 40%).

Training set

Training sets, generated by undertaking extensive ground work, were representative, complete and non-redundant. Representative pixels were selected on ground for all the LULC classes. Pixels whose DN values matched in different bands were dropped from the training set since they were considered as redundant. Later on training set was

modified gradually and pixels corresponding to Sub-classes were also included. Although perfect accomplishment of all these criteria was a difficult task, utmost care was taken because accuracy of the LULC assessment depended heavily on the training set data. The training set was modified through the application of MAAP during the course of DIP. The statistical parameter that measured the spectral overlap or separation between the training set LULC classes, acting as the artificial intelligence of MAAP, provided the necessary feedback while developing the training set. Training set classes, for which the condition of overlap persisted, were fragmented. The training set, which comprised of 6 classes initially as per the classification scheme, was gradually modified based on the feedback during the course of DIP through the application of MAAP. Finally the training set comprised of 9 classes/sub-classes (CSCs) after splitting Non-forest into 4 sub-classes (NF1, NF2, NF3 and NF4).

Programs used for Digital Image Processing

The 2 programs, MAAP and DAMP, developed by the author were used for this purpose. MAAP was used to generate the LULC map as per the modified classification scheme for the scene 1 of the present period. DAMP, in conjunction with MAAP, was used to produce the LULC map for rest of the scenes of the present and the past periods.

For the scene 1, MAAP was run to generate 8 MAAP algorithms that sequentially generated the LULC map comprising of all these 9 CSCs. For each MAAP algorithm, the assessment of LULC for each pixel was done by comparing the separation value and the

algorithm value as explained in chapter 2. The MAAP algorithm 1, the separation value 1 and the separation index 1, generated for the scene 1, have been produced below. The symbols - v1, v2, v3 and v4 corresponding to the DN values of any pixel of bands 1, 2, 3, and 4 respectively - have been used for this purpose.

MAAP algorithm 1 =

[[{v1*(1)}+{v2*(1)}+{v3*(1)}+{v4*(0)}] * [{v1^(0)}+{v2^(0)}+{v3^(0)}+{v4^(0)}]] / [[{v1*(-1)}+{v2*(-1)}+{v3*(0)}+{v4*(0)}] * [{v1*(-2)}+{v2*(-2)}+{v3*(1)}+{v4*(-1)}]] (3.1)

Separation value 1 = 0.0417; Separation index 1 = 0.2309 (3.2 & 3.3)

For stage 1, all the CSCs were taken into consideration. The CSCs (GL, WA, NF1, NF2, NF3 and NF4) having algorithm values less than the separation values and the CSCs (VDF, DF and OF) having algorithm values greater the separation values were separated from each other. The same methodology was applied for the rest of the 7 MAAP algorithms. The LULC map was generated by undertaking DIP on this scene according to these MAAP algorithms. The areas within MTR were masked out later.

The satellite data of the adjacent scene 2 of the present period was spectrally modified through the application of DAMP so that the same set of MAAP algorithms generated earlier could be used for generating the LULC map. For this purpose, common areas of

the 2 satellite data (of the scenes 1 and 2) and the corresponding LULC map of the scene 1 comprising of 9 CSCs were masked out.

Depending on these data, DAMP algorithms were generated by DAMP for modifying the DN values of the satellite data for all the bands of the scene 2. For band 1 the DAMP algorithm 1, rm1, the ratio of the means of the scenes 1 and 2, and rsd1, the ratio of the standard deviations of the scenes 1 and 2 have been produced below. The symbol pv1, corresponding to the DN value of any pixel of the band 1, has been used for this purpose.

DAMP algorithm 1 =

$$[-9 + pv1] * [1 + 1 * rm1 + 1 * (rm1 \wedge 2)] * [1 + 2 * rsd1 - 2 * (rsd1 \wedge 2)] \tag{3.4}$$

$$rm1 = 1.13245; \qquad rsd1 = 1.24772 \qquad (3.5 \;\&\; 3.6)$$

After generating all the 4 DAMP algorithms by applying DAMP, the satellite data of the scene 2 was spectrally modified through the application of DAMP based on these DAMP algorithms. The satellite data of the scene 3 of the present period and all the 4 scenes of the past period were spectrally modified similarly through the application of DAMP.

The LULC maps were generated by undertaking DIP on these modified scenes according to the MAAP algorithms generated earlier through the application of MAPP on the scene 1 of the present period. The areas within MTR were masked out later. All the

Non-Forest sub-classes were clubbed together to produce the LULC maps comprising of 6 LULC classes in accordance with the original classification scheme.

For the scenes 1 and 2 of the present period, accuracy assessment was based on ground verification. For rest of the scenes of the present and the past periods, it was found by using a new method, which was based on a new method based on the formula:

accuracy y = Ǔ* accuracy x * relative accuracy (3.7)

The accuracy has been assessed by ground thruthing for the scene 1 of the present period (2004) LULC map and by the metrics for accuracy for all other scenes of the present as well as past periods as explained in chapter 2. The terms used in the above formula, which has been copied from equation 2.10, have been defined: óaccuracy xô as the accuracy of the LULC map of the scene x (say map x) whose accuracy assessment was based on ground verification; óaccuracy yô as the accuracy of the LULC map of the scene y (say map y), which was spectrally modified with the help of scene x and whose accuracy assessment was based on the new method; órelative accuracyô as the accuracy of the LULC map of the scene y relative to the LULC map of the scene x within the common area; and óǓô as the accuracy factor. For finding out the value of Ǔ, the accuracy based on the ground verification was used for óaccuracy yô corresponding to the scene 2 of the present period.

Since Ŭ, the accuracy factor, is an important parameter in finding out the accuracy, it should be found with utmost care otherwise there is chance of error. Instead of using the value of Ŭ from just one set of maps, an average value of Ŭ obtained by using adjacent scenes would decrease the chance of error. The accuracy factor is highly dependent on the local conditions of ground, so this should not be used for scenes that are distant from scene x. All the pixels in map y that do not match with map x are left out and treated as wrong classification, which may not always be true. In other words, pixels wrongly classified in map x and having mismatch with map y would mean that they might have been correctly classified. Yet those pixels are not included in the correctly classified category for the simple reason that there is no way out to ascertain the veracity. Hence, the accuracy found by this method is the most conservative calculation, actual accuracy may be higher.

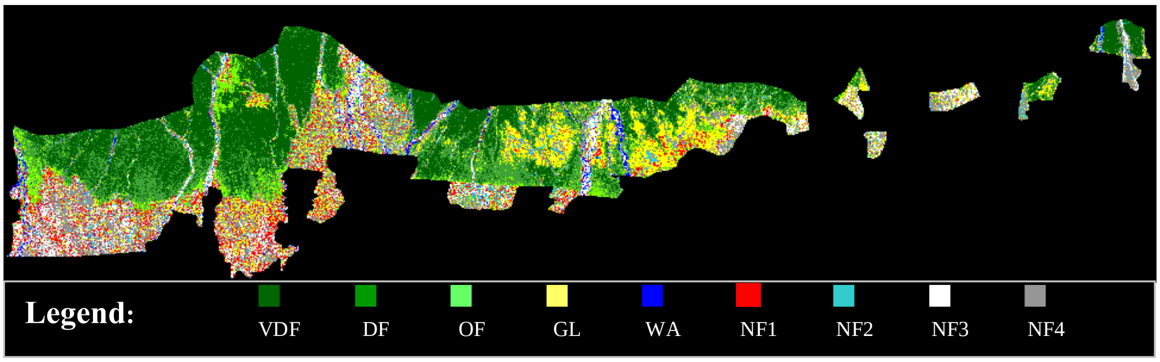
Results

Rapid assessment of LULC for 2004

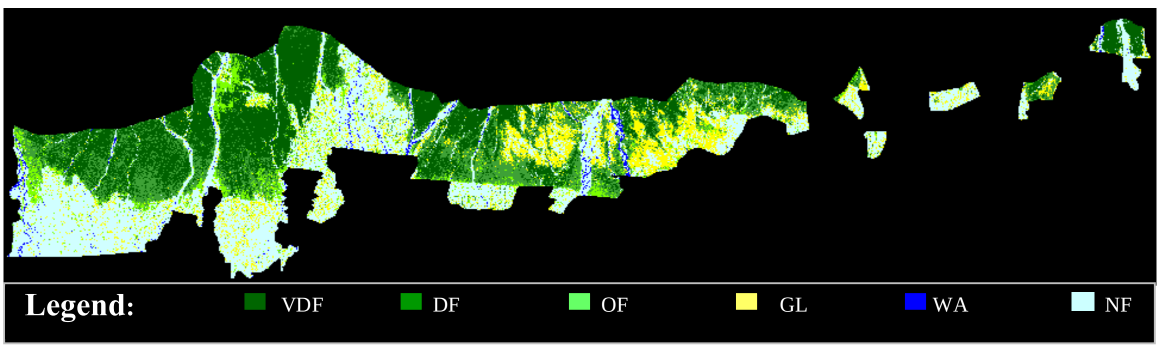
The LULC maps comprising of 9 Classes/Sub-Classes, according to the modified classification scheme, and of 6 classes, according to the original classification scheme, were generated by mosaicing the corresponding LULC maps of all the 3 scenes of 2004 that cover the entire tiger reserve (figure 3.1). The overall accuracy was 91.12%, which was taken as the weighted average of the accuracies (91.23%, 90.58% and 89.24%) of the LULC maps corresponding to the 3 scenes.

Figure 3.2. Top to bottom for MTR for 2004: (a) LULC map comprising of 9 classes/sub-classes and (b) LULC map comprising of 6 LULC classes

a



b



The following groupings of classes (say Class Groups), have been defined to analyze the results on the LULC maps of the 2 periods and the corresponding change map: Total Green Area (TGA) has been taken as VDF + DF + OF + GL, Total Forest Area (TFA) as VDF + DF + OF, Total Non-Green Area (TNGA) as NF + WA and Total Non-Forest Area (TNFA) as NF + WA + GL.

In 2004, Total Green Area in MTR, which includes Forest and Grassland, was 64.33%; Total Forest Area, with the figure of 52.77%, was more than half the area of the tiger reserve; and forests having canopy density more than 30%, which includes Very Dense Forest and Dense Forest, was 46.99%.

The northern regions of the tiger reserve had more forests than the southern regions. Grasslands were confined mostly in the central regions; both the flanks on the left and the right had less Grassland. Within Total Green Area, Very Dense Forest constituted 44.65% followed by Dense Forest, which constituted 28.39%. Grassland accounted for 17.98%, while Open Forest was very less (just 8.98%). Within Total Forest Area, Very Dense Forest and Dense Forest accounted for 54.44% and 34.61% respectively. Both of these accounted for 89.05% of Total Forest Area, while Open Forest accounted for just 10.95%.

Total Non-Forest covered 35.67%, including 34.33% Non-Forest and 1.34% water. Within Total Non-Forest, Non-Forest and Water accounted for 96.23% and 3.77% respectively. The biggest LULC class was Non-Forest, which included human inhabitations, agriculture, roads and other built up areas.

Table 3.2. Areas figures and percentages of LULC classes in 2004 and 1990 for MTR

Sl. no.	**LULC class**	**1990**		**2004**	
		Area (sq km)	**% wrt area of MTR**	**Area (sq km)**	**% wrt area of MTR**
1	Very dense forest (VDF)	934.49	32.94	814.99	28.73
2	Dense forest (DF)	532.96	18.79	518.1	18.26
3	Open forest (OF)	121.34	4.28	163.92	5.78
4	Grassland (GL)	318.78	11.24	328.08	11.56
5	Water (WA)	50.01	1.76	38.15	1.34
6	Non-forest (NF)	879.53	31.00	973.89	34.33
Total		**2837.12**	**100.00**	**2837.12**	**100.00**

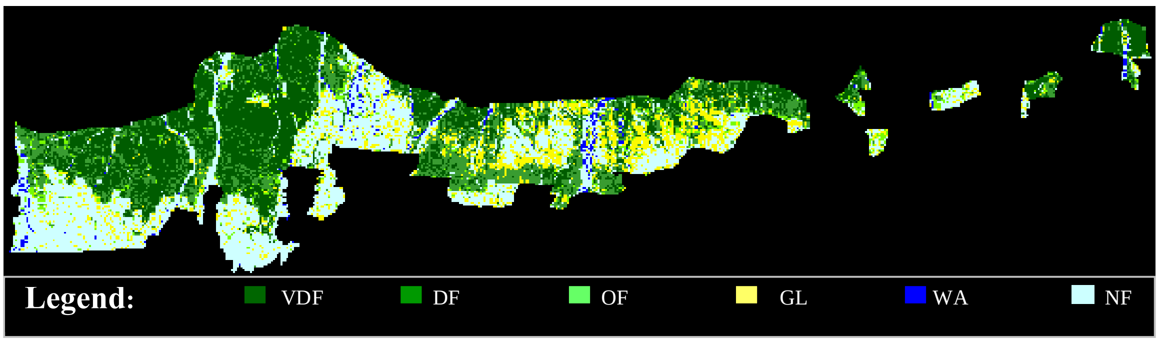
wrt: with respect to

Rapid assessment of LULC for 1990

Similar LULC maps were generated for 1990 by mosaicing the 4 scenes of that period (figure 3.3). The overall accuracy was 89.67%, which was taken as the weighted average of the accuracies (89.61%, 89.79%, 90.34% and 89.06%) of the LULC maps corresponding to the 4 scenes.

MTR had excellent forest and grassland in 1990. Total Green Area, which included forest and Grassland, was 67.24%, Total Forest Area was 56.00%, and forests having canopy density more than 30%, which included Very Dense Forest and Dense Forest, was more than half the area of the tiger reserve with the outstanding figure of 51.72%.

Figure 3.3. LULC map of 1990 for MTR



Not only was the area under forests very high in the tiger reserve, the density was also excellent. Within Total Green Area, Very Dense Forest constituted 48.99% followed by Dense Forest, which constituted 27.94%. Grassland accounted for 16.71%, while Open Forest was extremely less (just 6.36%). Within Total Forest Area, Very Dense Forest and Dense Forest accounted for 58.82% and 33.55% respectively. Both of these accounted for 92.36% of Total Forest Area, while Open Forest accounted for just 7.64%.

Total Non-Forest covered 32.76%, including 31.00% Non-Forest and 1.76% water. Within Total Non-Forest, Non-Forest and Water accounted for 94.62% and 5.38%

respectively. Non-Forest was next only to Very Dense Forest among all the LULC classes.

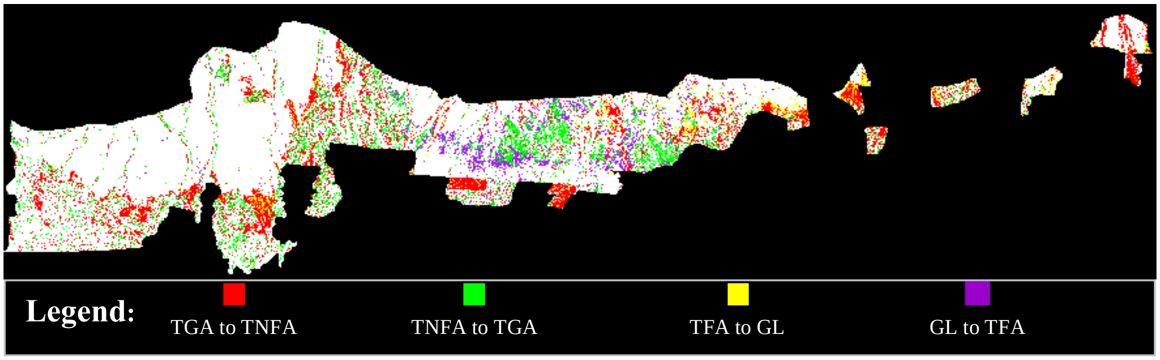
Assessment of change in LULC for 1990-2004

The LULC change map for the tiger reserve was generated for the period 1990-2004 by overlaying the LULC map of 2004 over the LULC map of 1990. The change map comprised of 36 classes since the LULC maps for both the periods had 6 LULC classes.

To enhance the visual effect, the LULC change map, comprising of 4 classes, was also generated with the LULC maps of 1990 and 2004 after formation of 3 groups of classes consequent upon clubbing the similar LULC classes (figure 3.4). The groups included for this purpose were Total Forest Area, Grassland and Total Non-Forest Area.

The data regarding the LULC change map for 1990-2004 revealed that there was marked deterioration in the tiger reserve. The Total Green Area decreased by 4.32% or 82.48 sq km during this period, which was 2.91% of the total area of the tiger reserve. Total Forest Area had even more alarming figures as it went down 5.78% or 91.79 sq km during the 14 years, which was 3.23% of the total area of the tiger reserve.

Figure 3.4. LULC change map for 1990-2004 showing 4 classes for MTR



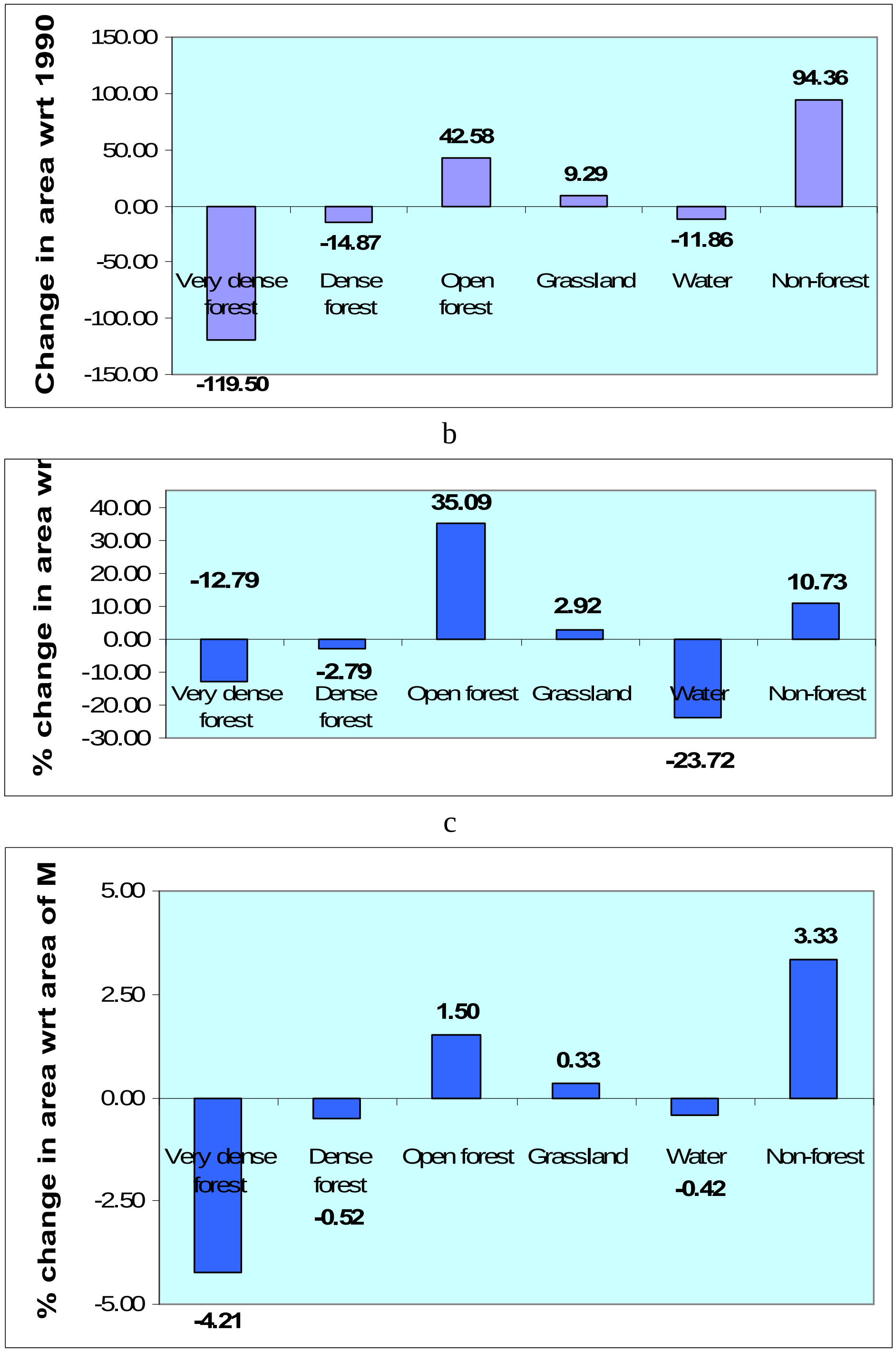
TGA: Total Green Area (VDF + DF + OF); GL: Grassland

TFNA: Total Non Forest Area (WA + NF)

The forests had degraded considerably over this period, which is clear by the figures on the loss of forest having higher canopy density. Very Dense Forest faced the most severe brunt as it decreased 12.79% or 119.50 sq km within just 14 years. This was 4.21% of the reserve area. Dense Forest too has gone down, but to a lesser extent. The loss in Dense Forest was 2.79% or 14.87 sq km, which was 0.52% of the total area of the tiger reserve. Open Forest, on the other hand, increased primarily due to conversion of Very Dense Forest and Dense Forest into Open Forest. The increase in Open Forest was a whopping 35.09% or 42.58 sq km, which was 1.50% of the reserve area.

Figure 3.5. Top to bottom for LULC change during 1990-2004 for MTR in terms of: (a) Area, (b) Percentage wrt 1990 and (c) Percentage wrt the total area of MTR

a



On the other hand areas devoid of vegetation had shown increase in area pointing to the fact that areas under vegetation has turned into non-vegetation. Total Non-Green Area and Total Non-Forest Area, which behaved exactly in the opposite manner with Total Green Area and Total Forest Area respectively, increased 8.88% or 82.48 sq km and 7.35% or 91.8 sq km respectively during this period. Non-Forest showed marked increase in area. It increased by 10.73% or 94.36 sq km, which was 3.33% of the area of the tiger reserve.

Table 3.3. Area figures and percentages of LULC change during 1990-2004 for MTR

Sl. No.	**LULC class**	**Area for 1990 (sq km)**	**Area for 2004 (sq km)**	**Difference in area for 1990-2004**		
				Area (sq km)	**% wrt 1990**	**% wrt area of TR**
1	Very dense forest	934.49	814.99	-119.50	-12.79	-4.21
2	Dense forest	532.96	518.10	-14.86	-2.79	-0.52
3	Open forest	121.34	163.92	42.58	35.09	1.50
4	Grassland	318.78	328.08	9.30	2.92	0.33
5	Water	50.01	38.15	-11.86	-23.72	-0.42
6	Non-forest	879.53	973.89	94.36	10.73	3.33

Grassland increased and Water decreased during this period. Grassland showed lots of flux across other LULC classes. The net increase in Grassland was 2.92% or 9.30 sq

km, which was just 0.33% of the reserve area. This was largely at the cost of forest areas, but some Non-Forest areas also turned into Grassland. Loss in Water was a serious concern. Water went down by 23.72% or 11.86 sq km, which was 0.42% of the area of the tiger reserve. Rivers changed their course in a big way at many places.

Table 3.4. Area figures and percentages of class groups for LULC change during 1990-2004 for MTR

LULC class group	**Area for 1990 (sq km)**	**Area for 2004 (sq km)**	**Difference in area for 1990-2004**		
			Area (sq km)	**% wrt 1990**	**% wrt area of TR**
Total Green Area	1907.57	1825.09	-82.48	-4.32	-2.91
Total Forest Area	1588.79	1497.01	-91.78	-5.78	-3.23

The LULC change maps pointed several disturbing trends. During the period 1990-2004, Total Green Area deteriorated considerably in the tiger reserve. Forests degraded, Water decreased and Non-Forests increased. Forests, in general, deteriorated over these years, but it was more glaring on the southern fringes of the tiger reserve. This was primarily due to the decrease in Very Dense Forest and Dense Forest. Forests turned into grassland and there was increase in Total Non-Forest Areas. The southern edges of forests were completely wiped out at several places.

Discussion

The new programs to assess LULC have generated an accuracy of 91.12%, which is better than most of the similar studies in India. Accuracy of 88% was reported for the studies for 2000 for Mahananda Wildlife Sanctuary and the adjoining Baikunthapur Reserve Forest, West Bengal, India wherein only 3 LULC classes were delineated as against the 6 LULC classes in this study (96). The LULC assessment in the Western Ghats in India for 1995 had an accuracy of 80.54% (99) and the one done in the Central Himalayas for 1998 had an accuracy of 80% (97). Accuracy level of 82.15% was obtained in another study for 1998 in the north-eastern India (98). Many studies do not even report the accuracy level! The metrics used for ascertaining accuracy of the LULC maps is extremely helpful, especially when conditions really prohibit ground verification or when accurate and reliable reference data are not available. The approach was particularly useful for the inaccessible areas of the reserve and for the past periods. Rapid assessment in a true sense, except geo-referencing pre-processing for various regions was discarded; even the training sets were not developed for the subsequent scenes. Monitoring of LULC thus can be very rapid and cost-effective.

According to the data generated at national level by the FSI, MTR had excellent forests, both in terms of coverage and density. For 2004, the Total Forest Area in MTR (52.77%) was way beyond the national figure of 21.00% according to FSI (92). Additionally Grassland (11.56% of MTR), which is so important from the biodiversity perspective, has never been assessed by FSI. The possibility of Grassland being classified

by FSI as forest or as Non-Forest can not be ruled out. In stark contrast to the pervasive extent of degradation in India, forest in MTR was in good health. Within Total forest Area, Very Dense Forest, Dense Forest and Open Forest comprised 54.44%, 34.61% and 10.95% respectively for MTR, while the corresponding figures were 12.09%, 46.17% and 41.74% for India according to FSI (92).

During 2000-2005 the annual deforestation rates for humid tropical forests of the world were 0.10%, 0.26%, 0.28% and 0.36% respectively for Africa, Asia-Oceania, Central America and South America (91). By contrast, in India, natural forests, decreased at the rate of 1.50 to 2.7% per year during 1990-2000 (101), and Total Forest Area increased at the rate of 0.05% during 2004-2006 (SFR2005, SFR2009). Forest loss in the Western Ghats was 1.16% per year during 1997-1995 (99), while in the Himalayas within India; the figure was 0.82% per year during 1990-2000 (100). However, the deforestation rate in Kameng and Sonitpur Elephant Reserve in the north-eastern India was 1.38% per year during 1994-2000 (23). The annual deforestation rate in MTR, 0.41% (or 6.56 sq km per year) during 1990-2004 is much less, but we have to keep in mind that MTR is a protected area. Some studies have also reported increase in natural forests. For example in nearby, Mahananda Wildlife sanctuary, the forests increased at the rate of 0.99% per year during 1990-2000 (96).

Other studies on MTR confirm the observed rates of deforestation. One study confined to the core area, where forests were treated as one class and not classified into

different density classes, reported an annual deforestation rate of 0.02% during 1977-1998 and 0.46% during 1998-2006 (94). Two studies, which did not assess Water and Grassland, were done by FSI where the annual deforestation rate was 0.86% and 0.14% for the periods 1990-1998 (29) and 1997-2002 (28) respectively. FSI further reported decrease of 0.08% per year in Total Dense Forest and increase of 0.17% per year in Total Non-Forest Areas during 1997-2002 (28); whereas the decrease in Total Dense Forest was 0.65% per year and the increase in Total Non-Forest Areas was 0.53% according to the present study.

The southern region of the tiger reserve has undergone major deforestation which is close to human inhabitations, while the northern region has largely remained intact due to absence of population pressure, since Royal Manas National Park in Bhutan, lying across the boundary is well protected. Thus, anthropogenic pressure, apart from other natural causes, had been the most significant driver of change in MTR. A separatist movement during the 1990s aimed at carving out a new state from within Assam (95) is assumed to be responsible for loss of forests. . Large tracts of forest were clear felled during this period. Illicit felling and encroachment have also resulted in deforestation and degradation of the reserve (28, 94, 95). Presence of 1 village in the core area and of 57 surrounding villages subjects the reserve to tremendous pressure (95). Changing course of rivers, as clearly observed in this study, further aggravated this problem, although with a lesser magnitude.

The study that was done in the core area of MTR confirms the increase in Grassland, and decrease in Non-Forest and Water. Compared to the annual figures for MTR, where Grassland increased 0.21%, Non-Forest increased 0.77% and Water decreased 1.69% during 1990-2004, the study in the core area showed decrease of 0.56%, increase of 7.06% and decease of 3.15% in the respective LULC classes during the period 1998-2006 (94). Grassland was in a state of flux across other LULC classes, but the net increase was primarily due to Non-Forest converting into Grassland. Although the flux in Grassland was observed all over the reserve, gains were observed predominantly within and on the eastern regions of the core area, which is almost centrally located in the reserve. The increase in grasslands has positive impacts on wildlife, since grasslands, occurring largely on alluvial plains around rivers, provide food to the ungulates on which carnivores, including tigers, prey upon; but unfortunately grasslands have been colonized by invasive species like *Eupatorium sp., Melastoma sp.* and *Lea sp*. (94). The severe loss of water (23.72%) during these 14 years is detrimental to the wildlife. Rivers have changes their course and have also dried up. The most important river, Manas, entering from Bhutan on the north and flowing southwards across the core area of the reserve, has shown severe loss of water. The vacant areas, which were clear-felled during the agitation, may have been occupied by grasslands. Areas from water bodies have been taken over by Grassland: nearly 18.48% of the net increase is attributed to grasslands occupying such areas that were covered by water in 1990. Climate change and the loss in glaciers in the Himalayas, that feed the rivers of this region, might be the reason for the severe loss in water and drying up of rivers.

The tiger reserve needs urgent restoration measures and effective conservation planning to address the problems of deforestation, severe degradation and immense loss of water. Reducing anthropogenic pressure should be a priority. The forest department needs to monitor pressure points, particularly along the southern boundary of the reserve, and identify steps to mitigate these pressures by working with local communities. The impact of villages around the reserve on biodiversity should be examined, and the ways to reduce these impacts should be devised by working with local communities.

Conclusion

In absence of any appropriate long term monitoring plan, no scientific management plan could be conceived, even if conceived can not work successfully. Vital data on pertinent parameters, including forest and grassland, on even extremely important Protected Areas, including Tiger Reserves, Elephant Reserves and Biosphere Reserves, and biodiversity hotspots in many of the tropical forests, are missing either completely or are not on suitable temporal and spatial resolution. Resource constrains, inaccessibility of the study area and inability to accurately determine the accuracy of the LULC maps of the past periods refrain any serious attempt in the desired direction of developing scientific database. These constraints have been successfully addressed by generating the LULC maps of the past and the present periods and the LULC change map for the intervening period through the application of the state-of-art programs, Multi-Algorithm Automation Program and Data Automatic Modification Program. The accuracy metrices embedded in this artificially intelligent program, Data Automatic Modification Program,

have the ability to ascertain the statistical precision of the LULC map for different time periods that opens up new vistas to regularly monitor our forests in general and Protected Areas in particular in a very cost-effective manner by totally avoiding any ground verification of the area. Based on the rapid assessment of LULC and LULC change through the application of these programs, focused study on the location and extent of habitat loss and fragmentation could help develop appropriate management strategy in Protected Areas since this would help to understand the underlying causes and consequences.

CHAPTER 4

ASSESSMENT OF LULC AND LULC CHANGE IN RAJAJI NATIONAL PARK, UTTARAKHAND, INDIA AND SIMULATION IN UTTARAKHAND, INDIA

Abstract

The anthropogenic pressure, on the Shivalik range in India adjacent to the Himalayas, due to the developmental paradigm has led to rapid changes in land use land cover (LULC) especially in the recent past. An important part of Rajajiï Corbett Tiger Conservation Unit (RCTCU), Rajaji National Park (RNP), with an area of 840.24 sq km, is facing deforestation and habitat loss. Three state-of-art geo-spatial programs, Multi-Algorithm Automation Program (MAAP), Data Automatic Modification Program (DAMP) and Multi-Stage Simulation Program (MUSSIP), developed by the author, have been used to demonstrate how effectively advanced technologies like Remote Sensing, Geographic Information Systems and geo-spatial simulation could be used as Decision Support System for managing protected areas. Based on rapid assessments, of LULC for 2004 and 1990 through the application of MAAP, and DAMP in conjugation with MAAP respectively, LULC change map for RNP was generated. Altogether 13 MAAP algorithms were generated for the LULC classification through MAAP and 4 DAMP algorithms, one for each band, were generated for spectral modification of the

satellite data of the past period through DAMP. During 1990-2004, grassland increased 47.20% or 64.61 sq km, mostly at the expense of forests which decreased 16.82% or 97.80 sq km. For the period 2004-2018, simulation and scenario analysis were carried out based on the 4 MUSSIP algorithms, generated through the application of MUSSIP, for an area of 50*50 pixels (1.2 km * 1.2 km) right on the fringe of RNP. The study revealed that the total forest would decrease by 17.82%, 28.51% and 10.91% by 2018 with the normal rate, with the accelerated rate (10% more than the normal rate) and with the decelerated rate (10% less than the normal rate) of the human population growth respectively.

Introduction

The land use and land cover change vividly demonstrates pervasiveness of deforestation and degradation of forest areas. Globally, over the last 300 years (from 1700 to 1990), forests and grasslands have decreased by 16% and 31% respectively, whereas croplands and pastures have increased substantially by 371% and 611% respectively (1). Deforestation is the most significant LULC change (54, 55, 91). The deforestation rate during 2000-2005 was as high as 13 million hectares per year (2). More than 70 percent of the loss of forest has been at the expense of agriculture (4). In the tropics and subtropics, plantations and industrial crops are replacing species rich forest ecosystems: Chaco thorn forests of Argentina and Bolivia and Dypterocarp forest of Borneo are being replaced by soybean cultivation and oil palm plantations respectively

(14). The tropical dry forests and seasonal forests are likely to replace moist and dry Savannahs (16).

In India, although the total forest increased 29,000 hectares per year during 2000-2005 (2), much of this increase is due to plantations. The natural forests in recent years have declined: total dense forest having canopy greater than 30% decreased by 44,900 hectares per year during 2004-2006 (8). Land, too, has degraded in India: 92% of the area in Rajasthan and Gujarat has been affected by desertification (16).

Uttarakhand has high forest cover (46.80% in 2006) (8) and relatively low human population density. However deforestation in recent years is threatening to bring down the forest cover in the state that is the source of many perennial rivers. The increase in the forest cover during 1996-2004 (0.66% per year) almost stopped during 2004-2006; and the increase in total dense forest having canopy more than 30% during 1996-2004 (0.76% per year) turned negative (deforestation rate: 0.01% per year) during 2004-2006 (8, 92, 102).

The state has 6 national parks, 6 wildlife sanctuaries including 2 World Heritage Sites, 2 conservation reserves and 1 biosphere reserve. Fragmentation and degradation of the protected areas has resulted in deterioration of the habitat, especially for the tiger population in the Rajajiï Corbett Tiger Conservation Unit (RCTCU) that has been identified as an important tiger conservation unit (103, 104). Altogether 5 out of the 12

reserve forest divisions in the RCTCU have been converted into monoculture plantations (104). *Lantana,* an exotic invasive species has spread throughout the understorey, threatening the regeneration of native species (105, 106). Moreover, nearly 200 families of the Gujjars, local people, are still residing inside the PA (109, 110).

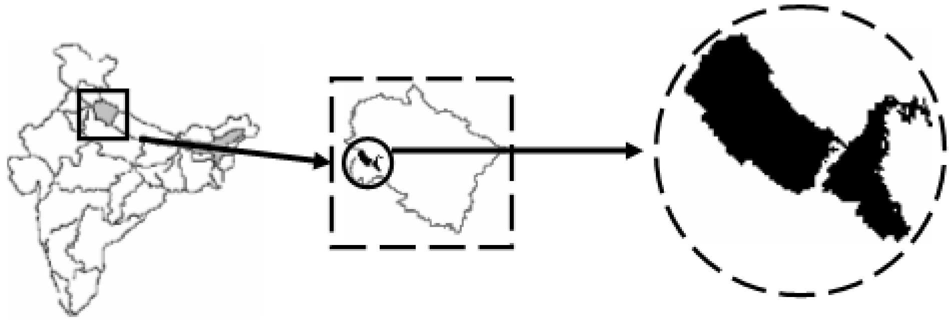
Although Rajaji National Park is one of prime conservation areas of the country and is subject to immense anthropogenic pressures, there is no study that documents LULC change or its consequences for the long term viability of the park. Here, using new GIS based monitoring and simulation tools that I have developed, I assess land use and land cover change in the Rajaji National Park. Specifically, I address these questions: 1. What is the extent of land use and land cover change from 1990 to 2004? 2. What is the spatial pattern of land use and land cover change? 3. Given the current trends, what will be the magnitude of future changes in land use and land cover?

Study area

Two study areas were taken with different objectives. RNP was chosen for the study related to the assessment of LULC change. Situated in Uttarakhand, a northern state in India, RNP lies in the Shivalik range in the foothills of the Himalayas. With a total geographic area of 820.42 sq km, the national park lies between latitude 29^{O} 51ô to 30^{O} 15ôN and longitude 77^{O} 57ô to 78^{O} 24ôE. The Ganges river flows across RNP towards the south. The 3 urban centers ï Dehradun in the north-west, Haridwar in the south-east and Rishikesh in the north-east - are very close to this PA. The national park is a part of

RCTCU and has rich biodiversity. There are 49 species of mammals, 315 species of birds, 9 species of lizards, 28 species of snakes and many species of butterflies (110).

Figure 4.1. Location map of Rajaji National Park, Uttarakhand, India



Since simulation is extremely time intensive, it was undertaken for a smaller area of 1.2 km * 1.2 km right on the fringe of RNP having 50*50 pixels. It extends between latitude 30^{O} 04ô24.84ò to 30^{O} 04ô45.98ò N and longitude 78^{O} 11ô12.82ò to 78^{O} 11ô57.74ò E. The non-perennial west to east flowing river, Song, which has almost dried, splits this area in almost 2 halves. The northern portion overlaps with the populated areas of Jogiwala and Chiddarwala, the 2 suburbs located in Dehradun district, and the southern portion falls on the RNP. This area was purposely chosen because all the LULC classes were adequately represented and all the agents of change taken into consideration were present in this area.

Methodology

Satellite data

Multi-spectral Indian Remote Sensing, Linear Imaging Self Scanning satellite data, IRS P6 - LISS 3 of path/row 096/050 dated Nov 13, 2004, with a resolution of 23.5 m was used for the LULC classification for the present period (2004). All the 4 bands were taken into consideration during DIP. Multi-spectral LANDSAT, Thematic Mapper satellite data, of path/row 146/039 dated Oct 21, 1990, with a resolution of 30 m was used for the LULC classification for the past period (1990). Source of this data was the Global Land Cover Facility (http://glcf.umiacs.umd.edu). For carrying out DIP, bands 2, 3, 4 and 5 were stacked and resampled so that the resolution becomes the same as that of the data pertaining to the present period. Except accurate geo-referencing, no other preprocessing operation was undertaken for these satellite data.

Classification scheme

The classification scheme for assessment of LULC for the present and the past periods included 6 LULC classes: Very Dense Forest (VDF; having canopy density more than 70%), Dense Forest (DF; having canopy density between 40% - 70%) and Open Forest (OF; having canopy density between 10% - 40%), Grasslands (GL), Water (WA) and Non-Forest (NF; excluding Water).

The classification scheme for the LULC maps for simulation purpose was modified. A new LULC class, called Total Dense Forest (TDF), was formed by clubbing Very Dense Forest and Dense Forest. Water was clubbed together with Non-Forest (NF). Since human population has known detrimental effect on forests and grasslands, a new LULC class, called Human Inhabitation (HI), was carved out from Non-Forest. Open Forest (OF) and Grassland (GL) were left unmodified. Hence the classification scheme for simulation purpose comprised of 6 modified LULC classes.

The following groupings of classes (say Class Groups), have been defined to analyze the results on the LULC assessment: Total Dense Forest (TDF) has been taken as VDF+DF, Total Forest Area (TFA) as VDF + DF + OF, Total Green Area (TGA) as VDF + DF + OF + GL, Total Non-Green Area (TNGA) as NF + WA and Total Non-Forest Area (TNFA) as NF + WA + GL. For the results of simulation, Total Non-Green Area (TNGA) has been defined as NF + HI and Total Non-Forest Area (TNFA) as NF + HI + GL.

Training set

Training sets, for the study done in the PA, generated by undertaking extensive ground work, were representative, complete and non-redundant. Although perfect accomplishment of all these criteria was a difficult task, utmost care was taken because accuracy of the LULC assessment depended heavily on the training set data. The training set was modified through the application of MAAP during the course of DIP. The

statistical parameter that measured the spectral overlap or separation between the training set LULC classes, acting as the artificial intelligence of MAAP, provided the necessary feedback while developing the training set. Training set classes, for which the condition of overlap persisted, were fragmented. The training set, which comprised of 6 classes initially as per the classification scheme, was gradually modified based on the feedback during the course of DIP through the application of MAAP. Finally the training set comprised of 14 CSCs after splitting Very Dense Forest into 3 sub-classes (VDF1, VDF2 and VDF3), Dense Forest into 2 sub-classes (DF1 and DF2), Open Forest into 2 sub-classes (OF1 and OF2) and Non-forest into 5 sub-classes (NF1, NF2, NF3, NF4 and NF5). Similarly training sets, for the study on simulation, were also generated.

Input data for simulation

Attributes, what we call drivers of change, put pressure on ecosystem, thereby changing LULC. Ecosystems are highly complex and dynamic with interactions taking place among different components. The quantum of change in the LULC depends on the severity and the type of the drivers. All the drivers do not affect ecosystem with equal force; but some may be more harmful than others, while others may have positive effects too.

Biotic factors like human population; physical factors like elevation and slope; environmental factors like forests, grasslands and water bodies; and the sustainability factor that includes legal aspects, enforcement mechanisms, institutional framework,

social, cultural values etc, play important role in determining changes in the LULC. LULC maps of the present and past periods (2004 and 1990) were generated according to the modified classification scheme for simulation. The information on the extent of human population was generated by delineating a separate class of Human Inhabitation in the LULC maps of both the periods. Since exact information on population of the study area was not known, population data of Dehradun district, a surrogate, was used instead. Source for DEM was the Global Land Cover Facility (http://glcf.umiacs.umd.edu). Data on slope was generated using DEM. The boundary map of RNP and the road map were obtained from the FD.

Programs used for Digital Image Processing

The 2 programs, MAAP and DAMP, developed by the author were used for this purpose. MAAP was used to generate the LULC map as per the modified classification scheme for LULC assessment for the present period. DAMP, in conjunction with MAAP, was used to produce the LULC map for the past period.

For the scene of the present period, MAAP was run to generate 13 MAAP algorithms that sequentially generated the LULC map comprising of all these 14 CSCs. For each MAAP algorithm, the assessment of LULC for each pixel was done by comparing the separation value and the algorithm value as explained in chapter 2. The MAAP algorithm 1, generated for the scene, has been produced below. The symbols - v1, v2, v3 and v4

corresponding to the DN values of any pixel of bands 1, 2, 3, and 4 respectively - have been used for this purpose.

MAAP algorithm 1 =

[{(1.5*v1)+(-0.5*v2)+(0.5*v3)+(0.5*v4)} / {(-2.5*v1)+(0.5*v2)+(-0.5*v3)+(-0.5*v4)}] /

[{(1^v1)+(2^v2)+(-.5^v3)+(0^v4)} / {(0*v1)+(0*v2)+(1.5*v3)+(0*v4)}] (4.1)

The separation value 1 and the separation index 1, generated for the scene, have been produced below:

Separation value 1 = - 0.0285; Separation index 1 = 0.4462 (4.2 & 4.3)

For stage 1, all the CSCs were taken into consideration. The CSCs (VDF1, VDF2, VDF3, DF1, DF2, NF1, NF2, NF3, NF4 and NF5), having algorithm values less than the separation values and the CSCs (OF1, OF2, GL and WA), having algorithm values greater the separation values were, separated from each other. The same methodology was applied for the rest of the 12 MAAP algorithms. The LULC map was generated by undertaking DIP on the scene according to these MAAP algorithms. The area within MTR was masked out later.

The scene of the satellite data of the past period was spectrally modified through the application of DAMP so that the same set of MAAP algorithms generated earlier could be used for generating the corresponding LULC map. For this purpose, common areas of

the 2 satellite data (of the present and the past periods) and the corresponding LULC map of the present period comprising of 14 CSCs were masked out.

Depending on these data, DAMP algorithms were generated by DAMP for modifying the DN values of the satellite data for all the bands of the scene of the past period. For band 1 the DAMP algorithm 1; m11 and m12, the means of the DN values of the scenes of the present and the past periods respectively; and sd11 and sd12, the standard deviations of the DN values of the scenes of the present and the past periods respectively have been produced below. The symbol pv1, corresponding to the DN value of any pixel of the band 1 for the scene of the past period, has been used for this purpose.

DAMP algorithm 1 =

$$3.8 + pv1 * [- 0.6 + (-1.7 * m11 - 1.8 * sd11) / (- 2.2 * m12 + 1.6 * sd12)] \quad (4.4)$$

$$m11 = 83.27; \quad sd11 = 17.58; \quad m12 = 28.79; \quad sd12 = 07.61 \quad (4.5 \text{ to } 4.8)$$

After generating all the 4 DAMP algorithms by applying DAMP, the scene of the past period was spectrally modified through the application of DAMP based on these DAMP algorithms.

The LULC map, comprising of 14 LULC CSCs, were generated by undertaking DIP on this modified scene of the past period according to the MAAP algorithms generated earlier through the application of MAPP on the scene of the present period. All the sub-

classes of their respective LULC classes were clubbed together to produce the LULC maps comprising of 6 LULC classes in accordance with the original classification scheme. The accuracy assessment was done as explained in chapter 3.

Assessment of LULC change

The LULC change map for the national park was generated for the period 1990-2004. This was generated by overlaying the LULC map of 2004 over the LULC map of 1990. The change map comprised of 36 classes since the LULC maps for both the periods had 6 LULC classes. To enhance the visual effect, the LULC change map, comprising of 9 classes, was also generated with the LULC maps of 1990 and 2004 after formation of 3 groups of classes: Total Forest Area, Grassland and Total Non-Green Area.

Program used for simulation

The program, MUSSIP, developed by the author, was used to simulate LULC over time taking various agents of change into account for 3 purposes ï validation, modeling for future LULC maps and scenario analysis. For validation, the base LULC map and final LULC map, generated earlier by undertaking DIP of the satellite data, corresponding to 1990 and 2004 were taken. Taking all the agents of change into account, simulation of the base LULC map of 1990, through the application of MUSSIP, generated the simulated LULC map of 2004. The simulated LULC map of 2004 was validated against the final LULC map of 2004. The base LULC map of 2004 was taken for generating simulated LULC maps of the future periods. Simulation of this base LULC

map of 2004 was undertaken, through the application of MUSSIP, to generate the simulated LULC map of 2018 assuming that the present trends in various agents of change would continue in future too. Under scenario analysis the trends in various agents of change were incrementally changed and the consequent simulated LULC maps for the future periods were generated.

Potentials were developed for all the agents of change. Three potentials - Environmental Global (v_EG), Environmental Local (v_EL) and Environmental Focal (v_EF) - were developed regarding environment. All the pixels of the study area were included for the potential for Environmental Global, while the potentials for Environmental Local and Environmental Focal were based on the neighborhood having 7*7 pixels and 3*3 pixels respectively. The potential for road (v_road) was based on the distance from road. The potential for sustainability (v_ sustainability) was taken as 0.5 so that lower and higher values could be assigned to it later on depending upon the contributing factors. Potentials were also generated for population (v_hpop), DEM (v_dem), slope (v_slope) and the PA boundary (v_pa_boundary).

The total time period, for which simulation undertaken for validation purpose, was 14 years (1990-2004). Simulation was carried out for smaller time intervals of 2 year each and the total number of iterations was 7. Hence 7 iterations of simulation on the base LULC map of 1990 generated the simulated LULC map of 2004.

Simulation was done in stages by automatically forming groups by clubbing different LULC classes at different stages through the application of MUSSIP. Simulation was done for these groups rather than for classes. After obtaining the optimum solution and the corresponding MUSSIP algorithm for any stage, one of these groups was automatically selected for the next stage and grouping of classes was done within that selected group by bifurcation. Again the optimum solution, along with the corresponding MUSSIP algorithm, was found for this stage. This process of group formation for the subsequent stages based on the bifurcation of the selected group was repeated until each group was represented by an individual LULC class. Results from all the possible combinations of group formations were compared to figure out the optimum simulation, the corresponding set of optimum MUSSIP algorithms and the corresponding optimum route for group formation. The MUSSIP algorithm 1 for stage 1 has been shown below where pv1 stands for the DN value of any pixel of base LULC map of 1990.

MUSSIP algorithm 1 =

0.866 + (pv1) * (1 ï 1 * v_EG) * (1 + 0 * v_EF) * (1 ï 1 * v_EL) * (1 ï 1 * v_dem) * (1 + 0 * v_slope) * (1 + 0 * v_road) * (1 + 0 * v_pa_boundary) * (1 ï 1 * v_sustainability) * (1 * v_hpop) (4.9)

Simulation was accomplished in 4 stages. During stage 1, 2 groups - Total Forest Area and Total Non-Forests Area - were formed by bifurcating the entire LULC classes. During stage 2, 3 groups were formed. Total Non-Forests Area was bifurcated into 2

groups: GL, and Total Non-Green Area; Total Forest Area remained intact as a group. During stage 3, 4 groups were formed. Total Non-Green Area was bifurcated into 2 groups: NF and HI; Total Forest Area and GL remained intact as separate groups. During stage 4, 5 groups were formed. Total Forest Area was bifurcated into 2 groups: TDF and OF; GL, NF and HI remained intact as separate groups.

The metrics, index_mussip, as defined in chapter 2, was used to generate the optimum MUSSIP algorithms and validate the results. Additionally pixel-to-pixel accuracy and kappa static were generated for all the 4 stages.

Based on the MUSSIP algorithms generated for the period 1990-2004, the simulated LULC map for the future period (2018) was generated through the application of MUSSIP in 7 iterations assuming that the present trends in various agents of change would continue in future too. Under scenario analysis, the trend in human population was incrementally changed and the consequent simulated LULC maps for 2018 were generated. Different scenarios emerged when the rate of growth of human population was changed. The normal rate of growth in human population was 25% in the past. The rate of growth was decreased 10% under the scenario 1; so the new rate of growth was 90% of the normal growth rate. Similarly the rate of growth was increased 10% under the scenario 3; so the new rate of growth was 110% of the normal growth rate. The simulated LULC maps were generated for 2004-2018 under the 3 scenarios, including the scenario 2 which correspond to the normal rate of growth.

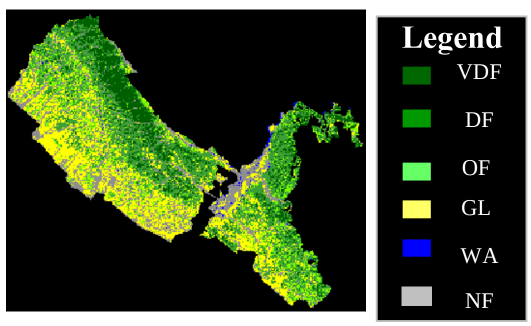
Results

All the results have been shown below:

Rapid assessment of LULC for 2004

The LULC maps comprising of 14 Classes/Sub-Classes, according to the modified classification scheme, and of 6 classes, according to the original classification scheme, were generated for 2004 through the application of MAAP (figure 4.2). The overall accuracy was 94.87%.

Figure 4.2. LULC map of 2004 for RNP



Total Green Area, which includes forest and Grassland, was 83.51%, Total Forest Area (58.95%), was more than half the area of the PA, and Total Dense Forest was 47.94%. Total Non-Forest covered 16.49%, including 15.96% Non-Forest and 0.53% water. Within Total Non-Forest, Non-Forest and Water accounted for 96.76% and 3.24% respectively.

Table 4.1. Areas figures and percentages of LULC classes in 2004 and 1990 for RNP

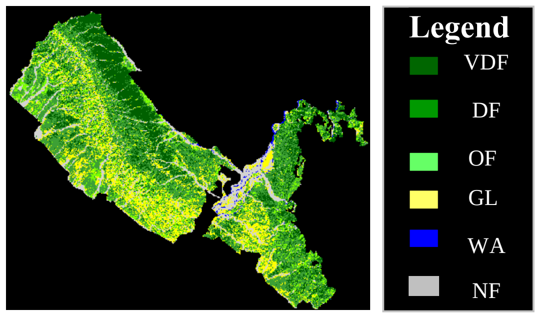
Sl. no.	LULC class	1990		2004	
		Area (sq km)	**% wrt area of RNP**	**Area (sq km)**	**% wrt area of RNP**
1	Very dense forest (VDF)	169.74	20.69	127.18	15.50
2	Dense forest (DF)	319.06	38.89	266.13	32.44
3	Open forest (OF)	92.65	11.29	90.34	11.01
4	Grassland (GL)	136.88	16.68	201.49	24.56
5	Water (WA)	5.84	0.71	4.38	0.53
6	Non-forest (NF)	96.24	11.73	130.90	15.96
Total		**820.42**	**100.00**	**820.42**	**100.00**

Within Total Green Area, Very Dense Forest and Dense Forest accounted for 18.56% and 38.84% respectively, while Grassland accounted for 29.41% and Open Forest was less (13.19%). Within Total Forest Area, Very Dense Forest and Dense Forest accounted for 26.30% and 55.03% respectively. Both of these together accounted for 81.32% of Total Forest Area, while Open Forest accounted for 18.68%.

Rapid assessment of LULC for 1990

Similar LULC maps were generated for 1990 (figure 4.3). The overall accuracy was 94.10%.

Figure 4.3. LULC map of 1990 for RNP



Total Green Area, which included forest and Grassland, was 87.56%, Total Forest Area was 70.87%, and Total Dense Forest was more than half the area of the PA with an outstanding figure of 59.58%. Total Non-Forest covered 12.44%, including 11.73% Non-Forest and 0.71% water. Within Total Non-Forest, Non-Forest and Water accounted for 94.28% and 5.72% respectively.

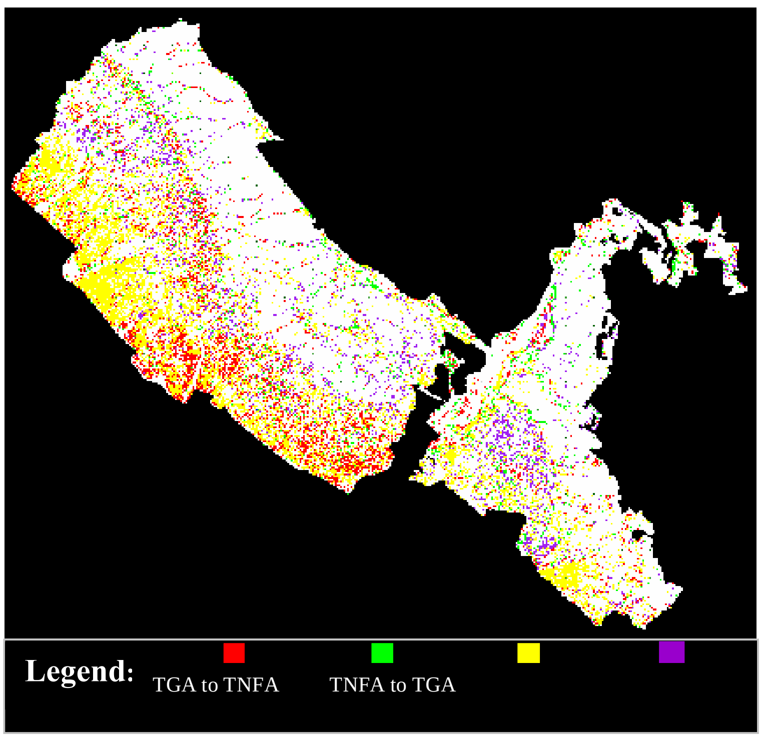
Not only was the area of forests very high in the PA, the density of forests was also excellent. Within Total Green Area, Dense Forest constituted 44.42% followed by Very Dense Forest, which constituted 23.63%. Grassland accounted for 19.06%, while Open Forest was quite less (12.90%). Within Total Forest Area, Very Dense Forest and Dense

Forest accounted for 29.19% and 54.87% respectively. Both of these together accounted for 84.07% of Total Forest Area, while Open Forest accounted for just 15.93%.

Assessment of change in LULC for 1990-2004

The LULC change map for 1990-2004, comprising of 4 classes and based on the 3 groups of classes: Total Forest Area, Grassland and Total Non-Green Area, was generated for RNP. This has been shown as figure 4.4.

Figure 4.4. LULC change map for 1990-2004 showing 4 classes for RNP



TGA: Total Green Area (VDF + DF + OF); GL: Grassland

TFNA: Total Non Forest Area (WA + NF)

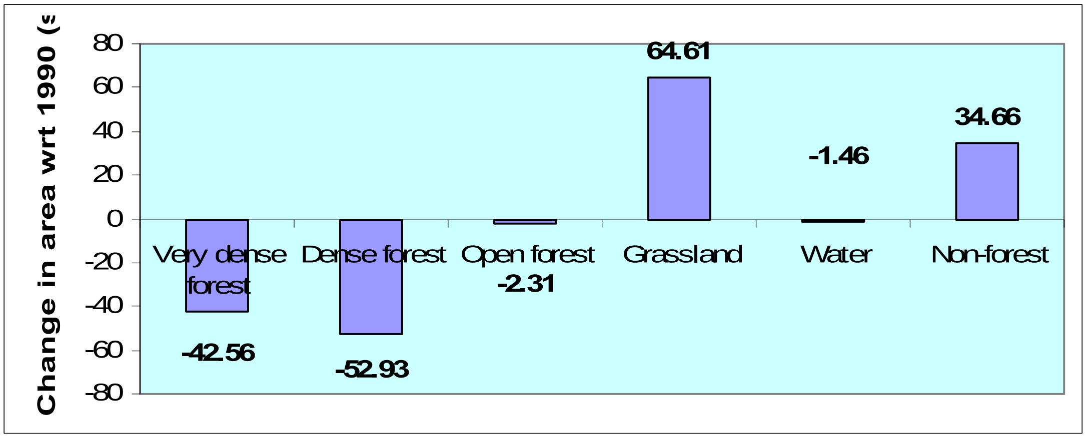
The data regarding the LULC change map for the period 1990-2004 revealed that there was marked deterioration in the PA. Total Green Area decreased by 4.62% or 33.19 sq km during this period, which was 4.05% of the total area of the PA. Total Forest Area decreased more markedly - by 16.82% or 97.80 sq km during the 14 years, which was 11.92% of the total area of the PA.

Table 4.2. Area figures and percentages of LULC change during 1990-2004 for RNP

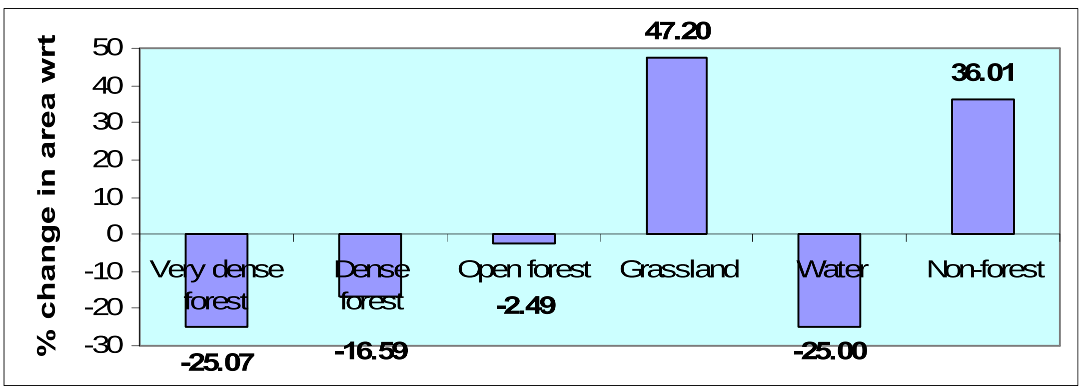
Sl. no.	**LULC class**	**Area for 1990 (sq km)**	**Area for 2004 (sq km)**	**Difference in area for 1990-2004**		
				Area (sq km)	**% wrt 1990**	**% wrt area of RNP**
1	Very Dense Forest	169.74	127.18	-42.56	-25.07	-5.19
2	Dense forest	319.06	266.13	-52.93	-16.59	-6.45
3	Open forest	92.65	90.34	-2.31	-2.49	-0.28
4	Grassland	136.88	201.49	64.61	47.20	7.88
5	Water	5.84	4.38	-1.46	-25.00	-0.18
6	Non-forest	96.24	130.9	34.66	36.01	4.22

Figure 4.5. Top to bottom for LULC change during 1990-2004 for RNP in terms of: (a) Area, (b) Percentage wrt 1990 and (c) Percentage wrt the total area of MTR

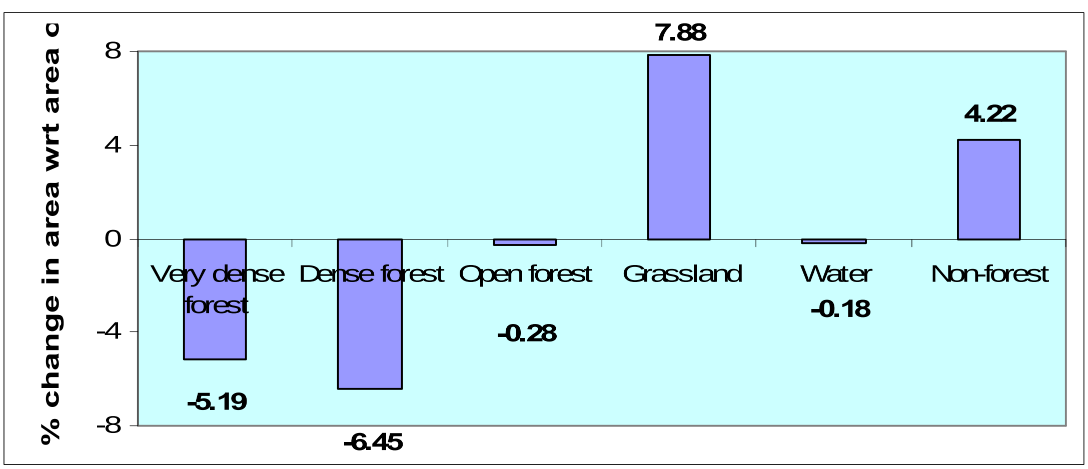
a



b



c



The forests also considerably degraded over this period. Very Dense Forest faced the most severe brunt as it decreased 25.07% or 42.56 sq km within just 14 years. This constituted 5.19% of the PA. Dense Forest too has gone down considerably, but to a lesser extent. The loss in Dense Forest was 16.59% or 52.93 sq km, which was 6.45% of the total area of the PA. Open Forest decreased just 2.49% or 2.31 sq km, which was 0.28% of the PA area.

Total Non-Green Area and Total Non-Forest Area, which behaved exactly in the opposite manner with Total Green Area and Total Forest Area respectively, had increased 32.52% or 33.20 sq km and 40.93% or 97.81 sq km respectively during this period. Non-Forest has shown marked increase in area. It increased by 36.01% or 34.66 sq km, which was 4.22% of the area of the PA.

Grassland increased and water decreased during this period. Grassland has shown lots of flux across other LULC classes. The net increase in grassland was a whopping 47.20% or 64.61 sq km, which was 7.88% of the PA. This was largely at the cost of forest areas. Loss in water was a serious concern. Water went down significantly by 25.00% or 1.46 sq km, which was 0.18% of the area of the PA.

The changes in LULC have been noticed mostly in the southern areas of the park along the boundary, which is a low lying plain. The loss in Total Green Area has been mostly confined in the lower or southern region of the park if a diagonal is supposed to

run from north-west to south-east splitting the park into 2 regions. Total Forest Area has turned into Grassland largely in the lower region. These adversely affected regions are close to human inhabitations. The park has 2 big portions of land well separated by urban settlements and connected by a few slender corridors (fig 4.3). The changes in Total Green Area and Total Forest Area are more widespread in the western portion of the park. Huge areas of Total Forest Area have turned into Grassland in many areas in the southern region in the eastern portion along the boundary. The northern half of the park is largely intact due to absence of human inhabitations, contiguity with forests across the northern boundary, undulated terrain and high altitude.

Simulation of LULC

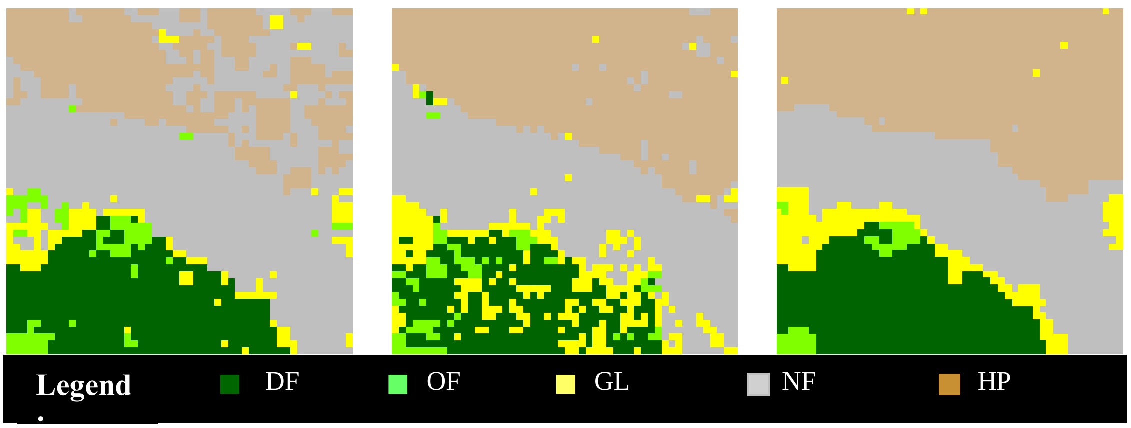
Results of validation through the simulation of LULC for the past period (1990-2004), modeling for future LULC maps through the simulation of LULC for the future period (2004-2018) and scenario analysis for the future period (2004-2018) are described below:

Based on the MUSSIP algorithms, simulated LULC map for 2004 was produced by simulating the base LULC map of 1990, through the application of MUSSIP, in 7 iterations. The LULC maps and the corresponding area figures have been shown below:

The values of all the metrics, index_mussip, pixel-to-pixel accuracy and kappa statistic, were generated for all the stages. The values of index_mussip for the stage 1, 2,

3 and 4 were 88.23%, 77.59%, 78.89% and 73.66%. Similarly the values for pixel-to-pixel accuracy for these stages were 93.40%, 87.80%, 84.08% and 81.72% and the values for kappa for these stages were 79.04%, 72.63%, 77.20% and 74.16%.

Figure 4.6. Left to right: (a) LULC map of 1990, (b) LULC map of 2004 and (c) Simulated LULC map of 2004



Based on the MUSSIP algorithms, simulated LULC map for 2018 was produced by simulating the base LULC map of 2004, through the application of MUSSIP, in 7 iterations (figure 4.7).

The real and the simulated LULC maps of 2004 matched considerably, the areas under different LULC classes and groups of classes also matched. There was perfect matching between the real and simulated results for Total Green Area as both were 28.72% of the total area and for Total Non-Green Area as both were 71.28% of the total area. For LULC classes within Total Green Area and Total Non-Green Area, there were

some differences in the magnitude, but the trends were same. Decrease in areas for Non-Forest, Total Dense Forest and Open Forest, and increase in areas for Human Inhabitation and Grassland were observed both in the real and simulated LULC maps of 2004.

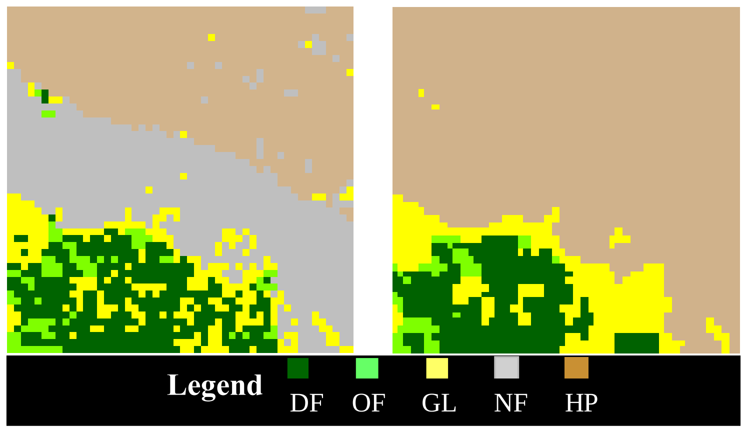
Table 4.3. Areas figures in percentage for LULC classes for the real and simulated LULC maps for the period 1990-2004

LULC class	Base LULC of 1990	Final LULC of 2004	Simulated LULC of 2004
Total Dense Forest	19.64	14.64	19.28
Open Forest	3.56	3.32	1.84
Grassland	5.16	10.76	7.60
Non-Forest	48.04	33.76	31.32
Human Inhabitation	23.60	37.52	39.96

The validation results supported the fact that simulation done by MUSSIP yielded excellent results. Simulation during stage 1 resulted in formation of 2 groups, Total Forest Area and Total Non-Forests Area, through bifurcation of all the LULC classes. The areas in each group for the simulated and real data were matching and pixel-to-pixel matching was also high (93.4%). It was inferred that this sort of high matching could not be attributed to chance factor alone as kappa was as high as 79.0%. In other words this result was 79.0% better than what could be expected due to chance factor alone. The

pixel-to-pixel matching were 87.80%, 84.08% and 81.72% respectively for stages 2, 3 and 4 respectively. The values of kappa suggest that the results were 72.63%, 77.20% and 74.16% better than what could be expected due to chance factor alone.

Figure 4.7. Left to right: (a) LULC maps of 2004 and (b) Simulated LULC map of 2018



This study revealed that all the LULC classes, including the forests and Grassland, would continue their past trends during the future period. Total Forest Area, that decreased 22.59% during 1990-2004, would decrease by 17.82% during 2004-18. Within Total Forest Area, Total Dense Forest and Open Forest, that decreased 25.46% and 6.74% respectively during 1990-2004, would decrease by 14.75% and 31.33% respectively during 2004-2018. While Grassland would continue to increase (by 17.47% during 2004-2018), but with a lesser magnitude it did during 1990-2004.

Table 4.4. Areas figures in percentage for LULC classes for the real and simulated LULC maps for the period 2004-2018

LULC class	**Base LULC of 2004**	**Simulated LULC of 2018**	**LULC change for 2004-2018**	
			% wrt 2004	**% wrt total area**
Total Dense Forest	14.64	12.48	-14.75	-2.16
Open Forest	3.32	2.28	-31.33	-1.04
Grassland	10.76	12.64	17.47	1.88
Non-Forest	33.76	0.00	-100	-33.76
Human Inhabitation	37.52	72.6	93.5	35.08

Table 4.5. Areas figures in percentage for LULC classes for the simulated LULC maps for 2018 under 3 scenarios

LULC class	**Rate of change of human population wrt the normal growth rate**		
	90%	**100%**	**110%**
Total Dense Forest	14.44	12.48	9.28
Open Forest	1.56	2.28	3.56
Grassland	11.40	12.64	12.36
Non-Forest	0.04	0.00	0.00
Human Inhabitation	72.56	72.60	74.80

The analysis of the data, related to the LULC maps generated under the 3 scenarios by changing the rate of growth in human population for the period 2004-2018, revealed severe detrimental impacts on the LULC consequent upon the anthropogenic pressure. Total Forest Area would decrease by 10.91%, 17.82% and 28.51% during the future period under the scenarios 1, 2 and 3 respectively; and Total Forest Area would occupy 16.00%, 14.76% and 12.84% of the total area under the respective scenarios. Human Inhabitation would encroach not only on the green areas, but it would also engulf all the area of Non-Forest. Human Inhabitation would increase by 93.39%, 93.50% and 99.36% and its area would be 72.56%, 72.60% and 74.80% with respect to the total area respectively under the respective scenarios. Non-Forest would lose all its area to Human Inhabitation.

Table 4.6. Areas figures in percentage for changes in LULC class groups for the simulated LULC maps during 2004-2018 under 3 scenarios

LULC class group	**Rate of change of human population wrt the normal growth rate**		
	90%	**100%**	**110%**
Total Forest Area	-10.91	-17.82	-28.51
Total Green Area	-4.60	-4.60	-12.26
Total Non-Forest Area	2.39	3.90	6.24
Total Non-Green Area	1.85	1.85	4.94

Discussion

The programs, MAAP and DAMP, and the tools used in the studies have produced excellent results. Based on the 13 MAAP algorithms, generated through the application of MAAP, an accuracy of 94.87% was achieved for the LULC assessments for 2004, which is better than most of the similar studies. Accuracy of 99% was obtained for the LULC assessment in Catskill-Delaware in the north-eastern USA for 2001, where only 2 LULC classes (Total Forest Area and Total-Non-Forest Area) were delineated and aerial photographs were used for verification (47). For Mahananda Wildlife Sanctuary, West Bengal, India, accuracy of 88% was reported for 2000 wherein only 3 LULC classes were delineated (96). The LULC assessments in the Western Ghats in India for 1995, in the Central Himalayas for 1998 and in the north-eastern India in the north-eastern India for 1998 had accuracies of 80.54% (99), 80% (97) and 82.15% respectively (98). Many studies do not even report the accuracy level! Many authors have expressed concern over the accuracy assessment of the past period (52, 83). The LULC map for 2004, having an accuracy of 94.10%, generated through the application of DAMP and MAAP, was very accurate and rapid, and the metrics used for ascertaining the accuracy was extremely useful. Hence this suits accuracy of the inaccessible areas when conditions really prohibit any ground verification and for the past periods when accurate and reliable reference data is either not available or expensive. Although accuracy of the LULC map, used for Catskill-Delaware in the north-eastern USA for 1992, was 90% for only 2 LULC classes, using aerial photographs of 1994 for verification proved to be quite expensive (47). In

southern Chile, accuracy values of 88.8%, 89.6% and 91.9 were obtained for the LULC maps of for 1976, 1985 image and 1999 respectively (35).

The simulation program, MUSSIP, yielded good results. A new metrics, index_mussip, was used for optimization of results. For stage 1, when Total Forest Area and Total Non-Forest Area were taken as 2 groups, index_mussip, pixel-to-pixel accuracy and Kappa were 88.23%, 93.40% was 0.7904. Overall pixel-to-pixel accuracy of 90.9% and kappa of 0.7319 were obtained for the simulation for Catskill-Delaware in the north-eastern USA for 1992-2001 (47). The values for pixel-to-pixel accuracy and kappa obtained in southern Chile were 88.04% and 0.7430 respectively for 1976-1999 (35) and in Costa Rica in between 84-86% and 0.34-0.53 respectively for all the combinations of data pertaining to the periods 1940, 1961 and 1983 (36). Pixel-to-pixel accuracy of 80% and kappa of 0.38 were obtained for the simulation for Arunanchal Pradesh in the north-eastern India for 1988-2021 (112).

In RNP, Total Forest Area was 58.95%, of which Total Dense Forest and Open Forest constituted 81% and 18.68% respectively in 2004. For the same period, the corresponding figures for India were 21.00%, 58.45% and 41.55% respectively, and for Uttarakhand were 45.86% 77.18% and 22.83% respectively (92). On the other hand Corbett Tiger Reserve, Uttarakhand, India had 90.82% Total Forest Area in 2002, of which Total Dense Forest was 91.65% and Open Forest was 8.35% (28). Similarly Nilgiri

BR in south India had 88.70% Total Forest Area in 1998, of which Total Dense Forest and Open Forest were 60.65% and 31.62% respectively (29).

The deforestation rate (1.20% per year) during 1990-2004 in RNP was the highest in India, especially considering other deforestation studies including protected and non-protected areas. The fragmentation witnessed all over indicated presence of population pressure from Gujjars, a tribal community, residing inside the PA and the nearby urban centers. The annual rates of deforestation in the Western Ghats, the Himalayas within India, Nanda Devi BR, Uttarakhand, India and Nilgiri BR were 1.16% during 1997-1995 (99), 0.82% during 1990-2000 (100), 1.04% during 1990-1998 (29) and 0.08% during 1990-1998 (29) respectively. On the contrary, Total Forest Area increased at the annual rate of 0.15% and 0.66% during 1990-2004 in India and Uttarakhand respectively (92, 111), and in Mahananda Wildlife sanctuary the annual rate of increase of Total Forest Area was 0.99% during 1990-2000 (96).

The changes in LULC during 1990-2004 have been noticed mostly in the southern areas of the park along the boundary, which is a low lying plain, whereas the northern areas along the boundary are largely intact due to absence of human inhabitations, undulated terrain and high altitude. Biotic pressure has been the most significant driver of change in RNP (104). Apart from the human population residing across the southern boundary, 3 Taungia villages and 177 Gujjar families still resided inside the park in 2008 despite major rehabilitation and relocation initiative undertaken by the FD during the

early 2000s (109, 110). In addition to Haridwar and Rishikesh, urban centers have mushroomed all along the roads near the southern boundary of the park. Developmental activities, such as roads, railways and hydropower canal (107), and tourism (110) have also affected the park. Although huge areas of Total Forest Area have turned into Grassland in many areas in the southern region along the boundary, such conversions have occurred mostly in the western portion of the park. Openings created due to illicit removal of forest produce may have been occupied by grasslands. The increase in grasslands (3.36% per year) has positive impacts on wildlife, since grasslands provide food to the ungulates on which carnivores prey upon, but unfortunately grasslands have been colonized extensively by *Lantana camara* and *Parthenium hysterophorus* (105, 108, 110). Scarcity of water in the park (110), which is detrimental to the wildlife, has been confirmed by the finding in this study regarding the severe loss of water (25.00%). Construction of hydro-electric projects upstream and loss of glaciers in the Himalayas consequent upon climate change, that feed the rivers of this region, might be the reason for severe loss in water and drying up of rivers.

The study area for simulation that lost 22.59% of Total Forest Area during 1990-2004 at the rate 1.61% per year, the simulated results for the future period showed that it would lose 17.82% of Total Forest Area during 2004-2018 at the rate 1.27% per year. In a study done in Catskill-Delaware in the north-eastern USA, the deforestation rate of 1.30% per year during 1992-2001 would increase to 1.70% per year during 2001-2011 (47). With the deforestation rate of 1.34%, the Total Forest Area that decreased 8.04% in 6 years

(1997-2003) would decrease 13.59% in 10 years (2003-2013) in East Kalimanthan (85). Another study in East Kalimanthan that assumed the deforestation rate of 2.90% per year for the past to continue in future too, loss in Total forest Area was 16.22% in 6 years (1997-2003) and 24.73% in 10 years (2003-2013) (38). The same study showed that 20.83% of Total Forest Area would be lost during 2003-2013 in the PAs in East Kalimanthan (38). Taking into account the anticipated growth of the human population in Arunanchal Pradesh, the LULC was simulated for the period 1988-2021 and it was found that the Total Forest Area would decrease at the rate 1.52% per year (112). Based on these scenarios analysis, it has been well established that human population would have extremely adverse impacts on forests during 2004-2018. Under normal human population growth rate, the area under Total Forest Area would decrease from 17.96% in 2004 to 14.76% in 2018; if the rate decreases by 10%, Total Forest Area would occupy 16% area; and if the rate increases by 10%, Total Forest Area would reduce to just 12.84% of the study area during 2004-2018.

Due to the development paradigm and rising population, LULC is changing at a rapid pace. The findings of both the studies comprehensibly establish the fact that forests are decreasing at a rapid pace. There is urgent need for a monitoring regime for rapid assessment of LULC, simulation modeling and scenario analysis in the present circumstances. Since human population would play a big role in shaping the LULC in future, appropriate policy interventions should be initiated in time to contain the anthropogenic pressure and obtain the desired effects on LULC.

Conclusion

Rapid changes in LULC, including grassland which has been assessed for the first time in RNP, due to the exponential increase in anthropogenic pressures consequent upon intense development, particularly urbanization, make this study extremely relevant from the management perspective. Rapid assessment of the LULC of the past and the present periods, and the LULC change through the application of the state-of-art programs, Multi-Algorithm Automation Program (MAAP) and Data Automatic Modification Program (DAMP), would be helpful in adopting appropriate management strategy in PAs since focused analysis on the location and extent of habitat loss establishes cause and effect relationship regarding wildlife, man-animal conflict etc. The accuracy metric embedded in the artificially intelligent program, DAMP, has the incredible ability to ascertain the statistical accuracy of the LULC map for different time periods, which naturally opens up new vistas to regularly monitor our forests in general and Protected Areas in particular in a very cost-effective manner by totally avoiding any ground verification of the area.

The simulated geo-spatial data could serve as Decision Support System for adopting appropriate policy interventions regarding different agents of change for optimally managing any area in an integrated, scientific, objective and effective manner. It has been vividly demonstrated that based on the advanced technologies like simulation and scenario analysis through the application of Multi-Stage Simulation Program (MUSSIP), a cutting edge mathematical program, simulated data for the future periods may be

generated after taking into account various drivers of change into account. From environmental perspective, this program could be equally effective in generating optimum scenario of LULC by optimizing solution for Green House Gas emissions instead of LULC. Since future Green House Gas emissions could be accurately simulated for the future periods through the application of MUSSIP, precise management prescriptions may be generated for meeting the challenges of adhering to the obligations under international treaties and for Reducing Emissions from Deforestation and Degradation.

CHAPTER 5

APPLICATIONS OF THE ADVANCED TECHNOLOGIES

Abstract

The new methodologies and tools regarding assessment, monitoring and simulation of LULC, as explained in chapter 2, enable us to manage LULC, especially the forest areas, in India in a scientific and effective manner. India has a very long history of forestry, but advances in technology have not been fully utilized for management purpose. Although remote sensing has been used over the last three decades to generate spatial data for all of India, these data have never been practically integrated in the management plans. The present chapter focuses on the application of the programs, MAAP, DAMP and MUSSIP, for the management of forests from both, retrospective and prospective, perspectives.

Introduction

The problems of deforestation and degradation in many regions across the country, at the backdrop of the burgeoning anthropogenic pressures apart from various other factors like organized illicit felling and trade in timber and wildlife, have not been adequately addressed. Despite the presence of fairly robust institutional framework in form of the Forest Department in the states and strong governance regime at the federal as well as at

the state level, these problems continue. Decrease of 936 sq km of very dense forest in the country during the period 2004-2006 is testimony to the extensive degradation of forests (8, 92). Significant losses in forests have taken place in Nagaland, Andhra Pradesh, Arunanchal Pradesh, Tripura and Assam (8).

LULC monitoring in India

The Forest Survey of India (FSI) is mandated by law by the Ministry of Environment and Forests, Government of India to generate spatial and tabular data on forests on a biennial basis. Based on satellite data, it assesses forest cover for the entire country (328.73 M ha), and compiles and publishes its findings as the óState of Forest Reportsô (SFRs). Starting in 1987, 11 SFRs have been published, with the latest one in 2009. Currently, the data generated by FSI is not used to make working/management plans by states.

One of the major drawbacks for use of the data has been frequent changes in the methodology adopted by the FSI for image interpretation and for the classification scheme. Even after switching over from a visual mode to digital mode of satellite data interpretation in 1997 for the entire country, visual interpretation still persists, of course to a lesser extent. Apart from supervised classification, on screen visual interpretation and manual generation of polygons for the change detection still play a major role in LULC assessment (8). This leads to new benchmarking of the geo-spatial data on forest cover with each new assessment. As new methodology sets in, the assessment prior to the

current one is reassessed and the corresponding data revised leading to enormous amount of additional work. All other previous assessments are not reassessed and left out as such. This makes data comparison across different time periods absolutely impossible. Changes in the classification scheme and the reporting format further aggravate the problem. Mangrove, which was treated as one class, started being classified into Dense Forest and Open forest since 2001 (113). Dense Forest was further split into 2 density classes: Very Dense Forest and Moderately Dense Forest in 2003 (21). This leads to a situation where there is no data on Very Dense Forest prior to 2003, and data on total Dense Forest before and after 2001 are just incomparable!

Although the idea of assessing óTrees Outside Forestô (TOF), which stated in 2003, was good, the approach adopted by the FSI has inherent limitations. For masking out the areas for assessing TOF, since the maps of the recorded forest areas, including Reserve Forest, Protected Forest and Unclassed Forest, are not available for the entire country, FSI instead uses the óGreenwashô areas ï areas shown as green in the Survey of India toposheets, which are quite old and not updated. Secondly, the accuracy level in TOF is 1 ha or nearly 18 pixels with a linear spatial resolution of 100 m, which is quite coarse. All these complicated methodologies, which result in increasing the work and decreasing the precision level, certainly raises questions regarding the competence of FSI to accurately delineate forests close to such areas that have similar reflectance emerging from ground.

The hybrid approach and case specific methodology is time and resource intensive. It has already been emphasized how frequent changes in the methodology further aggravates these problems. These prevailing conditions led to gradual delay in the successive assessments and publication of the SFRs, and finally unable to catch up the pace, one SFR (of 2007) was just dropped in hope that the next one could be in time.

All the problems explained above could be simultaneously addressed by applying the new methodologies and tools developed by the author. The assessment of LULC could be done rapidly through the application of MAAP and DAMP. Monitoring of LULC on repetitive basis could be done at a rapid pace in extremely cost effective manner. The problem of TOF areas could also be addressed successfully since these programs produce good results in complex reflectance conditions too. If the change in the classification scheme is imminent, assessment of LULC of the past periods could be easily done. Additionally, the accuracy metric could provide the accuracy of the past periods. Similarly in future too, monitoring could be done by using these programs and the accuracy could be assessed even without any ground verification, thereby further reducing the cost and enhancing speed.

The programs, MAAP and DAMP, are capable of delineating grasslands which is extremely important, especially from the perspective of managing wildlife. Absence of grassland in the FSI maps is a serious limitation. Many PAs across India have witnessed deterioration in PAs (23, 28, 29), heightened incidences of animal-wildlife conflict and

plummeting wildlife resource base. Grassland and the eco-tone with the forests are very important for the survival of wildlife, including the tigers, since these provide excellent conditions for habitat and food availability. Apart from poaching, deforestation and forest degradation, information on the extent and changes in grassland could have helped manage our forest areas and wildlife in a better manner.

If the rapid monitoring regime for repetitive LULC assessment based on the new technology is adopted through the application of MAAP and DAMP, time saved could be effectively used in value addition of the database that could be more meaningful for generating plans and policy interventions. The foremost task would be to digitize all the recorded forest areas and various administrative boundaries including division, Reserve Forest, Protected Forest, Unclassed Forest, range and beat. This could help generate data on deforestation, degradation, grassland and water loss etc for each of these administrative units. Plans regarding protection and mitigation measure could be made based on the severity and extent of the problem. Based on the geo-spatial data on deforestation and degradation, vulnerability zonation could be done based on the proximity from these areas for which buffer of various distances could be used. Plantation could also be taken up in these areas and in the buffers. These vital information could be incorporated in the management plans depending upon the vulnerability intensity. Apart from the PAs, this approach could immensely help other forest areas and the corridors, which are often neglected and wildlife connectivity is compromised.

The growing menace of invasive species could also be tacked effectively by using these technologies and innovations. Forests in India are infected with invasive species like *Lantana camara, Parthenium hysterophorus*, *Ipomia sp., Eupatorium sp. etc* (94, 104, 106). Occurrence of species not only damages the habitat, but also leads to man-animal conflict since the abode of animals is destroyed. Application of suitable treatment for eradication of invasives could follow only after its accurate assessment, which has so far remained elusive. The program, MAAP, is capable of delineating different species based on the ground reflectance, however complex and overlapping that might be.

Water conservation programs need a real thrust since water crisis is going to be one of the biggest challenges in India. The studies done by the author, in MTR and RNP, reveal decrease of 23-25% of surface water during 1990-2004. Another study done in Rajasthan, Punjab, Haryana and Delhi has shown that the loss in underground water was 17.76 cu km per year during the period 2002-2008 (24). Although comprehensive water conservation strategy requires an exhaustive list of policy interventions including climate change mitigation, hydrology modeling etc; few pertinent steps in right direction could help mitigate the crisis in a remarkable way. All barren and degraded land in the catchment areas could be identified easily once LULC map is generated. These areas need to have proper green cover that could help percolation and stop soil erosion, which could eventually raise the plummeting water table. Special attention is needed where slope is high. Buffer areas, around water bodies, including, rivers, lake and streams,

require urgent biological treatment like plantation of appropriate species, if devoid of green cover. These steps could help recharge and conserve water which would have positive impact on green cover. This effect cascades since increase in green cover, in turn, help conserve more water.

Apart from the steps suggested above, PAs need special focus, where specific policy interventions could be designed by simulation technique through the application of MUSSIP. In India, there are altogether 668 PAs, including 99 National Parks and 523 Wildlife Sanctuaries, occupying 158,745 sq km which is 4.83% of the total geographic area of the country and 22.98% of the total forest cover (16). All the 39 Tiger Reserves, 11 Biosphere Reserves and selected national parks could be taken up early for the simulation studies. Rest of the PAs could be subsequently taken up in a phased manner. Each PA has unique set of problems and drivers of change. These may range from human and cattle population to invasive species and developmental activities like dam construction, building of communication networks, mining etc. Simulation and scenario analysis could act as decision support system in focusing on the drivers of change that have adverse impacts on the PAs. Optimum scenarios and the corresponding policy interventions for each driver of change could be generated through the application of MUSSIP. This scientific approach could help in maintaining and improving the habitat, wildlife and ecosystem of the PAs.

This approach could also be of immense use in deciding policy issues related to granting approval to developmental projects like mining, roads, railways, dams etc. Scenario analysis could be undertaken to accurately quantify the adverse impacts on the prospective areas due to the mining activity for the future periods through the application of MUSSIP. Positive impacts of other drivers of change on the area, consequent upon the plan implementation, could be determined for the future periods through scenario analysis. The set of policy interventions for each driver of change, apart from mining, could be decided that could offset the adverse impacts on PA due to mining. Such approach could be adopted for other developmental activities too. This could help the Ministry of Environment and Forests, Government of India in granting approval to the developmental activities.

Simulation technique could help countries meet their international obligations like Kyoto Protocol and reap rich dividends from REDD intervention once it comes in force. Simulation, as a tool, what has been described so far, was based on optimizing area as a fundamental unit. Instead GHG absorbed by the green cover could be the basis of optimization. This would require additional database on the GHG absorption rates for various species and the geo-spatial data on species composition. The programs, MAAP and DAMP, could be used for the assessment of various species. This approach of reducing net GHGs by optimizing GHG absorption could provide enough leeway for other developmental initiatives for economic development of the country. Secondly, through appropriate policy interventions different drivers of change could be treated in

specific manner that could reduce deforestation and degradation (38). In international arena, under the aegis of UNFCCC, as the world fraternity is desperately looking for ameliorative actions on climate change, days are just limited when nations, including India, undertaking such initiatives could qualify for windfall monetary gains under the REDD mechanism.

Conclusion

The monitoring regime, spearheaded by the FSI, needs reforms and qualitative improvement for meeting the challenges of the forestry sector in India. Frequent changes in the methodology in the assessment of forest cover and in the classification scheme, and the complex methodology adopted for the image processing of satellite data is a serious problem. There are problems related to TOF and Greenwash areas, apart from non-assessment of grassland that is so important from the wildlife perspective. The new tools and methodologies, MAAP, DAMP and MUSSIP, could provide better monitoring regime. Assessments could be accurate and rapid. Simulation technique could provide scientific pathways to manage Pas across the country.

CHAPTER 6

CONCLUSION

In the recent times, planners of forest and ecosystems face challenge in breaking the streak of jinx riddled with the menacing increase in the pressures emanating from all the corners. Even if the cause and effect relationship, regarding degradation and ecosystem services, like habitat loss and wildlife, deforestation and environmental deterioration etc, is well established and precisely quantified, which as a matter of fact is beyond our complete comprehension, the even bigger conundrum lies in finding panacea for all of these. Serious consequences of our developmental paradigm have found overt expressions of extreme environmental events that ultimately would jeopardize human welfare.

Financial constraint is more often quoted as one of the biggest hindrances, which might not be a genuine reason all the time, in providing the solution, the fact remains that in tropical regions, especially in the developing countries, this holds true most of the time. There is no denying that for building adequate database, which is a prerequisite for developing sound and scientific plans, resources are indeed required for various purposes

like repetitive monitoring, ground verification, purchasing of satellite data, especially the very high resolution ones, and hiring professionals having expertise in DIP and GIS.

Even if we are able to overcome the financial constraints some how, technological constraints put enormous limitations on generating robust database and hence on developing scientific plans. The tropical forest ecosystems are extremely complex and difficult to understand because of wide diversity among species, age gradations, sites and the dynamics between ecosystem components. The difficulty in rapid assessment of LULC and simulation of LULC, and the nagging problem of accuracy assessment of the LULC maps of the past periods ï are just a few examples from the pile of technological problems.

Taking into consideration these problems and constraints, the research work was undertaken primarily from the 2 perspectives ï 1. development of mathematical geo-spatial programs that could address the technological limitations and circumvent the financial constraints, even in a limited manner, and 2. demonstration of the effectiveness of these programs in developing a robust database and its use as DSS from the planning perspective by undertaking various studies in the tropical forests of India. While developing the programs, focus all along had been to minimize dependence on human judgment and interference, to generate solutions in more automated manner and to avoid all the non-essential procedures without compromising the accuracy of the outputs. Relentless effort was consciously made to provide flexibility to the users to predefine

their own values of various independent parameters so as to suit the requirements of the prevailing ground conditions.

Three state-of-art geo-spatial programs developed by the author to address the pertinent issues of conservation and sustainability are: MAAP, DAMP and MUSSIP. Based on satellite data, MAAP produces the LULC map of the present period, MAAP in conjunction with DAMP produces the LULC maps of the past periods as well as of the adjacent areas whereas MUSSIP produces the simulated data of the future periods. MUSSIP has the built-in analysis capability that analyses different scenarios under different states of agents of change that have the potential to influence the LULC. Structure of these programs is so advanced that, from millions of algorithms, they automatically select the best one leading to incredible accuracy and precision level. No DIP or GIS professional is required, since these programs are fully expert systems as the LULC maps and the detailed analysis are generated automatically.

Fitted with artificial intelligence, all of these programs are really expert systems and are very advanced apart from other unique features. These programs automatically generate a set of optimum algorithms that is best suited to the desired objectives. These programs are versatile so far as workability with different input data is concerned. MAAP and DAMP work equally well with different number of bands and with different types of satellite data having similar, if not the same, resolution. Similarly, the type and number of input layers may also be varied while working with MUSSIP. Many path breaking

concepts have been incorporated in these programs. For the LULC maps of all the periods, except the present ones, DAMP, in conjunction with MAAP, provides a metric for accuracy assessment. This is extremely helpful for the past periods where there is no way to verify the ground conditions, as well as for the future periods where ground verification may be totally done away with saving time and resources. A new metric, based on a combination of indices, was generated for the validation of the simulated LULC data generated through the application of MUSSIP. Purposely MAAP and DAMP was developed to work in rapid, simple and cost effective manner. The preprocessing procedure is totally done away with. MAAP automatically takes into account complex reflectance patterns emerging from ground while generating MAAP algorithms thereby enhancing the accuracy level and it also provides the facility of prompting hints - when and how - to modify the training set so that the accuracy may be enhanced.

Studies in the 2 PAs, MTR and RNP, was undertaken to generate data on LULC and to demonstrate the immense use of the relevant information from the planning perspective. The LULC change map was generated by the post-classification comparison method for both the PAs, while simulation was carried out in a smaller area right on the boundary of RNP. The studies, regarding assessment of LULC for the present and the past period and the change in LULC for the intervening period (1990-2004), revealed alarming conditions in MTR and RNP: Total Green Area, comprising of forests and Grassland, decreased 4.32% and 4.62% respectively; Total Forest Area decreased 5.78% and 1.82% respectively; forests, having canopy density more than 30% decreased 9.16%

and 19.54 % respectively; Water, including rivers, decreased 23.72% and 25.00% respectively; and Non-Forest, in turn, increased 10.73% and 36.01% respectively. The study regarding simulation revealed that Total Forest Area would decrease by 17.82% during 2004-2018 with the normal rate of human population growth. The scenario analysis showed that Total Forest Area would decrease by 28.51% and 10.91% during this period with the accelerated rate (10% more than the normal rate) and with the decelerated rate (10% less than the normal rate) of human population growth respectively. Since the studies clearly pointed out that ecosystem services were severely impaired with the decrease in forests and the trends in forests were either likely to continue or might even worsen in future, proper remedial actions are warranted at the earliest before the resilience of the forest ecosystems is breached precipitating the point of no-return.

It was vividly demonstrated that based on these advanced technologies, through the application of these cutting edge mathematical programs, robust data on LULC over the temporal horizon could be generated, which could help in decision making process regarding monitoring, policy interventions and various other planning aspects. The assessment of LULC and change in LULC, through the application of MAAP and DAMP, could be extremely rapid and accurate, and could be immensely cost effective. The scarce resources saved due to these programs could be utilized in social sectors benefiting country in a huge way, especially in the developing countries. Success of various plans, which have bearing on LULC, and their implementation, could be easily

assessed by having such a monitoring system in place. Such approach could be very useful in primary sector for monitoring natural resources like forests, grasslands, rivers and other water bodies etc, in secondary sector for monitoring agriculture, urban development, mining etc and in tertiary sector for monitoring factors, like environmental amenities, that influence tourism etc.

Taking into account various drivers of change into account, the simulated geo-spatial data obtained by simulation and scenario analysis through the application of MUSSIP could serve as DSS for adopting appropriate policy interventions regarding different agents of change for optimally managing any area in an integrated, scientific, objective and effective manner. Adverse impacts of various drivers of change could be effectively controlled by simulation through the application of MUSSIP. Appropriate policy interventions could be developed scientifically for developmental activities like mining, dam construction, communication networks etc.

From the environmental perspective, these programs could be equally effective in generating optimum scenario of LULC by optimizing solution for Green House Gas emissions. Since future Green House Gas emissions could be accurately simulated for the future periods through the application of MUSSIP, precise management prescriptions could be generated for meeting the challenges of adhering to the obligations under international treaties and for reducing Emissions from Deforestation and Degradation. Globally the scientific community has been trying hard to find any plausible management

strategies that could help our planet. These works could be seen as an honest attempt in the same direction.

ENDNOTES

1. Lambin E. F., et al. 2003. Dynamics of Land-Use and Land-Cover Change in Tropical Regions. Annual Review Environment Resource, 28, 205ï 241.

2. Food and Agricultural Organization (FAO). 2006. Global Forest Resources Assessment 2005. FAO, Rome.

3. Food and Agricultural Organization (FAO). 2000. Global Forest Resources Assessment 2000. FAO, Rome.

4. United Nations Millennium Project. 2005. Environment and Human Well-being: A Practical Strategy. Summary version of the report of the Task Force on Environmental Sustainability. The Earth Institute at Columbia University, New York, USA.

5. Ministry of Environment and Forests (MoEF), Government of India. 2001. State of Environment Report, Biodiversity 2001. MoEF, New Delhi.

6. Ministry of Environment & Forests (MoEF), Government of India. 2001. Nation Action Programme to Combat Desertification, In the Context of United Nations Convention To Combat Desertification (UNCCD) Volume-I, Status of Desertification. 2001. MoEF, New Delhi.

7. Forest Survey of India (FSI), Ministry of Environment and Forests, Government of India. 2000. State of Forest Report. 1999. FSI, Dehradun, India.

8. Forest Survey of India (FSI), Ministry of Environment and Forests, Government of India. 2009. State of Forest Report. 2009. FSI, Dehradun, India.

9. Heywood, V.H. (ed.). 1995. Global Biodiversity Assessment. United Nations Environment Programme. 1995. Cambridge University Press, Cambridge.

10. International Union for Conservation of Nature (IUCN). 2008. Red List of Threatened Species. http://www.iucnredlist.org/documents/2008RL_stats_table_1_v1223294385.pdf. Accessed Sep 13, 09.

11. Intergovernmental Panel on Climate Change (IPCC). 2007. Climate Change 2007: Synthesis Report. IPCC, Valencia, Spain.

12. Chapin F. S., et al. 2000. Consequences of changing biodiversity, Nature 405, 234-242.

13. Hughes J. B., et al. 1997. Population Diversity: Its Extent and Extinction. Science 278, October 24, 689-692.

14. Fargione D. S., et al. 2006. Biodiversity Loss Threatens Human Well-Being. PLoS Biol 4(8): e277. doi:10.1371/journal.pbio.0040277.

15. Khoshoo, T.N. 1996. Biodiversity in the Indian Himalayas: conservation and utilization. In Banking on Biodiversity, edited by Sheggi P Kathmandu: International Centre for Integrated Mountain Development.

16. Ministry of Environment and Forests (MoEF), Government of India. 2009. State of Environment Report, India. 2009. MoEF, New Delhi.

17. International Union for Conservation of Nature (IUCN). 2008. Red List of Threatened Species. http://www.iucnredlist.org/documents/2008RL_stats_table_5_v1223294385.pdf. Accessed Sep 23, 09.

18. Foley J. A., et al. 1997. Global Consequences of Land Use. Science 309, July 22, 570-574.

19. Food and Agricultural Organization (FAO). 2008. Contribution of the forestry sector to national economies, 1990-2006, by A. Lebedys. Forest Finance Working Paper FSFM/ACC/08. FAO, Rome.

20. World Resource Institite. Water Resources and Freshwater Ecosystems. http://earthtrends.wri.org/searchable_db/results.php?years=2006-2006,2007-2007&variable_ID=12&theme= 2&cID=&ccID=0. Accessed: Sep 15, 2009.

21. Forest Survey of India (FSI), Ministry of Environment and Forests, Government of India. 2005. State of Forest Report. 2003. FSI, Dehradun, India.

22. Jha C. S., et al. 2005. Forest fragmentation and its impact on species diversity: an analysis using remote sensing and GIS. Biodiversity and Conservation 14, 1681ï 1698.

23. Kushwaha S. P. S., et al. 2004. Assessment of habitat loss in Kameng and Sonitpur Elephant Reserves. Current Science, 87 (10), 1447-1453.

24. Rodell M., et al. 2009. Satellite-based estimates of groundwater depletion in India. Science 460, August 20, 999-1002.

25. Ministry of Environment and Forests (MoEF), Government of India. 2001. State of Environment Report, Land Degradation. 2001. MoEF, New Delhi.

26. Mulongoy K. J., et al. 2004. Protected Areas and Biodiversity: An overview of key issues. CBD Secretariat, Montreal, Canada and UNEP-WCMC, Cambridge, UK.

27. Chape, S., et al. 2003. United Nations List of Protected Areas. IUCN, Gland, Switzerland and Cambridge, UK and UNEP-WCMC, Cambridge, UK. ix + 44pp.

28. Forest Survey of India (FSI), Ministry of Environment and Forests, Government of India. Status of Forest Cover in Tiger Reserves. http://www.fsi.nic.in/pdf/tigerreserves.pdf. Accessed: Sep 18, 09.

29. Forest Survey of India (FSI), Ministry of Environment and Forests, Government of India. Status of Forest Cover in Biosphere Reserve. http://www.fsi.nic.in/biosphere_reserve_table.htm. Accessed: Sep 18, 09.

30. Intergovernmental Panel on Climate Change (IPCC). 2000. Summary for Policymakers, Land Use, Land-Use Change, and Forestry. IPCC, Montreal, Canada.

31. Lambin E. F., 1997. Modelling and monitoring land-cover change processes in tropical regions. Progress In Physical Geography, 21 (3), 375-393.

32. Coppin P., et al., 2004. Digital change detection methods in ecosystem monitoring: a review. International Journal of Remote Sensing, 25 (9), 1565ï 1596.

33. Rogan, J., et al., 2002. A comparison of methods for monitoring multitemporal vegetation change using Thematic Mapper imagery. Remote Sensing of Environment, 80, 143ï 156.

34. Carpenter, G. A., et al., 1999. A neural network method for efficient vegetation mapping. Remote Sensing of Environment, 70, 326ï 338.

35. Echeverria C., et al., 2008. Spatially explicit models to analyze forest loss and fragmentation between 1976 and 2020 in southern Chile. ecological modeling, 2 1 2, 439ï 449.

36. Pontius R. G. J., et al., 2001. Modeling the spatial pattern of land-use change with GEOMOD2: application and validation for Costa Rica. Agriculture, Ecosystems and Environment, 1775, 1-13.

37. Zollner P. A., et al., 2008. Influence of forest planning alternatives on landscape pattern and ecosystem processes in northern Wisconsin, USA. Forest Ecology and Management, 254, 429ï 444.

38. Harris N. L., et al., 2008. Identifying optimal areas for REDD intervention: East Kalimantan, Indonesia as a case study. Environmental Research Letters, 3, 1-11.

39. Jantz C. A., et al., 2010. Designing and implementing a regional urban modeling system using the SLEUTH cellular urban model. Computers, Environment and Urban Systems, 34, 1ï 16.

40. Silva E. A., et al., 2008. Strategies for landscape ecology: An application using cellular automata models. Progress in Planning, 70, 133ï 177.

41. Janssen, M.A., 2005. Agent-Based Modeling. Internet Encyclopaedia of Ecological Economics. Arizona State, US.
http://www.ecoeco.org/pdf/agent_based%20_modeling.pdf

42. Nangendo G., et al., 2007. Mapping East African tropical forests and woodlands - A comparison of classifiers. ISPRS Journal of Photogrammetry & Remote Sensing, 61, 393ï 404.

43. Lillesand T. M. and Kiefer R. W., 2002. Remote sensing and image interpretation, Fourth edition. John Wiley and Sons, New York.

44. Singh A., 1984, Tropical forest monitoring using digital Landsat data in northeastern India. Ph.D. thesis, University of Reading, Reading, England.

45. Rogan, J., and Chen, D., (2004). Remote sensing technology for mapping and monitoring land cover and land use change. Progress in Planning, 61, 301ī 325.

46. URL: http://mcst.gsfc.nasa.gov/index.php?section=13. Accessed January 10, 2011.

47. Tyrrell, M. L., et al., 2004. Dynamic models of land use change in Northeastern USA: Developing tools, techniques, and talents for effective conservation action. GISF Research Paper 003. New Haven, CT.

48. Soares-Filho B. S., et al., 2002. DINAMICA a stochastic cellular automata model designed to simulate the landscape dynamics in an Amazonian colonization frontier. Ecological Modelling, 154, 217.235.

49. Parker, D. C., et al., 2003. Multi-agent systems for the simulation of land-use and land-cover change: a review. Annals of the Association of American Geographers, 93, 314-337.

50. Veldkamp, A., 2004. Modelling land use change and environmental impact. Journal of Environmental Management, 72, 1ï 3.

51. Lu D., and Weng Q., 2007. A survey of image classification methods and techniques for improving classification performance. International Journal of Remote Sensing,. 28, 823ï 870.

52. Lu D., et al., 2003. Change detection techniques. International Journal of Remote Sensing, 25 (12), 2365ï 2407.

53. Singh A., 1986, Change detection in the tropical forest environment of northeastern India using Landsat. Remote Sensing and Tropical Land Management, edited by M . J. Eden and J. T. Parry (London: John Wiley & Sons), 237-254.

54. Hansen M. C., et Al., 2008. Humid tropical forest clearing from 2000 to 2005 quantified by using multitemporal and multiresolution remotely sensed data. PNAS, 105 (27), 9439ï 9444. www.pnas.org_cgi_doi_10.1073_pnas.0804042105.

55. Curran, L. M., et al., 2004. Lowland Forest Loss in Protected Areas of Indonesian Borneo. Science, 303, 1000-1003.

56. DeMers M. N., 2002. GIS modeling in raster.

57. Mas J. F., 1999. Monitoring land-cover changes: a comparison of change detection techniques. International Journal of Remote Sensing, 20, 139-152.

58. Shah C. A., et al., 2007. ICA mixture model algorithm for unsupervised classification of remote sensing imagery. International Journal of Remote Sensing, 28, 1711ï 1731.

59. Lu D., et al., 2007. Land-cover classification in the Brazilian Amazon with the integration of Landsat ETM+ and Radarsat data. International Journal of Remote Sensing, 28, 5447ï 5459.

60. Wang B., et al., 2001. Proceedings of the 2000 Northeastern Recreation Research Symposium. Gen. Tech. Rep. NE-276. Newtown Square, PA: U.S. Department of Agriculture, Forest Service, Northeastern Research Station. 193-200. http://nrs.fs.fed.us/pubs/gtr/gtr_ne276/gtr_ne276_193.pdf. Accessed Mar 18, 2010.

61. Huang X., and Jense J. R., 1997. A Machine-Learning Approach to Automated Knowledge-Base Building for Remote Sensing Image Analysis with GIs Data. Photogrammetric Engineering & Remote Sensing, 63 (10), 1185-1194.

62. Plaza A., et al., 2009. Recent advances in techniques for hyperspectral image processing. Remote Sensing of Environment, 113, S110ï S122.

63. Rindfuss R. R., et al., J 2004. Developing a science of land change: Challenges and methodological issues. PNAS, 101 (39), 13976ï 13981. www.pnas.org cgi doi 10.1073 pnas.0401545101.

64. Mather, P.M., 2004. Computer Processing of Remotely-Sensed Images: An Introduction, Third Edition. John Wiley & Sons, Chichester.

65. Desclée B., et al., 2006. Forest change detection by statistical object-based method. Remote Sensing of Environment, 102, 1ï 11.

66. Foody G. M., 2002. Status of land cover classification accuracy assessment. Remote sensing of environment, 185-201.

67. Chan J. C.-W., et al. 2003. Texture classification of logged forests in tropical Africa using machine-learning algorithms. International Journal of Remote Sensing, 24(6), 1401ï 1407.

68. DeFries R. S., and Chan J. C. W., 2000. Multiple Criteria for Evaluating Machine Learning Algorithms for Land Cover Classification from Satellite Data. Remote Sensing of Environment, 74, 503ï 515.

69. Brandt T. and Mather P. M., 2009. Classification Methods for Remotely Sensed Data, Second Edition. CRC Press, London, New York.

70. Pal, M., and Mather, P. M., 2003. An assessment of the effectiveness of decision tree methods for land-cover classification. Remote Sensing of Environment, 30, 554ï 565.

71. Singh A., 1989. Digital change detection techniques using remotely-sensed data. International Journal of Remote Sensing, 10, 989-1003.

72. Singh A., 1987, Spectral separability of tropical forest cover classes. International Journal of Remote Sensing. 8 (7), 971-979.

73. Mannan B., et al., 1998. Fuzzy ARTMAP supervised classification of multi-spectral remotely-sensed images. International Journal of Remote Sensing, 19 (4), 767-774.

74. Gao Y. and Mas J. F., 2008. ñA comparison of the performance of pixel-based and object-based classifications over images with various spatial resolutionsò, Online Journal of Earth Sciences, 2, 27-35.

75. Heurich M., 2008. Automatic recognition and measurement of single trees based on data from airborne laser scanning over the richly structured natural forests of the Bavarian Forest National Park. Forest Ecology and Management, 255, 2416ï 2433.

76. Kaiser G., and Schneider W., 2008. Estimation of sensor point spread function by spatial subpixel analysis. International Journal of Remote Sensing, 29, 2137ï 2155.

77. Rogan J., et al., Mapping land-cover modifications over large areas: A comparison of machine learning algorithms. Remote Sensing of Environment, 112, 2272ï 2283.

78. Friedl, M. A., and Brodley, C. E., 1997. Decision tree classification of landcover from remotely sensed data. Remote Sensing of Environment, 61, 399ï 408.

79. Pal M., 2006. M5 model tree for land cover classification. International Journal of Remote Sensing, 27, 825-831.

80. Zambon, M., et al., 2006. Effect of alternative splitting rules on image processing using classification tree analysis. Photogrammetric Engineering and Remote Sensing, 72, 25-30.

81. Rogan, J., et al., 2003. Land-cover change mapping in California using classification trees with Landsat TM and ancillary data. Photogrammetric Engineering and Remote Sensing, 69, 793ï 804.

82. Friedl M. A., et al., 1999. Maximizing Land Cover Classification Accuracies Produced by Decision Trees at Continental to Global Scales. IEEE Transactions On Geoscience And Remote Sensing, 37, 969-97.

83. Pontius R. G. J., and Petrova S. H., 2010. Assessing a predictive model of land change using uncertain data. Environmental Modelling & Software, 25, 299ï 309.

84. SONG C., et al., 2001. Classification and change detection using Landsat TM data: when and how to correct atmospheric effect. Remote Sensing of Environment, 75, 230-244.

85. Petrova S., et al., 2007. Carbon and Co-Benefits from Sustainable Land-Use Management, Deliverable 22: Quantification of carbon benefits in conservation project activities through spatial modeling: East Kalimantan, Indonesia as a Case Study. Winrock International, Arlington, USA.

86. Pontius R. G. J., et al., 2004. Useful techniques of validation for spatially explicit land-change models. Ecological Modelling, 179, 445ï 461.

87. Wickramasuriya R. C., et al., 2009. The dynamics of shifting cultivation captured in an extended Constrained Cellular Automata land use model. Ecological Modelling, 220, 2302ï 2309.

88. Evans T. P., and Kelly H., 2004. Multi-scale analysis of a household level agent-based model of landcover change. Journal of Environmental Management, 72, 57ï 72.

89. Le Q. B. et al., 2008. Land-Use Dynamic Simulator (LUDAS): A multi-agent system model for simulating spatio-temporal dynamics of coupled humanï landscape system. I. Structure and theoretical specification. Ecological Informatics, 3, 135-153.

90. Potter C., et al., 2001. Ecosystem modeling and dynamic effects of deforestation on trace gas fluxes in Amazon tropical forest. Forest Ecology and Management, 152, 97-117.

91. Asner G. P., et al., 2009. A Contemporary Assessment of Change in Humid Tropical Forests. Conservation Biology, 23, 1386ï 1395.

92. Forest Survey of India (FSI), Ministry of Environment and Forests, Government of India. 2008. State of Forest Report. 2005. FSI, Dehradun, India.

93. URL: http://www.manasassam.org/research.asp.

94. Sarma P. K., Et Al., 2008. Land-use and land-cover change and future implication analysis in Manas National Park, India using multi-temporal satellite data. Current Science,. 95 (2), 223-227.

95. URL: http://projecttiger.nic.in/manas.htm.

96. Nagendra H., et al., 2009. Landscapes of Protection: Forest Change and Fragmentation in Northern West Bengal, India. Environmental Management, 44, 853ï 864.

97. Prabhakar R., et al., 2006. How degraded are Himalayan forests? Current Science, 91 (1), 61-67.

98. Roy P. S. and Sharma P. K., 2002. Forest cover assessment in north-east Indiað the potential of temporal wide swath satellite sensor data (IRS-1C WiFS). International Journal of Remote Sensing 23, 4881ï 4896.

99. Jha C. S., et al., 2000. Deforestation and land use changes in Western Ghats, India. Current Science, 79 (2), 231-238.

100. Pandit M. K., et al. 2007. Unreported yet massive deforestation driving loss of endemic biodiversity in Indian Himalaya. Biodiversity Conservation, 16, 153ï 163.

101. Puyravaud J., et al., 2010. Policy perspective, Cryptic destruction of Indiaŝ native forests. Conservation Letters, doi: 10.1111/j.1755-263X.2010.00141.x.

102. Forest Survey of India (FSI), Ministry of Environment and Forests, Government of India. 1998. State of Forest Report. 1997. FSI, Dehradun, India.

103. Jhala Y. V., et al., 2008. Status of Tigers, Co-predators and Prey in India by National Tiger Conservation Authority, New Delhi, India and Wildlife Institute of India, Dehradun, India.

104. Johnsingh A. J. T., et al., 2003. Status of tiger and leopard in Rajajiï Corbett Conservation Unit, northern India. Biological Conservation, 111, 385ï 393.

105. De A., 2007. Patterns of plant species diversity in the forest corridor of Rajajiï Corbett National Parks, Uttaranchal, India. Current Science, 92, 90-93.

106. Love A., et al., 2009. Management of Lantana, an invasive alien weed, in forest ecosystems of India. Current Science, 97, 1421-1429.

107. Nandy S., et al., 2007. Monitoring the Chillaï Motichur wildlife corridor using geospatial tools. Journal for Nature Conservation, 15, 237-244.

108. Kimothi M. M., et al., 2008. Remote sensing to map the invasive weed, Lantana camara in forests. Tropical Ecology 51(1): 67-74.

109. Joshi R. and Pande G. S., 2007. Rehabilitation of Gujjar community from the Rajaji National Park: An approach for biological diversity conservation through restoration ecology. National Academy Science Letters, 30 (9-10), 263-267.

110. Ravi A.B., 2008. Discovering Rajaji National Park. Bishen Singh Mahendra Pal Singh. Dehradun, India.

111. Forest Survey of India (FSI), Ministry of Environment and Forests, Government of India. 1993. State of Forest Report. 1993. FSI, Dehradun, India.

112. Menon S., et al., 2001. Identifying Conservation-Priority Areas in the Tropics: a Land-Use Change Modeling Approach. Conservation Biology, 15 (2), 501ï 512.

113. Forest Survey of India (FSI), Ministry of Environment and Forests, Government of India. 2002. State of Forest Report. 2001. FSI, Dehradun, India.

REFERENCE LIST

Asner G. P., et al., 2009. A Contemporary Assessment of Change in Humid Tropical Forests. Conservation Biology, 23, 1386ï 1395.

Brandt T. and Mather P. M., 2009. Classification Methods for Remotely Sensed Data, Second Edition. CRC Press, London, New York.

Carpenter, G. A., et al., 1999. A neural network method for efficient vegetation mapping. Remote Sensing of Environment, 70, 326ï 338.

Chan J. C.-W., et al. 2003. Texture classification of logged forests in tropical Africa using machine-learning algorithms. International Journal of Remote Sensing, 24(6), 1401ï 1407.

Chape, S., et al. 2003. United Nations List of Protected Areas. IUCN, Gland, Switzerland and Cambridge, UK and UNEP-WCMC, Cambridge, UK. ix + 44pp.

Chapin F. S., et al. 2000. Consequences of changing biodiversity, Nature 405, 234-242.

Coppin P., et al., 2004. Digital change detection methods in ecosystem monitoring: a review. International Journal of Remote Sensing, 25 (9), 1565ï 1596.

Curran, L. M., et al., 2004. Lowland Forest Loss in Protected Areas of Indonesian Borneo. Science, 303, 1000-1003.

De A., 2007. Patterns of plant species diversity in the forest corridor of Rajajiï Corbett National Parks, Uttaranchal, India. Current Science, 92, 90-93.

DeFries R. S., and Chan J. C. W., 2000. Multiple Criteria for Evaluating Machine Learning Algorithms for Land Cover Classification from Satellite Data. Remote Sensing of Environment, 74, 503ï 515.

DeMers M. N., 2002. GIS modeling in raster.

Desclée B., et al., 2006. Forest change detection by statistical object-based method. Remote Sensing of Environment, 102, 1ï 11.

Echeverria C., et al., 2008. Spatially explicit models to analyze forest loss and fragmentation between 1976 and 2020 in southern Chile. ecological modeling, 2 1 2, 439ï 449.

Evans T. P., and Kelly H., 2004. Multi-scale analysis of a household level agent-based model of landcover change. Journal of Environmental Management, 72, 57ï 72.

Fargione D. S., et al. 2006. Biodiversity Loss Threatens Human Well-Being. PLoS Biol 4(8): e277. doi:10.1371/journal.pbio.0040277.

Foley J. A., et al. 1997. Global Consequences of Land Use. Science 309, July 22, 570-574.

Food and Agricultural Organization (FAO). 2000. Global Forest Resources Assessment 2000. FAO, Rome.

Food and Agricultural Organization (FAO). 2006. Global Forest Resources Assessment 2005. FAO, Rome.

Food and Agricultural Organization (FAO). 2008. *Contribution of the forestry sector to national economies, 1990-2006*, by A. Lebedys. Forest Finance Working Paper FSFM/ACC/08. FAO, Rome.

Foody G. M., 2002. Status of land cover classification accuracy assessment. Remote sensing of environment, 185-201.

Forest Survey of India (FSI), Ministry of Environment and Forests, Government of India. 1993. State of Forest Report. 1993. FSI, Dehradun, India.

Forest Survey of India (FSI), Ministry of Environment and Forests, Government of India. 1998. State of Forest Report. 1997. FSI, Dehradun, India.

Forest Survey of India (FSI), Ministry of Environment and Forests, Government of India. 2000. State of Forest Report. 1999. FSI, Dehradun, India.

Forest Survey of India (FSI), Ministry of Environment and Forests, Government of India. 2002. State of Forest Report. 2001. FSI, Dehradun, India.

Forest Survey of India (FSI), Ministry of Environment and Forests, Government of India. 2005. State of Forest Report. 2003. FSI, Dehradun, India.

Forest Survey of India (FSI), Ministry of Environment and Forests, Government of India. 2008. State of Forest Report. 2005. FSI, Dehradun, India.

Forest Survey of India (FSI), Ministry of Environment and Forests, Government of India. 2009. State of Forest Report. 2009. FSI, Dehradun, India.

Forest Survey of India (FSI), Ministry of Environment and Forests, Government of India. Status of Forest Cover in Biosphere Reserve. http://www.fsi.nic.in/biosphere_reserve_table.htm. Accessed: Sep 18, 09.

Forest Survey of India (FSI), Ministry of Environment and Forests, Government of India. Status of Forest Cover in Tiger Reserves. http://www.fsi.nic.in/pdf/tigerreserves.pdf. Accessed: Sep 18, 09.

Friedl M. A., et al., 1999. Maximizing Land Cover Classification Accuracies Produced by Decision Trees at Continental to Global Scales. IEEE Transactions On Geoscience And Remote Sensing, 37, 969-97.

Friedl, M. A., and Brodley, C. E., 1997. Decision tree classification of landcover from remotely sensed data. Remote Sensing of Environment, 61, 399ï 408.

Gao Y. and Mas J. F., 2008. ñA comparison of the performance of pixel-based and object-based classifications over images with various spatial resolutionsò, Online Journal of Earth Sciences, 2, 27-35.

Hansen M. C., et Al., 2008. Humid tropical forest clearing from 2000 to 2005 quantified by using multitemporal and multiresolution remotely sensed data. PNAS, 105 (27), 9439ï 9444. www.pnas.org_cgi_doi_10.1073_pnas.0804042105.

Harris N. L., et al., 2008. Identifying optimal areas for REDD intervention: East Kalimantan, Indonesia as a case study. Environmental Research Letters, 3, 1-11.

Heurich M., 2008. Automatic recognition and measurement of single trees based on data from airborne laser scanning over the richly structured natural forests of the Bavarian Forest National Park. Forest Ecology and Management, 255, 2416ï 2433.

Heywood, V.H. (ed.). ***1995****.* ***Global Biodiversity Assessment****. United Nations Environment Programme. 1995. Cambridge University Press, Cambridge.*

Huang X., and Jense J. R., 1997. A Machine-Learning Approach to Automated Knowledge-Base Building for Remote Sensing Image Analysis with GIs Data. Photogrammetric Engineering & Remote Sensing, 63 (10), 1185-1194.

Hughes J. B., et al. 1997. Population Diversity: Its Extent and Extinction. Science 278, October 24, 689-692.

Intergovernmental Panel on Climate Change (IPCC). 2000. Summary for Policymakers, Land Use, Land-Use Change, and Forestry. IPCC, Montreal, Canada.

Intergovernmental Panel on Climate Change (IPCC). 2007. Climate Change 2007: Synthesis Report. IPCC, Valencia, Spain.

International Union for Conservation of Nature (IUCN). 2008. Red List of Threatened Species. http://www.iucnredlist.org/documents/2008RL_stats_table_1_v1223294385.pdf. Accessed Sep 13, 09.

International Union for Conservation of Nature (IUCN). 2008. Red List of Threatened Species. http://www.iucnredlist.org/documents/2008RL_stats_table_5_v1223294385.pdf. Accessed Sep 23, 09.

Janssen, M.A., 2005. Agent-Based Modeling. Internet Encyclopaedia of Ecological Economics. Arizona State, US. http://www.ecoeco.org/pdf/agent_based%20_modeling.pdf.

Jantz C. A., et al., 2010. Designing and implementing a regional urban modeling system using the SLEUTH cellular urban model. Computers, Environment and Urban Systems, 34, 1-16.

Jha C. S., et al. 2005. Forest fragmentation and its impact on species diversity: an analysis using remote sensing and GIS. Biodiversity and Conservation 14, 1681ï 1698.

Jha C. S., et al., 2000. Deforestation and land use changes in Western Ghats, India. Current Science, 79 (2), 231-238.

Jhala Y. V., et al., 2008. Status of Tigers, Co-predators and Prey in India by National Tiger Conservation Authority, New Delhi, India and Wildlife Institute of India, Dehradun, India.

Johnsingh A. J. T., et al., 2003. Status of tiger and leopard in Rajajiï Corbett Conservation Unit, northern India. Biological Conservation, 111, 385ï 393.

Joshi R. and Pande G. S., 2007. Rehabilitation of Gujjar community from the Rajaji National Park: An approach for biological diversity conservation through restoration ecology. National Academy Science Letters, 30 (9-10), 263-267.

Kaiser G., and Schneider W., 2008. Estimation of sensor point spread function by spatial subpixel analysis. International Journal of Remote Sensing, 29, 2137ï 2155.

Khoshoo, T.N. 1996. Biodiversity in the Indian Himalayas: conservation and utilization. In Banking on Biodiversity, edited by Sheggi P Kathmandu: International Centre for Integrated Mountain Development.

Kimothi M. M., et al., 2008. Remote sensing to map the invasive weed, Lantana camara in forests. Tropical Ecology 51(1): 67-74.

Kushwaha S. P. S., et al. 2004. Assessment of habitat loss in Kameng and Sonitpur Elephant Reserves. Current Science, 87 (10), 1447-1453.

Lambin E. F., 1997. Modelling and monitoring land-cover change processes in tropical regions. Progress In Physical Geography, 21 (3), 375-393.

Lambin E. F., et al. 2003. Dynamics of Land-Use and Land-Cover Change in Tropical Regions. Annual Review Environment Resource, 28, 205ï 241.

Le Q. B. et al., 2008. Land-Use Dynamic Simulator (LUDAS): A multi-agent system model for simulating spatio-temporal dynamics of coupled humanï landscape system. I. Structure and theoretical specification. Ecological Informatics, 3, 135-153.

Lillesand T. M. and Kiefer R. W., 2002. Remote sensing and image interpretation, Fouth edition. John Wiley and Sons, New York.

Love A., et al., 2009. Management of Lantana, an invasive alien weed, in forest ecosystems of India. Current Science, 97, 1421-1429.

Lu D., and Weng Q., 2007. A survey of image classification methods and techniques for improving classification performance. International Journal of Remote Sensing,. 28, 823ï 870.

Lu D., et al., 2003. Change detection techniques. International Journal of Remote Sensing, 25 (12), 2365ï 2407.

Lu D., et al., 2007. Land-cover classification in the Brazilian Amazon with the integration of Landsat ETM+ and Radarsat data. International Journal of Remote Sensing, 28, 5447ï 5459.

Mannan B., et al., 1998. Fuzzy ARTMAP supervised classi® cation of multi-spectral remotely-sensed images. International Journal of Remote Sensing, 19 (4), 767-774.

Mas J. F., 1999. Monitoring land-cover changes: a comparison of change detection techniques. International Journal of Remote Sensing, 20, 139-152.

Mather, P.M., 2004. Computer Processing of Remotely-Sensed Images: An Introduction, Third Edition. John Wiley & Sons, Chichester.

Menon S., et al., 2001. Identifying Conservation-Priority Areas in the Tropics: a Land-Use Change Modeling Approach. Conservation Biology, 15 (2), 501ï 512.

Ministry of Environment & Forests (MoEF), Government of India. 2001. Nation Action Programme to Combat Desertification, In the Context of United Nations Convention To Combat Desertification (UNCCD) Volume-I, Status of Desertification. 2001. MoEF, New Delhi.

Ministry of Environment and Forests (MoEF), Government of India. 2001. State of Environment Report, Biodiversity 2001. MoEF, New Delhi.

Ministry of Environment and Forests (MoEF), Government of India. 2001. State of Environment Report, Land Degradation. 2001. MoEF, New Delhi.

Ministry of Environment and Forests (MoEF), Government of India. 2009. State of Environment Report, India. 2009. MoEF, New Delhi.

Mulongoy K. J., et al. 2004. Protected Areas and Biodiversity: An overview of key issues. CBD Secretariat, Montreal, Canada and UNEP-WCMC, Cambridge, UK.

Nagendra H., et al., 2009. Landscapes of Protection: Forest Change and Fragmentation in Northern West Bengal, India. Environmental Management, 44, 853ï 864.

Nandy S., et al., 2007. Monitoring the Chillaï Motichur wildlife corridor using geospatial tools. Journal for Nature Conservation, 15, 237-244.

Nangendo G., et al., 2007. Mapping East African tropical forests and woodlands - A comparison of classifiers. ISPRS Journal of Photogrammetry & Remote Sensing, 61, 393ï 404.

Pal M., 2006. M5 model tree for land cover classification. International Journal of Remote Sensing, 27, 825-831.

Pal, M., and Mather, P. M., 2003. An assessment of the effectiveness of decision tree methods for land-cover classification. Remote Sensing of Environment, 30, 554ï 565.

Pandit M. K., et al. 2007. Unreported yet massive deforestation driving loss of endemic biodiversity in Indian Himalaya. Biodiversity Conservation, 16, 153ï 163.

Parker, D. C., et al., 2003. Multi-agent systems for the simulation of land-use and land-cover change: a review. Annals of the Association of American Geographers, 93, 314-337.

Petrova,S., et al., 2007. Carbon and Co-Benefits from Sustainable Land-Use Management, Deliverable 22: Quantification of carbon benefits in conservation project activities through spatial modeling: East Kalimantan, Indonesia as a Case Study. Winrock International, Arlington, USA.

Plaza A., et al., 2009. Recent advances in techniques for hyperspectral image processing. Remote Sensing of Environment, 113, S110ï S122.

Pontius R. G. J., and Petrova S. H., 2010. Assessing a predictive model of land change using uncertain data. Environmental Modelling & Software, 25, 299ï 309.

Pontius R. G. J., et al., 2001. Modeling the spatial pattern of land-use change with GEOMOD2: application and validation for Costa Rica. Agriculture, Ecosystems and Environment, 1775, 1-13.

Pontius R. G. J., et al., 2004. Useful techniques of validation for spatially explicit land-change models. Ecological Modelling, 179, 445ï 461.

Potter C., et al., 2001. Ecosystem modeling and dynamic effects of deforestation on trace gas fluxes in Amazon tropical forest. Forest Ecology and Management, 152, 97-117.

Prabhakar R., et al., 2006. How degraded are Himalayan forests? Current Science, 91 (1), 61-67.

Puyravaud J., et al., 2010. Policy perspective, Cryptic destruction of Indiaôs native forests. Conservation Letters, doi: 10.1111/j.1755-263X.2010.00141.x.

Ravi A.B., 2008. Discovering Rajaji National Park. Bishen Singh Mahendra Pal Singh. Dehradun, India.

Rindfuss R. R., et al., J 2004. Developing a science of land change: Challenges and methodological issues. PNAS, 101 (39), 13976ï 13981. www.pnas.org cgi doi 10.1073 pnas.0401545101.

Rodell M., et al. 2009. Satellite-based estimates of groundwater depletion in India. Science 460, August 20, 999-1002.

Rogan J., et al., Mapping land-cover modifications over large areas: A comparison of machine learning algorithms. Remote Sensing of Environment, 112, 2272ï 2283.

Rogan, J., and Chen, D., (2004). Remote sensing technology for mapping and monitoring land cover and land use change. Progress in Planning, 61, 301ï 325.

Rogan, J., et al., 2002. A comparison of methods for monitoring multitemporal vegetation change using Thematic Mapper imagery. Remote Sensing of Environment, 80, 143ï 156.

Rogan, J., et al., 2003. Land-cover change mapping in California using classification trees with Landsat TM and ancillary data. Photogrammetric Engineering and Remote Sensing, 69, 793ï 804.

Roy P. S. and Sharma P. K., 2002. Forest cover assessment in north-east Indiað the potential of temporal wide swath satellite sensor data (IRS-1C WiFS). International Journal of Remote Sensing 23, 4881ï 4896.

Sarma P. K., Et Al., 2008. Land-use and land-cover change and future implication analysis in Manas National Park, India using multi-temporal satellite data. Current Science,. 95 (2), 223-227.

Shah C. A., et al., 2007. ICA mixture model algorithm for unsupervised classification of remote sensing imagery. International Journal of Remote Sensing, 28, 1711ï 1731.

Silva E. A., et al., 2008. Strategies for landscape ecology: An application using cellular automata models. Progress in Planning, 70, 133ï 177.

Singh A., 1984, Tropical forest monitoring using digital Landsat data in northeastern India. Ph.D. thesis, University of Reading, Reading, England.

Singh A., 1986, Change detection in the tropical forest environment of northeastern India using Landsat. Remote Sensing and Tropical Land Management, edited by M . J. Eden and J. T. Parry (London: John Wiley & Sons), 237-254.

Singh A., 1987, Spectral separability of tropical forest cover classes. International Journal of Remote Sensing. 8 (7), 971-979.

Singh A., 1989. Digital change detection techniques using remotely-sensed data. International Journal of Remote Sensing, 10, 989-1003.

Soares-Filho B. S., et al., 2002. DINAMICA.a stochastic cellular automata model designed to simulate the landscape dynamics in an Amazonian colonization frontier. Ecological Modelling, 154, 217.235.

SONG C., et al., 2001. Classification and change detection using Landsat TM data: when and how to correct atmospheric effect. Remote Sensing of Environment, 75, 230-244.

Tyrrell, M. L., et al., 2004. Dynamic models of land use change in Northeastern USA: Developing tools, techniques, and talents for effective conservation action. GISF Research Paper 003. New Haven, CT.

United Nations Millennium Project. 2005. Environment and Human Well-being: A Practical Strategy. Summary version of the report of the Task Force on Environmental Sustainability. The Earth Institute at Columbia University, New York, USA.

URL: http://mcst.gsfc.nasa.gov/index.php?section=13. Accessed January 10, 2011.

URL: http://projecttiger.nic.in/manas.htm.

URL: http://www.manasassam.org/research.asp.

Veldkamp, A., 2004. Modelling land use change and environmental impact. Journal of Environmental Management, 72, 1ï 3.

Wang B., et al., 2001. Proceedings of the 2000 Northeastern Recreation Research Symposium. Gen. Tech. Rep. NE-276. Newtown Square, PA: U.S. Department of Agriculture, Forest Service, Northeastern Research Station. 193-200. http://nrs.fs.fed.us/pubs/gtr/gtr_ne276/gtr_ne276_193.pdf. Accessed Mar 18, 2010.

Wickramasuriya R. C., et al., 2009. The dynamics of shifting cultivation captured in an extended Constrained Cellular Automata land use model. Ecological Modelling, 220, 2302ï 2309.

World Resource Inistitite. Water Resources and Freshwater Ecosystems. http://earthtrends.wri.org/searchable_db/results.php?years=2006-2006,2007-2007&variable_ID=12&theme= 2&cID=&ccID=0. Accessed: Sep 15, 2009.

Zambon, M., et al., 2006. Effect of alternative splitting rules on image processing using classification tree analysis. Photogrammetric Engineering and Remote Sensing, 72, 25-30.

Zollner P. A., et al., 2008. Influence of forest planning alternatives on landscape pattern and ecosystem processes in northern Wisconsin, USA. Forest Ecology and Management, 254, 429ï 444.