

Spatial modelling of land use dynamics and its impacts on plant resources and its ecosystem services in the Eastern Ghats, India

A Thesis submitted during the year 2021 to the University of Hyderabad in
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Centre of Earth, Ocean and Atmospheric Sciences, School of Physics

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I hereby declare that, this thesis entitled “***Spatial modelling of land use dynamics and its impacts on plant resources and its ecosystem services in the Eastern Ghats, India***” is the result of investigation carried out by me in the Centre for Earth, Ocean and Atmospheric Sciences (School of Physics), University of Hyderabad, India under the direct guidance and supervision of Profs. V. Chakravarthi, and P. S. Roy is a bonafide research work and free from plagiarism. I also declare that it has not been submitted previously, in part or in full to this University or any other University or Institute, for the award of any degree or diploma.

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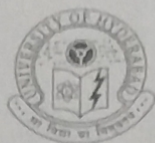
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Preface

The changes in land use and land cover (LULC) are one of the major driving factors for biodiversity loss and environmental degradation. Globally, about 40% of deforestation has been occurred in tropical and subtropical regions because of large-scale commercial agriculture. Increase in the human population, their demand for food, settlements, exploitation of economic resources and the development of infrastructures on different natural habitats lead to large scale landscape changes. In addition, indiscriminate deforestation has resulted in the shrinkage of species' habitats, fragmentation, edge changes and changes in community structure and composition; thereby, distressing the species distribution in many areas. Forest fragmentation can result in homogenization, human-wild life conflicts, reduction in habitat quality for forest-interior species, and increased susceptibility to predators, parasites, and invasive species. Thus, changes in landscape patterns would unambiguously influence the ecological process and the existence of species at greater extents.

Mapping of long term changes in LULC is important to study the linkages between habitats, climate, and species. However, acquiring detailed information of the species distribution based on the ground truth is often laborious and limited. In such a scenario, long-term global coverage of satellite remote sensing data could provide useful and vital information on wide range of scales in a consistent, borderless and repeatable manner. Furthermore, the Geographic Information System (GIS) provides an indispensable platform for data management, data integration, data visualization, data analysis, and retrieval of remote sensing data in a wide canvas.

The Eastern Ghats (EGs), located between 11°30' and 22°0' N latitudes and 76°50' and 86°30' E longitudes, are discontinuous chain of hill ranges running almost parallel to the east coast of India through the states of Odisha, Telangana, Andhra Pradesh, Karnataka and Tamil Nadu. They extend over a length of approximately 1750 km between the rivers of Mahanadi and Vaigai. The Eastern Ghats exhibit tropical climate and receives seasonal rainfall from both south-west and north-east monsoons. Evergreen, semi evergreen forests spread over in EGs in certain pockets and in the areas of high elevations. This forest cover is a repository for floral wealth, having more than 2600 species including angiosperms, gymnosperms, pteridosperms,

and pteridophytes. In addition, about 454 endemic species and 160 cultivated plant species are also available in this treasure.

However, the Eastern Ghats have experienced substantial LULC change and intensification of deforestation over the last few decades. The coupled impact of the changes in LULC and climate on species' distributions has not been studied/reported in Eastern Ghats in detail. The present research analyses the changes in habitat suitability of a selected group of RET and endemic species due to changes in LULC, climate and forest fragmentation. The satellite remote sensing, GIS technology along with a modeling strategy has been used to estimate the LULC change and habitat characteristics of selected plant groups in Eastern Ghats.

Land use and land cover (LULC) dynamics is known to have a direct impact on biodiversity, habitat, ecosystem services and integrity. The climate change, LULC dynamics and biotic response at ecosystem level are of great scientific research interest. The monitoring and mapping of distribution and habitat patterns of species play an important role in proposing new areas for conservation. To understand the driving processes and the impacts of LULC and climate change on the regional biodiversity, it is essential to quantify these impacts under different time scales viz., the past, present, and future, using an effective approach. Modeling is a robust method of analysing the potential impacts of changing LULC and climate on biodiversity, allowing the exploration of possible future states and consequences.

The aim of the present research is to understand the pattern, and the impacts of long-term Land Use/Land Cover change (LULCC) on the forest cover, plant resources and ecosystem services in the Eastern Ghats of India.

The objectives of the present research are to

- assess long-term (1920-2015) LULCC and its dynamics in the Eastern Ghats, followed by simulating future LULC (2025& 2050) based on the key physical and social drivers,
- assess the impact of LULCC on the landscape ecology of Eastern Ghats,
- analyse and simulate the impact of LULC and climate change on the habitat of selected plant species, and their distributions,
- document plant resource values and its ecosystem services,
- find out effective management strategies and conservation areas.

Data sets

Topographical maps of U.S. Army Map Service (1920), historical forest type maps of Census Commissioner for India (1940), and French Institute of Pondicherry (1960) have been used. The standard Level 1 multi-date multi-temporal Landsat images from the sensors viz; Multispectral Scanner System (MSS) (1975 and 1985), Thematic Mapper (TM) (1995 and 2005), Enhanced Thematic Mapper (ETM+) (2005) and Operational Land Imager (OLI) (2015) were also used in the study.

Socioeconomic data

The village and district population data of EGs for the years 2001 and 2011 were obtained from the Office of the Registrar General & Census Commissioner, India (<http://www.censusindia.gov.in>). Data relating to rivers, roads, rail networks, locations of villages and cities were accessed from the OpenStreetMap of India for the year 2015 (<https://www.openstreetmap.in>). Protected Area (PA) maps were collected from Wild Life Institute of India.

Topographic data

Digital Elevation Model (DEM) from the Shuttle Radar Topography Mission Digital Elevation Model (SRTM DEM; at 30m resolution) was used in the study. Other topographic proxies such as slope and aspect were derived from the SRTM DEM data in the ARC GIS 10.3 environment.

Soil data

ISRIC soil-type data at 250 m resolution for the year 2016 were downloaded for the Eastern Ghats region (<https://www.isric.org/explore/soilgrids>). In addition, the erosion, drainage, and flood capacity data of the region were obtained from the National Bureau of Soil Survey and Land Use Planning (NBSS&LUP) for the year 2005.

Plant species data

965 plant samples collected from 28 field plots during the fieldwork were used in the analysis together with the data obtained from the national-level project ‘Biodiversity Characterization at Landscape Level’. The sampled plant species were categorized as endemic or RET species according to the IUCN Red List. A total of 22 endemic and 28 RET species were found from 1598 species recorded from the ground-sampled points. The endemic species were recorded at 295 locations, and RET species at 799 locations, respectively.

Climate data:

Current and future bioclimatic variables of WorldClim Version 1.4 (<http://www.worldclim.org/>) were used in the analysis. IPCC AR5 scenarios (IPCC 2014) were used to simulate future trends. These scenarios include one stringent mitigation scenario (RCP2.6), two intermediate scenarios (RCP4.5 and RCP6.0), and one scenario with very high levels of greenhouse gas emissions (RCP8.5) (IPCC, 2014). Future climate projections from the output of 10 global climate models (GCMs) from the fifth phase of the Coupled Model Inter-comparison Project (CMIP5) (Collins et al., 2011) were used.

Methodology

Data preparation

The historical maps were geometrically corrected and the satellite images were pre-processed for suppressing the effects of the atmosphere and noise. The study area is then extracted from the multiple sensor scenes for each year by sub-setting. Finally all the subset images were mosaicked to obtain a single image of the study area. The satellite images and historical maps were brought into the projection WGS 84 Universal Transverse Mercator (UTM) Zone 44.

Classification scheme

USGS classification system was adopted for LULC classification. In the first stage, the Level II 21 land classes were derived from the satellite data viz, evergreen, semi-evergreen, dry evergreen, moist deciduous, dry deciduous, littoral and swamp forest/riverine, forest plantation, degraded forest, scrub land (open/closed), thorn forest, dry deciduous scrub, dry evergreen scrub, grassland, woodland, orchard, cropland, water bodies, permanent wetland, built up (both urban rural)/industries, barren land, mining. Later, 21 land classes were aggregated into six Level I land classes such as forest, scrub/grassland, agriculture, waterbody, built up, barren and uncultivable land.

Mapping of land classes

The mapping of land classes were carried out with the help of onscreen visual interpretation technique. The historical maps and satellite images of 1920, 1940, 1960 and 2015 were digitized separately to derive LULC maps for respective years. The 2015 forest type and LULC vector layer was overlaid on the 2005 satellite data and the polygons were edited for the

changed areas. Thus, the forest type vector map for year 2005 was finalised. The process is repeated for 1995, 1985 and 1975.

Assessment of forest cover change dynamics

The dynamics of forest cover change from 1920 to 2015 was assessed through a change matrix method. This was realized by comparing the number of pixels falling into each category of land class at one time period and the characteristics of the same pixels in the previous time period.

Accuracy assessment

Field sample points and additional points collected from Google Earth images were used to evaluate the classification accuracy of the constructed maps. A total of 2971 ground points in the proportion of land class area collected from field as well as from Google Earth images (CNES/Astrium) of 2015 were used to determine Level II LULC class. The field sample points 852 in number were used to evaluate the accuracy of Level II vegetation type map of 2005.

Landscape ecological analysis

Fragmentation of landscape were evaluated both spatially and statistically. The spatial analysis of forest fragmentation was carried out with 4 main categories namely, patch, edge, perforated, and core based on a specified edge width of 500 m. In addition, the following metrics were used to find out the intensity of forest fragmentation: Edge Density (ED), Number of Patches (NP), Total Edge Length (TEL), Largest Patch Index (LPI), Overall Core Area (OCA), Effective Mesh Size (EMS), Shannon Diversity Index, and Simpson Evenness Index.

Simulation of present and future potential plant species distributions

The present and future potential distributions of endemic and RET species were simulated using maximum entropy bioclimatic modeling technique (MaxEnt v3.3.3j). The model is executed at 1 km resolution with input data consisting of 799 records of RET species and 295 presence records of endemic species. The correlation between all the variables was checked prior to modelling. The model was set up in such a way that the effects of climate and LULC changes can be assessed separately. To achieve this, MaxEnt was run initially with climate variables (simulation I). Then it was run with climate, topographic, and edaphic variables (simulation II), after which it was run by integrating all the factors, such as climate, topographic, edaphic, and LULC variables (simulation III).

Estimation of degradation and species habitat loss risk

The risk of species habitat was analysed by posting the sampling points on different fragmentation levels of protected areas (PA) and outside the PA (OPA) of forest and scrub/grassland. Along with RET and endemic species the species with economic and medicinal values were also considered for the estimation. Further, the forest fragmentation maps of each year (1920 - 2015) were overlaid on habitat suitability maps of RET and endemic plant species groups for the estimation of habitat threat due to changes in landscape pattern.

LULC simulations

The Monte Carlo cellular automata (CA) based artificial neural network (ANN) was used for LULC simulations. The model uses raster LULC categories for two time periods, i.e., from the past to 2005 (t) and present to 2015 (t+1) and raster files of explanatory variables. The kappa statistics were used to validate the accuracy of the simulated LULC maps.

Assessment of plant ecosystem functions

Using the available plant species data, the benefits provided by each species (ecosystem functions) in the specific location were identified. This has been realized through interviewing forest officials and local people besides using the available literature. The status of the species namely local, regional and national endemism and vulnerability were recorded as per the Red Data Book of the International Union for Conservation of Nature (IUCN) and their importance were taken into account.

The research work presented in this thesis is organized into seven chapters as detailed below

Chapter 1 consists of general introduction briefing about the land system science and its challenges, causative effecting factors, and the role of earth observation in studying the land system change. This chapter also give a literature review about the historical background of land use land cover changes, the current and future trends of land use land cover changes in various parts of the globe. The research questions are also included.

Chapter 2 details about the study area including its geology, climatic conditions, vegetation types, biological diversity, agro ecological zones, soil characteristics, water resources and reservoirs, population and culture, and sacred groves.

Chapter 3 focuses on analysing the long-term land use land cover and its dynamics in the Eastern Ghats. The study reveals that, by and large, the Eastern Ghats have lost 15.83% of its

forest area over a span of ~100 years. For the study period from 1920 to 2015, it is estimated that about 7.92% of forest area was converted into agriculture, and up to 3.80% into scrub/grassland respectively. LULC simulations reveal an increase in built-up land from 3665.00 sq.km in 2015 to 3989.56 sq.km by 2050. There is a minor increase of 0.04% in the area under agriculture in 2050 when compared to 2015.

Chapter 4 deals with the landscape characterisation of the Eastern Ghats. It was found that the total number of forest patches have been increased from 1509 in 1920 to 9457 in 2015, core area has declined from 93461.05 sq.km in 1920 to 61262.11 sq.km in 2015, and edge length has increased to 2.20 sq.km in 2015 as compared to 0.82 sq.km in 1920.

In Chapter 5, assessment of the ecological importance of plant resources in the Eastern Ghats is presented. It has been demonstrated that Simlipal National Park, districts like Baleswar, and Gajapati of Odisha state, Srikakulam and Chittoor of Andhra Pradesh, Biligiriranga hills, Nagarjunasagar-Srisailem sanctuary, Gundla Brahmeswaram sanctuary, Nallamalai hill ranges, Sri Venkateswara sanctuary, Sathyamangalam wildlife sanctuary, Kalrayan and Kolli hills had highest number of species.

Chapter 6 discusses on how the changes in LULC and climate (for both current and future scenarios) affect the habitat suitability of endemic and RET species of the Eastern Ghats. The habitat simulations show that the combined effects of climate and land use change have a greater influence on the decline of potential distributions of species. Climate change and the prevailing rate of LULC change will reduce the extents of the habitats of endemic and RET species (~ 60% and ~ 40%, respectively). Habitat reduction has mainly occurred in the districts of Gajapati (Odisha state), Mahbubnagar (Telangana state) and also in Nallamalai and Kolli hill ranges. The species mostly spread across and the suitable habitats was found outside the ranges of protected areas.

The Chapter 7 epitomize the overall conclusions derived from the present research followed by the recommendations for preventing further decline in the extent and habitat quality of the RET and endemic species in the Eastern Ghats.

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List of abbreviations

LULC	: Land Use and Land Cover
MSS	: Multispectral Scanner
TM	: Thematic Mapper
ETM+	: Enhanced Thematic Mapper
LISS	: Linear Imaging Self-Scanning System
SPOT	: French: <i>Satellite Pour l'Observation de la Terre</i> means Satellite for observation of Earth
NASA	: National Aeronautics and Space Administration
USGS	: United States Geological Survey
LDCM	: Landsat Data Continuity Mission
OLI	: Operational Land Imager
NIR	: Near Infra-Red
ASTER	: The Advanced Spaceborne Thermal Emission and Reflection Radiometer
MODIS	: Moderate Resolution Imaging Spectroradiometer
TRMM	: Tropical Rainfall Measuring Mission
RISAT	: Radar Imaging Satellite
SRTM	: Shuttle Radar Topography Mission
SWIR	: Short-wave infrared
MWIR	: Middle Wavelength Infrared
LWIR	: Long-Wave Infrared
TIR	: Thermal Infrared
FIR	: Far infrared radiation
GIS	: Geographical Information Systems
Envisat	: Environmental Satellite
MERIS	: MEdium Resolution Imaging Spectrometer
IGBP	: International Geosphere Biosphere Programme
ESA	: European Space Agency
NOAA	: The National Oceanic and Atmospheric Administration
FAO	: Food and Agriculture Organization

JAXA	: Japan Aerospace Exploration Agency
PALSAR	: The Phased Array type L-band Synthetic Aperture Radar
WDPA	: The world data base on protected areas
GLCF	: The Global Land Cover Facility
UNEP	: The United Nations Environment Programme
HDP	: Human dimensions of global environmental change programme
BCE	: Before Common Era
A.D.	: Anno Domini
B.C.	: Before Christ
HYDE	: History Database of the Global Environment
ha	: Hectare
IMD	: India Meteorological Department
Sq.km	: Square Kilometre
IUCN	: International Union for Conservation of Nature
UNESCO	: The United Nations Educational, Scientific and Cultural Organization
AEZ	: Agro ecological zone
ANN	: Artificial Neural Network
EO	: Earth Observation
CA	: Cellular Automata
ISRIC	: International Soil Reference and Information Centre
ERDAS	: Earth Resources Data Analysis System
WGS	: World Geodetic System
UTM	: Universal Transverse Mercator
MOLUSCE	: Modules for Land Use Change Evaluation
RCP	: Representative Concentration Pathway
NTFP	: Nontimber forest products
MaxEnt	: Maximum entropy
RET	: Rare, Endangered, and Threatened
IPCC	: Intergovernmental Panel on Climate Change
SDM	: Species Distribution Modelling

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Chapter 1

Introduction

1.1 General

Land is the basic entity which connects all living organisms with the environment (“Reenberg, 2006; Verburg et al., 2015”). It provides food, shelter and other livable amenities to the organisms. The ever-increasing population, food demands, settlements and exploitation of economic resources are imposing immense pressure on the land leading to degradation of land across the globe (“Foley et al., 2005; FAO, 2016”). Forest ecosystems are one of the primary foci of land conversions. It is estimated that ~75% of the natural forest area around the world has been affected by human activities since the last ice age (“Ellis and Ramankutty, 2008”). More forest lands were cleared and croplands are being increased due to intensified irrigation activities. Globally, ~40 percent of deforestation has occurred in the tropics and subtropics due to large-scale commercial agriculture (“FAO, 2016”). Indiscriminate removal of forests has resulted in the shrinkage of species habitats, fragmentation, edge changes and changes in community structure and composition; thereby, distressing the species distribution in many areas (“Brearley, 2011”). Many countries across the globe require effective ways for timely assessment and monitoring of deforestation towards conservation and management strategies of forests. Knowing the land characteristics and its dynamics are very important for coining new management strategies.

1.2 The land system science and challenges

Land is a complicated system of many components and these components are always in interaction with each other in various ways. Due to the interrelation and occurrence of many environmental components the land system is considered as an important entity on the globe. “Turner et al. (2007)” defines the land system science as an “interdisciplinary field that seeks to understand the dynamics of land cover and land use as a coupled human–environment

system to address theory, concepts, models, and applications relevant to environmental and societal problems, including the intersection of the two". So, the human interactions to the environment acts a major function in the land systems at global as well as at local scales. The human–environment coupled interactions include the changes in land utility practices and the associated land cover changes ("Galvani et al., 2016"), changes in climate pattern along with its connections to greenhouse gas fluxes in terrestrial ecosystems ("Jia et al., 2019"), changes on agricultural system, food quality and production ("Porter et al., 2014"), production of biomass ("Gaba, 2018"), and the ecosystem functioning ("Stige and Kvile, 2017"). These interactions are influenced by the human behaviour, characteristics of policy makers and components of land over past and future ("Lambin et al., 2006"). The trends, practises and decisions of the past and present are playing important roles to the current state of the landscape, a heuristic analysis of changes in past and present land use helps to provide perceptions about processes like socio-economic and biophysical components which form shifts in land utilization ("Rounsevell et al., 2012").

The studies on land changes are largely concentrated towards mapping the land cover and associated conversions. The emergence of remote sensing technology with the availability of satellite images provides a hassle-free opportunity to map the LULC. Researchers are using satellite images from Landsat sensors viz, MSS, TM, ETM+, IRS LISS-I and LISS-III for studying LULC changes at global/national level. The availability of high-resolution satellite images in a wide spectrum (spectral resolution) is enabling us to access more products and services. High-resolution satellites like Rapid Eye, Geo eye, IKONOS, QuickBird, LISS- IV and WorldView have the capability to monitor biological diversity at species level and medium resolution sensors like TM, ETM+, LISS-II, LISS-III, SPOT etc. helps to monitor species at community level ("Secades et al., 2014").

1.3 Land use and land cover change and its drivers

Changes in LULC is an important factor for shaping the landscape and environmental conditions of a particular area. On the other hand, the land cover of an area is determined by the biophysical and socioeconomic components of that region ("Rounsevell et al., 2012"). Changes can happen due to natural and anthropogenic activities. In general, LULC changes are driven by proximate (direct) causes and underlying (in-direct) driving forces ("Duraismy et al., 2018"). The proximate causes are the anthropogenic activities in the local level, which

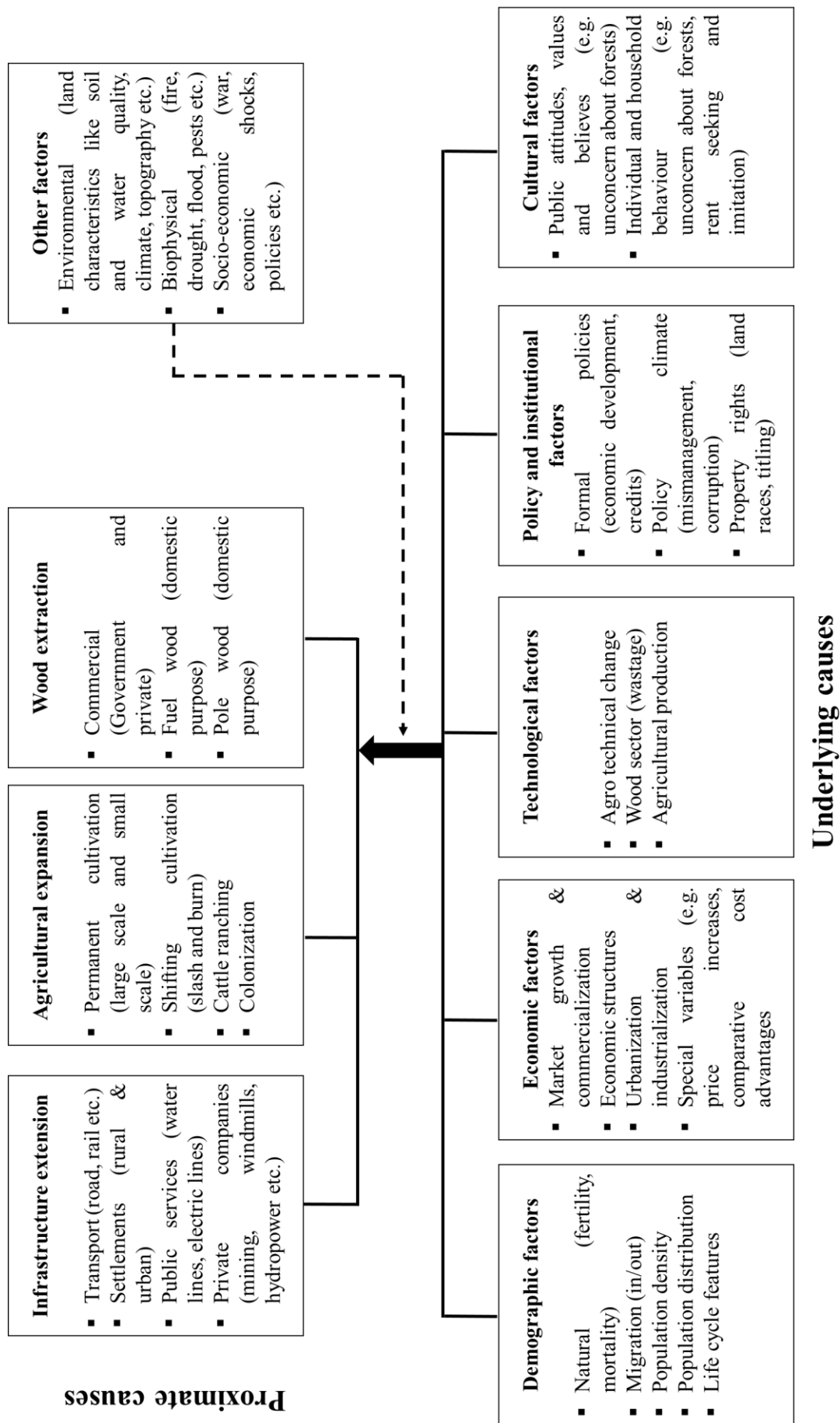


Figure 1.1. Causes and factors of LULC change, special concern with deforestation (“Geist and Lambin, 2002”)

create immediate actions. For example, expansion of agriculture can directly affect the degradation of forests. On the other hand, the elemental driving factors have an indirect impact from the local, national and global level. The underlying driving factors includes the economical, institutional, technological, cultural and demographic changes (“Geist and Lambin, 2002”). A frame work of LULC driving forces is shown in Fig 1.1.

1.4 The Earth observations for land system sciences

The emergence of remote sensing paves better options to gather information from even difficult terrains. Since the launch of Landsat-1 by the National Aeronautics and Space Administration (NASA) in 1972, satellite remote sensing is being extensively used for gathering synoptic information on the earth (“Roy et al., 2017”). At present remote sensing is playing important roles in different domains viz., forestry, agriculture, land management, infrastructure development, and biodiversity assessment etc. To gather information at the global, regional or local scales different resolutions are used. Different spatial and temporal scaling sensors (Fig. 1.2) which gather images at higher spatial resolution are useful for the studies at region level. The spatial, spectral, temporal resolutions and spatial extent of satellite sensors (“Turner et al., 2003; Wulder et al, 2004”) are important components for deciding the information gathered through remotely sensed data. The sensor characteristics such as spatial, spectral, temporal and radiometric resolutions determine the information that is produced from satellite remote sensing data (“Kerr and Ostrovsky, 2003”).

Landsat represents longest running program in the earth observation domain with a history of more than 40 years. Access to temporal data sets of global coverage and medium resolution attracted researchers. The historical collection of land imageries from 1972 is available from NASA and USGS portals. These historic data sets are potential sources to study the landscape of a particular region at different time scales. The derived LULC information is useful for monitoring the changes in the landscape for a certain time period. These LULC maps used for gathering information about the LULC pattern, civilization, habitat fragmentation, productivity, land utilization and anthropogenic threats. By knowing the long term LULC pattern one can find the major threats over the landscape and can do necessary management and conservation practices (“Wulder et al., 2004”). General LULC conversions such as conversion of forest land to agriculture and plantation, agricultural land to fallow and water resource can be detectable through Landsat. Currently, the Landsat Data Continuity Mission

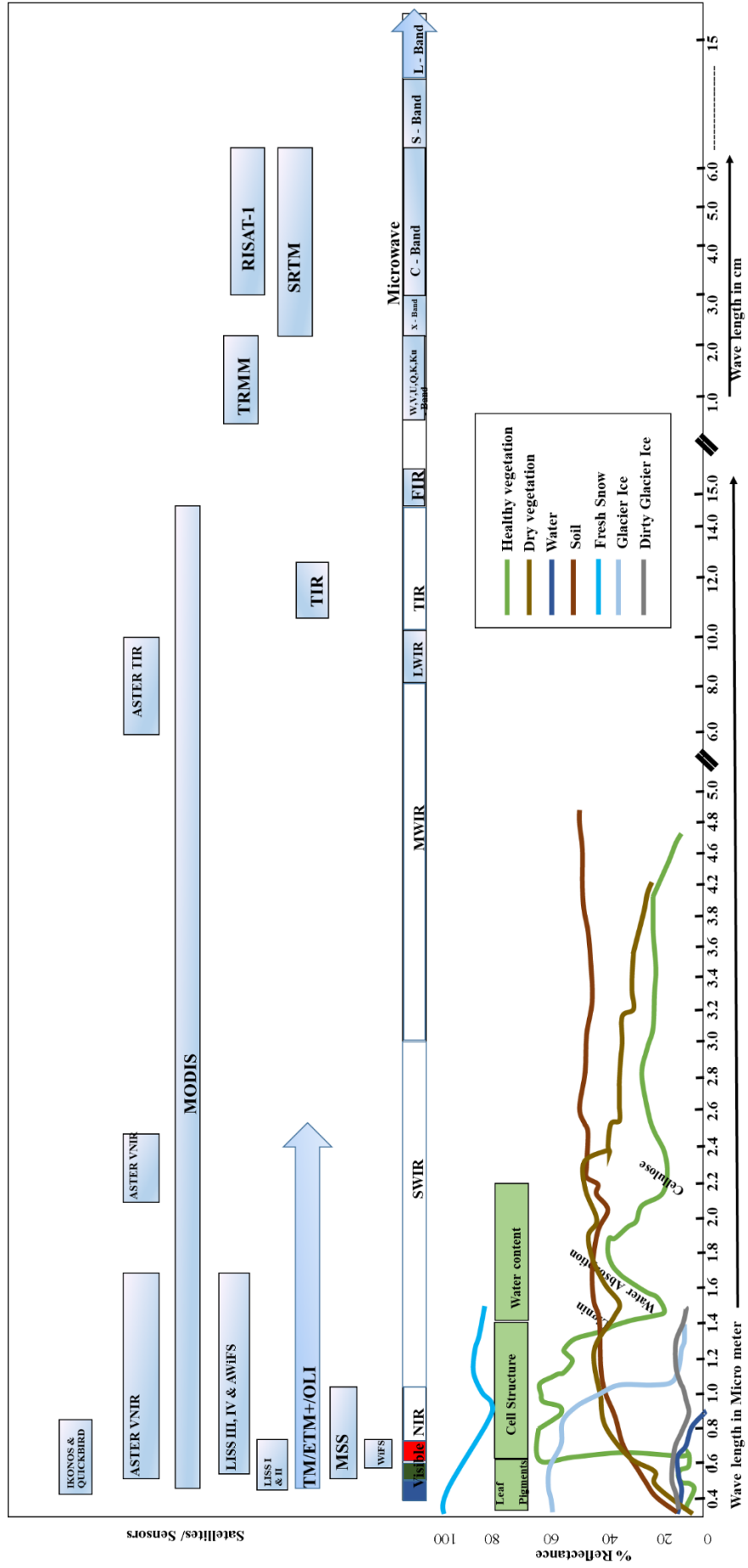


Figure 1.2. Spectral resolutions of common sensors along with spectral response curves of different materials.

(LDCM) Landsat 8 on board OLI sensor launched in early 2013 with 11 bands continuing the earth observation. The blue, green, red and NIR bands and its combinations giving different land features (“Willis, 2015”). Panchromatic and medium-scale aerial photographs has been utilised for many places since 1940.

In addition of these satellite images spatial data is also enriching the data by way of providing geographically linked or located data with the help of remote sensing and geographical information systems (GIS). These data sets are available in the form of categorical maps which are mainly derived with the help of semi-automated techniques of remote sensing images as main input.

The current popular global land cover maps are, GlobCover Land Cover version V2 (2012) of European Space Agency, which is providing up-to-date global land cover maps with ENVISAT MERIS time series images with 300m resolution; MODIS12C1 Land Cover Type Yearly L3 Global product with 500m to 0.05 arc degrees resolutions produced from MODIS Land cover maps (“Friedl et al., 2002”); 100m global land cover map of ESA prepared from the Proba-V remote sensing system in 2012; The National Oceanic and Atmospheric Administration (NOAA) global land cover map by the Suomi NPP satellite; FAO's ~1km Global Land Cover (ISO standard Land Cover Classification System) Network released in 2014 Global Land Cover-SHARE product (“Latham et al., 2014”); GlobeLand30 of National Geomatics Center of China produced 30m full coverage global land cover maps for the years 2000 and 2010 released in 2014 (www.globallandcover.com).

Among the Forest cover/vegetation type, Japan Aerospace Exploration Agency (JAXA) has released a global 25m-resolution PALSAR mosaic of forest/non-forest map (2007-2010) in the year 2014. “Hansen et al. (2013)” had prepared changes in forests throughout the globe in scales varying from local to global for the period 2000 to 2012 using Landsat 7 satellite images. The FAO's forest resource assessment provides the world's forest coverage at five to ten year intervals (“FRA, 2010”). The world data base on protected areas (WDPA) provides most comprehensive global database of PA (“<https://www.iucn.org/theme/protected-areas/our-work/parks-achieving-quality-and-effectiveness/world-database-protected-areas-wdpa>”).

The other popular global maps are GLCF water mask map at 250 m resolution (“Carroll et al., 2009”), The World Wild Life Fund's global grasslands (“Dixon et al., 2014”), The global distribution of coral reefs by UNEP World Conservation Monitoring Centre (UNEP-WCMC)

and the WorldFish Centre in collaboration with WRI (World Resources Institute) and TNC (The Nature Conservancy).

1.5 Review of literature

In a classic book ‘The origin of species’, Charles Darwin stated that “it is not the most intellectual of the species that survives; it is not the strongest that survives; but the species that survives is the one that is able best to adapt and adjust to the changing environment in which it finds itself” and human beings are one of the highly adaptive species on the Earth (“Megginson, 1963; Massey, 2013”). The productive strategies and social organization of human beings made them distinct from other animals (“Redman, 1999”). The human intelligence, socio-economic and technological development made significant degradation to the environment (“Erlandson et al., 2002”). In the past the Earth has undergone five major extinctions such as the Ordovician-Silurian (440 million years ago), Devonian (360 million years ago), Permian-Triassic (251.4 million years ago), Triassic-Jurassic (200 million years ago), and Cretaceous-Paleogene (65 million years ago), and these events had caused high impacts on the global environment and its species (“Raup, 1986”). “Barnosky et al. (2011)” opines that human activities could lead to the sixth mass extinction as human induced LULC changes trigger many natural processes including the climate change.

LULC studies are initiated on a variety of scales starting from global to local. The land cover changes can happen in two ways (“Meyer and Turner, 1992”). For example, conversion may take place from one type of land cover to another (for e.g., forest to agriculture) also it may take place within a specific land cover (for e.g., waste land to scrubland). Many programmes have been launched at the global level to study the changes in LULC, among which the International Geosphere-Biosphere Programme (IGBP) is one. The IGBP programme had started in 1987 with a mission “to coordinate international research on global-scale and regional-scale interactions between Earth's biological, chemical and physical processes and their interactions with human systems”. After making extensive studies on various pressures on earth systems due to the human activities this programme was ended in 2015. The human dimensions of global environmental change programme is yet other initiative to study LULC changes (“Hogan, 2007”).

1.5.1 Historical background of land use land cover change

Knowledge on the historical background of LULC changes is important for better understanding of sustainable land utilization, and to formulate new plans and policies for improving the land system. The changes in land cover were started ever since the evolution of human civilization. The studies on genomic sequencing show that the divergence of modern human beings was started about 350,000 to 260,000 years ago (Paleolithic age) in South Africa (“Schlebusch et al., 2017”). A few studies on the archaeological and fossil dating have reported the evolution of *Homo sapiens* about 160,000- 195,000 years ago in Ethiopia (“Tattersall, 2009”). During this period humans had used stone tools and had control over the fire. Hunting was the main livelihood activity of this age people. The control over fire by the people had modified the habitats, which ultimately had led to the extinction of mega fauna in Late Pleistocene (“Barnosky et al., 2004; Lambin et al., 2006; Moss and Kershaw, 2007”). There were strong evidences of human inhabitation and farming on tropical forests which started thousands of years ago (for e.g., in Africa around c. 200000, Java c. 125000, China c.100000, Philippines c. 60000, Borneo and Melanesia c. 45000 years, South Asia c. 36000, South America c. 13000) (“Roberts et al., 2017”).

The early human civilization had started during the Neolithic age (~10,000 BCE). The people began to grow plants and animals for food then started settledown in permanent places (“Lambin et al., 2006”). The agricultural revolution was first started around 10,000 B.C. in the Fertile Crescent Levant (now Lebanon) region of the Middle East, Western Asia (“History.com Editors”). Eventually it has spread across various regions of the globe viz, Mesopotamia, China, Eastern U.S., New Guinea, the Sahel, Mesoamerica and the Andes. The people in different regions of the globe started converting forests, river valleys, hills, woodlands and grasslands for cultivation, and for cattle grazing (“Goldewijk and Ramankutty, 2009”). The fossil pollen studies from the Near East (Middle East) reveals that natural vegetation deterioration in this region was mainly due to the increase of farming lands, wood exploitation and the population. This activity had started in the Neolithic and developed throughout the Bronze Age (“Cordova, 2005”). Wood exploitation which was started between 12,500- and 9,000-years B.C. due to forest clearing for agricultural activities in the Pre-Pottery Neolithic period (“Yasuda, et al., 2000”) had resulted in deforestation in many parts such as Ghab Valley, Lebanese mountains, Mount Hermon, and the Palestinian highlands. One of the Neolithic sites of Ain Ghazal in central Jordan in Near East around 6000 B.C was abandoned due to the degradation of fragile ecosystem (“Rollefson et al., 1992”).

The impacts of ancient civilizations to the environment through anthropogenic deterioration has led to the failure of ancient civilizations such as Maya and Indus Valley (“Redman, 1999; Lambin et al., 2006”). “Anselmetti et al. (2007)” found that the Maya civilization has changed the soil erosion rates of Lake Salpetén for the past ~6000 years in the tropical lowlands of northern Guatemala. “Emery (2007)” reported significant reduction in animal population in Maya civilization because of hunting and forest clearance. “Fisher et al. (2003) and Beach et al. (2015)” reported about the deforestation and degradation of wetlands in Maya civilization between 3000 to 1000 B.C. due to the increased population and agricultural activities. The large-scale landscape modifications are also reported in the Amazon region due to crop cultivation by ancient humans in the past 6,000 years (“Bush et al., 1989; Heckenberger, et al., 2008; Schaaf et al., 2012; Bush, et al., 2016; McMichael et al., 2017”). The pollen records from Yucatán Peninsula of Mexico reveals the alterations of landscape due to human activities about 3300-4000 years back (“Islebe et al., 2018”).

The first farming in South Asia began at Mehrgarh, in Baluchistan, during the New Stone Age between 11,000 B.C. to ~3000 B.C. (“Gangal et al., 2014”). The Indus Civilization was the biggest urban culture during the period 2600 B.C. to 1900 B.C., which had resulted thousands of Indus settlements covering 800,000 km² area. Those areas are now in Pakistan and north-western India with a population of around 1 million people (“Robinson, 2015”). Mohenjo Daro and Harappa were the two big cities/settlements of Indus Civilization (“Possehl, 1997; Avari, 2007”). During the Vedic and post-Vedic era of 2000 B.C. to 300 B.C., the Indo-Aryans had expanded from Punjab to Ganga basin by cutting down the forests for agriculture (“Avari, 2007”).

“Li et al. (2006)” recorded woodland and steppe vegetation changes due to agricultural practices in Western Liaohe River Basin, one of the cradles of ancient (~5400 B.C) Chinese civilization in north-eastern China. “Bennet et al. (1992)” had recorded changes in tree cover and replacement of herb and fern communities by plants of heathland and mires in the Catta Ness, Lunnasting, Shetland during 7500 to 5400. “Kouki (2009)”, had studied the settlement and land-use change in the hinterland of the ancient city of Petra, southern Jordan from ~300 B.C. until ~700 A.D., and concluded that large expansion of settlement and agriculture led to the land use change. The literatures of Plato (428/427-348/347 B.C.) and Aristotle (384-322 B.C.) also reported primary forests degradation in the Greece around 2500 B.C. (“Lambin et al. 2006”).

Human population growth is the major driving force for the global change over the time (“Goldewijk et al., 2011”). Even though people started domestication of plants and animals during the end of Pleistocene (Neolithic period), the population thence was mere 6 million (“Goldewijk et al., 2011”). “Goldewijk et al. (2009, 2011)” have estimated the growth in global population since 10,000 B.C. The population was around 2 million in 10,000 B.C., 18 million in 5000 B.C., 188 million in A.D. 1, 210 million in A.D. 500, 555 million in A.D. 1600, 1000 million in A.D. 1800, 1658 million in A.D. 1900, 2520 million in A.D. 1950, 3681 million in A.D. 1970, 6096 million in A.D. 2000, and 7700 million in 2019 (“<https://www.worldometers.info/world-population/>”) (Fig. 1.3).

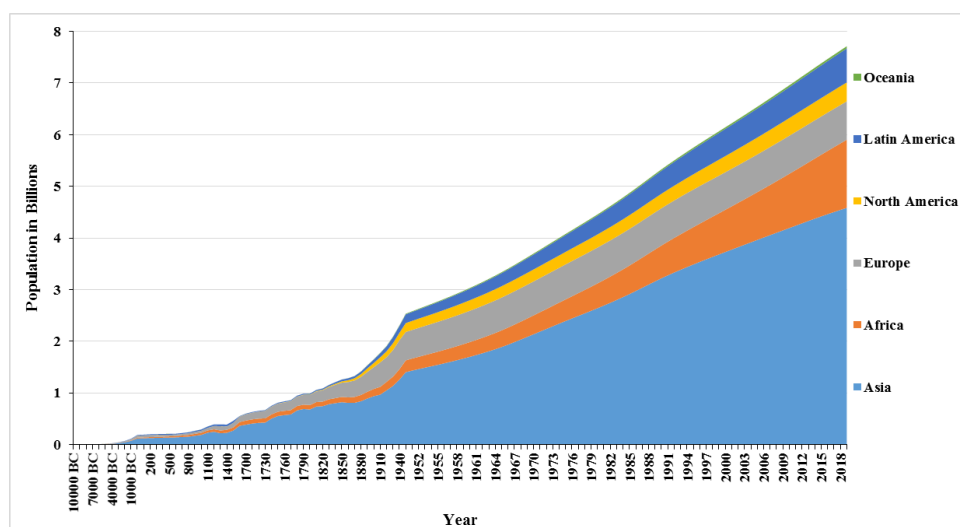


Figure 1.3. Region wise global population, since 10000 B.C. (“Goldewijk et al. 2009, 2011; HYDE, 2016; UN, 2017”)

1.5.2 Current trends of global LULC change

A noticeable increase in land utilization and LULC change has started from 1700s due to the advancement in Industrial revolution and globalization (“Goldewijk and Ramankutty, 2009”). The land transformation for agricultural activities has resulted in the decline of forest cover. The increase in population and technological improvement in the agricultural sector in the form of mechanization, introduction of chemical fertilizers, irrigation techniques and Green revolution have increased the agricultural production drastically after 1700s.

The global agricultural area has increased from ~0.001 million km² in 8000 B.C. to 0.008 million km² in 1600, and now the world agricultural area is ~48 million km² (combined land area under cropland and grazing land) in 2016 (“FAO, 2016; Goldewijk et al., 2017”) (Fig 1.4). The cropland alone has increased from 0.3 million km² in 5000 B.C. to 1.3 million km² in A.D.

1, 2.3 million km² in A.D. 1500, 8.5 million km² in A.D. 1900, and now it is ~16 million km² in 2016 (“FAO, 2016; Goldewijk et al., 2017”) (Fig 1.5). Similarly, the grazing/pasture land has increased from ~0.003 million km² in 5000 B.C. to 1.1 in A.D. 1, 2.2 million km² in A.D. 1500, 12.9 million km² in A.D. 1900, and 34 million km² in 2016 (“FAO, 2016, Goldewijk et al., 2017”) (Fig 1.6).

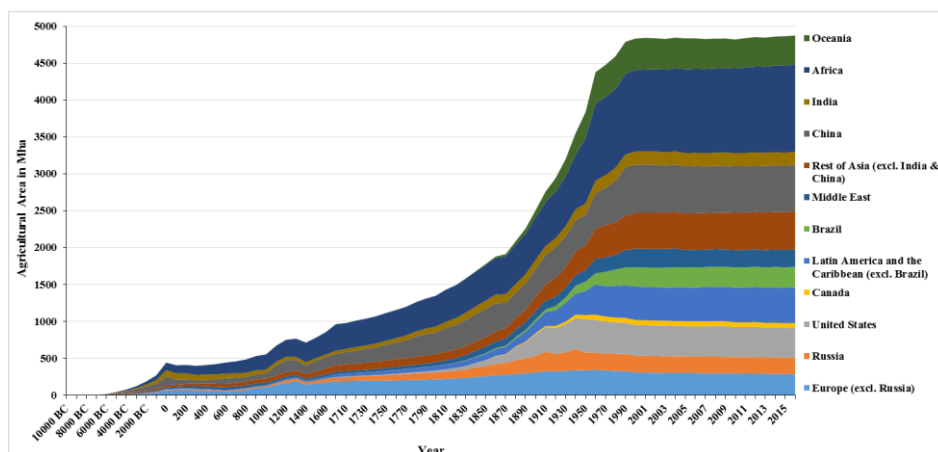


Figure 1.4. Region wise global total land use for agriculture, measured combination of land for cropland and grazing in hectares (“Goldewijk et al., 2017”; <https://themasites.pbl.nl/tridion/en/themasites/hyde/>)

On the other hand, the global forest area was reduced from ~53 million km² in 1700 (“Lambin et al., 2006”) to ~41 million km² in 1990, 39 million km² in 2015 (“FAO, 2016”) (Fig 1.7). The savannas and grassland area has shown a decrease from 30-32 million km² in 1990 to 12-23 million km² in 2015 (“Lambin et al., 2006; FAO, 2016”). The deforestation and agricultural activities in the forested areas have led to soil erosion, sedimentation, extinction of biological diversity and land degradation in many parts of the globe (“Hughes, 2017”).

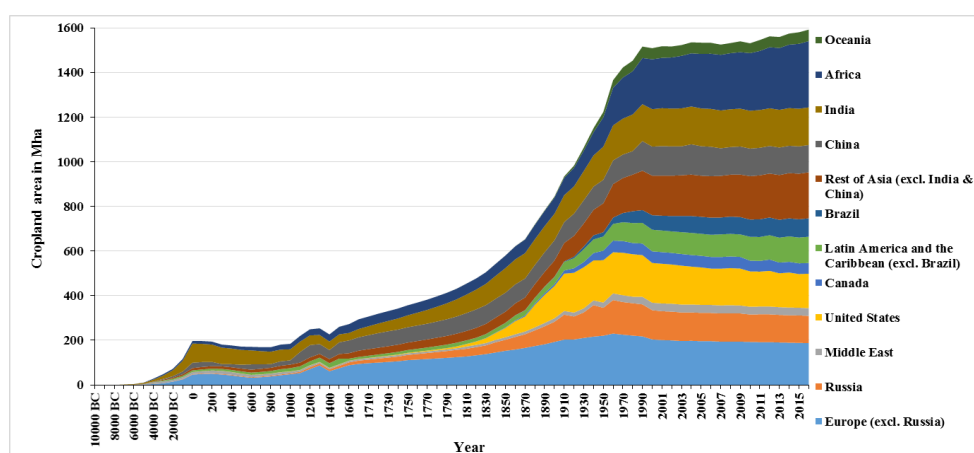


Figure 1.5. Region wise global total cropland area in hectares (“Goldewijk et al., 2017”, <https://themasites.pbl.nl/tridion/en/themasites/hyde/>)

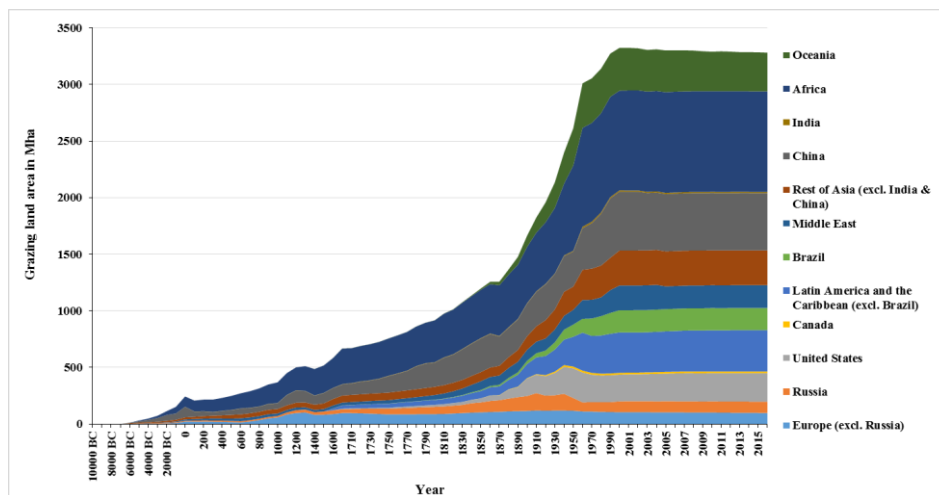


Figure 1.6. Region wise global total land used for grazing in hectares (“Goldewijk et al., 2017” <https://themasites.pbl.nl/tridion/en/themasites/hyde/>”).

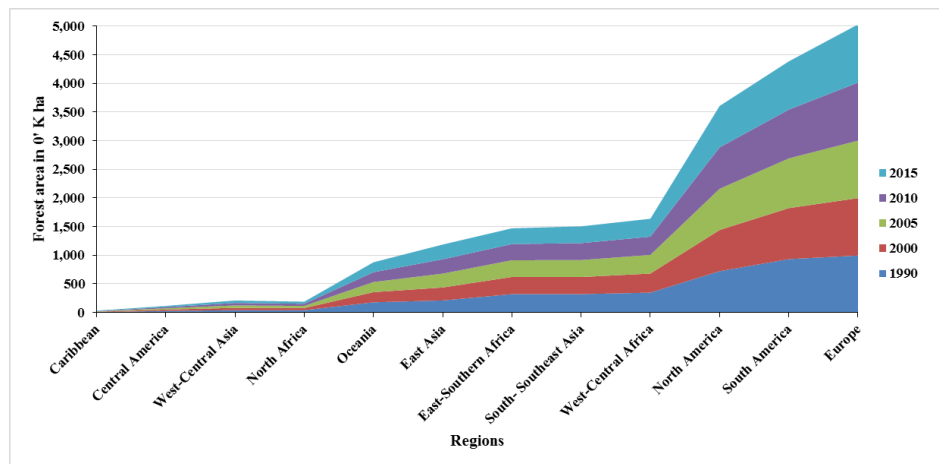


Figure 1.7. Changes in forest area in different regions of the world from 1990-2015 (“FAO, 2016”).

Agricultural intensification is one of the pivotal factors for many environmental problems viz., habitat destruction, loss of biological diversity, climate change, and degradation of land as well as freshwater (“Foley et al., 2011”). It is to note that about 38% of the earth's land surface is under cultivable category, and globally many natural ecosystems are cleared or converted for the agriculture activity (for e.g., grasslands 70%, savanna 50%, temperate deciduous forest 45%, and tropical forests 27%) (“Ramankutty et al., 2008; Foley et al., 2011”). Clearing of tropical forests can cause increase in 12% of greenhouse gas emissions (“Bonan, 2008; van der Werf et al., 2009”), losses of biodiversity (“Giam, 2017”) and ecosystem services (“Foley et al., 2007”), water degradation (“Haigh et al., 2004”), soil erosion and degradation (“Lal,

1996”), increased energy use (“Bawa and Dayanandan, 1997”), and widespread pollution (“Keller et al., 1991”).

Along with industrial revolution, the European colonization has accelerated the cropland expansion in various regions of the globe. For e.g., during 1700s about 2-3% of the global land surface was under cultivation and the major cultivated areas were concentrated in the Europe, Indo- Gangetic Plains, Eastern China, and Africa. After the European colonization, the settlement and cropland expansion were increased very rapidly in North America, Latin America, South Africa, and the Former Soviet Union and continued till the 20th century (“Lambin et al., 2006”). During 1600-1850, colonization of Europeans to other parts of the world have influenced the global economy, natural resources, settlements, developments and the LULC. They have exploited the primary forests of Asiatic Russia and North America for their economic development. In the 19th and early 20th century large areas of land in the Asia and Latin America have been used for timber extraction, farming and pasture. Moreover, Europeans have encouraged the local people to clear natural forests to grow rubber (Malaysia), cacao (Africa), tea (India), coffee (Brazil), and bananas (Central America) (“Goldewijk and Ramankutty, 2009”). In Brazil, the deforestation process was started in the 16th century after the European colonization by the way of agricultural intensification, mining, and coffee (during 1830’s) plantations (“Richards, 1984”). Between 1850 and 1985, around 370 million hectares (~28 percent) of forest in Latin America was converted into other land classes (“Houghton et al., 1991”). About 44% of the forest reduction was happened due to the pasture expansion, croplands have contributed to 25%, degraded lands to 20% and shifting cultivation to 10% (“Grigg, 1987”). During 1870s and 1880s substantial agricultural settlements have initiated in the Great Plains and the Midwest by replacing huge acres of grasslands. The Golden Age of American Agriculture is known as the era from 1898 to 1914. Different land acts (for e.g., Homestead Act of 1862) and infrastructure developments in the early 1800s had led to the rapid increase in settlements in North America. Early 20th century has witnessed the abandonment of croplands and regrowth of forests in parts of eastern United States of America.

The high demand of fodder and fuel has eventually accelerated the rate of deforestation in different regions for example in Europe and China. Between 7000 B.C. and 5500 B.C the agricultural revolution of Middle East spread to the Europe as well. This along with the population growth (18 M in ca. A.D. 600, to 39 M in A.D. 1000, to 76 M in the early 13th century) has caused large scale deforestation. In Levant and Mediterranean primary forests are removed for mining, military activities and settlements (“Goldewijk and Ramankutty, 2009”).

The history of land conversions in Australia had started with the arrival of European settlers in 1788. The land modification was started with cattle ranching and then the cropland expansion at the expense of eucalyptus forests in different regions of the country.

In Sub-Saharan Africa, European colonization had introduced changes between 1850 and 1900, which had caused rapid expansion of cropland and population. After the Second World War, the Sub-Saharan Africa had faced rapid increase in forest cover and subsequent reductions due to increase in population and livestock. A reduction from 735 Mha in 1961 to 713 Mha in 1994 of forest/woodland area was caused by cropland expansion, illicit and damaging logging activities, overgrazing, and droughts (“Goldewijk and Ramankutty, 2009”).

Agriculture activity had started in the central and northern parts of the Yellow River in China, along with Mesopotamia, as early as 10000 years ago. The studies of “Liu and Tian (2010)” show that before 1700s around 10.1% (~95 Mha) of the total land area was under cropland and 1.6 Mha under the settlement. During this time around 70.4 Mha of forest/woodland and 24.5 Mha of non-forest land were converted to cropland in China. Between 1700 and 2005 about 38.4 Mha of forest cover (21.8%) was lost, grassland and shrub area was decreased by 15.0 Mha and 3.6 Mha, whereas cropland was increased by 39.7 Mha (41.8%), urban land by 17.1 Mha. Recent studies (“WB, 2019”) show that the cropland and forest areas in China cover nearly 122 Mha and 20.98 Mha, respectively.

In most of the Asian countries (like India, Sri Lanka, Bangladesh, Myanmar, Thailand, Laos, Cambodia, Vietnam, Malaysia, Brunei, Singapore, Indonesia and the Philippines) records of LULC change are available since 1880 (“Richards and Flint, 1994”). According to “Richards and Flint (1994)” the forest/woodland (and wetlands as a whole) was decreased by 131 Mha over a span of 100 years (1880-1980). At the same time the agricultural land had risen by 106 Mha. This shows that the forest cover (81%) and wetlands were converted or used for agricultural purpose. Along with the agricultural expansion and timber extraction, collection of firewood, fodder and forest products also had contributed to deforestation. In Malaysia, the agricultural land became almost three times during 1880-1980 showing an increase of 1202% in the plantation. Also, a large portion of wetlands ~40% were converted into other land-use classes. In the 19th century, British people have introduced the rubber and oil palm plantations in the croplands (80%) of Peninsular Malaysia. Ultimately, in 1961 Malaysia became the world's biggest oil palm producer (“FAO 2006”). A significant increase in agricultural land from 21% in 1966 to 39% in 1982 was reported. Subsequently, forest cover was reduced from 73% -

~51% in early 1950s to 1982 (“Brookfield et al. 1990”). In 2015, cropland area was nearly 86270 km² and that of forest was 222091.9 km² in Malaysia (“WB, 2019”).

The countries such as India, Bangladesh and Sri Lanka have recorded a loss of ~40% of forest cover during 1880-1980 due to conversion of forest to cultivated area (40% of 44 Mha), livestock (108% increase), and population explosion (210%). The rise in population and simultaneous demand for food requirement had resulted in the increase of cultivable land. The world wars were also responsible for forest degradation in India to meet wartime needs. Overgrazing of livestock was also another reason attributed to the reduction in the natural forest extent. Even though forest protection laws and acts have been enforced (for e.g., the Indian Forest Act of 1878), overexploitation of natural vegetation is still continuing for agriculture and other activities. The settled cultivation in India had begun around 7000 years ago in the Indo-Gangetic Plain. In early 1850s large scale land conversions have started due to the implementation of irrigation projects. Further, in the late 19th century livestock-based products shoot the world economic regime. Several hectares of natural forests, grasslands, scrublands were destroyed for cattle grazing (“Richards, 1984”). During the 20th century, India has undergone significant LULC transformation owing to high population growth (from 200M to 1200M according to “Richards and Flint, 1994; DES, 2010”) and other economic developments. “Richards and Flint (1994)” had noted a decrease of 19 Mha in the forest cover, and an increase of 20 Mha in the cropland area during 1880-1950. On the other hand, “Tian et al. (2014)” reported that the forest cover has decreased by 26 Mha, cropland area has increased by 48 Mha, whereas grass/shrub lands decreased by 20 Mha during 1880-2010. “Tian et al. (2014)” also have reported that the cropland expansion was the major reason for deforestation in different regions of the country for example in the central east and southern areas.

Estimates indicate that between 1950 and 1980, more forests were cleared as compared to the 18th and 19th centuries. Since 1700, the forest cover was declined by 20% whereas the cropland area has increased by four times (“Goldewijk and Ramankutty, 2009”). “Ellis et al. (2010)” have observed the anthropogenic transformations of biomes from 1700 to 2000 and found that about 95% of the globe was in wild lands and semi-natural human biome in 1700. By 2000, 55% of earth’s ice-free land was converted into rangelands, croplands, villages and densely populated human biome, and <45% of the terrestrial biosphere remains for wild and semi natural. When compared to the changes occurred during 1700-1800 the transformations got increased in the 20th century. During 1700s half of world population resided in semi natural lands. But in 2000s only 4% population reside in the semi natural lands and more than half of

the population was concentrated in the villages, and now half of the population live in cities (“UNFPA, 2007”).

1.5.3 Future trends of global LULC

The rise in population is figured as the most common driver for land use change in future. UN population projections show a growth of 1.4 billion population in 2050 under different projection scenarios viz, Low, Medium and High projections (“UN, 2009”) (Fig. 1.8). As per Medium Variant estimate, the world population is projected to high at 9.4 billion by about 2075, beyond which it declines to 9.2 billion by 2100. This rise in population increases per capita production of the world by about 22 percent.

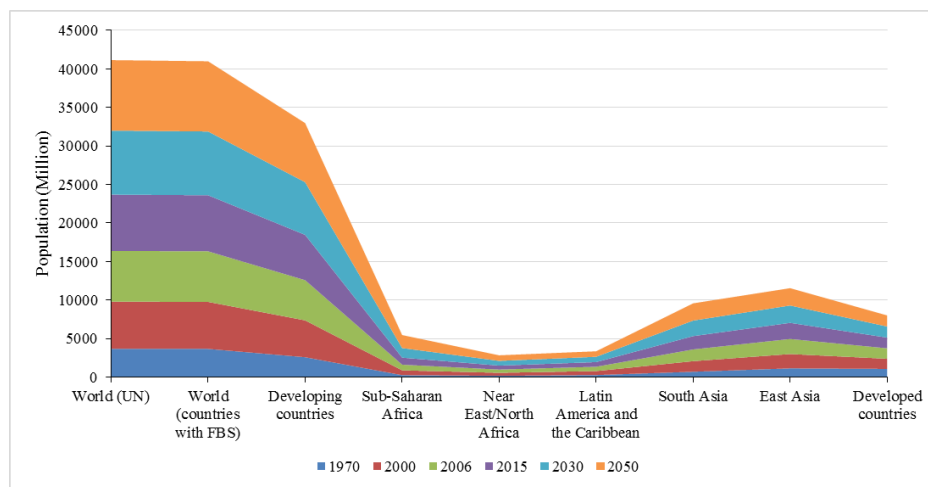


Figure 1.8. World and countrywide projected population (“UN, 2009”).

The FAO projections show that the croplands are expected to grow by 7% worldwide by 2030 (“Alexandratos and Bruinsma, 2012”) (Fig 1.9). “D’Amour et al. (2017)” reported an expansion in urban area with the loss of 1.8-2.4% croplands by 2030. GLUDM predicted an increase of 18% global agricultural land between 2005 and 2050 (“Haney and Cohen, 2015”). According to FAO predictions till 2050 the global arable land will grow but the rate of expansion will be at a pace which is slower than over the past 50 years (“Ritchie and Roser, 2020”) (Fig 1.10). On the other hand, global forest area projections show decrease in overall area from 0.13% per year in 2000 to 0.06% per year by 2030 (“d’Annunzio et al., 2015”) (Fig 1.11). Cropland expansion and urbanization are the top two drivers for forest cover loss (“Alexandratos and Bruinsma, 2012”).

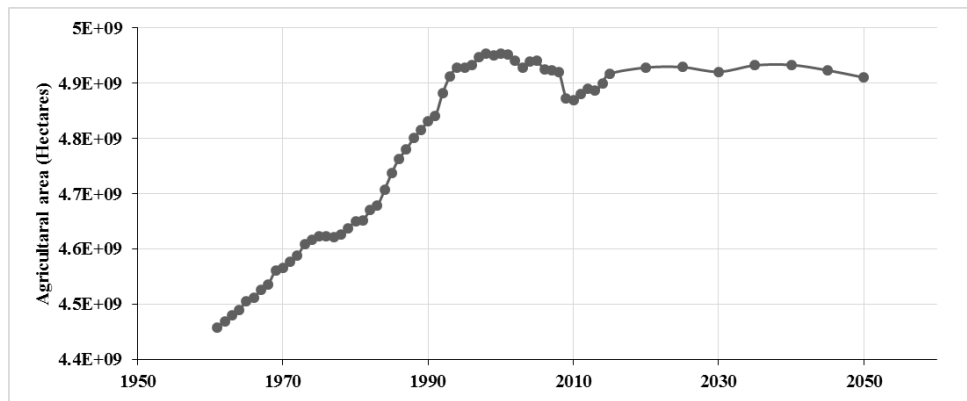


Figure 1.9. Measured and projected global agricultural land area (Alexandratos and Bruinsma, 2012)

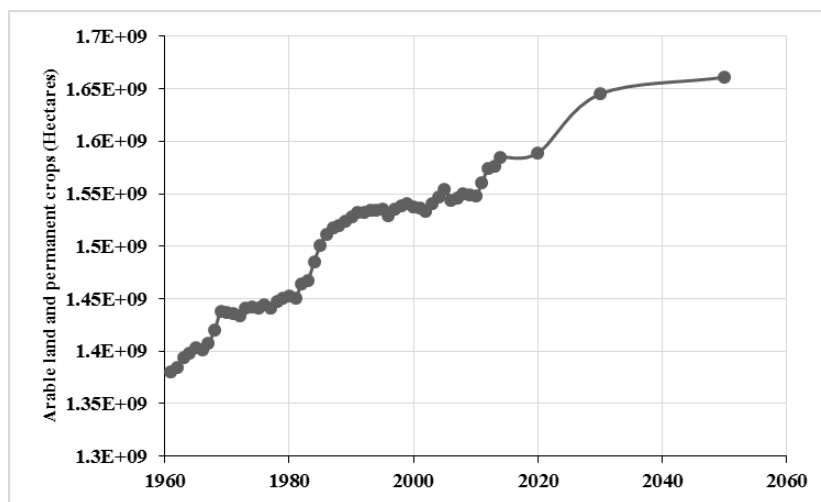


Figure 1.10. Measured and projected global arable land and permanent crops ("Ritchie and Roser, 2020").

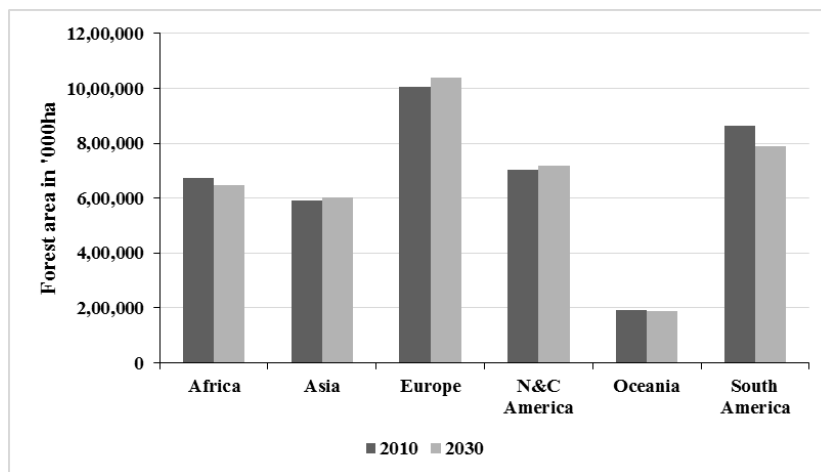


Figure 1.11. Projected global forest area, region wise ("d'Annunzio et al., 2015")

It is reported that the LULC change caused by anthropogenic activities have the capacity to alter even the rainfall and temperature patterns (“Luyssaert et al., 2014”). Therefore, mapping of long-term changes in LULC is important to study the linkage between habitats, climate, and species. However, acquiring detailed information of the land based on ground surveys is often laborious and herculean task. In such scenarios, long-term global coverage of satellite remote sensing data could provide useful and vital information on a wide range of scales in a consistent, borderless and repeatable manner. Satellite remote sensing technology has provided a new dimension to build the land change processes in varying temporal intervals at different resolutions (“Singh et al., 2010”). Furthermore, the GIS provides an indispensable platform for data management, data integration, data visualization, data analysis, and retrieval of remote sensing data in a wide canvas (“Goodchild, 2009”).

1.6 Statement of purpose

Land is one of the basic components of life. As it depends on many other components viz, soil, climate, biogeochemical cycles etc., the variations in land cover will cause many physical changes in the environment. As most of the changes are anthropogenic, the land use changes are old as humankind itself. The human needs for food and shelter impose huge pressure on land. Now-a-days researchers are exploring LULC changes with the help of remote sensing and geographic information system. Remote sensing plays an important role in variety of domains viz., forestry, agriculture, land management, infrastructure development, and biodiversity assessment. Satellite remote sensing will help to monitor land and biodiversity in direct and indirect ways. High-resolution satellite images are useful for inventoring species at individual level in inaccessible areas. Vegetation indices derived from remote sensing data provide accurate conjecture of uniqueness and richness in an area, thereby they serve as an outstanding mechanism towards diversity and conservation research, particularly in sequestered landscapes. Accessibility of high-resolution satellite images in a wide spectrum enables one to access more products and services. High-resolution satellite sensors have the capability to monitor biological diversity at species level, and medium resolution sensors help monitoring species at community level.

1.7 Research questions and objectives

The research question of the present study is to understand the pattern, and the impacts of long-term land use/land cover changes on the forest cover, plant resources and ecosystem services of Eastern Ghats in India.

This research question is addressed through the following objectives namely,

- Assessment of long-term (1920-2015) LULC changes and its dynamics in the Eastern Ghats followed by simulating future LULC (2025& 2050) in the light of key drivers,
- Assessment of the impact of LULC change on the landscape ecology of Eastern Ghats,
- Analysis and simulation of the impact of LULC and climate change on the habitats of selected plant species and their distributions,
- Document of plant resource values and its ecosystem services, and to find out the effective management strategies and conservation areas.

Chapter 2

Study Area – The Esatern Ghats

2.1. General

The Eastern Ghats or *Pūrbaghāṭa* are discontinuous chain of hill ranges runs collateral to the east coast of India covering the States of Tamil Nadu, Karnataka, Andhra Pradesh, Telangana, and Odisha. Eastern Ghats are located between 11°30' - 22°0' N latitudes and 76°50' - 86° 30' E longitudes (Fig. 2.1). Eastern Ghats are considered as an important physiographic entity due to its vast bio-geographic, environmental, geological, socio-economic, cultural and spiritual significance. The Eastern Ghats are broadly divided into Northern and Southern parts, and these two parts merge together at Kondapalli village of Krishna District in Andhra Pradesh (“Pullaiah and Rao, 2002”). Eastern Ghats comprise of 42574 villages that come under 232 taluks and 51 districts (“Census, 2001”) spread over five States (Fig 2.2). The State of Andhra Pradesh occupies 39.64% geographical area of Eastern Ghats, followed by Odisha (31.26%), Tamil Nadu (19.09%), Karnataka (6.29%), and Telangana (3.72%). Dharmapuri district in Tamil Nadu, Y.S.R. Kadapa in Andhra Pradesh, Kandhamal and Rayagada in Odisha are mostly occupied by Eastern Ghats. Due to the presence of four major rivers viz, Godavari, Krishna, Kaveri and Mahanadi the Eastern Ghats are experiencing more erosion (“Ramesh and Kalpana, 2015”).

The Eastern Ghats stretches between the rivers of Mahanadi and Vaigai across a length of 1750 km along the east coast. The average width Eastern Ghats in the northern part is ~220 km and in southern part it is ~100 km. Eastern Ghats are bounded by the Mahanadi basin in north; Nilgiri hills in south; Bastar, Telangana, Karnataka and Tamil Nadu uplands in the west, and coast of Bay of Bengal on the east (“Pullaiah and Rao, 2002”). The elevation of Eastern Ghats range form 5m to 1787m with an average of 750m amsl. The Sathyamangalam hill ranges of Eastern Ghats in Tamil Nadu is meeting point between the Western Ghats and Eastern Ghats. Hence, it has high ecological importance by way of dispersal path between the ghats. A number

of tribal communities (nearly 62 in number) largely dependent on the Eastern Ghats for their livelihoods (“EPTRI-ENVIS 2009”).

With diversified tropical forests, this region characterises rich biodiversity and natural resources. The forests of Nallamalai (Kurnool), Palakonda, Kondapalli (Krishna), Seshachalam ranges (Y.S.R Kadapa), Javadi hills (North Arcot), Shevaroy and Kalrayan (Salem), Kolli hills (Namakkal) and Similipal (Mayurbhanj) are the known places for rich biological diversity in Eastern Ghats.

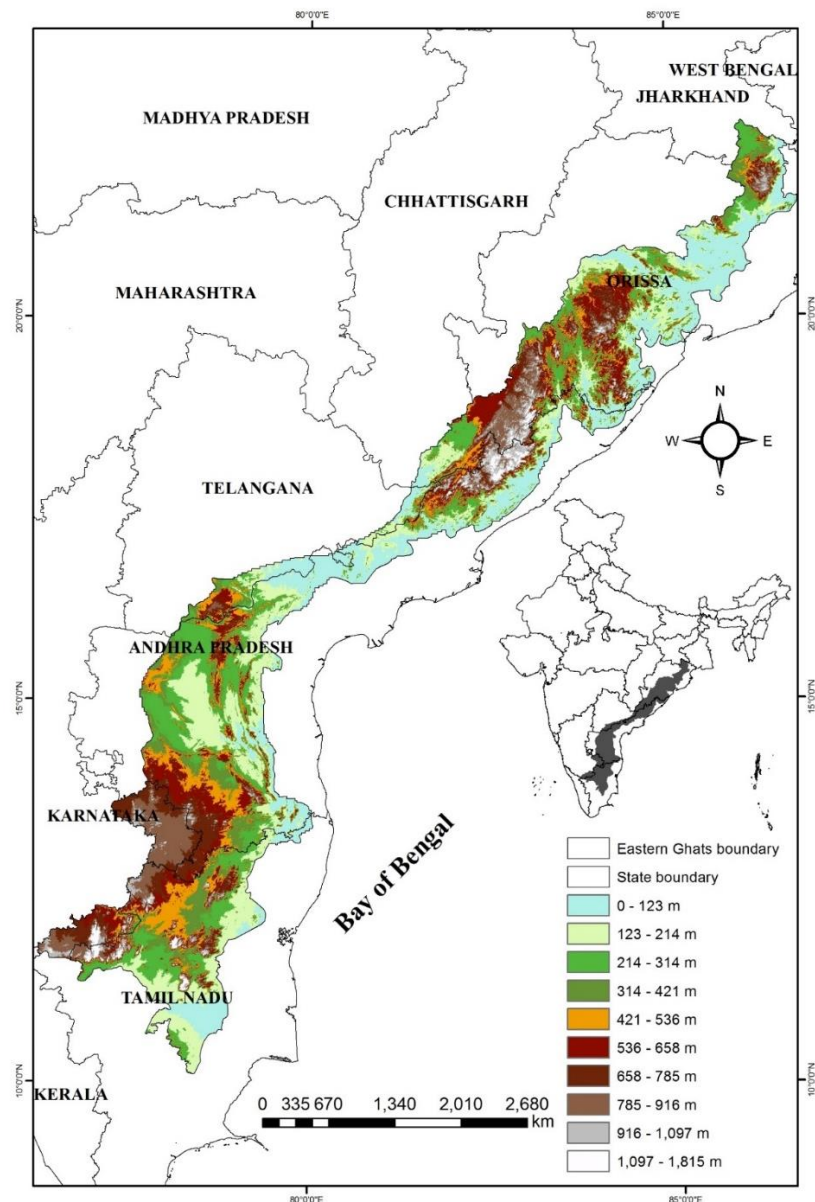


Figure 2.1. Geographic location (inset), and topography (derived from SRTM DEM), Eastern Ghats, India

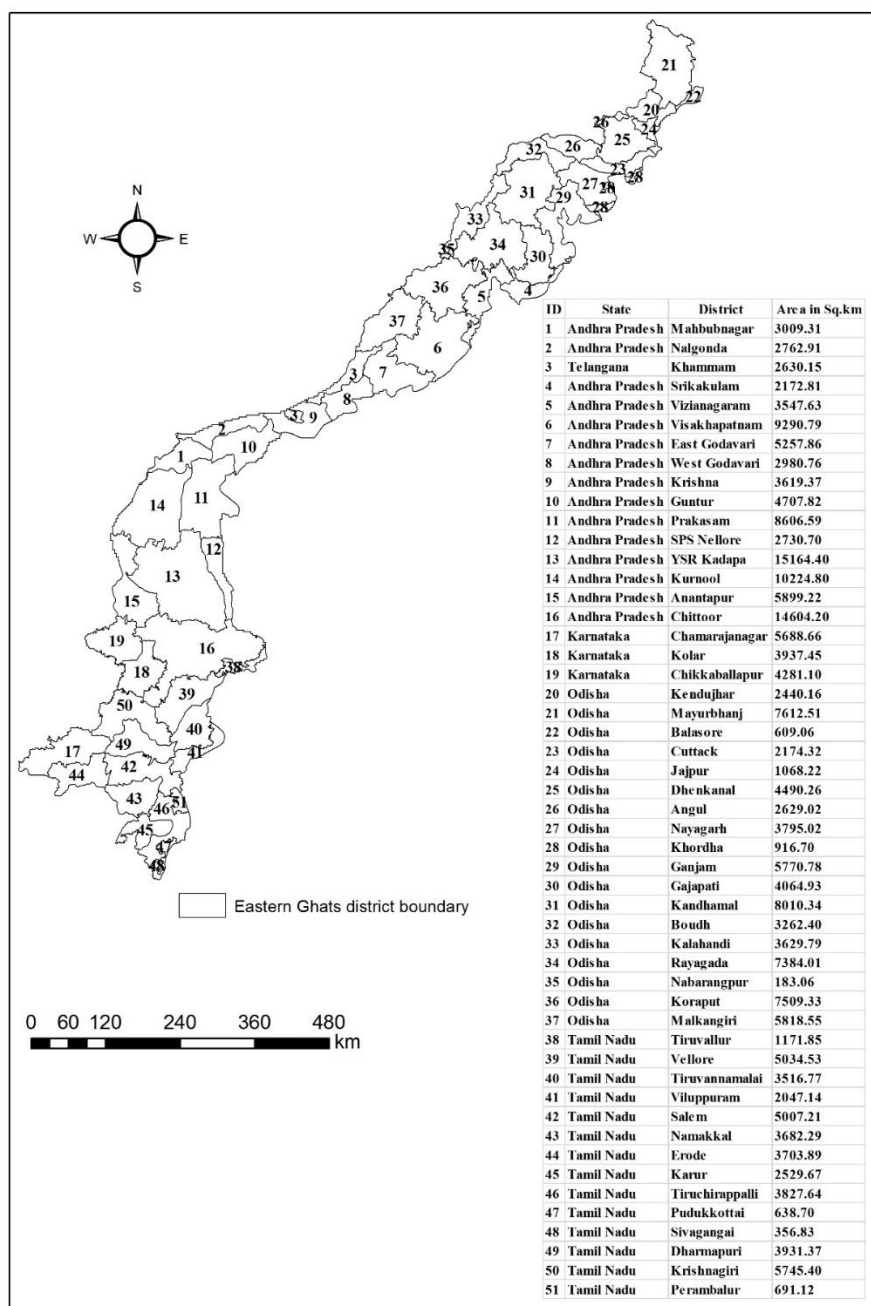


Figure 2.2. District administrative boundary of Eastern Ghats in five states (Census of India, 2011)

2.2. Climate

By and large Eastern Ghats exhibit tropical climate. Due to the dry ecological conditions this region is distinguished as the second driest place of India after western Rajasthan. This tropical region receives monsoonal rainfall from both south-west and north-east. The mean annual temperature of Eastern Ghats varies between 18.4°C to 34.25°C (Fig. 2.3). The northern

Eastern Ghats experience relatively cooler climate when compared to other parts (Fig 2.4a). The mean annual rainfall varies from 125mm to 2000 mm (Fig 2.4b) in Eastern Ghats. The northern Eastern Ghats receive high rainfall than the central and southern parts (Fig 2.4b). The patterns of annual minimum, maximum, and mean rainfall of this region for the last over 100 years (1900-2010) are shown in Fig. 2.5.

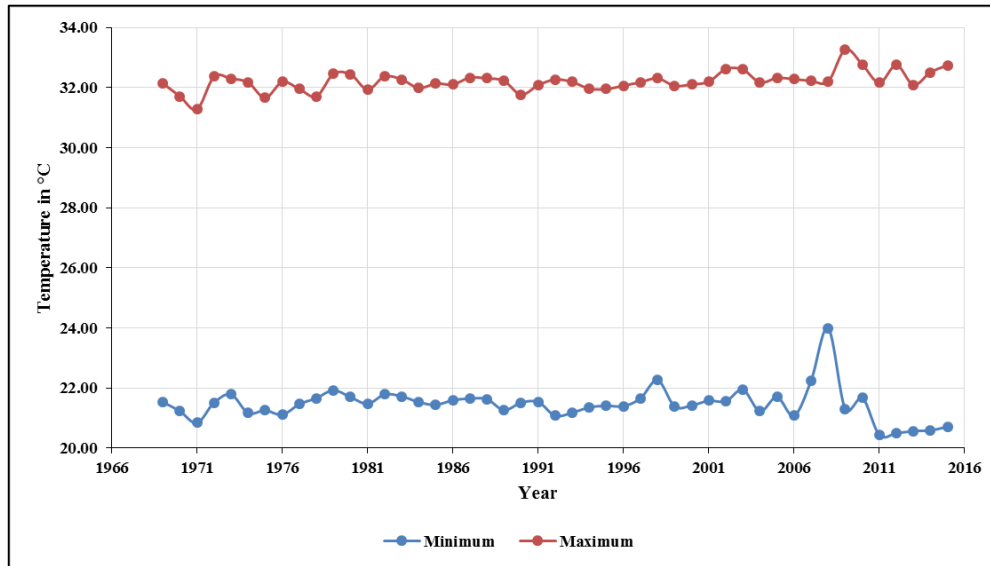


Figure 2.3. Pattern of annual minimum and maximum temperatures in Eastern Ghats from 1969-2015 (IMD)

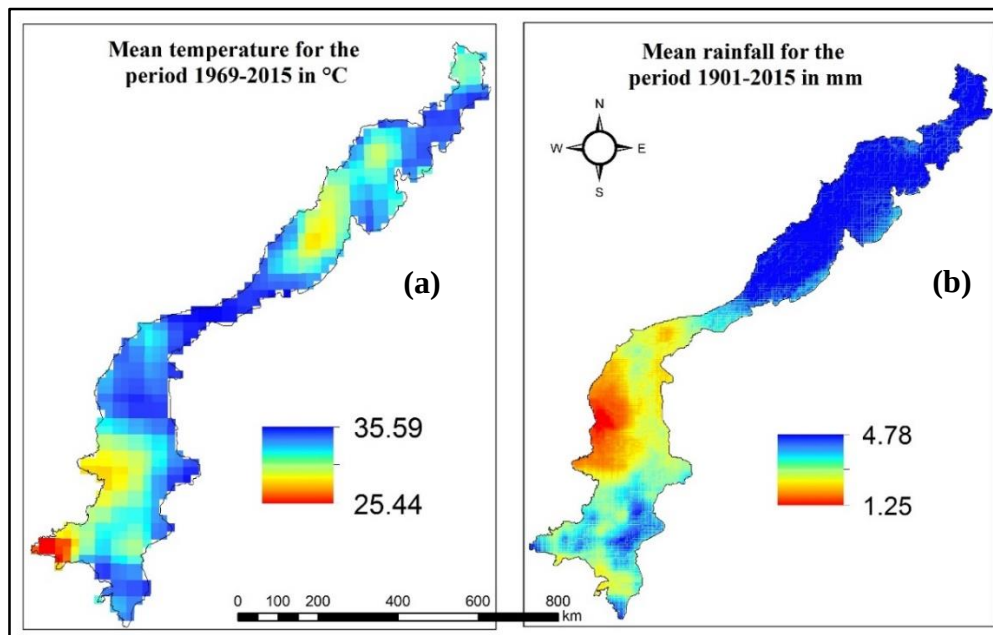


Figure 2.4. Spatial distribution of mean temperature (1969-2015) and rainfall (1901-2015,) Eastern Ghats (worldclim.org)

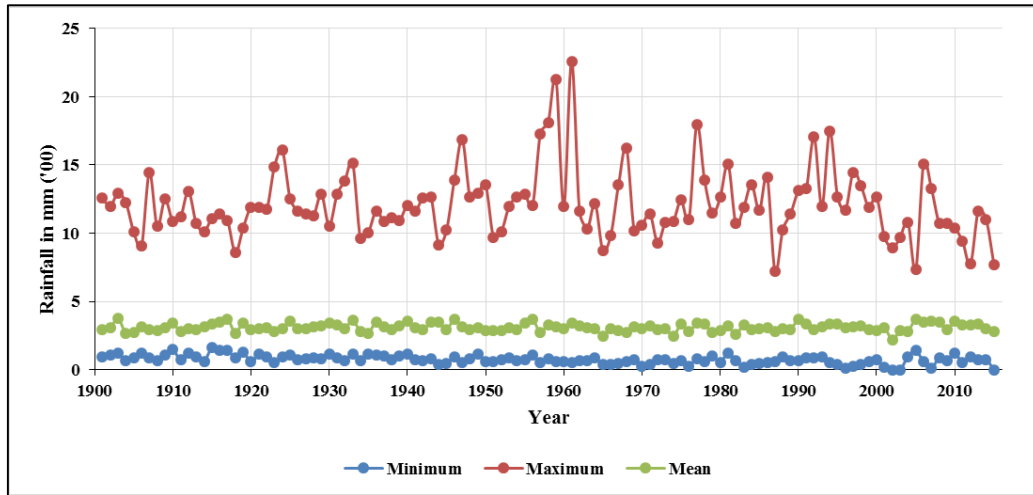


Figure 2.5. Pattern of annual minimum, maximum, and mean rainfall in Eastern Ghats for the period 1901-2015 (IMD)

The average monthly wind speed for the period 1970-2000 in Eastern Ghats is shown in Fig. 2.6. June month has recorded the highest wind speed (2.68m/s), whereas October the lowest (1.23 m/s). The spatial distribution of mean monthly wind speed in Eastern Ghats is shown in Fig. 2.7.

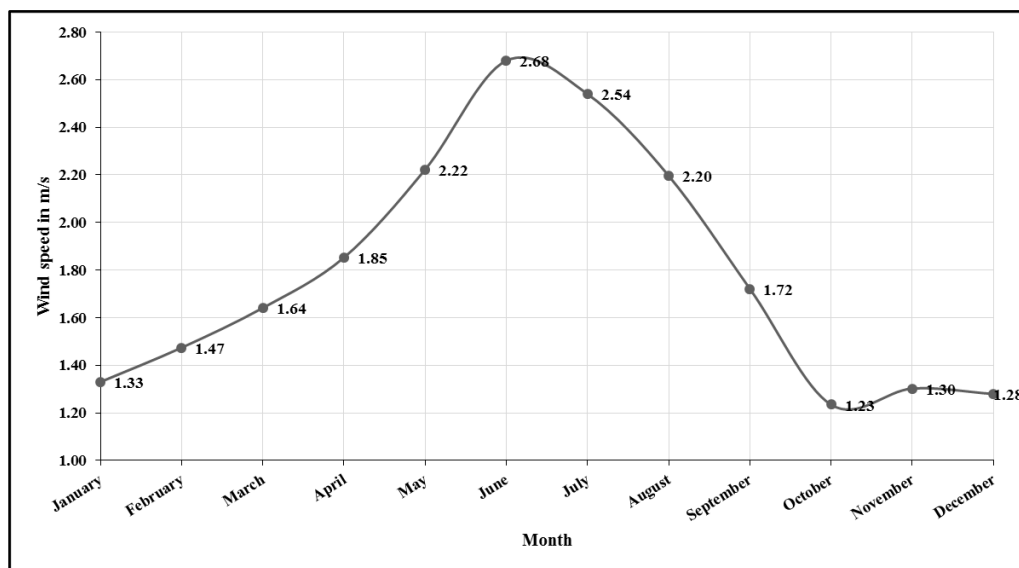


Figure 2.6. Pattern of mean monthly wind speed in Eastern Ghats for the period 1970-2000 ("Fick and Hijmans, 2017")

Southern Eastern Ghats in the state of Tamil Nadu has recorded the highest wind speed, whereas the northern Eastern Ghats falling in the state of Odisha show less wind speed (Fig. 2.7). During winter the southern Eastern Ghats exhibit high wind speed when compared to the northern part. During summer period the wind speed is low and uniform all over the Eastern

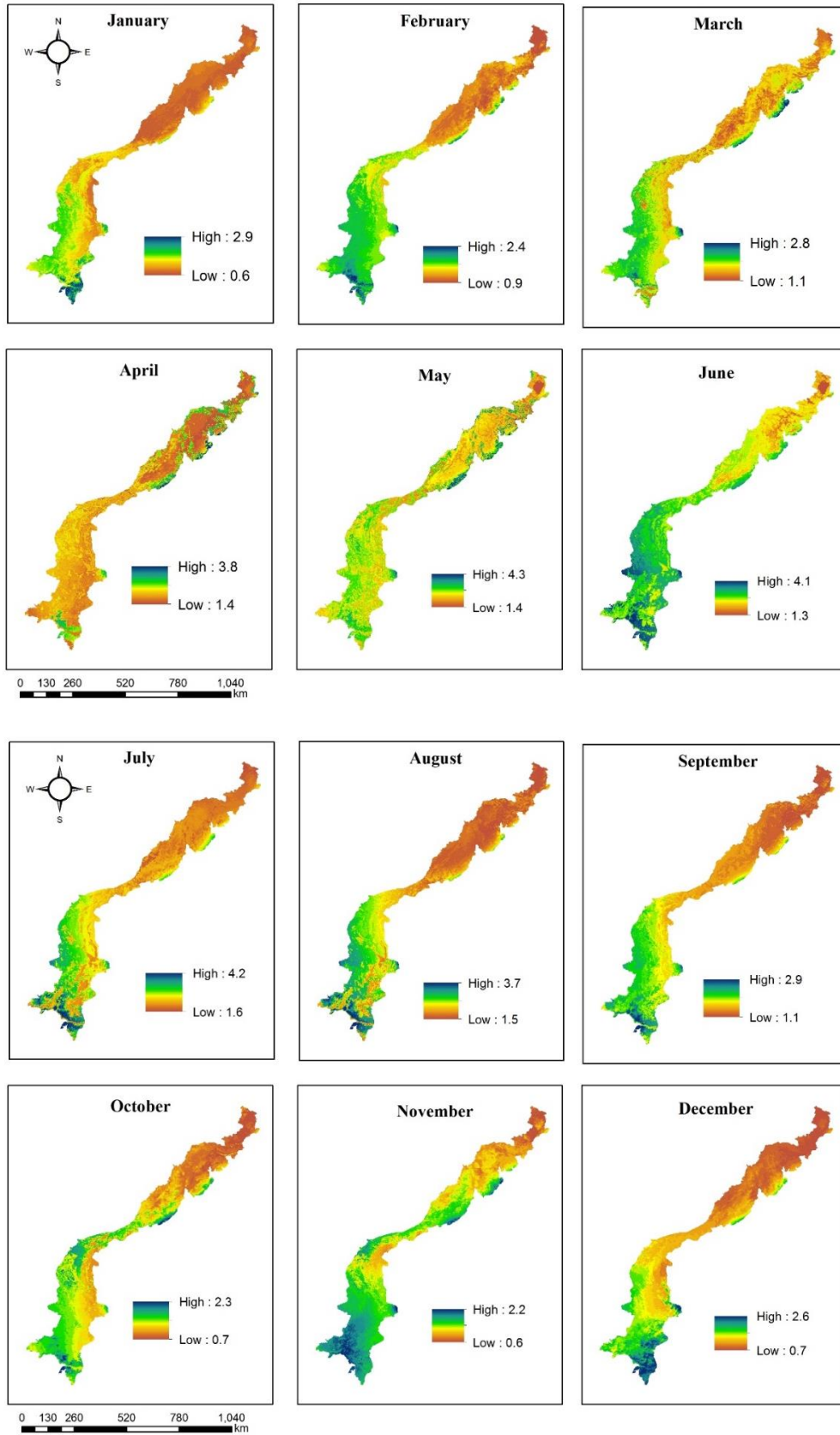


Figure 2.7. Spatial distribution of mean monthly wind speed in Eastern Ghats (m/s)

Ghats. The Pattern of mean monthly solar radiation in Eastern Ghats for the period 1970-2000 is shown in Fig. 2.8 (“Fick and Hijmans, 2017”). The mean solar radiation varies from 17091.96 MJ /m² (July) to 23729.74 MJ /m² (March) (Fig 2.8). The spatial distribution of mean monthly solar radiation in Eastern Ghats is shown in Fig. 2.9. During the months of January to March, southern Eastern Ghats receive high solar radiation and then it gradually shifts to the central part in the following months. From September onwards it again shifts back to the southern part (Fig. 2.9). According to Köppen-Geiger climate classification the Eastern Ghats are falling in the type *Aw* which is having an equatorial climate of minimum temperature $\geq +18^{\circ}\text{C}$ and the minimum precipitation of < 60 mm in winter (“Kottek et al., 2006”).

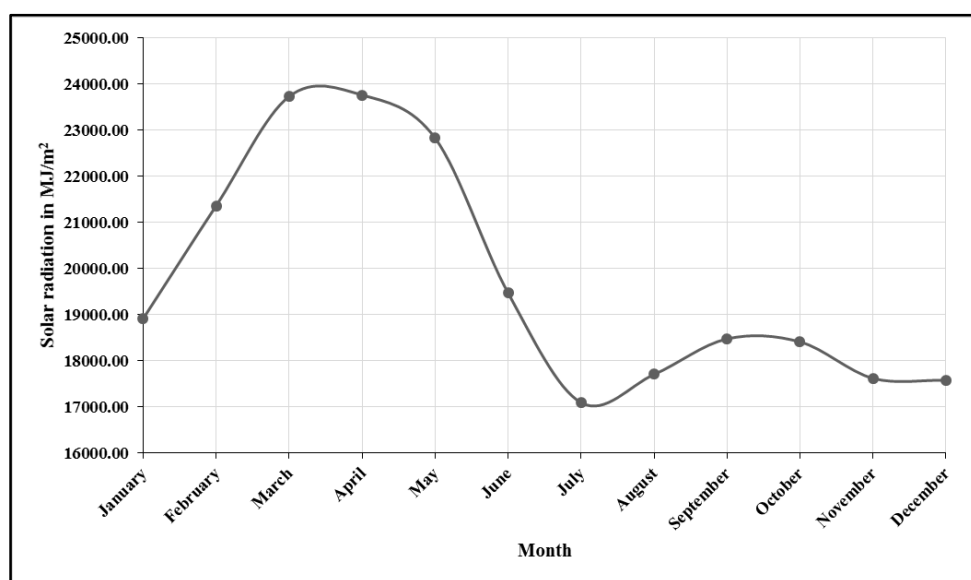


Figure 2.8. Pattern of mean monthly solar radiation in Eastern Ghats for the period 1970-2000 (“Fick and Hijmans, 2017”)

2.3 Vegetation type

The Indian sub-continent has nine floristic zones. The Eastern Ghats are one among them and the vegetation is largely occupied with deciduous forests and scrub jungles (“Mani, 1974”). Patches of evergreen, semi evergreen forests are also found in certain pockets and in areas of high elevations. In addition, degraded thorny forests are spread over the Eastern Ghats due to the degradation of primary vegetation. Mangrove swamps also can be seen in the water logging wet land areas of the Eastern Ghats. The common plant species found in the forests are; *Pterocarpus santalinus* L.f. (Near Threatened ver 3.1), *Shorea robusta* Gaertn., *Shorea tumbuggaia* Roxb. (Endangered B1ab (i,ii,iii,v) + 2ab(i,ii,iii,v) ver 3.1), *Syzygium alternifolium*

(Wight) Walp. (Endangered A2cd ver 3.1), *Santalum album* L. (Vulnerable A1d ver 2.3), *Terminalia pallida* Brandis (Vulnerable A2cd ver 3.1), *Albizia amara* series, *Hardwickia binata* series, *Tectona grandis* series, *Anogeissus latifolia* (Roxb. ex DC.) Wall. ex Guillem. & Perr. *Cochlospermum*, *Gyrocarpus*, *Givotia* spp. (“Pullaiah and Rao, 2002”).

As per “Champion and Seth (1968)”, the vegetation of Eastern Ghats is classified into

1) Evergreen forests: These are dense forests having large number of tree species. The tree heights are 45m and above. The mean temperature in these regions varies between 18°C to 27°C, and the rainfall is above 2000mm.

2) Tropical semi-evergreen forests: These are medial group of evergreen and deciduous forms. The temperature in these region varies between 16°C – 26°C and the annual rainfall varies between 2000mm-2500mm.

3) Tropical moist deciduous forests: These forests contain mostly deciduous trees with an average height of 40m and above. The temperature in these regions varies between 24°C -27°C, and mean annual rainfall varies from 1500mm-2000mm.

4) Southern tropical dry deciduous forests: These are thin forests with tree height vary between 13-20m. The temperature varies between 18°C – 23°C, and the annual rainfall varies between 1000-1300mm.

5) Northern mixed dry deciduous forests: The height of tree species in these forests rarely exceeds 15m. The mean temperature varies between 17°C -30°C, and the annual rainfall varies from 900mm-1500mm.

6) Dry savannah forests: This type consists mostly of degraded vegetation containing thorny shrubs.

7) Tropical thorny forests: These are thorny hard wooded open forests with height of species varies from 6 to 9m. The temperature in these regions varies between 25.5°C – 32°C, and the annual rainfall is less than 50mm.

8) Tropical dry evergreen forests: These are low forests, where the average height of species varies from 9 to 12m. Mean annual temperature varies between 27°C – 28°C, and the annual rainfall is as low as 50mm.

9) Tropical dry evergreen scrub: These are climax forest type with degraded forms of trees.

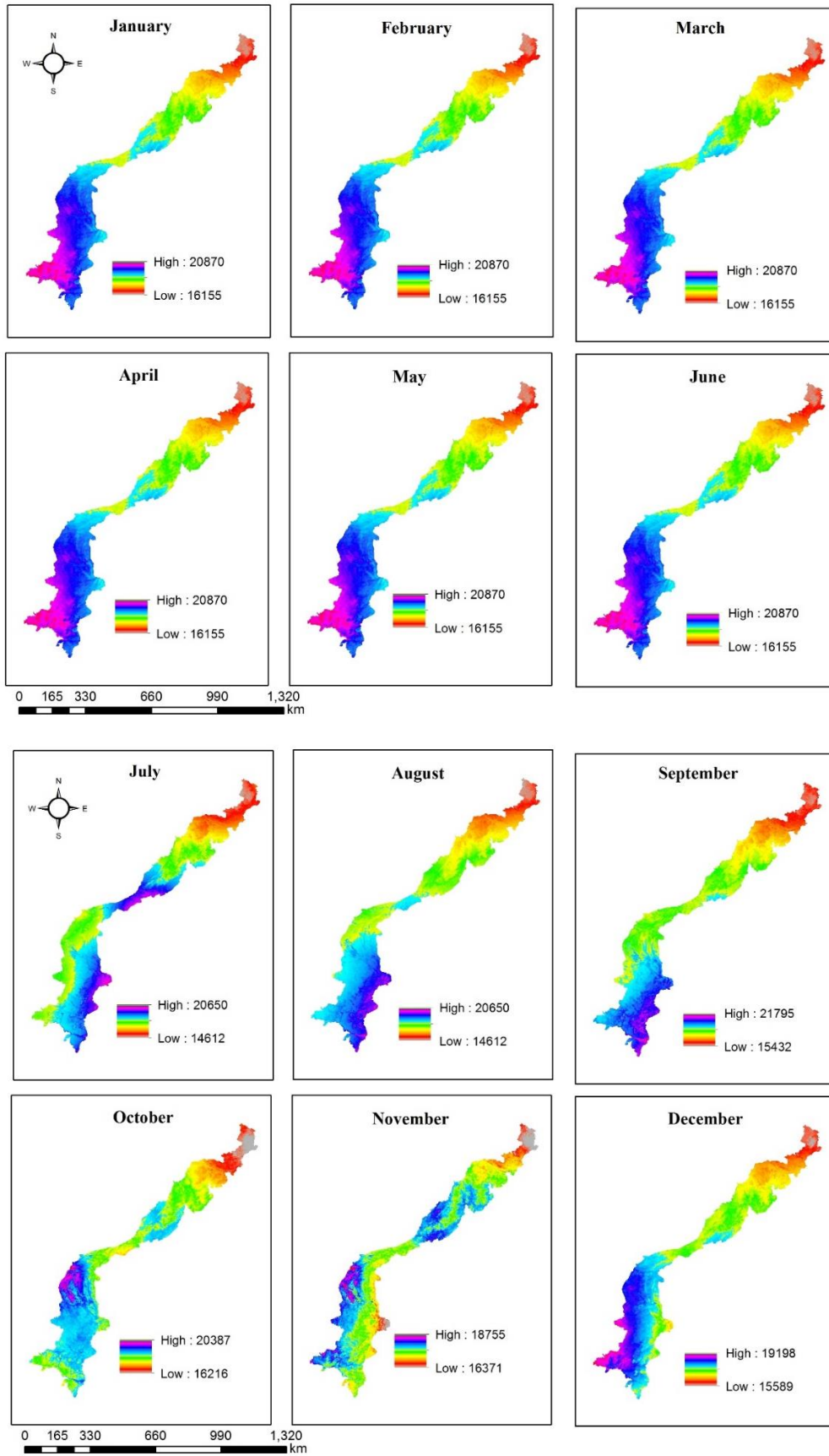


Figure 2.9. Spatial distribution of mean monthly solar radiation of Eastern Ghats in MJ/m^2

Table 2.1 Vegetation types in Eastern Ghats ("Champion and Seth, 1968")

Class	Group	Sub-group	Major floristics composition	Soil and rock	Occurrence
Moist tropical forests	1-Tropical wet evergreen forests	1A- Southern tropical wet evergreen forests	C4 West coast tropical evergreen forest <i>Dipterocarpus indicus, Calophyllum elatum, C.wightianum, Hopea wightiana, Holigarna arnottiana</i>	Laterite, gneiss, granite	Ratnagiri district southwards
	General edaphic and seral types of wet evergreen forests	Edaphic and seral types	E2 Wet bamboo breaks <i>Ochlandra</i> spp.	Laterite	South India, along streams or wettest sites
	2- Tropical semi evergreen forests	2B- Northern tropical semi evergreen forests	C3 Orissa semi evergreen forest <i>Artocarpus lakoocha</i> (D), <i>Michelia champaca</i> (E), <i>Celtis tetrandra</i> (D), <i>Bridelia tomentosa</i> (D), <i>Aphanamixis polystachya</i>	Alluvial	Odisha hills at 800 m and in lower permanently moist valley
	General edaphic and seral types of semi-evergreen forests	Edaphic climax types	E2 Wet bamboo breaks <i>Ochlandra</i> spp.	Laterite	South India, along streams or wettest sites
3- Tropical moist deciduous forests	moist deciduous forests	3B- South Indian moist deciduous forests	C1 Moist teak - bearing forest 1c Slightly moist teak forest <i>Terminalia tomentosa, Adina cordifolia, Scheichera oleosa</i>	Red soil	Throughout peninsular India

Contd..

3C- North Indian moist deciduous forests	C1 Very moist sal-bearing forest	<i>Shorea robusta</i> , <i>Dillenia pentagyna</i> , <i>Terminalia tomentosa</i> , <i>Bridelia retusa</i> , <i>Adina cordifolia</i>	Alluvial	Angul in Odisha
	1d Peninsular (coastal) sal forest			
	C2 Moist sal-bearing forest	<i>Shorea robusta</i> , <i>Syzygium cumini</i> , <i>Bauhinia</i> spp., <i>Albizia chinensis</i> , <i>Cedrela toona</i>	Laterite, trap and crystalline rocks	Kalahandi in Odisha
	2e Moist peninsular sal forest (i) Moist peninsular high level sal			
	(ii) Moist peninsular low level sal	<i>Shorea robusta</i> (va), <i>Terminalia tomentosa</i> (va), <i>Adina cordifolia</i> (a), <i>Mitragyna parvifolia</i> (f), <i>Lagerstroemia parviflora</i> (f)	Yellow loam soil and crystalline rock	Angul division in Odisha
	2S1 Northern secondary moist mixed deciduous forest	<i>Mangifera indica</i> (E), <i>Anthocephalus cadamba</i> , <i>Alstonia scholaris</i> (E), <i>Dillenia pentagyna</i> , <i>Schleichera oleosa</i>		Dhuanali in Odisha
Dry tropical forests	5- Tropical dry deciduous forests	C2 Red sanders bearing forest	Quartzite	Cuddapah, Kurnool, Chittoor and Nelloor in Andhra Pradesh
	5A- Southern tropical dry deciduous forests	<i>Pterocarpus santalinus</i> , <i>Anogeissus latifolia</i> , <i>Hardwickia binata</i> , <i>Terminalia chebula</i> , <i>T.tomentosa</i>		

Contd..

	C3 Southern dry mixed deciduous forest	<i>Anogeissus latifolia</i> , <i>Terminalia tomentosa</i> , <i>Diospyros tomentosa</i> , <i>Chloroxylon swietenia</i> , <i>Hardwickia binata</i>	Shallow soil	Nallamalais, South Kurnool, South Cuddapah, Ananthapur in Andhra Pradesh, Central Salem in Tamil Nadu
5B- Northern tropical dry deciduous forests	C1 Dry sal-bearing forest	<i>Shorea robusta</i>	Red soil, alluvial, sandstone, conglomerate	Odisha
	C2 Northern dry mixed deciduous forest	<i>Adina cordifolia</i> , <i>Lagerstroemia parviflora</i> , <i>Anogeissus latifolia</i> , <i>Terminalia tomentosa</i> , <i>Dalbergia latofolia</i>	Crystalline and sedimentary	Angul and Kalahandi in Odisha
Degradation stage	DS1 Dry savannah forest	<i>Emblica officinalis</i> (c), <i>Bauhinia retusa</i> , <i>Arundinella setosa</i> , <i>Dillenia</i> , <i>Cymbopogon martini</i>	Laterite	Kalahandi in Odisha
	DS4 dry grassland	<i>Sehima nervosum</i> , <i>Chrysopogon fulvus</i> , <i>Themeda triadra</i> , <i>Eremopogon foveolatus</i> , <i>Heteropogon contortus</i>	Laterite	Hills, hill slopes and valleys

Contd..

6- Tropical thorn forests	Edaphic climax types	E4 Hardwickia forest	<i>Hardwickia binata</i> , <i>Acacia chundra</i> , <i>Pterocarpus santalinus</i> , <i>P. marsupium</i> , <i>Chloroxylon swietenia</i>	Gravel	South Cuddapah, Tirupati Hills
		E9 Dry bamboo breaks	<i>Dendrocalamus strictus</i> , <i>Boswellia serrata</i> , <i>Sterculia urens</i> , <i>Cochlospermum religiosum</i> , <i>Anogeissus latifolia</i>	Alluvial	Salem
6A-Southern tropical thorn forests		C1 Southern thorn forest	<i>Albizia amara</i> , <i>Acacia chundra</i> , <i>Azadirachta indica</i> , <i>Cassia fistula</i> , <i>Dolichandrone facata</i>	Black cotton, laterite	Chittoor in Andhra Pradesh and Salem in Tamil Nadu
	Degradation stage	DS2 Southern Euphorbia scrub	<i>Euphorbia tirucalli</i> , <i>Capparis sp.</i>	Shallow, rocky and alkaline	Krishnagiri
7- Tropical dry evergreen forests		C1 Tropical dry evergreen forest	<i>Manilkara hexandra</i> , <i>Canthium dicoccum</i> , <i>Zizypus glaberrima</i> , <i>Acacia leucophloea</i> , <i>Syzygium cumini</i>	Laterite	South Cuddapah, Nellore in Andhra Pradesh

The classification of characteristic species and different soils found in the Esatren Ghats are given in Table 2.1 “(Champion and Seth, 1968)”. Different forest types found in the Eastern Ghats are illustrated in Fig. 2.10.

2.4 Biological diversity

Due to complex geography, isolated mountains, valleys, and plains the Eastern Ghats harbours pronounced biological diversity. When compared to the other mountain systems such as the Himalayas and the Western Ghats, the knowledge on the Eastern Ghats ecology and biodiversity is rather sparse. Eastern Ghats has a floral wealth of more than 2600 species of angiosperms, gymnosperms, pteridosperms, pteridophytes, with more than 160 species of cultivated plants (“Kannaiyan, 2015”). This number includes about 454 endemic species as well. Eastern Ghats are known for floral diversity than fauna. Some of the significant endemic and threatened faunal species of Eastern Ghats are Jerdon's Courser (Critically Endangered C2a (ii) ver 3.1 bird species endemic to Andhra Pradesh part of Eastern Ghats), Great Indian Bustard (Critically Endangered A2a+4acd; C1 ver 3.1), Tufted Gray Langur (Near Threatened ver 3.1), Marsh Crocodile (Vulnerable A2cd ver 3.1), Indian Star Tortoise (Vulnerable A4cd ver 3.1), Leith's Softshell Turtle (Vulnerable A1c ver 2.3), Elliot's Earth Snake (endemic to India), Nagarjuna Racer (Data Deficient ver 3.1, endemic to Nagarjuna Hill in Andhra Pradesh), Beddome's Coral Snake (Data Deficient ver 3.1, endemic to India), and King Cobra (Vulnerable A2acd ver 3.1). Some of the noteworthy plant communities includes Red Sandalwood (Near Threatened ver 3.1, endemic to southern Eastern Ghats), *Cycas beddomei* (Endangered B1ab(i,ii,iii,iv,v)+2ab(i,ii,iii,iv,v) ver 3.1, endemic to Tirupati-Kadapa Hills in Andhra Pradesh), *Boswellia ovalifoliolata* (Vulnerable A2cd; B1ab(i,ii,iii) ver 3.1, endemic to the state of Andhra Pradesh), *Terminalia pallida* Brandis (Vulnerable A2cd ver 3.1, endemic to Andhra Pradesh and Tamil Nadu) (<http://www.iucnredlist.org/>). Eastern Ghats also harbour good population of Indian elephant, Indian tiger and Indian leopard. Selected flora and fauna found during the field visits are illustrated in Fig 2.11.

To protect the biodiversity, several protected areas have been established in the Eastern Ghats (Fig. 2.12), which includes one biosphere reserve, three national parks and 17 wildlife sanctuaries/tiger reserves (Table 2.2). Some parts of the Krishna wild life sanctuary are covered in the Eastern Ghats, which harbours world's pristine mangrove forests. The Sathyamangalam forest has an assemblage of several rare and endemic species. This area is contiguous to some



Degraded forests of Ahobilam



Thorny forests of Guntur



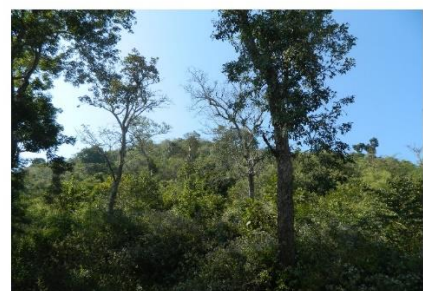
Thorny forests of Thiruvannamalai



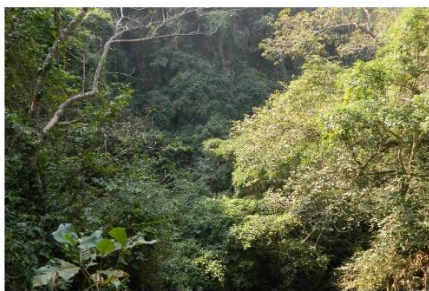
Scrub forests of Thiruvannamalai



Deciduous forests of Thiruvannamalai



Semi deciduous forest of Narsipatnam



Reverine forests of Srikakulam



Sal forests of Srikakulam



Bamboo forests of Polavaram



Scrub forests of Chittoor

Fig 2.10 Typical forest types found in Eastern Ghats, India

Table 2.2 List of protected areas and their significance, Eastern Ghats

Sl. No	Name	Status	Location	Year of declaration	Area (sq.km)	Significance
1	Nandankanan	Wild Life Sanctuary	Bhubaneswar, Odisha	29-12-1960	4.37	One of the world's first zoo to breed white and Melanistic tiger. The rich biodiversity includes 704 species of plants, 13 species of mammals, 15 species of reptiles, 71 species of birds, 20 species of amphibians, 85 species of butterflies and 51 species of spiders ("Annual report, 2015-16").
2	Biligiri Rangaswami Temple	Wild Life Sanctuary	Chamarajnagar, Karnataka	27-06-1974	539.52	Unique ecosystem with the combined influence of Western and Eastern Ghats. Situating between the Kaveri and Kapila rivers. Rich with endemic plant species. The biodiversity includes around 250 number of bird's species, 22 reptile species, and 116 species of butterflies.
3	Bandipur	National Park	Chamarajnagar, Karnataka	1974	880.02	Tiger reserve with higher tiger population
4	Satkosia Gorge	Wild Life Sanctuary	Angul, Angul, Cuttack, Nayagarh & Boudh, Odisha	1976	988.30	It is a habitat of 400 plant species, 38 mammals, and 31 reptiles. The endangered gharial avialis gangeticus also found here. Three forest villages, and migratory birds.
5	Papikonda	National Park	East Godavari & West Godavari, Andhra Pradesh	1978	1012.86	Composed of unique flora and fauna and the fauna is dominated with tiger.
6	Baisipalli	Wild Life Sanctuary	Nayagr, Odisha	06-05-1981	168.35	Mahanadi River passes through this sanctuary. Composed with Sal and riverine forests. The fauna includes tigers and elephants.

Contd..

7	Kotagarh	Wild Life Sanctuary	Kandhamal, Odisha	03-12-1981	446.67	Tiger habitat and one of the oldest elephant corridors from Boudh, Karlapat and Lakhari valley in Gajapati district's Gandahati waterfall region is adjoining with the forests.
8	Chandaka Dampara	Wild Life Sanctuary	Bhubaneswar, Odisha	December,1982	175.79	The Indian elephant are the noticeable animal in this sanctuary.
9	Rajiv Gandhi (Nagarjunasagar-Srisailem)	Wild Life Sanctuary	Kurnool, Prakasam, Guntur, Nalgonda & Mahbubnagar, Andhra Pradesh	1983	3727.82	It is IUCN category IV protected area and largest tiger reserve in India. About 26 tribal villages are resides in the core area.
10	Kuldiha	Wild Life Sanctuary	Balasore, Odisha	04-01-1984	272.75	Elephant sanctuary with rich Sal forest
11	Lakhari Valley	Wild Life Sanctuary	Gajapati & Ganjam, Odisha	08-02-1985	174.95	Composed of moist deciduous forests, and high number of elephants.
12	Cauvery	Wild Life Sanctuary	Chamarajnagar, Ramanagar & Mandya, Karnataka	14-01-1987	1027.53	Composes IUCN category IV protected area. Cauvery River flows through this sanctuary. The forests are mainly composed of <i>Hardwickia binata</i> and <i>Albizia amara</i> . It supports good number of Indian elephants.
13	Sri Lankamalleswaram	Wild Life Sanctuary	Kadapa, Andhra Pradesh	1988	464.42	IUCN category IV protected area and best known for Critically Endangered bird Jordan's Courser. The floral community includes 1400 different kinds of plants under the 176 different families.
14	Rollapadu	Wild Life Sanctuary	Kurnool, Andhra Pradesh	1988	6.14	Only habitat in Andhra Pradesh for the Critically Endangered A2a+4acd great Indian bustard.

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15	Sri Venkateswara	National Park	Chittoor & Cuddapah, Andhra Pradesh	September, 1989	353.00	Comprises high number endemic and endangered flora & fauna.
16	Gundla Brahmeswaram	Wild Life Sanctuary	Prakasam & Kurnool, Andhra Pradesh	1990	1194.00	Tiger reserve
17	Kaundinya	Wild Life Sanctuary	Chittoor, Andhra Pradesh	December, 1990	357.60	Elephant sanctuary in which elephants are return to this sanctuary after 200 years in 1984.
18	Karlapat	Wild Life Sanctuary	Kalahandi, Odisha	15-10-1992	144.96	Sal and Bamboo forests are common with the presence of elephant, and leopard.
19	Simlipal	Biosphere Reserve	Mayurbhanj, Odisha	22-06-1994	5569	Largest Sal zone in India also tiger reserve under 'Project Tiger' Scheme of Government of India. Characterised by 1,076 number of vascular plants species in that about 93 are orchid species. The <i>Eria meghasaniensis</i> and <i>Tainia hookeriana</i> orchids are endemic to the area. The faunal diversity includes various species of founa viz, 42 mammals, 264 birds, 39 reptiles and 12 amphibians among them 52 are endangered. A total of 1,265 villages are located within Simlipal and about 73% of all inhabitants are aboriginals ("UNESCO, 2015").
20	Sri Penusila Narasimha	Wild Life Sanctuary	Nellore, Andhra Pradesh	15-09-1997	1030.85	Composed with dry evergreen forest
21	Satyamangalam	Wild Life Sanctuary	Erode, Tamil Nadu	03-11-2008	1411.60	Diverse area with the influence of both Western and Eastern Ghats. Also have significant population of tiger

parts of Bandipur Tiger reserve in the Western Ghats. Other than these protected areas a number of community managed sacred groves are also seen in this area (details are in section 2.9).

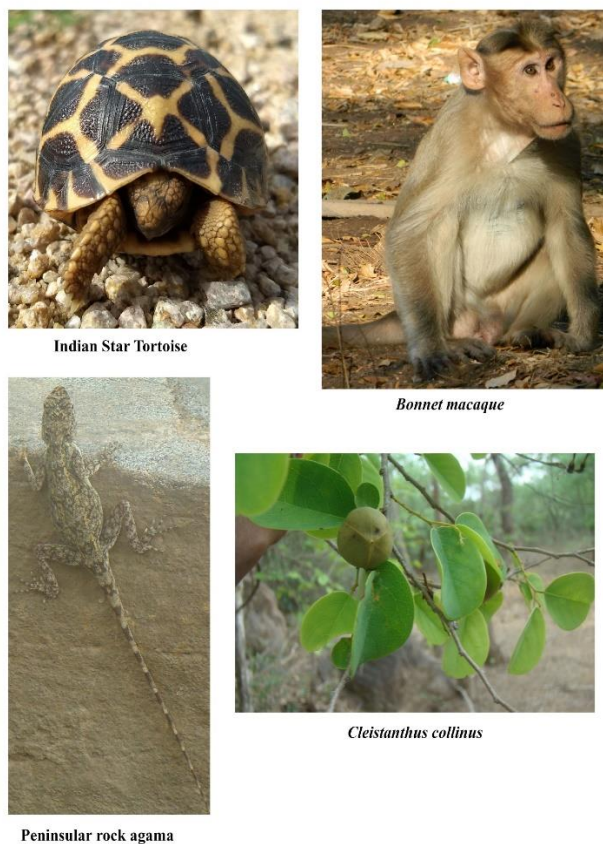


Figure 2.11. Diversity of flora and fauna identified during the field visits in the Eastern Ghats.

2.5. Agro Ecological Zones (AEZs)

Agriculture constitutes one of the major economic activities in the Eastern Ghats. More than 70% of human population in the Eastern Ghats are involved in agriculture-related activities (“Singh, 2013”). AEZs are the land units classified in terms of climatic conditions, soil types, water availability which are suitable for certain types of crops (“Ahmad et al., 2017”). The AEZs are vital for effective management of natural resources. Out of 20 AEZs of India (“Meiyyappan et al., 2016”), Eastern Ghats contain 6 AEZs (Table 2.3, Fig 2.13).

2.6. Geology

Eastern Ghats are older than Himalayas and Western Ghats (“Reddy et al., 2006”). These are formed around 2600 million years ago (“Shaw et al., 1997”) and constitute a vital component of the Precambrian crust of India with polycyclic granulite terrain (“Bhattacharya, 1997”). The

Table 2.3. Agro-Ecological Zones of Eastern Ghats (National Bureau of Soil Survey and Land Use Planning, India, Gajbhiye and Mandal 2000; Meiyappan et al., 2016")

Ecosystem type	AEZ	Physiography	Climate	Soils	Crop growing period	PET* (mm)	Major crops
Arid ecosystem	AEZ3	Karnataka Plateau (Rayalseema as inclusion)	Hot arid	Red and black soils	<90 days	1800–1900	Sorghum, safflower, cotton, groundnut, sunflower, sugar cane
Semiarid ecosystem	AEZ7	Deccan plateau (Telangana) and Eastern Ghats	Hot semi-arid	Red and black soils	90-150 days	1600–1700	Millets, oilseeds, rice, cotton & sugar cane under irrigation
	AEZ8	Eastern Ghats and Tamil Nadu Uplands and Deccan (Karnataka) Plateau	Hot semi-arid	Red loamy soils	90-150 days	1300–1600	Millets, pulses, oilseeds, sugar cane & rice under irrigation
Sub humid ecosystem	AEZ12	Eastern Plateau (Chhotanagpur) and Eastern Ghats	Hot sub humid	Red and lateritic soils	150-210 days	150–180	Rice, pulses, millets
Coastal ecosystem	AEZ18	Eastern Coastal Plain	Hot sub humid to semiarid	Coastal and Deltaic alluvium-derived soils	90-210+ days	1200–1900	Rice, coconut, black gram, lentil, sunflower, groundnut
	AEZ19	Western Ghats and Coastal Plain	Hot humid-per humid	Red, lateritic and coastal alluvium-derived soils	210+ days	1400–1600	Rice, tapioca, coconut, spices

*Potential evapotranspiration

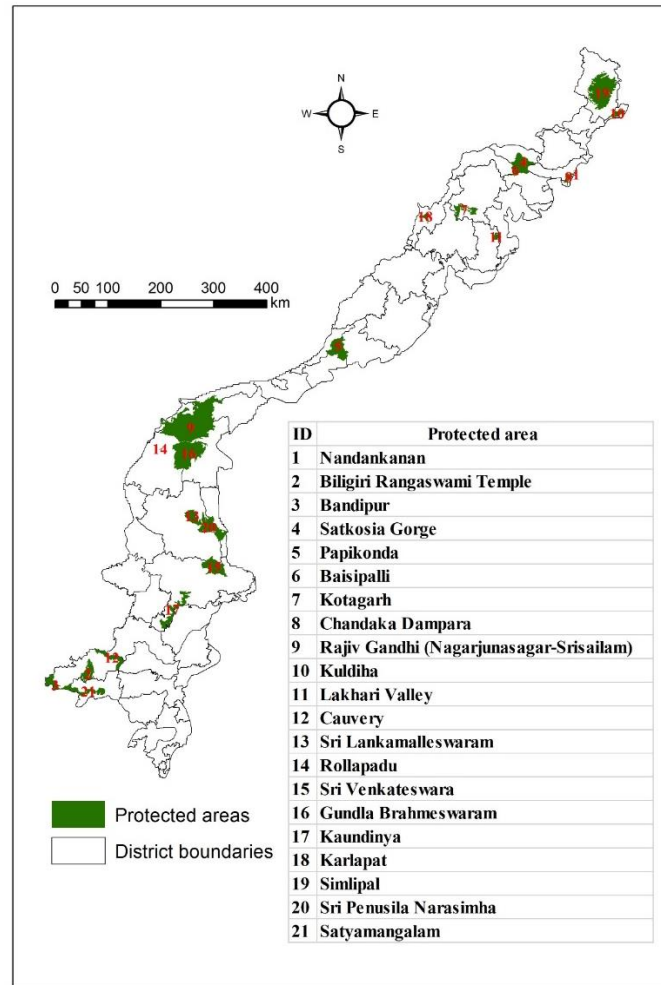


Figure 2.12. Distribution and locations of protected areas in the Eastern Ghats (Source: Wild life Institute of India)

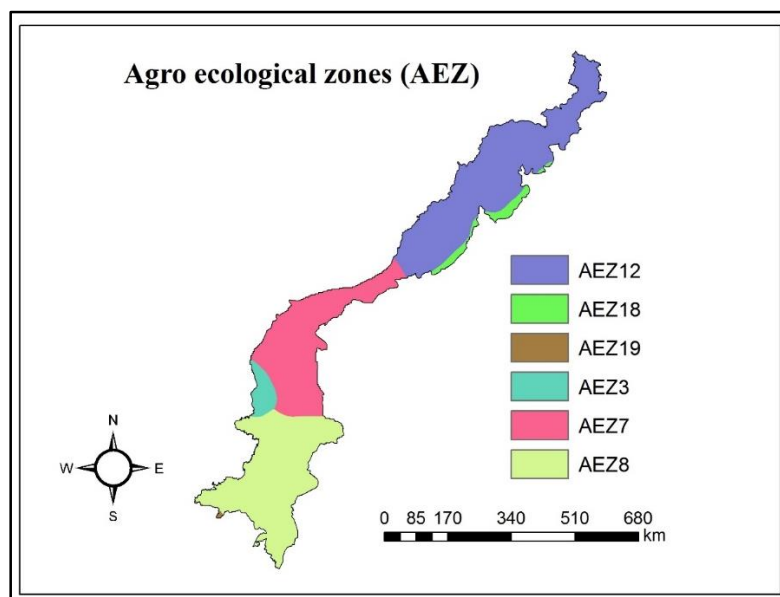


Figure 2.13. Agro ecological zones of the Eastern Ghats

Eastern Ghats chain consists of khondalites, charnockites, gneises, and schists of igneous and sedimentary origin (“Madireddi and Subba Rao, 2000”). Moreover, phosphorous-rich granites, alumina, iron, and bauxite occur in different parts of the Eastern Ghats. Old Dharwar schists are seen near Nellore, Prakasam, Guntur, Anantapur and Mehboobnagar districts, and recent plio-pleistocene alluvium in Krishna and Godavari districts respectively (“Pullaiah and Rao, 2002”).

2.7. Soils

The soils of Eastern Ghats are of Pleistocene origin (“Chauhan, 1998”). Red soil is the dominant type found throughout the Eastern Ghats. Black (cotton) soil with clayey nature is the second most common soil type found in the Eastern Ghats in low elevation areas. High land areas are mostly covered with lateritic soils, whereas low lying areas are covered with alluvial soil.

2.8. Water resources and reservoirs

There are about 21 rivers originate from Eastern Ghats including Sabari, Indrāvati, Vellar, and Ponnaiyar. The five main rivers of the peninsular India viz, Godavari, Mahanadi, Kaveri, Krishna and Tungabhadra flow through Eastern Ghats. Except the Mahanadi and Godavari, all the rivers in Eastern Ghats are seasonal rivers (“Pullaiah and Rao, 2002”). These rivers cater the needs of people living in these areas by means of agriculture, irrigation and drinking water.

There are about 137 dams existing in Eastern Ghats to support hydro-electric projects and irrigation (Fig 2.14). The states of Andhra Pradesh and Odisha host 50 hydro projects, Tamil Nadu has 31, Karnataka and Telangana are having 3 each in the Eastern Ghats region (<http://www.india-wris.nrsc.gov.in>). The Grand Anicut (also called as *Kallanai*), in Thanjavur district of Tamil Nadu is one among the ancient irrigation systems in world build in second century during old Chola Dynasty (“Agoramoorthy and Hsu, 2008”). The details of available dams and reservoirs in the Eastern Ghats are given in Table 2.4.

2.9. Population and culture

Due to broken chain like topography and ease of accessibility to hilly terrain and surrounding plains, the Eastern Ghats are densely populated. The total population of Eastern Ghats is 1.2 million, out of which 0.1 million comprises the tribal population (“Census, 2011”). The hills and rivers of Eastern Ghats are acting as traditional homeland for indigenous tribal groups, including the Vulnerable Tribal Groups (VTGs).

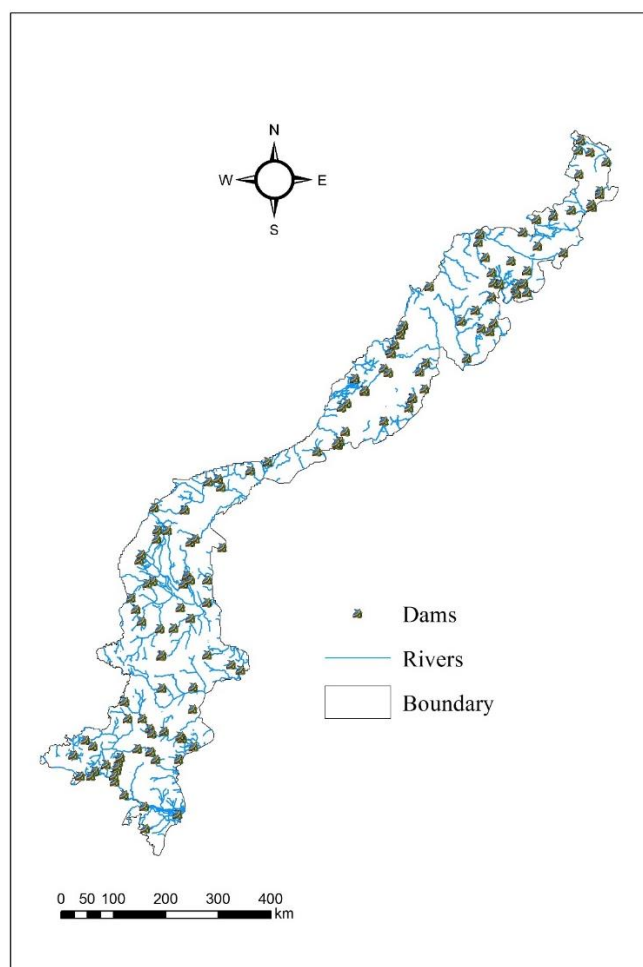


Figure 2.14 River networks and dams in Eastern Ghats

These communities mostly confined to the forested and hill-top villages. There are ~62 types of tribal communities living in the Eastern Ghats falling in Odisha State. Tribal groups such as Khond, Gond, Santal, Kolha, Munda, Saora, Shabar, and Bhottada almost constitute 64.2% of the total tribal population in the state. Other communities like Bhumij, Bhuiya, Oraon, Paroja, Kisan, Bhumia, Binjhal, and Koya constitute 18.1% population (“Census, 2001). In the State of Andhra Pradesh 32 types of tribal communities are residing in the Eastern Ghats. Some of the important tribal groups in Andhra Pradesh are Andh, Koya, Kulia, Mali, Hill Reddy, Valmikis, Jatapu, Nayak, Pardhan, Dhulia, Gadaba Gond, Chenchu, Goudu, Khond, Konda Kammara, Konda Reddi, Reddi Dora, and Bagata. The tribal communities namely, Chenchu, Gadaba, Kolam, Konda redid, Khond, Porja, Savara, and Thoti are classified under vulnerable category. Even though Tamil Nadu State has more than 36 variants of tribal communities, only three tribal communities viz, Malayali, Sholaga, and Urali are living in the Eastern Ghats.

Table 2.4. Details of hydro projects in the Eastern Ghats

Sl. No	Name of dam	District	State	River	Completed /operational since	Irrigation	Water supply	Flood control	Hydroelectricity (MW)	Navigation	latitude	longitude
1	Annamayya (Cheyyeru)	Y.S.R.	Andhra Pradesh	Cheyyeru	1979	x					14.21367	79.017688
2	Arniar Dam	Chittoor	Andhra Pradesh	Araniar	1958	x					13.41695	79.74265
3	Arniar Weir	Chittoor	Andhra Pradesh	Araniar	1958	x					13.325807	79.904202
4	Bahuda	Chittoor	Andhra Pradesh	Bahuda	1962	x					13.557635	78.505752
5	Bhupathipalem	East Godavari	Andhra Pradesh	Seethapallivagu	2007	x					17.446848	81.765134
6	Buggavagu	Guntur	Andhra Pradesh	Boggulavagu	1961	x					16.483465	79.543948
7	Buggavanka	Y.S.R.	Andhra Pradesh	Buggavanka	1993	x					14.400129	78.835509
8	Chennarayana wamy Gudi	Ananthpur	Andhra Pradesh	Papagni	1954	x					14.157399	78.155221
9	Chitravathi Dam	Y.S.R.	Andhra Pradesh	Chitravathi, Penar	1972	x					14.558779	77.960589
10	Cumbum	Prakasam	Andhra Pradesh	Gundlakamma & Jampaleru		x					15.526468	78.999757
11	Donkarai (S.H.E.S)	East Godavari	Andhra Pradesh	Sileru	1983				x		17.93433	81.79503
12	Forebay Lower Sileru (S.H.E.S) Dam	Khammam	Andhra Pradesh	Sileru	1978				x		17.86528	81.7017
13	Gandipalem	Nellore	Andhra Pradesh	Pillaperu	1964	x					14.877233	79.306286
14	Gorakallu Dam	Kurnool	Andhra Pradesh	Krishna, Paleru, Mallama selavagu	1981	x			x		15.57051	78.402983
15	Guntanwada Weir	Visakhapatnam	Andhra Pradesh	Sileru	1967				x		17.86437	81.702765

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(Forbay Dam)						
16	Hirmandala m	Srikakulam	Andhra Pradesh	Vamsadhara	x	18.687908 83.961993
17	Indira Sagar /Polavaram	West Godavari, East Godavari	Andhra Pradesh	Godavari	2019 x	17.286142 81.661571
18	Jalleru Dam	West Godavari	Andhra Pradesh	Jalleru	1977 x	17.214056 81.637612
19	Kakarla Dam	Prakasam	Andhra Pradesh	Peddavagu	x	15.590562 79.089546
20	Konam	Visakhapatnam	Andhra Pradesh	Pedol	1977 x	18.006547 82.965754
21	Kovvadakal va	West Godavari	Andhra Pradesh	Kovvada kalva	2004 x	17.244573 81.607627
22	Krishnapuram	Chittoor	Andhra Pradesh	Kaulasthali	1980 x	13.007727 78.52444
23	Lankasagar	Khammam	Andhra Pradesh	Kottaleru	1963 x	16.926508 80.37182
24	Lower Sagileru	Y.S.R.	Andhra Pradesh	Pennar	1959 x	14.953438 78.948297
25	Mallimadugu	Chittoor	Andhra Pradesh	Konakalva and Rallakalva	1955 x	13.586294 79.318888
26	Mopadu	Prakasam	Andhra Pradesh	Manneru	1921 x	15.438840 79.567813
27	Mylavaram Dam	Y.S.R.	Andhra Pradesh	Pennar	1983 x	14.847444 78.340508
28	Nagarjuna Sagar	Nalgonda	Andhra Pradesh	Krishna	1974 x	16.574444 79.312222
29	Paidigam	Srikakulam	Andhra Pradesh	Mahendranaya	x	19.960661 84.570573
30	Paleru ,Owk Dam	Kurnool	Andhra Pradesh	Krishna,Paleru, Mallama selavagu	1981 x	15.211417 78.102119
31	Peddagedda	Vizianagaram	Andhra Pradesh	Peddagedda	2007 x	18.469988 83.112808
32	Pedderu	Chittoor	Andhra Pradesh	Pedderu	1977 x	13.577075 78.518522

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33	Pincha	Y.S.R.	Andhra Pradesh	Pincha	1954	x	14.042790	78.718032
34	Raiwada	Visakhapatna m	Andhra Pradesh	Sarada	1977	x	18.016552	82.981364
35	Somasila	Nellore	Andhra Pradesh	Pennar	1986	x	14.488611	79.304444
36	SPVBS Dam	Y.S.R.	Andhra Pradesh	Pennar		x	14.803065	78.885916
37	Srisailem (N.S.R.S.P) Dam	Kurnool	Andhra Pradesh	Krishna	1984	x	16.086780	78.896650
38	Srisailem H.E.Project	Kurnool	Andhra Pradesh	Krishna	1974		16.086261	78.897002
39	T.Sundupalli Dam	Y.S.R.	Andhra Pradesh	Pennar		x	14.875266	79.007053
40	Thandava(Sri Raja Sagi Suryanarayana Raju (Srssr))	Visakhapatna m	Andhra Pradesh	Thandava	1964	x	17.621721	82.461262
41	Thatipudi	Vizianagaram	Andhra Pradesh	Gosthani	1963	x	18.172109	83.194916
42	Varadaraja Swamy Gudi	Kurnool	Andhra Pradesh	Munimadugulavagu	1988	x	15.733989	78.413635
43	Varaha	Visakhapatna m	Andhra Pradesh	Varaha	1963	x	17.853056	82.912064
44	Veligallu	Y.S.R.	Andhra Pradesh	Papagni	2006	x	14.031237	78.477036
45	Velugodu Dam	Kurnool	Andhra Pradesh	Pennar	1996	x	15.726361	78.592631
46	Vengalaraya Sagaram	Vizianagaram	Andhra Pradesh	Suvnamukhi	1988	x	18.623134	83.221735
47	Yeddula Eswaraiah GandhiKoata	Y.S.R.	Andhra Pradesh	Pennar	1993	x	14.807795	78.250560
48	Yerracalva	West Godavari	Andhra Pradesh	Yerracalva	1988	x	17.099444	81.254444

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49	Yogivemana	Anantapur	Andhra Pradesh	Maddeleru River	1993	x	14.357483	78.051550
50	Zurreru	Kurnool	Andhra Pradesh	Zurreru	1963	x	15.309454	78.138399
51	Chickkahole Dam	Chamarajanagar	Karnataka	Chickkahole	1958	x	11.834237	76.987939
52	Gundal Dam	Chamarajanagar	Karnataka	Gundal	1980	x	12.092574	77.198851
53	Uduthorehall	Chamarajanagar	Karnataka	Uduthorehall	2008	x	11.995058	77.328186
54	Alubani	Mayurbhanj	Odisha	Subarnarekha		x	22.003329	86.601400
55	Badanalla	Rayagada	Odisha	Badanalla	1997	x	19.327999	83.879212
56	Bagh Barrage	Baudh	Odisha	Bagh	1995	x	20.834130	84.249177
57	Baghalati	Ganjam	Odisha	Bahuda	1996	x	19.141193	84.394002
58	Baghua Dam	Ganjam	Odisha	BAGHUA	1980	x	19.952563	84.941091
59	Baghua reservoir	Ganjam	Odisha	BAGHUA	1983	x	19.876327	84.867888
60	Balimela Dam	Malkangiri	Odisha	Sileru	1977	x	18.140317	82.121814
61	Bankabal	Mayurbhanj	Odisha	Bankabal	1981	x	22.183369	86.308918
62	Bhanjanagar Dam	Ganjam	Odisha	Baranganalla	1966	x	19.951597	84.587174
63	Bidhyapur Barrage	Kendujhar	Odisha	Salandi	1982	x	21.238290	86.316343
64	Chheligada	Gajapati	Odisha	Badajore		x	19.197055	84.239100
65	Dadara Ghati	Dhenkanal	Odisha	Gambharia nalla	1988	x	21.057211	85.288644
66	Daha(OD) Dam	Ganjam	Odisha	Daha&Kalinga	1985	x	19.977455	84.470499
67	Dahuka Weir	Nayagarh	Odisha	Dahuka ,Baghamari	1968	x	20.176228	85.090167
68	Deo(OD) Dam	Mayurbhanj	Odisha	Deo	1992	x	21.812410	86.091540
69	Deriang Dam	Anugul	Odisha	Lingara&Mathili	1978	x	20.840483	85.032023

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70	Dhanei Dam	Ganjam	Odisha	Dhanei	1977	x	19.781581	84.892498
71	Ghodahada Dam	Ganjam	Odisha	Ghodahada	1978	x	19.290875	84.460490
72	Harabhangi	Gajapati	Odisha	Harabhangi	1998	x	19.516925	84.135408
73	Indrawati Dam	Nabarangapur	Odisha	Indravathi	1996	x	19.276267	82.828665
74	Kalo Dam	Mayurbhanj	Odisha	Kalo	1980	x	21.515256	86.459810
75	Kapur Dam	Nabarangapur	Odisha	Kapur	1994	x	19.196359	82.779578
76	Khadakhai Dam	Mayurbhanj	Odisha	Khadakhai	1984	x	22.219657	86.095104
77	Kuanria Dam	Nayagarh	Odisha	Kuanria	1971	x	20.352122	84.803130
78	Machkund Diversion Weir	Koraput	Odisha	Machkund	2000	x	18.532387	82.464497
79	Mahanadi Barrage	Cuttack	Odisha	Mahanadi	1991	x	20.470901	85.759950
80	Muran Dam	Koraput	Odisha	Muran	1981	x	19.105991	82.762209
81	Nesa Dam	Mayurbhanj	Odisha	Nesa	1978	x	22.400032	86.144706
82	Pilasalki Dam	Kandhamal	Odisha	Salki	1985	x	20.424835	84.338552
83	Podagada Dam	Nabarangapur	Odisha	Podagada	1996	x	19.196358	82.779857
84	Ramiala Dam	Dhenkanal	Odisha	Ramiala	1990	x	21.112274	85.597018
85	Ret Dam	Kalahandi	Odisha	Ret	2013	x	19.936142	83.310711
86	Salandi (Hadagarh)	Kendujhar	Odisha	Salandi	1965	x	21.288197	86.295817
87	Salki Weir	Baudh	Odisha	Salki	1957	x	20.686399	84.211691
88	Sapua (Medium) Dam	Dhenkanal	Odisha	Sapua nalla	2006	x	20.594979	85.294026
89	Satiguda Barrage	Koraput	Odisha	Kolab	1993	x	18.836869	82.581175

Contd..

90	Satiguda Dam	Malkangiri	Odisha	Satiguda/Satiguda Nalla	1986	x	18.362619	81.942226
91	Sorisamuli Weir	Ganjam	Odisha	Badanadi		x	20.156962	84.444856
92	Soroda Dam	Ganjam	Odisha	Padma	1986	x	19.739616	84.434525
93	Sunei Dam	Mayurbhanj	Odisha	Sunei River	1990	x	21.453193	86.461911
94	Surlikonda Barrage	Malkangiri	Odisha	Potteru	1978	x	18.359873	81.933156
95	Telengiri(T. M.I.P) Dam	Koraput	Odisha	Telengiri	2003	x	18.941746	82.663035
96	Balimela	Malkangiri	Orissa	Sileru	1977	x	18.157777	82.110277
97	Budhabudia ni	Nayagarh	Orissa	Budhabudiani	1980	x	19.965277	85.019444
98	Jalaput	Koraput	Orissa	Sileru	2000	x	18.457777	82.548611
99	Ramilala	Dhenkanal	Orissa	Ramilala	1983	x	21.116111	85.596111
100	Remal	Kendujhar	Orissa	Ramal	1985	x	21.199444	85.929444
101	Salandi	Kendujhar	Orissa	Salandi	1965	x	21.291111	86.296111
102	Salia	Ganjam	Orissa	Salia	1977	x	19.800648	85.074593
103	Upper Kolab	Koraput	Orissa	Kolab	1993	x	18.788306	82.603701
104	Anaimaduvu Dam	Salem	Tamil Nadu	Anaimaduvu	1993	x	11.774272	78.429559
105	Barur Dam	Krishnagiri	Tamil Nadu	Barur		x	12.307760	78.319503
106	Bhavani Kattalai Barrage - I	Namakkal	Tamil Nadu	Bhavani		x	11.382861	77.712687
107	Bhavanisagar	Erode	Tamil Nadu	Bhavani	1955	x	11.470277	77.108611
108	Chekkannur Barrage	Salem	Tamil Nadu	Cauvery	1987	x	11.727412	77.780910
109	Chinnar Dam	Krishnagiri	Tamil Nadu	Chinnar	1977	x	12.478751	77.929402
110	Gomukhinadi Dam	Viluppuram	Tamil Nadu	Gomukhinadhi	1965	x	11.778760	78.830330

Contd..

111	Gunderipalla m Dam	Erode	Tamil Nadu	Gunderipallam	1978	x	11.561989	77.370758
112	Ichambadi Anicut	Dharmapuri	Tamil Nadu	Pennaiyar	1981	x	12.221742	78.354732
113	Jadarpalaya m	Namakkal	Tamil Nadu	Cauvery		x	11.158339	77.880931
114	Kattalai Bed Regulator	Karur	Tamil Nadu	Cauvery		x	10.960591	78.233893
115	Kelavarapall i Dam	Krishnagiri	Tamil Nadu	Ponniar	1993	x	12.769740	77.874925
116	Kodiveri Anicut	Erode	Tamil Nadu	Bhavani		x	11.473148	77.296426
117	Koneripatti Barrage	Erode	Tamil Nadu	Cauvery	1988		11.576304	77.743568
118	Krishnagiri Dam	Krishnagiri	Tamil Nadu	Ponniar	1958	x	12.477999	78.188081
119	Lower Bhavani Dam	Erode	Tamil Nadu	Bhavani	1955	x	11.471108	77.113427
120	Mettur	Salem	Tamil Nadu	Cauvery	1934	x	11.803611	77.808611
121	Nerunjipettai Barrage	Erode	Tamil Nadu	Cauvery	1988		11.643116	77.758172
122	Pambar Dam	Krishnagiri	Tamil Nadu	Pambar	1983		12.263748	78.567867
123	Ponnanian Dam	Karur	Tamil Nadu	Ponnanian	1974	x	10.578886	78.259459
124	Rajathope Kanar Dam	Chittoor	Tamil Nadu	Rajathopekanar	1997	x	13.024520	79.076640
125	Sathanur Annicut	Tiruvannamalai	Tamil Nadu	Ponniar	1968	x	12.138525	78.890823
126	Sathanur Dam	Tiruvannamalai	Tamil Nadu	Ponniar	1958	x	12.183168	78.850199
127	Shenbagathope Dam	Tiruvannamalai	Tamil Nadu	Kamandalar	2007	x	12.644565	79.068247
128	Thandarai Anicut	Tiruvannamalai	Tamil Nadu	Cheyar	1975	x	12.001149	79.088500

Contd..

129	The Grand Anicut (Kallanai)	Thanjavur	Tamil Nadu	Kaveri	c. 200 AD	x	10.830512	78.818324
130	Thoppaiyar Dam	Dharmapuri	Tamil Nadu	Thoppaiyar	1986	x	11.956880	78.107940
131	Urachikottar Barrage	Erode	Tamil Nadu	Cauvery	1989	x	11.484119	77.703826
132	Vaniar Dam	Dharmapuri	Tamil Nadu	Vaniar	1985	x	11.903343	78.328281
133	Varattupallam Dam	Erode	Tamil Nadu	Varattupallam	1978	x	11.675822	77.561166
134	Venkatasumuthiram	Dharmapuri	Tamil Nadu	Vaniar	1981	x	11.906455	78.342788
135	Nagarjunasagar Tail Pond Dam	Nalgonda	Telangana	Krishna	2014	x	16.627485	79.489459
136	Pulichintala	Nalgonda	Telangana	Krishna	2013	x	16.771696	80.055193
137	Yellur Dam	Mahbubnagar	Telangana	Krishna		x	16.120449	78.354649

FAO: <http://www.fao.org/nr/water/aquastat/dams/index.stm>
 WRIS-India: <http://www.india-in/wrpinfo/index.php?title=Large Dams in India>

In the Esatern Ghats, most of the tribal communities are living in hilly and plain areas depending upon the nature of forest and its products for various livelihood activities (“Christoph. 1982”). On hilly regions and slopes these tribes practise shifting cultivation (Podu) as the major component of the subsistence economy (“Mundoli, 2011”). In recent times, the life style and occupation of the tribes have been improved due to the launch of government policies, increasing health care amenities, educational facilities, and better infrastructure facilities including roads, drinking water, electricity etc.

2.10. Sacred groves

A number of community managed ancient sacred groves can be seen in the Eastern Ghats. There are about ~1500 sacred groves are identified in the Eastern Ghats, out of which 750 are in that the State of Andhra Pradesh, 448 in Tamil Nadu and 322 in Odisha (“Jonathan, 2008”).

Chapter 3

Long-term LULC changes and its dynamics in the Eastern Ghats

3.1. General

Human activities are largely transformed the global landscape in the millennia (“Lambin et al., 2006”). The changes in LULC are the main driving factors, which would influence and affect an ecosystem. The expansion of cropland at the expense of forest cover is the leading factor of the LULC change (“Dissanayake et al., 2017”). On the other hand, the demand for food, settlements and infrastructure facilities to cater the needs of the increasing population is also contributing to the changes in the natural habitats. The LULC change would affect the climate, biodiversity, and ecosystem services. Hence, understanding the long-term human ecological relationships are essential for knowing the ecological dynamics in local and global scales (“Grimm et al., 2000”).

3.2. Definitions of Land use and Land cover

The Food and Agriculture Organization of the United Nations (FAO) defines land cover as the “observed biophysical cover on the Earth’s surface” (“FAO, 2000”) such as forests, grasslands, waterbodies etc. The land use is defined as the “arrangements, activities and inputs people undertake in a certain land cover type to produce, change or maintain it” (“FAO, 1998”) which includes agricultural lands, built ups, fallow lands etc. This definition of LULC brought out the importance of classification scheme in the land science. According to “Duhamel et al. (2009)” land cover is an ‘observed’ entity, where the source of observation can be anything from field inventories to the use of satellite images. Since land use is a by-product of human footprint on land cover it is difficult to ‘observe’ unless knowing the real background of the area. For example, without having a prior knowledge of an area it is often difficult to say whether the forest is converted into an agriculture or to any other land cover.

3.3. LULC classification system

The purpose of LULC classification system is to bring the information from different sources of maps into a single system. For example, the LULC maps derived from topographical sheets, aerial photographs and satellite remote sensing can vary with the scale/resolution, definitions of ground features, method of data collection, data coverage and date and year of data collections (“Anderson et al., 1976”). The classification system helps to overcome these issues in certain level. Now-a-days several classification systems are available for classifying features from the maps of different platforms. In each system of classification, the land features are defined. “Anderson (1971)” had suggested four level classification system, which is known as U.S.G.S. land use classification system/Anderson LULC classification system. This hierarchical classification system, consists of nine land features in the level I class, allows one to create thematic maps using coarse resolution remote sensing data to ground surveyed data (“Gomasca, 2009”). Later in 1976, FAO come up with another classification system with a consistent framework for the classification and mapping of land cover with eight major land classes in the first phase and its sub divisions in the second phase (“FAO, 1976”). Using Anderson (1971) classification system as the base US Earth Satellite Corporation (EarthSat) in 1990 suggested another classification system *EarthSat GeoCover Land Cover Legend*, which consists of thirteen classes. *National Land Cover Data (NLCD) Classification System* (1992) is a modified classification system based on National Land Cover Data set 1992 (NLCD1992) which has 21 land classes (“USGS, 1999”). In 1996, the *IGBP Data and Information System* (DIS) has produced a new classification system consisting of seventeen land classes (“Belward, 1996”). Later, “Thompson (1996)” suggested *South African Standard Land Cover Classification System* which consists of three hierarchical level with 12 land classes in level I, 23 subclasses in level II and user defined subcategories in level III. During 1998 Global Observation of Forest Cover (GOFC)/ Global Observation of Land Cover Dynamics (GOLD) proposed another mixed Land and Forest Cover Classification having 9 land classes (“Skole et al., 1998”). In India, the Directorate of Economics and Statistics (DES) in the Ministry of Agriculture is collecting land data on the nine-fold classification system (“DES, 2008”). According to the type and resolution of data one can use any of the classification system.

3.4. Land dynamics

The changes in the physical, environmental and socioeconomic aspects of the land and their multi-scale interactions in the past, present and future is known as land dynamics (“Veldkamp,

2009”). By knowing the history of land conversion of a place for decades to centuries will help to formulate effective land management plans (“Lambin et al., 2003”). Appropriately produced maps can provide hints on the activities/variables which led to the land conversions. These activities/variables are called land change drivers. The study of land dynamics also help to find out the land change drivers in an area. The major driving factors towards land conversion includes socio-economic conditions, mining, climate change etc.

3.5. Types of maps

Appropriate data sets are important for studying LULC changes over space and time. Maps and images are the most important types of data used for LULC studies. A map is a two-dimensional representation of the earth (“Harley, 1987”) and an image is an array of pixels with varying colour information (“Russ, 1990”). These data sets are varied with time, scale, resolution and mode of capturing.

- **Topographic maps:** The USGS defines Topographic maps as “detailed record of a land area, giving geographic positions and elevations for both natural and man-made features” (“Kaufman, 1980”). These maps are primarily aimed for topographic surveying.
- **Aerial photographs:** These are photographs of Earth’s topography taken from the space with the help of high resolution cameras mounted on aircrafts (“USGS, 1997”).
- **Satellite images/ Earth observation/ Remote sensing:** These are the earth’s images captured with the help of sensors mounted on satellites (“Lillesand & Kiefer, 1987”). These images are varied with spectral, temporal, radiometric, and spatial resolutions.
- **Vegetation maps:** These maps are prepared from observed spatial patterns or from model simulations of local or global scale (“Monserud & Leemans, 1992”).

3.6. Classification techniques

The LULC maps are generated by classifying the pixels based on their spectral reflectance of images from various platforms or maps using appropriate mapping/classification techniques. The maps produced by a suitable technique can be used to check the change detection of land features. Change detection is one of the important aspects in LULC studies, where it finds the changes in land features between two time spans. Different techniques are adopted over time for pre or post-classification and change detection of satellite images. Some of the important classification techniques are briefly explained below.

- **Univariate image differencing:** It is a pixel based direct comparison technique in which each pixel in two time periods is subtracted to produce a new map having changes between two time periods (“Singh, 1989”).
- **Image ratioing:** It is a technique of ratioing two spectral bands of data. It enhances the image (“NRCAN, 2015”).
- **Regression analysis:** In this change detection technique pixel from first time period is considered to be a linear function of the pixel of second time period. Then using least square regression one can regress to other (“Singh, 1989”).
- **Vegetation index differencing:** It measures the difference between two distinct spectral bands of a time period by ratioing the bands. It emphasizes the strong variations in the sensitivity of spectral response curves of different features and suppress the topographic effects (“Hussain et al., 2013”).
- **Change Vector Analysis (CVA):** It characterizes the radiometric changes in multispectral remote sensing data sets. It uses two spectral channels to map both the magnitude and the direction of change between the two input spectral images for each date (“Dewi et al., 2017”).
- **Principal Component Analysis (PCA):** It is a multivariate analysis which reduces the number of spectral components to fewer principal components accounting for the most variance in the original multispectral images (“Singh, 1989”) having almost all information present in the primary dataset.
- **Tassel cap transformation:** It is the conversion of the original bands of a satellite image into a new set of bands with defined interpretations. It is the weighted sums of distinct channel readings and can be expressed as

$$u = R^T x + r,$$

where, u is the value of pixels of different bands after tassell cap transformation, R is the coefficient of the TCT, x is the value of pixels of different bands, and r is used to make sure that the elements of vector u are always positive (“Chen et al., 2019”).

- **Texture analysis:** The pattern of information found in an image is called texture. It is one of the important spatial features in an image. The texture-based analysis can be realized by structural and statistical methods. The former method considers texture as a repetition of some features, with certain placement rule for example, Fourier spectrum analysis. The later one characterizes the stochastic properties of the spatial distribution of grey levels in an image (“He and Wang, 1990”).

- **Post-classification comparison:** In this one would compare the change maps produced from two time periods separately after classification. It allows to produce a new change map with a complete matrix of change (“Serra et al., 2019”).
- **Multi-date direct comparison:** The data sets of two time periods are classified using either supervised or unsupervised classification methods. In supervised classification first the user needs to produce training sets containing ground cover types of interest. This training sets train the classifier and subsequently produce the thematic map of interest (“Richards, 2012”). In unsupervised classification an unknown data pixel is clustered according to their properties. This cluster of pixel values allow the data to classify according to different land use and land cover classes (“Sharma and Verma, 2020”).
- **Artificial Neural Network (ANN):** ANN classify satellite data based on a rapid match using weighting factors that are pre-determined (“Gopal, 2016”). ANN effectively identifies the patterns and other underlying data structures in multidimensional satellite images with the help of a non-parametric supervised algorithm.
- **Support Vector Machine (SVM):** Like ANN, SVM is also a supervised non-parametric binary statistical learning technique. SVM appropriately divides the data points into two classes by identifying the optimal hyperplane. SVM can pick the hyperplane with the highest margin from the infinite number of hyperplanes. Margin refers to the difference between the classifier and the training points or vector of support (“Mountrakis et al., 2011”).
- **Decision tree:** This nonparametric classification method divides the available training data into subsets representing a single class resulting in a large and complex tree (“Berhane et al., 2018”).
- **GIS Integration:** It helps image interpretation by integrating GIS ancillary data of the satellite image or the place of mapping (“Zhuang et al., 1999”).
- **Spectral Mixture Analysis (SMA):** This technique is used prominently in hyperspectral remote sensing. Finding the appropriate endmember is an important process in SMA. The reflectance spectra derived from a sensor is composed of a mixture of ground features called as “spectral endmembers”. Each ground feature spectrum's best-fit weighting coefficients, which must be one, are interpreted as the relative area occupied by each component in a pixel (“Somers et al., 2011”).

- **Fuzzy change detection:** It is a knowledge-based method with no statistical assumptions about the data distributions. The satellite images are generally fuzzy in nature due to the association of two or more land features. These kinds of stochastic associations are determined to describe characteristics of an image. So, a pixel belongs to a land feature class with a membership degree and the sum of all land feature class degrees is 1 (“Wang and Jamshidi, 2004”).
- **Multi-sensor data fusion for change detection:** This technique is effectively used for the optimal use of large quantities of multiple sourced data. It produces the inferences by merges data from various sources and sensors (“Dong et al., 2009”).
- **Direct object comparison:** An object in a satellite image is a group of spatially and spectrally similar pixels. The direct object comparison compresses the image segmentation. It is a process of object wise partitioning of images (“Blaschke, 2010”).
- **Multi-temporal object change detection:** This is widely used object-oriented technique in change detection studies. Two time period maps of an area are classified using appropriate classification method and to find the changes (“Du et al., 2013”).
- **Visual interpretation:** This technique classifies the images by visual identification of objects in an image. The objects been identified with the help of its tone, shape, size, pattern, texture, shadow, and association (“Lu et al., 2004”).

3.7. Importance of Earth observation in LULC mapping

The emergence of remote sensing (RS) technology has dramatically increased the use of earth observation data in different sectors. Long-term global coverage of satellite remote sensing data could provide useful and vital information on a wide range of scales in a consistent, borderless and repeatable manner. Satellite remote sensing technology has provided a new dimension to build the land change processes in varying temporal intervals at different resolutions (“Singh et al., 2010”). The data from different satellites are often used for monitoring, assessing and management of the LULC. The use of satellite imagery has made land cover mapping much more realistic. Furthermore, the Geographic Information System (GIS) provides an indispensable platform for data management, data integration, data visualization, data analysis, and retrieval of remote sensing data in a wide canvas (“Goodchild, 2009”). Land cover maps derived from remote sensing data could yield meaningful information on global/regional/local assessments and policy makings (“Lambin et al., 2003; Potapov et al., 2008; Gomez et al., 2016; Duveiller et al., 2020”).

Unambiguously, RS technology helps in collecting the data even in difficult and inaccessible terrains. After the launch of the first ever earth observation satellite, Landsat 1 in 1972 by NASA, satellite remote sensing has been used extensively for gathering synoptic information on the Earth (“Roy et al., 2017”). The spatial, spectral, temporal resolutions, and spatial extent of satellite sensors (“Lillesand et al., 2015”) are important components for deciding the information gathered through remotely sensed data. The information that produced from remotely sensed data is directly linked to spatial, spectral, temporal and radiometric resolutions of the sensor (“Zhang, 2020”).

3.8. Indian Scenario

Satellite remote sensing technology is being extensively used in India to study the changes in landscape at different scales (“Roy et al., 2015a”, Rao and Pant, 2001; Niyogi et al., 2010; Singh et al., 2011”). With the help of Landsat MSS/TM, IRS 1C–LISS III, and Resourcesat1 satellite data sets, Roy et al. (2015a) had analysed the decadal LULC changes in India for a 20 year period from 1985-2005, and found that the cropland had increased from 47.55% to 49.34%, built-up area from 1.03% to 1.44%, whereas, forest cover had decreased from 23.25% to 22.18%. On the other hand, the growing population in India has put tremendous pressure on the land in terms of settlements, thereby, the urbanization becomes one of the prevalent land transformations in India (“Taubenböck et al, 2009”). The first national level forest cover map prepared by NRSA (now, NRSC) with the help of Landsat images for two time periods viz, 1972-75 and 1980-82 (“FSI, 1987”) had revealed an overall reduction of 2.79% in the country’s forest cover (16.89% in 1972-75 to 14.10% in 1980-82). On the other hand, the national level forest cover map prepared by Forest Survey of India (FSI) for the period 1981-83 had estimated the total forest cover of the country as 19.7% (“FSI, 1987”). From 1987 onwards FSI is publishing national level forest cover reports with the help of satellite images and ground checks (Fig 3.1).

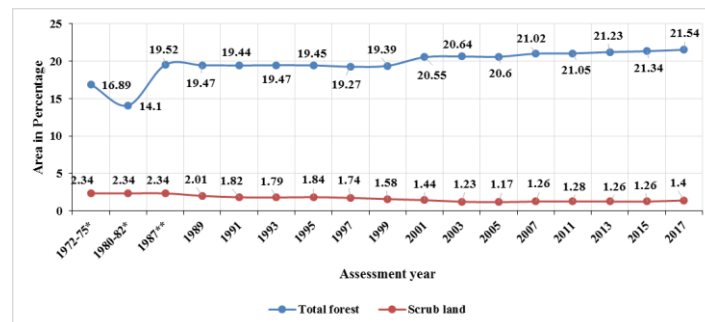


Figure 3.1. Change in forest and scrub land in India from 1972 to 2017 (“FSI, 1987-2017”)

3.9. Significance of LULC studies in the Eastern Ghats, India

Eastern Ghats are rapidly changing biogeographic regions in India, where most of its forests are on the edge of extinction leaving only small areas of forests being contiguous (“Jayakumar et al., 2002”). The Forests of Eastern Ghats are largely deforested for agriculture, dam construction, settlement, transportation, mining and timber logging for a period of more than ten decades (“Jayakumar and Arockiasamy, 2003”). The Eastern Ghats are largely composed of deciduous type of vegetation. Even though Eastern Ghats come under major floristic zones of India, not much attention has been paid for its forest conservation. The broken chain like topography makes the Eastern Ghats more vulnerable for human encroachments and settlements. Though, several studies have been reported on the LULC change, biodiversity, fire and conservation aspects in the forests of Western Ghats and Himalayas (“Nogué et al., 2017; Gaucherel et al., 2016; Kale et al., 2016; Behera et al., 2005; Bhagwat et al., 2005; Kushwaha et al., 2005; Jha et al., 2000, Myers et al., 2000; Menon and Bawa, 1997”) not much work has been done on these aspects in the Eastern Ghats (“Jayakumar, et al. 2002, Muthumperumal and Parthasarathy, 2010; Ramachandran et al., 2016; Naidu and Kumar, 2016; Kumaraguru et al., 2016”).

3.10. Future land use simulations

Land use modelling is a quantitative technique for simulating the future changes in the land use with the help of existing and projected economic and social data sets. Modelling often helps the decision makers to compare and manage the potential impacts of land use change at different scales viz, global, regional and local. The future simulations of LULC dynamics can be realized with the help of different models. Because many natural and anthropogenic factors simultaneously influence the LULC change, simulations of future LULC is often complicated (“Lambin et al., 2001”; Yang et al., 2012”). Researchers are using different methods to model LULC changes at various scales and regions at different time scales (“Pijanowski et al., 2002; Civco, 2007; Verburg, 2008”). Many existing models use the possible predictor variables to simulate the future LULC changes. Predictor variables are the components which would effect and make changes in the land system. Modelling of land use would help one to explore the key processes that are responsible for landscape changes (“Lambin et al., 2001”). Landscape models are spatially explicit and characterised by empirical to process-based, static to dynamic, simple to complex, and low to high spatial and temporal resolution (“Costanza and Voinov, 2004”). The LULC models usually addresses two queries such as location and the quantity of

change (“Trisurat et al., 2011”). Depending upon the scale, region and environmental factor a number of LULC models are being used.

Selection of a LULC model is application dependent. For example, Parker et al. (2001) had classified land use predictive models into six broad class viz; analytical, statistical, expert system based, system dynamics based, cellular and hybrid based (“Trisurat et al., 2011”). “Kaimowitz and Angelsen (1998)” had attempted modelling using deforestation aspect in terms of micro, regional, or macro-economic aspects. “Agarwal et al. (2002)” had described 19 LULC models that were based on the dimensions of space, time, and human decision-making aspects. Some of the important LULC models are described below.

3.10.1. Types of LULC models

Statistical Models: These are commonly and most widely used approaches in modeling. These methods are based on statistical matching of spatio-temporal trends and predictor variables (“Brown et al., 2012”). The predictor variables are distance to village, cities, waterbodies, roads, population, economic activities, climatic variables like precipitation and temperature and environmental variables like slope and soil.

System Models: These models check the relationship between the cause and effects of LULC change through a feedback loop structure with the help of variables like physical, socio-economical and demographical. This allows to address complex interactions of land use and environmental variables dynamically (“Haghani et al., 2003”).

Models based on Economic Principles: These models analyse the relationship between land value and land use (“El-Barmelgy et al., 2014”).

Models based on Spatial Interaction: These models address the relationship between activities and zones based on relative accessibilities, bid-rents, capacities and technical coefficients (“Silveira and Dentinho, 2010”).

Evolutionary Algorithms: Using the population-based approaches these methods coin multiple optimal solutions in a single model execution (“Bekele and Nicklow, 2005”).

Genetic Algorithms: These methods are scenario generators which identify a range of acceptable solutions for multiple goals by exploring potential combinations within a reasonable period of time (“Yoon et al., 2019”).

Optimisation Techniques: These methods involve optimization of the size as well as the spatial pattern of land use (“Chen et al., 2006”).

Cellular Models: The Cellular Automata (CA) are spatially and temporally discrete, abstract computational systems. They consist of a finite set of homogenous cells on a grid of specified shape that evolves through a number of discrete time steps according to a set of rules based on the states of neighboring cells (“Berto et al., 2017”).

Multi-Agent Models: These models simulate complex phenomenon. With the help of concurrently working independent agents, modellers can explore connections between people's micro-level activities and macro-level trends that arise from their interplay (“Tisue and Wilensky, 2004”).

Microsimulation: Microsimulation is a computer based method to simulate a data set in compliance with predetermined probabilistic laws. It looks for the interactions of individual units (“Ballas et al., 2005”).

Hybrid Models: These methods employ combination of enlisted techniques. Now-a days these methods are being used extensively in LULC simulations (“Trisurat et al., 2011”).

3.11. Review of Literature

LULC change is identified as a major factor which influences the biodiversity, species distribution and ecosystem services (“Foley et al., 2005”). The Eastern Ghats are also experienced major LULC shifts in recent decades, like other tropical areas of the world (“Rawat, 1997; Jayakumar et al., 2009; Reshma et al., 2018”). Forest ecosystems are one of the primary focus of land conversions. It is estimated that ~75% of the natural forest area around the world has been affected by human activities since the last ice age (“Ellis and Ramankutty, 2008”). The ever-increasing population, their food demands, need of settlement and exploitation of economic resources are the major factors responsible for the degradation of forest cover and biodiversity across the globe (“Newbold et al., 2015; FAO, 2016”). Globally, ~40 percent of deforestation has occurred in the tropics and subtropics due to large-scale commercial agriculture (“FAO, 2016”). Land cover maps derived from remote sensing data could yield meaningful information on global/regional/ local spatial assessments of vegetation distribution (“FRA, 2000; Lambin et al., 2003; Potapov et al., 2008; Gómez et al., 2016”).

Several studies have been reported on the land use land cover change at different scales over the time. For e.g., “Borrelli et al. (2017)” had estimated 3.3% change in the global gross land stock between the years 2001 to 2012, with an overall decline of 2.26 million sq. km of forest cover, increase of 2.17 million sq. km of semi-natural vegetation, and expansion of nearly 0.1 million sq. km of cropland. Based on visual interpretation, “Zeng et al. (2018)” had assessed

the expansion of cropland as well as the loss of forest cover in the Southeast Asia during 2000 to 2014. “Liu et al. (2019)” have documented 5694 sq. km annual increase of global urban area between 2000 and 2010. “Van Vliet (2019)” has reported that global urban land has been increased from 33.2 Mha to 71.3 Mha from 1992 to 2015, which had resulted in the loss of 3.3 Mha of forest cover, and 4.6 Mha of shrubland. “Estoque et al. (2019)” has studied the forest cover loss in the Southeast Asia and estimated 80 Mha of forest cover loss between 2005 and 2015. Recently, “Huang et al. (2020)” have reported large scale land transitions in Europe during 1992 to 2015. The land transitions mainly occurred due to the decline in agricultural land and increase in forest cover and urban settlements. Some important case studies on LULC from different corners of the globe are also been reported (for e.g., “Zhao et al., 2017; Hu et al., 2019; Appiah et al., 2020”). Long-term or historical LULC studies would play key role in land management and policy making. For example, Moulds et al. (2018)” had prepared a high-resolution gridded LULC map for the Indian subcontinent for the period 1960 and 2010. They have reported that the agricultural land and urbanization have increased considerably. Similarly, “Chen et al. (2019)” had studied the land dynamics of Taiwan between 1904 and 2015. “

Estimating the future changes in LULC is an important and crucial exercise in LULC studies. The global LULC simulations are vital for knowing the future status of carbon cycle, land condition, water availability etc. “Hurt et al. (2011)” have simulated the global land transitions with Global Land-use Model and opined that shifting cultivation would make the land transitions faster than wood land harvesting during the period from 1500 - 2100. “Cao et al. (2019)” have studied the global LULC change from 2010-2100 using Global change assessment model with cellular automata (GCAM-CA) and predicted that cropland area would increase, whereas the forest, grassland, and shrubland areas decrease. “Feddema et al. (2005)” also have reported global agricultural expansion under A2 scenario for 2100. “Soares-Filho et al. (2006)” opined that by 2050 expansion of agricultural land would cause 40% decrease of the Amazon forest resulting in high carbon emission and species extinction. “Stehfest et al. (2019)” have opined that the global cropland and pasture area may decrease in 2050 under sustainability scenario and cropland would increase in regional rivalry scenario. Local and regional simulations also report the impacts of agricultural intensifications in the biodiversity and the land. “Castillo et al. (2020)” reported that by 2030 most of the agricultural lands in Spain will be abandoned. “Estoque et al. (2019)” simulated the changes in forest cover in Southeast Asia under different scenarios and found that forest cover will decrease drastically

by 2050 under regional rivalry and the fossil-fuelled development. But there is an increase in forest cover under the sustainability scenario in this region. “Sleeter et al. (2017)” reported decrease in grasslands, shrublands, forests and croplands by 2100 in California due to human pressure. “Rimal et al. (2018)” simulated a possible decrease in cropland due to urban expansion in Kathmandu valley during 2024 and 2032. “Sohl et al. (2014)” reports similar results viz., by 2100 urban and agricultural expansions cause a decrease in natural land cover such as grassland, forest, and shrubland in the United States. “West et al. (2014)” argues that during 2005-2095 the grasslands of United States will be replaced by croplands. “Ordonez et al. (2014)” showed that the increase in agricultural use would affect the biodiversity and ecosystem services of US by 2050. “Chen et al. (2020)” reported urban expansion and resultant reductions in the areas of forests and agriculture in Chongqing, China by 2030. “Feng and Tong (2019)” also reported similar results from other parts of China. “De Oliveira et al. (2020)” stated an increase in agriculture, forest, and urban areas by 2030 in Rio Doce State Park, Brazil. “Liping et al. (2018)” have studied the future LULC changes in Jiangle, China in land classes and estimated that the area of land classes of water, construction, bare land and farmland would increase in 2025 and 2036 against the present status. “Estoque et al. (2019)” have estimated a gain of 19.6 million ha in forest cover by 2050 in sustainability scenario.

India is experiencing major LULC changes due to expansion of agriculture, urbanization and economic exploitation of natural resources (“Goldewijk and Ramankutty, 2004; Tian et al., 2014”). Researchers are actively engaged in LULC studies under different levels that includes national (“Roy et al., 2015”), state and district wise (“Areendran et al., 2013”), sub-district wise (“Chaudhary et al., 2008”), village wise (“Tiwari et al., 2010”), river basin wise (“Garg et al., 2019”), protected area wise (“Mukherjee et al., 2020”) etc. “Paul et al. (2016)” have reported domination of woody savannas especially over Central, Peninsular and Northeast India during 1980s. The agricultural intensification in the country is the major reason for conversion of woody savanna to cropland. “Niyogi et al. (2010)” also had reported significant agricultural intensification in the Northern India. “Ambinakudige and Choi (2009)” have attributed the cause for decrease in paddy land in Western Ghats during 1991 and 2002 to the coffee plantations. Based on the Landsat 5 (TM) and Landsat 8 (OLI/TIRS) data sets, “Mathan and Krishnaveni (2020)” have estimated the expansion of Chennai city during 1988, 1997, 2006, and 2017 and documented that large part of the agriculture/fallow land, vegetation land, and water bodies/wetlands have been converted to built-up area. Similar studies have also been carried out for the cities of Delhi by “Mohan and Kandya (2015)” during 2001–2011, and

Mumbai by “Zope et al., (2016)” between 1966, 2001 and 2009. “Meiyappan et al. (2017)” have reported a number of LULC change studies from different parts of India. “Kale et al. (2016)”, based on coupled logistic regression and Markov model, have predicted that the forest cover in Western Ghats of India would decrease in 2025. “Singh et al. (2018)” have showed that agricultural and built-up land area in the Tons River Basin, Madhya Pradesh basin would expand by 2025. Similarly, “Anand and Oinam (2020)” assessed the future LULC of Manipur River basin in the lesser Himalayan ranges. Their simulations suggest that the water bodies, agriculture land and built-up area would increase, whereas wetland area would decrease in 2030.

Not much work has been carried out or reported on the LULC change in the Eastern Ghats. Most of the available studies are confined to either small pockets or local level. For e.g., “Jayakumar et al. (2000, 2002)” have mapped and assessed the forest type and its current status from Kolli hills with the help of Landsat TM and IRS-1C LISS III images. “Balaguru et al. (2003)” have studied the vegetation types in different slopes of the Shervarayan hills with the help of IRS 1C LISS III data. “Jayakumar et al. (2009)” have estimated the forest dynamics of Eastern Ghat hill ranges falling in the Tamil Nadu state for the years 1990 and 2003 with the help of Landsat TM and IRS LISS III. Using IRS LISS III data for two seasons (November - December 2004 and February-May 2005), “Ambastha and Jha (2010)” had mapped the vegetation type of Eastern Ghats of Tamil Nadu. “Areendran et al. (2010)” studied the vegetation type in the Eastern Ghats with the help of both IRS LISS III data and field investigations. Similarly, using IRS P6 LISS III data “Pattanaik et al. (2010)” have assessed the landscape characteristics of Kuldiha wild life sanctuary in Odisha state and estimated different forest cover types in this region. “Anupama et al. (2014)” have estimated the land use land cover and vegetation changes of Nallamalai Hills for the past 200 years using pollen analysis and remote sensing data. They have reported that no significant changes in the forest cover has been observed during the last ~ 30 years. Using toposheets and satellite images “Reddy et al. (2014)” have brought out a first order picture of deforestation in the Eastern Ghats since 1930 to 2013. According to them the forest cover in Eastern Ghats has been decreased from 45.6% in 1930 to 31.7% in 2013. “Dash et al. (2018)” studied the forest cover changes in Koraput district of Odisha for the years 1932, 1973, 1990, 2004 and 2013 and reported 26.9% reduction in forest cover from 1932-2013.

Significant loss of forest cover in parts of Eastern Ghats (“Patnaik et al., 2011; Ramesh and Kaplana, 2015; Saranya et al., 2016”) has exerted tremendous pressure on the sustenance of

Table 3.1. List of data sets used for mapping of forest type and LULC of the Eastern Ghats from 1920-2015

(a): Topographical maps* used in the study (U.S. Army Map Service, 1955)

Edition	Sheet	Title	Year of Survey	Producer/compiled/Printed by	Year of compilation
2AMS	nc-43-03	Calicut	1916	Army Map Service (LU), Corps of Engineers, 4-59, U.S.Army, Washington	1954
2AMS	nc-43-04	Erode	1916-1929	Army Map Service (LU), Corps of Engineers, 4-59, U.S.Army	1953
2AMS	nc-43-08	Dindigul	1925-32	Army Map Service (LU), Corps of Engineers, 4-59, U.S.Army	1954
2AMS	nc-44-01	Salem	1930-31	Army Map Service (LU), Corps of Engineers, 4-59, U.S.Army	1954
1AMS	nc-44-05	Tiruchirappalli	1929-30	Army Map Service (LU), Corps of Engineers, 11-55, U.S.Army	1953
1AMS	nd-43-04	Bellary	1927-31	Army Map Service (LU), Corps of Engineers, 7-61, U.S.Army	1955
1AMS	nd-43-08	Ananthapur	1927-29	Army Map Service (LU), Corps of Engineers, 7-61, U.S.Army	1955
1AMS	nd-43-12	Tumkur	1925	Army Map Service, Corps of Engineers, 6-61, U.S.Army	1955
1AMS	nd-43-16	Mysore	1910-25	Army Map Service, Corps of Engineers, 11-59, U.S.Army	1954
1AMS	nd-44-01	Kurnool	1921-22	Army Map Service, Corps of Engineers, 11-56, U.S.Army	1954
2AMS	nd-44-02	Chirala	1919-30	Army Map Service, Corps of Engineers, 3-59, U.S.Army	1954
1AMS	nd-44-05	Cuddaph	1918	Army Map Service , Corps of Engineers, 11-56,U.S.Army	1954
2AMS	nd-44-06	Nellore	1918	Army Map Service, Corps of Engineers, 3-59, U.S.Army	1954
1AMS	nd-44-09	Kolar	1923-43	Army Map Service, Corps of Engineers, 9-60, U.S.Army	1954

Contd..

1AMS	nd-44-10	Madras	1916-17	Army Map Service (LD) , Corps of Engineers, 12-57, U.S.Army	1954
1AMS	nd-44-13	Bangalore	1912-13	Army Map Service (LD), Corps of Engineers, 9-59, U.S.Army	1954
1AMS	nd-44-14	Canjeeveram	1914-16	Army Map Service (LD) , Corps of Engineers, 11-56, U.S.Army	1954
1AMS	ne-44-03	Jagdapur	1869- 1942	Army Map Service (LUMB) Corps of Engineers, 7-63, U.S.Army	1954
1AMS	ne-44-04	Bhawanipatna		Army Map Service (LUSX), Corps of Engineers, 11-59, U.S.Army	1954
1AMS	ne-44-07	Malakanagiri	1930-33	Army Map Service (LUBM) Corps of Engineers, 4-63, U.S.Army	1954
1AMS	ne-44-08	Vizianagaram	1932-34	Army Map Service (LUBM), Corps of Engineers, 7-63, U.S.Army	1954
1AMS	ne-44-10	Yellandalapad	1924-25	Army Map Service (LUBM), Corps of Engineers, 9-63, U.S.Army	1954
1AMS	ne-44-11	Samalkot	1925-33	Army Map Service (LUBM) Corps of Engineers, 7-63, U.S.Army	1954
1AMS	ne-44-12	Visakhapatnam	1951 & 1948	Army Map Service (LUSX) , Corps of Engineers, 8-59, U.S.Army	1954
1AMS	ne-44-13	Wanparti	1922- 1924	Army Map Service (LUBM) Corps of Engineers, 7-63, U.S.Army	1954
1AMS	ne-44-14	Vijayawada		Army Map Service (LUBM) Corps of Engineers, U.S. Army	1954
1AMS	ne-44-15	Cocanada	1938-41	Army Map Service (LUBM) Corps of Engineers, 7-63, U.S.Army	1954
1AMS	ne-45-1	Berhampur	1951	Army Map Service (LUBM) Corps of Engineers, 7-63, U.S.Army	1954
1AMS	ne-45-5	Parlakimidi	1938 1936 & 1934	Army Map Service (LUBM) Corps of Engineers, 8-63, U.S.Army, Washington	1954
1AMS	nf-44-16	Bolangir	1874- 1945	Army Map Service (NSS& H), Corps of Engineers, 2- 60, U.S.Army, Washington	1955

Contd..

1AMS	nf-45-6	Jamshedpur	1913-43	Army Map Service (NSS & H) , Corps of Engineers, 10-59, U.S.Army, Washington	1955
1AMS	nf-45-09	Deogarh	1924-34	Army Map Service (NSS & H), Corps of Engineers, 2-62, U.S.Army, Washington	1955
1AMS	nf-45-10	Balasore	1924-29	Army Map Service (NSS & H), Corps of Engineers, 3-62, U.S.Army, Washington	1954
1AMS	nf-45-13	Angul	1930-33	Army Map Service (NSS & H), Corps of Engineers, 3-62, U.S.Army, Washington	1955
1AMS	nf-45-14	Cuttack		Army Map Service (NSS & H), Corps of Engineers, 10-59, U.S.Army, Washington	1954

*Scale of the data: 1:250,000

(b) Historical forest type maps used in the study (French Institute Pondicherry (FIP), 1960; Census Commissioner for India, 1942)

Sheet	Title	Original scale	Published by	Year of publication	Prepared by	Based on
NC 43, 44	Cape Camorin	1:1000000	ICAR	1961	FIP	SOI map
NE 43, 45	Godavari	1:1000000	ICAR	1963	FIP	SOI map
NE 44, 45	Jagannath	1:1000000	ICAR	1963	FIP	SOI map
ND 44	Madras	1:1000000	ICAR	1962	FIP	SOI map
ND 43	Mysore	1:1000000	ICAR	1965	FIP	SOI map
NF 45	Orissa	1:1000000	ICAR	1973	FIP	SOI map
NF44	Waiganga	1:1000000	ICAR	1971	FIP	SOI map
Reg.No. 2217 E.42-1,201	India forest, Irrigation and water power map	1:1,4,435,200	SOI	1942	Census Commissioner for India	

(c) Satellite images used in the study

1. For the year 1975

Satellite, Sensor and Spatial Resolution	Path	Row	Season/Date of Acquisition		
			January-March	April-June	Sep-Dec
		44,46	-	-	07-11-1972
		45	18-01-1973	-	-
	150	47	01-01-1973	-	-
		48	24-01-1973	-	-
		46	24-02-1973	-	-

Contd..

151	47	20-01-1973	-	-
	48	08-01-1977	-	-
Landsat 1, MSS, 60m	48	04-07-1975	-	-
	49,50	26-02-1973	-	27-11-1977
153	51	07-02-1977	-	18-09-1977
	52	27-01-1977	-	19-09-1977
	53	21-01-1973	-	-
	49	22-01-1973	-	30-11-1977
154	50, 51	27-02-1973	-	19-09-1977
	52	27-02-1973	-	30-11-1977
155	50,51,52	10-02-1973	-	-

2. For the year 1985

Satellite, Sensor and Spatial Resolution	Path	Row	Season/Date of Acquisition		
			January- March	April–June	Sep–Dec
	139	45,46	-	21-04-1985	20-09-1985
	140	45,46,47	-	28-04-1985	19-09-1985
	141	46,47,48	-	19-04-1985	26-09-1985
Landsat 4, MSS, 56m	142	47,48,49, 50,51,52	-	26-04-1985	17-09-1985
	143	49,50,51, 52,53	-	17-04-1985	24-09-1985
	144	49,50,52, 51	02-03-1986	24-04-1985	15-09-1985

3. For the year 1995

Satellite, Sensor and Spatial Resolution	Path	Row	Season/Date of Acquisition		
			January- March	April–June	Sep–Dec
	139	45	13-01-1993	05-05-1993	05-11-1996
		46	-	05-05-1993	15-12-1993
		44	20-01-1993	31-05-1994	04-11-1993
	140	45	04-01-1993	31-05-1994	04-11-1993
		46	04-01-1993	31-05-1994	-
		47	04-01-1993	26-04-1993	-
	141	45,46, 47,48	16-03-1993	03-05-1993	-
Landsat 4, TM, 30m		47	26-02-1993	01-05-1993	11-12-1993

Contd..

	48	01-02-1993	11-06-1993	18-11-1993
142	49,51	-	11-06-1993	-
	52	-	25-08-1991	-
	48,49	26-02-1993	01-05-1993	27-12-1993
	50	26-02-1993	01-05-1993	-
143	51	14-03-1993	01-05-1993	27-12-1993
	52	14-03-1993	01-05-1993	-
	53	04-03-1993	-	-
	48	05-03-1993	24-05-1993	16-11-1993
	49,50	05-03-1993	-	16-11-1993
144	51	16-01-1993	-	16-11-1993
	52	16-01-1993	-	-
	53	-	05-03-1993	-

4. For the year 2005

Satellite, Sensor and Spatial Resolution	Path	Row	Season/Date of Acquisition		
			January- March	April-June	Sep-Dec
	139	45	06-01-2005	14-05-2005	24-12-2005
		46	06-01-2005	14-05-2005	06-11-2005
		44	13-01-2005	-	13-11-2005
	140	45	13-01-2005	21-05-2005	13-11-2005
		46	13-01-2005	05-05-2005	13-11-2005
		47	14-02-2005	05-05-2005	13-11-2005
		45	20-01-2005	12-05-2005	12-11-2005
		46	20-01-2005	12-05-2005	12-11-2005(TM)
	141	47	21-02-2005	12-05-2005	12-11-2005(TM)
		48	13-02-2005	12-05-2005	12-11-2005(TM)
Landsat 5, ETM+, 30m		47	12-02-2005	19-05-2005	11-11-2005
		48	12-02-2005	20-06-2005	11-11-2005
	142	49	12-02-2005	20-06-2005	29-12-2005
		51	12-02-2005	19-05-2005	29-12-2005
		52	28-02-2005	19-05-2005	10-12-2004
		48,49	19-02-2005	10-05-2005	18-11-2005
		50	19-02-2005	26-05-2005	01-12-2004
	143	51	27-02-2005	26-05-2005	01-12-2004
		52	26-01-2005	26-05-2005	17-12-2004
		53	23-03-2005	27-04-2006	20-12-2005
		48	02-02- 2005(TM)	17-05-2005	27-12-2005
		49,50	17-01-2005 (TM)	01-05-2005	27-12-2005

Contd..

144	51	25-01-2005	12-04-2004	27-12-2005
	52	10-02-2005	12-04-2004	30-12-2006
	53	10-02-2005	15-04-2005	30-12-2006

5. For the year 2015

Satellite, Sensor and Spatial Resolution	Path	Row	Season/Date of Acquisition		
			January- March	April–June	Sep–Dec
	139	45,46	10-01-2015	18-05-2015	28-12-2015
		44	02-02-2015	10-06-2015	19-12-2015
	140	45	17-01-2015	10-06-2015	03-12-2015
		46,47	17-01-2015	10-06-2015	16-12-2014
	141	46	09-02-2015	30-06-2014	26-12-2015
		47,48	06-02-2014	30-06-2014	26-12-2015
		47	13-02-2014	23-05-2015	19-12-2016
	142	48,49	19-02-2016	23-05-2015	19-12-2016
Landsat 8, OLI, 30m		51	17-03-2014	24-06-2015	19-12-2016
		48	23-02-2015	30-05-2015	24-12-2015
		49	23-02-2015	30-05-2015	06-11-2015
		50	04-02-2014	30-05-2015	24-12-2015
	143	51	23-02-2015	30-05-2015	21-10-2015
		52	23-02-2015	15-06-2015	26-12-2016
		53	23-02-2015	15-06-2015	26-12-2016
		48,49,50	13-01-2015	24-06-2016	15-12-2015
	144	51	13-01-2015	06-06-2015	26-11-2014
		52	11-02-2014	24-06-2016	05-12-2014

biodiversity (“Rawat, 1997”). Many sensitive species are likely to be vanished from the forests or might be facing extinction because of the habitat loss, fragmentation and climate change (“Nemésio et al., 2016”). The recent threats faced by the Eastern Ghats include deforestation and fragmentation due to hydropower projects and mining (“Jayakumar and Arockiasamy, 2003”). The massive impoundments that dam and their reservoirs have formed between the states of Andhra Pradesh and Odisha borders have submerged thousands of hectares of forest land (“MoEF and Kalpavriksh, 2004”).

3.12 Methodology

3.12.1 Data products

The analysis was carried out with the help of historical maps (1920, 1940 and 1960) and multi-date multi-temporal Landsat images from the sensors like MSS (1975 and 1985), TM (1995 and 2005), ETM+ (2005) and OLI (2015). The standard Level 1 images of 1975, 1985, 1995, 2005 and 2015 were downloaded as orthorectified form from the earth explorer website (<https://earthexplorer.usgs.gov/>) of USGS. The detailed descriptions of historical maps and satellite images used in the present study are given in Table 3.1 (a-c). Satellite data for three seasons have been used in the present study viz., winter (January to March), pre-monsoon (April to May), and post-monsoon (October to December). The satellite images were selected in such a way that all the scenes were free from (less than 3%) cloud cover. The ancillary data, such as vegetation type map of India for the year 2005 (“Roy et al., 2015b”), LULC maps for the years 1985, 1995 and 2005 (“Roy et al., 2015a”), and High-resolution Google Earth images were also used for the mapping of present LULC.

For simulating future LULC change, the village and district population data of the Eastern Ghats for the years 2001 and 2011 were obtained from the Office of the Registrar General & Census Commissioner, India (<http://www.censusindia.gov.in>, accessed on 16th August 2018). The details of census metadata was obtained from “http://www.censusindia.gov.in/2011census/HLO/Metadata_Census_2011.pdf”. Data relating to the rivers, roads, rail networks, and locations of villages and cities were accessed from the OpenStreetMap of India for the year 2015 (“<https://www.openstreetmap.in>, accessed on 16th August 2018). The topographic data such as DEM obtained from the Shuttle Radar Topography Mission Digital Elevation Model (SRTM DEM at 30 m resolution) (“<https://earthexplorer.usgs.gov/>”) was also used. Other topographic proxies such as slope and aspect were derived from the SRTM DEM data in the ARC GIS 10.3 environment. ISRIC soil-type data of 250 m resolution (“Hengl et al., 2017”)

for the year 2016 were downloaded for the Eastern Ghats region (<https://www.isric.org/explore/soilgrids>). Additionally, the erosion, drainage, and flood capacity data of the region were obtained from the National Bureau of Soil Survey and Land Use Planning (NBSS & LUP) for the year 2005. The details of data sets used for the simulation of future LULC changes are given in the Table 3.2.

Table 3.2 Details of datasets used for LULC change future simulations (Reshma et al., 2020)

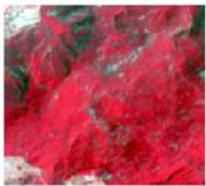
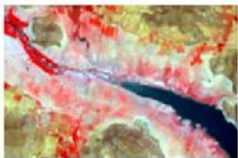
Category	Data	Year	Resolution	Data source
Land class	Historical maps and Satellite images	2005, 2015	Varying	Details are in Annexure 4 (a-c)
Anthropogenic influence	Population	2001, 2011	Tabular	http://www.censusindia.gov.in Census of India (2001, 2011)
	Population density	2005-2070	250m	Projected using 2001 & 2011
Topography	Elevation	2000	30m	https://earthexplorer.usgs.gov USGS SRTM data (2015) *
	Slope			
	Aspect			
Soil	Drainage	2000	Vector	“NBSS&LUP, India (2002)” **
	Erosion			
	Flooding			
Climate	Annual precipitation	2005-2050	1km	http://www.worldclim.org WorldClim version 1.4
	Annual temperature			
Social	Distance to waterbodies	2015	Vector	https://www.openstreetmap.in OpenStreetMap
	Distance to transport networks			
	Distance to city			
	Distance to villages			

*United States Geological Survey Shuttle Radar Topography Mission (USGS SRTM).

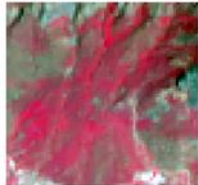
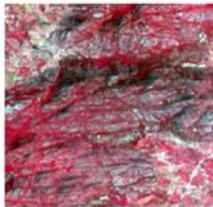
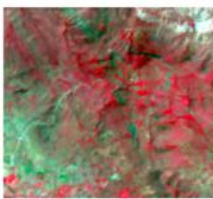
**National Bureau of Soil Survey and Land Use Planning (NBSS&LUP).

3.12.2. Data Preparation

Pre-processing of historical maps and satellite images were carried out prior to image classification in order to bring the images to a standard projection. The standard data preparation methodology is shown in Fig. 3.4. The historical maps were geometrically corrected with the help of geometric correction tool available with ERDAS Imagine 2015

Land class	Satellite image view (Landsat 8 OLI)	Ground view	Description
Evergreen			Bright red to dark red tone, varying size, irregular discontinuous shape with smooth to medium texture
Semi evergreen			Pinkish to red tone, varying size with irregular discontinuous shape
Dry Evergreen			Pinkish to red tone, irregular edges with discontinuous pattern
Moist deciduous			Dark red tone, smooth size with irregular pattern
Dry deciduous			Irregular shape with unclear edges and light tone
Riverine			Dark red to pinkish tone with association of waterbodies
Forest plantation			Dark red to red tone, large to medium size and regular with sharp edges
Degraded forest			Pinkish red to green tone, irregular pattern with medium smooth texture

Contd..

Scrub land			Pinkish red to light green tone, coarse texture with varying shape
Thorn forest			Light red tone with irregular discontinuous pattern
Dry deciduous scrub			Pinkish red to light red tone with coarse texture
Dry evergreen scrub			Pinkish red tone, regular shape with continuous pattern
Grassland			Greenish to pinkish tone with smooth texture and irregular pattern
Woodland			Pinkish red tone, irregular pattern with smooth texture
Orchard			Dark red tone, smooth texture, large to medium size with regular pattern
Cropland			Bright red to red tone with regular shape and medium to smooth texture

Contd..

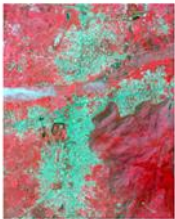
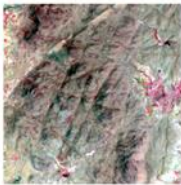
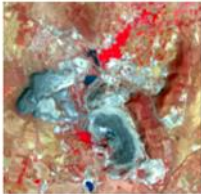
Water bodies			Smooth and light to dark blue areas with irregular sinuous
Permanent wetland			Smooth and light to dark blue tone, wide areas with irregular sinuous
Built up			Cyan or greenish tone, coarse texture, clustered pattern with irregular and discontinues shape
Barren land			Pinkish red or light brown or whitish tone with irregular pattern
Mining			Grey/blue/ whitish tone, irregular to regular pattern with rocky appearance

Figure 3.2. Interpretation keys used for the mapping of forest type and LULC of Eastern Ghats (Lillesand and Kiefer, 1987, Reshma et al., 2018)

Table 3.3. Land use and land cover classification and its descriptions used in the study (Anderson et al., 1976; Reshma et al., 2018)

LEVEL I	LEVEL II	DESCRIPTION
Forest	Evergreen	Includes all land classified either as forest under any legal enactment, or administered as forest, whether State-owned or private, and whether wooded or maintained as potential forest land. Includes area of crops within the forest and grazing lands or areas open for grazing within the forests.
	Semi evergreen	
	Dry Evergreen	
	Moist deciduous	
	Dry deciduous	
	Littoral and swamp forest/Riverine	
	Forest plantation	
	Degraded forest	
Scrub/ Grassland	Scrub land (open/ closed)	Consist of open woodland characterised by thorny trees with short trunks and low, branching crowns, spiny and xerophytic shrubs, and dry grassland. Includes forests that have been degraded through intensive agriculture and grazing into stunted and open thorn scrub, dominated by trees. Includes all grazing land whether it is permanent pasture and meadows or not. Includes village common grazing land.
	Thorn forest	
	Dry deciduous scrub	
	Dry evergreen scrub	
	Grassland	
	Woodland	
Agriculture	Orchard	Includes all cultivable land and land under plantations (both forest plantation and commercial plantation). Cultivable waste land includes land available for cultivation, whether taken up or not taken up for cultivation once, but not cultivated during the last five years or more in succession including the current year for some reason or the other. Such land may be either fallow or covered with shrubs and jungles which are not put to any use. They may be accessible or inaccessible and may lie in isolated blocks or within cultivated holdings and fallow lands are classified under this category.
	Cropland	
Water body	Water bodies	Includes all water bodies
	Permanent wetland	
Built up	Built up (both urban rural)/industries	Includes all land occupied by buildings, roads and railways or under water, e.g. rivers and canals, and other land put to uses other than agriculture.
Barren and Un-cultivable Land	Barren land	Includes all land covered by mountains, deserts, etc. Land which cannot be brought under cultivation except at an exorbitant cost is classified as un-cultivable whether such land is in isolated blocks or within cultivated holdings.
	Mining	

software. Prior to image interpretation, Level 1 (<https://landsat.usgs.gov/landsat-processing-details>) satellite images were pre-processed for suppressing the effects of the atmosphere (“Chavez, 1996”) and noise (“Lillesand et al., 2015”). The study area was then extracted from the multiple sensor scenes for each year by sub-setting. Finally, all the subset images were netted to obtain a single image of the study area. The satellite images and historical maps were brought into the WGS 84 UTM Zone 44 projection. The satellite images for the year 1975 and 1985 were then re-sampled using nearest neighbourhood algorithm to a common resolution of 30 m.

3.12.3. Classification Scheme

In the present study, the USGS classification system (“Anderson et al., 1976”) was adopted for LULC classification. Initially, 21 land classes of Level II (Table 3.3) (“IGBP, 1990”) were derived from the satellite data. Later, the 21 land classes were further aggregated into six-fold Level I land classes such as forest, built up, barren and uncultivable land, scrub/grassland, water body and agricultural land.

Prior to the classification interpretation keys/symbols were built following “Lillesand and Kiefer (1987)” (Fig. 3.2). A set of interpretation symbols is needed for each LULC form to minimize the error in interpretation. Interpretation symbols are based on scale, shape, color, hue, texture, shadow, etc. of the land forms.

3.12.4. Mapping of land classes

Fig. 3.3 shows the methodology (after “Roy et al., 2015b”) adopted for mapping the land classes (LULC and Vegetation type mapping) of the Eastern Ghats from 1920-2015 (Reshma et al., 2018). Mapping of land classes was carried out with the help of onscreen visual interpretation technique. The historical maps of 1920, 1940 and 1960 were digitized separately to derive LULC maps for respective years. The vector layers of vegetation type, and LULC of 2015 are prepared with the help visual interpretation technique on 24 scenes of Landsat OLI images (Table 3.1). The combination of SWIR and visible band were used in certain places to distinguish different forest types such as evergreen, mangroves, riverine forest etc. A minimum mapping unit of 36 pixels or 3.24 ha (“Lillesand and Kiefer, 1987”) was fixed and the exercise was performed in the Arc GIS 10.2, QGIS and ERDAS Imagine 2015 platforms. Seasonal changes in the LULC are checked by imposing the resultant 2015 vector map over the three season scenes of Landsat and then these details are aggregated in the vector form. Ground truth data was also collected in different parts of the Eastern Ghats in different field seasons and

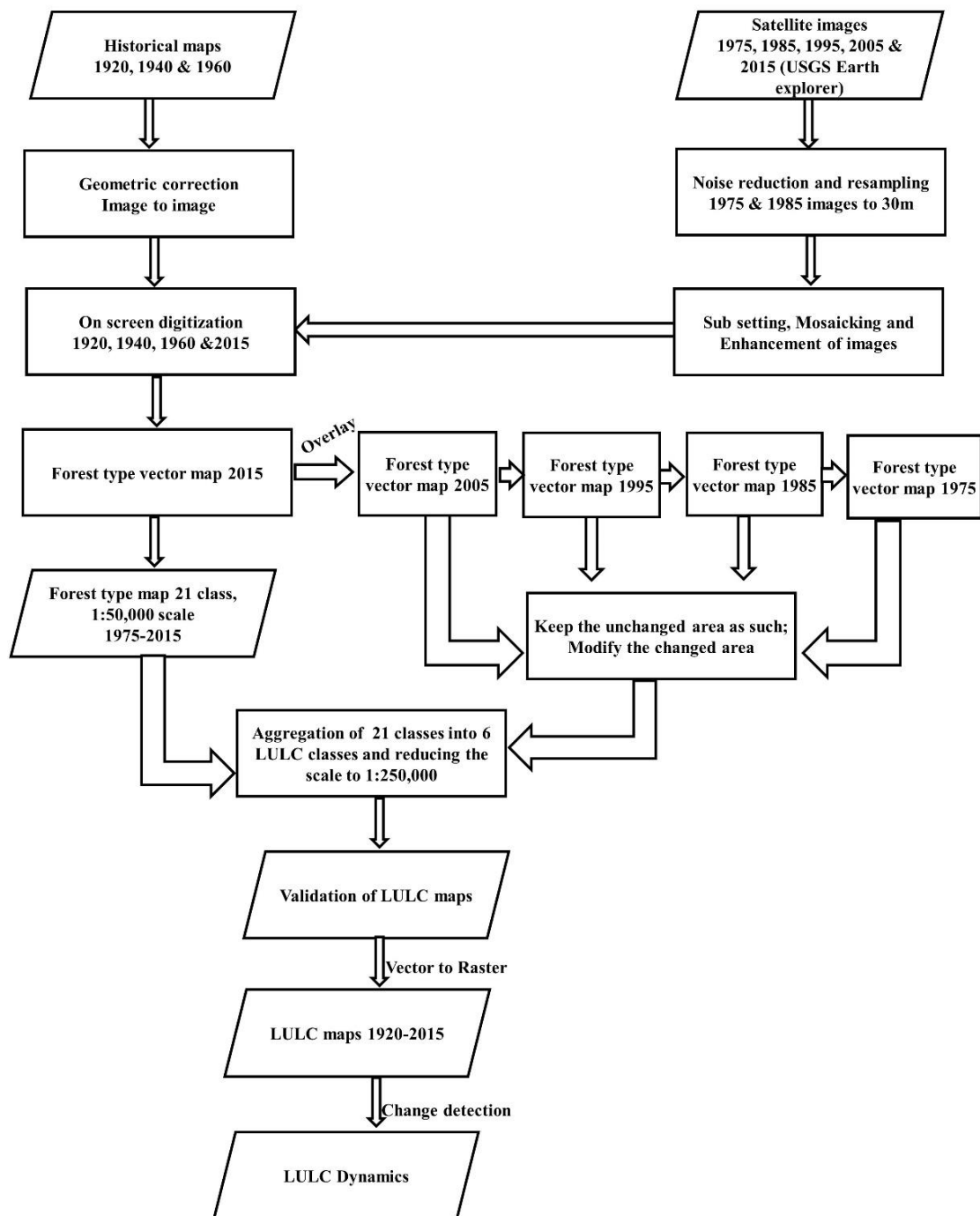


Figure 3.3 Flow chart showing the methodology for long term LULC map preparation and analysis of LULC dynamics (Reshma et al., 2018).

used in the study. The final vector map of 2015 was produced after correcting it in the light of ground truth data and ancillary information available from existing maps such as LULC maps of India for the years 1985, 1995 and 2005 (“Roy et al., 2015a”) and the forest type map of India for the year 2005 (“Roy et al., 2015b”). The 2015 vector maps were taken as reference layer for preparing the maps of 1975, 1985, 1995 and 2005 (Reshma et al., 2018). To realize this the 2015 vector layer was overlaid on the 2005 satellite data and the polygons were edited for the changed areas and the forest type vector map for year 2005 was finalised. Then the final 2005 vector map was overlaid on 1995 satellite data and the process was repeated for 1995. The same procedure was repeated for 1985 and 1975 years and maps were prepared. All the forest type maps were prepared in 1:50000 scale. The 21 class forest type databases (2015, 2005, 1995, 1985 and 1975) are then aggregated into 6 LULC classes. These maps along with 1920, 1940 and 1960 maps are brought into the GIS environment and then converted to raster LULC maps in the scale of 1:250,000.

3.12.5. Assessment of forest cover change dynamics

The dynamics of forest cover change from 1920 to 2015 was assessed through a change matrix method (Reshma et al., 2018). The six-fold LULC raster maps of each year (2015, 2005, 1995, 1985, 1975, 1960, 1940 and 1920) were used for change dynamics analysis. This was realized by comparing the number of pixels falling into each category of land class at one time period and the characteristics of the same pixels in the previous time period. Matrix model available with ERDAS Imagine 2015 was used for this purpose. A new thematic layer (change maps) produced from LULC maps of 1920-2015 time periods contain different combinations of “from-to” change classes. Then the changes of forest to other classes were analysed.

3.12.6. Accuracy Assessment

Field sample points, and additional points collected from Google Earth images were used to evaluate the classification accuracy (“Congalton, 1991”) of the constructed maps (Reshma et al., 2018). A total of 2971 ground points in the proportion of land class area collected from Google Earth images (CNES/Astrium) of 2015 were used to determine Level II LULC class. About 852 field sample points were used to evaluate the accuracy of Level II vegetation type map of 2005. The consumer, producer, Kappa and overall accuracies of the Level II classes of vegetation type maps of 2015 and 2005 were evaluated by overlaying the ground sample points on 30m raster maps. Due to the absence of ground sample points, accuracy assessment was not done for the years 1995, 1985, 1975, 1960, 1940 and 1920. The 2005 vector map was overlaid

on the satellite images of 1995, 1985, 1975 and the consecutive year maps were prepared and thereby ensured the accuracy. After applying the geometric correction (map to image) using ~50 GCP points and first order polynomial, the maps derived from historical topographical sheets are prepared.

3.12.7. Simulating future populations

The compound rate growth method (“Eberhardt, 1987”) has been used in the present study to simulate populations at different time periods (Reshma et al., 2020). Estimation of annual population growth rate is essential for simulating future populations. The annual population growth rate provides the change in population size as a factor of time, which enables one to better simulate the population growth or decline for future years. Initially, the annual population growth rate was estimated at two points in time (for example, 2001 and 2011) as (Reshma et al., 2020)

$$R = \left[\left(\frac{P_n}{P_0} \right)^{\frac{1}{n}} - 1 \right] \times 100, \quad (3.1)$$

where, R = annual rate of growth, P_0 = population in the base year (2001), P_n = population in the current year (2011), and n = number of intermediary years i.e., 10.

The annual growth rate obtained from the total populations of the years 2001 and 2011 was used to simulate the population of the Eastern Ghats for the year 2050 using the equation

$$P_n = P_0 \left(1 + \frac{R}{100} \right)^n. \quad (3.2)$$

Here, P_n stands for the projected population.

3.12.8. Future LULC simulations

In recent times, models based on the application of artificial neural networks are being used extensively in LULC simulations (“Pijanowski et al., 2002; Kavzoglu and Mather, 2010”). In the present study, Monte Carlo cellular automaton (CA) based ANN has been used to simulate land use dynamics as it is proved as effective to handle nonlinear systems and simulate multiple land use changes (“Pijanowski et al. 2014”). Future LULC in the Eastern Ghats simulations were carried out using the Modules for Land Use Change Evaluation (MOLUSCE) version 3.0.13 plugin (<https://plugins.qgis.org/plugins/molusce/>) in Quantum GIS version 2.18.13, developed by Asia Air Survey Co. Ltd. The model uses raster LULC categories for two time periods, past-2005 (t) and present-2015 (t+1) and raster files of explanatory variables or factors. The model was trained using the CA model to predict the LULC changes from the past to the present. Finally, the ANN was used to predict the future LULC (for the years 2025 and 2050)

using the derived mode, the current LULC, and current factors. The kappa statistics (“Pontius 2000”) (standard kappa, kappa histogram, and kappa location) were used to validate the accuracy of the simulated LULC maps. A total of 14 driving factors derived from original datasets (Table 3.1) were normalized and used to estimate the occurrence of each LULC class in 2025 and 2050, including the past (2005) and the present (2015) LULC patterns, topographic factors (elevation, aspect, and slope), social factors (population, population density, location of city, villages, and railroad and water networks), climatic and environmental factors (soil parameters, temperature, and precipitation) and future climate factors (temperature and precipitation as per the RCPs) (Fig. 3.4). To bring all the spatial datasets into the same resolution resampling was performed to bring them to a cell size of 250 m.

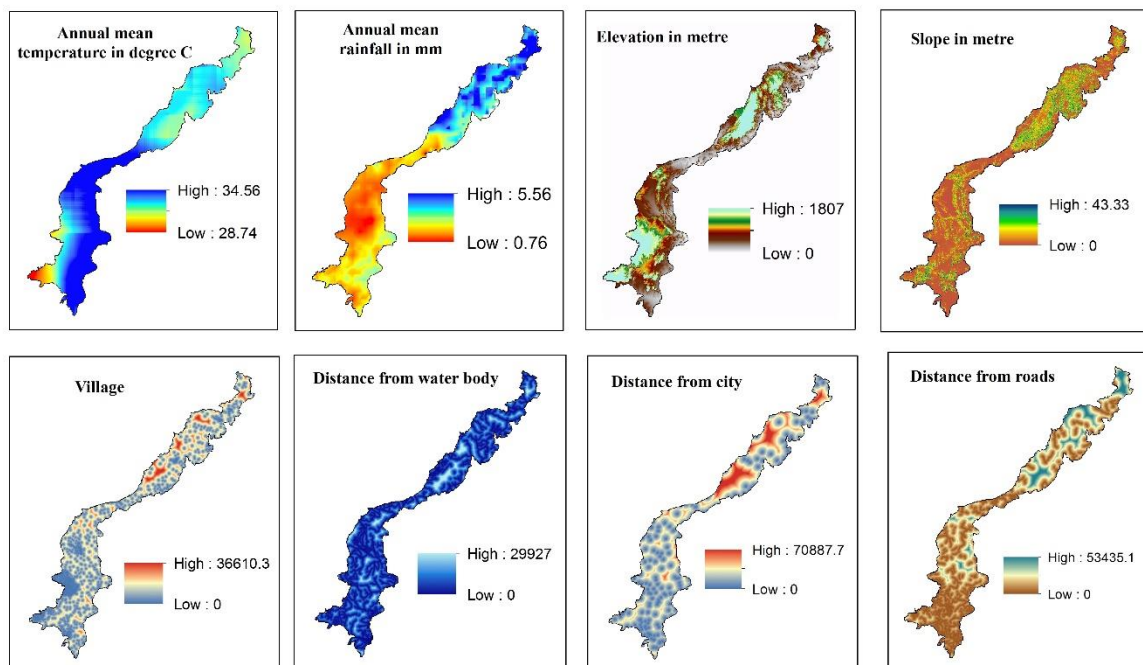


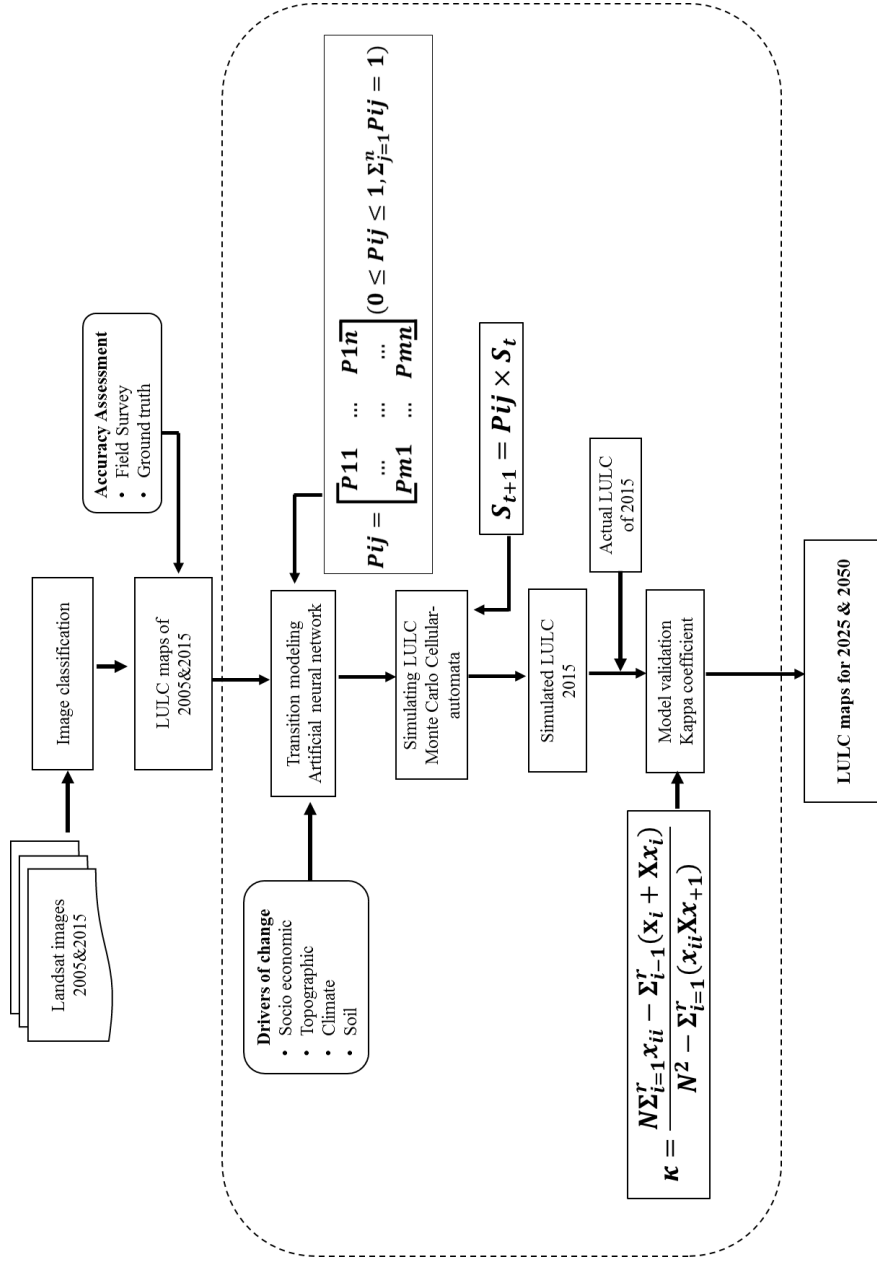
Figure 3.4 Environmental predictors for simulating future LULC in Eastern Ghats

The flow chart of the methodology adopted for simulating the LULC of the Eastern Ghats is shown in Fig. 3.5.

3.13 Results

3.13.1. LULC change and forest cover loss

The loss in the forest cover and changes in other land classes of Eastern Ghats were estimated from 1920 to 2015 and given in Table 3.4. Agriculture was the predominant land class in all the assessed time periods. An increase in the agriculture area from 45.84% (of the total area of



Note: P_{ij} is the probability of change of land use i to j ; m and n are the number of land use types. S_{t+1} and S_t are the states of land use at given times $t + 1$ and t , respectively (“[Arsanjani et al., 2013](#)”).

r = number of rows and columns in the error matrix, N = total number of observations (pixels), X_{ii} = observation in row i and column i , $X_{i.}$ = marginal total of row i , and $X_{.i}$ = marginal total of column i (“[Congalton 1991](#)”).

Figure 3.5 Flow chart of methodology adopted for simulating LULC of Eastern Ghats (Reshma et al., 2018)

Table 3.4 Area distribution of different land classes of Eastern Ghats from 1920-2015 (Reshma et al., 2018)

Land Classes	1920	1940	1960	1975	1985	1995	2005	2015						
	km ²	km ²	km ²	km ²	km ²	km ²	km ²	km ²						
	%	%	%	%	%	%	%	%						
Forest	95511.57	43.40	94753.92	43.05	71897.58	32.66	60838.76	27.62	60732.70	27.60	60723.65	27.59	60680.33	27.57
Scrub/ Grassland	1215.28	0.55	3419.95	1.55	24363.61	11.07	35004.29	15.91	34853.40	15.84	34991.95	15.90	34824.93	15.81
Agriculture	100882.53	45.84	100920.56	45.86	101478.37	46.10	102148.70	46.41	102435.87	46.54	102425.46	46.54	102708.47	46.48
Water body	5708.75	2.59	5713.67	2.60	5417.63	2.46	5608.31	2.55	5489.51	2.49	5411.98	2.46	5338.82	2.50
Settlements	157.40	0.07	157.40	0.07	1148.60	0.52	3659.13	1.65	3638.85	1.66	3642.31	1.66	3665.70	1.71
Barren and Un-cultivable Land	16604.48	7.54	15114.51	6.87	15774.21	7.17	12820.81	5.83	12886.41	5.86	12875.60	5.85	12818.42	5.94

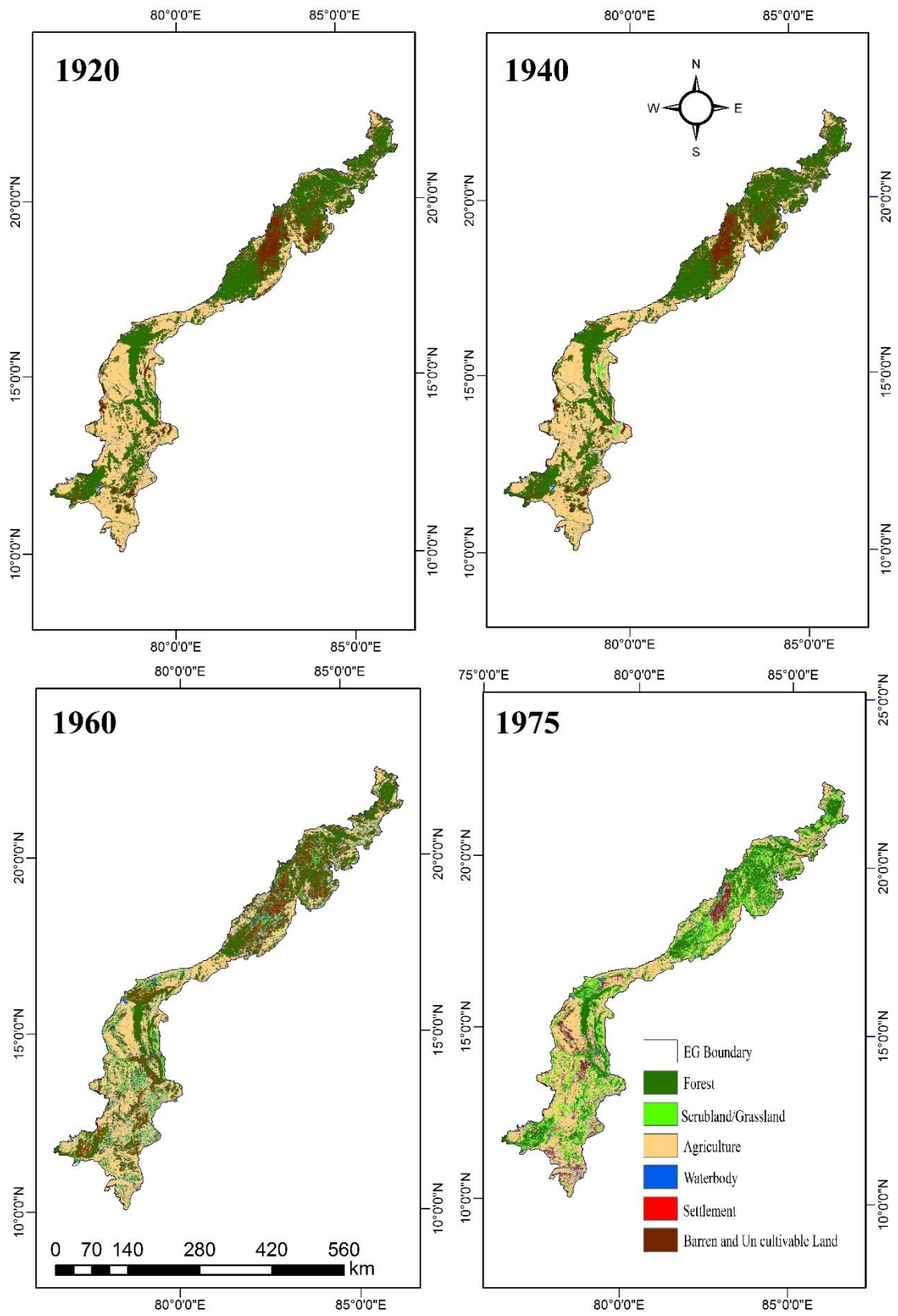
Eastern Ghats) in 1920 (100882.53 km²) to 46.48% in 2015 (102289.09 km²) was observed. Forest was the second dominant land class with 43.40% (95511.57 km²) of occupancy in 1920. The scrub/grassland shows an increasing trend (15.26%) from 1920 to 2015. The present study brought out four major observations: (i) about 7.92% of forest cover has been converted into the agriculture land; (ii) from 1920 to 1960 about 4.1% of the deforested area were converted to scrub/grassland; (iii) subsequent to 1975 the deforestation has led to the settlements (0.06%), and mining and related activities (0.16%) (Area under settlement was 3659.13 km² in 1975, which was increased to 3762.9 km² in 2015; likewise, 622.81 km² of the mining area in 1975 was increased to 962.12 km² in 2015); (iv) agriculture land was left fallow and got converted to scrublands. The LULC changes of different years (1920-2015) is shown in Fig 3.6.

3.13.2. Forest cover change dynamics

The percentage change in forest cover from 1920 to 2015 is shown in Fig. 3.7 (Reshma et al., 2018). The forest cover which was 43.40% of the total geographical area of Eastern Ghats in 1920 got reduced to 27.52% in 2015. During 1940 and 1960, about 6.99% of forest area was converted into the agricultural land, 3.80% to scrub/grassland and about 0.95% into settlement/barren land. After 1975, a meagre amount of forest area (0.07%) was converted to other land classes (Fig. 3.7). On the other hand, during 1960-75 and 1995–2005, marginal conversion of barren land (0.02%) and scrub/grassland (0.22%) to forest area was recorded. The conversion of land classes to other classes during 1920–1940, 1940–1960, 1960–1975, 1975–1985, 1985–1995, 1995–2005, 2005–2015 is shown as change matrix in Table 3.5 a–g (Reshma et al., 2018). Overall, about 7.92% of the forest was converted into agricultural land, further these agricultural lands were converted to scrublands and barren lands. This assessment demonstrates the disturbance of land and its transition in Eastern Ghats.

3.13.3 Extent of forest types affected due to deforestation

In forest type assessment, the area under different moist and dry deciduous forests were deduced (Reshma et al., 2018) and given in Table 3.6 for the period of 1975–2015 and shown in Fig. 3.8. Different forest types were affected mainly due to the urbanization, mining and other development activities that include construction of dams, roads, and irrigation projects. The total mined area was 622.81 km² in 1975 and it increased to 962.12 km² in 2015.



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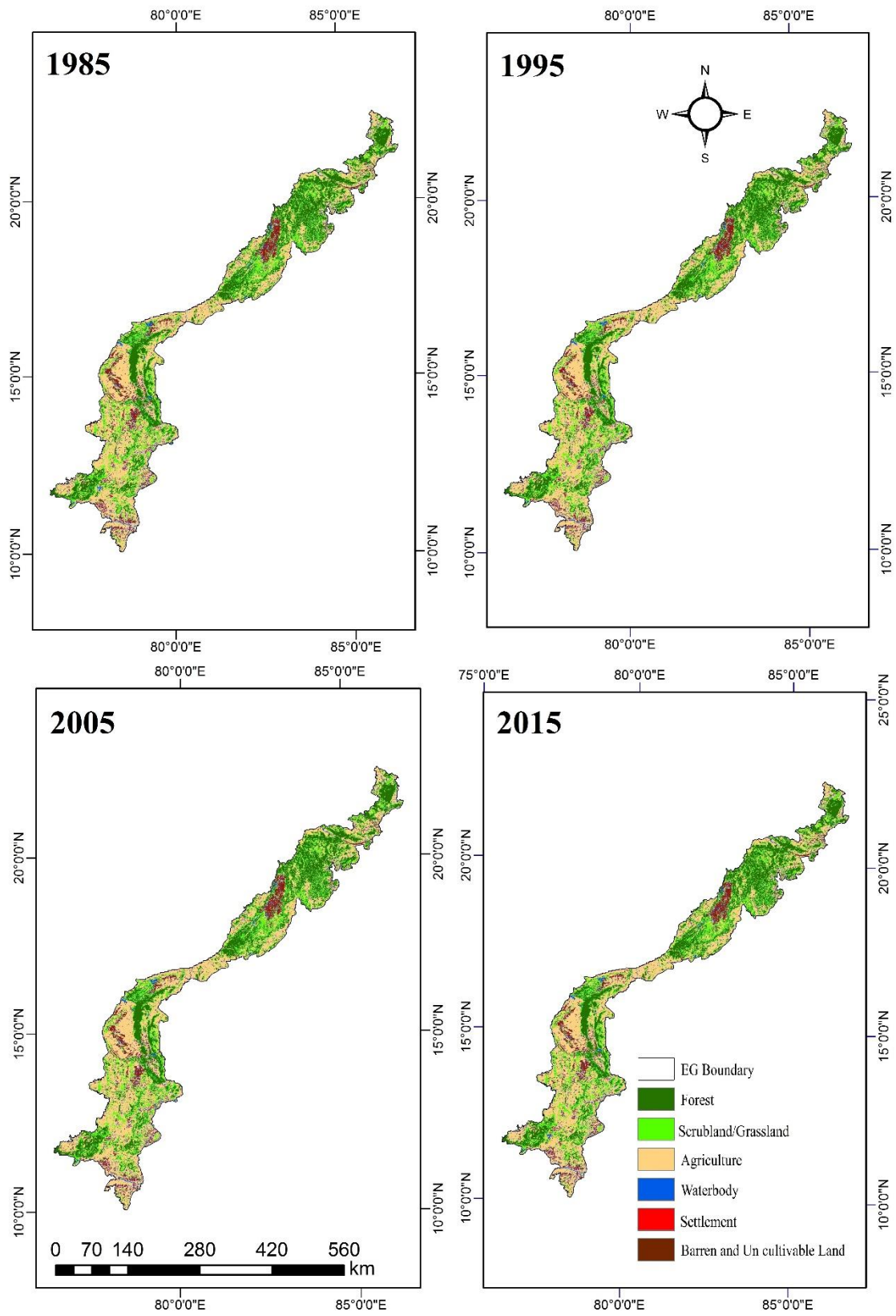


Figure 3.6. Land use and land cover maps of the Eastern Ghats from 1920-2015 (Reshma et al., 2018)

Table 3.5. LULC change matrix of Eastern Ghats from 1920-2015 (area in km²) (Reshma et al., 2018)

(a) 1920-1940

	Forest	Settlements	Barren and Un-cultivable Land	Scrub/ grassland	Water body	Agriculture	Area in 1920
Forest	94733.10	0.00	8.13	651.64	17.96	100.74	95511.57
Settlements	0.00	157.40	0.00	0.00	0.00	0.00	157.40
Barren and Un-cultivable Land	15.03	0.00	15069.33	1520.08	0.00	0.04	16604.48
Scrub/ Grass land	5.79	0.00	1.52	1205.33	0.00	2.64	1215.28
Water body	0.00	0.00	0.09	13.23	5695.42	0.01	5708.75
Agriculture	0.00	0.00	35.44	29.68	0.29	100817.11	100882.53
Area in 1940	94753.92	157.40	15114.51	3419.95	5713.67	100920.55	220080

(b) 1940-1960

	Forest	Settlements	Barren and Un-cultivable Land	Scrub/ grassland	Water body	Agriculture	Area in 1940
Forest	67896.38	109.25	2085.08	8370.57	898.54	15394.10	94753.92
Settlements	0.00	149.25	0.39	1.32	1.87	4.57	157.40
Barren and Un-cultivable Land	0.14	27.75	7533.31	4236.24	604.40	2712.68	15114.51
Scrub/ grassland	0.14	25.87	136.16	2403.46	39.85	814.48	3419.95
Water body	0.37	0.59	4.15	247.32	1937.07	3524.17	5713.67
Agriculture	0.56	835.90	6015.13	9104.70	1935.90	83028.37	100920.56
Area in 1960	67897.58	1148.60	15774.21	24363.61	5417.63	105478.37	220080.00

(c) 1960-1975

	Forest	Settlements	Barren and Un-cultivable Land	Scrub/ grassland	Water body	Agriculture	Area in 1960
Forest	65736.69	3.51	99.51	1435.95	26.55	595.37	67897.58
Settlements	0.00	1142.30	3.33	1.49	1.49	0.00	1148.60
Barren and Un-cultivable Land	56.37	1.19	15399.00	114.72	16.34	186.58	15774.21
Scrub/ Grass land	0.00	3.70	1650.26	22244.93	30.36	434.36	24363.61
Water body	0.00	1.31	18.78	30.06	5220.13	147.35	5417.63
Agriculture	2.28	45.94	284.70	536.39	509.97	104099.08	105478.37
Area in 1975	65795.34	1197.94	17455.59	24363.55	5804.83	105462.74	220080.00

Contd..

(d) 1975-1985

	Forest	Settlements	Barren and Un-cultivable Land	Scrub/ grassland	Water body	Agricultur e	Area in 1975
Forest	65710.26	0.00	11.54	0.32	0.15	73.08	65795.34
Settlements	0.06	1196.39	1.49	0.00	0.00	0.00	1197.94
Barren and Un-cultivable Land	3.17	0.93	17432.54	1.55	1.78	15.63	17455.59
Scrub/ grass land	3.61	0.00	34.13	24201.89	10.80	113.12	24363.55
Water body	0.70	0.02	3.77	4.38	5609.82	186.15	5804.83
Agriculture	19.33	1.33	19.26	0.15	6.30	105416.37	105462.74
Area in 1985	65737.12	1198.67	17502.72	24208.29	5628.85	105804.36	220080.00

(e) 1985-1995

	Forest	Settlements	Barren and Un-cultivable Land	Scrub/ grassland	Water body	Agriculture	Area in 1985
Forest	65469.92	0.1413	2.8863	222.1416	3.3381	38.6937	65737.12
Settlements	0	1191.59	3.7017	0	0.0513	3.3264	1198.67
Barren and Un-cultivable Land	4.9428	0.6678	17450.79	12.5343	14.3352	19.4454	17502.72
Scrub/ Grass land	0.0072	0	22.5639	24183.39	0.747	1.5876	24208.29
Water body	0.0072	0.0288	130.4703	3.8133	5474.303	20.2257	5628.85
Agriculture	0.5154	0.441	32.6499	3.5892	3.5929	105763.6	105804.36
Area in 1995	65475.39	1192.869	17643.06	24425.46	5496.367	105846.8	220080.00

(f) 1995-2005

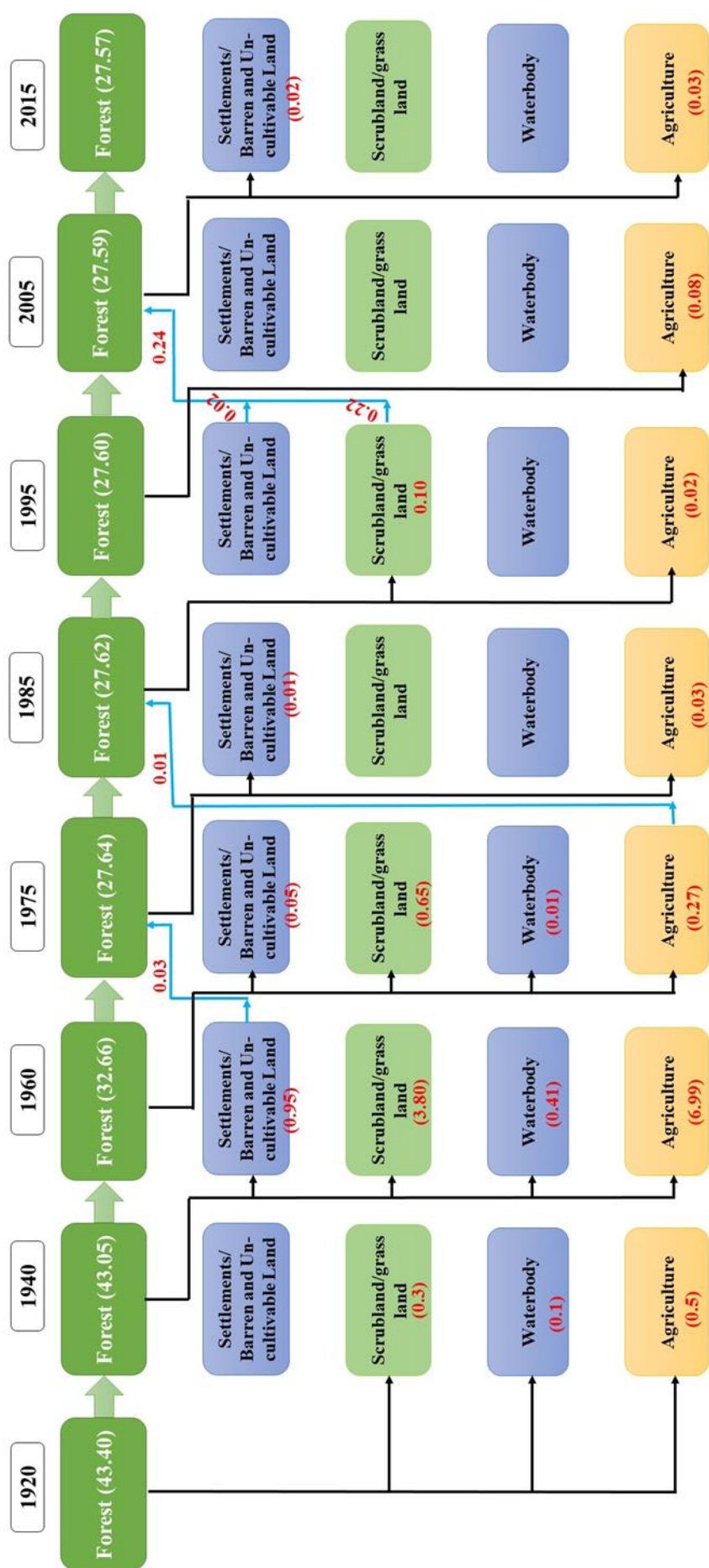
	Forest	Settlements	Barren and Un-cultivable Land	Scrub/ grassland	Water body	Agriculture	Area in 1995
Forest	65286.46	0.00	0.00	0.20	6.08	182.66	65475.39
Settlements	0.08	1185.97	6.25	0.00	0.13	0.44	1192.87
Barren and Un-cultivable Land	1.74	1.75	17435.51	2.96	54.73	146.38	17643.06
Scrub/ Grass land	22.04	0.02	57.80	24277.25	19.57	48.78	24425.46
Water body	2.81	0.07	10.59	1.03	5300.74	181.13	5496.37
Agriculture	65.60	50.88	88.31	2.84	300.80	105338.42	105846.85
Area in 2005	65378.73	1238.69	17598.44	24284.27	5682.05	105897.82	220080.00

(g) 2005-2015

	Forest	Settlements	Barren and Un-cultivable Land	Scrub/ grassland	Water body	Agriculture	Area in 2005
Forest	65272.50	0.38	40.00	4.17	0.60	61.08	65378.73
Settlements	0.00	1194.42	0.53	0.02	0.04	43.68	1238.69
Barren and Un-cultivable Land	0.00	16.15	17572.56	0.15	3.20	6.38	17598.44
Scrub/ grass land	1.11	5.91	63.99	24204.28	3.51	5.47	24284.27
Water body	6.22	0.81	35.20	19.64	5286.95	333.23	5682.05
Agriculture	55.08	89.11	163.83	37.66	53.11	105499.03	105897.82
Area in 2015	65334.91	1306.78	17876.10	24265.92	5347.42	105948.88	220080.00

Table 3.6 Area distribution under different forest types, land use and land cover of Eastern Ghats during 1975-2015 (Reshma et al., 2018)

Vegetation class	1975			1985			1995			2005			2015		
	km ²	%		km ²	%		km ²	%		km ²	%		km ²	%	
Evergreen	408.24	0.19		408.09	0.19		408.10	0.19		408.10	0.19		408.10	0.19	
Semi-evergreen	2839.17	1.29		2837.95	1.29		2838.02	1.29		2838.31	1.29		2837.04	1.29	
Dry Evergreen	221.77	0.10		221.77	0.10		221.76	0.10		221.76	0.10		236.78	0.11	
Moist deciduous	22557.08	10.25		22537.43	10.24		22508.10	10.23		22544.15	10.24		22523.38	10.23	
Dry Deciduous	31462.88	14.30		31421.81	14.28		31396.58	14.27		31369.05	14.25		31366.55	14.25	
Litoral and swamp forest/Riverine	1372.44	0.62		1354.86	0.62		1362.59	0.62		1354.12	0.62		1355.17	0.62	
Forest plantations	1976.97	0.90		1979.39	0.90		1977.77	0.90		1971.32	0.90		1934.65	0.88	
Degraded forest	0.22	0.00		0.22	0.00		1.10	0.00		2.94	0.00		4.04	0.00	
Scrub land (open/closed)	25103.14	11.41		24952.45	11.34		25086.66	11.40		24919.27	11.32		24905.92	11.32	
Thorn forest	1813.06	0.82		1813.06	0.82		1812.65	0.82		1812.67	0.82		1807.90	0.82	
Dry deciduous scrub	3625.43	1.65		3625.46	1.65		3625.40	1.65		3625.88	1.65		3607.89	1.64	
Dry evergreen scrub	153.35	0.07		153.34	0.07		153.31	0.07		153.31	0.07		153.31	0.07	
Grassland	897.63	0.41		897.62	0.41		897.21	0.41		897.28	0.41		896.54	0.41	
Woodland	3411.68	1.55		3411.46	1.55		3410.85	1.55		3410.64	1.55		3411.17	1.55	
Orchards	2784.12	1.27		2774.32	1.26		2771.72	1.26		2744.12	1.25		2787.54	1.27	
Cropland	99364.57	45.15		99675.74	45.22		99667.93	45.29		99978.53	45.29		99515.73	45.43	
Water body	5580.08	2.54		5462.28	2.48		5381.69	2.45		5312.34	2.41		5470.42	2.49	
Wet lands	28.23	0.01		27.20	0.01		30.25	0.01		26.43	0.01		26.96	0.01	
Built up (both urban rural)/industries	3659.13	1.65		3637.98	1.66		3648.64	1.66		3672.03	1.67		3762.90	1.71	
Barren land	12198.00	5.54		12225.09	5.55		12204.29	5.55		12183.71	5.54		12106.97	5.50	
Mining	622.81	0.28		662.47	0.30		672.45	0.31		635.86	0.29		962.12	0.44	



Black lines indicate forest conversion to other classes and blue lines indicates conversion of other classes to the forest; the converted area values are given along with the land class in percentages. The numbers in the red colour indicates the percentage area conversion of forest to the particular land classes

Figure 3.7. Transition of forest cover into other classes (in %) (Reshma et al., 2018)

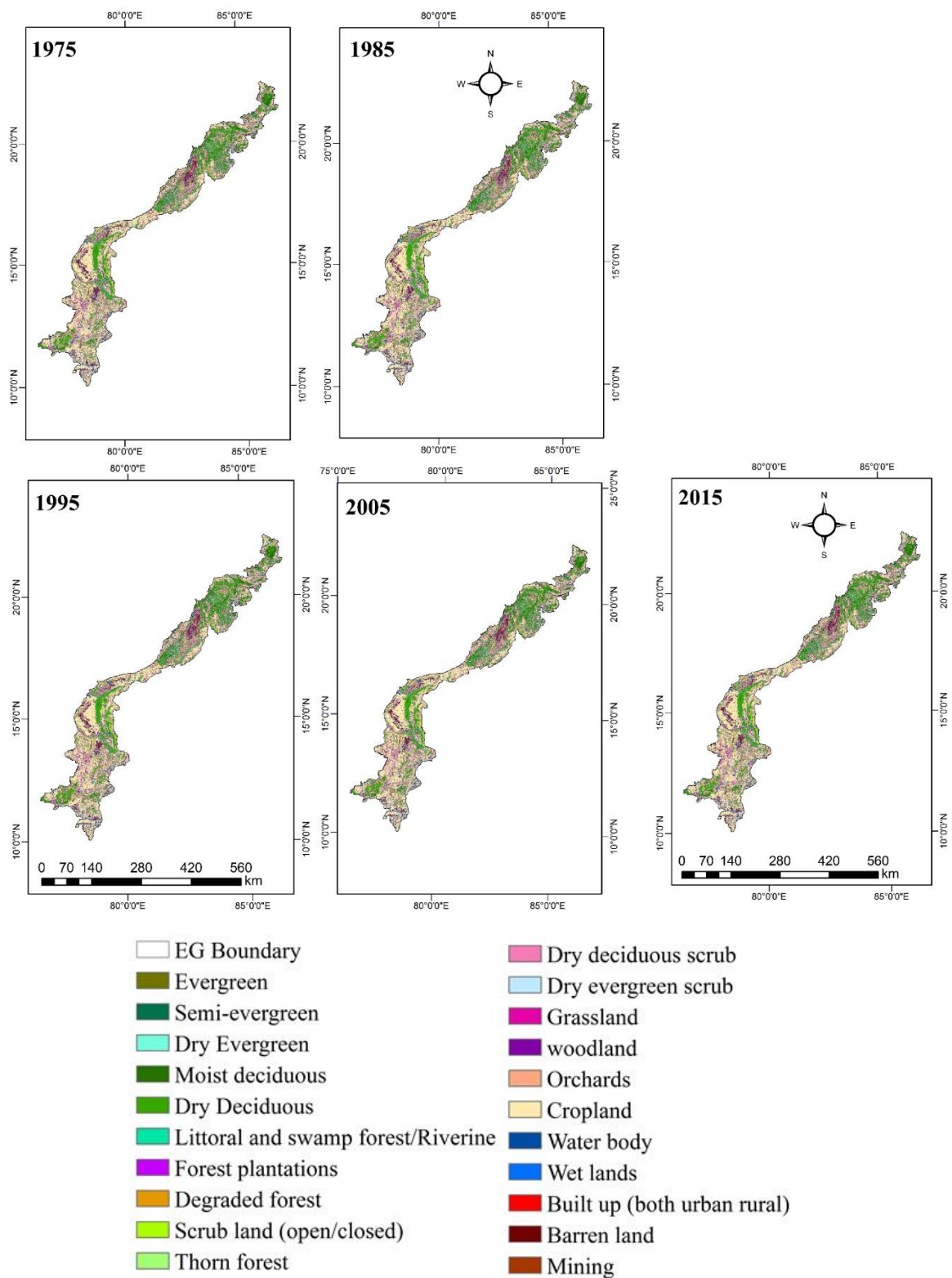


Figure 3.8 Forest type map of Eastern Ghats from 1975-2015 (Reshma et al., 2018)

Table 3.7 Area under each LULC class for years 2005, 2015 and 2050 (Reshma et al., 2020)

LULC class	Actual			Simulated		
	2005		2015	2015		2050
	sq.km	%	sq.km	sq.km	%	%
Forest area	60723.65	27.59	60680.33	60601.93	27.54	27.40
Scrubland	34824.93	15.82	34788.62	34825.02	15.82	15.79
Agriculture	102708.47	46.67	102289.09	102804.88	46.71	46.52
Water body	5338.82	2.43	5497.44	5304.26	2.41	2.53
Built up	3665.70	1.67	3756.90	3665.00	1.67	1.81
Barren land	12818.42	5.82	13067.95	12879.18	5.85	5.95

3.13.4 Validation of classified maps

Classification accuracy was carried out for the derived LULC and forest type maps for 2005 and 2015. The overall accuracies for 2005 and 2015 were 93.77%, and 93.33% respectively, and the Kappa coefficient (Khat) values were 0.91 and 0.92, respectively (Reshma et al., 2018). It is to note that Kappa coefficient of >0.80 represents a strong agreement and good accuracy (“Congalton, 1991”).

3.13.5 Trends in future populations

The simulations were run assuming that the annual population growth of 1.01 of the past 10 years (2001–2011) will continue in future. According to the 2011 census, the total population of Eastern Ghats was 1.2 million. Simulations show that by 2050 the total population in Eastern Ghats would be increased by 1.12% over that of 2011 (Fig. 3.9). The total population is expected to reach 2.6 million by 2050.

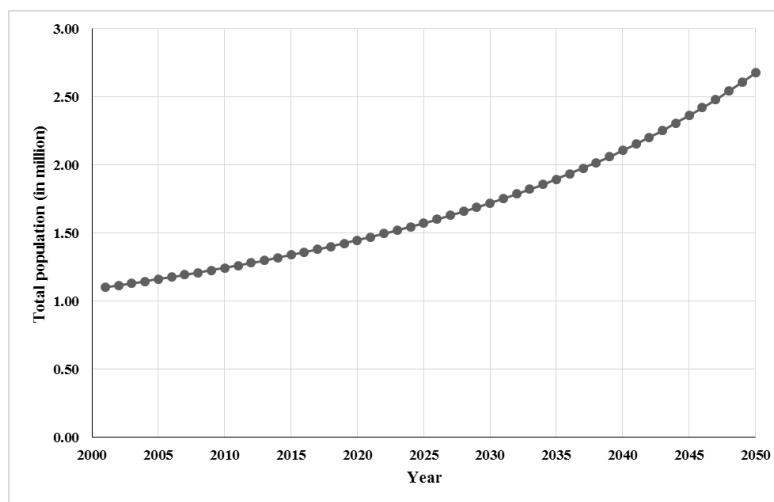


Figure 3.9. Present and projected population in Eastern Ghats, 2000-2050 (Census, 2011)

3.13.6 Simulated land use and land cover

The simulated CA model for LULC for 2015 was validated on the basis of the kappa statistics as well as a comparison of each pixel of the simulated LULC type with the actual LULC data (Table 3.7). The kappa statistics (value of 0.91) and the overall accuracy (greater than 91%) suggest that there is good agreement between the predicted and the actual values of the LULC types of the base year. As shown in Table 3.7, the difference in area between the two maps (actual and simulated) for the year 2015 reveals that all LULC classes have errors less than 5%. The spatial pattern analysis (Fig. 3.10) shows a clear spatial change in LULC throughout the

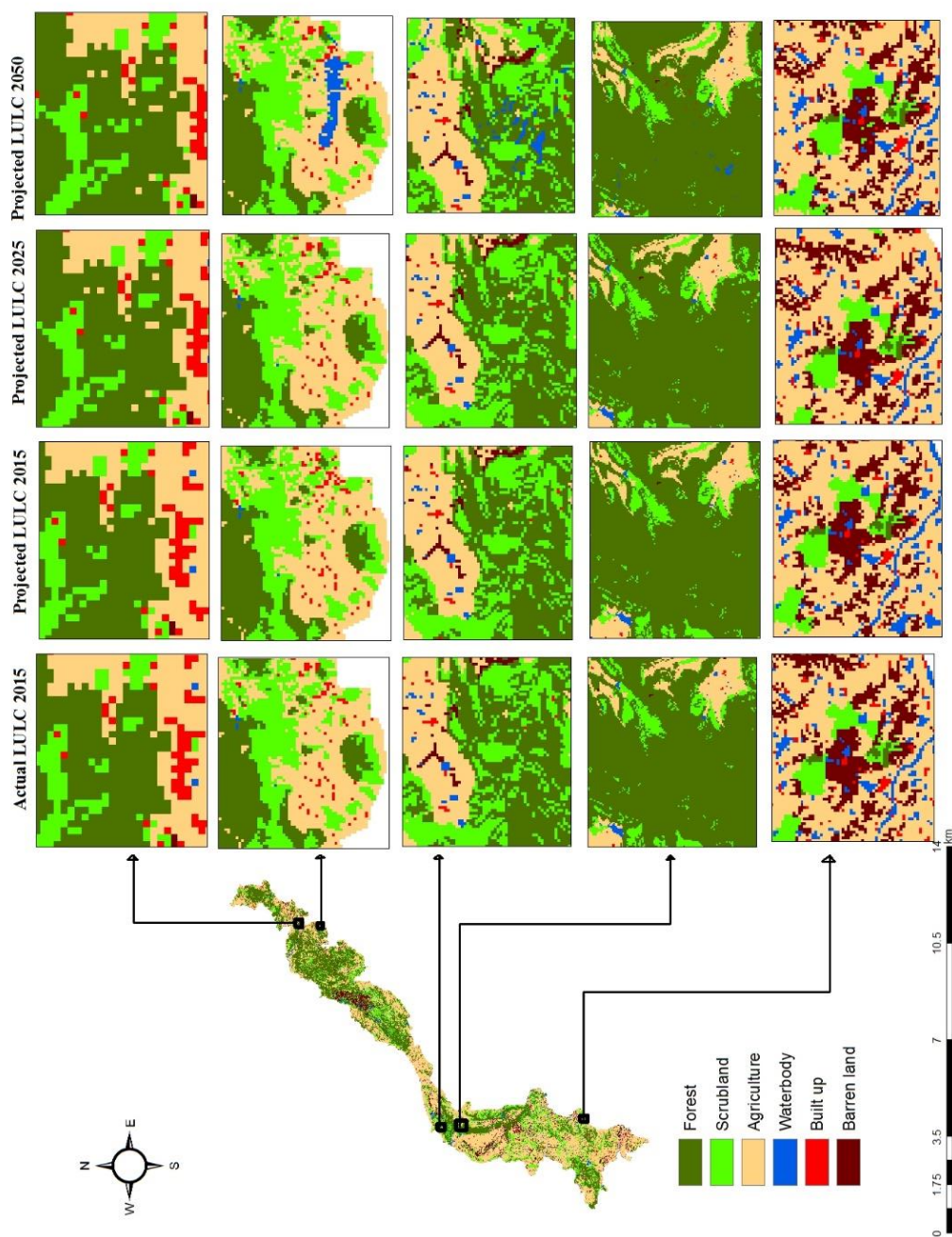


Figure 3.10 Temporal Land-use land-cover maps (enhanced window) of the Eastern Ghats for 2015 (actual and predicted), and 2050 (Reshma et al., 2020).

study period. The current trend shows that the agricultural land continues to be the dominant land class in the Eastern Ghats. The proportion of built-up land was 1.71% in 2015, 1.74% in 2025, and 1.81% in 2050. By 2050, the proportion of built-up land is likely to expand and spread to other parts of the region (Fig. 3.10, Table 3.7). From the temporal pattern analysis (Table 3.7), it was found that in 2015 forest, agricultural land, scrubland, water bodies, built-up land, and barren land occupied 27.57%, 46.48%, 15.81%, 2.50%, 1.81%, and 5.94%, respectively, of the total landscape of the Eastern Ghats.

Overall, agricultural land (~46%) is the dominant land class, followed by forest (~27%). Furthermore, the projected LULC of Eastern Ghats for 2050 indicates that the overall forest cover will decrease by 0.17% compared with 2015. Agricultural land will increase by 0.04% in 2050 compared with what it was in 2015. Waterbodies will increase by 0.03% in 2050 (Fig. 3.10). The newly build dams and irrigation projects causes an increase in waterbody. Another finding is that scrubland will decrease by 0.02% in 2050. On the other hand, built-up land will increase from 1.71% in 2015 to 1.81% in 2050. The population growth significantly affects the land use and land cover pattern in the Eastern Ghats. The demand for land will increase for human needs such as food, development etc. which cause the encroachment of land in different regions of Eastern Ghats. Due to broken chain like physiography the encroachment will be high in all the parts of Eastern Ghats. Although urban expansion will likely be slower, the after effects due to urban expansion will be high. Barren land will show an increase of 0.01% in 2050 (Table 3.7). The left out agricultural lands increase the chances of land conversion to barren land. Along with it the soil erosion and leaching out of nutrients from the soil causes the development of barren lands.

3.14 Discussions

3.14.1 Land use and land cover change dynamics

A few studies have been reported on Eastern Ghats and its LULC change (“Dash and Misra, 2001; Jayakumar and Arockiasamy, 2003; Kumaraguru et al., 2016; Ramachandran et al., 2016”). However, these studies were carried out on either small study regions over short time periods or at different administrative units. On the other hand, the present study is first of its kind to systematically map the changes in the LULC of Eastern Ghats as well as its effect on the forest cover over a long period of time from 1920 to 2015. One of the major findings of this study is the changes in the land cover that has caused a loss of 15.83% forests in the Eastern Ghats over a period of past 95 years. This decline of forest cover was the result of land use

activities primarily for agriculture, mining and timber extractions. The effects of agriculture expansion on forest loss were also documented elsewhere across the globe (“Morton et al., 2006; Byerlee et al., 2014; Zeng et al., 2018”).

During 1920 -1960, the forest cover of Eastern Ghats had decreased by 10.39%. Similar studies on the LULC change from different parts of India show that major deforestation had been taken place during the period of British rule, as well as in early years after the independence (“Ravikanth et al., 2000; Tian et al., 2014”). Same trends were reflected in the present study as well. Anthropogenic activities were one of the major drivers of the degradation of forests (“Geist and Lambin, 2002”). The present study reveals 6.99% increase in the agricultural land during 1940–1960. The cropland expansion in the Eastern Ghats could offset the pressure even more, due to increasing need of population (population of Eastern Ghats has been increased from 81 million to 123 million during 2001–2011 (“Census, 2011”). Special initiatives, such as Grow More Food Campaign (1940s) and Green Revolution (1960s) have put more pressure on forest resources for producing more food, which had resulted in agricultural expansion in this area (“Ravikanth et al., 2000”). Even though large part of forest conversion had occurred due to the agriculture expansion during the past 95 years, the total agricultural area has increased only by 0.64% in the Eastern Ghats. Change studies shows that majority of the agricultural lands were now converted into the settlement, barren land and scrubland classes (Table 3.5). Due to the lack of soil fertility after three or four-time crop cultivation, the lands are being abundantly left uncultivated which is allowing the formation of scrubs to grow on the land or become a barren land. The mechanization of agriculture and use of chemical fertilizers cause soil erosion and finally led to the degradation of land (“Ali, 2004; Pender et al., 2007; Karamesouti et al., 2015”).

Finding of the conversion of forest into scrub/grassland (disturbed ecosystem) was another highlight in this study. There was a meagre change noticed from forest to scrub/grassland (651.64 sq.km) and barren land to scrub/grassland (1520.08 sq.km) during 1920–1940. The conversion of forest to scrub/grassland was mainly happened during 1940–1960 due to over extraction of timber and other resources (which includes fuel wood collection, and livestock grazing). Significant conversion of forest to scrub/grassland were recorded in different parts of India in the last few decades (“Rao and Pant, 2001; Areendran et al., 2013; Meiyappan et al., 2016”). Several researchers also reported forest conversions to scrubland in different parts of Eastern Ghats (“Schmerbeck, 2011; Schmerbeck et al., 2015”). “Jayakumar et al. (2009)” reported the conversion of open deciduous forest to thorny forests in Eastern Ghats of Tamil

Nadu state. The conversion of forests into other land classes would influence the ecosystem in different ways viz, altering the soil properties (“Schwendenmann and Pendall, 2006”), productivity of plants and its diversity (“Briggs et al., 2005”), and carbon storage (“Murdiyarso and Wasrin, 1995”) etc.

Increase of mining area from 0.28% in 1975 to 0.44% in 2015 in Eastern Ghats had caused notable degradation of interior forest of the region. In addition, the area under settlements has increased from 0.07% in 1920 to 0.56% in 2015. Population projections are also showing the possibility of increase of human settlements in the Eastern Ghats region (“DeFries and Pandey, 2010”). All these factors not only causes over exploitation of the natural resources but also would lead to the degradation of forest and biodiversity (“Palmer et al., 2010”). Though the Eastern Ghats has lost its 40% of natural forests, positive trends towards regain of forest cover has been reported in parts in recent times (Reshma et al., 2018). This is happened due to the strict implementation of the laws and policies for protection of forests and biodiversity. Restoration of forest cover is also been reported from other parts of the world. “Hansen et al. (2013)” had reported a gain of 0.8 million km² global forests during 2000-2012. Notable forest recovery trends were documented in the last few decades such as Colombia (“Sánchez-Cuervo et al., 2012”), Australia (“Shoo et al., 2013”), China (“Hua et al., 2016”) and Brazil (“Molin et al., 2017”).

Though future simulation studies involve some uncertainties such studies provide important information on species distributions, range shifts, food production and help mitigation and adaptation planning. Simulations of populations, land use, climate, and species can provide an overview of the behaviour and responses of different ecosystem processes under future conditions. Changes in the land system and climate due to human activities in the present era have important repercussions on natural systems (“Venter et al., 2016”), resulting in deforestation, habitat loss, species extinction, etc. Knowing global and regional trends will be helpful for effective management of the health of ecosystems. Focussing beyond 50 years is good for formulating sustainable plans and policies for the future (“Vaidyanathan 2018”).

3.14.2. Changes in ecosystem due to population, LULC and climate changes

Population growth in many parts of the world is leading to the degradation of natural resources (“Forsyth 2017”). The population of the Eastern Ghats was 1.2 million in 2011 and is expected to touch 2.6 million by 2050. The world population of 7.3 billion is expected to reach 8.5 billion by 2030, 9.7 billion in 2050, and 11.2 billion in 2100 (“UN DESA 2017”). The ungovernable

population growth (with a current growth rate of 2.13%) may lead to high per capita consumption and lead to degradation of natural resources, high demand for land, food, and basic amenities (“Alexandratos and Bruinsma, 2012; d’Amour et al., 2017”). Projections of LULC in the Eastern Ghats indicate 0.14% decrease in the forest cover by 2050, which is more or less inline with 0.26-0.19% decrease in global forest cover by 2030 (“d’Annunzio et al., 2015”). Projections of the built-up and barren land show an increase of 0.14% in 2050 (Table 3.7). Transformation of forests in relation to population growth and urbanization in the tropics have been well studied (“deFries et al. 2010; Seto et al., 2012; Browder 2002”), and the Eastern Ghats are not an exception (“Salghuna et al. 2018”). Other factors such as mining, the need for agricultural land, and tourism are also accelerating the rate of deforestation in the Eastern Ghats. The field studies revealed that people are extensively using the forest as a major source of firewood, collect medicinal plants from it, graze cattle in it (fodder), and cultivate various crops in it. These activities are very intense in the Eastern Ghats because of the ease of access to it. The extent of agricultural land in the Eastern Ghats is expected to increase by 0.04% by 2050 to cater the demand of growing population. In tropical and subtropical Asia, agriculture is the main driver for forest loss (“deFries et al., 2010; FAO 2017”), and 80% of the deforestation worldwide is caused by agricultural expansion (“FAO 2017”).

Landscape Characterisation

4.1. General

In 1939, a German bio-geographer, Carl Troll, had introduced the term landscape ecology. It is defined as the “interaction between spatial pattern and ecological process and the causes and consequences of spatial heterogeneity across a range of scales” (“Turner et al., 2001”). The structure of a landscape is one of the significant components in landscape ecology, which often play an essential role in the patterns and ecological processes occurring throughout a landscape (“Šímová and Gdulová, 2012”). So, any anthropogenic activity which disrupts the landscape structure will negatively affect the functional integrity of an ecosystem. The study of landscape structure is therefore help to maintain a healthy and diverse ecosystem.

Landscape ecology mainly focus on the spatial process of fragmentation (“Rudel et al., 2005”). Fragmentation is a process of breaking the continuous ecosystem, habitat or land cover into several small patches. Undoubtedly, such a process can cause habitat loss, species extinction, isolation and edge effect etc. (“Bogaert et al., 2004”). Fragmentation could also lead to reduction in the forest area, therefore, in some places it may cause extinction of endemic species (“Harper, 2007, Lander et al., 2019, Püttker et al., 2020”), and in some places it may increase invasive species (“With, 2004”). Fragmentation also results due to anthropogenic activities (“Li et al., 2010”) such as construction of roads and dams, agriculture activity and logging (“Haddad et al., 2015”). The other impacts of fragmentation includes reduction in core habitat area (“Morelli et al. 2020”), loss of connectivity (Almenar et al., 2019; Grande et al., 2020), increase in patch size (“Fahrig, 2020”) and edge effects (“Broadbent et al., 2008”).

Habitat loss is one of the dominant effects of landscape fragmentation (“Fahrig, 2003”). Forests are being fragmented due to resource extraction, conversion of forest area into other land types and development activities. The fragmented forests become less productive, hence, the community composition is also disturbed to a great extent (“Laurance et al., 2006”). Besides, fragmentation reduces habitat quality, microclimate (“Ewers et al., 2013”) of the forest interior, ecosystem processes (“Riitters et al., 2002; Tapia-Armijos et al., 2015”) and ecosystem services

(“Kettle and Koh, 2014; Uddina et al., 2015”). Therefore, fragmentation analysis is crucial for species conservation (“Wintle et al., 2019”).

Spatial heterogeneity and its quantifications are very important in landscape ecology to find the relationships between ecological processes and spatial patterns. The evolution of landscape indices has greatly helped the researchers to analyse the landscape structure and spatial heterogeneity of landscapes (“Szabo et al., 2008”). In addition, new developments in GIS softwares’ has revolutionized the use of these indices. Landscape indices help to determine the shape and the spatial configuration of the patches and also the situation, isolation and connectivity of the patch types (“Csorba and Szabó, 2012”). On the other hand, landscape matrices help to map the pattern of land change (“Rainis, 2003; Uddin et al., 2015”) in an area over a period. These matrices also help to find out the changes in the geometry of the area, size of each class, and the fragmentation (“Munsi et al., 2012”), thereby one can find the link between spatial characteristics of various landscape matrices such as patches, classes of patches or an entire landscape. The use of landscape matrices is considered to be one of the effective tools for monitoring forest fragmentation. A number of landscape matrices are in vogue to study the landscape ecology (“McGarigal, 2015”).

The landscape indices are calculated in three hierarchical levels (1) standard patch level, (2) class level and (3) landscape level (“McGarigal, 2002”). The different aspects of landscape spatial configuration are the size distribution and density, shape complexity, core area, isolation, contrast, dispersion, contagion, subdivision, and connectivity of the landscape patches (“McGarigal, 2002; Símová and Gdulová, 2014”). Most popularly used landscape indices to assess landscape structure are the number of patches (NP), patch density (PD), edge density (ED), patch richness (PR), and mean patch size (MPS).

4.2. Review of literature

Humans are believed to be responsible for destruction of landscapes since Holocene in different parts of the world (“Turvey, 2009”). The landscape fragmentation by human beings had caused mega faunal extinction in different times across the Eurasia between c.14 000 and 10 000 years BP (“Turvey, 2009”). For example, Megaloceros had disappeared due to habitat loss and contraction of forest cover around 7000 years’ BP (“Stuart et al. 2004”). Similarly, Tasmanian tiger, and *Thylacinus cynocephalus* had disappeared from the earth due to their habitat reduction by the start of the Holocene (“Johnson, 2006”). “Laurance et al. (1998a),” had assessed the consequences of habitat fragmentation on tree-community in the central Amazonia

and found that fragmentation had affected the microclimate, mortality, damage, and turnover rates in the forest. “Pütz et al. (2014)” had attributed deforestation of tropical forests to major source of CO₂ emissions. Also “Brinck et al. (2017)” showed that deforestation in tropics is not only responsible for direct carbon emissions, but also increases the edge of the forest, where trees experience increased mortality. “Jacobson et al. (2019)” studied the human induced habitat loss and fragmentation and argued that it is the main cause for the loss of biological diversity and ecosystem services.

A few case studies are available on the assessment of forest fragmentation at local, regional and global scales (“Zhu et al., 2004; Echeverria et al., 2008”). For e.g., “Harper et al. (2007)” had estimated the forest fragmentation of Madagascar forests from 1950s to 2000 and found that 40% decrease of forest cover had caused 80% reduction of ‘core forest’ of > 1 km from a non-forest edge. “Tapia-Armijos et al. (2015)” reported a decline in mean patch size and increasing isolation of the forest fragments in Ecuador from 1976-2008 due to deforestation and fragmentation. The study of “Andronache et al. (2019)” on the deforestation of Apuseni Mountains has revealed a reduction of 3.8% tree cover because of 17.7% increase in fragmentation and 29% expansion in heterogeneity. Similarly “Niebuhr et al. (2015)” have estimated the fragmentation level of Brazilian Atlantic rainforest and found that more than 80% of the forest fragments are less than 50 ha in size, and 75% of the forests are away from less than 250 m; whereas in United States, less than half of the forests are found in landscapes with more than 90% cover, and approximately 60% are located within 150 m from the edges. In another study “Li et al. (2010)” had reported that extreme fragmentation was noticed in Australia-Pacific, and least fragmentation in South America. Geospatial indices showed that both African and South American forests were severely disrupted by agricultural operations, while natural disasters played a crucial role in North America forest fragmentation. “Taubert et al. (2018)” recorded more than 130M forest fragments over the tropical and sub-tropical America, Africa and Asia-Australia. Also, in the Amazon area forest fragments cover almost 45% of the total forest, while the largest fragment on Borneo in Asia covers only 18% of the total forest cover. “Haddad et al. (2015)” have analysed the global forest fragmentation for a period of 35 years and reported that 20% of world’s forests are within 100 m of forest edge, whereas 70% of forests are within 1 km of forest edge.

In the Indian context, “Jha et al. (2005)” had reported decreasing species diversity with increasing number of fragmented patches in Vindhyan highlands. “Roy et al. (2013)” based on the spatial map of 2005 had reported that about 67.28% of the Indian forest area was intact,

whereas 26.70% area was less fragmented, 4.38% area was moderately fragmented and 1.64% area was highly fragmented. “Reddy et al. (2013a)” have estimated the spatial patterns of forest fragmentation in all the biogeographic zones of Indian forests during 1975-2005 and showed that patches having less than 1 km² area are more than 90% of the total number of forest fragments with mean forest patch size of 187 ha at national level. This study highlighted that total core area was highest for Islands (87.4%) followed by Eastern Himalayas (82.5%), Deccan (78.9%), Deserts (76.4%), and Eastern Ghats (76%). In another study “Reddy et al. (2013b)” have assessed the forest cover and forest type in Odisha state during the periods of 1924–1935, 1975, 1985, 1995 and 2010 and reported that the number of forest patches (per 1,000) are 2.463 in 1935, 10.390 in 1975, 11.899 in 1985, 12.193 in 1995 and 15.102 in 2010. “Chakraborty et al. (2019)” examined the effects of habitat fragmentation on the parasite diversity of wild mammalian host species in the Anamalai hills. Studies to assess the effects of forest fragmentation in different biological richer areas of the country in different time periods have been carried out for e.g., in Western Ghats (Giriraj et al., 2010; Kasodekar et al., 2019; Osuri et al., 2019), Hindu Kush Himalaya (Sharma and Roy, 2007; Sharma et al., 2016; Sahana et al., 2018;), North-east (Lele et al., 2008), Sundarbans (Sahana et al., 2005), Gujarat forests (Bhatt et al., 2015). Due to the peculiar discontinuous structure of the Eastern Ghats it has experienced high human pressure since colonial periods. This area is being exploited for many natural resources and eventually led to the habitat loss of many species and high population of invasive species. This has resulted in the increase of more fragmented regions as well as vanishing of primary vegetation in Eastern Ghats.

4.3 Methodology

The analysis of landscape ecology in the Eastern Ghats is carried out following Fig. 4.1

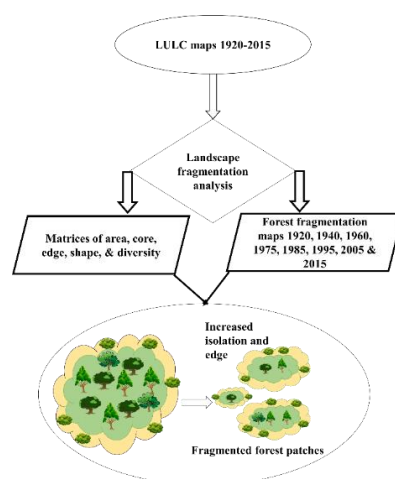


Fig 4.1. Framework for analysis of landscape ecology in Eastern Ghats

4.3.1 Data sets

The long term LULC maps prepared from historical maps and satellite images for the year 1920,1940,1960,1975,1985,1995,2005 and 2015 were used for the fragmentation and landscape composition analysis.

4.3.2 Landscape characterisation

Different landscape ecological parameters were evaluated both spatially and statistically (Reshma et al., 2018). The spatial analysis of forest fragmentation was carried out with the help of Landscape Fragmentation Tool v2 (LFT v2) (“Vogt et al., 2007”) in the ARCGIS 10.3.1. LFT maps the types of fragmentation present in specified land class (i.e., forest class) into 4 main categories - patch, edge, perforated, and core - based on a specified edge width of 500 m (“Soille and Vogt, 2009”). The ‘core’ forest is the intact forest consisting of interior forest pixels far from forest edge. The ‘patch’ forest makes up small fragments and too small to be considered as core forest. Edge (boundaries of relatively large perforations and the exterior boundaries of core forest regions) and perforated (boundaries between core forest and relatively small perforations) forests occur along the periphery of tracts containing core forests. The ‘Core’ forest was further divided into ‘small core’ (<1.01 sq.km), ‘medium core’ (1.01–2.02 sq.km), and ‘large core’ (>2.02 sq.km) areas based on the area of a given core patch (“Vogt et al. 2007”).

In addition to this landscape metrics for forest class was estimated using Quantum GIS Land cover statistics (LecoS) (“Jung, 2016”) suite for each individual classified LULC image (1920, 1940, 1960, 1975, 1985, 2005 and 2015). LecoS provides a comprehensive set of spatial statistics and descriptive metrics of the pattern at the patch, class, and landscape levels. The following metrics were used to find out the intensity of forest fragmentation: Edge Density (ED), Number of Patches (NP), Total Edge Length (TEL), Largest Patch Index (LPI), Overall Core Area (OCA), Effective Mesh Size (EMS), Shannon Diversity Index (SHDI), and Simpson Evenness Index (SIEI) (Table 4.1).

4.4 Results

4.4.1 Changes in landscape pattern

Landscape characterization with respect to patch formation within the extended forests, edge, perforations, intact and contiguous forests were analyzed and assigned to a patch size class from 1920–2015 (Table 4.2) (Reshma et al., 2018). Forest degradation and deforestation were

Table 4.1. Landscape Indices for forest fragmentation analysis (Reshma et al., 2018)

Acronym	Metric type	Equation	Range value	Description	Units	Reference
ED	Edge density	Total Edge (TE) /Total Landscape Area (TLA)	$ED \geq 0$	Absolute measure of total edge length of a particular patch type	m/ha	“Rutledge (2003)”
NP	Number of Patches	Number of patches that belong to the same class	$1 \leq NP \leq N_{max}$	The number of patches for the class, in one landscape unit.	-	“McGarigal et al., (1995)”
TEL	Total Edge Length	$\sum_{k=1}^m e_{ki}$	$TE \geq 0$, without limit.	Sum of the lengths of all edge segments involving the corresponding patch type	m	“Elkie et al., (1999)”
LPI	Largest Patch Index	Area of largest patch/TLA	$0 < LPI \leq 1$	Percentage of landscape area occupied by the largest patch of a class.	-	“Forman (1995)”
OCA	Overall Core Area	$OCA = \sum_{j=1}^n a_{ij}^c (1/10,000)$	$OCA \geq 0$, without limit	Aggregated (summed) over all patches of the corresponding patch type.	ha	“McGarigal et al. (1995)”
EMZ	Effective Mesh Size	$EMZ = \frac{1}{A_{Total}} \sum_{i=1}^n A_i^2$	-	The size of the patches when the landscape is divided into S areas (each of the same size) with the same degree of landscape division as obtained for the observed cumulative area distribution.	ha	“McGarigal et al. (1995)”

Contd..

SHDI	Shannon Diversity Index	$-\sum_{i=1}^m (P_i * \ln P_i)$	SHDI ≥ 0 , without limit	Measure of diversity in community ecology	-	“McGarigal and Marks (1994)”
SIEI	Simpson Evenness Index	$1 - \frac{\sum_{i=1}^m P_i^2}{1 - (\frac{1}{m})}$	$0 \leq \text{SIEI} \leq 1$	It is the relative abundance of different patch types	-	“McGarigal and Marks (1995)”

min E = minimum total length of edge in a particular class; ei = total length of edge (or perimeter) of class i; min ei = minimum total length of edge (or perimeter) of class i; max ei = maximum total length of edge (or perimeter) of class i; eik = total length (m) of edge in landscape involving patch type (class) i; includes landscape boundary and background segments involving patch type i; Pi = proportion of the landscape occupied by patch type (class) i.; n= Number of patches in the landscape of patch type (class) I; aijc = Core area (m2) of patch ij based on specified buffer width (m); ATotal = total area of the region investigated.

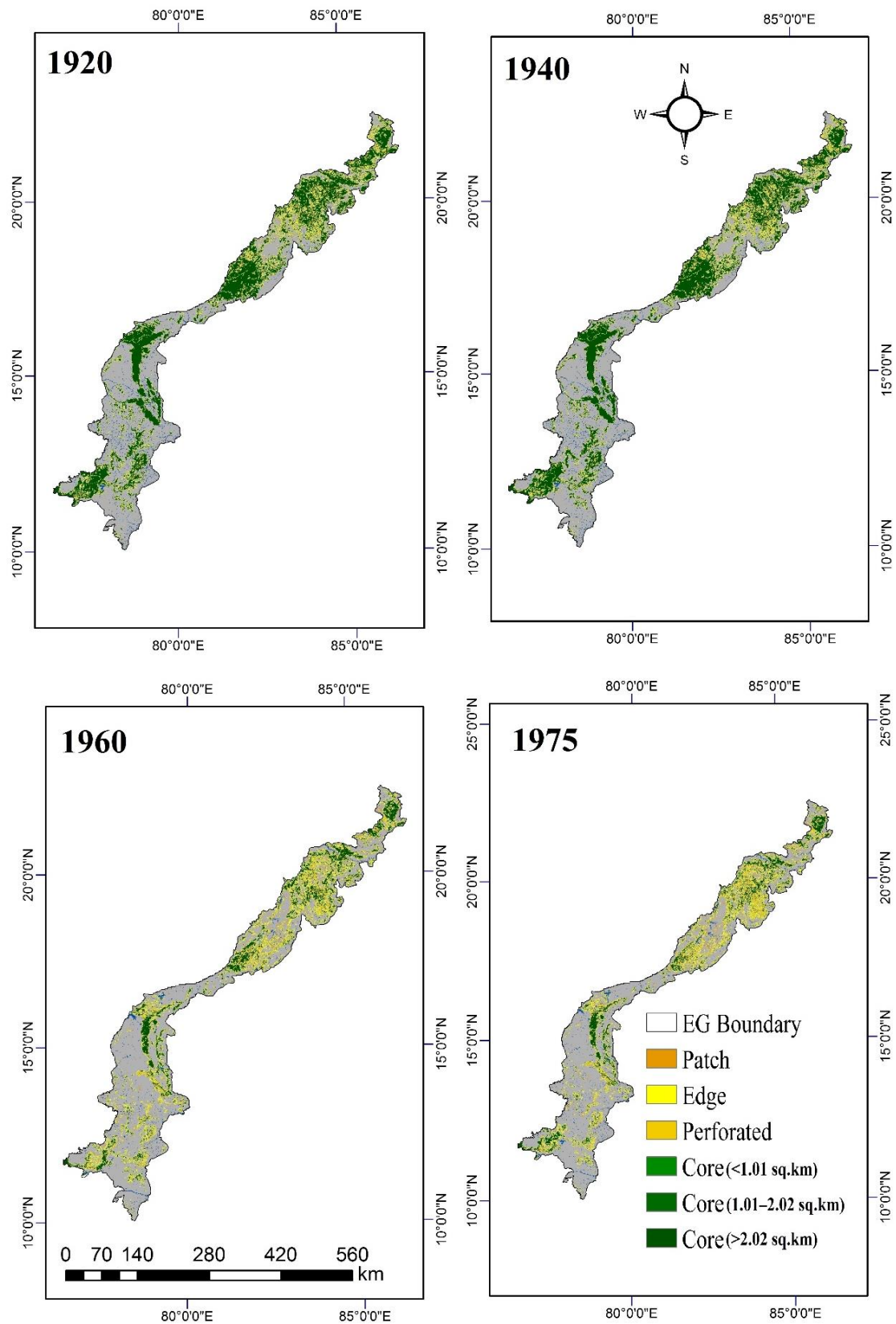
Table 4.2. Forest fragmentation and landscape diversity statistics, Eastern Ghats from 1920-2015 (Reshma et al., 2018)

Landscape Metrics	1920	1940	1960	1975	1985	1995	2005	2015
Edge Density	0.0004	0.0004	0.0010	0.0010	0.0010	0.0010	0.0010	0.0010
Number of Patches	1379	1509	9156	9345	9382	9404	9425	9457
Total Edge Length	82.18	80.10	215.30	218.49	218.74	218.89	218.93	220.81
Largest Patch Index	9.56	9.56	7.10	6.49	6.47	6.48	6.58	6.48
Overall Core Area	93461.05	93027.47	63103.80	62695.17	61555.66	61528.59	61417.99	61262.11
Effective Mesh Size	4216.16	4216.29	1597.15	1435.10	1431.70	1430.97	1429.90	1410.11
Shannon Index*	1.03	1.06	1.26	1.28	1.28	1.28	1.28	1.28
Simpsons Index*	0.59	0.60	0.66	0.67	0.67	0.67	0.67	0.67

*Landscape diversity index

Table 4.3. Fragmentation status of disturbed scrublands in the Eastern Ghats from 1920-2015 (Reshma et al., 2018)

Landscape Metrics	1920	1940	1960	1975	1985	1995	2005	2015
Edge density	1.44E-05	2.85E-05	0.001	0.001	0.001	0.001	0.001	0.001
Number of patches	438	598	25182	24468	24533	24495	24859	24913
Total Edge length	3179400	6265200	228256920	232338180	232001580	232357500	232161060	231897720
Largest Patch Index	0.02	0.24	0.36	0.36	0.36	0.36	0.36	0.36
Overall Core area	630918000	2749770000	25078100400	25642967400	25498081800	25703980200	25372586700	25362369900
Effective Mesh Size	27342.42	2035257.29	7006960.73	7364173.35	7347097.34	7717964.54	7321555.96	7314797.48



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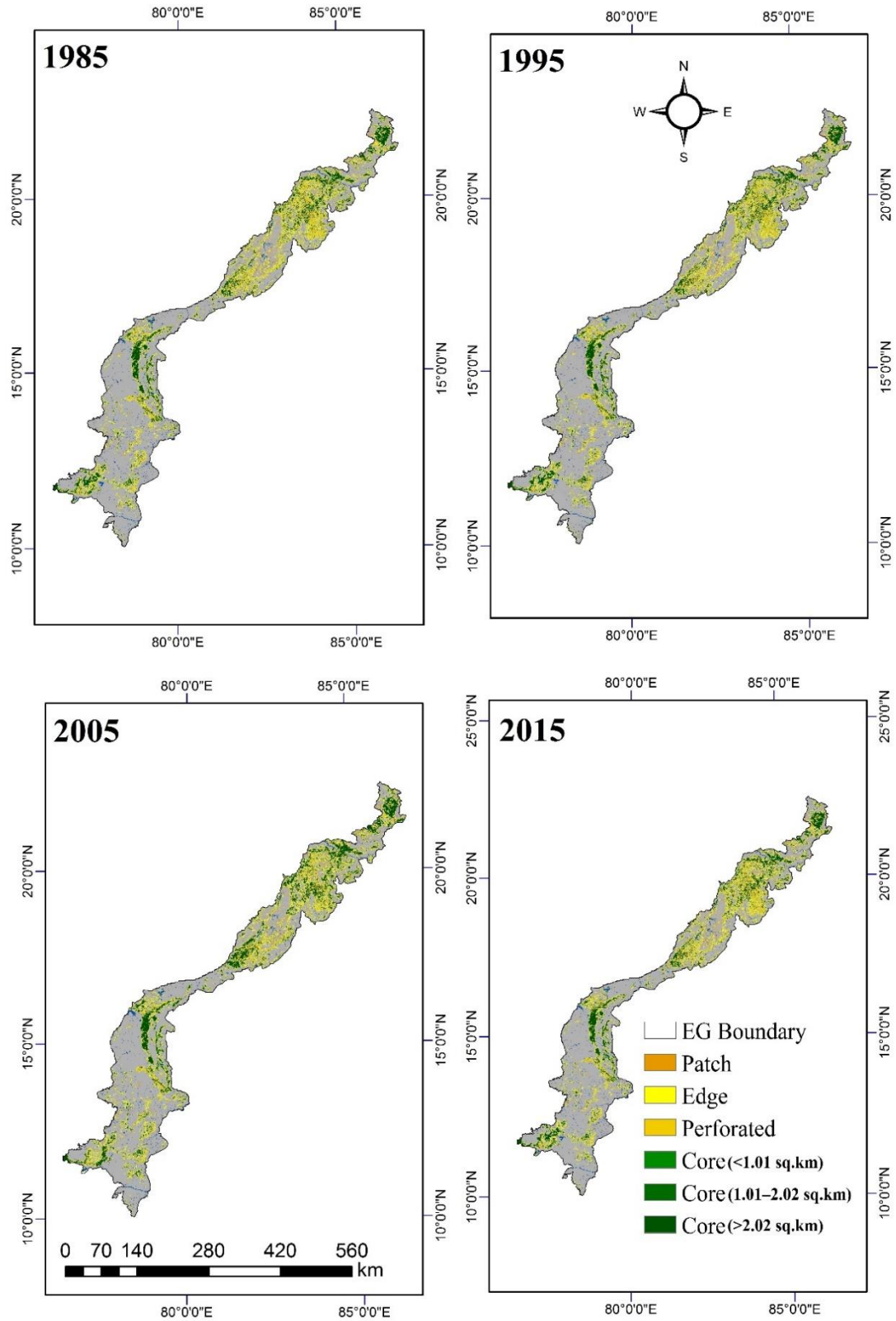


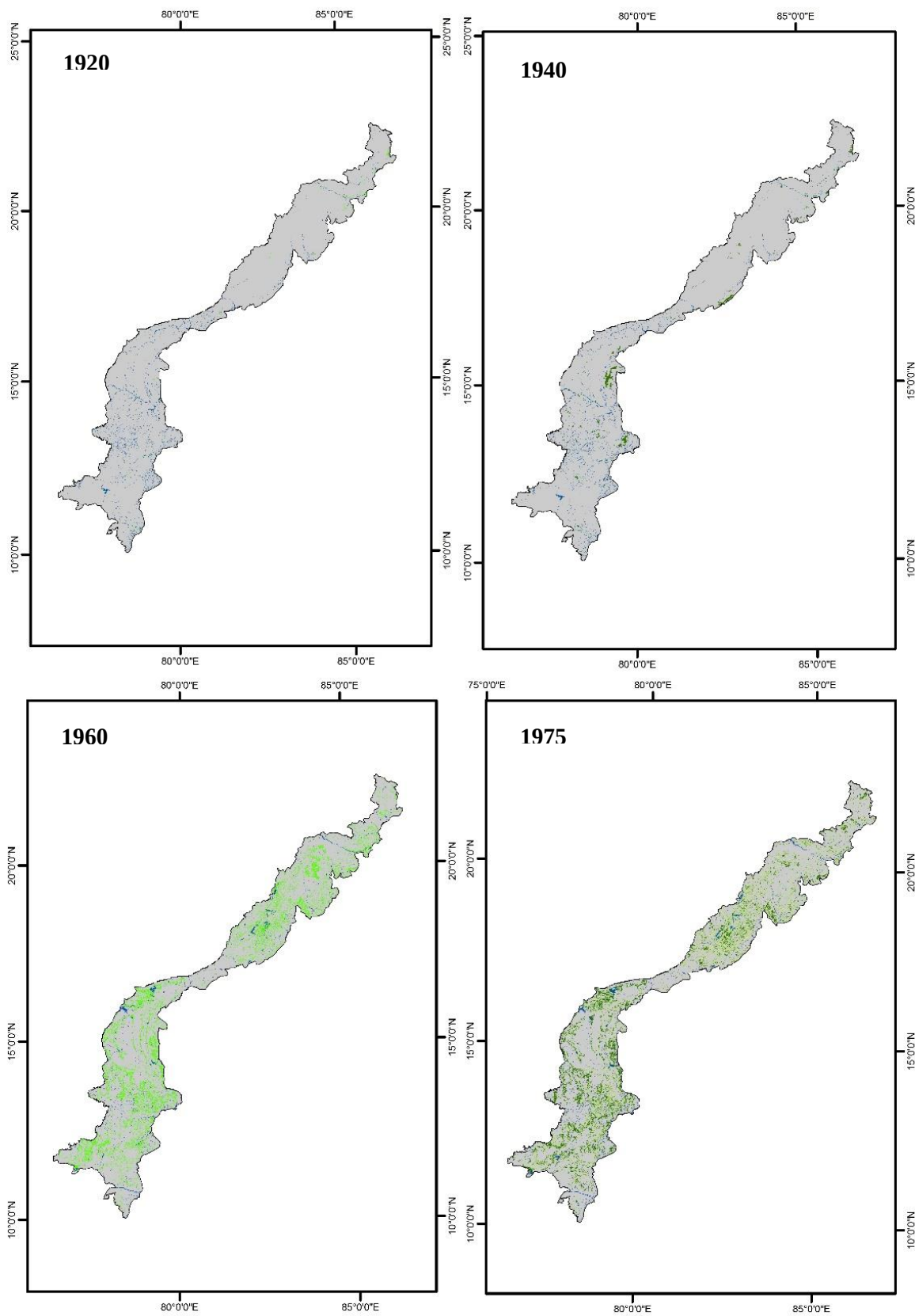
Figure 4.2. Forest fragmentation map of Eastern Ghats from 1920-2015(Reshma et al., 2018)

found to be associated with the degree of spatial fragmentation of the forests. The landscape pattern shows that the major changes were occurred during 1940 and 1960. The large patches of forests in 1920 are now fragmented, and the patch count was increased from 1379 (in the year 1920) to 9457 in 2015. There was a noticeable increase in the edge of forest patches from 1920 to 2015 (0.82 sq.km in 1920 and 2.20 km² in 2015). Forest with a recorded LPI of 9.56 during 1920 has reduced to 6.48 in 2015. The OCA under forests was estimated as 93461.05 km² in 1920 and now becomes 61262.11 km² in 2015. This inference clearly indicates that severe fragmentation and loss of forests were occurred during the study period. The forest fragmentation maps are shown in Fig 4.2. The fragmentation trends of scrubland have also been analysed (Table 4.3) to know the status and species distribution in the different fragmented classes (Reshma et al., 2018). The spatial changes in scrubland fragmentation were shown in Fig 4.3.

4.5 Discussions

4.5.1 Landscape dynamics

Forest fragmentation of Eastern Ghats (1920–2015) has been assessed which provides a stark contrast in land-use dynamics and extent of biodiversity risk in the area. Forest degradation and deforestation were found to be associated with the degree of spatial fragmentation of the landscape. Accessibility to forests in the Eastern Ghats is relatively easy when compared to Western Ghats owing to its less complex terrain which makes the degree of fragmentation in the Eastern Ghats to be on the higher side. Overall, the values of the metrics obtained in this study (Table 4.2) suggest that the changes in LULC has increased the heterogeneity of the landscape and resulted in a large variety of fragmentation patterns. To quantify the landscape composition, we have used Shannon and Simpson diversity indices. Shannon and Simpson indices of diversity and evenness might be expected to vary in their response to landscapes with varying richness. The heterogeneity of the landscape has increased from 1920 to 2015, indicating high fragmentation and habitat reduction. Likewise, low values of evenness indicate that one or a few land covers dominate, whereas high values indicate that relatively equal numbers of patches belong to each land class (“Morris et al., 2014”). The higher variation of the size (Fig. 4.2) and increased number of the patches induced a higher variation in the total edges and the reduction in the overall core area of the forest. The loss of forested area, increase in isolation, and greater exposure to human activities along fragmented edges are vulnerable to long-term changes in the structure and function of the remaining fragments (“Haddad et al.,



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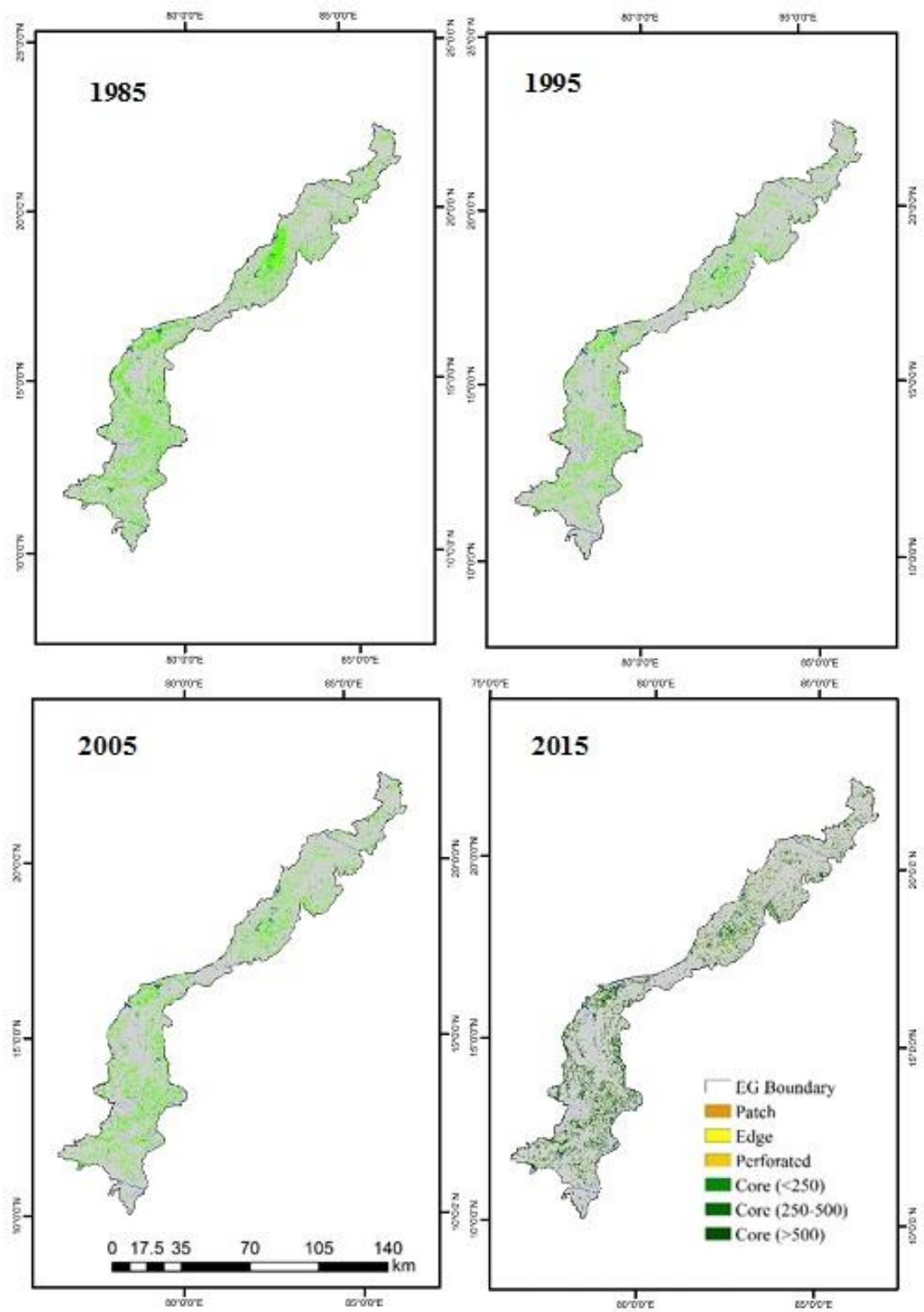


Figure 4.3. Scrubland fragmentation maps of Eastern Ghats from 1920-2015 (Reshma et al., 2018)

2015”). Forest fragmentation, directly and indirectly, affects the overall landscape by altering the patterns of landscape further reduction in the species habitat (“Conceição and de Oliveira, 2010”) and functioning.

4.5.2 Impacts of fragmentation of land classes over space and time

Fragmentation is one of the important foot print for human activities in the forests for the release of greenhouse gasses (“Laurance et al., 1998; DeFries et al., 2007; Smith et al., 2014; Brinck et al., 2017”) and it is considered to be the major threat to terrestrial biodiversity (“Krauss et al., 2010”). The forest fragmentation potentially influences ecological processes and functions such as biomass, carbon stock (“Putz et al., 2014”), hydrological cycle and nutrient cycles (“Haddad et al., 2015”). The continuous and long-term fragmentation can lead to deforestation which will finally result the habitat loss and degradation (“Hanski, 2011; Taubert et al., 2018”). While considering the biodiversity the habitat loss is one of the worst effects which will restrict the movements of species for food, breeding and other activities (“Niebuhr et al., 2015”). The species which are in restricted distribution (endemic species) have been expected to be highly vulnerable due to habitat fragmentation.

Eastern Ghat forest ecosystems are one of the primary focuses of land conversions. Indiscriminate removal of forests has resulted in the shrinkage of species habitats, fragmentation, edge changes and changes in community structure and composition; thereby, distressing the species distribution in many areas (“Brearley, 2011”). Forest fragmentation, in which the forest is reduced to patches, can have a marked negative impact on biodiversity (“Uddin et al., 2015”). Among others, it can result in homogenization (“Lôbo et al., 2011”), human-wild life conflicts (“Acharya et al., 2017”), reduction in habitat quality for forest-interior species (“Arroyo- Rodríguez and Mandujano, 2006”), loss of forest health due to changes in microclimate (“Ewers and Banks-Leite, 2013”) and increased susceptibility to predators, parasites, and invasive species (“Thuiller et al., 2008”). Thus, the changes in landscape patterns would certainly influence the ecological process and the existence of species at greater extents (“Pătru-Stupariu et al., 2017”).

Chapter 5

Assessment of Ecological importance of plant resources

5.1. General

Plants are placed in the first trophic level in an ecosystem because they produce food using the sunlight. Plants act as major part in determining the ecosystem services and function such as providing food, maintaining water and other nutrient cycles, climate regulation, provide habitat for faunal communities and many more (“Díaz et al., 2007; Isbell et al., 2011; Quijas et al., 2012; Gamfeldt et al., 2013”). Different plant forms such as shrubs, grasses, trees, herbs, and its associations have varied resource use pattern (“Lundholm et al., 2010”) and ecosystem functioning. According to The Economics of Ecosystems and Biodiversity (“TEEB, 2020”) ecosystem services are categorised into four types namely provisioning services, regulative services, habitat and supporting services, and cultural services.

Provisioning services: These are the products and energy outputs obtaining from the ecosystems. It includes food, raw materials, medicinal resources etc.

Regulative services: Ecosystems regulatory capacities are included in this category, which includes climate regulation, carbon sequestration, maintain soil quality etc.

Habitat and supporting services: The kind of support it gives to maintain ecosystem processes such as soil formation, habitat, genetic resource, primary production etc.

Cultural services: These are the non-material benefits obtaining from the nature such as aesthetic, spiritual, mental, tourism etc.

The plant species abundance and richness determine the services of an ecosystem. Ecosystem properties are highly influenced by the characteristics of dominant plants (“Grim, 1998”). The interactions between plants and animals provide enormous benefits to the ecosystems. The pollination, and seed dispersal are also included in it. This mutualistic combination determines

the stability and healthy functioning of an ecosystem through food chains (“Schleuning, 2015”).

5.2 Review of literature

In recent past, “Muthumperumal and Parthasarathi (2013)” have studied both ecological and economic importance of liana species in the southern part of Eastern Ghats and found that lianas provide varying ecologic and economic benefits such as fruit rewards, medicine, edible fruits etc. “Khan et al. (2014)” have studied in detail the plant species usage in the western Himalayan range. “Steinauer et al. (2017)” found that the characteristics of plant traits would play a prime role in preserving ecosystem services. “Wang et al. (2017)” have investigated the resource value of *Fritillaria* species, the extract of which is being used extensively in Chinese medicine since many centuries. Studies of “Kaluza et al. (2017)” shows that plant richness would affect the resource availability of a region. “Nathan et al. (2017)” demonstrated the effects of plant traits along with environmental gradients in functional diversity and ecosystem function. “Vezzani et al. (2018)” have studied the importance of plants on the soil structure and found that in combination with low soil disturbance, continuous plant growth helps in macro-aggregate scale structure, add more carbon and leads to substantial microbial biomass, metabolic diversity and soil ecosystem functioning capability.

“Bian et al. (2019)” have investigated the phytoremediation characteristics of bamboo species and reported that bamboo species have the ability to absorb heavy metals. “Bastazini et al. (2019)” after examining the system of seed dispersal found that loss of important centralistic plant species and their functional diversity can lead to the collapse of ecosystems. “Garrido et al. (2019)” documented that replacement of certain plant communities would affect the plant functions. “Salamon et al. (2020)” studied the importance of plant resources on the composition and functioning of soil communities. “Bogoni et al. (2020)” investigated the importance of flagship species on Brazilian forest and found their implications of historical *Araucaria angustifolia* (Bert.) O. Kuntze. The logging and deforestation, as well as vertebrate defaunation have led to the changes in baseline ecological process of *A. angustifolia* and thereby affected its regeneration, community reassembly, and seed downsizing, eventually causing its decline. Many studies have found that the structural and functional diversity of plant communities play a major role in the seed dispersal mechanism, which is one of the important ecosystem functions (“Quitián et al., 2019”).

Table 5.1.1. The ecosystem benefits of plant communities

Benefit	Examples	Ecosystem services	Description	References
Timber/ Economic	Wood	Provisioning services	Wood from trees used for construction purposes	“Ramage et al. (2017)”
Dye	Dyeing agent	Provisioning services	Plants which yield natural dye	“MEA (2005)”
Medicinal	Drugs, seeds, roots, biochemical	Provisioning services	Plants that are used as conventional medicines and provide the pharmaceutical industry with raw materials.	“TEEB”
NTFP*	Resins, bamboo, fibres, fuel, and palms	Provisioning services	Products other than timber are extracted from forests that have important local and economic uses	“Ahenkan and Boon, (2011)”
Food	Fruits, vegetables, tubers	Provisioning services	This comprises the wide variety of plant-derived food items or plant as such	“MEA (2005)”
Fodder	Grazing, forage for deer, livestock	Provisioning services	Plant and plant materials used as forage or fodder for livestock or other wild animals	“Anonymous, (1947)”
Raw material	Toy, furniture, boat, jewellers	Provisioning services	Ecosystems provide a broad variety of building and fuel materials, such as wood, biofuels and vegetable oils directly derived from wild and cultivated plant species.	“TEEB”

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Ornamental	Orchids, flowering plants	Provisioning services	Plant products and flowers are used as ornaments, although these resources are also culturally defined by their importance.	“MEA (2005)”
Stress regulation	Mangroves, neem	Regulating services	Plants which prevent extreme environmental conditions such as drought, saltness etc.	“TEEB”
Tolerance to soil erosion	Grass, banyan tree	Regulating services	Vegetative cover/plants which plays an significant function in soil retention as well as landslide prevention.	“MEA (2005)”
Biological control	Pest and insect repellents such as neem	Regulating services	Plants which resist pest naturally. It contains pest-resistant genes	“MEA (2005)”
Faunal dependency	Nest, larval host, honey, nester	Supporting services	Species provide needs which supports the survival of faunal community	“TEEB”
Religious/Cultural	Sacred trees, magical purpose, worship	Cultural services	Plants or plant materials that provide ecosystems with aesthetic, artistic, educational, spiritual, and/or science values.	“Costanza, (1997)”

*Non-timber forest products

5.3 Methodology

5.3.1. Assessment of plant ecosystem functions

The plant species data were gathered from field inventories as well as from the national-level project bearing entitled “Biodiversity Characterization at Landscape Level” (“Roy et al., 2012”). From a total 45440-point locations spread over the study area, 1598 plant species were recorded. With the help of this plant species data, the benefits provided by each of them (ecosystem functions) in the specific location were identified (Table 5.1). This process is repeated in each sampling point. This process has been done through interviewing forest officials, local people and available literature in the form of databases and published articles (Table 5.2). The geographical status and importance of the plant species such as local, regional and national endemism and vulnerability were considered according to IUCN Red Data Book. An illustration of plant benefits is shown in the Fig 5.1.



Figure 5.1 Schematic sketch of plant benefits and ecosystem functions which form the ecosystem services of plant species.

5.4. Results

5.4.1. Plant beneficial attributes towards ecosystem functioning and services

From a total 1598 plant species 151 families were identified. The species comprising of 439 trees, 207 climbers, 311 shrubs and 641 herbs. The benefits provided by each type were identified and classified into 13 ecosystem functions in the four-ecosystem services (Table 5.1). The plant beneficial attributes are classified under three major categories according to its

Table 5.2 List of databases used in the present study to assess the ecosystem services of plant species in the Eastern Ghats.

1. **The Plant List:** <http://www.theplantlist.org/>. Accessed on 23rd October 2017
The Plant List provides the Accepted Latin name for most species
2. **India Biodiversity Portal:** <http://indiabiodiversity.org/>. Accessed on 23rd October 2017
3. **The Tropical Plants Database:** <http://tropical.theferns.info/>. Accessed on 23rd October 2017
Contains information on the edible, medicinal and many other uses of several thousand plants that can be grown in tropical regions.
4. **The Global Biodiversity Information Facility (GBIF):** <http://www.gbif.org/>. Accessed on 23rd October 2017
Is an international open data infrastructure, funded by governments allows anyone, anywhere to access data about all types of life on Earth, shared across national boundaries via the Internet.
5. **Kerala Plants:** <http://keralaplants.in/>. Accessed on 23rd October 2017
6. **IUCN Red List:** <http://www.iucnredlist.org/>. Accessed on 23rd October 2017
The IUCN Red List of Threatened Species provides taxonomic, conservation status and distribution information on plants, fungi and animals that have been globally evaluated using the IUCN Red List Categories and Criteria (<http://www.iucnredlist.org/about/introduction>).
7. **efloraofindia:** <https://sites.google.com/site/efloraofindia/home>. Accessed on 23rd October 2017
Database of Indian Plants
8. **eFlora of India:** <http://efloraindia.nic.in/>. Accessed on 23rd October 2017
The Botanical Survey of India (BSI). eFlora of India is an open-access online database of India's plant diversity to document over 18,000 flowering plant species of India. This portal makes the information in the Flora of India volumes published by BSI available in the digital format.
9. **Global Plants:** <http://plants.jstor.org/>. Accessed on 24th October 2017
Global Plants is a community-contributed database used by students and researchers worldwide.

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10. **The Invasive Species Compendium (ISC):** <http://www.cabi.org/>. Accessed on 24th October 2017. It is an encyclopaedic resource that brings together a wide range of different types of science-based information to support decision-making in invasive species management worldwide.
11. **PROTA4U:** <https://www.prota4u.org/>. Accessed on 16th November 2017
12. **World Agroforestry database:** <http://www.worldagroforestry.org/treedb>. Accessed on 16th November 2017
13. **Plantillustrations.org :** <http://plantillustrations.org/>. Accessed on 16th November 2017
For botanical illustration of plants.
14. **Plant Info:** <http://www.jntbgri.in/plantinfo/PlantList/Manage/login.asp> Accessed on 19th November 2017.
A centralized database on plant diversity of Kerala state of Indian subcontinent, which offers all information related to the plants.
15. **Plants of Southeast Asia :** <http://www.asianplant.net/>. Accessed on 19th November 2017.
16. **IBIS-Flora Beta Version:** <http://flora.indianbiodiversity.org/>. Accessed on 19th November 2017.
IBIS – Flora, a first of its kind portal, caters to users with an extensive database carrying information of a total of 21,764 species, 515 subspecies, 2,514 varieties, 4 sub varieties and 58 forma belonging to 3,667 genera, 271 families and 50 orders of APG III. Around 95,161 synonyms have been compiled of which 40,000 come from numerous Indian literatures while the others are from international open access sources. IBIS-Flora contains distribution maps for 14,899 species and has more than 65,000 Bibliography from regional Flora.
17. **Digital Flora of Karnataka:** <http://florakarnataka.ces.iisc.ac.in/>. Accessed on 22nd November 2017.
The Center for Ecological Sciences (CES), Indian Institute of Science houses a herbarium of a fairly large number of specimens of native and naturalized plants collected by many taxonomists and researchers from India and abroad. This herbarium is recognized internationally by the acronym ‘JCB’. The collection consists of more than 14,000 specimens, from Vascular plants to Lichens. The collection is richest in plants from the State of Karnataka with holdings from the adjoining states of Tamil Nadu and Kerala as well. Another significant collection is, several hundred specimens from the forests of Western Ghats, an area not well represented in most South Indian

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Herbaria. Specific groups represented well in the Herbarium include Cyperaceae, Fabaceae, Orchidaceae, Poaceae, Scrophulariaceae, Ferns and allies, those reflecting the primary research interests of the past staff.

18. **Grassbase, Royal Botanic Gardens, Kew:** <http://www.kew.org/data/grasses-db>. Accessed on 22nd November 2017.

19. **IBIN:** <http://www.ibin.gov.in/>. Accessed on 22nd November 2017.

Indian Bio resource Information Network (IBIN) is being developed as a distributed national infrastructure to serve relevant information on diverse range of issues of bio resources of the country to a range of end users.

20. **Regional Plant Resource Centre (RPRC):** <http://www.rprcbbsr.com/>. Accessed on 22nd November 2017.

RPRC has a collection of 29 species of plants, which are endemic/ rare/endangered/ threatened plants to Eastern Ghats region.

21. **Gingersofindia:** <http://www.gingersofindia.com/>. Accessed on 22nd November 2017.
Database for gingers

22. **Butterflies of India:** <http://www.ifoundbutterflies.org>. Accessed on 3 December 2017.
An internet-based and peer-reviewed resource devoted to Indian butterflies and its host plants.

23. **ENVIS-FRLHT:** <http://envis.frlht.org>. Accessed on 3 December 2017

24. **Kew Royal Botanic Gardens:** <http://www.kew.org>. Accessed on 3 December 2017.

The global resource for plant and fungal knowledge, building an understanding of the world's plants and fungi upon which all our lives depend. Accessed on 3 December 2017.

importance in ecosystem and human beings viz; ecological, economic and aesthetic importance. The number of species which provide various ecosystem functions are given in Table 5.3.

5.4.2 Ecological importance: Faunal dependency, stress regulation, soil erosion control and biological control are factors which we considered as ecological importance from the available data. Fauna depend plants for food as well as shelter. For example, the birds used to eat the fruits of species such as *Alangium salviifolium* (L.f.) Wangerin, *Psydrax dicoccos* Gaertn., *Cassytha filiformis* L., *Ficus mollis* Vahl., *Ficus religiosa* L., *Garuga pinnata* Roxb., *Memecylon umbellatum* Burm. f., and *Sapindus emarginatus* Vahl. The animals and reptiles depend certain plant parts such as leaves, bark and fruits as their food such plant species includes *Acalypha fruticosa* Forssk. (Monitor lizards observed eating the flowers), *Albizia lebbeck* (L.) Benth., *Borassus flabellifer* L. *Cleistanthus monoicus* (Lour.) Müll.Arg. *Grewia villosa* Willd., *Syzygium nervosum* A.Cunn. ex DC. (Elephants eat leaves, fruits, and bark), *Psydrax dicoccos* Gaertn., *Eriolaena lushingtonii* Dunn, *Ficus mollis* Vahl, *Terminalia bellirica* (Gaertn.) Roxb. *Ficus religiosa* L., (Fruits eaten by bear, squirrel, monkey), *Grewia villosa* Willd., *Kyllinga nemoralis* (J.R.Forst. & G.Forst.) Dandy ex Hutch. & Dalziel, *Stachytarpheta jamaicensis* (L.) Vahl., *Suregada lanceolata* (Willd.) Kuntze, *Zornia gibbosa* Span. (Leaves and fruits eaten by sambar and spotted deer), *Suaeda maritima* (L.) Dumort. (Fruits are eaten by common langur). Many plant species acts as a major nectar and pollen source for butterflies and moths such species includes *Acacia auriculiformis* Benth., *Acacia caesia* (L.) Willd., *Acacia ferruginea* DC., *Acacia sinuata* (Lour.) Merr., *Albizia lebbeck* (L.) Benth., *Albizia odoratissima* (L.f.) Benth., *Anogeissus latifolia* (Roxb. ex DC.) Wall. ex Guillem. & Perr., *Capparis grandis* L.f., *Tarenna asiatica* (L.) Kuntze ex K.Schum., *Crotalaria paniculata* Willd., *Dalbergia spinosa* Roxb., *Grewia hirsuta* Vahl, *Hedychium coronarium* J.Koenig, *Lagerstroemia speciosa* (L.) Pers., *Maytenus heyneana* (Roth) D.C.S.Raju & Babu(unre), *Miliusa eriocarpa* Dunn(unre), *Pterospermum acerifolium* (L.) Willd., *Senna floribunda* (Cav.) H.S.Irwin & Barneby, *Tephrosia noctiflora* Baker, *Cyanthillium albicans* (DC.) H.Rob. The following species acts as larval host plants for butterflies *Acacia torta* (Roxb.) Craib (*Charaxes bharata*, *Surendra quercetorum*, *Prosotas nora*, *Prosotas dubiosa*, *Zinaspas todara*), *Aristolochia indica* L. (*Pachliopta aristolochiae*, *Troides minos*, *Pachliopta hector*), *Cadaba fruticosa* (L.) Druce (*Neptis jumbah*), *Getonia floribunda* Roxb.

Table 5.3. Number of species which provide different ecosystem functions

Ecosystem function	Total no. of Species	Life Form			No. of RDB species	No. of Endemic species
		Tree	Climber	Shrub		
Faunal dependency	229	104	27	44	54	3
Timber/Economic	145	95	9	21	20	13
Religious/Cultural	49	22	8	7	12	4
Dye	26	19	1	2	4	5
Medicinal uses	920	295	137	171	317	100
Forest Products	198	124	14	26	34	41
Food	266	103	45	43	75	40
Fodder	135	66	9	14	46	42
Raw material	112	64	10	20	18	28
Stress regulation	44	25	1	9	9	12
Tolerance to soil erosion	27	9	1	4	13	7
Ornamental	142	40	10	41	51	26
Biological control	29	15	4	2	8	3

The plants like *Agave sisalana* Perrine are good in trapping more carbon dioxide and help for tolerating flood events. *Bothriochloa bladhii* (Retz.) S.T.Blake and *Brachiaria mutica* (Forssk.) Stapf are good in preventing and sustaining during the floods. Many species are tolerant towards droughts *Acacia auriculiformis* Benth., *Acacia ferruginea* DC., *Acacia leucophloea* (Roxb.) Willd., *Albizia amara* (Roxb.) B.Boivin, *Azadirachta indica* A.Juss., *Butea monosperma* (Lam.) Taub., *Diospyros melanoxylon* Roxb., *Firmiana simplex* (L.) W.Wight, *Zanthoxylum armatum* DC. Etc. *Albizia procera* (Roxb.) Benth., *Anisomeles malabarica* (L.) R.Br. ex Sims, *Bauhinia variegata* L., *Cassia fistula* L., *Dalbergia sissoo* DC., *Endosamara racemosa* (Roxb.) R.Geesink etc., are characterised with insect and pest control.

5.4.3 Economic importance: Timber is one of the major economic sources from the plants. Many species are used for furniture, constructing houses and ships. Few of such species includes *Acacia spp.*, *Acronychia pedunculata* (L.) Miq., *Antidesma acidum* Retz., *Aporosa octandra* (Buch. -Ham. ex D.Don) Vickery, *Butea monosperma* (Lam.) Taub., *Dalbergia spp.*, *Dolichandrone falcata* (Wall. ex DC.) Seem., *Ficus spp.*, *Gardenia resinifera* Roth, *Hardwickia binata* Roxb., *Kleinia grandiflora* (Wallich ex DC.) N.Rani, etc. A list of timber yielding species are given in the supplementary table 2(excel sheet). The species like *Acacia praemorsa* P.J.Lang & Maslin, *Adenostemma lavenia* (L.) Kuntze, *Aegiceras corniculatum* (L.) Blanco, *Albizia lebbeck* (L.) Benth., *Ardisia solanacea* (Poir.) Roxb., *Bischofia javanica* Blume, *Butea monosperma* (Lam.) Taub., *Cassytha filiformis* L., *Tephrosia purpurea* (L.) Pers., *Erythrina stricta* Roxb. Etc are dye yielding plants.

A number of plants used for various medicinal purposes. Some of such species includes *Herissantia crispa* (L.) Brizicky, *Aegle marmelos* (L.) Corrêa, *Aerva lanata* (L.) Juss., *Andrographis paniculata* (Burm.f.) Nees, *Asparagus racemosus* Willd., *Limonia acidissima* Groff, *Terminalia paniculata* Roth(unre) etc are few among them. The species such as *Acacia nilotica* (L.) Delile, *Actinodaphne angustifolia* Nees, *Aegle marmelos* (L.) Corrêa, *Boswellia serrata* Roxb. ex Colebr., *Pterolobium hexapetalum* (Roth) Santapau & Wagh Etc are known for non-timber forest products (NTFP) which includes gum, honey etc.

5.4.4 Aesthetic importance: Which includes the plant species which is used for religious, cultural interests and ornamental purposes. *Aegle marmelos* (L.) Corrêa the leaves of this tree used for worshipping Lord Shiva. The plants such as *Spatholobus parviflorus* (DC.) Kuntze, *Pterocarpus santalinus* L.f. also known for its religious aspects. A decent number of species are using for ornamental purposes which includes *Acampe rigida* (Buch. -Ham. ex Sm.)

P.F.Hunt, *Acrostichum aureum* L., *Adiantum venustum* D. Don, *Aerides maculosa* Lindl., *Agave americana* L., *Ageratum houstonianum* Mill., *Albizia odoratissima* (L.f.) Benth., *Amorphophallus bulbifer* (Roxb.) Blume, *Bambusa bambos* (L.) Voss.

The abundance of species in accordance with different ecosystem services are shown in Fig. 5.2. The full list of plant species with recorded, benefits and its uses given in the supplementary Table 5.3.

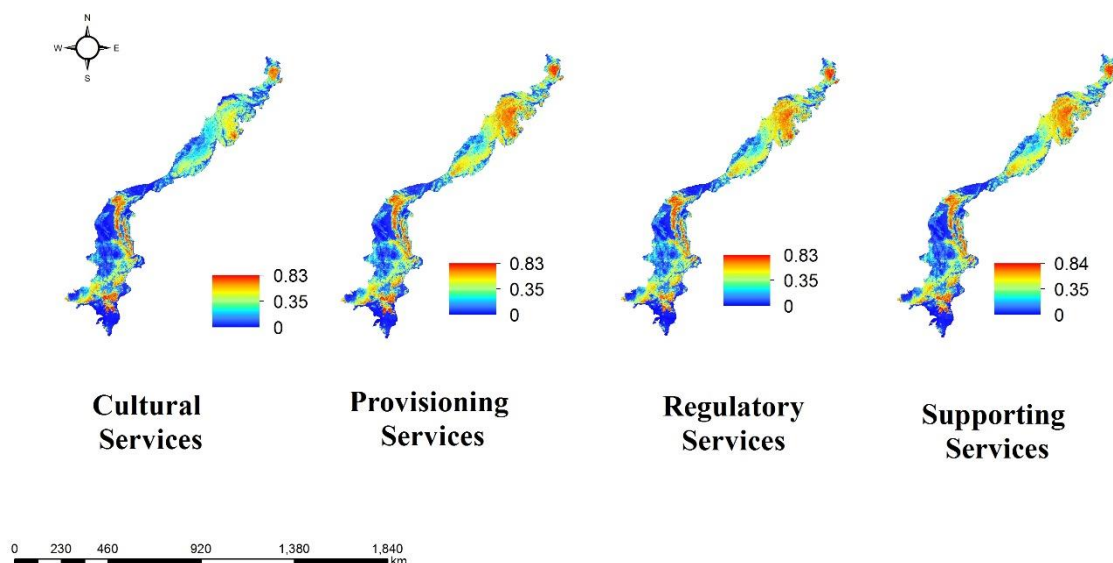


Figure 5.2. The species abundance map of Eastern Ghats having four ecosystem services types.

5.5 Discussion

The Eastern Ghats of India is one of the distinctive ecosystems that support abundant diversity of floral communities (“Pullaiah et al., 2002”). The flora bears and provides vast variety of ecosystem services. In the current analysis the plant samples from all the parts of Eastern Ghats been collected to get a good representative sampling. The broken chain like topography of the Eastern Ghats is providing accessibility and high human activities inside the forests. So even though Eastern Ghats are blessed with rich plant diversity the utilization is remarkably high. In the current analysis the maximum plant utilization is for medicinal purposes around 920 plant species are used as medicine in different parts of Eastern Ghats. The common names of some of the species are directly giving the utilization. For example, *Acacia caesia* (L.) Willd. is called as soap bar, *Acacia concinna* (Willd.) DC. as soap pod, *Acacia sinuata* (Lour.) Merr. as soapnut and *Sapindus emarginatus* Vahl. as Notched Leaf Soapnut due to its soapy nature in different plant parts. Likewise, *Ceiba pentandra* (L.) Gaertn. called as white silk-cotton tree, *Euphorbia*

hirta L. as asthma herb, *Strychnos potatorum* L.f. as clearing nut tree. In the similar way some of them are named with place names after the abundant occurrence or first record in that particular area. Examples are *Acalypha indica* L. as Indian Acalypha, *Adiantum venustum* D. Don as Himalayan Maidenhair Fern, *Albizia lebbeck* (L.) Benth. as East Indian Walnut, *Anisomeles malabarica* (L.) R.Br. ex Sims as Malabar catmint, *Atalantia racemosa* Wight ex Hook. as Bombay Atalantia, *Commelina benghalensis* L. as Bengal dayflower, *Phyllanthus maderaspatensis* L. as Madras Leaf-Flower and many more.

The plants like *Abutilon persicum* (Burm.f.) Merr. (“Churi, 2020”), *Aegle marmelos* (L.) Corrêa (“Churi et al., 2020”), *Combretum latifolium* Blume, *Cryptostegia grandiflora* Roxb. ex R.Br., *Desmodium alysicarpoides* Meeuwen, *Glochidion zeylanicum* var. *tomentosum* (Dalzell) Trimen, *Kyllinga nemoralis* (J.R.Forst. & G.Forst.) Dandy ex Hutch. & Dalziel, *Litsea floribunda* Gamble (unres), *Madhuca longifolia* (J.Koenig ex L.) J.F.Macbr., *Mimosa himalayana* Gamble, *Mucuna monosperma* Wight, *Solanum americanum* Mill., *Solanum anguivi* Lam., *Urochloa panicoides* P.Beauv., *Wendlandia heynei* (Schult.) Santapau & Merchant are used by different species of butterflies as their larval host plant (“Churi, 2020”). Species like *Habenaria commelinifolia* (Roxb.) Wall. ex Lindl. (“Suetsugu and Tanaka, 2014”), *Hibiscus lunariifolius* Willd., *Premna serratifolia* L., *Rostellularia prostrata* (C.B.Clarke) R.B.Majumdar(unre) and *Turnera ulmifolia* L. are used by butterflies as nectar source plant. In this way it supports pollination. The studies (“Bennett et al., 2020”) shows that the land use change limits the pollinators and thereby increases the risk in species existence.

Places viz. Simlipal national park, the districts like Baleswar, and Gajapati of Odisha state, Srikakulam and Chittoor in Andhra Pradesh, Biligiriranga hills, Nagarjunasagar-Srisailem sanctuary, Gundla Brahmeswaram sanctuary, Nallamalai hill ranges, Sri Venkateswara sanctuary, Sathyamangalam wildlife sanctuary, Kalrayan and Kolli hills had the high number of species. This can be due to its protected area status.

Chapter 6

Habitats and their conservation

6.1. General

The term ‘habitat’ is originated from the Latin word ‘habitāre’, which means to inhabit. Habitat is defined as “the resources and conditions present in an area that produce occupancy – including survival and reproduction – by a given organism. Habitat is organism-specific; it relates the presence of a species, population, or individual (animal or plant) to an area’s physical and biological characteristics. Habitat implies more than vegetation or vegetation structure; it is the sum of the specific resources that are needed by organisms” (“Hall et al., 1997”). Habitat is the one of the important concepts in ecology (“Kirk et al., 2018”). It directly influences the strength of organisms via resource variance and environmental conditions (“Johnson, 2007”).

Habitat conservation is being implemented in different ways across the globe that includes government legislations, nature preservation such as protected areas, reducing and recycling of wastes, and various steps to the climate change. Conservation is of two kinds - in situ and ex situ conservation. The former is the protection of genetic resources such as plants and animals in its natural habitat which includes the protected area. The latter is the protection after relocating the biological diversity to another similar ecosystems for example herbariums etc (“Ajayi, 2019”). Sampling is very important in both the conservation strategies as it provides good information about an ecosystem and how to protect it.

The influence of human beings directly or indirectly modifies the habitats of species and different functional processes on the Earth. Plant communities are prime and important components of an ecosystem (“Giam et al., 2010”). They control numerous ecological processes and support a wide variety of organisms. Therefore, the threats faced by a floristic community affect the entire ecosystem. These threats are primarily changing in LULC (“Foley et al., 2005; Cardinale et al., 2012; Souza et al., 2015; Gerstner et al., 2014”) and climate (“Segan et al., 2016; Schleuning et al., 2016”). Change in the LULC and climate may alter the distribution ranges of species and restrict interactions among them (“Oliver and Morecroft

2014; Elmhagen et al., 2015”), which will ultimately lead to habitat loss and species extinction. Human-induced habitat loss is the primary reason for species risk (“Ceballos et al., 2015; Hanski, 2011; Tilman and Lehman, 2001”). Human activities like fuel wood collection, and timber extraction has a significant impact on the forest and its species. The IUCN argues that habitat loss is the prime threat faced by 85% of the species described in the IUCN’s Red List (“IUCN 2012”). IUCN has classified the species in different categories depending on its threat and conservation values (see <https://www.iucnredlist.org/>). The habitats of Endemic, rare, endangered, and threatened (RET) species need to be mapped and conserved effectively because of their restricted distributions and ease of loss.

Eastern Ghats are the unique habitats in the East coast of India harbouring mainly the plant species. Though a good number of protected areas are established in the Eastern Ghats towards conservation, their effectiveness is debatable (“Rawat, 1997”) because of the increase in the number of mining activities, irrigation projects, timber logging and other developmental activities.

The present and future trends of species distributions under changing LULC and climate regimes have been extensively studied in different parts of the world (see for e.g., “Dyderski et al., 2018; Sirami et al., 2017”). Species distribution models (SDMs) are one of the effective tools that ecologists often use to map the potential and actual distributions (habitats) of species and their interactions with environmental parameters (“Elith and Leathwick 2009”). To fully understand the driving process and the impacts of LULC and climate change on the regional biodiversity, it is essential to quantify these impacts under different time scales viz., the past, present, and future, using an effective approach. Modeling is a robust method of analyzing the potential impacts of changing LULC and climate on biodiversity, allowing the exploration of possible future states and consequences (“Rounsevell et al., 2006”). India occupies only 2.4% of the global land area, though it accounts for 7–8% of the recorded species of the world (“MoEF 2008”). The projected and the future effects of climate and LULC changes on biodiversity as well as plant species have been studied mostly on North-East (Deb et al. 2017), Western Ghats (“Chitale et al., 2014; Kale et al., 2016”) and Gangetic planes (“Tsarouchi et al. 2014”) of the country. Even though Eastern Ghats are distinguished with species diversity and endemism, only few studies are reported/available from this region on the climate and LULC change aspects (“Remya et al., 2015”). The Eastern Ghats of India has experienced substantial LULC change and intensification of deforestation over the past few decades (“Rawat 1997; Balaguru et al., 2006; Reshma et al., 2018”). However, the coupled impacts of LULC and

climate changes on species distributions have been studied only modestly in the study region (“Sirami et al., 2017”).

In the present research, the magnitude of the impact of changing LULC and climate on the potential distributions of plants with conservation values, such as endemic and RET species, in the Eastern Ghats is studied taking into account the present and future (2050 and 2070) scenarios. Artificial neural networks, maximum entropy, and demographic modelling approaches have been used to simulate the LULC, potential species distributions, and human population in the future. The potential distributions of endemic and RET species were simulated with different future Representative Concentration Pathways (RCPs 2.6, 4.5, 6.0, and 8.5) of the fifth assessment report (AR5) of the Intergovernmental Panel on Climate Change (IPCC) (“IPCC 2014”).

6.2. Endemic plant species

Endemic species are native species which are restricted to a particular geographic region (“CBD, 2009”). Endemism exists because of evolution in relation to geographic isolation (“Vanderplank and Ezcurra, 2020”). These species are unique to certain locations. Endemic species are defined as “the species of a plant or animal which are unique to a defined geographic unit such as an island/nation or habitat type and not found elsewhere”. The phenomenon of endemism is influenced by the climatical, physical and biological variables in a place (“Chitale et al., 2014”). Some common traits have been observed among the endemic plant species which are inhabit sheer slopes and rock outcrops, yield less flowers and seeds, and are less fertile than their common counterparts (“Lavergne et al., 2004”).

“Nayar (1996)” had estimated the presence of 2,150 endemic plants in Peninsular India. India is a megadiverse country having 18,532 diversified flowering plants among which 4,303 are endemic (“Singh & Dash, 2017”). The Eastern Ghats harbours 2760 flowering plants recorded in which 454 are endemic to this area (“Kannaiyan, 2015”). The angiosperm flora of India is characterised by high endemism, which is next to Australian flora. Globally, the Indian subcontinent stands as one of the wealthiest floristic diversity zones. The floral richness includes high number of endemic plant species found 1286 numbers in Southern Western Ghats, 1808 in Eastern Himalayas and 454 in Eastern Ghats. A total of 5725 angiosperm endemic taxa which covers 33.5% of the Indian flora are found in 35 hot spots. The populations of Endemic species are much more fragile than other species. Once the endangered species are extinct, the biodiversity of these species is lost forever. (TBGRI, Bio-informatics centre).

The natural forests across the Indian landscape are habitat of numerous endemic species, but these systems are highly fragmented and require conservation policies (“Roy et al., 2013”). Endemic species are poor competitors, and least tolerant to environmental stress (“Lavergne et al., 2004”). The climate change and threats from invasive species cause vulnerability and extinction of these species due to its restricted distribution and small population (“Chitale et al., 2014”). “Myers et al. (2000)” hypothesised that conservation of endemic species is equal to the conservation of species richness habitats itself. The estimation of current and future distributions of endemic species gives crucial information about its habitat and could be useful towards the management and conservation activities (“Chitale et al., 2014”). Habitat depletion, fragmentation and degradation, invasive species, over-exploitation and changing climatic conditions figured as serious threats to species under endemism (“Baillie et al., 2004; Hermý et al., 2007”).

6.3. Rare, Endangered and Threatened (RET) species

RET species are the one which are naturally rare due to small population or restricted distribution, endangered due to threatened with extinctions and threatened by various natural or anthropogenic activities (“Jain et al., 1983”). The IUCN has assessed that more than 32,000 global species are threatened with extinction (“IUCN, 2020”). The endangered species is described as “any species of organism that faces a high risk of extinction within a portion or the entirety of its geographic range” (“IUCN, 2001”). Vulnerable and Endangered count for all taxa listed as Critically Endangered, and Vulnerable qualify for all listed as Endangered. These categories are jointly defined as 'threatened' (“IUCN, 2012a”). The IUCN has classified the species into eight threat groups such as, Extinct, Extinct in the Wild, Critically Endangered, Endangered, Vulnerable, Near Threatened, Least Concern and Data Deficient, depending on whether they meet population trend, population size, structure and geographical range requirements. The species under Critically Endangered, Endangered or Vulnerable are together listed as 'Threatened' (“IUCN, 2012b”).

Five quantitative criteria are used to assess whether or not a taxon is threatened and, if threatened, which threat group belongs to Critically Endangered, Endangered or Vulnerable (“IUCN, 2017”). Those are species or taxon found at three geographic sites with an area of 12 km², having a good population size which does not decline, it should not have any current threat but reasonable causative factors must be available which could cause the species to decline, and finally this threat must make species extinct or critically endangered in a short

duration (“IUCN, 2017”). The taxon occurs at three locations covering an area of 30 km²; the population does not decline; there are no current threats and it is very unlikely that the species will become extinct or critically endangered in a short period of time (“IUCN, 2017”). The species come under endangered category when it is “in danger of extinction within the foreseeable future throughout all or a significant portion of its range” and threatened when it is “likely to become an endangered species within the foreseeable future throughout all or a significant portion of its range” (“USFWS, 2013a”).

6.4. Species Distribution Models

Species Distribution Models (SDMs) (also called as Ecological Niche Modeling/Habitat Suitability Modeling) are one of the common techniques used for analysing the species distributions in relation to physical environment. “Elith & Leathwick (2009)”, define SDM as a model which relate location of the occurrence of species in relation to environmental conditions or the spatial characteristics of the locations. The SDMs then find the areas of potential species’ distributions according to the bioclimatic variables with specific model algorithm. The bioclimatic variables are variables derived from the climate data records of monthly minimum, maximum, mean temperature, and mean precipitation (“Karger et al., 2017”). It constitutes a range of data sets viz, annual ranges, seasonality and extreme or limiting environmental factors. The codes for bioclimatic variables by Worldclim are given in Table 6.1 (Reshma et al., 2020). The models based on bioclimatic variables are widely used to estimate climate change responses to potential species distribution.

BIOCLIM: It is the first SDM, which was based on the correlation method to model species distribution with the help of 35 climate variables (“Booth et al., 2014”). BIOCLIM is a simple, flexible and powerful modelling tool to evaluate distributions on a variety of spatial, and temporal scales (“Busby, 1991”). It uses only species occurrence data along with environmental variables to check the probability of occurrence of species in a location. Even though it uses the environmental predictor variables it does not counts the interactions between predictors. Use of categorical variable data is not possible in this model (“Booth et al., 2014”). As a range-based model, BIOCLIM interpolates climatic conditions of the locations in which the species are found. If the range of values of all climate parameters is within the range of the current location of occurrence of the species, BIOCLIM is classified as climate-appropriate (“Beaumont et al., 2005”).

Table 6.1 Bioclimatic variables used in the study (“<http://www.worldclim.org>”)

Code	Variable
BIO1	Annual mean temperature
BIO2	Mean diurnal range (mean of monthly (maximum temperature - minimum temperature))
BIO3	Isothermality (BIO2/BIO7) * 100
BIO4	Temperature seasonality (standard deviation * 100)
BIO5	Maximum temperature of warmest month
BIO6	Minimum temperature of coldest month
BIO7	Temperature annual range (BIO5 - BIO6)
BIO8	Mean temperature of wettest quarter
BIO9	Mean temperature of driest quarter
BIO10	Mean temperature of warmest quarter
BIO11	Mean temperature of coldest quarter
BIO12	Annual precipitation
BIO13	Precipitation of wettest month
BIO14	Precipitation of driest month
BIO15	Precipitation seasonality (coefficient of variation)
BIO16	Precipitation of wettest quarter
BIO17	Precipitation of driest quarter
BIO18	Precipitation of warmest quarter
BIO19	Precipitation of coldest quarter

MaxEnt: This algorithm models the potential distributions of species from presence only data along with a set of environmental parameters viz, climatic factors, soil, elevation, vegetation type etc. in a location (“Phillips et al., 2006”). The environmental variables are also called as features (“Phillips et al., 2008”). The six feature classes used in the MaxEnt software are, Linear (L), quadratic (Q), product (P), threshold (T), hinge (H), and category indicator (C) (“Phillips et al., 2005”). Each of these classes represents the shape of the response curve. It is an efficient deterministic algorithm which guarantees converge to the optimal (maximum entropy) probability distribution of the species (“Phillips et al., 2006”). MaxEnt outputs gives environmental suitability of a species rather than probability of occurrence.

Surface Range Envelope: It uses envelop style method to simulate species distribution. This method uses environmental conditions of a location to model the occurrence of species in other parts. It assumes the normal distributions of predictor variables (“Araújo et al., 2012”).

Genetic Algorithm for Rule-set Prediction (GARP): The GARP SDM is based on genetic algorithm (“Stockman et al., 2006”). It is a presence-absence model. GARP finds the non-random associations between the observations of presence and background absence and predictors of the environment. Four different modelling approaches are used to simulate the distribution of organisms, namely atomic, logistic regression, bioclimatic envelope, and negated bioclimatic envelope laws (“Hernandez et al., 2006”).

Generalized linear models (GLM): GLM is a presence/absence model often called as logistic regression model. It comes under the category of statistical fit of correlative models. In this statistical method of SDM, the species responses are fitted with regression to some of the environmental variables (“Thuiller et al., 2003”). This model is good for simulating the suitability of single species. The GLMs have three important components namely (1) probability distribution of the response variable (2) a combination of all predictor variables also called as the linear predictor which has overall score for the environmental suitability and (3) link function which describes how the mean of the response depends on the linear predictor. Categorical predictors can be used in GLMs. It often requires large data set and sample size for reliable predictions.

Generalized additive models (GAM): GAM is an extended form of GLM viz, a non-parametric statistical fit of correlative model. It is a presence/absence model. It is used when the relationship between the variables is more complex (“Guisan et al., 2002”). Similar to

GLM, GAM also has three components. This model also uses categorical data in modeling exercises.

Regression and Classification tree analysis (RCTA): Like GAM, RCTA is also a non-parametric statistical fit of correlative model. RCTA is a presence/absence model. This model uses predictors which produce homogeneous responses (“Thuiller 2003”). The tree keeps building by splitting the data on a single explanatory variable. Use of a pruning function helps to reduce the complexity and overfitting.

Multivariate adaptive regression splines (MARS): MARS is a presence/absence model. It is a flexible non-parametric regression model which make multiple linear regression models across the range of predictor variables (“Elith and Leathwick, 2007”). Which means it uses piecewise basis functions to define relationships between a response and some set of predictor variables. It is able to model complex nonlinear relationships between response and explanatory variables (“Friedman, 1991”). It is very effective with large number of predictor variables.

Mixture discriminant analysis (MDA): This presence/absence model is based on a mixture of linear regression models. In MDA the distributions are modelled as a mixtures of subclass distributions, each subclass represented by a Gaussian distribution (“Ju et al., 2003”). It is a multivariate technique in which a group of categorical variables are used to simulate the future distributions (“Wilks, 2019”).

Random forest (RF): RF is an ensemble classifier that uses supervised learning or bagging algorithm. This model is an ensemble of decision trees in which all the trees are trained in a bagging method (“Li and Wang, 2013”). The correlated variables are well handled by RF.

Boosted Regression Tree (BRT): This presence/absence model is an ensemble method that uses a combination of statistics and machine learning for fitting. BRT uses a merger of two algorithms such as decision tree, and boosting builds (“Elith et al., 2008”). Similar to Random Forest models for improving model accuracy this model repeatedly fit many decision trees. It often finds random subset of all data for each new tree that is built. The random subsets have same number of data points from whole dataset. The used data sets back to the full dataset for selecting in subsequent trees. In RF each occurrence has an equal probability of being selected in subsequent samples which is called as bagging method. Whereas in BRT input data are weighted in subsequent trees which is called as boosting method (“Elith et al., 2008”). Like

GLM, BRT models can be fitted to a variety of response types viz, Gaussian, Poisson, binomial, etc.

Generalized boosting model: It is a presence/absence model. Similar to BRT GBM also uses a combination of decision tree and boosting builds algorithms. It works like BRT the only difference is the poorly modelled dataset by previous trees has a higher probability of being selected in the new tree (“Li et al., 2013”). By fitting the previous trees, the model continuously tries to improve its accuracy.

Artificial Neural Networks: ANNs are computer programs inspired from human brain to process the data. This multi model forecasting method allows complex nonlinear relationships between the response variable and its predictors (“Botella et al., 2018”). Like neurons in biological brain ANNs has a number nodes and connections. ANNs typically trained by a back-propagation mode which consisting of an input layer, a number of hidden layers and an output layer (“Scrinzi et al., 2007”). This input layer in SDM contains the environmental variables. The information from each input node will be fed to the hidden layers which give a weightage to the input data according to the connections. ANNs is a presence/absence model having high predictive power and handles large data sets.

Domain: This presence only model follows Gower-similarity (“Gower et al., 2017”) to find the species suitability. This algorithm allocates an average multivariate distance in the output layer between the environmental variables and the adjacent cell in the training set (“Carpenter et al., 1993”), which is scaled to a minimum and maximum value (0-1) to find the probability distributions.

Circles: This geographical model uses presence only approach. This method does not use any environmental variables to find the distribution. Instead, it uses known occurrence points for species and simulates the presence of a species within a circle with a given radius around the occurrence points. (“Hijmans and Elith, 2015”).

Convex Hull: Like circles, this geographical model uses presence only method without environmental variables. It makes a convex hull enclosing all occurrence points in which all the occurrence points fall within the polygon (“Cornwell et al., 2006”).

Inverse Distance Weighted (IDW) model: IDW is a geographical model uses only occurrence data without environmental variables to simulate the habitat suitability of species. It checks the likelihood presence of a species in an area based on the distance of that area to a known

occurrence point. The spatial relation among the samples is used to calculate the species occurrence for an unknown location. The average species occurrence of surrounding known locations weighted by their inverse distance from the unknown locations (“Roberts et al., 2004”).

Voronoi hull model: Like other geographical models coronoid hull also uses species location to simulate habitat suitability. It predicts the occurrence of species inside voronoi hulls around observed occurrences, and absent outside those hulls (“Hijmans et al., 2015”).

6.5 Review of literature

From the time of development researchers are using of SDMs to estimate suitable habitats for various species both in current and future climate. “Shafer et al. (2001)” had estimated future changes in tree and shrubs in western North America. Studies of “Brooks et al. (2002)” reveal that many species in the Caribbean, Tropical Andes, Philippines, Mesoamerica, Sundaland, Indo-Burma, Madagascar, and Chocó–Darién–Western Ecuador will be lost due to deforestations. Based on the projected distributions of 1,350 plant species in the 21st century under different climate scenarios, “Thuiller et al. (2005)” had reported that half of the European plant species would be under threaten by 2080. “Loarie et al. (2008)” reported 80% reductions in range size of 66% endemic plant taxa in California is due to climate change. “Giam et al. (2010)” suggest that in the absence of potentially mitigating factors many threatened plants species would become extinct. “Segan et al. (2016)” found that climate change can cause habitat loss and fragmentation in many global ecoregions and nearly half of ecoregions will become impacted during the 21st century in RCP 8.5. “Yi et al. (2016)” reported the improvement of habitat suitability of *Homonoia riparia* Lour with global warming. “Fain et al. (2017)” investigated the habitat suitability of coffee for Puerto Rico for the period 2011–2100 and reported that by 2070 highly suitable habitat would be reduced by 60– 84%. “Deb et al. (2017)” investigated the habitat loss of Sal (*Shorea robusta*) and Garjan (*Dipterocarpus turbinatus*) across South Asia and continental parts of Southeast Asia. They reported that by 2070 under RCP4.5 and RCP8.5 suitable habitats for Sal will decline by 24% and 34% and for Garjan by 17% and 27%, respectively. “Dyderski et al. (2017)” quantified the range shifts in 12 European forest tree species by 2061–2080 under three different scenarios of climate change. “Abolmaali et al. (2018)” reported the influence of elevation, annual precipitation, and precipitation of coldest quarter on *Daphne mucronata* Royle, a vulnerable medicinal plant, in Central Iran. “Shirk et al. (2018)” estimated habitat shifts and contraction of of Pinus

strobiformis with the help of multi-scale optimization approach in the mountains of Arizona, and northern Mexico by 2080. “Morelli et al. (2020)” reported 29–59% habitat reduction from deforestation, 14–75% from climate change, and 38–93% from both in combination by 2070 of ruffed lemurs in Madagascar. “Marchioro et al. (2020)” assessed the degradation and habitat reduction of Brazilian pine due to agricultural conversion and climate change. Together with agricultural conversion and extreme degradation, illegal timber mining has reduced the forest cover by 13%, with climate change posing additional challenges to the species. “Staude et al. (2020)” reported local extinction risks are high in species with small ranges. At the same time, the changes in climate and LULC increases the suitable habitat of invasive species (“Gairola et al., 2016; Ji et al., 2017; Carboni et al., 2018”).

India is also experiencing habitat loss for many floral communities because of climate and LULC. The increase of invasive species is one of the hardest hits in plant distribution due to climate change. “Chitale et al. (2014)” found shifts in endemic plant species in the regions of Himalayas, Western Ghats, and Indo-Burma after examining the A1B scenario for 2050 and 2080. “Manish et al. (2016)” reported 18% loss of potential distributions of endemic angiosperms in Sikkim Himalaya by 2050 and 2070. “Priti et al. (2016)” predicted the range shifts of five plant species of Myristicaceae family in the Western Ghats in response to climate change for two scenarios (A1B and A2A). “Pramanika et al. (2018)” reported drastic reduction in the suitable habitat of the threatened *Garcinia indica* across the northern Western Ghats for 2050 and 2070. “Thapa et al. (2018)” predicted the potential distribution of eleven invasive alien plant species in parts of Kailash, Western Himalaya under various climate scenarios of 2050 and 2070. They reported an expansion in the distribution of invasive plants under RCP 2.6 and RCP 8.5. “Panda and Panda (2019)” assessed the habitat suitability of two invasive plants such as *Chromolaena odorata* and *Tridax procumbens* for current and future (2050 and 2100) climate conditions and reported its invasions in the Eastern Ghats, Western Ghats, Eastern Himalaya and the north-eastern regions of India.

In the Eastern Ghats also a few studies are reported on the species distribution and habitat suitability. “Babar et al. (2012)” reported that potential distributions of *Pterocarpus santalinus* L.f. (Red Sanders) are found outside the protected areas thus facing serious anthropogenic pressure due to economic and medicinal use. “Remya et al. (2015)” reported the loss of suitable habitat of *Myristica dactyloides* for two time periods 2050 and 2070 in the Kolli hills of Eastern Ghats.

This chapter presents the magnitude of impact of changing LULC and climate on the potential distributions of plants with conservation values such as endemic and RET species in the Eastern Ghats in the present and future scenarios (Reshma et al., 2020).

6.6 Data sets

Socioeconomic data. The village and district population data of the Eastern Ghats for the years 2001 and 2011 were obtained from the Office of the Registrar General & Census Commissioner, India (<http://www.censusindia.gov.in>). The details of census metadata was obtained from http://www.censusindia.gov.in/2011census/HLO/Metadata_Census_2011.pdf. Data relating to rivers, roads, rail networks, and locations of villages and cities were accessed from the OpenStreetMap of India for the year 2015 (<https://www.openstreetmap.in>). Protected Area (PA) map was obtained from the Wild Life Institute of India.

LULC and topographic data. LULC maps of 1995, 2005, and 2015 were prepared using 30m resolution Landsat images of sensors TM (1995 and 2005), ETM+ (2005) and OLI (2015). The LULC maps include six classes (Anderson level I), viz., forest, scrubland, agriculture, waterbody, built-up land, and barren land. DEM data from the Shuttle Radar Topography Mission Digital Elevation Model (SRTM DEM; at 30 m resolution) (<https://earthexplorer.usgs.gov/>) were used. Other topographic proxies such as slope and aspect were derived from the SRTM DEM data in the ARC GIS 10.3 environment.

Soil data. ISRIC soil-type data at 250 m resolution (“Hengl et al., 2017”) for the year 2016 was downloaded for the Eastern Ghats region (<https://www.isric.org/explore/soilgrids>). Additionally, erosion, drainage, and flood capacity data of the region were obtained from the National Bureau of Soil Survey and Land Use Planning (NBSS & LUP) for the year 2005.

Plant species data. The data set of the national-level project ‘Biodiversity Characterization at Landscape Level’ (“Roy et al., 2012”) was used, along with data from additional sampling points of field visits to the Eastern Ghats during the year 2017–2018. The sampled plant species were categorized as endemic or RET species according to the IUCN Red List. Among the 1598 species recorded from the ground-sampled points, 22 are endemic species and 28 are RET species. The endemic and RET species were recorded at 295 and 799 locations, respectively (Fig. 6.1).

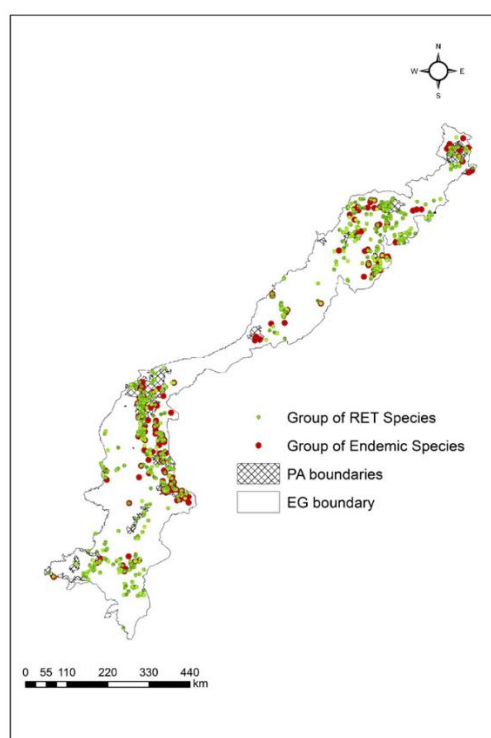
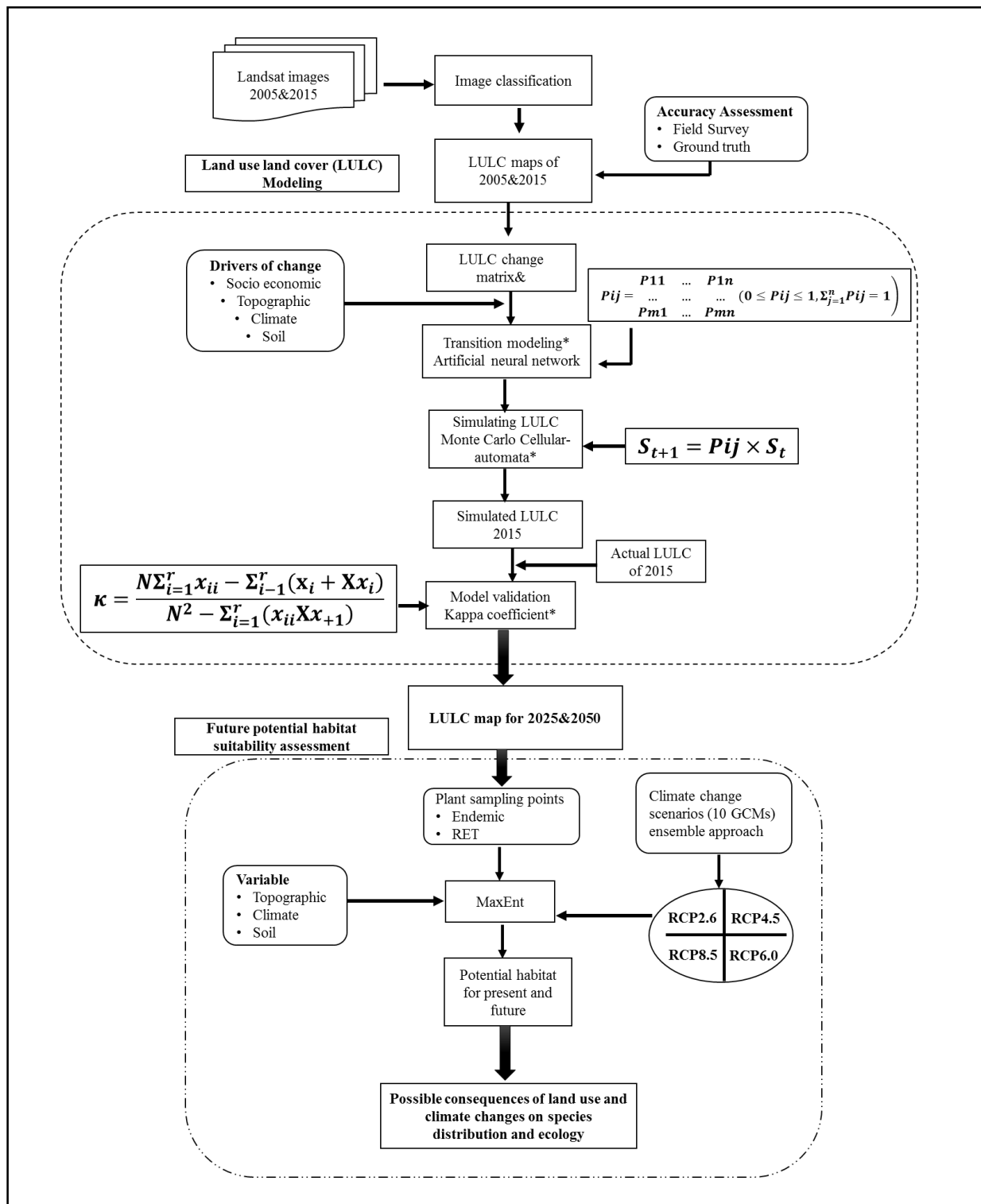


Figure 6.1. Sampling points of endemic and RET species in Eastern Ghats (Reshma et al., 2020)

Climate data: Current and future bioclimatic variables of WorldClim Version 1.4 (<http://www.worldclim.org/>) (Table 6.1) were used in the analysis. IPCC AR5 scenarios (IPCC 2014) were used for future estimates. These scenarios include one stringent mitigation scenario (RCP2.6), two intermediate scenarios (RCP4.5 and RCP6.0), and one scenario with very high levels of greenhouse gas emissions (RCP8.5) (“IPCC 2014”). 1 km × 1 km grid cells were allocated to the dependent variable with the highest likelihood of prediction.

Climate scenario interpretations: RCP2.6 indicates that emissions will peak by 2020 and declined to near zero by 2080, which may result in a radiative forcing of around 2.6 W/m² in the middle of the century and then decline afterwards (“van Vuuren et al., 2011”). RCP2.6 makes most suitable scenario for croplands, wherein the increase in extent is faster than current trends, with the grassland area unchanged and forest vegetation declines compared to current trends. RCP4.5 stabilizes the radiative forcing at 4.5 W/m² in the year 2100, after which there is no further increase (“Thomson et al., 2011”). RCP4.5 suggests decline in the crop and grassland areas and an increase in the area under natural vegetation through accelerated reforestation. RCP6.0 stabilizes the radiative forcing at 6.0 W/m² in the year 2100, without any further increase (“Masui et al., 2011”). The stabilization mainly happens because of the



Note: P_{ij} is the probability of change of land use i to j ; m and n are the number of land use types. S_{t+1} and S_t are the states of land use at given times $t + 1$ and t , respectively (“Arsanjani et al., 2013”).

r = number of rows and columns in the error matrix, N = total number of observations (pixels), X_{ii} = observation in row i and column i , X_i = marginal total of row i , and X_{+i} = marginal total of column i (“Congalton, 1991”).

Figure 6.2. Flow chart of methodology adopted to assess the impact of land use /land cover and climate change on forest ecosystem services (Reshma et al., 2020)

changes in the short-lived species and LULC. This makes the current cropping area trend to continue, but the extent of grasslands will reduce alarmingly, with the natural vegetation showing a trend similar to that of RCP4.5. On the other hand, RCP8.5 stabilizes the radiative forcing at 8.5 W/m^2 in 2100 under the conditions of a large population and slow income growth (“Riahi et al., 2011”). This scenario makes the land use continue at the current trend, with an increase in crop and grassland areas and a decline in forest cover. Future climate projections from the output of 10 global climate models (GCMs) (Table 6.2) from the fifth phase of the Coupled Model Inter-comparison Project (CMIP5) (“Collins et al., 2011”) were used. Ten GCMs were chosen in order to get the full range of variation in the models in CMIP5, which is a multi-model ensemble.

6.7 Methodology

The overall workflow of the methodology is shown in Fig. 6.2

6.7.1 Simulation of potential plant species distributions and habitat suitability

The future potential distributions of endemic and RET species were simulated using the well-known maximum entropy bioclimatic modeling technique (MaxEnt v3.3.3j) (“Phillips et al., 2006”). MaxEnt is one of the most widely used SDM algorithms for bioclimatic modelling owing to its high predictive accuracies even when the data are limited (“Elith and Leathwick 2009”). Since MaxEnt follows a correlative approach, the model seeks a correlation between species occurrence and environmental variables to predict the relative suitability of habitats (“Phillips et al., 2006”). MaxEnt has been used in different regions to model the distributions of one or multiple species (“Elith et al., 2011”). To project the future (2050 and 2070) potential distributions of endemic and RET species in a $1 \text{ km} \times 1 \text{ km}$ grid, all the climatic and environmental datasets were resampled at a 1 km resolution to make sure that all the layers were at the same resolution and extent. The list of bioclimatic variables used in the study is shown in Table 6.1. The correlation between all the variables (for all GCMs) was checked prior to modelling. The ensemble of these 10 models was used for the projections. MaxEnt was run for both present and projected climate change scenarios for endemic and RET species. The model was set up in such a way that the effects of climate and LULC changes are assessed independently. To achieve this, MaxEnt was run initially with climate variables (this run is referred to hereafter as simulation I). Then it was run with climate, topographic, and edaphic variables (simulation II), after which it was run by integrating all the factors including climate, topographic, edaphic, and LULC variables (simulation III). This process was repeated for both

Table 6.2. Description of global climate models (GCMs) used in the study (Reshma et al., 2020)

Global climate model	Institutions	Original resolution (°)	Description
BCC-CSM1-1	Beijing Climate Centre, China	2.81 × 2.77	Fully coupled global climate–carbon model including interactive vegetation and global carbon cycle, in which the atmospheric, ocean, land, and sea ice components are fully coupled and interact with each other through fluxes of momentum, energy, water, and carbon at their interfaces (“Wu et al., 2014”)
CCSM4	National Centre for Atmospheric Research, USA	0.93 × 1.25	Composed of four separate models simultaneously simulating the earth's atmosphere, ocean, land surface, and sea ice and one central coupler component (“Gent et al., 2011”)
GISS-E2-R	NASA-Goddard Institute for Space Studies, USA	2.00 × 2.50	Includes fully interactive chemistry related to ozone in historical and future simulations, and interactive methane in future simulations (“Schmidt et al., 2014”)
HadGEM2-ES	Met Office Hadley Centre, UK	1 × 1	Comprises underlying physical atmosphere, ocean, and earth system components such as terrestrial and ocean carbon cycle and tropospheric chemistry. Terrestrial vegetation and carbon are represented by the dynamic global vegetation model TRIFFID, which simulates the coverage and carbon balance of five vegetation types (broadleaf tree, needle leaf tree, C3 grass, C4 grass, and shrub) (“Martin et al., 2011”)
IPSL-CM5A-LR	Institut Pierre Simon Laplace, France	1.87 × 3.75	Includes an interactive carbon cycle, a representation of tropospheric and stratospheric chemistry, and a comprehensive representation of aerosols (“Dufresne et al., 2013”)
MIROC5	Atmosphere and Ocean Research Institute, The University of Tokyo, Japan; National Institute	1.40 × 1.40	It is a Coupled atmosphere model (which is based on a global spectral dynamical core) ocean model (which includes a sea ice model)

Contd..

	for Environmental Studies, Japan; Japan Agency for Marine-Earth Science and Technology		and its coupled with a land model (that includes a river module) (“Watanabe et al., 2010”).
MIROC-ESM	Japan Agency for Marine-Earth Science and Technology; Atmosphere and Ocean Research Institute, The University of Tokyo; National Institute for Environmental Studies	2.81×1.77	The atmospheric component is coupled with the land module; it also has an aerosol transportation model, a terrestrial ecosystem component called the spatially explicit individual-based dynamic global vegetation model, and an ocean ecosystem component (“Watanabe et al., 2011”).
MIROC-ESM-CHEM	Japan Agency for Marine-Earth Science and Technology; Atmosphere and Ocean Research Institute, The University of Tokyo; National Institute for Environmental Studies	2.81×1.77	An atmospheric chemistry-coupled version of MIROC-ESM (“Watanabe et al., 2011”).
MRI-CGCM3	Meteorological Research Institute, Tsukuba, Japan	1.13×1.13	Composed of atmosphere–land, aerosol, and ocean ice models. Atmospheric component is interactively coupled with aerosol model to represent direct and indirect effects of aerosols with a new cloud microphysics scheme (“Yukimoto et al., 2011”).
NorESM1-M	Uni Research AS; [L]Bjerknes Centre at the University of Bergen; Centre for Intern Climate and Environmental Research; Norwegian Meteorological Institute; Department of Geosciences, University of Oslo; Norwegian Computing Centre; Norwegian Institute for Air Research; Norwegian Polar Institute	2.5×1.875	Based on the CCSM4, it differs from CCSM4 by an isopycnic coordinate ocean model and advanced chemistry–aerosol–cloud–radiation interaction schemes (“Bentsen et al., 2013”).

endemic and RET species for all the 10 GCMs. The Pearson's correlation coefficient between the species distributions of similar RCPs was determined for each GCM to compare the spatial correlation between the outputs of different GCMs for the same scenarios.

6.7.2 Analysis of changes in habitat suitability

To check the percentage area changes under different climatic conditions of present and future for endemic and RET plant groups, the modelled species distributions were categorized into five thresholds according to the sensitivity, in the range between 0 and 1. The threshold classes were as follows: extremely suitable (>0.7), highly suitable ($0.6-0.7$), moderately suitable ($0.5-0.6$), less suitable ($<0.5-0$), and unsuitable (0). A value close to 1 indicates that a region is highly suitable for the occurrence of a particular species, whereas, regions with values close to or equal to 0 are not suitable (i.e., the species may become vulnerable to climate change and LULC change).

It is mainly focussed to observe the changes and range expansion or contraction of potential habitats in relation to the present condition for both plant groups under four RCPs. When there is no change in potential habitats in future projections, it indicates that under changing environmental factors the species in the raster cell under consideration would still be located in its climatic niche in 2050 and 2070. The expansion and contraction of a range in future projected habitats indicate an increase and decrease of the habitat area of a given species in both present and future. On the other hand, a range expansion indicates that the habitat of a species does not occur currently but is predicted to occur in 2050 and 2070. Similarly, a range contraction indicates that the available habitat will shrink to the desirable areas under the constraint of future environmental conditions. The negative and contracted areas are the parts where the occurrence of the species is severely threatened. These areas are considered unsuitable regions for the species.

6.7.3 Estimation of degradation and species habitat loss risk due to fragmentation

The risk of species habitat was analyzed by posting the sampling points on different fragmentation levels of protected areas (PA) and outside the PA (OPA) (other core forest cover delineated outside the PA) of forest and scrub/grassland. Along with RET and endemic species the species with economic and medicinal values also considered for this estimation.

6.8 Results

6.8.1 Area under the curve (AUC) and species distributions

The AUC scores of the modelled outputs were determined to ensure the best fit. The scores under the present conditions of endemic and RET species were 0.89 and 0.79 in simulation I, 0.92 and 0.81 in simulation II, and 0.93 and 0.82 in simulation III. The average AUC scores of the 10 GCMs (standard deviations (SD) has been given) were computed for 2050 and 2070. The average AUC scores for endemic and RET species in 2050 were 0.90 (0.005 SD) and 0.799 (0.004 SD) in simulation I. In simulation II, they were 0.91 (0.002 SD) and 0.82 (0.003 SD), respectively, in 2050. In simulation III, the AUC scores increased to 0.93 (0.004 SD) and 0.83 (0.002 SD), respectively (Fig. 6.3).

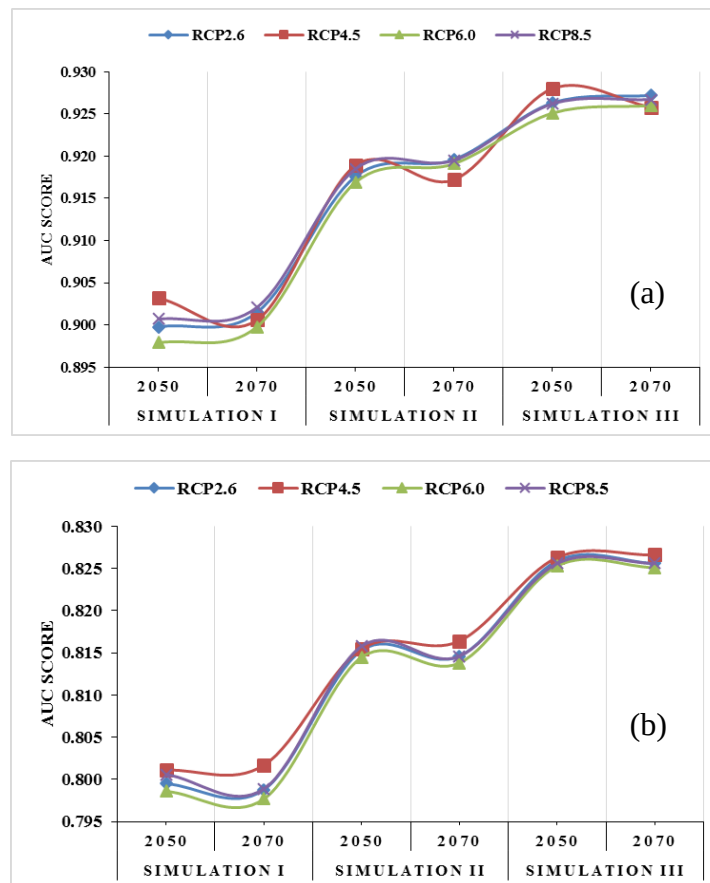


Figure 6.3. Area under the curve (AUC) of potential distributions of species: (a) endemics; (b) RET species (Reshma et al., 2020).

The AUC scores of the endemic and RET species for 2070 were 0.90 (0.003 SD) and 0.799 (0.003 SD) in simulation I. In simulation II, they were 0.92 (0.003 SD) and 0.81 (0.002 SD).

In simulation III, the AUC scores were 0.93 (0.002 SD) and 0.83 (0.001 SD), respectively. These findings indicate that the first simulation explains the potential distribution better in terms of climatic factors and the second model provides a better explanation of the combined impacts of the changes in climate and LULC on the potential distributions of species. The AUC scores of the endemic and RET species are shown in Figs. 6.3a and b.

6.8.2 Spatial and temporal changes in potential species distributions under changing climate and LULC

Endemic species were mostly distributed in the core areas of forests and thus had restricted distributions. Potential distributions were observed in Similipal, the Kalahandi ranges, the Mahendragiri hill ranges, the Nallamalai-Seshachalam hill ranges, and the Kolli and Kalrayan hill forests. There is a large reduction of the habitats of endemic species, particularly in the core areas of forests (Fig.. 6.4). The potential distributions of RET species were significantly more extensive all over the Eastern Ghats. Specifically, they were found in Similipal, Gajapati District (Odisha), the Nallamalai-Seshachalam hill ranges, Satyamangalam, BR hills, and the Kolli and Kalrayan hill forests. RET species were distributed not only in the core areas of forests but also in the adjoining areas and periphery of forests (Fig. 6.5). Therefore, the influence of anthropogenic activities on RET species is more when compared to endemics. The LULC reduced the spatial distribution of RET species.

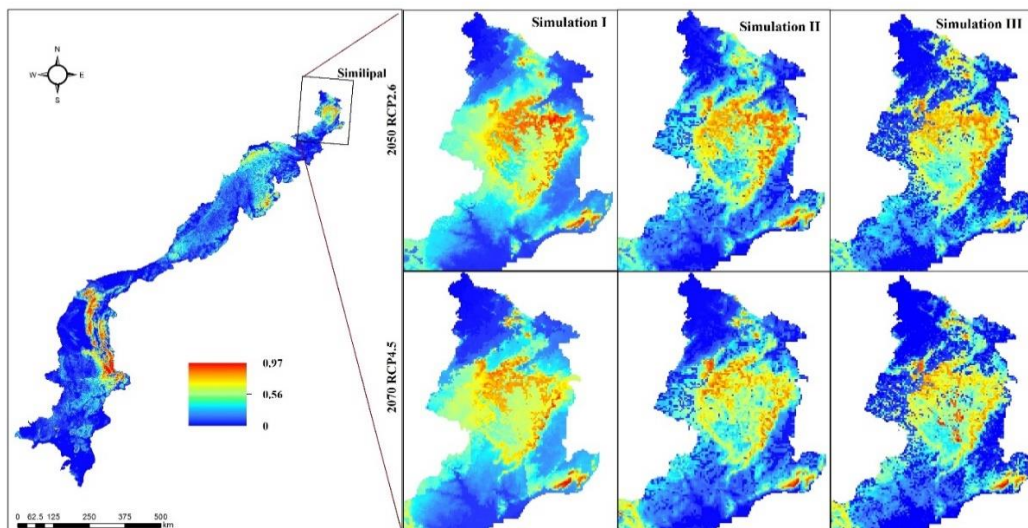


Figure 6.4. Range shifts in the suitable habitats of endemic plant species in the Similipal and surrounding areas of Eastern Ghats (Reshma et al., 2020)

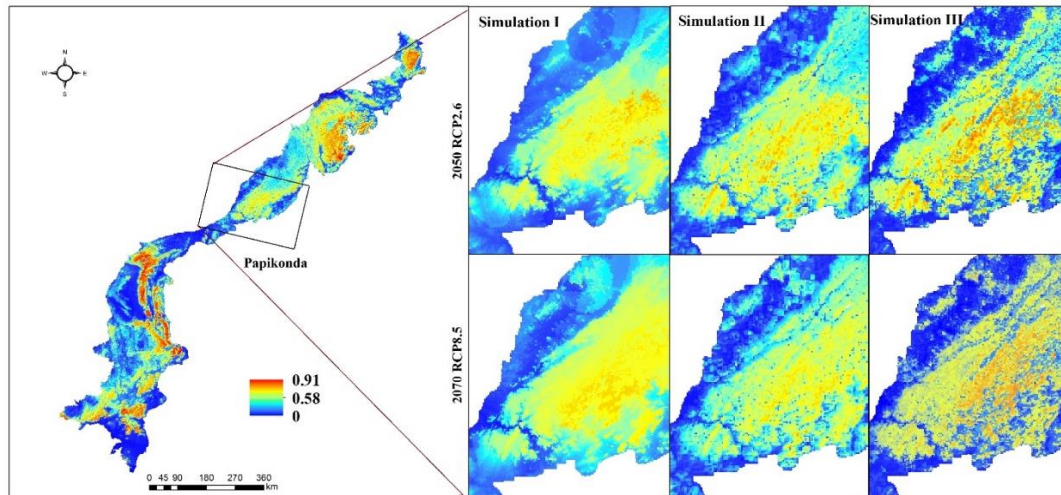


Figure 6.5. Range shifts in the suitable habitats of RET plant species in the Papikonda and surrounding areas of Eastern Ghats (Reshma et al., 2020)

There were increases and decreases in the suitability of habitats in all the regions of the Eastern Ghats in all the four scenarios. But the changes in the northern region were more dynamic in comparison to other parts. The ensemble values of the areas under different suitability classes of different scenarios from the 10 GCMs were analyzed for habitat loss (area reduction). In general, simulation III shows significant decreases in area compared to simulations I and II (Tables 6.3 and 6.4). There is a strong shift in the species distribution ranges under the four climate scenarios (RCPs 2.6, 4.5, 6.0, and 8.5). Under the current conditions, 0.58% (simulation I), 0.67% (simulation II), and 0.30% (simulation III) of the area of endemics species fall within extremely suitable class. In contrast, highly suitable class shows a slight increase over the present. It was found that simulation I gives large area suitability for species occurrence. With the addition of the LULC component, there is an increase (15.79%) in unsuitable class (Fig. 6.6a). However, simulations with only climate variables show an increase in the areas of all the suitability classes except the less suitable class. Only marginal changes are observed in areas of high and moderately suitable classes even after the addition of LULC component in the analysis. Interestingly, after adding the LULC variable in RCP2.6, the area of the highly suitable class shows an increase of 0.04%, whereas the area remains constant with RCP8.5. The percentage areas under the less and not suitable classes show an increase of ~6% under all RCPs. It indicates the habitat degradation/loss in the Eastern Ghats. The 2070 simulations also show a similar pattern except for an increase of the area of the highly suitable class under RCP4.5 (0.77% decline) and RCP6.0 (0.81% increase) (Fig 6.6b).

Table 6.3 The percentage of area (multimodal mean) under different threshold classes of endemic species (Reshma et al., 2020)

Period	Suitability Class	Simulation I					Simulation II					Simulation III				
		RCP2.6	RCP4.5	RCP6.0	RCP8.5	RCP2.6	RCP4.5	RCP6.0	RCP8.5	RCP2.6	RCP4.5	RCP6.0	RCP8.5	RCP2.6	RCP4.5	RCP8.5
2050	Extremely suitable	0.60	0.56	0.54	0.57	0.57	0.56	0.57	0.55	0.28	0.29	0.28	0.27	0.28	0.28	0.27
	Highly suitable	3.64	3.59	3.93	3.85	3.02	3.11	3.14	3.07	3.07	3.1	3.13	3.07	3.07	3.13	3.07
	Moderately suitable	6.03	5.95	5.01	5.72	5.54	5.42	5.74	5.5	5.13	5.04	5.28	5.2	5.28	5.28	5.2
	Less suitable	45.07	45.02	42.75	45.29	36.26	36.59	37.39	36.49	31.14	31.54	31.44	31.16	31.14	31.54	31.16
	Not suitable	44.66	44.88	47.77	44.57	54.61	54.32	53.17	54.39	60.39	60.03	59.87	60.29	60.39	60.03	60.29
2070	Extremely suitable	0.62	0.70	0.70	0.65	0.54	0.58	0.57	0.54	0.26	0.27	0.3	0.29	0.26	0.27	0.29
	Highly suitable	3.27	3.04	3.43	3.66	3.02	3.09	3.01	3.09	3	3.13	3.08	3.12	3	3.13	3.12
	Moderately suitable	5.91	6.33	6.18	6.16	5.57	5.6	5.74	5.63	5.07	5.22	5.26	5.11	5.07	5.22	5.11
	Less suitable	44.37	45.62	47.66	46.92	35.52	36.99	35.76	37.09	30.45	31.67	31.06	31.28	30.45	31.67	31.28
	Not suitable	45.83	44.31	42.03	42.61	55.35	53.75	54.92	53.64	61.23	59.7	60.3	60.2	61.23	59.7	60.2
Present	Extremely suitable	0.58					0.67					0.3				
	Highly suitable	3.09					2.74					3				
	Moderately suitable	7.10					5.59					5.24				
	Less suitable	46.85					39.7					33.27				
	Not suitable	42.39					51.99					58.18				

Table 6.4 The percentage of area (multimodal mean) under different threshold classes of RET species (Reshma et al., 2020)

Period	Suitability Class	Simulation I					Simulation II					Simulation III				
		RCP2.6	RCP4.5	RCP6.0	RCP8.5	RCP2.6	RCP4.5	RCP6.0	RCP8.5	RCP2.6	RCP4.5	RCP6.0	RCP8.5			
2050	Extremely suitable	0.01	0.01	0.01	0.01	0.07	0.07	0.07	0.07	0.01	0.01	0.01	0.01			
	Highly suitable	7.38	7.34	7.14	7.36	6.31	6.25	6.27	6.36	6.13	6.01	6.03	6.06			
	Moderately suitable	20.53	22.44	22.12	21.67	19.04	19.12	18.88	19.07	17.46	17.39	17.47	17.45			
	Less suitable	51.14	49.41	50.83	49.82	43.85	44.12	43.68	43.53	37.16	37.66	37.54	37.36			
	Not suitable	20.95	20.80	19.91	21.14	30.73	30.42	31.1	30.96	39.24	38.93	38.95	39.13			
2070	Extremely suitable	0.00	0.01	0.00	0.00	0.08	0.07	0.07	0.08	0.01	0.02	0.01	0.01			
	Highly suitable	7.12	7.72	7.76	7.15	6.29	6.26	6.35	6.35	5.95	5.99	6.05	6.05			
	Moderately suitable	22.85	22.71	22.79	23.92	18.89	18.98	19.35	19.33	17.48	17.21	17.59	17.67			
	Less suitable	48.65	44.97	50.13	49.07	43.52	44.06	43.72	43.33	37.1	37.72	37.46	37.26			
	Not suitable	21.38	24.60	19.31	19.85	31.22	30.61	30.51	30.91	39.45	39.07	38.89	39.01			
Present	Extremely suitable	0.00					0.07					0.01				
	Highly suitable	7.22					6.47					5.86				
	Moderately suitable	22.85					19.01					17.82				
	Less suitable	51.04					46.13					37.67				
	Not suitable	18.89					29.03					38.63				

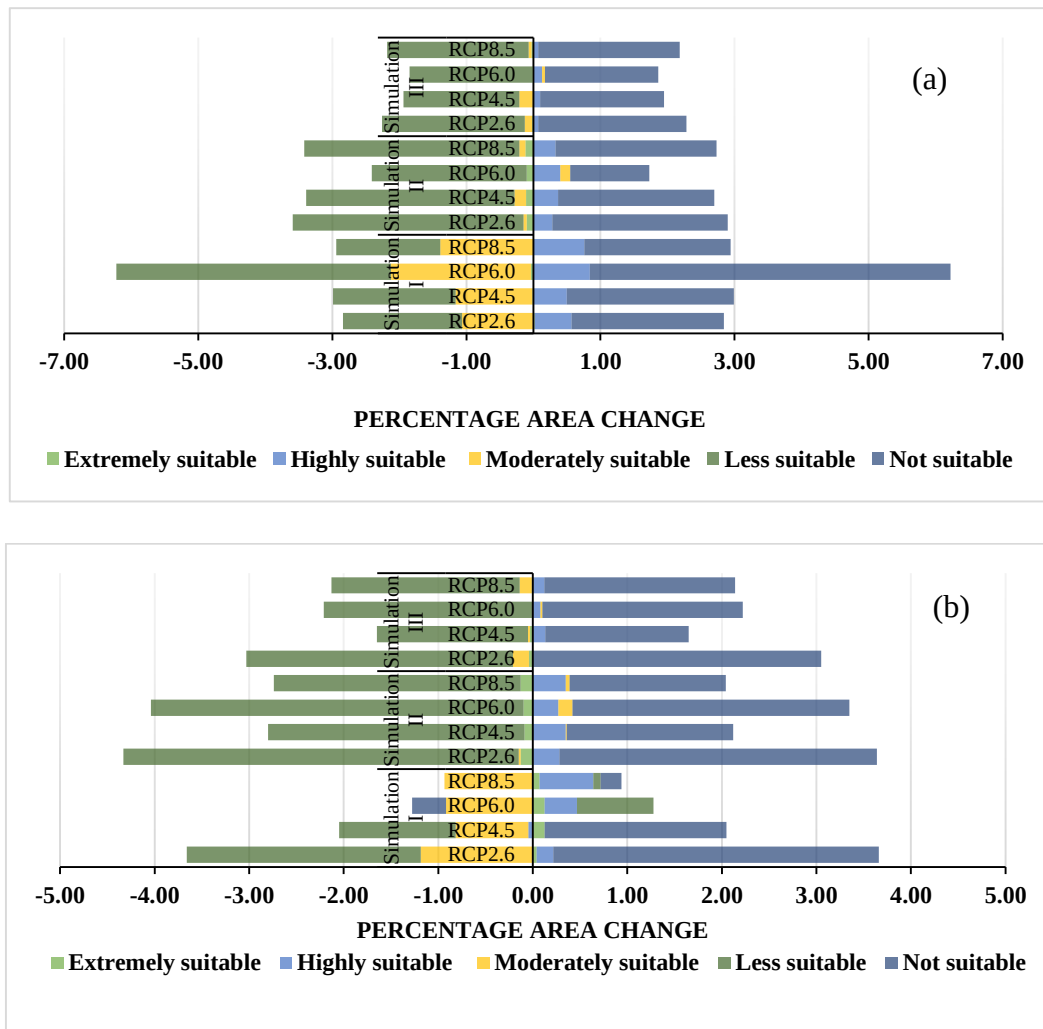


Fig 6.6 Change of percent area of plant distributions from the present to the future: (a) endemics, 2050, (b) endemics, 2070 (Reshma et al., 2020)

In contrast, the RET group shows a greater decrease in the area of the extremely suitable habitat after the addition of LULC (Fig 6.7a). The percentage of area decrease is as follows: 0.06% (extremely suitable), 0.60% (highly suitable), 1.19% (moderately suitable), and 8.46% (less suitable). There is an overall increase of 9.60% of the non-suitable area. The future simulation for 2050 retains the area under the extremely suitable class under all emission scenarios. In the climate-only case, the moderately suitable class shows small increases except under RCP6.0. The simulations for 2070 (Fig. 6.7b) show drastic decrease in the areas under the highly suitable, moderately suitable, and less suitable classes. The area under the extremely high suitability class shows an increase of ~0.01% under RCP2.6.

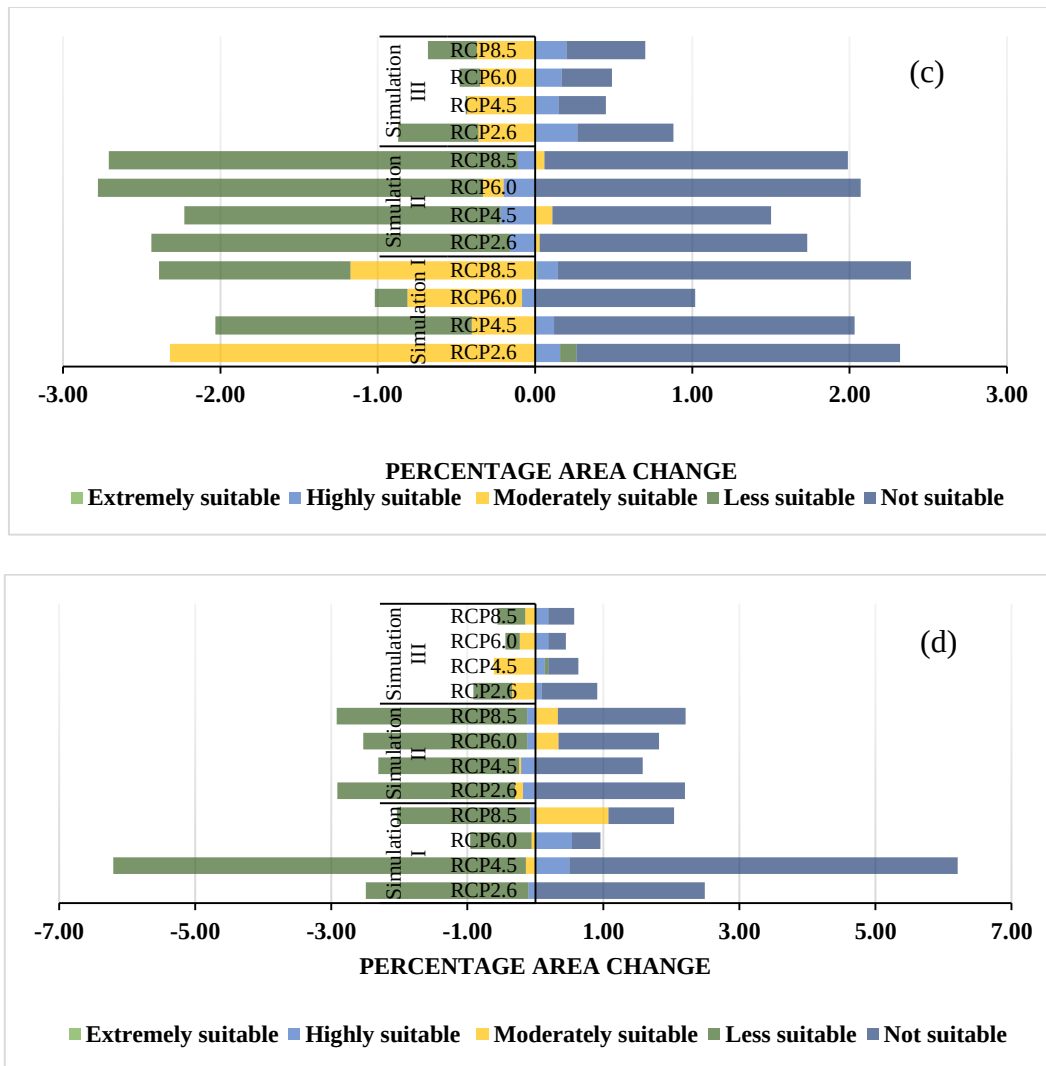


Fig 6.7 Change of percent area of plant distributions from the present to the future (a) RET species, 2050; (b) RET species, 2070 (Reshma et al., 2020)

The area under the non-suitable class also increases. In general, potential areas suitable for endemic and RET species are expected to decrease and the non-suitable areas are expected to increase in the Eastern Ghats. The analysis shows that the habitat loss of endemic and RET species will increase due to LULC change.

6.8.3 Habitat suitability and influence of climatic and LULC variables on species distributions

The present analysis shows that habitat suitability of the investigated plant groups is mostly influenced by LULC practices, slope, and soil characteristics. The influence of climatic variables on endemic species was significant compared to RET species (Tables 6.5 and 6.6). Temperature has a significant influence on the distributions of endemic species. Variables such

Table 6.5 Percent contributions of variables for modelling the potential habitat suitability of endemic plant species (Reshma et al., 2020)

as isothermality (15%), mean temperature of wettest quarter (6%), annual precipitation (7%), precipitation of wettest quarter (5%), precipitation of warmest quarter (4%), and precipitation of coldest quarter (7%) have high percentage contributions. In simulation I, slope contributes more than 25% for simulating suitable habitat of endemic species. Slope is one of the major factors controlling the availability of sunlight, water, soil nutrients, wind and temperature in some ecosystems (“Zeng et al., 2014”). In simulation III, the contribution of LULC was found to be more than 45%. On the other hand, RET species distributions were more dependent on the geographic factors. For instance, the contribution of slope was around 50% in simulation II. Also, rainfall is the major influencing factor in defining the potential habitat of RET species. Bioclimatic variables such as mean temperature of wettest quarter, precipitation of wettest month, precipitation of wettest quarter, precipitation of driest quarter, annual precipitation, and soil parameters have a greater influence on RET species distributions (Table 6.6). In simulation III, more than 50% of the distributions were influenced by LULC.

The percentage contributions of the predictors vary with RCP for both the plant groups. Mean temperature of wettest quarter (4.8%) and precipitation of warmest quarter (6.3%) had significant contributions in the simulation III of 2050 for endemic species with RCP4.5. Precipitation of wettest quarter contributes 10% in RCP2.6. In case of simulation I, the isothermality and precipitation of wettest month had significant contribution (15%). The percentage contributions of isothermality (16.6%) were 2 times more than the precipitation of warmest quarter (7%) and the mean temperature of wettest quarter (9.4%) in 2050 with RCP4.5. The contributions of annual precipitation (9.9%) and precipitation of coldest quarter (9%) in 2050 with RCP6.0 were contributed equally. In 2070, with RCP2.6, the isothermality (16.7%) and precipitation of wettest month (2.6%) had significant contributions. In RCP4.5, mean temperature of wettest quarter (9.1%) has the highest contribution among the other climatic variables, whereas in RCP8.5 annual precipitation (8.2%) and precipitation of coldest quarter (10.1%) have significant contributions. In contrast, for RET species, in 2050, the contributions of mean temperature of wettest quarter with RCP4.5 (12.1%) and of contribution of precipitation of wettest month with RCP8.5 (9%) are high. In 2070, with RCP2.6, the highest contributions are mean temperature of wettest quarter (9.6%) and annual precipitation (8.6%).

6.8.4 Plant species habitat and fragmentation

The status of species distribution in the protected areas (PA) and outside protected areas (OPA) of the Eastern Ghats are analysed for two important vegetation covers i.e., forest and scrubland.

Table 6.6 Percent contributions of variables for modeling the potential habitat suitability of RET plant species (Reshma et al., 2020)

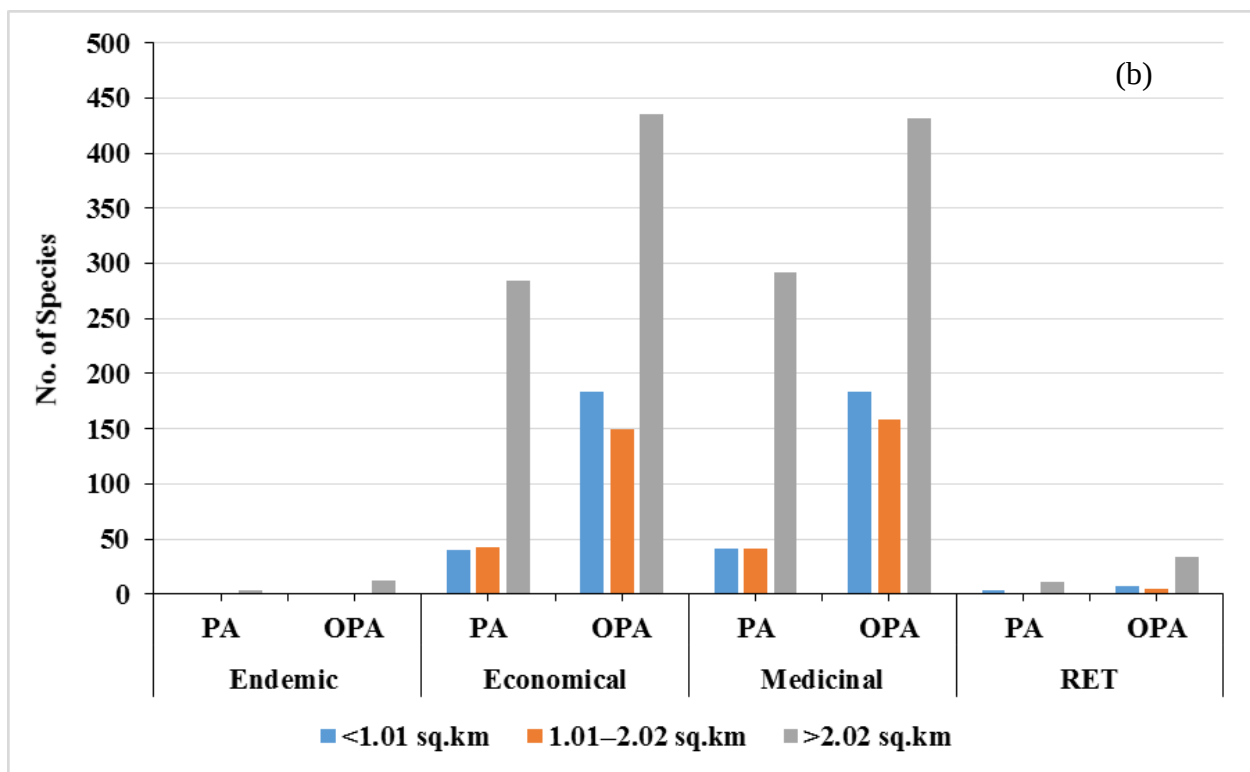
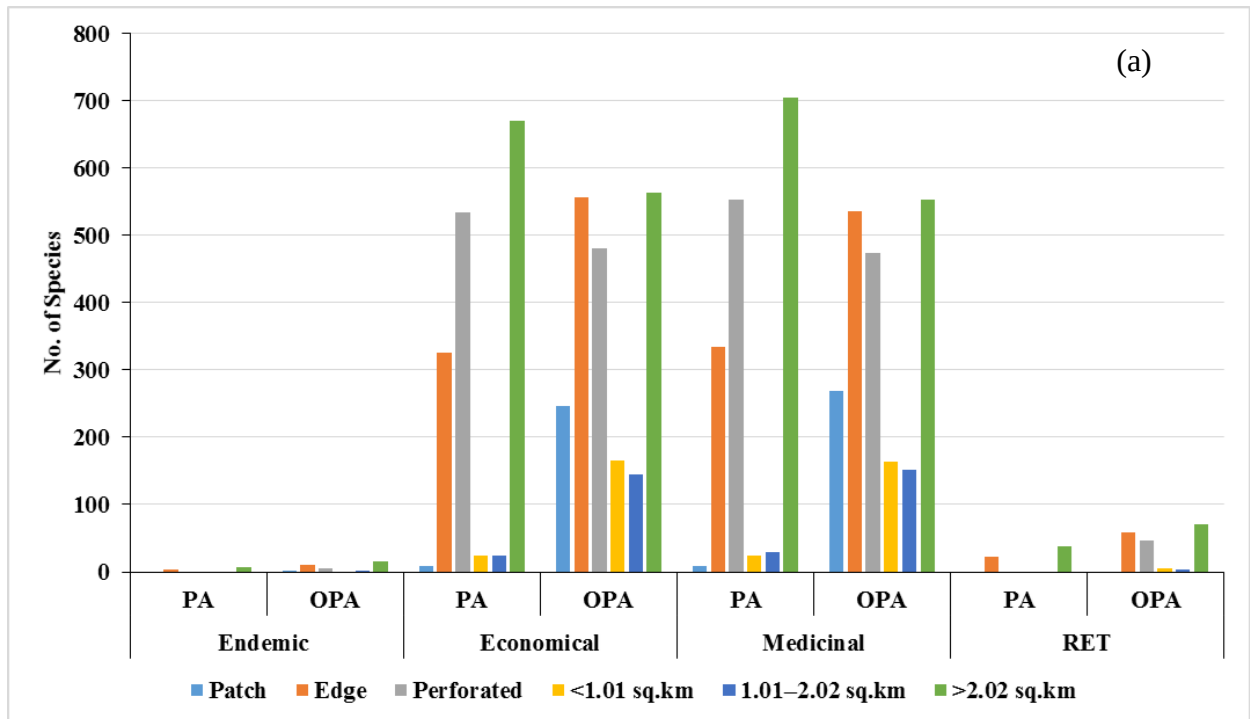


Figure 6.8. Distribution of species in protected areas (PA) and outside protected areas (OPA), (a) forest; (b) scrubland (Reshma et al., 2018)

For this, the assemblages of endemic, RET, economically and medicinally important species in different fragmentation ranges in the PA and OPA (for both forest and scrubland) were estimated. Summing up of number of species found in the PA and OPA are given in Figs. 6.8 a and b.

Out of 1598 species recorded from the sampled data, 1207 species were concentrated in OPA (Fig. 6.8a). Among them, 48.58% species were recorded under medicinally important category. 42.52% of them were found in the large core area followed by perforated (33.37%) areas of PA (Fig. 6.8a). Similarly, economically important species were found more at core (42.19%) areas of PA and edges (25.81%) of OPA. Similarly out of 245 individuals belong to RET category, 62% were found in OPA; whereas 46 individuals recorded under endemic species, 76.08% were found in the OPA. In the case of scrublands, the majority of species were present in the large core areas (Fig. 6.8b) followed by small core area of OPA. Wild species are most sensitive to habitat fragmentation and declining drastically (Fig. 6.8a). Which means, the influence of habitat fragmentation is more in forest species than in scrubland species. Due to fragmentation, the species are often finding their habitats in the fragmented patches, therefore, vulnerable to its existence. To test the effects of fragmentation on plant species in response to fragment area the percentage vegetation cover in different fragmentation levels for both PA and OPA of forest and scrubland (Figs. 6.9a and b) was analyzed. In case of forest, 35% of forest area is at the edges and 25% is in the large core area of OPA. Similarly, in case of scrubland 65% of scrubland area is in the large core area of OPA.

6.9 Discussions

Habitat conservation has to be done through proper management strategies. The nature of habitat conservation varies from place to place. In addition, climate change triggers many sectors in biodiversity leading to habitat loss and at places to even species extinction. This increases the risk of in-situ habitat conservations (“Wilkening et al., 2019”). Knowing the future distribution of species and its habitats are important for proper planning of conservation strategies. Even though future-simulations have some sort of uncertainties, such studies provide vital information on species distributions, range shifts, food production and thus help mitigation and adaptation planning. Simulations of populations, land use, climate, and species can provide an overview of the behaviour and responses of different ecosystem processes under future conditions. Changes in the land system and climate due to human activities in the present era have important repercussions on natural systems (“Venter et al., 2016”), resulting in

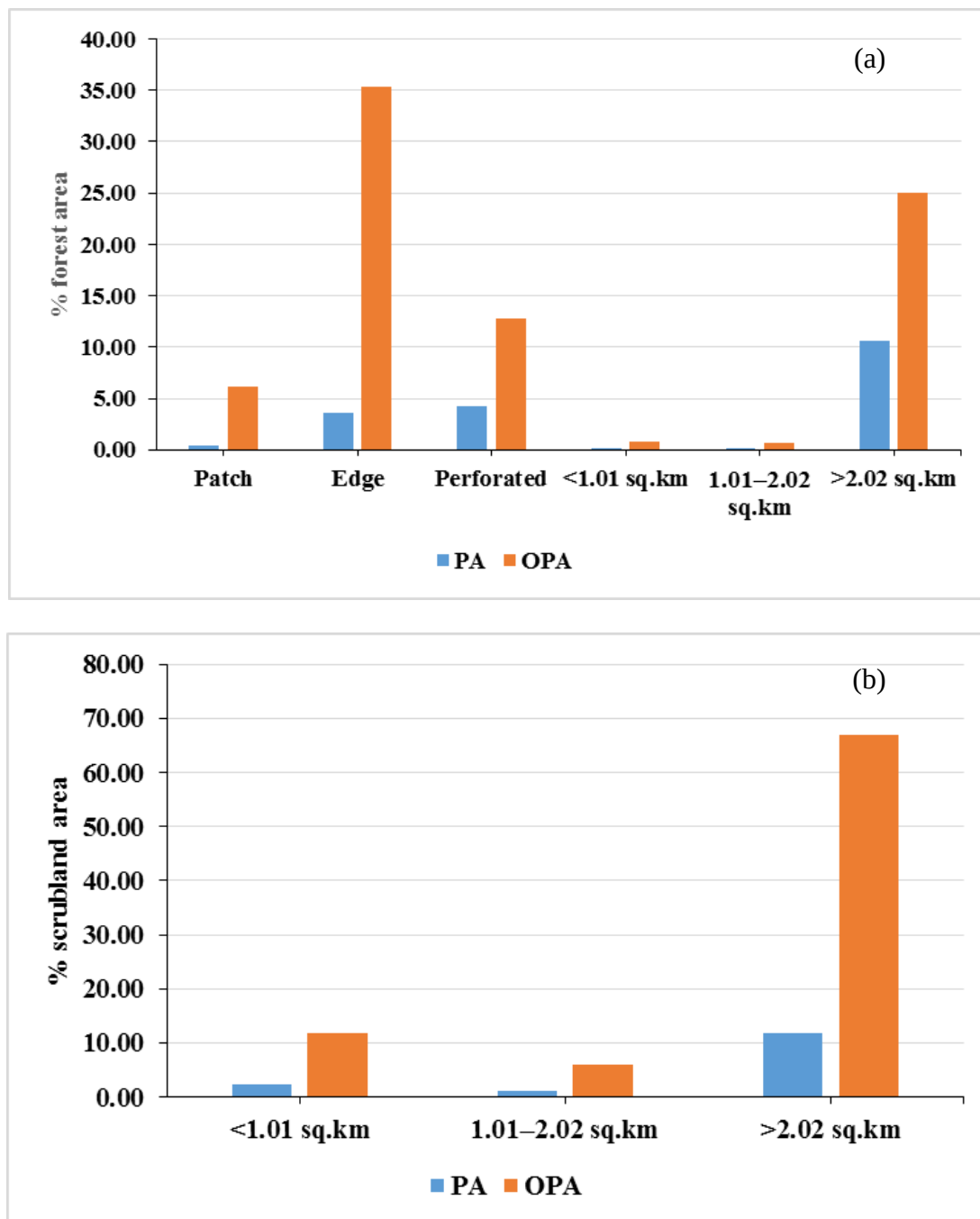


Figure 6.9. Percentage area of forest cover in protected areas (PA) and Outside protected area (OPA) (a) Forest; (b) Scrub/grassland

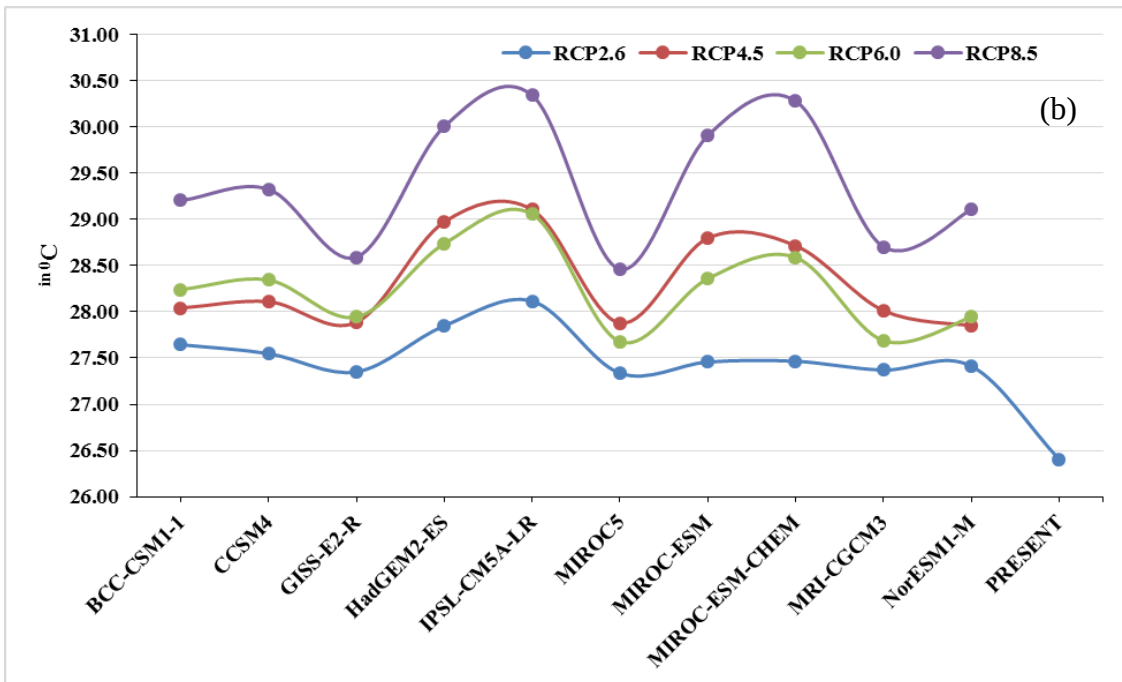
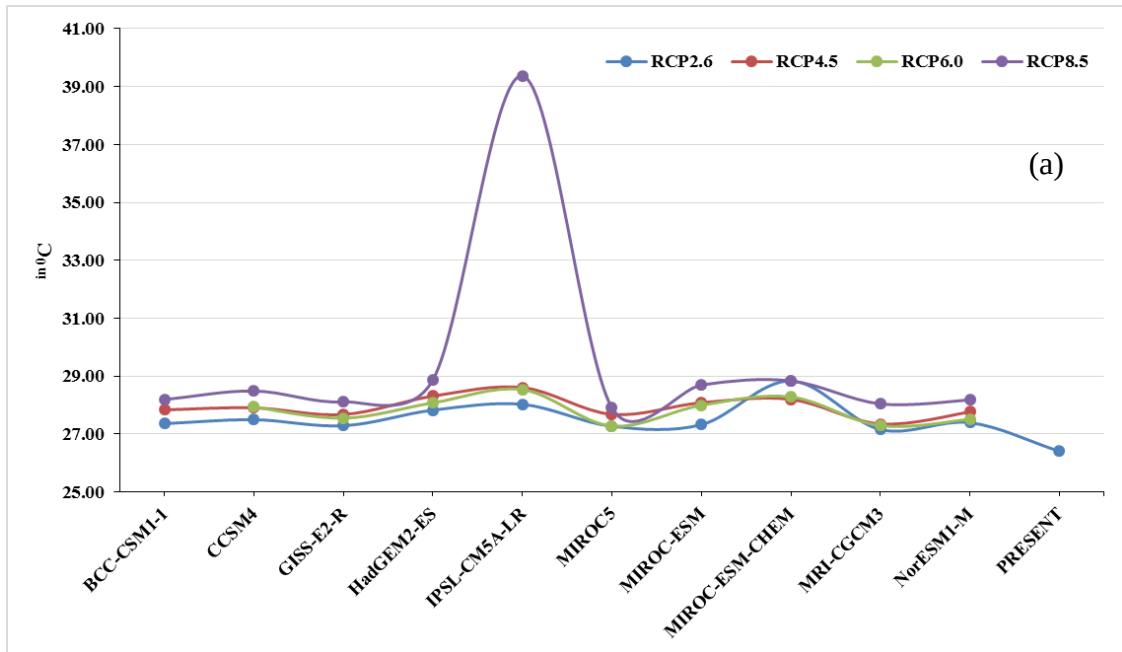


Figure 6.10. Variation in mean temperature in Eastern Ghats with different GCMs under different RCPs (a) 2050 (b) 2070

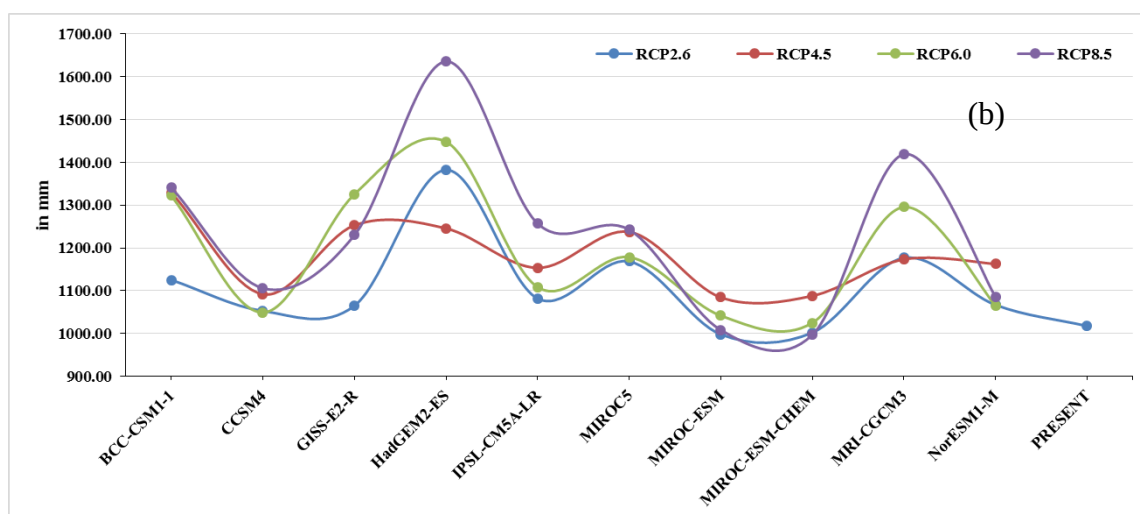
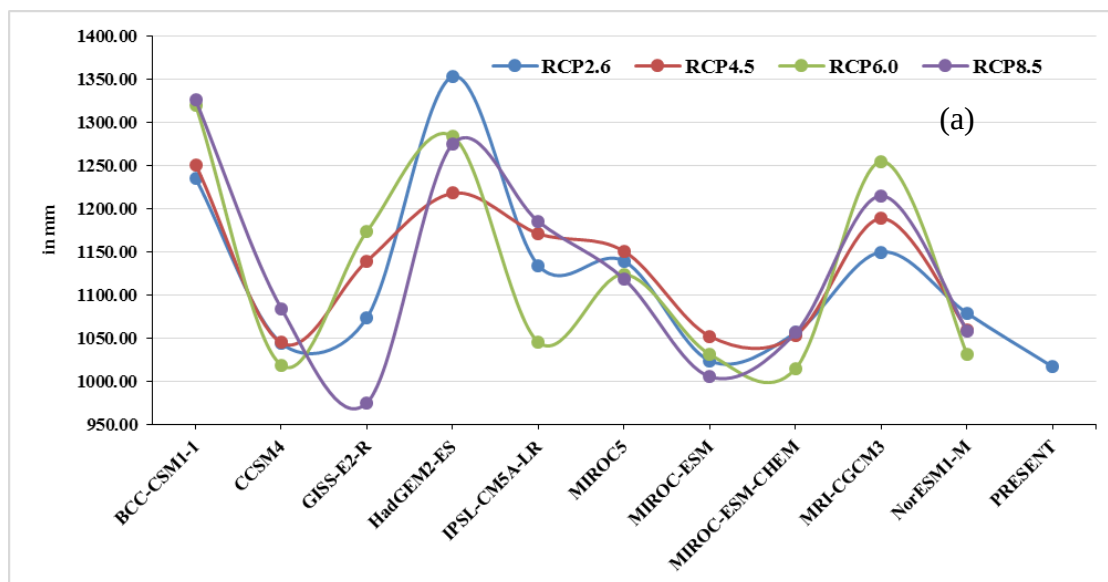


Figure 6.11. Variation in rainfall in Eastern Ghats with different GCMs under different RCPs (a) 2050 (b) 2070

deforestation, habitat loss, species extinction, etc. Knowing global and regional trends will be helpful for effective management of the health of ecosystems. Focussing beyond 50 years is good for formulating sustainable plans and policies for the future (“Vaidyanathan, 2018”). In the present study the possible impacts of climate and LULC on the distributions of two important plant groups, endemics and RET species, in the Eastern Ghats are investigated.

6.9.1 Changes in ecosystem due to climate changes

The climate plays an important role in the healthy functioning of an ecosystem. Studies of species–climate relationships help one to understand the distributions of species and their responses to future climate change (“Wieczynski et al., 2018”). One of the most obvious and immediate responses to climate change is the increase in temperature. In the Eastern Ghats, the mean temperature is likely to increase by 1.8°C in 2050 to 1.98°C in 2070 when compared to present (Fig. 6.10), with a maximum temperature increase of 3.07°C observed with RCP8.5 (2050). The rainfall is also expected to increase by 113.53 mm in 2050 and 160.65 mm in 2070 with respect to present (Fig. 6.11). “IPCC 2014” reports that the highest increase of the global temperature will be 2.6°C to 4.8°C, under RCP8.5 at the end of the 21st century (2081–2100). Changes in LULC would intensify different emission drivers and influence the regional climate (“Murphy and Ravishankara, 2018”).

6.9.2 Potential distributions of plant species under present and future conditions

The MaxEnt species distribution model simulates suitable habitats by combining bioclimatic and environmental variables. From these simulations, one can evaluate the threat factors and determine the sites that are suitable for species. The supply of services offered by forest ecosystems, direct (e.g., food, fodder) or indirect (e.g., pollination, climate change regulation), is generally determined by the diversity of flora (as well as fauna) producing them (“Hughes et al., 1998”). Hence, changes in species’ populations and distributions have a substantial impact on the ecosystem.

A strong relationship has been observed between the potential habitat suitability of endemic and RET plants with changing climate and LULC in the Eastern Ghats (Fig. 6.12). The changes in LULC and climate would accelerate the reduction of suitable habitats not only in the present but also in future (“Tyler et al., 2017”). Based on the studies carried out in the Himalayan region, “Manish et al. (2016)” predicted that significant reduction in the potential habitat of endemic angiosperm species would take place under the projected future climate. Changes in climate would affect the endemic species more than the RET species, whereas, the RET groups

are more vulnerable to LULC changes. Slope plays an important role in the distribution of both endemic and RET species in all cases. These are essential parameters for the development of microclimatic conditions, which are crucial for plant distributions (“Feng et al., 2011; Shimono et al., 2010”). The influence of temperature-related variables on the habitat suitability is significant for endemic plants. “Zhang et al. (2014) reported that the increasing global temperature has had a strong influence on the growing period of *Populus euphratica*. In contrast, precipitation has played a key role in determining the distribution of potential habitats of RET plants. The studies of Abolmaali et al. (2018) on *Daphne mucronata* has revealed that higher elevations and high precipitation would produce habitats that are unsuitable for these species. In the Eastern Ghats, high precipitation, or changes in precipitation and LULC affect the distribution of RET plants since those are the major distribution factors. Areas with low elevations and high temperatures are unsuitable habitats for endemic species. There are suitable habitats for both endemic and RET species in high-elevation areas with less disturbance, particularly in the core forest areas. More changes could occur in the forest peripheries. The leaching out of soil nutrients due to increased precipitation would also influence the distribution pattern. Since the distribution of endemic species is restricted, the chances of extinction are high in this group. Other species that are better adapted to environmental changes will occupy the place of these plants.

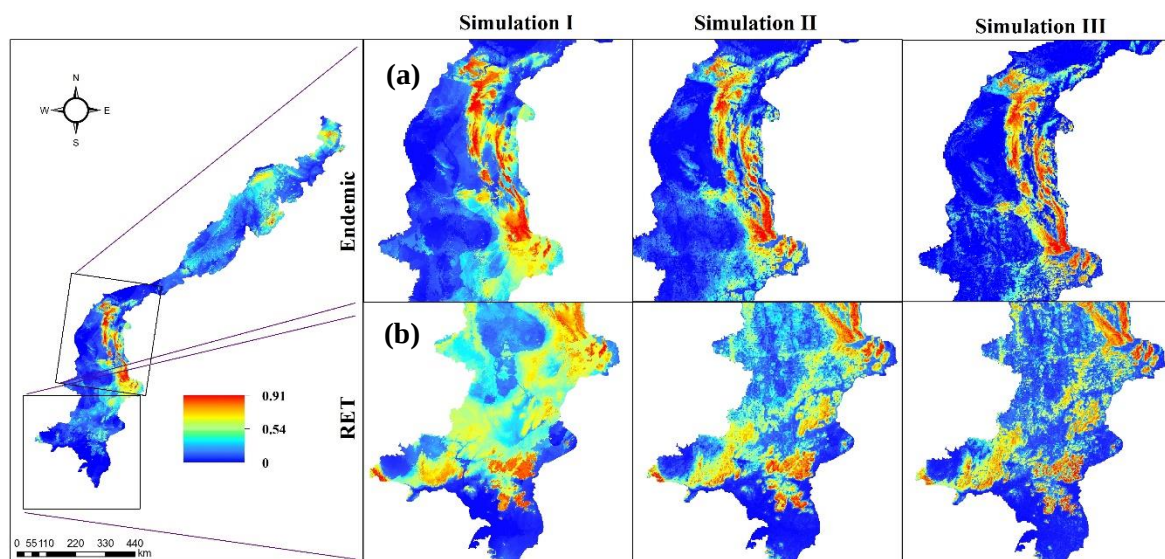


Figure 6.12. The notable changes in species distributions due to climate, environmental and LULC variables under present conditions (a) potential distributions of endemic species in the Nallamalai region of Eastern Ghats (b) potential distributions of RET species in the southern part of the Eastern Ghats (Reshma et al., 2020).

6.9.3 Changes in species habitat and distribution due to fragmentation

The present analysis show that less fragmented and less disturbed landscapes are more favourable foci for the endemic species when compared to the RET species. Interestingly, endemic species showed suitable habitat even outside the forest areas. However, both the groups are equally affected by fragmentation throughout study period. During 1920s the habitat was intact and continuous for both the species. In 2015, the intact forests got fragmented and resulted in the isolation of habitats. Also, majority of suitable habitats are found under large core areas. Characteristic changes along the time trajectory include: (i) decline in the total area of fragmented habitats; (ii) decrease in the size of many habitat fragments (large core areas become scarce, small fragments predominate); (iii) increased number of patches of fragments from similar habitat; (iv) increase in the edges of the habitats. Large core area is continuously fragmented throughout the period of study, resulting in a large proportion of edge habitat. The isolation of habitats eventually affect local populations of RET and endemic species by restricting the species interactions (“Christie and Knowles, 2015”). Furthermore, it causes unavoidable changes in the ecological processes within fragmented habitats (“Western, 2001”). For instance, it can include shifts in forest structure and biodiversity (“Didham, 2010”), loss of species richness and changes in species composition when compared to contiguous habitat (“Ewers and Didham, 2006”). Based on the previous studies (“Gray et al., 2016; Thomas and Gillingham, 2015”), the distributions of specialised group plants (plant species rendering economically, medicinally important; endemic and RET category) in PA and OPA are analysed, which is of more concern for conservation (“Secretariat of the CBD, 2010”). The analysis shows that samples from PA contained more species diversity and abundance than samples from OPA (Fig. 6.8), even though they don't have more forest cover as compared to OPA (Fig. 6.9). In contrast, the protected sites don't have more endemic and RET group of species (Fig. 6.8) are widely distributed outside the protected sites. These two specialized groups determine the measures of community characteristics that are often considered in conservation priorities (“Gray et al., 2016”). A large difference in species richness and abundance has occurred between the forest and scrubland (Fig. 6.8). Particularly in protected areas, facilitated conservation is most effective as they minimize the impacts of human land utilization patterns (“Gray et al., 2016”). However, in OPA the human-dominated land use (such as agriculture and settlement) and disturbances regime will restrict the higher biodiversity (“Spear et al., 2013”). The present study reveals that species richness is high in large core areas at a greater distance from the PA and OPA borders. Moreover, endemic and RET species found

in less fragmented patches, which indicates that these plant communities can be preserved better in areas having less human interference. Some of the recent studies also support this view (See for e.g., “Angulo et al., 2016; Tole, 2002”). Also, it was found significant species assemblage in the edge and perforated patches of the forests (Fig. 6.8); about 22 (number includes species from both PA and OPA) endemic species and 81 RET species. The species which occur in the edges are at high risk. If proper measures are not taken in these areas the LULC change and fragmentation will cause serious threats to the habitat of these species.

6.9.4 Conservation prioritization and challenges

Identification of regions (outside protected areas) with exceptional levels of species richness, endemism and those species with other ecological value/use have the greatest importance for proposing new areas for conservation. Lack of funding and studies compel the conservation community to ignore such areas, which have most outstanding and representative areas for biodiversity (“Venter et al., 2014”). Conservation status represents an estimate of the ability of an ecoregion to maintain viable species populations, to sustain ecological processes, and to be responsive to short- and long-term environmental changes (“Olson and Dinerstein, 2002”). It is important to acquire representative samples of group of RET and endemic species of Eastern Ghats within which they occur to find out the conservation areas. There are many other factors that may be used in the prioritization process such as ecological function, conservation feasibility (i.e., political, social, economic, cultural factors), or human utility. These parameters are not considered as discriminators to identify the priority areas because they are unavailable since 1920. The development and implementation of strategies for conservation areas, however, require careful attention to ecological function and non-biological factors. The habitat distribution model was also used to assess broad trends in threats of LULC change among different regions of Eastern Ghats. The forests of the Nallamalai hill ranges and Seshachalam are known for their pronounced endemism. The Tamil Nadu state part of Eastern Ghats harbors diverse and unusual assemblages and displays notable endemism. In Odisha state, forests of Eastern Ghats are notable for their diversity in RET group of species which are threatened mainly due to the mining industry. These long-isolated forests have many other unusual taxa and unique communities. The central part of Andhra Pradesh covering Nallamalai and Seshachalam hills is a regional centre of endemism for a range of species. MaxEnt has been used to map the geographic distribution of endemic and RET group of species and modeled both species category across the Eastern Ghats. High endemism has been recorded in the southern Andhra Pradesh region of Eastern Ghats. The RET species occurrence also recorded

in the same range but it widely distributed in other parts of Eastern Ghats as well. The MaxEnt result of endemic group of species shows that the southern Eastern Ghats are poor in endemism (Fig. 6.13) or the area is not a suitable habitat for endemic species. As compared to endemic species, the RET species distribution is remarkably high in the Eastern Ghats (Fig. 6.12). Apparently in Eastern Ghats the habitat reduction has mainly occurred in the districts of Gajapati (Odisha state), Mahbubnagar (Telangana state) and in Nallamalai and Kolli hill ranges. The percentage of forest area under current protection was 18.5, which includes 7.5% of forest fragments (Fig. 6.9), whereas 81% of forest area is under outside the protected areas. Sri Venkateshwara National Park in the Seshachalam Hills, Gundlabrahmeshwaram Sanctuary in Nallamalais and some parts of Srisailem-Nagarjunasagar Tiger Reserve, had the least degraded forests due to their PA status. However, the collection of non-timber forest products, bamboo harvesting, and livestock grazing continues in all areas irrespective of legal status (“Rawat, 1997”).

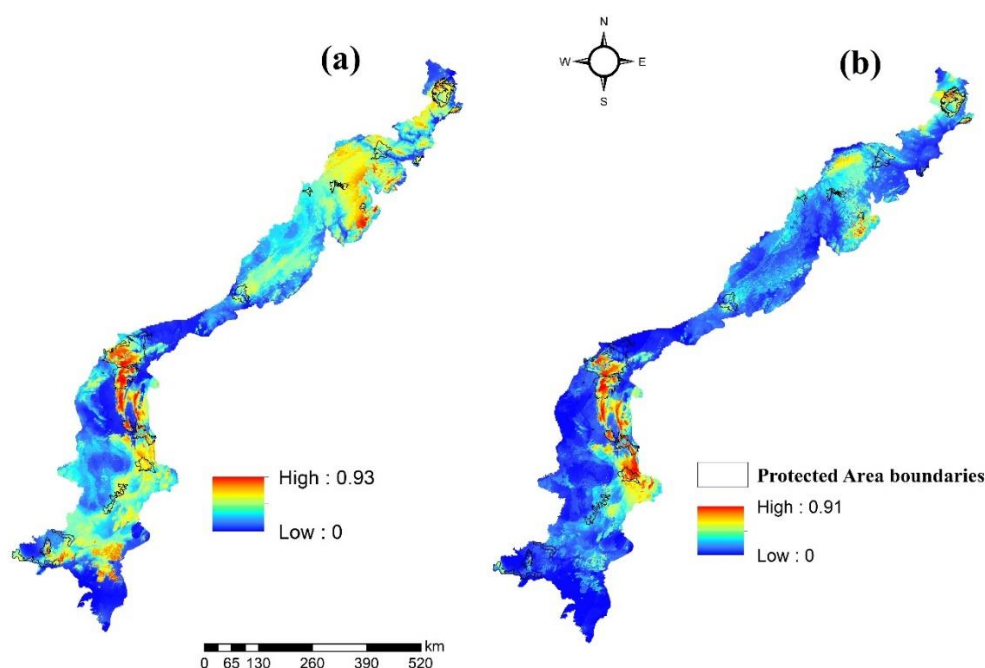


Figure 6.13. Habitat distribution of group of (a) rare, endangered, threatened (RET) and (b) endemic plant species in Eastern Ghats with PA boundaries (Reshma et al., 2018).

The Eastern Ghats are often ignored by conservationists and stakeholders in favour of the Western Ghats and Eastern Himalayas (“Rao et al., 2010”). But the present study and other relevant works (“Ramesh and Kalpana, 2015; Roy et al., 2013”) show that this region is equally

important for identifying priorities and conservation areas considering the habitat threat for species. A promising approach is to identify conservation areas or hotspots featuring exceptional concentrations of species under risk such as, endemic species or species under threat (viz, RET due to human and climate drivers). These plant groups (endemic and RET) have already lost 11.4% of their primary habitat, due to LULC change, habitat fragmentation and poor conservation efforts and policies. Furthermore, the major challenges for the conservation of plant diversity in the Eastern Ghats are i) the inevitable damages due to the anthropogenic land use and population growth; ii) lack of awareness of the importance of the local species and biodiversity; iii) lack of availability of long-term data sets and monitoring; iv) lack of implementation of laws and policies v) need for high-quality empirical studies on different taxa and ecosystems.

Conclusions

The major findings presented in this thesis are mainly on the following lines.

The present study revealed that the patterns of LULC change has led to forest fragmentation and transition by different land classes in the Eastern Ghats from 1920 to 2015. The changes of LULC has resulted in the loss of potential habitats for the specialized plant groups, such as RET and endemic plant species.

During the study period (1920 to 2015), considerable forest areas in the Eastern Ghats were either converted to other land classes or severely degraded. Timber logging, dam construction, road-rail networks and other developmental activities were the major drivers for forest cover change prior to 1960s.

After 1960s, the anthropogenic pressure on land has increased by many folds to augment various demands such as mining, urban development, and agricultural practices. These demands have influenced the forest cover by the way of deforestation and fragmentation. The patterns of the landscape in the Eastern Ghats have changed significantly due to forest fragmentation.

The species assemblage is high in core areas and significant species composition is found in the forest edges. The overall habitat suitability for RET and endemic group of plant species has been decreased. For most of the specialized plant groups, suitable habitat areas are found outside the protected area.

For the first time, the present study reports the potential habitat loss of plants of conservation values in the Eastern Ghats using the RCPs recommended by IPCC AR5.

The changes in the potential distribution of endemic and RET plant species in Eastern Ghats are significant in response to future LULC and climate change. The effects of these components on the plant distributions vary with different ranges. The ANN and MaxEnt approaches were used in this study to simulate the changes in the LULC and potential distributions of the bioclimatic habitats of plant species. This approach gives a good idea about the changes in the

LULC and species habitat and also predict future ranges of species. However, it is important to note that the simulated LULC changes are moderate; still, they will have significant impacts on species' habitats and ranges.

The changes in species habitats vary differently for endemic and RET species. The results of this study indicates that increase in population also has an impact on the LULC and potential habitat distribution of the plant species. The areas of future habitat of endemic species simulated by the model are restricted towards the core of the forests. However, the RET species' habitats vastly distributed all-over Eastern Ghats. The land use activities in the Eastern Ghats will severely restrict the suitable habitat of the species and its dispersal. In general, most of the drivers influencing the habitat loss are political, social, or individual decision making. Therefore, it is vital to provide decision makers at all levels with science-based information regarding potential impacts of their decisions on plant communities and human well-being. The changes in LULC and climate largely influences the supply of many services for example loss of suitable habitat, breeding ground and season etc.

Even though Eastern Ghats has many protected areas, appropriate conservation strategies need to be initiated on the threatened areas to prevent further decline in the extent and habitat quality of the RET and endemic species. The study recognizes the need for carrying out future research using more localized ecosystem services and quantifying them. It is suggested that more detailed models integrating diverse drivers and localized LULC scenarios be utilized in the future, together with a greater number of case studies, in order to provide more accurate estimates as the basis for better-informed and more sustainable landscape decisions.

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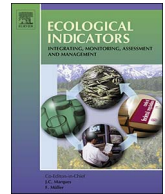
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Original Article

Long-term land use and land cover changes (1920–2015) in Eastern Ghats, India: Pattern of dynamics and challenges in plant species conservation



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ABSTRACT

Natural resources are experiencing unprecedented pressures due to land use and land cover (LULC) changes. Such changes in LULC have significantly affected the extent and condition of forests in the Eastern Ghats of India causing a decline in the forest cover as well as disturbing the habitats of several rare, endangered, threatened (RET) and endemic species. The current study attempts to determine the habitat suitability and threat of a selected group of plants viz, RET and endemic species. This is realized in light of LULC change and forest fragmentation over a period of ~100 years to understand the possible conservation strategies in the study area. Historical maps and satellite images from 1920 to 2015 were used to develop the LULC and fragmentation maps. MaxEnt species distribution model were used to simulate the distribution of RET and endemic species. Our study reveals that, by and large, the Eastern Ghats have lost 15.83% of its forest area over a span of ~100 years. For the study period from 1920 to 2015, it is estimated that about 7.92% of forest area was converted into agriculture, and up to 3.80% into scrub/grassland respectively. Also, it was found that the total number of forest patches have been increased from 1509 in 1920–9457 in 2015, core area has declined from 93461.05 sq.km in 1920–61262.11 sq.km in 2015, and edge length has increased to 2.20 sq.km in 2015 as compared to 0.82 sq.km in 1920. Best suitable habitats of RET and endemic species have reduced by 0.08% and 0.22% respectively. Habitat reduction has mainly occurred in the districts of Gajapati (Odisha state), Mahabubnagar (Telangana state) and also in Nallamalai and Kolli hill ranges. The species mostly spread across and the suitable habitats was found outside the rages of protected areas. From the present study we recommend that appropriate conservation strategies should be initiated on these threatened areas to prevent further decline in the extent and habitat quality of the RET and endemic species in Eastern Ghats.

1. Introduction

The unprecedented land use and land cover (LULC) change over the last century has resulted in the loss of many habitats and important species (MEA, 2005; McGill, 2015). It is estimated that ~75% of the natural forest area around the world has been affected by human activities since the last ice age (Ellis and Ramankutty, 2008). The ever increasing population, their food demands, need of settlement and exploitation of economic resources are the major factors responsible for the degradation of forest cover and biodiversity across the globe (Foley et al., 2005; Lambin and Meyfroidt, 2011; Newbold et al., 2015; FAO, 2016). Globally, ~40 percent of deforestation has occurred in the tropics and subtropics due to large-scale commercial agriculture (FAO, 2016).

Forest ecosystems are one of the primary focuses of land conversions. Indiscriminate removal of forests has resulted in the shrinkage of species habitats, fragmentation, edge changes and changes in community structure and composition; thereby, distressing the species distribution in many areas (Brearley, 2011). Local richness, rarefied richness, and total abundance are being strongly influenced by land usage patterns and its intensities (Drummond and Loveland, 2010; Ramankutty and Foley, 1999). Forest fragmentation, in which the forest is reduced to patches, can have a marked negative impact on biodiversity (Uddin et al., 2015). Among others, it can result in homogenization (Lôbo et al., 2011), human-wild life conflicts (Acharya et al., 2017), reduction in habitat quality for forest-interior species (Arroyo-Rodríguez and Mandujano, 2006), loss of forest health due to changes in microclimate (Ewers and Banks-Leite, 2013) and increased

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susceptibility to predators, parasites, and invasive species (Thuiller et al., 2008). Thus the changes in landscape patterns would certainly influence the ecological process and the existence of species at greater extents (Pătru-Stupariu et al., 2017).

India is experiencing major LULC changes due to expansion of agriculture, urbanization and economic exploitation of natural resources (Goldewijk and Ramankutty, 2004; Tian et al., 2014). Haddad et al. (2015) have reported that the LULC change caused by anthropogenic activities have the capacity to alter even the rainfall and temperature patterns. Therefore, mapping long term changes in LULC is important to study the linkage between habitats, climate, and species. Also effective quantification of loss in biodiversity is necessary to identifying large-scale conservation priorities (Skidmore et al., 2015). However, acquiring detailed information of the species distribution based on ground truth is often laborious and limited. In such a scenario, long term global coverage of satellite remote sensing data could provide useful and vital information on a wide range of scales in a consistent, borderless and repeatable manner. Satellite remote sensing technology has provided a new dimension to build the land change processes in varying temporal intervals at different resolutions (Singh et al., 2010). Furthermore, the Geographic Information System (GIS) provides an indispensable platform for data management, data integration, data visualization, data analysis, and retrieval of remote sensing data in a wide canvas (Goodchild, 2009). Land cover maps derived from remote sensing data could yield meaningful information on global/regional/local spatial assessments of vegetation distribution (FRA, 2000; Lambin et al., 2003; Potapov et al., 2008; Gómez et al., 2016).

With this background, we analyzed the LULC change pattern of the Eastern Ghats and its consequences on the habitats of rare, endangered, threatened (RET) and endemic species. The monitoring and mapping of distribution and habitat patterns of species play an important role in proposing new areas for conservation. In this study, the analysis was done to assess the intensity of habitat destruction of a selected group of RET and endemic species due to LULC change and habitat fragmentation. The Eastern Ghats are most rapidly changing frontier in India, most of its forests are already on the edge of extinction and very small area of forests remain contiguous (Jayakumar et al., 2002). The Forests of Eastern Ghats are largely deforested landscape, cleared for agriculture, dam construction, settlement, transportation, mining and logging for timber for more than ten decades (Jayakumar and Arockiasamy, 2003). We have used remote sensing and GIS technologies together with a modeling strategy to find out the LULC change and habitat characteristics. The present study aims to address the following research questions: LULC change for the past ~100 years; landscape and habitat level changes for a group of RET and endemic species; and, identification of conservation areas for plant species in the Eastern Ghats.

2. Materials and methods

2.1. Study area

The Eastern Ghats of India are located between 11° 30' and 22° 0' N latitudes and 76° 50' and 86° 30' E longitudes (Fig. 1). It is a habitat of more than 2600 plant species; most of which are traditionally used for medicinal/other economic purposes. These species were heavily altered by anthropogenic activities in the past century (Chittibabu and Parthasarathy, 2000). The Eastern Ghats are broadly divided into Northern and Southern Eastern Ghats. Due to broken chain like topography and ease of forest accessibility, the hilly terrain and the surrounding plains of Eastern Ghats are densely populated. No systematic studies are reported so far in Eastern Ghats to show how the species have been affected in the light of LULC change, increasing temperature and changing rainfall pattern.

Significant loss of forest cover in parts of Eastern Ghats (Patnaik et al., 2011; Ramesh and Kaplana, 2015; Saranya et al., 2016) has

exerted tremendous pressure on the sustenance of biodiversity (Rawat, 1997). Many sensitive species are likely to be vanished from the forests or might be facing extinction because of the habitat loss, fragmentation and climate change (Nemésio et al., 2016). The recent threats faced by the Eastern Ghats include deforestation and fragmentation due to hydropower projects and mining (Jayakumar and Arockiasamy, 2003). The massive impoundments that dams and their reservoirs have formed between the Andhra Pradesh and Odisha borders have submerged thousands of hectares of forest land (MoEF and Kalpavriksh, 2004). The plant inventories and surveys are carried out in parts of Eastern Ghats to study the distribution and pattern of floral diversity (Rao et al., 2013; Pullaiah and Rao, 2002; Muthumperumal and Parthasarathy, 2013). Babar et al. (2012) used ecological Niche modeling for understanding the distribution patterns of *Pterocarpus santalinus* in Eastern Ghats. Little is known about the biodiversity of Eastern Ghats as no comprehensive studies on spatial change and species diversity was conducted so far (NRSA, 2007).

2.2. Data products

The analysis was carried out with the help of historical maps (1920, 1940 and 1960) and multi-date multi-temporal Landsat images from the sensors viz; Multispectral Scanner System (MSS) (1975 and 1985), Thematic Mapper (TM) (1995 and 2005), Enhanced Thematic Mapper (ETM+) (2005) and Operational Land Imager (OLI) (2015). The standard Level 1 images of 1975, 1985, 1995, 2005 and 2015 were downloaded as orthorectified form from the earth explorer website (<https://earthexplorer.usgs.gov/>) of United States Geological Survey (USGS). The detailed descriptions of historical maps and satellite images used in the present study are given in Table S1 (a–c). We have used the data for three seasons, viz. winter (January to March); pre-monsoon (April to May) and post-monsoon (October to December). The satellite images were selected in such a way that all the scenes was free from (less than 3%) cloud cover. The ancillary data, such as vegetation type map of India for the year 2005 (Roy et al., 2015a), LULC maps for the years 1985, 1995 and 2005 (Roy et al., 2015b), and High resolution Google Earth images were also used in the study. Field sample points to the tune of 2971 were collected from the national-level project 'Biodiversity Characterization at Landscape Level' (Roy et al., 2012; Roy et al., 2015a). The Shuttle Radar Topography Mission Digital Elevation Model (SRTM DEM) 30 m data (<https://earthexplorer.usgs.gov/>), WorldClim Version 1 current bioclimatic data (<http://www.worldclim.org/>), Protected Area (PA) map from Wild Life Institute of India were used in the modeling to analyse the habitat suitability through Maximum Entropy (MaxEnt) algorithm.

2.3. Data preparation

Pre-processing of historical maps and satellite images were carried out prior to image classification in order to bring the images to a standard projection. The standard data preparation methodology is shown in Fig. 2a, b. The historical maps were geometrically corrected with the help of geometric correction tool available with ERDAS Imagine 2015 software. Prior to image interpretation, Level 1 (<https://landsat.usgs.gov/landsat-processing-details>) satellite images were pre-processed for suppressing the effects of the atmosphere (Chavez, 1996) and noise (Lillesand et al., 2015). The study area then extracted from the multiple sensor scenes for each year by sub setting. Finally all the subset images were mosaicked to obtain a single image of the study area. The satellite images and historical maps were brought into the projection WGS 84 Universal Transverse Mercator (UTM) Zone 44. The satellite images for the year 1975 and 1985 were then re-sampled using nearest neighborhood algorithm to a common resolution of 30 m.

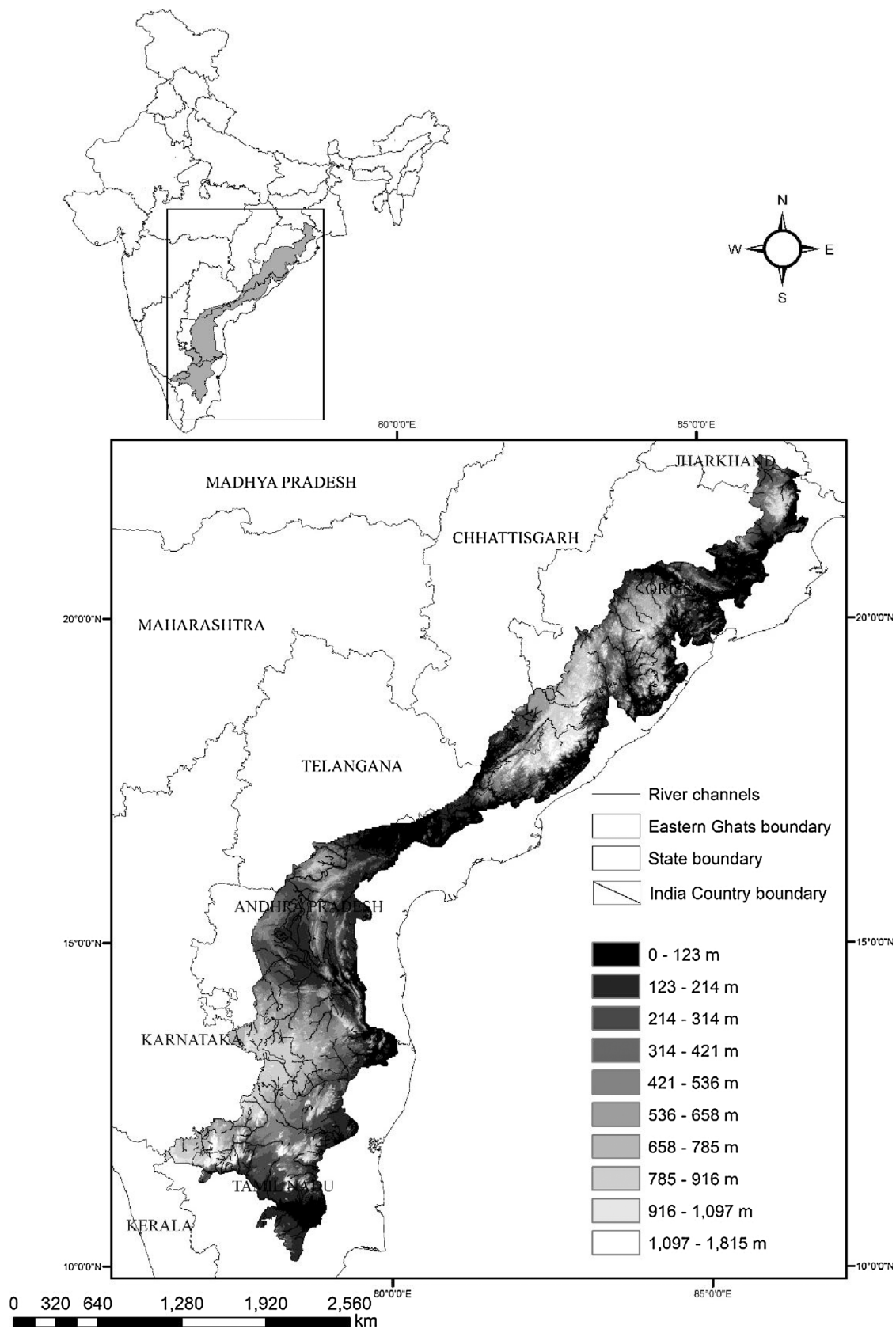


Fig. 1. Location map of Eastern Ghats on Indian continent in digital elevation model and river network.

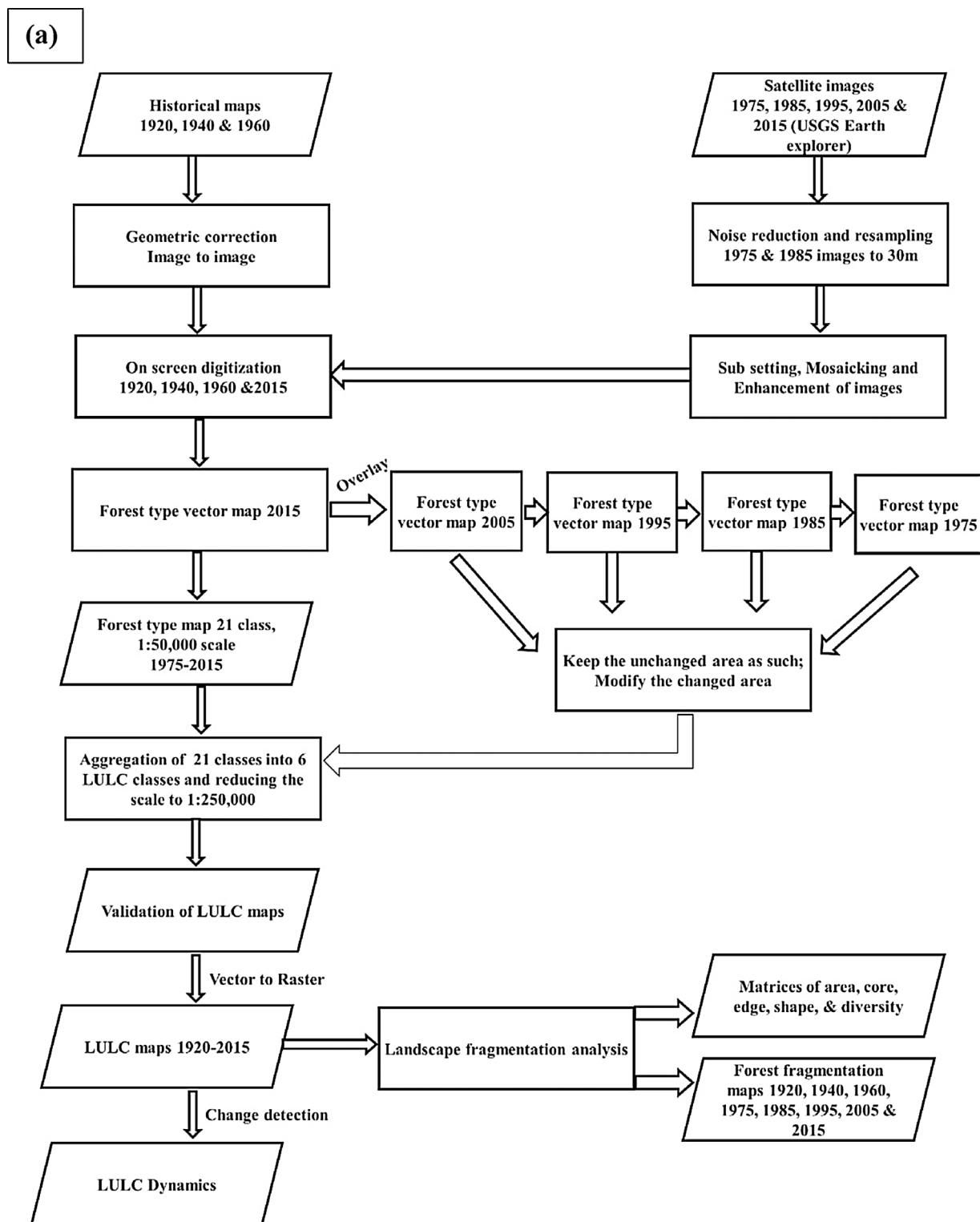


Fig. 2. Flow chart of Methodology. (a) Mapping and landscape analysis of Eastern Ghats from 1920 to 2015; (b) Analysis of habitat suitability of a group of rare, endangered, threatened (RET) and endemic species.

Annual Mean Temperature; Mean Diurnal Range (Mean of monthly (max temp - min temp)); Isothermality; Temperature Seasonality; Max Temperature of Warmest Month; Min Temperature of Coldest Month; Temperature Annual Range; Mean Temperature of Wettest Quarter; Mean Temperature of Driest Quarter; Mean Temperature of Warmest Quarter; Mean Temperature of Coldest Quarter; Annual Precipitation; Precipitation of Wettest Month; Precipitation of Driest Month; Precipitation Seasonality; Precipitation of Wettest Quarter; Precipitation of Driest Quarter; Precipitation of Warmest Quarter; Precipitation of Coldest Quarter[#]z is a vector of 'J' environmental variables at location x_i , and λ is a vector of regression coefficients, with $z(x_i)\lambda = z_1(x_i)\lambda_1 + z_2(x_i)*\lambda_2 + \dots + z_J(x_i)*\lambda_J$ (Merow et al., 2013).

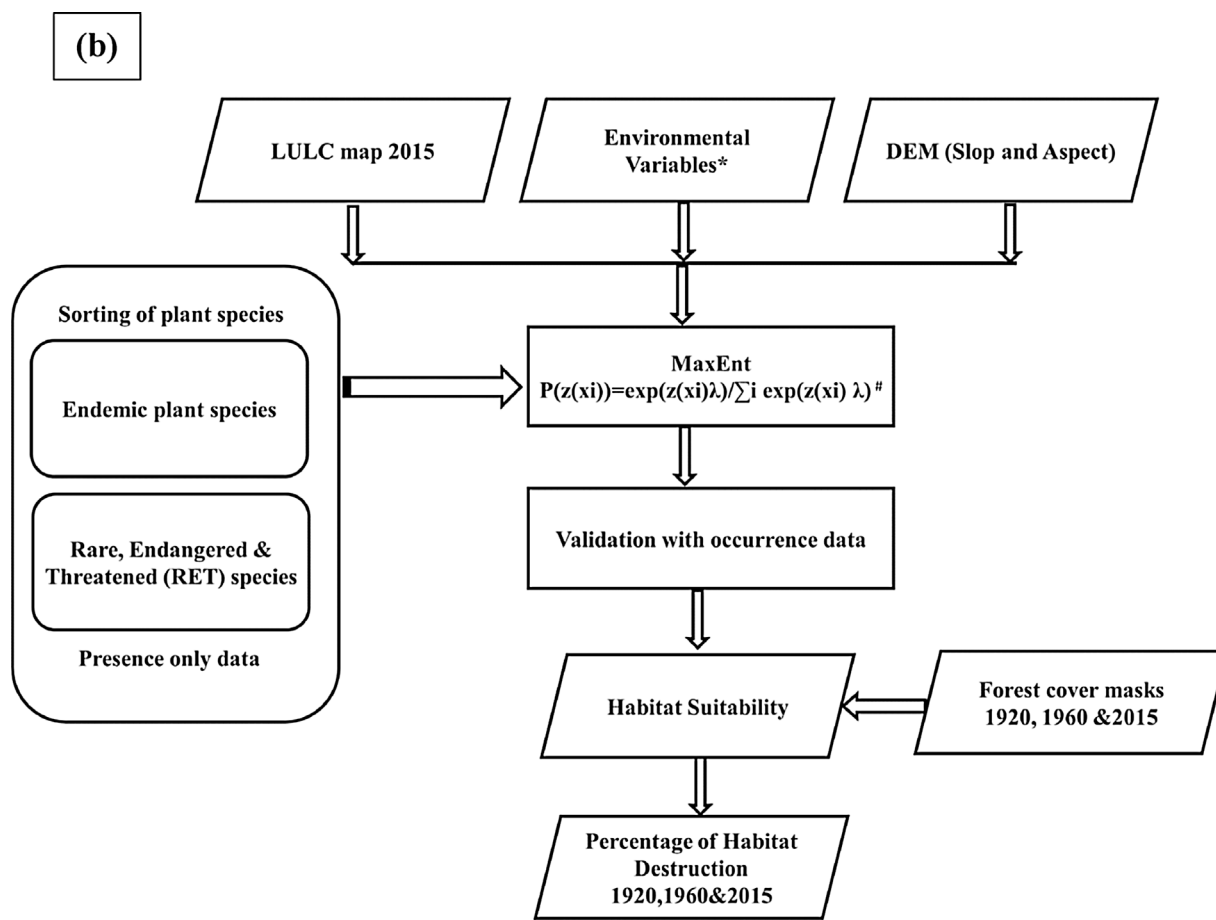


Fig. 2. (continued)

2.4. Classification scheme

The Food and Agricultural Organization (FAO) defines land cover as the observed biophysical cover on the Earth's surface (FAO, 2000) and land use as the arrangements, activities and inputs people undertake in a certain land cover type to produce, change or maintain it (FAO, 1998). In the present study, the USGS classification system (Anderson et al., 1976) were adopted for LULC classification. First, the Level II 21 land classes (IGBP, 1990) were derived from the satellite data (Table 1). Later, the 21 land classes were further aggregated into six fold Level I land classes such as forest, scrub/grassland, agriculture, waterbody, built up, barren and uncultivable land.

2.5. Mapping of land classes

Fig. 2a shows the methodology (after Roy et al., 2015b) adopted by us for mapping the land classes of the Eastern Ghats from 1920 to 2015. The mapping of land classes were carried out with the help of onscreen visual interpretation technique. The historical maps of 1920, 1940 and 1960 were digitized separately to derive LULC maps for respective years. The detailed methodology is provided in the supplementary material (Methodology Text S1a).

2.6. Assessment of forest cover change dynamics

The dynamics of forest cover change from 1920 to 2015 was assessed through a change matrix method. The six fold LULC raster maps of each year (2015, 2005, 1995, 1985, 1975, 1960, 1940 and 1920) were used for change dynamics analysis. This was realized by comparing the number of pixels falling into each category of land class at one time period and the characteristics of the same pixels in the

previous time period. Matrix model available with ERDAS Imagine 2015 were used for this purpose. A new thematic layer (change maps) produced from LULC maps of 1920–2015 time periods, containing different combinations of “from-to” change classes. Then the changes of forest to other classes were analyzed.

2.7. Accuracy assessment

Field sample points and additional points collected from Google Earth images were used to evaluate the classification accuracy (Congalton, 1991) of the constructed maps. A total of 2971 ground points in the proportion of land class area collected from Google Earth images (CNES/Astrium) of 2015 were used to determine Level II LULC class. The field sample points 852 in number were used to evaluate the accuracy of Level II vegetation type map of 2005. The detailed methodology is in the supplementary material (Methodology Text S1b).

2.8. Landscape ecological analysis

Fragmentation of landscape were evaluated both spatially and statistically. The spatial analysis of forest fragmentation was carried out with the help of Landscape Fragmentation Tool v2 (LFT v2) (Vogt et al., 2007). LFT maps the types of fragmentation present in specified land class (i.e., forest class) into 4 main categories – patch, edge, perforated, and core – based on a specified edge width of 500 m (Soille and Vogt, 2009). The ‘core’ forest is the intact forest consisting of interior forest pixels far from forest edge. The ‘patch’ forest make up small fragments and too small to be considered as core forest. Edge (boundaries of relatively large perforations and the exterior boundaries of core forest regions) and perforated (boundaries between core forest and relatively small perforations) forests occur along the periphery of tracts

Table 1
The land use and land cover classification and its descriptions used in the study.

LEVEL I	LEVEL II	DESCRIPTION
Forest	Evergreen	Includes all land classified either as forest under any legal enactment, or administered as forest, whether State-owned or private, and whether wooded or maintained as potential forest land. Includes area of crops within the forest and grazing lands or areas open for grazing within the forests.
	Semi evergreen	
	Dry Evergreen	
	Moist deciduous	
	Dry deciduous	
	Littoral and swamp forest/	
	Riverine	
	Forest plantation	
Scrub/grassland	Degraded forest	Consist of open woodland characterised by thorny trees with short trunks and low, branching crowns, spiny and xerophytic shrubs, and dry grassland. Includes forests that have been degraded through intensive agriculture and grazing into stunted and open thorn scrub, dominated by trees. Includes all grazing land whether it is permanent pasture and meadows or not. Includes village common grazing land.
	Scrubland (open/closed)	
	Thorn forest	
	Dry deciduous scrub	
	Dry evergreen scrub	
	Grassland	
	woodland	
	Orchard	
Agriculture		Includes all cultivable land and land under plantations (both forest plantation and commercial plantation). Cultivable waste land includes land available for cultivation, whether taken up or not taken up for cultivation once, but not cultivated during the last five years or more in succession including the current year for some reason or the other. Such land may be either fallow or covered with shrubs and jungles which are not put to any use. They may be accessible or inaccessible and may lie in isolated blocks or within cultivated holdings and fallow lands are classified under this category.
Waterbody	Cropland	Includes all waterbodies
	Water bodies	
Built up	Permanent wetland	Includes all land occupied by buildings, roads and railways or under water, e.g. rivers and canals, and other land put to uses other than agriculture.
	Built up (both urban rural)/ industries	
Barren and Un-cultivable Land	Barren land	Includes all land covered by mountains, deserts, etc. Land which cannot be brought under cultivation except at an exorbitant cost is classified as un-cultivable whether such land is in isolated blocks or within cultivated holdings.
	Mining	

containing core forests. The ‘Core’ forest was further divided into ‘small core’ (< 1.01 sq.km), ‘medium core’ (1.01–2.02 sq.km), and ‘large core’ (> 2.02 sq.km) areas based on the area of a given core patch (Vogt et al., 2007).

In addition, we have used landscape metrics for forest class, which was estimated using Quantum GIS Land cover statistics (LecoS) (Jung, 2016) suite for each individual classified LULC image (1920, 1940, 1960, 1975, 1985, 2005 and 2015). LecoS provides a comprehensive set of spatial statistics and descriptive metrics of the pattern at the patch, class, and landscape levels. The following metrics were used to find out the intensity of forest fragmentation: Edge Density (ED), Number of Patches (NP), Total Edge Length (TEL), Largest Patch Index (LPI), Overall Core Area (OCA), Effective Mesh Size (EMS), Shannon Diversity Index, Simpson Evenness Index (Table S2).

2.9. Habitat suitability analysis for conservation priority

To find the priority areas MaxEnt algorithm (Warren et al., 2014; Merow et al., 2013) were implemented on selected plant groups viz; group of RET and endemic species. Among the 2971 ground sample points, 1693 individual species were identified and 28 species was recorded as RET and 22 species as endemic. MaxEnt estimates the probability of occurrence, particularly the degree of habitat suitability based on the density of the environmental covariates at the presence sites (species occurrence), and their density in the entire study area (Phillips et al., 2006). The algorithm searches for a solution that has maximum entropy (i.e. closest to a null model whereby a species/species group has no environmental preferences), subject to the constraint that the means of the environmental covariates at the sites that are predicted to have a high suitability are close to the means across the observed locations. We used the default setting for MaxEnt version 3.3.3 k

(allowing for transformations of the covariates by enabling “auto-features” with the default thresholds for conversion, maximum number of background points = 10000; maximum number of iterations = 500; convergence threshold = 0.00001; fit regularization parameter = 1; default prevalence = 0.5). The model is executed at 1 km resolution with input data consisting of 799 records of RET species and 295 presence records endemic species.

2.10. Estimation of degradation and species habitat loss risk

Habitat degradation analysis was carried out to find the habitat degradation of RET and endemic species. The resultant MaxEnt output which shows the distribution of RET and endemic species was overlaid on the forest masks of 1920, 1960 and 2015 (~4-decade interval) to assess the percentage of shrinkage of habitat area of concerned group of species. We have provided threshold values to different ranges for habitat suitability such as highly suitable (> 0.7), moderately suitable (0.6–0.7), suitable (0.5–0.6) and less suitable or unsuitable (< 0.5).

The risk of species habitat was analyzed by posting the sampling points on different fragmentation levels of protected areas (PA) and outside the PA (OPA) (other core forest cover delineated outside the PA) of forest and scrub/grassland. Along with RET and endemic species the species with economic and medicinal values also considered for this estimation. Further, the forest fragmentation maps of each year (1920–2015) were overlaid on habitat suitability maps of RET and endemic plant species groups for the estimation of habitat threat due to changes in landscape pattern.

Table 2
Area distribution of different land classes from 1920 to 2015.

Land Classes	1920		1940		1960		1975		1985		1995		2005		2015	
	sq.km	%	sq.km	%	sq.km	%	sq.km	%	sq.km	%	sq.km	%	sq.km	%	sq.km	%
Forest	95511.57	43.40	94753.92	43.05	71897.58	32.66	60838.76	27.64	60775.95	27.62	60732.70	27.60	60723.65	27.59	60680.33	27.57
Scrub/grassland	1215.28	0.55	3419.95	1.55	24363.61	11.07	35004.29	15.91	34853.40	15.84	34991.95	15.90	34824.93	15.82	34788.62	15.81
Agriculture	100882.53	45.84	100920.56	45.86	101478.37	46.10	102148.70	46.41	102435.87	46.54	102425.46	46.54	102708.47	46.67	102289.09	46.48
Waterbody	5708.75	2.59	5713.67	2.60	5417.63	2.46	5608.31	2.55	5489.51	2.49	5411.98	2.46	5338.82	2.43	5497.44	2.50
Settlements	157.40	0.07	157.40	0.07	1148.60	0.52	3659.13	1.65	3638.85	1.66	3642.31	1.66	3665.70	1.67	3756.57	1.71
Barren and Un-cultivable Land	16604.48	7.54	15114.51	6.87	15774.21	7.17	12820.81	5.83	12886.41	5.86	12875.60	5.85	12818.42	5.82	13067.95	5.94

3. Results

3.1. LULC change and forest cover loss

The loss in forest cover and changes in other land classes were estimated from 1920 to 2015 (Table 2). Agriculture was the predominant land class in all the assessed time periods. An increase in the agriculture area from 45.84% (of the total area of Eastern Ghats) in 1920 (100882.53 sq.km) to 46.48% in 2015 (102289.09 sq.km) was observed. Forest was the second dominant land class in 1920 with 43.40% (95511.57 sq.km) occupancy (Table 2). The scrub/grassland shows an increasing trend (15.26%) from 1920 to 2015. Our study brought out four major observations: (i) about 7.92% of forest cover has been converted into agriculture; (ii) from 1920 to 1960 about 4.1% of the deforested area were converted to scrub/grassland; (iii) after 1975 the deforestation has led to settlement (0.06%), and mining and related activities (0.16%) (Area under settlement was 3659.13 sq.km in 1975, and increased to 3762.9 sq.km in 2015; likewise, 622.81 sq.km of the mining area in 1975 has increased to 962.12 sq.km in 2015); (iv) agriculture land is left fallow and getting converted to scrubland. The LULC changes of different years (1920–2015) is shown in Fig. 3.

3.2. Forest cover change dynamics

The percentage change in forest cover from 1920 to 2015 is shown in Fig. 4. The forest cover which was 43.40% of the total geographical area of Eastern Ghats in 1920 got reduced to 27.52% in 2015. During 1940 and 1960, about 6.99% of forest area was converted into the agricultural land, 3.80% to scrub/grassland and about 0.95% into settlement/barren land. After 1975, a meager amount of forest area (0.07%) was converted to other land classes (Fig. 4). On the other hand, during 1960–75 and 1995–2005, marginal conversion of barren land (0.02%) and scrub/grassland (0.22%) to forest area was recorded. The conversion of land classes to other classes during 1920–1940, 1940–1960, 1960–1975, 1975–1985, 1985–1995, 1995–2005, 2005–2015 is shown as change matrix in Table S3 (a–g). Overall, about 7.92% of the forest was converted to agricultural land further these agricultural lands are being converted to scrublands and barren lands. This assessment demonstrates the disturbance of land and its transition in Eastern Ghats (Fig. S1).

3.3. Extent of forest types affected due to deforestation

During the forest type assessment for the period of 1975–2015 (Fig. S2), the area under moist and dry deciduous forests were reduced (Table 3). Different forest types were prone to deforestation during the assessed period mainly due to urbanization, mining and other developmental activities such as; dam and road construction and irrigation projects. The total mined area was 622.81 sq.km in 1975 and is increased to 962.12 sq.km in 2015.

3.4. Validation of classified maps

Classification accuracy was carried out for the derived LULC and forest type maps from 2005 and 2015. The overall accuracies for 2005 and 2015 were 93.77%, and 93.33% respectively, and the Kappa coefficient (Khat) values were 0.91 and 0.92, respectively. It may be noted that Kappa coefficient > 0.80 represents a strong agreement and good accuracy (Congalton, 1991).

3.5. Changes in landscape pattern

Landscape characterization with respect to patch formation within the extended forests, edge, perforations, intact and contiguous forests were analyzed and assigned to a patch size class from 1920–2015 (Table 4). Forest degradation and deforestation were found to be

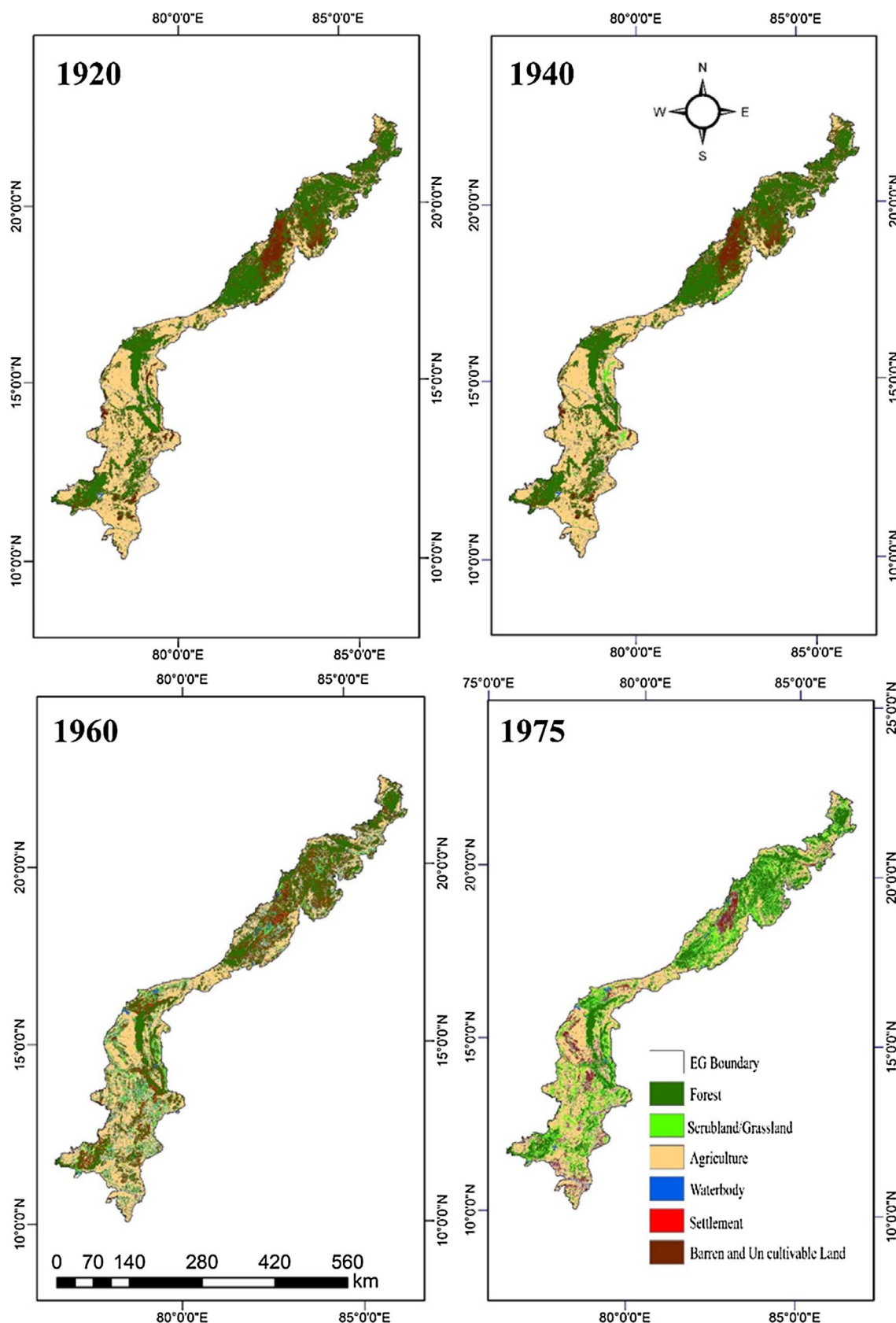


Fig. 3. Land use and land cover maps of the Eastern Ghats from 1920 to 2015.

associated with the degree of spatial fragmentation of the forests. The landscape pattern shows that the major changes were occurred during 1940 and 1960. The large patches of forests in 1920 are now

fragmented, and the patch count was increased from 1379 (in the year 1920) to 9457 in 2015. There was a noticeable increase in the edge of forest patches from 1920 to 2015 (0.82 sq.km in 1920 and 2.20 sq.km

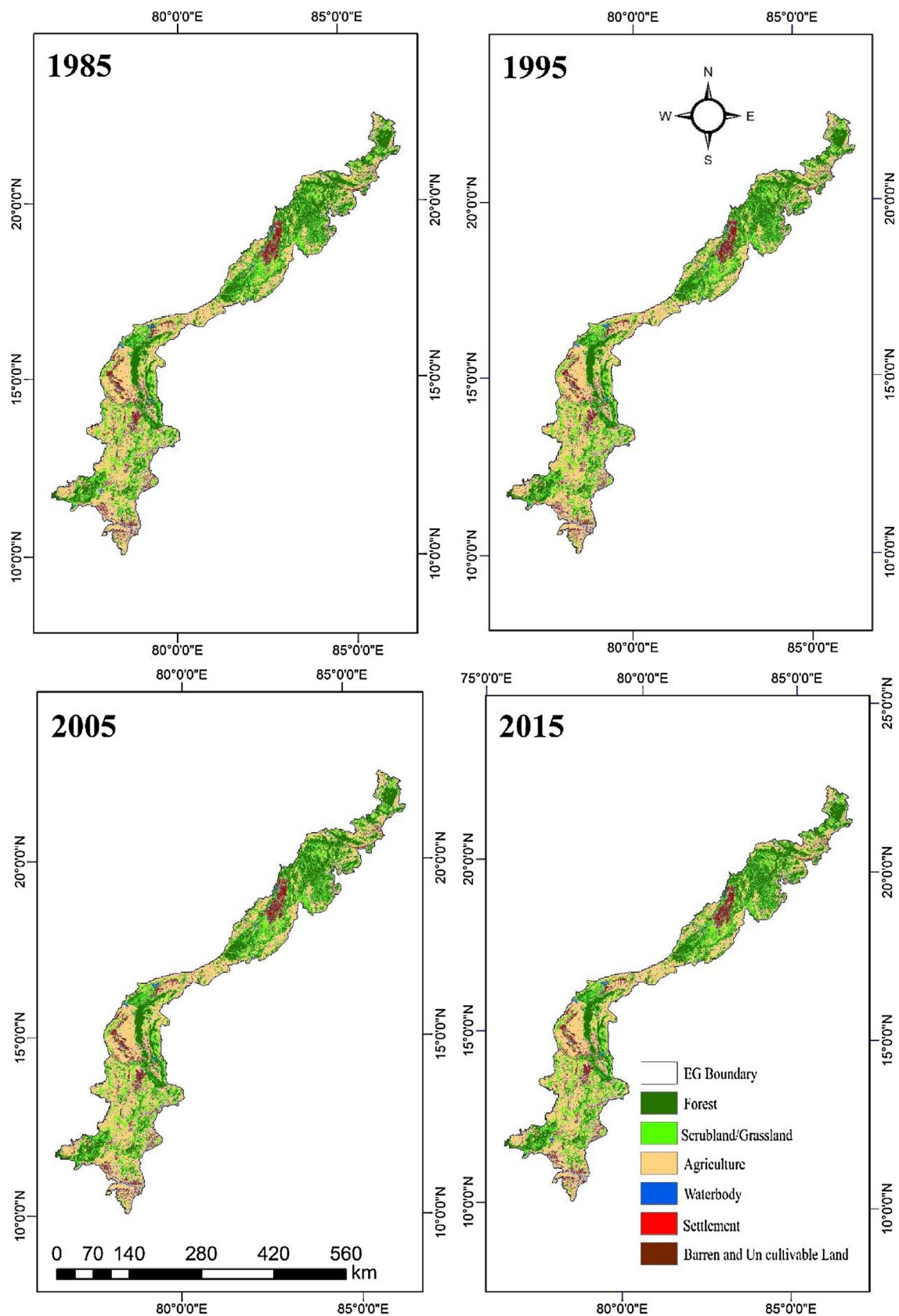


Fig. 3. (continued)

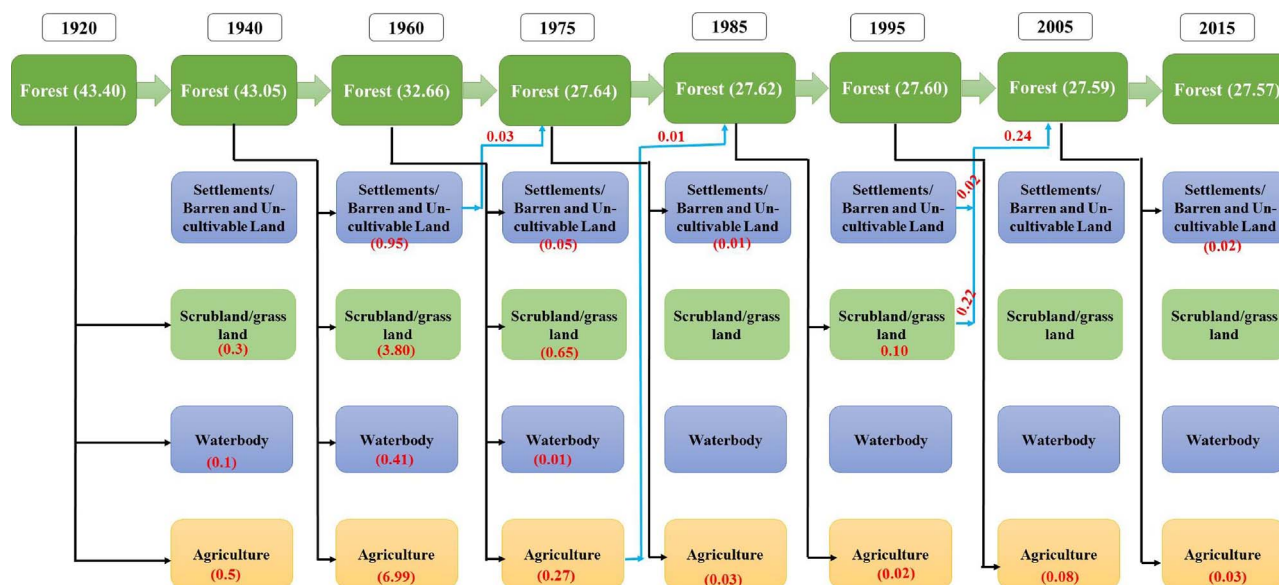


Fig. 4. Transition of forest cover into other classes (values are in percentage).

in 2015). Forest with a recorded LPI of 9.56 during 1920 has reduced to 6.48 in 2015. The OCA under forests was estimated as 93461.05 sq.km in 1920 and now becomes 61262.11 sq.km in 2015. This inference clearly indicates that severe fragmentation and loss of forests were occurred during the study period. The forest fragmentation maps are shown in Fig. S3.

3.6. Habitat suitability for group of RET and endemic species

The RET species shows distribution patterns all over the Eastern Ghats (Fig. 5a). The habitat suitability analysis for RET group of species shows that the potential spreading of the species is much larger than the actual locations. Nallamalai hill ranges shows very high habitat suitability. Kolli hills, Kalrayan hills and Similipal national park shows medium distribution of RET species. Potential habitats with high suitability thresholds were distributed in the northern Eastern Ghats. The districts such as Kandhamal, Gajapati of Odisha state and Erode,

Dharmapuri and Salem of Tamil Nadu had wide area of good habitat suitability. In total, 19.21% of area was found to be suitable for RET group of species and 43.46% area does not suitable.

In the second analysis, we have focused on the habitat suitability of a group of endemic species. The group of endemic species range was more restricted than the group of RET species. High level of endemism and habitat suitability was found in the Nallamalai region (Fig. 5 b). The relatively better endemic range has observed in the Similipal and southern parts of the Odisha state. Particularly in the districts of Kandhamal, Ganjam and Gajapati. About, 10.66% of area was estimated as suitable for group of endemic species whereas 51.81% area does not. It is interesting to note that the Nallamalai hill ranges which are known to be suitable habitat for RET species are equally suitable for endemic species as well. The habitat suitability map was overlaid on the map of PA to identify suitable areas other than PA to survey for habitat suitability. The results indicate that for most of the species, habitat suitable areas lie OPA.

Table 3

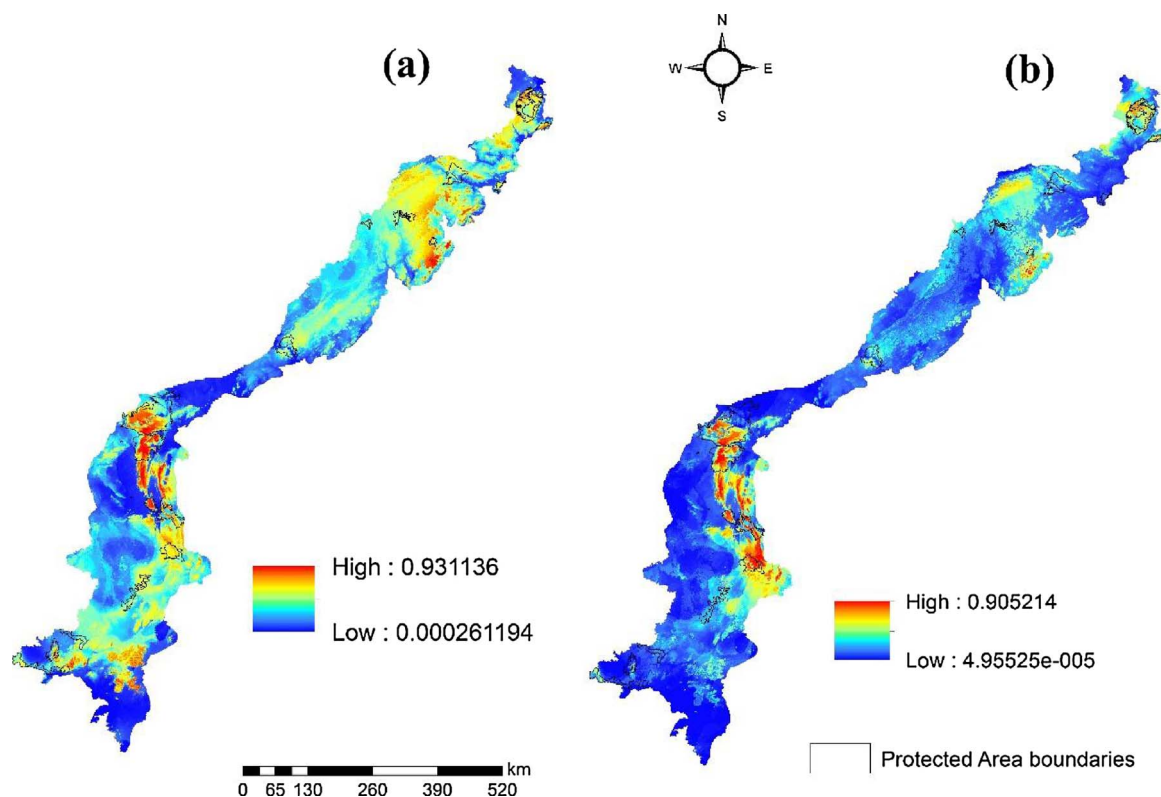
Detailed area distribution statistics in different forest type and land use and land cover during 1975–2015.

	1975		1985		1995		2005		2015	
	sq.km	%	sq.km	%	sq.km	%	sq.km	%	sq.km	%
Evergreen	408.24	0.19	408.09	0.19	408.10	0.19	408.10	0.19	408.10	0.19
Semi-evergreen	2839.17	1.29	2837.95	1.29	2838.02	1.29	2838.31	1.29	2837.04	1.29
Dry Evergreen	221.77	0.10	221.77	0.10	221.76	0.10	221.76	0.10	236.78	0.11
Moist deciduous	22557.08	10.25	22537.43	10.24	22508.10	10.23	22544.15	10.24	22523.38	10.23
Dry Deciduous	31462.88	14.30	31421.81	14.28	31396.58	14.27	31369.05	14.25	31366.55	14.25
Littoral and swamp forest/Riverine	1372.44	0.62	1354.86	0.62	1362.59	0.62	1354.12	0.62	1355.17	0.62
Forest plantations	1976.97	0.90	1979.39	0.90	1977.77	0.90	1971.32	0.90	1934.65	0.88
Degraded forest	0.22	0.00	0.22	0.00	1.10	0.00	2.94	0.00	4.04	0.00
Scrubland (open/closed)	25103.14	11.41	24952.45	11.34	25086.66	11.40	24919.27	11.32	24905.92	11.32
Thorn forest	1813.06	0.82	1813.06	0.82	1812.65	0.82	1812.67	0.82	1807.90	0.82
Dry deciduous scrub	3625.43	1.65	3625.46	1.65	3625.40	1.65	3625.88	1.65	3607.89	1.64
Dry evergreen scrub	153.35	0.07	153.34	0.07	153.31	0.07	153.31	0.07	153.31	0.07
Grassland	897.63	0.41	897.62	0.41	897.21	0.41	897.28	0.41	896.54	0.41
woodland	3411.68	1.55	3411.46	1.55	3410.85	1.55	3410.64	1.55	3411.17	1.55
Orchards	2784.12	1.27	2774.32	1.26	2771.72	1.26	2744.12	1.25	2787.54	1.27
Cropland	99364.57	45.15	99675.74	45.22	99667.93	45.29	99978.53	45.29	99515.73	45.43
Waterbody	5580.08	2.54	5462.28	2.48	5381.69	2.45	5312.34	2.41	5470.42	2.49
Wetlands	28.23	0.01	27.20	0.01	30.25	0.01	26.43	0.01	26.96	0.01
Built up (both urban rural)/industries	3659.13	1.65	3637.98	1.66	3648.64	1.66	3672.03	1.67	3762.90	1.71
Barren land	12198.00	5.54	12225.09	5.55	12204.29	5.55	12183.71	5.54	12106.97	5.50
Mining	622.81	0.28	662.47	0.30	672.45	0.31	635.86	0.29	962.12	0.44

Table 4

The forest fragmentation and landscape diversity statistics of Eastern Ghats from 1920 to 2015.

Landscape Metrics	1920	1940	1960	1975	1985	1995	2005	2015
Edge Density	0.0004	0.0004	0.0010	0.0010	0.0010	0.0010	0.0010	0.0010
Number of Patches	1379	1509	9156	9345	9382	9404	9425	9457
Total Edge Length	82.18	80.10	215.30	218.49	218.74	218.89	218.93	220.81
Largest Patch Index	9.56	9.56	7.10	6.49	6.47	6.48	6.58	6.48
Overall Core Area	93461.05	93027.47	63103.80	62695.17	61555.66	61528.59	61417.99	61262.11
Effective Mesh Size	4216.16	4216.29	1597.15	1435.10	1431.70	1430.97	1429.90	1410.11
Shannon Index ^a	1.03	1.06	1.26	1.28	1.28	1.28	1.28	1.28
Simpsons Index ^a	0.59	0.60	0.66	0.67	0.67	0.67	0.67	0.67

^a Landscape diversity index.**Fig. 5.** Habitat distribution of group of (a) rare, endangered, threatened (RET) and (b) endemic plant species in Eastern Ghats.**Table 5**

Percentage habitat decrease of group of endemic and rare, endangered, threatened (RET) species.

	Threshold	1920		1960		2015	
		Endemic	RET	Endemic	RET	Endemic	RET
Highly suitable	> 0.7	3.70	4.38	3.61	4.36	3.48	4.30
Moderately Suitable	0.6–0.7	3.45	7.02	3.37	6.25	3.30	6.23
Suitable	0.5–0.6	4.38	10.92	4.01	8.69	3.88	8.68
Not Suitable	< 0.5	88.83	77.70	55.86	47.69	51.81	43.46

3.7. Challenges for plant species conservation

The percentage shrinkage of highly suitable habitat area for group of RET and endemic species during the study period (1920–2015) are 0.08% and 0.6% respectively. Likewise, the percentage shrinkage of moderately suitable areas for group of RET and endemic species are 0.79% and 0.15% respectively. The percentage shrinking of suitable habitat area from 1920 to 2015 for a group of RET and endemic species

was 0.5% and 2.24% respectively. However, the percentage of unsuitable areas for group of RET and endemic species during 1920–2015 was 77.70% and 88.83% respectively. The decrease of unsuitable areas from 77.7% to 43.46% for group of RET and from 88.83% to 51.81% for endemic species is attributed to the degradation of the habitat quality of different plant species in the Eastern Ghats rather than to the increase in suitable area (Table 5).

We also analyzed the status of species distribution in the PA and OPA of the Eastern Ghats for two important vegetation covers i.e., forest and scrubland. For this, we have estimated the assemblages of endemic, RET, economically and medicinally important species in different fragmentation ranges in the PA and OPA (for both forest and scrubland). Summing up of number of species found in the PA and OPA are given in Fig. 6(a, b). A total of 1693 species were recorded from the sampled data, 1207 species were concentrated in OPA (Fig. 6a). The distribution of species is shown in (Fig. S4). Among them, 48.58% species were recorded under medicinally important category and 42.52% of them were found in the large core area followed by perforated (33.37%) areas of PA (Fig. 6a). Similarly, economically important species were found more at core (42.19%) areas of PA and edges (25.81%) of OPA. A total of 245 individuals belong to RET category,

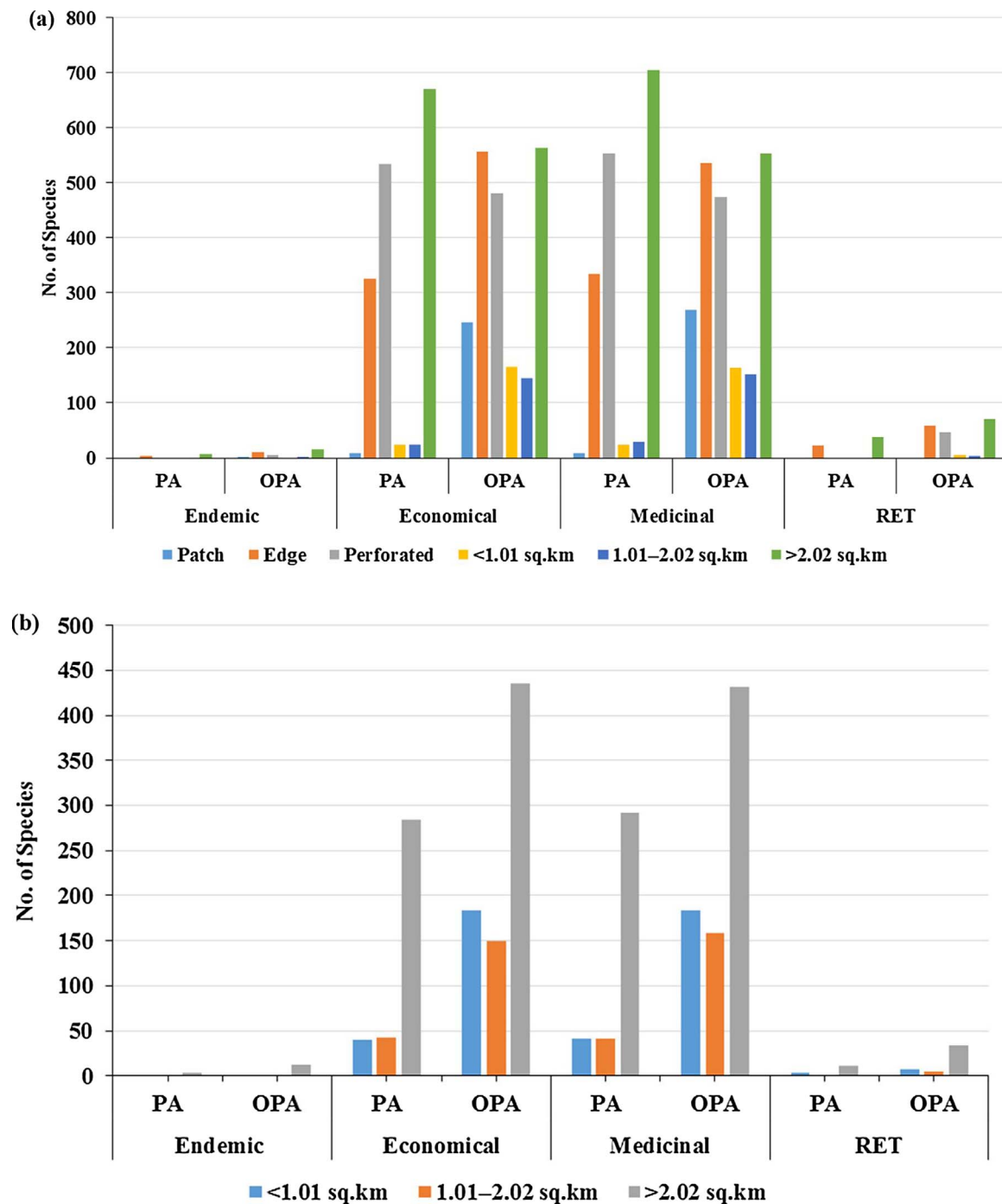


Fig. 6. Distribution of species in protected areas (PA) and outside protected areas (OPA): (a) forest; (b) scrubland.

62% were found in OPA, while 46 individuals recorded under endemic species, 76.08% were found in the OPA. In the case of scrublands, the majority of species were present in the large core areas (Fig. 6b) followed by small core area of OPA. Wild species are most sensitive to habitat fragmentation and declining drastically (Fig. 6a). Which means, the influence of habitat fragmentation is more in forest species than scrubland species. Due to fragmentation, the species are often finding their habitats in the fragmented patches, therefore, vulnerable of its existence. To test the effects of fragmentation on plant species in response to fragment area we analysed the percentage vegetation cover in different fragmentation levels for both PA and OPA of forest and scrubland (Fig. S5 (a, b)). In case of forest, 35% of forest area were at the edges and 25% are in the large core area of OPA. Similarly in case of

scrubland 65% of scrubland area is in the large core area of OPA.

4. Discussions

4.1. Land classes change dynamics

Although a range of studies have been reported about Eastern Ghats (Dash and Misra, 2001; Kumaraguru et al., 2016; Ramachandran et al., 2016) and its LULC change (Jayakumar and Arockiasamy, 2003), these studies were typically carried out for either small study regions over short time periods, or, on the level of administrative units. To the best of our knowledge, the present study is the first of its kind to consistently map the changes in the extent of LULC change as well as effects of these

changes on forests and plant habitat across the Eastern Ghats over an extended period of time. We have analyzed spatial patterns of LULC change in the Eastern Ghats since 1920 up to 2015 with an interval of approximately 15 years. The major findings were, the LULC changes that have caused the loss of forest cover of about 15.83% in the Eastern Ghats over a period of past 95 years. This decline of forest cover was the result of land use activities, primarily for agricultural expansion, mining and timber extraction. During 1920–1960, the Eastern Ghats show a decline of 10.39% of forest cover. Similar LULC change studies conducted in different parts of India shows that major deforestation had taken place during the period of British rule, as well as in early years after the independence (Ravikanth et al., 2000; Tian et al., 2014). Similar trends were reflected in our study as well. Anthropogenic activities were one of the major drivers of the degradation of forests (Geist and Lambin, 2002). We found an increase of 6.99% in the agricultural land during 1940–1960 (Fig. 4). The cropland expansion in the Eastern Ghats could offset the pressure even more, due to increasing need of population (population of Eastern Ghats has been increased from 81 million to 123 million during 2001–2011 (Census, 2011)). Special initiatives, such as Grow More Food Campaign (1940s) and Green Revolution (1960s) have put more pressure on forest resources for producing more food, which had resulted in agricultural expansion in this area (Ravikanth et al., 2000). Even though large part of forest conversion had occurred due to agricultural expansion during the past 95 years, the total agricultural area has increased only by 0.64% in the Eastern Ghats. Change studies shows that majority of the agricultural lands were now converted into the settlement, barren land and scrubland classes (Table, S3). Due to the lack of soil fertility after three or four-time cropping in the same area, the lands are being left uncultivated allowing the scrubs to grow or become barren lands.

The conversion of forest into scrub/grassland (disturbed ecosystem) was another highlight in our study. There was a meager change noticed from forest to scrub/grassland (651.64 sq.km) and barren land to scrub/grassland (1520.08 sq.km) during 1920–1940. The conversion of forest to scrub/grassland was mainly happened during 1940–1960 due to over extraction of timber and other resources (which includes fuel wood collection, and livestock grazing). Significant conversion of forest to scrub/grassland were recorded in different parts of India in the last few decades (Rao and Pant, 2001; Arendran et al., 2013; Meiyappan et al., 2016). Several researchers are also reported related issues concerning forest conversions to scrubland in different parts of Eastern Ghats (Schmerbeck, 2011; Schmerbeck et al., 2015). Jayakumar et al. (2009) have reported conversions of open deciduous forest to thorny forests in the Eastern Ghats falling in the State of Tamil Nadu.

Even though the Eastern Ghats forest has lost its 40% of natural forest, the recent trends show positive trends towards gaining forest area. This because of the strict implementation of laws and policies for the protection of forest and biodiversity. However, the increase of mining area from 0.28% in 1975–0.44% in 2015 should be taken into serious concern. Likewise, the area under settlements has increased from 0.07% in 1920–0.56% in 2015, and the fact that the population projections are also showing the possibility of increase of human settlements in the Eastern Ghats region (DeFries and Pandey, 2010). It not only causes over exploitation of the resource, but also would lead to the degradation of forest and biodiversity (Palmer et al., 2010).

4.2. Changes in landscape characteristics

We have mapped the forest fragmentation of Eastern Ghats (1920–2015) that provide a stark contrast in land-use dynamics and extent of biodiversity risk in the area. Forest degradation and deforestation were found to be associated with the degree of spatial fragmentation of the landscape. Accessibility to forests in the Eastern Ghats is relatively easy when compared to Western Ghats owing to its less complex terrain which makes the degree of fragmentation in the Eastern Ghats to be on the higher side. Overall, the values of the metrics

obtained in this study (Table 4) suggest that the changes in LULC has increased the heterogeneity of the landscape and resulted in a large variety of fragmentation patterns. To quantify landscape composition, we have used Shannon and Simpson diversity indices. Shannon and Simpson indices of diversity and evenness might be expected to vary in their response to landscapes with varying richness. The heterogeneity of the landscape has increased from 1920 to 2015, indicating high fragmentation and habitat reduction. Likewise, low values of evenness indicate that one or a few land cover dominate, whereas high values indicate that relatively equal numbers of patches belong to each land class (Morris et al., 2014). The higher variation of the size (Fig. S3) and increased number of the patches induced a higher variation in the total edges and the reduction in the overall core area of the forest. The forest area loss, increase in isolation, and greater exposure to human activities along fragmented edges are vulnerable to long-term changes in the structure and function of the remaining fragments (Haddad et al., 2015). Forest fragmentation, directly and indirectly, affects the overall landscape by altering the patterns of landscape further reduction in the species habitat (Conceição and de Oliveira, 2010) and functioning.

4.3. Changes in species habitat and distribution due to fragmentation

Our results shows that endemic species tended to be located in less fragmented and less disturbed landscapes than RET species. Interestingly endemic species showed suitable habitat even outside the forest areas (Fig. 5b). However, both the groups are equally affected by fragmentation throughout study period. During 1920 the habitat was intact and continuous for both the species. In 2015, the intact forests got fragmented and resulted in the isolation of habitats. Also, majority of suitable habitats are found under large core areas. Characteristic changes along the time trajectory include: (i) decline in the total area of fragmented habitats; (ii) decrease in the size of many habitat fragments (large core areas become scarce, small fragments predominate); (iii) increased number of patches of fragments from similar habitat; (iv) increase in the edges of the habitats. Large core area is continuously fragmentation throughout the period of study, resulting in a large proportion of edge habitat. The isolation of habitats eventually affects local populations of RET and endemic species by restricting the species interactions (Christie and Knowles, 2015). Furthermore, it causes unavoidable changes in the ecological processes within fragmented habitats (Western, 2001). For instance, it can include shifts in forest structure and biodiversity (Didham, 2010), loss of species richness and changes in species composition when compared to contiguous habitat (Ewers and Didham, 2006).

Based on the previous studies (Gray et al., 2016; Thomas and Gillingham, 2015), we analysed the distributions of specialised group plants (plant species rendering economically, medicinally important; endemic and RET category) in PA and OPA, which is more concern for conservation and typically protected by international conventions (Secretariat of the CBD, 2010). The overall analysis shows that samples from PA contained more species diversity and abundance than samples from OPA (Fig. 6 a & b), even though they don't have more forest cover as compared with OPA (Fig. S5 a & b). In contrast, the protected sites don't have more endemic and RET group of species (Fig. 6 a & b) and they are widely distributed in outside the protected sites. These two specialized groups determine the measures of community characteristics that are often considered in conservation priorities (Gray et al., 2016). The greatest differences in species richness and abundance occurred between forest and scrubland (Fig. 6a & b). Particularly in protected areas, facilitated conservation is most effective as they minimize the impacts of human land utilization patterns (Gray et al., 2016). However, in OPA the human-dominated land use (such as agriculture and settlement) and disturbances regime will restrict the higher biodiversity (Spear et al., 2013). The present study revealed species richness was higher in the large core areas at a greater distance from the PA and OPA borders. Moreover, endemic and RET species found in less

fragmented patches, which indicates that these plant communities can be preserved better in less human interference areas. Some of the recent studies also support our results (Angulo et al., 2016; Tole, 2002). Interestingly, we found significant species assemblage in the edge and perforated patches of the forests (Fig. 6 a & b); about 22 (number includes species from both PA and OPA) of endemic species and 81 RET species. The species which occur in the edges are at high risk. If we do not give enough priority to these areas the LULC change and fragmentation will make serious threats to the habitat of these species.

4.4. Conservation prioritization and challenges

Identification of regions (outside protected areas) with exceptional levels of species richness, endemism and those species with other ecological value/use have the greatest importance for proposing new areas for conservation. Lack of funding and studies compel the conservation community to ignore such areas which have most outstanding and representative areas for biodiversity (Venter et al., 2014). Conservation status represents an estimate of the ability of an ecoregion to maintain viable species populations, to sustain ecological processes, and to be responsive to short- and long-term environmental changes (Olson and Dinerstein, 2002). It is important to acquire representative samples of group of RET and endemic species of Eastern Ghats within which they occur to find out the conservation areas. There are many other factors that may be used in the prioritization process such as ecological function, conservation feasibility (i.e., political, social, economic, cultural factors), or human utility. We did not use these parameters as discriminators to identify the priority areas because they are unavailable since 1920. The development and implementation of strategies for conservation areas, however, require careful attention to ecological function and non-biological factors. The habitat distribution model was also used to assess broad trends in threats of LULC change among different regions of Eastern Ghats. The forests of the Nallamalai hill ranges and Seshachalam are known for their pronounced endemism. The Tamil Nadu state part of Eastern Ghats harbors diverse and unusual assemblages and displays notable endemism. In Odisha state, forests of Eastern Ghats are notable for their diversity in RET group of species which are threatened mainly due to the mining industry. These long-isolated forests have many other unusual taxa and unique communities. The central part of Andhra Pradesh covering Nallamalai and Seshachalam hills is a regional center of endemism for a range of species. We have used MaxEnt to map the geographic distribution of endemic and RET group of species and modeled both species category across the Eastern Ghats. High endemism has been recorded in the southern Andhra Pradesh region of Eastern Ghats. The RET species occurrence also recorded in the same range but it widely distributed in other parts of Eastern Ghats as well. The MaxEnt result of endemic group of species shows that the southern Eastern Ghats are poor in endemism (Fig. 5) or the area is not a suitable habitat for endemic species. As compared to endemic species, the RET species distribution is very high in the Eastern Ghats (Fig. 5). Apparently in Eastern Ghats the habitat reduction has mainly occurred in the districts of Gajapati (Odisha state), Mahabubnagar (Telangana state) and also in Nallamalai and Kolli hill ranges.

The percentage of forest area under current protection was 18.5, which included 7.5% of forest fragments (Fig. S5). Whereas 81% of forest area under outside the protected areas. Of the total 30% of total forest area in Eastern Ghats are intact. Sri Venkateshwara National Park in the Seshachalam Hills, Gundlabbrahmeshwaram Sanctuary in Nallamalais and some parts of Srisailem-Nagarjunasagar Tiger Reserve, had the least degraded forests due to their PA status. However, the collection of non-timber forest products, bamboo harvesting, and livestock grazing continues in all areas irrespective of legal status (Rawat, 1997).

The Eastern Ghats are often ignored by conservationists and stakeholders in favor of the Western Ghats and Eastern Himalayas (Rao et al., 2010). But the current study and recent literature (Ramesh and

Kalpana, 2015; Roy et al., 2013) show that this place is a premium on identifying priorities and conservation areas in light of species habitat threat. A promising approach is to identify conservation areas or hot-spots or areas featuring exceptional concentrations of species under risk. Such as, endemic species or species under threat (viz, RET due to human and climate drivers) which experiencing exceptional loss of habitat. By focusing on these areas where there is greatest need of conservation, conservationists can take necessary steps towards the challenge of large-scale species extinctions ahead. Here, we focus on specialized group of plant species (endemic and RET), concentrating a large proportion of conservation support in these areas would help from mass extinction of species and its habitat. These plant groups has already lost 11.4% of their primary habitat, due to LULC change, habitat fragmentation and also by the absence of conservation efforts and lack of policies. However, a species-based approach is likely to protect more areas that are threatened by habitat loss, fragmentation and valuable for different use by society. Furthermore, the major challenges for the conservation of plant diversity in the Eastern Ghats are i) the inevitable damages due to the anthropogenic land use and population growth; ii) lack of awareness of the importance of the local species and biodiversity; iii) lack of availability of long term data sets and monitoring; iv) lack of implementation of laws and policies v) need for high-quality empirical studies on different taxa and ecosystems. We do not attempt a study of a future plan for the Eastern Ghats protected area network, which would entail the inclusion of further social, economic and biological considerations. We assume all areas in which the species shows its high concentrations (Figs. 5 and 6) are available for protected area expansion, but in reality factors such as opportunities for landholder engagement, public accessibility and feasibility would impact on this availability.

5. Conclusions

The present study revealed that the patterns of LULC change has led to forest fragmentation and transition by different land classes in the Eastern Ghats from 1920 to 2015. Moreover, the changes of LULC indicated by the loss of potential habitats for the specialized plant groups, such as RET and endemic plant species. During the study period, considerable forest areas in the Eastern Ghats have either been converted to other land classes or severely degraded. Timber logging, dam construction, road-rail network and other developmental activities were the major drivers of forest cover change before 1960s. After 1960, the anthropogenic pressure on land increased by various demands such as mining, urban development, and agricultural practices. These demands influenced the forest cover by the way of deforestation and fragmentation. However, in spite of a long history of deforestation in the Eastern Ghats, more than 60% of the forest area continues to remain forested throughout the study period. The overall forest cover in the Eastern Ghats is degraded, and many areas are not able to recover. And few of these degraded areas are remaining as scrubland. After 1960 the agricultural fallow lands also being converted to scrubland. The patterns of the landscape have changed significantly due to forest fragmentation. The species assemblage is high in core areas and significant species composition has found in the forest edges. The overall habitat suitability has been decreased for RET and endemic group of plant species. Most of those specialized plant group suitable habitat areas are found outside the protected area ranges. By concentrating on these areas where needs are greatest and where the pay-off from safeguard measures would be greatest, conservationists can engage in a more systematised response to the challenge of large scale impending extinctions and habitat degradations and improve the habitat quality.

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Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at <http://dx.doi.org/10.1016/j.ecolind.2017.10.012>.

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Land use and climate change impacts on distribution of plant species of conservation value in Eastern Ghats, India: a simulation study

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Abstract Effective monitoring of the current status of species distributions and predicting future distributions are very important for conservation practices at the ecosystem and species levels. The human population, land use, and climate are important factors that influence the distributions of species. Even though future simulations have many uncertainties, such studies can provide a means of obtaining species distributions, range shifts, and food production and help mitigation and adaptation planning. Here, we simulate the population, land use/land cover and species distributions in the Eastern Ghats, India. A MaxEnt species distribution model was used to simulate the potential habitats of a group of endemic (28 species found in this region) and rare, endangered, and threatened (RET) (22 species found in this region) plant species on the basis of IPCC AR5 scenarios developed for 2050 and 2070. Simulations of populations in 2050 indicate that they will increase at a

rate of 1.12% relative to the base year, 2011. These increases in population create a demand for more land for settlement and food productions. Land use land cover (LULC) simulations show an increase in built-up land from 3665.00 km² in 2015 to 3989.56 km² by 2050. There is a minor increase of 0.04% in the area under agriculture in 2050 compared with 2015. On the other hand, the habitat simulations show that the combined effects of climate and land use change have a greater influence on the decline of potential distributions of species. Climate change and the prevailing rate of LULC change will reduce the extents of the habitats of endemic and RET species (~60% and ~40%, respectively). The Eastern Ghats have become extensively fragmented due to human activities and have become a hotspot of endemic and RET species loss. Climate and LULC change will enhance the species loss and ecosystem services.

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Introduction

The influence of human beings has directly or indirectly modified the distributions of species and different functional processes on earth. These processes include the cycling of elements, climate regulation, and the hydrological cycle. The anthropogenic activities affect these processes and ultimately cause depletion of natural resources, global warming, and species extinction (Ripple et al. 2017). Plant communities are the prime members and among the important structural components of an ecosystem (Giam et al. 2010). They control numerous ecological processes and support a wide variety of organisms. Therefore, the threats faced by a floristic community affect the entire ecosystem. These threats are primarily changes in land use/land cover (LULC) (Foley et al. 2005; Cardinale et al. 2012; Souza et al. 2015; Gerstner et al. 2014) and climate (Segan et al. 2016; Schleuning et al. 2016). Changing LULC and climate may alter the distribution ranges of species and restrict interactions among species (Oliver and Morecroft 2014; Elmhagen et al. 2015), which will ultimately lead to habitat loss and species extinction. Human-induced habitat loss is the primary reason for several species at risk (Ceballos et al. 2015; Hanski 2011; Tilman and Lehman 2001). The human activities like fuel wood collection and timber extraction have a significant impact on the forest and its species. The International Union for Conservation of Nature (IUCN) assesses habitat loss as being the prime threat faced by 85% of the species described in the IUCN's Red List (IUCN 2012). IUCN have classified species in different categories depending on its threat and conservation values (see <https://www.iucnredlist.org/>). The species of special concern, such as endemic, and rare, endangered and threatened (RET) species habitats need to be mapped out in effective manner due to their restricted distributions and ease of habitat loss. Endemic species are native species which are restricted to a particular geographic region (CBD 2009) whereas RET species are the one which are naturally rare due to small population or restricted distribution, endangered due to threatened with extinctions, and threatened by various natural and anthropogenic activities (Jain and Rao 1983). The present and future trends of species

distributions under changing LULC and climate regimes have been extensively studied in different parts of the world (see for, e.g., Dyderski et al. 2018; Sirami et al. 2017). Species distribution models (SDMs) are one of the effective tools that ecologists often use to map the potential and actual distributions (habitats) of species and their interactions with environmental parameters (Elith and Leathwick 2009).

To fully understand the driving processes and the impacts of LULC and climate change on the regional biodiversity, it is essential to quantify these impacts under different time scales, viz., the past, present, and future, using an effective approach. Modeling is a robust method of analyzing the potential impacts of changing LULC and climate on biodiversity, allowing the exploration of possible future states and consequences (Rounsevell et al. 2006). India occupies only 2.4% of the global land area though it accounts for 7–8% of the recorded species of the world (MoEF 2008). The projected and the future effects of climate and LULC changes on biodiversity as well as on plant species have been studied mostly on North-East (Deb et al. 2017), Western Ghats (Chitale et al. 2014; Kale et al. 2016), and Gangetic planes (Tsarouchi et al. 2014) of the country. Even though Eastern Ghats are distinguished with species diversity and endemism, only a few studies are available in this region regarding climate and LULC change aspects (Remya et al. 2015). The Eastern Ghats of India has experienced substantial LULC change and intensification of deforestation over the past decades (Rawat 1997; Balaguru et al. 2006; Reshma et al. 2018). The coupled impacts of LULC and climate changes on species distributions have been studied only marginally both at regional scale and global scales (Sirami et al. 2017).

We have attempted to study the magnitude of impact of changing LULC and climate on the potential distributions of plants with conservation values such as endemic and RET species in the Eastern Ghats taking into account the present and future (2050 and 2070) scenarios. We have used artificial neural networks, maximum entropy, and demographic modeling approaches to simulate the LULC, potential species distributions, and human population in the future. The potential distributions of endemic and RET species were simulated with different future Representative Concentration Pathways (RCPs 2.6, 4.5, 6.0, and 8.5) of the fifth assessment report (AR5) of the Intergovernmental Panel on Climate Change (IPCC) (IPCC 2014).

Materials and methods

Study area

The Eastern Ghats of India, with broken hill ranges, hold unique ecosystems. They extend in a north-east to south-west direction along the east coast of the Indian peninsula through the states of Odisha, Telangana, Andhra Pradesh, Karnataka, and Tamil Nadu. Their floral diversity is rich (Pullaiah and Rao 2002) (Fig. 1), and they have a large tribal population (Fig. S1). They are located between latitudes 11° 30' and 22° 0' N and longitudes 76° 50' and 86° 30' E. The state of Andhra Pradesh covers 39.64% geographical area of Eastern Ghats, followed by Odisha (31.26%), Tamil Nadu (19.09%), Karnataka (6.29%), and the Telangana (3.72%). The districts such as Dharmapuri (Tamil Nadu), YSR (Andhra Pradesh), Kandhamal, and Rayagada (Odisha) are Eastern Ghats. The Mahanadi basin marks the northern boundary of the Eastern Ghats while the southern boundary is the Nilgiri hills, to the west lie the tips of Bastar, Telangana and Karnataka plateaus, and Tamil Nadu uplands. The coastal area in the east limits its eastern part (Pullaiah and Rao 2002). This tropical region receives seasonal rainfall from both the south-west and north-east monsoons. The Eastern Ghats are typically covered by deciduous vegetation and scrub jungle (Mani 1974). They are a repository of floral wealth, with more than 2600 species of angiosperm, gymnosperm, and pteridosperm, and pteridophyte, including about 454 endemic species, as well as 160 species of cultivated plants (Kannaiyan 2015). The ecosystems of this region are among the most exploited and degraded ecosystems of India (Puyravaud et al. 2010; Ramachandran et al. 2016). The broken-chain topography of the Eastern Ghats provides people for easy access to the forests, making them susceptible to anthropogenic pressures such as mining (Rao et al. 2013), livestock grazing, fuel wood collection, deforestation (Jayakumar et al. 2002; Naidu and Kumar 2016; Reshma et al. 2018), intensified agricultural land (Prasad et al. 2001), and urbanization (Ramesh and Kaplana 2015).

Datasets

Socioeconomic data: The village and district population data of the Eastern Ghats for the years 2001 and 2011 were

obtained from the Office of the Registrar General & Census Commissioner, India (<http://www.censusindia.gov.in>, accessed on 16th August 2018). The details of census metadata can be obtained from http://www.censusindia.gov.in/2011census/HLO/Metadata_Census_2011.pdf. Data relating to rivers, roads, rail networks, and locations of villages and cities were accessed from the OpenStreetMap of India for the year 2015 (<https://www.openstreetmap.in>, accessed on 16th August 2018). The details of data collection in openstreetmap can be obtained from https://wiki.openstreetmap.org/wiki/Main_Page.

LULC and topographic data: LULC maps of 1995, 2005, and 2015 were prepared using 30 m resolution Landsat images of sensors Thematic Mapper (TM) (1995 and 2005), Enhanced Thematic Mapper (ETM+) (2005), and Operational Land Imager (OLI) (2015). The LULC maps include six classes (Anderson level I), viz., forest, scrubland, agriculture, waterbody, built-up land, and barren land (Fig. 1) (see Reshma et al. 2018 for more details about data preparation and classification). DEM data from the Shuttle Radar Topography Mission Digital Elevation Model (SRTM DEM; at 30 m resolution) (<https://earthexplorer.usgs.gov/>) was also used. Other topographic proxies such as slope and aspect were derived from the SRTM DEM data in the ARC GIS 10.3 environment.

Soil data: ISRIC soil-type data of 250 m resolution (Hengl et al. 2017) for the year 2016 were downloaded for the Eastern Ghats region (<https://www.isric.org/explore/soilgrids>). Additionally, the erosion, drainage, and flood capacity data of the region were obtained from the National Bureau of Soil Survey and Land Use Planning (NBSS&LUP 2002) for the year 2005.

Plant species data: The dataset of the national-level project “Biodiversity Characterization at Landscape Level” (Roy et al. 2012) was used, along with data from additional sampling points of field visits to the Eastern Ghats carried out during the year 2017–2018. The sampled plant species were categorized as endemic or RET species according to the IUCN Red List. Among the total of 1598 species recorded from the ground-sampled points, 22 endemic species and 28 RET species were identified. The endemic species were recorded at 295 locations, and the RET species were recorded at 799 locations.

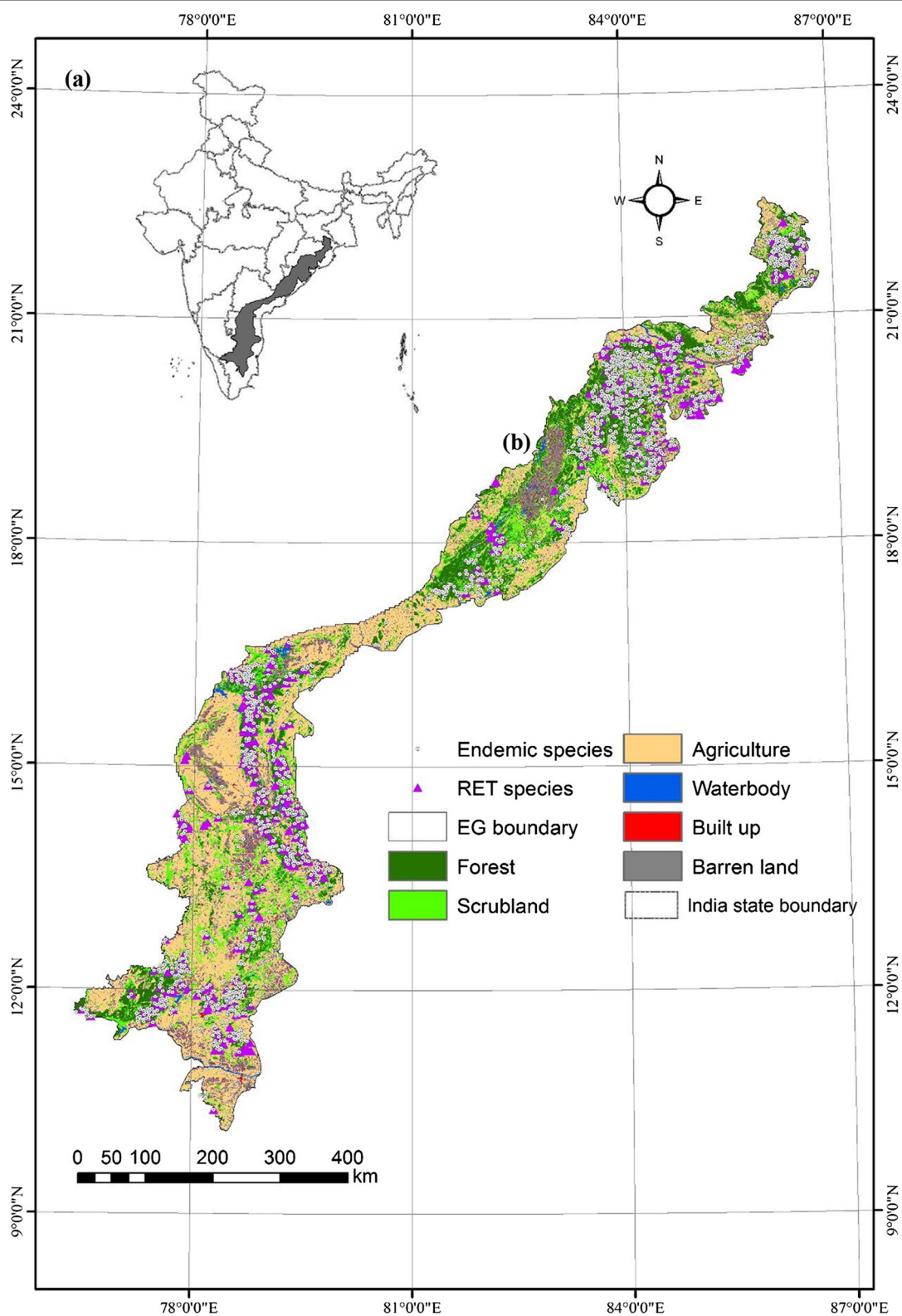


Fig. 1 (a) Location of Eastern Ghats; (b) land use land cover map of Eastern Ghats for 2015 showing sampling locations of endemic and RET species

Climate data: Current and future bioclimatic variables of WorldClim Version 1.4 (<http://www.worldclim.org/>) were used (Table 1) in the analysis. IPCC AR5 scenarios (IPCC 2014) were used for future simulations. These scenarios include one stringent mitigation scenario (RCP2.6), two intermediate scenarios (RCP4.5 and RCP6.0), and one scenario with very high levels of greenhouse gas emissions (RCP8.5) (IPCC 2014). 1 km × 1 km grid cells were allocated to the dependent variable with the highest likelihood of prediction.

Climate scenario interpretations: RCP2.6 indicates that emissions will peak by 2020 and then decline to near zero by 2080, which may result in a radiative forcing of around 2.6 W/m² in the middle of the century and then decline afterwards (van Vuuren et al. 2011). RCP2.6 makes most suitable scenario for croplands, wherein the increase in extent is faster than current trends, with the grassland area unchanged and forest vegetation declines compared to current trends. RCP4.5 stabilizes the radiative forcing at 4.5 W/m² in the year 2100, after which there is no further increase (Thomson et al. 2011). RCP4.5 suggests decline in the crop and grassland areas and an increase in the area under natural vegetation through accelerated reforestation. RCP6.0 stabilizes the radiative forcing at 6.0 W/m² in the year 2100, without any further increase (Masui et al. 2011). The stabilization mainly happens because of the changes in the short-lived species and LULC. This makes the current cropping area trend continue, but the extent of grasslands will reduce alarmingly, with the natural vegetation showing a trend similar to that of RCP4.5. RCP8.5 stabilizes the radiative forcing at 8.5 W/m² in 2100 under the conditions of a large population and slow income growth (Riahi et al. 2011). This scenario makes the land use continue at the current trend, with crop and grassland areas increasing and forest cover decreasing. Future climate projections from the output of 10 global climate models (GCMs) (Table 2) from the fifth phase of the Coupled Model Inter-comparison Project (CMIP5) (Collins et al. 2011) were used. Ten GCMs were chosen in order to get the full range of variation in the models in CMIP5, which is a multi-model ensemble.

Simulating future populations

We have used the compound rate growth method (Eberhardt 1987) to simulate populations at different time periods. Estimation of annual population growth

Table 1 The bioclimatic variables used in the study (adapted from <http://www.worldclim.org>)

Code	Variable
BIO1	Annual mean temperature
BIO2	Mean diurnal range (mean of monthly (maximum temperature–minimum temperature))
BIO3	Isothermality (BIO2/BIO7) × 100
BIO4	Temperature seasonality (standard deviation × 100)
BIO5	Maximum temperature of warmest month
BIO6	Minimum temperature of coldest month
BIO7	Temperature annual range (BIO5–BIO6)
BIO8	Mean temperature of wettest quarter
BIO9	Mean temperature of driest quarter
BIO10	Mean temperature of warmest quarter
BIO11	Mean temperature of coldest quarter
BIO12	Annual precipitation
BIO13	Precipitation of wettest month
BIO14	Precipitation of driest month
BIO15	Precipitation seasonality (coefficient of variation)
BIO16	Precipitation of wettest quarter
BIO17	Precipitation of driest quarter
BIO18	Precipitation of warmest quarter
BIO19	Precipitation of coldest quarter

rate is essential for simulating future populations. The annual population growth rate provides the change in population size as a function of time, which enables to better simulate the population growth or decline for future years. To start with, the annual growth rate of population was computed at two points of time (say 2001 and 2011), using the formula

$$R = \left[\left(\frac{P_n}{P_0} \right)^{\frac{1}{n}} - 1 \right] \times 100$$

where R = annual rate of growth; P_0 = population in the base year (2001); P_n = population in the current year (2011); and n = number of intermediary years (10).

The annual growth rate obtained from the total populations of the years 2001 and 2011 was used to simulate the population of the Eastern Ghats in the year 2050 using the equation

$$P_n = P_0 \left(1 + \frac{R}{100} \right)^n$$

Here, P_n stands for the projected population.

Table 2 Description of global climate models (GCMs) used in the study

Global climate model	Institutions	Original resolution (°)	Description
BCC-CSM1-1	Beijing Climate Centre, China	2.81×2.77	Fully coupled global climate–carbon model including interactive vegetation and global carbon cycle, in which the atmospheric, ocean, land, and sea ice components are fully coupled and interact with each other through fluxes of momentum, energy, water, and carbon at their interfaces (Wu et al. 2014)
CCSM4	National Centre for Atmospheric Research, USA	0.93×1.25	Composed of four separate models simultaneously simulating the earth's atmosphere, ocean, land surface, and sea ice and one central coupler component (Gent et al. 2011)
GISS-E2-R	NASA-Goddard Institute for Space Studies, USA	2.00×2.50	Includes fully interactive chemistry related to ozone in historical and future simulations, and interactive methane in future simulations (Schmidt et al. 2014)
HadGEM2-ES	Met Office Hadley Centre, UK	1×1	Comprises underlying physical atmosphere, ocean, and earth system components such as terrestrial and ocean carbon cycle and tropospheric chemistry. Terrestrial vegetation and carbon are represented by the dynamic global vegetation model TRIFFID, which simulates the coverage and carbon balance of five vegetation types (broadleaf tree, needle leaf tree, C3 grass, C4 grass, and shrub) (Martin et al. 2011)
IPSL-CM5A-LR	Institut Pierre Simon Laplace, France	1.87×3.75	Includes an interactive carbon cycle, a representation of tropospheric and stratospheric chemistry, and a comprehensive representation of aerosols (Dufresne et al. 2013)
MIROC5	Atmosphere and Ocean Research Institute, The University of Tokyo, Japan; National Institute for Environmental Studies, Japan; Japan Agency for Marine-Earth Science and Technology	1.40×1.40	It is a Coupled atmosphere model (which is based on a global spectral dynamical core) ocean model (which includes a sea ice model) and its coupled with a land model (that includes a river module) (Watanabe et al. 2010).
MIROC-ESM	Japan Agency for Marine-Earth Science and Technology; Atmosphere and Ocean Research Institute, The University of Tokyo; National Institute for Environmental Studies	2.81×1.77	The atmospheric component is coupled with the land module; it also has an aerosol transportation model, a terrestrial ecosystem component called the spatially explicit individual-based dynamic global vegetation model, and an ocean ecosystem component (Watanabe et al. 2011).
MIROC-ESM-CHEM	Japan Agency for Marine-Earth Science and Technology; Atmosphere and Ocean Research Institute, The University of Tokyo; National Institute for Environmental Studies	2.81×1.77	An atmospheric chemistry-coupled version of MIROC-ESM (Watanabe et al. 2011)
MRI-CGCM3		1.13×1.13	

Table 2 (continued)

Global climate model	Institutions	Original resolution (°)	Description
	Meteorological Research Institute, Tsukuba, Japan		Composed of atmosphere–land, aerosol, and ocean ice models. Atmospheric component is interactively coupled with aerosol model to represent direct and indirect effects of aerosols with a new cloud microphysics scheme (Yukimoto et al. 2011)
NorESM1-M	Uni Research AS; Bjerknes Centre at the University of Bergen; Centre for Intern Climate and Environmental Research; Norwegian Meteorological Institute; Department of Geosciences, University of Oslo; Norwegian Computing Centre; Norwegian Institute for Air Research; Norwegian Polar Institute	2.5×1.875	Based on the CCSM4, it differs from CCSM4 by an isopycnic coordinate ocean model and advanced chemistry–aerosol–cloud–radiation interaction schemes (Bentsen et al. 2013).

Future LULC simulations

Artificial neural network-based models have been used extensively for LULC simulations (Pijanowski et al. 2002; Kavzoglu and Mather 2010). In the present study, we have used a Monte Carlo cellular automata (CA)-based artificial neural network (ANN) that can simulate land use dynamics more realistically owing to its ability to handle nonlinear systems and simulate multiple land use changes (Pijanowski et al. 2014). Future LULC in the Eastern Ghats simulations were carried out using the Modules for Land Use Change Evaluation (MOLUSCE) version 3.0.13 plugin (<https://plugins.qgis.org/plugins/molusce/>) in Quantum GIS version 2.18.13, developed by Asia Air Survey Co. Ltd. The model uses raster LULC categories for two time periods (past-2005 (t) and present-2015 ($t+1$)) and raster files of explanatory variables or factors (Fig. S1). The model was trained using the CA model approach to predict the LULC changes from the past to the present. Finally, the ANN was used to predict the future LULC (for the years 2025 and 2050) using the derived mode, the current LULC, and current factors. The kappa statistics (Pontius 2000) (standard kappa, kappa histogram, and kappa location) was used to validate the accuracy of the simulated LULC maps. A total of 14 driving factors derived from the original datasets (Table 3) were normalized and used to estimate the occurrence of each LULC class in 2025 and 2050, including the past (2005) and the present (2015) LULC patterns,

topographic factors (elevation, aspect, and slope), social factors (population, population density, location of city, villages, railroad and water networks), climatic and environmental factors (soil parameters, temperature, and precipitation) and future climate factors (temperature and precipitation as per the RCPs) (Fig. S2). All the spatial datasets were resampled to a cell size of 250 m so as to bring them to the same resolution. A flowchart explaining the steps is shown in Fig. 2.

Simulation of potential plant species distributions

The future potential distributions of endemic and RET species were simulated using the well-known maximum entropy bioclimatic modeling technique (MaxEnt v3.3.3j) (Phillips et al. 2006). MaxEnt is one of the most widely used SDM algorithms for bioclimatic modeling owing to its high predictive accuracies even when the data are limited (Elith and Leathwick 2009). Since MaxEnt follows a correlative approach, the model seeks a correlation between species occurrence and environmental variables to predict the relative suitability of habitats (Phillips et al. 2006). MaxEnt has been used in different regions to model the distributions of one or multiple species (Elith et al. 2011). To project the future (2050 and 2070) potential distributions of endemic and RET species in a 1 km $\times$ 1 km grid, all the climatic and environmental datasets were resampled at a 1 km resolution to make sure that all the layers were at the same resolution and extent. A list of all the bioclimatic

Table 3 Details of datasets used for the land use land cover projections

Category	Data	Year	Resolution	Data source
Land class	Land use and land cover data	1995, 2005, 2015	30 m	Reshma et al. (2018)
Anthropogenic influence	Population	2001, 2011	Tabular	http://www.censusindia.gov.in , Census of India (2001, 2011)
Topography	Population density	2005–2070	250 m	Projected using 2001 and 2011 data
	Elevation	2000	30 m	https://earthexplorer.usgs.gov , USGS SRTM data (2015)*
	Slope			
	Aspect			
Soil	Drainage	2000	Vector	NBSS&LUP, India (2002)**
	Erosion			
	Flooding			
	Annual precipitation	2005–2050	1 km	http://www.worldclim.org , WorldClim version 1.4
Social	Annual temperature			
	Distance to waterbodies	2015	Vector	https://www.openstreetmap.in , OpenStreetMap
	Distance to transport networks			
	Distance to city			
Plant sample	Distance to villages			
	Plant species data	2005, 2017, 2018	Vector	Roy et al. (2012), field inventory

*United States Geological Survey Shuttle Radar Topography Mission (USGS SRTM)

**National Bureau of Soil Survey and Land Use Planning (NBSS&LUP)

variables used in the study is shown in Table 1. The correlation between all the variables (for all GCMs) was checked prior to modeling. The ensemble of these 10 models was used for the projections. MaxEnt was run for both present and projected climate change scenarios for endemic and RET species. The model was set up in such a way that the effects of climate and LULC changes can be assessed independently. To achieve this, MaxEnt was run initially with climate variables (this run is referred to hereafter as simulation I). Then it was run with climate, topographic, and edaphic variables (simulation II), after which it was run by integrating all the factors, such as climate, topographic, edaphic, and LULC variables (simulation III). This process was repeated for both endemic and RET species for all the 10 GCMs. The Pearson's correlation coefficient between the species distributions of similar RCPs was determined for each GCM to compare the spatial correlation between the outputs of different GCMs for the same scenarios.

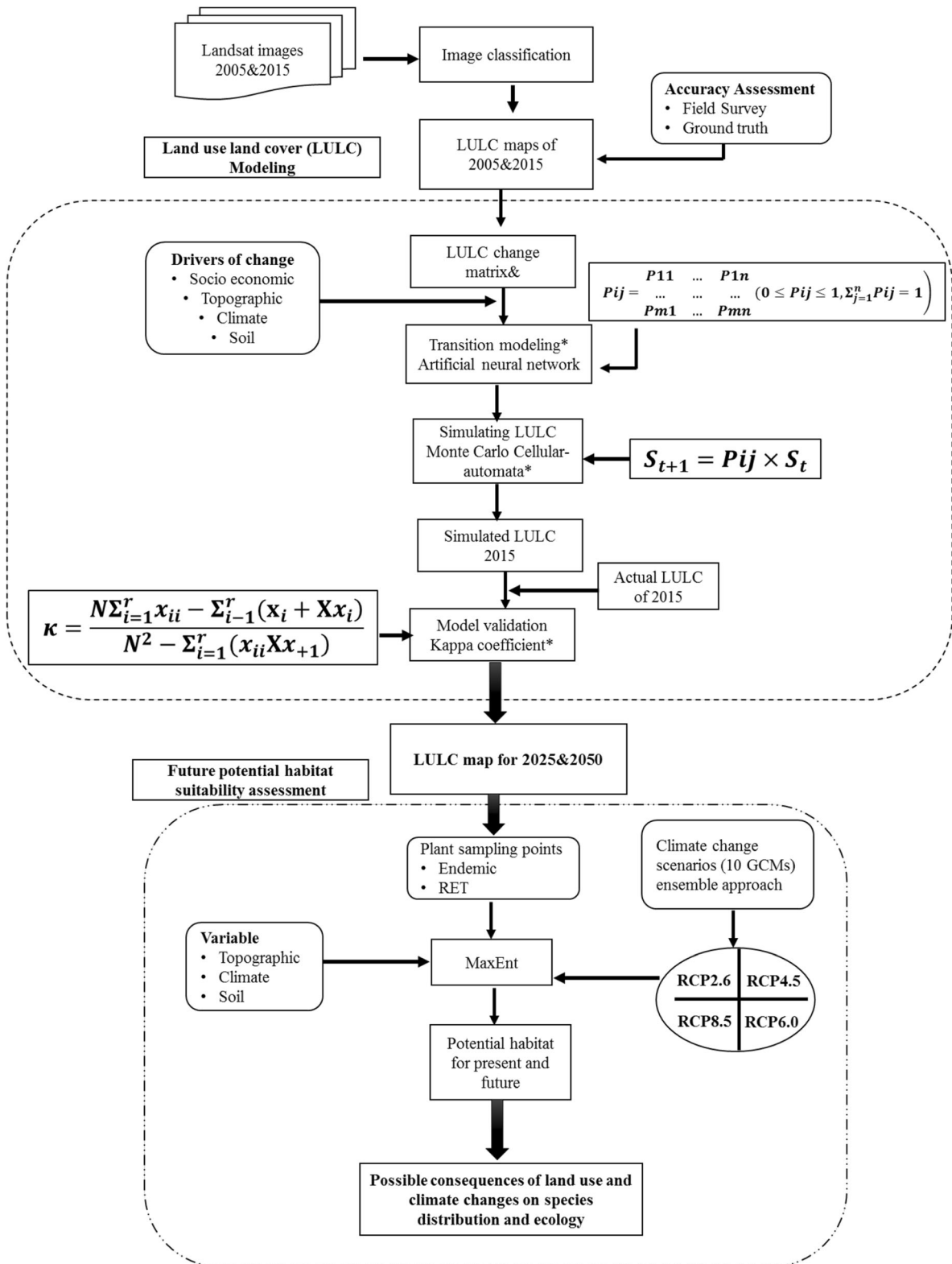
Analysis of changes in habitat suitability

To check the percentage area changes under different climatic conditions of present and future for

endemic and RET plant groups, the modeled species distributions were categorized into five thresholds according to the sensitivity, in the range between 0 and 1. The threshold classes were as follows: extremely suitable (> 0.7), highly suitable ($0.6–0.7$), moderately suitable ($0.5–0.6$), less suitable (< 0.5 to > 0), and unsuitable (0). A value close to 1 indicate that a region is highly suitable for the occurrence of a species, whereas, regions with values close to or equal to 0 are not suitable (i.e., the species may become vulnerable to climate change and LULC change).

We have mainly focused mainly to observe the changes and range expansion or contraction of potential habitats in relation to the present condition for both the

Fig. 2 Flowchart of methodology adopted to assess the impact of land use/land cover and climate changes on forest ecosystem services. Note: P_{ij} is the probability of change of land use i to j ; m and n are the number of land use types. $St+1$ and St are the states of land use at given times $t+1$ and t , respectively (Arsanjani et al. 2013). r = number of rows and columns in the error matrix, N = total number of observations (pixels), X_{ii} = observation in row i and column i , X_{i+} = marginal total of row i , and X_{+i} = marginal total of column i (Congalton 1991)



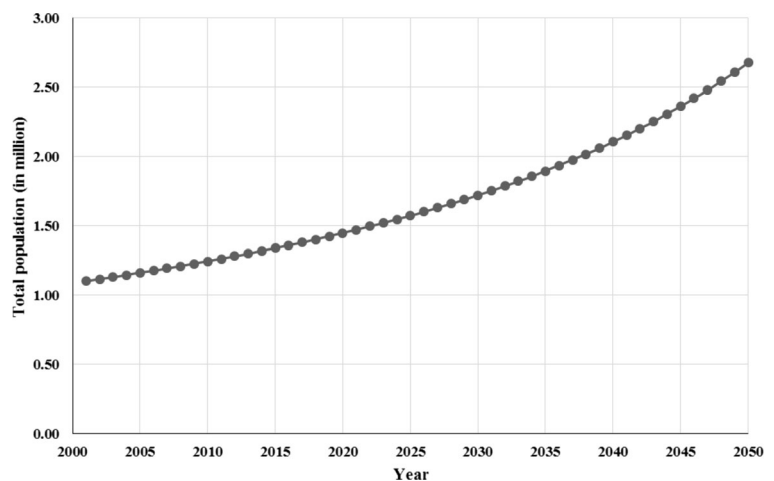
plant groups under four RCPs. When there is no change in the potential habitats in the future projections, it indicates that under changing environmental factors the species in the raster cell under consideration would still be located in its climatic niche in 2050 and 2070. The expansion and contraction of a range in future projected habitats indicate an increase and decrease of the habitat area of a given species in both present and future. On the other hand, a range expansion indicates that the habitat of a species does not occur currently but is predicted to occur in 2050 and 2070. Similarly, a range contraction indicates that the available habitat will shrink to the desirable areas under the constraint of future environmental conditions. The negative and contracted areas are the parts where the occurrence of the species is severely threatened. These areas are considered unsuitable regions for the species.

Results

Trends in future populations

The simulations were run assuming that the annual population growth of 1.01 of the past 10 years (2001–2011) will continue. According to the 2011 census, the total population in the Eastern Ghats was 1.2 million. The population simulation shows that by 2050 the total population in the Eastern Ghats would increase by 1.12% over that of 2011 (Fig. 3). The total population is expected to reach 2.6 million by 2050.

Fig. 3 Projections of total population in the Eastern Ghats



Simulated land use and land cover of Eastern Ghats

The simulated CA model for LULC for 2015 was validated on the basis of the kappa statistics as well as a comparison of each pixel of the simulated LULC types with the actual LULC data (Table 4). The kappa statistics (value of 0.91) and the overall accuracy (greater than 91%) suggest that there is a good agreement between the predicted and the actual values of the LULC types of the base year. As shown in Table 4, the difference in area between the two maps (actual and simulated) for the year 2015 indicates that all the LULC classes have errors less than 5%. Table 4 shows the trend of the spatial distribution of LULC changes in the years 2005, 2015, 2025, and 2050. The spatial pattern analysis (Fig. 4) shows a clear spatial change in LULC throughout the study period. The current trend shows that the agricultural land continues to be the dominant land class in the Eastern Ghats. The proportion of built-up land was 1.71% in 2015, 1.74% in 2025, and 1.81% in 2050. By 2050, the proportion of built-up land is likely to expand and spread out to other parts of the region (Fig. 4, Table 4). From the temporal pattern analysis (Table 4), it was found that in 2015 the area under forest, agricultural land, scrubland, water bodies, built-up land, and barren land was 27.57%, 46.48%, 15.81%, 2.50%, 1.81%, and 5.94%, respectively, of the total landscape of the Eastern Ghats.

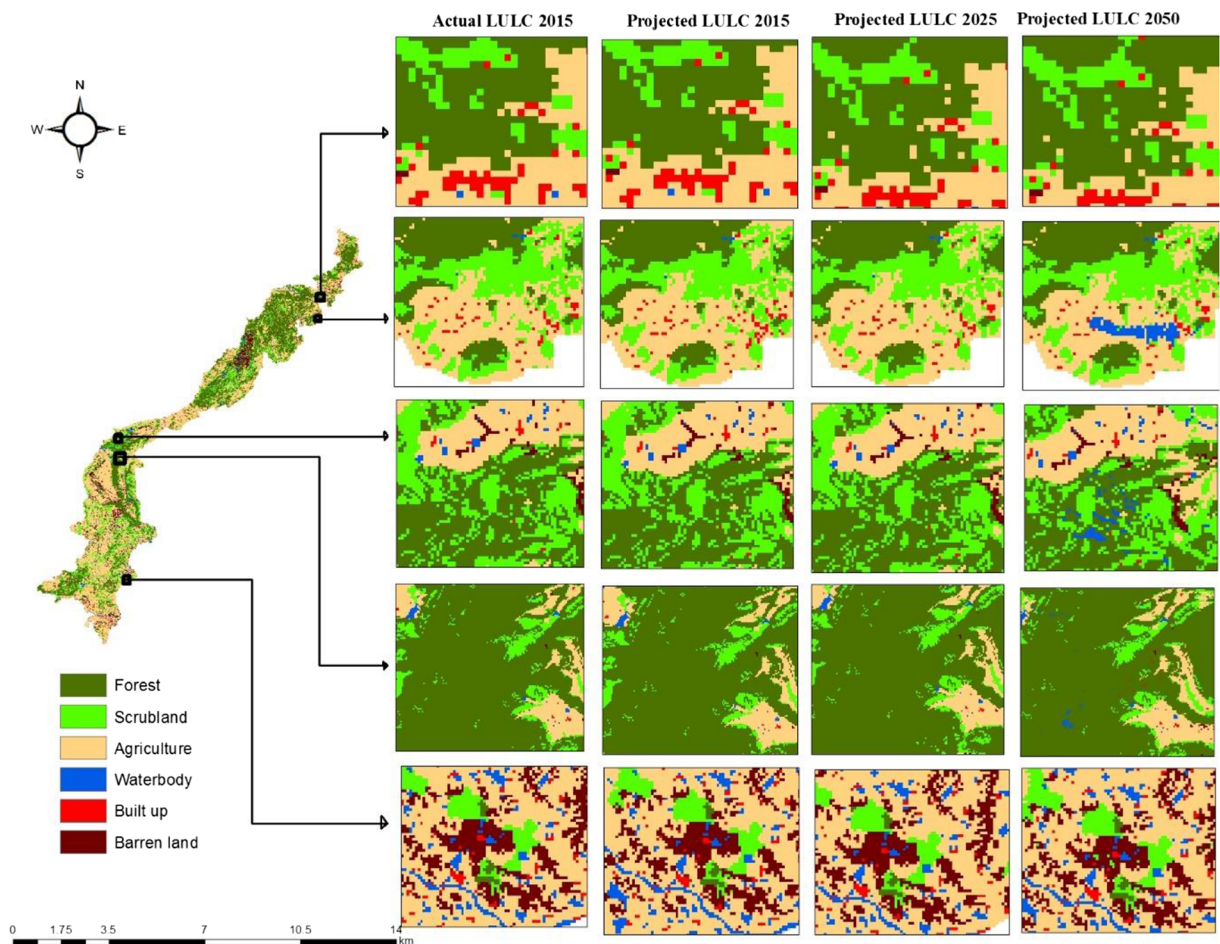
Overall, agricultural land (~46%) is the dominant land class (Fig. 1), followed by forest (~27%). Furthermore, the projected LULC of Eastern Ghats for 2050 indicates that the overall forest cover would decrease by 0.17% compared to the year 2015. Agricultural land will increase by 0.04% in 2050 compared to what it was in

Table 4 Areas under the LULC classes in 2005, 2015, 2025, and 2050

LULC class	Actual area				Simulated area					
	2005		2015		2015		2025		2050	
	(km ²)	(%)	(km ²)	(%)	(km ²)	(%)	(km ²)	(%)	(km ²)	(%)
Forest	60,723.65	27.59	60,680.33	27.57	60,601.93	27.54	60,540.38	27.51	60,296.71	27.4
Scrubland	34,824.93	15.82	34,788.62	15.81	34,825.02	15.82	34,801.08	15.81	34,745.85	15.79
Agricultural land	10,2708.47	46.67	102,289.09	46.48	102,804.88	46.71	102,416.3	46.54	10,2384.8	46.52
Waterbodies	5338.82	2.43	5497.44	2.5	53,04.26	2.41	5443.817	2.48	5571.29	2.53
Built-up land	3665.7	1.67	3756.9	1.71	3665	1.67	3750.33	1.74	3989.56	1.81
Barren land	12,818.42	5.82	13,067.95	5.94	12,879.18	5.85	13,127.62	5.96	13,092.18	5.95

2015. Waterbodies will increase by 0.03% in 2050 (Fig. 4). Scrubland would decrease by 0.02%. On the other hand, built-up land increases from 1.71% in 2015 to 1.81% in 2050. The population growth significantly

affects the land use and land cover pattern in the Eastern Ghats. The demand for land will increase for human needs such as food, development etc. which ultimately leads to the encroachment of land in different regions of

**Fig. 4** Temporal land use land cover maps (enhanced window) of the Eastern Ghats for 2015 (actual and predicted), 2025, and 2050

Eastern Ghats. Due to broken chain like physiography the encroachment will be high in all the parts of Eastern Ghats. Although urban expansion is likely be slower, but the after effects due to urban expansion would be certainly high. On the other hand, the area under barren land would increase by 0.01% in 2050 (Table 4). The left out agricultural lands increase the chances of land conversion to barren land. Along with it the soil erosion and leaching out of nutrients from soil also trigger the development of barren lands.

AUC and species distributions

The scores of the area under the curve (AUC) of the modeled outputs were determined to ensure the best fit. The scores under the present conditions of endemic and RET species were 0.89 and 0.79 in simulation I, 0.92 and 0.81 in simulation II, and 0.93 and 0.82, respectively, in simulation III. The average AUC scores of the 10 GCMs (standard deviations (SDs) have been given) were computed for 2050 and 2070. The average AUC scores for endemics and RET species in 2050 were 0.90 (0.005 SD) and 0.799 (0.004 SD) in simulation I. In simulation II, they were 0.91 (0.002 SD) and 0.82 (0.003 SD), respectively. In simulation III, the AUC scores increased to 0.93 (0.004 SD) and 0.83 (0.002 SD) (Fig. 5), respectively.

The AUC scores of the endemics and RET species for 2070 were 0.90 (0.003 SD) and 0.799 (0.003 SD), respectively, in simulation I. In simulation II, they were 0.92 (0.003 SD) and 0.81 (0.002 SD), respectively. In simulation III, the AUC scores were 0.93 (0.002 SD) and 0.83 (0.001 SD), respectively. These findings reveals that simulation I explains the potential distribution better in terms of climatic factors and the second model provides a better explanation of the combined impacts of the changes in climate and LULC on the potential distributions of species. The AUC scores of the endemics and RET species are shown in Fig. 5a and b.

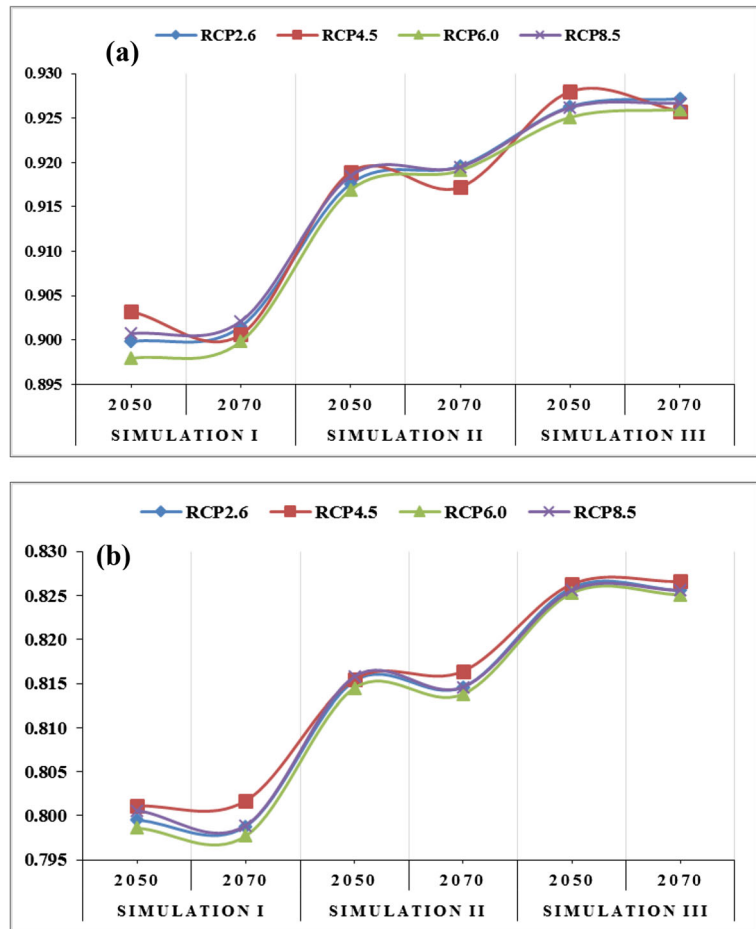
Spatial and temporal changes in potential species distributions under changing climate and LULC

Endemic species were mostly distributed in the core areas of forests and thus had restricted distributions. Potential distributions were observed in Similipal, the Kalahandi ranges, the Mahendragiri hill ranges, the Nallamalai-Seshachalam hill ranges, the Kolli and Kalrayan hill forests. There was a large reduction of

the habitats of endemic species, particularly in the core areas of forests (Fig. S3). The potential distributions of RET species were significantly more extensive all over the Eastern Ghats. Specifically, they were found in Similipal, Gajapati District (Odisha), the Nallamalai-Seshachalam hill ranges, Satyamangalam, BR hills, and the Kolli and Kalrayan hill forests. RET species were distributed not only in the core areas of forests but also in the areas adjoining forests and in the periphery of the forests (Fig. S4). Therefore, the influence of anthropogenic activities on RET species will be greater than that on the endemics. Further, the LULC has reduced the spatial distribution of RET species. There were increases and decreases in the suitability of habitats in all the regions of the Eastern Ghats in all the four scenarios. But the changes in the northern region were more dynamic compared with the other parts.

The ensemble values of the areas under different suitability classes of different scenarios from 10 GCMs were analyzed to estimate habitat loss (area reduction). In general, simulation III shows significant decreases in area compared to simulations I and II (see Supplementary Tables 1 and 2). There is a strong shift in the species distribution ranges under the four climate scenarios (RCPs 2.6, 4.5, 6.0, and 8.5). Under the current conditions, 0.58% (simulation I), 0.67% (simulation II), and 0.30% (simulation III) of the area of endemics species falls within the extremely suitable class. In contrast, the highly suitable class shows a slight increase over the present. We found that the model under simulation I gives large area suitability for species occurrence. With the addition of the LULC component, there is an overall increase (15.79%) in the area of unsuitable class (Fig. 6a). However, simulations with climate variables alone have shown increase in the areas of all the suitability classes except the less suitable class. There is hardly any change the areas of highly and moderately suitable classes even after the addition of the LULC component. Interestingly, after adding the LULC variable in RCP2.6, the area of highly suitable class shows an increase of 0.04%, however, the area remains constant with RCP8.5. The percentage areas under less suitable and not suitable classes show an increase of ~6% under all RCPs. It indicates the habitat degradation/loss in the Eastern Ghats. The 2070 simulations also show a similar pattern except for an increase of the area of the highly suitable class under RCP4.5 (0.77% decline) and RCP6.0 (0.81% increase) (Fig. 6b).

Fig. 5 Area under the curve (AUC) of potential distributions of species. **a** Endemics. **b** RET species



In contrast, the RET group shows large decrease in the area of the extremely suitable habitat after the addition of LULC (Fig. 6). The percentage decrease in area is as follows: 0.06% (extremely suitable), 0.60% (highly suitable), 1.19% (moderately suitable), and 8.46% (less suitable). There is an increase of 9.60% of the nonsuitable area. The future simulation for 2050 retains the area under the extremely suitable class under all emission scenarios. In the climate-only case, the moderately suitable class shows a minor increase except under RCP6.0. The simulations for 2070 show drastic decrease in the areas comes under highly suitable, moderately suitable, and less suitable classes. The area under the extremely high suitable class shows an increase of ~0.01% under RCP2.6. The area under the nonsuitable class also show an increasing trend. In general, potential areas suitable for endemic and RET species are expected to decrease and the nonsuitable areas are expected to increase in the Eastern Ghats. The analysis shows

that the habitat loss of endemic and RET species will increase mainly due to LULC change.

Habitat suitability and influence of climatic and LULC variables on species distributions

Our results show that the habitat suitability of the investigated groups of plants is mostly influenced by LULC practices, slope, and soil characteristics. The influence of climatic variables on endemic species was significant when compared to RET species (see Tables S3 and S4). Temperature has a significant influence on the distributions of endemic species. Variables such as isothermality (15%), mean temperature of wettest quarter (6%), annual precipitation (7%), precipitation of wettest quarter (5%), precipitation of warmest quarter (4%), and precipitation of coldest quarter (7%) have the highest percentage contributions. In simulation I, slope contributes more than 25% for simulating the habitat suitability of

endemic species. Slope is one among the major factors controlling the availability of sunlight, water, soil nutrients, the wind and temperature in some ecosystems (Zeng et al. 2014). In simulation III, the contribution of LULC was found to be more than 45%. On the other hand, RET species distributions were more dependent on the geographic factors. For instance, the contribution of slope was around 50% in simulation II. Also, rainfall is the major influencing factor in defining the potential habitat of RET species. Bioclimatic variables such as mean temperature of wettest quarter, precipitation of wettest month, precipitation of wettest quarter, precipitation of driest quarter, annual precipitation, and soil parameters had a greater influence on RET species distributions (Table S4). In simulation III, more than 50% of the distributions were influenced by LULC.

The percentage contributions of the predictors vary with RCP for both the plant groups. Mean temperature of wettest quarter (4.8%) and precipitation of warmest quarter (6.3%) had significant contributions in the simulation III of

2050 for endemic species with RCP4.5. Precipitation of wettest quarter contributes 10% in RCP2.6. In case of simulation I, the isothermality and precipitation of wettest month had significant contribution of 15%. The percentage contributions of isothermality (16.6%) was 2 times higher than the precipitation of warmest quarter (7%) and the mean temperature of wettest quarter (9.4%) in 2050 with RCP4.5. The contributions of annual precipitation (9.9%) and precipitation of coldest quarter (9%) in 2050 with RCP6.0 were contributed equally. In 2070, with RCP2.6, the isothermality (16.7%) and precipitation of wettest month (2.6%) had significant contributions. In RCP4.5, mean temperature of wettest quarter (9.1%) had the highest contribution among other climatic variables. Whereas in RCP8.5, annual precipitation (8.2%) and precipitation of coldest quarter (10.1%) had significant contribution. In contrast, for RET species, in 2050, the contributions of mean temperature of wettest quarter with RCP4.5 (12.1%) and of contribution of precipitation of wettest month with RCP8.5 (9%) were high. In 2070, with RCP2.6, the

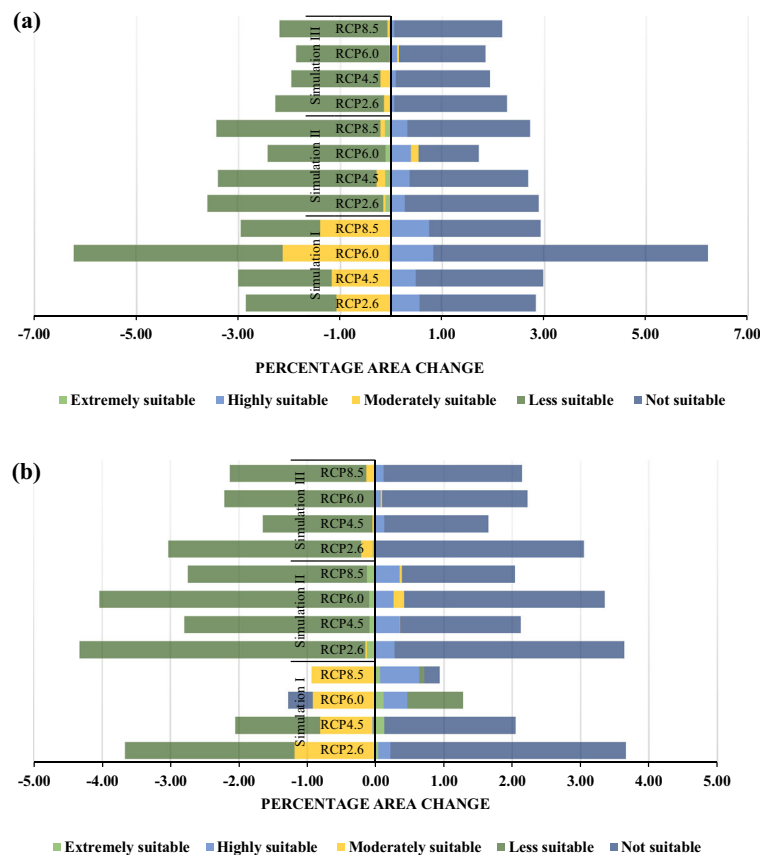


Fig. 6 Change of percent area of plant distributions from the present to the future. **a** Endemics, 2050. **b** Endemics, 2070. **c** RET species, 2050. **d** RET species, 2070

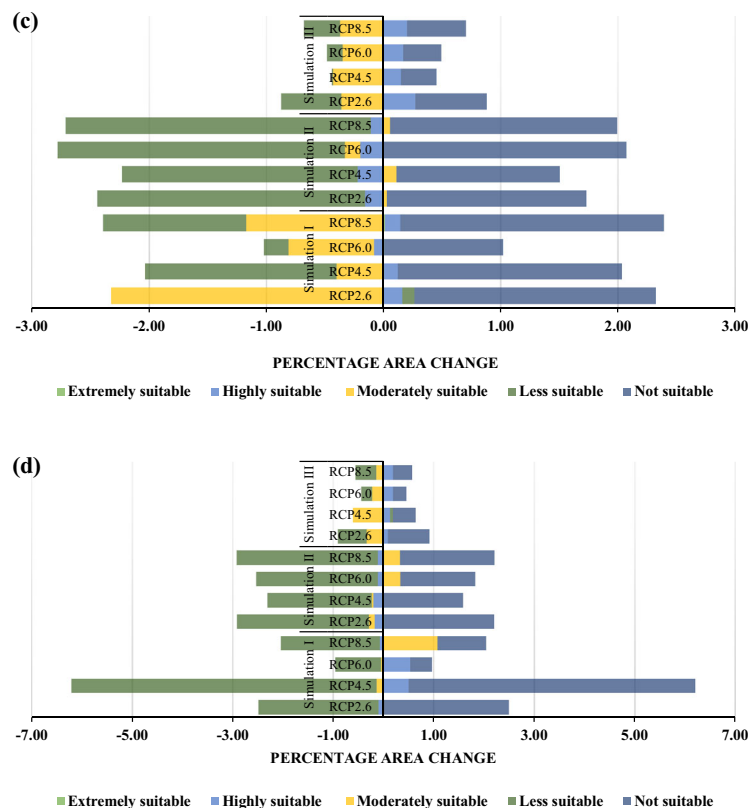


Fig. 6 (continued)

highest contributions were those of mean temperature of wettest quarter (9.6%) and annual precipitation (8.6%).

Discussion

Even though future simulations have many uncertainties, such studies can provide a means of obtaining species distributions, range shifts, and food production and help mitigation and adaptation planning. Simulations of populations, land use, climate, and species can provide an overview of the behavior and responses of different ecosystem processes under future conditions. Changes in the land system and climate due to human activities in the present era have important repercussions on natural systems (Venter et al. 2016), resulting in deforestation, habitat loss, species extinction, etc. Knowing global and regional trends will be helpful for effective management of the health of ecosystems. Focusing beyond 50 years is good for formulating sustainable plans and policies for the future (Vaidyanathan 2018). In the present study, we projected the population, LULC, and species distributions in a very

important biogeographic region of peninsular India, the Eastern Ghats. We have analyzed the possible impacts of climate and LULC on the distributions of two important groups of plants, namely endemics and RET species.

The changes in ecosystem due to population, LULC, and climate changes

Population growth in many parts of the world is leading to the degradation of natural resources (Forsyth 2017). India is the second most populous country in the world, with 1.21 billion people (Census of India 2011). The population of the Eastern Ghats was estimated to be 1.2 million in 2011 and is expected to reach 2.6 million by 2050, following a growth rate of 1.01 during 2001–2011. The world population of 7.3 billion is projected to increase to 8.5 billion by 2030, 9.7 billion in 2050, and 11.2 billion in 2100 (UN DESA 2017). By 2022, India will be the most populous country in the world (UN DESA 2017). The ungovernable population growth (with a current growth rate of 2.13%) may lead to high per capita consumption and lead to degradation

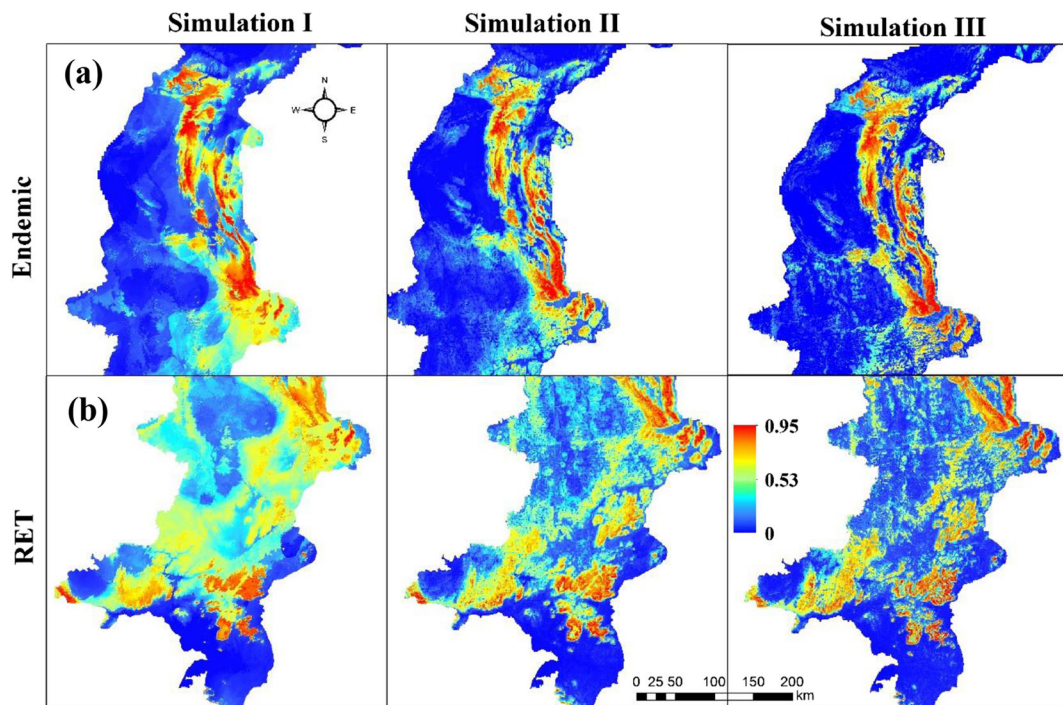


Fig. 7 The notable changes in species distributions due to climate, environmental, and LULC variables under present conditions. (a) Potential distributions of endemic species in the Nallamalai region

of Eastern Ghats. (b) Potential distributions of RET species in the southern Eastern Ghats

of natural resources, and high demands for land, food, and basic amenities (Alexandratos and Bruinsma 2012; d'Amoura et al. 2017). Projections of LULC in the Eastern Ghats indicate that there will be 0.14% decrease in the forest cover in 2050. This projection is supported by other studies. For example, d'Annunzio et al. (2015) projected a decrease in global forest cover by 2030, with a decrease rate of 0.26–0.19%. Projections of the built-up and barren land show an expected increase of the area by 0.14% in 2050 (Table 4). Transformation of forests in relation to population growth and urbanization in the tropics have been studied well (deFries et al. 2010; Seto et al. 2012; Browder 2002), and the Eastern Ghats are not an exception (Salghuna et al. 2018). Other factors such as mining, the need for agricultural land, and tourism are also accelerating the rate of deforestation in the Eastern Ghats. Our field studies revealed that people are using the forest extensively as a major source of firewood, medicinal plants, fodder, and for cultivation. The extent of agricultural land in the Eastern Ghats is expected to increase by 0.04% by 2050 in tropical

and subtropical Asia, agriculture is the main driver for forest loss (DeFries et al. 2010; FAO 2017), and 80% of the deforestation worldwide is caused by agricultural expansion (FAO 2017).

The climate plays an important role in the healthy functioning of an ecosystem. Studies of species–climate relationships help to understand the distributions of species and their responses to future climate change (Wieczynski et al. 2018). One of the most obvious and immediate responses to climate change is the increase in temperature. In the Eastern Ghats, the temperature is likely to increase by 1.8 °C (2050) to 1.98 °C (2070) above the present (Fig. S5), with a maximum temperature increase of 3.07 °C with RCP8.5 (2050). The rainfall is also projected to increase, by 113.53 mm (2050) and 160.65 mm (2070) above the present condition (Fig. S6). IPCC (2014) reports that the highest increase of the global temperature will be 2.6 to 4.8 °C, under RCP8.5 at the end of the twenty-first century (2081–2100). Changes in LULC intensify different emission drivers and influence the regional climate (Murphy and Ravishankara 2018).

The potential distributions of plant species under present and future conditions

The MaxEnt species distribution model simulates suitable habitats by combining bioclimatic and environmental variables. One can evaluate the threat factors and determine sites that are suitable for species from these simulations. The assessment of the extents of habitats in the future and threats are very important in the conservation of species and protecting the ecosystem. The supply of the services offered by forest ecosystems, direct (e.g., food, fodder) or indirect (e.g., pollination, climate change regulation), is generally determined by the diversity of the flora (as well as fauna) producing them (Hughes et al. 1998). Hence, changes in species' populations and distributions can have a substantial impact on an ecosystem.

A strong relationship has been observed between the potential habitat suitability of endemic and RET plants and changing climate and LULC in the Eastern Ghats. The changes in LULC and climate accelerate the reduction of suitable habitats in the future as well as in the present (Tyler et al. 2017). Similar studies (Manish et al. 2016) conducted in the Himalayan region have found potential habitat reduction in endemic angiosperm species under projected future climates. Changes in climate affect the endemic species more than they do for RET species. However, the RET groups are more vulnerable to LULC changes. Slope plays an important role in the distribution of both endemic and RET species in all cases. These are essential parameters for the development of microclimatic conditions, which are crucial for plant distributions (Feng et al. 2011; Shimono et al. 2010). The influence of temperature-related variables on habitat suitability is greater for endemic plants. Zeng et al. (2014) report that the increasing global temperature has had a strong influence on the growing period of *Populus euphratica*. In contrast, precipitation has played a key role in determining the distribution of potential habitats of RET plants. The studies of Abolmaali et al. (2018) on *Daphne mucronata* found that higher elevations and greater precipitation produce habitats that are unsuitable for this species. In the Eastern Ghats, high precipitation, or changes in precipitation and LULC affect the distribution of RET plants since those are major distribution factors. Areas with low elevations and high temperatures will be unsuitable habitats for endemic species. There are suitable habitats for both endemic and RET species in the high-elevation areas with less disturbance, preferably in the core forest areas. More changes could occur in the forest peripheries. The leaching out of soil nutrients due to increased precipitation

would also influence the distribution pattern. Since the distribution of endemic species is restricted, the chances of extinction are high in this group. Other species that are better adapted to environmental changes will occupy the place of these plants.

Conservation strategies for changing land use and climate

Forward-looking approaches with different scenarios and disturbance factors are very important for the effective management and conservation of biological diversity. For example, in the Eastern Ghats, the species distribution is highly impacted by land use changes (Fig. 7). Land use, environmental variables, and climate changes must be considered together with the current distribution of threatened species to determine the locations that are prone to high plant biodiversity losses. Our analysis shows that current and future distributions of species are mostly concentrated in the core areas. Hence, the edges of the forests and species found in the edge are more prone to threat. On concentrating these areas, we can better conserve species. Conservation strategies are largely dependent on the population and the economic activities in the area. The tropics, in particular countries near the equator, are losing more plant biodiversity than other regions of the world (Giam et al. 2010). The Eastern Ghats are being altered severely with commercial mining, logging, dams, and road widening. Also, the tribal population depends heavily on the vegetation for livelihoods. Community-based management programs are one of the best options for long-term conservation (Berkes 2007) of biological diversity. Species inventories, which identify and record species, in specific locations will also be of help in future conservation efforts (Corlett 2016).

Conclusions and recommendations

For the first time, we have reported the potential habitat loss of plants of conservation values in the Eastern Ghats using the RCPs recommended by IPCC AR5. The results of this study indicate that changes in the potential distribution of endemic and RET plant species in Eastern Ghats are significant in response to future LULC and climate change. The effects of these components on the plant distributions are varying with different ranges. The ANN and MaxEnt approach used in this study simulates changes

in the LULC and potential distribution of the bioclimatic habitat of plant species. This approach give a good idea about changes in the LULC and species habitat also predict future ranges of species. However, it is important to note that the simulated LULC changes are moderate; still they can have significant impacts on species' habitats and ranges. This will provide the magnitude and direction of change one may expect to observe in the distributions of species due to LULC and climate changes. The changes in species habitat change with endemic and RET species differently. The results of this study also indicate that the increase in population also has an impact on the LULC and potential habitat distribution of the plant species. The areas of future habitat of endemic species simulated by the model are restricted towards the core of the forests. However, the RET species habitat are vastly distributed all-over Eastern Ghats. The land use activities in the Eastern Ghats will severely restrict the suitable habitat of the species and its dispersal. In general, most of the drivers influencing the habitat loss are political, social, or individual decision making. Therefore, it is vital to provide decision makers at all levels with science-based information regarding potential impacts of their decisions on plant communities and human well-being. We recognize the need for carrying out future research using more localized ecosystem services and quantifying them. It is suggested that more detailed models integrating diverse drivers and localized LULC scenarios be utilized in the future, together with a greater number of case studies, in order to provide more accurate estimates as the basis for better-informed and more sustainable landscape decisions.

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