AN INTEGRATED MODELLING OF AGRO-INDUSTRIAL LANDSCAPE DYNAMICS IN INDIA

Thesis

Submitted in partial fulfilment of the requirements for the degree of

DOCTOR OF PHILOSOPHY

by

SUPARNO GHOSH

DEPARTMENT OF APPLIED MECHANICS & HYDRAULICS

NATIONAL INSTITUTE OF TECHNOLOGY KARNATAKA,

SURATHKAL, MANGALORE -575025

July, 2018

D E C L A R A T I O N

by the Ph.D. Research scholar

I hereby *declare* that the Research Thesis entitled "**An Integrated Modelling of Agro-Industrial Landscape Dynamics in India**" which is being submitted to the **National Institute of Technology Karnataka, Surathkal** in partial fulfilment of the requirements for the award of the Degree of **Doctor of Philosophy** in the **Department of Applied Mechanics and Hydraulics** is a *bona fide report of the research work carried out by me*. The material contained in this Research Thesis has not been submitted to any University or Institution for the award of any degree.

Suparno Ghosh.

112031 AM11F08, SUPARNO GHOSH

(Register Number, Name & Signature of the Research Scholar)

Department of Applied Mechanics and Hydraulics

National Institute of Technology Karnataka, Surathkal

Place: NITK-Surathkal

Date: 27th July, 2018

C E R T I F I C A T E

This is to *certify* that the Research Thesis entitled "**An Integrated Modelling of Agro-Industrial Landscape Dynamics in India**" submitted by **Suparno Ghosh** (Register Number: 112031 AM11F08) as the record of the research work carried out by him, is *accepted as the Research Thesis submission* in partial fulfilment of the requirements for the award of degree of **Doctor of Philosophy**.

Prof. Amba Shetty
(Research Guide)

Prof. A Mahesha 24/10/2018
(Chairman - DRPC)

Chairman (DRPC)
Department of Applied Mechanics & Hydraulics
National Institute of Technology Karnataka Surathkal
Mangalore -575025,Karnataka,INDIA

DEPARTMENT OF APPLIED MECHANICS AND HYDRAULICS
NATIONAL INSTITUTE OF TECHNOLOGY KARNATAKA,
SURATHKAL, MANGALURU – 575 025

To my parents and all teachers, Who brought me to university

ACKNOWLEDGEMENTS

Ya Devi sarva bhuteshu Buddhi-rupena samsthitha
Namastasye Namastasye Namastasye Namo Namaha.

Our ancient scripture says - The intellect within all of us is manifestation of the Divine. Thus, honouring the Intellect, the Consciousness is honouring the divine.

I would like to warmly thank each and every one who enriched my knowledge and helped in my Ph.D. research. My research would have been impossible without the aid and constant support from my research supervisor Prof. Amba Shetty. Her critiques and comments has been instrumental in guiding me to shape the research work.

I express my sincere gratitude to the members of Research Progress Assessment Committee, Prof. Santhosh George, Department of MACS, and Prof. Varghese George, Department of Civil Engineering, for their continuous support, encouragement and pragmatic critique throughout my work.

I convey my regards to the professors of Department of Applied Mechanics & Hydraulics, especially the present Head of Department (HOD) Prof. A. Mahesha and former HODs Prof. M.K. Nagaraj, Prof. Subba Rao and Prof. G.S. Dwarakish for their technical suggestions, help and encouragement during the course of study. I wholeheartedly thank them for creating all the necessary infrastructure facilities for my research which enabled me to carry out my research with all necessary facilities at my disposal.

I am extremely thankful to Mr. Vikram R., NRDMS, Udupi; Smt. Mamatha KS, NRDMS Dakshina Kannada and the officials at DC office in Mangalore and Udupi for providing me necessary data.

I express my sincere appreciation to Prof. Peter H. Verburg, for providing Dyna-CLUE model and giving crucial technical supports when it was needed most. I also appreciate Mr. Pulakesh Das for his generous help and giving me hands-on training on Dyna-CLUE model.

I would like to thank all my co-scholars for their continuous encouragement and selfless assertiveness. I would like to acknowledge the help and support by all the fellow friends and all other well-wishers for their direct and/or indirect help at various stages of this research work. I would like to thank the supporting staff of the department Mr. Balakrishna, Mrs. Prathima, Mr. Harish, Mr. Jagadish, Mr. Seetharam, Mr. Gopal, Mr. Anand and Mr Niranjan for all their logistic and other indirect help during my Ph.D work. Timely help offered by administrative staff of NITK is gratefully acknowledged. I also applaud the security guards at main building who always have provided the key pass to our lab with a smiling face even if it is middle of the night.

My heart-felt appreciation and thanks goes to all my family members, especially my Baba and Maa who stood by me in all weather and had to bear my long absence from home.

ABSTRACT

The biophysical compositions of the earth surface are land covers and the different human uses of land covers are land uses. Hence, both are not same. Increasing human uses are altering Earth's natural environment and land cover in rapid pace. Despite the structured development in mathematical modelling and characterization of LCLU using remote sensing techniques; systematic understanding of LCLU change process remain underexplored. In India, due to agricultural and industrial policy reforms, land conversions are taking place at a high rate. There is an apt need for scientific studies on LCLU system. The objective of this study is to investigate location specific LCLU change driving factors and find the consequent effects of these drivers LCLU changes in pre-industrial and industrialized landscape. Applicability of integrated LCLU change model for Indian condition is evaluated by integrating Dyna-CLUE model with System Dynamics (SD) model. An attempt has also been made to investigate the utility of temporal remote sensing data (acquired through space borne sensors at regular interval) to produce LCLU maps.

The current study has been carried out in a typical agriculture dominated landscape as this region is undergoing rapid industrialisation and urbanisation since last decade. LCLU dynamics are assessed using multi date remote sensing data. Google Earth (GE) is used for collecting training and validation samples as well as historical infrastructure information. Data are also gathered from field, secondary and tertiary sources.

LCLU map is prepared from multi date IRS remote sensing data using Maximum Likelihood supervised Classification algorithm to a satisfactory level of accuracy. A set of eight commonly accessed drivers are identified from relevant literature. Further, nine more drivers are listed with the help of local knowledge. Gathered data spatially mapped as proximate drivers and used as independent variable in Binary Logistic regression. Binary Logistic Regression (BLR) analysis is carried out to investigate the LCLU change drivers. For modelling pre-industrial landscape, year 1997 LCLU map is used as base. For this a linear interpolation model is used to estimate the aggregate LCLU change. Then Dyna-CLUE model is used to spatially model the changes. R^2, *RMSE*(ha) and *RSR* are employed to evaluate the model's performance. Evaluation

using estimated LCLU data has demonstrated very good result. However, when error evaluation is done using actual LCLU data, accuracy has dropped significantly. Validation is also carried out for spatial domain using actual LCLU images as validator. With the advancing time steps, accuracy has reduced. Hence it is anticipated that introduction of more complex model to estimate the aggregate LCLU change may improve the accuracy.

Modelling of industrialized landscape, is facilitated using System Dynamic model. Each of the LCLU classes are modelled as sub-systems. Besides, Population is also modelled as a subsystem, which pertains one-way influence on LCLU classes. LCLU maps of the year 1997, 2003 and 2005 are used for the calibration of model. Coefficient of determination (R^2) for calibration is 0.94. Validation using 2007 and 2010 LCLU maps is 0.96. Estimated LCLU quantities from SD are used in Dyna-CLUE model. This time "Other Land Uses" class is merged with "Waste land" class as it is <1% of total area. In Logistic regression year 1997, 2005, 2007 and 2010 LCLU maps are used as dependent variables. LCLU map of the year 2010 fared better Area under ROC curves (AUC) values in comparison to other years. Hence, it is used in final modelling. LCLU demands between the Year 1997 and 2009 (Baseline Scenario) are used for model calibration. Kappa statistics are employed to evaluate the agreement between GE samples and consecutive simulation result of the same year. The overall accuracy is found to be of average values. Model results are significantly improved during scenario simulation.

This study has demonstrated the capability of virtual earth and temporal remote sensing data to LCLU time series database creation. LCLU change drivers available in the study area, are also examined. Apart from the commonly used drivers, location specific drivers are also tested successfully. After the analysis, it is found biophysical drivers are more dominant followed by population density. Researcher's defined drivers such as Ground water, Road density are providing further insight into the change process. For better insight, drivers are separately analysed for industrialized landscape. Model's simulation capability is sensitive toward the scale and resolution of drivers. Hence, insignificant drivers are removed during calibration of the final model. It is also observed that, class wise accuracy has relationship with the LCLU dynamics. This

research also highlights model's response to a sudden LCLU change. Such abrupt changes can only be modelled using a base map with hotspots of changes are clearly visible.

Keywords: LCLU change, Land Use policy, System Dynamics, Change Modelling, Dyna-CLUE.

TABLE OF CONTENTS

List of Figures

List of Figures cont.

List of Tables

CHAPTER 1

INTRODUCTION

1.0 BACKGROUND

Land in India is changing in a rapid pace since past decades. There is a shortfall understanding of land change process. The main goal of the present study is contributing towards systematic understanding of landscape dynamics in India and try to model the same by adopting an integrated approach.

This chapter introduces this area of research under the following headings.

- Land, land cover and land use, a brief overview
- Factors influencing land use change
- Problems of land use change in India
- A crucial account of India’s contemporary land use policies
- Land acquisition, rehabilitation and resettlement policy
- Scope for research and finally objectives proposed for the research work

1.1 LAND, LAND COVER AND LAND USE, A BRIEF OVERVIEW

Land, a delineable area on terrestrial earth surface, encompasses entire biosphere immediately above and below the earth surface. It includes human activities and human settlement patterns. Thus all physical as well as socio-economic attributes of earth’s surface are recognized as land resources (Sombroek and Sims, 1995). Our material, social and cultural needs have been fulfilled by land since time immemorial. The ecosystem services available from any landscape are arranged, altered, modified as land use patterns by human interventions to produce commodities and services for human consumption (Turner et al., 1994; Burkhard et al., 2009). Complex interrelationship between land cover and land use can be one to one when a single land use may correspond to a single land cover. Sometimes this can be one to many if multiple uses are supported by a single land cover class. Sometimes, a single system of land use could grow over several distinct land cover class (Briassoulis, 2009). Hence, Land Cover and Land Use are not same.

Factors influencing land use change

Local biophysical factors, such as biotic productivity, resistance to soil erosion, water retention capacity, ground water recharge and ground water availability directly determine considerable range of land's suitability for different uses. These factors provide considerable choices to land managers (Rossiter, 1996). Thus, land uses are function of different biophysical landscape factors, habitats factors (Bastian and Röder, 1998) and refined by several other socio-economic factors (Figure 1.1). To understand land use dynamics, climate change and eco-sustainability, it is important to have a clear idea on the association and (or) distinction between land, land cover and land use.

Awareness on broad segregation among proximate alongside underlying causes of land use change is also required (Geist et al., 2006). Local changes in land may contribute to global changes (i.e. global warming, climate change) through physical process of land cover change. Changes may possibly arise from complete alteration or slight modification of existing land cover and land use (Briassoulis, 2000). Global forces attenuate local factors facilitated by institutional structures and at the cadastral level people intercept those opportunities or hindrances to drive land changes (Lambin et al., 2001). These changes are typically theorised to be exponential with anthropogenic pressure (Verburg et al., 1999; Lambin et al., 2001; Rao and Pant, 2001; Sudhira et al., 2004; Ahadnejad et al., 2009; Sun et al., 2013). In practice, instead a single factor exposition, it would make sense if a structured approach is adopted. Many external driving forces put forward quite a few land use options to stake holders. From many options, stake holders choose a land use under the influence of local bio-physical, socio-cultural, infrastructure and political issues (Lambin et al., 2000; Aspinall, 2004; Verburg et al., 2004b) and most importantly revenue growth (Alig et al., 1988; Irwin and Geoghegan, 2001; Samranpong et al., 2009; Bonilla-Moheno et al., 2012).

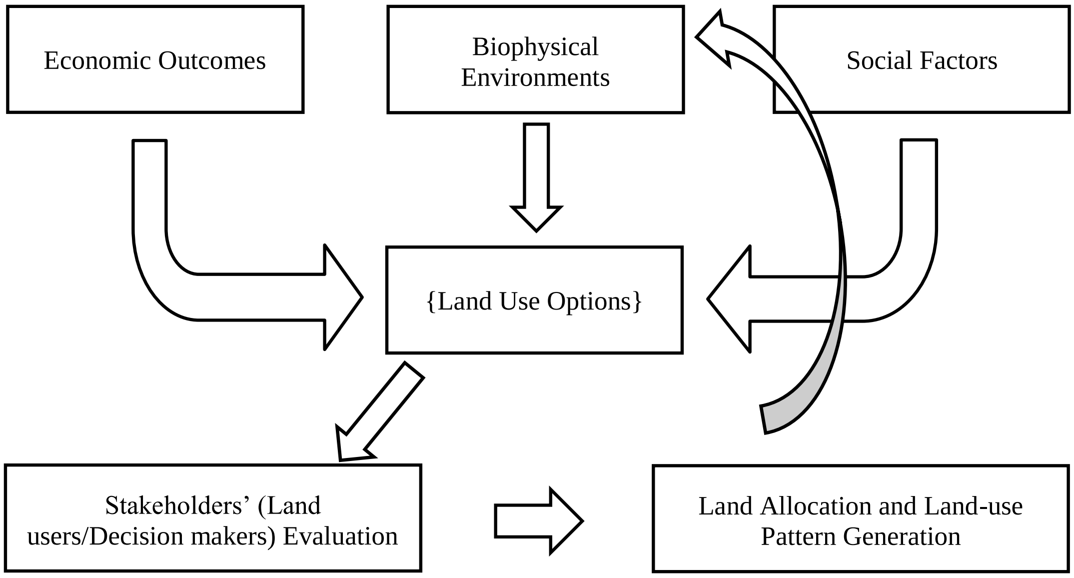


Figure 1.1 Factors, influence the land use change

Biophysical factors, such as slope, geomorphology, climate and soil are some of the most important factors that provide minimum requirements for the interchanging of land between different uses (Aspinall, 2004; Overmars and Verburg, 2005; Bonilla-Moheno et al., 2012). Availability of water largely controls land use changes. Thus proximity to water sources (Overmars and Verburg, 2005; Serra et al., 2008), land irrigability (Kumar et al., 2002) play an important role in controlling the land use dynamics. Other abrupt biophysical activities, (for example forest fire; Serra et al., 2008), are found to be significant in determining the expansion or attenuation of a land cover types. In most cases direct effects of natural factors are limited as they do not manifest the change within a short period (Zhao et al., 2013). Usually gradual and irregular factors drive land-use dynamics in combination (Lambin et al., 2001).

Policy factor of land use change has become more complex and interlinked in today's globalized world. A policy of importing a product from another country could displace an existing land use there (Lambin and Meyfroidt, 2011). Exporting agricultural or mining products causes significant pressure on land and consequently on biodiversity (Weinzettel et al., 2013). Globalization may also rebound the technical advancement or remit labour forces and purchasing power from a distant location which can cascade one change to another (Lambin and Meyfroidt, 2011). Furthermore, complex procedures of globalization are yet to be understood completely. Its apparent effects are increasing poverty, lack of education, environmental damage. Globalization also brings some opportunities, such as widespread economic openings among countries, transmission of technology, overall lifestyle change, and increasing awareness about ecosystem. All these will directly or indirectly affect the exploitation and distribution of resources including industrialization and urbanization over diverse space (Lim, 2005).

1.2 PROBLEMS OF LAND USE CHANGE IN INDIA

Comprehensive policy reforms in India since early sixties, were far-reaching and were inclusive of industrial, trade, and agricultural policy changes (for e.g. Five year plans, Green revolution). Although, the most ambitious reforms were in industrial policy by means of allowing private investments during early nineties. The reforms have facilitated economic dynamism accompanied with industrialization and urbanization (Ghatak and Ghosh, 2011; O'Mara and Seto, 2014). Incidentally, there have been reports that, imitation of the European industrialization model of more than 200 years, within a period of 20 years in India may residue a huge upshot.

In India, 17% of world's population is living on 2.6% of the world's geographical area. 'Per capita availability' of land in India has been declined from 0.89 hectares in 1951 to 0.27 hectares in 2007-08 (DoLR, 2012). Per capita land footprint (amount of biologically productive land required to satisfy the consumption per average inhabitant) in India is 0.55 gha/p, when it holds only 8% of world's total land footprint (Weinzettel et al., 2013). In addition, India's green revolution from early 1960s resulted in large-scale land use changes and instigated largest environmental change in contemporary human history (Tsarouchi et al., 2014). Diversion of agricultural and forest lands to built-up lands and stagnating agricultural yields indicate an increased pressure on land resources and ecosystem services around the globe and especially in the Indian context (Burkhard et al., 2009; Nagendra et al., 2014). Added to this, displacement of rural communities and consequent dispute over compensation has become widespread in India like other developing countries in Asia (Cao et al., 2008). Fear of losing livelihood, unequal distribution of benefit, economic hardship and resultant dissatisfaction over new land use ultimately led to anti-land conversion protests. One such example was at Singur, in the Indian state of West Bengal (Ghatak et al., 2013).

Amidst several protests and unrest over land use conversion, Central Government in India is forced to re-examine existing land use policies and taking actions to provide sustainable development over and above fair compensation and maintain food security (Sharad et al., 2013). Sustainable use of multi-dimensional land, brings well-being to a society. However, policy reform alone may not be enough to meet the need. Sustainable development plan must poise the outcomes across combination of four dimensions - the economic, the social, and the environmental and certainly at the fourth dimension, the governance (McNeill et al., 2014). Hence, it is essential to incorporate scientific knowledge to achieve the sustainability goal and to implement policy guidelines.

1.3 AN ACCOUNT ON INDIA'S CONTEMPORARY LAND USE POLICIES

In true sense, competition among different land uses is obvious (Havel, 1986; Verburg, and Overmars2007). Thus conflict also arises as a consequence of unfair competition. Land-use planning is a way to assume the best land-use option by ensuing policy guidelines and considering existing suitable natural resource-base (FAO, 1993). Land use policy reform is a major policy initiative in India which has come to a reality through different phases of five years plans since the independence (DoLR, 2013). The Department of Land Resources (DoLR) of Ministry of Rural Development (MoRD), Government of India - the sole authority to mandate with land reforms, land record modernisation, watershed management and reforming land acquisitions acts, is proposing to bring out "National Land Utilization Policy"(DoLR, 2013). This national level policy will guide states to adopt and formulate their own policies to command and regulate land uses in an efficient and ethical way to fulfil community need at the same time safeguarding natural resources and averting land use conflicts (DoLR, 2012). The draft of the "National Land Utilization Policy" is under scrutiny by several organizations and stake holders (Solution Exchange, 2014). Eventually "National Land Utilization Policy" would act as a guiding framework for systematic planning. It prioritizes state's concerns to ensure food security as well as sustainable development by pursuing seven objectives;

i) Protection of agricultural lands from land use conversions.

ii) Identification and protection of land for social development.

iii) Preservation of historic and cultural heritage.

iv) Preservation and conservation of natural reserves.

v) Maintain ecosystem services.

vi) Promotion of properly guided and coordinated development.

vii) Generalizing implementation framework for different level of implementation. Unlike existing self-contradictory and random planning units (as e.g. urban area plan v/s industrial investment zone plan etc.), whole country will be divided into some Land Utilisation Zones (LUZs) based on the predominant use of the land. These LUZs will be divided further into various Land-use Management Areas (LMAs) to undertake independent plan or wherever possible integrated into other plan. It is expected that, Regional Development Plan should cover the entire area of LUZ followed by mosaic of detailed Development Plans or Site Master Plans prepared for sub-regions within it (DoLR, 2013). Essentially the draft policy is vague about the use of up-to-date land use related data, competitive interest between different land uses, mechanism of preparing land use plans and master plans etc. The scale of different plans is also not very explicitly mentioned in this report.

1.4 LAND ACQUISITION, REHABILITATION AND RESETTLEMENT POLICY

Before the implementation of 'NLUP' policy, "The Right to Fair Compensation and Transparency in Land Acquisition, Rehabilitation and Resettlement Act", 2013 (popularly known as LARR Act, 2013) is passed in the parliament. It highlights some of the policy measures, which point towards key considerations for planning and management of land utilization zones (Chapter 9 in DoLR, 2013). Such policy measures are; (i) Affected people should get resettlement, rehabilitation at alternative sites and payment of compensation before disposition due to land acquisition, additionally, special attention must be paid on those who directly depend on the land for livelihood. (ii) Prevention of arbitrary agricultural land acquisition to safeguard food security. (iii) In addition, if multi-crop irrigated land is to be acquired, a comparable area of cultivable wasteland shall be developed for agricultural purposes to prioritize food-security. (iv) Special attention should be given to marginalised community affected by new land utilization and tribesmen's right to land should be preserved. (v) Social impact assessment study should be conducted before enacting new land use.

Incidentally LARR Act, 2013 is being criticized since its initiation. Many economist as well as other stake holders have feared that it will slip the nation from the mark of industrialization and economic prosperity, even without ensuring protection of the vulnerable (Ghatak & Ghosh, 2011; Pavaskar & Lala, 2014). The effects of land diversion for industry/infrastructural development in India are hitherto completely unfold. The resultant socioeconomic transitions are likely to rift those who are benefitted from those, whose livelihoods are severely jeopardized (Shah, 2013). However, in a recent amendment (LARR, 2014) to the original act, the authority has ease the norms for acquisition of agricultural land for some particular cases like national security, social infrastructures etc. It also has exempted social impact assessment of land acquisition for those purposes. Perhaps LARR Act, 2013 is a firm attempt to replace the age old colonial, tainted and misused land acquisition policy with an egalitarian and prudently eco sustainable policy framework (Gupta, 2014). In addition, rate of compensation given for acquired land is inexplicit by nature. It should have been explicitly associated with, spatially varied disparity in soil fertility, access to irrigation, cost of living, employment opportunities etc. (Ghatak and Ghosh, 2011).

Hasty land conversion process due to outdated biophysical as well as infrastructural land quality information could lead to people's dissatisfaction and conflicts (Ghatak et al., 2013). Thus state-of-the-art land information is crucial to deal with present land use change related challenges and policy implementation in India. Application of remote sensing, GIS, GPS, participatory mapping help in the modernization of land information (Solution Exchange, 2014). However, means and methods to apply remote sensing and GIS are not clearly mentioned in those policy guidelines (DoLR, 2012; DoLR, 2013; LARR, 2013).

1.5 SCOPE FOR RESEARCH

It is the right time to bring out a new line of policy setups for India in view of increasing conflicts over land use change. The effects of changing economy and increasing amount of capital flow on land use change is largely unknown. Moreover, wellbeing of the common citizens requires proper plan. For successful implementation of different policies and guidelines, use of remote sensing and GIS are advocated in both DoLR, 2013 and LARR, 2014. Yet, the technical parameters of using remote sensing and GIS to solve land use change related problems are nowhere explicitly discussed. In this research, an attempt has been made to introduce problems of land change science in India. Plenty of literature deals with different aspects of land (some are reviewed in the following section of this thesis) and are accessible in the 'web of knowledge' (Müller and Munroe, 2014).

It is essential to convey different aspects of land use science into a single flow of understanding to address contemporary issues. Thus multidisciplinary approach is recommended. This is because land use science is considered by a varied range of disciplines which is ranging from geography to economics, water resource engineering to agronomics. Another reason could be inherent uncertainties of land use change itself. Certainly, modelling and scenario analysis would provide opportunities to ease such uncertainty but they would also have some limitations. Above all, increasing complexities of land use change science may be taking it away from addressing the real life problems. So it was necessary to link the scientific, academic world with real life problems. Perhaps, reluctant attitude towards multidisciplinary approach is one possible reason for the shortfall of systematic understanding of land use changes.

1.6 OBJECTIVES

The main goal of the present study is contributing towards systematic understanding of land use changes in India, specifically for an Agro-Industrial landscape. Within this scope, the following objectives are defined

1) Explore the utility of Google Earth and multi date IRS remote sensing data to produce land use time series.
2) Investigation of location specific drivers of land use change.
3) Modelling of pre-industrial landscape using an appropriate model
4) Modelling industrialized landscape and simulating three realistic scenarios namely;

    i.) Predominant agriculture based land use.

    Agricultural activities are dominant in the present study area. This scenario depicts that the existing agriculture base LU will keep dominating in future. Other LU classes may change with the current rate.

    ii.) Extensive industrialization and urbanization.

    This scenario portrays, what if industrialization and urbanization would become very rapid. Hence, conversion to built-up area could also become high in comparison to other classes.

    iii.) Nature conservation scenario.

    In this scenario, expansion of farm land, plantation and built-up area will be under control to protect the nature. Natural vegetation cover may increase due to afforestation.

1.7 ORGANIZATION OF THE THESIS

The rest of this thesis is organized as follows.

Chapter Two reviews number of literature from different branches related with land cover and land use to understand the overall progress in land use science. A systematic literature review is presented, starting from characterization of land surface features using remote sensing to land use change modelling and scenario analysis. Literature gaps have been identified to accomplish research objectives.

Chapter Three provides detail methods framed to complete the research work. It also provides a brief account of Dyna-CLUE Model, Logistic regression and model evaluation techniques. Reason behind choosing the study area and a detail account of study area is also given along with data used in this study.

Chapter Four describes mapping of input parameters. Uncertainty of land use change modelling heavily depends on input parameters. Hence LU classification, validation and mapping of other LU change drivers are discussed. First objective of the study is discussed in this chapter.

Chapter Five presents objective two and three. Investigation on drivers and modelling of LU changes for pre-industrial landscape is discussed. Results and validation of modelling and conclusion from the second and third objectives are presented.

Chapter Six discusses the modelling of industrialized landscape using System Dynamics (SD) model. The results from this model are going to be used as one of the input parameters in next chapter. These two chapters together fulfil objective three.

Chapter Seven discusses spatial modelling of industrialized landscape by integrating SD and Dyna-CLUE models. Drivers are analysed for the modelling of industrialized landscape. Different aspects of modelling parameters are discussed. Three different scenarios of future LU changes are presented.

Chapter Eight summarises and concludes the finding of this research work. Limitations of the study and future scope are presented.

A literature review on land related studies are presented in the following chapter in order to find the literature gap and fulfil the objectives.

CHAPTER 2

LITERATURE REVIEW

2.1 INTRODUCTION

In order to address the contemporary problems of land use changes in India, it is necessary to have a detail account of land related studies. Planning and many other scientific researches widely anticipate knowledge of land cover and land use (Verburg et al., 2009). Remote sensing (RS) is most frequently used means for gathering land cover and land use information. RS and GIS together has also often been employed to change detection as well as to handle conflicts between cultural and natural resources (Robinette, 1991). From land use mapping to land use change modelling, different literary tradition of land use studies are progressively evolving. To identify the research gaps and to fulfil the objectives, literature from the following themes are reviewed and are presented under the following headings.

- Characterization of land surface features
- Land change process and Potential land uses
- Socioeconomic aspects of land use change
- Advent of land use system sciences
- Land use change modelling
- Land use change modelling using Dyna-CLUE models
- System Dynamics models

2.2 CHARACTERIZATION OF LAND SURFACE FEATURES

Biophysical compositions of earth surface i.e. land cover are very important to scientifically understand numerous facets of earth system (Verburg et al., 2009). Quantification and detection of land cover and land use change are very much spatial as well as temporal scale dependent. Analysis of land cover and land use change cause-effect relationship demands input from multiple sources including remote sensing data (Anderson et al., 1976). There are several models, techniques and tools to digitally analyse and extract information from satellite images (Zhang and Kirby, 1997; Johnson et al., 2002; Shetty et al., 2005).

It is a well-known fact that water and irrigation are important determinant of land use (Kumar et al., 2002) where watersheds act like closed system (Adinarayana, 1997). Watersheds provide the basic natural resource needed for the existence of life. Reddy et al. (2013) have attempted to link biophysical resource units of a watershed system with future food demand of local inhabitant in order to understand the human carrying capacity of land. Integration of land and watershed studies could prompt sustainable land uses (Rao, 2001) by complementing several different land uses and make a balance between conflicting objectives (Xiaoli, 2009).

Satellite based remote sensing data also provide few meteorological parameters (Jain et al., 2011). A range of such extracted information could be successfully used to assess spatially distributed soil characteristics (Gopal et al., 2014) and moisture availability in agricultural fields (Mishra et al., 2006; Reshmidevi et al., 2008). In addition satellite images together with other secondary data such as temperature, precipitation and elevation can be used for knowledge based irrigated areas classification (Thenkabail et al., 2007). Keeping in mind the present objectives of this study, it is more important to know how these information are related with land use pattern generation than what more information can be extracted from satellite images.

2.3 LAND CHANGE PROCESS AND POTENTIAL LAND USES

Preliminary biophysical characteristics such as climate, relief, soil etc. influence the land qualities for different crops and other land uses (FAO, 1976). Irrigation, manure, pest control and several other techniques of ecosystem engineering has enabled human being to modify biophysical land properties to improve land qualities and thus produce biomass to a great extent (Ellis and Ramankutty, 2008). These land qualities are indirectly calculated from biophysical land characteristics - quantified through remote sensing techniques and reconnaissance survey as direct measurement is not possible (Rossiter, 1996). The biophysical properties of landscape promote or inhibit land’s performance for biomass production (Merwe et al., 1997). Land suitability evaluation is a procedure to assess this performance for specific usage (FAO, 1976; FAO., 1993). Land evaluation plays an active part in the process of land use planning and modelling by comparing, recognizing, delineating and proposing different contradictory land use objectives (F.A.O., 1976).

For land suitability evaluation, integration of several thematic layers of land resources (Hyman, 1984; Kuhad and Karwasra, 1987) is a common practice. Multi-criteria overlay analysis is used extensively by assigning suitable weights to each layer (Hyman, 1984; Robinette, 1991; Merwe et al., 1997; Kumar et al., 2002; Martin and Saha, 2009; Pourebrahim 2011; Reddy et al., 2013).

During the last century, land evaluation procedures have evolved from the "USDIBR, 1951 Agricultural Land Capability Classification" to a variety of quantitative, mechanistic analytical models. On the basis of ; i) the degree of computation, ii) the descriptive complexities and iii) the scale of process, Bouma (1997) has identified five different levels of land evaluation approaches with an increasing degree of complexity. Naturally the demand for high quality data and cost of project increases with increased complexities. Increasing complexities does not always demonstrate a better predictive ability (Bouma, 1997 in Manna et al., 2009). Automation of procedures, integration with crop simulation models and adoption of GIS capabilities has resulted in development of many software tools such as; ALES (Rossiter, 1990), Micro LEIS DSS (Rosa et al., 2004; Shahbazi et al., 2009), RULES (Riveira et al., 2008), ALSE (Elsheikh et al., 2013) etc.

These models present a thematic approximation of land suitability. They are meant for envisaging the potential land uses based available land characteristics. They are not capable of predicting the future land use patterns. Patterns of land use evolve from human intrusions. The biophysical land characteristics greatly determine human interference and considered as biophysical drivers of land use change along with other human and socioeconomic drivers (Veldkamp and Fresco, 1996).

2.4 SOCIOECONOMIC ASPECTS OF LAND USE CHANGES

Certainly, the economic land evaluation justifies bio-physical land suitability into a reality (Rossiter, 1995). Biophysical land evaluation can be extended to economic land evaluation based on FAO framework and spatial analysis in GIS (Rossiter, 1995; Samranpong et al., 2009). The economic factors behind land use decision making are well established (Lambin et al., 2000). People usually engage their land, which yields the greatest return of land resources (Alig et al., 1988). The economic activities have two way relationship – in one hand land and land qualities determine the economic potential of land resources and in the other hand economic utilization affect the land qualities. Low agricultural investments, less agricultural productivity, poor investments in public goods are caused by insecure economic relationship with land due to unfair land tenure system (Banerjee and Iyer, 2005). Conversely, flourishing economy may cause rise in population density, which significantly drives land use change (Sun et al., 2013). Therefore the economic outcome and political institution of land not only affects land production but also land holdings and land use pattern (Bakshi, 2008). Not merely in profit maximization; local experiential knowledge of farmers play an important role in organization of agricultural land use pattern (Raedeke and Rikoon, 1996). At the local level land use change agents – i.e. farmers, play crucial role in designing agricultural landscape (Schaller et al., 2012). Land use decision made by the farmers are influenced by their age, education level, occupation, number of children, household size as well as the status of plot they are cultivating (Ghatak et al., 2013). Hence, overlooking this human dimension in land use studies may restrain, understanding of mechanism that underlies land transformation (Karali et al., 2011). Local level land use decisions are not free from intermediation especially in globalized world.

2.5 ADVENT OF LAND USE SYSTEM SCIENCES

Indeed, human interaction has instigated direct transformation of about half of the Earth’s land surface and intrusion on most of the rest (G.L.P., 2005). Hence land use activities and environmental change is a coupled human-environment system where socio-economic as well as ecological and biophysical components are sub-systems (Mather, 2006). Various interlinked elements and several sub elements act concurrently in a system. This interdependencies in their relationship should be analysed carefully (Oliveira, 1973). Figure 2.1 is showing a conceptual representation of land use system. Vague understanding of land use system could be eradicated by addressing theory, concepts, models, and applications relevant to environmental and societal problems as well as the the synthesis of these two (Turner et al., 2007 in Rounsevell et al., 2012).

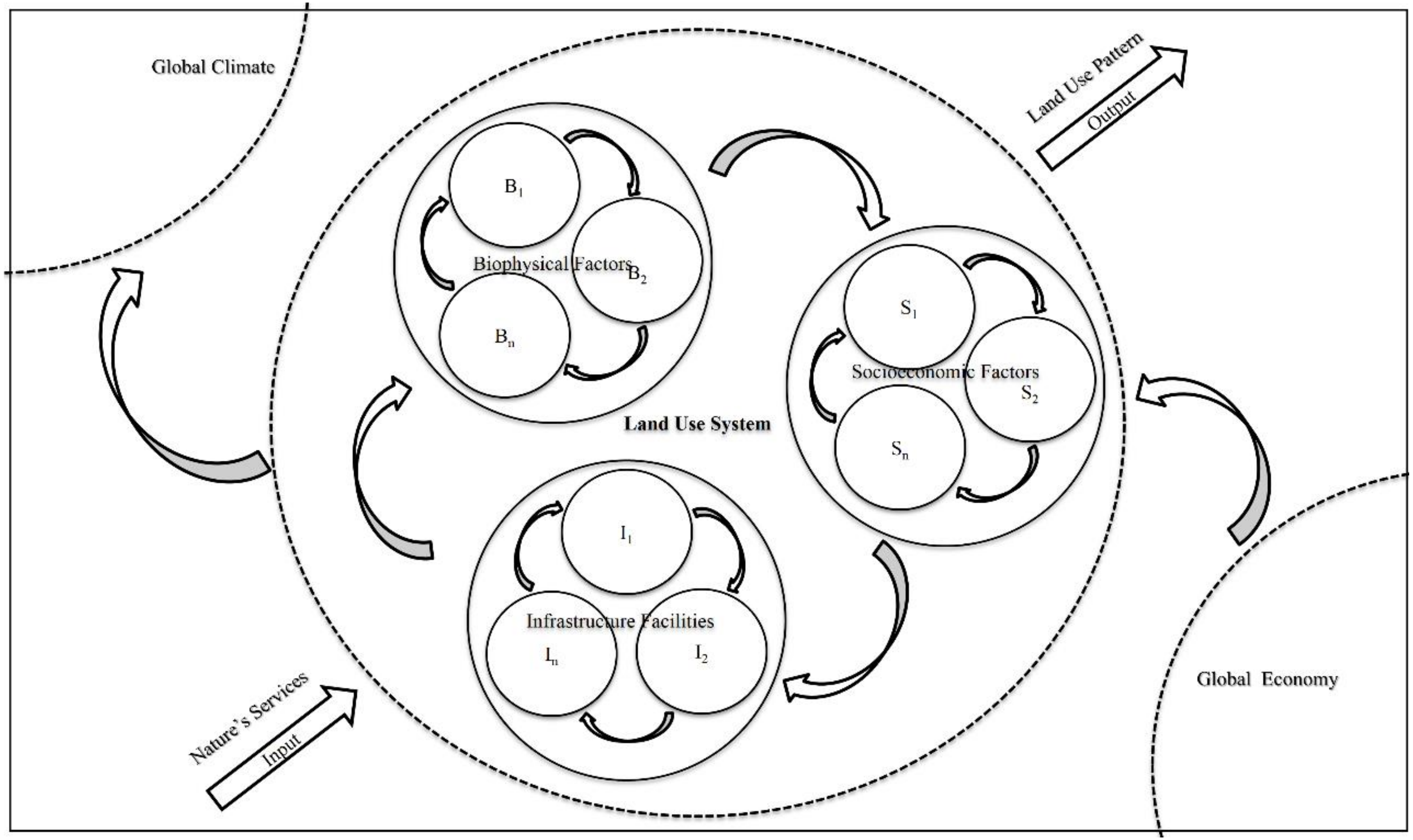


Figure 2.1 Conceptual representation of land use system.

Land system is the terrestrial interface of Earth System, which is identical to the coupled socio-environmental system at global-scale (G.L.P., 2005). Changes in one component of land system may bring changes to the overall performance even at the local level system in both positive and negative ways (Prinz, 1987; Joshi, 2005). To understand this system dynamics, multi-scale land use system analysis approach has more advantages over other available approaches such as land evaluation, land use change detection (Duivenbooden et al., 1998). Perhaps, the challenge lies in modelling different system components and subcomponents at different scale levels. For example, in Figure. 2.1, land use system has at least three subsystem – Biophysical, Socio-economic and Infrastructure. These subsystems further have several elements within it. They interact among themselves and produce land use pattern. Land use system at local or regional scale even interacts with economic system and climate system at global scale. A series of models could ease this problem by linking global level developments and its influences towards local level impacts on land use (Verburg et al., 2008). The heterogeneity of land use system is an important factor to consider in land use change modelling (Letourneau et al., 2012), the dynamics of which may not be represented by only land cover changes mapping (Letourneau et al., 2012; Rounsevell et al., 2012). Land use change models can provide a better understanding of land use systems' dynamics by combining relevant social and natural sciences at different scale levels (Rounsevell et al., 2012).

2.6 LAND USE CHANGE MODELLING

Land use change modelling has evolved as a multidisciplinary multi-scale activity to disentangle man-environment relationship. Based on the disciplinary origin, scale of analysis and complexities it handles, several attempts have been made to review and classify land change models (Lambin et al., 2000; Agarwal et al., 2002; Verburg et al., 2004a ; N.A.S., 2013; Sohl and Claggett, 2013; Mas et al.,2014). Land change models have been broadly classified into; static or dynamic, spatial or non-spatial, inductive or deductive, agent-based or pattern-based. According to Agarwal et al. (2002), a relevant land use change model should address three main dimensions. First two dimensions, space and time would provide a common setting for all biophysical as well as human processes and the third dimension to human decision making. Furthermore an appropriate treatment of time is indispensable to realistically simulate land system. Key points to remember, a land system involves multiple asynchronous change processes in the sense that they don't begin or end at the same time. However, they can loosely be synchronized on occasions. Based on the way a model simulates the change process, it can be process-based or transition-based. A process-based model simulates the causality of each change explicitly. While a transition-based models uses probability or similar terms to summarize the changes happened over a time interval. Time treatment becomes critical in temporal resolution of each individual process and the time delay between different sub-models (Liu and Anderson, 2004). Within these given setups, the complexities of land use system has been encountered by different modelling approaches, per se - (i) Cellular automata approach, (ii), Integrated modelling approach (iii) Agent-based models and several others. Most importantly, irrespective of what approach it may be, it is considerably preferred to be without overwhelming complications (Sohl and Claggett, 2013).

2.6.1 Cellular Automata Based Model

A cellular automata (CA) is a discrete dynamic system in which space is divided into spatial cells, and time progresses in discrete steps. Each cell in the system has one of a finite number of states. The states of each cell is determined by state of the cell itself and state of the cells in neighbourhood at a previous time step. The states of the cells lead through a set of locally defined transition rules and all cells update their states synchronously. The overall behaviour of the system is determined by the combined effects of all local transition rules. Thus the state of the system advances in discrete time steps. Among many others, notable advantages of CA based models are simple in model construction; easy to explore different scenarios by applying transition rules and an expert knowledge, and the regular spatial tessellation of CA models can be integrated with GIS (Liu, 2009).

2.6.2 Integrated Models

Irrespective of the advantages of CA based models, are often criticized for the expert knowledge required during specification of neighbourhood function and transition rules. And also these models do not address the competition between different land uses (Verburg et al., 2002). In comparison, an integrated model like CLUE, modularize different components of land use system and calculates the probability of changes driven by different factors at various scale levels (Veldkamp et al., 2001). Through a continuous development process, CLUE (Veldkamap and Fresco, 1996) model has evolved to CLUE-S (Verburg et al., 2002; Verburg and Overmars, 2007) followed by Dyna-CLUE (Verburg and Overmars, 2009) which now can combine top-down allocation of land use change to grid cells with a bottom-up determination for specific land use transitions. Integration with other models (Luo et al., 2010), SWAT (Zhang et al., 2013), artificial neural network (Lin et al., 2011) etc. could improve its applicability for different scenario analysis.

2.6.3 Agent Based Model

In contrast with previous two approaches, agent based models simulate scenarios of individual or community land use decisions taking into consideration the prevailing bio-physical, economic, and social preferences in a given time (Rajan and Shibasaki, 2000). Agents are autonomous components who can make independent decision through communication and interaction (Parker et al., 2003). "From a modelling point of view agents are software objects" (Karali et al., 2011). In comparison to other approaches agent based models are explicitly able to simulate autonomous, heterogeneous, and decentralized human decision making of the landscape. Agent based models act as a simulated social laboratory, represent complexities, adapt mechanisms, model the emergent phenomena. Parker et al., (2003) and Matthews et al. (2007), have identified five broad areas – policy analysis and planning, participatory modelling, explaining spatial patterns of land use or settlement, testing social science concepts, and explaining land use functions, for which agent based land use models (ABLUM) are developed.

2.7 LAND USE CHANGE MODELLING USING DYNA-CLUE MODEL

A single theory is inadequate to study and explain the complexities of land use system in all its aspects. For dealing with such issues it is necessary to use a spatially explicit multi-scale approach that identifies and quantifies land use driving forces and their interrelationships at various spatial scales (Veldkamp et al., 2001). An integrated model, such as CLUE can modularize different components of land use system and can calculate the probability of changes driven by different factors at various scale levels. Due to differences in data representation and other features that are typical for regional applications, CLUE-S model was developed (Verburg et al. 2002). CLUE-S model further developed to Dyna-CLUE model to combine the top-down allocation of land use change to grid cells with a bottom-up determination of conversions for specific land use transitions (Verburg & Overmars, 2009). The model is subdivided into two distinct modules, namely a non-spatial demand module, which estimates the area change for all land use types at an aggregate level and spatial module, which allocate the demanded changes over space. In the next section of this chapter, applicability of System Dynamics is explored for this purpose.

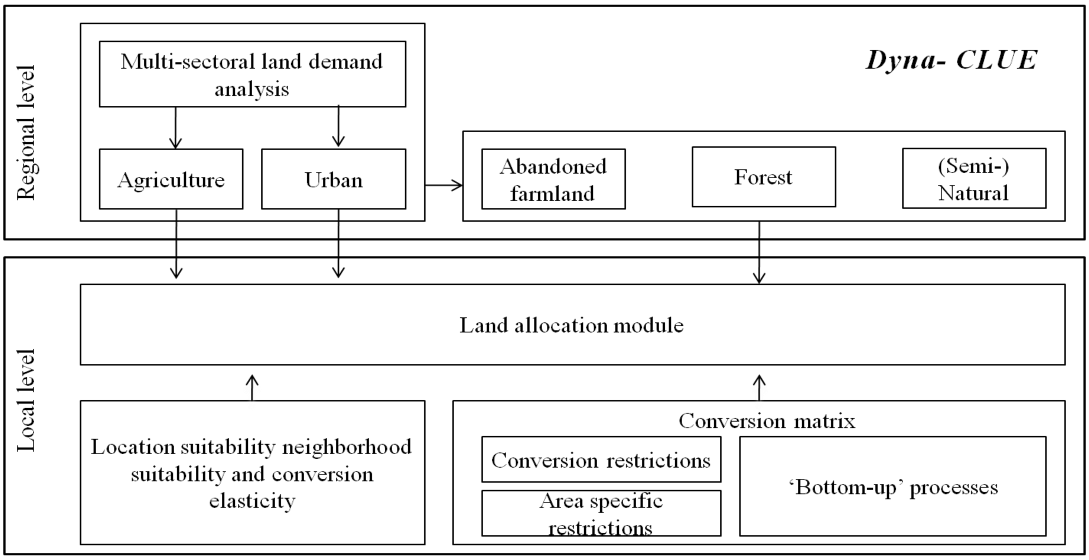


Figure 2.2 Overview of the Dyna-CLUE model (Verburg & Overmars, 2009).

The second module is a spatially explicit allocation module, where estimated land use demands are translated into land use changes at different locations within the study region using a raster-based system. Spatial module again has two parts. The first part aims at establishing relations between land use and its driving factors, explicitly considering scale dependencies. The second part aims at dynamically allocating demanded land use through an iterative procedure to ensure that a location gets most suitable land class. An overview of Dyna Clue model is given in Figure 2.2. CLUE-S and Dyna-CLUE are based on high-resolution data with a resolution ranging from 20 to 1,000 meters. The unit of analysis for this modelling approach is an area of land, which does not match with the agents of land-use change. Individual farmers or plot owners area usually not represented explicitly and the simulations usually do not match with the units of decision making (Verburg & Overmars, 2007).

CLUE-S has become very popular among the planner and environmental scientists. Numerous case studies and experiments are being conducted these days, especially in China. For example, Lin et al. (2011) have compared the abilities of logistic, auto-logistic and artificial neural network (ANN) models for quantifying relationships between land use and their drivers. In another study Zhang et al. (2013) have coupled CLUE-S model with SWAT model to simulate land use change and agricultural non-point source pollution control under two scenarios to optimize land use. Table 2.1, summarizes salient features of CLUE-S model when applied in many countries across the globe.

Table 2.1 Review of the CLUE model application

Author	Study Area	Model	Resolution	Remarks
Castella et al., 2007	Bac Kan, Vietnam	SAMBA, LUPAS, CLUE	250 m	Detail methodology for CLUE is not explicitly discussed.
Chen et al., 2008	China	iCLUE, GLP	1 km	There are three modules in the iCLUE model unlike two modules of CLUE model. Scenario discussed. Understanding of drivers is absent.
Verburg & Overmars, 2009	27 Countries of EU	Dyna-CLUE	1 km	Top-down and bottom-up processes are combined within a single allocation algorithm. Conversion elasticities were estimated by the expert with knowledge on the conversion costs for different land uses and spatial restrictions.
Luo et al., 2010	Sangong WS in Xinjiang, China	CLUE-S, SD	50 m	Driving factor – Groundwater table and quality, Soil type, Soil organic matter and nutrients, Altitude and Slope; Population density, Livestock density; and Accessibility to water sources, Roads and the Built-up areas.

Table 2.1 Review of the CLUE model (Cont.).

Author	Study Area	Model	Resolution	Remarks
Lin et al., 2011	Paochiao WS, Taiwan	CLUE-S, ANN	80 m	Abilities of Logistic, Auto-logistic, Artificial neural network (ANN) for analysing land use change and their drivers are tested. Based on local knowledge, seven were drivers selected. ANN-CLUE-S combination gave better result.
Sun et al., 2012	China	Dyna-CLUE	2 km	Ten land use class are estimated at national scale. Three scenarios are simulated. Aerial land use quantities at the national level are simulated using the SMLC model. Detail model specification not provided.
Zheng et al., 2012	Changqing, China	CLUE-S, SD	250 m	Only the social and economic factors are assumed to drive local land use. SD consists of three subsystems -Population, Economy, and Land Use. Six driving factor are considered. Conversion elasticities based on expert knowledge and observed behaviour in the recent past. Validation of CLUE-S result is not done.
Xu et al., 2013	Guangzhou, China.	CLUE-S, Entropy	90 m	This study proposed planning regulation coefficient for sustainable land-use planning in order to decrease entropy introduced by urban sprawl. CLUE-S model is used for predicting land-use change. Seven driving factors. ROC value ≥ 0.7 in all analysis. For each plan, land-use category-specific conversion settings were defined. Elasticity and transition rule were defined from land use transition.
Li et al., 2014	Daqing City, China	CLUE-S, SD, CA	90 m	SD model was constructed to predict the demand of each land use type at macro-scale level. Eight driving factors. CLUE-S and CA gave different result.

Table 2.1 Review of the CLUE model. (Cont.).

Author	Study Area	Model	Resolution	Remarks
Zhou et al., 2016	Xinzhuang, Changshu City, China	CLUE-S	20m	Markov model and linear interpolation are used to estimate the land use demand. Eleven driving factors. Elasticity defined by land use data and knowledge. Validation sampling windows (500m × 500m) were randomly selected.
Mohammady et al., 2017	Baghsalian WS, Iran	CLUE-S, WetSpa	30m	The magnitude of the effect of land use changes on run off parameters assessed by WetSpa model. land use change was simulated by CLUE-S. Detail account of the CLUE-S modelling was not given. Area under the ROC curve (AUC) was used. No output validation.
Pindozzi et al., 2017	Litorale Domizio-Agro Aversano, taly	Dyna-CLUE	100m	Land use changes were simulated in two different scenarios of land management condition. Total ten drivers were considered. Elasticity coef were assigned according to their capital investment level.
MEI et al., 2017	Zengcheng District, China	Logistic-CLUE-S, Autologistic-CLUE-S, NE-Logistic-CLUE-S, and NE-Autologistic-CLUE-S	150 m	This study developed a regression (NE-auto- logistic regression) method, which incorporated both spatial autocorrelation and self-organization, to improve CLUE-S. Ten drivers were selected. NE-Autologistic-CLUE-S model showed better result.
Liu et al., 2017	Lijiang River Basin, China	CLUE-S	300m	This study investigated the relationship between government policy and land use change. Total nine drivers are used. Three scenarios.

Table 2.1 Review of the CLUE model. (Cont.).

Author	Study Area	Model	Resolution	Remarks
Lagrosa et al., 2018	Tampa Bay WS, US.	Dyna-CLUE	100 m	Dyna-CLUE model was parameterized under baseline conditions. Fifteen drivers are used. Elasticity assumed from literature.
Sahoo et al., 2018	Gandheswari River basin, WB, India.	Dyna-CLUE,SDSM, SWAT	250 m	Drivers - Elevation, Slope, Rainfall, Temperature, Soil depth, Geology, Distance from the road, Distance from the rail, Distance from the river, Distance from built-up, Distance from crop land, Distance from forest cover. No detail account on land use modelling is provided.

2.8 SYSTEM DYNAMICS MODELS

Land use information is a key input to most of the national policy programs. Hence, studies on spatial distribution of land use dynamics are important (Suzanchi and Kaur, 2011). Perhaps the most common global practice to detect land use change is through remote sensing (Roy et al., 2001; Joshi et al., 2011) or by system approach (Verburg and Veldkamp, 2001). Comprehension of land system functions at different scale levels remains unexplored and an appropriate treatment of time is indispensable to realistically simulate land system as each individual process and the time delay between different sub-systems varies. Complex models, such as System Dynamics (SD) can capture processes from different temporal and spatial scale levels.

Initially System dynamics (SD) model was developed during 1950s to perceive the industrial process and for policy analysis in private and public sectors. Computer simulations through system dynamic programming languages such as SIMPLE, DYNAMO etc. have been employed to understand system behaviours in the business world. Coyle (1996) described - "System *dynamics deals with time-dependent behaviour of managed systems with the aim of describing the system and understanding, through qualitative and quantitative models, how information feedback governs its behaviour, and designing robust information feedback structures and control policies through simulation and optimization*".

SD estimates future land demand in accordance with the exogenous forces by embracing a top down approach (Li et al., 2014). In China, non-spatial model SD has become very popular among land use system researchers (Silva et al., 2014). Yet the majority of land use models are spatially explicit (Agarwal et al., 2001), non-spatial model comes into picture where active, dominant exogenous forces of land change are considered (Verburg et al., 2002). The exogenous factors from different scale level largely affect land use change process through socioeconomic systems (Lee et al., 2009). Along with neighbourhood characteristics, exogenous factors also shake the temporal dynamics of land use. SD models can also put up the interrelation between different land use classes. As a result, inherent complexities of land use system can effectively be documented by these models.

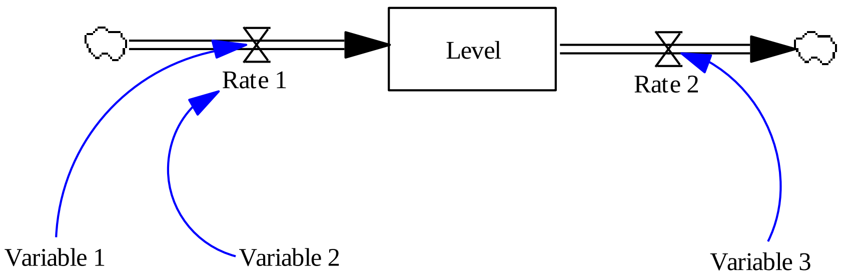


Figure 2.3 A simple stock and flow diagram (Shiflet and Shiflet, 2006).

System dynamics involves complex interactions among various system and subsystems. Conceptualization of several processes is achieved with the aid of diagrammatic tools (Ishida and Hattori, 2012). Formulation of complex problems in SD requires representation of problem in visually effective ways; for example, using causal loop diagrams. The details of it are shown in Table 2.2. The causal loop diagram is one of the earliest tools to conceptualize feedback system models. While criticizing Forrester's (1961) work, John (1982) proposed two more diagrammatic tools (i.) subsystem diagram and (ii.) policy structure diagram. A well-organized subsystem diagram can underscore the subtle feedback path within the model. A policy structure diagram simplifies representation of subsystem diagrams by means of stock, flow and other variables. Notably, stock is a state variable or a level which indicates accumulation or depletion of an entity over time. While flow is the rate of change in a stock which could be a control variable (Figure 2.3). The flow is also an indicator of a process (Ishida and Hattori, 2012; Wei et al., 2012). At present, causal loop diagrams and stock-flow diagrams are typically being used as elementary components of SD models. The objective of these diagrammatic tools remain in decision making capabilities and information networking, which support different policy design. Flexibilities of SD model in addressing multitude effects, makes it a candidature in solving societal engineering problems. Estimation of future land use change is not an exception.

Table 2.2 Essential components of SD models

SD component	Description	Usage
System / sub-system	A set of connected parts that form a whole	Abbreviates complexities.
Policy structure diagram	Focuses on decision making and information network that supports the policy.	More disciplined strategy in system linkages.
Stock, State, Level	Accumulation or depletion of an entity over time represented as quantities. Values are changed by accumulating or integrating rates.	Basic building block. Fundamental to generate behavior in a system
Flow, Rate, Control variable	Represents changes over time. These are used to represent activities that lead to inputs and outputs to stocks.	Input or output to the model
Connector	Indicate the dependencies between objects. Connectors transmit information to regulate flows.	Establishes feedback mechanism
Converters	Contain equations that generate an output value during each time interval of a simulation.	Store constant values. Information can be transformed for other variable.
Time delays	Return of the values from input can be delayed based on delay time, material or information.	Control on the response of the system is possible.
Feedback loop	A tool for adjusting control volume.	Allows for self-correction and adjusts its operation according to the optimal value.
Feedback mechanism	A process where the output is fed back to the input.	Used to adjust the desired output.
Visual modelling language (VML)	Provides a visual graphic interface to connect components.	Allows graphical model design for complex systems.

The complexity of a system increases as interacting sub-systems become finer and dynamic in nature; as well as further subdivided into parts (Hennekam and Sanders, 2002). System in a limitless environment poses issues of boundary condition. Hence, there would be less room for feedback relations. Some studies (Kashimbiri et al., 2005; Lin et al., 2006) aim at detecting feedback on a specific sub-system over the rest. In such cases, specific sub-system acts as whole. In addition, involvement of stake holders enhances the complexities of feedback mechanism. SD approach principally ensembles for all the circumstances typical in LAND USE system (Neuwirth and Peck, 2013; Yang et al., 2014). Table 2.2 provides a brief description of SD model components, especially using VensimPLE software package. Different SD components and their usages have been discussed. These components are universal in other software tools too.

2.8.1 Application of SD Models in India

In India, application of SD approach is yet to gain momentum for land change related studies and are being used to address different management and policy related problems. For example, Bhushan and Shah (2010) have prepared SD integrated model to simulate the supply chain management of the Indian telecommunication market. In another study Das and Dutta (2012) have used SD to simulate behaviour of a supply chain system. Nandi (2014) has estimated the future demand of coal in respect to the presently known coal reserve in India. He has also modelled three scenarios to observe the effect of different policy setups on environment management.

Talyan et al. (2007) have quantified methane emission from municipal solid waste taking into consideration different subsystems. Ahmad (2012) has applied SD to model municipal solid waste generation, collection, disposal, recycle and treatment. Using SD, Pai et al. (2014) and Ojoawo et al. (2014) have respectively estimated exponential increase in municipal solid waste and sewage generation with increasing population. Simulation of different policy setup on solid waste disposal and their effects on sustainable waste management is the most popular objective of those studies.

Applications of SD models are also reported in areas of ecology and environment. Government policies for protecting endangered species and its effects on their survival is simulated by Mathew et al. (2014). With increasing developmental activities and increasing carbon emission scenario; understandings of earth system components and processes of the carbon cycle are of significance. Impact of environmental change on the carbon cycle is modelled by Mukherjee et al. (2013). To our knowledge, SD is applied only for a limited numbers of land use change related problems in India. Mozumder and Tripathi (2014) is one such study. Their study aims at developing an artificial neural network based model using CA-Markov and SD. The main goal was to predict the future impacts of urban and agricultural expansion on a wetland in North Eastern India. In the contemporary situation, comprehension of the actual nature of land transition in India and the applicability of different SD model components to depict that could be a beneficial exploration.

2.8.2 Land Use Change Estimation Using SD

SD estimates future land demand in accordance with exogenous forces by embracing a top down approach (Li et al., 2014). In China, non-spatial model SD has become very popular among the land use change researchers (Silva et al., 2014). Yet the majority of land use models are spatially explicit (Agarwal et al., 2001), non-spatial model comes into picture where active, dominant exogenous forces of land change are considered (Verburg et al., 2002). The exogenous factors from different scale level largely affect land use change process through socioeconomic systems (Lee et al., 2009). Along with neighbourhood characteristics, exogenous factors also shake the temporal dynamics of land use. SD models can also put up the interrelation between different land use classes. As a result, inherent complexities of land use system can effectively be documented by these models. On the contrary, trend extrapolations and the intensity based non-spatial models are straight forward as they do not consider the interchangeability between different land use classes (Silva et al., 2014); thus seriously lacking in representing the complexities. Recognizing the complexities of land use change, Peña and Fuentes (2007) have divided their operational land use change model into sectors viz. economic sector, demographic changes and land change sector. Economic sector deals with industrial employment growth, demographic sector deals with population growth and the land change sector aims to model relations among industrial, residential and commercial uses. Eventually, working land use change models would complement the planning activities. Economic factors of probable spatial patterns of land use heavily influence the planning decisions. SD enables planers and scientists to experiment with and thus comprehend the complex interaction between economic sector and land use subsystems.

Heterogeneity and interrelations between sub-systems using spatial modelling frameworks are difficult to express. Therefore, weightage for these complex interactions are estimated externally and then fed into spatially explicit model to determine spatial allocation (Verburg et al., 1999; Verburg et al., 2002). Such an approach is embraced by Luo et al. (2010) by integrating CLUE-S (the Conversion of Land use and Effects at Small extent) with SD model. In their study SD is used mainly to estimate future land use demand. Efforts have also been made to integrate SD with Cellular Automata (CA) model to improve the spatial process representation (Chunyang et al., 2005; Mozumdar and Tripathi, 2014). In another study, SD has been integrated with multilayer perceptron (MLP) model. SD was employed to statistically predict the urban growth and then MLP was employed using Land Change Modeller (Clark Labs) program to spatially allocate, future urban growth pattern (Lee and Choe, 2011).

Mozumdar and Tripathi (2014) have used the SD method separately in accordance with Linear Extrapolation and Markov Chain to obtain distinct transition rules. SD method is exemplified to determine the desired land use class areas, aiming to understand the future impacts of land use change on a wetland ecology. SD is increasingly being employed for habitat systems analysis in line with human systems. Wu et al. (2015) have coupled SD, CLUE-S and ecosystem service value (ESV) coefficients. Their objectives were to estimate and map the temporal variation in ESV with changing land cover. Analogously, Li and Wu (2013) have investigated effects of urbanization on ESVs by integrating urban growth modelling and ESV methods. Effects of human system over the other habitat system is increasingly getting attention from the eco-system scientists. As land use is the interface of human system, some studies (Beall and Zeoli, 2008) have attempted to assess and attain land management decisions on other habitat systems using SD. Bringing the land use change processes and the ecosystem services dynamics together with in a single modelling framework has been advocated for more beneficial exploration (Wu et al., 2015). Most of these studies have conveyed that, SD is an apt tool in participatory analysis, where the decisions on environmental sub-system weights a lot. These studies also urge an integration of local knowledge and social concerns with the science. As human decisions and policies are aiding the changes in the states of environmental system.

For easy comprehension, observations and inferences on themes reviewed are presented in Table 2.3.

2.9 SUMMARY OF LITERATURE REVIEW

Table 2.3 Observations, inferences on themes reviewed.

Theme	Observations	Inferences
1. Biophysical characterization of land surface	i.) LU/LC is important in almost all natural resource studies. ii.) There are numerous techniques to mapping and extract biophysical information of land. iii.) Technically the term land cover and land use is not same and identical.	Careful observation of land cover and socioeconomic conditions may lead to proper understanding of land use change.
2. Evaluation of potential land uses	i.) Biophysical land properties largely control its' productivity by promoting or inhibiting a use. ii.) Potential land performance can be predicted by a range of land evaluation methods.	Land evaluation methods cannot predict the direction and dimension of future land use change.
3. Socioeconomic aspects of land use	i.) Biophysical land evaluation can be extended to and justified by economic land evaluation. ii.) Economic profitability, political institution, population density, infrastructure plays a major role in driving land use change.	Socioeconomic factors are very important land use change driver but not always. Especially in traditional society.

Table 2.3 Observations, inferences on themes reviewed (Cont.)

Theme	Observations	Inferences
4. Land use system	i.) Various interlinked biophysical and socioeconomic elements of land use act together as a whole in a system rather than individually. ii.) Analysis of land use system would have more advantages to understand land use process. iii.) A system of local level can be influenced by the system of higher level or vise a versa.	Quantitatively approximate and model the all the system component and characteristics is a challenge.
5. Land use modelling	i.) To model a land use system the land use change drivers should be identified first. ii.) The underlying land transformation mechanisms are yet to understand properly. iii.) Space, time and human decision making is major complexities of land use change models. iv.) No single model is independently efficient to capture all the complexities in both top-down and bottom-up approaches. v.) Mainly three types of land use change models are available, Integrated models, Cellular automata based models, Agent based models. vi.) CLUE is one of the most widely accepted integrated model with worldwide applications.	Case study specific modification and calibration of the adopted model would be a noble work. Human dimension plays most crucial role in designing landscapes. An integration of agent based model with other biophysical models would yield better results.

Table 2.3 Observations, inferences on themes reviewed (Cont.)

Theme	Observations	Inferences
6. System Dynamics Models	i.) SD could work beyond the neighborhood transitions and their states. ii.) SD models are capable to model the interacting behavior of land use and land cover. iii.) SD allows to execute the mental map of causal loop diagram to realistically simulate stock and flow interactions. iv.) It compares the intrinsic behaviors of both the exogenous and endogenous factors in the diagram itself. v.) Different land classes and socioeconomic subsystems within a single land use system are also interlinked among each other. Which means one land class gets converted to another following a sequence	SD is most competent where exogenous forces actively influence the system processes. Aggregated socioeconomic factors comply with scale variations can be interrelated among other land use subsystems. Since regional demand actively respond to the micro scale locational characteristics, land use estimation could be planned with respect to the exogenous forces instead of focusing only on local interactions.

2.10 LITERATURE GAP

Table 2.3, reveals that, whenever human-environment interaction is considered in the analysis, land use information plays an important role. There is a very structured development in the characterization of land use using remote sensing techniques. Regional planning, water resource planning & development, natural resource management, agronomy etc. are few of those many fields use land use data extensively. Remote sensing, GIS and complex mathematical modelling approaches have aided the well-structured studies evolution of biophysical characterization of terrestrial land surface, potential land use evaluation, and integrated watershed management. However, scientific understanding of the land use system remains unexplored.

- There is no such generalized manual or guidelines to list up the case specific land use drivers. Evaluation of potential land uses is unable to answer the future direction of land use change, though there is a possibility that potential land suitability of a particular land use types can act as a driving force for land use change. Incorporation of any land suitability model with a land use change model was not found.
- Though land use change modelling has been applied in many studies worldwide, human decision making dimension of these models are not properly understood. If there is an abrupt change in land use (as e.g. large scale heavy industry, dam construction etc.), how does the transition based model would respond is not yet reported. Application of land use change models to resolve conflicts between land use conversions is not found.
- In Indian condition a good numbers of literature are found on the topic of biophysical characterization of terrestrial land surface, evaluation of potential land uses, socio economic factors. However, studies on land use system, scenario development and land use modelling are not abundant.

Next chapter presents the methodology adopted to achieve the objectives of the research.

CHAPTER 3

RESEARCH METHOD AND MODEL STRUCTURE

3.1 INTRODUCTION

There is a need to scientifically understand drivers that are responsible for landscape dynamics, particularly in the Indian context. Understanding of drivers facilitates the modelling of land use changes and bridge the gap in understanding of land use change process. The objective of this chapter is to, explain in brief various steps that are involved in the execution of objectives of this research. And also briefly make a mention of the study area taken up for demonstration and the data used.

Accordingly, this chapter is organised under the following headings.

- Overall Method
  - Principle of Dyna-CLUE Model and its structure.
  - Study Area.
  - Data.

3.2 OVERALL METHOD

Figure 3.1, shows an overall method adopted in this research. Workflow of this study is designed in such a way that work would advance step by step. Broadly the workflow is divided into five parts:

- Mapping of input parameters.
- Land use change driver identification.
- Land use demand estimation.
- Spatial modelling of land use change.
- Validation of model's performance.

As some exogenous factors are incorporated in the land use demand estimation of post industrialization landscape, it has been kept out of the study boundary.

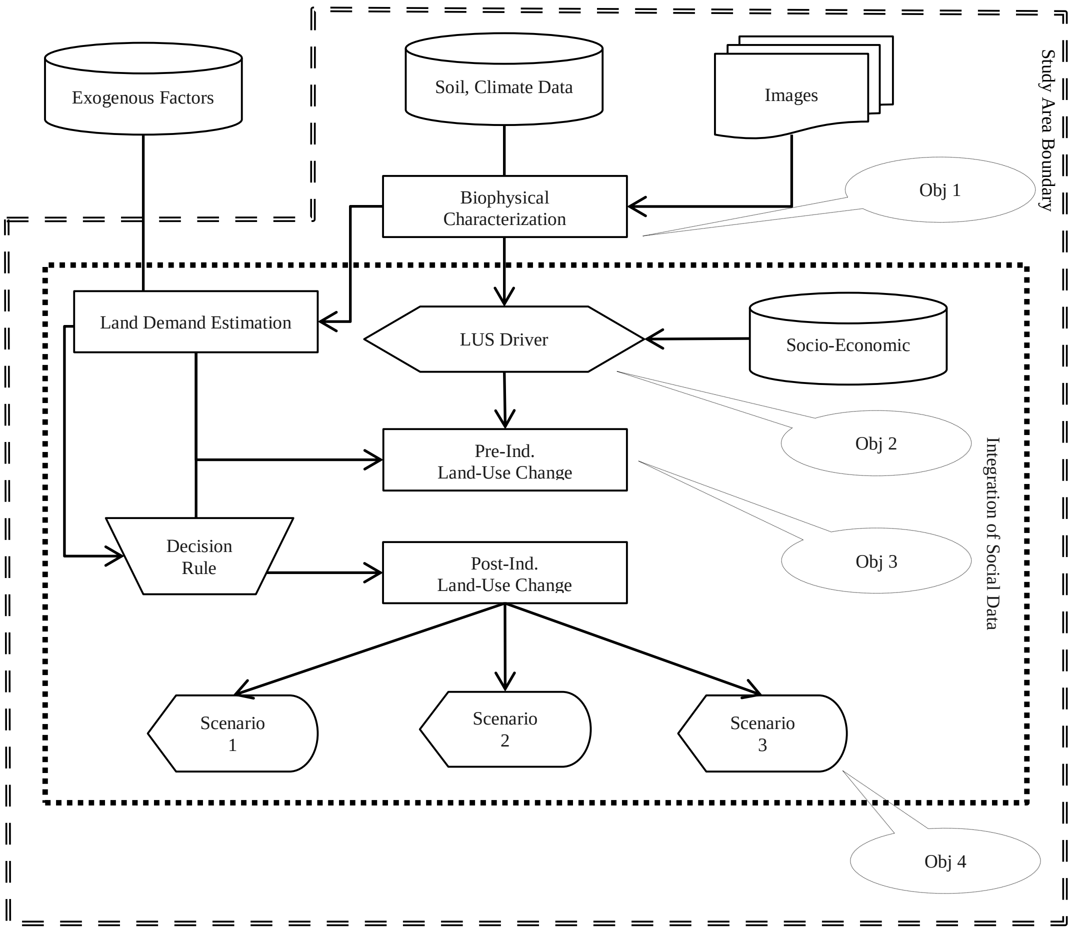


Figure 3.1 Schematic diagram for the overall methods of research.

3.2.1 Mapping of Input Parameters

Satellite images of the study area are classified using standard procedures in order to understand biophysical characteristics of land cover. Other biophysical parameters such as climate, terrain, soil are also mapped. Socioeconomic and biophysical data are used as drivers of land use change. Land use maps are prepared with a spatial resolution of 24m so that detail information remain intact. Driving factor are also prepared with same cell size. Model output validation is accomplished with existing land use maps. Spatial maps of proximate drivers are prepared in GIS environment. A detail account of this theme is presented in the next chapter.

3.2.2 Land Use Change Drivers Identification

Method adopted for potential driving factors identification is shown in Figure 3.2. Socio-economic and biophysical driving factors of land use change are location specific and scale dependent. They are selected based on experts' knowledge of study area and factors frequently identified in land-change studies (Geist and Lambin, 2002; Serra et al., 2008; Hersperge et al., 2010). A list of proximate land use change drivers are identified from literature and existing case studies (Lin et al. 2011). Accordingly, spatial maps of different drivers are prepared. Biophysical driver's maps are prepared using DEM, Streams map. Infrastructures information is collected from google earth (GE) and hand books and are mapped in GIS environment. Socio-economic data at the cadastral level are used for mapping of various socio-economic drivers such as, distance to transport, distance to river, distance to Bus stop, distance from Dams and population density. All drivers are not equally important for land-use change. A case specific hierarchy of drivers would be helpful. A binary Logistic regression model is used to identify the influence of each drivers on each land use class. For pre-industrialization and industrialized landscape modelling driver analysis procedures are carried out separately.

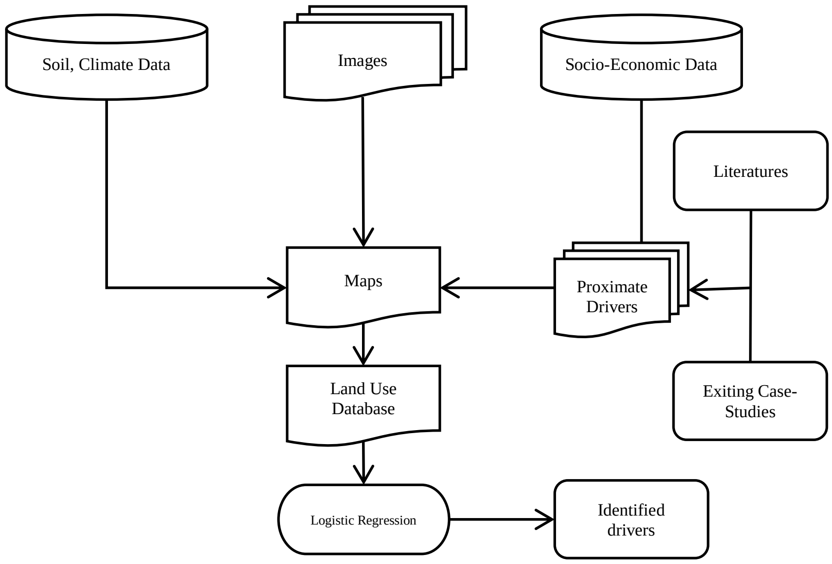


Figure 3.2 Schematic diagram for identification of land use change drivers.

3.2.3 Land Use Demand Estimation

Demand estimation is completed with two different methods for two different modelling activities. i.) Pre-industrialization landscape linear interpolation method is used and ii.) Industrialized landscape System-Dynamics model is used (Figure 3.3).

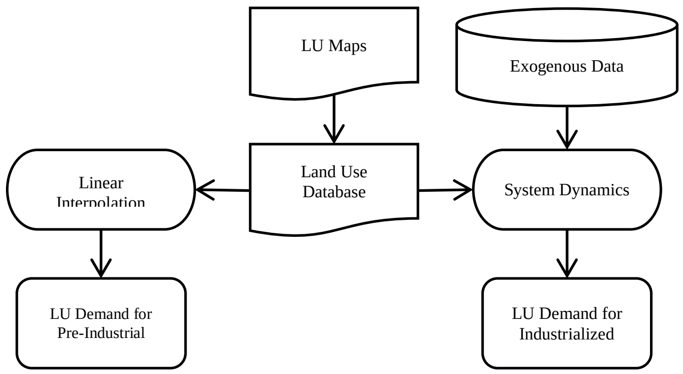


Figure 3.3 Method for land use demand estimation.

3.2.4 Spatial Modelling of Land Use Change

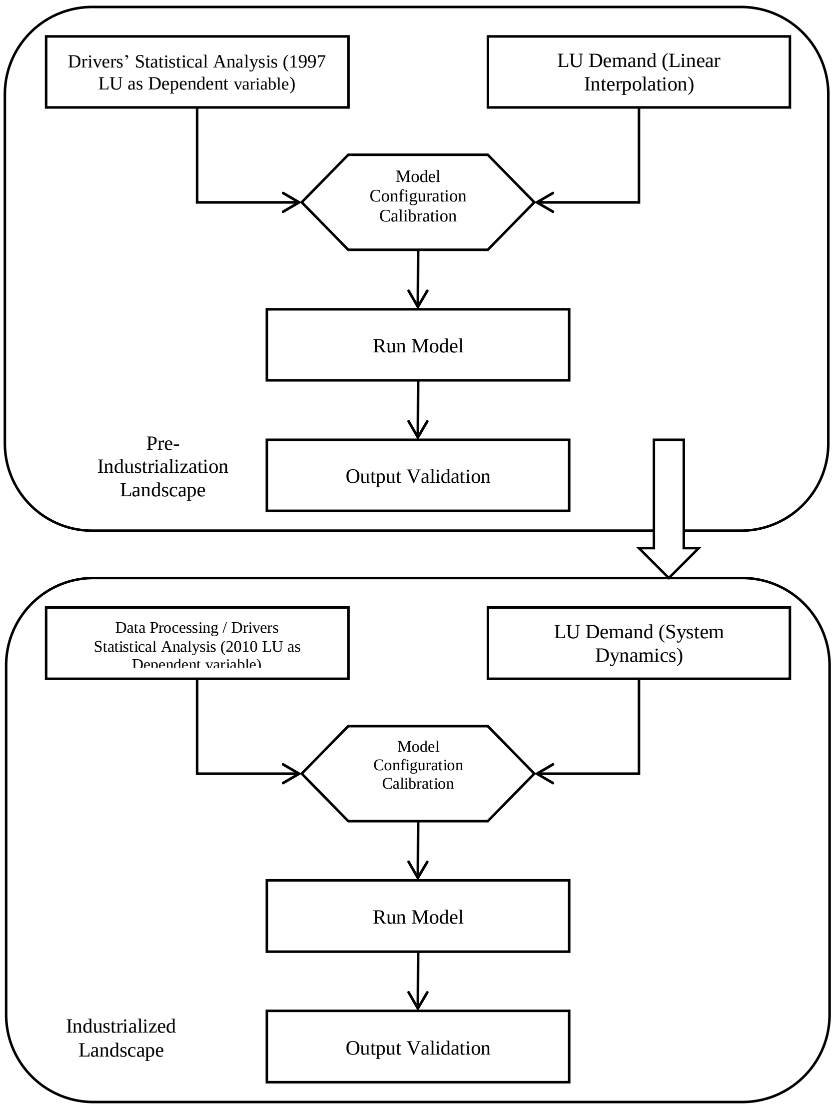


Figure 3.4 Schematic diagram for model development and validation.

A coal based thermal power plant was established within the study area in the year 2008. There was a drastic change in land use after this period. Three satellite images prior to this date are used to generate and validate pre-industrialization landscape. A thorough review of land use change process for spatial allocation of land use demand and exact specification of model is given in Verburg et al. (2002).

From historical LULC maps, land use demand is estimated. After modelling pre-industrialization landscape, industrialized landscape is modelled and future land use scenarios are generated for three development paths (Figure 3.4).

3.2.5 Evaluation of Model's Performance

In most environmental modelling projects, model output is compared with corresponding measured data. It is commonly assumed that predicted values contain error variance and observed data are error free. Validation of land use change modelling exercise in this study is facilitated in two ways,

- Validation of non-spatial domain and
- Validation of spatial domain.

Different statistics are used for validation in non-spatial and spatial domain

Non-spatial domain

In non-spatial domain, three different statics (Moriasi et al., 2007) are employed;

- Coefficient of determination (R^2),
- Root mean square error (RMSE) and
- RMSE-observations standard deviation ratio (RSR) to evaluate the model's capability of maintaining demanded land use quantities in simulated maps.

R^2 describes the proportion of variance in measured data that can be explained by the model. R^2 ranges from 0 to 1, with higher values indicating less error variance, and typically values greater than 0.5 are considered acceptable. It is expressed by equation 3.1.

$$R^2 = \left\{\frac{\sum_{i=0}^{N}(O_i-\bar{O})(P_i-\bar{P})}{\left[\sum_{i=0}^{N}(O_i-\bar{O})^2\right]^{0.5}\left[\sum_{i=0}^{N}(P_i-\bar{P})^2\right]^{0.5}}\right\}^2 \qquad \text{…..……… (3.1)}$$

Where O_i is observed data, P_i is predicted value and the over bar denotes the mean for the entire time period of the evaluation.

The Root Mean Square Error (RMSE) is a frequently used measure of model's simulation capability. RMSE is a valuable index because it indicates error in the units (or squared units) of the constituent of interest, which aids in analysis of results. RMSE values of 0 indicates a perfect fit. It compares difference between predicted and the observed values. These individual differences are also called residuals, and the RMSE serves to aggregate them into a single measure of predictive power. RMSE is defined in Equation 3.2.

$$RMSE = \sqrt{\frac{\sum_{i=0}^{N}(O_i - P_i)^2}{N}} \qquad \text{.................. (3.2)}$$

Though lower RMSE is considered as an indicator of better model performance, there are few explicit guidelines to determine what value is considered as a low RMSE (Moriasi et al., 2007). To deal with this ambiguity RMSE is standardized by the observations standard deviation in Equation 3.3 (Singh et al. 2004 in Moriasi et al., 2007). RMSE-observations standard deviation ratio or RSR is calculated as the ratio of the RMSE and standard deviation of measured data. Hence, unlike a standalone error index RSR combines both an error index and the additional information.

$$RSR = \frac{RMSE}{STDEV_O} = \frac{\left[\sqrt{\sum_{i=0}^{N}(O_i - P_i)^2}\right]}{\left[\sqrt{\sum_{i=0}^{N}(O_i - \bar{O})^2}\right]} \qquad \text{.................. (3.3)}$$

RSR varies from the optimal value of 0, which indicates zero RMSE or residual variation and therefore perfect model simulation, to a large positive value. Lower the RSR, lower the RMSE, and better the model simulation performance.

Spatial domain

Pixel to pixel comparison matrix, prepared with model output and classified images. Classified satellite images are used as observed data. Each pixel of the observed data is considered as the sample point and compared with simulated one. Percentage of mutual match between observed data and simulated data is mentioned beside individual class. Other than that, stratified random samples of land use class are also obtained from Google Earth (https://earth.google.com) historical satellite images. Those samples are used as observed data during validation. Kohen's Kappa statistics (Equation 3.4) is used to evaluate the overall agreement between model output and observed data.

Kohen's Kappa statistics $$\widehat{K} = \frac{N\sum_{i=1}^{r} x_{ii} - \sum_{i=1}^{r}(x_{i+} * x_{+i})}{N^2 - \sum_{i=1}^{r}(x_{i+} * x_{+i})} \quad \text{………………..} \ (3.4)$$

Where,

N is total sample size in the matrix

r is number of rows in matrix

x_{ii} is number in row i

x_{i+} and x_{+i} is row total and column total respectively.

Conditional Kappa statistics (Equation 3.5) is used to evaluate the class wise agreement between model output and observed data.

Conditional Kappa statistics

$$\widehat{K_i} = \frac{nn_{ii} - n_{i+}n_{+i}}{nn_{i+} - n_{i+}n_{+i}} \quad \text{………………..} \ (3.5)$$

Where,

n is total number of samples

n_{ii} is correctly classified samples

n_{i+} is i^{th} row

n_{+i} is i^{th} column

3.3 PRINCIPLE OF DYNA-CLUE MODEL AND ITS STRUCTURE

"The Conversion of Land Use and its Effects", most popularly known as 'CLUE' modelling framework was originally developed a decade ago. It is a Licence free software, developed in *IVM Institute for Environmental Studies*, freely downloadable from http://www.ivm.vu.nl. CLUE uses empirically quantified relations between land use and the driving factors in combination with dynamic modelling for competition between different land use types to simulate land use changes. CLUE model was not directly applicable for regional scale due to differences in data representation and other features that are typical for regional applications. Here regional scale refers to district level or a small watershed. Originally CLUE model was developed for countries or continents. Therefore, the modelling approach has been modified and is now called CLUE-S (the Conversion of Land Use and its Effects at Small regional extent). The more recent versions of CLUE model: Dyna-CLUE (Verburg and Overmars, 2009) and CLUE-Scanner has included new methodological advances. The Dyna-CLUE model is divided into two modules: the non-spatial and the spatial (Figure 3.5).

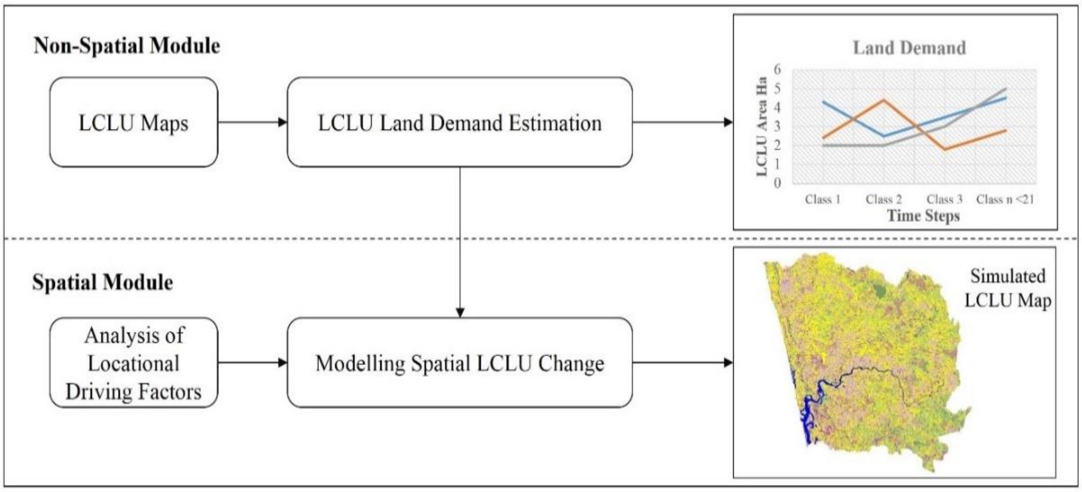


Figure 3.5 Dyna-CLUE model structure.

In the non-spatial module, aggregate area demands of different land use classes are calculated, while the spatial module translates the yearly demands into possible land-use changes at different locations within the given time frame in the study area.

3.3.1 Model Parameters

Land use demand: Land use demand estimation cannot be done using the Dyna-CLUE model user interface as it only supports the spatial allocation of land use change. For Land use demand different models are needed. Such model could be as simple as trend extrapolations to complex economic models. Demand estimation model should be chosen based on the nature of most important land use conversions taking place and the scenarios to be simulated.

Spatial policies and restrictions: Land use policies and land tenure can influence the outline of land use conversions. For the simulation of land use maps, areas with policy implementation and restriction must be indicated. Areas for which the policy is implemented is supplied as restriction layer.

Land use type specific conversion settings: Each land use class changes its states differently. Land use type specific conversion settings and their temporal characteristics are specified in a conversion matrix. This matrix defines: the possible and not possible interchangeability among different land use types and approximate time required for each change process.

Conversion elasticity: Conversion elasticity defines the flexibility of a land use types towards change. Land use class with high capital investment is not easily be converted to other uses as long as there is sufficient demand. Examples are residential locations, plantations with permanent crops (e.g., fruit trees), etc. A value needs to be specified for each land use class that represents the relative elasticity to change. Elasticity co-efficient ranges from 0 (easy conversion) to 1 (irreversible change) and defined by the user based on experience or observed behaviour in the recent past.

Time steps: Defines the time of a land use class in a location should remain the same before it can change into another class. This can be relevant in case of regrowth of forest.

Location Characteristics: Finally, a location most suitable for a specific type of land use at that moment gets converted. Suitability embodies the outcome of interaction between different actors and decision-making processes that have resulted in a spatial land use pattern. The preference is calculated using Equation (3.6).

$$R_{ki} = a_k X_{1i} + b_k X_{2i} + \dots \qquad \dots\dots\dots\dots (3.6)$$

Where R is the preference to devote location i to land use type k, $X_{1,2}$,... are biophysical or socio-economical characteristics of location i and a_k and b_k the relative impact of these characteristics on the preference for land use type k. R_{ki} is estimated as a probability because it cannot be observed or measured directly. A logit model is defined (Equation 3.7) to relate these probabilities with biophysical and socioeconomic location characteristics.

$$\text{logit}\,(P_i) = \ln\left(\frac{P_i}{1-P_i}\right) = \beta_0 + \sum_{j=0}^{n} \beta_j X_{j,i} \qquad \dots\dots\dots (3.7)$$

Where P_i : probability of a grid cell to be allocated with a specific land-use class in a specific location;

β_0 : constant obtained from the binary logistic regression model;

β_j : coefficients of driving factors estimated through the binary logistic regression model; and

$X_{j.i}$: the (j^{th}) location factor affecting the suitability of land-use (i).

Details of Logistic regression model is presented below

3.3.2 Logistic Regression

To understand locational preferences of each land use class, a Binary Logistic Regression (BLR) model is constructed relating each land use class and the possible driving factors. BLR is a form of statistical regression, is used when the dependent variable is dichotomous (0 or 1) and the independent variables are continuous or categorical. In logistic regression, the dependent variable follows Bernoulli distribution with an unknown probability p. Bernoulli distribution is a kind of Binomial distribution where n = 1. The occurrence of variable is 1 and not occurrence is 0. So the probability of occurrence is p and not occurrence is $q = 1 - p$. In logistic regression unknown p is estimated for any given linear combination of independent variables. Here a function is required to essentially link independent variables with the probability of occurrences of dependent variables which follow Bernoulli distribution. The natural log of the odds ratio (ratio between probability of occurrence and not occurrence) is that link function.

If p = 0, then $\ln\left(\frac{P_i}{1-P_i}\right) = \ln\left(\frac{0}{1-0}\right) = \ln 0 = undefined$. Similarly, if p = 1, then $\ln\left(\frac{P_i}{1-P_i}\right) = \ln\left(\frac{1}{1-1}\right) = \ln undefined = undefined$. Interestingly, when p = 0.5, then $\ln\left(\frac{P_i}{1-P_i}\right) = \ln\left(\frac{0.5}{1-0.5}\right) = \ln 1 = 0$ Thus, when the odds ratio is even the logit is 0. If it is plotted on a graph, 0 to 1 run along the x axis. However, it should be along the y axis to fulfill our objective. Inverse of the logit function can be used to achieve that. Part of Equation 3.6 is represented here again for better clarity, here P is between 0 and 1.

$$\text{logit}\,(P_i) = \ln\left(\frac{P_i}{1-P_i}\right) \quad \text{.................. (3.8)}$$

Then inverse of the logit is

$$log^{-1}(\alpha) = \frac{1}{1+e^{-\alpha}} = \frac{e^{\alpha}}{1+e^{\alpha}}$$

……………….. (3.9)

Here α is some number

For the present study, “some number” will be the linear combination of the driving factors (independent variables) and their coefficients. The Inverse-logit will return the probability of being a ‘1’ or the probability of occurrence of a particular land use class. A graphical representation of this function may look like Figure 3.6. Now 0 to 1 is on *y* axis.

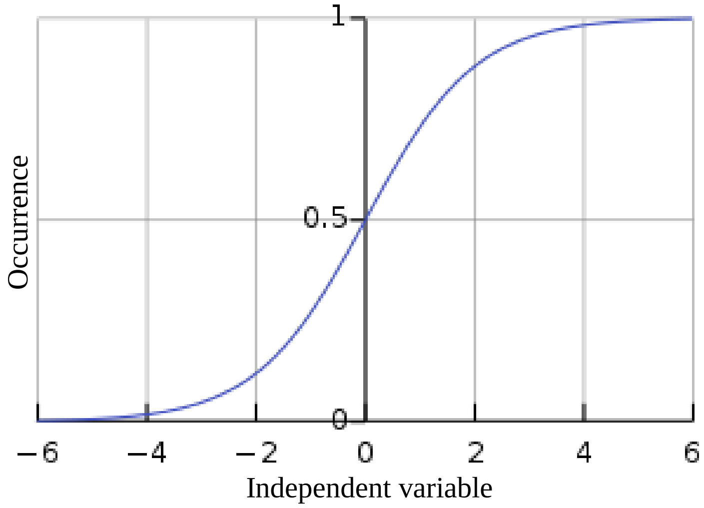


Figure 3.6 Graphical representation of the logistic regression.

In the case of land use maps, land-use classes are the dependent variables which could have a value of 0 or 1 to indicate the absence or presence of a particular land use class in a specific grid cell (Overmars and Verburg, 2005). The driving factors are independent variables in the equation. Hence, land use change probabilities should be on the *y* axis. In SPSS® software package an estimation model is developed that fits the Inverse logit model. The analysis gives the coefficients that can be input into the model.

The estimation of regression coefficients is a Maximum Likelihood Estimation or MLE. In this study the main goal is to estimate the probability of each cell to be allocated to a land use class. The natural logarithm of the odds ratio is equivalent to a linear function of the independent variables. The antilog of the logit function allows to find the estimated probability. The binary logistic regression model of Equation 3.7 is represented here again for better clarity,

$$\text{logit}\ (P_i) = \ln\left(\frac{P_i}{1-P_i}\right) = \beta_0 + \sum_{j=0}^{n} \beta_j\, X_{j,i}$$

Now a method is essential to solve the P. Using antilog this can be done. Hence,

$$\frac{P_i}{1-P_i} = e^{\beta_0+\beta_j X_{j,i}}$$

……………….. (3.10)

Or,

$$P_i = e^{\beta_0+\beta_j X_{j,i}}(1-P)$$

Or,

$$P_i = e^{\beta_0+\beta_j X_{j,i}} - e^{\beta_0+\beta_j X_{j,i}} * P_i$$

Or,

$$P_i + e^{\beta_0+\beta_j X_{j,i}} * P_i = e^{\beta_0+\beta_j X_{j,i}}$$

Or,

$$P_i\left(1 + e^{\beta_0+\beta_j X_{j,i}}\right) = e^{\beta_0+\beta_j X_{j,i}}$$

Or,

$$\hat{P}_i = \frac{e^{\beta_0+\beta_j X_{j,i}}}{1 + e^{\beta_0+\beta_j X_{j,i}}}$$

……………….. (3.11)

Then Known β is used to estimate the probability of a cell to change its state.

3.3.3 Allocation Procedure

Dyna-CLUE model is developed from CLUE-S model. It combines the land use demand of top-down approach to grids with a bottom-up determination of location specific land use transition factors. The analysis starts by clustering land use types into two groups: those that are driven by demand at the regional level and those for which no aggregate demand at the regional level can be determined. The spatial allocation module iteratively compares the allocated area of individual land use types to grids with the land use demand. Iterative process continue until the demand has been satisfied.

The allocation procedure allocates at time (*t*) for each location (*i*) the land use type (*lu*) with the highest total probability ($Ptot_{i,t,lu}$). The total probability is defined as the sum of the location suitability ($Ploc_{i,t,lu}$), neighbourhood suitability ($Pnbh_{i,t,lu}$), conversion elasticity ($ELAS_{lu}$) and competitive advantage ($COMP_{t,lu}$) in Equation (3.12).

$$Ptot_{i,t,lu} = Ploc_{i,t,lu} + Pnbh_{i,t,lu} + ELAS_{lu} + COMP_{t,lu}, \quad \ldots\ldots\ldots\ldots\ldots\ldots.. (3.12)$$

Among the model parameters, land use demand is very crucial. Accuracy of model output largely depends on this. A biophysical characterization of study area is usually carried out to generate land use time series data. land use time series data could be extrapolated to fill missing time step and could be used as land use demand parameter. Land use demand as well as spatial land use configuration are outcomes of interactions between different actors and decision making processes in study area. Different actors are spatially mapped as driving factors and used in statistical models as independent variables. However, it is difficult to map decision making processes directly. Thus finding a suitable study area and defining the study boundary are important task to do.

3.4 STUDY AREA

The choice of the study area has to be case specific. Selection of study area is planned based on land use complexity and availability of data. Criteria for this selection is explained in next section.

3.4.1 Criteria for Study Area Selection

Selection of study area for implementing integrated land change modelling needs certain parameters. In Chapter 1, India's complex transition phase from natural, agrarian landscape to a more commercial land uses and built environment is discussed. Hence study area should represent a complex agro-industrial landscape. The term-complex is also significant with respect to forces, that driving these changes. Land changes are de facto of land policies and other managerial forces. The availability of data for land use system analysis is also an important point to be considered. Among the choices available to select a study area, hydrological boundary could do better with the biophysical parameters. However, socioeconomic parameters are difficult to sort within a hydrological system boundary. Administrative units being an alternative possibility eases the availability of information on socioeconomic parameters. Hence, in this study an attempt has been made to merge the hydrological system with socioeconomic system.

3.4.2 A Detail Account of Study Area

Land use in coastal patches of Karnataka state are dynamic, especially since last decade. This study aims to estimate land use changes occurred in forty four administrative bodies (forty one villages and three towns) of Udupi and Dakshina Kannada district. This whole area belongs to erstwhile Dakshina Kannada district, but in the year 1997, some part of the area north to Shambhavi River was separated as Udupi district. Whole study area essentially falls under the lower Mulki watershed (Figure 3.7).

Geographical Setup: The western boundary of the study area is defined by Arabian Sea and the eastern by Western Ghats. Extends between 13^{o}03’10” N to 13^{o}14’46” N and 75^{o}45’34” E to 75^{o}54’31” E (Figure 3.7). This area is partly comprising of Shambhavi, Pangala and Nandini sub watersheds of Mulki watershed system. National Highway-66 is a major lifeline along with the hauling tracks of Konkan Railway. It covers an area of about 32386.4064 ha and consists of forty one villages and three urban areas namely Bada, Nadsal and Mulki TP. Topography of the study area is characterised with undulating terrain, beaches and marsh lands (waste land). Average elevation varies from mean sea level (0 m) at western part to 65 m in the east. There are some hillocks, buttes in the north and east sector.

Climate: Study area observes four distinct seasons; i) March to May, pre-monsoon hot summer, 2) June to September cool monsoon, 3) October to November, warm post monsoon, 4) December-February, mild winter. Average temperatures ranges from 22^{o}C to 36^{o}C with an annual average rainfall of 4035 mm. Humidity ranges from 61% to 91% throughout the year. The land-sea breezes are frequent with higher number of wind calms (<0.5 m/s). Wind blows towards East in winter, towards North-Northwest in pre-monsoon and towards West in monsoon.

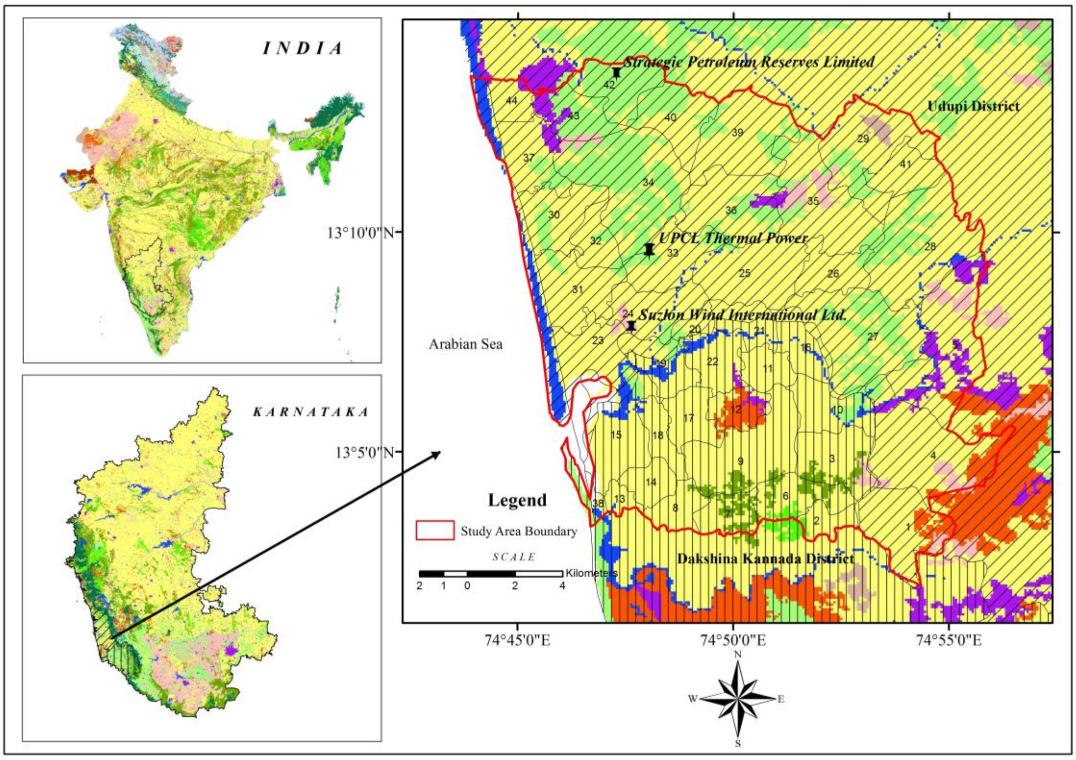


Figure 3.7 Location of the study Area (LULC Map, Roy et al, 2016).

Flora and Fauna: Tropical semi-wet type evergreen and deciduous vegetation are most commonly found in the study area. This region is ecologically very rich, full with wide ranges of flora and fauna. Acacia spp., Albizzia spp., etc. are the common terrestrial flora. Orchards of tropical fruits and horticultural crops like coconut, areca nut, coffee, pepper are prevalent (together classified as Plantation land). Paddy is the major crop. Pulses like black gram, green gram, horse gram, cow pea are also grown in some pockets. Vegetables like pumpkin, gourd, sweet potato, bean, brinjal, lady's finger, tomato, onion, garlic; are grown in the region. Other than valley fill area, the fertility of the land especially in coastal and midland zones is low and hence careful management is required.

Demography: The present study area fits in to coastal districts of Udupi as well as Dakshina Kannada of Karnataka. Cultivators and agricultural labourers together comprises about 35% of the workforce. Significant involvement of labour force in household industries are also observed.

Agriculture is the major occupation. Lack of irrigation facilities hinders intensive agriculture. Hence, engagement in other sectors are always seen. Coastal inhabitants find fishing a lucrative opportunity through well organized and mechanized techniques. Inland fisheries are also prevalent in backwaters and tributaries due to abundance of freshwater. Cashew-nut processing units, rice mills, coconut processing units, fish processing and canning, fish oil extraction units are few examples of agriculture based small-scale industries. There are other medium-scale industries such as fish net manufacturing, printing units, granite units, readymade garments, auto parts etc. (Ramachandra et al., 20112).

3.4.3 Developmental Activities in and around Study Area

A cluster of forty four administrative blocks falling within the districts of Dakshina Kannada and Udupi have agrarian based economy. The study area is also a hub of industries, educational institutions and commercial sectors. This area is characterised by high literacy rate, with Dakshina Kannada and Udupi being 88.6% and 86.2% (Census, 2011) respectively. Decadal growth of the region is very substantial. Economic growth of the region, measured in terms of gross district domestic product (GDDP), accounts infrastructure availability, industries and agrarian activities. Four river systems (Nandini, Shambhavi, Kamini and Pangala rivers) and lowlands, supply daily requirement of water for domestic, agriculture and industries. Dakshina Kannada is the third largest contributor to the state GDP (Global investor summit-Karnataka, 2016). The GDDP trends for Dakshina Kannada has been growing at 5.7%, whereas for Udupi the decadal growth is found to be 6.3%. Service sector, agriculture and allied industry sectors are major players contributing to the growth. Agriculture forms one of the important occupations of the people of this area. Fishing as a traditional business, and *beedi*, cashew nut, to some extent the tile industry act as the economic warehouse of this area. Demographic profile also indicates towards the economic activism. Among the total workers, only 6.3% in Dakshina Kannada and 24.7% in Udupi belong to agriculture sector.

Tertiary industry sector in both Dakshina Kannada and Udupi is well established. Parts of Dakshina Kannada, including the study area has been explicitly promoting industrialisation since years. As a result, Dakshina Kannada has entered into the list of most industrialised districts of the state. In addition, agro processing industries are vital in connection with economy of the study area. At present, this area acts as a major industrial hub for Udupi district and a micro economy zone for Dakshina Kannada district. Arrival of large scale industries in the study area are mostly due to economic reforms. During 90's special economic zone, phase-I has brought petroleum based refinery industry nearby Kuthethur, adjacent to the study area. Phase-2 of SEZ has added few other refinery units to the aforementioned project and a coal based thermal power plant in Udupi district is also added. Nandikooru and Yelluru villages are the industrial suburban of Udupi district. Udupi Power Corporation Limited (also known as LANCO) and SUZLON are among the significant industrial projects.

Under the special economic zone (SEZ) status, Mangalore Special Economic Zone or M-SEZ is an industrial suburb around Mangalore. South-Eastern parts of the study area (Places such as Kinnigoli, Kateelu etc.) have indirectly influenced by MSEZ, whereas Mulki TP and surrounding regions have affected by Kolnad industrial area, another industrial zone in Mangalore taluk. The Government of India has established several strategic crude oil storage plants throughout the country. One such plant has been built on the northernmost part of study area, Padur. Through several public private partnership programmes, national highways are also being upgraded. To summarise, economic developments of the region is a firm conglomeration of industrial, agriculture and service activities. These developments have brought changes in land use.

3.5 DATA

In order to estimate land use demand, multispectral satellite data (IRS LISS-III) with 23.6 m spatial resolution is used. Various geomorphological parameters such as elevation, slope, relative relief, etc. are extracted from ASTER DEM. This is freely available from USGS Global Data Explorer (http://gdex.cr.usgs.gov/gdex/). Apart from these, various thematic layers are prepared from different secondary data. Population data were collected from census of India portal and population density map was generated. Drainage network, location of dams, road network is derived from Google Earth. Soil map is collected from NBSSLUP. Geology, Geomorphology maps are derived from different secondary sources. Geospatial Data Centre in DC office, Udupi as well as Mangalore, have provided village administrative boundary and 2001 census data. An abstract of data product used, source and purpose is presented in Table 3.1.

Table: 3.1 Data products.

Source	Data Product	Resolution	Purpose
IRS Satellites, NRSC	Multispectral satellite images	23.5 m	Land cover land use map
Global Data Explorer, USGS https://gdex.cr.usgs.gov	ASTER DEM	30 m	Slope, Relative Relief
Survey of India	Topographical maps	1:50000	Drainage network
Google Earth(DigitalGlobe) https://earth.google.com	Digitized as Point shape files	Eye alt 1.6 km	Location of dams, industry, Bus stops
Google Earth(DigitalGlobe) https://earth.google.com/	Digitized as Line shape files	Eye alt 1.6 km	Road network
NBSSLUP	Digitized state soil map shape files with database	1:250000	Soil map
IRS Satellites, NRSC & Secondary sources	Multispectral satellite images & Reports, Maps	1:50000	Geology, Geomorphology
Census of India censusindia.gov.in	Decadal Census Data	NA	Demography
Govt. of Karnataka	District Gazetteer	NA	Economic Data
Geospatial Data Centre	Administrative boundary	1:10000	Population map, Economic map

3.5.1 Satellite Images

Seven multispectral medium resolution satellite images (IRS LISS-III) of different dates are obtained to classify the land use of study area. Indian Remote Sensing Satellites are providing quality satellite images since the late eighties. IRS satellites are primarily designed to provide systematic and repetitive data of nearly persistent luminous condition of the Earth’s surface. For the present study data from four different satellites are used (Table 3.2.). Among those IRS – 1D is a follow on of IRS

– 1C, a second generation of IRS series of Satellites. Both of these satellites have three payloads viz., PAN, LISS III & WiFS. In the other hand, IRS-P6 or ResourceSat-1 is upgraded to ResourceSat-2 (IRS-R2) with improved spectral bands to continue the data collection mission of ISRO. Each ResourceSat satellite is built with three electro optical cameras: LISS-3, LISS-4 and AWiFS. LISS-III sensor is configured to provide imageries in three visible bands as well as in a short-wave infrared band. The resolution and swath for visible bands are 23.5 m and 142 km, respectively. The ResourceSat data is widely being used in several natural resource monitoring projects, for example, crop monitoring, crop yield estimation, water resources, forest mapping, and many more. ResourceSat-2 continued to provide data in tandem with ResourceSat-1. Technical specifications of satellite images are briefed in Table 3.2.

Table: 3.2 IRS data products and their characteristics

Satellite ID	Image Date	LISS3-Band 2	LISS3-Band 3	LISS3-Band 4	LISS3-Band 5	Other Censors
IRS-1C	23/01/1997	0.52 - 0.59 µm 23.5m	0.62 - 0.68 µm 23.5m	0.77 - 0.86 µm 23.5m	1.55 - 1.75 µm 70.5m	PAN,WiFS
IRS- 1C	31/03/1998	-do-	-do-	-do-	-do-	PAN,WiFS
IRS- 1D	19/03/2003	-do-	-do-	-do-	-do-	PAN,WiFS
IRS-P6	05/01/2005	0.52 - 0.59 µm 23.5m	0.62 - 0.68 µm 23.5m	0.77 - 0.86 µm 23.5m	1.55 - 1.75 µm 23.5m	PAN, LISS-IV, AWiFS
IRS-P6	21/12/2007	-do-	-do-	-do-	-do-	PAN, LISS-IV, AWiFS
IRS-P6	03/01/2010	-do-	-do-	-do-	-do-	PAN, LISS-IV, AWiFS
IRS-R2	23/01/2013	-do-	-do-	-do-	-do-	PAN, LISS-IV, AWiFS, S-AIS

3.5.2 Google Earth (GE)

At present there are several virtual globe software's say; Bing map (https://www.bing.com/maps), Google map (https://maps.google.com/), Google earth or GE (https://earth.google.com). Among these, GE is the most popular. It visualizes images as a global mosaic of Earth of mid and high-resolution satellites and aerial imagery from multiple providers, including ancillary data-like pictures, address, etc. Moreover, it provides an opportunity to create geometric primitives such as points, lines, and polygons in vector format and attaches basic attributes with them (Potere, 2008;Yu and Gong, 2012; Pulighe et al., 2015). Since the year 2009 with the release of version 5, Google Earth has introduced 'Historical Image view' feature along with some other new features. This feature allows user to go back to the past and see images, given that historical images are available with the GE server (Hanke, 2009). These data are employed for collecting the validation sample points.

Next chapter details the preparation of input data for modelling.

CHAPTER 4

MAPPING OF INPUT PARAMETERS

4.1 INTRODUCTION

A coal based thermal power station has started functioning in the study area from the year 2008 (Detailed description of the study area is presented in section 3.4). After that project and other development activities, spatio-temporal changes in land use as well as other environmental changes have been reported (Ramachandra et al. 2012). Establishment of the thermal plant is the defining moment of land use changes in study area. Thus, this study is comprised of two phases:

i) Pre-industrial and

ii) Industrialized landscape.

The objectives of this chapter are;

(i) Show how historical medium resolution (10m to 60m) satellite data could be used to understand change in land use and land cover pattern to a satisfactory level of accuracy and to understand land use change trend.

(ii) To show how data from several sources can be integrated with in the GIS platform to prepare thematic maps of three categories of drivers. These drivers serve as an input to the, modelling activities to be carried out in the subsequent chapters of this thesis.

Accordingly, this chapter is discussed under the following headings.

- Biophysical characterization of study area
- Classification of satellite images
- Land use change trend
- Mapping of proximate drivers

4.2 BIOPHYSICAL CHARACTERIZATION OF STUDY AREA

A series of land use maps are prepared to quantify areas under each land class and to understand historical trends of land use change. Land use and land cover maps are used for assessing available land resources, to get a deeper insight into land change processes (Herold, 2006). Changes in land use also reveals demand for some commodities. For example, demand for tea, coffee had initiated different land classes to transform into plantation areas. Land use change models convert these demands for commodities and services into change in land cover areas (Verburg et al., 2009). For mapping land use and for change detection from local to national scales, medium resolution images (10–60 m) are frequently used (Gasparri & Grau, 2009). Ten to thirty meters of spatial resolution is generally sufficient for detecting land use patterns. Area under each land use class is attained by multiplying number of pixels allocated to a land use class by the area of a pixel. Often this pixel counting approach of area estimation is criticized due to the presence of bias for true proportion of area. Bias is generated due to asymmetric classification errors (Olofsson et al., 2013). Understanding of land cover dynamics largely depends on accuracy of classified maps.

4.2.1 Challenges

Unfortunately mainstream land dynamics studies tend to overlook the accuracy assessment of classified maps. Most probably, the lack of validator data for accuracy assessment of classified historical images is one of the reasons. Therefore evaluating classification accuracy of a series of historical satellite images is a critical challenge as much of model's prediction capability depends on satellite images. Among the diverse accuracy assessment methods, error matrix is mostly adopted technique where classified data and observed samples form a square array (Congalton, 2008). However, in case of historical images, it is nearly impossible to go back to field and collect reference data from a decade or even older landscape. Interestingly, reference data does not only mean, the data collected from field survey but also the approximated truth of ground condition (Lillesand & Kiefer, 2014). Thus high-resolution virtual earth such as, Google Earth historical images could be a very effective alternative source of samples for LULC classification accuracy assessment.

4.2.2 Applications of Virtual Earths

Developments in computer science, has opened an unparalleled opportunity to the scientific community. Virtual Earth is one such. Among the available virtual earth applications, Google Earth (GE) is most commonly used and it is freely available. There is a steady increase in publications related to GE in recent past. GE is being very useful in some key areas like data visualization, data collection, data exploration, data integration, modelling and simulation, validation, communication of research results and in decision-making (Yu and Gong, 2012). The positional accuracy of high-resolution GE data is also suitable for validation of most geo-scientific studies (Potere, 2008; Pulighe et al., 2015).

4.3 CLASSIFICATION OF SATELLITE IMAGES

Using NRSC – MOSPI twofold classification scheme (MOSPI, 2013) LULC map is prepared. Accordingly, in the area under investigation, following land use classes are examined:

i) Farmland – land used for annual crops such as paddy, lentil.

ii) Plantation – Planted vegetation having a distinguished pattern, used mainly for commercial purposes. For e.g. coffee, areca nut plantation, orchards.

iii) Natural vegetation – naturally grown tree cover consisting of Acacia spp, Albizzia spp.

iv) Fallow land – land left vacant, unused land for a prolonged time.

v) Wasteland – rocky outcrop and unproductive land.

vi) Other land uses – consisting of coastal sands, unused quarry.

vii) Built-up area – area under house, roads, bridges and other man made impervious surfaces.

viii) Water bodies – land areas filled with water.

Figure 4.1, shows the workflow of land use classification. Supervised land use classification is a human persuaded process. From sample collection to validation, human cognition capabilities play an important role, making it subjective and prone to interpretation errors. To make it more objective and rational, a novel approach is followed in this study. Whole workflow is distributed among three different users to avoid overlap in classification knowledge (Figure 4.1).

The very first step is to bring all the images into a single spatial reference. For that, UTM Projection (Zone 43-North) with WGS-1984 datum is used. Then training samples are collected for supervised classification. Supervised classification using Maximum Likelihood method is an efficient per pixel classification technique for land use mapping. Supervised classification offers a user more control over choosing of land class in respect to local geography and specific purposes. It also enables the user to detect serious errors in classification by thorough examination of training data (Campbell, 2010). Training area for each year is separately identified by visual interpretation. Local knowledge of User1 is enormously helpful to identify training samples. For identification of classification training samples, Google Earth is also employed.

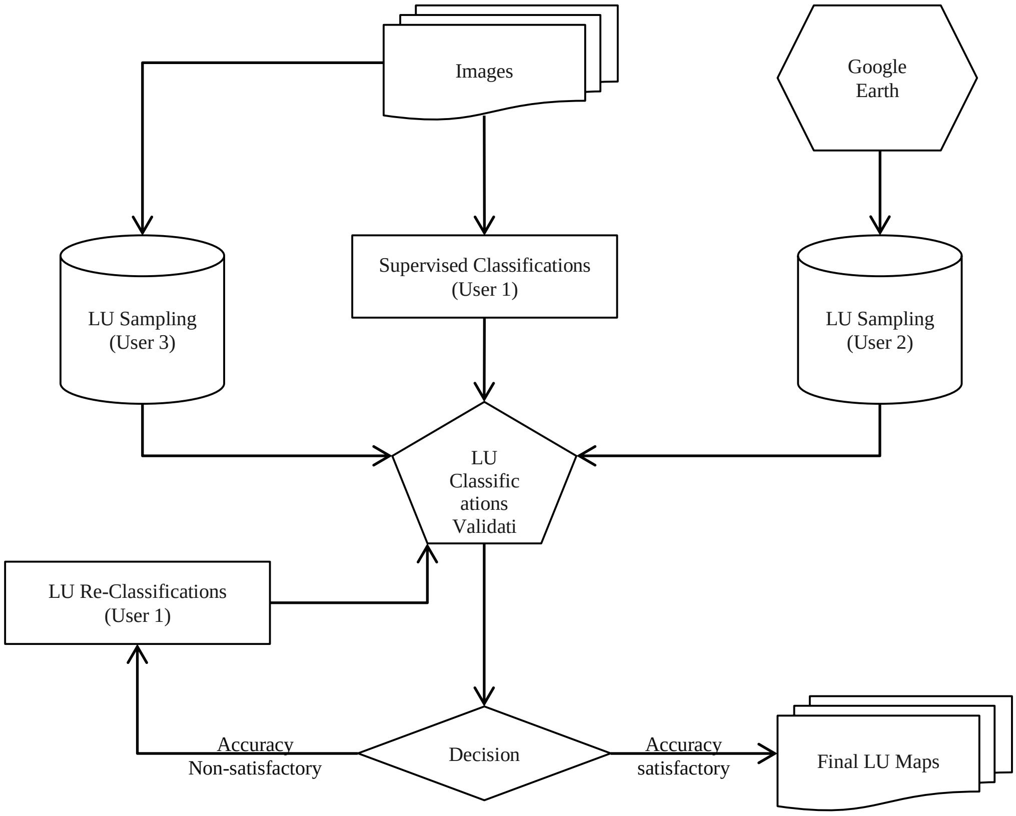


Figure 4.1 Schematic diagram for image classification method.

For classification, ERDAS Imagine® 2014 software package is used. From the satellite images, representative training samples for each planned land use classes are obtained. Mean vectors and covariance matrixes for MLC classifier are estimated using training samples. These two parameters determine the properties of the multivariate normal models. Equal probabilities are assumed since information on the prior probability for each class is not available. The final discriminant function *g(x)* is given in Equation 4.1.

$$g(x) \quad = -\ln(|\Sigma_i|) - (x - m_i)^t \, \Sigma_i^{\ -1}(x - m_i) \qquad \ldots\ldots\ldots\ldots\ldots \text{(4.1)}$$

Where m_i and $\sum_i$ are the mean vector and covariance matrix of the data in class ω_i N is the number of bands. In order to reduce poor classification due to small probabilities, threshold values T_i are determined for each class based on that 95% of the pixels would be classified. The threshold values T_i can be obtained using Equation (4.2).

$$T_i = -12.6 - \ln(|\Sigma_i|) \qquad \ldots\ldots\ldots\ldots\ldots \text{(4.2)}$$

The decision rule for maximum likelihood supervised algorithm is provided in Equation (4.3).

$$\text{x} \in w_i, \ \ if \quad g_i(x) > g_j(x) \ and \ g_i(x) > T_i \quad for \ all \quad j \neq i \qquad \ldots\ldots\ldots \text{(4.3)}$$

During Maximum likelihood classification, training data helps to agglomerate typical and normal distributed samples of values within the spectral classes within an image. Then characteristics of the training data are used to calculate the probability of belongingness of each of the unclassified pixels to each of the training data. Then these probabilities are used to allocate pixels to the most likely class (Richards & Jia, 2006).

4.3.1 Sampling

Workflow is planned in such a way that, three different users have done sample collection and validation in two different parts. It is hypothesised that distribution of works among different users might be helpful to avoid overlap of information class. Information class is extracted by means of visual interpretation. More importantly human interpretation capability varies from person to person. User1 has done the classification sampling and his involvement ends in classification. Validation, sampling is done by User2 and User3, using two distinct sources. For validation, random samples are collected by means of visual interpretation from the same image land use classification is done by User1. User2 has done this validation after sampling. Validation result is displayed in Table 4.1.

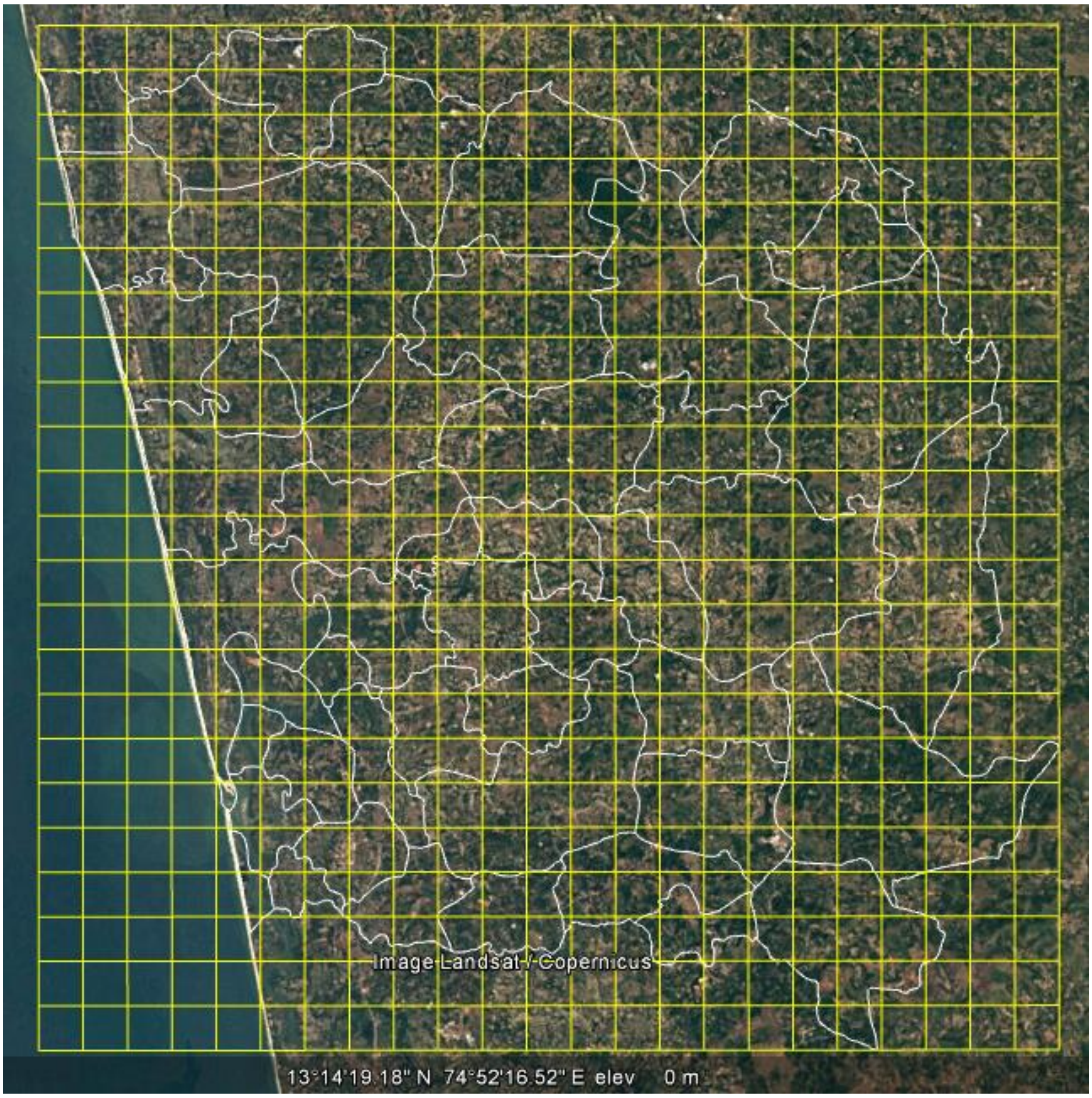


Figure 4.2 Sampling grid over the study area boundary and Google Earth image.

In the next part, User-3 has collected samples from Google Earth. A grid of 23X23 arrays is created using GIS tool. Size of each grid is decided to be 1000X1000 meters approximately. The grid is then exported to GE and samples are collected from grids (Figure 4.2), using stratified random sampling. Sampling is done in such a way that almost all grids contain a sampling point on an average. Usually the dominant land class within each grid cell is considered for sampling. However, even distribution of different land class all over the study area is also kept in mind. Number of samples for each class are proportionate to the respective cover areas. Inside the GE, ‘Placemarks’ are used to mark the designated land use classes for each grid.

Class names of each ‘Placemark’ is also noted. These ‘Placemarks’ are saved as KML file and later converted to shape file. In ArcGIS ‘Placemarks’ shape files are formatted – spatially adjusted with the images and class names are codified according to land cover class codes.

Area under study has GE historical images for the years 2004, 2006, 2010 and 2013 at an eye altitude of 1.6 km (image courtesy Digital Globe). For the respective images, image accusation dates were – 28th December, 2004; 23rd January and 8th December, 2006, 29th November, 2010; 4th April, 2013. Samples from respective years are named as GE-04, GE-06, GE-10 and GE-13 (Table 4.1). To validate an image from earlier date, samples of the nearest date are used. In ArcGIS ‘Extract by Point’ tool, is used get land use information from classified images at specified locations. So extracted point shape file is converted to an Excel file to calculate Kappa statistics. For this study, along with the overall accuracy class wise accuracy is also evaluated. Kohen’s Kappa (Equation 4.4) is used for evaluating the overall accuracy and Conditional Kappa (Equation 4.5) is used to evaluate the class wise accuracy (Congalton and Green, 2008).

Kohen’s Kappa statistics $$\widehat{K} = \frac{N\sum_{i=1}^{r} x_{ii} - \sum_{i=1}^{r}(x_{i+} * x_{+i})}{N^2 - \sum_{i=1}^{r}(x_{i+} * x_{+i})} \quad \ldots\ldots\ldots (4.4)$$

Where,

N is total sample size in the matrix

r is number of rows in matrix

x_{ii} is number in row i

x_{i+} and x_{+i} is row total and column total respectively

Conditional Kappa statistics $$\widehat{K}_i = \frac{nn_{ii} - n_{i+}n_{i+}}{nn_{i+} - n_{i+}n_{i+}} \quad \ldots\ldots\ldots (4.5)$$

Where,

n is total number of samples

n_{ii} is correctly classified samples

n_{i+} is i^{th} row

n_{+i} is i^{th} column

4.3.2 Results and Discussion

Accuracy assessment undertaken here is multiuser type – User3, classifications are done with samples from the same satellite images. User2, Classifications are done with samples from Google Earth. For both the users, accuracy is evaluated in two methods - Kohen's kappa and Conditional kappa. Cohen's Kappa (Equation 4.4) is used to express the overall agreement between classified and reference samples, whereas conditional Kappa (Equation 4.5) states the agreement between individual classes and reference samples.

It is evident from the observations that, samples taken from satellite images are of poor clarity. Identification and differentiation of different related classes such as Farmland, Plantation, and Natural Vegetation from satellite image samples are difficult. Low class wise accuracies are attributed towards a lesser overall accuracy. In aforesaid classes a pixel changes drastically compared to the surrounding pixels and the distinction between Natural Vegetation, Plantation are defined with some degree of uncertainty. This is directly influencing the values of Kohen's Kappa and Conditional Kappa.

For the year 1997, classification accuracy varies drastically between User3 (image samples) and User2 (GE-04 samples). While User3 has obtained agreeable result ($\hat{K}$ = 0.82), User2 managed to get moderate result ($\hat{K}$ = 0.52). Similar pattern is also observed for the year 1998 and 2003. Validation results were respectively $\hat{K}$ = 0.81, 0.86 and $\hat{K}$ = 0.44, 0.56 for User3 and User2. However, validation results by User2 with GE-04 samples has significantly improved for the year 2005. Here User3 (image samples) and User2 (GE-04 samples) have yielded comparable results. User3 has achieved $\hat{K}$ = 0.87 and User2 achieved $\hat{K}$ = 0.76 for the year 2005. Hence, it can be inferred that, accuracy using GE samples decrease if GE historical image date is away from the multispectral image acquisition date. Therefore, validation by the User3 is accepted for the year 1997, 1998 and 2003.

User2 can be seen with improving results since the validation of year 2005 and onwards. Year 2007 is also showing improving results. Samples from Google Earth

2006 historical image (GE-06) are used for this validation process. User3 and User2 have produced $\hat{K}$ = 0.90 $\hat{K}$ = 0.84 respectively. However, a close examination would reveal slight disagreement between the validation of User3 and User2. User3 has produced conditional kappa $\hat{K}_i$ = 0.8, 0.96, 0.96, 0.92, 1, 0.88, 0.77, 0.92 respectively for farm land, plantation, natural vegetation, fallow land, other land, waste land, built-up areas and water bodies. For the same land use classes, User2 has produced $\hat{K}_i$ = 0.93, 0.79, 0.78, 0.61, 1, 1, 0.95 and 1 respectively. A large variation in $\hat{K}i$ values can be seen in the plantation, natural vegetation, and fallow land classes. For the validation of the year 2010, GE samples from the same year image are used. User2 has produced consistently better accuracy values in comparison to User3 for all the class and overall level as well. The $\hat{K}i$ values produced by User2 for this year are, farmland =0.85, plantation = 0.8, natural vegetation = 0.97, fallow land =0.66, other land =0.95, wasteland = 0.97, built-up areas = 1 and water bodies = 1. All classes are showing improved accuracies. For the year, 2013 also better results are demonstrated. For the year 2010 and 2013 the overall accuracy ($\hat{K}$) produced by User2 were respectively, 0.88 and 0.96. Whereas User3 has produced $\hat{K}$ = 0.81 and 0.73 respectively for the year 2010 and 2013.

Therefore, it can be assessed that, accuracy assessment with the help of GE samples has yielded agreeable results both at class level and at overall level. Conditional Kappa values obtained for each class using satellite image sampling are small for the classes - farmland, plantation, natural vegetation and fallow land. In the contrary, values corresponding to GE samples are enhanced (Table 4.1).

Table 4.1 Year wise and class wise validation of land use classifications.

Image Date	23/01/1997		31/03/1998		19/03/2003		05/01/2005		21/12/2007		03/01/2010		23/01/2013	
	User 3	User 2 (GE-04)	User 3	User 2 (GE-04)	User 3	User 2 (GE-04)	User 3	User 2 (GE-04)	User 3	User 2 (GE-06)	User 3	User 2 (GE-10)	User 3	User 2 (GE-13)
Farm Land	0.82	0.38	0.81	0.23	0.92	0.47	0.92	0.70	0.80	0.93	0.73	0.85	0.76	0.94
Plantation	0.66	0.51	0.84	0.54	0.92	0.59	0.88	0.65	0.96	0.79	0.79	0.80	0.81	0.96
Natural Vegetation	0.82	0.81	0.84	0.81	0.96	0.58	0.88	0.84	0.96	0.78	1	0.97	0.82	0.97
Fallow Land	0.82	0.36	0.76	0.28	0.84	0.34	0.74	0.67	0.92	0.61	0.66	0.66	0.56	0.85
Other Land	1	0.77	0.74	0.68	0.95	0.74	0.92	0.84	1	1	0.82	0.95	0.88	1
Waste Land	0.94	0.52	1	0.43	0.96	0.62	0.92	0.77	0.88	1	0.94	0.97	0.71	0.97
Built-up Area	0.74	0.63	0.63	0.45	0.63	0.60	0.80	0.94	0.77	0.95	0.70	1	0.82	1
Water Bodies	0.94	0.95	0.84	0.91	0.74	0.94	0.96	0.93	0.92	1	0.88	1	0.51	1
Overall Accuracy	84.83%	58.22%	83.62%	52.03%	88.03%	62.69%	89.45%	79.44%	91.67%	87.02%	83.69%	89.95%	76.88%	96.74%
Kohen's Kappa	0.82	0.52	0.81	0.44	0.86	0.56	0.87	0.76	0.90	0.84	0.81	0.88	0.73	0.96

FL - Farm Land, PL – Plantation, NV - Natural Vegetation, FL - Fallow Land, OL - Other Land, WL - Waste Land, BA - Built-up Area, WB - Water Bodies.

4.3.3 Land Use Change Trend

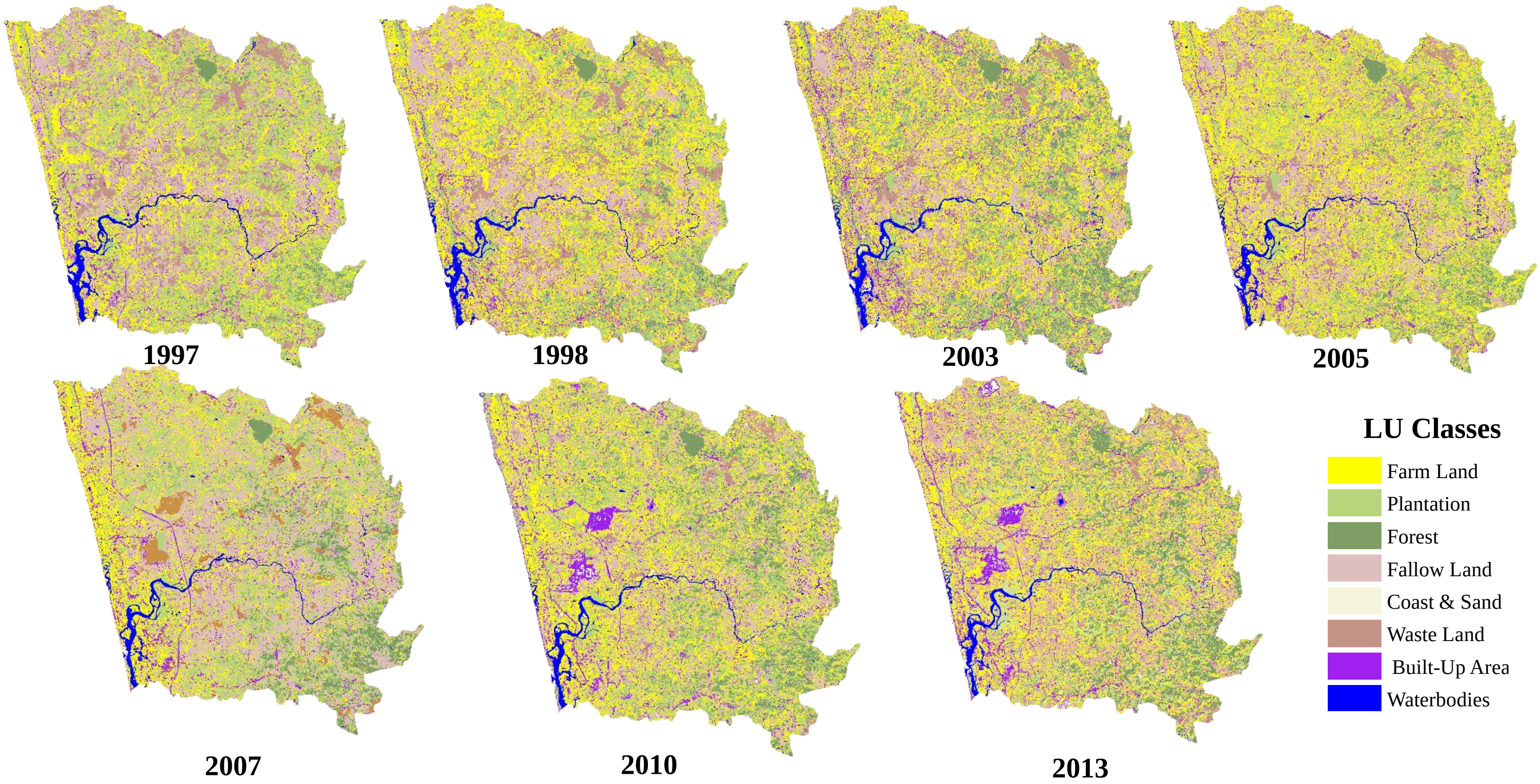


Figure 4.3 Land use classification by following NRSC – MOSPI twofold classification scheme.

Table 4.2 Percentage of area under different land use within study boundary.

LU Class	FL	PL	NV	FAL	OL	WL	BA	WB
1997	21.52	29.86	2.65	25.33	0.51	13.89	4.27	1.98
1998	31.09	23.91	3.08	21.73	0.59	12.43	5.26	1.91
2003	27.36	26.76	7.75	17.30	0.88	9.38	8.85	1.73
2005	32.42	22.29	4.89	22.74	0.65	10.00	5.09	1.92
2007	19.98	26.92	6.38	34.19	0.64	4.35	5.74	1.79
2010	27.68	25.78	8.97	23.58	0.88	4.55	6.68	1.87
2013	26.08	20.75	13.87	23.98	1.42	5.13	7.18	1.59

FL - farm land, PL – plantation, NV - natural vegetation, FAL - fallow land, OL - other land uses, WL - waste land, BA - built-up area, WB - water bodies.

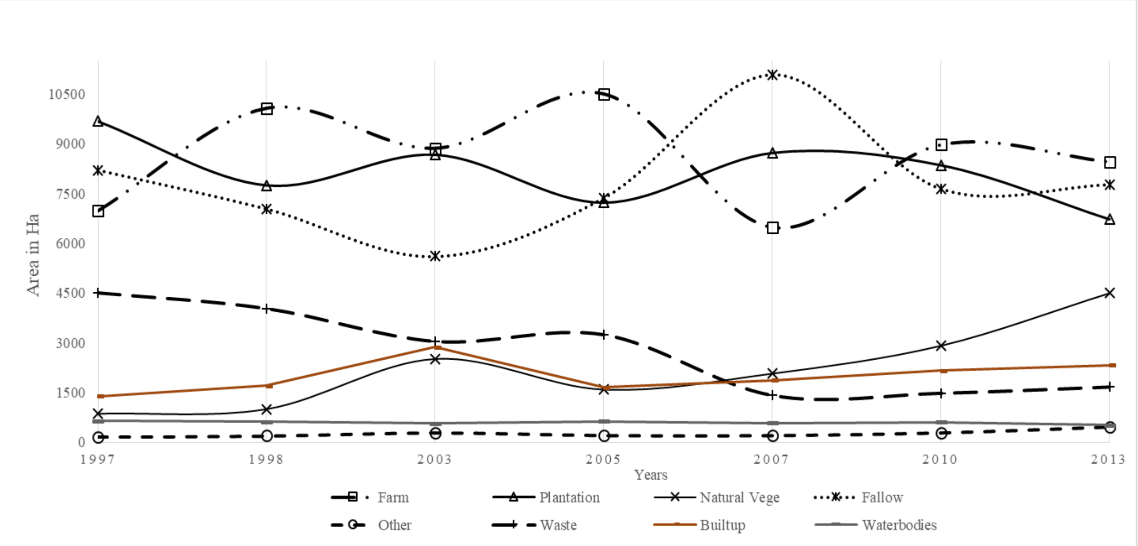


Figure 4.4 Land use change trend in the study area (year 1997 to 2013).

Table 4.2, Table 4.3, Figure 4.3 and Figure 4.4 show the pattern of land use dynamics in the study area between the years 1997 - 2013. Year to year change matrix (Table 4.2) also provides an interesting insight into the land use dynamics over the period of study. A sudden increase and decrease is registered among farmland, plantation, fallow and built-up land. From the year 1997 to 2003, farmland has increased by 4.56% on an average. This class shows a very erratic pattern of change over the years. From the year 2005 to 2007, a 12.44% decline in farmland is observed. Within the same period 11.45%, increase in fallow land is registered. Due to the deficit of monsoon rainfall during this period, lot of agricultural land was left vacant. During the years 2007 to 2010, fallow land has declined and farmland is increased.

Table 4.3 Year wise changes in land use class areas (in percent).

Change Date / LU Class	1997 to 1998	1998 to 2003	2003 to 2005	2005 to 2007	2007 to 2010	2010 to 2013	1997 to 2013
FL	9.57	-3.73	5.06	-12.44	7.70	-1.60	4.56
PL	-5.95	2.85	-4.47	4.63	-1.14	-5.03	-9.12
NV	0.43	4.67	-2.86	1.49	2.59	4.89	11.22
FL	-3.60	-4.42	5.44	11.45	-10.61	0.40	-1.35
OL	0.08	0.29	-0.23	0.00	0.24	0.53	0.91
WL	-1.46	-3.06	0.62	-5.65	0.21	0.58	-8.76
BA	1.00	3.59	-3.75	0.65	0.93	0.51	2.92
WB	-0.06	-0.18	0.19	-0.13	0.07	-0.27	-0.38

Among the other land classes, area under natural vegetation has continuously increased. This seemingly unusual fact is also supported by news reports (Rajendran, 2012) as reclamation of waste land through afforestation is continuing since past decades. Hence is the reduction of wasteland. built-up area has registered a sudden increase from the years 1998 to 2003 (3.59%) and also a sudden decrease between the years 2003 and 2005. Which is certainly impossible, as conversion to built-up area is an irreversible change. Thus, a misclassification is suspected for the year 2003. To know the actual situation on the ground a thorough investigation is done.

The 8th week rainfall pattern (Figure 4.5) in the Dakshins Kannada district unveils that during the year 2000 to year 2004, there was a shortfall of precipitation from the normal rate. The amount of rainfall across weeks/months plays a vital role for the agricultural activities. The period from June 8 to August 23 may be considered as the rainy period and any departure of rainfall during these days affects agricultural activities (Harsha, 2017). The wasteland and fallow land were very dry, remain vacant for longer duration, and would had almost similar reflectance like built-up area. Most likely, those lands have misclassified as Built-up land for year 2003 image due to similar reflection.

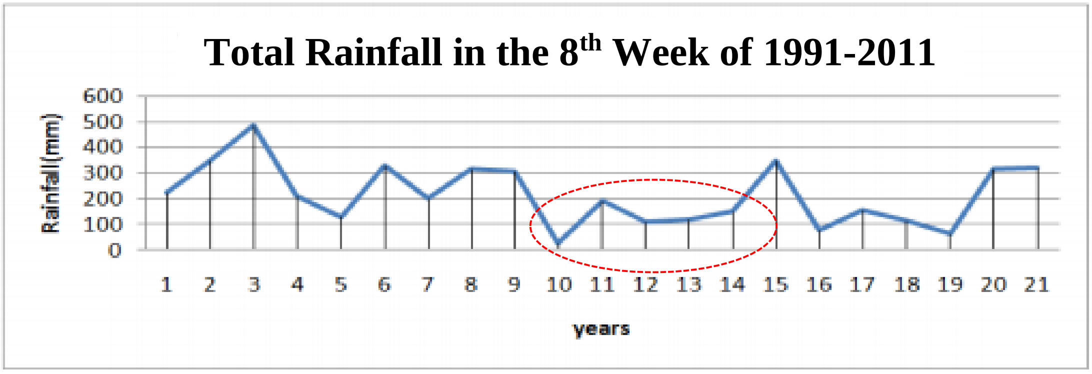


Figure 4.5 Rainfall pattern in Dakshina Kannada district for the year 1991-2011 (Harsha, 2017).

Apart from farmland and fallow land, land for plantation are the most dominating land classes in the study area. It is also observed that both farmland and fallow land have a tendency to convert to plantation. While the wasteland is steadily decreasing, natural vegetation and built-up land is increasing. Water bodies and ‘other land uses’ have not experienced many changes.

4.4 MAPPING OF PROXIMATE DRIVERS

Urbanisation is often the most important process of land use change. The interaction of urban land i.e. built-up area with other land-use types is interesting. Addressing recent as well as historic interactions may contribute to our understanding of land use change processes. This could provide an empirical foundation for the specification of land-use-change models (Verburg et al., 2004a; Ramachandra and Aithal, 2012; Reddy et al., 2013). In transition-based land-use-change models, probability function is used to estimate the likelihood change of a pixel by linking it with a set of land use change drivers. Before modelling the land use changes proximate drivers should be identified and mapped.

4.4.1 Identification of Proximate Drivers

Lack of theoretical understanding on land use system is the first roadblock to identify land use change drivers in India. Land use change is locally influential and scale dependent mechanism. Due to that, having a guideline or a handbook for listing up the proximate drivers of land use change is not possible. Some studies have used household survey to list up the proximate land use change drivers (Overmars and

Verburg, 2005; Kindu et al., 2015). Several other related literature such as district handbooks, planning report could also be assimilated to gain an insight into the proximate causes of land use change. In order to identify proximate land use change driving factors in present study area, a number of existing literature on land use change modelling are reviewed. Table 4.4 summarizes the proximate land use change drivers discerned from different literature. It is hypothesized that, these drivers could also be significant for the present study. They being – i) Distance from streams, ii) Drainage density iii) Geology, iv) Geomorphology, v) Slope, vi) Relative relief, vii) Soil, viii) Distance from roads and ix) Population density.

Table 4.4 Summary of proximate land use change drivers.

Drivers	Category	Source
Distance from streams, Drainage density	Biophysical	Behera et al., (2012); Chu et al., (2013); Li and Wu, (2013); Overmars and Verburg, (2005); Veldkamp and Fresco, (1996); Verburg et al., (2004b).
Geology, Geomorphology		Veldkamp and Fresco, (1996); Verburg et al., (2004b).
Slope, Relative relief		Behera et al., (2012); Chu et al., (2013); Koch et al., (2012); Li and Wu, (2013); Overmars and Verburg (2005); Veldkamp and Fresco, (1996); Verburg et al., (2004b); Zheng et al., (2012).
Soil		Li and Wu, (2013); Veldkamp and Fresco, (1996); Verburg et al., (2004b).
Distance from cities	Infrastructural	Behera et al., (2012); Koch et al., (2012); Li and Wu, (2013); Verburg et al. (2004b); Zheng et al. (2012).
Distance from roads		Agarwal et al. (2002); Behera et al., (2012); Chu et al., (2013); Li and Wu, (2013); Verburg et al., (2004b); Zheng et al., (2012)
Population density	Socioeconomic	Agarwal et al. (2002); Chu et al., (2013); Koch et al., (2012); Luo et al., (2010); Verburg et al., (2004b); Zheng et al., (2012).

Researcher himself with the help of experts on local phenomena included another eight drivers. They being – x) Ground water potential zone in Biophysical drivers group; xi) Distance from dams, water bodies, xii) Distance from major roads, xiii) Road density, xiv) Distance from bus stops, xv) Distance from industry location in Infrastructural drivers group. Distance from cities is not separately recognized, as ‘bus stops’ and ‘industry location’ are already included in the drivers list. Moreover, the study area does not contain many big cities. xvi) Economic status and xvii) Literacy gender parity index are also included in the socioeconomic drivers group.

4.4.2 Usage of Proximate Drivers

Spatial map of each drivers are prepared in GIS, keeping the cell size and extension identical to the land use maps. The driver maps are used as the independent variables and land use classes of the year 1997 as the dependent variables in Binary Logistic Regression. Driving factors are the proxies for causal factors behind land use change process and the decision-making (Overmars &Verburg, 2005). Driving factors responsible for the change of each land use class are identified from the odds ratio of logistic regression analysis. Hence, insignificant drivers from the proximate drivers list gets sorted out.

4.5 BIOPHYSICAL DRIVERS

4.5.1 Relative Relief

To understand the geomorphological features or morphometric characteristics of any area, analysis of relief is the primary step. Relief factor influences the human environment. Relief, cartography and scientific studies of earth’s surface have a very close, reciprocal relationship. Topographic maps were very fundamental base of thematic mapping for the last two centuries (Imhof, 2007). However, many topographic maps are often criticized for being out-dated and showing unrealistic contour patterns. Increasing availability of satellite image based digital elevation models (DEMs) are now frequently being used for regional-scale mapping and numerical modelling of landscapes. Geomorphometry is the ideal tool to understand the relief characteristics of a landscape. It is the mathematical analysis and measurement of the shape and dimension of different landforms. For example, an actual variation of altitude in a unit area with respect to its local base level expressed as relative relief (RR). RR is defined as the difference in height between the highest and the lowest points in the 1 km^2 grid area. The relative relief map of this region gives a clear picture of the nature of landforms.

The relative relief algorithm

First the relief range in 1 unit area (in this case 100m/100m) was calculated from the DEM (Hadley and Schumm, 1961). The difference between the maximum and minimum values in each unit area (zone) is assigned to the centroid in that zone (Equation 4.6).

The range is defined as:

$$\textit{Zonal Range} = \textit{Zonal Maximum} - \textit{Zonal Minimum} \quad \text{...…………} \quad (4.6)$$

Then those points were interpolated using IDW method. Inverse distance weighted (IDW) interpolation explicitly assumes that neighbouring things are more alike than those that are farther apart (de Smith et al., 2015). Relative relief maps in Figure 4.7(a) is showing the relief pattern in study area. East side is having high relative relief (51.61 m) due the presence of hillocks. Coastal area and valley region is with lower relative relief (0.31 m).

4.5.2 Slope

The slope is a characteristic of land that makes a definite angle to horizontal landscape. In geomorphology, landscape is made up of slope units. The slope may be defined as the vertical inclination between the hill top and valley bottom, stands with the horizontal line and expressed generally in the degrees.

In the present study slope is calculated using Strahler method (Figure 4.7(b)). This method calculates the maximum rate of change in value from one cell to its neighbours. The distance between a cell and its eight neighbours identifies the steepest downhill descent. Conceptually, the Slope function fits a plane to the z-values of a 3 x 3 cell neighbourhood around the processing or centre cell. The slope value of this plane is calculated using the average maximum technique.

The Slope algorithm

The rates of change (delta) of the surface in the horizontal (dz/dx) and vertical (dz/dy) directions from the centre cell determine the slope. Equation 4.7 and Equation 4.8 (Burrough and McDonell, 1998) are commonly used algorithms to calculate the slope. Slope is commonly measured in units of degrees.

$$\text{Slope in degrees} = \text{ATAN (rise / run)} * 57.29578 \qquad \ldots\ldots\ldots\ldots (4.7)$$

$$\text{Where, rise\_run} \;=\; \left\{\sqrt{\left(\left[\frac{dz}{dx}\right]^2 + \left[\frac{dz}{dy}\right]^2\right)}\right\} \qquad \ldots\ldots\ldots\ldots (4.8)$$

The values of the centre cell and its eight neighbours (Figure 4.6) determine the horizontal and vertical deltas. The neighbours are identified as letters from a to i, with e representing the cell for which the aspect is being calculated.

a	b	c
d	e	f
g	h	i

Figure 4.6 Surface scanning window

Equation (4.9) calculates the rate of change in the x direction for cell e

$$\frac{dz}{dx} = \frac{(\mathrm{c} + 2\mathrm{f} + \mathrm{i}) - (\mathrm{a} + 2\mathrm{d} + \mathrm{g})}{(8 * \mathrm{y\_cellsize})} \qquad \ldots\ldots\ldots\ldots\ldots (4.9)$$

Equation (4.10) calculates the rate of change in the y direction for cell e

$$\frac{dz}{dy} = \frac{(\mathrm{g} + 2\mathrm{h} + \mathrm{i}) - (\mathrm{a} + 2\mathrm{b} + \mathrm{c})}{(8 * \mathrm{y\_cellsize})} \qquad \ldots\ldots\ldots\ldots\ldots (4.10)$$

4.5.3 Geology and Geomorphology

Geology and Geomorphology map is extracted in vector format from different secondary sources. Especially articles by Avinash et al, (2014) and Shetty (2012) are very helpful. Following geological structures are available in study area 1) Laterite, 2) Magmatic Gneiss, 3) Dykes, 4) South Kanara Granite, 5) Coastal Sand. Vector Geology map is converted to raster and codes are assigned to each class accordingly. Figure 4.7(c) presents geology map. Likewise, geomorphology map is also prepared and Geomorphology map in Figure 4.7(d) is showing the class code according to this list 1) Moderately Weathered Pedi plain, 2) Shallow Weathered Pedi plain, 3) Denudational Hills, 4) Inselberg, 5) Pediment, 6) Valley Fills, 7) Young Coastal Plain, 8) Streams.

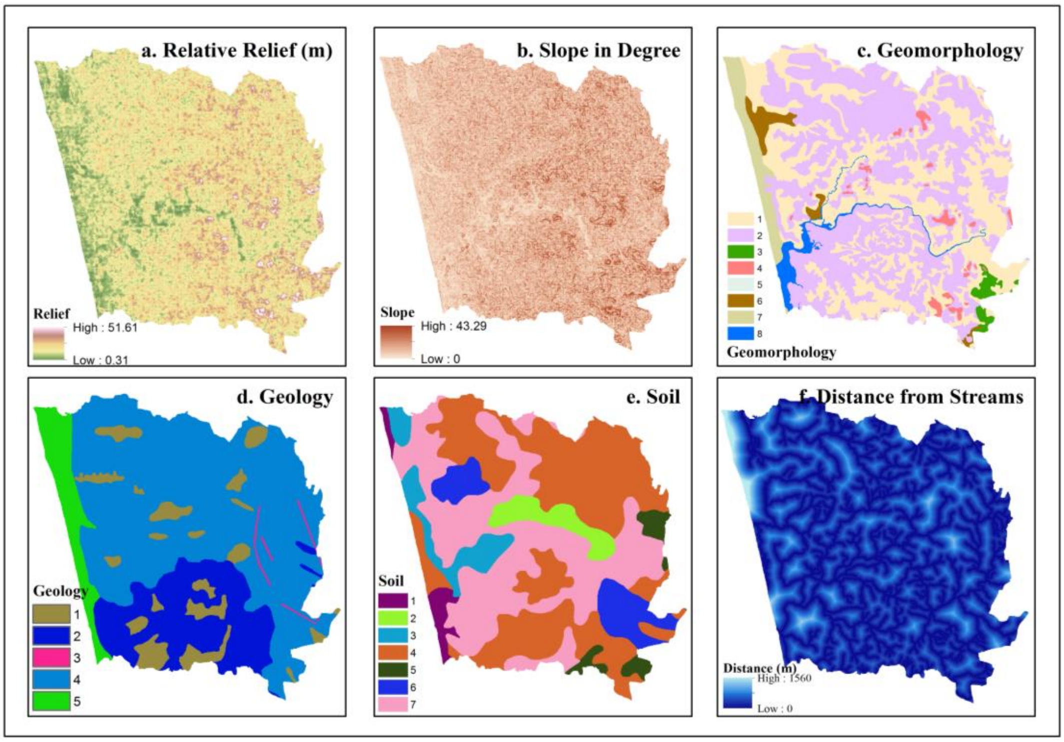


Figure 4.7 Biophysical Drivers

4.5.4 Soil

Detail soil map of Karnataka in vector format is collected from the National Bureau of Soil Survey & Land Use Planning (NBSS & LUP). The study area is clipped out from the main map and converted to raster map (Figure 4.7(e)). In the study area the following soil classes are available – 1) Very deep, moderately well drained, sandy soils with very low AWC on bars and ridges. 2) Deep, imperfectly drained, sandy over loamy soils of valleys, with shallow water table. 3)Very deep, poorly drained, loamy over sandy soils of marshes with very shallow water table. 4) Very deep, well-drained, gravelly clay soils with surface crusting and compaction on undulating uplands, with moderate erosion. 6) Very deep, well-drained, gravelly clay soils with low AWC on laterite mounds, with slight erosion. 7) Moderately deep, well-drained, gravelly clay soils with low AWC and surface crusting on undulating uplands, with moderate erosion. Soil types are coded with integer numbers, respectively from 1 to 7 and converted into raster.

4.5.5 Distance from Streams and Drainage Density

Drainage network is digitized from SOI toposheets using ArcGIS® 10.2. The Mulki river system is the main drainage in the study area. However, it does not cover the whole Mulki watershed. Not only that, parts of Pangala Hole and system are also included in the study area. Distance from Drainage (Figure 4.7(e)) and Drainage Density thematic map are prepared from drainage network.

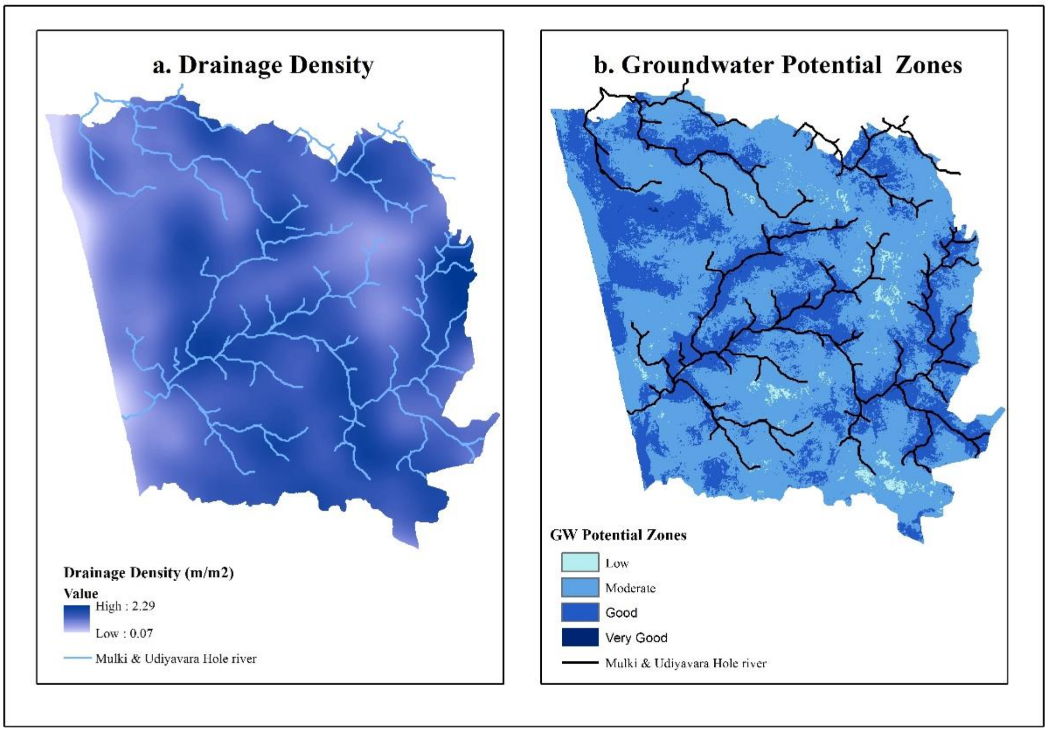


Figure 4.8 Drainage Density and Groundwater Potential Zones.

Drainage Density is calculated in units of length per unit of area using the ArcGIS Line Density tool (Equation 4.11). In this tool, a search radius is used to draw a circle around each raster cell. The length of each linear features within the circle are then multiplied by the population field value. The summed up values of these figures then divided by the circle's area. If L1 and L2 are the length of the portion of each linear features within the circle and the corresponding Population field values are V1 and V2, then

$$\text{Density} = \{(L1 * V1) + (L2 * V2)\} / (\text{area of circle}) \qquad \text{(4.11)}$$

If a population field other than NONE is used, the length of the line is considered its actual length times the value of population field for that line. To estimate the distance from each stream ArcGIS, Euclidean distance tool is used. Euclidean distance is calculated from the centre of the source cells to the centre of each of the surrounding cells. True Euclidean distance is calculated for each cell in the distance functions. In Figure 4.8(a) drainage density map is presented. Coastal area is having lower drainage density and valley area is having higher drainage density. Lowest drainage density value is 0.07 m/m^2 when higher drainage density is 2.29 m/m^2.

4.5.6 Groundwater Potential Zones

In the present study, fallow and waste land is being converted to plantation land. Availability of ground water is hypothesized to be one of the most important causal factor behind this change process. Remote Sensing and GIS are being applied for exploration of groundwater potential zones by many researchers around the world. Drainage network for the study area is digitized from SOI toposheets. Lineaments are identified by observing the pattern of drainage in toposheets and satellite images. The slope map is already derived from ASTER DEM. Geological map, Geomorphological map are also derived. Soil map is collected from the National Bureau of Soil Survey and Land Use Planning (NBSS & LUP). The groundwater potential zones are obtained by overlaying all these thematic maps in terms of weighted overlay methods (Equation 4.12). During weighted overlay analysis, the ranking was given for each individual parameter of each thematic map.

$$S = \sum W_i X_i \quad \text{…....…….. (4.12)}$$

Where, S is suitability, W_i is the weightage of each map score. X_i is the individual map layer. Output result in a form of ground water potential zone is displayed in Figure 4.8(b). It is showing four classes of potentiality, class 2 being Low, class 3 Moderate, class 4 Good, and class 5 Very Good. Class 1, i.e. Very Poor is not available in study area.

4.6 SOCIO-ECONOMIC DRIVERS

4.6.1 Population density

Choropleth mapping techniques are often used to map demographic data and socioeconomic information. The choropleth map spatially aggregates data into geographic areas or areal units (e.g., county, census tract, block group, etc.). Population data are associated with analytical errors due to the arbitrary nature of a real unit partitioning. Perhaps the most prominent of these errors is the modifiable areal unit problem (MAUP), defined as a situation in which modifying the boundaries and/or scale of data aggregation significantly affects the results of spatial data analysis (Mann and Chandra, 2013). If the spatial units are too large, the data's spatial variation tends to be reduced or averaged out. Since the value of the enumeration unit is spread uniformly throughout the areal unit, continuous geographic phenomena cannot be displayed (Sleeter, 2004). On the contrary, surface-based population representation offers certain advantages over areal unit representation. Population data can be aggregated to nearly any desired areal unit using surface-based representation and hence is not subject to the MAUP and other areal unit-derived problems (Bracken, 1993). Land use land cover data contain sufficient information, to infer population distribution. They can be used independently to model the spatial pattern of population density. Dasymmetric mapping of the present study is done following the methodology (Equation 4.13) proposed by Holloway et al. (1997).

$$P = \frac{R_A * \left\{\left(\frac{P_A}{P_A}\right) * \left(\frac{N}{E}\right)\right\}}{A_T} \qquad \text{.....……… (4.13)}$$

Where, P is the population of a cell,

R_A is the relative density of a cell with land use type A,

P_A is the proportion of cells of land-cover type A in the enumeration unit,

N is the actual population of enumeration unit (i.e., census block group)

E is the expected population of enumeration unit calculated using the relative densities. E equals the sum of the products of relative density and the proportion of each land-cover type in each enumeration unit.

A_T is the total number of cells in the enumeration unit.

The population density map is displayed in Figure 4.9(a). Map legend is showing number of person living per pixel, where pixel size is 24 m^2.

4.6.2 Economic Condition

Prevalent economic condition plays an important role in land use change as the overall economic condition is directly related to people's purchasing capacity. In this study because of the absence of household level or village level economic data, some proxy data are used as indicators of economic condition. A novel approach is hypothesized to evaluate the potential economic condition. Openly available spatial information was used to prepare, various thematic layers and are integrated using weighted overlay analysis (Equation 4.12). Study area is divided into three economic group (Figure 4.9(b)) - Poor, Moderate, and Opulent.

4.6.3 Modified Literacy Gender Parity Index (MGPI)

Originally UN proposed literacy Gender Parity Index (GPI, Equation 4.14) was used to calculate the parity in literacy between males and females for a given country or territory (UNESCO, 2008). This indicator can be calculated by geography (national, urban and rural) and age group (aged 15 years and over by five-year age groups or combinations of five-year age groups).

$$GPI_a^t = \left(\frac{LR_{a,f}^t}{LR_{a,m}^t}\right) \qquad \text{…....…….. (4.14)}$$

However, this equation may produce inconsistent results and can contradict the actual literacy rate. Which means, in many occasions it could misinterpret the reality. To avoid such incident GPI is normalized by the total population of age group *a* (Equation 4.15). MGPI is an index of gender equity in political and economic participation and decision-making as well as power over economic resources. A MGPI of 1 indicates parity between sexes. A MGPI under 1 indicated parity in favour of males, and a MGPI over 1 indicates parity in favour of females. Each pixel under each administrative unit assigned with corresponding *MGPI* value (Figure 4.9(c)).

$$MGPI_a^t = \left(\frac{PL_a^t - L_{a,f}^t}{PL_a^t - L_{a,m}^t}\right) \qquad \text{…....…….. (4.15)}$$

Where,

GPI_a^t is literacy gender parity index for the year *t* of age group a.

$LR_{a,f}^t$ is female literacy rate for the year *t*.

$LR_{a,m}^t$ is male literacy rate for the year *t*.

$MGPI_a^t$ is modified gender parity index for the year *t* of age group *a*.

PL_a^t is the literate population of age group a at time *t*.

$L_{a,f}^t$ is number of literate female of age group a in the year *t*.

$L_{a,m}^{t}$ is number of literate male of age group a in the year t.

In Figure 4.8, MGPI is represented for each administrative area.

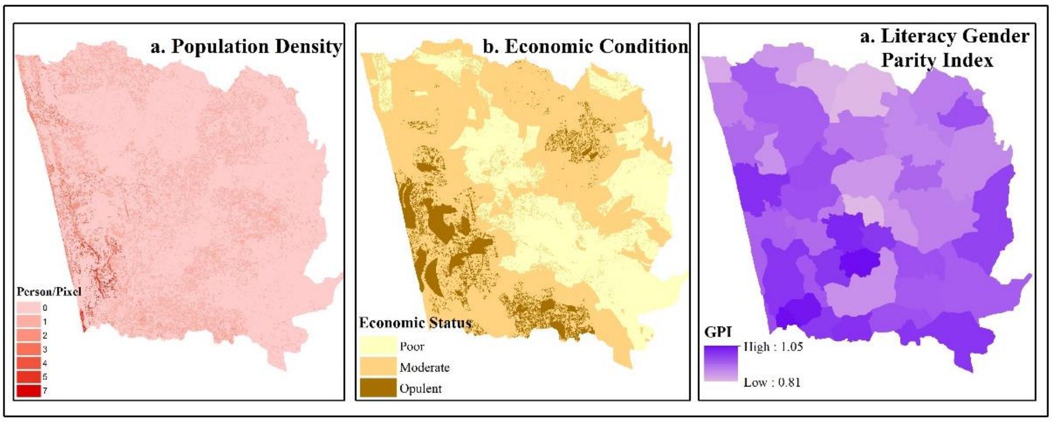


Figure 4.9 Socio-Economic Drivers.

4.7 INFRASTRUCTURAL DRIVERS

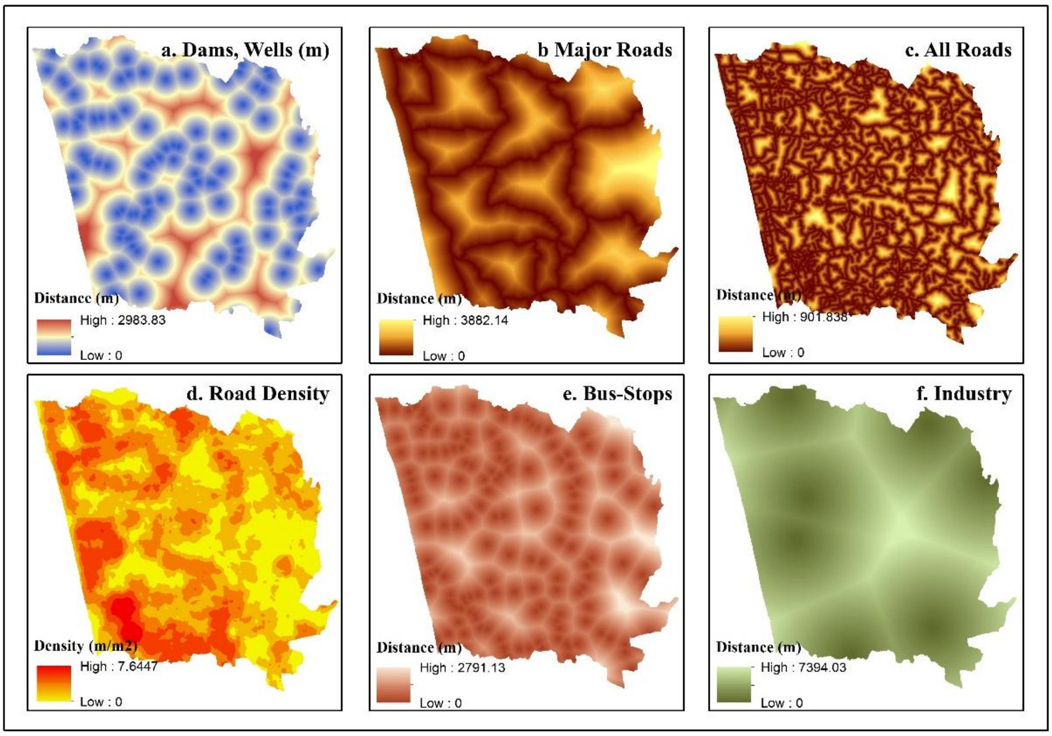


Figure 4.10 Infrastructure Drivers.

4.7.1 Distance from Dams and Wells

It has been observed that, to meet the increasing demand of water, a number of dams have been built in the last decade. Dams, bunds, ponds and wells are identified from high resolution Google Earth imagery and exported to GIS environment. Finally, Euclidean distance is calculated in ArcGIS distance toolbox. Output map is represented in Figure 4.10(a).

4.7.2 Roads

Road networks can also influence the land use dynamics as it provides the necessary access to natural resources. In most of the Indian state road network follows a chronological hierarchy, organized from the national highways to village roads. Distance from all types of roads and major roads are estimated in two different layers, as major roads and any other roads influence different land uses differently. For an example, Plantations are needed to be well connected and village roads are enough to serve that purpose. Likewise, national highway attracts more urbanization and Built-up area. Distance from all roads and major roads are separately estimated using the ArcGIS Euclidean distance tool. Figure 4.10(b) and 4.10(c) is showing maps of Major Road Distance and All Road Distance respectively. Legend value is showing distance in meters.

In general, the most developed areas or built-up areas have more numbers of roads. Developed road networks encourage different land classes to convert to Built-up land. Thus a road density layer is also estimated using the ArcGIS density tool (Equation 4.11). Rod density is estimated in meter per square meter unit (Figure 4.10(d)).

4.7.3 Bus Stops and Location of Big Industries

Figure 4.10(e)), shows distance from Bus stop and distance from big industries. Distance from bus-stop is important to map because often a built-up area grows near the communication hotspots. In the present study, locations of bus stops are identified from Google earth and Euclidean distance estimated in ArcGIS.

Similarly, location of big industries (Figure 4.10(f)) and housing projects influences surrounding land to get converted to built-up as peripheral services. Some big industries and housing project are spotted from Google earth and Euclidean distance is estimated in ArcGIS.

4.8 CONCLUSION

Historical moderate resolution satellite data can be used to a satisfactory level of accuracy to understand the changes in land use pattern. The novel, method employed to get an unbiased estimation of land use area has demonstrated its further applicability. To avoid the overlap of information class during sampling, classification process is divided among three different users as human recognition varies person to person. Use of high resolution GE historical images for validation sampling is also unique of its kind. It is observed the GE can successfully be employed for validation sample collection. However, applicability of GE samples decreases when it is away from classified image date. For example, GE sample from the year 2004 image has yielded overall accuracy 58.22%, 52.03% and 62.69% respectively for the classified map of the year 1997, 1998 and 2003. Whereas, over all accuracy for those same maps using image based samples are 84.83%, 83.62% and 88.03% respectively. Hence, it can be concluded that, when different persons do classification and validation, human knowledge has no overlapping.

The classified images have produced a land use time series. The pattern of land use dynamics is very interesting. The study area is predominantly rain fed agriculture-dominated landscape. With a below average rainfall Farmland converts to Fallow land. Wasteland to Natural vegetation conversion also took place due to afforestation.

GE is also used for drivers' data mapping. Especially, for infrastructure drivers data preparation. A total seventeen drivers are identified. Among these, nine are from existing literature and rest eight are identified with the help of local phenomena. All the drivers are mapped in GIS. For the preparation of socio-economic drivers like, Population density and Economic Condition, unique methodologies are adopted.

CHAPTER 5

MODELLING PRE-INDUSTRIAL LANDSCAPE

5.1 INTRODUCTION

Land use change modelling activities does not stop at just understanding of land use change process. It also assists in the exploration of future development scenarios (Verburg et al., 2004a). Different modelling approaches are specialized for different application areas. Integrated modelling approach couples many important aspects of land use change. It can also explicitly address multi-scale characteristics of land use system. Integrated modelling approach is also well known for addressing inherent multi-disciplinary nature of land use change. Combination and integration of different land use change modelling approach could be a feasible and potential solution (Sudhira et al., 2005; Luo et al., 2010; Zheng et al., 2012, Zhang et al., 2013) to understand land use change and its drivers.

The objectives of this chapter are;

(i) Investigate the influence of land use change driving factors of the study area in pre-industrial landscape

(ii) Model the pre-industrial landscape incorporating the drivers.

Accordingly, this chapter presents the details under the following headings.

- Investigation of land use driving factors
- Understanding of driving factors.
- Estimation of land use demand.
- Spatial modelling of pre-industrial landscape.

5.2 INVESTIGATION OF LAND USE DRIVING FACTORS

At the cell level, interchangeability among different land use types is determined by locational suitability. Location suitability is a weighted average of suitability based on empirical analysis. It captures historic and current location preferences in response to location characteristics (Verburg et al., 2008). To understand locational preferences of each land use class, Binary Logistic Regression (BLR) model is constructed relating each land use class and the possible driving factors. A brief description about Logistic Regression is presented in section 3.3.2.

Understanding the driving factors

Odds ratio$\left(\frac{P_i}{1-P_i}\right)$ referred as (Exp(β)) can effectively be used in interpreting the influence of each of drivers on land use change. Table 5.1, Table 5.2 and Table 5.3, presents the odds ratio (Exp(β)) for , Biophysical drivers, Infrastructural drivers and socioeconomic drivers respectively.

If there is an increment of one unit in the corresponding independent variable while rest of the factors remain unchanged, how it is going to affect the probability of occurrence of a dependent variable is understood by the odds ratio (Overmars and Verburg, 2005). In other words, when Exp(β) – 1 > 0 the probability increases upon an increase in the value of the independent variable, when Exp(β) – 1 < 0, probability decreases (Luo et al., 2010).

5.2.1 Bio-physical driving factors

Table 5.1 shows influence of Bio-physical drivers through the odds ratio. It can be observed that, natural vegetation are mostly on high relative relief and plantations are found where drainage density is high. Negative relation between the farm land and relative relief, slope, and distance from the streams show that farm lands are mostly organized on the flat land near the streams. Positive relation between plantation land and drainage density, relative relief, average slope depicts that most of the highly dissected rugged lands are used for plantation activities.

Drainage density and Potential Ground Water zone are not frequently reported drivers in literature. An attempt has been made in this study to use them as the proxy data for water availability as observed information is not available. Drainage Density is assumed as a proxy for irrigation from surface water and potential ground water zone for well-based irrigation. Table 5.1 shows drainage density has Exp(β)-1 =

-0.273 and 1.697 respectively for farm land and plantation. Whereas potential ground water zone has -0.431 and -0.44. Hence it can be inferred that, for agricultural activities surface water is the main source in the studied landscape. Distance from Dams in Table 5.3 further elaborate this hypothesis. Location of Built-up land 0.3519 is also influenced by ground water.

Table 5.1 Binary logistic regression analysis for Biophysical drivers.

		Farm Land	Plantation	Natural Vegetation	Fallow Land	Other Land	Waste Land	Built-up Area	Water Bodies
Drainage Density	β	-0.3195	0.9922	-3.6176	0.2124		.7024	-.7309	2.6428
	Exp(β)-1	-0.273	1.697	-0.973	0.237	-1	1.0186	-0.5185	13.0528
Geology	β	-0.1743	1.5833	16.1631	0.0323	-2.0985	-.2546	.3282	18.3601
	Exp(β)-1	-0.16	3.871	10460022.5	0.033	-0.8774	-0.2247	0.3884	94124120.3
Geomorphology	β	-0.5640	-0.5797	-1.3900	1.2436	4.9640	.8780	-1.1654	-18.9599
	Exp(β)-1	-0.431	-0.44	-0.751	2.468	142.1695	1.4061	-0.6882	-1
Ground Water	β	-0.3427	-0.5560	-0.5452	0.4426		.7931	.3015	-.6659
	Exp(β)-1	-0.29	-0.426	-0.42	0.557	-1	1.2103	0.3519	-0.4862
Relative Relief	β		0.0214	0.1230	-0.0573		.0362	-.0310	
	Exp(β)-1	-1	0.022	0.131	-0.056	-1	0.0368	-0.0305	-1
Slope	β	-0.0090	0.0162	0.0490	-0.0171				-.0456
	Exp(β)-1	-0.009	0.016	0.05	-0.017	-1	-1	-1	-0.0446
Soil	β	0.0410	0.4175	2.0185	-0.6351	-1.5601		-.1997	.8938
	Exp(β)-1	0.042	0.518	6.527	-0.47	-0.7899	-1	-0.181	1.4445
Stream Distance	β	-0.0007	0.0004	-0.0037	0.0005	.0061	.0010	-.0012	-.0035
	Exp(β)-1	-0.001	0	-0.004	0	0.0061	0.001	-0.0012	-0.0035

5.2.2 Socio-economic driving factors

Built-up land tends to be highly populated, close to roads and on plain land with good access to water. The present study found Exp(β)-1 = 4.1246 for the Population Density on Built-up Area (Table 5.2). Interestingly, people's Economic Status is not showing positive relation with Built-up Area (-0.9145). Instead of that, it is positive over Farm Land and Plantation. This is a typical characteristics of the present study area, as people who invest on farming and plantation activities are tend to live near their farms. Modified Literacy gender parity index (Mod GPI) is not so affecting land change driver.

Table 5.2 Binary logistic regression analysis for socioeconomic drivers.

		Farm Land	Plantation	Natural Vegetation	Fallow Land	Other Land	Waste Land	Built-up Area	Water Bodies
Economic Stat	β	1.5096	1.3887		0.0349			-2.4592	-5.9239
	Exp(β)-1	3.525	3.01	-1	0.036	-1	-1	-0.9145	-0.9973
Popun Density	β	-0.1051	0.4952	-0.3021	-0.5941	-.5389	-.4639	1.6340	-.8221
	Exp(β)-1	-0.1	0.641	-0.261	-0.448	-0.4166	-0.3712	4.1246	-0.5605
Mod GPI	β	-2.9472			-1.0477	11.8308		-4.0719	
	Exp(β)-1	-0.948	-1	-1	-0.649	137414.5811	-1	-0.983	-1

5.2.3 Infrastructural driving factors

Table 5.3, presents the influence of infrastructural drivers on land use change. It has been hypothesised at the beginning of this study, distance from dams could be very influential factor in determining location of Farmland and Plantation land. Dams store water which can effectively be used to irrigate the Farm land and Plantation. The negative odds ratio values from binary logistic regression suggest that, with increasing distance from dam location, probability of occurrence of farm land and plantation for the year 1997 land use decreases. Similar trend is also visible with built-up areas. Among the other infrastructural drivers road is most important. Distance from major roads and distance form all roads are not found to be very significant with allocation of most of the land use classes except fallow land and waste land. Road density is also positive over plantation and waste land. Which could mean, most of the service roads are built through plantation and waste land. Road density used to be high in densely settled areas. In the study area settlements were fragmented during the year 1997. Hence road density does not have a positive relation with built-up land. This study found, location of big industries are not far from farm lands. -1 odds ratio for the Industry Location independent variable with the farm land dependent variable clearly depicts that probability of occurrence of farm land decreases with increasing distance from the industry site. For future planning, it requires further attention while establish big industries. Acquiring farm land for industries often draws conflicts over land use conversion among the different stakeholders.

Table 5.3 Binary logistic regression analysis for infrastructural drivers.

		Farm Land	Plantation	Natural Vegetation	Fallow Land	Other Land	Waste Land	Built-up Area	Water Bodies
Dam Dist.	β			0.0007	-0.0003	.0018	.0002		-.0046
	Exp(β)-1	-1	-1	0.001	0	0.0018	0.0002	-1	-0.0046
All Roads	β	0.0006	-0.0010	0.0021		.0055		-.0008	.0047
	Exp(β)-1	0.001	-0.001	0.002	-1	0.0056	-1	-0.0008	0.0047
Major Roads	β	-0.0002	-0.0003	-0.002	0.0001	.0049	.0004	.0003	
	Exp(β)-1	0	0	-0.002	0	0.0049	0.0004	0.0003	-1
Road Density	β	-0.0625	0.1118	-0.6949	-0.0787	-.9241	.2230	-.1313	
	Exp(β)-1	-0.061	0.118	-0.501	-0.076	-0.6031	0.2498	-0.123	-1
Bus Stop	β	-0.0002	0.0001		-0.0002	-.0013	.0004	-.0008	
	Exp(β)-1	0	0	-1	0	-0.0013	0.0004	-0.0008	-1
Industry Loc	β		0.0001	0.0008	0.0000	.0004	-.0002	.0001	-.0011
	Exp(β)-1	-1	0	0.001	0	0.0004	-0.0002	1E-04	-0.0011

5.2.4 Discussion on drivers

Successfully land use change drivers are analysed. There are total seventeen number of proximate drivers of land use change. Among these, nine are most commonly found in literatures. All these drivers are not equally influential in the present study. Commonly available bio-physical drivers such as Drainage Density, Geology, and Geomorphology are most influential. In the contrary, Distance from Streams and Distance from Roads are least influential.

Apart from the commonly used drivers, eight more proximate drivers are considered based on local conditions. Among these, ground water potential zone, economic status, road density, industry location have provided interesting insight into the land use change process. A similar analysis is also done for industrialized landscape.

5.3 LAND USE DEMAND ESTIMATION (NON-SPATIAL MODULE)

Unlike the changes in cell level, aggregate level interchangeability among land use classes are defined by land use demand estimation. Land-use demands are time series estimation of aggregate land use classes within a study area. Demand estimation, essentially is a creation of continuous aggregate land use class dataset. Demand could be estimated using several methods, say linear extrapolation of historical trends, socioeconomic models or system dynamics. Linear interpolation is one such method, from which aggregated land use changes, are estimated. This method uses land use details of two temporal extremities and further extracts demand for the years in between. This method does not consider any causal factor of change in estimating the missing values.

Table 5.4 Estimated aggregate level land use demand in ha.

Year	Farm	Plantation	Natural Vegetation	Fallow	Waste	Built-up
1997	6968.79	9672.19	857.37	8202.70	4499.07	1381.36
1998	7410.01	9432.16	996.019	8102.26	4213.93	1427.09
1999	7851.24	9058.14	1039.07	7989.74	4183.87	1459.42
2000	8304.80	8751.11	1129.92	7883.26	4026.27	1486.11
2001	8738.17	8439.79	1220.77	7781.08	3880.64	1521.02
2002	9195.48	8137.06	1311.62	7670.31	3711.07	1555.94
2003	9632.59	7830.03	1402.47	7567.05	3550.25	1599.09
2004	10057.36	7542.21	1493.32	7461.11	3401.71	1625.77
2005	10498.58	7248.93	1584.17	7355.17	3244.92	1649.72

*Other Land Class - 165.13 ha and Water - 639.76 ha assumed constant. Total 32386.41 ha

In this study, intermittent land use data are estimated from classified satellite imagery for the years 1997, 1998, 2003 and 2005. The method (Equation 5.1) used for linear land use interpolation is stated in Silva et al. (2013) and involves three different periods: t_0, t, t_1 and three different land use quantities F_0, F_t and F_1.

$$F_t = \frac{F_1 + F_0(t_1 - t)/(t - t_0)}{1 + (t_1 - t)/(t - t_0)} \qquad \ldots\ldots\ldots\ldots\ldots\ldots (5.1)$$

Where F_t is the measure of land use at a given time, t; F_0 and F_1 corresponding to land use in time t_0 and t_1 respectively. Missing data between observed data values are estimated using this model. Table 5.4 summarizes the area computed for missing periods. The area under the 'Other' land class and 'Water bodies' are assumed to be constant throughout the simulation period.

5.4 SPATIAL MODELLING OF LAND USE CHANGES

Constant values (mentioned in Table 5.5) and the coefficient of regression (β) values (Table 5.1, Table 5.2, Table 5.3) derived from logistic regression are then input into the model (described in Chapter 3, section 3.2.4). For this part of the study, the model is configured only for baseline scenario simulation considering present trend of changes. Iterative process is allowed to end only if the average deviation between demanded changes and actually allocated changes attained to reach at ≤ 0.35%. At the same time maximum deviation between demanded changes (Table 5.4) and actually allocated changes should be minimally equal to 1 cell difference. For e.g., a land use type with a demand of 200 ha and a cell area of 4 ha, the value should be minimum (4/200)*100% = 2%, it is kept at 3%. Policies or tenure status of restricting one land use type from conversion should be included in the model. Spatial maps, indicating areas for such policy are usually included. For the present study, no area restriction is implemented. This is also necessary to understand land use change sequences. Because all land classes do not change at a time. One land class could not convert to two or more different classes at a time and some changes are irreversible. An A×A matrix is used for directing changes between classes, where 'A' equals number of land-use classes. It determines temporal dynamics of simulations, and indicates sequences of possible and impossible conversions among land use classes. Another important setting for land conversion is land conversion elasticity. Based on user knowledge and preferences, a set of elasticity is defined for each land use class. Finally all these parameters are combined to estimate total probability of each cell using Equation 3.12. For the present study neighbourhood suitability and competitive advantage assumed to be zero.

Conversion Elasticity

Elasticity coefficients are assigned for each land use classes to indicate resistance of each class to conversions. It is a scale that ranges from 0 (indicative of easy conversion) to 1 (indicative of hard conversion, i.e., irreversible change). The closer the values to 0 the easier is the land-use conversion, and the closer the values to 1 the harder is the land-use conversion. Based on the land use dynamics and knowledge gathered through literature a set of elasticity is defined for each land use class (Table 5.5).

Table 5.5 Constant values of the regression equation and Conversion Elasticity coefficient for each land class.

	Farm	Plantation	Natural Vegetation	Fallow	Other	Waste	Built-up	Water Bodies
Regression Constants	1.4806	-5.2083	-16.1905	-0.9378	26.5708	-5.1463	4.5018	1.2106
Conversion Elasticity	0.3	0.7	0.9	0	0	0	1	1

5.5 RESULTS AND DISCUSSION

The biophysical characterization of the study area has revealed, initially farm land and plantation were mutually interchangeable. Later both did not follow the trend. Discretely some waste land might have been converted due to social forestry (Figure 5.1a). Observed data were available for only for four time steps. To fill the rest demand estimation is done. Figure 5.1b is clearly showing that after demand estimation, the trend of land use dynamics is simplified. It could also influence the spatial allocation.

A two-step model evaluation approach is adopted in this research - evaluation of model's performance for aggregate level predictability and evaluation of spatial allocation ability. The Dyna-CLUE model has translated each land use demand time-step into a spatial map. Each pixel changes its states, based on total probability it gets (from Equation 3.12) and the user defined settings. Each demanded land use class quantity then spatially allocated throughout the study area. The aggregate land areas are recalculated from each simulated map (Figure 5.2) again. These are compared with the estimated land area of Table 5.4. The model itself is modular in nature and integrates different other models, thus only the spatial patterns of model results may not be enough to discern the model's capability.

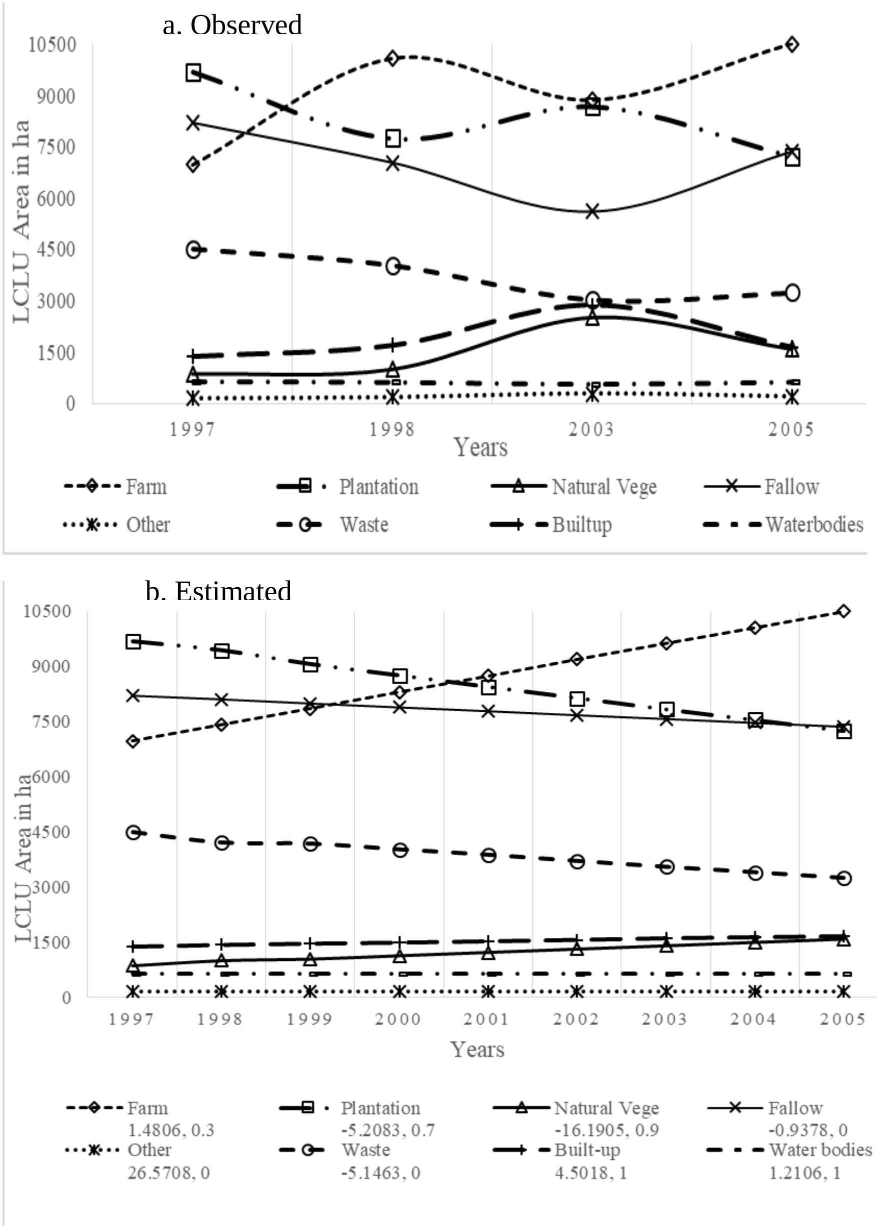


Figure 5.1 Comparison between observed and estimated land use demand.

For the present part of study, except ‘other land uses’ and ‘water bodies’, all land classes are showing very good relation between estimated and simulated land area (Table 5.6). The R^2 values are vague for ‘other land uses’ and ‘water bodies’ classes, where it reads respectively as 0.45 and 0. Such discrepancy arrives as correlation based measures i.e. R^2 is more sensitive to outliers than to observations near the mean (Legate and McCabe, 1999). ‘water bodies’ class is assumed to remain constant throughout the simulation period. Thus variations are not far from the mean.

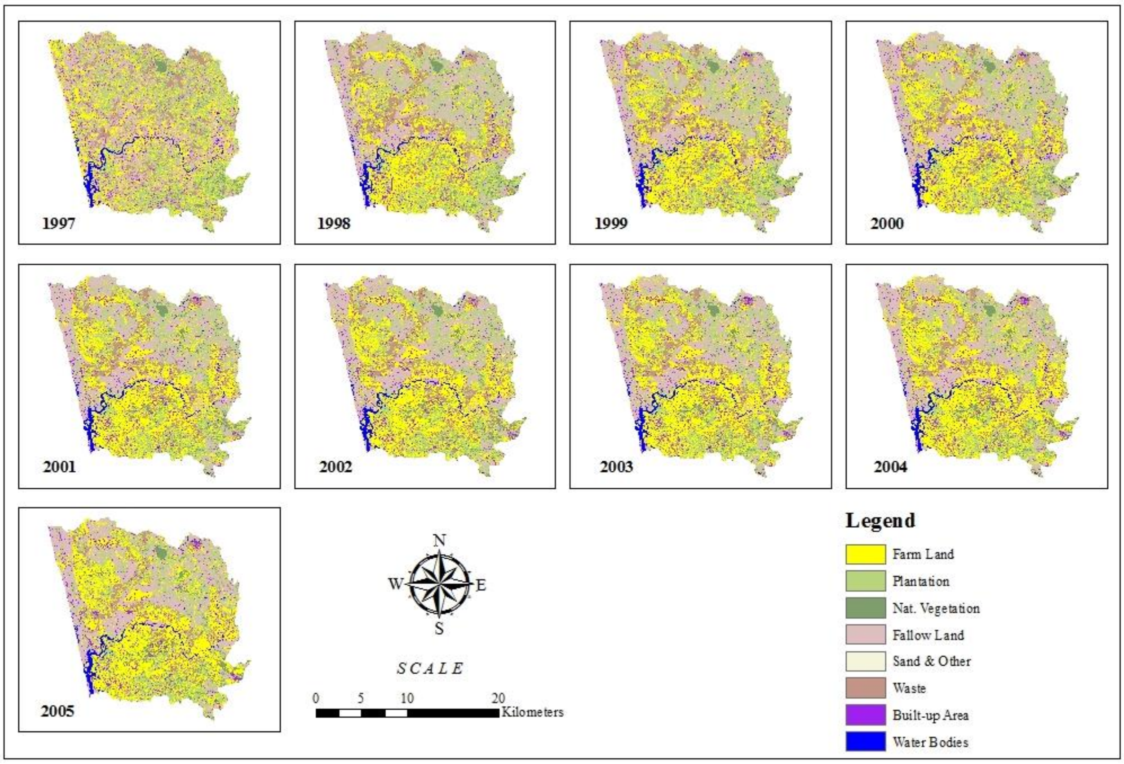


Figure 5.2 Simulated land use map of pre-industrial land for each time-step.

Table 5.6 Error evaluation of model using estimated land use data.

	Farm Land	Plantation	Natural Vegetation	Fallow Land	Other Land	Waste Land	Built-up	Water bodies
R^2	1	.99	1	1	.45	.99	.99	0
RMSE (ha)	8.600	11.956	0.571	2.399	24.693	6.302	11.907	6.139
RSR	0.002	0.004	0.000	0.002	0.635	0.005	0.044	~

RSR values in Table 5.6, confirms that, Natural Vegetation fares best simulation results with 0.00 RSR values. All other land classes except the ‘Other Land’, are showing good results. It demonstrates the model’s capability to simulate and maintain the quantity of demanded land classes for each time-step. However, model’s ability of spatial allocation need to be evaluated separately.

In the first time step, i.e. year 1997 (Figure 5.2) not much visible differences between the observed and simulated land use map is found. This time-step is the base year for simulation process, thus there is no significant changes between demanded land use and simulated land use. From the year 1998 onwards, simulated and observed land use maps are showing differences. The same statistical measures of model validation (described in the Equation 3.1, 3.2 and 3.3) are repeated using observed land use data as validator. Table 5.7 shows comparison between available observed land use data and simulated data at the aggregate level. 'water bodies' and 'other land uses' classes are assumed to be constant at the beginning of the simulation. Hence a perfect model fitting for these two classes are not expected. However, the other classes are also not up-to the mark. Among the land use classes 'natural vegetation' and 'waste land' are showing comparatively better result.

Table 5.7 Error evaluation of model using actual land use data.

	Farm Land	Plantation	Natural Vegetation	Fallow Land	Other Land	Waste Land	Built-up	Water bodies
R^2	0.341	0.324	0.5349	0.244	0.393	0.884	0.270	0.401
RMSE (ha)	1384.438	941.658	553.191	1115.726	62.664	272.977	648.953	45.787
RSR	1.011	1.008	0.851	1.189	1.413	0.462	1.137	1.539

After the comparison of aggregate level, simulated maps are spatially compared to the classified maps. The overall accuracy of simulated map of the year 1998 is 43.47%. Water land class is showing the best match (80.64%) with observed data. With 70.99% match, Plantation land class has also shown better prediction. All other land classes are performing below average to poor. Thus estimated demand and Elasticity coefficients along with the conversion sequence should be of much importance. Most of the previous articles are not equivocal regarding these issues. As such parameters are case specific and scale dependent. Thus it requires to employ expert knowledge and a detailed inspection of the study area characteristics.

Figure 5.3 and Figure 5.4 are showing the Pixel to pixel comparison matrix, prepared with model output and classified images. Classified satellite images are used as observed data. Each pixel of observed data is considered as the sample point and compared with the simulated one. Percentage of mutual match between observed and the simulated data is mentioned beside individual class. Decreasing percentage values depicts the decreasing agreement between observed and simulated data.

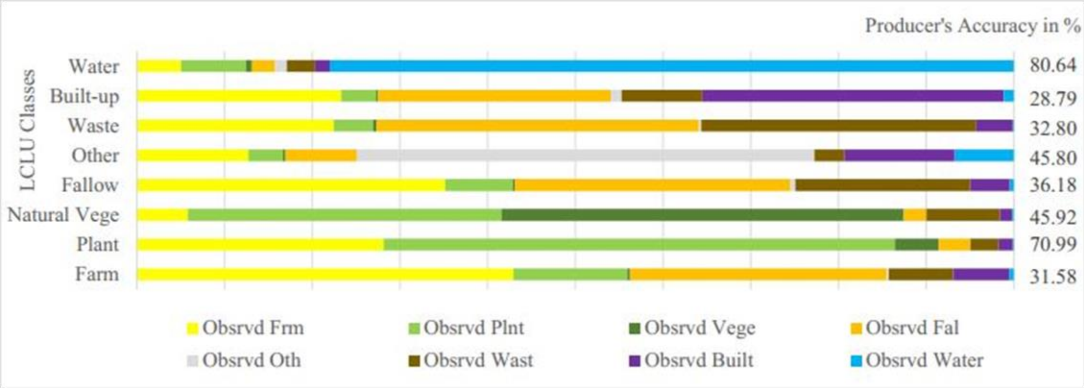


Figure 5.3 Observed v/s simulated error chart for the year 1998.

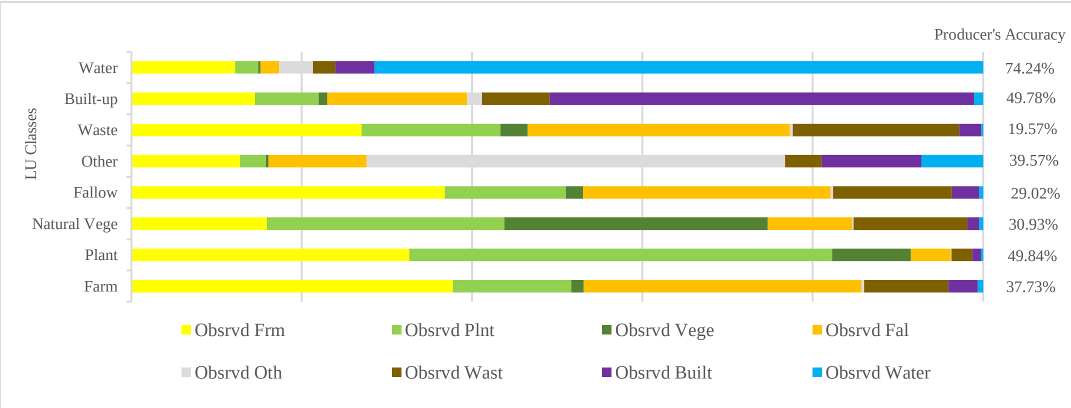


Figure 5.4 Error chart showing comparison between simulated and actual land use map of the year 2005.

In the year 2005 time step, overall accuracy is decreased to 37.63% (Figure 5.4). Water body class is again performed well at 74.24% while the estimated area remained constant. Interestingly, accuracy of Built-up class is increased from 28.79% to 49.78% and Plantation class is decreased from 70.09% to 49.84%. The importance of incorporating the experiences on land use change of local area is clearly visible. Verburg et al. (2006) has opined that -

"It is not particularly useful to attempt to crown a model as valid or to condemn a model as invalid based on validation results. It is more useful to state carefully that degree to which model is valid".

All in all, it can be said methodology of modelling followed in this study is the beginning step for the understanding of land use dynamics in India. With growing experience and knowledge further improvement can be done.

5.6 CONCLUSIONS

Total seventeen proximate drivers from three broad categories (Bio-physical, Infrastructural, Socio-Economic) are primarily examined. Among these, nine are frequently used in different literature. Rest of the eight drivers are included by the researcher himself with the help of experts on local phenomena.

Driving factors are independent variables and each land use class is dependent variable in the Logistic regressions analysis. It has revealed that biophysical drivers are the primary cause of land allocation. Even ground water availability is one of the determinant for the allocation of built-up lands. Among the socioeconomic drivers population density is the most influential, especially for the allocation of built-up land.

All drivers are not equally influential. Distance from dam (listed by researcher) is determining the location of Farmland, Plantation and Built-up lands. Distance from Roads are not found to be very significant. Instead, researcher's defined Road density, is providing an insight. Most of the service roads are built through Plantation and Waste land. Road density is not high in Built-up areas as settlements are fragmented. Big industries tend to locate near Farmland which may cause social uproar due to land acquisition.

Approaching to the Socio-Economic drivers, Population Density on Built-up Area is high. In the present study area people live in spacious and isolated houses surrounded with different plantations. Hence, Plantation land also found positive with population density. Economic status is positive over Farm Land (3.525) and Plantation (3.01). In this study area, people who invest on farming and plantation activities are tend to live near their farms. Modified Literacy gender parity index (Mod GPI) is not found to be influential land change driver.

Quantification of all linked sources which propagate uncertainties in integrated modelling framework is an essential requirement. Moreover, model validation is crucial in order to apply it in the decision making process. In the case of pre-industrial landscape modelling, the first phase of validation process is for aggregate land quantity and second phase is for evaluating the capability of spatial allocation. The input land demand is linearly interpolated. Quantity of input land use demands are well maintained in simulation results for almost all classes. However, the validation process for spatial domain suggests that model is underperforming in spatially allocating the demanded land use. This leads to two inferences, first, the spatial module of Dyna-CLUE model should be handled more carefully. Second, instead of linear trend models, other complex models can be explored.

In the next chapter a SD model is designed to estimate the land use demands for different realistic scenarios

CHAPTER 6

MODELLING INDUSTRIALIZED LANDSCAPE

6.1 INTRODUCTION

In the early 1990s, economic reforms have expedited economic dynamism along with industrialisation and urbanization (Ghatak and Ghosh, 2011; O'Mara and Seto, 2014). In the study area, after the thermal plant has started functioning, adjacent land irrespective of the land cover type, changed to a greater extent. Crop land, fallow land and vegetation are most susceptible to change into built-up land. Such activities may upset the entire landscape in an ecologically sensitive area (Ramachandra and Aithal, 2012). In addition, apprehending the influence of global or national level policy and economic activities on the local level land use change is also crucial (Verburg et al., 2008). The global or national level policies need to be considered for studying the local level land use changes.

Different policies directly or indirectly affect land use decisions. The factors govern a particular state of any land use class are of two types: endogenous and exogenous. Endogenous factor is the one whose state is determined by the states of other variables in the system. States of exogenous variables are determined by factors outside the causal system. Different states of land use as well as endogenous and exogenous factor are interlinked as a system (Figure 2.1). Perhaps the challenge is modelling the multi scale level system and sub-system components and interactions between them. Simulation of environmental processes including land use changes using different types of models are being attempted over the years. System dynamics (SD) model forms an ideal way to address land use changes occurred due to combined effort of endogenous and exogenous factors such as policy, growth rates etc.

The objective of this chapter is to show; how systems dynamics approach can be adopted to estimate land use changes in an industrialized landscape;

Accordingly, this chapter is discussed under the following headings

- Bringing System Dynamics into land se change modelling.
- Method of modelling SD-LU change.
- SD- LU demand model: calibration and validation.
- Prediction of future land use demand.
- Discussion and conclusions.

6.2 BRINGING SYSTEM DYNAMICS INTO LU CHANGE MODELLING

System concept was developed to streamline our understanding of complex behaviour of systems. It makes use of interactions which come within and across the system boundary. System dynamics (SD) is one of the tool to attain non-linear behaviour of system through the concept of feedback mechanism. Hence, SD is an entity-cause relationship model which deals with time-dependent behaviour of systems through qualitative and quantitative methods. Behaviour of the system is governed by information feedback that ultimately helps in designing robust information feedback structures and control policies through simulation and optimization (Coyle, 1996). SD is efficient in expressing series of temporal states of a variable, such as classes of land use. While addressing the dynamics of a land use system, temporal changes in states of a specific class are significant. Land use as a whole can be considered as a system upon which desired classes constitute its sub-systems. Changes encompassed due to socio-economic, policy drivers act as factors in defining level or state of that particular class. These concepts have been used in earlier studies by, Chunyang et al. (2005), Luo et al. (2010), Wei et al. (2012), and Wu et al. (2015).

Over the years, SD has evolved as a powerful tool to attain land use related environmental decisions at an aggregate level. Also, it has been functional by means of either loose coupling with spatial change models (Chunyang et al., 2005; Shen et al., 2007; Mozumder and Tripati, 2014; Wu et al., 2015) or tight coupling with GIS environment by involving a mediator (Lee et al., 2008; Newirth and Peck, 2013, Newirth et al., 2014). Further, SD is a novel approach to chalk up the probable future scenarios.

Research on complex land use change modelling using system approach is getting momentum in India. Here, industrial and urban growth is on a high. Growth in all sectors including infrastructure development have come into contact with the share of foreign direct investments (FDI). FDI indirectly affects land use dynamics, and the combination of FDI and other policies are of top-down nature. According to the new land reform policy, public participations and sustainability are important obligations in most land conversion projects. SD may provide a sole frame to analyse land use requirement-impact assessment. With this background, this chapter attempts to capture dynamics of land use change influenced by processes from different scale levels.

This chapter emphasizes on;

i) Estimating demand for land use changes through feedback mechanism of SD approach along a defined time frame;

ii) Designing scenarios of future land use for studied landscape.

This study proposes a land use demand estimation model using SD approach, where exogenous factors are major players. Widely used SD model Vensim-PLE® is used to construct the present states. This model has also been used to predict the demands for future scenarios.

6.3 CONCEPTUAL MODEL

Drivers of land use change are certainly not limited only within its neighbouring area. To model land use change, System dynamics has become a unique approach. Mainly because SD could work beyond the neighbourhood transitions and their states. Unlike spatial land change models, SD models are capable of modelling the interacting behaviour of land system. However, modelling physical dynamics is the exclusive domain area of spatial models. In SD approach, feedback mechanism fetches information from the action-outcome interactions. This, in turn changes the original information and the consequent actions. SD allows to execute the conceptual map of causal loop diagram to realistically simulate stock and flow interactions. It compares the intrinsic behaviours of both the exogenous and endogenous factors in the diagram itself. Therefore, SD methodology is one of the most preferred approaches to represent structural relations of a system. Under the purview of 'system' approach, feedback mechanism transforms states among the land use classes. Different land classes and socioeconomic subsystems within a single land use system are also interlinked among each other. Which means one land class gets converted to another following a sequence (Figure 6.1).

Figure 6.1, shows a conceptualized representation of land use system and sequential changes. It has been hypothesised that, land changes sequentially towards the advanced level of uses by the influence of prevailing biophysical and socioeconomic setup. For example, direct conversion of waste land to farm land is very difficult. Rather the wasteland can easily be improved to plantation or natural vegetation. Later natural vegetation can be converted to crop land or plantation. However, conversion of Planation land to Farmland is rather unusual. As an improvement of land for plantation requires higher investment and plantation usually gives higher return than any food crop. In Figure 6.1, an uninterrupted arrowed line represents a direct connection, an interrupted arrowed line represents indirect connection or influence. A {+} sign and a {-} sign respectively represents addition and reduction of the land area. A {+ -} sign represents two way linking, both reduction and addition is possible. In this figure the connection between Fallow land and crop land is two way. Therefore, fallow land can easily be converted to crop land by land improvement and conversely crop land would become fallow land if left uncultivated for a long period. Population growth variable is connected with the 'demand for housing' and 'food demand' variables using interrupted arrowed line. These two variables again connected with built-up land and crop land respectively. Which suggests, population growth influences the increase in built-up area and crop land through the growing demand of housing or food commodities respectively. This conceptual model would help to formulate the working methodology for land use change modelling using SD.

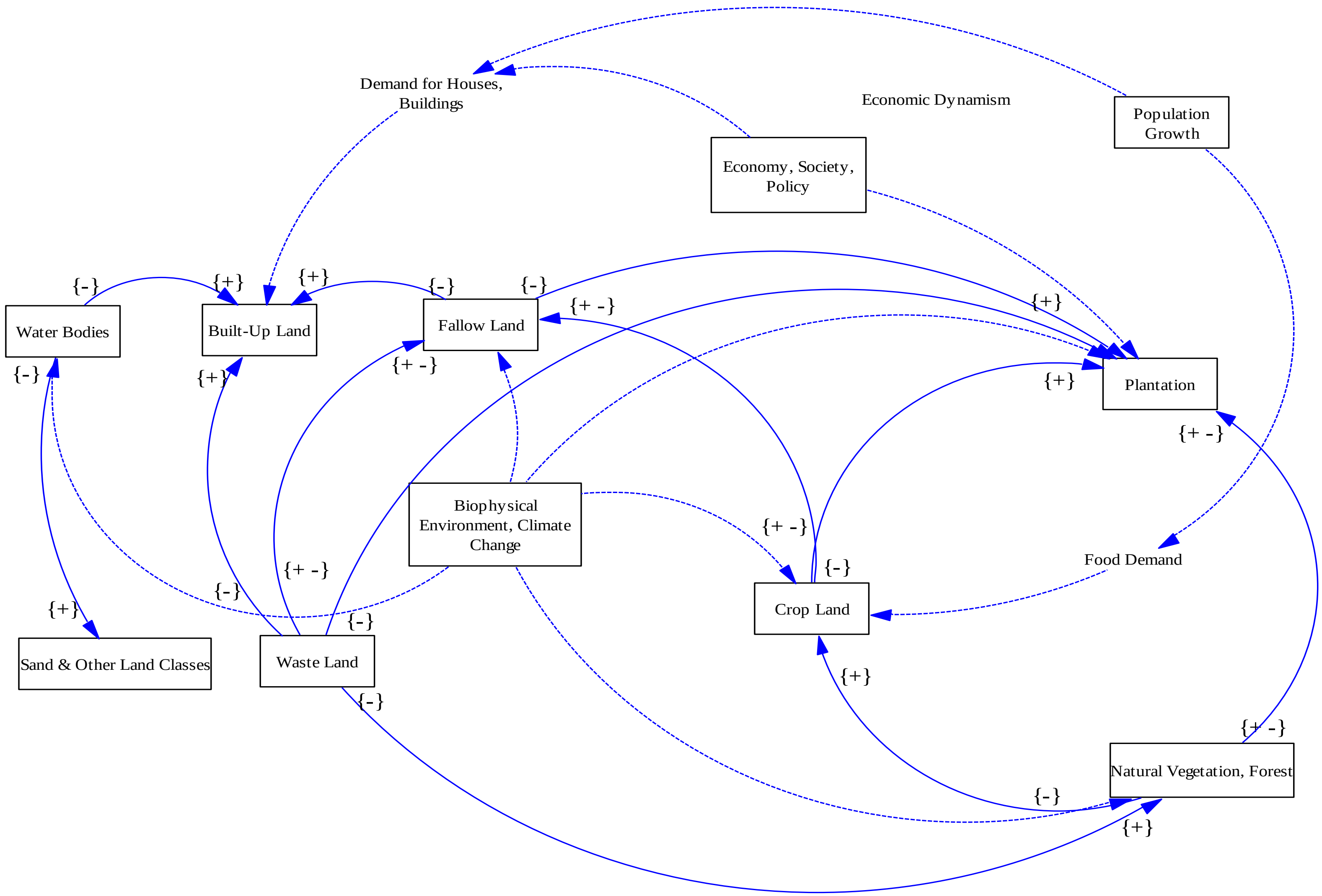


Figure 6.1 A conceptualized representation of land use system and sequential change using Vensim PLE.

6.4 METHOD

SD method attempts to estimate land use demands at an aggregate level. Significance of SD method in land use change modelling is to understand the dynamics of land use in connection with the system and several subsystems. Effects of each sub-system would assembled at combined level. The overall workflow (Figure 6.2) presented here consists of three stages;

- Organizing the data for specific conditions of the system viz. stock, level, auxiliary, constants and look-ups;
- Constructing the model;
- Calibrating and validating the constructed model. Later part of this study extends to scenario forecasting.

SD model for land use demand estimation consists of several components (Figure 6.2). The components involved are;

- Input to the model,
- Categorization into stock,
- Flow and constants,
- Stock flow diagram,
- Feedback networks and mathematical relations,
- Calibration and Validation,
- Scenario simulation, and lastly
- Land cover land use demands at output phase. Output of this model is aggregate, areal measures for various land use classes.

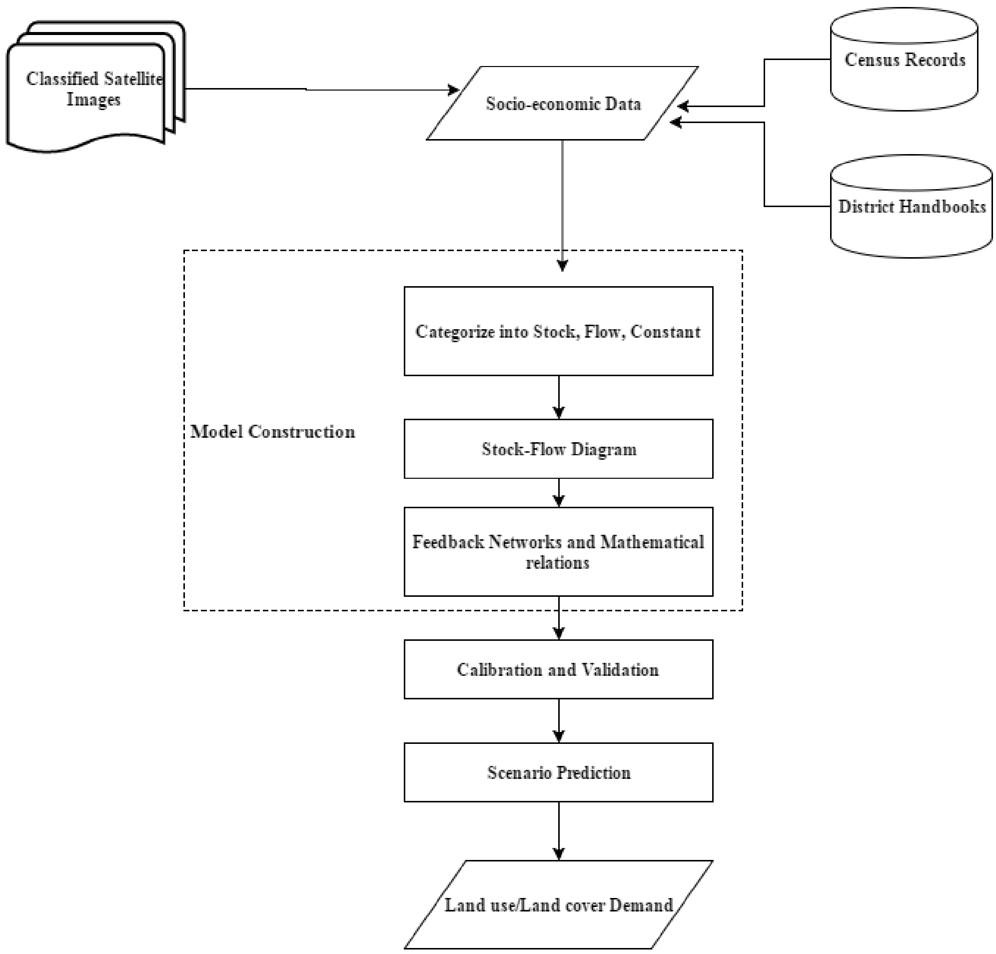


Figure 6.2 Schematic diagram of SD modelling workflow.

Each of the land use class types available in the region are framed separately as sub-systems. Availability of causal factors for modelling the likely changes get utmost importance. With the increasing number of causal factors, the degree of complexity in a stock-flow diagram increases, and hence the complexity of the model. Input for model construction phase is categorized data which includes both biophysical and socioeconomic data. Then different data sets are represented in the form of stock-flow diagram.

Values of stock variables are governed by level variables. Increase or decrease in level variables converge at state variable and attain a state value. Factors responsible for change in levels have to be attached at the specific level. Factors which may have a direct control on the state are also imaginable. Inter-changes among various land use type complement each other. Changes of each land use type are influenced by other land uses as well as prevailing demographic and socioeconomic factors. Model has to incorporate these aspects to predict future scenarios. Except the built-up which has shown a consistent increase, all sub-systems are designed for two-way change, either decrease or increase. One of the important consideration prior to model building is not having a unit. Thus all available parameters are converted to respective change ratios. There can be a direct relation between sub-systems, or an indirect relation which normalizes fluctuations corresponding to a particular subsystem. Crop price, gross domestic product, gross district domestic products are included as annually fluctuating variables using lookup options. Causality factors such as proximity, healthcare, migration, GDDP share are dealt in the flow level. There is also a link between the stock value built-up and flow variable built-up increase. Simulation of built-up (or any stock) at any time *t* is achieved by counting increments in built-up (flow values) in time *t* from the previous. An example of built-up land for mathematical formulation of SD state-level relation is given in Equation (6.1).

$$Builtup(t) = Builtup(t_0) + f(Economy, Population, Farmland, Waste, Plantation, fallow) \quad \ldots\ldots \; 6.1$$

Where built-up (t) is a function of economy, population, and other land uses, and adds to the built-up area of previous time step(t_0). As mentioned earlier, SD can account non-spatial socio-economic variables from a different scale level such as GDDP that become important in defining the increase in built-up land.

6.5 SUB-SYSTEMS

Sub-systems involved in Figure 6.2 are Population, Economy, Built-up, Farmland, Fallow, Natural vegetation, Plantation, Waste, Other and Water body.

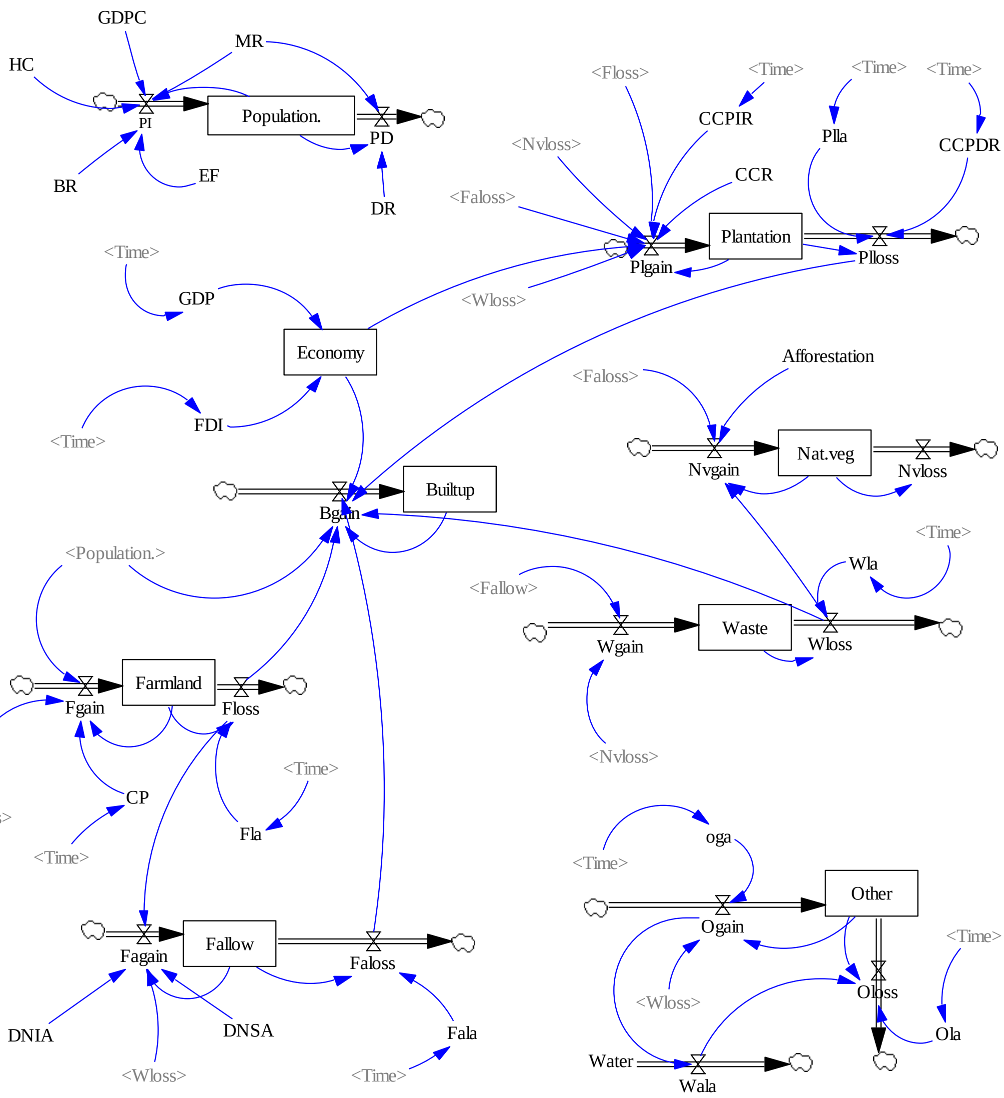


Figure 6.3 Land use demand estimation model

Descriptions of each of the objects involved in the SD model are given in Table 6.1, 6.2, 6.3, 6.4, 6.5, 6.6, 6.7, 6.8, and 6.9. For computational purpose, all these objects are made unit less. Changes happened over the years is assumed either as the ratio of change in the states to state of later year, or a constant change rate. The land use demand estimation model is presented in Figure 6.3. land use demand estimation model in SD, possesses ten sub-systems. All subsystems are interconnected and perform spontaneously at a time. This is useful in simulating actual complexity of land use changes. Design of this model has involved ten stock variables. Most of the other variables which act as causal factors are expressed as average change in their values for both the districts.

6.5.1 Population subsystem

Population subsystem (Table 6.1) is designed by two flow variables such as population increase and decrease.

Table 6.1 Descriptions of Objects in Population Sub-system.

Object	Name	Expression	Description
Population sub-system		*PI – PD*	*Difference of rates*
PI	Population Increase	(Population.*(BR*GDPC*EF*HC*MR))	Rate
PD	Population Decrease	(Population.*(-DR*MR))	Rate
HC	Health Care	0.6	At country level, a health care facility can cover 60% area surrounding to it.
BR	Birth Rate	0.18	Average birth rate of Dakshina Kannada and Udupi Districts.
EF	Educational Facilities	0.043	An educational institution can cover 43% of the total area.
GDPC	Gross Domestic Product Change	0.045	Ratio of change in GDP between two consecutive years to the later year.
MR	Migration Rate	0.11	Average migration rate of Dakshina Kannada and Udupi Districts. It includes migration from villages to villages, town to village.
DR	Death Rate	0.07	Average death rate of Dakshina Kannada and Udupi Districts.

Variables influencing population increase are educational facilities, birth rate, healthcare, gross domestic product change and migration. All these variables are represented as constant, which refers to a constant change rate throughout the years. Subsystem level is attained as a difference of population increase and population decrease. Although, this sub-system does not borrow any values from other sub-systems, it is critical as it contributes to the increase in farmland and built-up areas. Increase in built-up area is represented using built-up gain rate.

6.5.2 Built-up land subsystem

As built-up areas have not contributed its area towards any other classes, built-up loss rate is neglected. Factors responsible for built-up gain are loss of farmland, fallow land, wasteland and plantation lands (as given in Table 6.2). Economy and population variables are represented as a factor of total area. Farmland consists of two flow variables; farm land gain and Farmland loss. Farmland gain is either as a factor of socio-economic factors, or from level variables of other sub-systems as a gain. Gain of fallow land loss, population as a factor of population in the year 1997 and Farmland, crop price change contribute to the gain of farm land.

Table 6.2 Descriptions of objects in Built-up Sub-system.

Object	Name	Expression	Description
Built-up sub-system		**Bgain**	**It attains value of rate directly.**
Bgain	Built-up gain	(Economy * (Builtup/32386.4) / 100)+(0.006*Faloss)+ (0.005*Floss)+ (("Population."/122224)) + (0.001*Wloss) + (Plloss*0.002)	Rate. Built-up gain is from economy, loss in fallow land, fallow land loss, population, loss in waste land and loss in plantation land.

6.5.3 Farmland subsystem

Table 6.3 Descriptions of objects in Farmland Sub-system.

Object	Name	Expression	Description
Farm land		*Fgain-Floss*	*Difference of rates*
Fgain	Farm land gain	(0.12*Faloss)+(("Population."/122224)*Farmland)+(CP*Farmland/32386.4)	Rate Farm land gain is from fallow land loss, population with farmland and farm land.
Floss	Farm land loss	Farmland + Fla	Rate Farm land loss is from farm land, farmland loss area.
CP	Crop Price	Lookup([(1997,0)-(2010,1)],(1997,0), (1998,0.11236),(1999,0.0531915), (2000,0.0961538),(2001,0.037037), (2002,0.0357143),(2003,0),(2004,0.0344828),(2005,0.0169492),(2006,0.0166667), (2007,0.0769231),(2008,0.16129),(2009,0.166667), (2010,0.0970874))	Crop price change is expressed as a ratio of difference between crop prices of two successive values to the later price.
Fla	Farm land loss area	Lookup ([(0,0)-(2010,3000)], (1997,0), (1998,0), (1999,0), (2000,0), (2001,0), (2002,0), (2003,0), (2004,0), (2005,0), (2006,2014.19), (2007,2014.19), (2008,0), (2009,0), (2010,0))	Farm land loss area is expressed as a difference between two successive values of farm land.

Table 6.3 shows, descriptions for the objects involved in Farmland sub-system. Farmland loss area is entered from observed values which forms farm land loss. Farmland loss contributed towards a gain in Fallow land.

6.5.4 Fallow land subsystem

Fallow land gain and Fallow land loss, both constitute rate for Fallow land sub-system. Decrease in net irrigation area, decrease in net sown area, in addition to the loss from Waste land have caused gain in Fallow land. Decrease in net irrigated area and decrease in net sown area acts as a factor of total area to Fallow land. Fallow land loss is entered from Fallow land loss area (Table 6.4) which is obtained from observed data. Loss in Fallow land has given rise to the Farm land, plantation and natural vegetation land. Stock variable at Plantation land sub-system is obtained as the difference of plantation gain and plantation loss rate (Table 6.5).

Table 6.4 Descriptions of objects in Fallow land Sub-system.

Object	Name	Expression	Description
Fallow land		*Fagain – Faloss*	*Difference of rates*
Fagain	Fallow land gain	(DNIA * (Fallow/32386.4)) + (DNSA*(Fallow/32386.4)) + (0.12*Floss)	Rate. Fallow land gain is from decrease in net irrigation area with fallow, decrease in net sown area with fallow and loss in fallow land.
Faloss	Fallow land loss	Fala + 0.1*Fallow	Rate Fallow land loss is towards fallow loss area and fallow land itself
DNIA	Decrease in Net Irrigation Area	0.03	DNIA is calculated as the average ratio of the difference between net irrigation area of two years, 2009 and 2012 to the later year. This has assumed as constant for all years, for both the districts.
DNSA	Decrease in net Sown Area	0.000433	DNSA calculated as the average of ratio of difference between net sown area of two years 2009 and 2012 to the later year. This has assumed as constant for all years, for both the districts.
Fala	Fallow land loss area	Lookup ([(0,0) -(2010,2000)], (1997,0),(1998,166.6),(1999,40 .37),(2000,104.3),(2001,107.01),(2002,106.04),(2003,107.978) ,(2004,101.758),(2005,104.868) ,(2006,0),(2007,0),(2008,1137), (2009,1137), (2010,1137))	Fallow land loss area is expressed as a difference between two successive values of farm land.

6.5.5 Plantation land subsystem

Plantation land rate gain is taken from loss of waste land, loss of fallow land, natural vegetation loss, and fallow land loss. Cash crop price increase rate and cash crop change rate are considered as a factor of plantation land. Cash crop decrease rate, and plantation land loss area from observed data creates plantation loss rate. Fraction of plantation loss has contributed towards built-up gain. Prolonged densification of plantation may lead to the formation of natural vegetation. However, this phenomena is not accounted due to unavailability of parameters to quantify.

Table 6.5 Descriptions of objects in Plantation land Sub-system.

Object	Name	Expression	Description
Plantation		*Plgain – Plloss*	*Difference of rates*
Plgain	Plantation gain	((Economy*Plantation)/9672.19)+((CCPIR*Plantation)+(Plantation/9672.19))+Plantation*(CCR+(1/9672.19))+(0.6*Floss)+(0.2*Nvloss)+(0.45*Faloss)+(0.2*Wloss)	Rate Plantation gain from economy, cash crop price increase rate, plantation, fallow loss, natural vegetation and loss in waste land.
Plloss	Plantation loss	Plantation+Plla+((CCPDR*Plantation/32386.4))	Rate Plantation loss is from existing population, cash crop price decrease rate.
CCPIR	Cash Crop Price Increase Rate	Lookup ([(1997,-0.5) - (2010,1)], (1997,0),(1998,0.0359453),(1999,0.232901),(2000,0.182473),(2001,0),(2002,0),(2003,0),(2004,0.0835934),(2005,0.0708654),(2006,0.122611),(2007,0.290201),(2008,0),(2009,0), (2010,0.205152))	Cash Crop Price Increase Rate calculated as the average of ratio of difference between the values of two successive years to the later year at district level.
CCR	Cash Crop Change Rate	0.02948	Change in Cash Crop Rate, assumed as constant throughout the years.
CCPDR	Cash crop price decrease rate	Lookup([(0,-0.5)-(2010,10)], (1997,0), (1998,0),(1999,0),(2000,0),(2001,0.2558),(2002,0.4337),(2003,0.01838),(2004,0),(2005,0),(2006,0),(2007,0),(2008,-0.144314), (2009,0), (2010,0))	Cash Crop Price decrease Rate calculated as the average of ratio of difference between the values of two successive years to the later year at district level.
Plla	Plantation loss area	Lookup ([(0,0)-(2010,400)], (1997,0), (1998,228.506),(1999,381.7),(2000,309.226),(2001,306.5),(2002,306.5),(2003,306.5),(2004,306.5),(2005,306.5),(2006,0),(2007,0),(2008,123.2),(2009,123.2),(2010,123.2))	Plantation land loss area is expressed as a difference between two successive values of plantation land.

6.5.6 Natural Vegetation subsystem

Natural vegetation stock (Table 6.6) is obtained by subtracting rates: natural vegetation gain and natural vegetation loss. Natural vegetation gain accounts gain of land from fallow land loss and wasteland loss. Afforestation is a major factor which has been included in the model as a factor of total area. Natural vegetation loss is fixed as 0.01 percent per annum.

Table 6.6 Descriptions of objects in Natural vegetation Sub-system.

Object	Name	Expression	Description
Natural vegetation		*Nvgain – Nvloss*	*Difference of rates*
Nvgain	Natural vegetation gain	(0.1*Faloss)+(0.03*Wloss)+(Afforestation * Nat.veg / 32386.4)	Rate Natural vegetation gain accounts loss in fallow land, loss in waste land and afforestation.
Nvloss	Natural vegetation loss	0.001*Nat.veg	Rate Rate of decrease of natural vegetation per annum is 0.01 percent
Afforestation	Afforestation rate	0.01	Afforestation rate is the annual increase of forest by one percent of total forest cover of the state.

6.5.7 Wasteland subsystem

Natural vegetation loss contributes to wasteland gain. Rate of wasteland gain is due to both fallow loss and natural vegetation loss. Wasteland loss area from observed data confirms Wasteland loss. Part of wasteland loss converts into built-up gain as well. Sub-system for wasteland attains its stock value from two rates: waste gain and waste loss. Waste lands are exposed rocky surfaces, which later have a probability to convert itself into built-up areas. Natural vegetation loss and fallow land changes come under the purview of wasteland gain rate. Wasteland area loss from observed data were input to wasteland loss rate. Deduction of wasteland loss from wasteland gain generates wasteland stock. Variables used in waste subsystems are given in Table 6.7.

Table 6.7 Descriptions of objects in Wasteland Sub-system.

Object	Name	Expression	Description
	Waste	*Wgain – Wloss*	*Difference of rates*
Wgain	Waste gain	(0.25*Fallow) + ((Fallow/Waste) * 1.1)	Rate Waste gain from fallow land and waste land.
Wloss	Waste loss	Wla + Waste	
Wla	Waste loss area	Lookup([(0,0)-(2010,1000)],(1997,0),(1998,220.5),(1999,94.6982),(2000,157.6),(2001,157.6),(2002,158.6),(2003,156.636),(2004,162.857),(2005,159.746),(2006,907.603),(2007,0),(2008,0),(2009,0),(2010,0))	Waste land loss area is expressed as a difference between two successive values of waste land.

6.5.8 Water bodies and 'Other land uses' subsystem

'Other land uses' class has shown considerable change compared to that of water bodies. A minute land exchange is happening between water bodies and 'other land uses'. Stock of water bodies depend only on water loss area. Gain in other land is from losses of water bodies and 'other land' gain areas. Deduction of other land gain with other land loss forms the stock-other. These sub-systems converge together all along, making all possible conversions among each other. Descriptions of objects in other land and water body sub-systems are given in Table 6.8, and Table 6.9 respectively.

Table 6.8 Descriptions of objects in 'Other land uses' Sub-system.

Object	Name	Expression	Description
	Other land	*Ogain - Oloss*	*Difference of rates*
Ogain	Other land gain	Oga + Other + Wloss*0.0009	Rate. Gain of other land is from other, other land gain area and loss of waste land.
Oloss	Other land loss	Other + Ola + Wala*0.0009	Rate. Loss of other land from other, other land loss area and loss of water body.
Oga	Other land gain area	Lookup([(1997,0)(2010,30)],(1997,26.89),(1998,0),(1999,5.49),(2000,5.49),(2001,5.49),(2002,5.49),(2003,5.49),(2004,5.49),(2005,5.49),(2006,0),(2007,0),(2008,26.1312),(2009,26.13),(2010,26.13))	Other land gain area is expressed as a difference between two successive values of other land.
Ola	Other land loss area	Lookup([(0,0),2010,20)],(1997,0),(1998,0),(1999,15.9264),(2000,0),(2001,0),(2002,0),(2003,0),(2004,0), (2005,0), (2006,0.576),(2007,0.57), (2008,0), (2009,0),(2010,0))	Other land loss area is expressed as a difference between two successive values of other land.

Table 6.9 Descriptions of objects in Water body Sub-system

Object	Name	Expression	Description
	Water	*630 + Wala*	*Difference of rates*
Wala	Water loss area	1.5e-005 * Ogain	Rate Water loss to gain in other land.

6.6 RESULTS AND DISCUSSIONS

6.6.1 Calibration

Calibration and validation of the SD-LU demand model is performed. This helps to assess the predictive ability of any model. Calibration is a process of estimation and adjustment of model parameters and constraints to improve the agreement between model output and a dataset. While validation is a demonstration that a model within its domain of applicability possesses a satisfactory range of accuracy consistent with the intended application of model (Rykiel, 1996). Model is calibrated with observed land use data for the period 1997 to 2005 and similarly validation for the period 2007 and 2010. Future demand for land use are predicted for three scenarios, guided by historical and present growth in the region. Main influencing factors which possess a hold on the behaviour of system are tuned according the scenario to simulate.

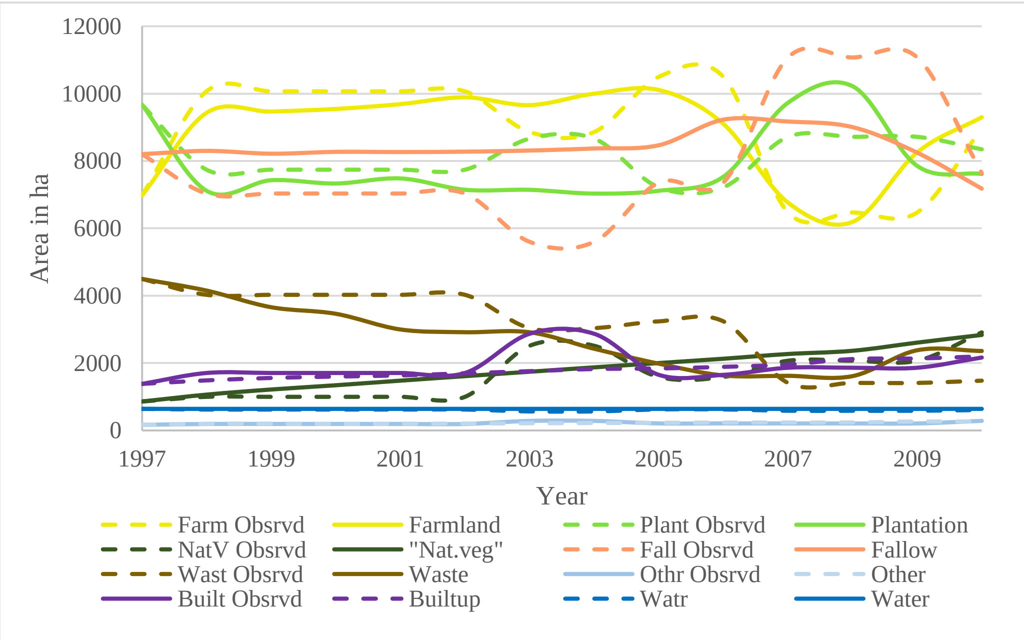


Figure 6.4 Comparison between observed and SD simulated land use demand.

SD - LU demand model is calibrated with observed land use data obtained from remotely sensed images acquired in the years 1997, 2003 and 2005. Land use simulation from SD Model is shown in Figure 6.4. Accuracy for calibration in terms of coefficient of determination (r^2) is 0.94. Coefficient of determination for model validation is 0.96. Validation results indicate towards the ability of the model for future prediction.

6.6.2 Discussion

Demands for different land use are simulated. To keep the total area constant for all the time-steps, simulation results are manually adjusted. Simulation for the period of 1997 to 2009 (Figure 6.5) are named as Baseline Scenario and will be used as land use demand for the calibration of Dyna-CLUE in Chapter 7.

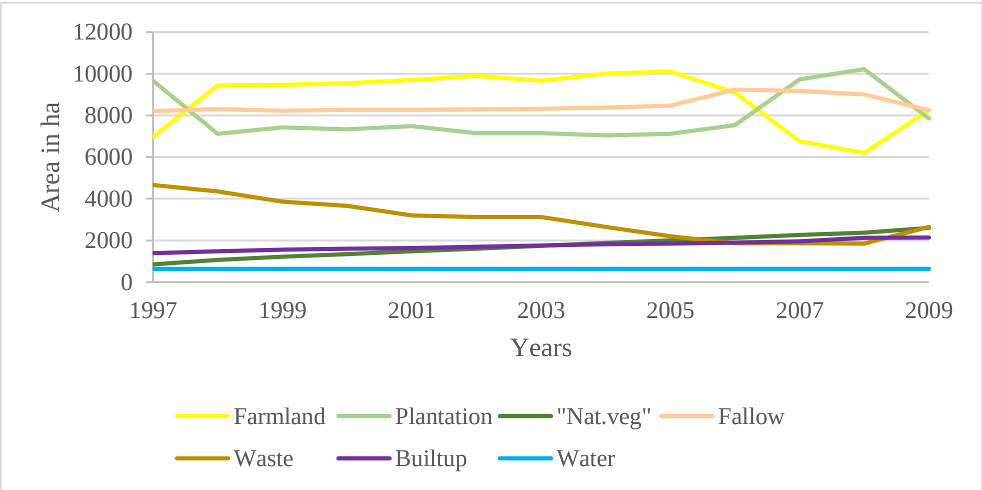


Figure 6.5 Land use demand for Baseline Scenario.

In addition, three land use demand scenarios are predicted for the years 2010-2030. For all the scenarios, water bodies are assumed to be constant. As, the "Other land uses" class is <1% of total area, it is merged with waste land during the spatial modelling to avoid unnecessary complexities.

Future predictions, based on

a) Predominant agriculture based land use

b) Extensive industrialization and urbanization

c) Nature conservation

scenarios, are displayed respectively in the Figure 6.6, Figure 6.7, and Figure 6.8.

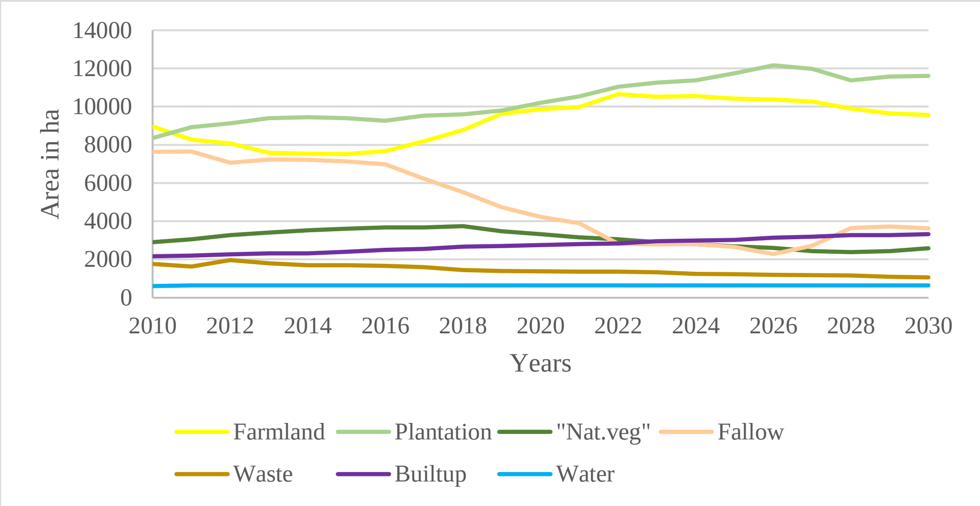


Figure 6.6 Predominant agriculture based land use.

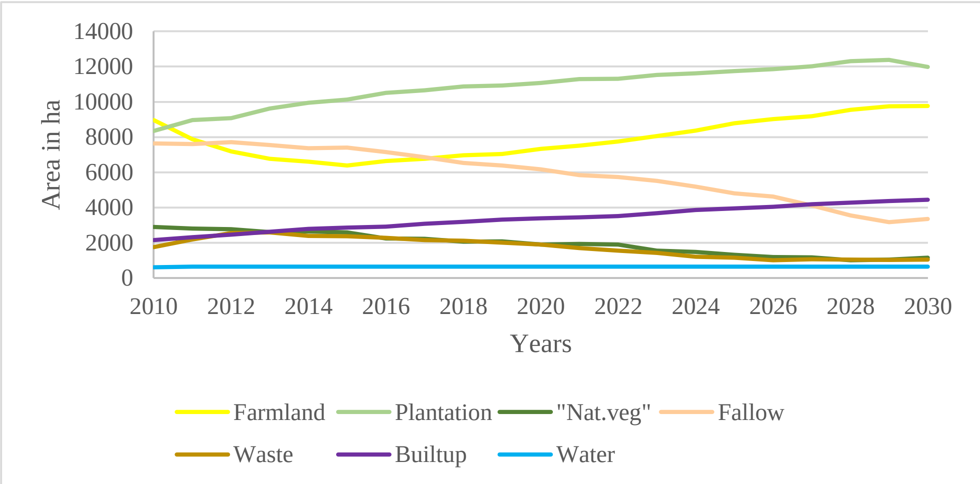


Figure 6.7 Extensive industrialization and urbanization.

Afore mentioned SD-LU change model is structured to inherit the system complexities and to work with various scale levels. Data and simulation results have shown a distinct fluctuations in model construction period (Figure 6.4). Across the simulation year, most of the land use have changed. These nonlinear progressions are successfully simulated by the aid of exogenous factors, which shows a definite outweigh of exogenous factors on land use change. Farmland is a prominent land use which forms a primary sector in the region. Water bodies are more or less constant over the decade. Built-up land inflation is smooth as compared to the farmland, fallow land. Increase in natural vegetation and built-up in the year 2006 and subsequent years, transformed a large amount of farm land and waste land. Certainly, economy of the study area has contributed towards these transformations either directly or indirectly. These changes are in accordance with economy of the region.

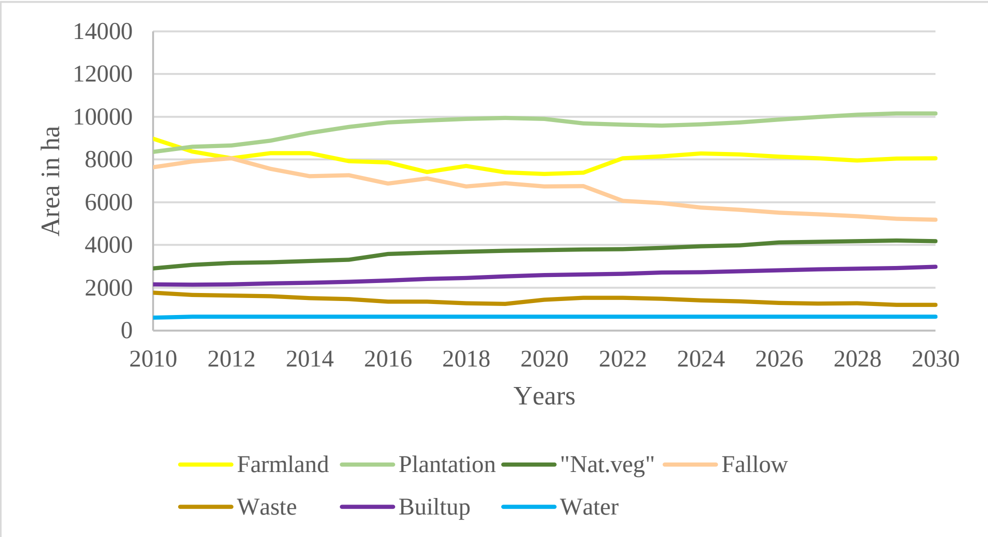


Fig. 6.8 Nature conservation scenario.

Land use changes for plantation land and farmlands are mutually interchangeable in the graph pattern. It converges in the year 2007. Model outputs are reasonably matching for crest-trough lying parts of the curve, as compared to that of actual values. On the other hand these changes accounts inter-transformations and economic aspects perfectly. Noticeable feature from the simulation is that the built-up and natural vegetation are increasing which is a factual trend in the study area. These results show a moderate hold on the model on simulation. Further prediction of land use demands for 20 years forward is performed.

6.6 CONCLUSIONS

Land use change system of the region encompassing forty four administrative units and several exogenous and endogenous factors is well represented using SD approach. Demand estimated in SD methodology is having a good correlation with the observed data. Land use simulation in SD is supported with multiple exogenous factors. Simulation from SD model has revealed the appropriateness of exogenous forces such as crop price, GDP towards different land use classes.

Increase in farmland for all three scenarios are due to consideration of exogenous factors. Normal growth scenario might drive a lesser fluctuating plantation land till the year 2025, and thereafter it may be expected to decrease. Increase in economic conditions of the region is not only from industrialization, but is also from increased production of raw materials from farmland and plantation lands.

CHAPTER 7

INTEGRATION OF SD AND DYNA-CLUE MODEL

7.1 INTRODUCTION

In the previous chapter System Dynamics approach is applied to simulate the aggregate land use changes. SD is efficient enough to capture the policy effects on land use changes. However, SD model's ability to represent the spatial process is weak because it cannot efficiently deal with a mass of spatial data. It is also not able to describe the distribution and situation of those spatial factors in the system. To cope with this, SD model is integrated with Dyna-CLUE, and the integration is demonstrated in this chapter. Precisely, the objective of this chapter is to;

Spatially model the land use change estimated by SD and also simulate three convincing scenarios of land use change.

The flow of events executed to achieve the objective is briefly described in Figure 7.1. This chapter discusses Dyna-CLUE methodologies, such as Drivers analysis and model configuration to spatially map the demanded land use from Chapter 6.

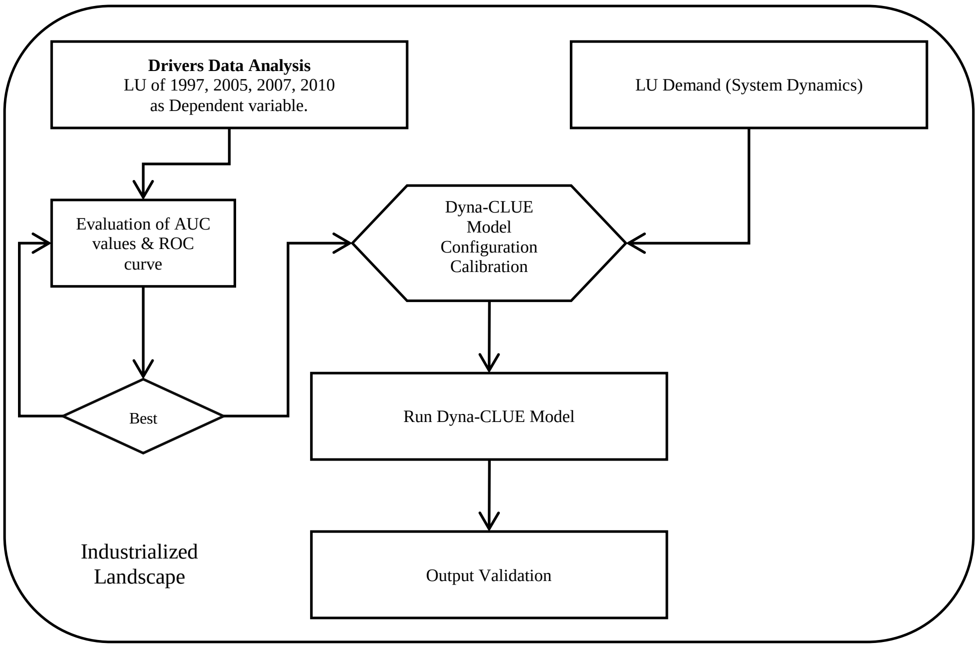


Figure 7.1 Schematic representation of SD and Dyna-CLUE integration.

Accordingly, this chapter is presented under the following headings

- Analysis of driving factors for industrial landscape using logistic regression
- Combining non-spatial and spatial module.
- Result and discussion.
- Conclusions.

7.2 ANALYSIS OF DRIVING FACTORS FOR INDUSTRIAL LANDSCAPE

The period between the year 1997 and 2009 is used for the calibration of Dyna-CLUE model. This period is named as the baseline scenario (Figure 6.5). For further understanding on the active driving factors in the industrialized landscape, Logistic regression is carried out separately. Four different land use maps (Year 1997, 2005, 2007 and 2010) are used as the dependent variables against a set of seventeen different independent variables. Later, independent variables are updated based their existing influence. Best model selected through the analysis of AUC and ROC. Dyna-CLUE model is calibrated and simultaneously regression equation is also updated. After that, three different future land use scenarios are also modelled from the year 2010 onwards. Year 2010, land use map is used as the reference map for modelling exercise since industrialization in the study area has become apparent during the year 2010.

SPSS® software platform is used to calculate the β coefficients for probability (Equation 3.11) estimation. The probability here refers to the likelihood of any grid cell changes its state. Table 7.1 presents land use class wise β coefficients and the AUC value for all the years. Area under the ROC curve or AUC values state a binary logistic regression's ability to describe a parameter. Most of the previous studies, solely presented the AUC value (often mentioned as the ROC value) without discussing anything about the pattern of the curve itself. A ROC curve or receiver operating characteristic curve is usually created by plotting the correct positive results among positive samples against the incorrect positive results occurred among negative samples at various threshold level. In this study, an attempt has been made to interpret the ROC curve following Pontius et al. (2014).

7.2.1 Area under the Curve (AUC)

The ROC curve is obtained by comparing the true positive and false positive classification for each possible classification. The ROC measures the degree to which high probability values are concentrated on the observations where the reference binary variable is present (presence of a land use class). The area under the ROC curve or AUC is estimated using an average of a number of trapezoidal approximations (Equation 7.1).

$$AUCtrapezoidal = \sum_{t=1}^{T-1} \{[X_{t+1} - X_t][Y_t + (Y_{t+1} - Y_t)/2]\} \quad \ldots\ldots\ldots\ldots\ldots.. 7.1$$

Where, (X_t, Y_t) is the coordinates for each point t on the ROC curve. X_t is the rate of false positives, or 1 minus specificity. Y_t is the rate of true positives or sensitivity, T = number of thresholds ≥ 2. Provided that, each and every bin contains secured observations with the same unique index value, and the ROC curve is completely certain.

In summary, the AUC value is intended to measure the capability of each logistic regression model. Many scientists have opined that the AUC does the same what the r^2 statistic does for ordinary least-squares regression, i.e. measure the goodness of fit (Lin et al. 2011). Stronger positive association is indicated by larger AUC values. The range of AUC value can be 0 to 1. AUC is a unit less summary metric that synthesizes the association between the reference binary variable and several independent variables by the probability.

Table 7.1 Binary Logistic Regression results.

		Farm	Plantation	Natural Vegetation	Fallow	Waste	Built-up	Water Bodies
1997	B_0	-1.4950	-3.1049	-5.3997	-0.9276	-2.7181	-5.5279	3.9522
	AUC	0.598	0.659	0.801	0.665	0.652	0.8	0.948
2005	B_0	-0.5136	-2.6159	-27.0696	-1.8432	-2.5942	-3.8374	2.5713
	AUC	.554	0.631	0.794	0.656	0.644	0.764	0.918
2007	B_0	0.803	-3.3954	-4.3951	-3.6431	-4.8072	-6.0716	3.9464
	AUC	0.647	0.650	.810	.641	.706	.753	.915
2010	B_0	.113	-2.683	-2.919	-1.434	-3.414	-6.079	3.734
	AUC	.703	.778	.770	.680	.663	.895	.948

A detail analysis from Table 7.1 reveals that, in comparison to other years, AUC values for the year 2010 have considerably improved, except for Natural vegetation and Wasteland. Hence, considering only AUC values for judging logistic regressions is bit tricky. Majority of related literature have reported the AUC values and not shown the ROC curve. Usually a particular levels of AUC is referred as low, good, high, or excellent to classify the AUC and judge the competence of the regression analysis. These universal rules are not related to any particular research question or case study, and thus damage the clarity of communication among scientists. Five specific causes are warned in literature against using the AUC:

(i) It ignores the predicted probability values and the goodness-of-fit of the model;

(ii) It summarizes the test performance over regions of the ROC space in which one would rarely operate;

(iii) It weights omission and commission errors equally;

(iv) It does not give information about the spatial distribution of model errors; and

(v) The total extent to which models are carried out highly influences the rate of well-predicted absences and the AUC scores (Lobo et al. 2008 in Pontius et al. 2014).

7.2.2 ROC curve

ROC curve is a quantitative method to compare a binary dependent variable versus its probability of change. The reference dependent variable shows presence versus absence of a feature. Observed depended variables, which is supposed to present higher probabilities more likely. A ROC curve is obtained by comparing the reference binary dependent variable with successive prediction. There are numerous applications of ROC curves - in remote sensing to evaluate classifications, in land change science to validate simulations, in atmospheric science to verify forecasts, in species distribution modelling to evaluate model outputs and most profoundly in medical sciences to predict the diseases. In Figure 7.1, prediction of land use classes for four different years are presented using ROC curves. After the evaluation, best fitting model can be selected for final modelling. Hence interpretation of these curves is very important.

7.2.3 Shape of ROC curves

The shape of ROC curves are important to interpret the association between probability values and presence or absence of a dependent variable. The ROC curve always originates at the (0, 0). Initial high probability values corresponds to the beginning section. Hence, none of the observations lie above the curve. Successive sections of the ROC curve are then obtained by lowering the upper limit of probability range so that more observations can be accommodated. Point (1, 1) is the end of ROC curve, which corresponds to the lowest probability values. The start of the curve near the origin relates to the section that captures the very highest ranking probability values. Whereas the end of the curve near the upper right corner relates to the section that captures the very lowest ranking probability values. ROC curve rises towards the vertical axis if the presence of Binary variable is concentrated on the high ranking probability values (for e.g. Figure 7.2, Plantation – in the year 2010). Likewise, it inclines towards the horizontal axis when the absence of binary variable is concentrated on the low ranking probability values.

Each section of ROC curve corresponds to numbers of dependent value. Two successive sections of ROC curve define a bin (minimal part of an object) of observed features. Thus the slope of a sections of the ROC curve is related to the density of the feature within a bin. A steep ascendant slope between successive sections indicates that all the observed binary variables within the bins are present. The slope would be horizontal in case the binary variables are absent. Steeper the slopes denser the occurrence of the binary variables feature within the bin. Interestingly, the design of ROC curve is such that it never goes negative.

A perfect probability value is 1. For a perfect probability, the ROC curve corresponds to a sequence of points that starts at (0, 0), proceeds up the vertical axis to the point (0, 1), and then goes right to the point (1, 1). High probability values are allocated in the curve where presence of the binary variable is observed. Hence, in other cases where such tendency of curve is observed, it can also be called a perfect probability even if the value is not 1.

A perfect probability also produces an AUC of 1. Researchers usually consider a random probability value to fix the standard value for comparison. Pontius et al. (2014) have opined to consider a uniform value to create a standard value. The uniform value would tie all observations with the same probability value. Thus, it will portray all observations as equally appropriate. It will not divide two observations from each other.

The diagonal ROC curve, extended from the lower left corner (0, 0) to the upper right corner (1, 1) represents uniform values.

7.2.4 Interpretation of ROC curve for the present study

Slopes of various segments of twenty eight ROC curves from seven different land use classes for four different years present important information (Figure 7.2). The ROC curve of **farmland** for the years 1997 and 2005 extends just above the uniform ROC line. This means for predicting the allocation of Farmland, probabilities are slightly better than uniform. However, for the year 2010 the curve has improved significantly. First segment of 2010 Farmland curve is moderately uplifting. Hence concentration of high probability values, described by the independent variables are increased.

First segment of the ROC curves for **plantation** for the year 2010 extends very sharply to the top and then last segment of the curve moves gently towards the right. It signifies, that there are decent numbers of features with high probability. ROC curves of other years are monotonous. Interestingly, there are very little differences in AUC values of these graphs with the year 2010 graph.

Graph for **natural vegetation** is consistently showing identical shape. First segment of the curves gently go upwards then resides between the uniform line and the horizontal line of Y = 1. It describes that, the probability value is predicting the allocation of persistence of Natural Vegetation better.

Other than the year 2010, all ROC graphs for **fallow land** are also almost identical. Year 2010 portrays very low progress of the first segment then ends along with the horizontal line of Y = 1. Hence, it can be concluded that the number of features with low probabilities are less in number in this analysis.

Graphs for **wasteland**, are different in shape for all the years. Last segment of the ROC curve for Wasteland, especially for the year 1997 and 2005 moving closely towards the uniform line. It means regression analysis is as good as uniform at predicting the depletion of Wasteland. However, the year 2007 and 2010 have registered different pattern. Middle portion of the year 2007 graph is swelled while the beginning part displays one unit stiff expansion and end part is gently culminating.

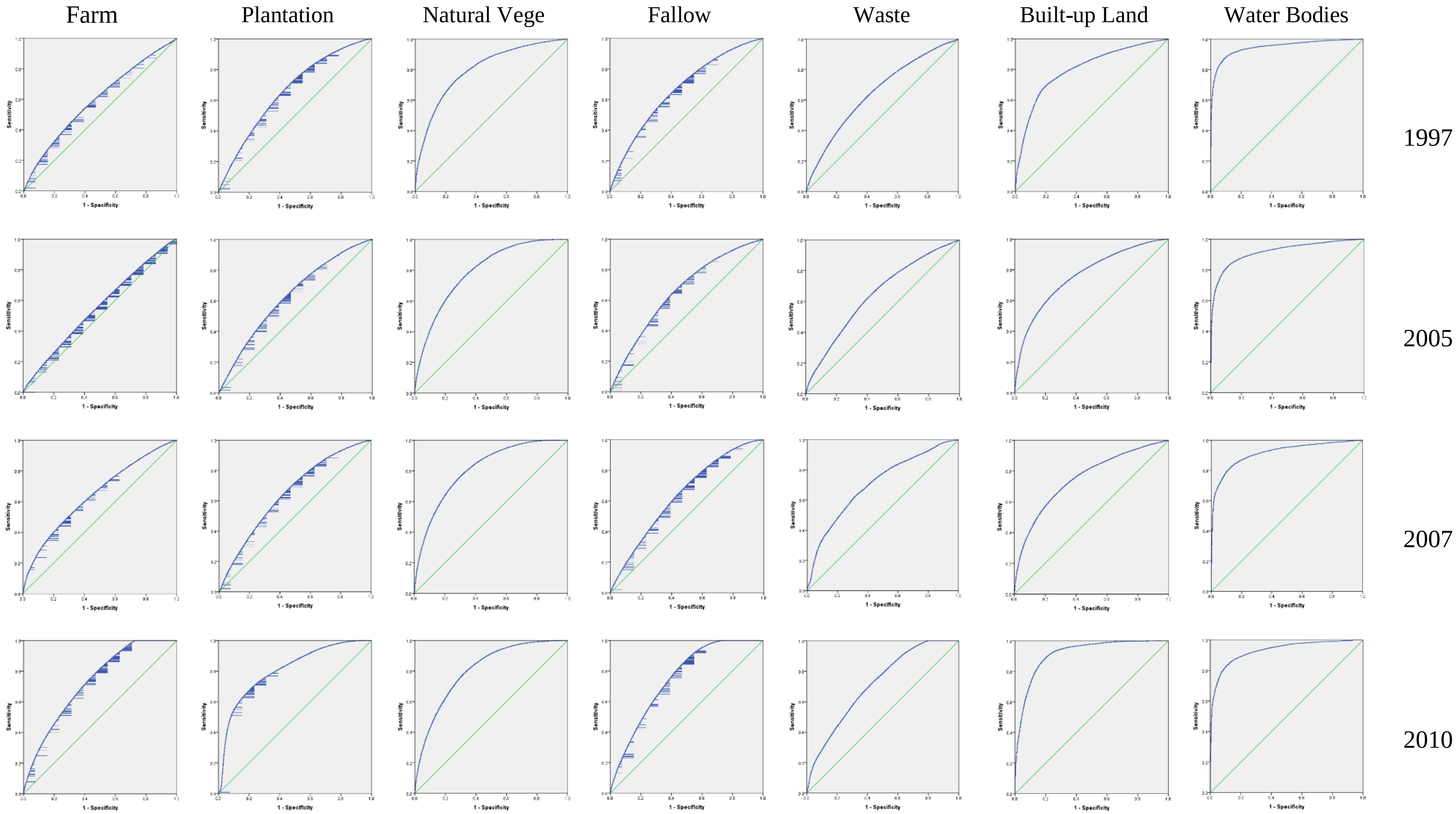


Figure 7.2 ROC curves for logistic regression analysis of four different years.

ROC curve for built-up land of the year 2010 has shown better pattern. This curve has expanded straight towards the vertex at 1, 1. Available drivers are able to describe this land use class very well. Water bodies have shown good pattern for all the years.

Majority of non-biophysical independent variables in logistic regressions are based on data obtained on or after the year 2010. Except water bodies, all other land classes are showing modest AUC values. Moreover, ROC curve patterns of 2010 have unveiled the distribution of the probability of a land use class. Most of the classes have shown stiff beginning, i.e. high probability of change for the presence. Which means, except Water bodies all other land classes are very dynamic and changed a lot during the course. Hence, logistic regressions using year 2010 dependent variables are used for the calibration of Dyna-CLUE model. Redundant independent variables are removed and equation updated simultaneously with other modelling parameters.

7.2.5 Examining land use change drivers in industrialized landscape

A detail examination of Table 7.2, Table 7.3 and Table 7.4 is done. Interestingly, almost all values are comparable with the Exp(β)-1 values from pre-industrial landscape. . Blank space in these table denotes no analysis was done.

Table 7.2 Odds ratio for bio-physical drivers of industrialized landscape.

Exp(β)-1	**Farm**	**Plantation**	**Natural Vegetation**	**Fallow**	**Waste**	**Built-up**	**Water Bodies**
Drainage Density	-0.2469	0.2214	-0.4139	0.5613	0.3221	4.4921	-0.6072
Geology	-0.1295	1.3058	4.9966	-0.1919	-0.5274	0.5172	1.2878
Geomorp hology	2.5548	1.1449	0.8983	1.8153			-0.0183
Ground Water	0.5047	-0.3056	-0.3315	88.4499	-0.645	0.6007	-0.9475
Relative Relief	-0.0321	0.0374	0.0938	-0.0374	0.0098	-0.0305	-0.0649
Slope	-0.0079	0.0227	0.0354	-0.0146		-0.0288	-0.0276
Soil	-0.4016	1.099	1.1054	-0.3198	-0.7133	0.5822	-0.7262
Stream Distance	-0.001	0.0007	0.0005	0.0003	0.0014		-0.0047

Among the biophysical drivers (Table 7.2), high relative relief, geology, geomorphology are determining the location of Natural Vegetation. Stream distance is an insignificant driver also in industrialized landscape. Drainage density is a decisive driver for plantation (0.2214). Unlike pre-industrial landscape, drainage density is positive over built-up area. Perhaps increasing built-up conversion and building projects near the water bodies could be the reason. There is a shift in the farmland driving factor. Farmlands are now more closely associated with potential ground water zones (0.5047). Geology, geomorphology, potential ground water zones, relative relief, slope, soil are significant.

Table 7.3 Odds ratio for socioeconomic drivers for industrialized landscape.

Exp(β)-1	**Farm**	**Plantation**	**Natural Vegetation**	**Fallow**	**Waste**	**Built-up**	**Water Bodies**
Economic Status	-0.1092	-0.4532	3.1454	0.0371		1.3732	0.46
Population Density	-1	3.841			-0.9903	8.7703	
Mod GPI				-0.6846			

Peoples' economic status is now positive over the built-up area (Table 7.3). Natural vegetation is also showing a positive relationship with economic status. Population density is increased on built-up area as well as on plantation land. Hence, it can be inferred that, drivers are also dynamically responding to the land use dynamics.

Table 7.4 Odds ratio for infrastructure drivers for industrialized landscape.

Exp(β)-1	**Farm**	**Plantation**	**Natural Vegetation**	**Fallow**	**Waste**	**Built-up**	**Water Bodies**
All Roads				-0.0009	0.0004	-0.0017	0.0024
Bus Stop				0	0		
Dam Dist.	0	0.0005	0.0011	-0.0006			
Industry Location				0	0		
Major Roads				0	0		
Road Density	0.0628	-0.0729	-0.1713	-0.0712		0.0802	

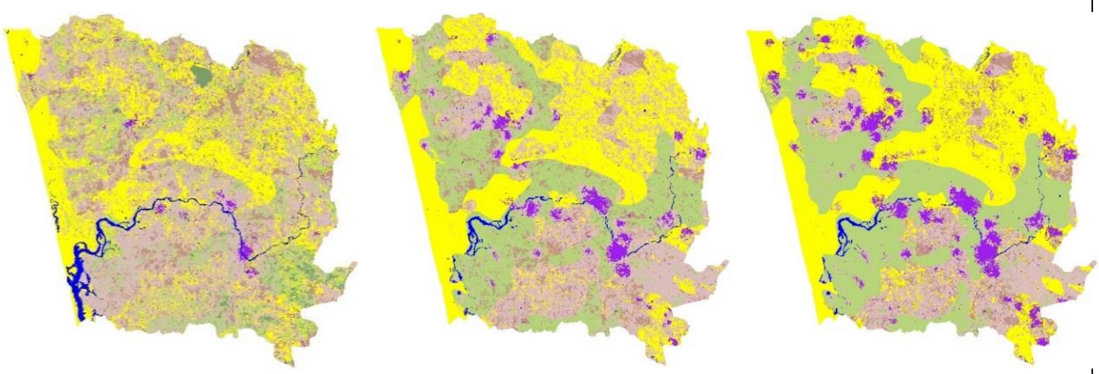
Many infrastructure drivers are removed and regression equation updated for rationalization and better *AUC* values. Road density is influential driver for this landscape also. Maybe, more roads are now available over built-up area and farmland. For the calibration of Dyna-CLUE, driver are further removed from the equation.

7.3 COMBINING NON-SPATIAL AND SPATIAL MODULE

Estimated land use demand for the baseline scenario (Figure 6.5) is primarily used for the calibration of Dyna-CLUE model. After calibration, simulation period is extended to the year 2030 and three scenarios are simulated separately. Several modelling parameters including independent variables in logistic regression are also rationalised and the model result is examined. Visual account and a brief description of each model run is given in the following section.

Drivers with odds ratio 1 are considered insignificant. For the very first model run insignificant drivers used in previous regressions (Table 7.1 for the year 2010) are removed.

3A	Farm	Plant	NatVeg	Fallow	Waste	Built	Water
β_0	-0.4503	-3.3854	-7.503	-6.9532	-3.1648	-2.2772	3.2208
AUC	.580	.800	.751	.630	.621	.706	.855
Drivers.	5	6	6	7	6	6	4
Elasticity	.1	.1	.1	.1	.1	.1	.9



1998 2005 2010

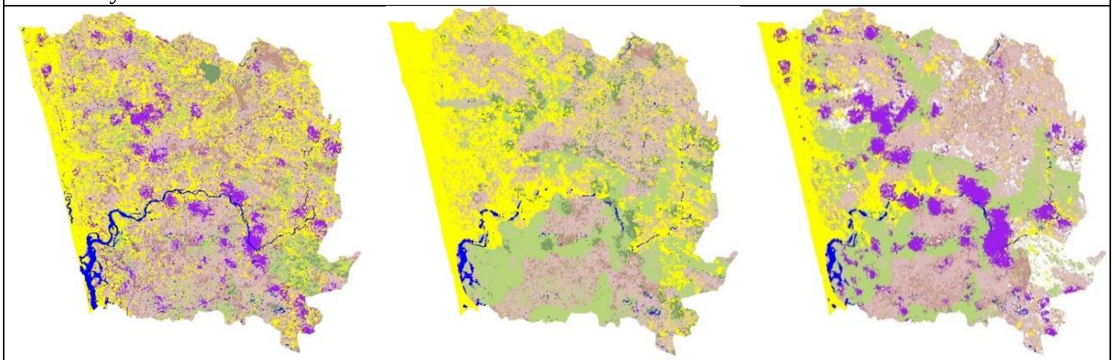
Matrix	Farm	Plant	NatVeg	Fallow	Waste	Built	Water
Farm	1	1	1	1	1	1	1
Plant	1	1	1	1	1	1	1
NatVeg	1	1	1	1	1	1	1
Fallow	1	1	1	1	1	1	1
Waste	1	1	1	1	1	1	1
Built	1	1	1	1	1	1	1
Water	1	1	1	1	1	1	1

Figure 7.3 Calibration of model, first run.

For Farmland, apart from some biophysical drivers, such as Geology, Geomorphology, Relative relief, Slope, Soil no additional drivers are selected. Similarly, for other land use classes only a few drivers are selected from the total of seventeen drivers (see Appendix V for further detail). Earlier, logistic regression analysis has shown their influence of land use change in the study area. Elasticity coefficients are kept 0.1 for all classes so that all the land classes could interchange freely. Change matrix is also allowed for free interchange. Figure 7.3 is showing three time-steps from this run. Imprint of Soil map (Figure 4.6) can clearly be observed on Farmland from a visual inspection of model output. Regression coefficients of predictor variable Soil, are -0.2325, 1.03, 1.2757, -0.2554, and -0.8254 respectively for the dependent variable farm, plantation, natural vegetation, fallow, and waste land. In this model run, Soil is not considered in the regression of built-up area and water bodies. This imprint is due to the scale effect as the soil map has coarser classification pattern.

For further understanding, soil map is removed from the regression equation of farmland. Rest of the independent variables are kept unchanged in this model run. Other model parameters are also kept unchanged as it was in previous step.

3Aα	Farm	Plant	NatVeg	Fallow	Waste	Built	Water
β_0	-0.450	-3.3854	-7.503	-6.9532	-3.1648	-2.2772	3.2208
AUC		.800	.751	.630	.621	.706	.855
Ind. Vari.	4	6	6	7	6	6	4
Elasticity	.1	.1	.1	.1	.1	.1	.9



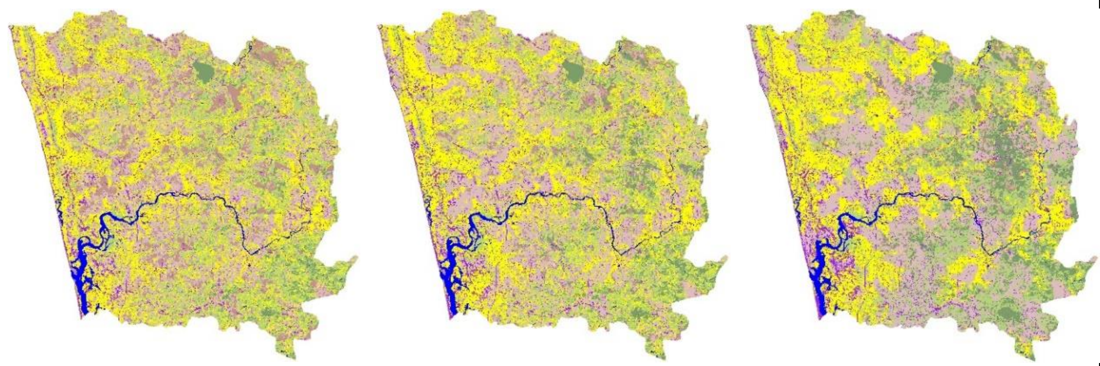
1998 2005 2010

Matrix	Farm	Plant	NatVeg	Fallow	Waste	Built	Water
Farm	1	1	1	1	1	1	1
Plant	1	1	1	1	1	1	1
NatVeg	1	1	1	1	1	1	1
Fallow	1	1	1	1	1	1	1
Waste	1	1	1	1	1	1	1
Built	1	1	1	1	1	1	1
Water	1	1	1	1	1	1	1

Figure 7.4 Model run after removing Soil variable from regression.

In Figure 7.4, model results can be seen free from soil map imprint effect. However, accumulation of land classes in a location can also be seen in Figure 7.4. That indicates towards the uncontrolled allocation of demanded land use. Surprisingly, model has left Natural Vegetation class blank for the year 2010 time step. It is not due to any restriction as land use change sequences, expressed by change matrix is allowed to move freely. However, another important parameter, iteration variable is allowed to deviate 40% between demanded changes and actually allocated changes and maximum allowed deviation is 200%, which are very high. Iteration variable is an indicator for the relative competitive strength of a land use class. From the next model run onwards these parameters are fine-tuned and model result observed (details of each model run are in Appendix VI).

3Bf1a	Farm	Plant	NatVeg	Fallow	Waste	Built	Water
β_0	0.1131	-2.6838	-2.9191	-1.4345	-3.4140	-6.0791	3.7344
AUC	.703	.778	.770	.680	.663	.895	.948
Ind. Vari.	6	8	7	6	6	10	7
Elasticity	.4	.7	.8	.4	.6	.9	1



3Bf1a	Farm	Plant	NatVeg	Fallow	Waste	Built	Water
Farm	1	1	0	1	0	1	0
Plant	0	1	1	1	0	1	0
NatVeg	0	0	1	0	1	0	0
Fallow	1	1	0	1	1	1	0
Waste	0	0	1	1	1	1	0
Built	0	0	0	0	0	1	0
Water	0	0	0	0	1	0	1

Figure 7.5 Final calibrated model run.

After several iterations, agreeable results are achieved. Figure 7.5, is showing the simulated baseline scenario. In logistic regression for this model run 6, 8, 7, 6, 6, 10 and 7 numbers of independent variables are used respectively for Farmland, Plantation, Natural Vegetation, Fallow land, Waste land, Built-up land, Water Bodies. None of the categorical data is used as independent variable (detail in Appendix V). Area under curve values for all analysis are from moderate to good. Elasticity of Farm land and Fallow land is set to 0.4 as these two classes are easy to get converted. With 0.6 elasticity, Waste land set to be second most prone to the conversion. In Figure 4.4, the tendency of change for each class can be seen. In the change matrix farm land is allowed to convert to plantation, fallow and built-up land. Plantation land can become land with natural vegetation or become fallow if left vacant. Plantation land is also allowed to become built-up. Fallow land can become natural vegetation area. Likewise waste land cannot directly become Farm land because huge land improvement would be essential.

7.4 RESULTS AND DISCUSSION

7.4.1 Validation of Calibration

It is important to acknowledge that any single model is not efficient enough to capture all the complexities of land use changes and integrated models need more experienced modeller. SD model and Dyna-CLUE model are integrated to simulate the land change process in the study area which is being affected from other scale levels.

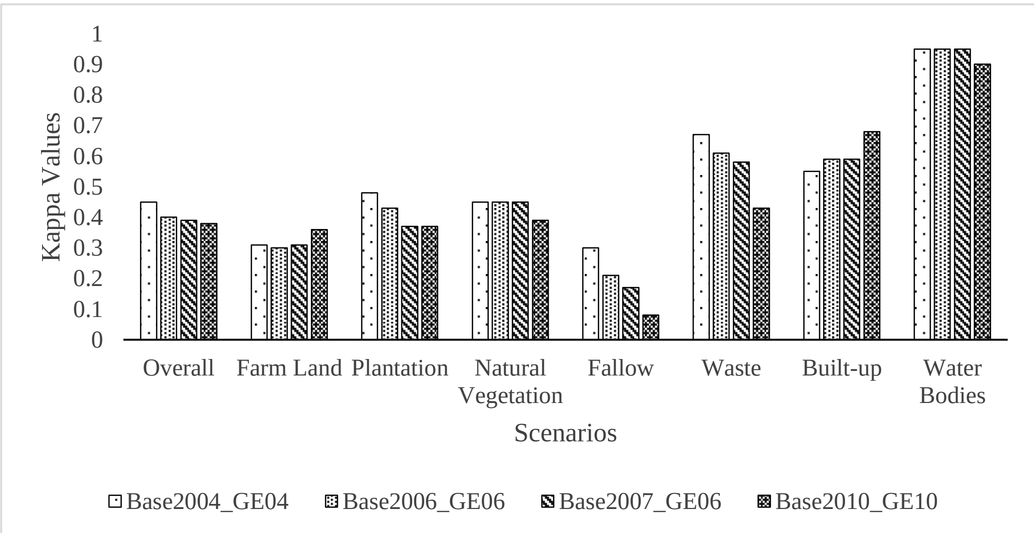


Figure 7.6 Overall and class wise validation for different time steps.

Within the given setup baseline scenario is simulated at the beginning. Among the time steps, land cover maps of the year 2004, 2006 and 2010 are evaluated by the Google Earth samples of respective years. Year 2007 is evaluated with GE 06. Kappa statistics (Equation 3.4 and Equation 3.5) are employed to evaluate the overall as well and class wise agreement between the simulated result and the reference data.

The overall accuracy value is found to be of average. For the baseline scenario (i.e. pre-industrialization era) overall accuracies are decreasing with forwarding time steps (Figure 7.6). Class wise accuracies reveal further details about modelling. Farmland, plantation and fallow land occupy major portion in the study area. Apart from natural vegetation, these three classes are also known to be more dynamic in comparison to other classes. For baseline scenario all these classes are showing below the average accuracy. Whereas, wasteland, built-up land and water bodies have predicted better. Looking back at the Figure 6.5, Figure 6.6, Figure 6.7 and Figure 6.8, it is clearly visible that these three classes have a unidirectional trend and less dynamics. Figure 7.5 is showing that, these three land classes had an elasticity coefficients of greater than 5 for that model run.

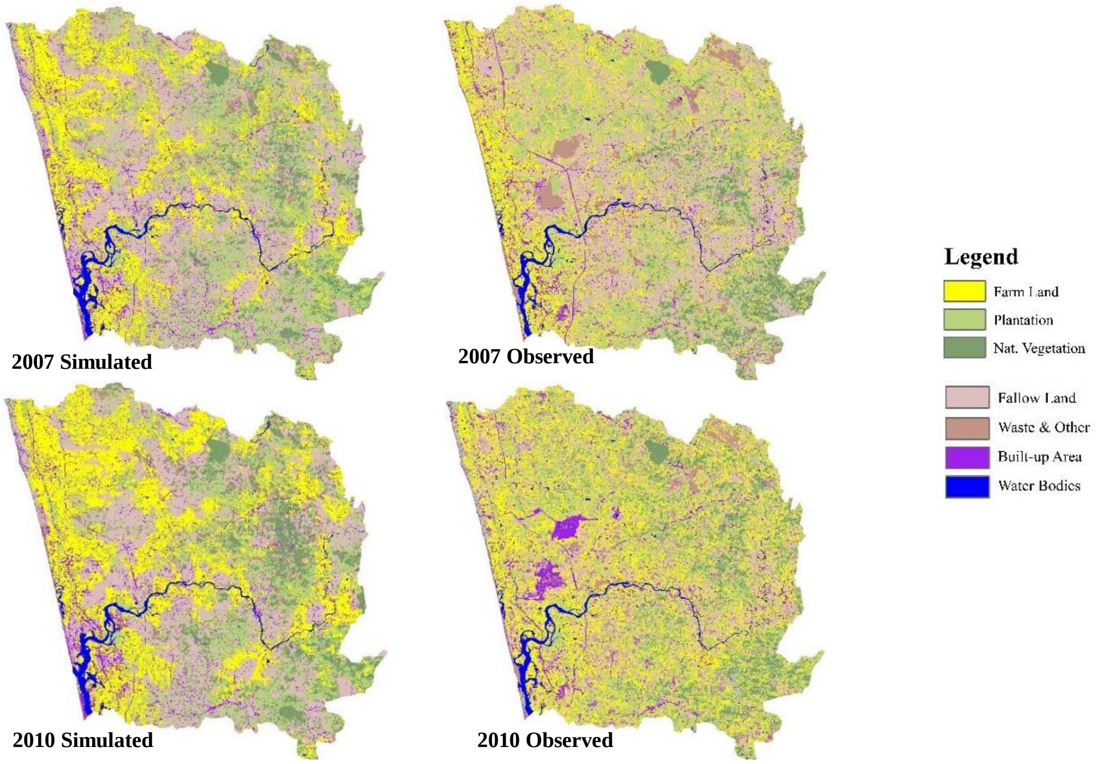


Figure 7.7 Simulated v/s Actual map showing sudden land use change.

In the study region, there was sudden large scale land use change due to industrialization during the year 2007 to year 2010. Even though demanded land uses fit quite well with the actual, simulated spatial maps are not able to show the abrupt changes (Figure 7.7). This is because, simulation in this model is done by fitting the trend of a base image (i.e. year 1997 in this case). Earlier literature have not discussed this issue. Prediction accuracy is also reduced due to this. Hence, it is essential to use a base map which shows these changes while simulating industrialized landscape (i.e. year 2010 land use map in this study).

7.4.2 Validation of Simulation

Figure 7.8 is depicting, Natural vegetation class and Water bodies have maintained the pattern during baseline scenario simulation. Whereas, Farm land and Plantation land tend to accumulate in some areas. Dynamics of these land classes are astonishing. In the contrary, post-industrialized period is showing better simulation outcomes because change direction of some dominant classes have become more stable.

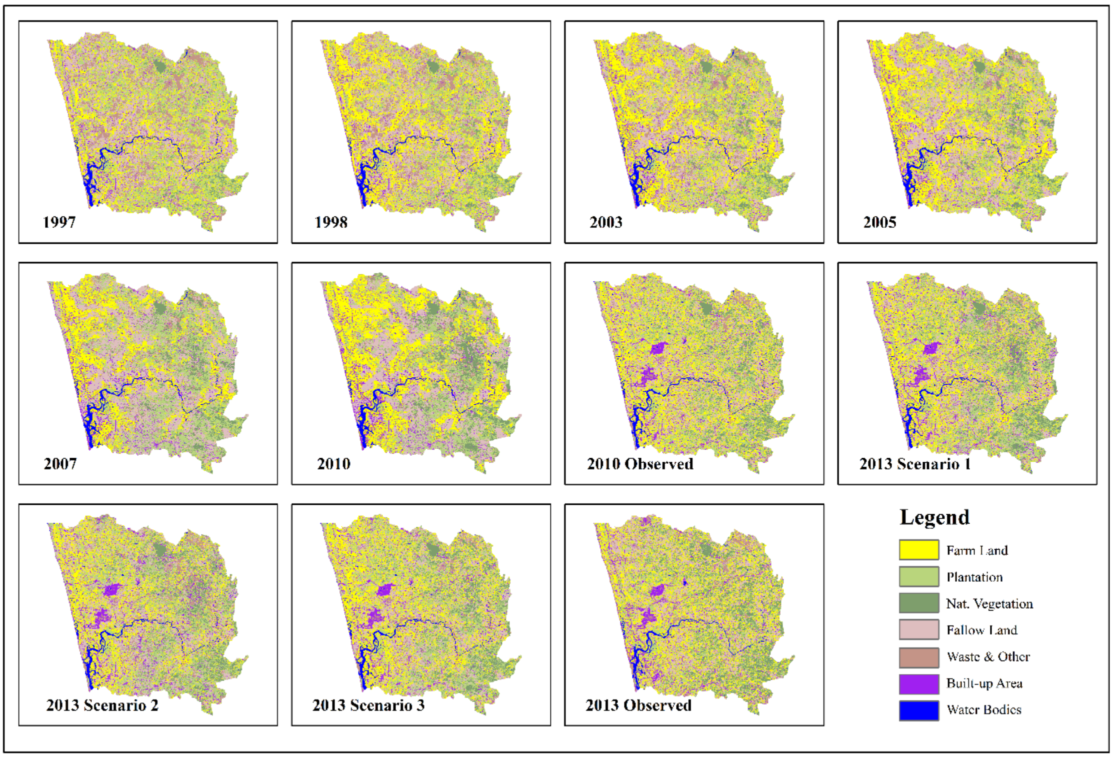


Figure 7.8 Simulation results for different time steps.

For industrialized scenarios, especially for the first scenario, i.e. Predominant agricultural based scenario, several modelling parameter are kept unchanged. Regression for all the land classes also remain as it is in calibration model run. Only the elasticity co-efficient and the change-matrix is altered. All the three scenarios simulation for the year 2013 are evaluated with the Google Earth Sample of the same year using the Kappa coefficients (Figure 7.9).

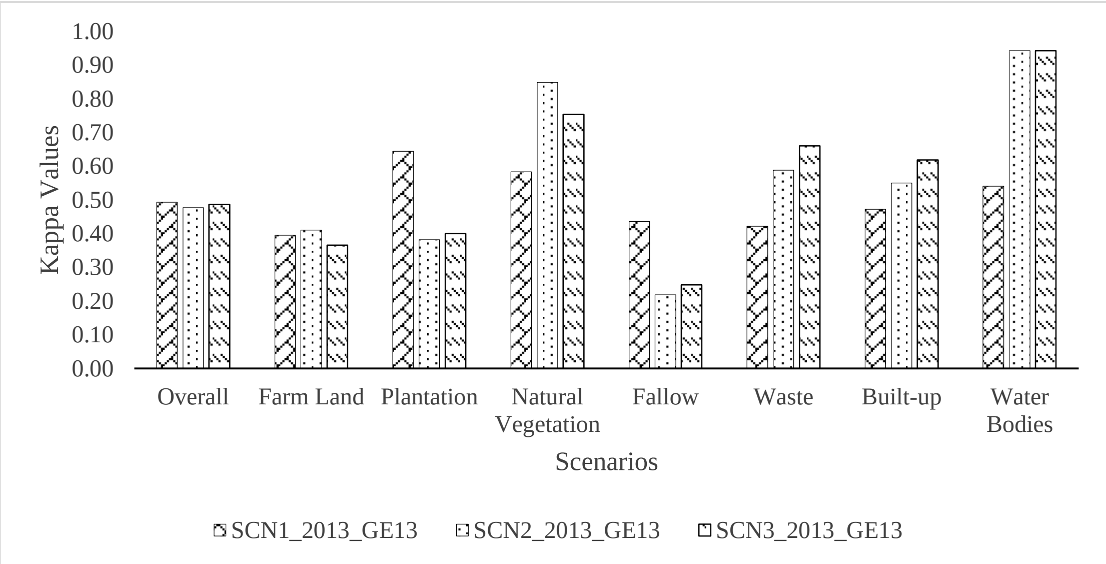


Figure 7.9 Simulation validation - Model's performance graph.

Model simulation capability is significantly improved in this exercise. Water bodies, Built-up land, Wasteland and Natural vegetation are showing improved agreement with the observed land use. Farmland, plantation land and fallow land have again shown less agreement with the observed data. Moreover, class wise accuracy also varies with different scenarios.

Figure 7.10 is showing the class wise variation in area for each land use classes under different scenarios. It can be seen that Farmland is varying in all scenarios in comparison to the observed area of year 2013. Area under Water bodies remain constant for all scenarios all year as it was assumed during demand estimation.

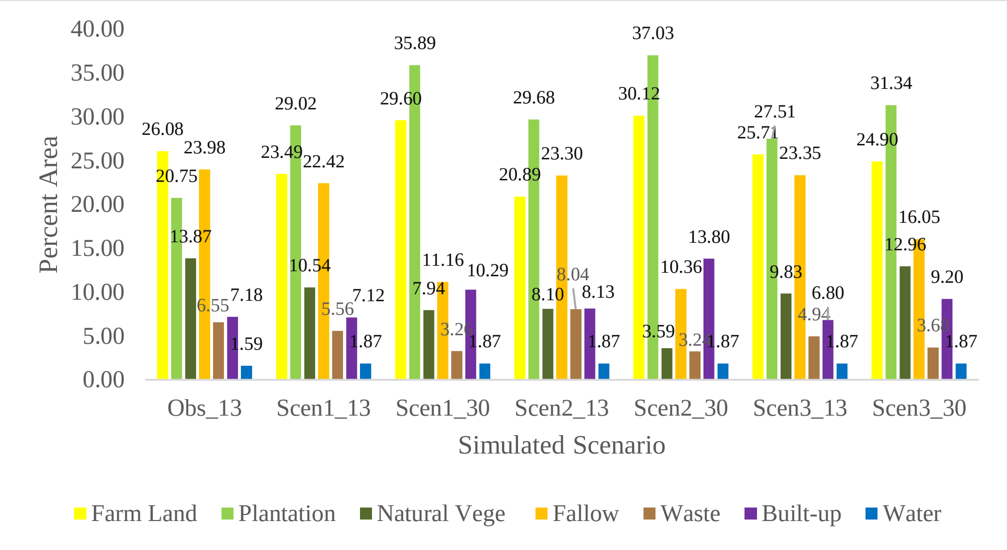


Figure 7.10 Land use class area under different scenarios.

7.5 CONCLUSIONS

Going with the goal of systematic understanding of land use changes in India, it can be concluded that, this study has revealed some unexplored dimension of land use change in India. This study is based on a complex agro-industrial landscape of coastal Karnataka. Since the last decade this area is experiencing many changes in land use pattern.

This chapter has explicitly discussed the AUC and RUC. When AUC only reveal a model's capability to describe dependent variable, ROC curve comprehensively demonstrate relationship and distribution of probabilities. Even when the AUC values are closely similar, ROC curve can help in judging the model. First part of ROC curve shows the concentration of high probability occurrence values while last part is meant for lowest ranking probabilities. Hence, steeper the beginning part, better the model.

This chapter also have analysed the drivers for industrialized landscape. Majority of the drivers, especially the biophysical drivers are almost identical in response to those in pre-industrial landscape.

The spatial modelling of land use change described in this chapter is 50% successful on an average to simulate the scenarios. Overall Kappa values for the three scenarios are 0.49, 0.48 and 0.49. Simulation of Water bodies are 60% to 90% successful. Interestingly, the total area under Water bodies are <2% and this class also is less dynamic (area was assumed constant). Apart from Water bodies, Natural Vegetation, Wasteland, Built-up area are also fared >60% accuracy in scenario simulation. Plantation land is approximately 70% matching with the observed data in the normal growth scenario but other two scenarios are showing less accuracy.

Effect of sudden land use change was not explicitly discussed in earlier literature. This chapter finds a suitable answer for that inquest. It finds, only with appropriate demand estimation and using reference map layer such changes can be simulated.

CHAPTER 8

SUMMARY AND CONCLUSIONS

8.1 SUMMARY

The main goal of the present study is contributing towards the systematic understanding of land use changes in India especially in Agro-Industrial landscape. An attempt has been made to evaluate the applicability of integrated land use change model for Indian case studies.

In this study, firstly investigation of location specific land use change drivers in an Agro-Industrial Landscape is done. It also aims at finding the consequent effects of these drivers on land use change through simulating realistic scenarios. This study addresses some typical Indian land use change conditions;

a) Scarcity of readily available data, especially ground truth data is countered by extensively using Google Earth platform. Other spatial and non-spatial data from several scattered sources are gathered and spatially mapped in GIS.

b) Lack of understanding on the land use change process is answered by analysing driving factors of pre-industrial and industrialized landscape dynamics using different years of land use map as dependent variable.

c) Modelling of land use change for pre-industrial and industrialized landscape is done by adopting integrated approach. Dividing the modelling timeline for two phases have helped in understanding complexities.

d) Understanding of land use change model is initiated by integrating Dyna-CLUE model with SD. How these models respond in different land use change conditions are apprehend.

Accordingly, the adopted approach has taken into account, data availability, use of satellite and ancillary data, spatial and temporal variability in parameters. This study has integrated data in GIS environment and developed a methodology to obtain better understanding on modelling of land use change.

8.2 CONCLUSIONS

OBJECTIVE 1: Explore the utility of Google Earth and historical satellite image to produce land use time series.

- A detail account on the application of virtual earth has been made use of. In this internet savvy globalized world, the Web is becoming the centre of activity for many scientific study. Google Earth can be provided to any registered user via the Internet at any time. If not all, many data these days can be gathered from the web free of cost. In upcoming years availability of data will also increase. Data gathered form Google Earth can be easily used as par requirement for a particular application.
- In this study, at first GE is used to gather the qualitative information through visual interpretation to aid the training sample collection for land use classification. Then validation samples are collected as points and validation done by different users.
- Historical moderate resolution satellite data can be used to a satisfactory level of accuracy to understand the changes in land use pattern. The novel, method employed to get an unbiased estimation of land use area has demonstrated its further applicability. To avoid the overlap of information class during sampling, classification process is divided among three different users as human recognition varies person to person. Use of high resolution GE historical images for validation sampling is also unique of its kind. It is observed the GE can successfully be employed for validation sample collection. However, applicability of GE samples decreases when it is away from classified image date. Hence, it can be concluded that, when classification and validation procedures are done by different persons, human knowledge have no overlapping.
- The classified maps have produced a land use time series. The pattern of land use dynamics is very interesting. The study area is predominantly rain fed agriculture dominated landscape. With a below average rainfall Farmland

converts to Fallow land. Wasteland to Natural vegetation conversion also took place due to afforestation.

- GE is also used for drivers' data mapping. Especially, for infrastructure drivers data preparation. A total seventeen drivers are identified. Among these, nine are from existing literature and rest eight are identified with the help of local phenomena. All the drivers are mapped in GIS. For the preparation of socio-economic drivers like, Population density and Economic Condition, unique methodologies are adopted.

OBJECTIVE 2: Investigation of location specific Land-Use change drivers

- A total of seventeen proximate drivers from three broad categories (Bio-physical, Infrastructural, Socio-Economic) are primarily identified. Among these, nine are frequently used in several literature reviewed. They being – i) Distance from Streams, ii) Drainage Density iii) Geology, iv) Geomorphology, v) Slope, vi) Relative Relief, vii) Soil, viii) Distance from Roads. ix) Population Density. Rest of the eight drivers are included by the researcher himself with the help of experts on local phenomena. They being – x) Ground water potential zone, xi) Distance from Dams, water bodies, xii) Distance from major roads, xiii) Road density, xiv) Distance from bus stops, xv) Distance from industry location xvi) Economic status and xvii) Literacy gender parity index are also included in the socioeconomic drivers group.
- Bio-Physical drivers are the most prominent drivers available in the study area. Natural vegetation are mostly on high relative relief and plantations are found where drainage density is high. Farmlands are mostly organized on the flat land near the streams. Drainage Density, is one such bio-physical driver which selected by the researcher. It is found to be influential in determining the location of Plantation and Wasteland.
- All infrastructural drivers are not equally influential. Distance from dam (listed by researcher) is determining the location of Farmland, Plantation and Built-up lands. Distance from Roads are not found to be very significant. Instead, researcher's defined Road density, is providing an insight. Most of

the service roads are built through Plantation and Waste land. Road density is not high in Built-up areas as settlements are fragmented. Big industries tend to locate near Farmland which may cause social uproar.

- Among the Socio-Economic drivers, Population density is high on Built-up land. However, in the present study area people live in spacious and isolated houses surrounded with different plantations. Hence, Plantation land also found positive with population density. Economic status is positive over Farm Land and Plantation. In this study area, people who invest on farming and plantation activities are tend to live near their farms. Modified Literacy gender parity index (Mod GPI) is not a very influential land change driver.
- The drivers for industrialized landscape are separately analysed. Over and above, majority of the drivers, especially the biophysical drivers are almost identical in response to those in pre-industrial landscape.

OBJECTIVE 3: Modelling of pre-industrialization landscape using an appropriate model.

- Dyna-CLUE model is chosen for pre-industrial landscape modelling. This integrated modelling approach addressed multi-scale characteristics of land use change and also integrates different disciplinary knowledge.
- Dyna-CLUE is modular in nature. In the non-spatial module time series estimation of aggregate land use classes are done separately using an independent model.
- For this objective, a linear interpolation method is used which does not consider any causal factors while estimating the land use demand. Land use maps of four years (years 1997, 1998 and 2005) are used for the estimation of nine years demand. Hence, simplification of the land use dynamics is inevitable.
- Estimated demands are then fed into the spatial module. Validation on non-spatial domain suggests that, the model is capable of maintaining class wise aerial values of land use while spatially allocate the input aerial demand.

- However, during spatial allocation maintaining the spatial pattern is completely a different issue. It is a complex interaction of the characteristics of used drivers and user defined parameters.

OBJECTIVE 4: Modelling post-industrialized landscape and simulating three realistic scenarios.

- Going with the goal of systematic understanding of land use changes in India, it can be concluded that, this study has revealed some unexplored dimension of land use change in India. This study is based on a complex agro-industrial landscape of coastal Karnataka. Since the last decade this area is experiencing many changes in land use pattern.
- AUC and RUC are explicitly discussed. When AUC only reveal a model's capability to describe dependent variable, ROC curve comprehensively demonstrate relationship and distribution of probabilities. Even when the AUC values are closely similar, ROC curve can help in judging the model. First part of ROC curve shows the concentration of high probability occurrence values while last part is meant for lowest ranking probabilities. Hence, steeper the beginning part, better the model.
- The spatial modelling of land use change described in this chapter is 50% successful on an average to simulate the scenarios. Overall Kappa values for the three scenarios are 0.49, 0.48 and 0.49. Simulation of Water bodies are 60% to 90% successful. Interestingly, the total area under Water bodies are <2% and this class also is less dynamic (area was assumed constant). Apart from Water bodies, Natural Vegetation, Wasteland, Built-up area are also fared >60% accuracy in scenario simulation. Plantation land is approximately 70% matching with the observed data in the normal growth scenario but other two scenarios are showing less accuracy.
- Effect of sudden land use change was not explicitly discussed in earlier literature. This chapter finds a suitable answer for that inquest. It finds, only

with appropriate demand estimation and using reference map layer such changes can be simulated.

Both LARR, 2014 and DoLR, 2013 have advocated the use of remote sensing and GIS in land use related problems in India. This study has successfully attempted that by i) providing a detail account on several literary discipline related to land use study, ii) addressing the knowledge gap, iii) providing an novel method to gather and represent data, and after all by iv) bringing integrated modelling for land use change. Though, there are some limitation in this study.

8.3 LIMITATIONS OF THE STUDY

a) To begin with the land use system modelling, experience and knowledge of the researcher were inadequate. With the due course situation has improved.
b) To simulate fine resolution land use change, finer resolution drivers' data are also essential. For the present study, biophysical drivers like Geology, Geomorphology, and Soil are not available.
c) Other socio-economic and infrastructure data are also readily not available. Collecting and mapping of those data are time consuming.

8.4 SCOPE FOR FUTURE STUDIES

- This study can further be improved by understanding the drivers in detail and incorporating finer resolution as well as dynamic drivers' information.
- This study has integrated top-down SD model with Dyna-CLUE model which successfully brought together top down determination of land use change with bottom up process. Integration of more bottom-up processes in modelling would be helpful.
- An Agent Based model can be used to understand the effect of future land use change on local people. It would be helpful in land use planning.
- Bringing a structured method to estimate the land conversion elasticity would be a novel contribution for future studies.

- Identified drivers can be verified through field observation. Dynamic drivers' information should be incorporated.
- This study is the beginning of systematic understanding and modelling of land use change in India. Despite the lack of experience and scarcity of data an attempt has been made to take the knowledge one step further. This study has novel contribution towards the understanding of the application of GE, land use change drivers in India, models response due to abrupt change.

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APPENDIX I

SD Simulated LCLU demand, Normal Growth scenario (Area in ha).

Time (Year)	Farmland	Plantation	Nat.veg	Fallow	Waste	Built-up	Water
2011	6968.79	9672.19	857.376	8202.7	4664.224	1381.36	639.7661
2012	7148.755	9661.81	1375.215	7656.119	4448.599	1456.143	639.7665
2013	7299.764	9766.015	1404.429	7231.511	4516.76	1528.16	639.767
2014	7533.598	9803.285	1613.164	7221.764	3975.548	1599.279	639.7674
2015	7820.425	9292.426	1803.736	7221.051	3938.435	1670.566	639.7678
2016	8167.348	8932.778	1978.368	6984.828	3940.611	1742.704	639.7682
2017	8583.008	9124.244	2139.164	6215.181	3868.763	1816.278	639.7686
2018	9077.914	9394.674	2288.127	5821.938	3272.107	1891.877	639.769
2019	9664.877	9749.221	2427.188	4735.008	3200.205	1970.138	639.7694
2020	9859.53	10197.68	2558.231	3926.442	3152.978	2051.775	639.7698
2021	9981.01	10753.04	2683.121	3897.535	2294.332	2137.598	639.7702
2022	10670.18	11431.69	2803.731	2811.932	1800.564	2228.543	639.7706
2023	10503.85	12054.02	2906.814	2791.504	1164.75	2325.699	639.771
2024	10510.93	11880.19	2904.861	2796.246	1224.064	2430.344	639.7714
2025	10495.44	11737.05	3060.011	2659.442	1250.698	2543.997	639.7718
2026	10360.91	11768.28	3220.611	2288.38	1439.983	2668.469	639.7722
2027	10360.14	11081.55	3413.474	2715.262	1370.263	2805.942	639.7726
2028	9899.809	10323.07	3553.19	3648.384	1363.117	2959.059	639.773
2029	9042.887	10769.77	3705.597	3723.675	1373.666	3131.042	639.7734
2030	9042.246	10492.89	3874.471	3616.236	1394.942	3325.85	639.7739

APPENDIX II

SD Simulated LCLU demand, Industrial Growth scenario (Area in ha).

Time (Year)	Farmland	Plantation	"Nat.veg"	Fallow	Waste	Builtup	Water
2011	6968.79	9672.19	857.376	8203.295	4663.629	1381.36	639.7659
2012	6785.556	10079.56	1175.215	7601.674	4647.408	1457.225	639.7664
2013	6661.559	10814.75	1404.689	7541.463	3797.242	1526.941	639.7668
2014	6595.885	10850.24	1613.715	7365.06	3728.288	1593.454	639.7672
2015	6589.441	10925.19	1803.936	7296.916	3472.983	1658.169	639.7676
2016	6645.03	11004.02	1827.011	7160.312	3388.495	1721.774	639.768
2017	6767.533	11046.13	2134.56	6962.939	3050.674	1784.806	639.7684
2018	6964.216	11050.55	2278.168	6536.985	3068.923	1847.793	639.7688
2019	7245.181	11221.63	2409.401	6239.951	2719.181	1911.296	639.7692
2020	7624.003	11266.74	2529.811	6159.731	2190.415	1975.937	639.7696
2021	8018.602	11296.21	2540.96	6142.09	1706.351	2042.421	639.77
2022	8752.431	11303.84	2594.442	6128.883	855.4746	2111.567	639.7704
2023	9556.084	11319.79	2751.954	5106.563	827.9034	2184.343	639.7708
2024	10382.96	11323.85	2757.099	4195.988	824.8232	2261.912	639.7712
2025	10394.82	11350.21	2798.902	4008.078	848.929	2345.692	639.7716
2026	10412.57	11359.34	2801.395	3832.099	903.7937	2437.438	639.772
2027	10477.37	11706.94	3208.924	2819.916	994.1377	2539.34	639.7724
2028	10454.97	11811.43	3216.195	2559.544	1126.266	2578.222	639.7728
2029	10313.58	11973.28	3411.399	2473.739	1308.629	2266.006	639.7732
2030	10298.34	11985.15	3528.381	2347.348	1552.497	2034.913	639.7736

APPENDIX III

SD Simulated LCLU demand, Eco-Sustainable Growth scenario (Area in ha).

Time (Year)	Farmland	Plantation	"Nat.veg"	Fallow	Waste	Builtup	Water
2011	6968.79	9672.786	857.376	8202.7	4663.628	1381.36	639.7661
2012	7113.089	9461.81	1175.217	8156.119	4384.262	1456.143	639.7665
2013	7299.764	9477.616	1404.434	7641.096	4395.569	1528.16	639.767
2014	7303.598	9482.285	1593.563	7421.764	4412.149	1533.279	639.7674
2015	7420.425	9519.073	1803.749	7257.581	4197.244	1548.566	639.7678
2016	7567.348	9332.029	1978.387	7124.828	4151.342	1592.704	639.7682
2017	7583.008	9224.244	2139.188	7109.858	3874.062	1816.278	639.7686
2018	7366.751	9394.674	2288.156	7234.263	3570.916	1891.877	639.769
2019	7664.877	9348.769	2427.224	6886.616	3499.014	1920.138	639.7694
2020	7959.53	9497.68	2558.273	6741.069	2938.31	2051.775	639.7698
2021	7981.01	9545.773	2683.169	6447.535	2951.551	2137.598	639.7702
2022	8152.805	9631.689	2803.786	6066.753	2933.059	2158.543	639.7706
2023	8303.852	9654.017	2922.04	5777.469	2863.559	2225.699	639.771
2024	8369.927	9745.328	3039.93	5646.246	2514.861	2430.344	639.7714
2025	8495.439	9837.049	3159.577	5439.442	2271.131	2543.997	639.7718
2026	8535.742	9868.285	3413.277	4988.38	2272.481	2668.469	639.7722
2027	8560.143	9987.844	3413.566	4715.262	2263.878	2805.942	639.7726
2028	8655.809	10156.86	3553.291	4648.384	1873.234	2859.059	639.773
2029	8632.887	10152.19	3705.706	4223.675	1901.132	3131.042	639.7734
2030	8511.246	10154.51	3874.589	4186.687	1793.751	3225.85	639.7739

APPENDIX IV

Logistic Regression of different dependent variables for different years.

		Farm		Plantation		Natural Vegetation		Fallow		Waste		Built-up		Water Bodies	
		β	Exp(β)	β	Exp(β)	β	Exp(β)	β	Exp(β)	β	Exp(β)	β	Exp(β)	β	Exp(β)
All Roads	*1997*			0	1	0.0019	1.0019					-0.0007	0.9992		
	2005					0.0013	1.0013					-0.0017	0.9982		
	2007					0.0012	1.0012					-0.0012	0.9987		
	2010							-0.0008	0.9991	0.0004	1.0004	-0.0016	0.9983	0.0024	1.0024
Bus Stop	*1997*	0	1	0	1										
	2005											0	1		
	2007											0	1		
	2010							0	1	0	1				
Dam Dist.	*1997*	0	1	0	1	0.0005	1.0005							-0.0004	0.9995
	2005					0.0006	1.0006					0	1	0	1
	2007			0.0004	1.0004	0	1					0	1		
	2010	0	1	0.0005	1.0005	0.0011	1.0011	-0.0005	0.9994						
Drainage Density	*1997*	-0.2292	0.7950			-0.4611	0.6305	0.1978	1.2187	0.3441	1.4108	0.6166	1.8526	-0.3212	0.7252
	2005	-0.1100	0.8958	0.0639	1.0660	-0.2288	0.7954	0.1687	1.1837	0.3346	1.3974	0.4115	1.5091	-0.3958	0.6731
	2007	-0.6564	0.5186	0.1978	1.2187	0.0775	1.0806	0.3945	1.4836	0.9016	2.4636	0.5204	1.6828	-1.0086	0.3646
	2010	-0.2834	0.7531	0.2000	1.2214	-0.5341	0.5861	0.4455	1.5613	0.2792	1.3221	1.7033	5.4921	-0.9343	0.3928
Geology	*1997*	-0.1492	0.8613	0.2325	1.2617	-0.1363	0.8725	-0.0054	0.9945	0.0824	1.0859	0.1288	1.1375	0.4957	1.6417
	2005	-0.1006	0.9042	0.0913	1.0956	2.9273	18.6781	0.1491	1.1608	-0.2637	0.7681	0.1501	1.1620	0.7101	2.0342
	2007	-0.2313	0.7934	0.3537	1.4243			0.2970	1.3459	-0.5812	0.5592	0.1353	1.1449	0.2170	1.2423
	2010	-0.1386	0.8705	0.8354	2.3058	1.7912	5.9966	-0.2130	0.8081	-0.7494	0.4726	0.4169	1.5172	0.8276	2.2878
Geomorphology	*1997*	1.3076	3.6976	0.2416	1.2733	0.9522	2.5916	1.2088	3.3495	-0.1673	0.8459	1.6472	5.1926	-0.9511	0.3862
	2005	0.9333	2.5429	0.2511	1.2855	1.2306	3.4233	1.3596	3.8949	-0.7970	0.4506	0.5115	1.6679	-0.4083	0.6647
	2007	0.9148	2.4965	0.0815	1.0849			0.4878	1.6288	-0.5151	0.5974	1.4404	4.2227	-1.9957	0.1359
	2010	1.2683	3.5548	0.7631	2.1449	0.6409	1.8983	1.0351	2.8153					-0.0183	0.9817

Ground Water	*1997*	-0.0851	0.9183	0.5421	1.7196	0.9428	2.5672	0.31334	1.3679	0.0594	1.0612	-0.6987	0.4971	-1.2771	0.2788
	2005	0.0076	1.0077	0.5339	1.7056	16.8580	20959161.516	0.5920	1.8077	-0.5038	0.6042	-0.3854	0.6801	-1.1267	0.3240
	2007	-0.2303	0.7942	0.4461	1.5622			0.2814	1.3250			0.1218	1.1296	-1.7816	0.1683
	2010	0.4085	1.5047	-0.3646	0.6944	-0.4026	0.6685	4.4936	89.4499	-1.0353	0.3550	0.4704	1.6007	-2.9453	0.0525
Industry Loc	*1997*	0	1	0	1										
	2005							0	1			0	1		
	2007											0	1		
	2010							0	1	0	1				
Major Roads	*1997*	0	1	0	1										
	2005											0	1		
	2007											0	1		
	2010							0	1	0	1				
Economic Stat	*1997*	0.0490	1.0502	-0.255	0.774	-0.5234	0.5924	0.0898	1.0939	0.0889	1.0930	0.3567	1.4286	-0.3808	0.68330
	2005	0.0686	1.0710	-0.3731	0.6885	-0.6353	0.5297	0.1067	1.1127	0.1863	1.2048	0.1381	1.1480	-0.1154	0.8909
	2007	0.0428	1.0438	-0.3384	0.7128	-0.6187	0.5386	0.8376	2.3108	0.0159	1.0160	0.2157	1.2407		
	2010	-0.1155	0.8908	-0.6035	0.5468	1.4220	4.1454	0.0364	1.0371			0.8642	2.3732	0.3784	1.4600
Popun Density	*1997*			0.2137	1.2382	-0.3199	0.7261	-0.5891	0.5548	-0.3863	0.6795	1.0454	2.8446	-0.6845	0.5042
	2005	-0.0909	0.9130	0.3160	1.3717	-0.3244	0.7229	-0.6689	0.5122	-0.4409	0.6434	0.8133	2.2553	-0.5834	0.5579
	2007	-0.0803	0.9227	0.3716	1.4501	-0.2453	0.7824	0.0364	0			0.8050	2.2367		
	2010	-19.9098	0	1.5771	4.8410					-17.9372	0.0097	2.2793	9.7703		
Road Density	*1997*	-0.0295	0.9709	0.0788	1.0820	0.0428	1.0437	-0.0656	0.9365	0.0369	1.0376	0.0339	1.0344	-0.2929	0.7460
	2005	0.0505	1.0518	0.0209	1.0211	-0.1091	0.8965	-0.0384	0.9622	-0.0155	0.9845			-0.1434	0.8663
	2007	0.0930	1.0975	0.0858	1.0895	-0.3763	0.6863					0.0889	1.0930		
	2010	0.0609	1.0628	-0.075	0.9271	-0.1878	0.8287	-0.0737	0.9288			0.0771	1.0802		

Relative Relief	*1997*	-0.0240	0.9762	0.0455	1.0465	0.1019	1.1073	-0.0603	0.9414	0.0123	1.0124	-0.0313	0.9691	-0.0973	0.9072
	2005	-0.0180	0.9820	0.0409	1.0418	0.0916	1.0960	-0.0579	0.9436	0.0120	1.0121	-0.0405	0.9602	-0.0711	0.9313
	2007	-0.0391	0.9615	0.0244	1.0247	0.1134	1.1201	-0.0408	0.9599	0.0197	1.0199	-0.0338	0.9666	-0.0710	0.9313
	2010	-0.0325	0.9679	0.0367	1.0374	0.0897	1.0938	-0.0381	0.9626	0.0097	1.0098	-0.0308	0.9695	-0.0670	0.9351
Slope	*1997*	-0.0038	0.9961	0.0219	1.0221	0.0319	1.0324	-0.0170	0.9831	-0.0047	0.9952	-0.0177	0.9824	-0.0602	0.9415
	2005	-0.0022	0.9977	0.0183	1.0185	0.0343	1.0349	-0.0150	0.9850	-0.0100	0.9900	-0.0186	0.9815	-0.0427	0.9581
	2007	-0.0169	0.9832	0.0197	1.0199	0.0370	1.0377	-0.0117	0.9883	-0.0102	0.9898	-0.0219	0.9783	-0.0408	0.9599
	2010	-0.0325	0.9921	0.0225	1.0227	0.03487	1.0354	-0.0146	0.9854			-0.0291	0.9712	-0.0279	0.9724
Soil	*1997*	-0.1075	0.8980	0.6644	1.9434	1.9100	6.7533	-0.7020	0.4955	-0.4016	0.6692	-0.0330	0.9674	-0.7803	0.4582
	2005	-0.1493	0.8612	0.5886	1.8016	1.3781	3.9673	-0.5010	0.6058	-0.2887	0.7492	-0.2267	0.7971	-1.2213	0.2948
	2007	-0.3845	0.6807	0.5683	1.7653	1.7064	5.5091	-0.4017	0.6691	-0.8879	0.4115	-0.2918	0.7469		
	2010	-0.5134	0.5984	0.7414	2.0990	0.7445	2.1054	-0.3853	0.6802	-1.2489	0.2867	0.4588	1.5822	-1.2950	0.2738
Stream Distance	*1997*	-0.0011	0.9988	0	1	-0.0010	0.9989	0.0005	1.0005	0.0011	1.0011			-0.0060	0.9939
	2005	-0.4834	0.6166							0.0008	1.0008	0	1	-0.0054	0.9945
	2007	-0.0006	0.9993	0.0006	1.0006	0	1							-0.0050	0.9949
	2010	-0.0009	0.9990	0.0007	1.0007	0.0005	1.0005	0.0003	1.0003	0.0014	1.0014			-0.0046	0.9953
Mod GPI	*1997*	1.0141	2.757	-0.4388	0.6448	-2.4640	0.0850	-1.1468	0.3176	-0.9745	0.3773	0.5808	1.7875		
	2005			-0.1732	0.8409			-0.9909	0.3712			0.9348	2.5467		
	2007	-0.3992	0.6708									1.2632	3.5368		
	2010							-1.15363	0.3154						

APPENDIX V

Logistic Regression of 2010 for different model run.

2010		Farm		Plantation		Natural Vegetation		Fallow		Waste		Built-up		Water Bodies	
		β	Exp(*β*)	*β*	Exp(*β*)	*β*	Exp(*β*)	*β*	Exp(*β*)	*β*	Exp(*β*)	*β*	Exp(*β*)	*β*	Exp(*β*)
All Roads	*3A*											-0.0025	0.9974		
	3Ba											-0.0018			
	3Bc											-0.0017	0.9982		
	3Be														
	3Bf1a														
Bus Stop	*3A*														
	3Bc											0.0002	1.0002		
	3Be														
	3Bf1a														
Dam Dist.	*3A*														
	3Ba														
	3Bc			0	1	0.0003	1.0003			0.0001	1.0000	0.0003	1.0003	-0.0001	0.9998
	3Be														
	3Bf1a	-0.0003	0.9996	0.00004	1.00004	0.0003	1.0003								
Drainage Density	*3A*			0.2657	1.3044	-0.1199	0.8869	0.3951	1.4845	0.4988	1.6469	0.4187	1.5199	-0.9856	0.3731
	3Ba	-0.1250	0.8824	0.4058	1.5006	-0.2832	0.7533	0.1775	1.1942	0.2862	1.3314	1.4072		-0.9856	0.3731
	3Bc	-0.1821	0.8334	0.3864	1.4718	-0.2587	0.7720	0.3991	1.4905	0.2465	1.2796	1.4693	4.3463	-2.0918	0.1234
	3Bf1a	-0.0762	0.9266	0.3864	1.4718	-0.2587	0.7720	0.3991	1.4905						
Geology	*3A*	-0.1733	0.8408			1.5093	4.5238			-0.5726	0.5640				
	3Bf1a														
Geomorphology	*3A*	0.3762	1.4567	0.0192	1.0194	0.4213	1.5240	0.8830	2.4181	-1.2829	0.2772				

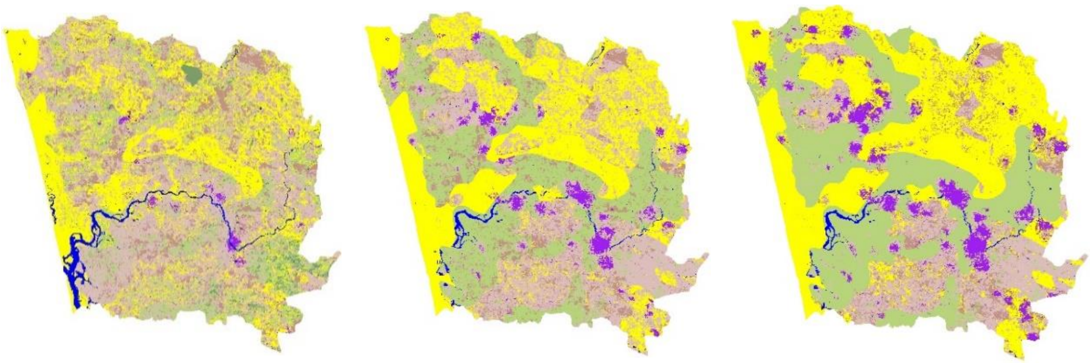
	3Bf1a														
Ground Water	*3A*							4.1512	63.5121			0.7864	2.1955	-3.0667	0.0465
	3Ba	0.7601	2.1386	0.1280	1.1366	1.2433	3.4671	4.4989	89.9222					-3.0667	0.0465
	3Bf1a														
Industry Loc	*3A*														
	3Bc			0	1										
	3Bf1a			0	1										
Major Roads	*3A*														
	3Ba														
	3Bc	-0.0001	0.9998	0	1							0	1		
	3Bf1a			0	1										
Economic Stat	*3A*											-0.9536	0.3853		
	3Ba	-0.0900	0.9138	-0.4917	0.6115	1.7560	5.7893	87.0000	3.4649						
	3Bf1a														
Popun Density	*3A*			1.6542	5.2289										
	3Ba	-19.8620	0									1.9189			
	3Bc	-19.7881	0	1.5255	4.5975	-18.4288	0	-19.5709	0	-17.8803	0	1.9115	6.7634	-16.2781	
	3Bf1a	-19.7837	0	1.5255	4.5975	-18.4288	0	-19.5709	0						

Road Density	*3A*														
	3Ba	0.1503	1.1622	-0.1171	0.8894										
	3Bc	0.0842	1.0879	-0.1201	0.8867	-0.3264	0.7214	0.1109	1.11734	-0.0143	0.9857	0.0804	1.0837	-0.5126	0.5989
	3Bf1a	0.1211	1.1288	-0.1201	0.8867	-0.3264	0.7214	0.1109	1.1173						
Relative Relief	*3A*	-0.0385	0.9622	0.0363	1.0370	0.0913	1.0956	-0.0408	0.9599	0.0065	1.0065	-0.0706	0.9318	-0.1561	0.8554
	3Ba	-0.0455	0.9555	0.0686	1.0710	0.1298	1.1386	-0.0553	0.9462	0.0095	1.0096	-0.0170		-0.1561	0.8554
	3Bc	-0.0524	0.9488	0.0573	1.0590	0.1140	1.1208	-0.0382	0.9624	0.0031	1.0031	-0.0247	0.9756	-0.1900	0.8269
	3Bf1a	-0.0492	0.9519	0.0573	1.0590	0.1140	1.1208	-0.0382	0.9624						
Slope	*3A*	-0.0122	0.9878	0.0161	1.01631	0.0255	1.0258	-0.0141	0.9859			-0.0320	0.9684	-0.0697	0.9326
	3Ba	-0.0112	0.9887	0.0299	1.0304	0.04295	1.0438	-0.0180	0.9821	0.0030	1.0030	-0.0156		-0.0697	0.9326
	3Bc	-0.0155	0.9845	0.0227	1.0229	0.0341	1.0347	-0.0075	0.9924			-0.0180	0.9821	-0.0905	0.9134
	3Bf1a	-0.0147	0.9853	0.0227	1.0229	0.0341	1.0347	-0.0075	0.9924						
Soil	*3A*	-0.2325	0.7925	1.03006	2.8012	1.2757	3.5813	-0.25544	0.7745	-0.8254	0.4380				
	3Ba														
	3Bc														
	3Bf1a														
Stream Distance	*3A*							0.0003	1.0003	0.0012	1.0012				
	3Ba	-0.0006	0.9993	0.0002	1.0002	0	1			0.0011	1.0011	0.0005			
	3Bc	-0.0008	0.9991			-0.0001	0.9998	0.0008	1.0008	0.0013	1.0013	0.0005	1.0005	-0.0057	0.9943
	3Bf1a					-0.0001	0.9998	0.0008	1.0008						
Mod GPI	*3A*														
	3Ba	-0.4603	0.6310												
	3Bf1a														

APPENDIX VI

Calibration of Dyna-CLUE model

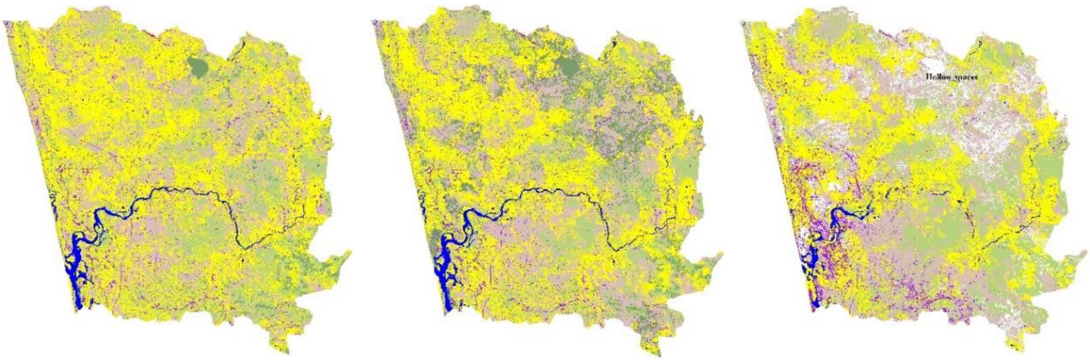
3B	Farm	Plant	NatVeg	Fallow	Waste	Built	Water
β_0	-0.450	-3.3854	-7.503	-6.9532	-3.1648	-2.2772	3.2208
AUC		.800	.751	.630	.621	.706	.855
Ind. Vari.	5	6	6	7	6	6	4
Elasticity	.1	.1	.1	.1	.1	.1	.9



1998 2005 2010

3B	Farm	Plant	NatVeg	Fallow	Waste	Built	Water
Farm	1	1	1	1	1	1	1
Plant	1	1	1	1	1	1	1
NatVeg	1	1	1	1	1	1	1
Fallow	1	1	1	1	1	1	1
Waste	1	1	1	1	1	1	1
Built	1	1	1	1	1	1	1
Water	1	1	1	1	1	1	1

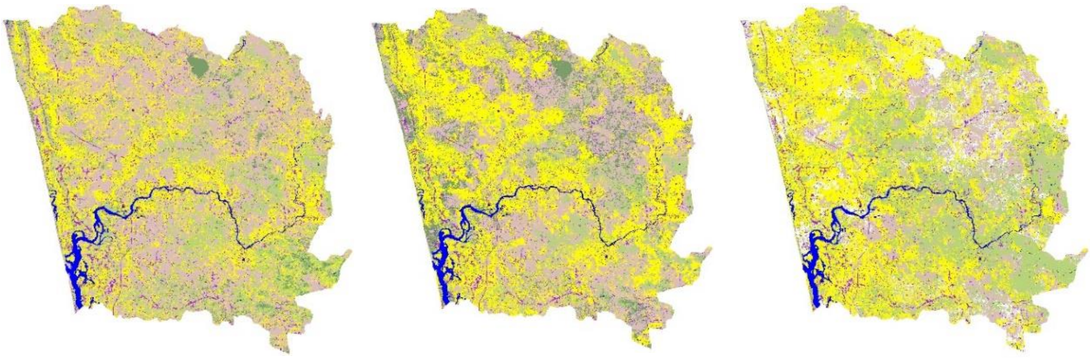
3Ba	Farm	Plant	NatVeg	Fallow	Waste	Built	Water
β_0	-0.0655	-2.2770	-6.3950	-6.9823	-3.6820	-5.3542	3.2208
AUC	.711	.776	.720	.632	.569	.879	.855
Ind. Vari.	9	8	5	5	4	6	4
Elasticity	.1	.1	.1	.1	.1	.1	.9



1998 2005 2010

3Ba	Farm	Plant	NatVeg	Fallow	Waste	Built	Water
Farm	1	1	1	1	1	1	1
Plant	1	1	1	1	1	1	1
NatVeg	1	1	1	1	1	1	1
Fallow	1	1	1	1	1	1	1
Waste	1	1	1	1	1	1	1
Built	1	1	1	1	1	1	1
Water	1	1	1	1	1	1	1

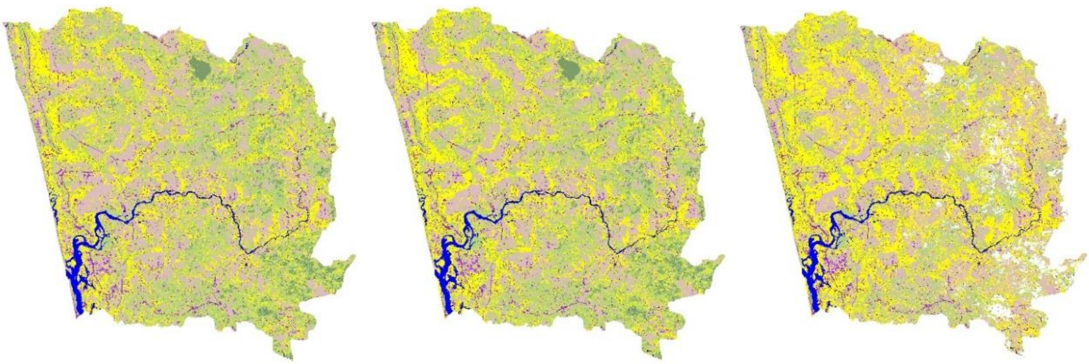
3Bb	Farm	Plant	NatVeg	Fallow	Waste	Built	Water
β_0	-0.0655	-2.2770	-6.3950	-6.9823	-3.6820	-5.3542	3.2208
AUC	.711	.776	.720	.632	.569	.879	.855
Ind. Vari.	9	8	5	5	4	6	4
Elasticity	.1	.2	.4	.1	.1	.8	.9



1998 2005 2010

3Bb	Farm	Plant	NatVeg	Fallow	Waste	Built	Water
Farm	1	1	1	0	0	1	0
Plant	0	1	1	1	0	1	0
NatVeg	1	1	1	0	0	0	0
Fallow	1	1	0	1	0	1	0
Waste	0	1	1	1	1	1	0
Built	0	0	0	0	0	1	0
Water	0	0	0	0	0	0	1

3Bc	Farm	Plant	NatVeg	Fallow	Waste	Built	Water
β_0	0.4286	-2.6838	-2.9191	-1.4345	-3.4140	-6.0791	3.7344
AUC	.705	.778	.770	.680	.663	.895	.948
Ind. Vari.	7	8	7	6	6	10	7
Elasticity	.1	.2	.4	.1	.1	.8	.9



1998 2005 2010

3Bc	Farm	Plant	NatVeg	Fallow	Waste	Built	Water
Farm	1	1	1	0	0	1	0
Plant	0	1	1	1	0	1	0
NatVeg	1	1	1	0	0	0	0
Fallow	1	1	0	1	0	1	0
Waste	0	1	1	1	1	1	0
Built	0	0	0	0	0	1	0
Water	0	0	0	0	0	0	1

3Bc1	Farm	Plant	NatVeg	Fallow	Waste	Built	Water
β_0	0.4286	-2.6838	-2.9191	-1.4345	-3.4140	-6.0791	3.7344
AUC	.705	.778	.770	.680	.663	.895	.948
Ind. Vari.	7	8	7	6	6	10	7
Elasticity	.6	.7	.8	.3	.5	.9	.9

1998 2005 2010

3Bc1	Farm	Plant	NatVeg	Fallow	Waste	Built	Water
Farm	1	3	10	1	0	1	0
Plant	0	1	5	5	1	1	0
NatVeg	0	1	1	0	1	0	0
Fallow	1	3	1	1	1	1	0
Waste	0	3	5	1	1	1	0
Built	0	0	0	0	0	1	0
Water	0	0	0	0	0	0	1

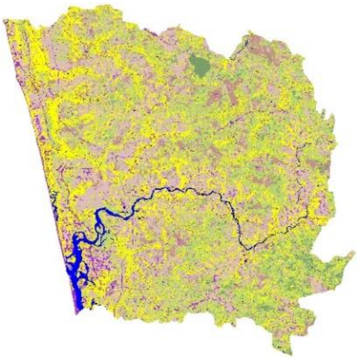
3Bd	Farm	Plant	NatVeg	Fallow	Waste	Built	Water
β_0	0.4286	-2.6838	-2.9191	-1.4345	-3.4140	-6.0791	3.7344
AUC	.705	.778	.770	.680	.663	.895	.948
Ind. Vari.	7	8	7	6	6	10	7
Elasticity	.6	.7	.8	.3	.5	.9	.9

1998 2005 2010

3Bd	Farm	Plant	NatVeg	Fallow	Waste	Built	Water
Farm	1	1	1	0	0	1	0
Plant	0	1	1	1	0	1	0
NatVeg	1	1	1	0	0	0	0
Fallow	1	1	0	1	0	1	0
Waste	0	1	1	1	1	1	0
Built	0	0	0	0	0	1	0
Water	0	0	0	0	0	0	1

3Bd1	Farm	Plant	NatVeg	Fallow	Waste	Built	Water
β_0	0.4286	-2.6838	-2.9191	-1.4345	-3.4140	-6.0791	3.7344
AUC	.705	.778	.770	.680	.663	.895	.948
Ind. Vari.	7	8	7	6	6	10	7
Elasticity	.6	.7	.4	.2	.5	.9	.9

1998



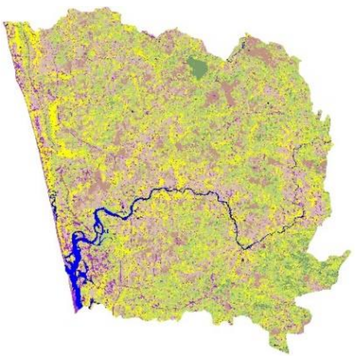
2005

NA

2010

3Bd1	Farm	Plant	NatVeg	Fallow	Waste	Built	Water
Farm	1	3	5	1	0	1	0
Plant	0	1	3	5	1	1	0
NatVeg	0	1	1	0	1	0	0
Fallow	1	3	1	1	1	1	0
Waste	0	3	5	1	1	1	0
Built	0	0	0	0	0	1	0
Water	0	0	0	0	0	0	1

3Bd2	Farm	Plant	NatVeg	Fallow	Waste	Built	Water
β_0	0.4286	-2.6838	-2.9191	-1.4345	-3.4140	-6.0791	3.7344
AUC	.705	.778	.770	.680	.663	.895	.948
Ind. Vari.	7	8	7	6	6	10	7
Elasticity	.6	.7	.4	.2	.5	.9	.9



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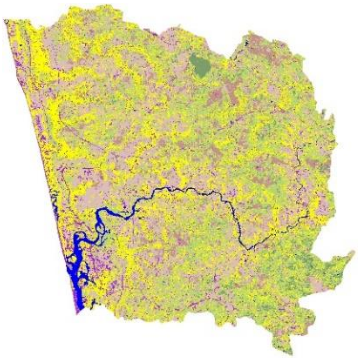

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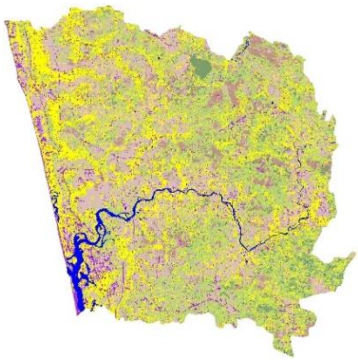
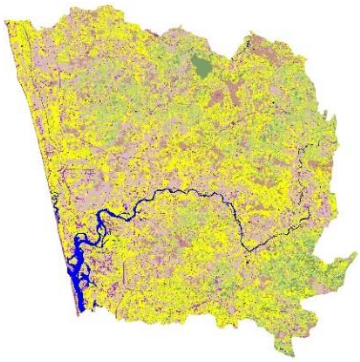


2010

3Bd2	Farm	Plant	NatVeg	Fallow	Waste	Built	Water
Farm	1	3	5	1	0	1	0
Plant	0	1	3	5	1	1	0
NatVeg	0	1	1	0	1	0	0
Fallow	1	3	1	1	1	1	0
Waste	0	3	5	1	1	1	0
Built	0	0	0	0	0	1	0
Water	0	0	0	0	0	0	1

3Be	Farm	Plant	NatVeg	Fallow	Waste	Built	Water
β_0	0.4286	-2.6838	-2.9191	-1.4345	-3.4140	-6.0791	3.7344
AUC	.705	.778	.770	.680	.663	.895	.948
Ind. Vari.	7	8	7	6	6	10	7
Elasticity	.6	.7	.4	.2	.5	.9	.9



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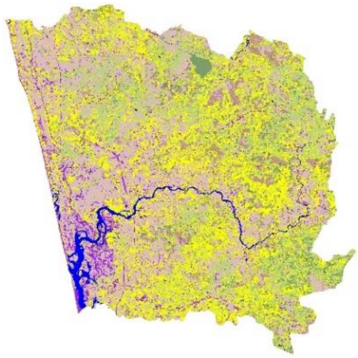

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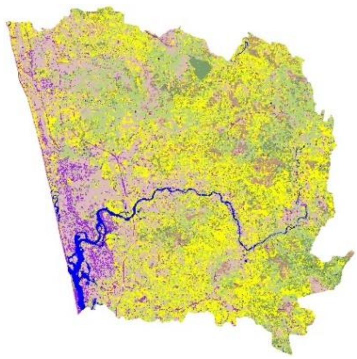
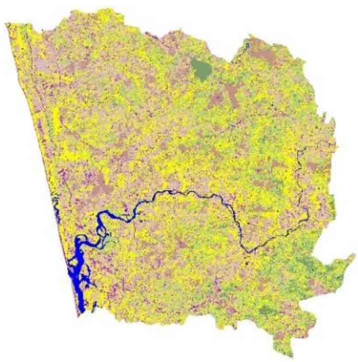


2010

3Be	Farm	Plant	NatVeg	Fallow	Waste	Built	Water
Farm	1	3	0	1	0	1	0
Plant	1	1	3	1	1	1	0
NatVeg	0	1	1	0	1	0	0
Fallow	1	3	5	1	0	1	0
Waste	0	3	3	1	1	1	0
Built	0	0	0	0	0	1	0
Water	0	0	0	0	0	0	1

3Be1	Farm	Plant	NatVeg	Fallow	Waste	Built	Water
β_0	0.4286	-2.6838	-2.9191	-1.4345	-3.4140	-6.0791	3.7344
AUC	.705	.778	.770	.680	.663	.895	.948
Ind. Vari.	7	8	7	6	6	10	7
Elasticity	.7	.8	.8	.7	.6	.9	1



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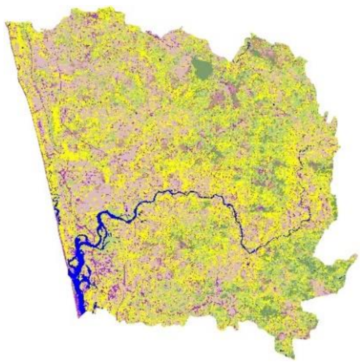


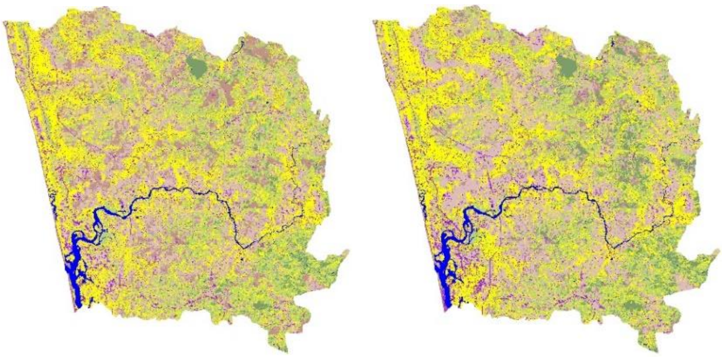
2005

NA

2010

3Be1	Farm	Plant	NatVeg	Fallow	Waste	Built	Water
Farm	1	1	0	1	0	1	0
Plant	0	1	1	1	1	0	0
NatVeg	0	0	1	0	1	0	0
Fallow	1	1	0	1	1	1	0
Waste	0	0	1	1	1	1	0
Built	0	0	0	0	0	1	0
Water	0	0	0	0	0	0	1

3Be2	Farm	Plant	NatVeg	Fallow	Waste	Built	Water
β_0	0.1131	-2.6838	-2.9191	-1.4345	-3.4140	-6.0791	3.7344
AUC		.778	.770	.680	.663	.895	.948
Ind. Vari.	6	8	7	6	6	10	7
Elasticity	.8	.8	.8	.7	.8	.9	1



NA

1998 2005 2010

3Be2	Farm	Plant	NatVeg	Fallow	Waste	Built	Water
Farm	1	1	0	1	0	1	0
Plant	0	1	1	1	0	0	0
NatVeg	0	0	1	0	1	0	0
Fallow	1	1	0	1	1	1	0
Waste	0	0	1	1	1	0	0
Built	0	0	0	0	0	1	0
Water	0	0	0	0	1	0	1

3Bf1	Farm	Plant	NatVeg	Fallow	Waste	Built	Water
β_0	0.1131	-2.6838	-2.9191	-1.4345	-3.4140	-6.0791	3.7344
AUC		.778	.770	.680	.663	.895	.948
Ind. Vari.	6	8	7	6	6	10	7
Elasticity	.8	.8	.8	.7	.8	.9	1

1998 2005 2010

3Bf1	Farm	Plant	NatVeg	Fallow	Waste	Built	Water
Farm	1	1	0	1	0	1	0
Plant	0	1	1	1	0	0	0
NatVeg	0	0	1	0	1	0	0
Fallow	1	1	0	1	1	1	0
Waste	0	0	1	1	1	0	0
Built	0	0	0	0	0	1	0
Water	0	0	0	0	1	0	1

PUBLICATIONS

JOURNAL PAPERS FROM THIS RESEARCH

Ghosh, S. & Shetty, A. (2017) "Modelling the land use system process for a pre-industrial landscape in India" Model. *Earth Syst. Environ*. 3(2), 703–717. https://doi.org/10.1007/s40808-017-0329-5

Ghosh, S. & Shetty, A., Bhat, V. (2018) "Explore the utility of Google Earth and historical satellite images to produce LCLU time series." (Under Review)

CONFERENCE PROCEEDINGS

Ghosh, S. & Shetty, A. (2012) "A Conceptual Framework to Model Sustainable Land Management Using Remote Sensing and GIS". *National Seminar on "Managing Land Resources for Sustainable Agriculture"*. October 12-13, 2012, NBSS & LUP, Nagpur, India.

BIODATA

Suparno Ghosh
NITK, Surathkal
Mangalore - 575025
Karnataka, INDIA
Email: suparnogis@yahoo.in
Contact: +919449688449

OBJECTIVES

Have a desire to know the world and apply my knowledge for the betterment of mankind. Finding a position in the field of *land change science* that would enable me to utilize my capabilities and experience by offering a satisfying career in good work culture with opportunities for learning and growth.

EDUCATIONAL BACKGROUND

Qualification	Branch/Stream	Year	University
Ph.D.	RS & GIS Applications	Ongoing	NITK, Surathkal
M. Tech.	GIS	2010	BDU, Tiruchirappalli
Masters	Geography	2007	C.S.J.M University Kanpur
Batchelor (Honours)	Geography	2005	University of Calcutta

WORK EXPERIENCE

Name of the Employer	*Address of the Employer*	*Designation*	*Duration of Work*	*Responsibilities*
DESCON Limited	Salt Lake City, Kolkata	GIS Executive	March, 2011 to December, 2011	Electricity Utility Mapping (RAPDRP)
Rajiv Gandhi University	Rono Hills, Arunachal Pradesh, India	Junior Research Fellow	July, 2010 to March 2011	Surveying using GPS and generation of Database, GIS Analysis
North Eastern Space Application Center	Shillong, Meghalaya, India	Project Trainee	December, 2009 to April 2010	Vectorization, Database Generation, Network Analysis

PUBLICATIONS

Title of Paper	*Authors*	*Journal/Conf.*	*Date*
Explore the utility of Google Earth and historical satellite image to produce LCLU time series.	Suparno Ghosh, Amba Shetty, Vishwanatha Bhat	(Under Review)	July, 2018
Modelling the land use system process for a pre-industrial landscape in India	Suparno Ghosh, Amba Shetty	Modeling Earth Systems and Environment, 3(2),703–717	June, 2017
A Conceptual Framework to Model Sustainable Land Management Using Remote Sensing and GIS	Suparno Ghosh, Amba Shetty	National Seminar on “Managing Land Resources for Sustainable Agriculture”	October 12-13, 2012