# MODELING LANDSCAPE DYNAMICS WITH BIODIVERSITY, ECOLOGY AND SOCIAL ASPECTS

Thesis submitted in partial fulfillment
of the requirements for the degree of

***Doctor of Philosophy***
*in*
***Spatial Informatics***

by

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# CERTIFICATE

It is certified that Mr. Setturu Bharath, Ph.D., has carried out a dissertation entitled **"MODELING LANDSCAPE DYNAMICS WITH BIODIVERSITY, ECOLOGY AND SOCIAL ASPECTS"** in partial fulfillment of the requirements for the award of Doctoral degree in Spatial Informatics. This work has been carried out under the supervision of Prof. KS Rajan, Lab for Spatial Informatics, International Institute of Information Technology, Hyderabad, India and Prof. TV Ramachandra, Centre for Ecological Sciences, Indian Institute of Science, Bangalore, India. This work is not submitted elsewhere for a degree.

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**Dedicated to**

*Late S Narasimha Murthy & Late S Vijaya Lakshmi,*

&

My Guides, Teachers, and People of India who helped me to do research

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## Abstract

Landscapes are the composition of dynamic components of complex ecological, economic, and cultural elements on which human and other life forms depend directly. Landscape dynamics driven by land use land cover (LULC) changes due to anthropogenic activities are affecting ecology, biodiversity, hydrological regime, and hence people's livelihood. There has been increasing apprehensions about environmental degradation, depletion of natural resources due to uncontrolled anthropogenic activities, and its consequences on long-term sustainability of socio-economic systems around the world. This necessitates an understanding of landscape dynamics and the visualization of likely changes for evolving appropriate strategies for prudent management of natural resources. Modeling of forest cover changes offers to incorporate human decision making on land use in a systematic and spatially explicit way through an accumulation of land use choices, social interaction, and adaptation at various levels. Several models developed by the research community so far has largely been utilized to evaluate the empirical studies, explore theoretical aspects of particular systems rather than forecasting their effectiveness across the various landscapes representing bio-physical dissimilarities. Hence, there is a need to demonstrate an appropriate modeling technique, that captures the current degradation in an effective way as compared with the traditional agent-based or non-agent based land use change modeling techniques.

In this regard, the objectives of current research are to understand and model the spatiotemporal patterns of landscape dynamics in the Uttara Kannada district of Central Western Ghats. This involves, (i) developing an appropriate modeling framework incorporating the spatiotemporal changes in the landscape at the regional level; (ii) implementing a hybrid model to capture the changes at the landscape level by integrating bio-ecological aspects with socio-economic growth; (iii) evaluating the environmental conditions in response to scenarios of drivers of change like developmental policies and their potential impacts; (iv) assessing the likely scenario of the landscape dynamics based on conservation policies of ecologically sensitive regions (ESR) and other recommendations.

The vegetation dynamics quantified using spatial data acquired through spaceborne sensors along with collateral data shows a decline in vegetation cover from 92.87% (1973) to 80.42%

(2016). Land use analyses through supervised classifiers based on the Gaussian maximum likelihood algorithm reveals a deforestation trend as evident from the decline of evergreen-semi evergreen forest cover to 29.5% (2016) from 67.73% (1973). In addition, agricultural spatial extent (7.00 to 14.3 %) and the area under human habitations (0.38% to 4.97%) have also shown a steep increase. This has also led to forest fragmentation (interior forest cover lost by 64.42 to 22.25 %) in the district. In order to visualize the likely changes, the current work proposes a modified Hybrid Fuzzy-Analytical Hierarchical Process-Markov Cellular Automata model by accounting for the land use changes and to evaluate the role of policy decisions. The impacts are noticed at the microscale (landscape level) with policies that are framed at a macro level and how they propagate under various scenarios.

To understand the landscape dynamics in the region, modeling has been carried out under four scenarios to account for potential changes driven by economic growth and climatic aspects at a landscape level. Modeling and visualization further confirm the loss of forest cover in near future with an increase in monoculture plantations from 14.8 to 17.97% and an increase in built-up area from 4.81 to 9.30 % by 2022 under business as usual (BAU) scenario. The proposed hybrid modeling approach with the constraints in the cellular automata technique has been used to simulate various scenarios (i) managed growth rate (2022), (ii) IPCC climate change rapid growth (2031, 2046), (iii) policy-induced constrained Ecological Sensitive Regions. The rapid growth rate scenario highlights a likely loss of forest cover by 11.1%, with an increase in plantations covering 20.9% and built-up as 10.2% of the region by 2046. Land use changes assessed through considering constraints of Ecological Sensitive Regions (ESR-1) and the protection of intact or contiguous (interior) forest patches, highlights the role of policy decisions in land use changes. ESR-1 protection scenario shows forest cover is likely to remain at 48% (2021) and 45% (2031) though there is an increase in built-up area from 5.8 to 7% (2031) and agriculture area. The comparison of policy scenario-1 (ESR-1) and scenario-2 (protection of interior forest) depicts scenario-1 focuses more on conservation and limits the growth to the ESR- 2, 3 and 4 regions, whereas scenario-2 shows growth can occur throughout the district excluding regions covered with interior forests, which is likely to induce further fragmentation of forests.

This research shows that the insights from the changes to the forest cover and its dynamics through modeling will aid decision making processes for formulating appropriate land use policies. It is important that such policies mitigate changes in the ecologically sensitive regions

and maintain sustenance of natural resources to ensure water and food security while supporting the livelihood of local people.

**Keywords** Landscape dynamics; Fragmentation; Land use land cover [LULC]; LULC changes; Modeling; Policies

# CONTENTS

## List of abbreviations

| | |
|---|---|
| **LULC** | Land Use Land Cover |
| **RS** | Remote Sensing |
| **GIS** | Geographic Information System |
| **GPS** | Global Positioning System |
| **CA** | Cellular Automata |
| **MCA** | Markov Cellular Automata |
| **MCCA** | Markov Chain Cellular Automata |
| **AHP** | Analytic hierarchy process |
| **AGBM** | Agent Based Models |
| **GEOMOD** | Geographical Modeling |
| **LCM** | Land Change Modeller |
| **EBM** | Equation Based Models |
| **SIM** | Spatial Interaction Models |
| **GA** | Genetic Algorithms |
| **MAS** | Multi Agent System Models |
| **NRC** | National Research Council |
| **CLUE** | Conversion of Land Use and its Effects |
| **SLEUTH** | Slope, Land use, Exclusion, Urban extent, Transportation and Hill shade |
| **MLIR** | Multiple Linear Regression |
| **DGVM** | Dynamic Global Vegetation Model |
| **GARP** | Genetic Algorithm for Ruleset Production, |
| **SVM** | Support Vector Machine |
| **ED** | Environmental Distance |
| **CSM** | Climate Space Model |
| **ESR** | Ecologically Sensitive Regions |
| **GHG** | Green House Gas |
| **MoEFCC** | Ministry of Environment and Forests and Climate Change |
| **IPCC** | Intergovernmental Panel on Climate Change |
| **GLP** | Global Land Project |
| **IGBP** | International Geosphere-Biosphere Programme |
| **IHDP** | International Human Dimensions Programme on Global Environmental Change |
| **ADTR** | Anshi-Dandeli Tiger Reserve |
| **LTM** | Lion-Tailed Macaque |
| **NDVI** | Normalized Difference Vegetation Index |
| **BAU** | Business As Usual Scenario |
| **HGS** | Historical Growth Scenario |
| **IFC** | Interior Forest Conservation |
| **WRF** | Without Reserve Forest protection |

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## 1.1. Landscape

The landscape is a mosaic of forested, non-forested fragments of land that differ from area to area depending on climate, land uses, and history (Forman and Gordron, 1986). Hence, landscapes are heterogeneous geographic areas, varying in composition and boundaries (structure) based on the ecological, geographical, or administrative units (ex: forest cover, a watershed, an urban area). The landscape structure and composition vary based on the existing feature's characteristics, which can be static or dynamic.

## 1.2. Landscape and its interactions

The landscape consists of interacting complex ecological, economic, and cultural components supporting biota. The interaction varies based on sizes and is influenced by either natural or anthropogenic activities. The ecological process in a landscape is characterized by aggregation, nonlinearity, flows, and diversity. Figure 1.1 outlines the various components of ecosystems interacting at a landscape level. The landscape is also manifested by configurations of topography, vegetation cover, land use, and settlement patterns, which delimits ecological and cultural processes and activities (Green et al., 1996; Arts et al., 2017).

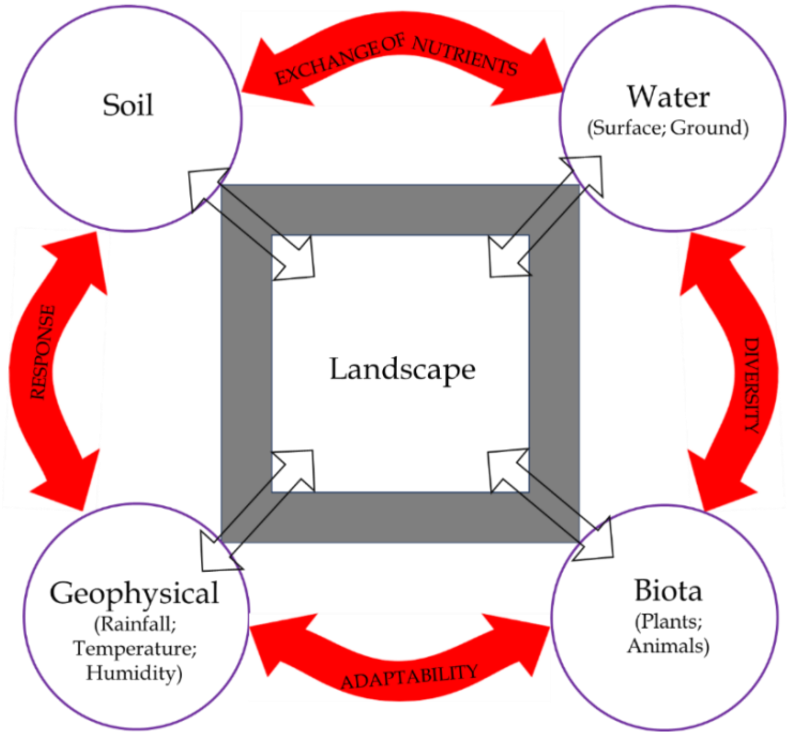



Figure 1.1. Landscape and its elements

Ecosystem functions (interaction among spatial elements, cycling of water and nutrients, biogeochemical cycles) of a landscape depends on its structure (size, shape, configuration) and constituent's spatial patterns (linear, regular, aggregated). The composition of a landscape is defined by the non-spatial elements that are distinguishable, and have supporting functions. The structure, composition, and components of a landscape define the spatial pattern or heterogeneity.

## 1.3. Landscape dynamics

Landscape dynamics represent the changes in landscape due to key disturbance factors, and also offers a historic array of variability in ecosystems. Land use, Land cover (LULC) are fundamental variables of a landscape, providing a link between biophysical environment and anthropogenic influences. Though they are interrelated, a clear distinction between LC and LU exists: LC refers to the biophysical earth surface and LU shaped by human, socio-economic, political influences on the LC (Lambin et al., 2001). LC categories include areas under vegetation (forest, savannah, plantations, scrublands, mangroves, grassland, etc.) and non-vegetation (soil, desert, water, etc.). LU refers to the human-induced changes in the LC for farming, industrial, residential, recreational purposes. LULC variables are critical features, which assist in understanding landscape structure and health. Notionally, LU due to anthropogenic activities transforms a landscape (NRC, 1999; 2001). LULC changes could be natural or human-induced. Natural events such as weather, flooding, fire, climate fluctuations, and ecosystem dynamics initiate changes in LC. Globally, LC today is altered principally by direct anthropogenic use such as agriculture, livestock grazing, forest harvesting and management, urban and suburban construction, and other developmental activities (Meyer, 1995). Natural disturbances alter forest landscape patterns differently from anthropogenic impacts (Mladenoff, 1993). Human-induced impacts of forest disturbance regimes have intensified the effect between patches compared to natural changes (Thom and Seidl, 2015). Figure 1.2 outlines the various drivers that directly or indirectly encourage landscape transitions. Physical, biological, social, economic aspects have been realized as the main drivers of landscape dynamics.

Comprehensive LULC information of a region offers an opportunity for relating spatial patterns to the ecological, environmental, and social process of a landscape and also provides a base for accounting the natural resources availability and its utilization. LULC changes involve changes due to human management of ecosystems that alter the biogeochemical cycles, climate, and hydrologic regime of a primeval ecosystem (Ramachandra and Savitha, 2008). The need for greater food production, with the dramatic growth in the world population, has led to a massive increase in cropland. Almost 40 percent of Earth's land surface had been converted to cropland and permanent pasture by the 1990s. This conversion has occurred largely at the expense of forests and grassland (Ramachandra et al., 2007). Foley et al., (2015) highlights how the advent of the industrial era with fossil fuel burning transformed a large proportion of the planet's tropical forests, resulted in 35% of the human-induced $CO_2$ equivalents in the atmosphere traced to the sum of LULC changes as compared to earlier deforestation and irrigation sectors sources of human-induced greenhouse gasses.

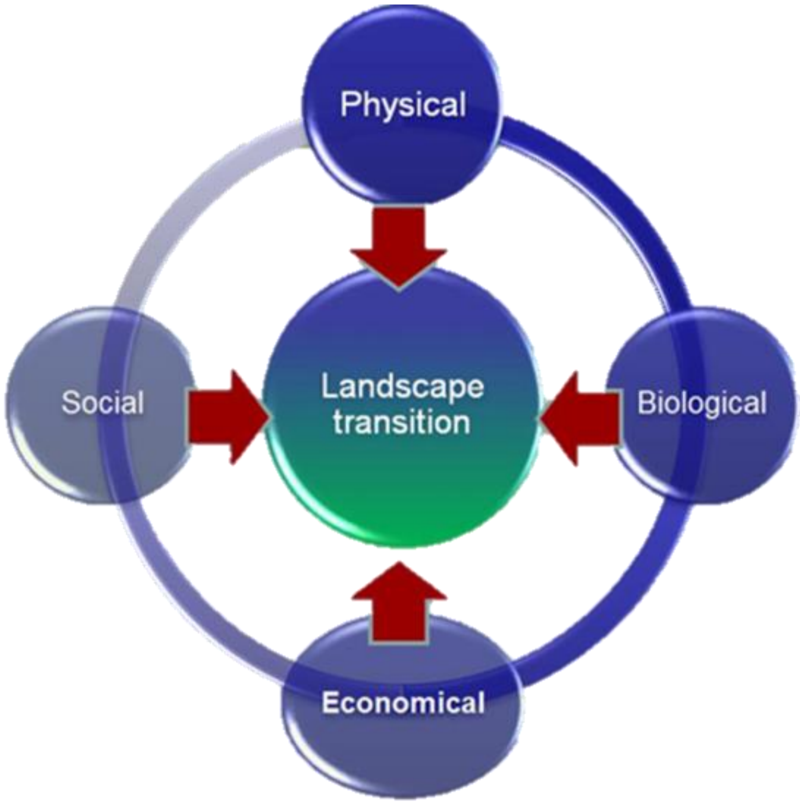



Figure 1.2. Landscape transition and its drivers

LU activities, primarily for agricultural expansion and timber extraction, have caused a net loss of 7 to 11 million $km^2$ of forest in the past 300 years. Forests cover globally about 31% as opposed to 50% of the earth's land area 8000 years ago (FAO, 2011) with the expanded extents of croplands, pastures, plantations, and urban areas. Hansen et al., (2013) have quantified global forest change and loss using satellite data from 2000 to 2012 at a spatial resolution of 30 meters. The study has highlighted global forest loss (2.3 million square kilometers) and gain (0.8 million square kilometers). The annual loss of forest cover was about 7 million hectares and an increase in agricultural land area was 6 million hectares since 2000-2010. The loss of forest cover was more in South Asia, Central, and South America, sub-Saharan Africa regions due to several factors (FAO, 2016). The unsustainable use of the planet's resources will have potential effects on biogeochemistry, water availability, food security, climate, and socio-economic systems (IPCC, 2007). LULC changes are driven by many factors that intensify the degradation of the ecosystem on the continuous process with time across space. Understanding these consequences is essential for the sustainable management of ecosystems towards biodiversity protection and human well-being.

## 1.4. Fragmentation of forest landscape

Forests, one of the most prime natural resources on the Earth provide vital benefits in socio-economic development and environmental protection for human beings in day to day life. Ecological connectivity would counter the determinant effects of fragmentation that facilitates the movement of ecological flows among source patches, to link among patterns, process, and functions in a landscape (Wu et al., 2017). The changes in forest structures and disrupting connectivity at an alarming rate highlight the consequences of anthropogenic activities rather than the natural process of climate change. The human-induced activities like unscientific timber logging, intensified agriculture, forest fire, and infrastructure development are causal factors for alterations in the forest structure. Forest fragmentation results in numerous isolated forest patches with the replacement of native forests. Fragmentation occurs when large expanses of forests are converted into smaller tracts of forest surrounded by other land uses, disrupting the continuity of the natural landscape (Roy et al., 2013). Munroe et al., (2005) highlighted potentially detrimental impacts on the provision of services and functions of forest ecosystems through the statistical relationship between landscape fragmentation and various socio-economic, biophysical, and spatial variables of the individual, privately owned parcels in Monroe County, Indiana.

Forest fragmentation is an outcome of deforestation and disturbance with subsequent edge effects, extending deep into remaining forest areas. Detrimental edge effects extend into interior forest areas from these transition zones. Edge creation will alter both, forest structure and composition of interior or intact contiguous forests as well as forest edges. The edge effect will lead to the often perishing of large trees within 300 m of the forest edge being replaced by densely spaced short-lived pioneers (Laurance et al., 2002), resulting in the decline of biomass (Harper et al., 2005), paving way for invasion. The negative impacts of edge effects on ecosystems include shifts in plant and animal community composition and changes in diversity

(Cagnolo et al., 2006; Joshi et al., 2016), seed dispersion, predation, fire susceptibility, altered microclimate, and increased carbon emissions (Laurance et al., 2002). A theoretical framework (Figure 1.3) has been prepared by identifying the process of fragmentation to explain the fragmentation stages with respect to drivers. The deforestation (led by the socio-economic process), agriculture expansions, human-induced forest fires are the prime drivers of forest degradation. The natural process is denoted as negligible effects. The earlier stages of forest fragmentation will lead to changes in forest structure and composition. The evergreen forests are turned to semi-evergreen due to changes in its microclimate, habitat, etc. Subsequently, edges will become prominent with higher light availability and loss of soil moisture due to disturbances. This will further directly impact seed dispersal, reduces the quantity of seed germination, while allowing invasive species, weeds, etc. These changes in forest structure and composition make fragments prone to vulnerabilities such as fire, etc. The fragmentation with cascading effects will disrupt many basic ecological process ultimately eroding or disturbing the ecosystem goods and services on which humans directly depended over larger areas.

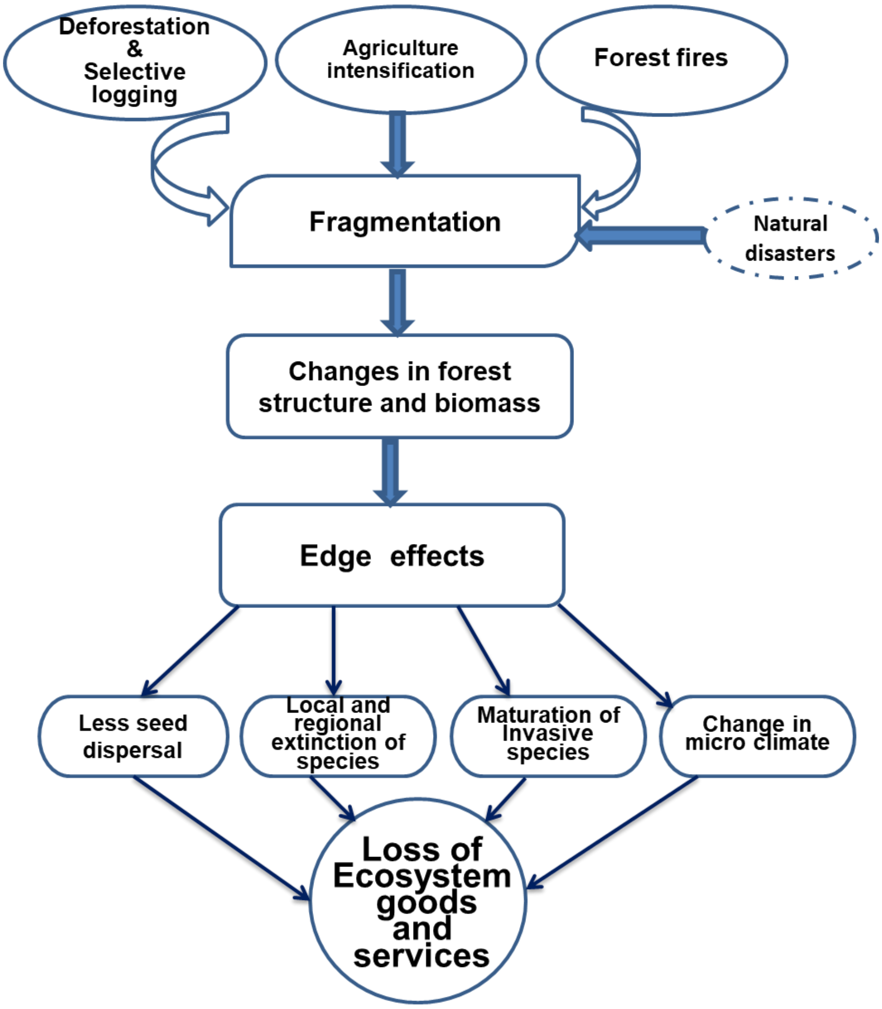



Figure 1.3. A theoretical framework of forest fragmentation and its adverse effects

## 1.5. Geospatial techniques for monitoring landscape dynamics

Advancement in procedures to integrate temporal information of LULC change matching the relevant ecological unit, addressing socio-political-economic units is still a challenge for researchers concerned with landscape science. Remote Sensing (RS) and Geographic Information System (GIS) are innovative tools for monitoring the Earth's surface in a spatially continuous and highly consistent pattern. The landscape spatial patterns assessment over a long period has become possible due to the availability of multitemporal coverage of RS images, which also aided in understanding the drivers of dynamics. Various parameters such as spatial (linear separation between two objects), spectral (the number and dimension of the specific wavelength interval (bands) in the electromagnetic spectrum), and temporal resolutions (how often the remote sensing system records the images of a particular area) are essential parameters in analyzing landscape dynamics. RS has become a prime tool for detection and characterization of change in key resource features, which allows resource managers to monitor landscape dynamics over large areas, including those areas where access is difficult and facilitates extrapolation of expensive ground measurements for monitoring and management (Li et al., 2003).

RS data along with GIS and GPS (Global positioning system) helps in the effective measure of landscape dynamics (Ramachandra et al., 2012a) in a cost-effective manner (Lillesand et al., 2014). Satellite RS technology has the ability to provide consistent measurements of landscape conditions, allowing detection of both abrupt changes and slow trends over time for resource managers (Kennedy et al., 2009; Fraser et al., 2009). LULC changes reflect the most significant impact on the environment due to human activities or natural forces revealed effectively by remote sensing for getting a wide impression (Zhou et al., 2008), potentially allowing for management strategies targeted toward cause rather than simply the symptoms of the cause (Kennedy et al., 2009). LU change is driven by a variety of factors, both environmental and societal, which are also scale-dependent, changes will be unnoticed if the spatial resolution of data is too coarse or if the extent is too small. So, the selection of appropriate resolution also plays a primary role. Hansen and Loveland (2012) reviews how the increased availability and improved quality of spatiotemporal RS data enabling the creation of LC maps over greater extents with the innovative analytical techniques, to monitor and analyze forest fragmentation of large areas in a digital format at a timely and cost-effective way as compared to expensive and detailed field surveys. De Leeuw et al., (2010) highlight how remote sensing and its allied developments have helped in framing policies to protect the environment. The improvement in space technologies since 1970s, has been aiding in framing environmental policies and created more demand for earth observation products. The temporal data helps in quantifying the extent of problems and which can be well communicated though interpreted maps or images followed by series of reports, that assist regulatory organizations to frame policies (Wu et al., 2007). The global scale policy instruments such as Intergovernmental Panel on Climate Change (IPCC) assessment reports have been more supported by Earth Observatory's data, which helped to contribute to framing policies on climate change adaptation and mitigation, management of forests, trade and arresting deforestation. Revenga et al., (2005) discusses how the current Earth Observation products across the globe help in assessing the state of the environment and landscape dynamics and farming effective policies.

## 1.6. Modeling landscape dynamics

The landscape is an interdependent, structurally complex system of heterogeneous elements, responds based on nested hierarchies among agents and their environment. Complexity is due to the presence of heterogeneous features of varied spatial aspects of landscape ecology. The comprehensive knowledge of LULC has become increasingly important for planning and visualization of likely changes to overcome the problems of haphazard and uncontrolled development (Kennedy et al., 2009; Rounsevell et al., 2012). Modeling (mimicking the real world) and visualization (simulation and prediction) of the landscape have become critical for the decision making and planning process for sustainability and efficient resource management. Modeling and visualization are considered as a conceptual, symbolic, or mathematical approach of the deriving relationship between the driving forces such as socio-economic, political, technological, natural, and cultural factors of a complex system and their influence on the landscape (Bürgi et al., 2004; Verburg et al., 2006). LULC change models combine two key components into an integrated system. The first component is **input** to the model that represents the landscape over which actors make decisions. The second component is **model and its validation** that describes the key actors with many discrete, interacting components, the behavior of the system, and decision-making architecture. These two components are integrated through the specification of interdependencies and feedbacks among agents in a landscape.

Modeling and visualization of landscape dynamics help in understanding complex ecological systems, especially that account for spatial process and spatial dynamics over long temporal scales and large spatial scales. Models of landscape change are extensively used to study the effects of both natural and human process on landscape patterns and ecological status. Modeling at the landscape level helps informal organizing of data, which provides a framework for comparison across systems. Landscape projection for future state necessitates understanding past trends, current LU status, change process, and their feedbacks. Modeling helps in addressing real or hypothetical 'what if' scenarios, and helps to interpolate or extrapolate an understanding of various ecosystem process, especially to extrapolate across scales in predictions about future landscape states. Landscape modeling integrating ecological and management issues provide insights for planning purposes in the management of an ecosystem. Landscape modeling also integrates ecological and management issues for research and planning purposes in the management of an ecosystem. Antrop, (2005) emphasized the need for understanding past landscape trends, process, and management as they offer valuable knowledge for more sustainable planning and management for future landscapes. Modeling requires the incorporation of credible assumptions, scenarios, etc. with the multiple datasets of socio-economic, ecological process, dynamics, and interactions (Gaucherel and Houet, 2009) to avoid negative consequences of anthropogenic activities.

Modeling allows identifying the most influential driving factors acting at a landscape and help in the management of where, when, and how to avoid major impacts to the system. The concept of considering the spatial distribution of ecosystem functions and services in modeling has become an effective approach in framing and identifying trade-offs and synergies within natural resource assessments (Wu et al., 2017), conservation planning (Maes et al., 2012; Schulz and Schröder, 2017). Cowling et al., (2008) developed an operational model for mainstreaming ecosystem services into local land use decisions and management. The ecosystem approach highlights the role of assessment from both the social and biological perspectives, as well as the need for an economic valuation. Stakeholder involvement and the establishment of learning are seen as essential in developing adaptive management strategies and forecasting (Garrido et al., 2017).

## 1.7. Modeling: Need, evaluation, and approaches

LULC changes are persistent with heterogeneous and also often express unique patterns, which can further influence the ecological process and flows in a landscape (Turner, 2010). These changes are needed to understand and visualize for framing effective policies and approaches for reducing abrupt changes to attain sustainable developmental goals. But, the current understanding of growth in forest landscape is limited due to the nature of changes at broad spatial and temporal scales. The disturbance corridors and their responses on biological, physical, and chemical process substantially limit the ability to understand future changes. The management of forest landscape in the absence of accounting or visualizing future changes provides either biased estimations or underestimates the process of changes and its impacts on the biogeophysical process. Predicting likely changes will help in formulating suitable policies, evaluating decisions, exploring possible desired forest protection and usage of resources. This necessitates the requirement of modeling by accounting complex ecological process with scientific assumptions and logical appropriation. Modeling helps to expand the knowledge base to forecast changes and approaches or policies required to mitigate changes by examining the large quantum of spatial and non-spatial data at a temporal scale. Models being used are (i) non-agent based models (Markov Cellular Automata - popular technique) and (ii) agent-based models (ABM) which account for the role of agents or decisive variables of transitions. Each agent represents complex behavior, may have their model of environment and interactions. Agents are established by defined rules, which represent the rational behavior of the system and the relationships that exist among these agents, which forms the major challenges to the model to capture. Though it is mathematically powerful and rigorous, these models do have short comes with respect to agents as they will have limited knowledge about future developments in the model and uncertainty cannot be captured explicitly in the decision process (Groeneveld et al., 2017). Models can be categorized in multiple ways based on theoretical and empirical considerations, the methods employed, and intended applications. During the past four decades, an ample variety of models emerged from the research community for the analyses and potential simulation of LULC changes for proposing alternative scenarios based on simple regression to advanced dynamic programming.

LULC change simulation and forecasting have been made based on various computer simulation models. Baker (1989) characterized models based on a scale such as whole landscape models, distributional landscape models, and spatial landscape models. The research essentially explains how the finest scale governs the simulation at a regional scale or global scale. Briassoulis (2000) has classified models according to the modeling techniques such as statistical/econometrics, spatial interaction, optimization, integrated, and 'other' modeling approaches. Further, Lambin et al., (2001; 2003) have distinguished empirical-statistical, stochastic, optimization, dynamic simulation, and integrated modeling approaches and their significant usages according to the region and application. The research focused on how the current agriculture trend can be forecasted effectively for the future and also accounts for the lacunas in the projecting future LU. Agarwal et al., (2001) used 19 various modeling techniques according to a three dimensional (3D) framework: space, time, and human decision making. The study highlights how the simulation was governed by agent and human decision making based on a specific application. Verburg et al., (2004) has discussed computer simulation models according to six features: level of analysis, cross-scale dynamics, driving factors, spatial interaction, neighborhood effects, temporal dynamics and level of integration. Heistermann et al., (2006) has categorized 18 computer simulation models analyzing land suitability and spatial interaction according to geographical, economic, and the integration of both. The models were reviewed based on major achievements, deficits, and potentials of existing regional to global scale LULC modeling and its implementation. The well-acknowledged modeling techniques are (i) Equation Based Models (EBM), (ii) Statistical Techniques, (iii) Expert Models, (iv) Evolutionary Models, (v) Economic Models, (vi) System Models, (vii) Spatial Interaction Models (SIM), (viii) Genetic Algorithms (GA), (ix) Optimization Techniques, (x) Cellular Models, (xi) Hybrid Models, (xii) Multi Agent System Models (MAS), and (xiii) Microsimulation Models.

The National Research Council (NRC) in the year 2014 has proposed a classification of the approaches for modeling LULC changes based on theoretical and empirical considerations. These were based on classification methods employed and the type of application. This classification proposes five categories, ranging from the models based on patterns to the models based on the agents of change, the latter of which are mostly interested in explaining the process leading to changes. Now, the sixth category has emerged which includes hybrid approaches (Table 1.1)

Table 1.1. Various modeling approaches and their limitations

| SNO | Modeling technique | Description | Examples | Limitations |
|---|---|---|---|---|
| 1 | Statistical/ Mathematical Models & Machine Learning | Generally automatized, software programs recognize and reproduce the patterns of change. They rely on equations that seek a static or equilibrium solution. | Set of equations based on theories of population growth and diffusion; cumulative LULC change over time | A numerical or analytical solution to the system of equations must be obtained; complexity; Simulation models with a combination of mathematical |

| | | | | |
|---|---|---|---|---|
| | | Based on rigorous statistical methods, use observations of changes to establish space and time relations between change and drivers. | | equations with other data structures should be well-calibrated. |
| 2 | Spatially Disaggregated models | Assess the econometric models in a structural and reduced manner to identify the causal relations having an influence on the spatial equilibrium of land systems. | Epidemiological studies | Static; Region specific; Intricate to account multiple driver's influence; operate at a very coarse spatiotemporal scale. |
| 3 | Economic Models | Use models of partial or general structural equilibrium to represent the demand of land by economic sectors within the regions based on general economic and commercial activity. | Linear programming linked to GIS information on land parcels | A numerical or analytical solution to the system of equations must be obtained; they account only to a limited extent for physical resource constraints, they do not commonly reflect the impact of demand on actual LU change process, and they rarely represent human behavior (which is not reflected through price mechanisms). |
| 4 | Cellular models | Integrates maps of LC and LU suitability, taking into account the neighborhood effect and information on the amount of change based on stationary transition probabilities (Parker et al., 2003; Adhikari and | CA_MARKOV for vegetation loss; forecasting urbanization | Static; Dynamic changes of agents were not accounted; forecast depends on neighbourhood land class; limited ability to reflect feedbacks in the system; good for regional scale than global scale. |

| | | | | |
|---|---|---|---|---|
| | | Southworth, 2012; Behera et al., 2012). | | |
| 5 | Agent-Based Models (ABM) | Simulate the heterogeneous decisions and actions of actors that interact on the land surface, which leads to LULC change. Also well known as rule based knowledge systems. Agent-based models focus on human actions of autonomous, interactive, share communication of decisions that link behavior to the environment (Verburg et al., 2006). | Rule based landscape prioritization; urbanization forecast; Symbolic artificial intelligence approaches such as expert systems | It can be difficult to include all aspects of the problem domain, which leaves room for gaps and inconsistencies; good for even global scale, but leads to complexity. |
| 6 | Hybrid Models | Includes applications combining different approaches in a single model or modeling framework. Very effective as it integrates qualitative knowledge in a quantitative fashion that enables the modeler to determine where given LUs are likely to occur. It has the ability to represent individual decision making and temporal and spatial dynamics effectively over previous models (Mosadeghi et al., 2015). | Integration of fractional agent-based and non-agent based (Fuzzy-AHP-CA); Cellular model tied to a system dynamics model | Complexity arises in behavior during the expert's judgment which integrates the sub-models within. Does not represent heterogeneous actors, institutional effects on decision making. |

## 1.8. Comparison of models: Spatial / Non-spatial and Static / Dynamic modeling

Spatial and non-spatial distinction is an important first division between different model types since it largely determines the type of research questions the model may answer for that application. Spatial models aim at spatially explicit representations of LULC changes over a spatial detail, in which LU change is indicated for individual pixels or at an administrative unit. This group of models is, therefore, able to explore spatial variation in LU change and account for variation in the social and biophysical environment. A few examples of spatial models are well-known models such as the Conversion of Land Use and its Effects (CLUE) model, the SLEUTH model (Slope, Land use, Exclusion, Urban extent, Transportation and Hill shade) (Silva and Clark, 2002) and Geographical Modeling (GEOMOD) (Pontius et al., 2001; Echeverria et al., 2008), Fuzzy-AHP-CA (Fuzzy-Analytical Hierarchy Process through Cellular Automata) (Keshavarzi et al., 2010; Mosadeghi et al., 2015). The group of non-spatial models focuses on modeling the rate and magnitude of LU changes without specific attention to its spatial distribution (Irwin and Geoghegan, 2001). Daniel et al., (2016) highlight the advantages of spatially explicit stochastic simulation models as compared to traditional spatial approaches of non-agent based models such as Markov Cellular Automata (CA), etc. The State-and-transition simulation model (STSM) has evolved as an advanced practice of spatially explicit stochastic simulation models to forecast landscape dynamics, well suited for characterizing ambiguity in model projections. The landscape has been divided into a set of discrete spatial units and simulates the discrete state of each cell forward as a discrete-time-inhomogeneous process to represent multiple types of transitions between pairs of states. Forest landscapes are of high degree complex ecological systems with spatial heterogeneity, intricate feedbacks through time, process that operate at a variety of scales. So, the selection of a relevant model with appropriate data is critical. Bürgi et al., 2010 articulates monitoring and modeling of landscape dynamics strongly depend on the scale and objectives of the planned applications by reviewing several research works and the hypothesis applied based on empirical methods. Thus, landscape change models should be appropriate for simulating identified social, economic, and ecological process, and their dynamics and interactions that shape landscapes (Baker 1989; Gaucherel and Houet 2009). The Global Land Project (GLP), ascertains the significance of integrated landscape modeling to understand the human-environmental system in detail with the International Geosphere-Biosphere Programme (IGBP) and the International Human Dimensions Programme on Global Environmental Change (IHDP). The series of workshops and debates concluded the need for the design of integrative models of natural and social systems in land change science for agricultural systems, urban systems, forest ecosystems in both developed and developing countries (Moran et al., 2005).

Verburg et al., (2010) illustrate the application of multiple models (Conversion of Land Use and its Effects; Integrated Model to Assess the Global Environment) at different scales to explore possible landscape trajectories in Europe for the year 2030 based on scenario conditions in terms of demographic, economic and policy change. Policy intervention aims to counteract the negative consequences of these changes and provide incentives for positive developments. Gibon et al., (2009) illustrate the need for an integrated and participatory approach that considers the socio-ecological process in the modeling and elaboration of scenarios for framing effective policies. Regarding the exploration of alternative land change futures, Verburg et al., (2010) assess possible future landscape changes based on contrasted scenarios. This provides a good indicator of likely future land configurations. Simulation and prediction of LU changes help to explore possible future, decision support systems to inform policy formulation. The results set indicators of ecological sustainability, or vulnerability of places and people to delimit the envelope of possible landscape futures and to define the plausibility of the occurrence of futures that connect local to global scales.

Wu et al., (2002) highlight integrating hierarchy theory, as well as empirical evidence help in addressing the complexity of modularity in the structure and functionality of heterogeneous landscapes in ecosystem modeling. Research initially focuses theoretical basis for the modeling approach with the hierarchical patch dynamics (HPD) paradigm and the scaling ladder strategy and then describes the general structure of a hierarchical urban landscape model (HPDM-PHX) with the population dynamics model. Evans et al., (2001) present a non-spatial model for deforestation in Altamira, part of the Amazon region. This parcel-level model calculates the utility of specific LU activities to identify those LUs that are most optimal at each time point, and labour is allocated to these activities based on the availability of household and wage labour with the effective incorporation of non-spatial data. Serra et al., (2008) explains how to model with non-spatial data by Multiple Linear Regression (MLIR) techniques. The research also highlights of effective spatial statistical tool alternative to MLIR used in LCLU change analysis is Multiple Logistic Regression (MLOR), mainly when dependent variables are dichotomous (presence or absence of a specific phenomenon) applied to explore what were the main driving forces for a specific LULC increase or decrease.

The dynamic and static division of modeling is another prime aspect of LULC change based on their temporal characteristics. Static models can be used to test knowledge of the driving factors of LU change, while dynamic models are used for projections of the future. Dynamic models incorporate temporal dynamics of LU systems, represented by agents and their behaviors between LUs in system evolution change trajectories. Static models such as coefficients of a regression model explaining the spatial distribution of LU changes as a function of several hypothesized driving factors are widely applied to predict future LULC changes and they often do not account for feedbacks and path dependencies (Overmars and Verburg, 2005). Dynamic LU change is well conceived by spatially explicit dynamic models such as multi-agent models, GEOMOD, CLUE and SLEUTH. ABM is an approach well-conceived as a dynamic modeling technique in recent years, mainly because it offers to incorporate the influence of human decision making on LU by accounting formal, spatially explicit social interaction and adaptation at different levels. Matthews et al., (2007) highlight the advantages of dynamic ABM techniques in individual decision-making entities and their interactions, to incorporate social processes and influences on decision making. The work tries to link social and environmental processes based on (i) policy analysis and planning, (ii) participatory modeling, (iii) explaining spatial patterns of LU, (iv) testing social science concepts, and (v) explaining LU functions. Studies of Poelmans and Van Rompaey, (2009) and Liu (2012) highlights dynamic hybrid models such as Fuzzy-AHP-CA estimations accounts for the influence of factors on LU based on distance relationship which aid in the spatial allocation process of the simulation and model future changes also helps to overcome the limitations of standalone CA model’s neighborhood effect and thereby improves relative probability. Myllyviita et al., (2011) has provided a detailed review of various modeling approaches and ascertain that no single method can commendably offer a decision support process. Traditional non-agent based, agent-based models usage cannot be generalized across the various landscapes. Whereas, hybrid methods are potential tools to help in structuring the problems of various landscapes, includes the participation of stakeholders, improve data quality, and offers the systematic evaluation of alternatives under various scenarios. Table 1.2 highlights the basic differences between non-agent (static) and agent-based (dynamic) modeling techniques.

Table 1.2. Difference between non-agent-based and agent-based modeling

| SNO | Non-Agent based modeling | Agent-based modeling |
|---|---|---|
| **1** | Computationally very simple as it depends on fixed neighborhoods (grid), which interact with each other and environment. | Computationally complex due to nearest neighbors (vary with time), as the agents are free to move, communicate as well as interact with the environment contributes to more realistic situations. |
| **2** | Follow simple rules to update state at any time depending on neighbourhood | Follows complex rules, which govern the state based on multiple object interactions and individual attributes. |
| **3** | Limited applications due to the simplest possible computation | Boundless applications owing to attributes or characteristics, depend upon the issue to be modeled |
| **4** | Fails to deal with social phenomena of a system to be modeled | ABM will give more realistic simulations, especially when dealing with social phenomena and complex adaptive systems. |
| **5** | Users need not have sound programming ability. | Users need to have sound programming ability to capture temporal and complex agent's behavior. |
| **6** | Transitions of each state depend on cell history | Transitions of each state need not depend on cell history, decision maker's choices alter the landscape or state. |
| **7** | Non-agent-based models are very strong at representing local spatial process but the very week at representing global and temporal changes in agents | Agent-based models are very strong representing local as well as global and temporal changes in agents |
| **8** | The simulation does not allow feedback between the environment and the non-spatial process. | Simulation approach allows for feedbacks between dynamic social and environmental process. |

## 1.9. Challenges associated with accuracy and validation of modeling

The modeling techniques require the validation of uncertainties or adequacy of analysis as errors can go unrecognized and produce biased or erroneous results (Batty and Torrens, 2001; Xu et al., 2009). An enormous volume of raw data in terms of the census, remote sensing or station measurements are increasingly processed by modeling, the inconsistencies might upsurge as the quality of data is poor. In addition, assumptions were made to define a bounded and tractable system of the dynamic landscape, and these assumptions can have important effects on model outcomes. For example, assumptions of imprecise influential process considered, impose of inappropriate spatial resolutions, scales (Holland et al., 2007). Errors might also occur in incorporating the complexity of interactions in modeling unexpected non-linear behaviors (Filatova et al., 2016). The selection of inappropriate thresholds in accounting agent's behavior also results in inaccurate predictions. Thresholds are used as a surrogate for measurements of the model's behavior that indicate a system (Barange et al., 2008). The imprecise thresholds can also shift slowly changing variables to change abruptly and result in chances of crossing them in one domain and scale react dynamically with the changes in other domains and scales. When modeling thresholds are explicitly specified, rigorous treatment of feedback loops in the model that adjusts the values of the thresholds may be needed (Kinzig et al., 2006). Predictions can only be accepted if the relationship between the independent and dependent variables expected to remain constant.

Synes et al., (2016) elucidate the choice of validation can be dependent on the type of model being used. For pattern-based approaches, verification and validation are relatively clear as pattern matches, then the model is verified and calibrated to a subset of that pattern. But, this approach to predict patterns in new geographic or climatic studies validation of final predictions is not possible (i.e. to test the model's predictive accuracy on independent data). Methods for assessing the accuracy of various datasets validation include the area under the curve (AUC), the Pearson correlation coefficient ($r^2$), comparing categorical maps through Kappa indices, etc., (Visser and De Nijs, 2006; Olofsson et al., 2014). Whereas, process-based models experience difficulties as they are not fully understood, often required to incorporate process, and also difficult to validate. If assumptions made as process models are static, then validation is simple and for dynamic process models validation is critical and requires rigorous exploration of model behavior through experiments or sensitivity and uncertainty analyses (Holderieath, 2016). Model verification and validation requires cautious judgment as model design and usage, with various analytical techniques for an understanding of model performance and validity. Apart from selecting suitable techniques, another constraint exists in the spatial and temporal context. They may be primarily experienced at large areas, difficulty in replicating these, even "sampling" and analyzing replicates, large-scale process may operate slowly, and even with good data too complex a system to predict behavior.

## 1.10. Landscape modeling: Case studies from India

The excessive modifications in the ecosystem due to increased human activities are examined by the scientific community across India. The studies have focused to address the status and impacts of landscape transition at a regional scale. Major studies focused on the local scale (micro-level) due to data availability. Forest cover transitions at the local scale are attempted by various researchers and few studies examined forecasting of changes (Table 1.3). Chaturvedi et al., (2011) have assessed climatic condition by using regional climate model of Hadley Centre (HadRM3) and Dynamic Global Vegetation Model (DGVM) IBIS for $A_2$ (High Green House Gas (GHG) emissions predicted till 21$^{st}$ century) and $B_2$ (Moderate GHG emissions when compared to $A_2$ scenario) scenarios to understand the impact of simulated climate change on forest ecosystem in India. The studies conducted in India had some limitations such as the coarse resolution of the data, use of BIOME which is an equilibrium model that does not capture the transient response of vegetation; thus, they have used DGVM to overcome these issues. Chitale et al., (2014) have created a model using MaxEnt software to assess the contribution of physiographic, climatic and disturbance factors in the future distribution of endemic plants, considering five combinations such as (i) only climate variables, (ii) disturbance and climate variables, physiographic and Climatic variables, (iii) only physiological variables, (iv) only disturbance variables, (v) disturbance and physiographic variables. The study predicts regions with cooler climates and higher moisture availability could serve as refugia for endemic plants in future climatic conditions such as Western Ghats, Himalayas, northeast India, etc. Tewari et al., (2014) have developed a dynamic growth model for teak plantation considering four state variables such as dominant height, number of trees per hectare, basal area, and a measure of site occupancy.

Renard et al., (2012) have used the MODIS hotspot database and MaxEnt algorithm to understand the environmental controls regulating the spatial distribution of forest quantitatively between 2003 and 2007. They have used independent contribution of topography, climatic and vegetation and developed a fire susceptibility model for the Western Ghats. Adhikari and Southworth (2012) have used the CA-Markov model to simulate the forest cover changes of

Bannerghatta National Park. They have developed four models of CA-Markov considering i) No policy intervention (Used 1973 and 1992 to predict 2007); ii) Policy intervention (used 1992 and 1999 to predict 2007); iii) Combined policy intervention and no policy intervention (used 1973 and 1999 to predict 2007); and iv) No policy intervention (used 1973 and 1992 to predict 1999). Mukhopadhaya (2016) has used the CA-Markov model to understand the deforestation analysis of the Doon valley, Dehradun. They have used the CA-Markov model as it takes into account both the spatial and temporal domain into account for predicting. Mondal et al., 2016 validated CA Markov LULC change prediction results with a statistical test of independence ($K^2$). The Markovian suitability was checked using the hypothesis of the goodness of fit ($Xc^2$) with the hypothesis established as actual transition probability of matrix from 1987 to 2007 years. The results indicate LULC change trends are dependent on the previous development of land. The calculated value of $\mathrm{Xc}^2$ is 0.52 and it is very less than significance 22.4 on critical region 0.05 with 13 degree of freedom. This study concludes that CA Markov model has the ability to specify the grid cell level location of future change and can be used as a potential technique for LULC change prediction results.

Giriraj et al., (2008) have simulated LU of the Kalakad-Mundanthurai Tiger Reserve using GEOMOD framework to find out the LU in 2020. They have used ABM (GEOMOD) which takes various parameters at the local level also into account for better prediction results. Krishnanjan et al., (2014) have performed biodiversity hotspot modeling and temporal analysis of Meghalaya. Then they compared fragmentation, homogeneity, interspersion, and disturbance in the bio-rich area over the transition to identify/delineate hot-spots. Kumar et al., (2014) have used a logistic regression model (LRM) to predict the forest cover dynamics in the Bhanupratappur Forest division, Chhattisgarh. They have used LRM because it takes into consideration factors like distance from the roads, settlements, topography, forest edge which are driving factors as independent variables.

Areendran et al., (2011) have developed a geospatial modeling technique to assess elephant habitat suitability and corridors in Chattisgarh. They have identified 3 major factors (Dense forest, Open forest, and non-forest vegetation types) and then they were divided into 3 levels of suitability (Proximity to a water body, Proximity to human habitation and Suitability) and they were assigned weights based on Satty's multi-criteria evaluation AHP (Analytic Hierarchy Process). Singh et al., (2015) have used 4 models to predict the environmental niche of swamp deer in Kanha Tiger Reserve, Madhya Pradesh. The models such as GARP (Genetic Algorithm for Ruleset Production), SVM (Support Vector Machine), ED (Environmental Distance), CSM

(Climate Space Model) uses bioclimatic indices along with DEM, results of all models were combined to get optimum result. Bharath et al., (2018) studied urbanization trends in Indian metropolitan cities of Delhi, Mumbai, Pune, Chennai and Coimbatore, through CA-Fuzzy-AHP model considering the influence of agent(s) of urban growth through soft computing techniques. The results express as post-2010 urban growth is more likely infilling, suggesting a complete concretization of the core area and further spread beyond its boundaries. This emphasizes essential attention from local authorities at natural balances and planning in terms of the provision of basic amenities to all stakeholders. Reddy et al., (2017) have used temporal RS data and modeled using the Artificial Neural Network of Land Change Modeller to predict the spatial pattern of past forest dynamics in India (predicted forest cover in 1880).

Table 1.3. Review of modeling studies in India

| Sno | Study area | Modeling technique | Description | Focused Aspect | Scale of study | Reference |
|---|---|---|---|---|---|---|
| 1 | India | Climate model of Hadley Centre (HadRM3) and dynamic global vegetation model (DGVM) IBIS | For $A_2$ (High GHG emissions predicted till 21st century) and $B_2$ (Moderate GHG emissions when compared to $A_2$ scenario) scenarios to understand the impact of simulated climate change on forest ecosystem in India | Climate Change scenarios | Global | Chaturvedi et al., 2011 |
| 2 | India | MaxEnt-physiographic, climatic distribution model | Future distribution of endemic plants in India is predicted based on climatic conditions, disturbance and physiographic variables response. | Species Distribution | Global | Chitale et al., 2014 |
| 3 | Karnataka | Dynamic growth model | Tree growth estimations based on dominant height, number of trees per hectare, basal area, and a measure of site occupancy | The mathematical model for Biomass Quantification | Regional | Tewari et al., 2014 |
| 4 | Bannerghatta National Park, Karnataka | CA-Markov model | Simulation and projection of forest cover changes based on various policy intervention scenarios | Future Forest cover status | Local | Adhikari et al., 2012 |
| 5 | Doon valley, Dehradun | CA-Markov model | Simulation of forest cover and predicting deforestation trends in future | Future Forest cover status | Local | Mukhopadhaya, 2016 |

| | | | | | | |
|---|---|---|---|---|---|---|
| 6 | Kamrup Metropolitan, Assam State | CA-Markov model | Validating CA Markov LULC change prediction with a statistical test of independence ($K^2$) using the hypothesis of the goodness of fit ($Xc^2$) | Urbanisation | Local | Mondal et al., 2016 |
| 7 | Kalakad-Mundanthurai Tiger Reserve | GEOMOD | ABM for predicting future forest cover in the tiger reserve. | Forest cover change | Local | Giriraj et al., 2008 |
| 8 | Bhanupratappur Forest division, Chhattisgarh | Logistic regression model (LRM) | Regression based estimation of forest cover changes based on agents. | Forest cover change | Local | Kumar et al., 2014 |
| 9 | Chattisgarh | Analytic Hierarchy Process (AHP) | Identifying habitat suitability for elephant corridors based on weightages of various factors. | Forest cover change | Local | Areendran et al., 2011 |
| 10 | Kanha Tiger Reserve (KTR), Madhya Pradesh | GARP (Genetic Algorithm for Ruleset Production, SVM (Support Vector Machine), ED (Environmental Distance), CSM (Climate Space Model) | Consideration of bioclimatic indexes and DEM in modeling for an optimum solution. | Forest cover change with respect to bio geo-climatic variable's response | Local | Singh et al., 2015 |
| 11 | India (Metropolitan Cities) | CA-Fuzzy-AHP | Modeling and prediction of the spatial pattern of urbanization in Delhi, Mumbai, Pune, Chennai and Coimbatore for with a buffer to account peri-urban growth. | Peri-urban growth and sprawl | Local | Bharath et al., 2018 |
| 12 | India *(emphasis on selected regions)* | Land Change Modeller (LCM) | Historical forest cover analysis for the year 1880 based on current LU maps. | Historical forest cover | Regional | Reddy et al., 2017 |

## 1.11. Policy initiatives for monitoring and management of landscapes

Good governance purely depends on policies and the instruments used for their implementation. The prudent management policies scrutinize the required information under various probable scenarios before implementation. Esty (2004) articulates the policy process under various stages as (i) identification of a problem and its formulation for better understandability, (ii) implementation under various scenarios, (iii) control and revision, (iv) evaluation of policy. The systematic conservation planning approach has been conceived as a vital tool for protecting the nature around the world in the era of climate change. Competition for natural resources with the landscape transformations have resulted in increased conflicts and reduced the biological and economic productivity with ecosystem degradation (Ramakrishnan, 2000; Moen and Keskitalo, 2010). The sustainable management of forest landscapes requires detailed policies, which include monitor and instruments for its implementation. This necessitates a comprehensive planning process considering driving forces of forest changes with mitigation measures through suitable policies.

Intergovernmental Panel on Climate Change (IPCC) is an international initiative to address the policy issues concerning global climate change based on the emissions scenarios up to the year 2100. The major objectives of IPCC scenarios are to address the global problems by guiding or strengthening scientific investigations as well as administrative endeavors with a set of solutions or alternatives. In this regard, Special Report on Emissions Scenarios (SRES) by IPCC addresses climate change, its impacts, and adaptation and mitigation options (Figure 1.4), which has formed the basis for analyses by the wider research and policy community of climate change and other environmental problems (Girod et al., 2009). SRES scenarios form a reference point for the political and societal discourse on climate change thereby policymakers can explore probable future developments in the global environment (Nakicenovic et al., 2000; IPCC, 2008). Scenarios of SRES portray the numerous driving forces such as population growth, socio-economic development, and their role in climate change. It also emphasizes on various future scenarios based on the source-sinks for greenhouse gas, the underlining energy systems, LU changes as well as deforestation. The scenarios are majorly grouped under four narratives (A1, A2, B1 & B2), which further subdivided based on different deforestation trends, environmental conditions, demography, socio-economic activities, and technological advancements. Figure 1.4 provided a complete description of the intended scenarios and interactions.

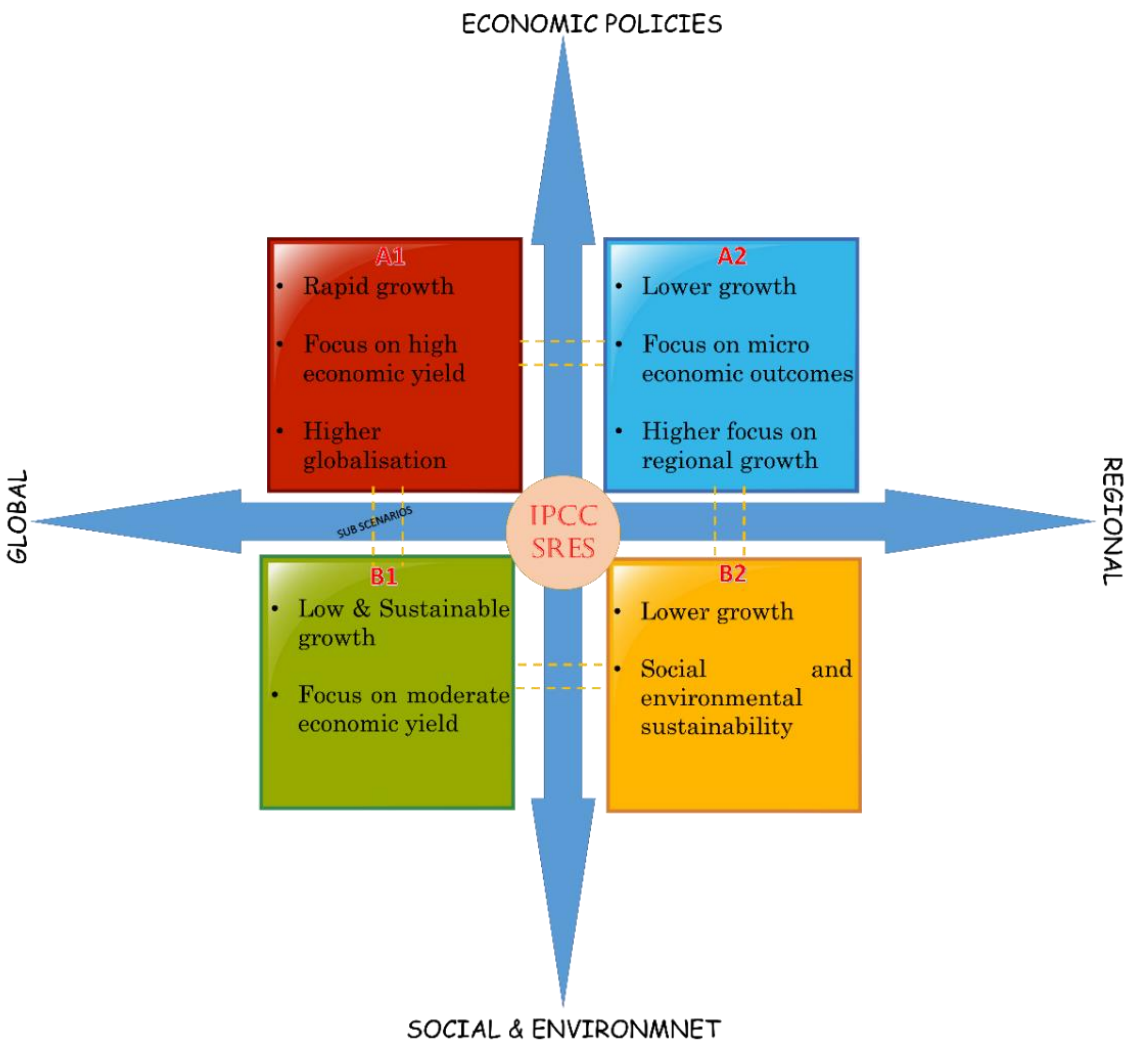



Figure 1.4. IPCC SRES framework

Systematic conservation planning by the prioritization of sensitive regions is another major initiative of policy implementation also known as ecological sustainable planning. It offers a set of guidelines that incorporate biological, social, and economic factors within the decisionmaking framework (Opdam et al., 2006; Watson et al., 2011). However, these actions are usually at global scales and there is less work demonstrating the use of a multidisciplinary approach in systematic conservation planning and prioritization of actions at the local scale (Tóth et al., 2011). So, to initiate further management interventions requires detailed planning and knowledge of a systematic conservation framework to demarcate conservation and community usage in a landscape. This framework resulted in the delineating Ecologically Sensitive Regions (ESR) - ‘unique’ regions that are biologically and ecologically valuable and are hence irreplaceable if destroyed.

ESRs treasure significant natural biotic and abiotic elements which could be degraded or lost as a result of incompatible development. In this regard, the Union Ministry of Environment and Forests and Climate Change (MoEFCC), Government of India has taken an initiative to protect forests and maintenance or restrict the location of industries and carry out certain operations only based on considerations like the ecological sensitivity under section 3 & 5 of Environment (Protection) Act 1986 (EPA). The MoEFCC had set up Pronab Sen Committee (2000) to identify parameters for designating Ecologically Sensitive Areas in the country to counter the rapid deterioration of the environment (MoEF, 2000). The structured protocol for defining the ESRs by a series of attributes, criteria to be used, the methodological process need to be adopted still requires a complete review and research (Gadgil et al., 2011). Geo-informatics based spatial decision support tools with empirical and statistical approaches are playing an important role that simultaneously meets conservation targets, transparency while minimizing social and economic costs to guide management actions and locations.

## 1.12. Research Gaps and motivation for current research

*Need for regional scale land use modeling:*

Forest landscape poses greater challenges in management due to natural and anthropogenic drivers acting across multiple scales. In order to address these challenges, it is necessary for a couple of human and natural systems perspective in planning. The global and regional environmental changes are due to LULC changes in the forest landscapes, which is also impacting livelihoods apart from threatening biodiversity and hydrologic services. To understand the causes and consequences of these changes, earlier studies have analyzed changes at a local scale and global scale through various techniques of modeling. Many modeling techniques have focused on demonstrating and exploring ideas and testing hypotheses, but ignored the fundamental realism of policies and their responses. They are more generalized to solve the location-specific problems rather than providing guidance to frame management actions. These approaches fail in projecting regional scale changes in high forested regions due to variability, the scale, and present status data. Also, the regional studies pose significant challenges to successful synthesis research in problem identification, interpretability, and comparability across the landscape and the limits of biases in the geographic coverage. The selection of suitable models for simulation and visualization of the regional forested landscape would require an integration of interdisciplinary knowledge and approaches. The evaluation of the best suitable model is not fully explored due to the constraints of data and complexity. The demand for global and regional knowledge generation will continue to grow in this era of climate change to support adaptation and mitigation policies consistent with both the local and global environmental, social, and economic contexts. Though the advancement of research across the globe tries to address dynamic behaviors but lacks in mainstreaming ecosystem management via integration of social systems. While modeling can be carried out at different scales varying from local community level to regional or global scale. Understanding individual actors or local decisionmaking or policies plays a major role in addressing regional land use changes with respect to the forested landscape. Uttara Kannada district in the Central Western Ghats has the distinction of having the highest forest cover has been experiencing uncontrolled forest degradation due to socio-economic problems. This necessitates a detailed understanding of the temporal changes for proposing a suitable model to capture regional dynamics, the process of forest transition, and its associated impacts.

*Challenges in modeling forested landscape:*

The standalone techniques available have proven to be complex, dynamic, high dimensional, and require sophisticated analytical approaches to accommodate the complexities of ecological and social systems. It has become imperative to experiment with diverse modeling techniques that capture both the active and passive process of the forested landscape in a precise form under scenarios of rapidly changing environmental conditions. Traditional static and established modeling tools fail to capture rapid changes in accordance with biophysical, socio-economic aspects, non-linear trends such as deforestation, policy-induced changes, etc. Non-agent-based modeling falls short to balance the data and generalizability to account for two-way feedbacks between the neighborhood within an ecological system. The agent-based modeling approaches have a substantial gap in predictive power, operative decision support for solving the multidisciplinary socio-ecological system (Verburg et al., 2016). These models merely depend on quantitative/qualitative data, ignore collecting micro-level interactions that influence decision making, and require long term time series data of agents (Groeneveld et al., 2017). Modeling forest cover dynamics should cover principles of nonlinearity, but traditional CA-Markov or static agent-based modeling techniques assume the linearity of the system. The modeling should focus on an integrative, multidisciplinary non-linear approach to study the structure and dynamics of forest ecosystems, which furthermore accounts uncertainties. It necessitates the integration of combined agent-based and non-agent based (hybrid) techniques that capture human and natural systems interactions as well as feedbacks in a model to mimic change trajectories of a forest landscape. Uttara Kannada district is an ideal case to address these issues to capture land use changes, associated forest fragmentation to address policy issues with a suitable model to forecast probable changes.

The Western Ghats forests one among 36 global biodiversity hotspots and 8 hottest hotspots of biodiversity with exceptional endemic flora and fauna while ensuring water sustenance, forms an important lifeline for peninsular India. It is considered as a water tower of India due to numerous streams originates and draining millions of hectares (Ramachandra and Bharath, 2020). But the forest landscapes are being transformed to other LUs for commercial establishments, hydroelectric projects, industries, monoculture plantations, etc. during the past four decades, Uttara Kannada district has been experiencing large scale forest cover change due to mismanagement and socio-economic problems. This necessitates a detailed understanding of the temporal changes for proposing a suitable model that captures these dynamics, the process of forest transition, and its associated impacts. So, the research attempts to address issues and focus on a detailed understanding of the role of disturbance regimes which helps in better-informed management decisions. The endeavor also explores the livelihood impacts with stringent conservation measures. Likely LU scenarios provide insights to the impact of policy-driven LU changes, which will help the administration to choose an appropriate policy for implementation.

## 1.13. Research Objectives

The objective of the current research is to understand and model the spatiotemporal patterns of landscape dynamics. This involves,

1. developing an appropriate modeling framework for incorporating the spatiotemporal changes in the landscape at the regional level;
2. implementing a hybrid model to capture the changes at the landscape level by integrating bio-ecological aspects with socio-economic growth;
3. evaluating the environmental conditions in response to the multiple scenarios as a consequence of policies and their outcomes; and
4. assessing the likely scenario of the landscape dynamics with the conservation of ecologically sensitive regions (ESR) and policy recommendations.

## 1.14. The organization of the thesis

The objectives of the current research are to understand and model the spatiotemporal patterns of landscape dynamics in the Uttara Kannada district of the Central Western Ghats. The work is presented in seven chapters.

Chapter 1 introduces the landscape, ecosystem process, and issues and concerns associated with land use land cover changes. It also includes the information associated landscape dynamics and outlines the essential steps to strengthen policy, planning, and decision making while identifying the gaps. It also presents various modeling techniques accounting LULC changes, linkages to policies, and development of a region based on various scenarios. This chapter elaborates on the necessity of modeling landscape dynamics and provides a detailed review of the different geospatial modeling techniques (spatial, non-spatial, statistical, geospatial, agent-based modeling techniques, etc.) and their effective usage in planning and natural resource management. The review also looks at various studies on forest land use changes and modeling techniques used for the Indian context.

Chapter 2 provides an overview of current modeling techniques and the development of a suitable hybrid model (Objective-1).

Chapter 3 provides a brief overview of the study area considered i.e. Uttara Kannada district, Central Western Ghats for implementation of models. The chapter provides details of geology, climate, rainfall, demography, the economic, historic significance of the region. It also articulates the various data sets used for the analysis and their significance.

Chapter 4 presents land use land cover dynamics in the Uttara Kannada district and fragmentation of forests.

Chapter 5 proposes the framework for identification of Ecologically Sensitive Regions (ESR) for conservation by integrating spatial, bio-geo climatic, and social variables. This chapter also provides the allowable developmental activities for the sustainable growth of the region.

Chapter 6 Modeling and simulation of the region is presented by reviewing various modeling techniques to simulate and project likely changes in the ecologically significant landscape. This chapter also presents the results of the proposed hybrid Fuzzy-AHP-MCCA technique and simulates likely changes under nine different scenarios (Objective-2 & 3). Chapter 6 also evaluates the likely scenario of the landscape dynamics with the conservation of ESR and policy recommendations (Objective-4). The model helps understand how the identification of Ecologically Sensitive Regions, and its integration in the model to set the limits for the growth under (i) implementation of conservation in ESR-1 and allowing development in ESR 2-4; (ii) limiting LU conversion by considering interior forest and protected areas as constraints; will affect the changes in the land use patterns.

Finally, in Chapter 7, the thesis presents the significant results from this modeling effort and the inferences that can be drawn on how the model helps policy and decisionmakers understand the impact of the choices made at a macro-scale and there impact at the local levels. It also discusses some of the potential extensions to this work.

# Chapter 2| MODELING FRAMEWORK FOR LANDSCAPE DYNAMICS

# CHAPTER 2 | MODELING FRAMEWORK FOR LANDSCAPE DYNAMICS

This chapter presents the current modeling framework for visualizing landscape dynamics with strengths and limitations. The standard models are not suitable for forested regions due to their heterogeneity and data availability. The earlier approaches failed to provide a single and robust model to capture the dynamics. Hence, the subsequent section discusses hybrid model with the integration of bio-ecological aspects with socio-economic variables.

## 2.1. Modeling framework for landscape dynamics

LULC changes simulation and forecasting models can be broadly divided into three major categories: empirical statistical model, Agent-Based (ABM) model, and raster neighborhood relationship-based model (ex. CA-Markov, etc.). The general framework for modeling landscape dynamics approach is depicted in Figure 2.1. The framework tries to highlight four major phases in modeling LULC such as ***calibration, simulation, validation, and forecasting***. In empirical models, past LUCC changes spatial distribution used to develop a mathematical model that estimates the change potential as a function of a set of explanatory variables. This mathematical model can also be based on theoretical assumptions based on the knowledge of past LULC change such as types of transitions and rates of change for model parameterization. The landscape is bio-geographically complex, composed of natural factors, human LU activities, and other impact factors so simulation by ABM will account the interactions among various components and feedback to the subsequent development of these interactions. Modeling performed using a spatially explicit approach, by non-spatial data is an important technique for projecting and exploring alternative future scenarios, for conducting experiments that help to understand and for quantitatively describing a key process. Calibration is defined as the estimation and adjustment of the model parameters and constraints to improve the agreement between model output and a data set (Mas et al., 2014). The calibration phase mainly focuses on examining a landscape's LULC maps at initial points in time $t_0$ and $t_1$ and accounting persistency of each LU feature across two time periods. The rate of change and area of change is estimated and then the prediction of some subsequent point in time $t_2$ simulated from $t_1$. The predicted map of $t_2$ is usually compared to a reference map (i.e., actual LU map or observed map), in order to evaluate the effectiveness of the simulation model.

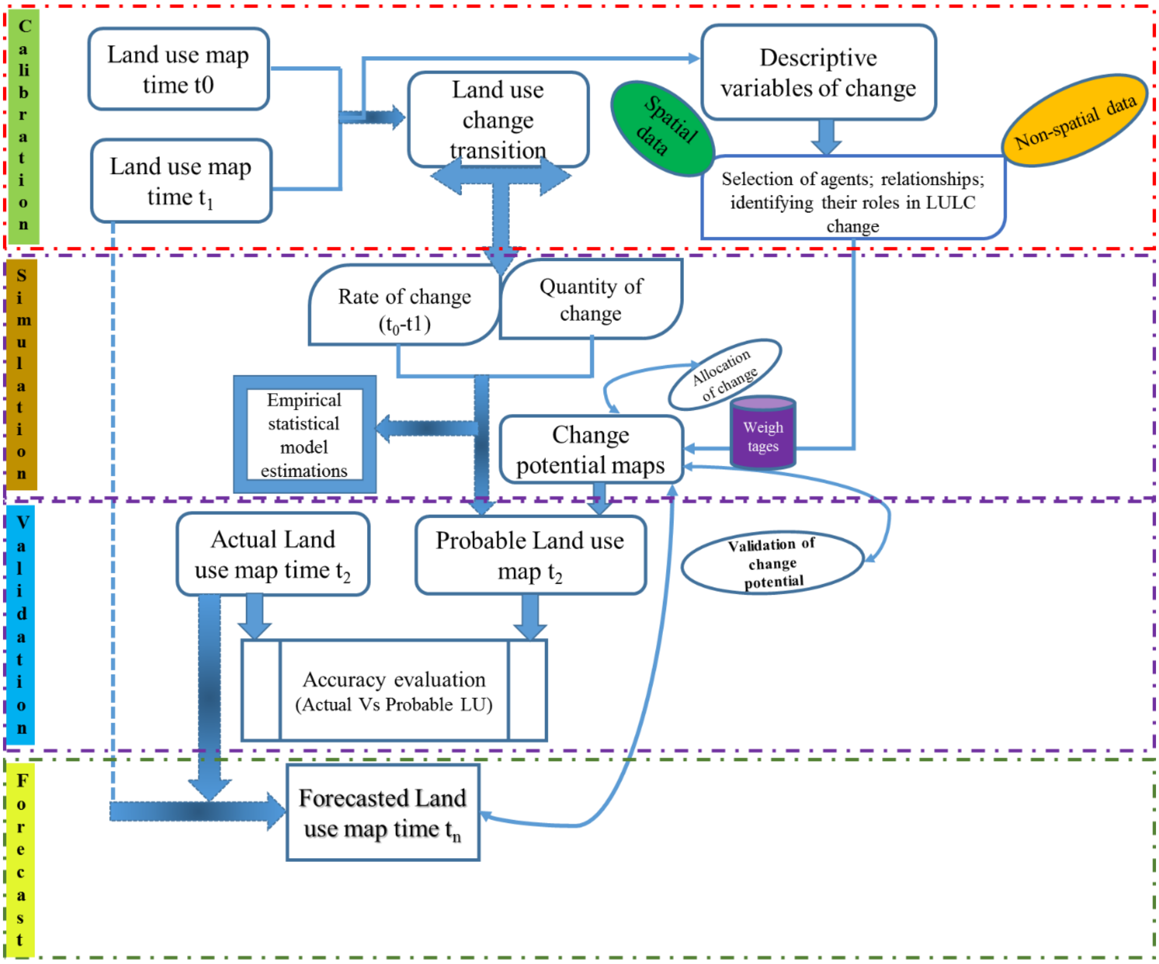



Figure 2.1. A general framework of a modeling approach

Validation is defined as a demonstration that a model within its domain of applicability possesses a satisfactory range of accuracy consistent with the intended application of the model. The validation phase tries to examine even if the agents are used for simulation checks the consistency of agents and transition potential regions with respective factors. If the predicted map of $t_2$ appears similar to the reference map, then the simulation model is considered as effective for forecasting. The predictions of respective LU maps were made based on previous LU maps and growth rate or agents transition potential maps. The projected LU will try to high light the regions of change based on earlier experiences or spatial transitions. If the projections are not satisfactory, the modeler may relook or review the agents considered or previous LU maps or empirical estimations and assumptions made. A comparison of the model to both a Null model and a random model is a well-acknowledged validation of projections to assess predictive power. The scale is important to consider during any comparison of maps because the scale can impact results and certain patterns may be evident (Kok et al., 2001; van Vliet et al., 2016).

## 2.2. Modeling techniques for forested landscape

Modeling and visualization of LULC help in analyzing complex systems of highly nonlinear behaviors using a closely coupled combination of driving factors and neighborhood that are described by general law or analytic descriptive formulas to link theoretical ideas with experimental observations. The prediction of the future states of forest ecosystems cannot be made with precision due to non-linear dynamics, cross-boundary interactions, the emergence of new drivers of change, frequently varying external drivers or boundary conditions, environmental variability, climate change, global economic scenarios. Yousefpour et al., 2012 has reviewed many approaches, models, scenarios, and concludes that simulation results need to present a series of probable outcomes rather than representing fixed consequences of change.

### 2.2.1. Markov Cellular Automata Model

Markov Cellular Automata (MCA) modeling concepts are utilized due to their flexibility, modeling power. Over a few decades, MCA concepts have been widely used to quantify the dynamics of LULC changes in the forest, urban, aquatic ecosystem, coastal zone management, etc. Figure 2.2 provides the general framework for modeling, which is the revised version of the model implemented for Tehran region (Arsanjani et al., 2011).

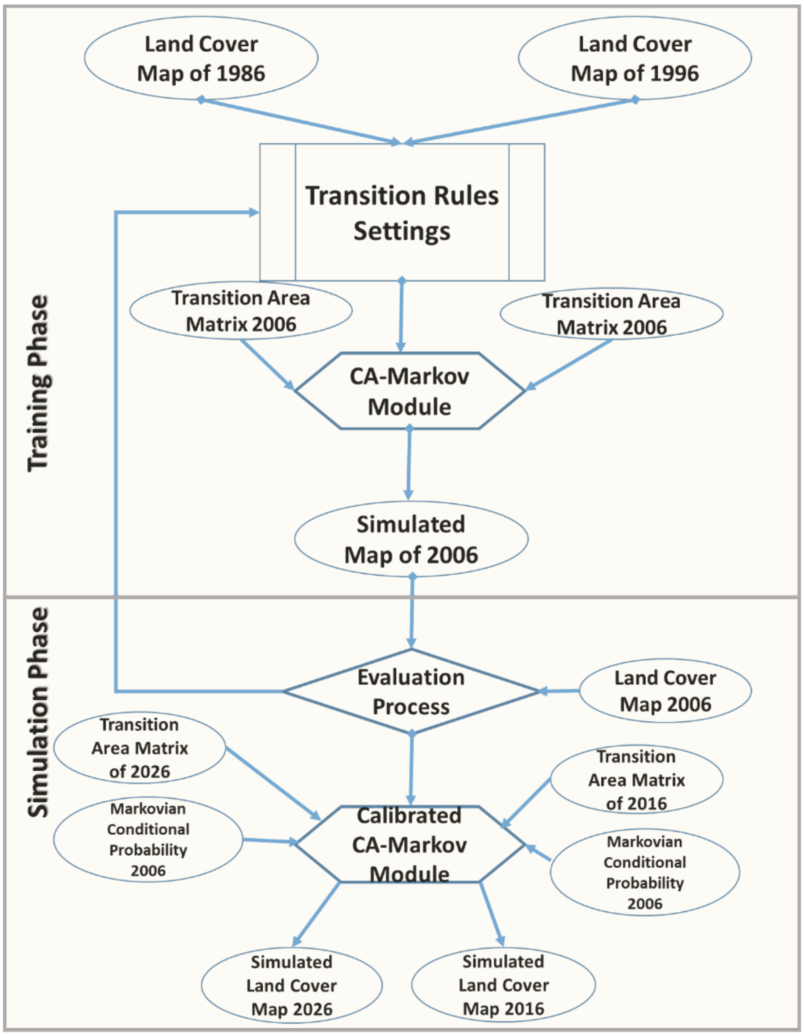



Figure 2.2 CAMarkov accounting land cover changes

### 2.2.1.1 Markov transitions

The Markovian technique is a random process, defines the suitability of state as a weighted linear sum of a series affecting factors, normalized to values in the range of 0-1 (0-presence & 1-absence) i.e., the state of a system at time $t_2$ is predicted from the state at time $t_1$ (Thomas and Laurence, 2006). The two temporal LU analysis maps were used to account for the stable and transformed LU categories which satisfy non-transition properties such as urban category to water or vice versa. The transition probability map and area matrix is obtained based on the probability distribution over the next state of the current cell that is assumed to only depend on the current state (Equations 1, 2 & 3). The neighborhood influence area is thus calculated as the summed effect of each transitional potential and its interaction with its neighbors and the transition rules. A transition probability matrix determines the likelihood of a pixel that will change from one LU category another category from time 1 to time 2. It has been detailed in Chapter 6, Section 6.2.1. Transition matrix is the result of cross-tabulation of the two images adjusted by the proportional error and is translated in a set of probability images, one for each LU category, which records the number of cells or pixels that are expected to change over the next time period.

$$P\{X_t = A\, X_0 = A_0, X_1 = A_1, \dots, X_{t-1} = A_i\} = P\{X_t = A_i | X_{t-1} = A_i\} \tag{1}$$

The original transition probability matrix (denoted by P) of LU type should be obtained from two former LU maps.

$$P(N) = P(N-1) * P \tag{2}$$

where, $P_{(N)}$ is state probability of any times, and $P_{(N-1)}$ is preliminary state probability.

Transition area matrix can be obtained by,

$$A = \begin{bmatrix} A_{11} & A_{12} & A_{13} \\ \vdots & \vdots & \vdots \\ A_{N1} & A_{N2} & A_{NN} \end{bmatrix} \tag{3}$$

where A is the transition area matrix; $A_{ij}$ is the sum of areas from the $i^{th}$ LU category to the $j^{th}$ category during the years from a start point to target simulation periods; and n is the number of LU types. The transition area matrix must meet the following conditions

i. $0 \le P_{ij} \le 1$

ii. $\sum_{i,j=0}^{n} P_{ij} = 1$

iii. $\chi = \sum \frac{(O_t - E_t)^2}{E_t}$

where $O_t$ is the observed number of transitions and $E_t$ is the expected number of transitions.

### 2.2.1.2 CA based modeling and prediction

CA was used to obtain a spatial context and distribution map which defines the state of the cell based on the previous state of the cells within a neighborhood, using a set of transition rules. The CA model can be expressed as (Equation 4),

$$S(t, t+1) = F(S(t), N, \gamma) \tag{4}$$

where S is the set of discrete cellular states, N is the Cellular field, t and t + 1 indicate the different times, $\gamma$ is constraints assigned 1 if a cell is available, 0 otherwise and F is the transformation function of cellular states in local space.

CA has a potential for modeling complex spatiotemporal process that made up of elements represented by an array of cells, each residing in a state at any one time, discrete number of categories (states), the neighborhood effect and the transition functions, which define what the state of any given cell is going to be in the future time period. CA conditional transition rules are an automated method that produces a set of descriptive rules or a decision tree ready to be used defines thresholds in the composition of the neighborhood and for the driving factors, which are additional values about each cell such as the land value, the distance to the main road, etc., to maximize the likelihood that a given cell configuration leads to the correct type of LU change. CA is always governed by a set of rules such as if-then statements as shown below (simplified version of the rule)

***IF there are two or three non-forest LU cells in the Neighborhood of a considered forest cell,***

***THEN***

***the cell stays alive as transforming to non-forest LU in the next generation;***

***IF there are less than two or more cells in the Neighborhood of a considered forest cell,***

***THEN***

***Cell stays in the same state in the next generation;***

Cellular automata (CA) give the spatial location of transitions. Markov provides the probability aspect of the transition map. CA-Markov model defines the neighboring territory using a CA filter. The CA filter creates spatial weights according to the distance of the neighboring territory from the cell to determine changes in the cellular status. A 5×5 filter shown in Figure 2.3 will be applied, which accounts for the significant neighborhood impact on the change of status. CA coupled with Markov chain LU predictions were made by using the transitional probability area matrix generated from previous LU datasets. The validity of the predictions was made with the reference LU maps. Based on these validations then visualization was made by considering an equal time interval. Accuracy of the simulation is done through the calculation of the Kappa index for location and quantity. The validity of the model results has been evaluated by comparing the KAPPA index of the agreement for each category, spatial patterns of LU type, and fractal parameter. KAPPA index can give summary static of agreement in terms of the proportion of the total number of pixels.

| | | | | |
|---|---|---|---|---|
| 0 | 0 | 1 | 0 | 0 |
| 0 | 1 | 1 | 1 | 0 |
| 1 | 1 | 1 | 1 | 1 |
| 0 | 1 | 1 | 1 | 0 |
| 0 | 0 | 1 | 0 | 0 |

Figure 2.3. A 5×5 mean contiguity filter to account the neighborhood

**2.2.1.3 Limitations of Markov Cellular Automata (MCA)**

Though MCA is widely used modeling techniques has some specific shortcomings (Arsanjani et al., 2013; Bharath et al., 2018) such as

- The model can simulate a dynamical system over a short time interval.
- Assumes the growth of the system as linear, but the real-world problems exhibit non-linear growth patterns.
- Lack of human decision-making influence.
- Unable to include drivers of change purely depends on cell neighborhood.
- The simulation does not allow feedback between the environment and non-spatial process.

**2.2.2. Empirical modeling technique: CLUE-S model**

Conversion of Land Use and its Effects Scanner modeling framework (CLUE-S) is used for simulating LU change based on the interactions such as spatial policies and restrictions, specifications of LU conversion, demand-based LU requirements and location characteristics. It is an empirical modeling technique integrated logistic regression to assess the various driving factors and constraints (Verburg et al., 2002). The model flow has been shown in Figure 2.4., which is the revised version of the model implemented (Verburg et al., 2002). The CA further assists to simulate the spatial changes based on growth input provided by logistic regression.

The execution of a model is divided into two distinct modules, namely, a non-spatial demand module that evaluates simple trend extrapolations to complex economic models and a spatially explicit allocation procedure that evaluates the scenarios.

The preference for LU conversion is evaluated based on the interactions of various actors over a landscape. The LU conversion preference is calculated as

$$M_{ni} = a_n X_{1i} + b_n X_{2i} + \cdots \quad (5)$$

where M is the preference to allocate location i to LU type n, $X_1$, $X_2$, etc., are biophysical or socio-economic factors acting at location i, $a_n$ and $b_n$ the relative impact of these characteristics on the preference for LU type n. The LU preference Rni cannot be measured directly, therefore to be calculated has a probability. A statistical regression model will be developed to indicate the probability of a certain grid cell to be transformed to other LU type due to a set of driving factors as following

$$log\left(\frac{PR_i}{1-PR_i}\right) = \beta_0 + \beta_1 X_{1,i} + \beta_2 X_{2,i} + \cdots + \beta_n X_{n,i} \quad (6)$$

where $PR_i$ is the probability of a grid cell for the occurrence of the considered land-use type and the X’s are the driving factors. The coefficient β is assessed through a logistic regression model, by considering various factors (independent variable) over a dependent variable such as LU.

The stepwise process is used in consideration of the relevant driving factors from a larger set of factors assumed to assess LU pattern. CLUE-S model conducts the allocation process by computing the total probability of all grid cells that transform from one LU to others. The total probability (TOTPROBPi, n) can be calculated for each LU type n as

$$\mathrm{TOTPROBPRi, n} = PR_{i,n} + ELAST_n + ITERAT_n \quad (7)$$

Where, $PR_{i,n}$ is the suitability of location i for LU type n (based on the logistic regression analysis), $ELAST_n$ is the conversion elasticity for LU n, and $ITERAT_n$ is an iteration variable of specific LU type which also an indicative of the relative competitive strength of the LU. The conversion matrix is generated by the maximization of the total probability compared against a set of conversion rules, which indicates conversions possible for each LU type. The site suitability (location) and neighbourhood conversion will be estimated using empirical methods or an expert's knowledge process, like constrained cellular automata models (Verburg et al., 2004).

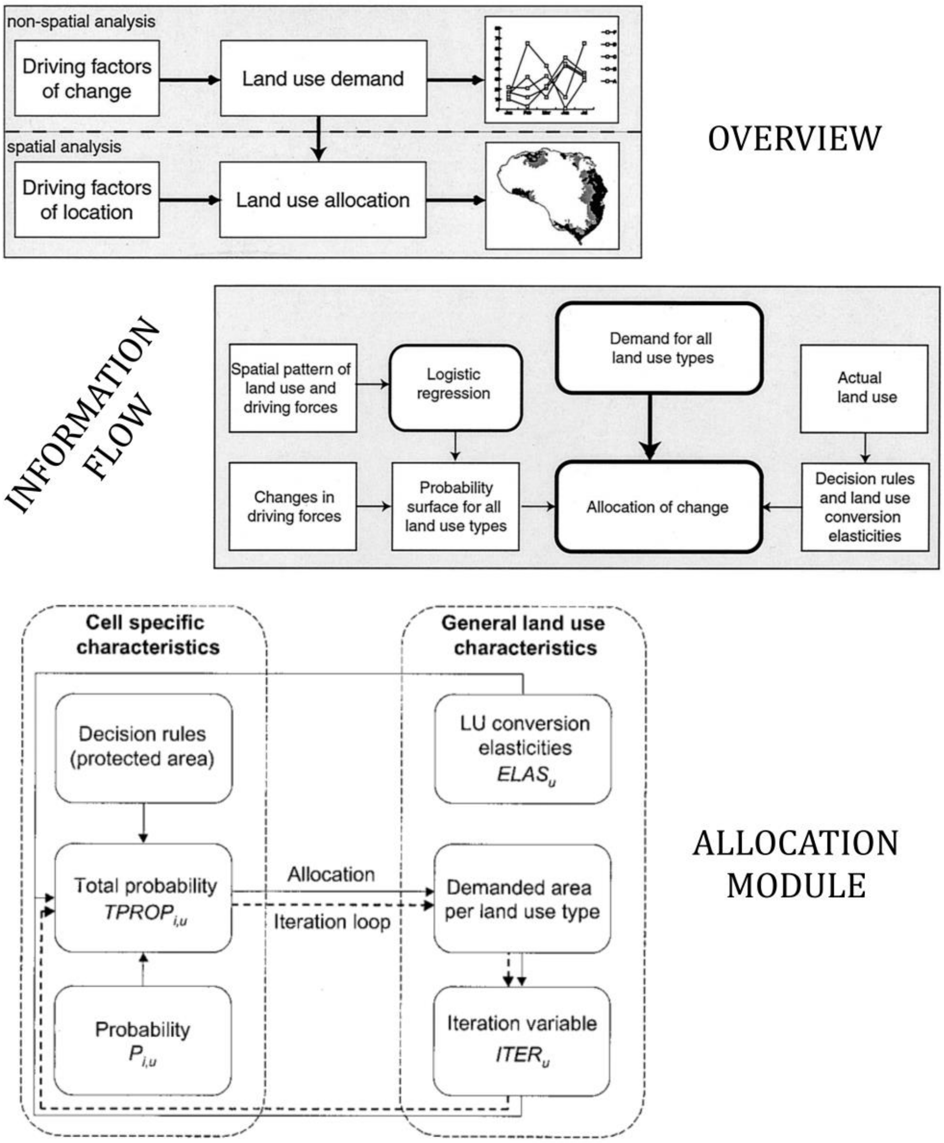



Figure 2.4. Logistic regression-based modeling of forest cover change

### 2.2.2.1 Limitations of CLUE-S

CLUE-S is improved with Dyna clue module to overcome the shortcomings in decision making for dynamic systems such as forested landscapes. But it has limitations such as

- Logistic regression models suffer from a lack of allocation process due to consideration of linear growth among factors.
- CLUE-S model estimates the probability of conversion for each LU type separately and does not sufficiently address the competition among the different LU types (Liu et al., 2017).

- The conversion matrix assumes the simulations of complex nonlinear changes in LU pattern as linear ignoring characteristics of complex non-linear systems, which results in imprecise estimations.
- The computation speed and memory allocation constraints such as maximum grid dimensions are rows-108, columns-128; the maximum number of LU types is 5; the maximum number of factors is 11. Ignoring these restrictions can cause the exit of a model as soon as try to run.
- The bias results are produced in case of higher heterogeneity and numerous driving forces.
- Suffers from higher spatial autocorrelation among factors across different spatial scales (Goldstein, 2011).

## 2.3. Proposed hybrid modeling technique- Fuzzy AHP MCCA

The standalone agent-based or non-agent based models have shortcomings due to data and computation limits. Hybrid modeling techniques can incorporate quantitative and qualitative factors together (Myllyviita et al., 2011). Qualitative factors can provide insights to structure problems in an effective way through interviews, expert opinion options, which need to be converted to spatial variables. Quantitative factors are the prime source for a model, needs to be evaluated through MCE, mathematical programming, optimization, etc. The evaluation of these factors can advance a new holistic view on the consequences of a decision, the influence of each factor, and stakeholder's preferences with respect to the landscape. Analysis of Fuzzy Analytic Hierarchy Process (Fuzzy-AHP) embeds the fuzzy theory to basic AHP, a widely used tool in various multicriteria decisionmaking problems, known as hybrid agent-based modeling (ABM). This involves pairwise comparisons of different alternatives with respect to multicriteria decision support. The capability to model complex dynamic systems with integration of Fuzzy-AHP process is a major reason for the widespread application of the Markov CA models to stimulate future LU changes in recent years (Chang et al., 2008; Kordi, and Brandt, 2012; Zhang et al., 2015). The hybrid model such as Fuzzy-AHP-MCCA has advantages compared with conventional modeling such as (i) containing dynamic spatial transitions, (ii) linking macro to micro driver's responses, which takes into account social, economic, dynamic, and spatiotemporal dimensions, (iii) priorities of comparison ratios for decision making, (iv) simplicity and visualization (Santé et al., 2010; Keshtkar and Voigt, 2016; Bharath et al., 2018).

### 2.3.1 Simulation and Future Prediction using the proposed modeling technique based on Hybrid FUZZY-AHP-MCCA

#### 2.3.1.1. Model conceptualization

LULC model is an abstraction of real-world landscape transition in mathematical form. In general, mathematically it can be defined as (Equation 8),

$$LU_{T+1} = \sum_{i,j=1}^{n}\left(LU_{Ti}, \Delta C_{ij}\right) \tag{8}$$

Where $LU_{T+1}$ is total change in LU for the time T+1, $LU_{Ti}$ is the land use of class i at time T. Change in LU from class i to class j and vice versa. LU change can be defined as a function of various influential factors and constraints (Equation 9) represents the change in forest cover, change in the agriculture area, etc.

$$\Delta C_{ij} = F\left(S_i, LU_{T,} LU_{T-1,} PC_{ij,}\right) \tag{9}$$

Where $S_i$ is the site suitability of class i, $PC_{ij}$ represents the probability of change from class i to class j. $LU_T$ is the land use at time T. $LU_{T-1}$ is the land use at time T-1. Site suitability of change from class i can be computed (Equation 10) from factors influencing change, weightage, and constraints using multi-criteria evaluation technique.

$$S_i = \prod_{i,k=1}^{m,n}(Const_i, W_{ik}, Fact_{ik}) \tag{10}$$

Here $Const_i$ is a binary function in a range of 0 to 1 which can be derived as (Equation 11),

$$Const_i = \prod\begin{bmatrix} Slope = 0 \;\forall\; Slope > 20\% \\ Slope = 1 \;\forall\; Slope \leq 20\% \\ PA = 0 \;\forall\; PA = Protected\ Area\ exists \\ PA = 1 \;\forall\; PA = Protected\ Area\ does\ not\ exists \\ \vdots \end{bmatrix} \tag{11}$$

$Fact_{ik}$ represents the various factors k that are responsible for the change in LU i. The factors and constraints used for the model are shown in Figure 3.5.

$$Fact_{ik} = \delta_N(I_k) \tag{12}$$

Where $I_k$ specifies factors such as industries, distance to the urban center, major roads, national highways, bus stops, etc., which contribute to the LU change. The individual contributing factors for different LU were normalized between 0 and 255 through fuzzy logic considering monotonically increasing or decreasing functions (Sigmoidal (S) or J curve), 255 indicates the maximum probability of change, while 0 indicates of no changes, which allows translating qualitative assessment into quantitative data by providing more logical and precise results. For data normalization through fuzzy for transforming input range I to normalized range N as,

$$\delta_N = I_{min} + (I_{max} - I_{min}) \times \frac{(N - N_{min})}{(N_{max} - N_{min})} \tag{13}$$

where $I_{min}$ and $I_{max}$ are the input range (0, 255), $N_{max}$ and $N_{min}$ are a range of factor values (distance, slope). For example, 400 in the range of $\{1 - 1000\}$ will be normalized as $0 + (255 - 0) \times (400 - 1) \div (1000 - 1)$, equivalent to 101 in the range of $\{0 - 255\}$. The factors are set based on each individual's influence, unlike the traditional fuzzy method. The mathematical relationship has been established to account for maximum upper bounds based on distance function.

$W_{ik}$ is the weight of factor k influencing land use i based on expert opinion. The weightages are derived for each factor using pairwise comparison matrices and their relative weights as Eigenvectors determined through AHP (Bernasconi et al., 2010) to measure the degree of importance between criteria or factors I and J. A response matrix $A = [a_{IJ}]_{(m,n)}$ is generated to measure the relative dominance of item I over item J with the decision maker's assessments $a_{ij}$, as pairwise comparisons that follow a uniform probability distribution (Equation 14).

$$a_{IJ} = \begin{bmatrix} 1 & a_{12} & \dots\dots & a_{n1} \\ \frac{1}{a_{12}} & 1 & \dots\dots & a_{n2} \\ \vdots & \vdots & \dots\dots & \vdots \\ \frac{1}{a_{1n}} & \frac{1}{a_{2n}} & \dots\dots & 1 \end{bmatrix}, \begin{bmatrix} \frac{W_1}{W_1} & \frac{W_1}{W_2} & \dots\dots & \frac{W_1}{W_n} \\ \frac{W_2}{W_1} & \frac{W_2}{W_2} & \dots\dots & \frac{W_2}{W_n} \\ \vdots & \vdots & \dots\dots & \vdots \\ \frac{W_n}{W_1} & \frac{W_n}{W_2} & \dots\dots & \frac{W_n}{n} \end{bmatrix}$$

$$a_{IJ} = \frac{W_I}{W_J} * e_{IJ} \tag{14}$$

where $W_I$ and $W_J$ are the priority weights belongs to vector $W_{ik}$ and $\sum W_{ik} = 1$, $e_{IJ}$ is inconsistency observed in the analysis.

The comparison matrix elements were compared pairwise to relate single element at the level directly and ranked by eigenvector of the matrix (Zhang et al., 2015) and eigenvalue of $\lambda_{max}$ is computed (Ying et al., 2007). A new vector $W'$ is obtained by multiplying pairwise comparison matrix and eigenvectors (Equation 15 & 16). The consistency of weightages is evaluated through the Consistency Index (CI) (Equation 17).

$$\begin{bmatrix} 1 & a_{12} & \dots\dots & a_{n1} \\ a_{21} & 1 & \dots\dots & a_{n2} \\ \vdots & \vdots & \vdots & \vdots \\ a_{n1} & a_{n2} & \dots\dots & 1 \end{bmatrix} \begin{bmatrix} W_1 \\ W_2 \\ \vdots \\ W_n \end{bmatrix} = \begin{bmatrix} W_1' \\ W_2' \\ \vdots \\ W_n' \end{bmatrix} \tag{15}$$

$$\lambda_{max} = \frac{1}{n} \times \left[\frac{W_1'}{W_1} + \frac{W_2'}{W_2} + \cdots \frac{W_n'}{W_n}\right] \tag{16}$$

$$CI = \frac{\lambda_{max} - n}{n-1} \tag{17}$$

where CI is the consistency index, $\lambda_{max}$ is the largest or principal eigenvalue; n is the order of the matrix. If CI = 0, the matrix had a complete consistency. The worse consistency will represent a greater value of CI.

The consistency ratio (CR) is calculated (Equation 18) by

$$Consistency\ Ratio\ (CR) = \frac{\boldsymbol{Consistency\ Index\ (CI)}}{\boldsymbol{Random\ Index\ (RI)}} \tag{18}$$

where RI is the average of the resulting consistency index (or also known as Random Index) depending on the order of the matrix. If CR value is less than 0.10, the matrix had a reasonable consistency, otherwise, the matrix should be altered for better CR.

**2.3.1.2. Simulation and prediction**

The influence of neighborhood development density is considered at a specific grid cell *p*, the neighborhood development density for land use type i (Equation 19) is defined as

$$PC_{ij} = \frac{\sum_{N\times N} COND(C_P^{t-1} = q)}{N\times N} \times W_{ik} \times r \tag{19}$$

here, $\sum_{N\times N} COND(C_P^{t-1} = i)$ represents the total number of grid cells within $N \times N$ window for a LU type i at the time t-1. $W_{ik}$ represents weight associated with each land use type i considered from AHP.

Cellular automata (CA) gives the spatial location of transition and LU predictions were made by using the transitional probability area matrix generated from previous LU datasets using the Markovian process. Unlike the traditional CA neighborhood, r is a growth factor induced for specific growth factors based on LU change rate computation. The growth rate r is estimated from actual $LU_T$ and $LU_{T-1}$. The growth rate is an external factor apart from all other factors considered in the modeling, which provides an advantageous to incorporate dynamic change and also elucidates the policy interventions over a temporal scale. The accuracy of prediction is evaluated using Kappa statistics by measuring agreement between predicted LU and current. The Kappa statistic is an excellent measure for comparing a map of “reality” versus some “alternative “map of higher accuracy (Pontius and Millones, 2011). Figure 2.5 portraits the flow of the model.

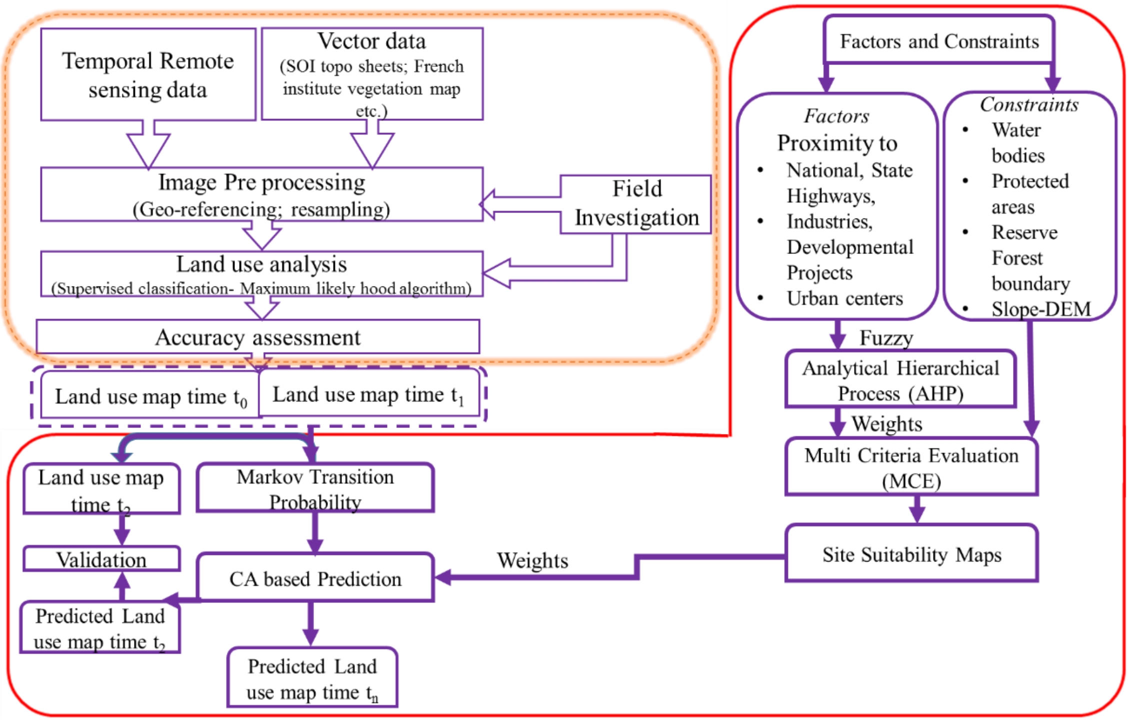



Figure 2.5. Proposed method flow for hybrid modeling approach

## 2.4. Conclusion

The chapter has proposed Hybrid Fuzzy-AHP-MCCA model design and framework suitable for forest landscapes, in addition to evaluating various modeling techniques with their limitations. Many modeling techniques proposed earlier were based on the data considerations and system-specific. Modeling techniques were proposed based on empirical or spatial or decision-oriented or analytical methods, each of them has certain restrictions in implementation. The review also emphasizes no single model is sufficient to quantitatively assess and predict the LU changes. The techniques for dynamic systems such as forested landscape requires up-to-date inputs and policies influencing change for visualization and forecasting. The proposed model will be effective in capturing the dynamic systems such as forested regions based on the definite inputs provided.

# CHAPTER 3 | MATERIALS AND METHOD

# CHAPTER 3 | STUDY AREA: UTTARA KANNADA DISTRICT

Chapter 3 provides a brief overview of the study area considered i.e. Uttara Kannada district, Central Western Ghats with details such as geology, climate, rainfall, demographic, economic, historic significance, etc. The chapter also presents various data sets used for the analysis and their significance.

The Western Ghats, a rare repository of endemic flora and fauna is one among 36 global biodiversity hotspots and home to a diverse social, religious, and linguistic group. The range of ancient hills that runs parallel to the west coast of India forms several ecological regions depending upon the altitude, latitude, rainfall, and soil characteristics. It spreads over a 1600 km from north to south covering an area of 160000 km$^2$. It harbors 4000 species of flowering plants with 38% endemic, 330 butterflies with 11% endemics, 156 reptiles with 62% endemics, 508 birds with 4% endemics, 120 mammals with 12% endemics, 289 fishes with 41% endemics, and 135 amphibians with 75% endemics. The region has enormous biodiversity and high endemism due to the humid tropical climate, geological and topographical characteristics. The entire region acts as a prime watershed of peninsular India with 37 west, 3 east flowing rivers and numerous streams. Karnataka state comprises of 30 districts and 13 districts located in the central portion of the Western Ghats of which only three are in the coastal belt. Uttara Kannada also is known as *North Canara* (Karwar district) (Kamath, 1985) (Figure 3.1), one among the three coastal districts lies between 13.92$^o$ to 15.53$^o$ N and 74.09$^o$ to 75.1$^o$ E covering approximately an area of 10,291 km$^2$. The district extends N-S to a maximum of 180 km and W-E to a maximum width of 110 km. The Arabian Sea borders it on west creating a long continuous through the narrow coastline of 120 km. Goa, Belgaum, Dharwad, Haveri form Northern-Eastern and Shimoga, Udupi form Southern boundaries for the district respectively. The following details provide distinct features of Uttara Kannada.

## 3.1 Salient features of Uttara Kannada

### 3.1.1. Agro Climate

The district has varied geographical features with thick forests, perennial rivers and diverse flora and fauna. Uttara Kannada has a tropical climate with a well-defined rainy season of about five months (June and November) when the south-west monsoon brings most of the rainfall and the climate remains hot and humid. It has the unique distinction of having 3 agro-climatic zones such as the coastal region with hot humid climate and 3000-4500 mm rainfall; the Sahyadri interior (500-1000 m height) with humid to the south and 4000-5500 mm rainfall; the plains with arid transition zone 1500-2000 mm rainfall.

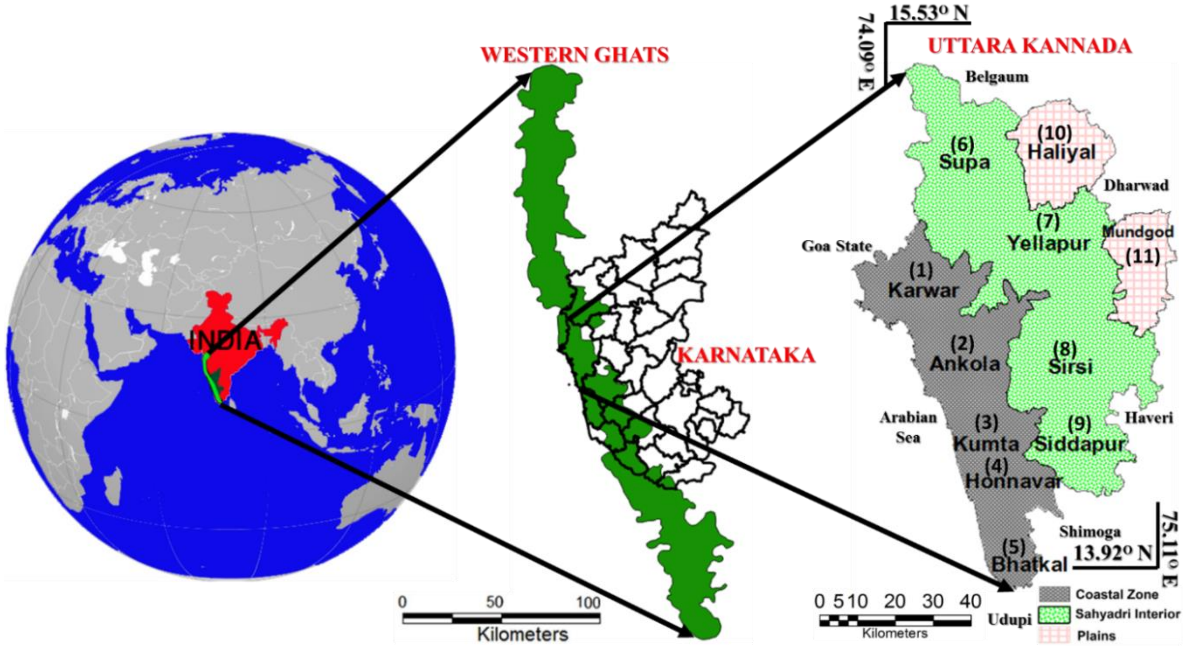



Figure 3.1. Uttara Kannada district, Karnataka, India: Geographical location and agroclimatic zones

### 3.1.2. Topography, Geology, and Geomorphology

Topographically, Uttara Kannada is divided into upland and low land based on the presence of the Sahyadri range (Figure 3.2.A). Uplands (Ghats) are the regions with 7,770 sq. km area and 500 to 1000 meters above the Sea level. Lowlands cover a region of 3,370 sq. km with elevation range 0-500 m. Shuttle Radar Topography Mission (SRTM) 1 Arc-Second Global elevation data of 30 meters resolution was downloaded from https://earthexplorer.usgs.gov/ website for understanding elevation pattern of the district. Geology of the district is based on the data of scale 1:100000 Department of Mines and Geology. The district has a rock formation of the Archaean complex, the oldest rock of the earth's crust. The Archaean formations are divisible into an older group of sediments and Igulous Viatrusives, all very highly metamorphosed, which are classified as the Dharwar system and a younger group of plutonic intrusive termed the Peninsular Gneisses (Figure 3.2.B). A capping of laterite, which is found in the western part of the district, nearly parallel to the coastline also consists of a varied assemblage of granite and schists. Soil and geomorphology details were compiled from Natural Resource Data

Management Centre (NRDMS), Bangalore. Soils in Uttara Kannada are forest brown soil, alluvial soil, coastal laterite soil, alluvial soil, laterite soil, and red soil. These have been further divided as shown in Figure 3.2.C. Red soil is divided into two i.e., gravelly clay soil and non-gravelly clay soil. Laterite is also divided into two gravelly clay soil and non-gravelly clay soil. Geomorphology of the region is dominated by denudation hills and plain lateritic shallow, medium types of landforms produced by erosion, weathering, deposition, transport, and tectonic process as shown in Figure 3.2.D.

### 3.1.3. Lotic ecosystems and spatial patterns of rainfall

Kali, Bedthi, Aganashini, Sharavathi, Venkatapur, Bhatkal, Belambar, Navgadde Halla, Hattikeri Halla, and Belambar are west flowing rivers, Dharma and Varada are east flowing rivers (Figure 3.3.A). The stream network was digitized from georeferenced topographic maps of Survey of India covering scale 1:50,000. The rivers are giving rise to magnificent waterfalls such as Jog fall in Sharavathi and other famous waterfalls include Lushington falls, where the river Aghanashini drops 116 meters, Magod falls, where the Bedthi river plunges 180 meters in two leaps, Shivganga falls, where the river Souda drops 74 meters, and Lalguli and Mailmane falls on the river Kali. The Kali river origins in Belgaum district flow through Supa, Karwar taluks. The Gangavali (Bedthi) river origins in Dharwad District flows through Yellapur and Ankola taluks. The Aghanashini river origins in Sirsi flows through Siddapur and Kumta taluks. Sharavati origins in Shimoga district, which forms the famous Jog Falls, flows through Honnavar taluk. The other rivers of the district are the Venktapur (origins in Bhatkal) and the Varada (origins in Sirsi). Uttara Kannada district has Supa reservoir, Tattihalla reservoir, Bommanahalli reservoir, Kaneri balancing reservoir, Kodasalli reservoir, Kadra reservoir across Kali river, and Gersoppa reservoir across Sharavathi river. The west flowing rivers break the shoreline of Uttara Kannada by deep and wide-mouthed estuaries. The presence of Western Ghats in Uttara Kannada causes orographic precipitation (Mechanical lifting of moist air masses over natural barriers such as mountains causes orographic precipitation) (Figure 3.3.B). Daily rainfall data from various rain gauge stations (point data) in and around the study area between 1901 and 2010 were considered for analysis of rainfall. The rainfall data used for the study were obtained from the Department of Statistics, Government of Karnataka; Indian Metrological Department (IMD), Government of India. The maximum rainfall is recorded in the coastal region and average rainfall toward the center of the basin and least rainfall toward the plains i.e., west to east. The mean annual rainfall is 4237 mm.

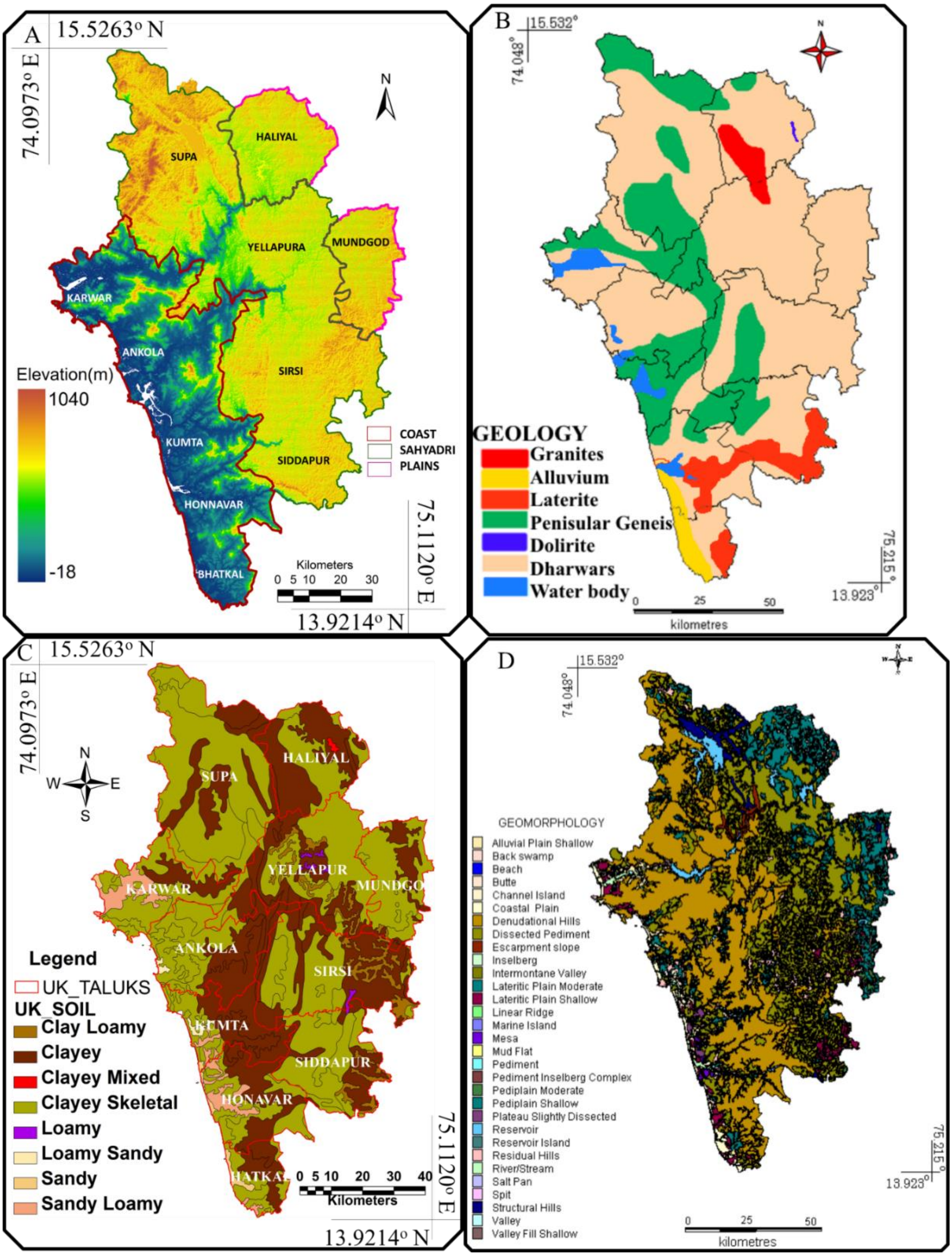



Figure 3.2 (A-D). Elevation, Geology, Soil, and Geomorphology of Uttara Kannada

### 3.1.4. Ecology

Uttara Kannada region has diverse forest types due to varied geographical, climatic conditions. This rugged terrain nurtures the forests as both primary and secondary forests can be seen (Glimpses of the district is attached as Appendix-1). Secondary forests have emerged because of pre-colonial, colonial period destructions, and phases of slash and burn cultivation by local communities. The forests can be broadly classified based on density under 4 categories such as Coastal mixed forest (partially open forest type dominated by moist deciduous to semi-evergreen, scrub vegetation type), Evergreen to semi-evergreen forest (medium to closed density dominated by native/endemic evergreen forest cover), Moist deciduous forest (medium density type dominated by semi-evergreen and moist requisite vegetation types) and Dry deciduous forest (open forest density types dominated by dry species, thorny bamboo, scrub forest) (Figure 3.3.C). The floral diversity portrays 1068 species of flowering plants under 138 families. Trees species represent 278 varieties (from 59 families), 285 species of shrubs (73 families), and 505 species of herb (55 families). The Moraceae, the family of figs (Ficus species), consists of 18 species providing key resources for animals, followed by Euphorbiaceae (16 species), Leguminosae (15 species), Lauraceae (14 species), Anacardiaceae (13 species) and Rubiaceae (13 species). Shrub species richness was pronounced in Leguminosae (32 species), Rubiaceae (24 species), and Euphorbiaceae (24 species). Among herbs grasses (Poaceae) were most specious (77 species), followed by sedges (Cyperaceae) with 67 species. Orchids (Orchidaceae) were also in good numbers. The region is home to critically endangered species of *Gymnacranthera canarica*, *Myristica fatua*, *Dipterocarpus indicus, Hopea ponga, Mastixia arborea, Vateria indica, Syzygium travancoricum, Semecarpus kathalekanensis* represents primary forest cover types that signifies the connection with Gondwana land (Ramachandra et al., 2015). Mangrove forests can be found in the river estuaries with rich marine fauna diversity. The major mangrove species present are *Rhizophora mucronata, Sonneratia alba, Avicennia marina, Avicennia officinalis, Kandelia candel, Rhizophora apiculata* and *Sonneratia caseolaris* (Mesta et al.,2014).

District has rich faunal diversity due to the diverse forest and geographical types. The region has 419 species of birds and 60% are endemic to the Western Ghats such as white-bellied blue flycatcher (*Muscicapa pallipes*), large Indian parakeet (*Psittacula eupatria*), great Indian hornbill (*Buceros bicornis*) etc. (Daniels et al., 1990). The mammal diversity includes lion-tailed macaque (*Macaca silenus*), elephant (*Elephas maximus*), slender loris (*Loris tardigradus*), tiger (*Panthera tigris*), leopard (*Panthera pardus*), Malabar civet (*Viverra* *civettina*), Indian wild dog (*Cuon alpinus*), sloth bear (*Melursus ursinus*), gaur (*Bos gaurus*), sambar (*Cervus unicolor*), spotted deer (*Axis axis*), etc. The district accounts 25 species (62.5% of Karnataka state bat population) of bats (Bates and Harrison, 2000). A wide variety of snakes are King Cobra, Cobra, Malabar Pit Viper, Hump-nosed pit Viper, Bamboo Pit Viper, Kraft, Ornate flying snake, wolf snake, etc. Butterflies include Crimson Rose, Common Rose, Leaf, Clipper, Tigers, Southern Birdwing, Cruiser, etc. Kali river accommodates at least 200+ marsh crocodiles and a good number of these can be sighted near the Dandelappa temple in Dandeli town. The region has endemic fish species such as *Puntius carnaticus, Puntius sahyadrensis, Mystus malabaricus.* Amphibians recorded covers 46 species across five river basins with high endemics such as *Pedostibes tuberculosus, Fejervarya kudremukhensis, Nyctibatrachus cf. major, Indosylvirana aurantiaca,* etc. Sharavathi river has rich and high endemic species, while Venkatapura shows poor endemism (Daniels, 2005; Chandran et al., 2010).

Karnataka state has 5 National Parks and 30 Wildlife Sanctuaries under the Indian wildlife protection act 1972. Uttara Kannada district has important protected areas namely Anshi National Park, Dandeli Wildlife Sanctuary (brought together under Dandeli-Anshi Tiger Reserve-ADTR), and Aghnashini Lion-Tailed Macaque (LTM) conservation reserve (Figure 3.3.D). The details of all protected areas are shown in Table 3.1.

Table 3.1. Details of Protected Areas in Uttara Kannada

| Sno | Name | Area (sq.km) | Conservation priority species | Priority locations |
|---|---|---|---|---|
| 1 | Anshi Dandeli Tiger reserve (ADTR) | 1365 | Conservation Tigers & Hornbills | Joida, Haliyal and Karwar taluks |
| 2 | Aghanashini LTM Conservation Reserve | 299.52 | Lion tailed macaque (LTM), Myristica swamps | Unchalli Falls, Kathalekan, Muktihole |
| 3 | Bedthi Conservation Reserve | 57.07 | Hornbills, *Coscinium fenestratum* (medicinal plant) & *Corypha umbraculifera* (rare endemic palm) | Magod Falls, Jenukallu Gudda, Bilihalla valley, Konkikote |

| | | | | |
|---|---|---|---|---|
| 4 | Shalmala Riparian Ecosystem Conservation Reserve | 4.89 | Diverse flora, fauna and as an important corridor in Western Ghats of Karnataka | Ramanguli |
| 5 | Hornbill Conservation Reserve | 52.50 | Hornbills | Kali River |
| 6 | Attivery Bird Sanctuary | 2.23 | Endemic birds | Mundgod taluk |

### 3.1.5. Administration

The district has been divided into 11 taluks for administrative purposes, (also known as Tehsil or Mandal is an agglomeration of villages). Supa taluk is the largest with an area of 1890.3 km$^2$ and Bhatkal is the smallest in with 351 km$^2$. Karwar town is the district headquarters which is the northernmost coastal taluk. These 11 taluks have been divided into 209 gram panchayats, further divided into 1289 villages of which 1243 are inhabited and the rest of the villages (46) (Table 3.2). Since the region has higher forest cover, for better administration district has divided into 6 forest divisions (5 territorial forest divisions and a wildlife division) as shown in Figure 3.3.E. The forest area under the control of the Forest Department is 7759 km$^2$ (93.53% of the total forest area). The forest area under revenue and other departments is 536 km$^2$.

### 3.1.6. Demography

The district has a population of 1437169 with 140 persons per sq. km density as per the census of 2011. The census of India data has been used for understanding the population trend for the years of 1991, 2001, 2011. The decadal growth rate (2001-2011) of the population is about 6.15% and male to female sex ratio shows for every 1000 males there are 975 females. Nearly 71 % of the population lives in villages and the remaining 29 % in towns. Taluk wise population density is computed (Figure 3.4) considering 1991, 2001, 2011 census data (http://censusindia.gov.in). Population density per sq. km shows Bhatkal, Karwar followed by Kumta are showing the higher density from 2001 to 2011 and Supa is outstanding by the least population density (Table 3.2). Village wise population details are shown in Figure 3.5 signifies coastal villages have densely populated as compared to Sahyadri. Forest-dwelling communities such as *Kunbis, Siddis, Goulis, Gondas,* and *Halakki Okkaligas* are directly and indirectly dependent on forest resources and have been protecting forests. Halakki Okkaligas are the original tribe and others are the migrants. In addition to these tribes Havyaka Brahmins, Saraswatas, Nayaks, Harijanas, Idigas, and Nadavas are the other ethnic communities reside in the region (Bhat et al., 2012). Appendix-3 provides details of forest-dwelling tribes distributed in the district and interaction with them during field investigation.

Table 3.2. Taluk wise population details

| **Taluk** | **Population** | | | **Population density (per sq. km)** | | | **Number of Villages** |
|---|---|---|---|---|---|---|---|
| | **1991** | **2001** | **2011** | **1991** | **2001** | **2011** | |
| **Ankola** | 91310 | 101549 | 107332.00 | 98 | 109 | 115 | 80 |
| **Bhatkal** | 129017 | 149338 | 161576.00 | 368 | 425 | **460** | 59 |
| **Haliyal** | 147064 | 159141 | 171426 | 172 | 186 | 201 | 129 |
| **Honnavar** | 145842 | 160331 | 166264.00 | 193 | 212 | 221 | 93 |
| **Karwar** | 140282 | 147890 | 155213.00 | 188 | 198 | 208 | 51 |
| **Kumta** | 134144 | 145826 | 154280.00 | 227 | 247 | 262 | 118 |
| **Mundgod** | 75046 | 90738 | 106174.00 | 111 | 134 | 157 | 90 |
| **Siddapur** | 91646 | 100870 | 97322 | 105 | 116 | 113 | 196 |
| **Sirsi** | 152935 | 175550 | 186908 | 116 | 133 | 142 | 228 |
| **Supa** | 46818 | 48914 | 52012 | 25 | 26 | 28 | 120 |
| **Yellapura** | 66156 | 73497 | 78662 | 51 | 56 | 60 | 125 |
| **Total** | 1220260 | 1353644 | **1437169** | 119 | 132 | **140** | 1289 |

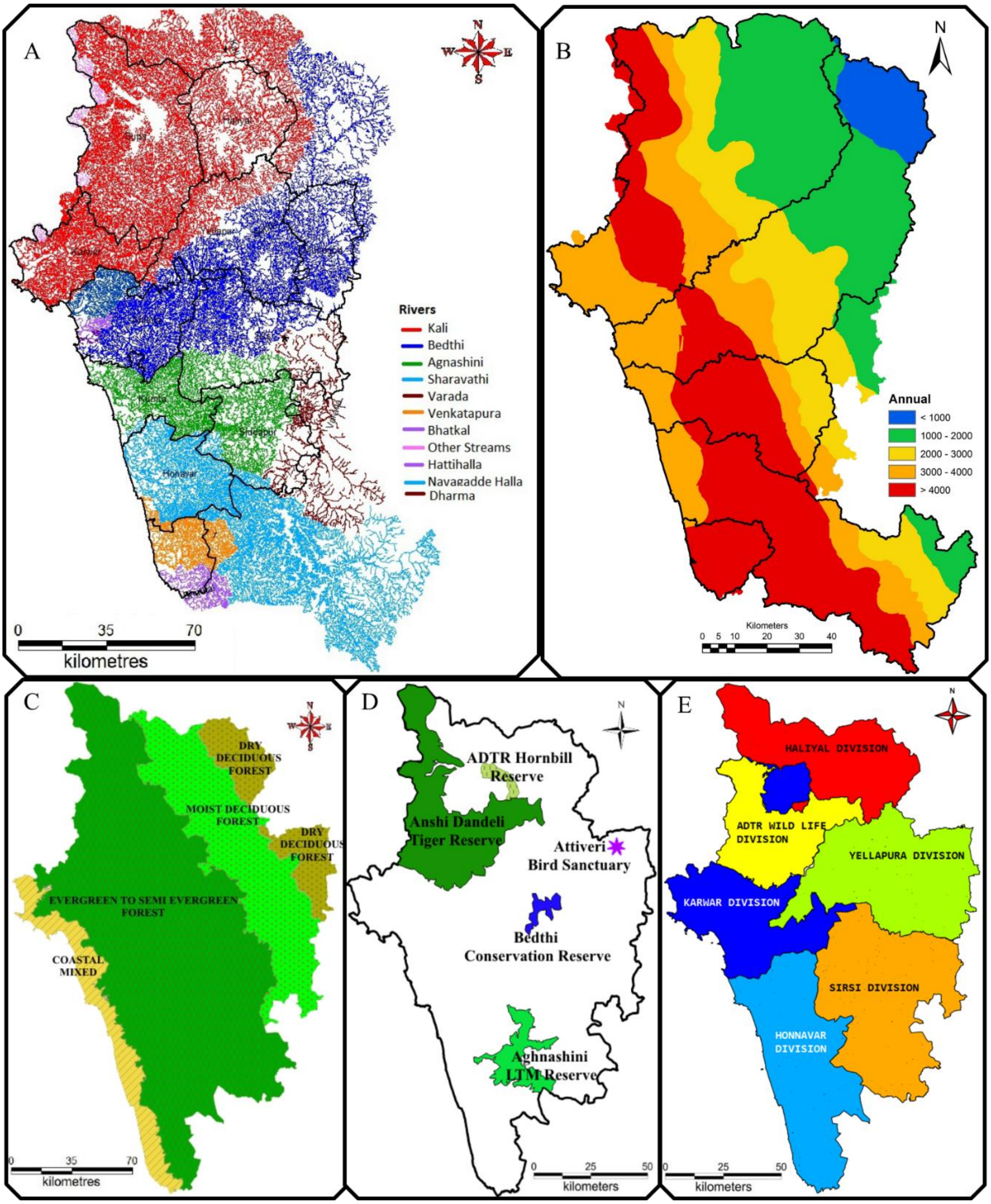



Figure 3.3 (A-E). Details of river basins, spatial rainfall pattern, forest cover types, protected areas, and forest divisions in Uttara Kannada district

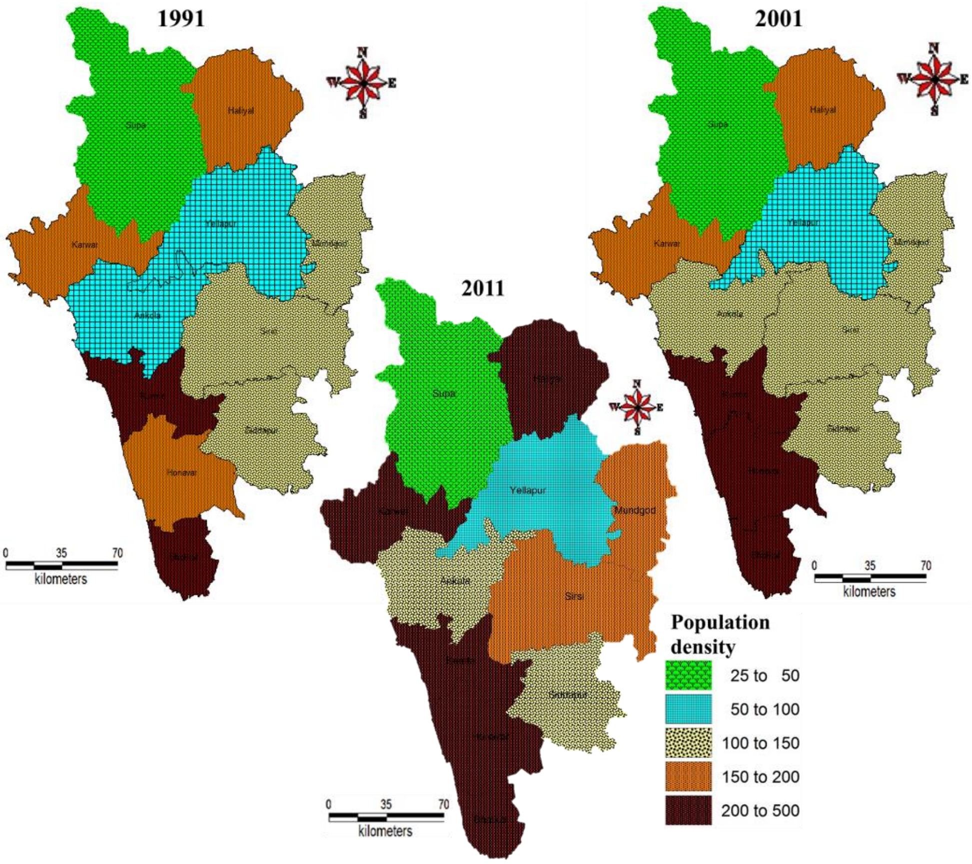



Figure 3.4. Population density of Uttara Kannada at taluk level

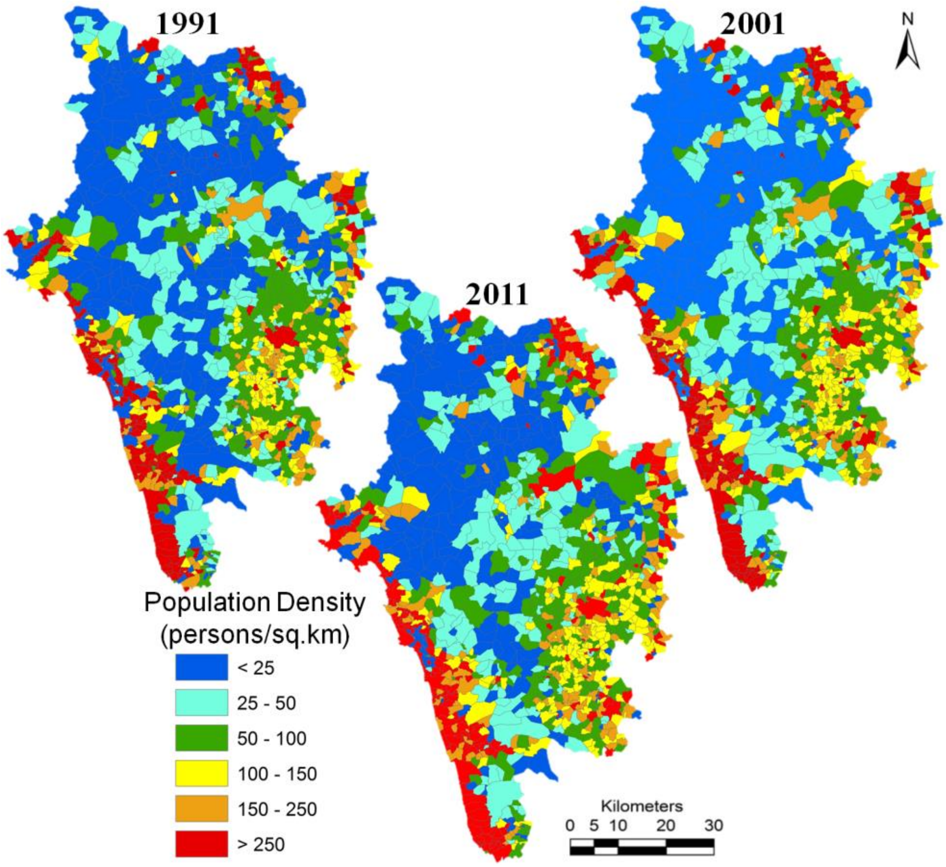



Figure 3.5. Population density of Uttara Kannada at the village level

### 3.1.7. History and Cultural significance

Uttara Kannada was under the rule of Sathavahanas (130-159 AD) and Kadambas during 350 - 525 AD, Banavasi was the capital. After the conquest of the Kadambas by Chalukyas, the region came under the successive rule of empires like Chalukyas, Rashtrakutas, Hoysalas, and Vijayanagar Empire. Famous Arab traveler Ibn Battuta is said to have stayed for a time in the district under the protection of Nawayath Sultan Jamal al-Din at Hunnur. This place is presently known as Hosapattana located in the Honnavar taluk. The district came under the rule of the Maratha empire from around 1700 to 1800 AD. It was ceded to the British at the conclusion of the Third Anglo-Maratha War in 1818. The British established North Kanara district as a part of the Bombay Presidency. This district was an important trade center since it was visited by Portuguese, French, Arabs, Dutch and British. Rabindranath Tagore, the Bengali poet, and Nobel laureate had paid a visit to this district during 1882. After India's independence in 1947, the Bombay Presidency was reconstituted as Bombay State. In 1956 the southern portion of Bombay state was added to Mysore state, which was renamed as Karnataka in 1972.

The Uttara Kannada has a rich diversity in culture and languages. The population is predominantly Hindu comprising of many communities called Bhandaris, Gramavokkaliga, Havyaka, Konkan Maratha, Goud Saraswat Brahmins, Daivajna Brahmins, Chitrapur Saraswat Brahmins, Vokkaligas, Sherugars, Namadhari naik, Nadavara, and Vaishya (Vanis). Muslims in the district are mainly of Nawayath descent. They live mostly in taluks of Bhatkal and Honnavar and speak Nawayathi. The Konkani speaking people include Christians also. People know languages such as Kannada, Konkani, Marathi, Tulu, and Urdu; 90% of the population can speak Kannada, Konkani, and Marathi languages. The cultural pattern of people has thus been influenced both by Maharashtra and Karnataka. The region is famous for unique Yakshagana (a classical theater art involves music, songs, dance, acting, dialogue, story, and unique costumes). Apart from Yakshagana, folk arts like Suggikunitha, Holi Dance, Hulivesha, Siddi Dance are famous and traditional. The region has numerous religious places such as Gokarna, Idugunji, Dhareshwara, Murudeshwara, Yana, Sahasralinga, Marikamba temple, and Banavasi temple.

## 3.2 Data and Method

LULC changes in Uttara Kannada district relies on an accurate interpretation of baseline conditions and changes in the surface spectral properties over time. The data utilized and method followed for landscape dynamics analysis is represented in Figure 3.6.

### 3.2.1. Data

#### 3.2.1.1. Remote sensing (RS) data

The spatiotemporal change detection process involves determining the changes associated with LULC considering geo-registered multitemporal RS data. RS data used in the study are a series of Landsat data (http://landsat.org), Google Earth (http://earth.google.com), and Bhuvan (http://bhuvan.nrsc.gov.in). The Landsat data is cost-effective, with high spatial resolution and freely downloadable from public domains. The detailed characteristics of RS data have been shown in Table 3.3. The data downloaded was cloud-free and covers the pre-monsoon period (January to May) across the decades for better comparison.

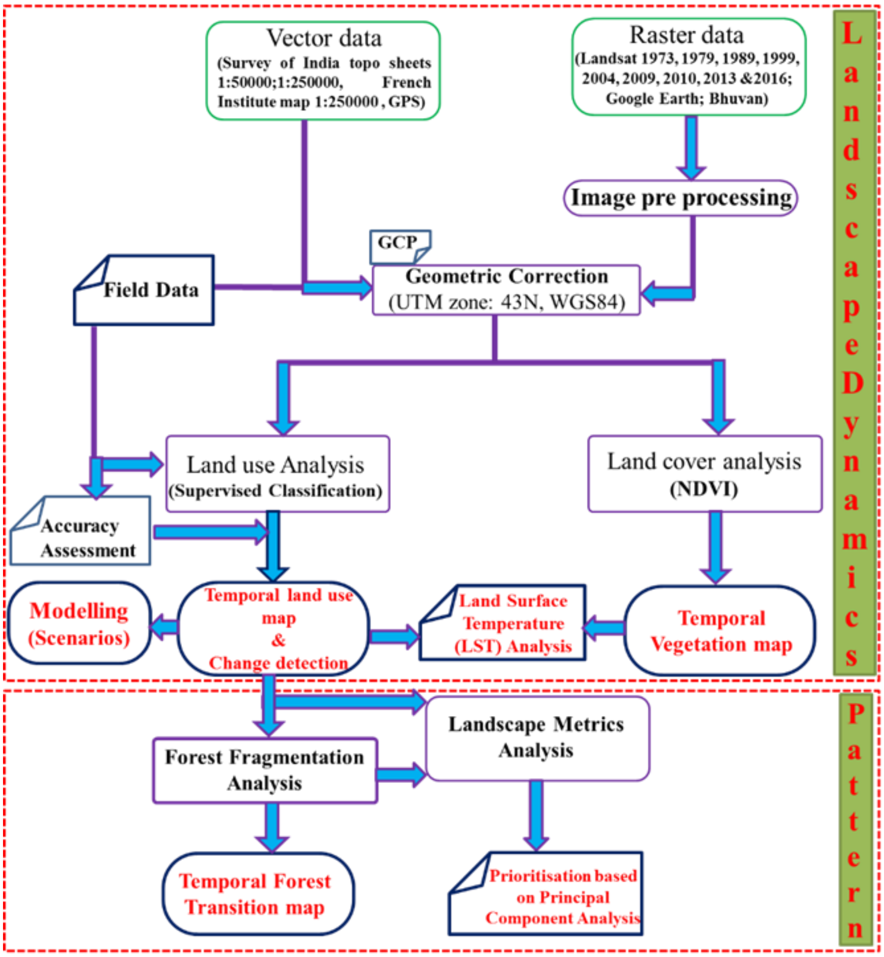



Figure 3.6. The approach used for landscape dynamics analysis

### 3.2.1.2. Ancillary data

Ancillary data include cadastral revenue maps (1:6000), the Survey of India (SOI) topographic maps (1:50000 and 1:250000 scales), US Army published maps of India and Pakistan at 1:250,000, Series U502 (1955), the vegetation map of South India developed by French Institute Pondicherry (1986) of scale 1:250000. Topographic maps provided ground control points (GCP's) to rectify remote sensing data and scanned paper maps. Vegetation map of South India (1986) of scale 1:250000 (Pascal, 1986) was digitized to identify various forest cover types to classify RS data of the 1980s. Other ancillary data includes forest division maps, administration boundary data, transportation data (road network), etc. Pre-calibrated **GPS (Garmin GPS unit)** is used for field data collection, which was used for RS data classification as well as for validation. Vector data of the district, taluk and village boundaries, drainage network, water bodies (lakes, ponds) were digitized from geo-referenced Survey of India topographic maps and cadastral maps. Population census and taluk wise village boundaries were collected from the Directorate of Census Operations, Bangalore region (http://censuskarnataka.gov.in).

Table 3.3. Details of RS data and source

| **Year** | **Satellite** | **Sensor** | **Spatial Resolution (m)** | **Temporal resolution (Days)** | **Spectral Resolution** | **Number of Bands** | **Path & Row** | **Date of Acquisition** | **Source** |
|---|---|---|---|---|---|---|---|---|---|
| 1973 | Landsat | Multi Spectral Scanner **(MSS)** | 57.5 | 18 | Visible Green (0.5 to 0.6 µm); Visible Red (0.6 to 0.7 µm); Near-Infrared (0.7 to 0.8 µm); Near-Infrared (0.8 to 1.1 µm) | 4 | 157-49; 157-50 | 02-Mar-73 | https://earthexplorer.usgs.gov/ |
| 1979 | | | | | | | 157-49; 157-50 | 30-Jan-79 | http://glcfapp.glcf.umd.edu:8080/esdi/index.jsp |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| 1989 | Landsat | Thematic Mapper **(TM)** | 28.5 | 16 | Blue (0.45 - 0.52 µm); Green (0.52 - 0.60 µm); Red (0.63 - 0.69 µm); NIR (0.76 - 0.90 µm); Shortwave Infrared-SWIR1 (1.55 - 1.75 µm); Thermal (10.40 - 12.50 µm→Resolution 120m *Resampled to 30 and supplied); SWIR2 (2.08 - 2.35 µm) | 7 | 146-49; 146-50 | 23-Feb-89 | http://glovis.usgs.gov/ |
| 1999 | | | | | | | 146-49; 146-50 | 20-Mar-99 | |
| 2004 | | | | | | | 146-49; 146-50 | 04-Mar-04 | https://earthexplorer.usgs.gov/ |
| 2007 | | | | | | | 146-49; 146-50 | 09-Mar-07 | http://glovis.usgs.gov/ |
| 2010 | Landsat | Enhanced Thematic Mapper Plus **(ETM+)** | 30 | 16 | Blue (0.45 - 0.52 µm); Green (0.52 - 0.60 µm); Red (0.63 - 0.69 µm); NIR (0.77 - 0.90 µm); Shortwave Infrared-SWIR1 (1.55 - 1.75 µm); Thermal (10.40 - 12.50 µm→Resolution 60m *Resampled to 30 and supplied); SWIR 2 (2.09 - 2.35 µm); Panchromatic | 8 | 146-49; 146-50 | 26-Mar-10 | http://glcfapp.glcf.umd.edu:8080/esdi/index.jsp |
| 2013 | | | | | | | 146-49; 146-50 | 29-Jan-13 | https://earthexplorer.usgs.gov/ |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | | | | | (0.52 - 0.90 µm →Resolution 15m) | | | | |
| 2016 | Landsat | Operational Land Imager **(OLI)** | 30 | | Ultra Blue (coastal/aerosol 0.435 - 0.451 µm); Blue (0.45 - 0.52 µm); Green (0.53 - 0.59 µm); Red (0.64 - 0.68 µm); NIR (0.85 - 0.88 µm); Shortwave Infrared-SWIR1 (1.57 - 1.65 µm); SWIR 2 (2.11 - 2.29 µm); Panchromatic (0.51 - 0.68 µm →Resolution 15m); Cirrus (1.363 - 1.384 µm); Thermal1 (10.60 – 11.19 µm); Thermal2 (11.50 – 12.51 µm →Resolution 100m *Resampled to 30 and supplied); | 11 | 146-49; 146-50 | 18-Mar-16 | https://earthexplorer.usgs.gov/ |

### 3.2.2. Method

#### 3.2.2.1. Pre-processing of data

RS data obtained were geo-referenced, rectified, and cropped corresponding to the study area. Geo-registration of RS data was done using ground control points collected from the field and also from known points (such as road intersections, etc.) collected from geo-referenced topographic maps published by the Survey of India. In the correction process numerous ground control points are located in on the distorted image and in terms of their ground coordinates typically measured from a map or located in the field, in terms of UTM coordinates or latitude and longitude. The Landsat satellite 1973, 1979 images have a spatial resolution of 57.5 m x 57.5 m (nominal resolution) was resampled to 30 m comparable to 2010-2016 data which are 30×30 m (nominal resolution) by reviewing various literature (Pohl, 1996; Gupta et al., 2000; Kumar et al., 2010; Ramachandra and Kumar, 2011; West et al., 2014; Skakun et al., 2017). Landsat ETM+ bands of 2010, 2013 were corrected for the SLC-off (Scan Line Corrector-off) by using image enhancement techniques, followed by nearest neighbor interpolation.

#### 3.2.2.2. Land cover (LC) analysis

The land cover analysis provides a broad view of the landscape. NDVI (Normalized Difference Vegetation Index) has been used to delineate the region under vegetation (Forest, Plantations, Horticulture, etc.,) and non-vegetation (Soil, Water, etc.). NDVI is most widely accepted and being applied among all techniques due to its sensitivity to highlight vegetation across various landscapes (Weismiller et al., 1977; Nelson, 1983; Ramachandra et al., 2009). NDVI is the 1$^{st}$ level of classification in understanding landscape dynamics. NDVI is computed by equation 20 considering spatial data of visible Red (0.63-0.69 μm) and Near Infra-Red (0.76-0.90 μm) bands. Healthy vegetation absorbs most of the visible light that hits it and reflects a large portion of the near-infrared light. Sparse vegetation reflects more visible light and less near-infrared light. NDVI for a given pixel always results in a number that ranges from minus one (-1) to plus one (+1). Very low values of NDVI (-0.1 and below) correspond to soil or barren areas of rock, sand, or built up. Zero indicates the water bodies. Moderate values represent low density vegetation (0.1 to 0.3), while high values indicate thick canopy vegetation (0.6 to 0.9). The outcome of NDVI (for the latest time period) was verified using data collected during field investigations and also through the online portal (Google Earth-http://earth.google.com).

$$\mathbf{NDVI} = {(\mathbf{NIR} - \mathbf{R})}\big/{(\mathbf{NIR} + \mathbf{R})} \qquad (20)$$

### 3.2.2.3. Land use (LU) analysis

The LU analyses provide a detailed overview of how the land being used/ altered due to anthropogenic activities. LU analysis of spatial data is done using a Supervised classifier based on the Gaussian Maximum Likelihood algorithm with training data (collected from field using GPS). Training data required for classification were collected through (i). Field Investigation using pre-calibrated handheld Global Positioning System - GPS; (ii). Online high-resolution spatial data – Google Earth (http://earth.google.com), Bhuvan (http://bhuvan.nrsc.gov.in). LU analysis involved (i) generation of False Color Composite (FCC) of RS data (bands–green, red, and NIR-near infrared). This composite image helps in locating heterogeneous patches in the landscape, (ii) selection of training polygons by covering 15% of the study area (polygons are uniformly distributed over the entire study area) (iii) loading these training polygons co-ordinates into pre-calibrated GPS, (vi) collection of the corresponding attribute data (LU types) for these polygons from the field. GPS helped in locating respective training polygons in the field, (iv) supplementing this information with Google Earth and Bhuvan, (v) 60% of the training data has been used for classification, while the balance is used for validation or accuracy assessment.

Maximum Likelihood algorithm has been widely applied as an appropriate and efficient classifier to extract information from remote sensing data (Atkinson and Lewis, 2000; Ramachandra et al., 2014a). This approach quantitatively evaluates variance and covariance of the category spectral response patterns when classifying an unknown pixel of remote sensing data, assuming the distribution of data points to be Gaussian (Duda et al., 2012). The statistical probability of a given pixel value being a member of a particular class are computed. After evaluating the probability in each category, the pixel is assigned to the most likely class (highest probability value). **GRASS GIS *(Geographical Resources Analysis Support System)*** software is used for the analysis, which is a free and open-source software having robust support for processing both vector and raster files accessible at http://wgbis.ces.iisc.ernet.in/grass/index.php. The land use classification is based on The International Geosphere-Biosphere Programme (IGBP) and thematic representation is based on the National Remote Sensing Centre (NRSC) color codes. The Published French Institute vegetation map (1:250,000) scale and field data provided the various forest cover types present in the district. Temporal remote sensing data have been classified under 11 categories through supervised classification techniques by using available multi-temporal “ground truth” information. The histogram for remote sensing data has been generated to understand the number of separable classes in the data. Appendix 3 provides a detailed explanation of this endeavor. Clusters were generated by providing the input as 64, 32, 16 numbers, and quantified the stable number of separable classes based on Mean, variance, standard deviation by sampling across 8288 points. The 64 clusters provided 68.50% points stable, 32 clusters showed 88.62% points stable, and finally, 16 classes showed 98.21% points stable. So, we have considered 11 separable classes for the entire analysis. Earlier time data were classified using the training polygon along with attribute details compiled from the historical published topographic maps, French institute vegetation maps, revenue maps, land records available from local administrative authorities, etc.

### 3.2.2.4. Accuracy assessment

The precision of classified data is evaluated through statistical accuracy assessment to quantify the agreement of LU classification with respect to the field data (ground condition), and which forms an important stage in the RS data classification. Accuracy assessments of the LULC classification have been evaluated through error matrix (also referred as a contingency table or confusion matrix), and computation of kappa ($\kappa$) statistics and overall (producer's and user's) accuracies. This is done to evaluate the quality of the information derived from remotely sensed data considering reference pixels. Kappa statistic compares two or more matrices and weighs cells in error matrix according to the magnitude of misclassification (Lillesand et al., 2014; Liu et al., 2007). Kappa coefficient is also known as KHAT statistic ($\kappa^{\wedge}$), a measure of the difference between the pixel agreement of ground truth data with classified data and the probability of a chance of the pixel (chance agreement) to be a particular class with reference data. Kappa is calculated as given below in equation 21. The value of Kappa ranges from 0 to1, which means if the true agreement reaches one (with values closest to 1 reflecting highest agreement) then chance agreement reaches zero and vice-versa. The producer’s accuracy measures errors of omission, through correctly classified pixels in a particular category as a percentage of the total number of pixels belonging to that category in the image. The user’s accuracy (UA) measures errors of commission, using the number of correctly classified pixels to the total number of pixels assigned to a particular category (Appendix 3).

$$\kappa^{\wedge} = \frac{\text{Observed accuracy} - \text{Chance agreement}}{1 - \text{Chance agreement}} \tag{21}$$

### 3.2.2.5. The annual rate of changes in LU

The annual change with respect to each LU category is computed by considering the respective LU spatial extent at two different periods. The annual rate of change is computed using equation 22, which helps to identify the magnitude of changes in the LU category (Puyravaud, 2003; Armenteras et al., 2006). This approach helps to determine change rates from “known cover” as observed forest cover by providing areas that had changed to non-forest (Tabor et al., 2010). This computation is based on the area that was classified as forest in the first date and changed to non-forest in the second date. The denominator for calculating change rates, called the “change base”, is essentially the area of forest classified in the first date to the second date. The annual change is calculated as,

$$Change\ rate = \left( {}^{\ln(A_{t1}) - \ln(A_{t0})} \big/ {}_{(t1 - t0)} \right) * 100 \qquad (22)$$

Where $A_{t1}$ is an area of LU class in a current year, $A_{t0}$ is an area of class in a base year, $t_1$ is the current year, $t_0$ is a base year and ln is the natural logarithm. The equation will result in a % change in each LU class with negative and positive. The negative changes indicate to rate of loss; whereas positive change rate indicates a gain in LU class.

### 3.2.2.6. Analysis of forest fragmentation

The forest fragmentation model is implemented to derive the spatial maps of forest fragmentation components using the sliding window analysis technique as outlined in Riitters et al., 2002. Fragmentation of forests by fixed-area kernels at the pixel level is estimated through the computation of $P_f$ (the ratio of the number of pixels that are forested to the total number of non-water pixels in the window) and $P_{ff}$ (the proportion of all adjacent (in cardinal directions only) pixel pairs that include at least one forest pixel, for which both pixels are forested) as given in equations 23 and 24 (Riitters et al., 2002; Kuèas et al., 2011; Ramachandra and Kumar 2011).

$$P_f = \frac{\text{Proportion of number of forest pixels}}{\text{Total number of non−water pixels in window}} \qquad (23)$$

$$P_{ff} = \frac{\text{Proportion of number of forest pixel pairs}}{\text{Total number of adjacent pairs of at least one forest pixel}} \qquad (24)$$

A moving window with a size of 5×5 pixels was used for analysis to maintain a fair representation of the proportion ($P_f$) of pixels in the window. The effective kernel of size is selected for spatial data of 30 m, based on earlier work (Riitters et al., 2002; Wickham et al., 2007; Kuèas et al., 2011; Prasad et al., 2009; Ramachandra and Kumar, 2011) as kernel size smaller than 5×5 has an effect of decreasing the average inter-patch distance, indicating less fragmentation, even though disintegration of interior forests might be evident (Riitters et al., 2004; Bogaert et al., 2004; Lindenmayer et al., 2008). Similarly, an increase of kernel size decreases the core area and this process may transform small core areas to form a discontinuous landmass (Ostapowicz et al., 2008; Kuèas et al., 2011). The computation of $P_f$ and $P_{ff}$ for a 5×5 grid of pixels is shown (Figure 3.7). Forest pixels are shaded as a green color with pattern and non-forest pixels are not shaded. Here, 15 of 25 pixels are forested and so $P_f$ equals 15/25=0. 6. Considering pairs of pixels in cardinal directions, the total number of adjacent pixel pairs is 40, and of these, 40 pairs include at least one forested pixel. Eight of those 40 pairs are **forest-forest** pairs, so $P_{ff}$ equals 8/40 = 0.2. Fragmentation analysis will provide a description of different components as shown in Table 3.4 that will help us to evaluate the health of forest of a region. Water bodies or river courses are considered non-fragmenting features, as these elements constitute natural corridors in a forested landscape, while anthropogenic landscape elements (such as buildings, roads, agricultural field, and barren land) are drivers of forest fragmentation.

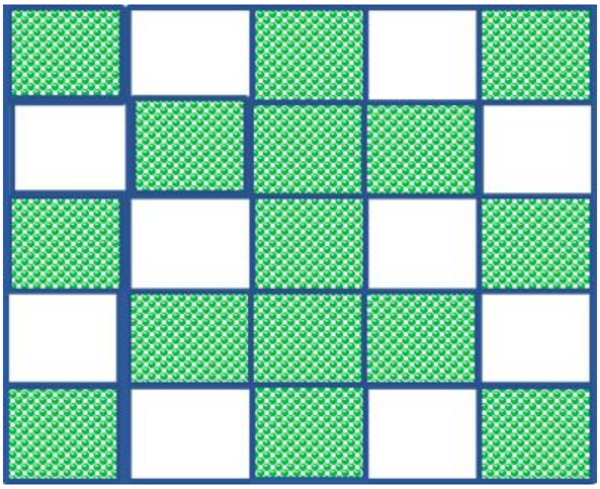


Figure 3.7. Model image for computation of $P_f$, $P_{ff}$ values

Table 3.4. Fragmentation components and their description

| **Fragmentation component** | **Description** | **Computation** |
|---|---|---|
| **Interior** | Forest pixels are far away from the forest-non forest boundary. | ($P_f$ = 1). All pixels surrounding the center pixel are forest. |

| | | |
|---|---|---|
| | Interior forested areas are surrounded by thicker forested areas. | |
| **Patch** | Forest pixels comprising small forested areas surrounded by a nonforested LC. | ($P_f < 0.4$). A pixel is part of a forest patch on a non-forest background, such as a small wooded lot within a built-up area. |
| **Perforated** | Forest pixels forming the boundary between an interior forest and relatively small clearings (perforations) within the forested landscape. | ($P_f > 0.6$ and $P_f – P_{ff} > 0$). Most pixels in the surrounding area are forested, but the center pixel appears to be part of the inside edge of a forest patch. This would occur if small clearings were made within a patch of forest. |
| **Edge** | Forest pixels that define the boundary between interior forest and large nonforested features. | ($P_f > 0.6$ and $P_f – P_{ff} < 0$). Most pixels in the surrounding area are forested, but the center pixel appears to be part of the outside edge of a forest. This would occur along the boundary of a large built-up area or agricultural field. |
| **Transitional** | Areas between edge type and non-forest types. If higher pixels are non-forest, then they will be tending to non-forest. | ($0.4 < P_f < 0.6$). About half of the cells in the surrounding area are forested and the center forest pixel may appear to be part of a patch, edge, or perforation depending on the local forest pattern. |

# CHAPTER 4 | QUANTIFYING LANDSCAPE DYNAMICS

# CHAPTER 4| QUANTIFYING LANDSCAPE DYNAMICS

This Chapter analyses land use land cover changes and fragmentation of forests in the Uttara Kannada district using temporal remote sensing data.

## 4.1 Quantifying Landscape changes

### 4.1.1. Land Cover (LC) analysis

The spatial extent of LC (areas under vegetation and non-vegetation) was analyzed using NDVI (Equation 20). Temporal LC reveals a decline of vegetation from 97.82% (1973) to 80.42% (2016). Areas under non-vegetation have increased from 2.18 % (1973) to 19.58% (2016), due to anthropogenic activities. Figure 4.1, 4.2 (a-f) depicts temporal vegetation cover details during 1973, 1979, 1989, 1999, 2010, 2013 and 2016.

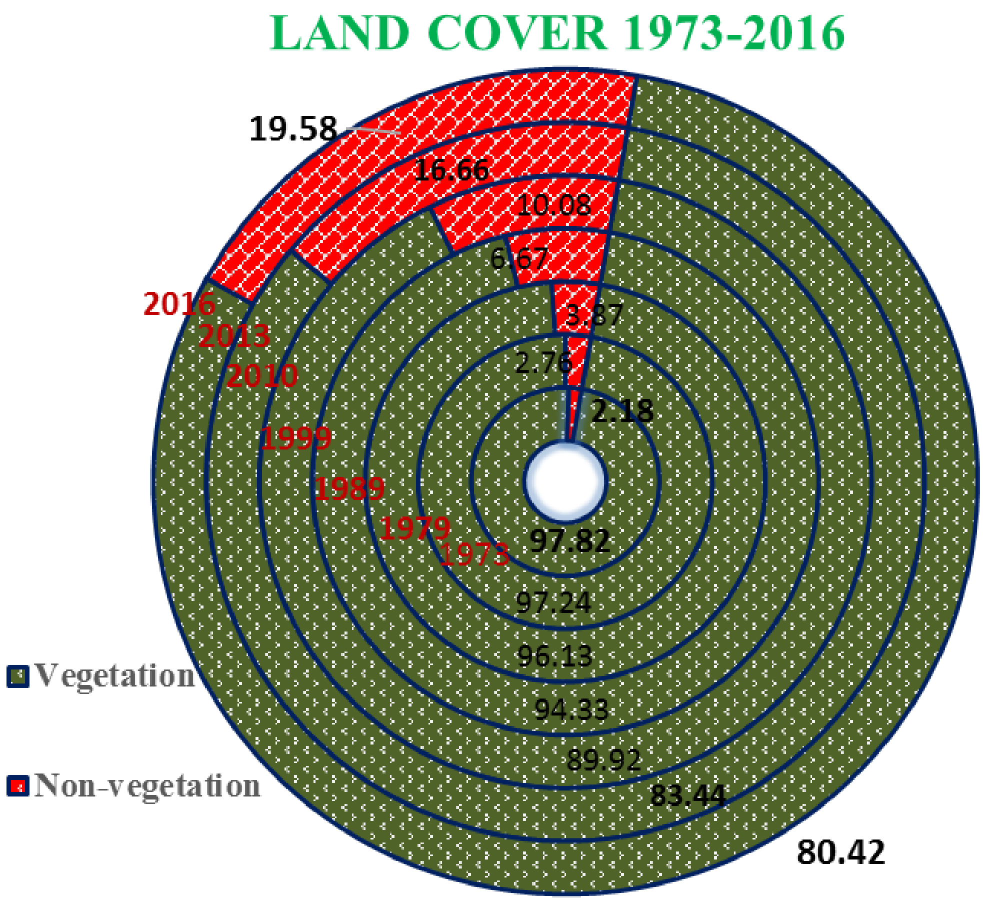



Figure 4.1. Temporal land cover analysis

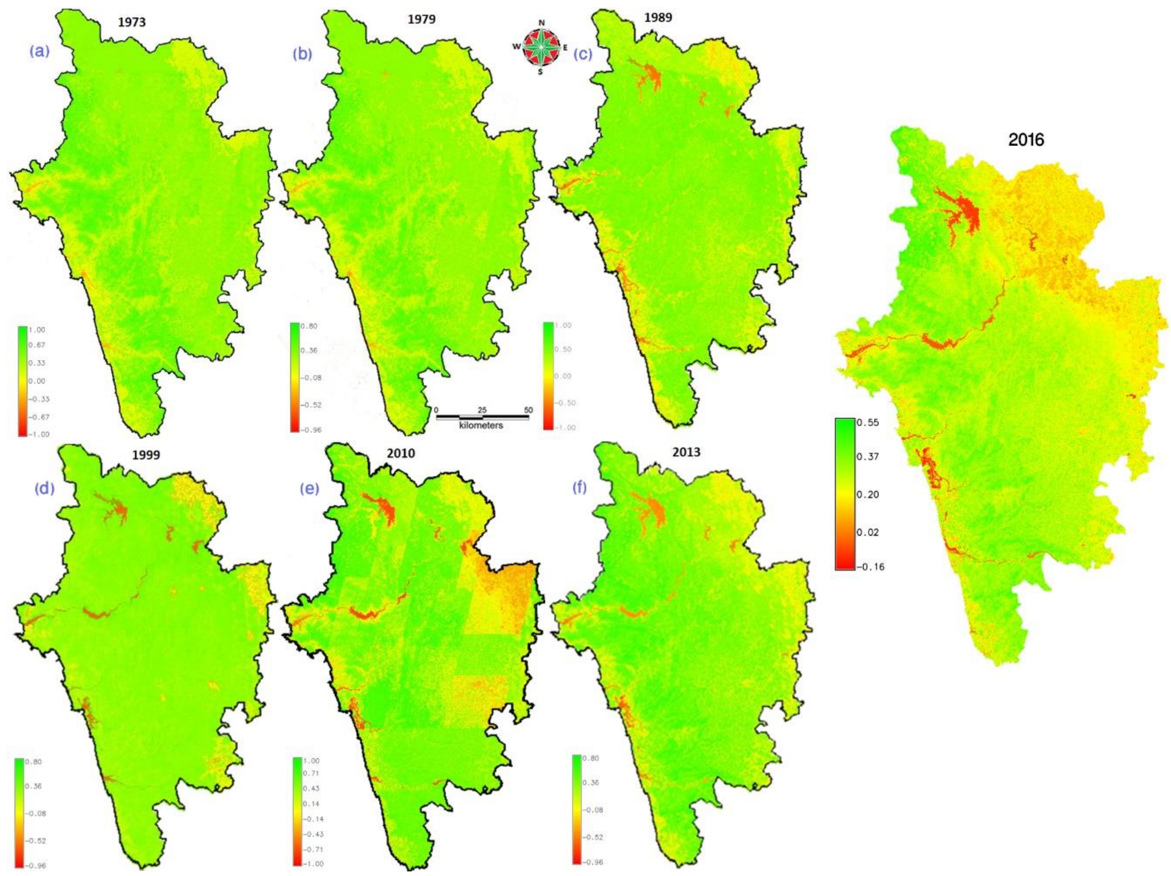



Figure 4.2(a-f). Land cover during 1973 to 2016

### 4.1.2. Land Use (LU) analysis

RS data of Landsat was classified into eleven LU categories through a supervised classifier based on Gaussian maximum likelihood classified using training data collected from the field. Similarly, LU for the previous time period was analyzed using collateral data as well as historical records. Figure 4.3A shows the training sites based on field investigations, used for LU classification. Table 4.1 and Figure 4.3B (a-f) provide spatial extent and temporal changes of each LU type from 1973 to 2016. Comparative assessment of LU across categories reveals the decline of vegetation cover in the district from 1973 to 2016. The reduction of area under evergreen forests from **67.73**% (1973) to **29.5**% (2016) due to anthropogenic activities involving the conversion of forest land to agricultural and horticultural activities, monoculture plantations and land releases for developmental projects. The transition of evergreen-semi evergreen forests to moist deciduous forests and some have been converted into plantations (such as Teak, Areca nut, Acacia spp., etc.). Enhanced agricultural activities is evident from the increase of agricultural LU from **7.00** to **14.3 %** (1973-2016) and the area under human habitations have increased during the last four decades, evident from the increase of built-up area from **0.38%** to **4.97%** (1973-2016). Unplanned developmental activities coupled with the enhanced agriculture and horticultural activities are the prime drivers of deforestation, leading to the irreversible loss of forest cover with the reduction of ecosystem goods and services. About **64355 Ha** of forest land is diverted for various non-forestry activities during the last four decades by the government apart from the encroachment of **7072 Ha** of forest area for agriculture, horticulture activities, etc. The ad-hoc approaches adopted in the implementation of major developmental projects such as Project Seabird, Gerusoppa dam, Supa dam, Kadra dam, Kaiga NPH, West coast paper mill, Tattihalla reservoir, etc., have impaired the ecosystem by affecting the sustenance of water and hence people's livelihood.

The increase in plantations of exotic species has led to the removal of forest cover and the disappearance of native species. *Acacia auriculiformis, Casuarina equisetifolia, Eucalyptus globulus, Tectona grandis* were planted widely under social forestry in the district. Acacia and Teak plantations constitute 10.78% and 7.67% respectively in the district. The dry deciduous forest cover is very less (1.27%) and is found mainly in the northeastern part of the district in Mundgod taluk and partly Haliyal taluk. Ecologically fragile swampy areas were encroached and converted to plantations of *Areca catechu, Cocos nucifera,* etc. Construction of new subdivision roads and buildings, widening of highways increased dramatically during the 1990s. The construction of roads and houses in valley slopes has also enhanced the episodes of landslides in the district. More recently, the impetus to industrialization has encouraged the concentration of human populations at taluks such as Karwar, Bhatkal, Honnavara, and Sirsi. The areas of each category were also compared with available administrative reports, statistical department data, and forest division annual reports. Figure 4.4 highlights the loss of forest cover from 1973 to 2016 as 197908 ha. The accuracy of classifications (Table 4.2), verified using field data and Google Earth data shows an accuracy of 82-92% with consistent results. Cautious steps were taken to make sure separate data sets are used for training and validation to attain greater accuracy by consistent classification and confirmation. Vegetation map of South India (scale 1:250000) and Survey of India Toposheets (scale 1:50000) were used for accuracy evaluation up to 1989 land use analysis, even though they had a coarse resolution in comparison to the actual data. This resulted in moderate accuracy (> 80%) as compared with the post-1990's data.

Category-wise LU changes were computed and listed in Table 4.3. Higher changes are noticed during 1973-79 followed by 2010 to 2016 (Figure 4.5). Non-forest regions such as agriculture, built environments show an increasing trend in each time period. The built-up area shows a positive increase of 15.31% $y^{-1}$(per year). The evergreen forest shows a change of -2.78% $y^{-1}$

during 1973-1979 and -2.80%$y^{-1}$ (2013-2016). The greater loss of evergreen forests is 3.53%$y^{-1}$ (2010-2013) due to major motorways expansion. Forest plantations and horticulture show an increase from 1973 to 2016, indicating the market's role in land conversion. The abrupt LU changes are due to large-scale developmental activities, and increased agriculture to meet the growing demands of the population.

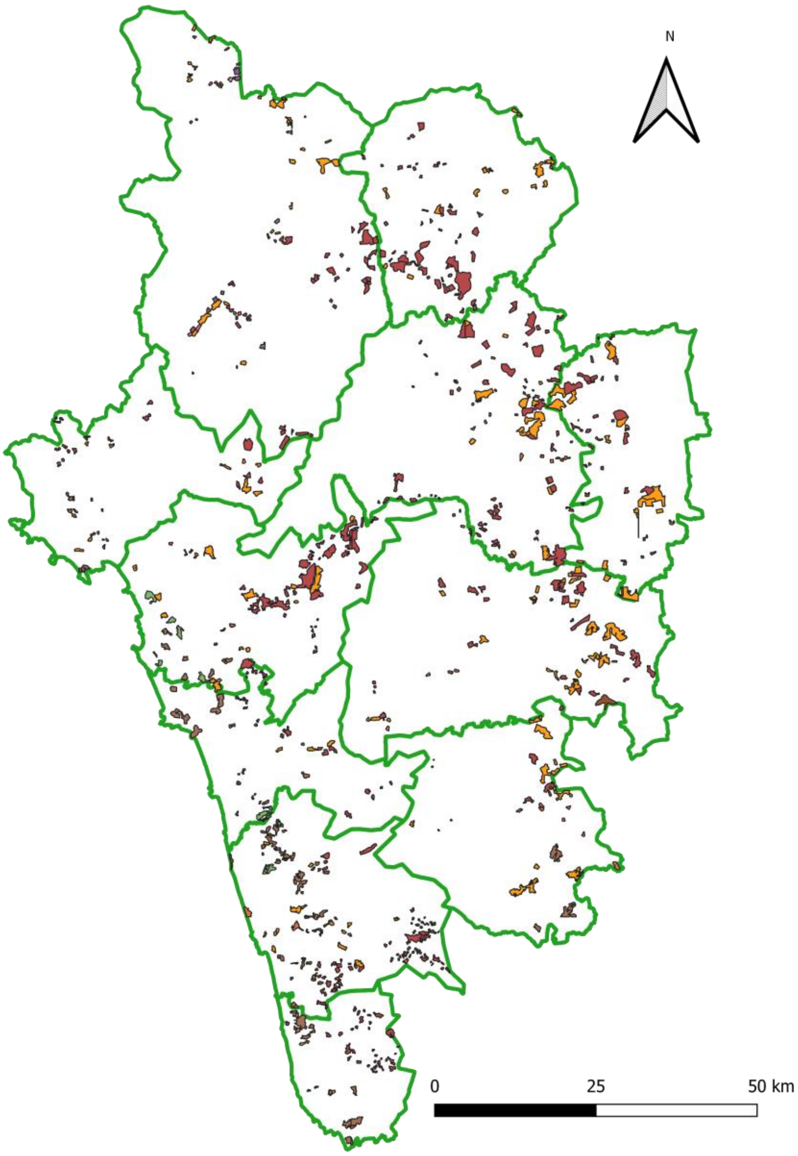



Figure 4.3A. Training sites selected for classification covering various LU features across the study region

Table 4.1. Spatial extent of each LU category from 1973 to 2016

| Year | 1973 | | 1979 | | 1989 | | 1999 | | 2010 | | 2013 | | 2016 | | Loss / Gain (1973-2016) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Category** | **Ha** | **%** | **Ha** | **%** | **Ha** | **%** | **Ha** | **%** | **Ha** | **%** | **Ha** | **%** | **Ha** | **%** | **(Ha)** |
| **Built-up** | 3886 | 0.38 | 9738 | 0.95 | 12982 | 1.26 | 21635 | 2.1 | 28491 | 2.77 | 31589 | 3.07 | 51132 | 4.97 | 47246 |
| **Water** | 7681 | 0.75 | 18527 | 1.8 | 16604 | 1.61 | 32983 | 3.21 | 26119 | 2.54 | 28113 | 2.73 | 28228 | 2.74 | 20547 |
| **Crop land** | 71990 | 7 | 103163 | 10.02 | 121167 | 11.77 | 138458 | 13.45 | 148187 | 14.4 | 145395 | 14.13 | 147109 | 14.3 | 75119 |
| **Open fields** | 14071 | 1.37 | 15988 | 1.55 | 34783 | 3.38 | 21945 | 2.13 | 30813 | 2.99 | 37660 | 3.66 | 42634 | 4.15 | 28563 |
| **Moist deciduous forest** | 95357 | 9.27 | 102967 | 10.01 | 143849 | 13.98 | 179075 | 17.4 | 166266 | 16.15 | 161996 | 15.74 | 164239 | 15.95 | 68882 |
| **Evergreen to semi evergreen** | 696978 | 67.73 | 589762 | 57.31 | 531872 | 51.68 | 423062 | 41.11 | 367064 | 35.66 | 330204 | 32.08 | 303585 | 29.5 | -393393 |
| **Scrub/grass** | 38109 | 3.7 | 58936 | 5.73 | 44123 | 4.29 | 47366 | 4.6 | 35158 | 3.42 | 40402 | 3.93 | 42083 | 4.09 | 3974 |
| **Acacia/Eucalyptus/ Hardwood plantations** | 40905 | 3.97 | 50321 | 4.89 | 55694 | 5.41 | 73977 | 7.19 | 119717 | 11.63 | 122927 | 11.94 | 110950 | 10.78 | 70045 |
| **Teak/ Bamboo/ Softwood plantations** | 13997 | 1.36 | 20896 | 2.03 | 21937 | 2.13 | 38588 | 3.75 | 44794 | 4.35 | 67111 | 6.52 | 78953 | 7.67 | 64956 |
| **Coconut/ Areca nut / Cashewnut plantations** | 20702 | 2.01 | 29675 | 2.88 | 32227 | 3.13 | 43623 | 4.24 | 53646 | 5.21 | 53993 | 5.25 | 47135 | 4.58 | 26433 |
| **Dry deciduous forest** | 25410 | 2.47 | 29113 | 2.83 | 13848 | 1.35 | 8374 | 0.81 | 9008 | 0.88 | 9873 | 0.96 | 13038 | 1.27 | -12372 |
| **Total Area** | 1029086 | | | | | | | | | | | | | | |

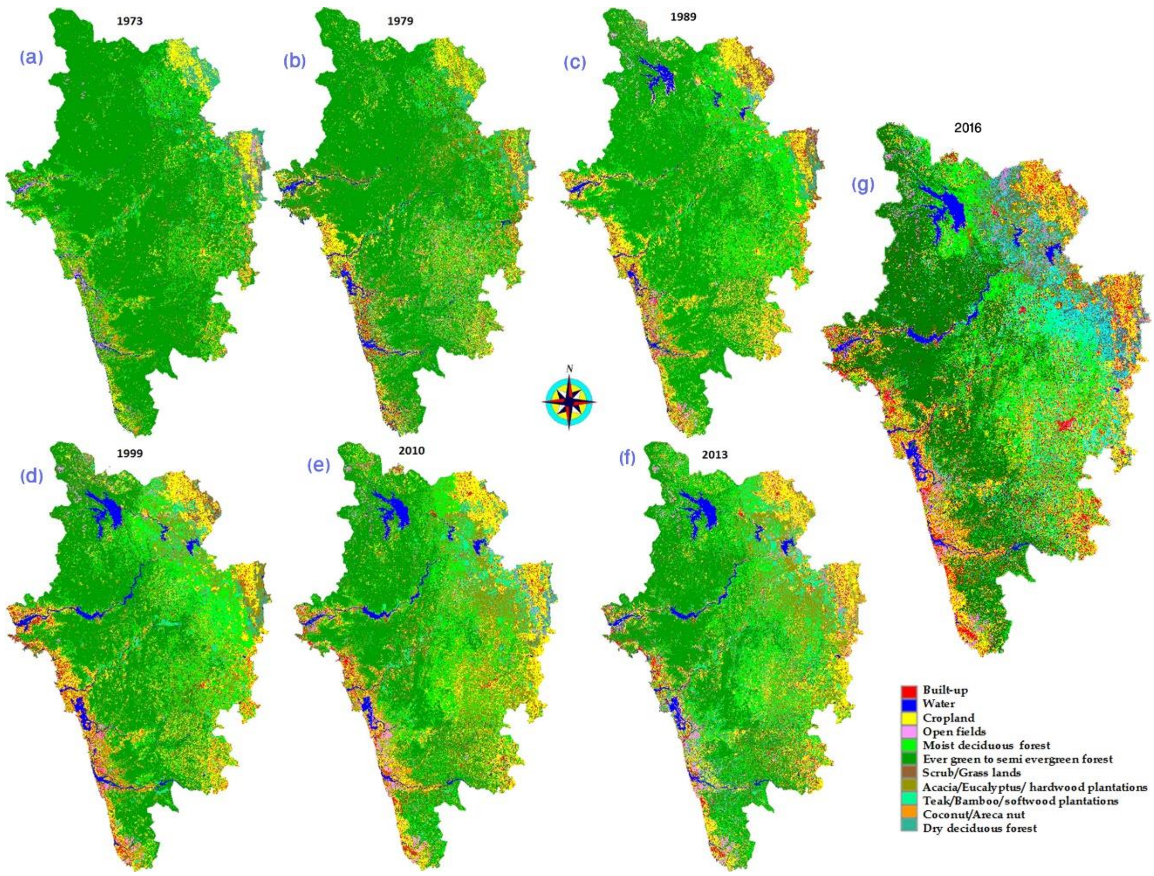
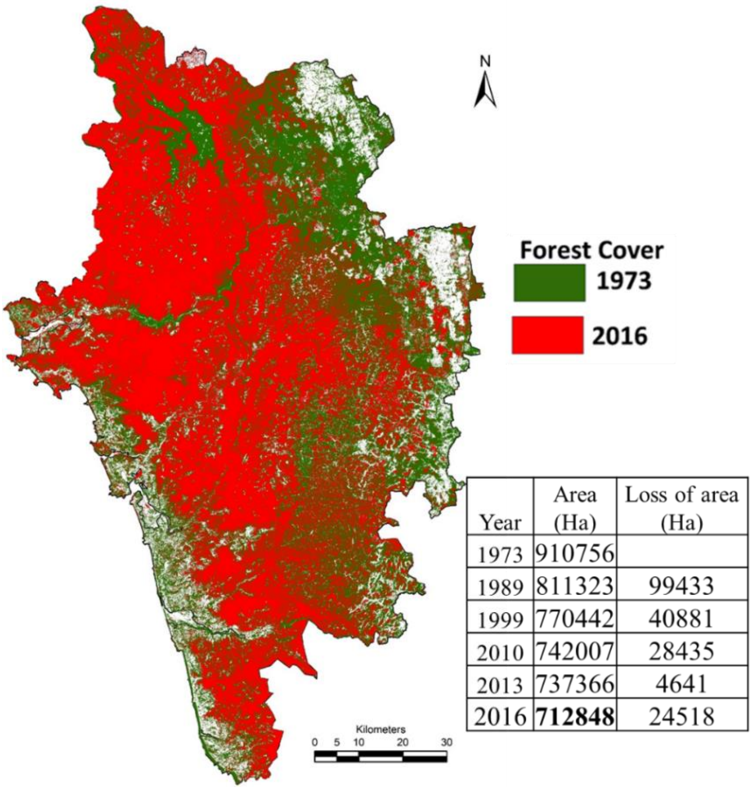



Figure 4.3B (a- f). LU change of Uttara Kannada district from 1973 to 2016




| Year | Area (Ha) | Loss of area (Ha) |
|---|---|---|
| 1973 | 910756 | |
| 1989 | 811323 | 99433 |
| 1999 | 770442 | 40881 |
| 2010 | 742007 | 28435 |
| 2013 | 737366 | 4641 |
| 2016 | **712848** | 24518 |

Figure 4.4. Temporal change in forest cover

Table 4.2. Accuracy assessment of the study

| Year | Accuracy | Built-up | Water | Cropland | Open land | Moist deciduous | Evergreen to semi | Scrub | Acacia | Teak | Coconut | Dry deciduous |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 1973 | PA | 67.61 | 90.73 | 83.14 | 86.54 | 82.36 | 90.24 | 58.92 | 72.39 | 74.85 | 50.16 | 92.27 |
| | UA | 66.69 | 89.94 | 79.26 | 86.42 | 81.5 | 89.82 | 57.52 | 71.58 | 78.18 | 66.02 | 91.84 |
| 1979 | PA | 68.66 | 92.00 | 95.45 | 81.73 | 68.2 | 93.00 | 64.41 | 65.58 | 47.18 | 38.57 | 46.47 |
| | UA | 90.00 | 85.40 | 74.30 | 78.56 | 85.1 | 89.15 | 90.78 | 93.43 | 94.84 | 94.67 | 74.10 |
| 1989 | PA | 98.28 | 99.62 | 95.83 | 91.58 | 88.8 | 94.59 | 92.28 | 97.44 | 84.41 | 38.83 | 80.89 |
| | UA | 77.6 | 95.53 | 87.09 | 93.84 | 97 | 97.84 | 98.16 | 74.33 | 59.18 | 73.75 | 70.07 |
| 1999 | PA | 79.88 | 98.14 | 98.62 | 76.22 | 88.7 | 98.02 | 85.61 | 89.93 | 81.63 | 88.22 | 88.86 |
| | UA | 88.4 | 97.67 | 98.35 | 83.32 | 95.9 | 96.68 | 84.79 | 85.81 | 82.4 | 89 | 31.5 |
| 2010 | PA | 60.34 | 99.77 | 97.49 | 89.81 | 87.9 | 93.91 | 93.24 | 92.53 | 78.68 | 89.92 | 86.78 |
| | UA | 94.14 | 99.56 | 90.11 | 89.13 | 85.5 | 96.3 | 85.7 | 90.98 | 91.1 | 80.02 | 86.85 |
| 2013 | PA | 92.53 | 95.32 | 80.00 | 86.25 | 92.8 | 96.53 | 67.71 | 69.08 | 78.68 | 91.03 | 97.49 |
| | UA | 23.87 | 96.80 | 98.10 | 68.05 | 88.5 | 98.90 | 13.59 | 94.10 | 91.10 | 97.70 | 90.11 |
| 2016 | PA | 93.22 | 95.17 | 89.82 | 59.53 | 91.61 | 98.69 | 93.18 | 75.91 | 32.44 | 93.42 | 68.12 |
| | UA | 54.25 | 99.74 | 95.90 | 87.05 | 93.81 | 96.02 | 87.75 | 32.42 | 47.74 | 87.02 | 85.04 |

| *Year* | ***Overall Accuracy*** | ***Kappa*** |
|---|---|---|
| 1973 | 82.52 | 0.81 |
| 1979 | 84.29 | 0.81 |
| 1989 | 92.22 | 0.89 |
| 1999 | 90.71 | 0.87 |
| 2010 | 91.51 | 0.89 |
| 2013 | 91.98 | 0.90 |
| 2016 | 90.0 | 0.88 |

Here, PA refers to Producer’s Accuracy and UA refers to User’s Accuracy.

Table 4.3. LU change rate (%) from 1973-2016

| Category | Time period | | | | | |
|---|---|---|---|---|---|---|
| | 1973-1979 | 1979-1989 | 1989-1999 | 1999-2010 | 2010-2013 | 2010-2016 |
| Built-up | **15.31** | **2.88** | **5.11** | **2.50** | **3.44** | **16.05** |
| Water | 14.67 | -1.10 | 6.86 | -2.12 | 2.45 | 0.14 |
| Crop land | 6.00 | 1.61 | 1.33 | 0.62 | -0.63 | 0.39 |
| Open spaces | 2.13 | 7.77 | -4.61 | 3.09 | 6.69 | 4.14 |
| Moist deciduous forest | 1.28 | 3.34 | 2.19 | -0.67 | -0.87 | 0.46 |
| Evergreen to semi evergreen forest | **-2.78** | **-1.03** | **-2.29** | **-1.29** | **-3.53** | **-2.80** |
| Scrub/grass lands | 7.27 | -2.89 | 0.71 | -2.71 | 4.63 | 1.36 |
| Acacia / Eucalyptus / Other Hardwood | 3.45 | 1.01 | 2.84 | 4.38 | 0.88 | -3.42 |
| Teak / Bamboo / other Softwood | 6.68 | 0.49 | 5.65 | 1.36 | 13.48 | 5.42 |
| Coconut / Areca nut / Cashew nut | 6.00 | 0.82 | 3.03 | 1.88 | 0.21 | -4.53 |
| Dry deciduous Forest | 2.27 | -7.43 | -5.03 | 0.66 | 3.06 | 9.27 |

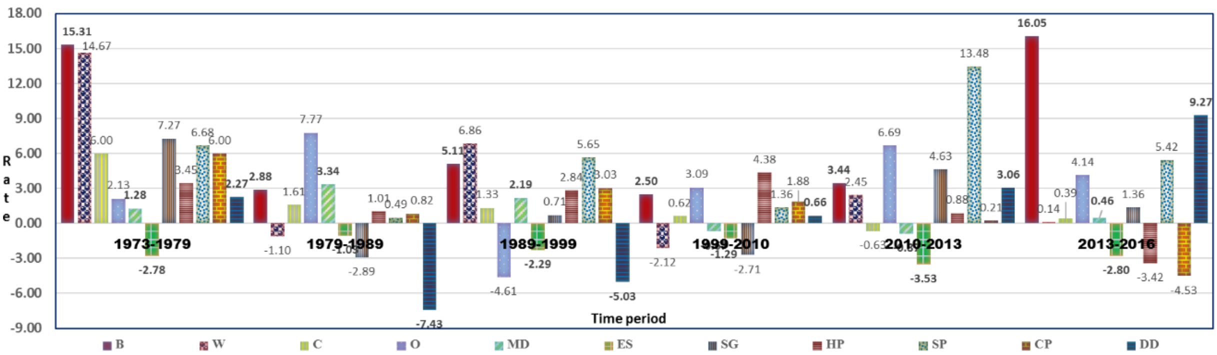



Figure 4.5. Temporal variation of LU change rate from 1973 to 2016

### 4.1.3. Analysis of forest fragmentation

Fragmentation of forests at the landscape level was assessed in order to understand the spatiotemporal patterns in forest degradation using temporal LU (1979 to 2016) information. Figures 4.6 and 4.7 (a-e) depict the temporal pattern of the fragmentation process in the Uttara

Kannada District. The district has high interior forests (64.42 %) in 1979. Edge forests (7.32 %) are located along linear corridors, such as roads, rivers, and boundary pixels of large forest patches. Patch forests are mainly located at the interfaces of forests, intermixed with agriculture and urban classes over small portions. The unscientific forest exploitation by the industrial sector peaked with the impetus of forest-based industries during the period from 1960 to the 1980s leading to selective felling of trees in the evergreen forests (Gadgil and Chandran, 1989). This has created canopy gaps and the spread of invasive exotic species, adversely affecting faunal species. Mining activities in the district leave significant ecological, economic, and social footprints much beyond the physical boundaries of mines by disrupting continuous forest patches (Ramachandra et al., 2014a). The decline in the area of interior forests from 64.42 % to 53.33 % (1979-1989), with an increase in edge forests (12 %) can be perceived due to the major activities such as industrialization, infrastructure development, intensified agriculture, manganese mining, a ferromanganese plant, a paper mill, and plantations. The region lost a major portion of its interior forest and reached 40.74 % from 53.33 % (1989-1999) with the increase in edge forests (16.35 %) due to the implementation of a series of hydroelectric projects, the construction of national routes NH-17, NH-63, NH-204, the Konkan railway line, and other infrastructure projects. By 2016, The area under non-forests has increased from 36.07 (1999) to 49.2 % (2016) with the loss of interconnectivity due to an increase of edges and perforated patches. The interior forests (22.25 %) exists only in the protected areas - sanctuaries, national parks, tiger reserves, sacred groves illustrate the signification of conservation regions or protected areas.

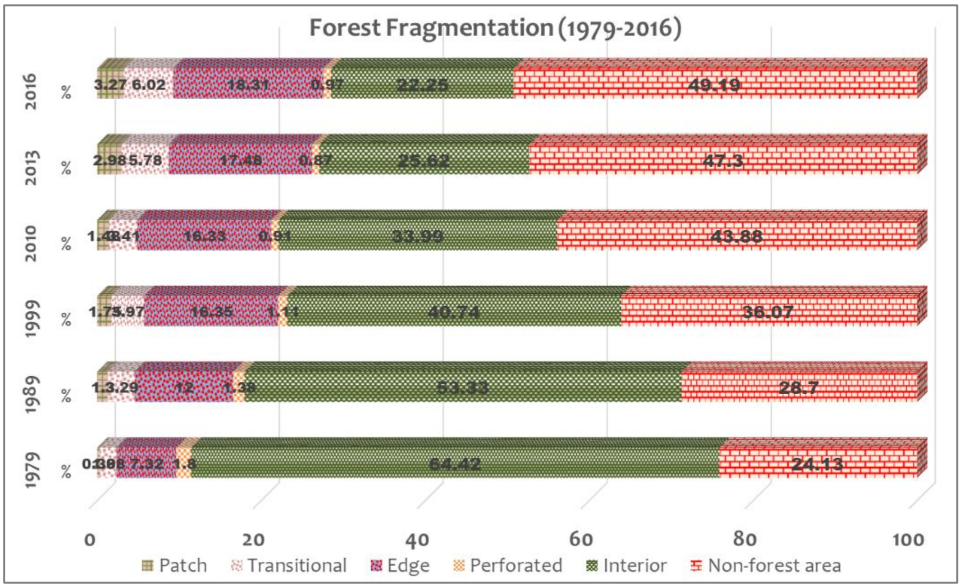



Figure 4.6. Spatiotemporal pattern of fragmentation from 1979 to 2016 at a landscape level

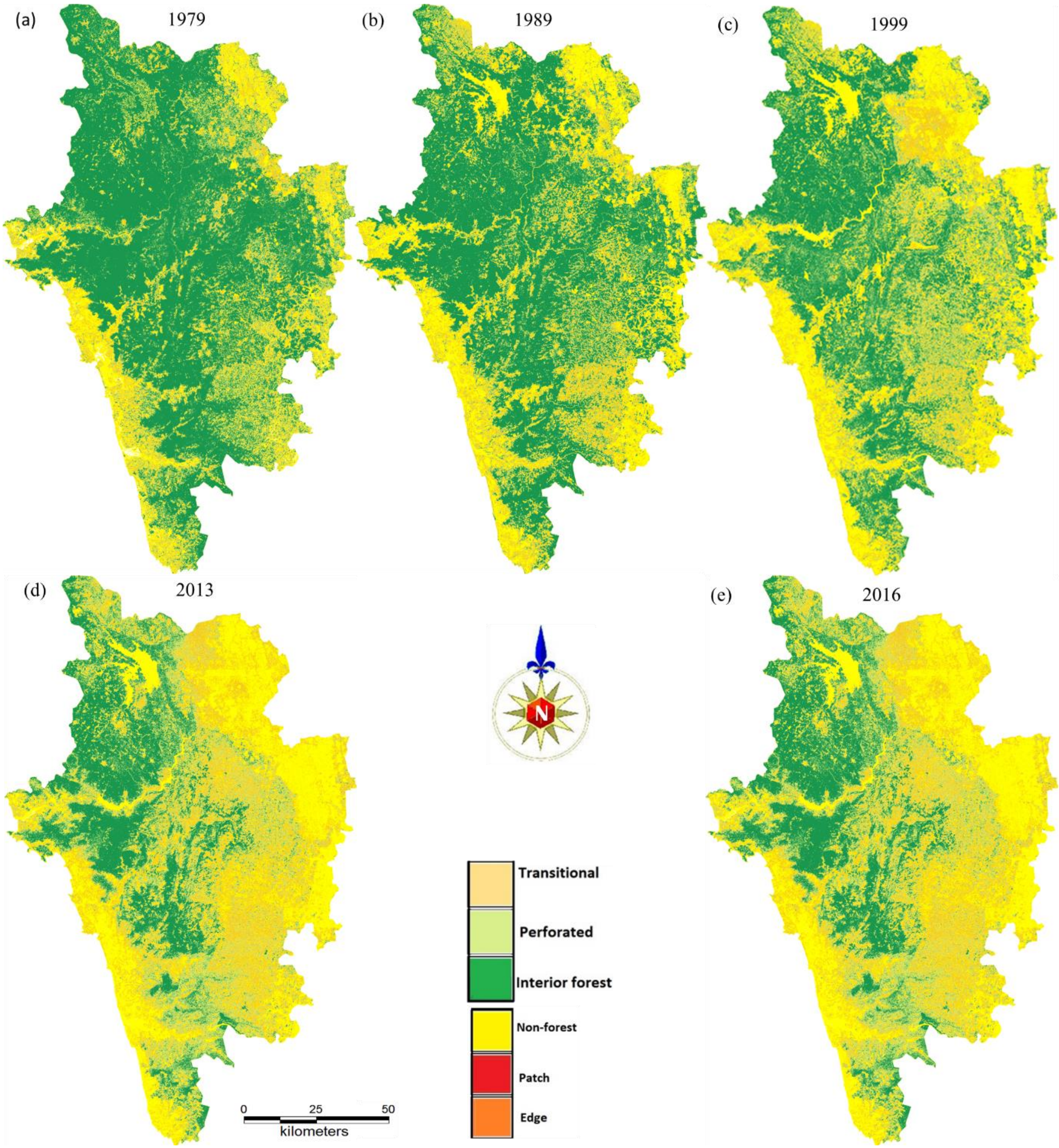



Figure 4.7 (a-e). Fragmentation of forests in Uttara Kannada from 1979 to 2016

## 4.2 Conclusion

NDVI reveals the decline of vegetation from 97.82% (1973) to 80.42% (2016). LU analyses of Uttara Kannada district highlights significant variation during the last four decades as evergreen forests have declined from 67.73% (1973) to 29.5% (2016) and area under human habitations and paved surfaces have reached 4.97% (2016). The decline in forest cover in Coastal taluks is due to housing, agriculture, transportation, etc. The accuracy assessment of LU classification using field data and Google earth data shows an accuracy of 82-92% with consistent results. Fragmentation analysis considering the spatial extent of forests, reveals that contiguous forests (interior forests) cover only 22.25%, LU under non-forest categories (cropland, plantations, built-up, etc.) covers 49.2% of the landscape. Temporal analyses reveal that forested landscape structure has changed from intact forests (in 1979) towards fragmented landscape with patchiness.

# CHAPTER 5 | POLICY FRAMEWORK FOR ECOLOGICAL CONSERVATION

## Prioritization of Ecological Sensitive Regions

# CHAPTER 5| PRIORITIZATION OF ECOLOGICAL SENSITIVE REGIONS

Ecologically sensitive regions at Panchayat levels (local administrative unit) were prioritized based on land cover, bio-geoclimatic, ecological, and social variables for conservation through appropriate policy intervention. This aided in delineating regions to be conserved on highest priority while identifying the regions for development for achieving ecologically sound, economically viable, and socially acceptable development goals through sustainable management of the ecosystem (Kibert et al., 2011). Sustainable development of a region requires an ecosystem approach, by integrating the complex functioning of ecosystems, influence on climate, diversity, economic values, ecological services at local as well as global scale. In this regard, an integrated holistic approach is proposed by considering all ecological and social components for developmental planning through the identification of Ecologically Sensitive Regions or zones (ESRs/ESZs). ESR are the unique ecological units expressing a diverse biotic and abiotic characteristic, which are potential regions of conservation.

## 5.1 Prioritization of Ecological Sensitive Regions for policy interventions

Identification of ESRs considering spatially both ecological and social dimensions of environmental variables helps in ecological and conservation planning as per the Biodiversity Act, 2002, Government of India. The research integrates ecological and environmental considerations into administration and prioritizes regions at Panchayat levels (local administrative unit) through weightage score metrics. ESRs are prioritized through considering landscape, biological (biodiversity-terrestrial, aquatic and estuarine), ecological (species diversity, endemism, conservation reserves), geo-climatic (rainfall, altitude, slope), renewable energy prospects (solar, wind, bio), social (population density, forest-dwelling communities) as outlined in Figure 5.1. The study area was divided into equal-area grids of 5’ × 5’ (168) covering approximately 9 × 9 km$^2$ for prioritizing at local levels. Developing a weightage metric score for prioritization requires knowledge of multi disciplines (Termorshuizen and Opdam, 2009), which integrates planning strategies for the present and future needs in the landscape. Assigning weightages based on the relative significance of themes (Beinat, 1997) provides a transparent mechanism for combining multiple data sets together to infer the significance. The weightage is given by equation 25,

$$Weighatge = \sum_{i=1}^{n} W_i V_i \qquad (25)$$

where, n is the number of unique data sets (variables), $V_i$ is the value associated with specific criterion i, and $W_i$ is the weight associated with that criterion. The variables and their significance have been outlined in Table 5.1. The rank value of 10 corresponds to the highest priority for conservation whereas high, moderate low, and least levels of prioritization were assigned 7, 5, 3, and 1 respectively. The detailed database covering themes from land to estuarine was used for ESR demarcation with the help of GIS techniques.

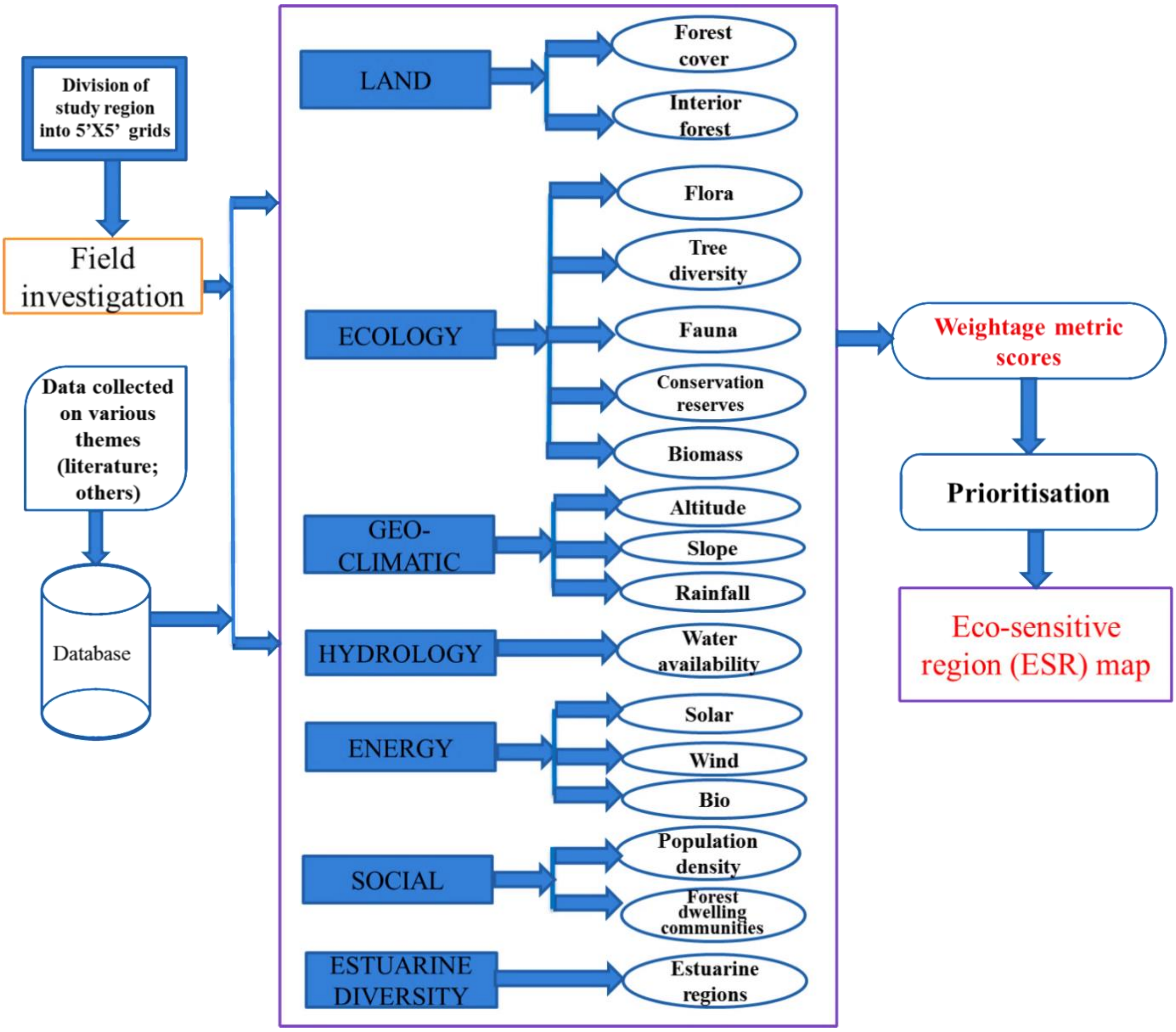



Figure 5.1. Protocol for prioritising regions for conservation

Table 5.1. The various themes considered and their weightages

| **S no** | **Themes** | **Weightages** | | | | | **Theme** |
|---|---|---|---|---|---|---|---|
| | | **1** | **3** | **5** | **7** | **10** | |
| 1 | Land Use | FC<20% | 20<FC<40% | 40<FC<60% | 60<FC <80% | FC > 80% | **LAND** |
| | Interior Forest | IF<20% | 20<IF<40% | 40<IF<60% | 60<IF<80% | IF> 80% | |
| 2 | Flora | NEND | END<30% | 30<END<50% | 50<END<70% | END>70% | **ECOLOGY** |
| | Tree Diversity | SHD<2 | 2<SHD<2.5 | 2.5 <SHD<2.7 | 2.7<SHD<3 | SHD>3 | |
| | Fauna | - | NEND | - | - | END | |
| | Conservation Reserves (CR) | - | - | - | - | National parks, Wild life reserves, Myristica swamps, Sanctuaries | |
| | Biomass (Gg) | BM<250 | 250<BM<500 | 500<BM<750 | 750<BM<1000 | BM>1000 | |
| 3 | Altitude | | <200 | 200-400 | 400-600 | >600 m | **GEO-CLIMATIC** |
| | Slope | - | - | - | Slope > 20% | Slope > 30% | |
| | Precipitation | - | 1000<RF<2000 mm | 2000<RF<3000 mm | 3000<RF<2000 mm | RF> 4000 mm | |
| 4 | Streamflow | WA<4 | 4<WA<6 | 6<WA<9 | 9<WA<12 | WA=12 | **HYDROLOGY** |
| 5 | Solar | - | - | <5 $KWh/m^2/day$ | 5-6 $KWh/m^2/day$ | 6-6.5 $KWh/m^2/day$ | **ENERGY** |
| | Wind | - | - | 2.4 to 2.55 m/s | 2.5 to 2.6 m/s | 2.6 to 2.7 m/s | |
| | Bio | SD<1 | SD>1 | 1>SD<2 | 2<SD<3 | SD>3 | |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| 6 | Population Density (PD) | PD>200 | 100<PD<200 | 100<PD<150 | 50<PD<100 | PD<50 | **SOCIAL** |
| | Forest-dwelling communities (Tribes) | - | | | Tribes are present then assigned 10; if no tribal population exists, then assigned as 0 | | |
| 7 | Estuarine Regions | - | low | moderate | high | very high | **ESTUARINE DIVERSITY** |

FC-forest cover; IF-interior forest cover; END-endemic; NEND-non-endemic; BM-biomass; SD-supply to demand ratio; WA-Water availability

**5.1.1. Land**

Landscape dynamics is considered as an essential variable to investigate forest pattern and anthropogenic disturbances over a period. Land use based on the analysis of temporal remote sensing data was considered and grids were prioritized based on the proportion of forest cover (Ramachandra and Bharath, 2018). Fragmentation of forests is computed based on the standard protocol (Riitters et al., 2004; Ramachandra et al., 2016). LU analysis revealed that the region has about 32.08% under evergreen-semi evergreen forests (Figure 5.2a) and higher forest cover (> 80%) was confined to the grids in Sahyadri region (Supa, Yellapura, Ankola, Sirsi taluks). The coastal taluks were having forest cover in the range 60-80% towards the eastern part whereas the western side degraded due to higher pressure. The plains showed the least cover (< 20%) reflecting higher degradation. Weightages were assigned to the grids based on the extent of forest cover (Figure 5.2b), grids in the Sahyadri region have highest ranking (10) compared to plains (1). Fragmentation analysis considering the spatial extent of forests reveal that contiguous forests (interior forests) cover only 22.25%, LU under non-forest categories (cropland, plantations, built-up, etc.) covers 49.2% of the landscape (Figure 5.2c) and Figure 5.2d gives the relative weightages based on the extent of interior forests across grids in coast, Sahyadri and plains.

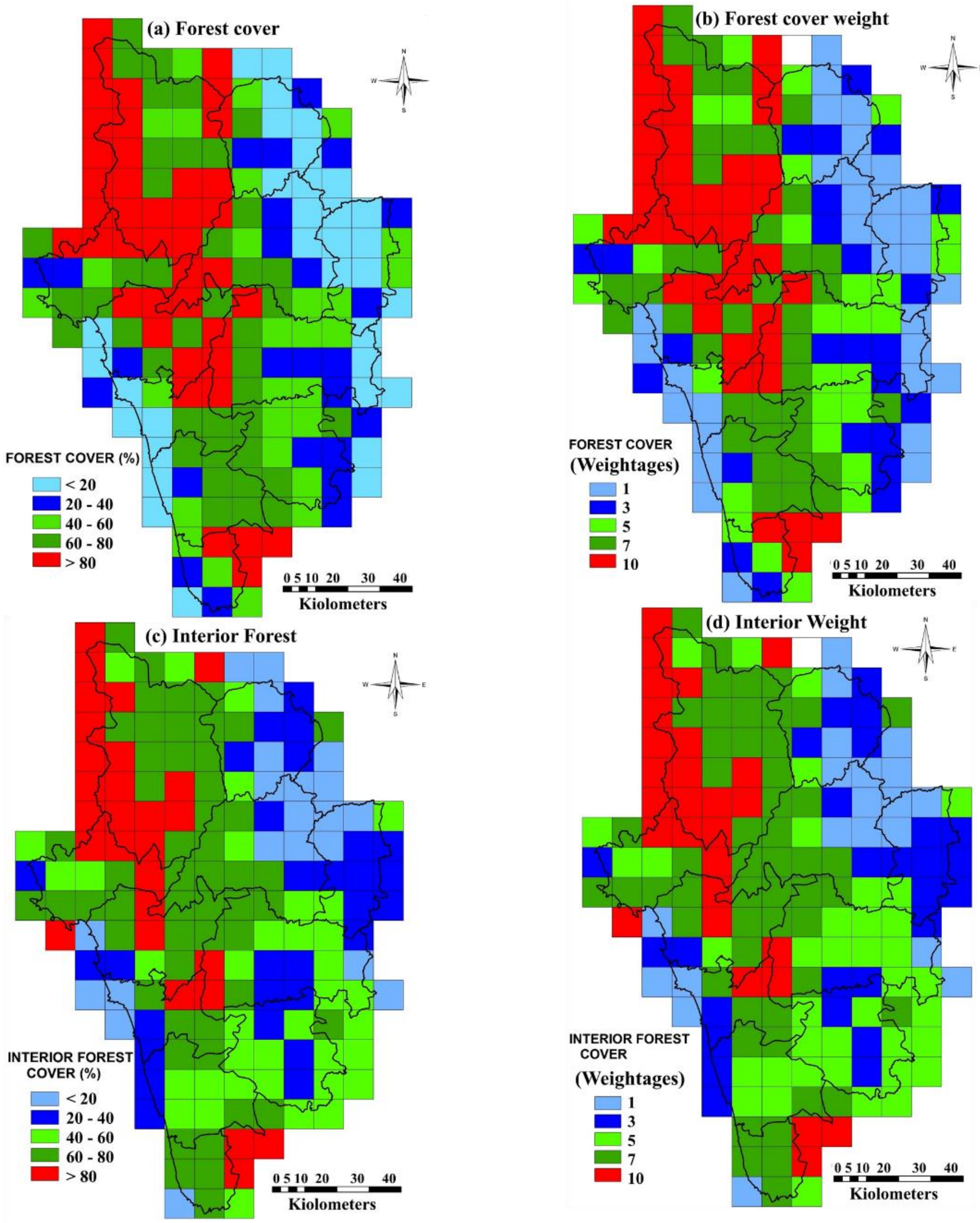



Figure 5.2. Landscape status (forest cover) and their weights/rank

### 5.1.2. Ecology

The ecological variables were assessed to understand diversity and resource availability. The field investigations were carried out and data of the tree basal area, biomass, estimates of carbon sequestration, species diversity, and the distribution of threatened species, etc., have been collected in 116 sample transects (Figure 5.3). Grids were assigned weights based on the data compiled from field investigations, and interaction with various stakeholders -researchers working in this region, forest officials, local people, subject experts (details of the field investigations with photographs are provided in Appendix 2). The trees of 130 cm height from the ground and minimum girth of 30 cm were measured to estimate the biomass and carbon sequestration along a transect length ranging up to 180 m, quadrats each of 20 × 20 m were laid alternatively on the right and left. The interval of 20 m length between successive quadrats was maintained and a number of quadrats depended on the species occurrence curve and the maximum number of quadrats per transect was 5. Shrub species were quantified in two sub-quadrats of 5×5 m at two diagonal corners within each tree quadrat. Within these sub-quadrats 1×1 m herb layer quadrat also laid.

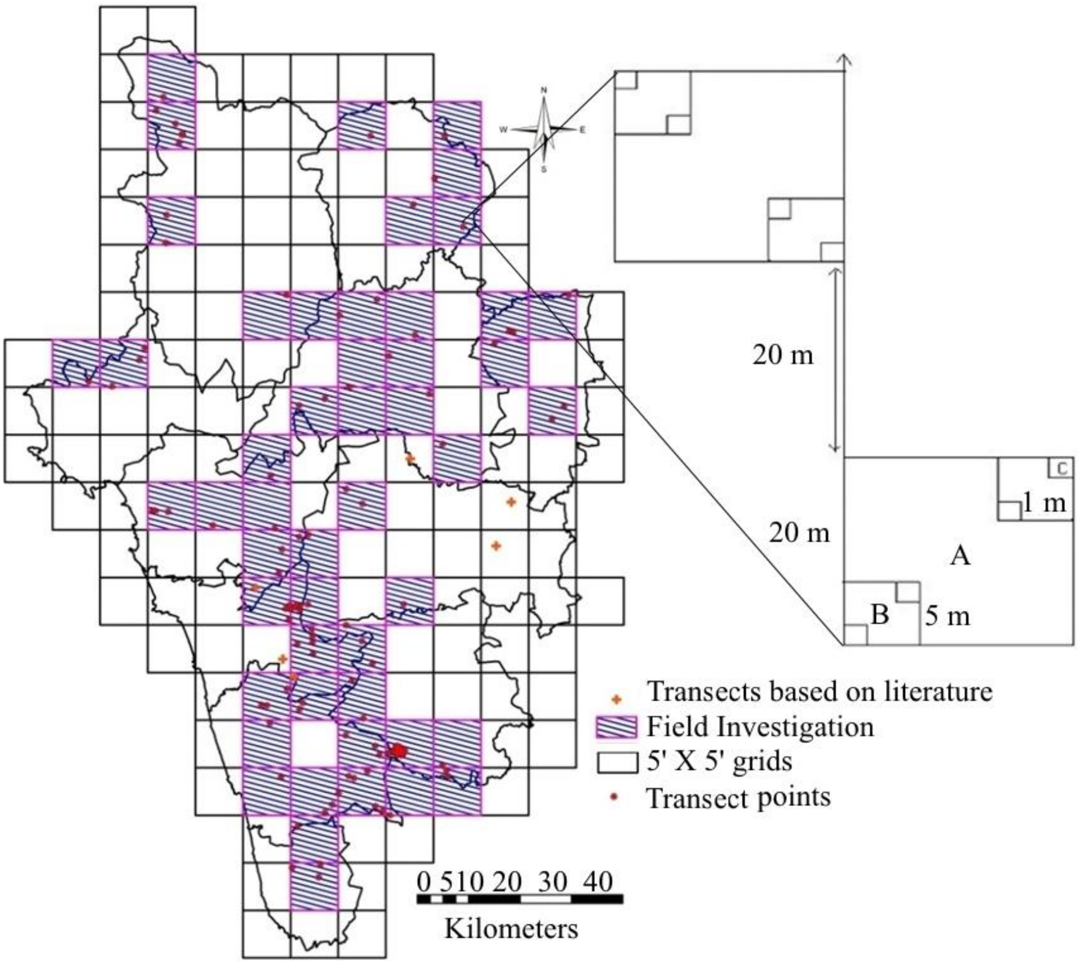


Figure 5.3. Transect used for field sampling

A detailed review of the literature published data, and ground-based surveys were considered to account for diversity. The total biomass of the district is **113823.58** Gg (Giga gram), the grids covering Sahyadri portions having greater biomass (>1200 Gg) followed by least in the plains (< 200 Gg). Evergreen, hill slopes, and sacred groves had higher basal area and biomass with diverse species, grids with higher standing biomass were assigned higher weightages (Figure 5.4a, b).

Shannon's diversity index (H') has been estimated to assess tree species diversity (Brose et al., 2003). Shannon's diversity index, (H') is defined as,

$$(H)' = -\sum_{i=1}^{n}(p_i)\ln p_i \tag{26}$$

where $p_i$is the proportion of the species relative to the total number of species ($p_i$) multiplied by the natural logarithm of this proportion (ln $p_i$) and the final product multiplied by -1 (Equation 26). Tree diversity showed that most evergreen to semi-evergreen forests has values ranging between 3 and 4 in Supa, Sirsi, Kumta, and Siddapur. Lower Shanon diversity was in dry deciduous and highly disturbed forests of Mundgod, Haliyal, Yellapura (eastern grids) (Figure 5.4c, d).

The diversity of flora and fauna is another important surrogate variable that helps in assessing the sensitivity of a region. The inventorying, mapping of the endemic tree, documentation of faunal species have been done to find out the areas of high endemism and congregations of threatened species. The region is home to 1068 species of flowering plants under 138 families. Moraceae is the dominant family with 18 species (covers keystone species providing a resource to the animals throughout the year), followed by Euphorbiaceae (16 species), Leguminosae (15 species), Lauraceae (14 species), Rubiaceae (13 species) and Anacardiaceae (13 species). Leguminosae (32 species), Rubiaceae (24 species) families are dominant under shrub species. Poaceae family pronounced higher diversity under herbs and grasses. The region has rich endemic and IUCN red list category species such as *Gymnacranthera canarica, Dipterocarpus indicus, Mangifera indica, Hopea ponga, Vateria indica, Mammea suriga, Syzygium travancoricum, Semecarpus kathalekanensis* etc. The weights based on the occurrence of endemic flora species illustrating Honnavar, Kumta, Sirsi, Bhatkal, Siddapur region have greater weights, and Mundgod and Haliyal show lower (Figure 5.4e, f).

The region has diverse faunal species of ecological importance (Figure 5.4g, h) and higher weightage was assigned based on endemism. The predators such as tiger (*Panthera tigris*), leopard, wild dog (dhole), and sloth bear are well distributed across the forests. Prey animals are spotted deer (*Axis axis*), bison (*Bos gaurus*), wild boar (*Sus scrofa*), sambar deer (*Cervus unicolor*), Indian muntjac (*Muntiacus muntjak*). Kali River is accommodating more than 200 marsh crocodiles (*Crocodylus palustris*). The district forms an important elephant corridor between Karnataka and Maharashtra states with a recorded population of 60+ elephants. The district 272 birds listed (19 are endemic) in the Dandeli alone echoes as a heaven for bird population (Daniels and Vencatesan, 2008). Prominent birds are Malabar Pied Hornbill, Indian Grey Hornbill, Malabar Grey Hornbill, Great Indian Hornbill, Emerald Dove, Malabar Trogon, etc. Butterflies include Crimson Rose, Common Rose, Leaf, Clipper, Tigers, Southern Bird wing, Cruiser, etc. A wide variety of snakes such as King Cobra, Cobra, Hump nosed pit Viper, Malabar Pit Viper, Bamboo Pit Viper, Kraft, Ornate flying snake, wolf snake etc. are found in plenty. The district has a rich endemic fish species such as *Gonoproktopterus kolus, Batasio sharavatiensis, Ehirava fluviatilis, Tetradon travancoricus, Puntius sahyadriensis, Salmostoma novacula, Puntius filamentosus,* etc. Conservation reserves, sanctuaries, national parks are being established under the Wildlife (Protection) Amendment Act of 2002 (Table 3.1). They are typically buffer zones or connectors and migration corridors, which protect habitats of rare, vulnerable, endangered flora/fauna. Higher weightage is assigned as shown in Figure 5.4i, j.

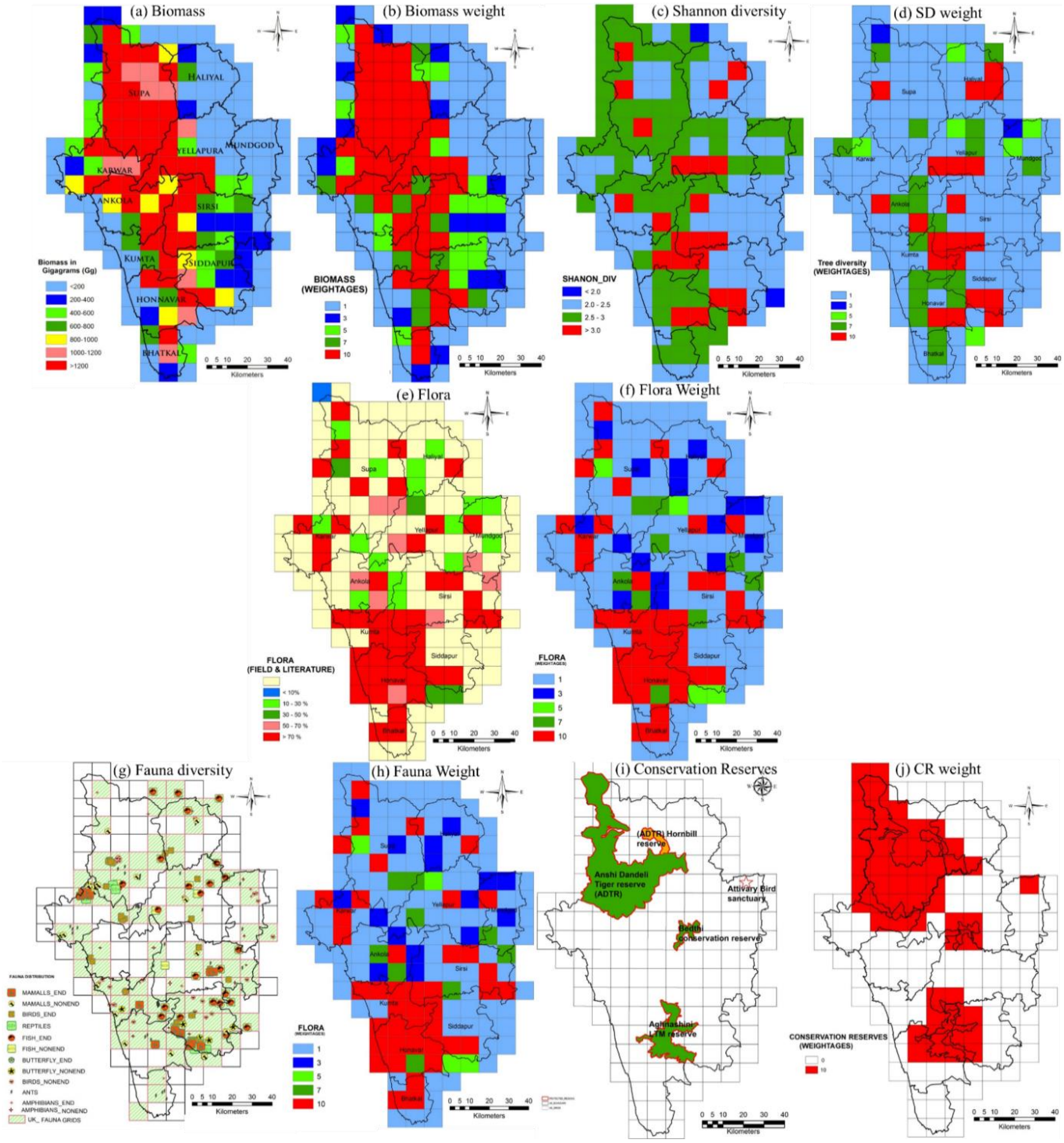



Figure 5.4. Ecological variables assessed

### 5.1.3. Geo-climatic variables

Geo-climatic variables such as altitude, slope, and rainfall reveal the diversity and climatic favourability associated with the ecological conditions of a region. The altitude profile is depicted in Figure 5.5a, which shows the highest elevation is 758 m in Supa taluk, grids were assigned weights (Figure 5.5b) as a higher priority for conservation and > 400 m is moderate and rest is of least concern. Figure 5.5c depicts the slope in the region while Figure 5.5d depicts the grids with weights assigned based on the sensitiveness of the slope. The rainfall quantum has been assed using point-based daily rainfall data from various rain gauge stations between 1901 and 2010 (Vinay et al., 2013; Ramachandra et al., 2020). The major portion of the district is in the high rainfall zone, except Mundgod and eastern parts of Haliyal. Grids are assigned weights based on the quantum and duration of rainfall (Figure 5.5e, f). High rainfall areas have high biodiversity values and higher conservation values. The subbasin wise analysis was carried out to account for perenniality, seasonal flows of the region (Figure 5.5g). Hydrological regime analysis reveals the existence of perennial streams in the catchment dominated by diverse forests with native vegetation (>60% cover) compared to the streams in the catchments of either degraded forests or dominated by monoculture plantations. Higher water yield (> 5 times) is observed even during the non-monsoon season in the streams with catchment dominated by native forests. Grids in Sahyadri regions shows 12 month's water availability in the streams and were assigned higher weightages (Figure 5.5h). Haliyal, Mundgod, eastern part of Yellapura showing stream flow as only 4 months due to scarce rainfall and monoculture plantations.

### 5.1.4. Energy

The conventional energy resources are eroding natural resources and causing a significant adverse effect on ecology in terms of pollution and other by-products. The potential of renewable energy sources is assessed (Solar, Wind, Bioenergy) at month-wise and captured the variations (Ramachandra et al., 2014 b, c, d). NASA's Surface Meteorology and Solar Energy (SSE) data revealed that solar energy is available greater than 10 months with higher potential. India Meteorological Department (IMD) observatories have shown the variability of wind energy, most effective during the period May to August in the absence of higher solar insulation. The household survey across the district has revealed that 82 to 90% of the households still depend on fuelwood and agro residues for domestic energy. Analyses of sector-wise contribution in the energy surplus zones show that horticulture residues contribute in the central dry zone, southern transition zone, and the coastal zone, while in the hilly zone, forests contribute more towards the available bioenergy. Adaptation of green technologies would aid in cutting down carbon footprint. Weightages are assigned based on the level and quantum of availability of energy from renewable resources (Figure 5.6a-f).

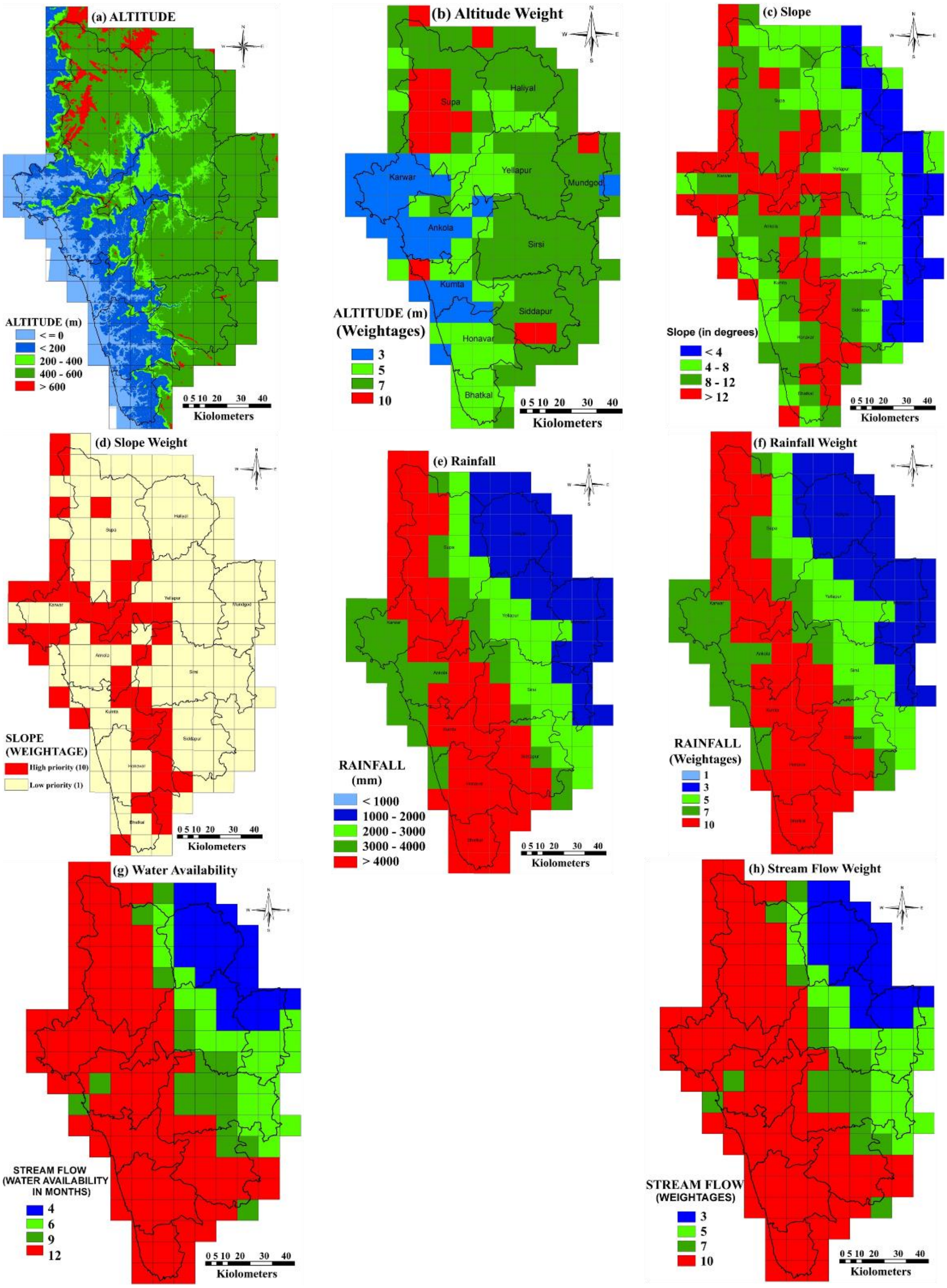



Figure 5.5. Climatic variables assessed and their respective weights

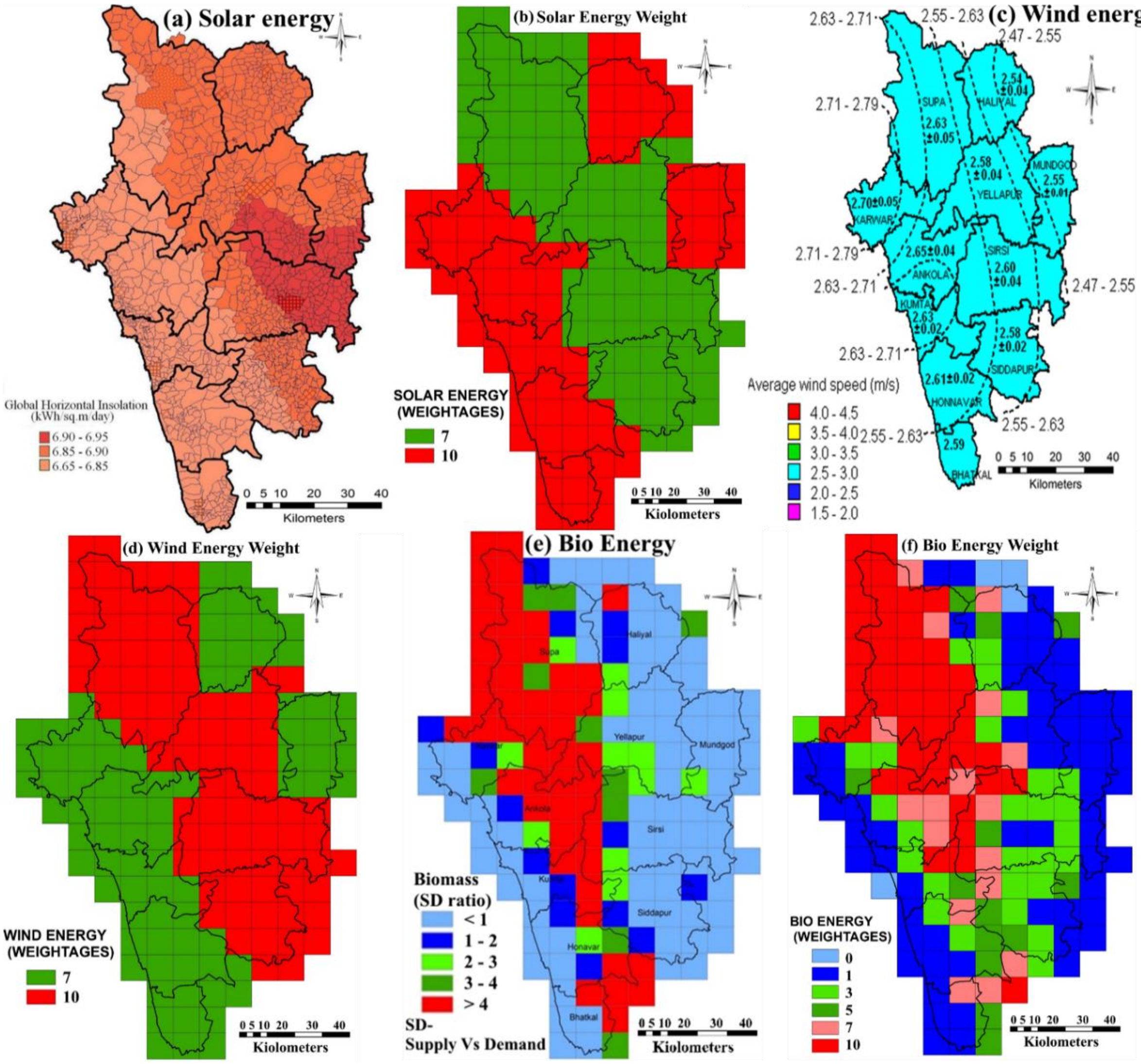



Figure 5.6. Energy prospects and weights

### 5.1.5. Social aspects

The Biological Diversity Act (BDA) of 2002 stipulates the conservation of biological diversity, sustainable use of its components with fair and equitable sharing of the benefits arising out of the use of biological resources, knowledge, and for matters connected therewith or incidental threat. Forest Rights Act 2006, the Government of India seeks to recognize and vest the forest rights and occupation in forest land in forest-dwelling Scheduled Tribes and other traditional forest dwellers who have been residing in forests for generations but whose rights could not be recorded. A large chunk of the population is directly dependent on these resources even today; trading them in conservation will be the unfruitful approach. Forest-dwelling communities (tribes) of the district were mapped at village level and the grids with tribal population are assigned higher weightage. Forest-dwelling communities such as Kunbis, Siddis, Goulis, Gondas were spatially mapped (Figure 5.7a) and were assigned the highest weights (Figure 5.7b), because these people are directly and indirectly dependent on forest resources while protecting forests. Grid wise population was computed by aggregating villages in the respective grid for 2011. An increase in population density will lead to the increasing exploitation of natural resources and the resulting loss of species and ecosystem richness, nature conservation (Paloniemi and Tikka, 2008). Grid wise population density was computed (Figure 5.7c) and weightages were assigned (Figure 5.7d). Grids with the lowest population density (< 50 persons) were assigned a higher weight (considering the likely lower anthropogenic stress) and vice versa.

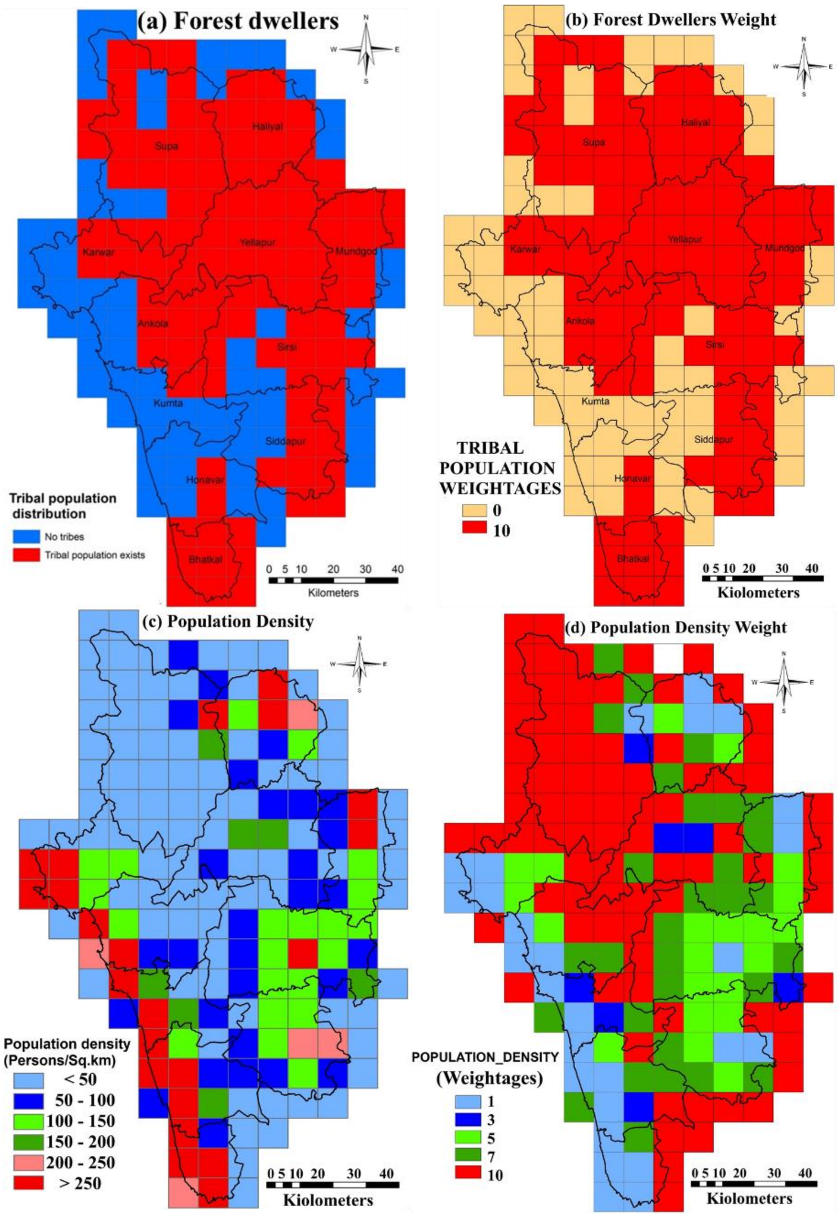



Figure 5.7. Social variables and weights

### 5.1.6. Estuarine diversity

Estuarine ecosystems are biologically productive, socio-economically vital, and aesthetically attractive while providing food and shelter for many vital biotic species and some are commercially very important (Qiaomin and Shuzhen, 2001). West coast estuaries of the district were assessed based on productivity, biodiversity, and human pressure (Mesta et al., 2014). The four major estuaries viz. Kali, Gangavali, Aghanashini, and Sharavathi (Figure 5.8a) are rich in mangrove species diversity and vital for fishery and cultivation of Kagga rice (salt-tolerant) varieties. The biological diversity analysis shows Agnashini and Ganagavali estuaries have higher fish diversity and mangrove species due to the absence of major anthropogenic activities (dam or hydro projects). Estuaries such as Sharavathi and Kali are severely disturbed with unplanned developmental activities, affecting the productivity of resources (fish, bivalves, etc.). Coastal grids were assigned weightages (Figure 5.8b), based on the biological diversity and productivity (considering provisional goods – fish, bivalves, sand, and salt).

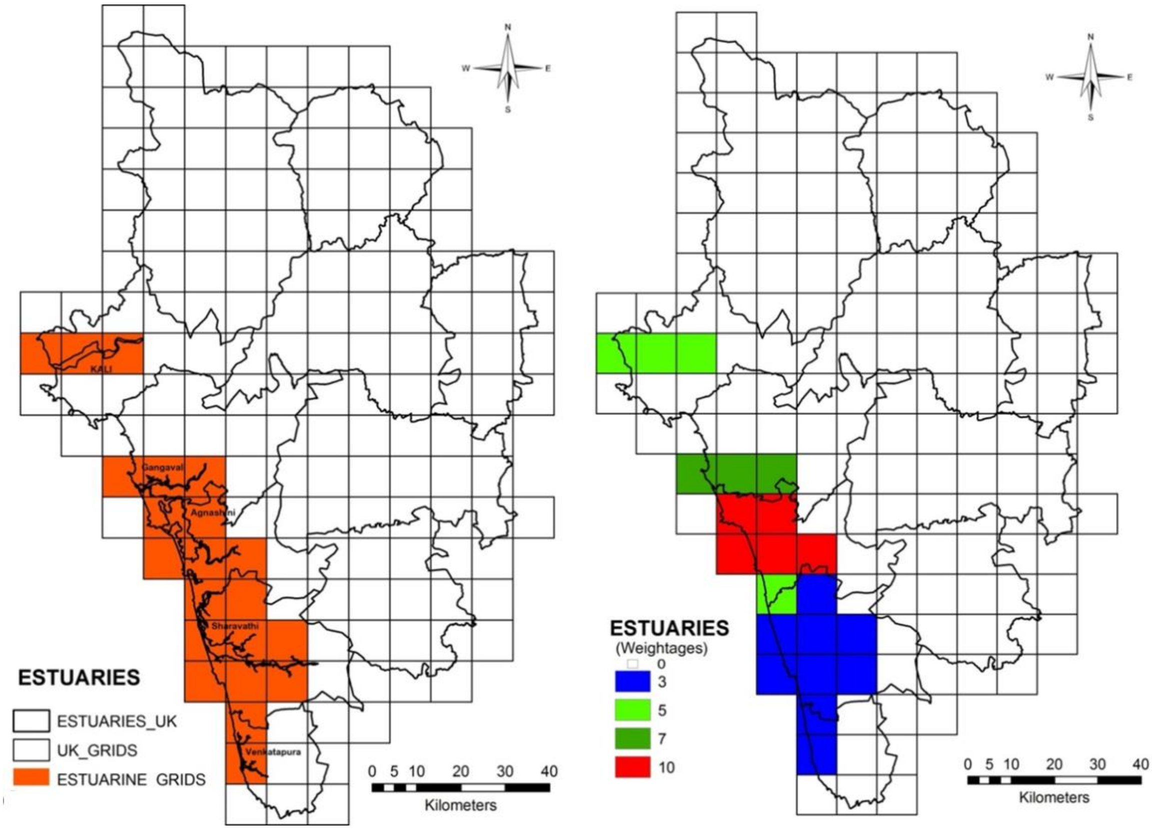



Figure 5.8. Estuarine diversity and weight

### 5.1.7. Ecological Sensitive Regions of Uttara Kannada

The spatial aggregation of landscape, biological, ecological, geo-climatic, renewable energy, and social variables has helped in prioritizing grids as ESR 1 (Regions of highest sensitivity), ESR2 (Regions of higher sensitivity), ESR3 (Regions of high sensitivity), and ESR4 (Regions of moderate sensitivity) respectively (Figure 5.9a) based on the composite metric score. Spatially 52.38% of the district represents ESR 1, 14.29% of the area represents ESR 2, 13.1 % of the area represents ESR 3 and about 20.23 % of the district is in ESR 4. Regions under ESR 1 and 2 are “no go area” for any developmental activities involving largescale land cover changes. ESR 2 have eco-sensitiveness similar to ESR 1 and the potential to become ESR 1 following eco-restoration measures. Figure 5.9b depicts ESR with taluk and gram panchayat (decentralized administrative units with a cluster of few villages) boundaries. Uttara Kannada district has 11 taluks and 209 panchayats. ESR analyses reveal that ESR 1 consists mainly of Supa, Yellapura, Ankola, Sirsi, Siddapur, Honnavar, and Kumta taluks. Considering panchayat level analyses, 102 panchayats are in ESR 1, while 37 panchayats in ESR 2, 33 panchayats in ESR 3, and 37 panchayats in ESR 4. Sahyadri and the eastern part of coastal regions represent the highest ecological sensitiveness. Table 5.2 provides the details of recommended regulated and prohibited activities across ESRs.

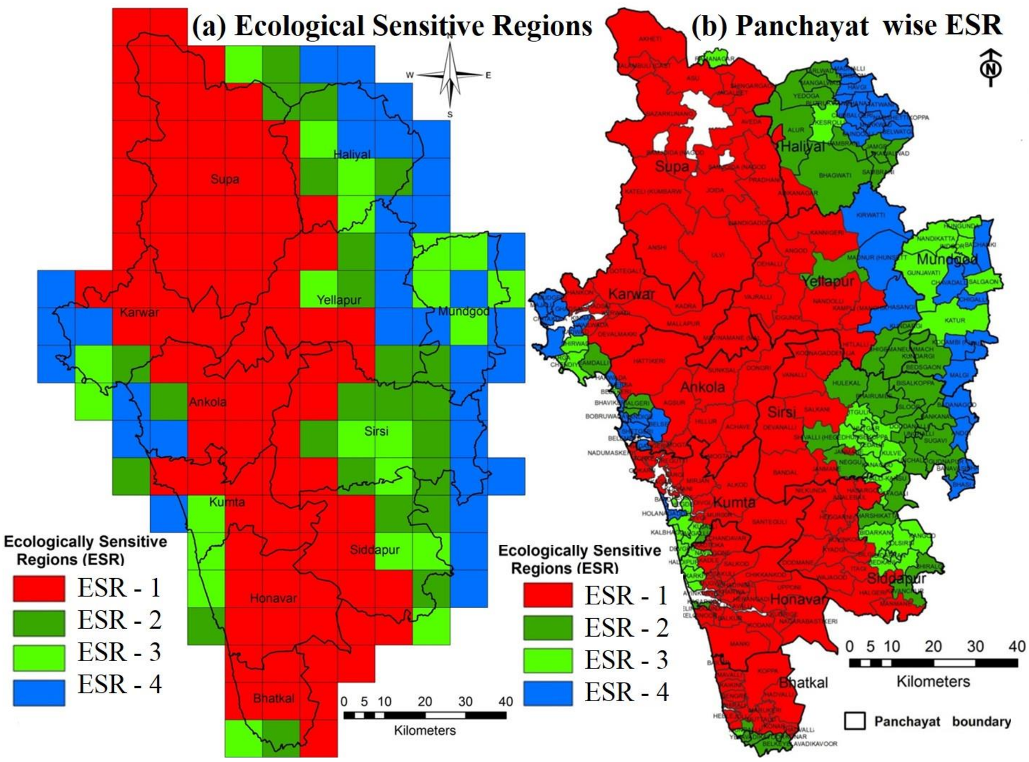



Figure 5.9. Uttara Kannada ESRs at panchayat level

These ESRs are eco-clusters setting the limits for sustainability and environmental friendly development. ESRs aid as a driver for greening regional economic policy and examines necessary incentive structures to foster eco-innovation as well as growth and employment in the local eco-industry sector (agro-processing, etc.). This approach aids in the conservation of ecology, biodiversity, water resources, culture, and traditions while paving way for location-specific economic development, primarily aimed at elevating levels of livelihood security. The outcomes envision the foundation of an on-going process to integrate ecological and environmental considerations into administration in the biodiversity-rich district of Karnataka. The integrated database on biodiversity and socio process furnishes analyzed data, advice, and management prescriptions to beneficiaries at every level from the village communities to the Government.

Table 5.2. Activities that can be allowed in ESR -1, 2 3 & 4

| SNO | ACTIVITIES | ECOLOGICALLY SENSITIVE REGIONS | | | |
|---|---|---|---|---|---|
| | | ESR-1 | ESR-2 | ESR-3 | ESR-4 |
| 1 | **FORESTS** | | | | |
| | a. Land Use change (Forest to non-forest usages) | × | × | × | × |
| | b. Monoculture plantations | × | × | × | × |
| | c. Extraction of medicinal plants (with strict regulations) | × | ✓ | ✓ | ✓ |
| | d. Forest improvement through Village Forest Committees (VFCs) | ✓ | ✓ | ✓ | ✓ |
| | a. Non-Timber Forest Product collection | ✓ (Strict regulation by department) | ✓(Strict regulation by department) | ✓(Strict regulation by department) | ✓ |
| | b. Encroachment of forests and Myristica swamps | × | × | × | × |

| | | | | | |
|---|---|---|---|---|---|
| 2 | **AGRICULTURE**<br>a. Agroforestry | ✓ | ✓ | ✓ | ✓ |
| | b. Organic farming | ✓ | ✓ | ✓ | ✓ |
| | c. Land Use change / Encroachments | × | × | × | × |
| | d. Genetically modified crops | × | × | × | × |
| | e. Animal Husbandry | ✓ | ✓ | ✓ | ✓ |
| 3 | **HORTICULTURE**<br>a. Organic farming | ✓ | ✓ | ✓ | ✓ |
| | b. Nitrogen and Phosphorus (N&P) fertilizers | × | × | × | ✓ Dosage as prescribed by Agriculture department |
| | c. Endosulfan | × | × | × | × |
| | d. Pesticide, weedicide | × | × | × | ✓ |
| | e. Watermelon & Muskmelon farming | ✓ | ✓ | ✓ | ✓ |
| 4 | **INDUSTRIES (Larger scale)**<br>a. Agro-processing industries | ✓ | ✓ | ✓ | ✓ |
| | b. Information Technology industries (IT) | × | × | ✓ | ✓ |
| | c. Red category (Polluting) industries | × | × | × | × |
| | d. Garment industries | × | × | ✓ | ✓ |
| | e. New establishment of Industries | × | × | × | ✓ (Allowed only after critical review by local stakeholders and experts) |
| | f. Nonpolluting (Green) Industries | × | × | ✓ | ✓ |
| 5 | **INDUSTRIES (Small scale)** | × | × | ✓ | ✓ |

| | | | | | |
|---|---|---|---|---|---|
| | (A) Garment industries | | | | |
| | (B) Domestic (Home-based) industries<br>a. Papad | ✓ | ✓ | ✓ | ✓ |
| | b. Mango processing | ✓ | ✓ | ✓ | ✓ |
| | c. Areca nut processing & Coir industries | × | ✓ | ✓ | ✓ |
| | d. Milk products and processing | ✓ | ✓ | ✓ | ✓ |
| | e. Dry fruits & Spices | ✓ | ✓ | ✓ | ✓ |
| | f. Fruit processing (Ex: Kokum Juice-*Garcinia indica*) | ✓ | ✓ | ✓ | ✓ |
| | g. Fish and sea products processing | ✓ | ✓ | ✓ | ✓ |
| | h. Beekeeping and bee nurseries | ✓ | ✓ | ✓ | ✓ |
| | i. Pongamia plantations for biofuel (in private lands) | × | × | ✓ | ✓ |
| | j. Biopesticides manufacturing | × | × | ✓ | ✓ |
| | k. Poultry farms and powdered eggs | × | ✓ | ✓ | ✓ |
| | l. Vegetable dyes; fruits and vegetable preservation | ✓ | ✓ | ✓ | ✓ |
| | m. Medicinal plants cultivation and processing | ✓ | ✓ | ✓ | ✓ |
| | n. Aromatic plants and essential oil distillation; orchids and cut flowers harvesting industries | × | ✓ | ✓ | ✓ |
| 6 | **TOURISM** | | | | |

| | | | | | |
|---|---|---|---|---|---|
| | a. Ecotourism | ✓ | ✓ | ✓ | ✓ |
| | b. Organic village and homestay | ✓ | ✓ | ✓ | ✓ |
| | c. VFC managed tourism | ✓ | ✓ | ✓ | ✓ |
| | d. VFC managed homestay tourism in higher forest cover regions and protected areas | ✓ | ✓ | ✓ | ✓ |
| | e. Arts and handicrafts museum and trade center | ✓ | ✓ | ✓ | ✓ |
| 7 | **MINING AND MINERAL EXTRACTION** | | | | |
| | a. Iron ore | × | × | × | × |
| | b. Manganese | × | × | × | × |
| | c. Bauxite | × | × | × | × |
| | d. Limestone | × | × | ✓ | ✓ |
| | e. Quartz | × | × | ✓ | ✓ |
| | f. Sand extraction (on a sustainable basis by the ban on exporting) | × | × | ✓ | ✓ |
| 8 | **WASTE DISPOSAL** | | | | |
| | a. Hazardous waste processing units | × | × | × | × |
| | b. Solid waste disposal | × | × | × | ✓ (For composting and manure preparation) |
| | c. Liquid waste discharge | × | × | × | ✓ (Treatment plants (Sewage Treatment Plants) for processing) |
| | d. Recycling and waste processing units | × | × | × | ✓ (compliant with Pollution Contral Board) |

| | | | | | |
|---|---|---|---|---|---|
| 9 | **TRANSPORTATION** | | | | |
| | a. Widening of highways | × | × | × | ✓ (Allowed only after strict Environmental Impact Assessment-EIA) |
| | b. Roads and expressways | | | | |
| | c. Rail and freight corridors | **Hubli - Ankola rail connectivity**: Implementation with Environment Management Plan, mechanism (post-project monitoring, strict regulation, and social audit)<br>**Talaguppa - Honnvar**: Passes through Lion-tailed macaque (LTM) habitat and ecologically sensitive – not to be permitted | | | |
| | d. Up gradation of existing infrastructure | × | × | ✓(Subject to EIAs, strict regulation and social audit) | ✓ |
| 10 | **ENERGY** | | | | |
| | a. Solar (Rooftop) | ✓ | ✓ | ✓ | ✓ |
| | b. Wind power | × | × | ✓ | ✓ |
| | c. Bioenergy | ✓ | ✓ | ✓ | ✓ |
| | d. Coal-based (Thermal power) | × | × | × | × |
| | e. Gas or liquid fuel-based | × | × | × | ✓ |
| | f. Hydropower (Major) | × | × | × | × |
| | g. Hydropower (Micro) | × | × | × | ✓ |
| | h. Nuclear power | × | × | × | × |

**Remarks**

- ESR_1 represents a zone of highest ecological sensitiveness; no further degradation be allowed. ESR-2 has the potentiality to become ESR-1 provided strict implementation norms and regulations for the improvement of degraded patches of forests. Further erosion of ESR-2 will have more adverse effects in ESR-1.
- Forest Rights Act to be implemented in its true spirit.
- Monoculture plantations are not allowed, existing exotics should be replaced by planting location-specific native species.

- Promote the use of renewable energy sources such as (solar, wind power) through incentive-based decentralized electricity generation.
- Mining is to be banned in ESR 1, ESR 2 and ESR 3
- No new licenses to be given for quarry and sand mining in ESR 1 and 2**.**
- Local agro-based industry to be promoted with strict regulations and social audits.
- Adapt development projects (discussed in the next section) which will have least environmental impact by involving local community members in decisionmaking and environmental monitoring.
- No new major roads, widening of highways.
- Proposed Talaguppa – Honnavar rail link to be shelved (which affects LTM habitat, and ESR1)
- Ecotourism (comparable to Goa and Kerala model and based on MoEF regulations) after taking into account social and environmental costs.
- The laterite formations are aesthetically pleasing, and particularly with the massive flowering of rainy season herbs. The terrain is ideal for tourism and scientific studies.

## 5.2 Conclusion

ESR framework has been proposed by integrating spatial, biogeoclimatic, and social variable's information for an effective policy initiative. This framework acts as a reference to propose the allowable activities and also helps in halting unsustainable development. The district has been demarcated into 4 zones as ESR1(Regions of highest sensitivity), ESR2 (Regions of higher sensitivity), ESR3 (Regions of high sensitivity), and ESR4 (Regions of moderate sensitivity). Spatially 52.38% of the district represents ESR 1, 14.29% of the area represents ESR 2, 13.1 % of the area represents ESR 3 and about 20.23 % of the district is in ESR 4. Regions under ESR 1 and 2 are “no go area” for any developmental activities involving large scale land cover changes. The decision-makers should at least protect the ESR-1, 2 regions by definite actions then the district conservation will be fruitful.

# CHAPTER 6| MODELING LANDSCAPE DYNAMICS

# CHAPTER 6 | MODELING LANDSCAPE DYNAMICS OF UTTARA KANNADA DISTRICT

This chapter provides the details on modeling landscape dyanmics with standalone techniques and draws the comparisions interms of limitations for the study area. It also provides implementing a hybrid model to capture the changes at the landscape level by integrating bio-ecological aspects with socio-economic growth aspects in response to the multiple scenarios as a consequence of policies and their outcomes.

## 6.1 Modeling Landscape Dynamics-scenario based approach

The LULC change is the basis for modeling of landscape dynamics. The various modeling techniques are evaluated to select the best approach for policy interventions. The various scenarios are assumed to investigate the best policy to be adopted for sustaining the natural resources of the region. The chapter presents the modeling and visualization of the region to forecast likely changes in this ecologically significant area. This chapter presents the results of the proposed hybrid Fuzzy-AHP-MCCA technique and further simulates LULC changes under various scenarios of current and future growth patterns, policy options. The various scenarios considered are

(i) Business As Usual Scenario (BAU) Scenario models LULC changes with constrained Non-Agent Based Approach
(ii) Historical Growth Scenario (HGS)
(iii) Managed Growth Rate Scenario using proposed hybrid modeling approach (P* and P-WRF)
(iv) IPCC SRES Framework based Climate Change and Growth Rate Scenarios (A2, A1B and A1)
(v) Forest Conservation Scenarios to asses the impact of policy interventions on land use change (ESR, IFC-Interior Forest Conservation)

### 6.1.1. Modeling LULC changes with constrained non-agent based approach - Business As Usual Scenario-BAU

Non-agent based CA-Markov (Cellular automata and Markov process) model has been used for modeling LULC changes under business as usual scenario (current growth rate) of Uttara Kannada. Unlike traditional CA-Markov the current analysis was done by incorporating constraints in the simulation. The constrained CA-Markov has been advantageous in maintaining the classes without undergoing neighborhood effects. The constraints considered for analysis are water bodies and protected areas. CA-Markov models have been incorporated for a better theoretical understanding of the complex, nonlinear relationships of the LULC process in Uttara Kannada district for simulating and forecasting changes effectively based on previous and current LU change rate. The method adopted for modeling is depicted in Figure 6.1. Initially, temporal LU maps have been prepared by classifying RS data with the help of field observation (see section 4.1.2). The LU maps have been reclassified to 7 categories for better representation within the model (Table 6.1). The reclassification of 11 categories to 7 has been done to forecast changes at the landscape level rather than inter-class changes.

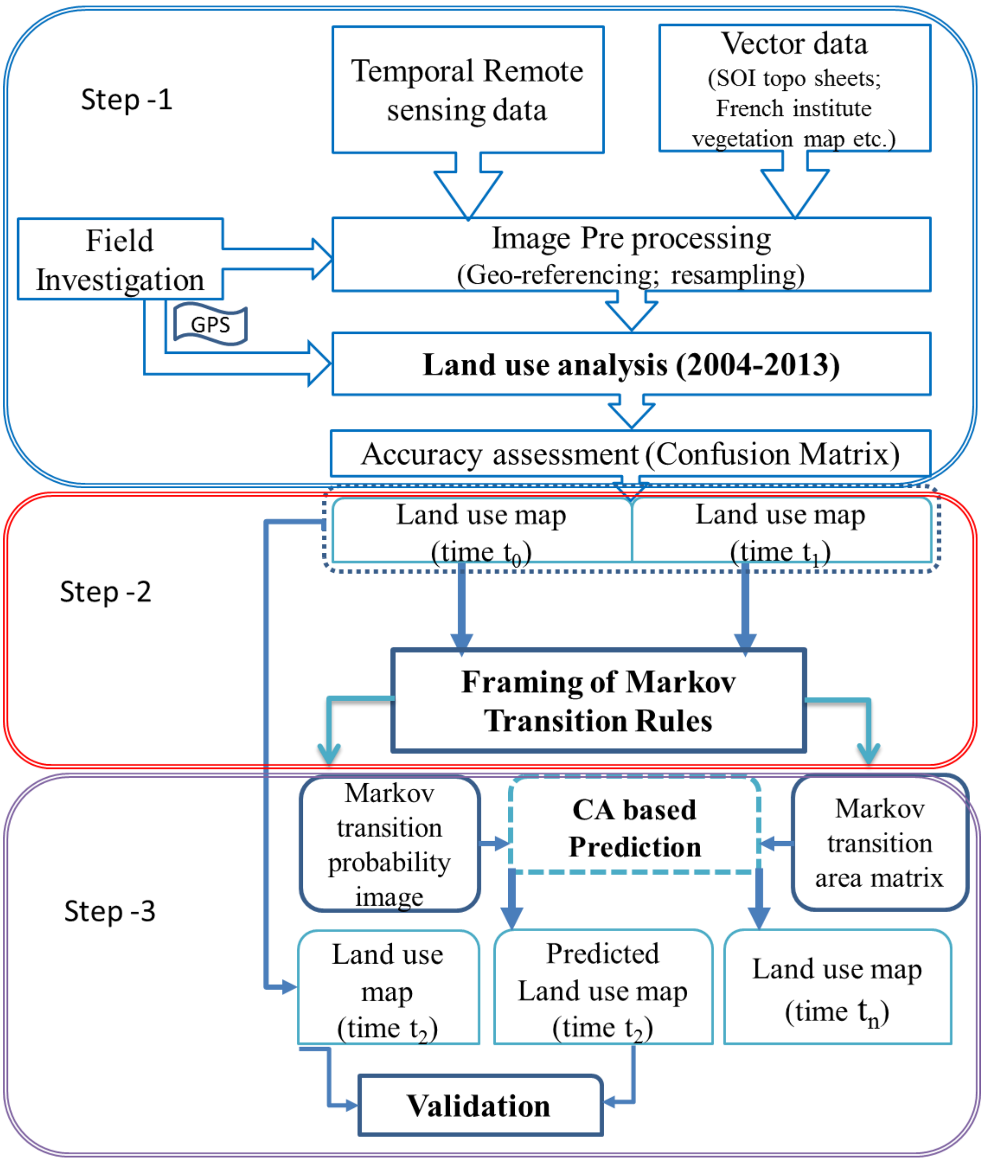


Figure 6.1. The approach used for modeling and visualisation analysis

Table 6.1. LU categories considered

| Sno | LU categories | Description |
|---|---|---|
| 1. | **Forest** | Evergreen to semi-evergreen, Moist deciduous forest, Dry deciduous forest, Scrub/grasslands |
| 2. | **Plantations** | Acacia/ Eucalyptus/ hardwood plantations, Teak/ Bamboo/ softwood plantations |
| 3. | **Horticulture** | Coconut/ Areca nut / Cashew nut plantations |
| 4. | **Cropland** | Agriculture fields, permanent sown areas |
| 5. | **Built-up** | Residential Area, Industrial Area, Paved surfaces |
| 6. | **Open fields** | Rocks, Quarry pits, Barren land |
| 7. | **Water** | Rivers, Tanks, Lakes, Reservoirs, Drainages |

Figure 6.2 and Table 6.2 depicts LU of the region from 2004-2010 and their spatial extents. The CA coupled with Markov chain LU predictions of 2010 and 2013 were made by using the transitional probability area matrix generated from 2004-2007; 2007-2010 respectively (Table 6.3). The diagonal elements represent persistency and non-diagonal elements represent the transition from class 1 to class 2 from year 1 to year 2. Validation of the prediction was made with the reference LU maps of 2007 and 2010. Based on these validations the simulation was made for 2022 by considering an equal time interval. This prediction has been done considering water bodies as a constraint and is assumed to remain constant over all time frames. The model was calibrated by validating the predicted versus the actual LU maps for the years 2010 and 2013 with an allowable error of 15%. The validation results are listed in Table 6.4 that provides a good agreement between the actual and predicted maps of 2010, 2013 with Kappa-standard index of optimum point as well as Kappa-location index values ranging between 0.82 and 0.92.

The simulated and predicted LU (Table 6.4a, Figure 6.3 (a-d)) shows a likely increase in built-up area and loss of forest cover. The process of LU transition is observed to be high due to urbanization in the vicinity of developmental projects - Project Seabird, Kaiga Nuclear Power House, and the national/state highways. The analysis highlighted the decline of forest cover from 60.4 (2010) to 48.90 % (2022) with an increase in monoculture plantations from 14.8 to 17.97%. The built-up area shows a greater increase from 4.81 to 9.30 % and the area under horticulture will reach 2.3 to 9.15 % by 2022. The Karwar town, Haliyal, Honnavar town, Sirsi town, Siddapur, Yellapura town, and its suburban regions will experience greater LU transition.

The natural vegetation is being replaced by the plantation activities indicating their further growth in future years. The coastal region has witnessed changes due to major developmental projects. Sahyadri Interior region shows transition due to monoculture, horticulture activities, and Plain region stating higher growth due to the existing towns and neighboring cities such as Hubli, Dharwad. The cropland intensification also witnessed nearby major reservoirs, streams, and huge lakes. This necessitates comprehensive LU management focusing on restoration of ecosystems to mitigate the impacts further. Analysis and comparison of the simulated and actual land-use maps of 2022 reveal that the CA-Markov model has provided insights in terms of change quantification and continuous-space change modeling (Table 6.4b).

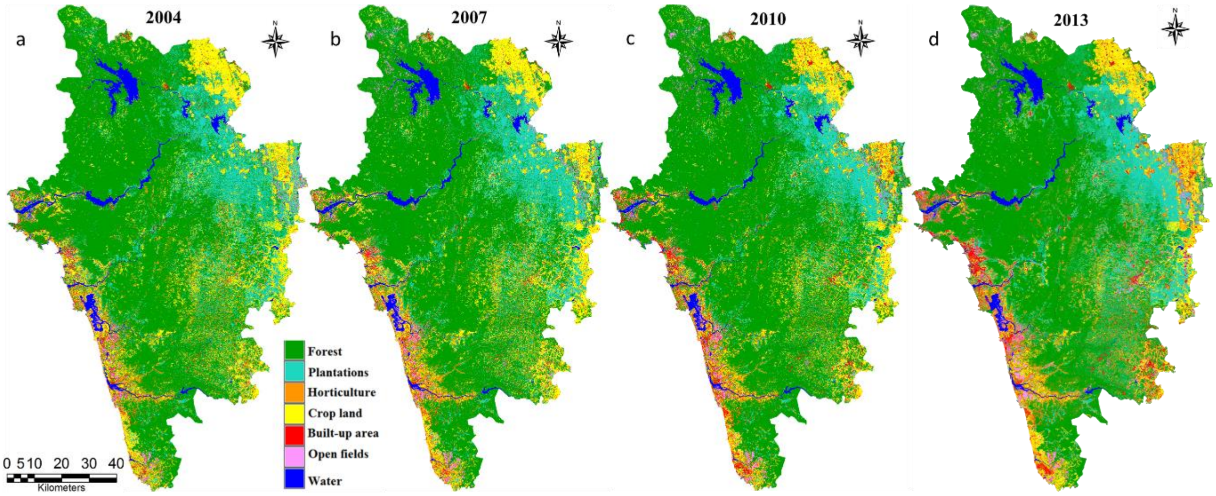



Figure 6.2 (a-d). LU of Uttara Kannada from 2004-2013

Table 6.2. The spatial extent of LU categories

| Year | 2004 | | 2007 | | 2010 | | 2013 | |
|---|---|---|---|---|---|---|---|---|
| **Category** | **Ha** | **%** | **Ha** | **%** | **Ha** | **%** | **Ha** | **%** |
| **Forest** | 622095.4 | 60.4 | 596451.3 | 57.9 | 582497.1 | 56.6 | 549298.6 | 53.4 |
| **Plantations** | 152499.4 | 14.8 | 159462.4 | 15.5 | 166699.5 | 16.2 | 184671.0 | 17.9 |
| **Horticulture** | 42798.1 | 4.2 | 47652.6 | 4.6 | 52371.8 | 5.1 | 53743.4 | 5.2 |
| **Crop land** | 136379.1 | 13.3 | 140339.9 | 13.6 | 139177.8 | 13.5 | 139302.5 | 13.5 |
| **Built-up** | 23482.8 | 2.3 | 26153.2 | 2.5 | 28491.0 | 2.8 | 36101.8 | 3.5 |
| **Open fields** | 21803.8 | 2.1 | 29758.7 | 2.9 | 29798.8 | 2.9 | 38087.3 | 3.7 |
| **Water** | 30204.4 | 2.9 | 29445.0 | 2.9 | 30227.1 | 2.9 | 28058.6 | 2.7 |

Table 6.3. Transition probability matrix for 2007-2010

| **Given** | **Probability of changing to** | | | | | | |
|---|---|---|---|---|---|---|---|
| | Forest | Plantations | Horticulture | Crop | Built-up | Open fields | Water |
| **Forest** | **0.824** | 0.027 | 0.071 | 0.023 | 0.012 | 0.043 | 0.001 |
| **Plantations** | 0.094 | **0.817** | 0.043 | 0.019 | 0.003 | 0.024 | 0.000 |
| **Horticulture** | 0.000 | 0.000 | **0.819** | 0.181 | 0.000 | 0.000 | 0.000 |
| **Crop** | 0.003 | 0.000 | 0.036 | **0.780** | 0.161 | 0.019 | 0.001 |
| **Built-up** | 0.053 | 0.000 | 0.023 | 0.052 | **0.744** | 0.124 | 0.004 |
| **Open fields** | 0.064 | 0.000 | 0.000 | 0.104 | 0.000 | **0.832** | 0.000 |
| **Water** | 0.036 | 0.000 | 0.018 | 0.053 | 0.033 | 0.060 | **0.800** |

Table 6.4a. Details of simulated 2013 and predicted LU for 2016, 2019, and 2022 under BAU scenario

| **Year** | **Simulated BAU_2013** | | **BAU_2016** | | **BAU_2019** | | **BAU_2022** | |
|---|---|---|---|---|---|---|---|---|
| **Category** | **Ha** | **%** | **Ha** | **%** | **Ha** | **%** | **Ha** | **%** |
| Forest | 543531.7 | 52.9 | 512756.9 | 49.9 | 483988.1 | 47.07 | 461386.4 | 44.87 |
| Plantation | 186451.4 | 18.1 | 193274.6 | 18.8 | 187754.2 | 18.26 | 184739.6 | 17.97 |
| Horticulture | 59965.68 | 5.83 | 66533.36 | 6.47 | 74443.87 | 7.24 | 77466.75 | 7.53 |
| Crop land | 140399.4 | 13.7 | 137448.0 | 13.4 | 141489.7 | 13.76 | 142953.0 | 13.90 |
| Built-up | 37337.11 | 3.63 | 55488.6 | 5.40 | 78158.36 | 7.60 | 94050.06 | 9.15 |
| Open fields | 31088.68 | 3.02 | 35087.27 | 3.41 | 35642.87 | 3.47 | 40460.87 | 3.93 |
| Water | 29489.02 | 2.87 | 27674.18 | 2.69 | 26785.96 | 2.60 | 27206.27 | 2.65 |

Table 6.4b. Accuracy of simulation as compared with actual LU

| **Kappa Index** | Simulated BAU_2010 | Simulated BAU_2013 |
|---|---|---|
| Kno | 0.87 | 0.86 |
| Klocation | 0.82 | 0.88 |
| Kstandard | 0.88 | 0.92 |

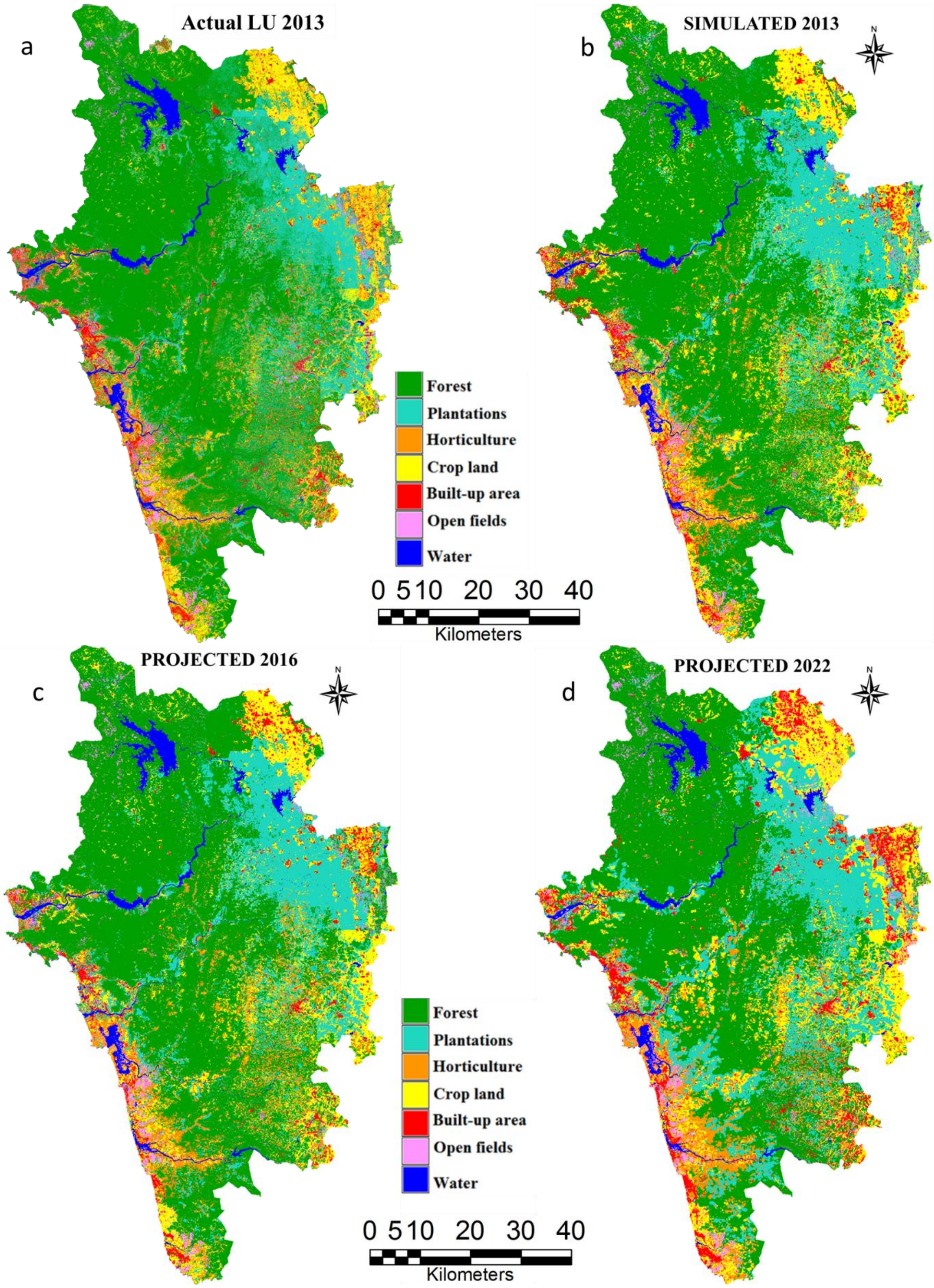



Figure 6.3 (a-d). Actual, Simulated and predicted LU of Uttara Kannada under BAU

**6.1.2. Historical Growth Scenario (HGS)**

This scenario aims to understand the historical trend of LU transition without considering agents and can also be referred to as Coordinated Ecological Sustainability (CES) Scenario. The analysis tries to understand regional anthropogenic changes in the absence of any external pressure of land conversion. BAU scenario explains the current state of the district with respect to the LU changes from $t_0$ to $t_1$ (for example accounting simple transition from 2004 to 2007; 2007 to 2010 etc., with transition potentiality based on neighborhood, which does not focus on the drivers which influence the change). Thus, BAU focuses on recent past activities and their induced changes.

The historical growth rate scenario assumes 1973-79 as the base period, where least anthropogenic pressure on the landscape was noticed. Post 1980 the policy-induced changes are noticed as the district depicted changes after 1979 with a series of developmental projects being taken up in the region such as the construction of dams, reservoirs, industries, and nuclear power project. The country witnessed breakthrough environmental legislations such as the Wild Life (Protection) Act, 1972 (enacted by the Parliament of India in order to conserve animals, birds, plants and the matters connected therewith in 1972); The Forest (Conservation) Act, 1980 (enacted for providing a higher level of protection to the forests and to regulate diversion of forest lands for non-forestry purposes. FC ACT, 1980 (prior approval of the Central Government is essential for de-reservation of forest lands and/or diversion of forest lands for non-forestry purposes) was framed during 1970 to 1980. However, these legislations were not very effective due to poor regulatory mechanisms leading to deforestation of large tracts of forests. Also, the forest department under the social forestry scheme and compensatory afforestation implemented large scale plantations of monoculture exotic species such as Acacia, Eucalyptus in the post-1980s. Compared to these, the period from 1973 to 1979 corresponds to the period with the least human interventions. Hence, the growth rate of 1973 to 1979 is considered (same transition between LU classes), to illustrate the likely scenario of least anthropogenic interferences.

Historical Growth rate scenario had the least influence by policy drivers but included local interaction. Under this scenario, management interventions are not considered to ensure that the historical forest cover changes have its capacity to transform or adapt to future conditions to continue to produce desirable goods and services. CA_MARKOV approach tries to integrate previous LU transitions and simulated with reference to the multi-temporal datasets. This analysis tries to understand LU transition from base year to next year and predicts likely LU. The core goal of the historical growth scenario is to highlight the benefits of environmental protection and sustainable management of forest resources without any radical changes.

The historical growth trend has been analyzed by accounting changes from 1973-1979 LU change rate. The simulated 1989 LU was validated with an actual 1989 LU. The simulated map of 1999 for historical trend analysis was generated using LU maps of 1979 and simulated LU of 1989. This approach is replicated for 2009 and 2016. The historical trend images, as well as current LU maps, were used and forecasted to the year 2022 and 2030. The major changes are noticed in terms of an increase in agriculture and plantation areas. Since CA models purely depend on neighborhood pixels, the major driving force of changes is noticed with agriculture and plantation class. As compared with actual LU change trend the loss of forest cover is minimal due to no external forces included such as major developmental projects etc., (as they were implemented post-2000). Figure 6.4 (a-d) shows the historical trend based estimation of LU changes. Figure 6.5 highlights temporal changes in forest and other LU areas as compared with actual LU maps. Figure 6.6 shows forecasted LU as per historical trend analysis. Tables 6.5, 6.6 show category wise historical LU change analysis as compared to actual LU (BAU scenario). This approach highlights changes in forest cover would be minimal compared to the BAU scenario, due to the absence of external pressure such as developmental projects (Figure 6.7).

Figure 6.8 outlines forest cover loss as per historical trends. Historical preference of urban to locate next to coasts or rivers can be seen from the overall analysis. The cropland is hardly attracted to built-up in the Sahyadri region and depicts the least growth. This approach is a harmonized, spatially explicit, ecologically sustainable growth prediction scenario that highlights the least changes as compared to current post-1989. Because post-1989 major developmental initiatives were taken across the district and which resulted in a major loss of forest cover. While the current trend analysis (BAU-scenario) highlights there could be more vulnerable changes in forest cover in the future, historical trend highlights minimum changes except for the eastern part of the district, where major agriculture and plantations were present. There is a chance of land conversion for agriculture in the plains such as Haliyal, Mundgod taluks. The historical growth scenario shows an ideal case of LU transition as compared with the current (BAU) growth rate. This scenario showed overall likely change in forest cover from

83 (1973) to 65% by 2030. While the actual LU of 2016 reflects further erosion of forest cover to 50.81%, highlighting mismanagement and over-exploitation of forests, which can make the region unsustainable.

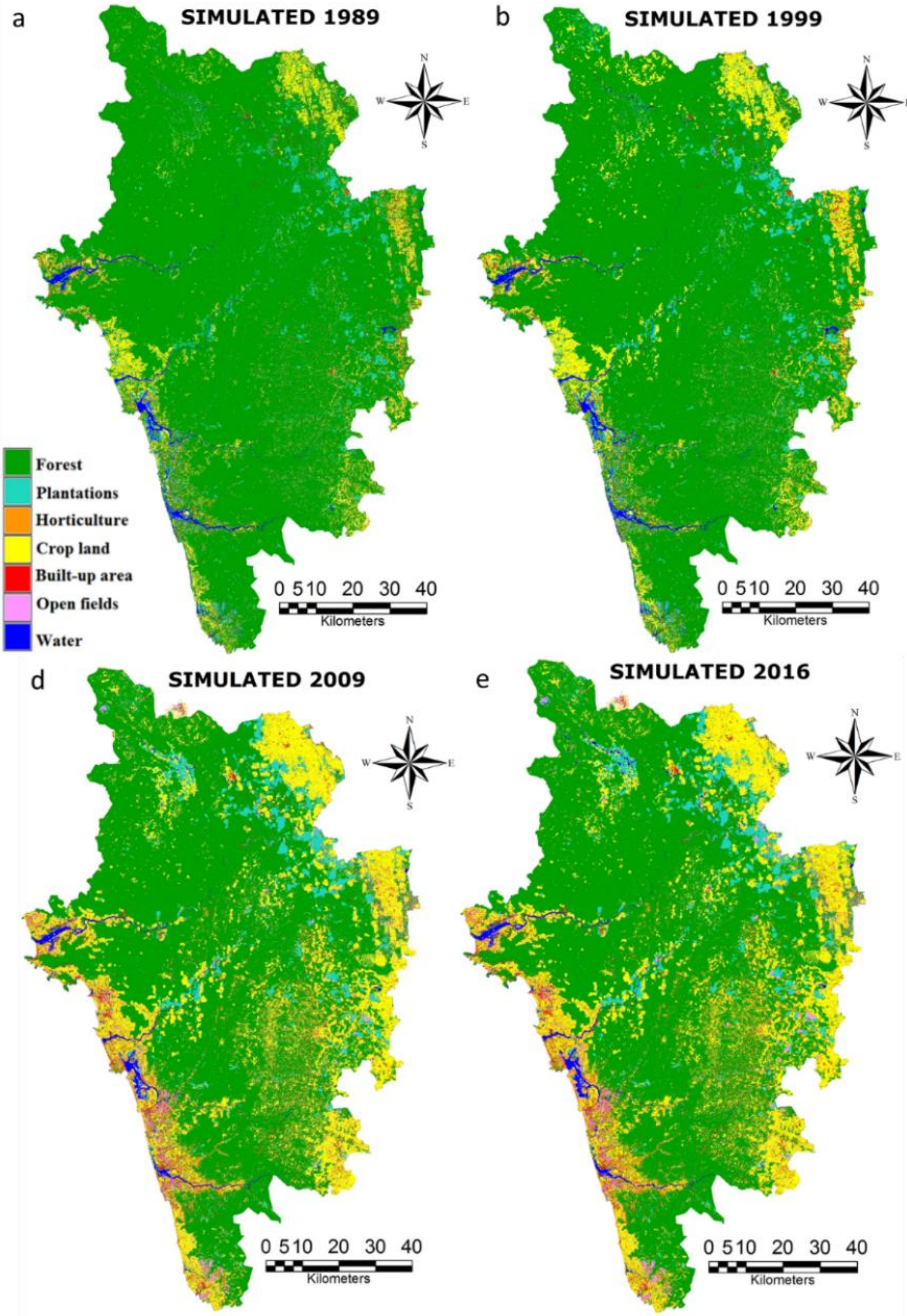



Figure 6.4. Simulated LU of Uttara Kannada for Historical Growth scenario asper historical trends

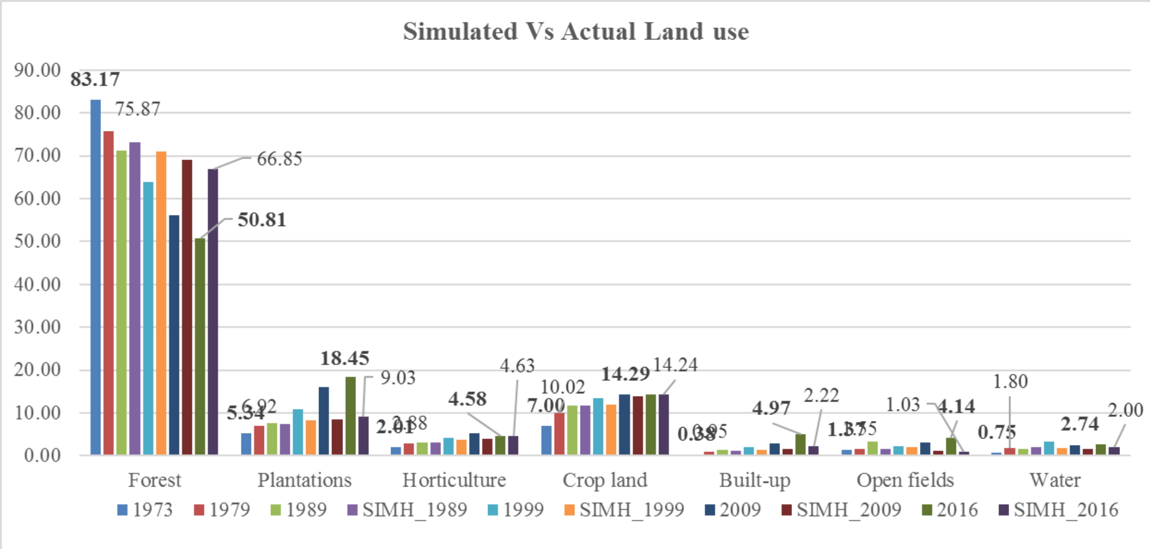



Figure 6.5. Simulated vs Actual trend of LU

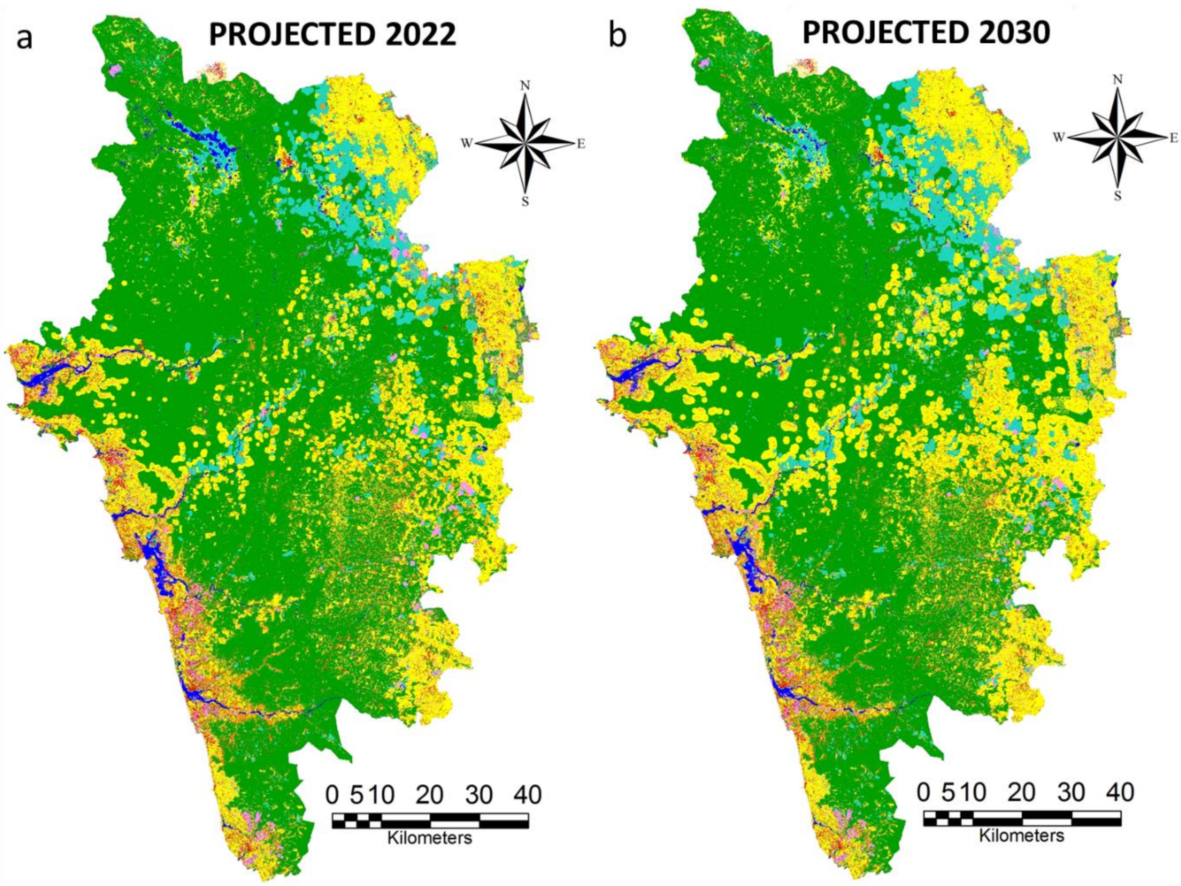



Figure 6.6. Projected LU for Historial Growth Scenario as per historic trends

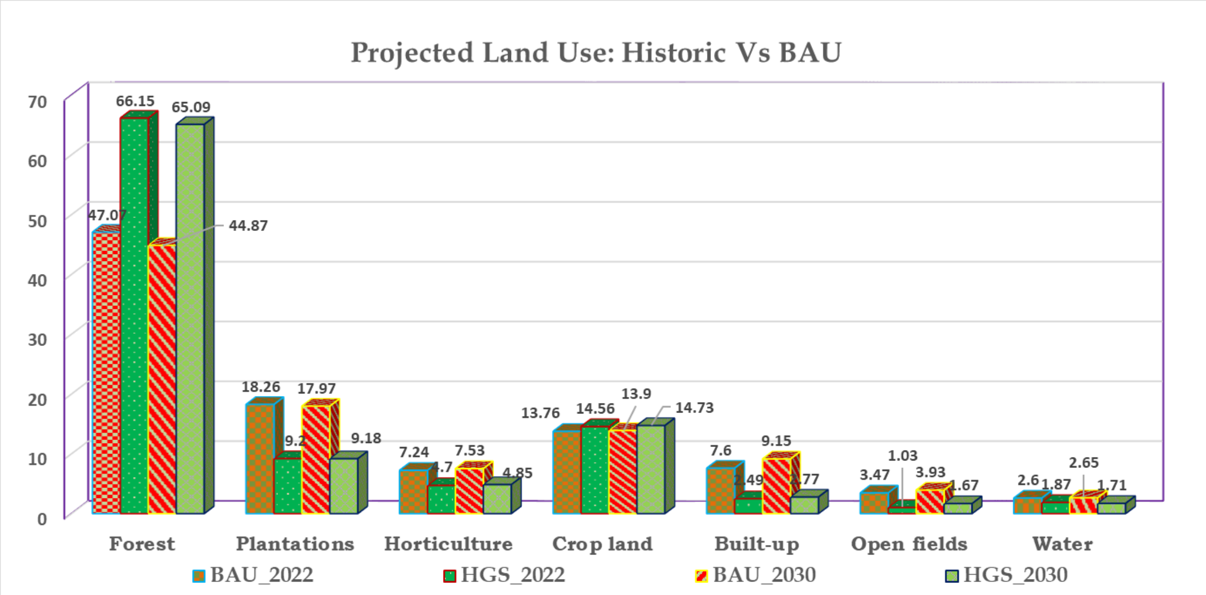



Figure 6.7. Projected LU based on historical (HGS) and BAU scenarios

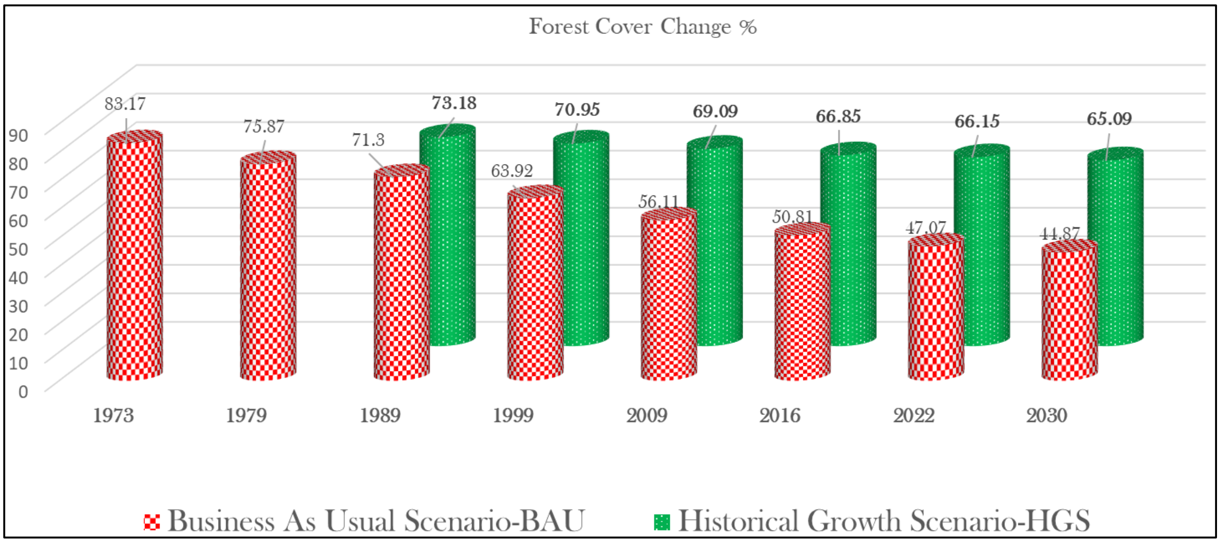



Figure 6.8. Change in forest cover as compared with both the trends

Table 6.5. LU analysis across various trends (HGS_YY is the simulated land use in the given year, and its next column is the actual land use area in that corresponding year)

| YEAR | 1973 | 1979 | 1989 | HGS_1989 | 1999 | HGS_1999 | 2009 | HGS_2009 | 2016 | HGS_2016 |
|---|---|---|---|---|---|---|---|---|---|---|
| **Category** | **%** | **%** | **%** | **%** | **%** | **%** | **%** | **%** | **%** | **%** |
| **Forest** | 83.2 | 75.87 | 71.30 | 73.18 | 63.92 | 70.95 | 56.11 | 69.09 | 50.81 | 66.85 |
| **Plantations** | 5.34 | 6.92 | 7.54 | 7.42 | 10.94 | 8.23 | 15.98 | 8.51 | 18.45 | 9.03 |
| **Horticulture** | 2.01 | 2.88 | 3.13 | 3.14 | 4.24 | 3.75 | 5.21 | 4.00 | 4.58 | 4.63 |

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| **Crop land** | 7.00 | 10.02 | 11.77 | 11.65 | 13.45 | 11.97 | 14.40 | 13.96 | 14.29 | 14.24 |
| **Built-up** | 0.38 | 0.95 | 1.26 | 1.12 | 2.10 | 1.35 | 2.77 | 1.59 | 4.97 | 2.22 |
| **Open fields** | 1.37 | 1.55 | 3.38 | 1.58 | 2.13 | 1.90 | 2.99 | 1.22 | 4.14 | 1.03 |
| **Water** | 0.75 | 1.80 | 1.61 | 1.92 | 3.20 | 1.86 | 2.54 | 1.64 | 2.74 | 2.00 |

Table 6.6. Forecasted LU across various trends

| YEAR | BAU_2022 | HGS_2022 | BAU_2030 | HGS_2030 |
|---|---|---|---|---|
| **Category** | **%** | **%** | **%** | **%** |
| **Forest** | **47.07** | **66.15** | **44.87** | **65.09** |
| **Plantations** | 18.26 | 9.20 | 17.97 | 9.18 |
| **Horticulture** | 7.24 | 4.70 | 7.53 | 4.85 |
| **Crop land** | 13.76 | 14.56 | 13.90 | 14.73 |
| **Built-up** | 7.6 | 2.49 | 9.15 | 2.77 |
| **Open fields** | 3.47 | 1.03 | 3.93 | 1.67 |
| **Water** | 2.6 | 1.87 | 2.65 | 1.71 |

### 6.1.3. Managed Growth Rate Scenario through the proposed hybrid model

The shortcomings due to data and computation limits were assessed with respect to the standalone agent-based or non-agent based analysis. Myllyviita et al., (2011) have shown the advantages of hybrid modeling techniques in evaluating quantitative and qualitative factors together. The new holistic evaluation factors through hybrid techniques can help to evaluate the consequences of a decision, the influence of each factor, and stakeholder's preferences with respect to the landscape.

***Simulation and Future Prediction using FUZZY-AHP-MCCA***

The detailed approach as depicted in Figure 6.9. Raster maps of the constraining factors and transition factors were generated at a common resolution of 30 m. The driving forces of LU changes and constraints (Table 6.7) were identified based on the LU history, review of published literature, and policy reports. Major drivers of landscape transitions are slopes, major highways, industries, core residential areas, etc. Entities such as water bodies, river course, protected areas, and reserve forests are considered as constraints as they are likely to change (Figure 6.10 and 6.11).

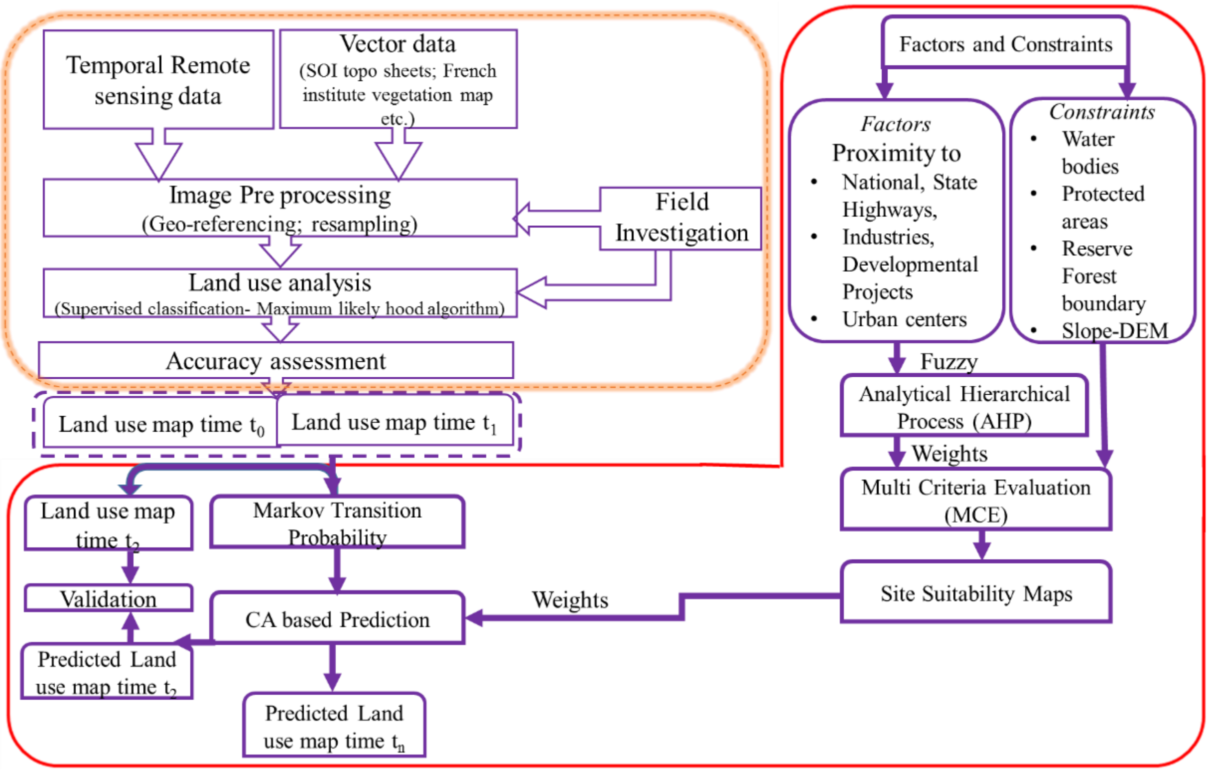



Figure 6.9. The method proposed for the hybrid modeling approach

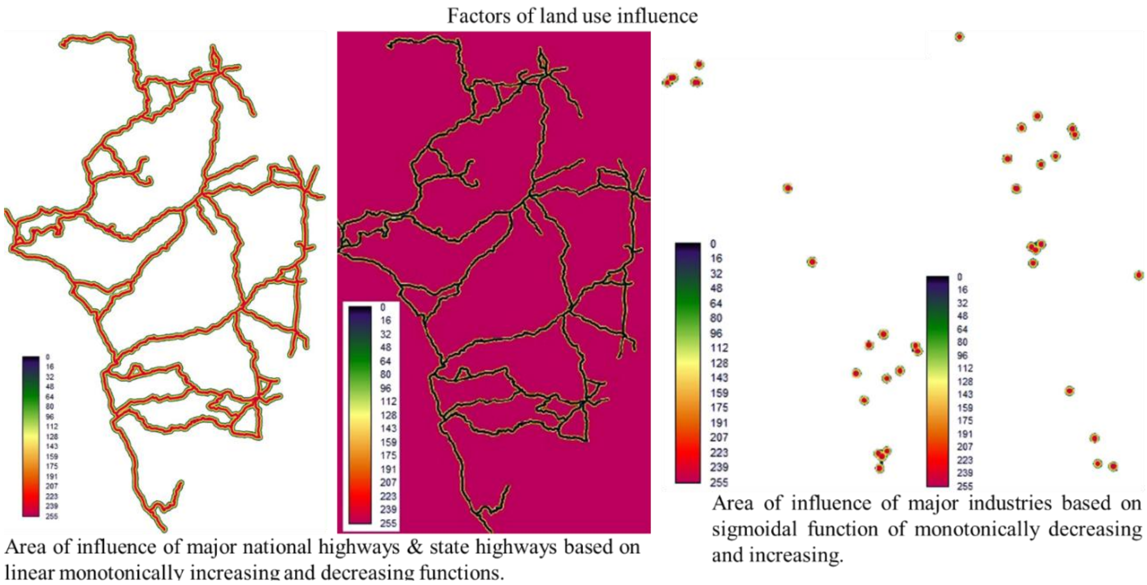



Figure 6.10. Factors of LU influence by fuzzy distance tool measurement

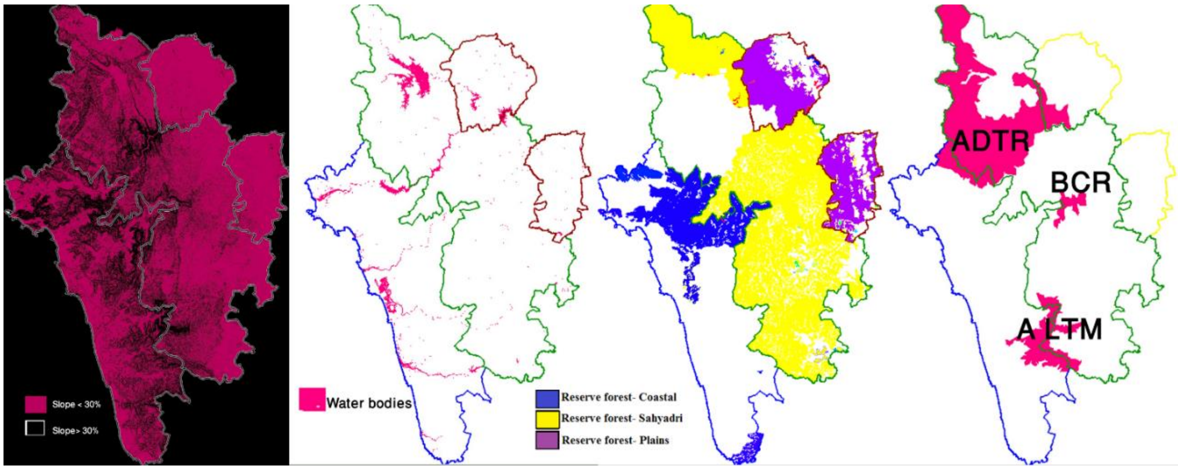



Figure 6.11. Constraints of LU transition

The consistency index CI is computed to evaluate the consistency of the judgment matrix (Equation 17). Consistency ratio (CR) was evaluated for three regions and acceptable CR from 0.04 to 0.09 is obtained for each LU (Table 6.8) based on (Equation 18). CR value below 0.1 indicates the model is consistent, obtained by the probability of the random weights from the landscape factors (Saaty, 2008) and applied for the subsequent process. CA process is implemented based on the site suitability (the probability of that cell's changing to a given class in the future) and the transition matrix (contains the number of cells that change in the time step derived from the number of cells of each class by multiplying the probability matrix) generated from Fuzzy-AHP. The simulation and prediction of LU changes at every single time step are computed based on current LU and the state of neighboring pixels. A diamond filter of 5×5 kernel size was applied to the cellular automata to consider neighborhood LU effects. Two scenarios were designed to emphasize the environmental protection and violation in the region and to simulate the future state of forests - (i) high protection scenario (**P***) considering the protection of reserve forest with the appropriate regulatory mechanism and (ii) least protection scenario (**P_WRF**-without reserve forest protection) with an increase in population and erosion of forest resources.

Table 6.7. Driving forces of landscape transitions

| Sno | Factors | Description |
|---|---|---|
| **1** | Slope | Related to erosion, especially in the high forested areas such as the Sahyadri region of the study area. Priority was given to lower slope inclination for LU transformation (Tang et al., 1998; Fu et al., 2006; Li et al., 2013). |

| | | |
|---|---|---|
| **2** | National highways, major roads | Major transitways have the influence of land transformation in forested areas and also responsible for fragmentation, edge formation (Terra and Santos, 2012; Ramachandra et al., 2014a), which increases housing density and agriculture. |
| **3** | Industrial activity | Industries and associated development in any region will influence landscape transition (Foley et al., 2005). |
| **4** | Core built-up areas | Core built-up areas have a greater probability of expansion in nearby areas next to it and act as a major transition of LU (Ramachandra et al., 2012a). |

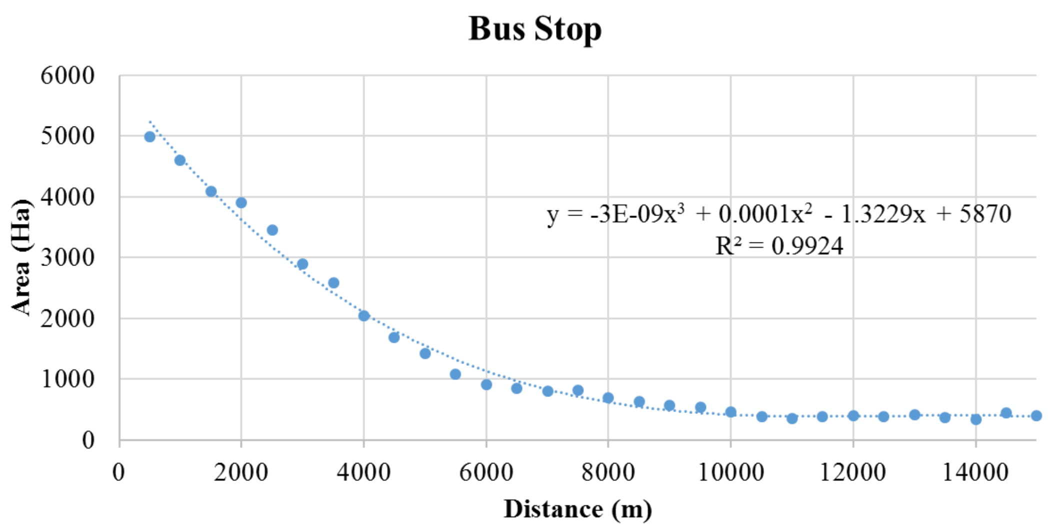
Table 6.8. Constraints used for landscape modeling

| **Sno** | Constraints | Description |
|---|---|---|
| **1** | Protected areas | Protected areas are prime regions of the landscape which protect biological diversity, maintain ecological integrity and provide livelihoods to local communities (Payés et al., 2013; Terra et al., 2014; Martinuzzi et al., 2015). Anshi Dandeli Tiger reserve (ADTR); Aghanashini Lion-tailed macaque (LTM) Conservation Reserve; Bedthi Conservation Reserve were created for conservation of tigers & hornbills, LTM, Myristica swamps and diverse flora, fauna. These regions are acting as an important corridor for wildlife and endemic flora in Western Ghats of Karnataka, protected by the Union government of India. |
| **2** | Reserve forests | These regions are protected under Indian Forest Act, 1927 (an area duly notified under the provisions of India Forest Act or the State Forest Acts having a full degree of protection) by the state government for conserving endemic flora and fauna. |
| **3** | Water bodies | Considered as a major source for food production and further expansions cannot be allowed in these regions. LU changes in the watershed will result in an irreversible loss (Steiner et al., 2000; Mesta et al., 2014; Ramachandra et al., 2020). |

| | | |
|---|---|---|
| **4** | Slope | LU changes in greater slopes (>30% is considered) will result in landslides and higher erosion (Ramachandra et al., 2012b; Muddle et al., 2015). |

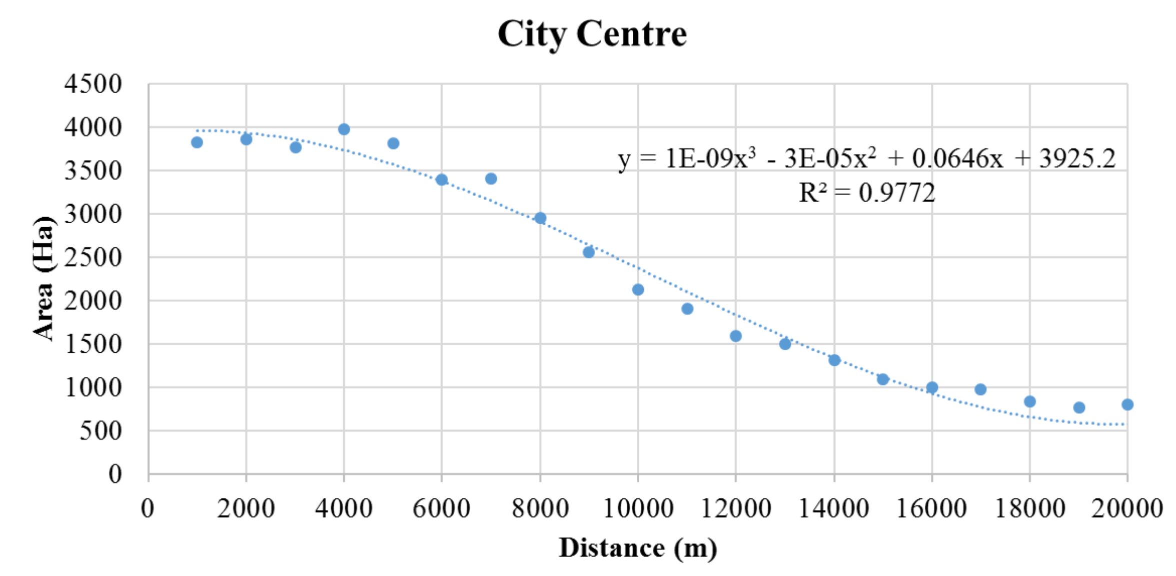
The hybrid Fuzzy-AHP-MCCA model was used for simulation and prediction of landscape status. Prominent non-linear agents considered to describe forest transition can be exponential or logistic, skewed or bimodal, or normal distributions along various gradients. The forest LU transition exhibits non-linear relationships such as monotonic, i.e., they increase or decrease based on the response of agents at differing rates. Alternatively, non-linear relationships also respond as non-monotonic, i.e., increasing up to certain ranges and decreasing on saturation. Non-linear feedbacks show unexpectedly large or small responses to gradually changing conditions as per forest cover and its driver's interactions (Messier et al., 2016). The variable thresholds are also incorporated to assess the dynamic behavior of factors such as social, legislative, and role of policies. These thresholds can provide quick responses of individual factors and unexpected shifts can occur in the forest ecosystem. The fuzzification function has been employed for normalizing the agents such as industries, national and state highways, bus stops across 0 to 255 range, where 255 represents the maximum probability of change, and 0 represents no change. The influence of each factor is evaluated across the various LU categories, which indicates a further zone of influence used for normalizing and prioritizing the weights. Figure 6.12 (a-g) shows the influence of each factor such as Bus stops, City centers, Developmental projects on the Built-up area. The factors show that with increased distance to these factors, their influence gets reduced, whereas developmental projects show their influence even at farther distances thus depicting higher LU change probabilities. Each LU category-specific limits are examined and used for normalizing and prioritizing.

(a)



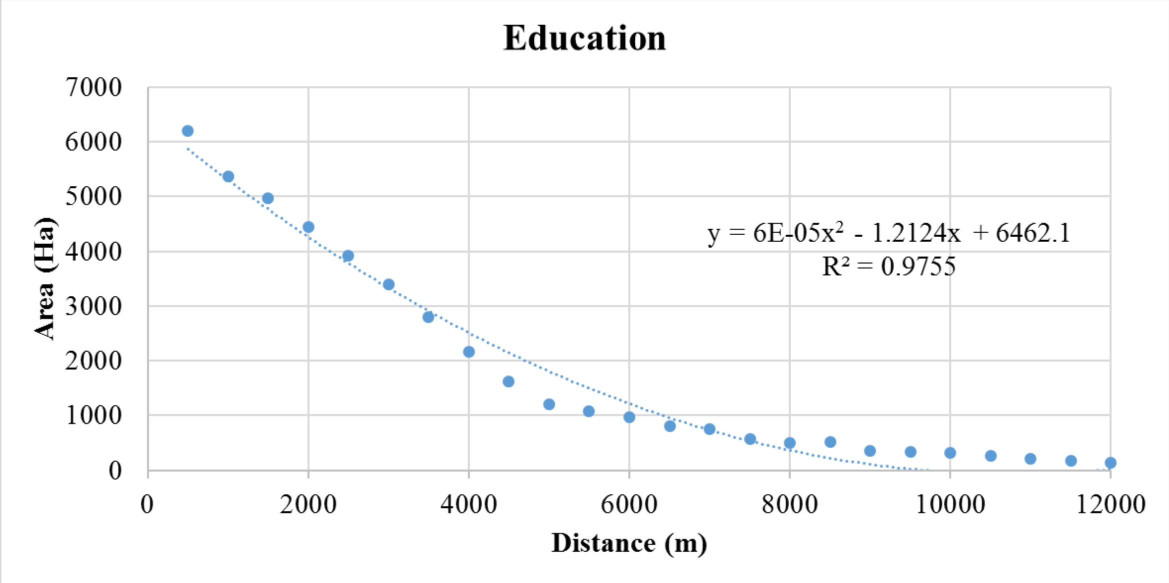

| Distance | < 250 m | 250 to 6000 m | > 6000 m |
|---|---|---|---|
| **Influence** | 255 (high influence) | $\frac{255 * (y - 905)}{4080}$ (reducing influence) | 0 (no influence) |

(b)



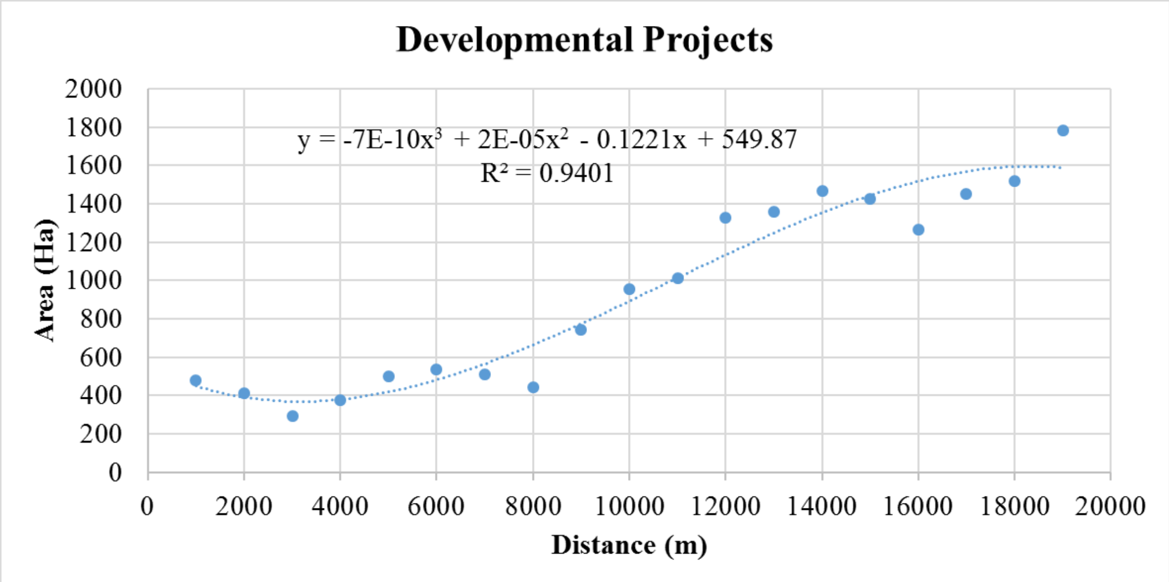

| Distance | < 4000 m | 4000 to 16000 m | > 16000 m |
|---|---|---|---|
| **Influence** | 255 (high influence) | $\frac{255 * (y - 998)}{2974}$ (reducing influence) | 0 (no influence) |

(c)



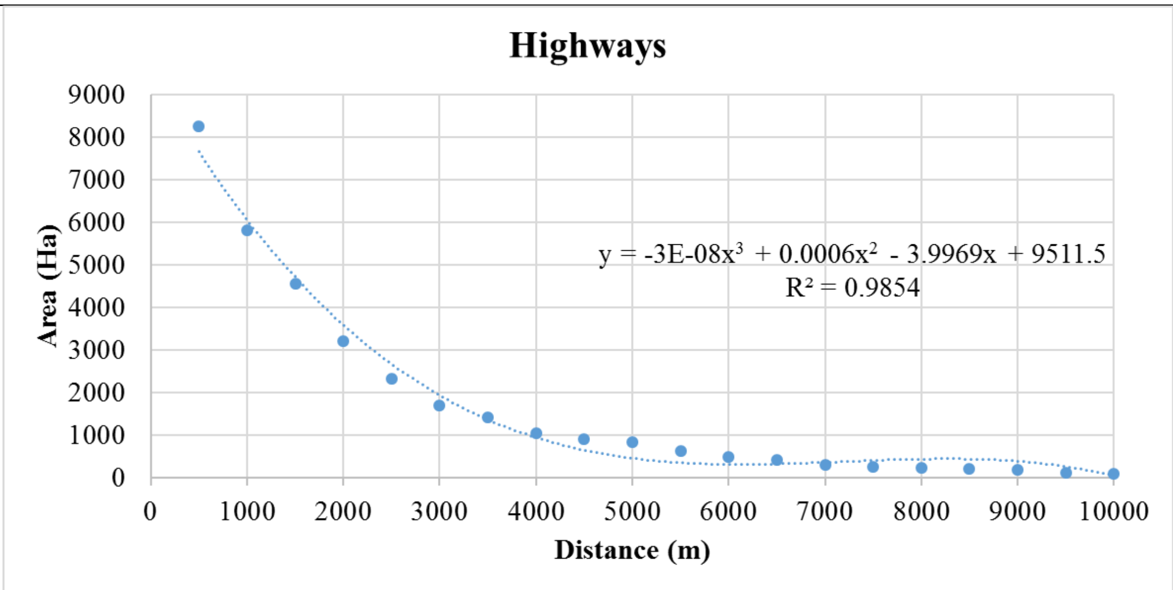

| **Distance** | < 500 m | 500 to 5000 m | > 5000 m |
|---|---|---|---|
| **Influence** | 255 (high influence) | $\frac{255*(y-1199)}{5009}$ (reducing influence) | 0 (no influence) |

(d)



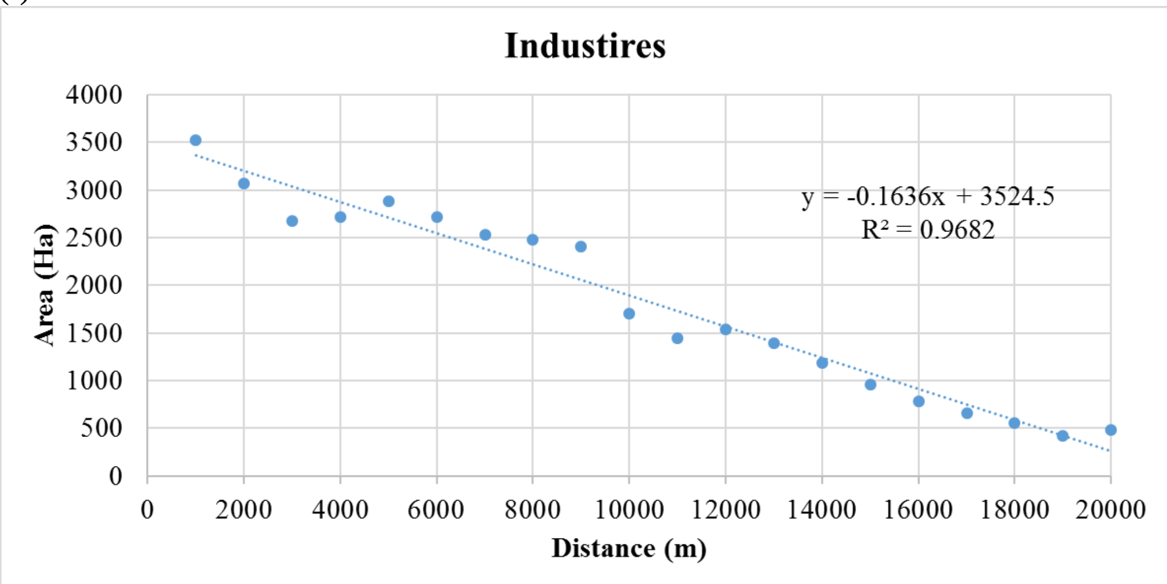

| **Distance** | < 4000 m | 1000 to 14000 m | > 14000 m |
|---|---|---|---|
| **Influence** | 0 (no influence) | $\frac{255*(y-397)}{1090}$ (increasing influence) | 255 (high influence) |

(e)



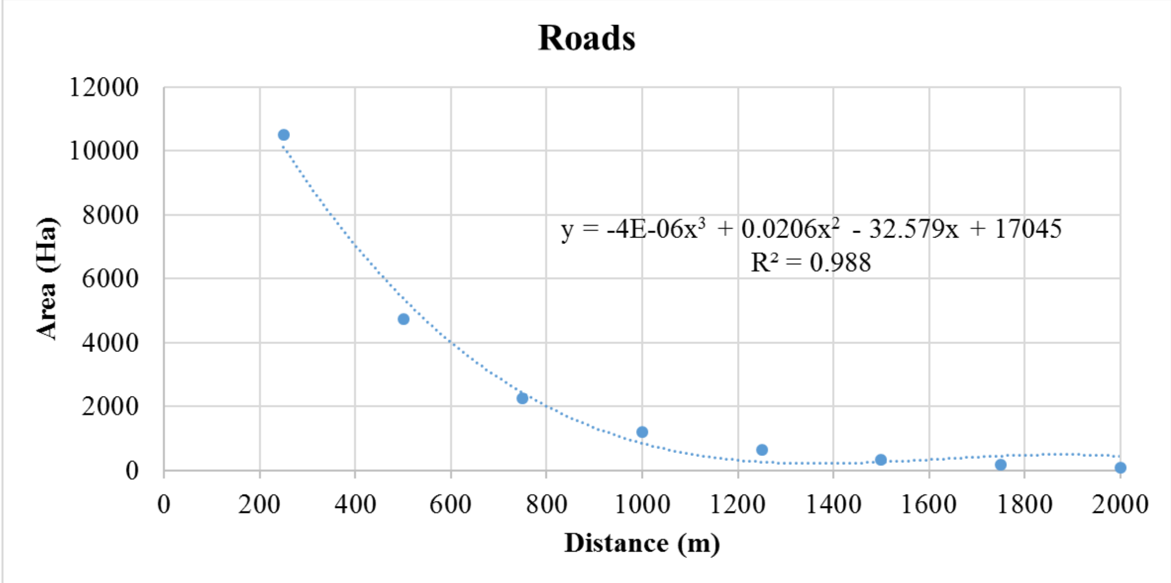

| Distance | < 500 m | 500 to 4000 m | > 4000 m |
|---|---|---|---|
| **Influence** | 255 (high influence) | $\frac{255*(y-1037)}{7219}$ (reducing influence) | 0 (no influence) |

(f)




| Distance | < 5000 m | 5000 to 18000 m | > 18000 m |
|---|---|---|---|
| **Influence** | 255 (high influence) | $\frac{255*(y-550)}{2332}$ (reducing influence) | 0 (no influence) |

(g)




| **Distance** | < 250 m | 250 to 1250 m | > 1250 m |
|---|---|---|---|
| **Influence** | 255 (high influence) | $\frac{255*(y-648)}{9587}$ (reducing influence) | 0 (no influence) |

Figure 6.12. Influence of factors on Built-up category

The distance of influence of each agent with different degrees of membership and representation function are measured and provided as input to the AHP weighting process, to aid in multi-criteria decision making through the synthesis of priorities. The weightages are assigned from values 1 (equally important) to 9 (extremely important) for each comparison. The relative value will be assigned by comparison to derive priority vectors for hierarchy levels. The consistency of the weightage matrix is evaluated by a consistency index and consistency ratio.

Markov Chain (MC) is used to determine the zone wise transition probability during 2004, 2007, 2010, and 2013 with a loop time of 3 years. CA with the site suitability and the transition matrix (generated by MC and Fuzzy-AHP-MCE) predicted spatially the changes considering two scenarios based on the neighboring pixels for 2022 (with the knowledge of transitions during 2004-2007, 2007-2010, and 2010-2013). The accuracy of the simulation is evaluated through Kappa statistics by comparing the simulated data with the actual LUs of 2010, 2013 (Table 6.9) for both scenarios – P*: with protection, P_WRF: without the protection of reserve forests, which indicates that CA_MC is a reliable estimator. The Fuzzy distance measurement has provided the potential transition of each LU based on factors that promote transition. AHP showed good consistency and was found suitable for predicting LUs. The projected LU of 2022

(Figure 6.13, Table 6.10) shows forest cover will reach 49 % with the implementation of protection measures by the regulatory framework. The urban area has expanded from 2 to 7% with industrial growth and economic activities. The increase in plantation area is due to the conversion of forests and also planting in degraded forest patches. Sahyadri Interior region shows moderate disturbances under high protection scenarios with changes in plantations and built-up LU classes (Figure 6.14). The ADTR, ALTM, Bedthi conservation reserve areas are under protection and will remain so with minimal disturbances.

Table 6.9. Validation of actual LU with simulated and Kappa value

| Index | 2010P* | 2010P_WRF | 2013P* | 2013P_WRF |
|---|---|---|---|---|
| **Kno** | 0.89 | 0.91 | 0.92 | 0.91 |
| **Klocation** | 0.9 | 0.9 | 0.94 | 0.92 |
| **Kstandard** | 0.83 | 0.87 | 0.92 | 0.89 |

(P* with protection; P_WRF: without the protection of reserve forests)

Projected LU of 2022P_WRF reflects that the lack of protection in the region will result in rampant forest changes. The forest area will reduce to 45.6 % with the increase in area under plantations, horticulture, and built-up in Karwar, Bhatkal, Honnavar Sirsi, Siddapur, and Haliyal taluks. Forest patches in the region would be only in protected areas and *Kans* (scared forests relic forest patches, protected since historical times) by 2022 due to lack of protection measures and with existing towns, villages becoming more urbanized due to the neighborhood effects of urban agglomerations. The uncontrolled land conversion would lead to an increase in agriculture and horticulture too.

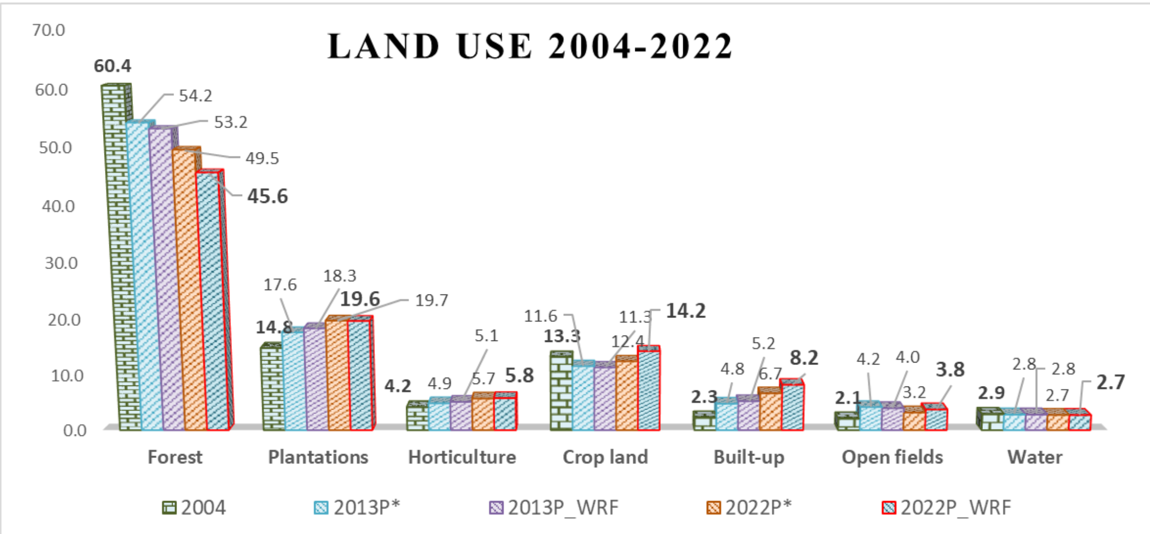



Figure 6.13. Temporal change of LU - category wise during 2004-2022

Table 6.10. LU details from 2004 to 2022

| Year | 2004 | | 2013P* | | 2013P_WRF | |
|---|---|---|---|---|---|---|
| **Category** | **Ha** | **%** | **Ha** | **%** | **Ha** | **%** |
| **Forest** | 622095.4 | 60.4 | 557467.6 | 54.17 | 546992.44 | 53.15 |
| **Plantations** | 152499.4 | 14.8 | 181251.09 | 17.61 | 188662.81 | 18.33 |
| **Horticulture** | 42798.1 | 4.2 | 50050.72 | 4.86 | 52778.76 | 5.13 |
| **Crop land** | 136379.1 | 13.3 | 119075.63 | 11.57 | 116672.01 | 11.34 |
| **Built-up** | 23482.8 | 2.3 | 49276.46 | 4.79 | 53973.77 | 5.24 |
| **Open fields** | 21803.8 | 2.1 | 42884.82 | 4.17 | 40936.83 | 3.98 |
| **Water** | 30204.4 | 2.9 | 29079.76 | 2.83 | 29069.46 | 2.82 |
| **Year** | **2022P*** | | | **2022P_WRF** | | |
| **Category** | **Ha** | | **%** | **Ha** | | **%** |
| **Forest** | 509766.57 | | 49.54 | 469544.75 | | 45.63 |
| **Plantations** | 202724.74 | | 19.70 | 202137.70 | | 19.64 |
| **Horticulture** | 58866.59 | | 5.72 | 59653.92 | | 5.80 |
| **Crop land** | 128003.83 | | 12.44 | 146491.25 | | 14.24 |
| **Built-up** | 68599.43 | | 6.67 | 84454.31 | | 8.21 |
| **Open fields** | 32827.05 | | 3.19 | 38622.91 | | 3.75 |
| **Water** | 28297.87 | | 2.75 | 28181.24 | | 2.74 |

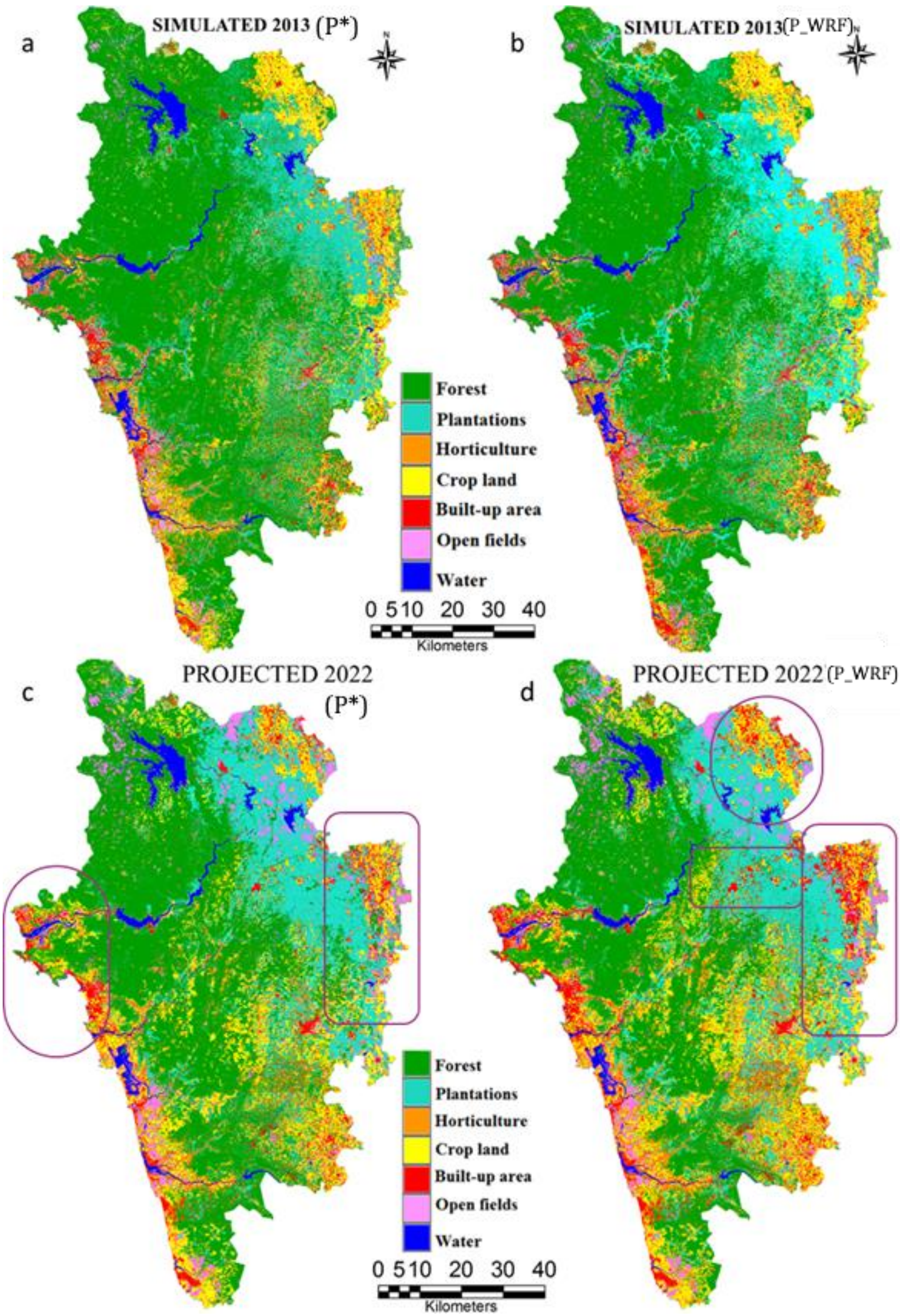



Figure 6.14. Projected LU of Uttara Kannada for Managed Growth rate scenarios of P* (with protection) and P_WRF (without the protection of reserve forests)

### 6.1.4. IPCC Climate Change Growth Rate Scenario

The hybrid Fuzzy-AHP-MCCA analysis was used for simulation and prediction of landscape status in 2046. Simulated LU maps of 2013 and 2016 were generated and validated with the reference LU of 2013 and 2016 and the kappa index. After successful validations, LU projections were simulated for the years 2021, 2031, and 2046. The projections were made to understand the impact of drivers at 5, 15, 30-year intervals based on the IPCC SRES framework (IPCC, 2000). The LU of 2013 and 2016 has used for predicting 2021 (low growth 5 year-A2) and similarly predicted for 2031, and 2046 (moderate growth rate 15 year-A1B; high growth rate 30 year-A1). The proposed hybrid Fuzzy-AHP-MCCA model was advantageous as growth rates could be provided as another input for the simulation model.

Table 6.11 highlights category wise likely LU from 2016 to 2046. The low growth rate (A2) scenario considers the built-up growth rate of pre-1990s (Chapter-4.1.2) as an input apart from the transition from 2013-2016. It shows likely loss of forest cover from 50.29 to 45.63 % with the increase in built-up area from 5 to 8 % from 2016-2021 (Figure 6.15). The moderate growth scenario (growth rate of post-2000’s-A1B) depicts land conversion due to cropland and built-up areas. The likely forest changes are shown as 50.29 to 44 % by 2031 (Table 6.11). The likely increase in plantation activities is noticed as for protecting land from further conversion. New agriculture mainly appears by replacing forests in most areas. Moreover, agriculture is attracted to urban through LU transition due to the available land. New clusters of built-up regions found in the coastal region close to existing towns are often taken over by suburbanization. The high growth rate scenario (A1-2046) shows loss of large tracts of forests due to an increase in built-up and agriculture (Figure 6.16. and 6.17) with uncontrolled developmental activities. The forests show a sharp decline to 39% with corresponding doubling up of the built-up areas within the same period. The likely built-up expansion has been seen in the eastern region also due to neighborhood effects. The coastal taluks undergo noticeable changes due to the peri-urban LU transition. The forests are likely to confine in the Sahyadri portion due to higher altitude and inaccessibility. This may have a severe impact on the biodiversity and sustainability of the region. The district is home to sensitive flora and fauna and if this kind of unsustainable LU changes is allowed to happen uncontrollably then it can result in an irreversible loss to the ecosystem.

Table 6.11. The spatial extent of each LU from 2016-2046

| **Scenarios** | **Actual LU** | | **Simulated LU** | | **Low Growth (A2)** | | **Moderate Growth (A1B)** | | **Rapid Growth (A1)** | |
|---|---|---|---|---|---|---|---|---|---|---|
| **Year** | 2016 | | IPCC_2016 | | A2_2021 | | A1B_2031 | | A1_2046 | |
| **Category** | Ha | % | Ha | % | Ha | % | Ha | % | Ha | % |
| **Forest** | 522945 | 50.8 | 517482 | 50.3 | 469544.8 | 45.6 | 452099 | 43.9 | 403540 | 39.2 |
| **Plantations** | 189903 | 18.5 | 195908 | 19 | 202137.7 | 19.6 | 207019 | 20.1 | 215197 | 20.9 |
| **Horticulture** | 47135 | 4.6 | 47141 | 4.6 | 59653.9 | 5.8 | 54097 | 5.3 | 60831 | 5.9 |
| **Crop land** | 147109 | 14.3 | 145754 | 14.2 | 146491.3 | 14.2 | 153200 | 14.9 | 170028 | 16.5 |
| **Built-up** | 51132 | 5.0 | 52138 | 5.1 | 84454.3 | 8.2 | 90043 | 8.7 | 104601 | 10.2 |
| **Open fields** | 42634 | 4.1 | 42429 | 4.1 | 38622.9 | 3.8 | 42833 | 4.2 | 46656 | 4.5 |
| **Water** | 28228 | 2.7 | 28234 | 2.7 | 28181.2 | 2.7 | 29795 | 2.9 | 28233 | 2.7 |
| **Accuracy (2016 vs IPCC_2016** | Kno=0.9 | | Klocation=0.88 | | | Kstandard=0.91 | | | | |

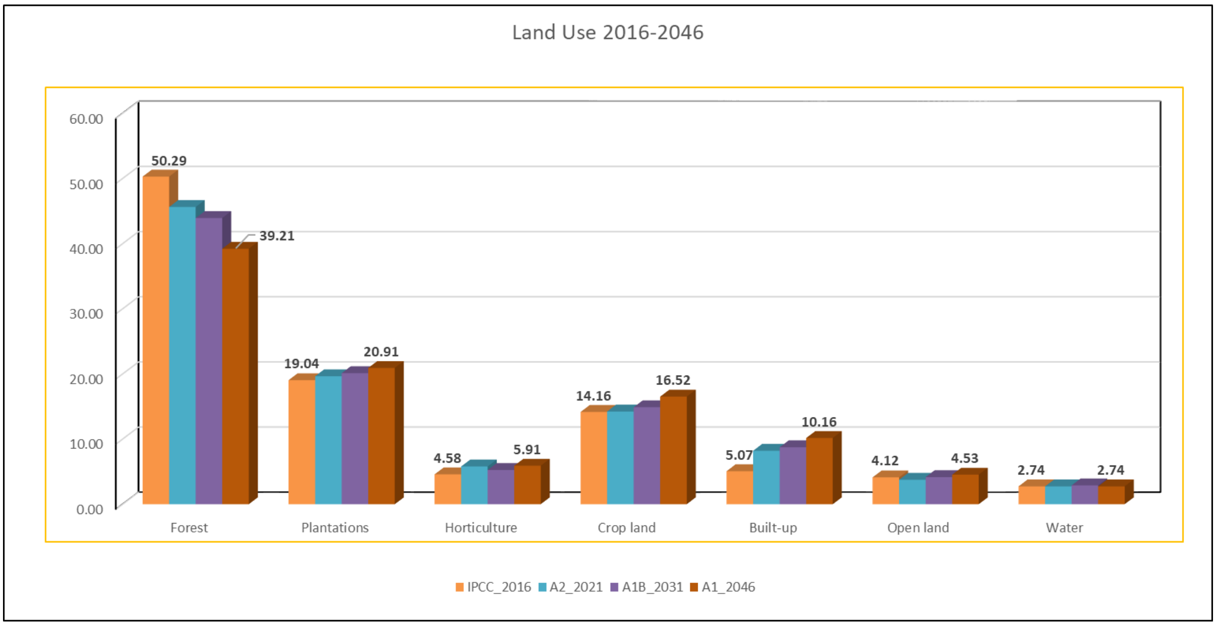



Figure 6.15. Projected LU for 2016 to 2046 under three different IPCC scenarios (A2 for 5yrs, A1B for 15yrs and A1 for 30yrs)

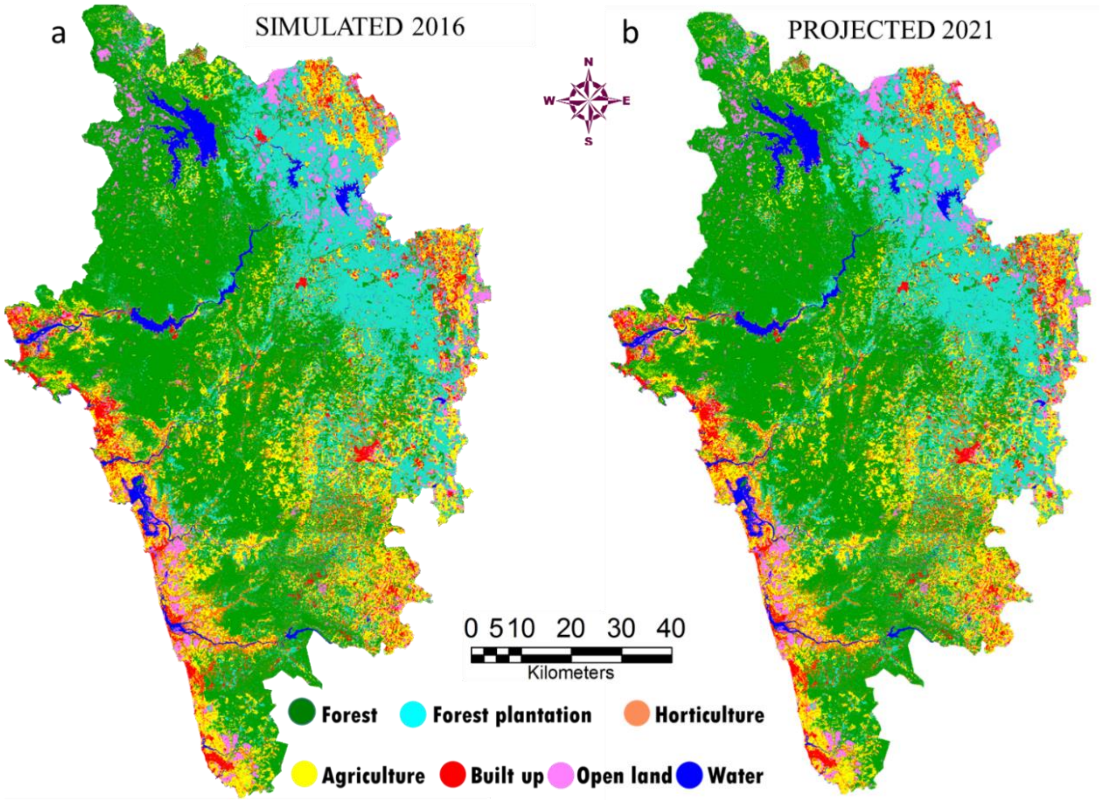



Figure 6.16. LU simulation for IPCC_2016 and projection for A2_2021

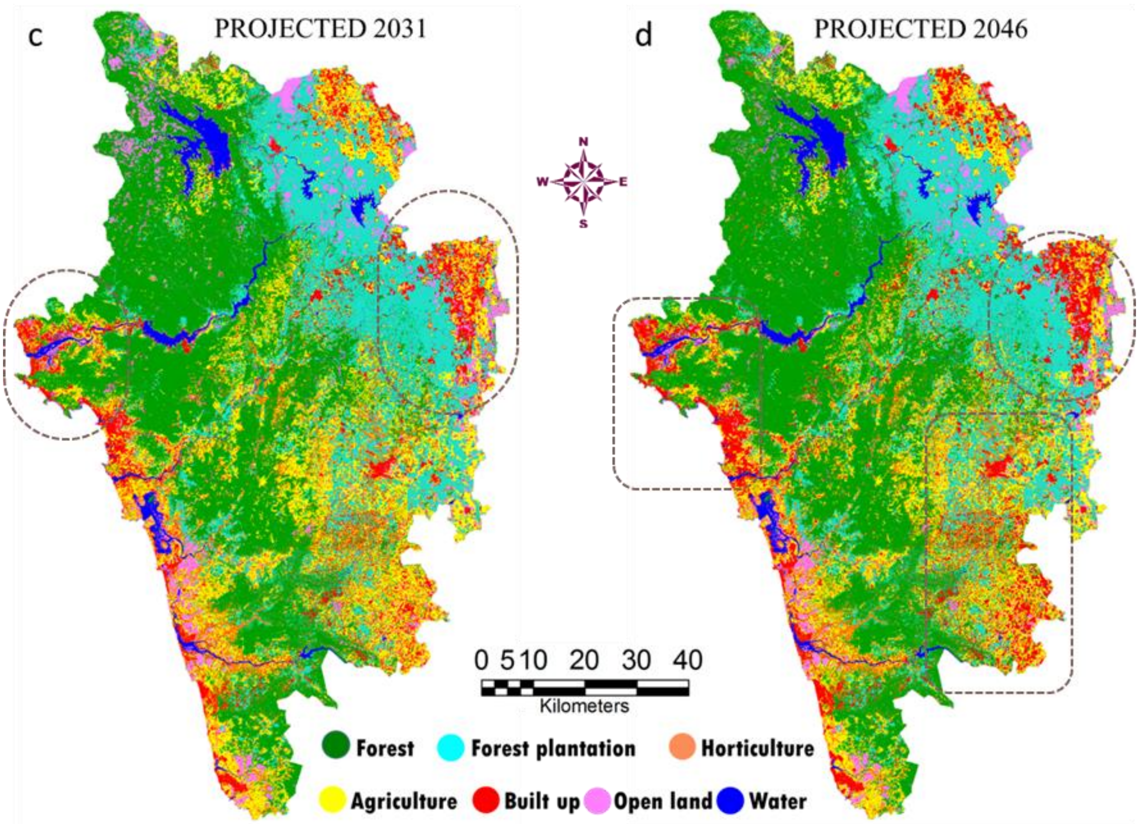



Figure 6.17. LU projections for A1B_2031, A1_2046

### 6.1.5. Conservation Scenarios - Integrating conservation of ESR; protection of Intact (interior) contiguous forests in the modeling framework

While the earlier scenarios looked at how different growth options impact the forests and other land uses, it is also important to see how explicit policy options focussed on forest conservation will affect the land use changes. Here, we propose to evaluate two such conservation scenarios

(i) ESR Scenario: Conservation in ESR-1 and allowing development across ESR 2-4 (see Chapter 5 for ESR delineation);
(ii) Intact/interior forests conservation (IFC) Scenario: limiting LU conversion by protecting the interior forest cover and protected areas.

Both of these are implemented within the proposed hybrid Fuzzy-AHP-MCCA modeling technique by considering them as spatial constraints to growth.

#### 6.1.5.1. ESR Scenario

ESR framework has provided regions of higher priority for conservation and probable areas for holistic development. The ESR-1 region represents a higher priority region that needs to be protected (mainly covered by protected areas, thick evergreen forest)and not to be disturbed by human activities. The limits for this scenario-1 has been implemented by considering ESR-1 as a constraint for LU conversion and allowing the LU change across all the other regions based on the underlying factors. Figure 6.18 shows the ESR-1 as a constraint (0-no LU conversion; 1-allowed LU conversion) and LU of 2013 and 2016 has been considered for the simulation and prediction. The simulated LU of 2016 has been evaluated with the actual LU of 2016 and shows good agreement with the actual LU having an overall Kappa value of 0.92 (Table 6.12). The LU of 2021 and 2031 has been projected to assess the likely changes under ESR 2-4. The taluks covered under ESR-2, 3&4 depict the LU transition while ESR-1 continues to be intact (Figure 6.19). The forest cover in the district is likely to remain close to 50% at 49.8% in 2021 and marginally decreases to 47.9% in 2031, signifying the role of the protection measures (Table 6.13) in limiting forest loss. The built-up land use is successfully accommodated in ESR-3 and 4 due to the constraints, which emphasizes that the policy intervention can indeed protect the forests that are rich in diversity and also ensure a sustainable developmental agenda without hampering much of the resources. In the absence of constraints, the higher LU conversion rates across the district can both damage and alter the region's eco-state, which is irreplaceable.

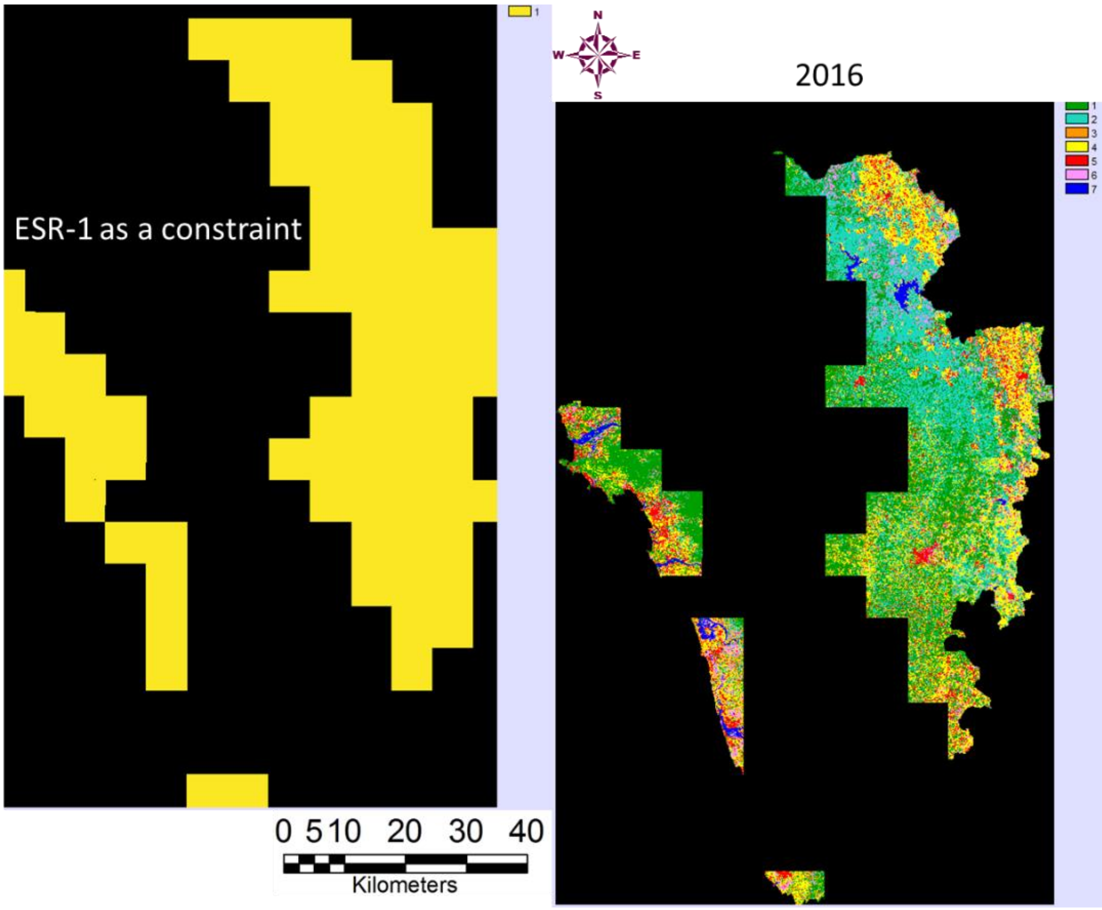



Figure 6.18. ESR-1 as a constraint for growth

Table 6.12. Projected LU under ESR scenario

| Year | Simulated ESR_2016 Vs Actual LU 2016 | Projected ESR_2021 | | Projected ESR_2031 | |
|---|---|---|---|---|---|
| **Category** | Kappa | Ha | % | Ha | % |
| **Forest** | 0.91 | 5,12,498 | 49.80 | 4,92,952 | 47.90 |
| **Plantations** | 0.92 | 1,65,509 | 16.08 | 1,57,090 | 15.27 |
| **Horticulture** | 0.91 | 57,219 | 5.56 | 57,375 | 5.58 |
| **Crop land** | 0.90 | 1,57,076 | 15.26 | 1,71,700 | 16.68 |
| **Built-up** | 0.88 | 57,487 | 5.59 | 73,164 | 7.11 |
| **Open fields** | 0.92 | 51,064 | 4.96 | 48,572 | 4.72 |
| **Water** | 0.98 | 28,233 | 2.74 | 28,233 | 2.74 |
| **Overall Kappa** | 0.92 | Total Area | | 1029086 | |

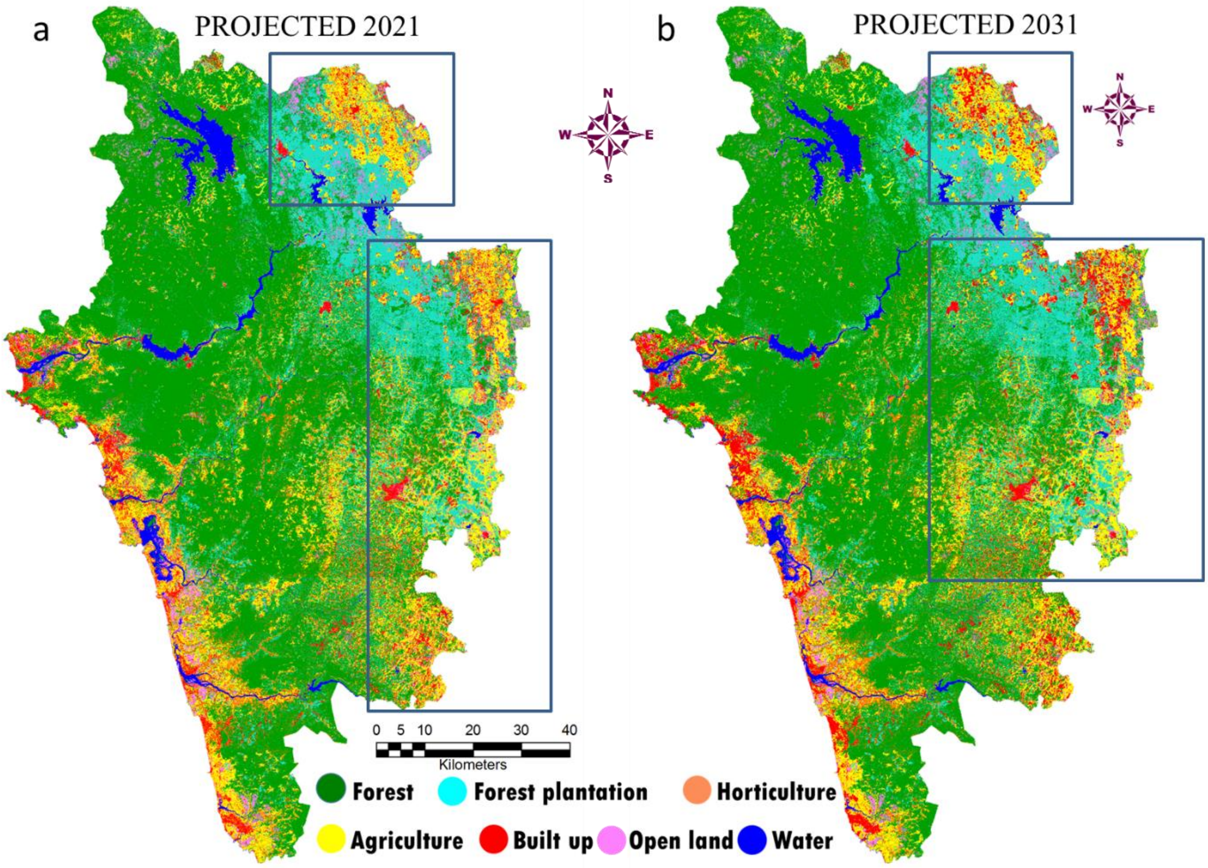



Figure 6.19. Projected LU under ESR constraint scenario

### 6.1.5.2. Intact/interior forests conservation (IFC) Scenario

In this scenario, the forest conservation is implemented by considering Interior Forest cover and Protected Areas as the constraints for LU conversion (Figure 6.20). This approach allows for the protection of interior forests by controlling its exploitation and sets the limits for unplanned growth. The likely changes in LU has been assessed to forecast regions of transitions, thus mitigating abrupt changes. The simulation has been done with LU of 2013 and 2016 datasets and considering the constraints. The Projected LU of 2021 and 2031 depicts the major changes in the taluks of Mundgod, Haliyal, Sirsi, Siddapur, Kumta, and Karwar region where the minimum area is covered under the interior forests (Figure 6.21). The forest cover is likely to be marginally low to the 2016 levels at 48.5% in 2021 and dip further to 44.6% in 2031. The built-up area is likely to increase to 5.8 in 2021 and 6.8 by 2031 with an associated increase in the area under agriculture (Table 6.13). The comparison of ESR and IFC scenarios indicate that while ESR focuses more on conservation and limits the growth to the ESR-3 and 4 regions, the IFC scenario allows for growth across the regions other than interior forest cover regions, thus inducing further fragmentation and imbalance in the ecosystem. The conservation of forests in the district is critical for the sustenance of livelihood, water availability, and biodiversity. Hence the administrators should focus on sustainable development by conserving at least ESR-1 areas.


Figure 6.20. Interior forest as a constraint for growth

Table 6.13. Projected LU changes as per IFC scenario

| Year | Simulated IFC_2016 Vs Actual LU 2016 | Projected IFC_2021 | | Projected IFC_2031 | |
|---|---|---|---|---|---|
| Category | Kappa | Ha | % | Ha | % |
| Forest | 0.79 | 499052 | 48.495 | 4,58,964 | 44.60 |
| Plantations | 0.94 | 169950 | 16.515 | 1,70,220 | 16.54 |
| Horticulture | 0.83 | 60911 | 5.919 | 60,640 | 5.89 |
| Crop land | 0.78 | 157284 | 15.284 | 1,83,943 | 17.87 |
| Built-up | 0.87 | 59906 | 5.821 | 69,908 | 6.79 |
| Open fields | 0.86 | 53750 | 5.223 | 57,178 | 5.56 |
| Water | 0.98 | 28233 | 2.744 | 28,233 | 2.74 |
| Overall Kappa | 0.87 | Total Area | | 1029086 | |

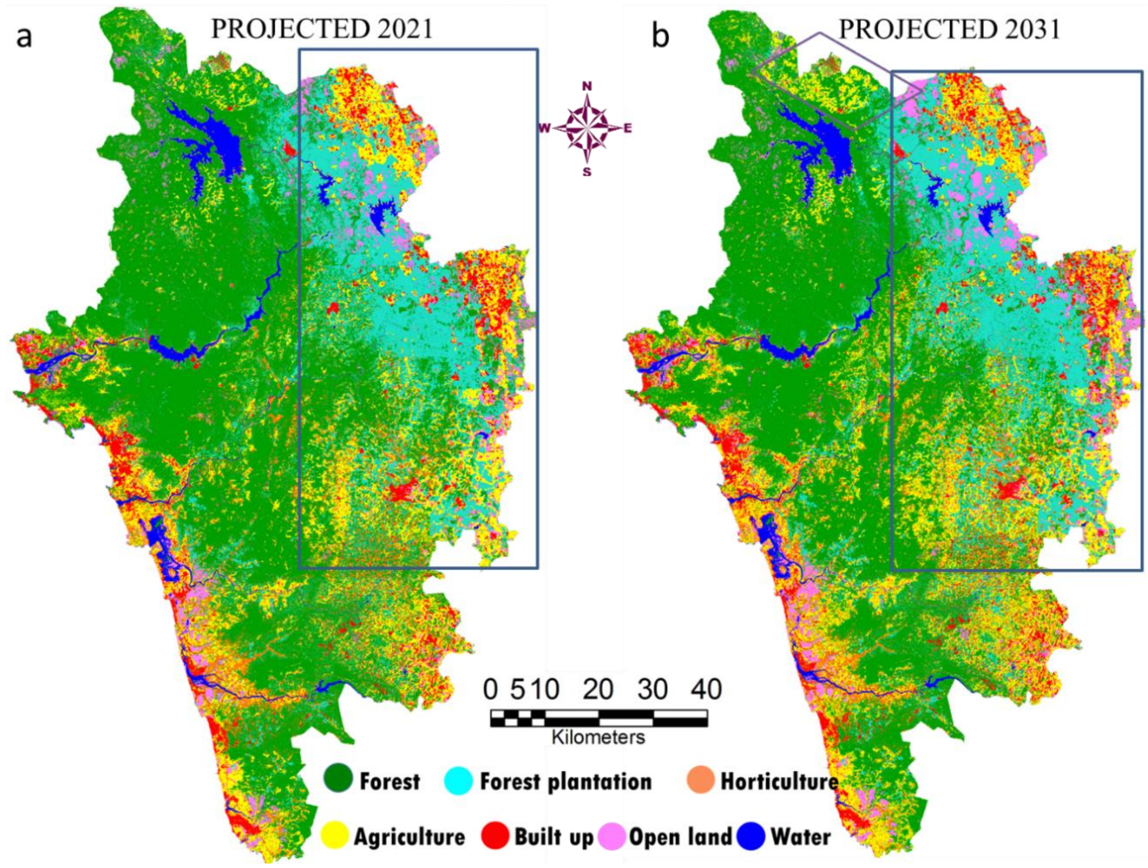



Figure 6.21. Projected LU under IFC scenario of interior forest and protected areas as a limit for growth

## 6.2 Conclusion

This chapter has shown that the choice of the appropriate parameters and the modeling paradigms of constrained CA-Markov model and hybrid Fuzzy-AHP- MCCA models can help us both understand the landscape dynamics, and allow for studying and assessing the impact of various decisions on the changes in land use patterns. Table 6.14 summarises the various scenarios proposed to model land use changes within this landscape based on local interactions and dynamics. The CA-Markov is mainly constructed as a linear presumption of the Markov model. But, the entire ecological and economic system in the district is not a simple linear model and is instead complex. The CA model here does not consider any environmental and socio-economic variables acting and the probable amount and location of change, which is evident as major changes are dependent on the neighborhood of existing developments that are obtained through a Markov Chain implementation. Recently, an increase in the built-up area due to the series of hydroelectric projects and other developmental activities are noticed, which the CA model is unable to predict. To overcome, the adverse effects caused by neighborhood, a hybrid Fuzzy-AHP-MCCA model was proposed and analyzed for changes under two scenarios of P* with Reserve forest protection and P_WRF without Reserve Forest protection. The loss of forest cover has been estimated as 4.63%, in 2013 to 7.52 %in 2022 under these two scenarios respectively. It highlights that the undulating terrains with the community protected reserves and several primary forest patches can be protected under scenario P* due to the protection, thus indicating the need for policy intervention. The IPCC scenarios further helped to investigate the LU changes under 3 growth scenarios, which portrays land conversions by considering the behaviors of the existing land uses, as well as other actors. Low Growth (A2) scenario shows loss of forest cover of 4.7%; Moderate Growth (A1B) scenario shows a loss of 6.4%, and Rapid Growth (A1) scenario shows a maximum loss of 11.1%. Conservation Scenarios depict ESR scenario is most sustainable growth option for the district. So, the hybrid approach of accounting human perception, neighborhood, and other biophysical drivers improves the precision of prediction.

Table 6.14 Summary of scenarios and observed trends

<table>
<tr><th>Sno</th><th colspan="2">Scenarios</th><th>Factors influencing change</th><th>Observed trend</th></tr>
<tr><td>1</td><td colspan="2">Business As Usual Scenario (BAU)</td><td>Economic growth (Developmental projects);<br>Social change (population density)</td><td>Higher deforestation rates;<br>Increased forest fragmentation</td></tr>
<tr><td>2</td><td colspan="2">Historical Growth Scenario (HGS)</td><td></td><td>Deforestation</td></tr>
<tr><td rowspan="2">3</td><td rowspan="2">Managed growth Scenario</td><td>Reserve Forest protection (P*)</td><td>Reserve forest protection; least economic growth influence</td><td>Least ecological disturbances; higher conservation of forests; Sustainable Development</td></tr>
<tr><td>Without Reserve Forest</td><td>Adhoc developmental</td><td>Higher deforestation without</td></tr>
</table>

| | | | | |
|---|---|---|---|---|
| | | Protection (P_WRF) | plans; higher economic growth | environmental protection |
| **4** | **IPCC Climate Change Growth Rate Scenario** | Low Growth (A2) | Least economic growth; Higher Environmental protection | Low deforestation rate; Higher conservation |
| | | Moderate Growth (A1B) | Judicious economic growth; Economic policies for development | Moderate deforestation rate |
| | | Rapid Growth (A1) | Higher economic growth (Developmental projects); least environment protection; and higher population density | Higher deforestation rates; Peri-urban growth; Unsustainable development |
| 5 | **Integrating ESR & Interior Forest-Policy Scenario** | ESR-Sustainable Growth (ESR); Interior Forest preserved with Moderate Growth (IFC) | | ESR scenario focuses on conservation and well-ordered developmental activities; IFC scenario depicts chances of peri-urban growth, increase in deforestation for accommodating developmental activities |

# CHAPTER 7 | CONCLUSIONS

The land use land cover (LULC) changes caused by anthropogenic activities have been altering the functional ability of an ecosystem. In this work, we study, quantify and project the landuse changes in the district of Uttara Kannada, where such modifications of the landscape is influencing the ecology, biodiversity, hydrologic regime and people's livelihood. The high conversion rates of natural vegetation to other uses by anthropogenic activities will impact the ecosystem of this part of Western Ghats. Vegetation cover assessment of Uttara Kannada district of Central Western Ghats shows a decline of vegetation cover from 92.87% (1973) to 80.42% (2016). Land use analyses reveal the trend of deforestation, evident from the reduction of evergreen semi-evergreen forest cover from 67.73% (1973) to 29.5% (2016). The major changes are the loss of 3329 $km^2$ of forest cover, while there is a gain of 471 $km^2$ in horticulture and 472 $km^2$ in built-up area over the last four decades.

Modeling of LULC changes were analyzed to capture the likely causes and/or drivers of change through an appropriate method based on review and assessment. While Agent-based modeling has the disadvantages of describing individual behavior rather than its aggregation at the landscape in its simulations, which are extremely complex and computationally intensive, the Non-agent based modeling approaches use the neighborhood effect and assumes the LULC change as linear. But most of the forest cover changes express non-linear behavior. Realizing the drawbacks with standalone non-agent and agent-based modeling techniques, the current wok has modified non-agent based modeling as a constraint-induced CA-Markov approach for analyzing LULC changes and also incorporated Fuzzy-AHP to develop a hybrid modeling technique. The primary scenario of business as usual (BAU) based on constrained CA-Markov analysis highlighted the decline of forest cover from 60.4 (2010) to 48.90% (2022) with an increase in monoculture plantations from 14.8 to 17.97%. It also showed that the built-up area increases from 4.81 to 9.30 % and the area under horticulture will reach to 9.15 % by 2022 from 2.3% in the corresponding period. The proposed hybrid modeling has proved to be more effective, computationally robust, and proficiently simulated non-linear behavior of factors that induce forest cover changes in the Uttara Kannada district. The research work has evaluated various modeling approaches and proposed a hybrid Fuzzy-AHP-MCCA technique to understand probable LULC changes due to a wide variety of biophysical and socio-economic factors including policy dimensions that induce change.

The historical growth scenario (HGS) based on the CA_Markov model accounts for the least anthropogenic disturbances in LU, especially limited forest loss due to neighborhood effects, and is unable to capture the policy-induced changes. This scenario showed overall likely change in forest cover from 83 (1973) to 65% by 2030. Further, to account for various drivers of change in the simulation, a hybrid modeling approach was developed and implemented to assess scenarios of managed growth rate with reserved forest protection (P*) and in the absence of protection (P_WRF). This approach proved to be efficient in simulating the forest transitions as compared to others and revealed that forests would change from 54.17 to 45 % by 2022 in the absence of reserve forest protection with increasing population density. The results have captured the inherent uncertainty of the traditional standalone modeling systems and forecasted the advantages of the hybrid approach through multi-criteria decision evaluation. The loss of forest cover has been estimated as 4.63% and 7.52 % from 2013 to 2022 under the two scenarios or forest protection and its absence respectively. The results also demonstrated a good accuracy of the prediction when compared with the actual land uses. IPCC scenarios further helped to investigate the LU changes under 3 growth scenarios, thus portraying land conversions by considering the behavior of the existing land use classes, as well as other actors. Low Growth (A2) scenario shows loss of forest cover of 4.7%; Moderate Growth (A1B) scenario shows a loss of 6.4%, and Rapid Growth (A1) scenario shows a loss of 11.1%. The scenario-based prediction has helped to understand short and long term LULC dynamics, which provides a base for effective decision making and in framing policies to curb uncontrolled changes in Ecologically Fragile Regions of the district. To assess the impact of such policies, ESR scenario was modeled with the ESR-1 region as a constraint for land use growth. This scenario exhibits the fruitfulness of conservation measures in retaining around 50% of forests in the entire landscape and also provided the options for development in the ESR-3 and 4 regions without affecting the natural resources. The forest cover of 4990 km$^2$ is likely to be conserved with the ESR-1 scenario whereas 4589 km$^2$ forest cover would be protected under the interior forest cover conservation (IFC) scenario. Likely increase of built-up cover to 599 km$^2$ and 699 km$^2$ were noticed under these two scenarios. Interior forest cover constrained scenario showed the chance of higher LU conversions with the fragmentation of forests as compared with the ESRscenario. The current analysis is limited to a district administrative unit in order to support policymakers at the appropriate administrative level. The model proposed can be extended to ecosystem-level such as river basins or community level to understand and differentiate the influence of people and activities required to preserve and/or conserve the natural landscapes, thereby arresting abrupt changes.

**Research Highlights:**

- Landscape dynamics are assessed through land use analysis using temporal remote sensing data through a supervised classifier based on the Gaussian Maximum Likelihood algorithm for the period 1973 to 2016.
- Land use analyses reveal the trend of deforestation, evident from the reduction of evergreen semi-evergreen forest cover from 67.73% (1973) to 29.5% (2016).
- Loss of forest cover of 3329 sq.km over four decades in the study region is due to the implementation of developmental projects such as the construction of a series of dams, etc.
- Fragmentation of forests is assessed through two indices such as $P_f$, $P_{ff}$, which indicates the loss of major tracts of contiguous interior forests due to anthropogenic influence in the Uttara Kannada district.
- The decline in the area of interior forests from 64.42 % to 22.25% (1979-2016) is noticed with an increase in higher edges and non-forest cover.
- Proposed Hybrid Fuzzy-AHP-MCCA model for the forest landscape with a systemic multi-criteria decision evaluation.
- Drivers of change were accounted for simulation to predict land uses of 2022 under two different scenarios such as reserve forest protection (P*) and absence of protection (P_WRF) using MCE.
- Hybrid modeling with a managed growth rate scenario approach has provided an efficient model of forest transitions as compared to other models. The model reveals that forest land cover would decrease by close to 10% from 54.17 to 45 % by 2022 in the absence of reserve forest protection with escalating population density.
- ESR scenario provided policy insights for conservation of the ecologically sensitive regions through likely protection of forest cover of 4990 $km^2$ with the constrained ESR-1 scenario leading towards the sustainable development of the region.

## SCOPE FOR FURTHER WORK

While this work did demonstrate the value of spatially-explicit modeling frameworks to assess the landscape level changes, the challenges in accessing and/or generating all relevant datasets can be a daunting task. Some of these can be handled with the increased availability of Open Data, and using more temporal datasets. Incorporating the policy dimensions across a region by mapping it into suitable actions and parameterization of the same within the model needs a good understanding of the study region. The proposed model is scale-independent and can be applied at various spatial and ecological scales, but will need appropriate decision making rules to connect the data inputs with the land use decisions at the individual, community, ecosystem, and administrative level. This also poses the challenge of accounting macro-level policy influences on micro-level changes. Some potential extensions to this work can be to incorporate intra-class changes, varied or multiple rates of change across the spatial and temporal extents.

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## Related Publications

**Book: 1**

**Peer Reviewed Journals: 08**

**Conference Proceedings: 07**

**Technical Reports: 02**

### Book

**Bharath, Setturu,** Rajan, K.S., Ramachandra, T.V., 2020. Modeling landscape dynamics in Central Western Ghats, 2020. Nova Science Publishers, NY, 11788 USA (Final Review-Accepted).

### Publications in Journals (Peer reviewed Journals)

- Ramachandra, T.V. and **Bharath, Setturu**, 2018. Geoinformatics based Valuation of Forest Landscape Dynamics in Central Western Ghats, India. J Remote Sensing & GIS, 7(227), p.2. [Research contribution: 50%]
- Ramachandra, T.V., **Bharath, Setturu,** Chandran, M.D.S. and Joshi, N.V., 2018. Salient Ecological Sensitive Regions of Central Western Ghats, India. *Earth Systems and Environment*, *2*(1), pp.15-34. [Research contributions: 35:35:15:15]
- Ramachandra, T.V., **Bharath, Setturu,** Rajan, K.S. and Chandran, M.D.S., 2017. Modeling the forest transition in Central Western Ghats, India. *Spatial Information Research*, *25*(1), pp.117-130. [Research contributions: 35:35:15:15]
- Ramachandra, T.V., **Bharath, Setturu.** and Chandran, M.D.S., 2016. Geospatial analysis of forest fragmentation in Uttara Kannada District, India. Forest Ecosystems, 3(1), p.10. (Impact Factor: 1.85) https://doi.org/10.1186/s40663-016-0069-4 [Research contributions: 40:40:20]
- Ramachandra, T.V., **Bharath, Setturu,** Rajan, K.S. and Chandran, M.D.S., 2016. Stimulus of developmental projects to landscape dynamics in Uttara Kannada, Central Western Ghats. *The Egyptian Journal of Remote Sensing and Space Science*, *19*(2), pp.175-193. [Research contributions: 35:35:15:15]

- **Bharath, Setturu,** Rajan, K.S. and Ramachandra, T.V., 2014. Status and future transition of rapid urbanizing landscape in central Western Ghats-CA based approach. *ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, *2*(8), p.69. [Research contributions: 40:35:25]
- **Bharath, Setturu,** Rajan, K.S., Ramachandra, T.V., 2013. Land Surface Temperature Responses to Land Use Land Cover Dynamics. Geoinfor Geostat: An Overview 1:4. doi:10.4172/2327- 4581.1000112. 4. [Research contributions: 40:35:25]

## Publications in Conference Proceedings

- **Bharath, Setturu,** Rajan, K.S., Ramachandra, T.V., 2019. Scenario based Modeling of Landscape dynamics in the Central Western Ghats. In proceedings of National Seminar for Research Scholars, Bangalore, India, Volume 3. *(Best Paper Award)*
- **Bharath, Setturu,** Rajan, K.S., Ramachandra, T.V., 2017. FOSS4G Modeling of forest cover transitions with Kaiga nuclear plant. In proceedings of FOSS4G-ASIA 2017, Hyderabad, India, Volume 3.
- **Bharath, Setturu,** Rajan, K.S., Ramachandra, T.V., 2017. Geo-Visualisation of land cover transitions in Karwar region of Central Western Ghats. In proceedings of International Symposium on Water Urbanism and Infrastructure Development in Eco-Sensitive Zones, Kolkata, India, Volume 2.
- **Bharath, Setturu,** Rajan, K.S., Ramachandra, T.V., 2016. Geo-visualisation of landscape dynamics in Sirsi and Haliyal forest divisions of Central Western Ghats, proceedings of National Conference on Challenges of Civil Engineering Innovations (NCCCEI 2016), At Bangalore from 4-5 May, 2016; Sri Venkateshwara College of Engineering NH 7, Vidyanagar, Bengaluru International Airport Road, Bengaluru - 562157.
- **Bharath, Setturu,** Rajan, K.S. and Ramachandra, T.V., 2014. Visualisation of Forest Changes in Uttara Kannada Proceedings Lake 2014.
- **Bharath, Setturu,** Bharath H.A, Rajan, K.S. and Ramachandra, T.V., 2012. Cost effective mapping, monitoring and visualisation of spatial patterns of urbanisation using FOSS. Proceeding of: FOSS 4G, Vol 2.

- **Bharath, Setturu,** and Ramachandra, T.V., 2012. Landscape dynamics of Uttara Kannada district. In National Conference on Conservation and Management of Wetland Ecosystems, Proceedings Lake 2012, Vol 9.


**Technical Reports:**


- **Bharath, Setturu,** Rajan, K.S., Ramachandra, T.V., 2017. Integrated modeling framework for visualising transitions in forest landscape, CES Technical Report 136, CES, Indian Institute of Science, Bangalore 560012.
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# Appendix 1: Glimpses of Uttara Kannada & Field Data Collection

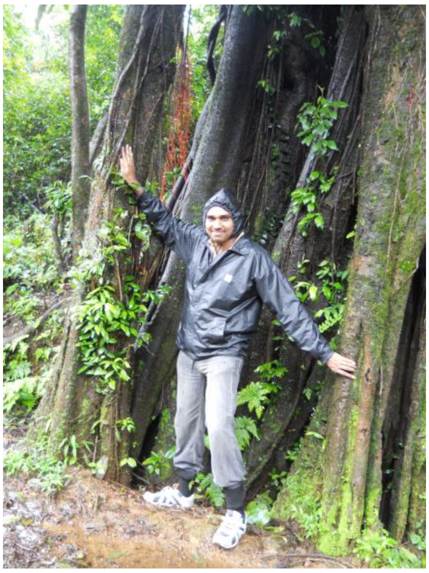
Vegetation Sampling and Field data collection

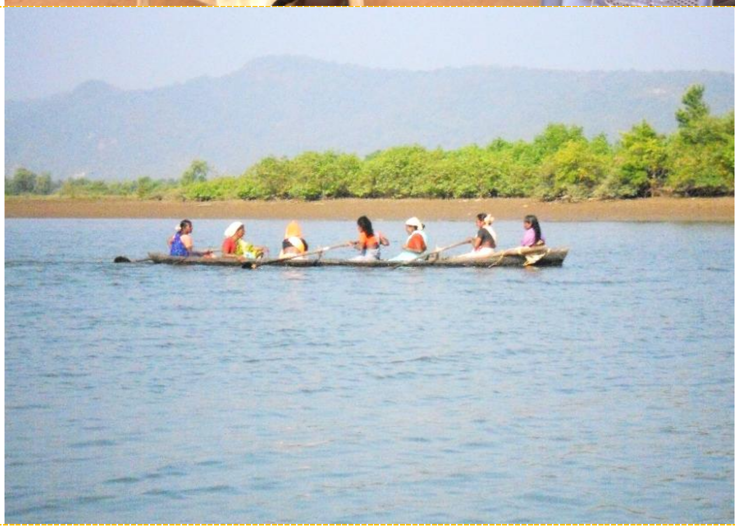

Measuring GBH


Transect sampling

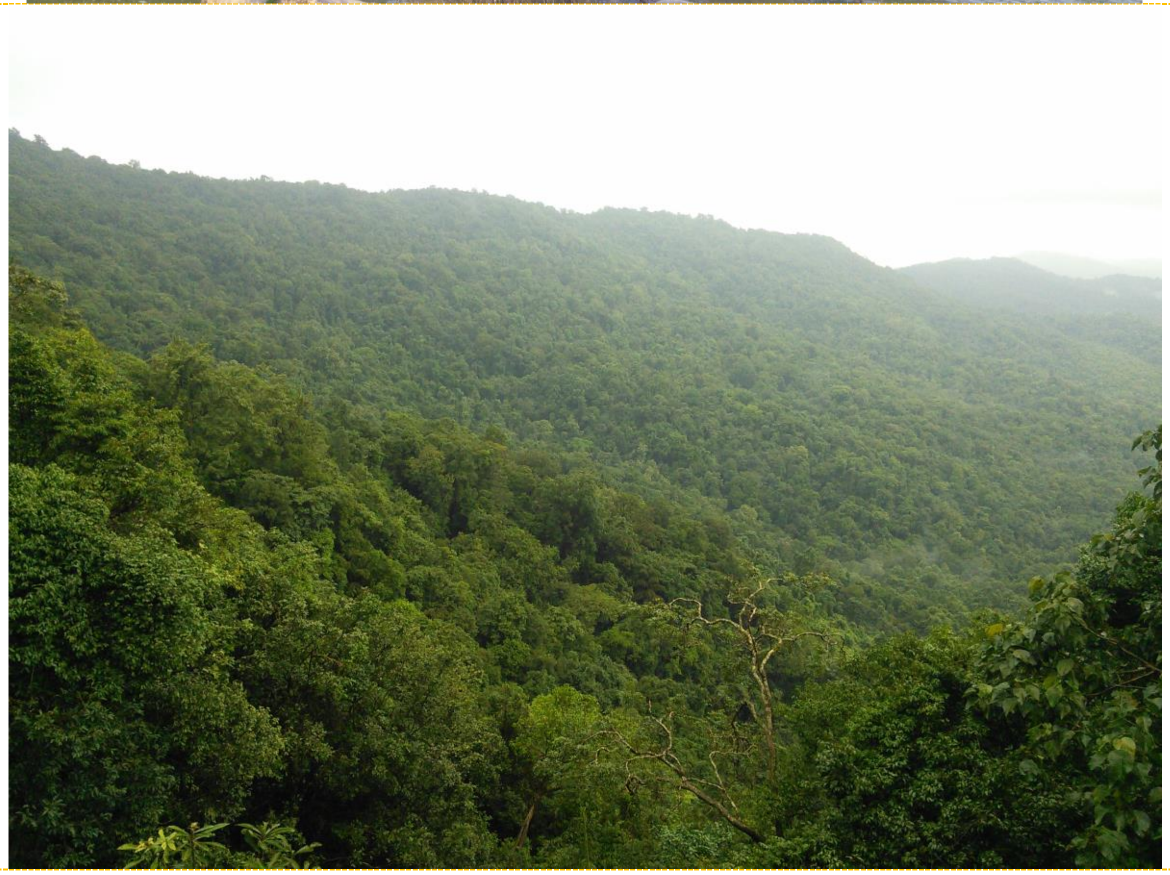

Garcinia gummi-gutta


Litter collection (manure)

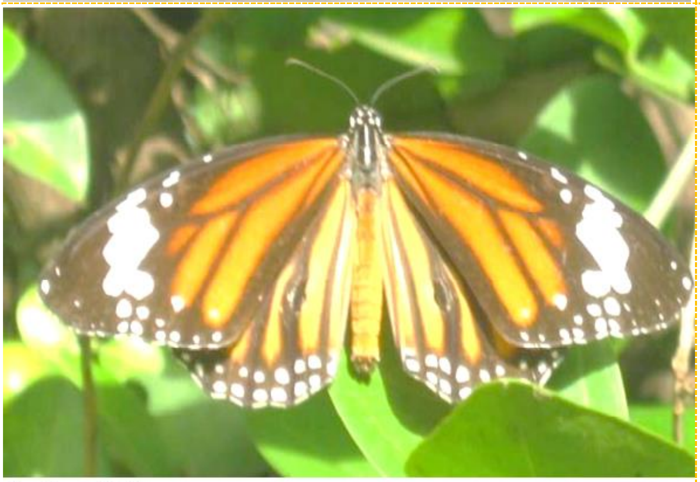




Landscape Elements & Biodiversity

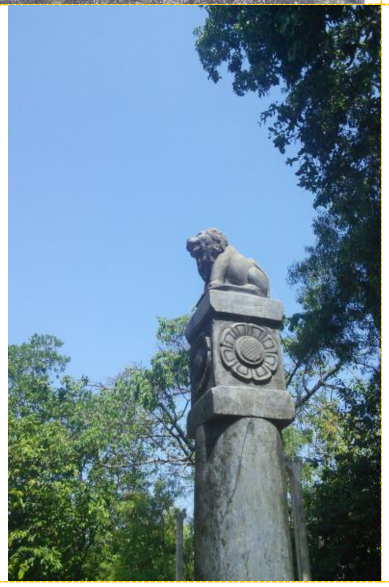


Mangroves

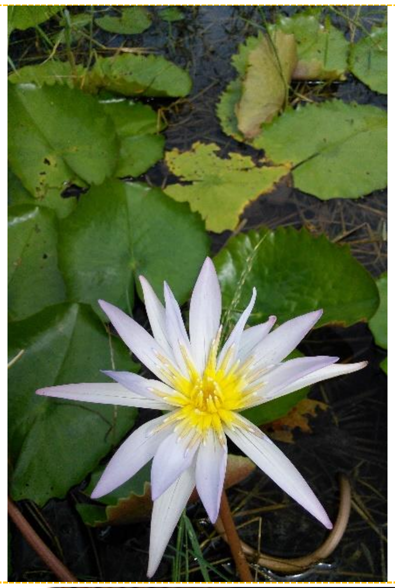


Striped Tiger

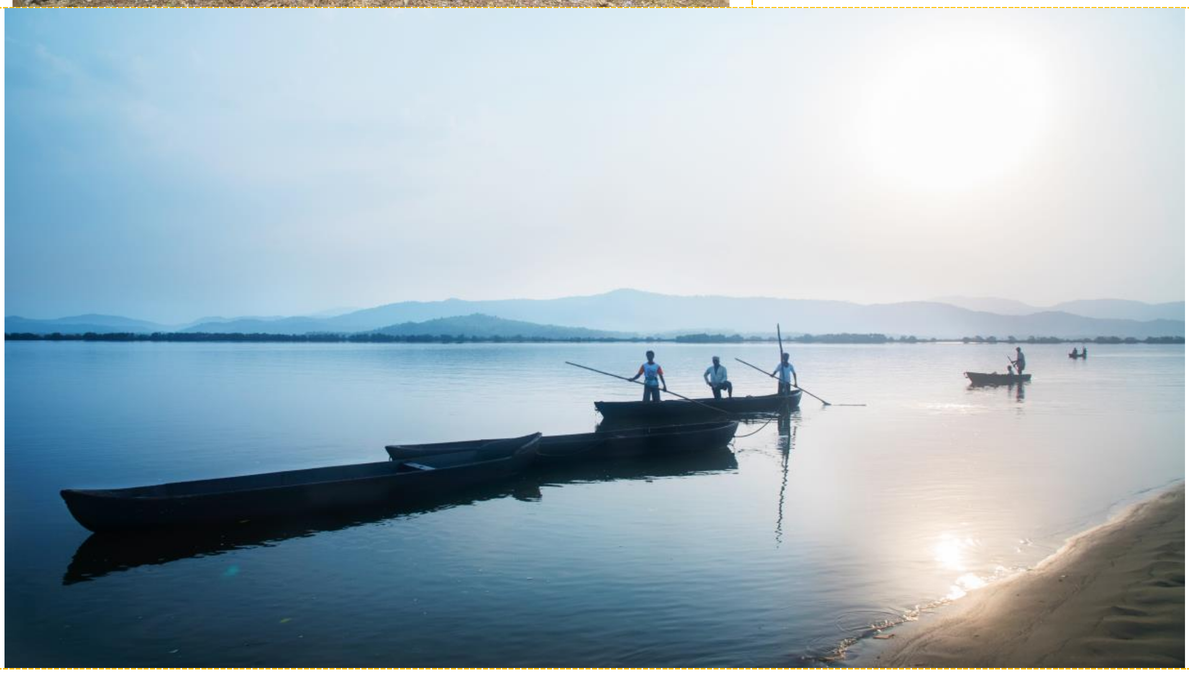
Sacred groves → Traditional way to protect Forests



Livelihood and indegeneous people



Threats→ Deforestation

# Appendix 2: Field Investigation (Primary data collection), Vegetation Sampling, and Secondary data collection

The detailed field investigation has been carried out in 116 transacts covering the 11 taluks of the district for understanding vegetation dynamics. The detailed database of species occurrence and endemism, IUCN conservation status covering greater than 8000 entries were made. Figure 2A shows grids selected for field and transacts covered for vegetation sampling. The study area was divided into 5’x5’ equal area grids (168) covering approximately 9 $km^2$ corresponds to the survey of India toposheet of 1:50,000 scale divisions. Field investigations were carried out in chosen grids with 116 transects and compiled data pertaining to the basal area, height, species, etc. Along a transect of 180 m, 5 quadrats each of 20x20 m were laid alternatively on the right and left, for tree study (minimum girth of 30 cm at GBH or 130 cm height from the ground), keeping intervals of 20 m length between successive quadrats. Within each tree quadrat, at two diagonal corners, two sub-quadrats of 5 m × 5 m were laid for shrubs and tree saplings (< 30 cm girth). Within each of these 2 herb layer quadrats, 1 sq. m area each was also laid down for herbs and tree seedlings. Climbers and other associated species were noted. Table 2A shows the basal area measurement for each quadrat generated from girth measurements. A rapid assessment was made to track vegetation changes from the densely populated coast through the rugged mountainous terrain to the undulating and drier eastern lands using point-centered quarter method along line transects Ankola (coastal) and Yellapura (hilly to undulating) taluks. Sampling efforts were higher in high endemism areas (eg. Kathalekan in Siddapur). The above ground biomass is estimated as a prime variable to analyze standing biomass and net carbon stored. The above ground standing biomass of trees is referred as the weight of the trees above ground, in a given area, if harvested at a given time. Carbon storage in forests is estimated by taking 50% of the biomass as carbon. The spatial distribution of endemic Flora has been shown in Figure 2B and Table 2B.

***Note:*** Ecological research team (**Setturu Bharath** is part of the team), carried out field investigations to (i) collect training data from all taluks during 2012 to 2017 for classifying remote sensing data, forest fragmentation analysis, modeling and validation (ii) vegetation survey (Setturu Bharah along with 4 members), (iii) hydrological investigations across select stream during 2015-2017, (iv) collected social data across the district during 2014-2016, (v) interactions with the local stakeholders

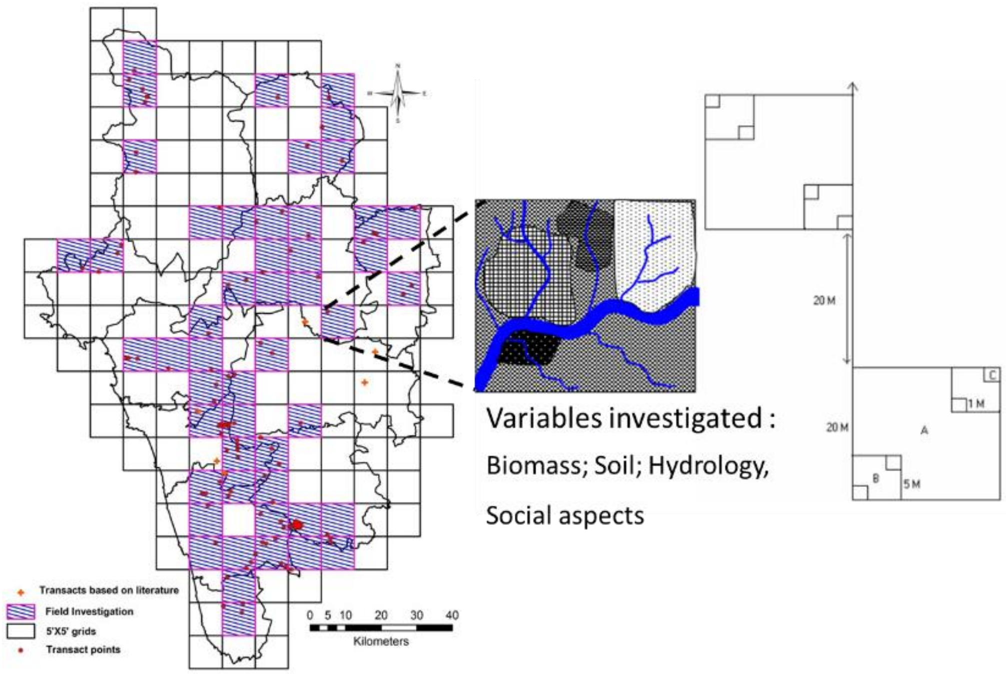



Figure 2.A. Distribution of transacts for vegetation sampling and transact cum quadrat method for sampling

Table 2.A. Transact cum Quadrat measurement across the district

| Latitude | Longitude | Transect No | Quadrat No | Locality | Taluk | Basal Area/Quadrat (m2) | Biomass (t/Quad) | Carbon (t/Quad) | Biomass (t/ha) | Carbon (t/ha) |
|---|---|---|---|---|---|---|---|---|---|---|
| 14.651 | 74.571 | **1** | 1 | **Asolli_1** | Ankola | 2.76 | 15.93 | 7.96 | 398.20 | 199.10 |
| 14.650 | 74.571 | | 2 | | | 1.38 | 6.51 | 3.26 | 162.85 | 81.43 |
| 14.650 | 74.571 | | 3 | | | 1.68 | 8.56 | 4.28 | 213.97 | 106.99 |
| 14.650 | 74.571 | | 4 | | | 0.82 | 2.77 | 1.39 | 69.28 | 34.64 |
| 14.650 | 74.571 | | 5 | | | 1.02 | 4.08 | 2.04 | 102.01 | 51.00 |
| 14.648 | 74.569 | **2** | 1 | **Asolli_2** | Ankola | 2.15 | 11.76 | 5.88 | 293.98 | 146.99 |

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| 14.648 | 74.569 | | 2 | | | 1.64 | 8.28 | 4.14 | 207.07 | 103.53 |
| 14.649 | 74.570 | | 3 | | | 1.47 | 7.13 | 3.56 | 178.18 | 89.09 |
| 14.649 | 74.560 | | 4 | | | 1.09 | 4.57 | 2.29 | 114.37 | 57.18 |
| 14.649 | 74.570 | | 5 | | | 1.41 | 6.72 | 3.36 | 167.95 | 83.98 |
| 14.585 | 74.534 | **3** | 1 | **Hosakere** | Ankola | 2.05 | 11.11 | 5.56 | 277.82 | 138.91 |
| 14.586 | 74.534 | | 2 | | | 1.03 | 4.16 | 2.08 | 104.11 | 52.06 |
| 14.586 | 74.534 | | 3 | | | 1.12 | 4.79 | 2.39 | 119.71 | 59.85 |
| 14.587 | 74.534 | | 4 | | | 1.65 | 8.39 | 4.19 | 209.68 | 104.84 |
| 14.587 | 74.534 | | 5 | | | 1.67 | 8.52 | 4.26 | 212.88 | 106.44 |
| 14.693 | 74.340 | **4** | 1 | **Hubli-Ankola Sector-1** | Ankola | 39.78 | | | 266.87 | 133.44 |
| 14.665 | 74.419 | **5** | 1 | **Hubli-Ankola Sector-2** | Ankola | 46.16 | | | 310.18 | 155.09 |
| 14.738 | 74.511 | **6** | 1 | **Hubli-Ankola Sector-3** | Ankola | 71.32 | | | 480.71 | 240.36 |
| 14.801 | 74.580 | **7** | 1 | **Hubli-Ankola Sector-4** | Ankola | 30.96 | | | 207.09 | 103.54 |
| 14.664 | 74.526 | **8** | 1 | **Kachinabatti** | Ankola | 1.27 | 5.77 | 2.89 | 144.28 | 72.14 |
| 14.664 | 74.527 | | 2 | | | 0.81 | 2.68 | 1.34 | 66.90 | 33.45 |
| 14.664 | 74.527 | | 3 | | | 0.70 | 1.91 | 0.96 | 47.81 | 23.91 |
| 14.664 | 74.528 | | 4 | | | 0.59 | 1.21 | 0.60 | 30.14 | 15.07 |
| 14.664 | 74.528 | | 5 | | | 0.32 | 2.02 | 1.01 | 50.61 | 25.31 |
| 14.627 | 74.539 | **9** | 1 | **Maabagi** | Ankola | 1.89 | 10.01 | 5.00 | 250.13 | 125.06 |
| 14.626 | 74.539 | | 2 | | | 1.71 | 8.76 | 4.38 | 219.01 | 109.50 |
| 14.626 | 74.539 | | 3 | | | 1.45 | 7.00 | 3.50 | 174.90 | 87.45 |
| 14.625 | 74.539 | | 4 | | | 1.68 | 8.56 | 4.28 | 214.12 | 107.06 |
| 14.625 | 74.538 | | 5 | | | 1.43 | 6.92 | 3.46 | 172.98 | 86.49 |
| 14.069 | 74.556 | **10** | 1 | **Dakshinakoppa** | Bhatkal | 1.93 | 10.25 | 5.13 | 256.37 | 128.18 |
| 14.069 | 74.556 | | 2 | | | 0.75 | 2.31 | 1.15 | 57.65 | 28.82 |

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| 14.069 | 74.556 | | 3 | | | 1.22 | 5.48 | 2.74 | 137.11 | 68.55 |
| 14.069 | 74.557 | | 4 | | | 1.36 | 6.39 | 3.19 | 159.72 | 79.86 |
| 14.068 | 74.557 | | 5 | | | 1.70 | 8.75 | 4.37 | 218.72 | 109.36 |
| 14.141 | 74.566 | | 1 | | | 2.08 | 11.29 | 5.65 | 282.35 | 141.18 |
| 14.141 | 74.566 | | 2 | | | 1.02 | 4.11 | 2.05 | 102.65 | 51.32 |
| 14.141 | 74.567 | **11** | 3 | **Gujmavu_Semiever** | Bhatkal | 1.45 | 7.04 | 3.52 | 176.00 | 88.00 |
| 14.141 | 74.567 | | 4 | | | 0.81 | 2.65 | 1.33 | 66.35 | 33.17 |
| 14.140 | 74.567 | | 5 | | | 1.24 | 5.57 | 2.78 | 139.21 | 69.60 |
| 14.052 | 74.603 | | 1 | | | 1.25 | 5.64 | 2.82 | 140.91 | 70.45 |
| 14.049 | 74.605 | | 2 | | | 1.20 | 5.30 | 2.65 | 132.40 | 66.20 |
| 14.049 | 74.605 | **12** | 3 | **Hudil_Evergr** | Bhatkal | 2.92 | 16.99 | 8.49 | 424.64 | 212.32 |
| 14.054 | 74.603 | | 4 | | | 1.14 | 4.94 | 2.47 | 123.59 | 61.80 |
| 14.055 | 74.603 | | 5 | | | 0.66 | 1.65 | 0.83 | 41.35 | 20.67 |
| 14.075 | 74.607 | | 1 | | | 4.36 | 26.75 | 13.37 | 668.73 | 334.37 |
| 14.075 | 74.606 | | 2 | | | 1.37 | 6.46 | 3.23 | 161.48 | 80.74 |
| 14.075 | 74.606 | **13** | 3 | **Hudil_Semiever** | Bhatkal | 1.29 | 5.92 | 2.96 | 147.90 | 73.95 |
| 14.074 | 74.607 | | 4 | | | 1.38 | 6.54 | 3.27 | 163.50 | 81.75 |
| 14.074 | 74.607 | | 5 | | | 0.83 | 2.81 | 1.40 | 70.23 | 35.12 |
| 15.351 | 74.823 | | 1 | | | 1.17 | 5.15 | 2.57 | 128.72 | 64.36 |
| 15.351 | 74.823 | | 2 | | | 0.83 | 2.82 | 1.41 | 70.58 | 35.29 |
| 15.352 | 74.823 | **14** | 3 | **Magvad** | Haliyal | 1.00 | 3.96 | 1.98 | 99.07 | 49.54 |
| 15.352 | 74.824 | | 4 | | | 0.95 | 3.64 | 1.82 | 91.11 | 45.55 |
| 15.352 | 74.824 | | 5 | | | 0.82 | 2.77 | 1.39 | 69.37 | 34.69 |
| 15.351 | 74.694 | **15** | 1 | **Yadoga** | Haliyal | 1.42 | 6.84 | 3.42 | 170.89 | 85.44 |
| 15.351 | 74.693 | | 2 | | | 0.70 | 1.95 | 0.97 | 48.71 | 24.36 |

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|---|---|---|---|---|---|---|---|---|---|---|
| 15.350 | 74.693 | | 3 | | | 0.87 | 3.07 | 1.54 | 76.80 | 38.40 |
| 15.350 | 74.693 | | 4 | | | 1.56 | 7.75 | 3.87 | 193.72 | 96.86 |
| 15.349 | 74.694 | | 5 | | | 0.71 | 2.01 | 1.01 | 50.33 | 25.16 |
| 14.352 | 74.501 | **16** | 1 | **Karikan-Lower Slope** | Honnavar | 1.01 | 4.05 | 2.03 | 101.31 | 50.65 |
| 14.352 | 74.501 | | 2 | | | 1.25 | 5.70 | 2.85 | 142.47 | 71.24 |
| 14.352 | 74.501 | | 3 | | | 1.76 | 9.10 | 4.55 | 227.57 | 113.78 |
| 14.352 | 74.501 | | 4 | | | 1.76 | 9.14 | 4.57 | 228.45 | 114.23 |
| 14.353 | 74.502 | | 5 | | | 2.59 | 14.74 | 7.37 | 368.51 | 184.25 |
| 14.261 | 74.718 | **17** | 1 | **Ambepal-1** | Honnavar | 1.83 | 9.61 | 4.81 | 240.34 | 120.17 |
| 14.261 | 74.718 | | 2 | | | 1.08 | 4.51 | 2.26 | 112.82 | 56.41 |
| 14.260 | 74.718 | | 3 | | | 0.88 | 3.15 | 1.58 | 78.83 | 39.42 |
| 14.260 | 74.717 | | 4 | | | 1.26 | 5.72 | 2.86 | 143.10 | 71.55 |
| 14.260 | 74.717 | | 5 | | | 1.25 | 5.64 | 2.82 | 141.01 | 70.50 |
| 14.260 | 74.722 | **18** | 1 | **Ambepal-2** | Honnavar | 1.85 | 9.71 | 4.86 | 242.87 | 121.43 |
| 14.261 | 74.721 | | 2 | | | 2.22 | 12.25 | 6.13 | 306.29 | 153.14 |
| 14.261 | 74.722 | | 3 | | | 2.81 | 16.27 | 8.14 | 406.82 | 203.41 |
| 14.262 | 74.721 | | 4 | | | 1.49 | 7.29 | 3.65 | 182.26 | 91.13 |
| 14.262 | 74.721 | | 5 | | | 1.39 | 6.60 | 3.30 | 164.90 | 82.45 |
| 14.226 | 74.665 | **19** | 1 | **Chaturmubasti-Moist Dec** | Honnavar | 1.32 | 6.11 | 3.06 | 152.86 | 76.43 |
| 14.226 | 74.666 | | 2 | | | 0.99 | 3.91 | 1.96 | 97.87 | 48.93 |
| 14.226 | 74.666 | | 3 | | | 1.07 | 4.44 | 2.22 | 110.89 | 55.44 |
| 14.225 | 74.666 | | 4 | | | 1.29 | 5.92 | 2.96 | 147.97 | 73.99 |
| 14.225 | 74.665 | | 5 | | | 0.89 | 3.20 | 1.60 | 80.10 | 40.05 |
| 14.276 | 74.701 | **20** | 1 | **Gerusoppa** | Honnavar | 0.93 | 3.47 | 1.73 | 86.67 | 43.33 |
| 14.274 | 74.701 | | 2 | | | 1.39 | 6.60 | 3.30 | 164.95 | 82.47 |

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|---|---|---|---|---|---|---|---|---|---|---|
| 14.245 | 74.701 | | 3 | | | 1.12 | 4.77 | 2.38 | 119.24 | 59.62 |
| 14.322 | 74.572 | | 4 | | | 0.79 | 2.56 | 1.28 | 64.12 | 32.06 |
| 14.322 | 74.572 | | 5 | | | 1.80 | 9.41 | 4.71 | 235.31 | 117.65 |
| 14.323 | 74.518 | **21** | 1 | **Gundabala** | Honnavar | 1.40 | 6.68 | 3.34 | 167.12 | 83.56 |
| 14.323 | 74.518 | | 2 | | | 1.15 | 4.99 | 2.50 | 124.84 | 62.42 |
| 14.322 | 74.572 | | 3 | | | 1.70 | 8.69 | 4.34 | 217.13 | 108.56 |
| 14.322 | 74.572 | | 4 | | | 0.67 | 1.76 | 0.88 | 43.91 | 21.96 |
| 14.322 | 74.572 | | 5 | | | 0.89 | 3.22 | 1.61 | 80.61 | 40.31 |
| 14.169 | 74.715 | **22** | 1 | **Hadgeri-1** | Honnavar | 3.64 | 21.86 | 10.93 | 546.56 | 273.28 |
| 14.169 | 74.715 | | 2 | | | 2.68 | 15.36 | 7.68 | 384.02 | 192.01 |
| 14.169 | 74.715 | | 3 | | | 2.04 | 11.02 | 5.51 | 275.62 | 137.81 |
| 14.169 | 74.716 | | 4 | | | 1.04 | 4.27 | 2.14 | 106.84 | 53.42 |
| 14.168 | 74.716 | | 5 | | | 1.33 | 6.23 | 3.12 | 155.76 | 77.88 |
| 14.161 | 74.728 | **23** | 1 | **Hadgeri-2** | Honnavar | 2.29 | 12.73 | 6.36 | 318.17 | 159.08 |
| 14.162 | 74.729 | | 2 | | | 1.63 | 8.27 | 4.14 | 206.81 | 103.41 |
| 14.162 | 74.728 | | 3 | | | 2.20 | 12.13 | 6.07 | 303.26 | 151.63 |
| 14.162 | 74.728 | | 4 | | | 1.52 | 7.49 | 3.75 | 187.33 | 93.66 |
| 14.163 | 74.728 | | 5 | | | 1.46 | 7.06 | 3.53 | 176.50 | 88.25 |
| 14.309 | 74.652 | **24** | 1 | **Halsolli** | Honnavar | 2.37 | 13.24 | 6.62 | 330.89 | 165.45 |
| 14.309 | 74.652 | | 2 | | | 2.29 | 12.69 | 6.34 | 317.13 | 158.56 |
| 14.309 | 74.652 | | 3 | | | 0.58 | 1.11 | 0.56 | 27.79 | 13.89 |
| 14.310 | 74.652 | | 4 | | | 2.43 | 13.66 | 6.83 | 341.42 | 170.71 |
| 14.310 | 74.653 | | 5 | | | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| 14.167 | 74.709 | **25** | 1 | **Hessige-1** | Honnavar | 0.71 | 2.03 | 1.02 | 50.77 | 25.39 |
| 14.167 | 74.709 | | 2 | | | 2.43 | 13.67 | 6.84 | 341.81 | 170.91 |

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|---|---|---|---|---|---|---|---|---|---|---|
| 14.168 | 74.709 | | 3 | | | 1.22 | 5.48 | 2.74 | 137.02 | 68.51 |
| 14.168 | 74.709 | | 4 | | | 2.42 | 13.59 | 6.80 | 339.81 | 169.91 |
| 14.168 | 74.709 | | 5 | | | 2.63 | 15.05 | 7.53 | 376.29 | 188.14 |
| 14.200 | 74.638 | | 1 | | | 2.82 | 16.28 | 8.14 | 406.97 | 203.48 |
| 14.199 | 74.633 | | 2 | | | 1.59 | 7.99 | 3.99 | 199.63 | 99.81 |
| 14.199 | 74.638 | **26** | 3 | **Hessige-2** | Honnavar | 1.89 | 9.98 | 4.99 | 249.44 | 124.72 |
| 14.200 | 74.638 | | 4 | | | 2.47 | 13.93 | 6.97 | 348.37 | 174.19 |
| 14.199 | 74.637 | | 5 | | | 1.01 | 4.04 | 2.02 | 101.02 | 50.51 |
| 14.179 | 74.627 | | 1 | | | 1.41 | 6.73 | 3.36 | 168.13 | 84.06 |
| 14.180 | 74.628 | | 2 | | | 1.22 | 5.46 | 2.73 | 136.54 | 68.27 |
| 14.180 | 74.628 | **27** | 3 | **Hessige-3** | Honnavar | 1.56 | 7.77 | 3.88 | 194.16 | 97.08 |
| 14.180 | 74.628 | | 4 | | | 0.97 | 3.78 | 1.89 | 94.49 | 47.25 |
| 14.181 | 74.628 | | 5 | | | 1.13 | 4.87 | 2.44 | 121.84 | 60.92 |
| 14.156 | 74.627 | | 1 | | | 2.09 | 11.35 | 5.68 | 283.78 | 141.89 |
| 14.156 | 74.627 | | 2 | | | 1.97 | 10.58 | 5.29 | 264.38 | 132.19 |
| 14.156 | 74.627 | **28** | 3 | **Hessige-4** | Honnavar | 3.06 | 17.95 | 8.97 | 448.68 | 224.34 |
| 14.156 | 74.628 | | 4 | | | 1.36 | 6.41 | 3.20 | 160.19 | 80.09 |
| 14.156 | 74.628 | | 5 | | | 1.83 | 9.58 | 4.79 | 239.62 | 119.81 |
| 14.353 | 74.513 | | 1 | | | 1.22 | 5.49 | 2.75 | 137.33 | 68.67 |
| 14.353 | 74.513 | | 2 | | | 1.34 | 6.29 | 3.15 | 157.32 | 78.66 |
| 14.353 | 74.512 | **29** | 3 | **Karikan-Semievergreen** | Honnavar | 1.23 | 5.52 | 2.76 | 137.96 | 68.98 |
| 14.353 | 74.512 | | 4 | | | 1.35 | 6.37 | 3.18 | 159.17 | 79.58 |
| 14.353 | 74.511 | | 5 | | | 1.65 | 8.35 | 4.18 | 208.87 | 104.44 |
| 14.352 | 74.501 | **30** | 1 | **Karikan Temple Side-Diptero Patch** | Honnavar | 3.47 | 20.74 | 10.37 | 518.62 | 259.31 |
| 14.352 | 74.501 | | 2 | | | 1.94 | 10.33 | 5.17 | 258.27 | 129.14 |

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|---|---|---|---|---|---|---|---|---|---|---|
| 14.352 | 74.501 | | 3 | | | 3.74 | 22.55 | 11.28 | 563.87 | 281.94 |
| 14.352 | 74.501 | | 4 | | | 3.91 | 23.71 | 11.85 | 592.70 | 296.35 |
| 14.353 | 74.502 | | 5 | | | 4.02 | 24.43 | 12.22 | 610.77 | 305.38 |
| 14.178 | 74.392 | **31** | 1 | **Mahime** | Honnavar | 1.68 | 8.60 | 4.30 | 214.88 | 107.44 |
| 14.294 | 74.654 | | 2 | | | 2.52 | 14.25 | 7.13 | 356.30 | 178.15 |
| 14.295 | 74.655 | | 3 | | | 2.73 | 15.69 | 7.85 | 392.36 | 196.18 |
| 14.295 | 74.655 | | 4 | | | 0.68 | 1.81 | 0.90 | 45.21 | 22.61 |
| 14.295 | 74.655 | | 5 | | | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| 14.272 | 74.707 | **32** | 1 | **Sharavathy View Point** | Honnavar | 1.00 | 3.99 | 2.00 | 99.86 | 49.93 |
| 14.271 | 74.707 | | 2 | | | 1.05 | 4.30 | 2.15 | 107.48 | 53.74 |
| 14.271 | 74.707 | | 3 | | | 2.69 | 15.44 | 7.72 | 385.99 | 192.99 |
| 14.271 | 74.707 | | 4 | | | 1.54 | 7.60 | 3.80 | 190.00 | 95.00 |
| 14.270 | 74.708 | | 5 | | | 0.66 | 1.67 | 0.84 | 41.84 | 20.92 |
| 14.358 | 74.575 | **33** | 1 | **Tulsani** | Honnavar | 1.48 | 7.24 | 3.62 | 180.97 | 90.48 |
| 14.359 | 74.575 | | 2 | | | 2.08 | 11.29 | 5.65 | 282.34 | 141.17 |
| 14.359 | 74.575 | | 3 | | | 1.07 | 4.46 | 2.23 | 111.59 | 55.79 |
| 14.360 | 74.575 | | 4 | | | 1.43 | 6.88 | 3.44 | 172.07 | 86.04 |
| 14.360 | 74.575 | | 5 | | | 1.22 | 5.49 | 2.74 | 137.15 | 68.57 |
| 14.347 | 74.570 | **34** | 1 | **Tulsani-2** | Honnavar | 1.59 | 7.96 | 3.98 | 199.00 | 99.50 |
| 14.346 | 74.570 | | 2 | | | 1.99 | 10.68 | 5.34 | 266.92 | 133.46 |
| 14.346 | 74.570 | | 3 | | | 0.82 | 2.76 | 1.38 | 68.99 | 34.49 |
| 14.345 | 74.570 | | 4 | | | 0.86 | 2.99 | 1.50 | 74.83 | 37.41 |
| 14.345 | 74.570 | | 5 | | | 0.92 | 3.41 | 1.71 | 85.29 | 42.64 |
| 15.352 | 74.364 | **35** | 1 | **Castle Rock Moist** | Joida | 0.35 | 2.25 | 1.13 | 56.37 | 28.18 |
| 15.352 | 74.365 | | 2 | | | 0.39 | 2.54 | 1.27 | 63.51 | 31.76 |

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| 15.353 | 74.365 | | 3 | | | 0.51 | 0.64 | 0.32 | 15.93 | 7.96 |
| 15.353 | 74.365 | | 4 | | | 0.40 | 2.61 | 1.30 | 65.24 | 32.62 |
| 15.353 | 74.365 | | 5 | | | 0.78 | 2.49 | 1.24 | 62.25 | 31.12 |
| 15.396 | 74.319 | **36** | 1 | **Castlerock IB** | Joida | 1.83 | 9.57 | 4.78 | 239.13 | 119.57 |
| 15.396 | 74.319 | | 2 | | | 1.01 | 4.05 | 2.02 | 101.19 | 50.60 |
| 15.396 | 74.319 | | 3 | | | 2.31 | 12.84 | 6.42 | 320.88 | 160.44 |
| 15.396 | 74.319 | | 4 | | | 2.87 | 16.63 | 8.32 | 415.84 | 207.92 |
| 15.396 | 74.320 | | 5 | | | 3.12 | 18.36 | 9.18 | 459.12 | 229.56 |
| 15.418 | 74.332 | **37** | 1 | **Castlerock-Semieverg** | Joida | 1.43 | 6.87 | 3.44 | 171.82 | 85.91 |
| 15.418 | 74.331 | | 2 | | | 0.63 | 1.49 | 0.75 | 37.31 | 18.65 |
| 15.418 | 74.331 | | 3 | | | 1.22 | 5.45 | 2.72 | 136.16 | 68.08 |
| 15.418 | 74.332 | | 4 | | | 0.69 | 1.86 | 0.93 | 46.44 | 23.22 |
| 15.417 | 74.332 | | 5 | | | 1.29 | 5.90 | 2.95 | 147.61 | 73.80 |
| 15.212 | 74.337 | **38** | 1 | **Gavni-Kangihole** | Joida | 3.16 | 18.62 | 9.31 | 465.50 | 232.75 |
| 15.212 | 74.337 | | 2 | | | 1.53 | 7.60 | 3.80 | 189.88 | 94.94 |
| 15.212 | 74.337 | | 3 | | | 1.22 | 5.45 | 2.72 | 136.25 | 68.12 |
| 15.213 | 74.338 | | 4 | | | 1.99 | 10.68 | 5.34 | 267.04 | 133.52 |
| 15.213 | 74.338 | | 5 | | | 1.84 | 9.64 | 4.82 | 241.00 | 120.50 |
| 15.339 | 74.359 | **39** | 1 | **Ivolli-Castle Rock** | Joida | 1.47 | 7.13 | 3.56 | 178.21 | 89.10 |
| 15.339 | 74.359 | | 2 | | | 1.13 | 4.82 | 2.41 | 120.54 | 60.27 |
| 15.418 | 74.327 | | 3 | | | 1.54 | 7.66 | 3.83 | 191.45 | 95.73 |
| 15.418 | 74.328 | | 4 | | | 1.07 | 4.47 | 2.24 | 111.79 | 55.90 |
| 15.418 | 74.328 | | 5 | | | 1.59 | 7.96 | 3.98 | 198.91 | 99.46 |
| 15.329 | 74.236 | **40** | 1 | **Joida Deciduous** | Joida | 2.09 | 11.38 | 5.69 | 284.46 | 142.23 |
| 15.329 | 74.236 | | 2 | | | 1.08 | 4.54 | 2.27 | 113.46 | 56.73 |

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| 15.329 | 74.236 | | 3 | | | 1.93 | 10.26 | 5.13 | 256.43 | 128.22 |
| 15.329 | 74.236 | | 4 | | | 1.84 | 9.67 | 4.83 | 241.65 | 120.83 |
| 15.329 | 74.236 | | 5 | | | 0.94 | 3.60 | 1.80 | 89.88 | 44.94 |
| 15.163 | 74.336 | **41** | 1 | **Kushavali** | Joida | 3.59 | 21.50 | 10.75 | 537.42 | 268.71 |
| 15.163 | 74.336 | | 2 | | | 4.03 | 24.55 | 12.27 | 613.67 | 306.83 |
| 15.164 | 74.336 | | 3 | | | 2.61 | 14.90 | 7.45 | 372.44 | 186.22 |
| 15.164 | 74.336 | | 4 | | | 2.33 | 12.98 | 6.49 | 324.52 | 162.26 |
| 15.164 | 74.337 | | 5 | | | 2.45 | 13.78 | 6.89 | 344.42 | 172.21 |
| 13.707 | 74.307 | **42** | 1 | **Gopishetta** | Karwar | 1.10 | 4.64 | 2.32 | 116.07 | 58.03 |
| 13.707 | 74.307 | | 2 | | | 1.45 | 7.00 | 3.50 | 174.96 | 87.48 |
| 14.920 | 74.201 | | 3 | | | 0.97 | 3.77 | 1.88 | 94.23 | 47.11 |
| 14.920 | 74.201 | | 4 | | | 1.16 | 5.03 | 2.52 | 125.76 | 62.88 |
| 14.920 | 74.201 | | 5 | | | 1.77 | 9.19 | 4.59 | 229.68 | 114.84 |
| 14.958 | 74.290 | **43** | 1 | **Goyar-Moistdec** | Karwar | 0.91 | 3.38 | 1.69 | 84.49 | 42.24 |
| 14.958 | 74.290 | | 2 | | | 2.50 | 14.16 | 7.08 | 354.10 | 177.05 |
| 14.959 | 74.290 | | 3 | | | 1.63 | 8.24 | 4.12 | 206.11 | 103.06 |
| 14.959 | 74.290 | | 4 | | | 1.40 | 6.66 | 3.33 | 166.45 | 83.23 |
| 14.959 | 74.290 | | 5 | | | 1.15 | 5.02 | 2.51 | 125.47 | 62.74 |
| 14.981 | 74.299 | **44** | 1 | **Kalni-Goyar** | Karwar | 2.56 | 14.54 | 7.27 | 363.61 | 181.81 |
| 14.981 | 74.300 | | 2 | | | 1.90 | 10.07 | 5.03 | 251.68 | 125.84 |
| 14.982 | 74.300 | | 3 | | | 1.94 | 10.35 | 5.17 | 258.69 | 129.34 |
| 14.982 | 74.300 | | 4 | | | 1.28 | 5.87 | 2.94 | 146.85 | 73.43 |
| 14.982 | 74.300 | | 5 | | | 1.33 | 6.21 | 3.11 | 155.26 | 77.63 |
| 14.920 | 74.201 | **45** | 1 | **Moist Deciduous** | Karwar | 0.60 | 1.26 | 0.63 | 31.38 | 15.69 |
| 14.843 | 74.260 | | 2 | | | 0.38 | 2.49 | 1.25 | 62.26 | 31.13 |

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| 14.843 | 74.261 | | 3 | | | 0.35 | 2.25 | 1.12 | 56.17 | 28.09 |
| 14.843 | 74.261 | | 4 | | | 1.00 | 3.97 | 1.98 | 99.13 | 49.56 |
| 14.843 | 74.261 | | 5 | | | 0.37 | 2.37 | 1.18 | 59.23 | 29.62 |
| 14.523 | 74.545 | **46** | 1 | **Devimane Campsite** | Kumta | 2.49 | 14.04 | 7.02 | 351.00 | 175.50 |
| 14.523 | 74.547 | | 2 | | | 2.09 | 11.34 | 5.67 | 283.45 | 141.73 |
| 14.523 | 74.547 | | 3 | | | 0.99 | 3.94 | 1.97 | 98.39 | 49.20 |
| 14.524 | 74.547 | | 4 | | | 1.31 | 6.07 | 3.03 | 151.72 | 75.86 |
| 14.524 | 74.548 | | 5 | | | 1.72 | 8.86 | 4.43 | 221.40 | 110.70 |
| 14.522 | 74.571 | **47** | 1 | **Devimane Sirsi Side** | Kumta | 2.33 | 12.95 | 6.48 | 323.85 | 161.93 |
| 14.523 | 74.571 | | 2 | | | 1.66 | 8.43 | 4.22 | 210.87 | 105.44 |
| 14.524 | 74.571 | | 3 | | | 1.20 | 5.31 | 2.65 | 132.64 | 66.32 |
| 14.524 | 74.571 | | 4 | | | 0.89 | 3.19 | 1.60 | 79.79 | 39.90 |
| 14.524 | 74.571 | | 5 | | | 1.99 | 10.69 | 5.34 | 267.20 | 133.60 |
| 14.527 | 74.563 | **48** | 1 | **Devimane Temple** | Kumta | 1.96 | 10.47 | 5.24 | 261.82 | 130.91 |
| 14.526 | 74.564 | | 2 | | | 1.48 | 7.23 | 3.61 | 180.73 | 90.37 |
| 14.527 | 74.565 | | 3 | | | 1.40 | 6.68 | 3.34 | 166.95 | 83.48 |
| 14.527 | 74.565 | | 4 | | | 1.41 | 6.75 | 3.37 | 168.67 | 84.33 |
| 14.527 | 74.565 | | 5 | | | 1.66 | 8.44 | 4.22 | 211.11 | 105.55 |
| 14.523 | 74.554 | **49** | 1 | **Devimane With Myr** | Kumta | 1.54 | 7.60 | 3.80 | 190.06 | 95.03 |
| 14.523 | 74.554 | | 2 | | | 1.41 | 6.76 | 3.38 | 169.05 | 84.52 |
| 14.524 | 74.554 | | 3 | | | 2.06 | 11.16 | 5.58 | 279.06 | 139.53 |
| 14.524 | 74.554 | | 4 | | | 2.80 | 16.15 | 8.08 | 403.87 | 201.93 |
| 14.524 | 74.555 | | 5 | | | 1.37 | 6.46 | 3.23 | 161.54 | 80.77 |
| 14.397 | 74.662 | **50** | 1 | **Hulidevra Kodlu** | Kumta | 1.80 | 9.40 | 4.70 | 235.03 | 117.52 |
| 14.397 | 74.662 | | 2 | | | 2.45 | 13.81 | 6.91 | 345.25 | 172.63 |

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| 14.397 | 74.662 | | 3 | | | 1.44 | 6.98 | 3.49 | 174.55 | 87.27 |
| 14.397 | 74.662 | | 4 | | | 1.98 | 10.63 | 5.32 | 265.85 | 132.92 |
| 14.398 | 74.663 | | 5 | | | 1.03 | 4.15 | 2.08 | 103.86 | 51.93 |
| 14.383 | 74.548 | **51** | 1 | **Kadnir** | Kumta | 1.27 | 5.82 | 2.91 | 145.56 | 72.78 |
| 14.383 | 74.547 | | 2 | | | 1.46 | 7.06 | 3.53 | 176.55 | 88.28 |
| 14.382 | 74.548 | | 3 | | | 1.30 | 6.00 | 3.00 | 149.94 | 74.97 |
| 14.381 | 74.574 | | 4 | | | 2.18 | 11.99 | 5.99 | 299.64 | 149.82 |
| 14.382 | 74.547 | | 5 | | | 1.42 | 6.84 | 3.42 | 170.89 | 85.45 |
| 14.463 | 74.592 | **52** | 1 | **Kalve** | Kumta | 1.18 | 5.20 | 2.60 | 129.91 | 64.95 |
| 14.464 | 74.592 | | 2 | | | 0.72 | 2.09 | 1.04 | 52.15 | 26.08 |
| 14.464 | 74.593 | | 3 | | | 1.02 | 4.12 | 2.06 | 102.99 | 51.49 |
| 14.464 | 74.593 | | 4 | | | 1.06 | 4.37 | 2.19 | 109.28 | 54.64 |
| 14.465 | 74.593 | | 5 | | | 1.45 | 7.05 | 3.53 | 176.32 | 88.16 |
| 14.464 | 74.594 | **53** | 1 | **Kalve_Moist Dec** | Kumta | 2.00 | 10.77 | 5.39 | 269.36 | 134.68 |
| 14.444 | 74.594 | **54** | 2 | **Kandalli-Devimane** | Kumta | 0.96 | 3.71 | 1.85 | 92.70 | 46.35 |
| 14.444 | 74.593 | | 3 | | | 1.37 | 6.46 | 3.23 | 161.43 | 80.72 |
| 14.443 | 74.593 | | 4 | | | 0.80 | 2.61 | 1.30 | 65.14 | 32.57 |
| 14.444 | 74.593 | | 5 | | | 0.62 | 1.40 | 0.70 | 35.04 | 17.52 |
| 14.528 | 74.552 | | 1 | | | 1.77 | 9.17 | 4.58 | 229.21 | 114.60 |
| 14.529 | 74.552 | **55** | 2 | **Mastihalla Devimane Arch** | Kumta | 1.55 | 7.68 | 3.84 | 192.07 | 96.03 |
| 14.529 | 74.552 | | 3 | | | 1.52 | 7.50 | 3.75 | 187.54 | 93.77 |
| 14.529 | 74.552 | | 4 | | | 1.32 | 6.14 | 3.07 | 153.51 | 76.76 |
| 14.529 | 74.553 | | 5 | | | 2.15 | 11.79 | 5.89 | 294.65 | 147.33 |
| 14.526 | 74.561 | | 1 | | | 2.46 | 13.87 | 6.94 | 346.83 | 173.41 |
| 14.526 | 74.561 | **56** | 2 | **Mastihalla Devimane** | Kumta | 1.11 | 4.72 | 2.36 | 117.99 | 58.99 |

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|---|---|---|---|---|---|---|---|---|---|---|
| 14.527 | 74.560 | | 3 | | | 2.06 | 11.17 | 5.58 | 279.21 | 139.61 |
| 14.527 | 74.560 | | 4 | | | 2.20 | 12.07 | 6.04 | 301.86 | 150.93 |
| 14.527 | 74.560 | | 5 | | | 1.78 | 9.26 | 4.63 | 231.49 | 115.75 |
| 14.530 | 74.555 | | 1 | | | 2.05 | 11.06 | 5.53 | 276.42 | 138.21 |
| 14.530 | 74.555 | | 2 | | | 1.47 | 7.18 | 3.59 | 179.51 | 89.76 |
| 14.531 | 74.555 | **57** | 3 | **Mathali-Kandalli-Devimane** | Kumta | 0.95 | 3.66 | 1.83 | 91.58 | 45.79 |
| 14.531 | 74.556 | | 4 | | | 2.06 | 11.13 | 5.57 | 278.31 | 139.16 |
| 14.531 | 74.556 | | 5 | | | 1.79 | 9.35 | 4.67 | 233.64 | 116.82 |
| 14.426 | 74.631 | | 1 | | | 0.45 | 0.22 | 0.11 | 5.57 | 2.78 |
| 14.426 | 74.631 | | 2 | | | 0.90 | 3.32 | 1.66 | 83.03 | 41.52 |
| 14.426 | 74.630 | **58** | 3 | **Sopp_Hosalli** | Kumta | 1.24 | 5.58 | 2.79 | 139.53 | 69.77 |
| 14.426 | 74.630 | | 4 | | | 1.70 | 8.73 | 4.36 | 218.21 | 109.11 |
| 14.427 | 74.630 | | 5 | | | 0.79 | 2.58 | 1.29 | 64.43 | 32.21 |
| 14.464 | 74.683 | | 1 | | | 1.78 | 9.25 | 4.63 | 231.31 | 115.66 |
| 14.464 | 74.683 | | 2 | | | 1.92 | 10.24 | 5.12 | 255.89 | 127.94 |
| 14.463 | 74.683 | **59** | 3 | **Sur_Jaddi** | Kumta | 0.93 | 3.49 | 1.75 | 87.34 | 43.67 |
| 14.465 | 74.683 | | 4 | | | 1.57 | 7.81 | 3.91 | 195.33 | 97.66 |
| 14.465 | 74.683 | | 5 | | | 0.95 | 3.63 | 1.82 | 90.85 | 45.43 |
| 14.466 | 74.679 | | 1 | | | 0.98 | 3.87 | 1.93 | 96.70 | 48.35 |
| 14.466 | 74.679 | | 2 | | | 0.76 | 2.33 | 1.16 | 58.17 | 29.09 |
| 14.466 | 74.680 | **60** | 3 | **Sur_Jaddi_Morse** | Kumta | 1.47 | 7.18 | 3.59 | 179.55 | 89.77 |
| 14.465 | 74.680 | | 4 | | | 1.19 | 5.27 | 2.64 | 131.84 | 65.92 |
| 14.465 | 74.880 | | 5 | | | 1.47 | 7.17 | 3.58 | 179.20 | 89.60 |
| 15.072 | 75.041 | **61** | 1 | **Attiveri-Teak Mixed** | Mundgod | 0.69 | 1.90 | 0.95 | 47.43 | 23.71 |
| 15.072 | 75.041 | | 2 | | | 0.29 | 1.88 | 0.94 | 46.96 | 23.48 |

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|---|---|---|---|---|---|---|---|---|---|---|
| 15.071 | 75.041 | | 3 | | | 0.48 | 0.42 | 0.21 | 10.45 | 5.23 |
| 15.071 | 75.042 | | 4 | | | 0.62 | 1.37 | 0.68 | 34.24 | 17.12 |
| 15.071 | 75.042 | | 5 | | | 0.29 | 1.85 | 0.93 | 46.29 | 23.14 |
| 14.964 | 74.876 | **62** | 1 | **Godnal** | Mundgod | 0.95 | 3.61 | 1.81 | 90.28 | 45.14 |
| 14.964 | 74.876 | | 2 | | | 1.96 | 10.45 | 5.22 | 261.24 | 130.62 |
| 14.962 | 74.876 | | 3 | | | 0.79 | 2.56 | 1.28 | 63.93 | 31.97 |
| 14.965 | 74.876 | | 4 | | | 2.20 | 12.13 | 6.06 | 303.18 | 151.59 |
| 14.965 | 74.876 | | 5 | | | 2.72 | 15.64 | 7.82 | 390.95 | 195.48 |
| 14.988 | 74.935 | **63** | 1 | **Gunjavathi** | Mundgod | 0.56 | 0.98 | 0.49 | 24.60 | 12.30 |
| 14.988 | 74.935 | | 2 | | | 0.79 | 2.53 | 1.27 | 63.37 | 31.69 |
| 14.987 | 74.934 | | 3 | | | 1.44 | 6.98 | 3.49 | 174.38 | 87.19 |
| 14.987 | 74.934 | | 4 | | | 0.50 | 0.56 | 0.28 | 13.91 | 6.95 |
| 14.987 | 74.934 | | 5 | | | 0.80 | 2.62 | 1.31 | 65.44 | 32.72 |
| 14.994 | 74.922 | **64** | 1 | **Karekopa-Gunjavathi** | Mundgod | 1.52 | 7.52 | 3.76 | 187.90 | 93.95 |
| 14.994 | 74.922 | | 2 | | | 1.57 | 7.81 | 3.90 | 195.24 | 97.62 |
| 14.994 | 74.922 | | 3 | | | 1.38 | 6.55 | 3.27 | 163.74 | 81.87 |
| 14.995 | 74.923 | | 4 | | | 1.36 | 6.40 | 3.20 | 160.05 | 80.02 |
| 14.995 | 74.923 | | 5 | | | 1.52 | 7.47 | 3.73 | 186.64 | 93.32 |
| 14.271 | 74.752 | **65** | 1 | **Kathalekan-Swamp-Gr8** | Siddapur | 1.61 | 8.10 | 4.05 | 202.54 | 101.27 |
| 14.271 | 74.752 | | 2 | | | 2.03 | 10.97 | 5.49 | 274.37 | 137.18 |
| 14.271 | 74.752 | | 3 | | | 1.82 | 9.53 | 4.76 | 238.21 | 119.10 |
| 14.271 | 74.752 | | 4 | | | 3.57 | 21.36 | 10.68 | 534.11 | 267.05 |
| 14.271 | 74.753 | | 5 | | | 1.98 | 10.62 | 5.31 | 265.61 | 132.81 |
| 14.267 | 74.740 | **66** | 1 | **Kathalekan-Non-Sw-Gr1** | Siddapur | 1.17 | 5.15 | 2.58 | 128.86 | 64.43 |
| 14.267 | 74.741 | | 2 | | | 1.66 | 8.45 | 4.22 | 211.14 | 105.57 |

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|---|---|---|---|---|---|---|---|---|---|---|
| 14.267 | 74.741 | | 3 | | | 1.51 | 7.43 | 3.72 | 185.84 | 92.92 |
| 14.267 | 74.741 | | 4 | | | 0.95 | 3.63 | 1.81 | 90.65 | 45.33 |
| 14.267 | 74.741 | | 5 | | | 1.25 | 5.66 | 2.83 | 141.45 | 70.72 |
| 14.279 | 74.742 | **67** | 1 | **Kathalekan-Non-Sw-Gr2** | Siddapur | 1.77 | 9.22 | 4.61 | 230.50 | 115.25 |
| 14.280 | 74.742 | | 2 | | | 1.51 | 7.44 | 3.72 | 186.08 | 93.04 |
| 14.280 | 74.742 | | 3 | | | 1.12 | 4.79 | 2.40 | 119.87 | 59.94 |
| 14.280 | 74.742 | | 4 | | | 2.62 | 14.97 | 7.49 | 374.35 | 187.18 |
| 14.280 | 74.743 | | 5 | | | 0.80 | 2.60 | 1.30 | 64.92 | 32.46 |
| 14.273 | 74.741 | **68** | 1 | **Kathalekan-Non-Sw-Gr3** | Siddapur | 1.43 | 6.88 | 3.44 | 171.99 | 85.99 |
| 14.273 | 74.741 | | 2 | | | 2.26 | 12.51 | 6.25 | 312.70 | 156.35 |
| 14.273 | 74.741 | | 3 | | | 3.06 | 17.92 | 8.96 | 448.07 | 224.04 |
| 14.274 | 74.742 | | 4 | | | 0.26 | 1.67 | 0.84 | 41.83 | 20.91 |
| 14.274 | 74.742 | | 5 | | | 2.07 | 11.24 | 5.62 | 281.12 | 140.56 |
| 14.273 | 74.741 | **69** | 1 | **Kathalekan-Non-Sw-Gr4** | Siddapur | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| 14.273 | 74.741 | | 2 | | | 0.06 | 0.28 | 0.14 | 6.93 | 3.47 |
| 14.273 | 74.741 | | 3 | | | 0.03 | 0.12 | 0.06 | 3.02 | 1.51 |
| 14.273 | 74.742 | | 4 | | | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| 14.274 | 74.742 | | 5 | | | 0.21 | 1.34 | 0.67 | 33.41 | 16.71 |
| 14.268 | 74.741 | **70** | 1 | **Kathalekan-Non-Sw-Gr5** | Siddapur | 1.17 | 5.15 | 2.58 | 128.78 | 64.39 |
| 14.268 | 74.742 | | 2 | | | 1.23 | 5.54 | 2.77 | 138.47 | 69.24 |
| 14.269 | 74.742 | | 3 | | | 1.93 | 10.26 | 5.13 | 256.57 | 128.28 |
| 14.269 | 74.742 | | 4 | | | 1.11 | 4.73 | 2.37 | 118.32 | 59.16 |
| 14.269 | 74.742 | | 5 | | | 2.52 | 14.28 | 7.14 | 357.06 | 178.53 |
| 14.270 | 74.745 | **71** | 1 | **Kathalekan-Non-Sw-Gr6-Kerihonda** | Siddapur | 2.56 | 14.52 | 7.26 | 363.10 | 181.55 |
| 14.270 | 74.745 | | 2 | | | 1.34 | 6.25 | 3.13 | 156.33 | 78.17 |

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|---|---|---|---|---|---|---|---|---|---|---|
| 14.270 | 74.745 | | 3 | | | 3.20 | 18.89 | 9.45 | 472.34 | 236.17 |
| 14.271 | 74.745 | | 4 | | | 1.43 | 6.87 | 3.43 | 171.69 | 85.85 |
| 14.271 | 74.746 | | 5 | | | 1.65 | 8.38 | 4.19 | 209.54 | 104.77 |
| 14.270 | 74.746 | **72** | 1 | **Kathalekan-Non-Sw-Gr7** | Siddapur | 1.04 | 4.26 | 2.13 | 106.51 | 53.26 |
| 14.270 | 74.747 | | 2 | | | 0.81 | 2.70 | 1.35 | 67.40 | 33.70 |
| 14.270 | 74.747 | | 3 | | | 1.16 | 5.09 | 2.54 | 127.19 | 63.60 |
| 14.271 | 74.747 | | 4 | | | 1.66 | 8.44 | 4.22 | 210.98 | 105.49 |
| 14.271 | 74.747 | | 5 | | | 1.03 | 4.17 | 2.09 | 104.31 | 52.16 |
| 14.269 | 74.747 | **73** | 1 | **Kathalekan-Non-Sw-Gr8** | Siddapur | 2.53 | 14.31 | 7.16 | 357.75 | 178.88 |
| 14.269 | 74.748 | | 2 | | | 1.59 | 7.98 | 3.99 | 199.40 | 99.70 |
| 14.269 | 74.748 | | 3 | | | 0.99 | 3.93 | 1.96 | 98.20 | 49.10 |
| 14.270 | 74.748 | | 4 | | | 2.59 | 14.77 | 7.38 | 369.21 | 184.60 |
| 14.270 | 74.748 | | 5 | | | 0.55 | 0.89 | 0.44 | 22.23 | 11.12 |
| 14.271 | 74.752 | **74** | 1 | **Kathalekan-Non-Sw-Gr9** | Siddapur | 2.11 | 11.52 | 5.76 | 287.94 | 143.97 |
| 14.266 | 74.750 | | 2 | | | 2.03 | 10.96 | 5.48 | 274.08 | 137.04 |
| 14.266 | 74.750 | | 3 | | | 1.34 | 6.26 | 3.13 | 156.38 | 78.19 |
| 14.266 | 74.751 | | 4 | | | 1.19 | 5.27 | 2.64 | 131.77 | 65.89 |
| 14.266 | 74.751 | | 5 | | | 1.25 | 5.68 | 2.84 | 142.04 | 71.02 |
| 14.452 | 74.778 | **75** | 1 | **Hartebailu-Soppinabetta** | Siddapur | 0.95 | 3.61 | 1.80 | 90.23 | 45.12 |
| 14.452 | 74.778 | | 2 | | | 0.53 | 0.76 | 0.38 | 18.95 | 9.47 |
| 14.452 | 74.779 | | 3 | | | 0.93 | 3.50 | 1.75 | 87.62 | 43.81 |
| 14.451 | 74.779 | | 4 | | | 0.64 | 1.51 | 0.75 | 37.66 | 18.83 |
| 14.451 | 74.779 | | 5 | | | 0.52 | 0.71 | 0.35 | 17.68 | 8.84 |
| 14.421 | 74.770 | **76** | 1 | **Hutgar-Evergreen** | Siddapur | 1.87 | 9.90 | 4.95 | 247.39 | 123.69 |
| 14.421 | 74.770 | | 2 | | | 0.82 | 2.73 | 1.37 | 68.29 | 34.15 |

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| 14.420 | 74.770 | | 3 | | | 1.28 | 5.85 | 2.93 | 146.36 | 73.18 |
| 14.419 | 74.770 | | 4 | | | 1.21 | 5.43 | 2.71 | 135.67 | 67.84 |
| 14.420 | 74.770 | | 5 | | | 0.92 | 3.45 | 1.72 | 86.19 | 43.10 |
| 14.275 | 74.741 | | 1 | | | 1.47 | 7.19 | 3.59 | 179.63 | 89.82 |
| 14.275 | 74.741 | | 2 | | | 1.08 | 4.49 | 2.25 | 112.26 | 56.13 |
| 14.275 | 74.741 | **77** | 3 | **Kathalekan-Swamp-Gr1** | Siddapur | 1.48 | 7.21 | 3.61 | 180.37 | 90.18 |
| 14.275 | 74.741 | | 4 | | | 1.62 | 8.14 | 4.07 | 203.59 | 101.80 |
| 14.276 | 74.742 | | 5 | | | 2.99 | 17.45 | 8.72 | 436.18 | 218.09 |
| 14.269 | 74.739 | | 1 | | | 1.85 | 9.71 | 4.85 | 242.65 | 121.33 |
| 14.269 | 74.739 | | 2 | | | 2.58 | 14.65 | 7.33 | 366.36 | 183.18 |
| 14.269 | 74.740 | **78** | 3 | **Kathalekan-Swamp-Gr2** | Siddapur | 1.20 | 5.31 | 2.66 | 132.81 | 66.41 |
| 14.270 | 74.740 | | 4 | | | 0.88 | 3.14 | 1.57 | 78.51 | 39.26 |
| 14.270 | 74.740 | | 5 | | | 1.51 | 7.40 | 3.70 | 185.09 | 92.54 |
| 14.274 | 74.854 | | 1 | | | 6.13 | 38.72 | 19.36 | 967.96 | 483.98 |
| 14.274 | 74.854 | | 2 | | | 4.96 | 30.84 | 15.42 | 770.90 | 385.45 |
| 14.275 | 74.854 | **79** | 3 | **Kathalekan-Swamp-Gr3** | Siddapur | 3.03 | 17.74 | 8.87 | 443.62 | 221.81 |
| 14.275 | 74.855 | | 4 | | | 1.97 | 10.55 | 5.27 | 263.69 | 131.84 |
| 14.275 | 74.855 | | 5 | | | 1.53 | 7.57 | 3.78 | 189.18 | 94.59 |
| 14.274 | 74.746 | | 1 | | | 3.15 | 18.58 | 9.29 | 464.52 | 232.26 |
| 14.274 | 74.746 | | 2 | | | 4.20 | 25.67 | 12.84 | 641.80 | 320.90 |
| 14.274 | 74.746 | **80** | 3 | **Kathalekan-Swamp-Gr4** | Siddapur | 2.57 | 14.59 | 7.30 | 364.79 | 182.40 |
| 14.275 | 74.746 | | 4 | | | 1.29 | 5.96 | 2.98 | 149.00 | 74.50 |
| 14.275 | 74.746 | | 5 | | | 1.00 | 4.00 | 2.00 | 99.94 | 49.97 |
| 14.273 | 74.745 | **81** | 1 | **Kathalekan-Swamp-Gr5** | Siddapur | 0.93 | 3.48 | 1.74 | 87.06 | 43.53 |
| 14.273 | 74.745 | | 2 | | | 1.58 | 7.91 | 3.95 | 197.63 | 98.82 |

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| 14.273 | 74.745 | | 3 | | | 0.74 | 2.22 | 1.11 | 55.53 | 27.76 |
| 14.273 | 74.745 | | 4 | | | 3.88 | 23.52 | 11.76 | 588.09 | 294.05 |
| 14.273 | 74.745 | | 5 | | | 1.56 | 7.76 | 3.88 | 194.07 | 97.03 |
| 14.266 | 74.748 | | 1 | | | 0.76 | 2.34 | 1.17 | 58.56 | 29.28 |
| 14.266 | 74.748 | | 2 | | | 1.44 | 6.96 | 3.48 | 174.06 | 87.03 |
| 14.266 | 74.748 | **82** | 3 | **Kathalekan-Swamp-Gr6** | Siddapur | 1.34 | 6.25 | 3.13 | 156.32 | 78.16 |
| 14.267 | 74.749 | | 4 | | | 3.03 | 17.71 | 8.86 | 442.85 | 221.42 |
| 14.267 | 74.749 | | 5 | | | 1.47 | 7.13 | 3.56 | 178.19 | 89.10 |
| 14.269 | 74.770 | | 1 | | | 1.25 | 5.68 | 2.84 | 142.10 | 71.05 |
| 14.269 | 74.770 | | 2 | | | 1.75 | 9.08 | 4.54 | 226.90 | 113.45 |
| 14.269 | 74.770 | **83** | 3 | **Kathalekan-Swamp-Gr7** | Siddapur | 0.45 | 0.27 | 0.13 | 6.72 | 3.36 |
| 14.269 | 74.771 | | 4 | | | 1.24 | 5.57 | 2.78 | 139.18 | 69.59 |
| 14.270 | 74.771 | | 5 | | | 1.66 | 8.47 | 4.24 | 211.79 | 105.90 |
| 14.266 | 74.748 | | 1 | | | 2.03 | 10.96 | 5.48 | 274.04 | 137.02 |
| 14.266 | 74.748 | | 2 | | | 2.74 | 15.74 | 7.87 | 393.46 | 196.73 |
| 14.266 | 74.748 | **84** | 3 | **Kathalekan-Swamp-Gr9** | Siddapur | 3.38 | 20.11 | 10.05 | 502.73 | 251.36 |
| 14.267 | 74.749 | | 4 | | | 1.41 | 6.75 | 3.38 | 168.87 | 84.44 |
| 14.267 | 74.749 | | 5 | | | 3.41 | 20.31 | 10.15 | 507.69 | 253.84 |
| 14.277 | 74.746 | | 1 | | | 1.84 | 9.63 | 4.82 | 240.81 | 120.40 |
| 14.277 | 74.746 | | 2 | | | 1.54 | 7.64 | 3.82 | 190.99 | 95.49 |
| 14.277 | 74.746 | **85** | 3 | **Kathalekan-Non-Sw-Above Settl-Gr4** | Siddapur | 1.46 | 7.09 | 3.54 | 177.16 | 88.58 |
| 14.277 | 74.747 | | 4 | | | 1.23 | 5.52 | 2.76 | 138.11 | 69.06 |
| 14.278 | 74.747 | | 5 | | | 1.11 | 4.71 | 2.36 | 117.82 | 58.91 |
| 14.280 | 74.738 | **86** | 1 | **Malemane-2** | Siddapur | 2.35 | 13.15 | 6.58 | 328.76 | 164.38 |
| 14.271 | 74.725 | | 2 | | | 1.36 | 6.40 | 3.20 | 160.09 | 80.05 |

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| 14.270 | 74.726 | | 3 | | | 1.36 | 6.43 | 3.21 | 160.74 | 80.37 |
| 14.300 | 74.726 | | 4 | | | 1.40 | 6.69 | 3.35 | 167.26 | 83.63 |
| 14.300 | 74.727 | | 5 | | | 1.21 | 5.36 | 2.68 | 134.11 | 67.06 |
| 14.229 | 74.830 | **87** | 1 | **Siddapur-Evergreen** | Siddapur | 0.80 | 2.58 | 1.29 | 64.51 | 32.25 |
| 14.229 | 74.830 | | 2 | | | 1.75 | 9.09 | 4.54 | 227.21 | 113.60 |
| 14.229 | 74.831 | | 3 | | | 0.91 | 3.33 | 1.67 | 83.31 | 41.65 |
| 14.229 | 74.832 | | 4 | | | 0.88 | 3.14 | 1.57 | 78.49 | 39.24 |
| 14.229 | 74.834 | | 5 | | | 1.71 | 8.76 | 4.38 | 219.06 | 109.53 |
| 14.319 | 74.698 | **88** | 1 | **Talekere** | Siddapur | 0.38 | 2.44 | 1.22 | 61.01 | 30.50 |
| 14.319 | 74.697 | | 2 | | | 0.77 | 2.43 | 1.22 | 60.83 | 30.42 |
| 14.320 | 74.697 | | 3 | | | 0.23 | 1.45 | 0.72 | 36.21 | 18.10 |
| 14.321 | 74.697 | | 4 | | | 0.38 | 2.44 | 1.22 | 61.03 | 30.51 |
| 14.620 | 74.697 | | 5 | | | 0.27 | 1.70 | 0.85 | 42.60 | 21.30 |
| 14.239 | 74.827 | **89** | 1 | **Joginmath-1** | Siddapur | 1.48 | 7.21 | 3.60 | 180.20 | 90.10 |
| 14.239 | 74.827 | | 2 | | | 1.12 | 4.80 | 2.40 | 119.92 | 59.96 |
| 14.239 | 74.826 | | 3 | | | 1.50 | 7.35 | 3.67 | 183.69 | 91.85 |
| 14.240 | 74.827 | | 4 | | | 1.54 | 7.66 | 3.83 | 191.45 | 95.72 |
| 14.240 | 74.827 | | 5 | | | 0.66 | 1.63 | 0.82 | 40.79 | 20.39 |
| 14.273 | 74.741 | **90** | 1 | **Kathlekan-1** | Siddapur | 1.04 | 4.26 | 2.13 | 106.51 | 53.26 |
| 14.273 | 74.741 | | 2 | | | 0.81 | 2.70 | 1.35 | 67.40 | 33.70 |
| 14.273 | 74.741 | | 3 | | | 1.16 | 5.09 | 2.54 | 127.19 | 63.60 |
| 14.274 | 74.742 | | 4 | | | 1.66 | 8.44 | 4.22 | 210.98 | 105.49 |
| 14.274 | 74.742 | | 5 | | | 0.96 | 3.73 | 1.86 | 93.16 | 46.58 |
| 14.274 | 74.754 | **91** | 1 | **Kathalekan-2** | Siddapur | 1.30 | 6.02 | 3.01 | 150.43 | 75.21 |
| 14.274 | 74.755 | | 2 | | | 0.98 | 3.83 | 1.92 | 95.83 | 47.91 |

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| 14.275 | 74.754 | | 3 | | | 1.23 | 5.55 | 2.78 | 138.82 | 69.41 |
| 14.274 | 74.755 | | 4 | | | 1.49 | 7.31 | 3.66 | 182.77 | 91.39 |
| 14.275 | 74.755 | | 5 | | | 1.13 | 4.82 | 2.41 | 120.45 | 60.22 |
| 14.279 | 74.742 | **92** | 1 | **Kathalekan-3** | Siddapur | 0.54 | 0.83 | 0.41 | 20.65 | 10.33 |
| 14.280 | 74.742 | | 2 | | | 0.87 | 3.07 | 1.54 | 76.80 | 38.40 |
| 14.280 | 74.742 | | 3 | | | 1.81 | 9.48 | 4.74 | 236.93 | 118.46 |
| 14.280 | 74.742 | | 4 | | | 1.13 | 4.84 | 2.42 | 120.92 | 60.46 |
| 14.280 | 74.743 | | 5 | | | 1.48 | 7.24 | 3.62 | 181.04 | 90.52 |
| 14.270 | 74.726 | **93** | 1 | **Malemane-3** | Siddapur | 2.14 | 11.72 | 5.86 | 293.08 | 146.54 |
| 14.270 | 74.725 | | 2 | | | 2.46 | 13.85 | 6.93 | 346.34 | 173.17 |
| 14.270 | 74.726 | | 3 | | | 0.71 | 2.02 | 1.01 | 50.51 | 25.25 |
| 14.270 | 74.726 | | 4 | | | 1.80 | 9.37 | 4.68 | 234.23 | 117.12 |
| 14.270 | 74.727 | | 5 | | | 1.42 | 6.79 | 3.40 | 169.82 | 84.91 |
| 14.249 | 74.820 | **94** | 1 | **Joginmath-2 Semi-Ever** | Siddapur | 1.96 | 10.51 | 5.25 | 262.66 | 131.33 |
| 14.249 | 74.820 | | 2 | | | 0.95 | 3.64 | 1.82 | 90.99 | 45.50 |
| 14.250 | 74.820 | | 3 | | | 3.07 | 18.00 | 9.00 | 450.02 | 225.01 |
| 14.250 | 74.820 | | 4 | | | 1.14 | 4.94 | 2.47 | 123.57 | 61.78 |
| 14.251 | 74.820 | | 5 | | | 1.29 | 5.97 | 2.98 | 149.24 | 74.62 |
| 14.270 | 74.745 | **95** | 1 | **Malemane-1** | Siddapur | 1.14 | 4.95 | 2.48 | 123.77 | 61.89 |
| 14.270 | 74.745 | | 2 | | | 1.75 | 9.08 | 4.54 | 226.98 | 113.49 |
| 14.270 | 74.745 | | 3 | | | 2.37 | 13.23 | 6.62 | 330.83 | 165.41 |
| 14.271 | 74.745 | | 4 | | | 0.98 | 3.82 | 1.91 | 95.61 | 47.80 |
| 14.271 | 74.746 | | 5 | | | 1.26 | 5.77 | 2.88 | 144.13 | 72.07 |
| 14.493 | 74.626 | **96** | 1 | **Bugadi-Bennehole** | Sirsi | 2.45 | 13.81 | 6.91 | 345.34 | 172.67 |
| 14.493 | 74.626 | | 2 | | | 3.00 | 17.56 | 8.78 | 439.09 | 219.55 |

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| 14.493 | 74.626 | | 3 | | | 1.76 | 9.12 | 4.56 | 228.12 | 114.06 |
| 14.493 | 74.626 | | 4 | | | 2.65 | 15.16 | 7.58 | 378.94 | 189.47 |
| 14.493 | 74.627 | | 5 | | | 1.36 | 6.43 | 3.22 | 160.81 | 80.41 |
| 74.661 | 14.708 | **97** | 1 | **Gondsor-Sampekattu** | Sirsi | 0.10 | 0.55 | 0.28 | 13.80 | 6.90 |
| 74.662 | 14.708 | | 2 | | | 0.30 | 1.93 | 0.97 | 48.26 | 24.13 |
| 74.662 | 14.709 | | 3 | | | 0.12 | 0.71 | 0.35 | 17.75 | 8.87 |
| 74.662 | 14.709 | | 4 | | | 0.06 | 0.06 | 0.28 | 1.44 | 0.72 |
| 74.662 | 14.709 | | 5 | | | 0.17 | 0.17 | 1.03 | 4.23 | 2.11 |
| 74.604 | 14.522 | **98** | 1 | **Hulekal-Sampegadde-Hebre** | Sirsi | 2.97 | 17.29 | 8.65 | 432.32 | 216.16 |
| 74.604 | 14.522 | | 2 | | | 1.27 | 5.78 | 2.89 | 144.52 | 72.26 |
| 74.605 | 14.522 | | 3 | | | 1.43 | 6.87 | 3.43 | 171.73 | 85.86 |
| 74.605 | 14.523 | | 4 | | | 2.52 | 14.27 | 7.14 | 356.81 | 178.40 |
| 74.605 | 14.523 | | 5 | | | 2.01 | 10.79 | 5.40 | 269.76 | 134.88 |
| 14.732 | 74.651 | **99** | 1 | **Kanmaski-Vanalli** | Sirsi | 3.28 | 19.43 | 9.72 | 485.82 | 242.91 |
| 14.732 | 74.651 | | 2 | | | 2.04 | 11.01 | 5.50 | 275.13 | 137.56 |
| 14.733 | 74.650 | | 3 | | | 2.12 | 11.56 | 5.78 | 289.07 | 144.54 |
| 14.733 | 74.650 | | 4 | | | 3.04 | 17.82 | 8.91 | 445.46 | 222.73 |
| 14.734 | 74.651 | | 5 | | | 0.95 | 3.66 | 1.83 | 91.41 | 45.70 |
| 14.546 | 74.695 | **100** | 1 | **Khurse** | Sirsi | 1.48 | 7.22 | 3.61 | 180.53 | 90.27 |
| 14.547 | 74.696 | | 2 | | | 0.62 | 1.40 | 0.70 | 35.12 | 17.56 |
| 14.547 | 74.696 | | 3 | | | 1.13 | 4.84 | 2.42 | 121.04 | 60.52 |
| 14.547 | 74.696 | | 4 | | | 0.79 | 2.55 | 1.28 | 63.83 | 31.91 |
| 14.547 | 74.696 | | 5 | | | 0.46 | 0.29 | 0.15 | 7.31 | 3.66 |
| 14.693 | 74.874 | **101** | 1 | **Masrukuli-Moistdec** | Sirsi | 3.16 | 18.65 | 9.32 | 466.14 | 233.07 |
| 14.693 | 74.874 | | 2 | | | 1.60 | 8.03 | 4.01 | 200.67 | 100.33 |

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| 14.693 | 74.875 | | 3 | | | 1.56 | 7.78 | 3.89 | 194.47 | 97.23 |
| 14.692 | 74.875 | | 4 | | | 0.94 | 3.59 | 1.80 | 89.82 | 44.91 |
| 14.691 | 74.875 | | 5 | | | 1.20 | 5.35 | 2.68 | 133.77 | 66.89 |
| 14.811 | 74.820 | | 1 | | | 1.15 | 4.96 | 2.48 | 123.98 | 61.99 |
| 14.811 | 74.820 | | 2 | | | 1.36 | 6.44 | 3.22 | 160.96 | 80.48 |
| 14.811 | 74.820 | **102** | 3 | **Hiresara-Bettaland** | Yellapur | 0.97 | 3.78 | 1.89 | 94.41 | 47.20 |
| 14.812 | 74.821 | | 4 | | | 1.99 | 10.66 | 5.33 | 266.52 | 133.26 |
| 14.812 | 74.821 | | 5 | | | 2.88 | 16.70 | 8.35 | 417.52 | 208.76 |
| 14.878 | 74.569 | **103** | 1 | **Hubli-Ankola Sector-5** | Yellapur | 73.09 | | | 492.73 | 246.36 |
| 14.890 | 74.614 | **104** | 1 | **Hubli-Ankola Sector-6** | Yellapur | 84.46 | | | 569.80 | 284.90 |
| 14.910 | 74.656 | **105** | 1 | **Hubli-Ankola Sector-7** | Yellapur | 48.15 | | | 323.65 | 161.83 |
| 14.965 | 74.726 | **106** | 1 | **Hubli-Ankola Sector-8** | Yellapur | 74.68 | | | 503.51 | 251.75 |
| 15.026 | 74.805 | **107** | 1 | **Hubli-Ankola Sector-9** | Yellapur | 70.87 | | | 477.70 | 238.85 |
| 15.021 | 74.676 | | 1 | | | 1.33 | 6.18 | 3.09 | 154.42 | 77.21 |
| 15.020 | 74.677 | | 2 | | | 1.03 | 4.15 | 2.07 | 103.71 | 51.86 |
| 15.021 | 74.676 | **108** | 3 | **Yellapur-Hasrapal** | Yellapur | 1.35 | 6.32 | 3.16 | 158.05 | 79.02 |
| 15.020 | 74.677 | | 4 | | | 1.63 | 8.26 | 4.13 | 206.53 | 103.27 |
| 15.020 | 74.677 | | 5 | | | 1.63 | 8.21 | 4.11 | 205.35 | 102.67 |
| 15.018 | 74.683 | | 1 | | | 0.83 | 2.82 | 1.41 | 70.49 | 35.24 |
| 15.018 | 74.682 | | 2 | | | 1.44 | 6.98 | 3.49 | 174.62 | 87.31 |
| 15.019 | 74.682 | **109** | 3 | **Yellapur-Hulimundgi** | Yellapur | 1.90 | 10.09 | 5.04 | 252.14 | 126.07 |
| 15.019 | 74.682 | | 4 | | | 1.50 | 7.37 | 3.68 | 184.21 | 92.11 |
| 15.019 | 74.682 | | 5 | | | 1.05 | 4.30 | 2.15 | 107.48 | 53.74 |
| 15.064 | 74.705 | **110** | 1 | **Yellapur-Lalgulli** | Yellapur | 1.55 | 7.71 | 3.86 | 192.82 | 96.41 |
| 15.065 | 74.705 | | 2 | | | 1.98 | 10.64 | 5.32 | 265.92 | 132.96 |

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| 15.065 | 74.705 | | 3 | | | 1.29 | 5.93 | 2.97 | 148.36 | 74.18 |
| 15.066 | 74.705 | | 4 | | | 2.19 | 12.04 | 6.02 | 301.11 | 150.55 |
| 15.066 | 74.705 | | 5 | | | 1.45 | 7.00 | 3.50 | 175.09 | 87.55 |

Table 2.B. IUCN red list species of the district based on field analysis

| Sno | Red listed species | Family | Category | Locations | Taluks | Remarks |
|---|---|---|---|---|---|---|
| 1 | *Gymnacranthera canarica* | Myristicaceae | Vulnerable | Alsolli 1, Alsolli 2, Halsolli, Kathalekan G1, G2, Kathalekan swamp T1, T2, T3, T4, T5, T6 | Ankola Honnavar Siddapur | Confined to Myristica swamps only |
| 2 | *Myristica fatua* | Myristicaceae | Endangered | Halsolli, Kathalekan swamps T1, T2, T5, T9 | Honnavar Siddapur | Confined to Myristica swamps only. In relics of primary forests |
| 3 | *Dipterocarpus indicus* | Dipterocarpaceae | Endangered | Alsolli 1, Alsolli 2, Ambepal 1, Ambepal 2, Hadageri 1, Hadageri 2, Karikan lower slope, Karikan s.evergreen, Karikan templeside, Kathalekan non-swamp grids G1, G2, G3, G4, G5, G6, G7, G8, Kathalekan swamp grids T1, T2, T3, T4, T5, T6, T7, T8, T9 | Ankola Honnavar Siddapur | New reports for Ankola in relics of primary forests. Northward range extension in the Western Ghats |

| | | | | | | |
|---|---|---|---|---|---|---|
| 4 | *Hopea Ponga* | Dipterocarpaceae | Endangered | Widespread in evergreen forests Honavar, Kumta, Siddapur, Sirsi, Ankola and sparingly in Karwar and Yellapur | Honnavar, Kumta, Siddapur, Sirsi, Ankola, Yellapura, Karwar | |
| 5 | *Vateria indica* | Dipterocarpaceae | Endangered | Kathalekan 3 | Siddapur | Planted widespread in the district; natural in Mattigar kan, Siddapur |
| 6 | *Syzygium travancoricum* | Myrtaceae | Critically Endangered | Kathalekan G8, Kathalekan swamp T3, T6, T8, T5 | Siddapur | Also found very sparingly in Ankola Ghats. Range extension in Uttara Kannada reported for first time |
| 7 | *Semecarpus kathalekanensis* | Anacardiaceae | New tree species | Kathalekan swamps T1, T2 | Siddapur | New tree species reported |

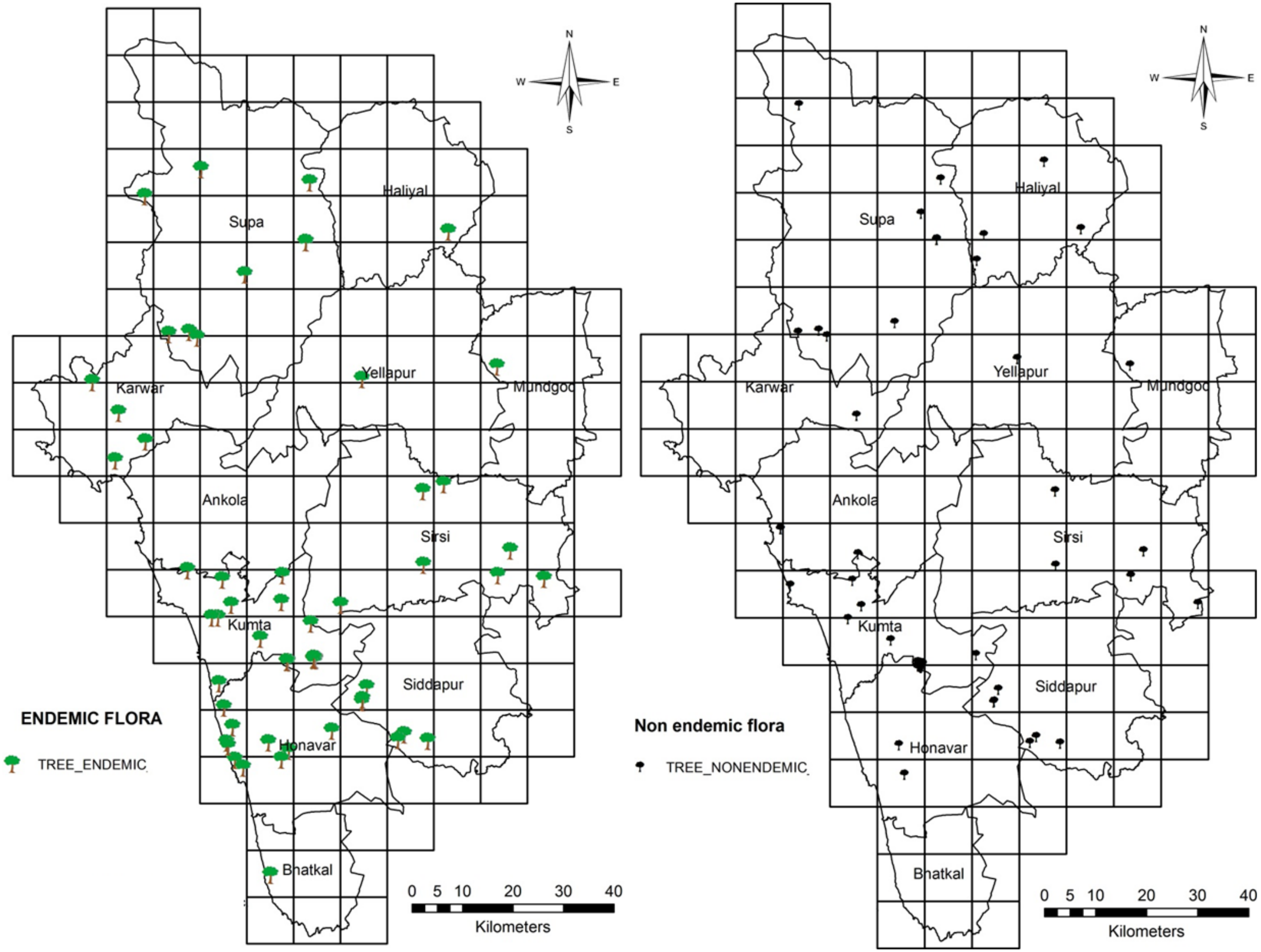
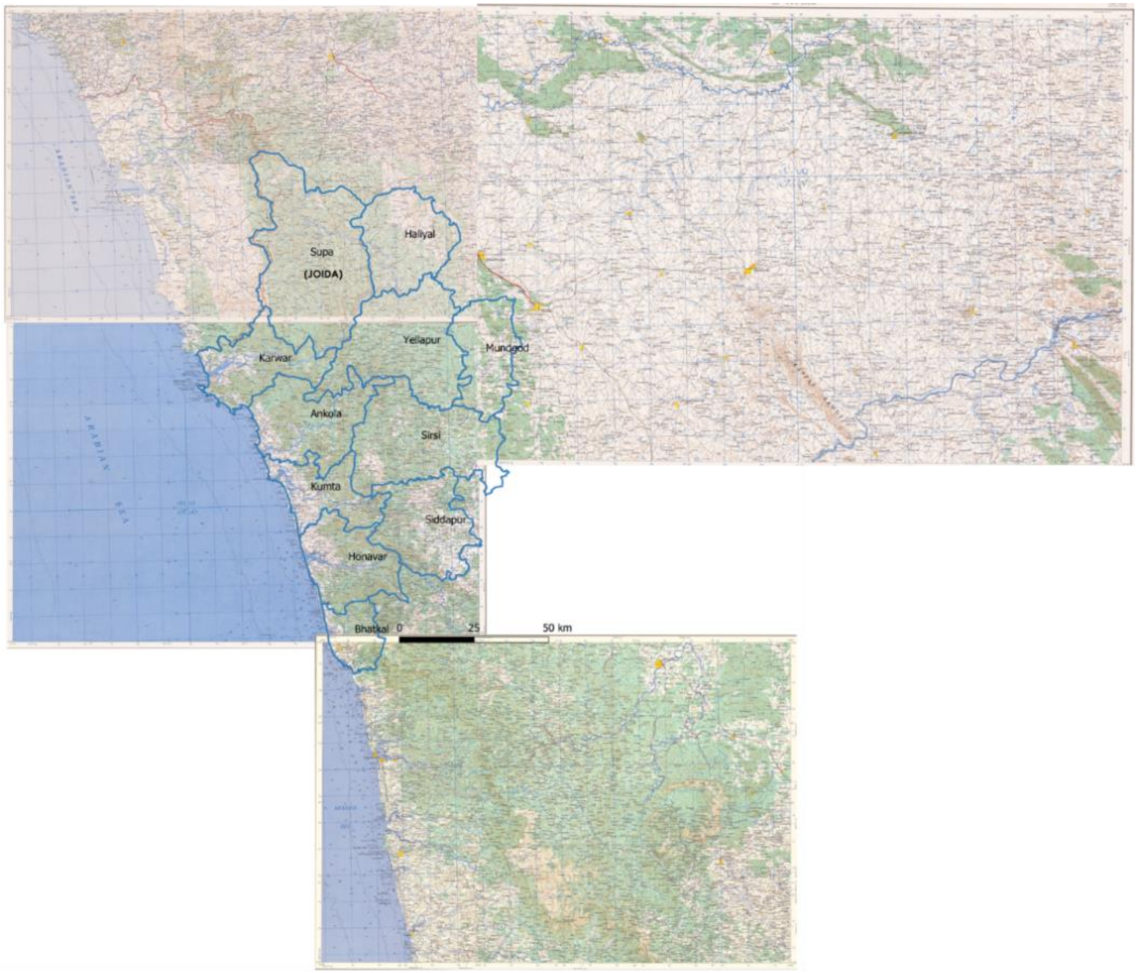



Figure 2.B. Flora distribution map based on literature and field study

Figure 2.C. GBH measurements in transact study




**India and Pakistan 1:250,000; Series U502, U.S. Army Map Service, 1955**
*** Green colour represents Forest cover**

Figure 2.D. US Army map of 1955

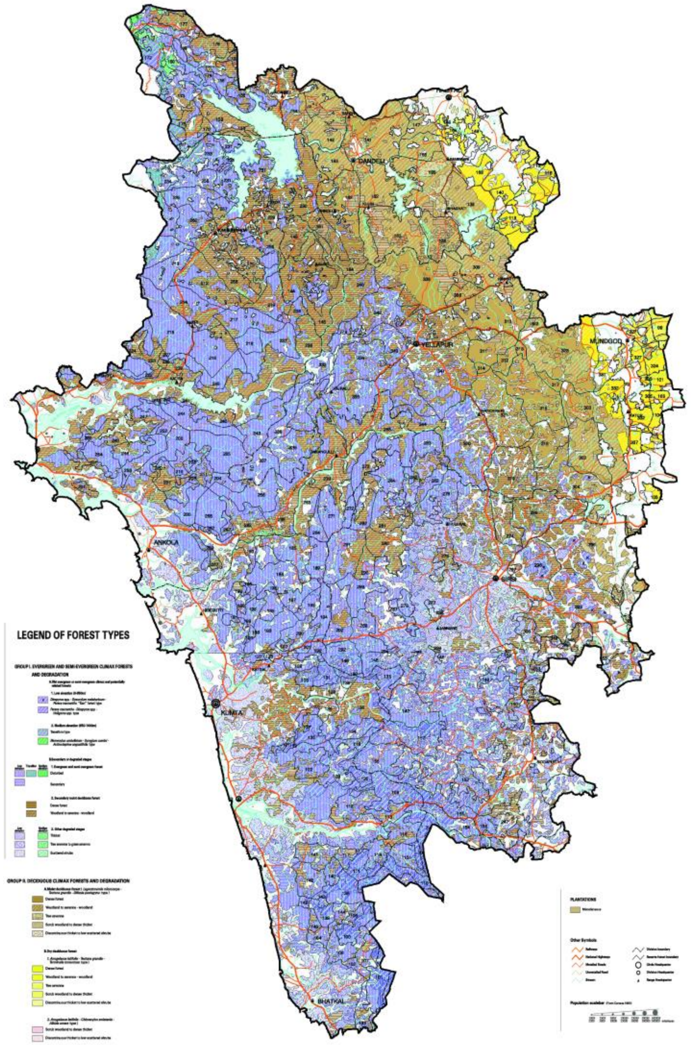



Figure 2.E. Digitised Vegetation map of South India - Uttara Kannada [used as a reference for pre-1990's land use classification]

# Appendix 3: Land Use classes identification and Accuracy Assessment

## Land use classes identification

The step-wise procedure explains the logic behind considering 11 land use classes, which were separable from remote sensing data.

Step 1: Histogram has been generated for the three-band stack of (NIR, Red, Green) to understand the number of different classes present in the data for the year 2013 and shown in Figure 3C. It shows the data follows a normal distribution, which is prime consideration before classification.

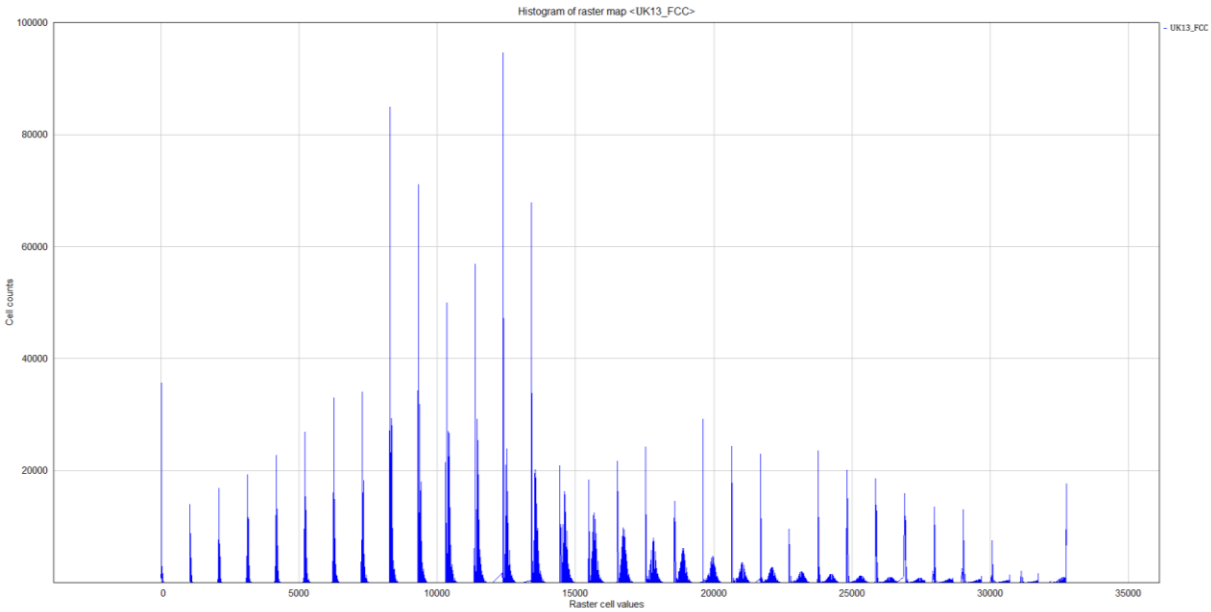



Figure 3.A. Histogram of the remote sensing data for the year 2013

**Statistics for Map(s) Histogrammed:**

Statistics for raster map <UK13_FCC>:

\-----------------------------------------------

Total cells: 11354157

Minimum: 0

Maximum: 32767

Range: 32767

Mean: 12212

Mean of absolute values: 12212

standard deviation: 7534.69

Variance: 5.67715e+07

Variation coefficient: 61.6992 %

Sum: 138656648805

1st quartile: 6329

Median (odd number of cells): 11452

3rd quartile: 16667

90th percentile: 22294

Step 2: Since the histogram has depicted there are a number of pixel pairs overlaps and which can be considered as each land use category. The clusters of the data have been generated by sampling across the 8288 points. The Clusters have been generated by providing the input as 64, 32, 16 numbers and quantified the stable number of separable classes based on Mean, variance, standard deviation. The 64 clusters provided 68.50% points stable, 32 clusters showed 88.62% points stable and finally, 16 classes showed **98.21%** points stable.

**Number of Clusters: 16**

```
#################### CLUSTER (Mon Jan 27 10:49:18 2014)################

Location: UK_ESR
Mapset:   UKLU
Group:    G13@UKLU
Subgroup: S
 UK13_B3E@UKLU
 UK13_B4E@UKLU
 UK13_B5E@UKLU
Result signature file: CLUSTER13

Cluster parameters
 Number of initial classes:    16
 Minimum class size:           17
 Minimum class separation:     0.000000
 Percent convergence:          98.000000
 Maximum number of iterations: 30

 Row sampling interval:        29
 Col sampling interval:        47

Sample size: 8288 points


means and standard deviations for 3 bands

 means   7823.34 7078 13902
 stddev  481.87 764.521 3007.58


initial means for each band

class 1    7341.47 6313.48 10894.4
class 2    7405.72 6415.42 11295.4
class 3    7469.97 6517.35 11696.4
class 4    7534.22 6619.29 12097.5
class 5    7598.47 6721.23 12498.5
class 6    7662.72 6823.16 12899.5
class 7    7726.97 6925.1 13300.5
class 8    7791.22 7027.03 13701.5
class 9    7855.47 7128.97 14102.5
class 10   7919.71 7230.91 14503.5
class 11   7983.96 7332.84 14904.5
class 12   8048.21 7434.78 15305.5
class 13   8112.46 7536.71 15706.5
class 14   8176.71 7638.65 16107.6
```

```
class 15   8240.96 7740.59 16508.6
class 16   8305.21 7842.52 16909.6


class means/stddev for each band


class 1 (949)
  means  7860.68 6725.36 6695.09
  stddev 508.261 342.251 1703.18

class 2 (76)
  means  7322.22 6584.34 11258.1
  stddev 400.516 535.332 232.997

class 3 (119)
  means  7401.74 6681.5 11678.8
  stddev 422.391 578.89 235.719

class 4 (144)
  means  7436.81 6725.36 12100.9
  stddev 370.866 593.458 242.881

class 5 (214)
  means  7528.25 6831.9 12486.1
  stddev 490.758 717.13 279.92

class 6 (299)
  means  7583.98 6917.67 12903.1
  stddev 443.887 759.595 275.814

class 7 (446)
  means  7642.41 6964.91 13327.7
  stddev 422.093 712.242 261.367

class 8 (570)
  means  7743.14 7090.15 13708.4
  stddev 441.507 734.321 286.836

class 9 (741)
  means  7772.2 7103.45 14128.9
  stddev 417.864 718.744 273.5

class 10 (800)
  means  7850.23 7178.9 14525
  stddev 412.263 693.301 273.288

class 11 (951)
  means  7847.08 7153.11 14966.1
  stddev 402.589 693.294 265.391

class 12 (883)
  means  7899.51 7204.25 15382.6
  stddev 418.07 748.123 286.884

class 13 (748)
  means  7918.99 7202.16 15814.6
  stddev 431.431 782.533 290.328

class 14 (495)
  means  7931.8 7185.21 16247.5
  stddev 455.517 784.658 300.757

class 15 (327)
  means  7967.62 7246.35 16660.4
  stddev 537.263 957.672 346.702

class 16 (526)
  means  8058.59 7326.64 17804.9
  stddev 681.343 1189.94 1050.62

class distribution
        949        76        119        144        214
        299       446        570        741        800
        951       883        748        495        327
        526

######## iteration 1 ###########
16 classes, 76.54% points stable
class distribution
        790       235        118        152        209
        306       461        570        730        821
        943       821        726        535        512
        359
```

```
######## iteration 2 ###########
16 classes, 70.31% points stable
class distribution
        782       198       113       300       105
        162       641       515       891       790
       1135       535       650       694       499
        278

######## iteration 3 ###########
16 classes, 88.47% points stable
class distribution
        780       190        86       364        83
        252       603       401      1090       606
       1148       549       751       644       532
        209

######## iteration 4 ###########
16 classes, 92.57% points stable
class distribution
        780       185        67       389       104
        315       604       334      1183       466
       1146       565       821       606       550
        173

######## iteration 5 ###########
16 classes, 94.32% points stable
class distribution
        780       182        65       402       109
        369       646       308      1172       353
       1129       623       839       604       556
        151

######## iteration 6 ###########
16 classes, 94.73% points stable
class distribution
        780       183        63       409       124
        410       707       293      1090       271
       1092       699       864       611       555
        137

######## iteration 7 ###########
16 classes, 95.26% points stable
class distribution
        780       184        62       410       137
        465       738       276      1034       224
       1061       720       892       629       548
        128

######## iteration 8 ###########
16 classes, 96.05% points stable
class distribution
        780       186        61       410       150
        504       746       269      1024       192
       1053       707       882       659       543
        122

######## iteration 9 ###########
16 classes, 96.61% points stable
class distribution
        780       187        61       409       165
        530       747       258      1024       171
       1078       674       856       695       535
        118

######## iteration 10 ###########
16 classes, 97.04% points stable
class distribution
        780       189        60       412       184
        542       751       246      1024       159
       1111       643       814       724       533
        116

######## iteration 11 ###########
16 classes, 97.47% points stable
class distribution
        779       191        62       412       195
        562       759       242      1015       152
       1153       594       763       763       532
        114

######## iteration 12 ###########
16 classes, 97.72% points stable
class distribution
```

```
       778        192         64        412        209
       577        762        241       1011        145
      1185        553        730        782        534
       113

######## iteration 13 ###########
16 classes, 97.83% points stable
class distribution
       777        192         65        416        217
       600        766        237       1000        137
      1213        518        694        811        533
       112

######## iteration 14 ###########
16 classes, 98.21% points stable
class distribution
       777        190         69        419        230
       614        768        229        988        135
      1243        493        661        826        536
       110

#################### CLASSES ####################
```

**16 classes, 98.21% points stable**

```
######## CLUSTER END (Mon Jan 27 10:49:18 2014) ########
```

*Note: for 16 clusters after 14th iteration, class distribution process has become saturated.

## Number of Clusters: 32

```
#################### CLUSTER (Tue Jun 28 15:23:56 2014) ####################

Location: UK_ESR
Mapset:   UKLU
Group:    G13@UKLU
Subgroup: S
 UK13_B3E@UKLU
 UK13_B4E@UKLU
 UK13_B5E@UKLU
Result signature file: CLUSTER13_32TRY

Region
  North:   1463462.76  East:    591858.36
  South:   1374208.93  West:    447981.19
  Res:          30.00  Res:         30.00
  Rows:          2975  Cols:         4796  Cells: 14268100
Mask: none

Cluster parameters
 Number of initial classes:    32
 Minimum class size:           17
 Minimum class separation:     0.000000
 Percent convergence:          70.000000
 Maximum number of iterations: 30

 Row sampling interval:        29
 Col sampling interval:        47

Sample size: 8288 points


means and standard deviations for 3 bands

 means   7823.34 7078 13902
 stddev  481.87 764.521 3007.58

initial means for each band

class 1    7341.47 6313.48 10894.4
```

```
class 2    7372.56 6362.8 11088.5
class 3    7403.65 6412.13 11282.5
class 4    7434.74 6461.45 11476.5
class 5    7465.82 6510.78 11670.6
class 6    7496.91 6560.1 11864.6
class 7    7528 6609.42 12058.6
class 8    7559.09 6658.75 12252.7
class 9    7590.18 6708.07 12446.7
class 10   7621.27 6757.4 12640.8
class 11   7652.35 6806.72 12834.8
class 12   7683.44 6856.04 13028.8
class 13   7714.53 6905.37 13222.9
class 14   7745.62 6954.69 13416.9
class 15   7776.71 7004.02 13610.9
class 16   7807.8 7053.34 13805
class 17   7838.88 7102.66 13999
class 18   7869.97 7151.99 14193.1
class 19   7901.06 7201.31 14387.1
class 20   7932.15 7250.64 14581.1
class 21   7963.24 7299.96 14775.2
class 22   7994.33 7349.28 14969.2
class 23   8025.42 7398.61 15163.2
class 24   8056.5 7447.93 15357.3
class 25   8087.59 7497.26 15551.3
class 26   8118.68 7546.58 15745.4
class 27   8149.77 7595.9 15939.4
class 28   8180.86 7645.23 16133.4
class 29   8211.95 7694.55 16327.5
class 30   8243.03 7743.88 16521.5
class 31   8274.12 7793.2 16715.5
class 32   8305.21 7842.52 16909.6


class means/stddev for each band

class 1 (936)
  means  7869.82 6728.73 6634.82
  stddev 503.953 338.182 1635.62

class 2 (32)
  means  7234.97 6469.19 11098.2
  stddev 279.35 359.786 139.699

class 3 (36)
  means  7363.58 6680.69 11215.6
  stddev 485.475 662.108 250.276

class 4 (38)
  means  7303.39 6541.47 11479.2
  stddev 375.331 488.521 193.074

class 5 (61)
  means  7414.59 6700.38 11627.1
  stddev 458.952 619.139 227.87

class 6 (60)
  means  7457.73 6757.1 11827.8
  stddev 416.26 618.782 223.146

class 7 (64)
  means  7397.27 6659.89 12064.1
  stddev 343.597 553.27 192.488

class 8 (85)
  means  7434.79 6741.69 12252
  stddev 355.283 580.691 216.013

class 9 (102)
  means  7526.05 6817.25 12428
  stddev 423.109 617.422 226.828

class 10 (105)
  means  7544.97 6846.64 12622.7
  stddev 559.147 816.109 309.341
```

```
class 11 (137)
  means  7567.99 6882.98 12826
  stddev 399.434 692.058 243.709

class 12 (162)
  means  7611.73 6962.49 13007.2
  stddev 469.55 800.775 278.854

class 13 (192)
  means  7582.79 6878.04 13254.7
  stddev 352.328 609.303 218.417

class 14 (256)
  means  7713.99 7074.37 13396.9
  stddev 528.716 859.556 300.519

class 15 (247)
  means  7734.61 7085.01 13596.8
  stddev 428.322 731.569 258.132

class 16 (304)
  means  7738.16 7072.68 13820.7
  stddev 395.955 666.663 231.408

class 17 (347)
  means  7746.65 7069.76 14024.2
  stddev 419.473 714.08 253.292

class 18 (370)
  means  7795.34 7136.14 14213.6
  stddev 415.393 728.25 257.516

class 19 (388)
  means  7852.95 7195.39 14393.8
  stddev 407.725 694.809 242.435

class 20 (386)
  means  7848.3 7164.33 14615.7
  stddev 426.924 699.799 252.618

class 21 (457)
  means  7831.97 7135.77 14839.7
  stddev 396.834 680.603 239.271

class 22 (467)
  means  7856.71 7176.37 15031.2
  stddev 410.951 720.848 252.258

class 23 (442)
  means  7909.95 7215.54 15231.5
  stddev 419.42 741.568 260.352

class 24 (416)
  means  7872.65 7160.56 15462.1
  stddev 407.189 709.617 247.081

class 25 (382)
  means  7906.73 7192.69 15657.8
  stddev 395.596 728.759 255.082

class 26 (364)
  means  7936.67 7231.03 15851.6
  stddev 463.817 851.91 293.729

class 27 (293)
  means  7939.82 7214.19 16069.6
  stddev 449.39 789.373 275.474

class 28 (224)
  means  7909.54 7154.11 16299.2
  stddev 477.154 792.009 279.773

class 29 (195)
```

```
  means  7962.14 7200.97 16495
  stddev 488.135 823.923 289.214

class 30 (157)
  means  7962.77 7248.13 16689.4
  stddev 532.029 969.357 333.743

class 31 (113)
  means  7963.89 7243.06 16898.2
  stddev 538.601 1023.86 348.68

class 32 (470)
  means  8069.63 7340.68 17905.4
  stddev 692.127 1205.82 1060.91

class distribution
        936        32         36         38         61
         60        64         85        102        105
        137       162        192        256        247
        304       347        370        388        386
        457       467        442        416        382
        364       293        224        195        157
        113       470

######## iteration 1 ###########
32 classes, 57.42% points stable
class distribution
        789       167         50         81         13
         55       105         93         65         88
        123        87        440        223        188
        221       436        255        492        335
        520       351        438        553        322
        269       229        438        133        104
        326       299

######## iteration 2 ###########
32 classes, 67.76% points stable
class distribution
        778       137         36        117         46
         58        91        114         53         81
        199        61        387        202        212
        258       512        249        368        386
        517       419        360        533        407
        185       220        432        184        136
        371       179

######## iteration 3 ###########
32 classes, 88.62% points stable
class distribution
        773       112         36        139         50
         51       101        114         62         91
        212        95        355        162        299
        261       490        293        244        459
        526       496        240        472        423
        171       265        402        286        113
        366       129

###################### CLASSES ######################
```

**32 classes, 88.62% points stable**

```
######## CLUSTER END (Tue Jan 28 15:23:56 2014) ########
```

*Note: for 32 clusters after 3$^{rd}$ iteration only class distribution process has become saturated.

**Number of Clusters: 64**

```
###################### CLUSTER (Tue Jan 28 16:22:05 2014)################
```

```
Location: UK_ESR
Mapset:   UKLU
Group:    G13@UKLU
Subgroup: S
Resolution: 30.00
Rows: 2975    Columns:4796 Cells:14268100

 UK13_B3E@UKLU
 UK13_B4E@UKLU
 UK13_B5E@UKLU
Result signature file: CLUSTER13_64TRY


Cluster parameters
 Number of initial classes:    64
 Minimum class size:           17
 Minimum class separation:     0.000000
 Percent convergence:          50.000000
 Maximum number of iterations: 30

 Row sampling interval:        29
 Col sampling interval:        47

Sample size: 8288 points

means and standard deviations for 3 bands

 means   7823.34 7078 13902
 stddev  481.87 764.521 3007.58


initial means for each band

class 1    7341.47 6313.48 10894.4
class 2    7356.77 6337.75 10989.9
class 3    7372.07 6362.02 11085.4
class 4    7387.36 6386.29 11180.9
class 5    7402.66 6410.56 11276.3
class 6    7417.96 6434.83 11371.8
class 7    7433.26 6459.1 11467.3
class 8    7448.55 6483.37 11562.8
class 9    7463.85 6507.64 11658.2
class 10   7479.15 6531.91 11753.7
class 11   7494.45 6556.19 11849.2
class 12   7509.74 6580.46 11944.7
class 13   7525.04 6604.73 12040.2
class 14   7540.34 6629 12135.6
class 15   7555.63 6653.27 12231.1
class 16   7570.93 6677.54 12326.6
class 17   7586.23 6701.81 12422.1
class 18   7601.53 6726.08 12517.6
class 19   7616.82 6750.35 12613
class 20   7632.12 6774.62 12708.5
class 21   7647.42 6798.89 12804
class 22   7662.72 6823.16 12899.5
class 23   7678.01 6847.43 12995
class 24   7693.31 6871.7 13090.4
class 25   7708.61 6895.97 13185.9
class 26   7723.91 6920.24 13281.4
class 27   7739.2 6944.51 13376.9
class 28   7754.5 6968.78 13472.3
class 29   7769.8 6993.05 13567.8
class 30   7785.1 7017.33 13663.3
class 31   7800.39 7041.6 13758.8
class 32   7815.69 7065.87 13854.3
class 33   7830.99 7090.14 13949.7
class 34   7846.29 7114.41 14045.2
class 35   7861.58 7138.68 14140.7
class 36   7876.88 7162.95 14236.2
class 37   7892.18 7187.22 14331.7
class 38   7907.48 7211.49 14427.1
```

```
class 39   7922.77 7235.76 14522.6
class 40   7938.07 7260.03 14618.1
class 41   7953.37 7284.3 14713.6
class 42   7968.67 7308.57 14809
class 43   7983.96 7332.84 14904.5
class 44   7999.26 7357.11 15000
class 45   8014.56 7381.38 15095.5
class 46   8029.86 7405.65 15191
class 47   8045.15 7429.92 15286.4
class 48   8060.45 7454.19 15381.9
class 49   8075.75 7478.47 15477.4
class 50   8091.05 7502.74 15572.9
class 51   8106.34 7527.01 15668.4
class 52   8121.64 7551.28 15763.8
class 53   8136.94 7575.55 15859.3
class 54   8152.24 7599.82 15954.8
class 55   8167.53 7624.09 16050.3
class 56   8182.83 7648.36 16145.8
class 57   8198.13 7672.63 16241.2
class 58   8213.43 7696.9 16336.7
class 59   8228.72 7721.17 16432.2
class 60   8244.02 7745.44 16527.7
class 61   8259.32 7769.71 16623.1
class 62   8274.62 7793.98 16718.6
class 63   8289.91 7818.25 16814.1
class 64   8305.21 7842.52 16909.6


class means/stddev for each band


class 1 (929)
  means  7874.09 6729.16 6602.69
  stddev 502.213 335.281 1599.03

class 2 (13)
  means  7170.92 6479 10990
  stddev 353.4 518.444 197.079

class 3 (14)
  means  7270.64 6532.36 11062.1
  stddev 335.261 485.92 187.243

class 4 (22)
  means  7333.82 6596.95 11135.1
  stddev 467.076 659.006 240.816

class 5 (17)
  means  7392.59 6694.41 11214.9
  stddev 425.479 551.575 198.843

class 6 (14)
  means  7378.21 6701 11298.4
  stddev 476.914 638.357 230.068

class 7 (23)
  means  7229.09 6416.26 11512.9
  stddev 234.87 229.929 103.836

class 8 (22)
  means  7397.73 6674.32 11530.9
  stddev 443.414 571.456 213.572

class 9 (32)
  means  7307.91 6584.22 11661.8
  stddev 385.48 564.103 213.866

class 10 (25)
  means  7519.2 6815.08 11675.6
  stddev 477.443 624.938 234.979

class 11 (33)
  means  7450.73 6744.73 11819.3
  stddev 424.332 608.447 224.924
```

```
class 12 (31)
  means  7458.48 6743.81 11916.5
  stddev 405.41 617.758 230.908

class 13 (32)
  means  7364.59 6666.09 12056.9
  stddev 375.059 649.503 216.445

class 14 (36)
  means  7462.72 6722.44 12129.4
  stddev 352.767 513.325 190.914

class 15 (34)
  means  7479.12 6800.38 12206.4
  stddev 383.014 661.103 232.184

class 16 (48)
  means  7450.62 6733.23 12330.2
  stddev 403.557 580.141 204.907

class 17 (52)
  means  7497.71 6778.9 12416.8
  stddev 413.662 608.805 219.291

class 18 (54)
  means  7580.8 6919.3 12478.1
  stddev 511.148 755.739 268.138

class 19 (53)
  means  7539.51 6822.96 12608.5
  stddev 575.575 794.854 295.965

class 20 (45)
  means  7502.82 6793.91 12727.1
  stddev 411.481 693.143 244.513

class 21 (73)
  means  7586.11 6928.49 12779.8
  stddev 442.866 772.369 262.961

class 22 (64)
  means  7536.25 6833.89 12912.7
  stddev 360.056 620.631 213.05

class 23 (90)
  means  7574.79 6918.61 12988.9
  stddev 500.904 824.202 288.4

class 24 (72)
  means  7659.96 7017.75 13058.4
  stddev 422.516 751.97 263.02

class 25 (91)
  means  7586.76 6874.14 13212.5
  stddev 359.166 618.802 218.315

class 26 (100)
  means  7598.85 6902.93 13304.7
  stddev 360.497 646.344 220.42

class 27 (119)
  means  7644.49 6981.06 13382.1
  stddev 402.236 741.102 256.063

class 28 (133)
  means  7771.98 7156.07 13422.3
  stddev 618.896 957.325 337.375

class 29 (131)
  means  7715.63 7050.08 13566.2
  stddev 466.221 754.913 268.254

class 30 (116)
```

```
  means  7761.53 7124.02 13639.7
  stddev 378.636 686.694 237.328

class 31 (137)
  means  7697.45 7017.95 13791.4
  stddev 384.565 613.533 215.242

class 32 (162)
  means  7772.22 7120.18 13848.8
  stddev 403.549 704.464 240.422

class 33 (163)
  means  7728.34 7038.99 13981
  stddev 422.146 711.181 250.43

class 34 (181)
  means  7766.01 7104.07 14059.3
  stddev 420.003 721.127 251.031

class 35 (167)
  means  7765.82 7094.85 14168.1
  stddev 453.222 749.516 265.612

class 36 (192)
  means  7816.03 7167.65 14246.3
  stddev 387.307 725.604 248.638

class 37 (205)
  means  7831.12 7152.5 14351.9
  stddev 376.643 615.891 216.677

class 38 (176)
  means  7866.8 7216.6 14431
  stddev 402.736 695.075 237.419

class 39 (196)
  means  7885.46 7234.91 14530.8
  stddev 498.176 826.193 287.948

class 40 (194)
  means  7831.25 7129.55 14668
  stddev 371.602 620.712 214.486

class 41 (204)
  means  7804.25 7106.02 14786.5
  stddev 393.783 666.325 229.059

class 42 (236)
  means  7849.79 7163.53 14864.3
  stddev 416.569 717.922 247.543

class 43 (242)
  means  7839.71 7153.93 14973.6
  stddev 432.963 760.046 261.842

class 44 (219)
  means  7861.04 7173.43 15068.9
  stddev 376.074 656.009 223.386

class 45 (212)
  means  7914.38 7220.38 15154.5
  stddev 396.959 694.8 237.734

class 46 (220)
  means  7906.23 7218.2 15261.4
  stddev 440.631 780.789 268.778

class 47 (201)
  means  7871.9 7169.2 15379.9
  stddev 403.841 704.736 242.908

class 48 (209)
  means  7849.63 7102.23 15504.7
  stddev 378.204 645.882 224.099
```

```
class 49 (202)
  means  7943.79 7282.11 15548.6
  stddev 413.168 793.356 269.127

class 50 (172)
  means  7886.73 7126.3 15699.9
  stddev 385.193 647.055 225.137

class 51 (196)
  means  7918.37 7231.45 15771.5
  stddev 472.598 848.001 290.574

class 52 (178)
  means  7942.7 7231.73 15871.1
  stddev 433.367 824.877 277.616

class 53 (158)
  means  7927.48 7204.43 15987.9
  stddev 442.141 808.693 275.846

class 54 (136)
  means  7974.41 7249.86 16073.7
  stddev 506.036 882.848 302.628

class 55 (127)
  means  7922.99 7184.68 16197.4
  stddev 470.231 770.462 268.592

class 56 (114)
  means  7885.46 7138.28 16324.4
  stddev 455.585 788.2 268.156

class 57 (96)
  means  7935.47 7149.94 16418.2
  stddev 372.081 666.127 227.722

class 58 (88)
  means  7958.12 7219.97 16496.9
  stddev 615.72 1007.72 352.157

class 59 (95)
  means  7935.85 7152.72 16619.4
  stddev 390.651 652.112 234.113

class 60 (78)
  means  8042.41 7409.65 16647.8
  stddev 636.687 1174.33 401.052

class 61 (66)
  means  7924.03 7162.85 16828.1
  stddev 406.237 783.786 258.592

class 62 (53)
  means  7919.66 7134.62 16938.8
  stddev 422.517 858.228 291.477

class 63 (61)
  means  7947.3 7231.57 17022.6
  stddev 575.214 1035.97 363.424

class 64 (434)
  means  8087.43 7365.5 17971.7
  stddev 712.314 1243.25 1076.64

class distribution
        929         13         14         22         17
         14         23         22         32         25
         33         31         32         36         34
         48         52         54         53         45
         73         64         90         72         91
        100        119        133        131        116
        137        162        163        181        167
        192        205        176        196        194
```

```
       204        236        242        219        212
       220        201        209        202        172
       196        178        158        136        127
       114         96         88         95         78
        66         53         61        434

######## iteration 1 ###########
64 classes, 40.26% points stable
class distribution
       789        147         14          4         27
         2         75          4         30         55
         5          8         96          2         11
        83         15         73          6        119
        20        113          9         55        145
       209         20        326         37         51
       221        108        286         28        221
       101         84        167        391        136
       471         94        173        105        230
        66         56        550        293        339
        33         58         88         92         63
       324         34         15        128        164
        37        264         65        253

######## iteration 2 ###########
64 classes, 68.50% points stable
class distribution
       778        121          6          6         32
         5         85         24         36         46
        15         11         72         18         25
        80         26         48         22         98
        31        102         48         65        129
       182         83        235         91         87
       168         66        253        149        224
       116        137        136        264        177
       328        229        189        146        165
       153        163        401        149        280
       126         65        143         88         98
       262         74         78        124        141
        92        215        131        151

#################### CLASSES ####################
59 classes, 68.50% points stable
######## CLUSTER END (Tue Jan 28 16:22:05 2014) ########
```

*Note: For 64 Clusters after 2nd iteration only class distribution has become saturated.

## NRSC colour codes for land use categories

| S.No. | lu-code | Description | COLOR-CODE | | | Symbol |
|---|---|---|---|---|---|---|
| | | | R | G | B | |
| 1 | 010000 | Built up land (Urban / Rural) | 255 | 0 | 0 | |
| 2 | 020101 | Kharif crop land | 255 | 255 | 0 | |
| 3 | 020102 | Rabi crop land | 220 | 220 | 0 | |
| 4 | 020103 | Zaid crop land | 145 | 150 | 0 | |
| 5 | 020104 | Double / triple crop land(Area sown more than once) | 255 | 165 | 0 | |
| 6 | 020201 | Current fallow land | 250 | 200 | 150 | |
| 7 | 020300 | Plantations / orchards | 25 | 215 | 190 | |
| 8 | 030100 | Evergreen / Semi-Evergreen forest | 0 | 160 | 0 | |
| 9 | 030200 | Deciduous forest | 0 | 255 | 0 | |
| 10 | 030400 | Shrub forest / degraded forest / forest scrub | 100 | 140 | 20 | |
| 11 | 030600 | Littoral / Swamp (Mangrove / Fresh water swamp) | 0 | 100 | 175 | |
| 12 | 040000 | Grassland & Grazing Land | 50 | 50 | 50 | |
| 13 | 050000 | Other Wastelands: Salt affected land/Sandy area/Mine dumps/Industrial waste/Dumps/Barren rock/Stony | 255 | 150 | 255 | |
| 14 | 050200 | Gullie/Ravines | 175 | 0 | 175 | |
| 15 | 050301 | Scrubland | 255 | 0 | 255 | |
| 16 | 070000 | Water bodies : Rivers/Streams/Lakes/Ponds/Reservoir/Tanks/Ash | 0 | 0 | 255 | |
| 17 | 080000 | Snow covered/Glacial area | 225 | 255 | 255 | |
| 18 | 090100 | Shifting cultivation areas | 180 | 100 | 50 | |

Figure 3.B. NRSC colour codes for land use classes

Source: https://www.nrsc.gov.in/sites/default/files/pdf/ebooks/Chap_2_LULC.pdf

## Accuracy Assessment

The accuracy assessment report for the year 2010 land use with Confusion Metrix (Error Matrix or Contingency Table) has been generated using the GRASS GIS-r.kappa command providing the base map and reference map. Collected reference data i.e., “ground truth from field estimates or toposheets”, has been compared with the classified image. Producer Accuracy, User Accuracy, Overall Accuracy and Kappa value were estimated across each land use type (Table 3A). The major diagonal of the error matrix represents the properly classified categories. The non-diagonal elements of the matrix represent errors of omission or commission.

Producer Accuracy (PA) with respect to each class is the ratio of correctly classified pixels to the respective row sum or the total number of reference sites for that class. The Producer's Accuracy is a complement of the Omission Error. Producer's Accuracy is also calculated as 100% - Omission Error.

$$PA = \frac{\text{Correctly classified pixels}}{Row\, Total\, of\, respective\, class} \times 100$$

User Accuracy (UA) with respect to each class is the ratio of total correctly classified pixels to the column total. The User's Accuracy is a complement of the Commission Error. User's Accuracy as 100% - Commission Error.

$$UA = \frac{\text{Correctly classified pixels}}{Columan\, Total\, of\, respective\, class} \times 100$$

Overall Accuracy (OA):

It is the ratio of the sum of the principal diagonal element of the matrix (DT) by the total sum of the matrix.

$$OA = \frac{DT}{TOTAL\, NUMBER\, OF\, PIXELS} \times 100$$

Here, DT is Principal Diagonal elements total, i.e., DT=D1+D2+D3

Kappa Statistics:

$$\kappa^{\wedge} = \frac{\text{Observed accuarcy} - \text{Chance agreement}}{1 - \text{Chance agreement}}$$

Kappa value ranges between -1 to 1. -1 represents no agreement, 0 represents a random agreement, 1 represents perfect agreement.

## ACCURACY ASSESSMENT

**LOCATION: UK_ESR Thu Dec 13 16:27:13 2012**

**MAPS: MAP1 = UTTARAKANNDA_DISTRICT_CLASSIFIED_2010@UKLU**

**MAP2 = UTTARAKANNDADISTRICTCLASSIFIED_REF_2010@UKLU**

Table 3A. Error matrix generated

**Error Matrix**

| MAP1 (BASE-CLASSIFIED) | | cat# | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | Row Sum |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| MAP2 (REFERENCE) | Built-up | 1 | 5105511 | 6216 | 4553892 | 369020 | 389077 | 42522 | 79762 | 139572 | 13179 | 84879 | 474 | 10784104 |
| | Water | 2 | 4797 | 10427173 | 622 | 8914 | 1788 | 1186 | 3869 | 737 | 2152 | 0 | 0 | 10451238 |
| | Crop land | 3 | 181148 | 446 | 63510261 | 307445 | 180919 | 296300 | 55653 | 394214 | 120524 | 68521 | 31592 | 65147023 |
| | Open fields | 4 | 42555 | 6269 | 431365 | 7844335 | 126596 | 89331 | 53599 | 87223 | 13 | 52850 | 1 | 8734137 |
| | Semi evergreen forest | 5 | 21531 | 20776 | 321130 | 114132 | 55896113 | 3567876 | 530587 | 948494 | 161803 | 1993450 | 22 | 63575914 |
| | Evergreen forest | 6 | 24532 | 5937 | 461966 | 80689 | 6834175 | 148262070 | 517854 | 657396 | 10788 | 1025914 | 3187 | 157884508 |
| | Scrub/grass land | 7 | 5740 | 4066 | 51885 | 32869 | 253960 | 196466 | 11629687 | 242802 | 40157 | 12781 | 2552 | 12472965 |
| | Acacia / Eucalyptus plantations | 8 | 18546 | 1251 | 475598 | 28628 | 1147273 | 634350 | 405992 | 47760337 | 728960 | 394312 | 18889 | 51614136 |
| | Teak/ Bamboo plantations | 9 | 6252 | 1482 | 530098 | 341 | 155898 | 28767 | 275883 | 1944674 | 11138358 | 69989 | 4410 | 14156152 |
| | Coconut _Areca nut plantations | 10 | 12492 | 17 | 111741 | 14885 | 355877 | 842411 | 14840 | 302777 | 5510 | 14838842 | 2740 | 16502132 |

| | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Dry deciduous forest | **11** | 314 | 0 | 31857 | 7 | 9 | 3166 | 2677 | 17951 | 5229 | 3081 | 421896 | 486187 |
| | | Column Sum | 5423418 | 10473633 | 70480415 | 8801265 | 65341685 | 153964445 | 13570403 | 52496177 | 12226673 | 18544619 | 485763 | 411808496 |

| Category | % Commission | % Omission | Estimated Kappa | PRODUCER'S ACCURACY | USER'S ACCURACY | OVERALL ACCURACY | KAPPA |
|---|---|---|---|---|---|---|---|
| Built-up | 39.66 | 5.86 | 0.47 | 60.34 | 94.14 | **91.51** | **0.89** |
| Water | 0.23 | 0.44 | 1.00 | 99.77 | 99.56 | | |
| Crop land | 2.51 | 9.89 | 0.97 | 97.49 | 90.11 | | |
| Open fields | 10.19 | 10.87 | 0.90 | 89.81 | 89.13 | | |
| Semi evergreen forest | 12.08 | 14.46 | 0.86 | 87.92 | 85.54 | | |
| Evergreen forest | 6.09 | 3.70 | 0.90 | 93.91 | 96.30 | | |
| Scrub/grass land | 6.76 | 14.30 | 0.93 | 93.24 | 85.70 | | |
| Acacia / Eucalyptus plantations | 7.47 | 9.02 | 0.91 | 92.53 | 90.98 | | |
| Teak/ Bamboo plantations | 21.32 | 8.90 | 0.78 | 78.68 | 91.10 | | |
| Coconut _Areca nut plantations | 10.08 | 19.98 | 0.89 | 89.92 | 80.02 | | |
| Dry deciduous forest | 13.22 | 13.15 | 0.87 | 86.78 | 86.85 | | |
| Obs Correct | | Total Obs | | % Observed Correct | | | |
| 376834583.00 | | 411808496.00 | | 91.51 | | | |

# Appendix 4: Forest Dwellers of Uttara Kannada

Table 4.A. Forest-dwelling communities (tribes) of Uttara Kannada district based on the field investigation and available literature

| | Forest Dwelling Communities | | | |
|---|---|---|---|---|
| Taluk | SIDDI | KUNABI | GONDA | GOULI |
| ANKOLA | ✓ | ✓ | | |
| BHATKAL | | | ✓ | ✓ |
| HONNAVAR | ✓ | | | |
| KARWAR | ✓ | ✓ | | ✓ |
| KUMTA | | | | |
| SIDDAPUR | | | ✓ | |
| SIRSI | ✓ | | | ✓ |
| SUPA | ✓ | | | ✓ |
| YELLAPURA | ✓ | ✓ | | |
| HALIYAL | ✓ | ✓ | | |
| MUNDGOD | ✓ | | | ✓ |

Halakki tribe person


Gouli tribes


Interacting with Siddis


Siddi Tribe –Yellapur Taluk


Kunabi tribe in Joida taluk


Interaction with farmers, District administration members

Figure 4.A. Interaction with the forest-dwelling communities