Decadal forest cover change in Jehlum Valley forest division of Kashmir Himalayas using remote sensing and GIS technique

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Thesis

Submitted to

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Master of Science in Forestry

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DEDICATED

To

My Late Grandmother

(May Allah grant her highest place in paradise)

Grandmothers hold our tiny hands for just a little while,

But our hearts forever

Sher-e-Kashmir
University of Agricultural Sciences & Technology of Kashmir
Faculty of Forestry

Certificate – I

This is to certify that the thesis entitled, **"Decadal forest cover change in Jehlum Valley forest division of Kashmir Himalayas using remote sensing and GIS technique"** submitted in partial fulfillment of the requirements for the award of the degree of **Master of Science in Forestry,** to the **Faculty of Forestry, Sher-e-Kashmir University of Agricultural Sciences & Technology of Kashmir** is a record of bonafide research work carried out by **Mr. Zaid Bashir Wani (Regd. No. 2015-For-50-M)** under my supervision and guidance. No part of the thesis has been submitted for any other degree or diploma.

It is further certified that any help or information received during the course of investigation has duly been acknowledged.

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We, the members of the Advisory Committee of **Mr. Zaid Bashir Wani (Regd. No. 2015-For-50-M),** a candidate for the degree of **Master of Science in Forestry** have gone through the manuscript of the thesis entitled, **"Decadal forest cover change in Jehlum Valley forest division of Kashmir Himalayas using remote sensing and GIS technique"** and recommend that it may be submitted by the student in partial fulfillment of the requirements for the award of the degree.

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This is to certify that the thesis entitled**, "Decadal forest cover change in Jehlum Valley forest division of Kashmir Himalayas using remote sensing and GIS technique"** submitted by **Mr. Zaid Bashir Wani (Regd. No. 2015-For-50-M)** to the **Faculty of Forestry, Sher-e-Kashmir University of Agricultural Sciences & Technology of Kashmir** in partial fulfillment of the requirements for the award of the degree of **Master of Science in Forestry** was examined and approved by the Advisory Committee and External Examiner on …………….

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ABSTRACT

Remote sensing (RS) and Geographic Information System (GIS) techniques have turned out to be effective tools for analyzing different alluded natural elements like vegetation cover, soil disintegration, and also urban development and all the more by and large, the varieties in the Landuse/Landcover (LULC) over some undefined time frame. The utilization of RS information as of late has been of gigantic help in checking the changing pattern of forest cover. Mapping of LULC and change detection utilizing RS and GIS procedures is a savvy strategy for evaluation of forest cover and forest density of an area.

The present investigation entitled, "Decadal forest cover change in Jehlum Valley forest division of Kashmir Himalayas using remote sensing and GIS technique" was carried out during 2015-2016. The change was analyzed for a period

of 10 years i.e., from 2005 to 2015. Landsat OLI and TM satellite images (of 30m resolution) of the year 2015 and 2005 were used. Mapping was performed on 1:50,000 scale using ArcGIS software, and for image enhancement ERDAS imagine software was used. Extensive ground truthing was employed to supplement accuracy assessment and a total of 133 ground truth points were taken for data collection. The overall classification accuracy of the mapping was 92.48% and the Kappa coefficient was 0.87. The study area was delineated via visual image interpretation technique into 10 LULC classes viz., forest, forest scrub, agriculture, grassland, snow, waterbody, horticulture, wasteland and agroforestry respectively. Forest cover density map was classified into three classes on the basis of crown density viz., closed forest, open forest, forest scrub. Furthermore, two additional classes grassland and non forest were also delineated. The results obtained from change analysis were used to identify the drivers of forest cover change using a close ended semi-structured interview schedule. The responses were assigned scores for ranking of drivers using statistical analysis.

The comparison of maps of 2005 and 2015 revealed that the total forest area has reduced by 0.48% from 2005 to 2015. The area under agriculture has declined by 0.87% during the same period. Horticulture has shown an increase of 0.8 % during the decade. It was also found that the area under closed forest reduced by 1.05% from 2005 to 2015 while as open forest, forest scrub and grassland has increased by 0.57 %, 0.27% and 0.08% respectively. In terms of area, conversion of closed forest into open forest (851.48 ha), closed forest into forest scrub (104.77 ha), and open forest into forest scrub (33.26 ha) ascribes to forest degradation whereas conversion of 111.42 ha, 59.87 ha and 26.61 ha of land from closed forest, forest scrub and open forest into non forest can be attributed to deforestation.

Statistical analysis of drivers of forest cover change for Jehlum Valley forest division in the nearby villages witnessing negative change as revealed from forest cover mapping, show poverty/lack of employment, illicit felling for timber and population growth as the top most ranked drivers. A small positive change at certain places around forest areas was also experienced as a result of two positive drivers viz., plantation/afforestation measures by the state forest department (SFD) and degree of forest protection. As a rule, the investigation uncovered that the forest cover of J V forest division has lessened in the most recent decade, the greater part of the forests are in corrupted condition. A check in timber pirating, tending to the issues of joblessness, afforestation and most elevated level of forest assurance can control facilitate corruption of the forests of the said division. There is a need to manage and follow up on the notable drivers by the concerned forest division in order to alter the course of deforestation and forest degradation in the study area.

Keywords: Landuse/Landcover, forest cover density, change detection, remote sensing, GIS, Landsat OLI, TM, Kappa, Jehlum Valley, afforestation.

Signature of Student

Dated: ___________

Signature of Major Advisor

Dated: ________________

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Place: Benhama, Ganderbal

Dated: Zaid Bashir Wani

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Abbreviations

ETM	Enhanced Thematic Mapper
FCC	False Colour Composite
FAO	Food and Agriculture Organization
FSI	Forest Survey of India
GIS	Geographical Information System
GPS	Global Positioning System
IRS	Indian Remote Sensing
Ha	Hectare
LISS	Linear Imaging Self Scanning
Km	Kilometer
LULC	Landuse/Landcover
MMU	Minimum Mapping Unit
NRSA	National Remote Sensing Agency
OLI	Operational Land Imager
RS	Remote Sensing
SDG’s	Sustainable Development Goals
SFD	State Forest Department
TM	Thematic Mapper
USGS	United States Geological Survey

Chapter-1

INTRODUCTION

There are barely any landscapes on the earth's surface that have not been altogether changed or are not being modified by people in some way. Mankind's existence on the earth and his change of the area has profoundly affected the common habitat (Yang, 2001). Land is one of the most essential natural assets, as life and numerous developmental activities are dependent on it (Jiya *et al.*, 2016). Forests all around the planet are facing tremendous pressure resulting in deforestation and degradation owing to the anthropogenic activities like urbanization and increase in farming practices. Forests are essential for life on earth. Three hundred million people worldwide live in forests and 1.6 billion depend on them for their livelihoods. Forests are the largest stores of carbon after oceans and provide habitat for 80 percent of the world's terrestrial biodiversity (FERN, 2017). Forests play crucial roles in accomplishing sustainable development goals (SDG's) such as poverty elimination, protecting and renovating water cycle, right to use sustainable energy and combating climate change (FAO, 2016). Forests are a profitable asset giving sustenance, protection, natural habitat, fuel and day by day supplies like medicinal ingredients and paper. Forests assume a critical part in adjusting the world's carbon dioxide (CO_2) supply and trade, acting as a key connection between the climate, geosphere and hydrosphere. With the present exhaustion of forested territories around the globe, it is vital that we deal with these renewable resources in a reasonable and sustainable way. Forest cover is defined as "All lands, more than one hectare in area, with a tree canopy density of more than 10% irrespective of ownership and legal status. Such lands may not necessarily be a recorded forest area. It also includes orchards, bamboo and palm" (FSI, 2011).

Forest management and new technology is interconnected as technology supports management procedures, consequently contributing towards worldwide forest resource management and protection (Beckline *et al*., 2017). The precise mapping and supervising of forests is crucial for the sustainable management of forest ecosystems (Pimple *et al*., 2017). Remote sensing (RS) systems have ended up being effective device for the examination of different alluded ecological elements like vegetation cover, soil disintegration, and additionally urban expansion and all the more for the most part, the variety in the Landuse/Landcover (LULC) over some undefined time frame (Deilami *et al*., 2014). The utilization of remote sensing and Geographic Information System (GIS) techniques provides an effectual scheme for monitoring temporal and spatial changes of land (Mohamed, 2017). Viewing earth from the space is currently essential to understand the impact of man's utilization of resources (Kiran, 2013).

Remote sensing offers a swift and cost efficient way of forest cover mapping to check deforestation (Francis *et al*., 2017). Satellite information has turned into a noteworthy application in forest change recognition on account of its remarkable scope. Forest cover today is modified basically by coordinate human use and any origination of worldwide change must incorporate the inescapable impact of human activities (Sajjad *et al*., 2015). An improvement in the Landsat satellite series has been very handy for a variety of forest mapping applications (Pimple *et al*., 2017). As demonstrated in their investigations general data about change is vital for forest cover maps and the management of common assets. Forest resource maps were generally arranged from forest inventories including aerial photography and fieldwork (Suhaili *et al*., 2006). However present day innovations, GIS approach and remote sensing (RS) from satellite platforms offer an option and economic device for forest mapping (Suhaili *et al*., 2006).

India has diverse physio-geographic regions because of its varying climate thus these diverse regions support varying forest types The total geographical area of India is 32,87,263 km^2 having recorded forest area of 701,673 km^2 which is 21.34 percent of the total geographical area of the country. The tree cover of the country is estimated to be 92,572 km^2 which is 2.82 percent of the total geographical area. The total forest and tree cover of the country is 794,245 km^2 which is 24.16 percent of the geographical area of the country (FSI, 2015). The forest cover as per different densities in India is given in Table 1 below.

Table-1: Forest cover of India

Class	**Area km^2**	**Percent of geographical area**
	Forest cover	
a) Very dense forest	85,904	2.61
b) Moderately dense forest	3,15,374	9.59
c) Open forest	3,00,395	9.14
Total forest cover	**7,01,673**	**21.34**
Scrub	41,362	1.26
Non forest	25,44,228	77.40
Total geographic area	**32,87,263**	100.00

Jammu and Kashmir state is one of the important regions of the world in terms of the forest wealth. Total geographical area of Jammu and Kashmir is 2,22,236 km^2 having recorded forest area of 20,230 km^2 which is 9.10 percent of the state's total geographical area and 2.65 percent of the total geographical area of the country respectively. The tree cover of the state is estimated to be 8,354 km^2 which is 3.76 percent of the total geographical area of the state. The total forest and tree cover of the state is 31,342 km^2 which is 14.10 percent of the total geographical area of the state and 3.95 percent of total geographical area of the country respectively (FSI, 2015). With the ever-increasing population of the state, forests have been placed under enormous pressure arising out of increasing demand for fuelwood, fodder, timber and other forest products including the minor forest produce (Wani *et al*., 2015). This has resulted in acute degradation of forest resources. Additionally the state forest cover hovering below 10% as reported by Forest Survey of India (FSI, 2015) is far from the target as envisaged under the state and national forest policy and indicates the level of anthropogenic pressure that the state's forests are going through. Hence, there is an immense need of assessing the forest cover and change detection.

1.1 Landuse/Landcover (LULC) and Forest cover mapping

The LULC pattern of an area is a result of standard and economic variables and their usage by man. Land is turning into a rare asset because of colossal rural and statistic pressure. Subsequently, data on LULC and conceivable outcomes for their ideal use is fundamental for the determination, arranging and execution of land use plans to meet the expanding requests for essential human needs and welfare. Additionally, this data helps in observing the progression of land use coming about out of changing requests of expanding population (Kiran, 2013). Although the terms Landuse and Landcover are frequently used conversely, their genuine implications are very unique. Landuse alludes to human exercises that happen on earth's surface (How the land is being utilized, for example, private lodging or farming) however Landcover alludes to the normal or man-made physical properties of the land surface (Tiwari and Kanduri, 2011). The basic objective of studying LULC changes is to explore the social, economic and spatial causes of changes so that suggestion can be given on the efficient use of land and patterns of development (Jiya *et al*., 2016).

India is one of only a handful couple of nations of the world to have a scientific and logical arrangement of forest cover appraisal. The forest cover mapping in India began in 1987 and from that point onwards consistent evaluation of forest cover is being carried out by Forest Survey of India (FSI). Presently, FSI is utilizing IRS P6, Resourcesat LISS III (Linear Imaging Self Scanning III) satellite data which has a resolution of 23.5 m. The forest cover mapping is being completed at 1:50,000 scale with a minimum mapping unit (MMU) of one hactare (FSI, 2015). Mapping forest cover in the current circumstances has picked up significance which is attributable to anthropogenic exercises like agribusiness, mining, deforestation and development (Yang, 2001). Quantifying forest cover change is a fundamental component of sustainable conservation planning. Hence examining forest cover change has turned out to be a key tool for forest management (Francis *et al.*, 2017).

With a specific end goal to build and implement proficient forest management approaches, it is essential to have dependable data about the LULC. LULC change has turned into a focal segment in current techniques for overseeing common resources and observing change. Since late 1960's, the quick advancement of the idea of vegetation mapping has prompted expanded investigations of LULC change around the world. Giving an exact appraisal of the degree and strength of the world's forests, grasslands and agricultural assets has turned into a vital need (Yang, 2001).

1.2 Change detection

Change detection frequently includes looking at aerial photos or satellite imagery of an area taken at various periods (Petit, 2001). The procedure is most of the time related with environmental monitoring, natural resource management or measuring urban improvement. Change detection, as defined by Hoffer (1978) is the temporal effects as variation in spectral response involves situations where the spectral characteristics of the vegetation or other cover type in a given location change over time. Singh (1989) described change detection as a process that observes the differences of an object or phenomenon at different times. Changes in forest cover are frequently the after effect of anthropogenic influence (e.g. population expansion) and natural factors like varying climate. Understanding landscape patterns, changes and associations between human exercises and natural phenomena are fundamental for legitimate land administration and decision enhancement (Prakasam *et al*., 2010).

LULC change discovery is basic process for better comprehension of landscape dynamic amid a known timeframe having practical administration. LULC change has been perceived as an imperative driver of natural change on all spatial and transient scales (Tansey *et al*., 2006). Changes may include the nature or force of progress however may likewise incorporate spatial (forest cover reduction at town level or for a vast scale agro industrial plant) and time perspectives. LULC changes additionally include the adjustment, either immediate or backhanded, of normal natural surroundings and their effect on the biology of an area (Rogan, 2004). Remote sensing innovation for determining the spatial information, GIS for undertaking coordinated investigation, introduction of spatial and related credit information are observed to be significantly more powerful to known the change recognition of LULC (Lillesand *et al*., 2001).

Change detection studies together with spatial analysis provide an efficient tool for scientists and policy makers for resourceful land management plans (Jiya *et al*., 2016). Recognizing changes using satellite information considers auspicious and dependable estimation of changes in the pattern of land use over an immense territory of land. In addition, it likewise empowers basic information into the GIS framework (Deilami *et al*., 2014). To identify change, an examination of at least two satellite images obtained at various intervals can be utilized to assess the transient reflectance contrasts that have happened between them (Lunetta and Elvidge, 1999). The satellite remote sensing is most appropriate for investigation of canopy closures (Roy and Pant, 1994).

1.3 Drivers of forest cover change

Primary drivers affecting forest alteration comprise of population explosion and varying food consumption patterns and agricultural advancements such as shifting markets, technological advancements and dynamic policy interventions; land-tenure security; and the governance of LULC change (FAO, 2016). Agriculture is the most significant driver of deforestation, yet with contrasts in geographic appropriation of the significance of commercial versus subsistence farming. For quite a long time the fundamental observation was that developing populaces of moving cultivators and smallholders were the principle driver of forest changes. All the more as of late, it is demonstrated that commercial actors play a bigger and expanding part in the development of agriculture into forests and for some nations commercial agriculture is predominant over subsistence farming (Boucher *et al*., 2011).

Drivers of forest change are divided into two types, proximate or direct drivers and hidden or indirect drivers. Proximate or direct drivers of deforestation and forest degradation are human exercises and activities that straightforwardly affect forest cover and result in loss of carbon stocks while basic or indirect drivers are mind boggling associations of social, monetary, political, social and innovative procedures that influence the direct drivers to cause deforestation or forest degradation (Kissinger *et al*., 2012). Recent remote sensing information combined with population and financial patterns delineates that agricultural production for local urban development and agricultural exports to different nations are the essential drivers of tropical deforestation (DeFries *et al*., 2010). Population expansion and population density are firmly interrelated with expanded interest for agricultural land, pressure on fuelwood, simpler access to remote forests because of framework improvement, land tenure arrangements, agro technological change and expanded interest for forest items (Rademaekers *et al*., 2010). Poor administration, degradation, low capacity of public forestry agencies, land tenure uncertainties and lacking natural resource planning/monitoring can be imperative underlying drivers of deforestation and forest degradation; for instance with respect to the implementation of forest policies and battling unlawful logging (Rademaekers *et al*., 2010).

Chapter-2

REVIEW OF LITERATURE

The outcome of previous studies forms the base for further scientific enquiry. Moreover review of related studies help us to conceptualize our research theme and to set research methodologies. Accordingly, the ensuing section gives a brief account of various studies conducted at National and International levels relating to the present theme. A lot of workers have made a significant contribution in the proposed field of study. Keeping in view the multiple perspectives of the study entitled, "**Decadal forest cover change in Jehlum Valley Forest Division of Kashmir Himalayas using remote sensing and GIS technique**" an account of literature was reviewed under different headings as given below.

2.1 LULC/ Forest cover mapping

Basavarajappa *et al.* (2017) conducted LULC mapping in Chamarajanagara Taluk of Karnataka using LISS-III satellite images in combination with Google Earth image through ArcGIS software and delineated the level 1, level 2 and level 3 LULC classes using both Digital Image Processing (DIP) and Visual Image Interpretation Techniques (VIIT) with partial Ground Truth Checks (GTC). In level 1 classification, the study area was delineated into six classes viz., Agricultural land, Built-up land, Forest, Wastelands, Water bodies and others respectively. These classes were delineated into further subclasses in level 2 and level 3 classifications.

Doke (2017) carried out LULC mapping of Konkan region, Maharashtra using multitemporal Landsat TM data and identified 8 LULC classes viz., dense forest, open forest, scrub, cropland, fallow land, wetland, settlement and water bodies respectively. Furthermore, he also reported that cropland occupied the highest area of 10814 km^2 (35.17%) of the total area whereas the lowest area of 678 km^2 (2.18%)

was occupied by settlement. Also, dense forest occupied second largest area 5653 km^2 (18.39%). Moreover, ground truthing was employed for evaluating the accuracy LULC analysis.

Francis *et al.* (2017) evaluated temporal and spatial forest cover changes in Udupi district of Karnataka between the years 1973 to 2016 and classified the study area into 11 LULC classes viz., dense forest, areca nut and coconut plantation, water body, built up land, fallow land, barren land, grassland, agricultural land, other vegetation, rubber plantation and sand soil. Landsat Multispectral Scanner (MSS), Landsat 5 Thematic Mapper (TM), Landsat 7 (ETM+), IRS (LISS III) and Landsat 8 Operation Land Imager (OLI) for the years 1973, 1981, 1991, 2003, 2012 and 2016 respectively was used.

Kara (2017) studied LULC pattern of Izmir Province, Turkey using 30 m spatial resolution Landsat images (OLI and TM) of 1986 and 2015 as the main data along with GIS and remote sensing procedures. The study generated a transition matrix for deducing change and used object-based image classification technique for creating segments before classification. An accuracy of 93% was reported. Furthermore, the study also revealed that main features of LULC change in study area were increase of area of impervious surfaces and decrease in natural areas such as forests and meadows.

Rwanga and Ndambuki (2017) studied LULC of Limpopo province and identified agriculture (4638 km^2), built up areas (1309 km^2), shrubs (499 km^2), mixed forest (372 km^2), water body (283 km^2) and barren/bare land (37 km^2) as the major LULC classes. Agriculture was reported as dominant Landuse type which occupied about 65.0% of the total study area. They obtained an overall classification accuracy of 81.7% and Kappa coefficient (K) of 0.722. Landsat 8 (OLI) images of 2015 were used to generate LULC map.

Ankana (2016) studied land and forest management by LULC analysis using remote sensing and GIS in Chakia tehsil and identified 4 LULC classes namely built up, agricultural land, forest and water bodies. IRS P6, LISS III (2004, 2013, 2014; Path 102, Row 54) were used for the preparation of the thematic map of LULC (2013 and 2014) and the changing pattern of land LULC during the last ten years (2004-2014).

Okoro *et al*. (2016) studied mapping of tropical Landcover change in Niger Delta, Nigeria for the time periods 1999-2005 and 2009-2015 using remote sensing and GIS. They identified and classified a total of five land-cover types namely water, built-up areas, cropland, forest and oil palm. The study also showed an increase of 280587.29 ha and 30626.86 ha in cropland and water whereas forest, oil palm and built up area showed a decrease of 92494.33 ha, 64366.92 ha and 154352.90 ha respectively. The proposed approach yielded an overall accuracy and Kappa coefficient of 70.33% and 0.62 for the first image composite period, and 84.5% and 0.80 for the second image composite period respectively.

Wani *et al.* (2016) studied multi-temporal (1980-2030) forest cover dynamics in Kashmir Himalayan region for assessing deforestation and forest degradation in the context of REDD+ policy and found out that about 126 km^2 and 139 km^2 of the study area (3375.62 km^2) experienced deforestation and forest degradation from 1980-2009. Furthermore, a positive change was also witnessed for a small area (23.31 km^2) while an area of about 1514 km^2 sustained no change. Landsat data Multispectral Scanner (MSS), Thematic Mapper (TM) and Enhanced Thematic Mapper (ETM+) were used for the years 1980, 1990 and (2001, 2009) respectively and change detection analysis between the dates was performed. Also ground truthing was used to authenticate maps.

Sajjad *et al.* (2015) studied application of remote sensing and GIS in forest cover change in tehsil Barawal, district Dir, Pakistan and applied supervised image classification technique on Landsat 5 satellite images of 2000 and 2012. They identified five main classes namely agriculture, forest, barren land, snow and water. The results showed that the area of forest, barren land, agriculture, water and snow in the year 2000 was 49.54 ha, 43.39 ha, 5.19 ha, 1.4 ha and 0.49 ha and area in the year 2012 was 37.17 ha, 41.46 ha, 12.69 ha, 5.05 ha and 3.72 ha respectively.

Wijayaa *et al.* (2015) studied assessment of large scale Landcover change classifications and drivers of deforestation in Indonesia and identified 23 LULC classes from land cover data, presenting spatial information of forests, agriculture, plantations, non-vegetated lands and other LULC categories.

Forest canopy density of Gir National Park was evaluated using remote sensing and GIS and satellite imagery was utilized to generate spatial data of forest density (Alam *et al.* 2014). It was found that approximately 63.5 percent of forest area was covered with forest canopy density of less than 10–40%, while 35.89 percent forest area was found with the density class of 40 to more than 70%.

Banerjee *et al.* (2014) estimated large area tree canopy density at spatial resolutions of 30 m coarse resolution satellite images and tested the Forest Canopy Density (FCD) model by using Landsat TM image in an old growth forest of north forest division of India. The overall classification accuracy and Kappa Coefficient was found to be 80% and 0.74 respectively.

Deilami *et al.* (2014) conducted a research to detect and monitor Landuse/Landcover change in Iskandar Malaysia using remote sensing and GIS. Four LULC classes namely forest, oil palm, urban and water body were identified and mapped. They also reported that forest cover and urban area had increased by almost 16.74% and 3.94% respectively whereas oil palm area decreased by almost 8.57%.

Wani *et al.* (2013) studied forest cover assessment and REDD+ opportunities in the southern region of Kashmir Himalayas using Landsat (MSS, TM and ETM+) data and generated forest type and density maps for the years 1980, 1992, 2001 and 2009 through visual interpretation of Landsat satellite data. Before generation of change matrices (1980-1992, 1992-2001 and 2001-2009) and inter-decadal change maps, the maps were subjected to accuracy assessment. The overall accuracy for 2009 map was observed as 90.04% with a Kappa coefficient of 0.84. Overall accuracy was found to be 89.06% for 2001, 88.28% for 1992 and 79.42% for 1980 with the respective Kappa coefficients observed as 0.84, 0.83 and 0.79. They also found that considerable portion of LULC was occupied by evergreen dense forests in 2009 comprising of about 24.81% of the classified area compared to 24.87% in 2001, 26.46% in 1992 and 27.15% in 1980. Whereas, 11.27% of the study area was occupied by evergreen open forests while as the same was about 11.62% in 2001, 11.38% in 1992 and 11.34% in 1980.

Rimal (2011) studied the application of remote sensing and GIS on Landuse/Landcover change in Kathmandu, Nepal and identified five LULC classes as Urban (Built-up), Water body, Forest area, Open field and cultivated land using supervised image classification. All Landsat images of Kathmandu city including Kathmandu Metropolitan and Lalitpur Sub-Metropolitan city (1976 MSS, 1989 TM, 2001 ETM+ and 2009 ETM+) were rectified through remote sensing. They also observed that Landuse statistics and transition matrices are important to analyze the changes of LULC maps of the Kathmandu Metropolitan with using IDRISI GIS.

Rikimaru *et al*. (2002) developed biophysical analysis model for obtaining FCD using Landsat TM data image analysis and identified four factors viz. vegetation, bare soil, thermal and shadow of FCD.

2.2 Change detection

Batar *et al.* (2017) examined the changes that took place between 1976 and 2014 in the forests of Garhwal Himalayan region in India. The study period was divided into two period's viz., 1st period (1976–1998) and 2nd period (1998–2014). They found out that in the 1st period (1976–1998), there was a foremost switch from forest cover (dense and open forest) to agriculture land (44.79 km^2), from forest to scrub land (25.33 km^2), from forest to barren land (5.86 km^2), and from forest to built-up area (2.18 km^2). Additionally, the 2nd period (1998–2014) showed a further major loss of forest cover (dense and open forest), being converted to agriculture land (39.8 km^2), scrub land (29.95 km^2), built-up area (4.13 km^2), barren land (3.51 km^2), and pasture land (5.13 km^2). Thus the study area registered a net loss of 122.35 km^2 in the forest cover during the two periods.

Chaudhary and Kumar (2017) analyzed the changes in LULC in Koshalya-Jhajhara (K-J) watershed from the years 1999-2000 to 2015-2016 by using Landsat (7 ETM+ and 8) data for mapping and monitoring. Nine LULC categories were identified viz., dense forest, open forest, scrub forest, built-up compact, built-up sparse, industry, cropped in 2 seasons, fallow land and water body. They reported that built-up had witnessed major change in the study area showing an increase from 7.12 km^2 to 24.84 km^2 between the years 1999 and 2016. In addition, they also reported that area under forest and agriculture had decreased from 109.35 km^2 to 96.78 km^2 and from 12.61 km^2 to 7.35 km^2 respectively.

Kumar (2017) monitored and assessed LULC change detection of Kamrup district, Assam between 1977-2010 using Landsat MSS, TM and ETM+ images of 1977, 1987 and 2010 and classified the map into six major categories viz., dense forest, open forest, agriculture land, urban settlement, water body and sand respectively. He reported that the original dense forest cover was about 29.08% (1335.42 km²) of the total mapped area in 1977 which was decreased up to 23.83% (1094.16 km²) in 1987 and 22.34% (1025.81 km²) in 2010. Also, the overall accuracy was 76.34% in 1977, 89.56% in 1987 and 92.34% in 2010.

Qamer *et al.* (2017) estimated forest cover loss in western Himalaya, Pakistan between the years 1990 to 2010 and found out that approximately 170,684 ha forest area had been lost during the study period. They also categorized forest into six forest cover classes (i.e., dense coniferous forest, sparse coniferous forest, dense mixed forest, sparse mixed forest, and sparse broadleaved forest) on the basis of canopy density and presence of species. Moreover, the study period was bifurcated into two periods 1990 to 2000 and 2000 to 2010. Thus forest cover maps of the years 1990, 2000 and 2010 were generated using Landsat data.

Shafiq *et al.* (2017) analyzed Landuse/Landcover change detection between the years 2002 and 2014 in Lolab watershed of Kashmir valley and delineated a total of seven LULC categories through visual image interpretation. The study revealed that the total area under agriculture was reduced by 1.04 percent during the study period while as horticulture showed an increase of 1.86 percent. Furthermore, area under forests was reduced from 45.31% in 2002 to 44.61% in 2014 with a decrease of 0.7%.

Jiya *et al.* (2016) studied change detection analysis of Aluva taluk using remote sensing and GIS and identified 8 LULC classes namely built up, agriculture, crop land, wasteland, forest evergreen, forest deciduous and plantations respectively.

The study showed an increase of 30.42 km^2, 29.47 km^2 and 15.84 km^2 in built up, crop land and plantations whereas a considerable reduction of 57.314 km^2 in forest area respectively. Multispectral satellite data of Landsat was used to map and monitor Landuse changes during the period of 2000 to 2010 and ERDAS imagine 9.2 were used for LULC classification.

Sarmin *et al.* (2016) studied Landcover dynamics of Sungai Pulai Mangrove Forest (SPFM) in Johor, Peninsular Malaysia between 2004 and 2014 using remote sensing and GIS. The overall accuracies calculated for the years 2004, 2009 and 2014 were 76%, 87% and 84% with Kappa coefficients as 0.71, 0.85 and 0.82 respectively. The study revealed a decrease of 2,498 ha of mangrove cover whereas an increase of 3,905 ha in other vegetation during the decade. The study also revealed that the main cause of reduction of mangrove cover was land conversion to new built up area and agriculture plantation such as oil palm.

Bhatt *et al.* (2015) investigated the use of remote sensing and GIS techniques for vegetation types and Landuse change detection in Chamoli district of Uttarakhand, India. The study revealed a reduction of 257.28 km^2 of forest from 1976 to 2006. The forest cover was 3966.40 km^2 in 1976 and in 2006 it decreased to 3709.12 km^2. They also found agriculture to wasteland observed a maximum change of 7767.00 km^2, followed by forest to agriculture 21.72 km^2, forest to wasteland 156.85 km^2 and forest to snow 80.35 km^2. Landsat MSS of 1976 and Landsat TM 2006 satellite remote sensing data and the US army topographic maps on 2:50,000 scale were used in the study.

Jovanovic *et al.* (2015) studied Landcover change detection in region of mountain Zlatibor (Serbia) during the period (1985 – 2013). The study revealed that area under forests was reduced to about 1000 ha while the built up area was doubled (grown about 600 ha) during the examined period. The results also highlighted the importance of change detection techniques in land cover for the rapidly developing areas. Vegetation indices differencing, supervised classification and object based classification were the methods used in the study for analyzing satellite images with the object of identifying Landcover change detection.

Kayet and Pathak (2015) studied remote sensing and GIS based Landuse/Landcover change detection mapping in Saranda Forest, Jharkhand, India and assessed LULC vicissitudes of the year 1992, 2005 and 2014 of the Saranda forest. They also employed statistics, matrix in the classification map, and calculated user accuracy for each class. GIS software (ArcMap) was employed to read the thematic maps and ground truth survey to carry out the classification and to check the accuracy. The result of the work showed lessening the dense forest area and the water bodies, quick expansion of built-up (mining area), wasteland, open forest, agricultural land.

Pandian *et al.* (2014) studied changes in LULC parts of Coimbatore and Tiruppur districts through remote sensing and GIS approach using SOI (Survey of India) toposheets, Landsat imagery of 2000 and IRS-P6-LISS-III 2009. The study reported a reduction of 303.3 km^2 in cropland from 2000 to 2009, an increase in fallow land and built-up-land by 417.8 km^2 and 4.9 km^2 respectively. Moreover, plantation land with scrub, wet logged, barren rocky, tanks and reservoirs also experienced the change.

Stibig *et al.* (2014) assessed change in tropical forest cover of Southeast Asia from 1990 to 2010 and estimated the total forest cover of Southeast Asia to be 268 mha in 1990 that reduced to 236 mha in 2010, with annual change rates of 1.75 mha and 1.45 mha for the periods 1990–2000 and 2000– 2010 respectively. The vast majority of forest cover loss (2000–2010) occurred in insular Southeast Asia. The results also confirmed the conversion of forest cover to cash crops plantations (including oil palm) as the main cause of forest loss in Southeast Asia. Furthermore logging and the replacement of natural forests by forest plantations were two further important change processes identified in the region. A systematic sample of 418 sites (10 km × 10 km size) located at the one-degree geographical confluence points and covered with satellite imagery of 30 m resolution was used for the assessment and accuracy the results was assessed through an independent consistency assessment, performed from a subsample of 1572 mapping units.

Yismaw *et al.* (2014) studied the forest cover change detection using remote sensing and GIS in Amhara region, Ethiopia. NDVI, image differencing and post-classification comparison change detection methods were employed. It was found that forest cover had declined from 6044 ha to 2446.9 ha during the last 30 years (1973-2003) by using. The annual rate of forest cover change between 1973 and 2003 was 120 ha/year. They also reported that socioeconomic factors like population growth, the demand for the expansion of agricultural land, fuelwood and construction materials were the major driving forces for the observed forest cover changes.

Nagarajan and Poongothai (2011) studied the trend in Landuse/Landcover change detection by RS and GIS application in Tamil Nadu, India and observed that about 52.89 percent of land is devoted to agricultural practices under agriculture and cropland has a major impact over the hydrological processes of the basin. They further reported that change detection of LULC changes aids in providing optimal solutions for the selection, planning, implementation and monitoring of development schemes to meet the increasing demands of human needs has led to land management.

Diallo *et al*. (2009) studied the Landuse/Landcover change detection in Puer and Simao using remote sensing. The images were mapped using ArcGIS. They reported that severe LULC changes have occurred in croplands (+24.90%), forest or shrub land (-18.77%) and building (+16.72%) areas. They also found that unused area constituted the most extensive type of LULC.

Frimpong (2009) analyzed the change detection of forest cover in Owabi catchment area in Kumasi, Ghana using multi-temporal remote sensing data and GIS based technique. The results of the analysis showed that from 1986 to 2002 and 2002 to 2007 the forest covers has decreased by 2136.6 ha and 1231.56 ha respectively. It emerged that from 1986 to 2007, forest covers were reduced by 3368.16 ha. The study showed that increase in human activities and population explosion within the catchment area were the reason for the reduction of forest cover. Landsat TM image of January 11, 1986, Aster image of 15th January 2002 and Landsat ETM image of 24th February 2007 were analyzed using Erdas Imagine and ArcGIS software for the study.

Wani *et al*. (2009) studied forest cover mapping and change detection analysis (1960's To 1970's) in some areas of Madhya Pradesh using remote sensing and GIS and found that a non-forest area of 7.1 km^2 had converted to the forest area and forest area of 93.42 km^2 has converted to non-forest area. The net deforestation of 86.32 km^2 took place in the area from 1960's to 1970's. Damoh, Satna and Sidhi districts of Madhya Pradesh had most significant deforestation rate. The mapping was done on 1:50,000 scale using satellite data of 1970s (Landsat MSS) and change detection analysis was carried out in comparison to the data of 1960s (SOI Toposheets on 1:50,000 scale).

Reis (2008) analyzed Land use/Land cover changes using remote sensing and GIS in Rize, Turkey. Supervised classification technique was applied to Landsat images of 1976 and 2000. Ground truthing was employed for accuracy assessment of maps. The results showed severe Landuse/Landcover changes in agricultural (36.2%) (Especially in tea gardens), urban (117%), pasture (-72.8%) and forestry (-12.8%) areas between 1976 and 2000. Furthermore it was also observed that the LULC changes occurred mostly in coastal areas and in areas having low slope values.

Mengistu and Salami (2007) assessed the change detection in some parts of south-western Nigeria between the years 1986 to 2002. The results showed a reduction of 8178 ha, 23269 ha and 9367.3 ha of disturbed/degraded forest, High forest and Montane forest respectively. It was also observed that increasing population and economic activities were noted to be putting pressure on the available land resources.

Jayakumar *et al.* (2002) carried out a study to identify the status of forest in the Kolli hills using remote sensing and GIS. The study showed a reduction of 25 ha of dry evergreen forest and about 35 ha and 1306 ha decrease in the semi-evergreen and dry deciduous forests between the year 1990 and 1999 respectively. Mapping was performed on 1: 50,000 scale and the weighted overlay analysis revealed the forest areas in Kolli hills are prone to degradation and would be a good source of information for planners for effective conservation.

Pant *et al.* (2000) interpreted aerial photographs and Landsat TM False Color Composite (FCC) image for detecting the changes on forest vegetation in Western Himalayas and identified LULC categories viz. Oak, Deodar, Pine, Miscellaneous, Oak-Deodar, Oak-Pine, degraded forest, scrub/shrub, agriculture, habitation and lime stone quarries by creating the database of the maps and subsequent analysis under

GIS domain. They also reported that a total change of 17.31 km^2out of a total area of 64.12 km^2 during the studied period. Further, it was reported that most of the changes (70% out of total change) have occurred in the Oak forest area and among all the types of changes; forest degradation was the highest one.

2.3 Drivers of change

Hassen and Assen (2017) investigated the rapidity and pattern of LULC dynamics and their major drivers in the Gelda catchment of Lake Tana Watershed and identified population pressure, grouping of land alteration of 1975, forest expansion, villagization plan of 1980's, recurrent changes in political makeup and civil war as the major drivers of LULC change.

Makunga and Misana (2017) assessed the drivers of forest cover change in Masito-Ugalla ecosystem, Tanzania and identified poverty, lack of employment, population growth, and poor levels of education, corruption and misuse of public funds by politicians and senior government officials; and high demand for fuelwood as the underlying drivers of forest cover change. Furthermore, a total of 101 respondents were selected as the sample size for the study and the procedures used for data collection included household questionnaire interviews, focus group discussions, in-depth interviews, analysis of satellite images and direct observation.

Papua New Guinea's CCDA (2017) assessed drivers of deforestation and forest degradation and identified commercial logging, family agriculture, commercial agriculture, fire, small scale logging, fuel wood and mining as drivers of forest cover change.

Anonymous (2017) analyzed drivers of deforestation and forest degradation and recognized unsustainable commercial timber exploration (including illegal logging, lack of adherence to management plans by concessionaires and license holders, and weak enforcement) and unsustainable extraction of wood for domestic uses particularly charcoal as the drivers within the forestry sector. Also, forest conversion into agriculture (including commercial agricultural expansion, shifting subsistence cultivation and livestock) were identified as the prevailing drivers of deforestation outside of the sector.

Ryan *et al.* (2017) studied drivers of decadal forest cover loss in Africa's Albertine Rift region and found out national population change and tea production as the two topmost negative drivers of forest change. Additionally, they also identified meat production and local population density as negative drivers whereas the production of the local staple crop cassava as the positive driver of forest change.

Sathurusinghe (2017) assessed drivers of deforestation and forest degradation in Sri Lanka and identified poor land policy, political interference, poor coordination, encroachments, infrastructure development projects, localized degradation, population growth, agricultural mechanization and commercialization as the main drivers of forest cover loss.

John *et al.* (2015) analyzed drivers affecting forest change in the Greater Mekong Subregion (GMS) and identified six direct negative drivers namely 1) Expansion of agriculture and plantation estates such as cash crops, cacao, coffee, rubber and oil palm 2) Development of infrastructure and roads allowing access to previously inaccessible areas 3) Mineral and gas exploitation 4) Dam and water infrastructure development along the Mekong river and its tributaries 5) Illegal and unsustainable logging 6) Forest fires. Among the indirect negative drivers of deforestation and forest degradation affecting forests in the GMS were 1) Demographic change, e.g. high population growth and high population density 2)

Economic change, e.g. increase in domestic and foreign investment and trans boundary trade 3) Governance, e.g. corruption and weak law enforcement.

Katumbi and Mkandawire (2015) assessed drivers of deforestation and forest degradation in Malawi and discovered charcoal production (40%); firewood production (32%); infrastructure development (13%); timber production (11%) and agricultural expansion (4%) as the core driving forces of deforestation and forest degradation in Dzalanyama forest reserve.

Wachiye *et al.* (2013) studied the patterns of land use change, drivers for those changes and the vulnerability of forests in Nandi North forest zone in Kenya between the years 1986 to 1995 and 1995 to 2006 and identified extreme poverty, planned deforestation for development needs, and unsustainable forest practices such as illegal logging, charcoal burning and encroachment were seen as key drivers of land use change. They also generated vulnerability map which categorized the forest into four degrees of varying vulnerability namely: highly vulnerable, moderately vulnerable, vulnerable and least vulnerable starting from the easily accessible to least accessible.

Walker *et al.* (2013) assessed demand-side interventions to reduce deforestation and forest degradation and identified global demand for food, wood products, biofuels and other agricultural products as major drivers of deforestation and forest degradation. They also identified variety of demand-side measures like legislation, public procurement policies, voluntary bilateral arrangements, multi-stakeholder roundtables, independent certification, moratoria, voluntary disclosure, investor activism and consumer campaigns developed and implemented over the last decade or more by government, private sector and civil society. The study reviewed demand side measures affecting five types of ‘forest risk commodity’, namely timber, soy, palm oil, beef/leather and biofuels.

Hosonuma *et al.* (2012) assessed drivers of forest change in developing countries and identified commercial agriculture as the most important driver of deforestation, followed by subsistence agriculture. In addition, they also identified timber extraction and logging drivers of the forest degradation, followed by fuelwood collection and charcoal production, uncontrolled fire and livestock grazing. Moreover, they also correlated that deforestation drivers are similar in Africa and Asia, while degradation drivers were more similar in Latin America and Asia.

Kissinger *et al*. (2012) analyzed the underlying drivers of deforestation and forest degradation of the world and found that 93% of countries identified weak forest sector governance and institutions, including conflicting policies beyond the forest sector, and illegal activity (related to weak enforcement) as critical underlying drivers of deforestation and degradation . Furthermore the study revealed that most commonly reported driver was population growth (51%), followed by poverty (48%) and insecure tenure (48%). 41% of countries explicitly mention international and market forces, particularly commodity markets, prices, and foreign direct investment as key underlying drivers.

Anonymous (2010) analyzed drivers and underlying causes of forest cover change in the various forest types of Kenya and summarized drivers in order of importance as clearance for agriculture; linked to rural poverty and rapid population growth, unsustainable utilization (including timber harvesting, charcoal production, grazing in forests), and past governance and institutional failures in the forest sector.

Hecht *et al.* (2005) studied globalization, forest resurgence, and environmental politics in El Salvador identified several socioeconomic drivers specific to El

Salvador as having an influence on the forest transition process. Among them were the 1980s armed conflict, the urbanization of population due to industrialization, the income from remittances from outside the country, the reduction of rural population due to migration are among the factors that have contributed to this forest transition.

Lambin *et al.* (2001) analyzed the global causes of land use change and land cover change and identified powerful economic drivers of deforestation and forest degradation including economic booms in forest harvesting, agricultural colonization and an increasing national and international demand for non food agricultural products (e.g. biofuel), agricultural subsidies and other policies, infrastructure policies (e.g. construction of new roads), and possibly weak governance of land and forest.

Chapter-3

MATERIAL AND METHODS

3.1 Study area

The present study entitled **"Decadal forest cover change in Jehlum Valley forest division of Kashmir Himalayas using remote sensing and GIS technique"** was carried out in Jehlum Valley Forest Division of Kashmir during the year 2015-2016.

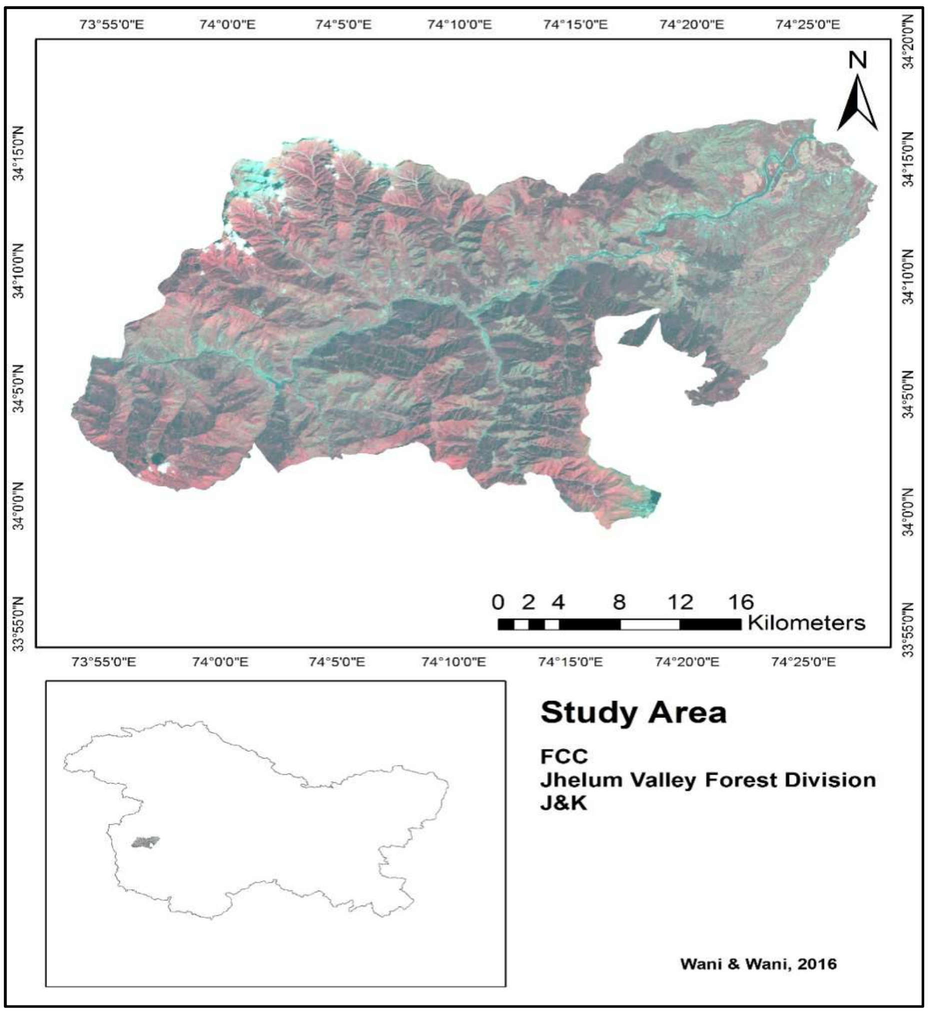

Fig. 1: False Colour Composite (FCC) of the study area

3.1.1 Location of study area

Jehlum Valley forest division lies in the Baramulla district of Kashmir province in the northeast Srinagar. The forest division is situated approximately between latitude 33º 55′ and 34º 15´ north and longitude 73º 55′ and 74º 30′ east. The False Color Composite (FCC) of the study area is given in Fig. 1. The administrative setup of J V forest division comprises as under:

Baramulla Range

Boniyar Range

Uri Range

Doabgah Range

3.1.2 Configuration of study area

The configuration of the region is for the most part uneven and the geology differs from general and direct close to the low lying territories to exceptionally steep and abrupt in the inside extents. The elevation of the region ranges from 1162 m (the lowest contour near Isham) to 4399 m (the most astounding top in Kazinag range). The business forest belt happens between 550 m and 2900 m. A portion of the imperative glades of this division are Chor Khud, Gabberwar, Boisian, Babagail and so forth. Powerful mountain ranges like Pir Panjal and Kazinag isolate the Division from the Poonch and the Langate forest division individually. Some grand pinnacles exist on these mountain Ranges, the most forcing of which are Kala Pahar (4399 m), Al Pathri (4218 m) and Chor Panjal (4349 m). As common of the Kashmir Valley, the slopes of the division in Baramulla are flanked at places by Karewas, the low lying alluvial stores.

3.1.3 Forest types and species composition

In the revised classification of forest types of India by Champion and Seth, the Kashmir valley forests have been managed under groups 12, 13, 14 and 15. The different groups recognized in reference to the broad classification of Champion and Seth (Groups 9, 12, 14 and 15) are as per the following:

Kashmir valley temperate forests

Kashmir valley sub-alpine forests

Kashmir valley Alpine forests

Kashmir subtropical forests

Out of the total geographical area of district Baramulla which goes under Jehlum valley forest division, around 65 percent of territory is covered with forests. The fundamental tree types of the forests of this tract comprise of three noteworthy conifers, i.e. Deodar, Kail and Fir. Spruce and Yew likewise jump out at a little degree in blend. These Forests stretch out in a persistent belt from Tosamaidan edge, isolating the PirPanjal forest division and the J V forest division down the hilly belt up to the line of actual control in the Uri sector on the left bank of the stream Jehlum. On the opposite side of the waterway, the forests reach out from Gosainteng Baramulla upto the line of actual control for the most part on the southern inclines of the Kazinag edge.

Deodar (*Cedrus deodara*) forests happen in immaculate or in blended frame on very much depleted soils. Its fundamental coniferous partner is Kail (*Pinus wallichiana*) which prospers well as a colonizer on uncovered inclines, and declined locales. Fir (*Abies pindrow*) happens on higher heights than the Deodar-Kail forests, by and large in unadulterated shape. Blended coniferous forests of the three species likewise happen in the progress belt between the two altitudinal zones. The Fir forests become dim step by step with the elevation and at last converge with the snow capped field lands. Deodar-Kail forests are blended with broadleaved species on cooler aspects and in depressions and Nallas. Fir is likewise blended with such broadleaved vegetation at great heights. Among conifers, the most essential species include Deodar, Kail, Fir, Spruce, Chir and Yew, though Walnut, Horse chestnut, Ash, Maple, Birdcherry, Alder, Willow, Poplar, Elm, Birch, Arkhol and Pohu are most vital broadleaved species happening in the division.

3.1.4 Climate and geology

As far as climate is concerned, altitudinal variation and differing topographical feature are the two fundamental elements in charge of the variety in temperature and precipitation from place to place. Towards the west of the Division, the low-lying zones have very sweltering summers and mellow winters (normal for subtropical atmosphere). There is no snowfall in the zones around Uri. The higher mountain all around, however encounter apparent snowfall and frost and are in this regard much the same as of Kashmir Valley. Though the precipitation for the most part happens as winter snow and spring downpours, the regions towards Boniyar and Uri encounter monsoon rains.

The investigation completed as of late by the Geological Survey of India in the region, established that Boniyar group with the exception of the lowermost limestone part incorporates the second rate metasediments going from phyllites to slates. The Uri Group has gotten its name for the most ideal topography in Uri-Lagama zone. The Karewa Group unconformable overlies the Uri Group. The Group has an conglomerate bed at the base took after by sandstone informal lodging clay bed at the best. The geology of this group is best uncovered around Baramulla town.

3.1.5 Streams and Nallas

The tract is crossed by river Jehlum from Baramulla downwards partitioning the encompassing forests generally into two equivalent parts. The tract is likewise crossed by various Nallas and streams which drain into the river Jehlum. The fundamental tributaries are Ningli Nalla, Mundri Nalla, Boniyar Nalla, Lachipora Nalla, Uri Nalla and Salamabad Nalla. The other imperative nallas of the division are

Bagna, Islamabad, Zamboorpattan, Nambla, Limber, Goalto, Nawa-Dardkote and so forth.

3.2 Materials

The materials used are described under following 2 headings:

3.2.1 Lab work

Satellite data

Landsat OLI/ TM: The satellite data specifications of Landsat OLI and TM are given in Table 2.

Table-2: Specifications of Landsat OLI and TM sensor

Satellite data specifications		
Sensor	Landsat OLI	Landsat TM
Spatial resolution	30 m (15 m pan)	30 m (120 m thermal)
Spectral range	0.43 – 1.39 µm	0.45 – 12.5 µm
No. of bands	9	7
Temporal resolution	16 days	16 days
Image size	185 km × 180 km	183 km × 172 km
Sensor type	Push broom	Opto-mechanical
Swath	185 km	185 km

Software

Image processing software (ERDAS Imagine)

Mapping software (ArcGIS)

Statistical software for data analysis

3.2.2 Field Work

GPS (Ground truth location, Latitude/Longitude/Altitude)

Spherical crown densiometer (crown density)

Sunto clinometer (slope)

Map prints (ground truthing)

3.3 Methodology

3.3.1 Objective 1 methodology:

Procurement of satellite data

Satellite data of the study area was procured from National Remote Sensing Centre (NRSC) Hyderabad.

Preprocessing of satellite data

The satellite data procured was preprocessed for different making a False Color Composite with the desired band combinations using image processing software. Different image enhancement techniques were also employed for better interpretation of different Landuse/Landcover (LULC) types.

Preliminary survey of the study area

Preliminary survey was carried out in the study area to get the first hand information about the land use, vegetation types and biodiversity, topography, accessibility etc. The information generated was used to decide about the nature of mapping to be done and the number of LULC classes to be delineated.

Landuse/Landcover (LULC) map/Forest density map (2005/2015)

Mapping of satellite data was carried out using mapping software (ArcGIS) at 1:50000 scale. The satellite data was delineated into different LULC types and different forest density classes on the basis of crown density as follows:

Landuse/Landcover (LULC) Map

Forest

Forest scrub

Grassland

Agriculture

Agroforestry

Horticulture

Habitation

Water body

Snow

Wasteland

Forest density Map (FSI, 2005)

Closed forest 40-70% crown density

Open forest 10-40% crown density

Forest scrub < 10% crown density

Grasslands

Non forest

Accuracy Assessment of Forest density map

The Forest density map generated using the required software's was validated on the ground through ground truth points. The following information was collected from the ground truth points for accuracy assessment:

Forest Range

Forest Block

Forest Compartment

Dominant specie/species

Latitude/Longitude

Altitude (m)

Crown density

Slope

Validation of Forest density map

The producer's accuracy and overall accuracy of the forest type density maps was generated using error matrix and on the basis of these accuracies KAPPA (KHAT coefficient) was also calculated. *Producer's accuracy* is a measure of error of omission and *User's Accuracy* is a measure of error of commission. KAPPA analysis is a discrete multivariate technique used in accuracy assessment (Congalton *et al.*, 1983).

$$Producer's\ Accuracy = \frac{Number\ of\ correctly\ classified\ pixels\ in\ each\ category}{Total\ number\ of\ validation\ points\ used\ for\ that\ category\ (column\ total)}$$

$$User's\ Accuracy = \frac{Number\ of\ correctly\ classified\ pixels\ in\ each\ category}{Total\ number\ of\ validation\ points\ used\ for\ that\ category\ (row\ total)}$$

$$Overall\ Accuracy = \frac{Number\ of\ correctly\ classified\ pixels}{Total\ number\ of\ validation\ points}$$

$$k = \frac{N\sum_{i=1}^{r} x_{ii} - \sum_{i=1}^{r}(x_{i+} \times x_{+i})}{N^2 - \sum_{i=1}^{r}(x_{i+} \times x_{+i})}$$

Where k = Kappa coefficient
r = number of rows in the error matrix
N = Number of observations
x_{ii} = the number of observations in row i and column i (on the major diagonal)
x_{i+} = total number of observation in row i (shown as marginal total to right of the matrix)
x_{+i} = total number of observation in column i (shown as marginal total at bottom of the matrix)

3.3.2 Objective 2 methodology:

Generation of forest density change map and change matrices

The forest density maps generated for 2005 and 2015 were used to generate a change map and change matrices using the intersection method in image processing software.

Analysis of change matrices

The change areas were identified and the percentage of area transferred to the other category was assessed for the time period (Table 3).

Table-3: Change matrix of forest categories

		2015 (Area ha)					
		Closed forest	Open forest	Forest scrub	Grassland	Non Forest	Total
2005 (Area ha)	Closed forest						
	Open forest						
	Forest scrub						
	Grassland						
	Non Forest						
	Total						

3.3.3 Objective 3 methodology:

The results obtained from change analysis were used to identify the drivers of forest cover change using a close ended semi-structured interview schedule in 4 villages (2 each for positive and negative change) for the purpose. 10 respondents from each village were selected within the defined boundaries of J V forest division for assessing the drivers of change.

The responses were assigned scores for ranking of drivers using statistical analysis. Top ranking drivers finally lead us to the critical drivers of change. The flowchart of the whole methodology is shown in Fig. 1.

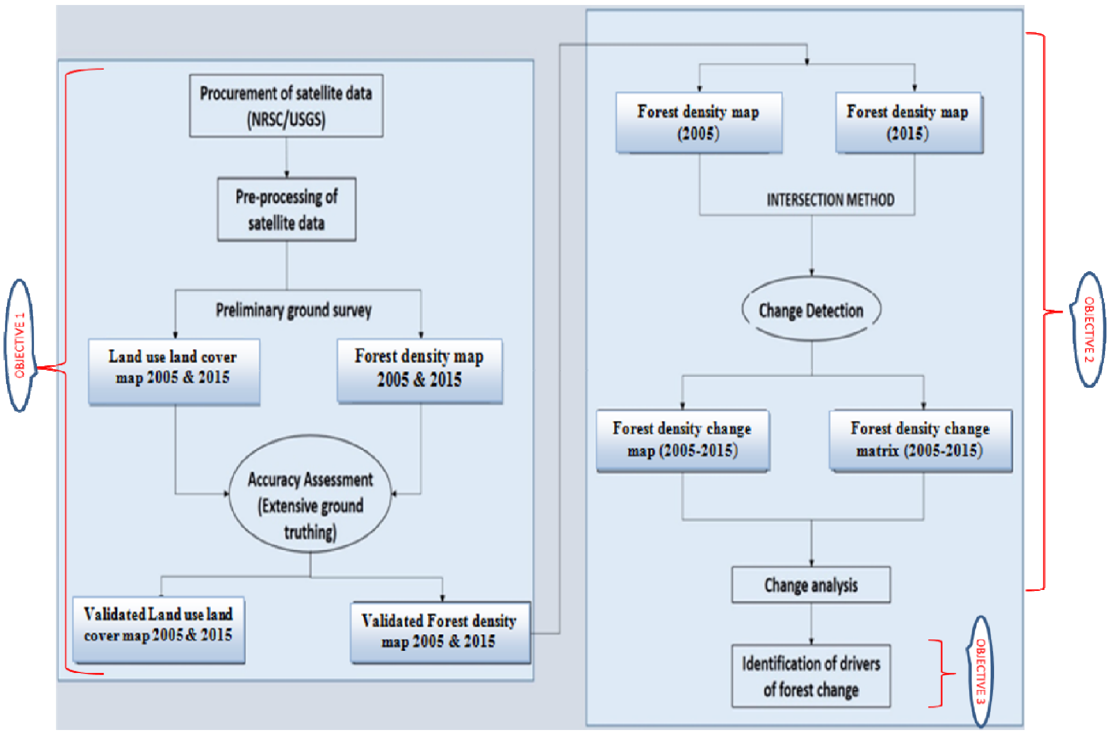

Fig. 2: Flowchart of the methodology adopted

Chapter-4

EXPERIMENTAL FINDINGS

4.1 Landuse/Landcover (LULC)

LULC (2005) and LULC (2015) of J V forest division have been shown in Table 4 and Table 5 respectively. Landuse/Landcover map (2015) reports that there has been a notable change in Landuse/Landcover during the decade (2005-2015) in J V forest division. Among all the LULC classes, forest occupied maximum area of the map i.e. 44.45% while as snow with an area of 1.79% occupied minimum portion of the map. The percentage of area under agriculture has shown a decrease from 3.52% in 2005 to 2.65% in 2015. The habitation area has increased from 9.26% in 2005 to 10.34% in 2015. The area under horticulture has slightly increased from 7.43% in 2005 to 7.81% in 2015. Likewise area under grasslands has shown a slight increase from 4.66% to 4.98% from 2005 to 2015. Wasteland area has decreased from 13.17% to 12.70% during the decade similarly area under agroforestry has shown a slight decrease from 1.36% in 2005 to 1.33% in 2015. Percentage of area under snow and water bodies has remained constant at 1.79% and 2.55% throughout the whole decade. The forest area has decreased from 44.93% in 2005 to 44.45% in 2015 whereas percentage of area under forest scrub has increased from 11.33% to 11.41% during the decade. Different colors have been assigned to represent various Landuse/Landcover classes in LULC map 2015 and LULC map 2005. Landuse/Landcover map (2005) and Landuse/Landcover map (2015) reveals the area under different LULC classes as shown in Fig. 2 and Fig. 3 respectively.

Table-4: Landuse/Landcover of J V Forest Division (2005)

Class	Area (ha)	%
Agriculture	3474.08	3.52
Agroforestry	1345.40	1.36
Forest	44336.60	44.93
Forest Scrub	11180.57	11.33
Grassland	4601.63	4.66
Habitation	9140.07	9.26
Horticulture	7337.33	7.43
Snow	1764.49	1.79
Wasteland	12993.32	13.17
Waterbody	2514.52	2.55
Total	**98688**	**100.00**

Table-5: Landuse/Landcover of J V Forest Division (2015)

Class	Area (ha)	%
Agriculture	2610.97	2.65
Agroforestry	1308.81	1.33
Forest	43864.30	44.45
Forest Scrub	11258.73	11.41
Grassland	4912.61	4.98
Habitation	10207.74	10.34
Horticulture	7708.19	7.81
Snow	1764.49	1.79
Wasteland	12537.64	12.70
Waterbody	2514.52	2.55
Total	**98688**	**100.00**

Table-6: Change matrix LULC of J V forest division (2005 to 2015)

2015 (ha)

2005 (ha) Class	Agricu-lture	Agrofor-estry	Forest	Forest Scrub	Grassland	Habita-tion	Hortic-ulture	Snow	Wastela-and	Water body	Grand Total
Agriculture	**2567.73**	16.63	0	0	0	246.13	628.63	0	14.97	0	**3474.08**
Agroforestry	0	**1290.52**	0	0	0	18.29	36.59	0	0	0	**1345.40**
Forest	43.24	1.66	**43864.30**	138.03	196.24	83.15	0	0	9.98	0	**44336.60**
Forest Scrub	0	0	0	**11120.70**	0	59.87	0	0	0	0	**11180.57**
Grassland	0	0	0	0	**4601.63**	0	0	0	0	0	**4601.63**
Habitation	0	0	0	0	0	**9140.07**	0	0	0	0	**9140.07**
Horticulture	0	0	0	0	0	302.67	**7034.66**	0	0	0	**7337.33**
Snow	0	0	0	0	0	0	0	**1764.49**	0	0	**1764.49**
Wasteland	0	0	0	0	114.75	357.55	8.31	0	**12512.70**	0	**12993.32**
Waterbody	0	0	0	0	0	0	0	0	0	**2514.52**	**2514.52**
Grand Total	**2610.97**	**1308.81**	**43864.30**	**11258.73**	**4912.61**	**10207.74**	**7708.19**	**1764.49**	**12537.64**	**2514.52**	**98688**

4.1.1 Landuse/Landcover (LULC) change matrix

Landuse/Landcover change matrix has been shown in Table 6. LULC change matrix (2005-2015) of J V forest division reveals that out of the total area of 98688 ha, forest occupied maximum portion of the division viz., 44336.60 ha while as minimum area of 1764.49 ha was occupied by snow. Out of the 3474.08 ha area under agriculture in 2005, 2567.73 ha remained unchanged during the decade, the rest got converted into agroforestry (16.63 ha), habitation (246.13 ha), horticulture (628.62 ha) and wasteland (14.96 ha) respectively. The total area under forest in 2005 was 44336.60 ha with an area of 43864.30 ha remaining constant throughout the decade while as the rest of area got converted into agriculture (43.24 ha), agroforestry (1.66 ha), forest scrub (138.03 ha), grassland (196.24 ha), habitation (83.15 ha), and wasteland (9.98 ha) respectively. Out of the total area of 7337.33 ha under horticulture, 7034.66 ha witnessed no change from 2005 to 2015 while the rest of an area of 302.67 ha was converted to habitation. In Forest scrub class an area of 11120.70 ha remained unchanged out of the total area of 11180.5694 ha in 2005 with the rest of an area of 59.87 ha getting converted into habitation. Due to conversion of an area of 196.24 ha and 114.75 ha from forest and wasteland category, the total area under grassland has increased from 4601.63 ha to 4912.62 ha respectively. Similarly, wasteland has shown a net decrease of 455.67 ha during the decade. During the decade an area 18.29 ha and 36.59 ha got converted into habitation and horticulture from agroforestry class out of the total area of 1345.40 ha in 2005 with an area of 1290.52 ha witnessing no change during the decade. In case of wasteland, the total area under this class was observed to be 12993.32 ha in 2005 with an area of 12512.70 ha showing no change throughout the decade; the rest of area was converted to grassland (114.75 ha), habitation (357.55 ha) and horticulture (8.315 ha) respectively.

A total of 133 ground truth (GT) points of the study area were taken randomly. The location of ground truth points for J V forest division (2015) is shown is Fig. 10. The

Landuse/Landcover maps of 2005 and 2015 are shown in Fig. 3 and Fig. 4 respectively.

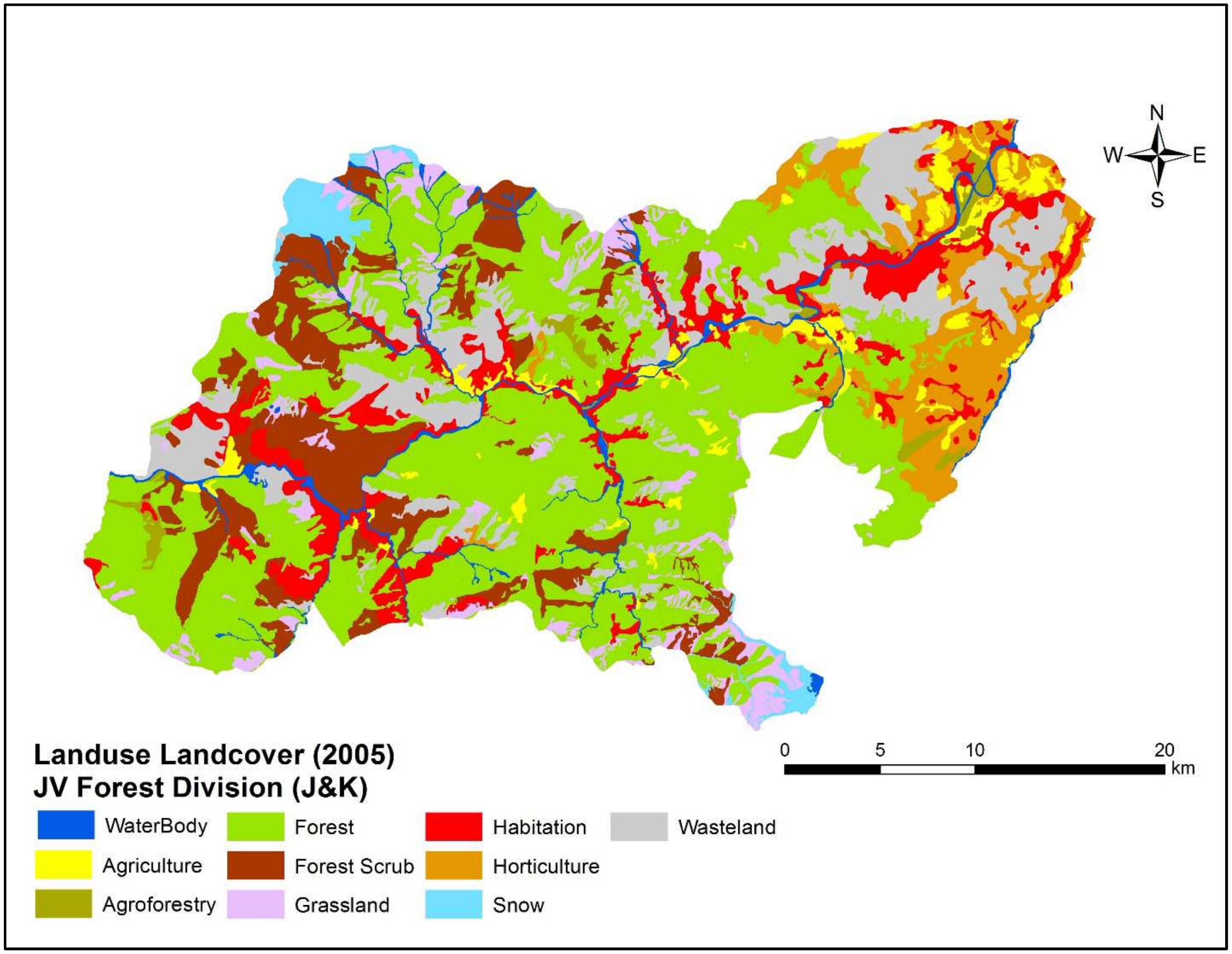

Fig. 3: Landuse/Landcover map (2005) of J V forest division

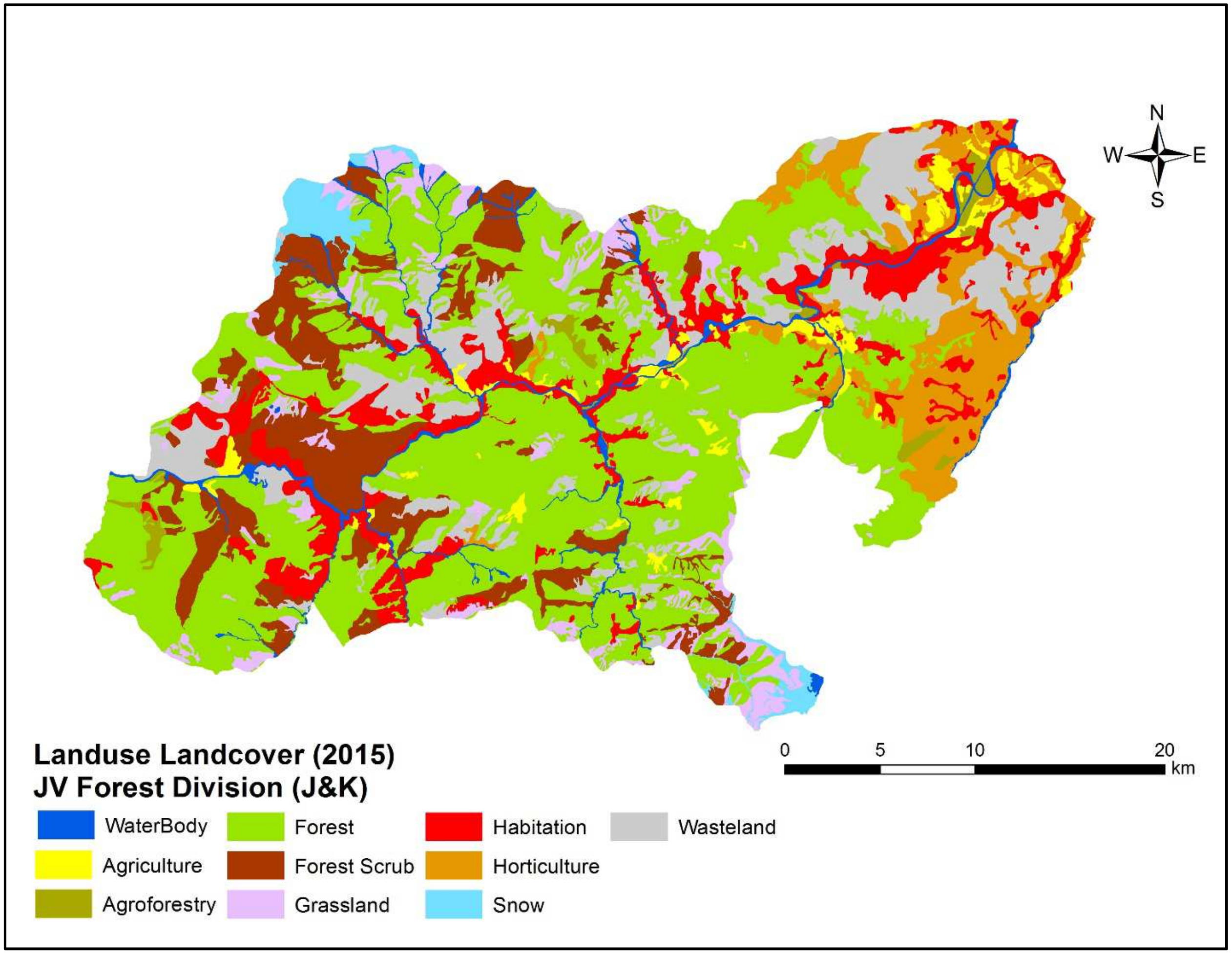

Fig. 4: Landuse/Landcover map (2015) of J V forest division

4.2 Forest cover density

Forest cover density of J V forest division of 2005 and 2015 has been shown in Table 7 and Table 8 respectively. The forest cover density (2015) of the J V forest division reveals that non forest category occupied maximum portion (39.17%) of the total area (98688 ha) while as grassland occupied minimum portion (4.98%) of the division. The percentage of area under open forest category in 2015 was 17.93% while as it was 17.36% of the total area in 2005. Forest scrub category witnessed a slight increase from 11.33% of the total area in 2005 to 11.41% in 2015. The area under closed forest has decreased by 1.05% of the total area of the forest division during the decade. Also grassland area was 4.66% in 2005 as compared to 4.98% in 2015. The non forest category witnessed slight increase from 39.08% to 39.17% during the decade (2005-2015).

The forest cover density maps of 2005 and 2015 have been shown in Fig. 5 and Fig. 6 respectively. Different colours have been designated to represent various forest cover density classes with non forest represented by yellow colour and dense forest category by dark green colour.

The forest cover status (ha) under different forest categories for the years 2005 and 2015 has been shown in Fig. 7, Fig. 8 and Fig. 9. The figures reveal that the area under open forest category is slightly higher in 2015 than in 2005; however the trend is reverse in case of closed forest category where the area under closed forest is more in 2005 than in 2015.The area under grassland is slightly higher in 2015 as compared to 2005. The figures further reveal that the area under non forest category, forest scrub category has remained broadly unchanged with no significant increase or decrease in area under these categories as shown in histogram (Fig. 7) and two pie charts (Fig. 8 and Fig. 9).

Table-7: Forest canopy density of J V Forest Division (2005)

Forest Class	Area (ha)	%
Closed Forest	27200.70	27.56
Grassland	4601.63	4.66
Non Forest	38569.20	39.08
Open Forest	17136	17.36
Forest Scrub	11180.60	11.33
Total	**98688**	**100.00**

Table-8: Forest canopy density of J V Forest Division (2015)

Forest Class	Area (ha)	%
Closed Forest	26166.30	26.51
Grassland	4912.62	4.98
Non Forest	38652.40	39.17
Open Forest	17698.10	17.93
Forest Scrub	11258.80	11.41
Total	**98688**	**100.00**

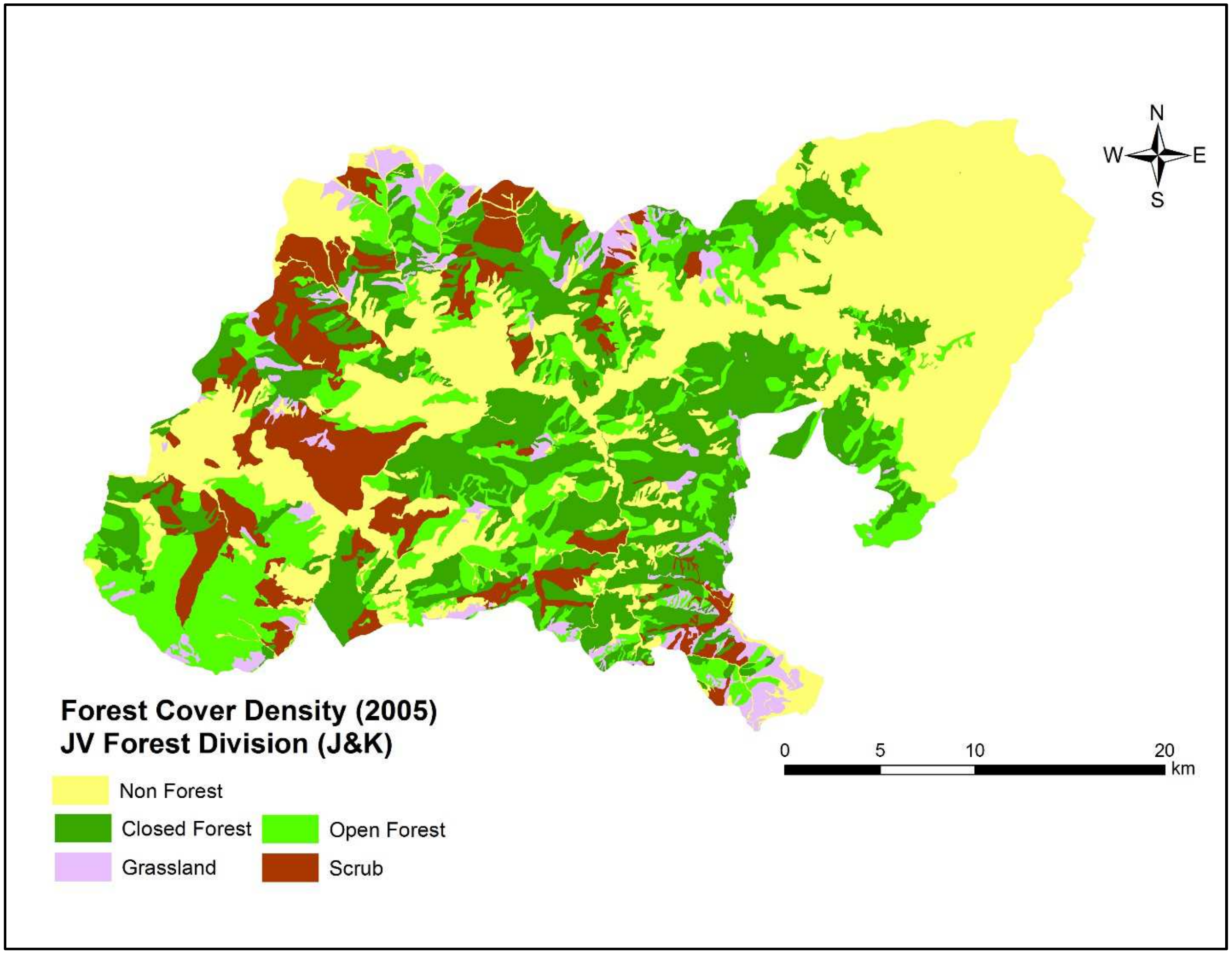

Fig. 5: Forest cover density map (2005) of J V forest division

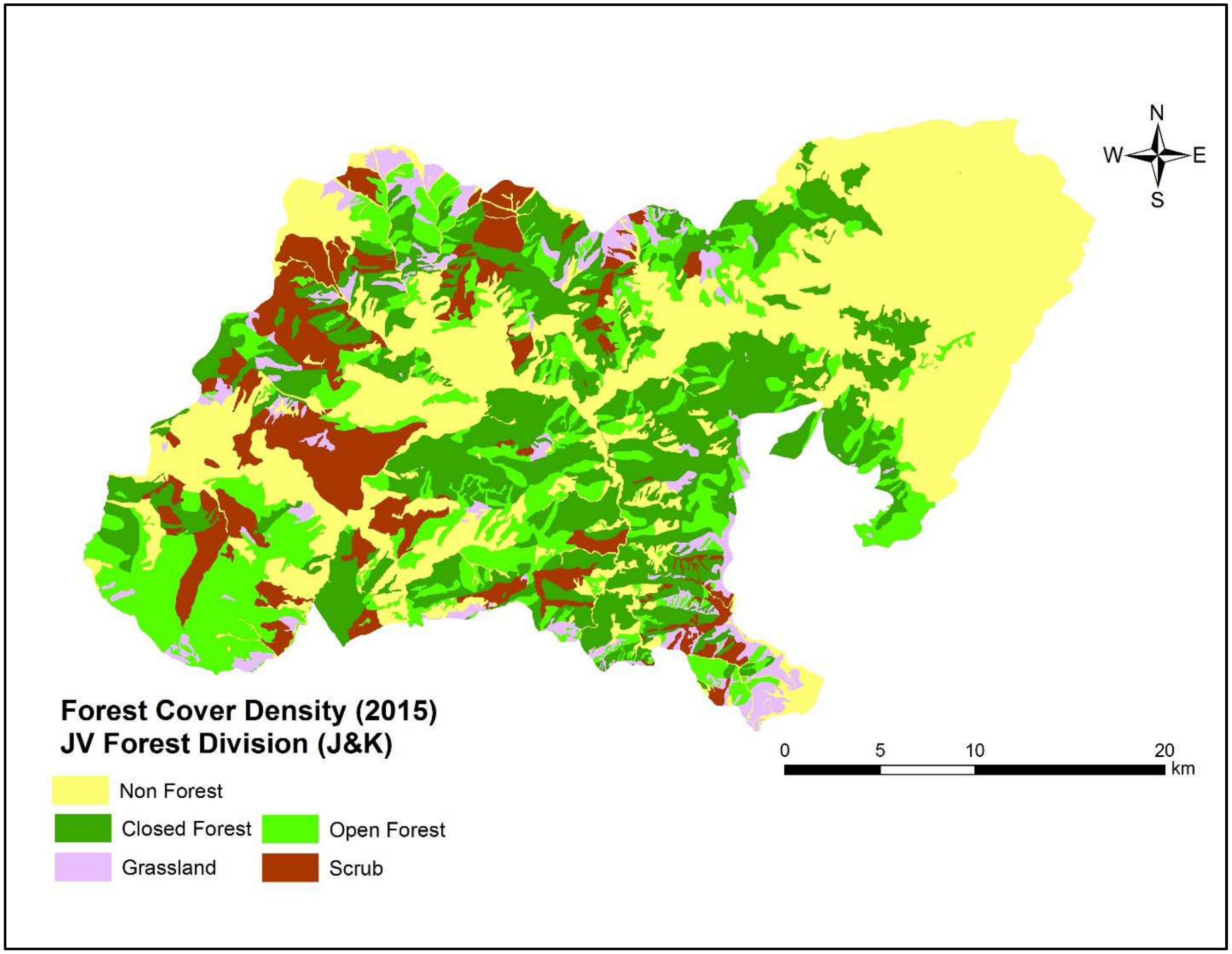

Fig. 6: Forest cover density map (2015) of J V forest division

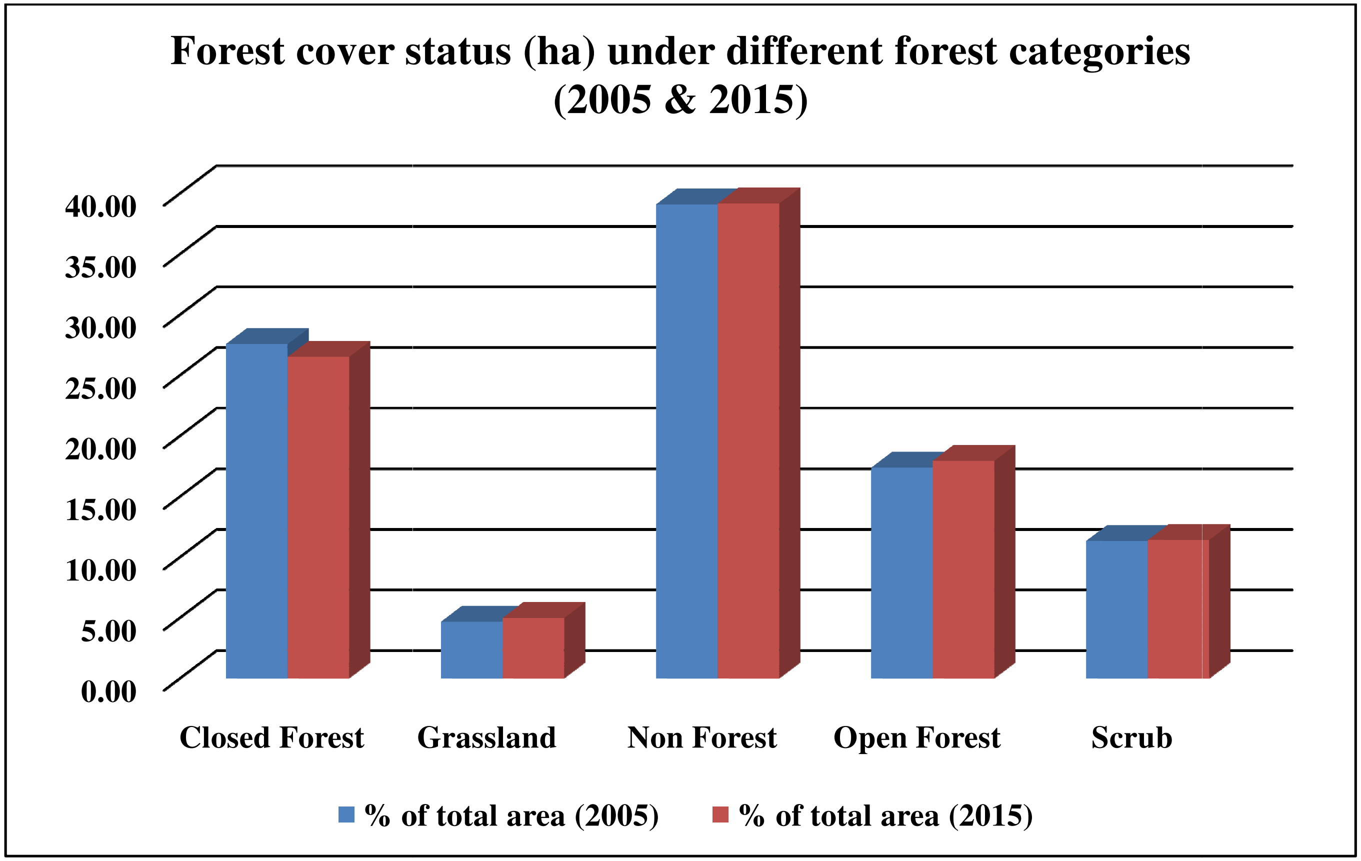

Fig. 7: Forest cover status (ha) under different forest categories for the years 2005 and 2015

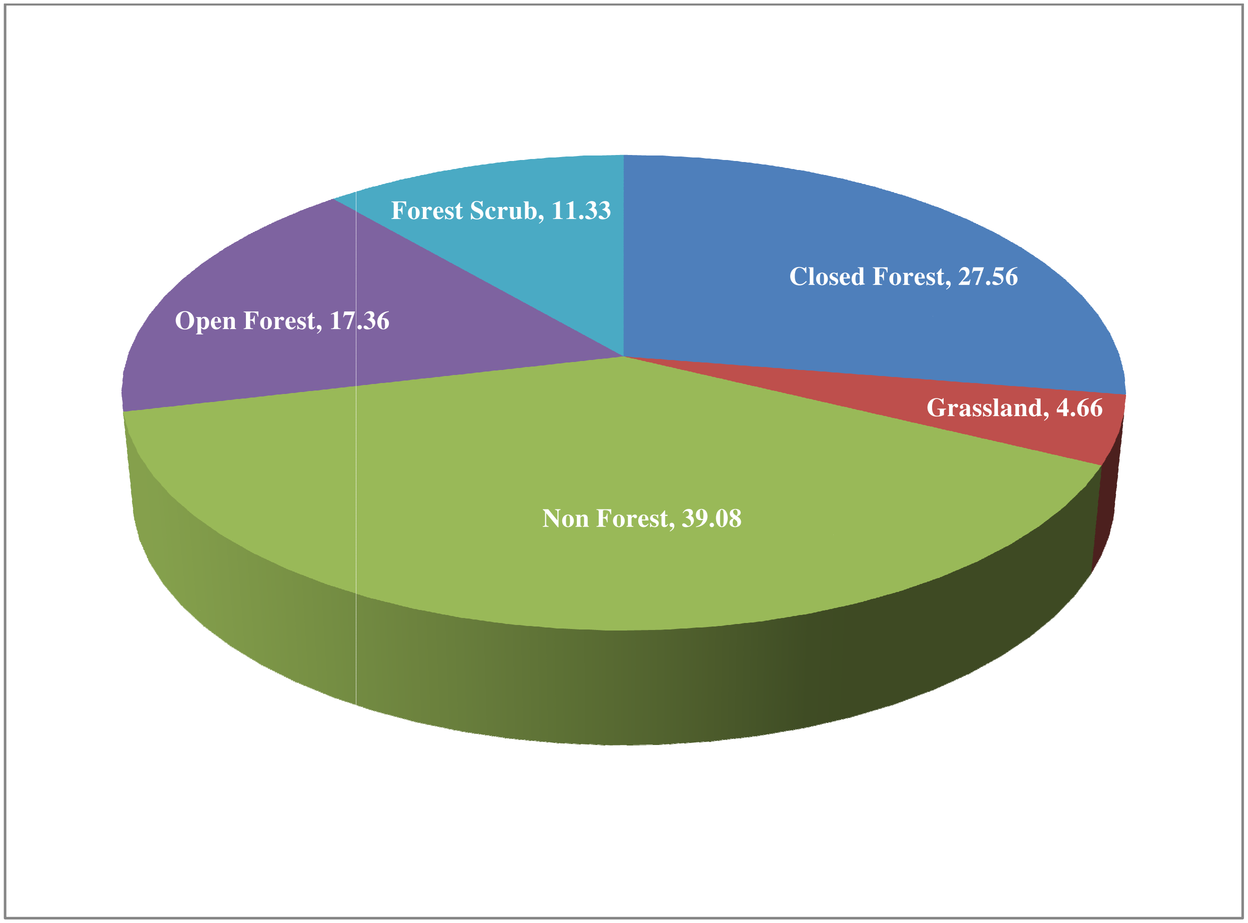

Fig. 8: Forest cover of J V forest division under different categories (%) in 2005

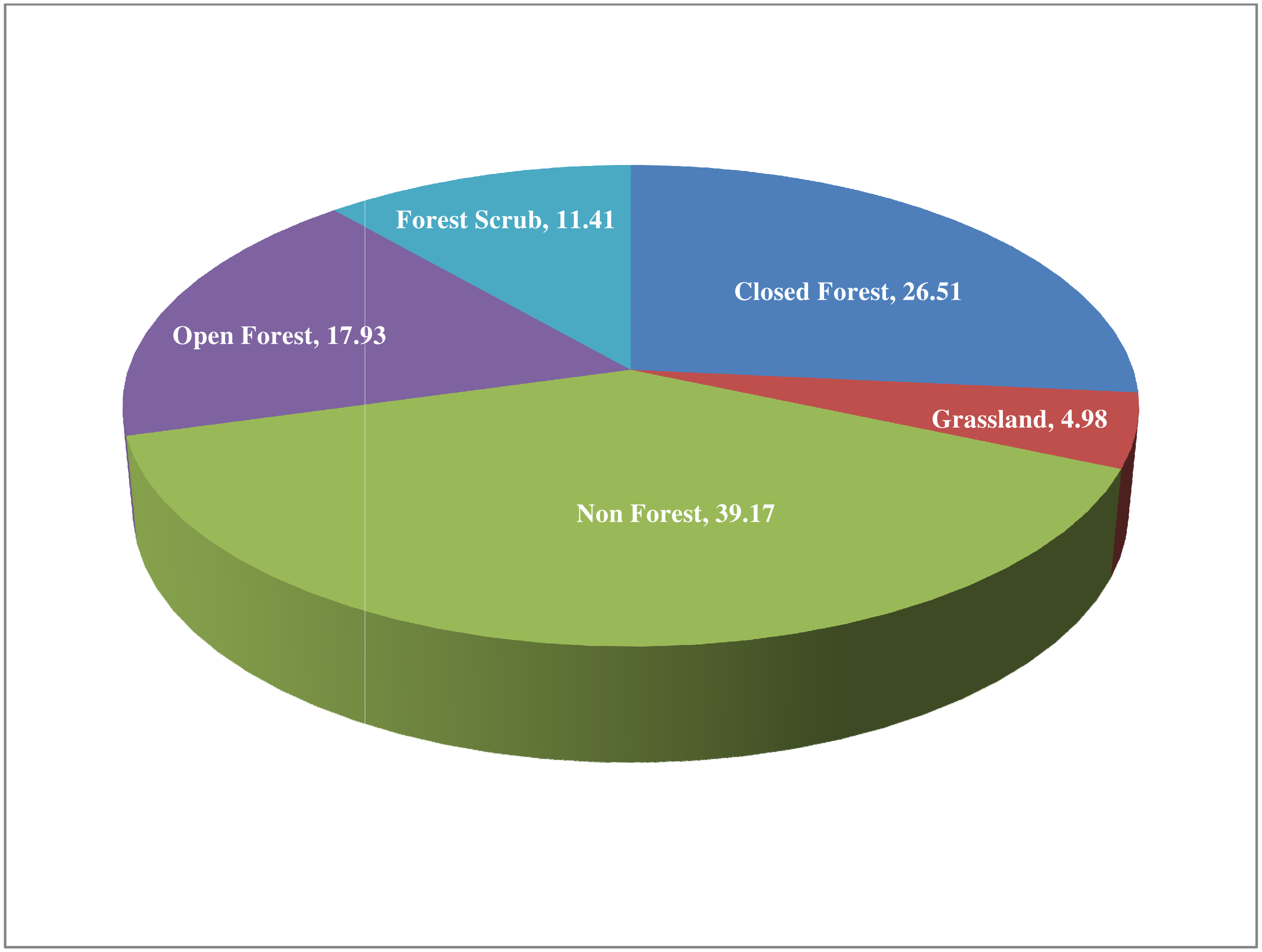

Fig. 9: Forest cover of J V forest division under different categories (%) in 2015

4.3 Accuracy Assessment

The total number of reference points (ground truth points) for accuracy assessment and map validation was 133 at various places of the study area (Fig. 10). The overall classification accuracy of forest density map of 2015 came out to be 92.48%. The overall classification accuracy of forest density map 2015 was calculated on the basis of producer's accuracy and user's accuracy as shown in table 10. The error matrix of forest density map of the study area is shown in Table 9.

The conditional kappa for each category was calculated using kappa formula. Kappa for non forest, open forest, forest scrub, closed forest and grassland category was found to be 0.8549, 0.839, 1, 0.9035 and 0.8992 respectively. The overall kappa statistics was calculated as 0.8757 as shown in Table 11.

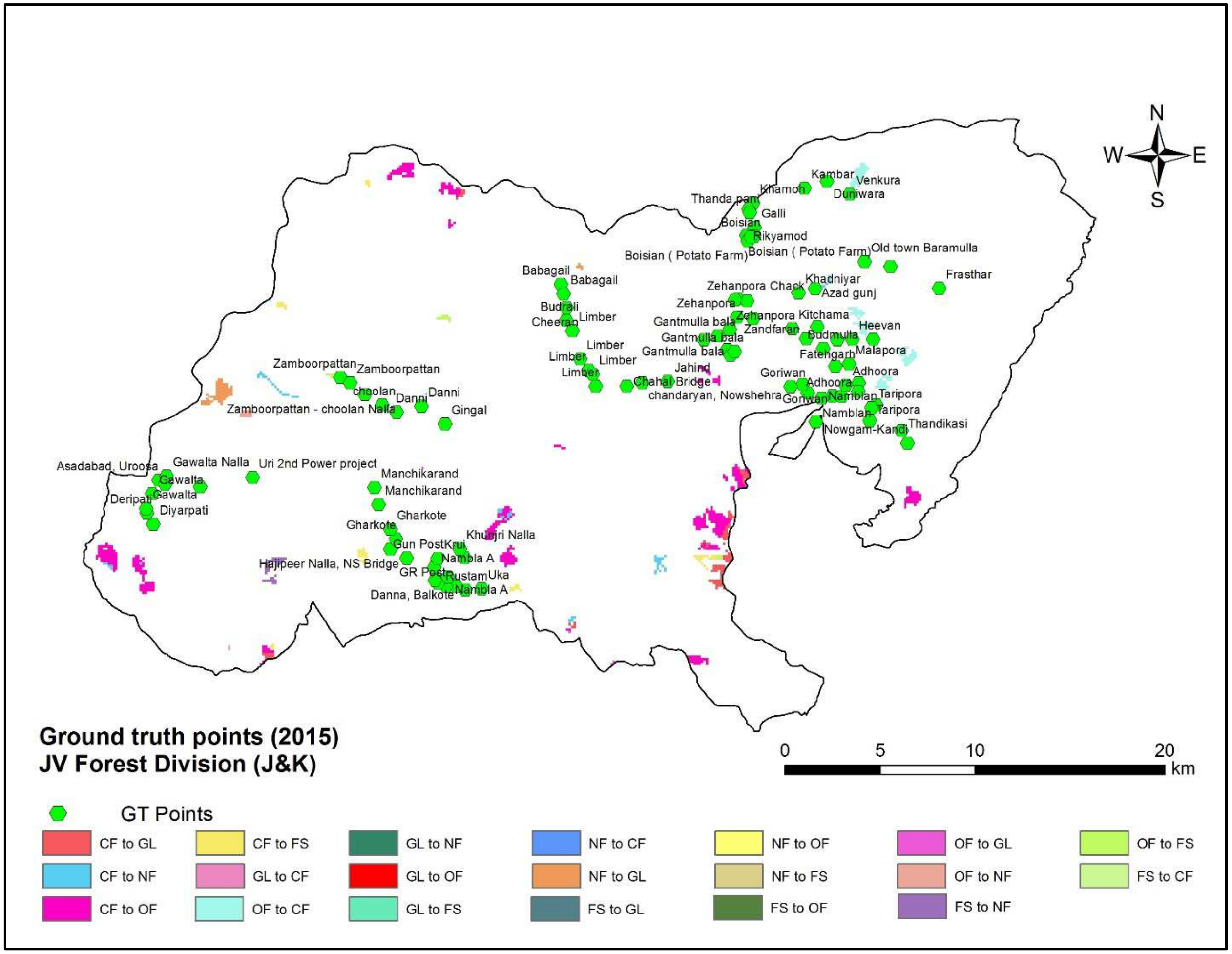

Fig. 10: Location of ground truth points of J V forest division (2015)

Table-9: Error matrix for forest density map (2015) for J V forest division

Classified Data	**Background**	Non Forest	Open Forest	Forest Scrub	Closed Forest	Grassland	**Row Total**
Non Forest	0	74	1	0	1	3	79
Open Forest	0	0	12	0	2	0	14
Forest Scrub	0	0	0	3	0	0	3
Closed Forest	0	0	2	0	24	0	26
Grassland	0	1	0	0	0	10	11
Column Total	**0**	**75**	**15**	**3**	**27**	**13**	**133**

Table-10: Accuracy assessment for validation of forest density map (2015)

Class	Reference Totals	Classified Totals	Number Correct	Producers Accuracy	Users Accuracy
Non Forest	75	79	74	98.67%	93.67%
Open Forest	15	14	12	80.00%	85.71%
Forest Scrub	3	3	3	100.00%	100.00%
Closed Forest	27	26	24	88.89%	92.31%
Grassland	13	11	10	76.92%	90.91%
Totals	133	133	123		

Overall Classification Accuracy = 92.48%

Table-11: Conditional Kappa for each Category

Class	Kappa
Non Forest	0.8549
Open Forest	0.839
Forest Scrub	1
Closed Forest	0.9035
Grassland	0.8992
Overall Kappa Statistics	**0.8757**

4.4 Forest cover density change matrix

Change matrix in ha (Forest cover density) of J V forest division from 2005 to 2015 has been shown in tabular form in Table 12 as well as in Fig. 11. Forest cover density change matrix (2005-2015) of J V forest division reveals that out of the total area of 98688 ha, non forest category occupies the highest area of 38569.25 ha with minimum area of 4601.63 ha being occupied by grassland. The total area under closed forest category was 27200.66 ha in 2005 with an area of 25943.40 ha remaining unchanged, the rest of area being transformed into forest scrub (104.77 ha), grassland (189.59 ha), non forest (111.42 ha) and open forest (851.48 ha) respectively. In forest scrub out of the total area of 11180.57 ha in 2005, 11120.70 ha witnessed no change while the rest of 59.87 ha was converted into non forest category. Change matrix also reveals that grassland with total area of 4601.63 in 2005 ha has witnessed net increase of 310.99 ha during the decade. Out of the total area under open forest category i.e. 17135.97 ha in 2005 16846.60 ha remained unchanged with the rest of area being converted into closed forest (222.85 ha), forest scrub (33.26 ha), grassland (6.65 ha), and non forest (26.61 ha) category respectively. The forest density change matrix further reveals that out of the total area of 38569.25 ha under non forest category in 2005, 38454.50 in witnessed no change, the rest of area of 114.75 ha got converted into grassland.

The forest cover density change map shown in Fig. 11 reveals the changes in different forest density categories with conversion of closed forest to open forest (CF to OF) being the most dominant change among the forest density classes. Different colours are designated to various category transformations while as the rest of area witnessing no change is represented by no colour as shown in the change map. The change of area from closed forest, open forest, forest scrub, grassland and non forest to other categories have been shown in histograms (Fig. 13, Fig. 14, Fig. 15, Fig. 16 and Fig. 17 respectively). The overall graphical summary of all forest density classes has been shown in Fig. 18.

Table-12: Change matrix forest cover density of J V forest division (2005 to 2015)

	Change matrix (ha)						
		2015					
	Class	**Closed Forest**	**Forest Scrub**	**Grassland**	**Non Forest**	**Open Forest**	**Grand Total**
2005	**Closed Forest**	**25943.40**	104.77	189.59	111.42	851.48	**27200.66**
	Forest Scrub	0.00	**11120.70**	0.00	59.87	0.00	**11180.57**
	Grassland	0.00	0.00	**4601.63**	0.00	0.00	**4601.63**
	Non Forest	0.00	0.00	114.75	**38454.50**	0.00	**38569.25**
	Open Forest	222.85	33.26	6.65	26.61	**16846.60**	**17135.97**
	Grand Total	**26166.25**	**11258.73**	**4912.62**	**38652.40**	**17698.08**	**98688**

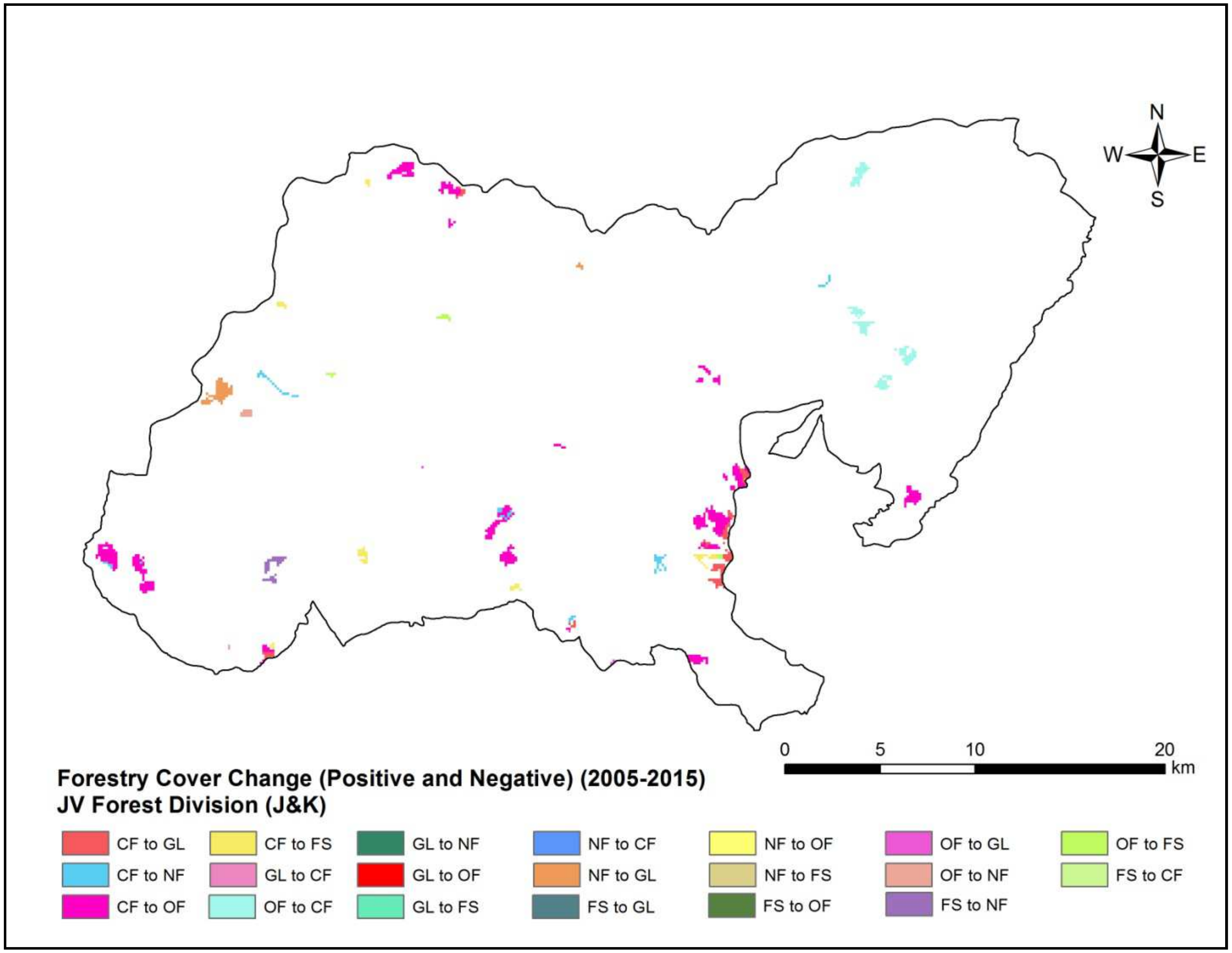

Fig. 11: Forest cover density change map 2005-2015 of J V forest division

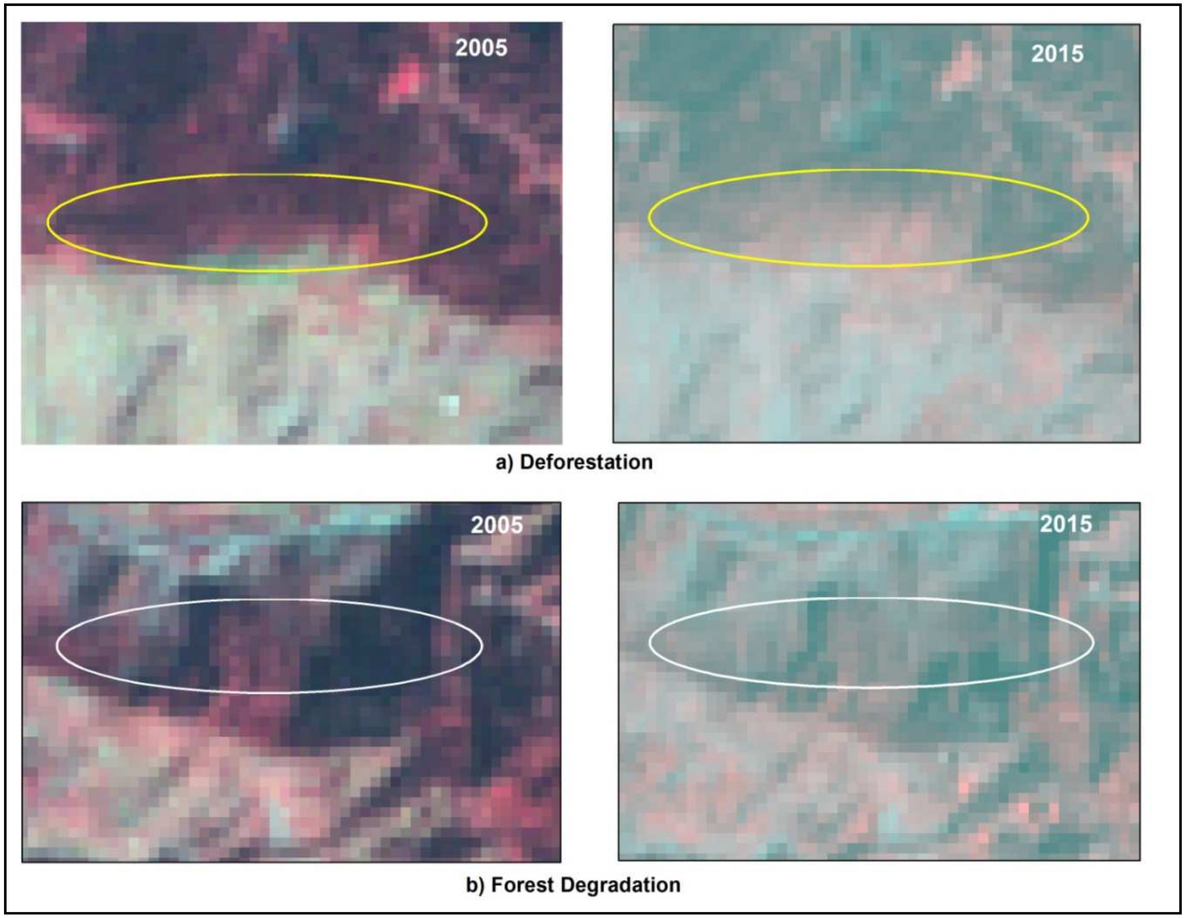

Fig. 12: Image interpretation key for visualization of deforestation and forest degradation in J V forest division from 2005-2015

For change detection of J V forest division, an interpretation key was used. Interpretation was done using different elements of image interpretation viz., tone and texture. In case of deforestation, the tone is dark red in 2005 image depicting dense forest while as it is pinkish in 2015 image depicting grassland as shown in Fig. 12. Similarly in case of forest degradation, the tone is dark red and texture is mostly smooth depicting dense forest while as in case of 2015 image the tone is mixed and texture is rough depicting open forest. Thus it is certain that J V forest has witnessed deforestation and forest degradation during the decade as shown in Fig. 12 respectively.

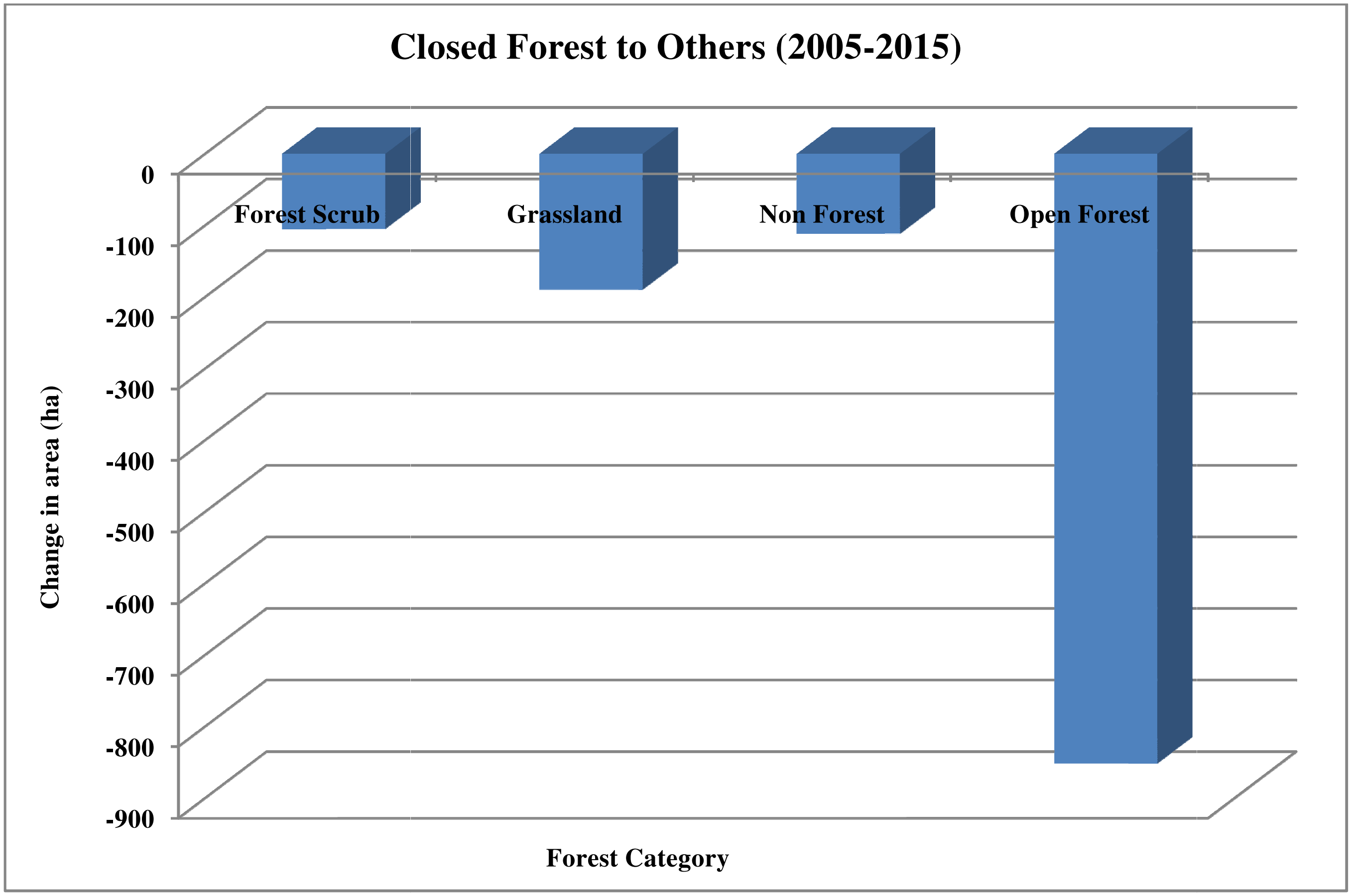

Fig. 13: Forest dynamics from Closed Forest to Others (2005 to 2015) in J V forest division

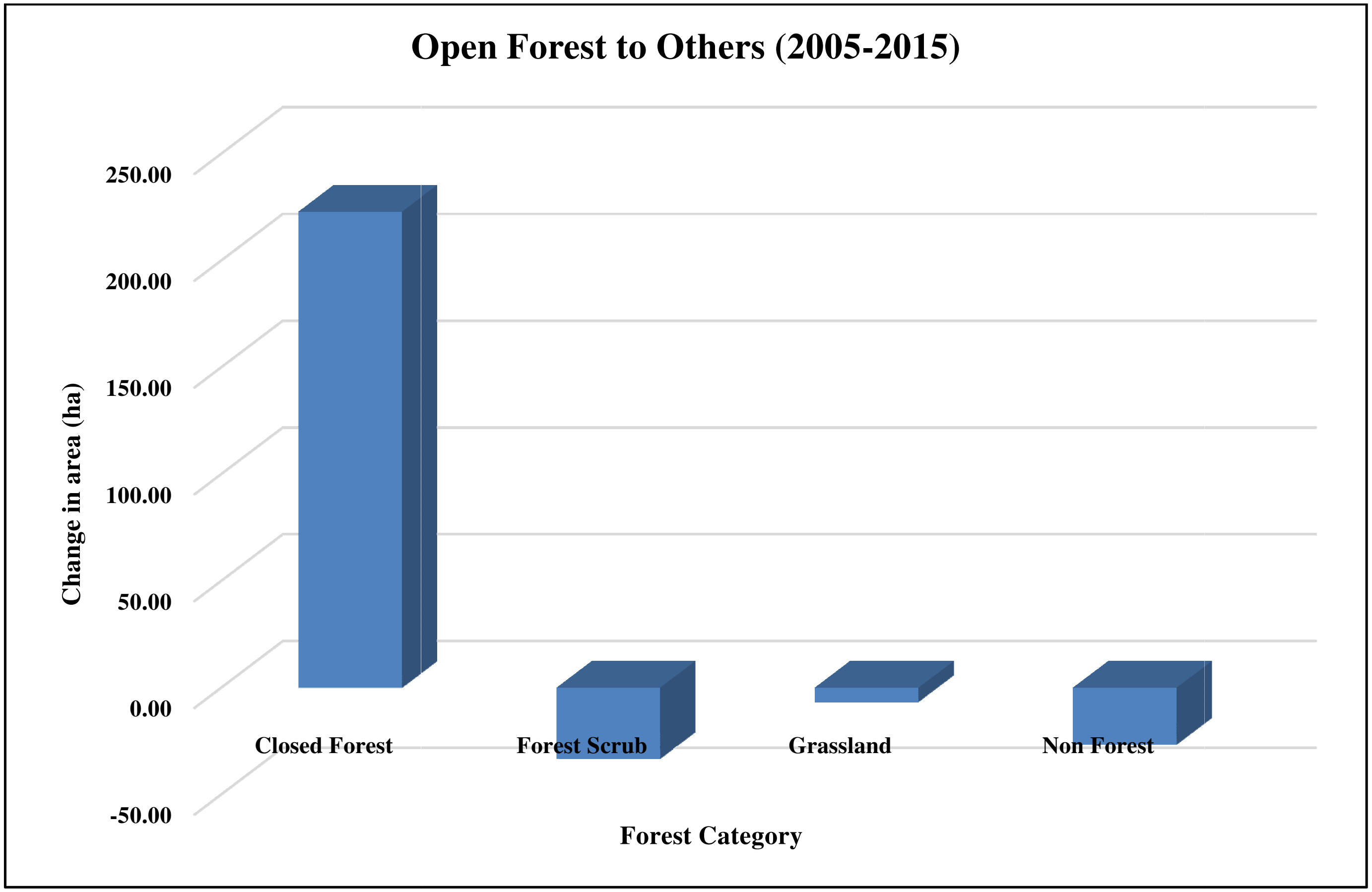

Fig. 14: Forest dynamics from Open Forest to Others (2005 to 2015) in J V forest division

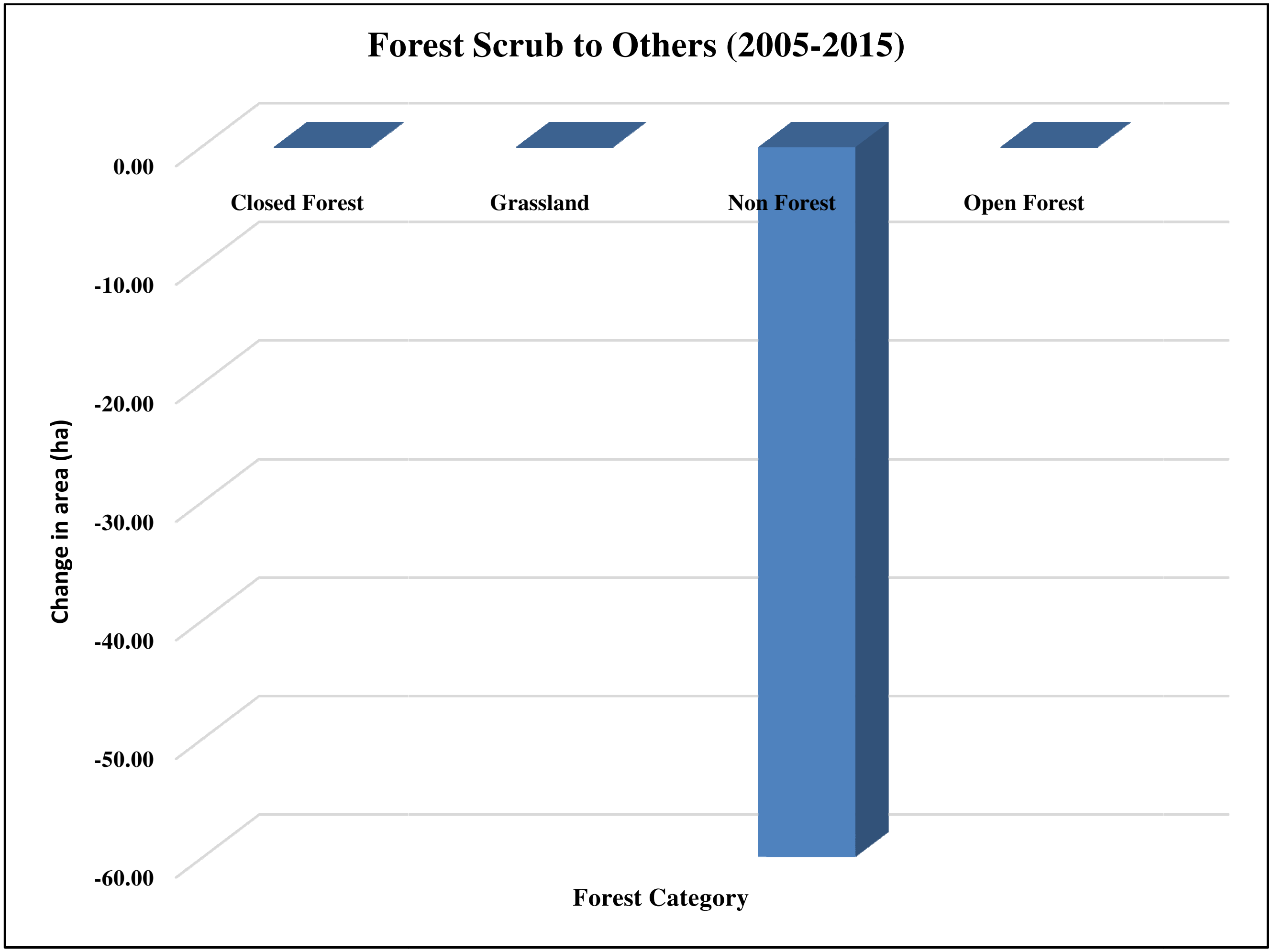

Fig. 15: Forest dynamics from Forest Scrub to Others (2005 to 2015) in J V forest division

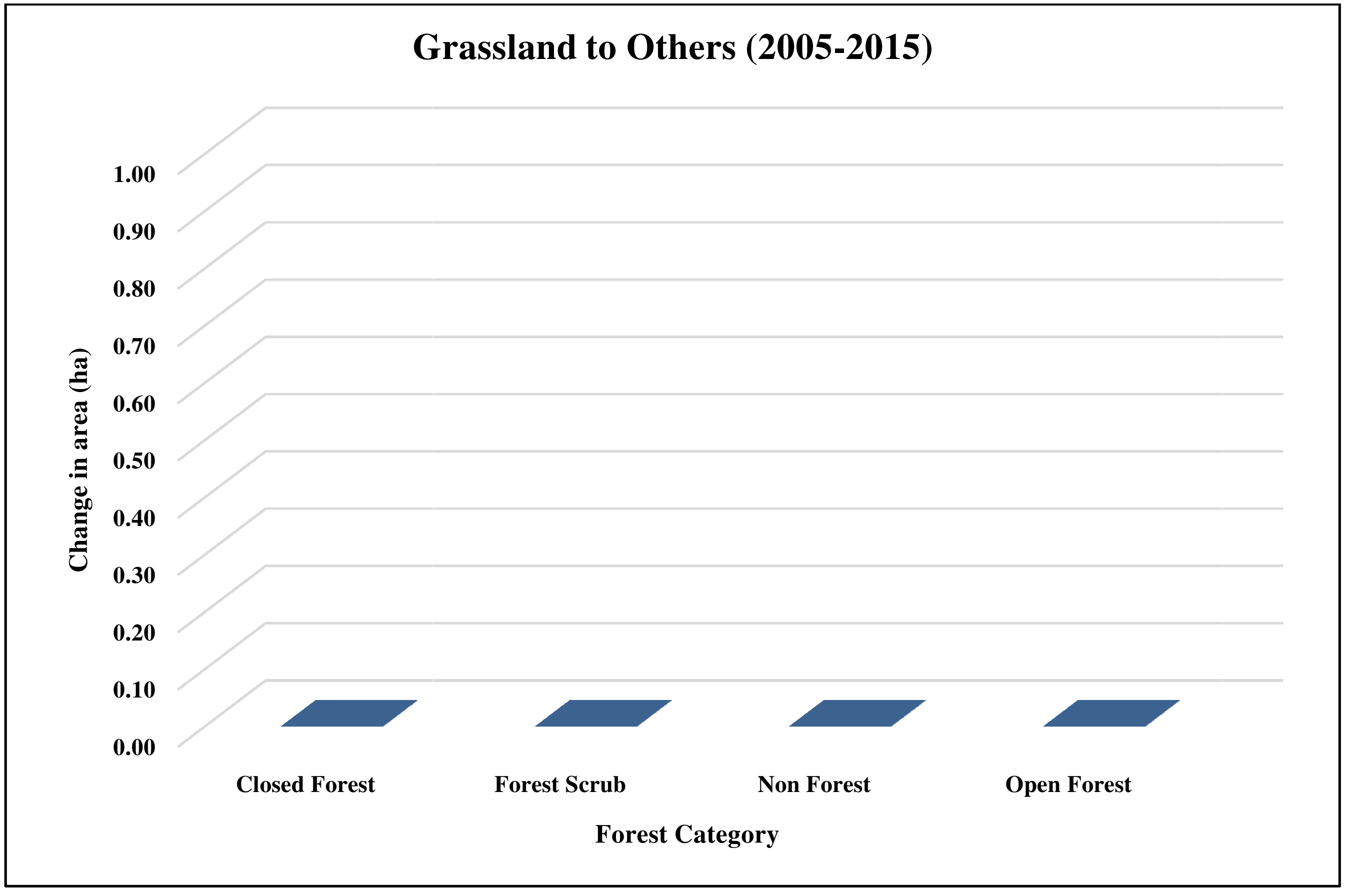

Fig. 16: Forest dynamics from Grassland to Others (2005 to 2015) in J V forest division

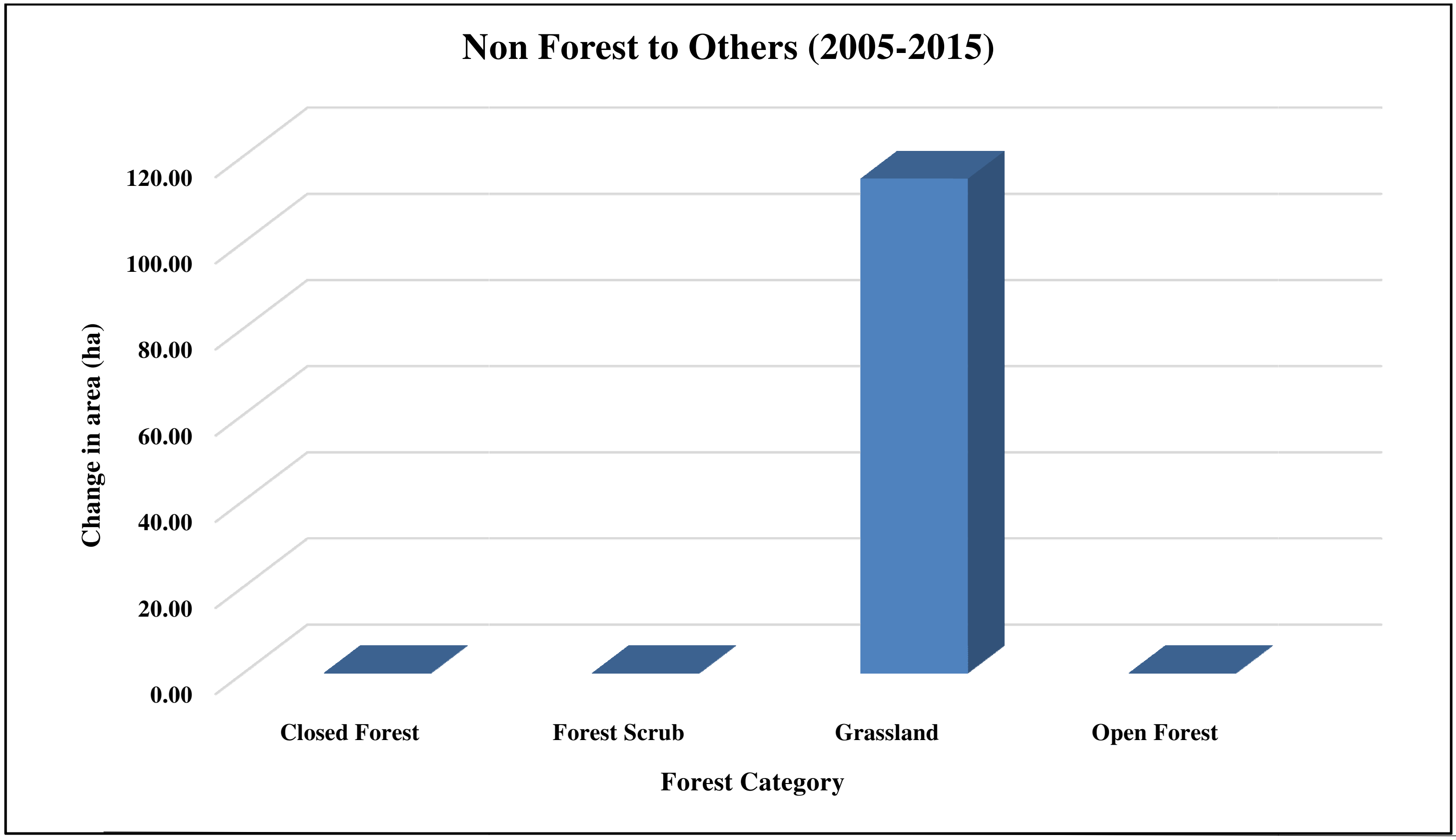

Fig. 17: Forest dynamics from Non Forest to Others (2005 to 2015) in J V forest division

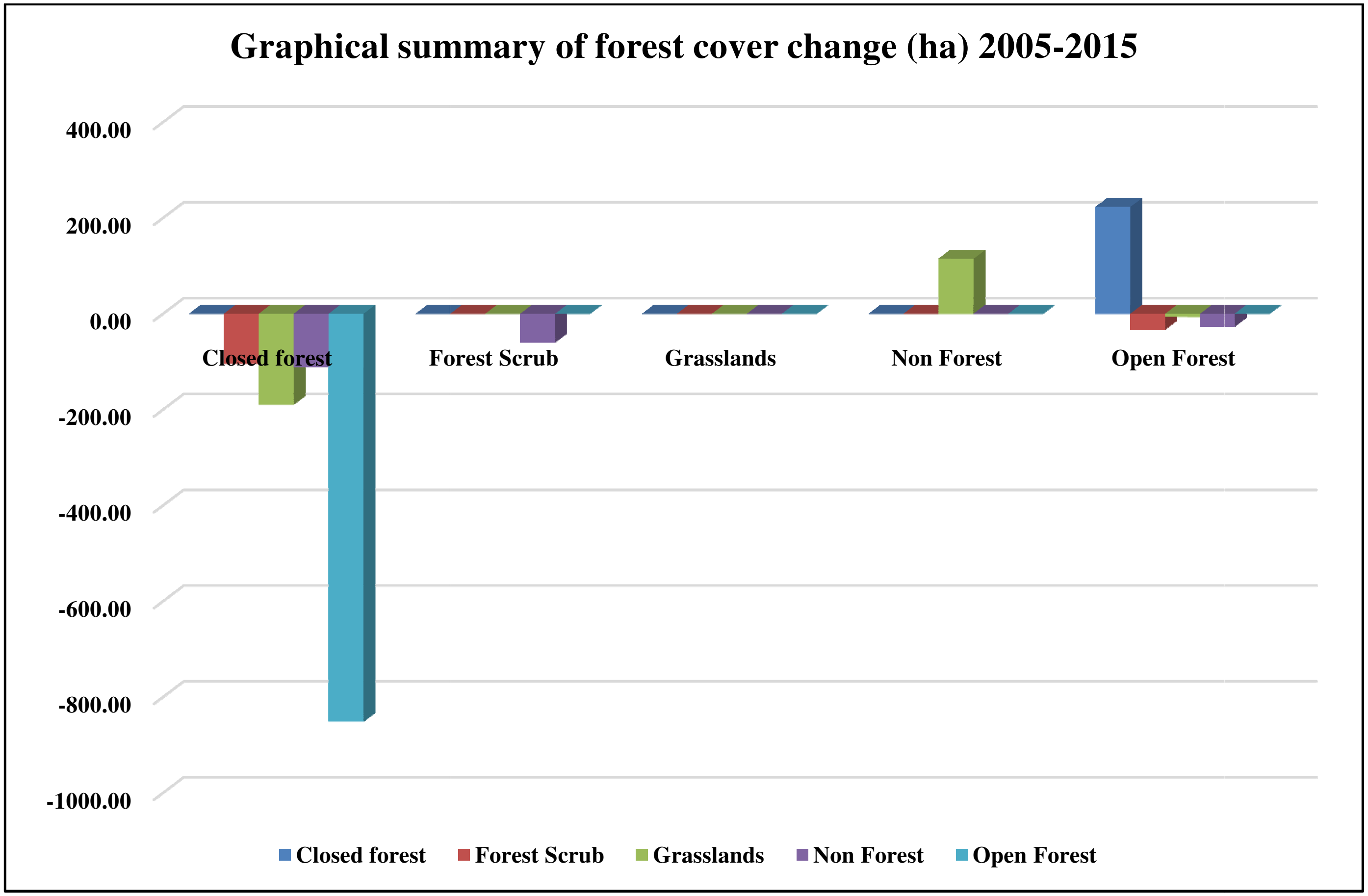

Fig. 18: Forest cover dynamics of all categories (2005 to 2015) in J V forest division

4.5. Drivers of change

The results obtained from the change analysis were used to identify drivers of forest cover change in J V forest division using semi structured interview schedule. For this purpose four nearby villages were selected, two for each category viz., two villages namely Gohan and Patusa for the positive drivers of change and two villages namely Bernate and Shala Dajan for the negative drivers of change. The location of the villages has been shown in Fig. 19. Ten respondents from each village were selected within the defined boundaries of the selected forest division and questions related to forests were asked to them as per questionnaire. The total number of respondents for both categories was 40. The responses were assigned scores for ranking of drivers using statistical analysis. The approach of the respondents regarding drivers of change was ranked from 1-6, rank 1 depicted strong agreement while as rank 6 depicted strong disagreement. The questionnaire was analyzed using simple statistics and following two tables were obtained (Appendix-I). The results obtained have been shown in Table 13 and Table 14. The location of villages witnessing negative and positive changes has been depicted in Fig. 19 respectively.

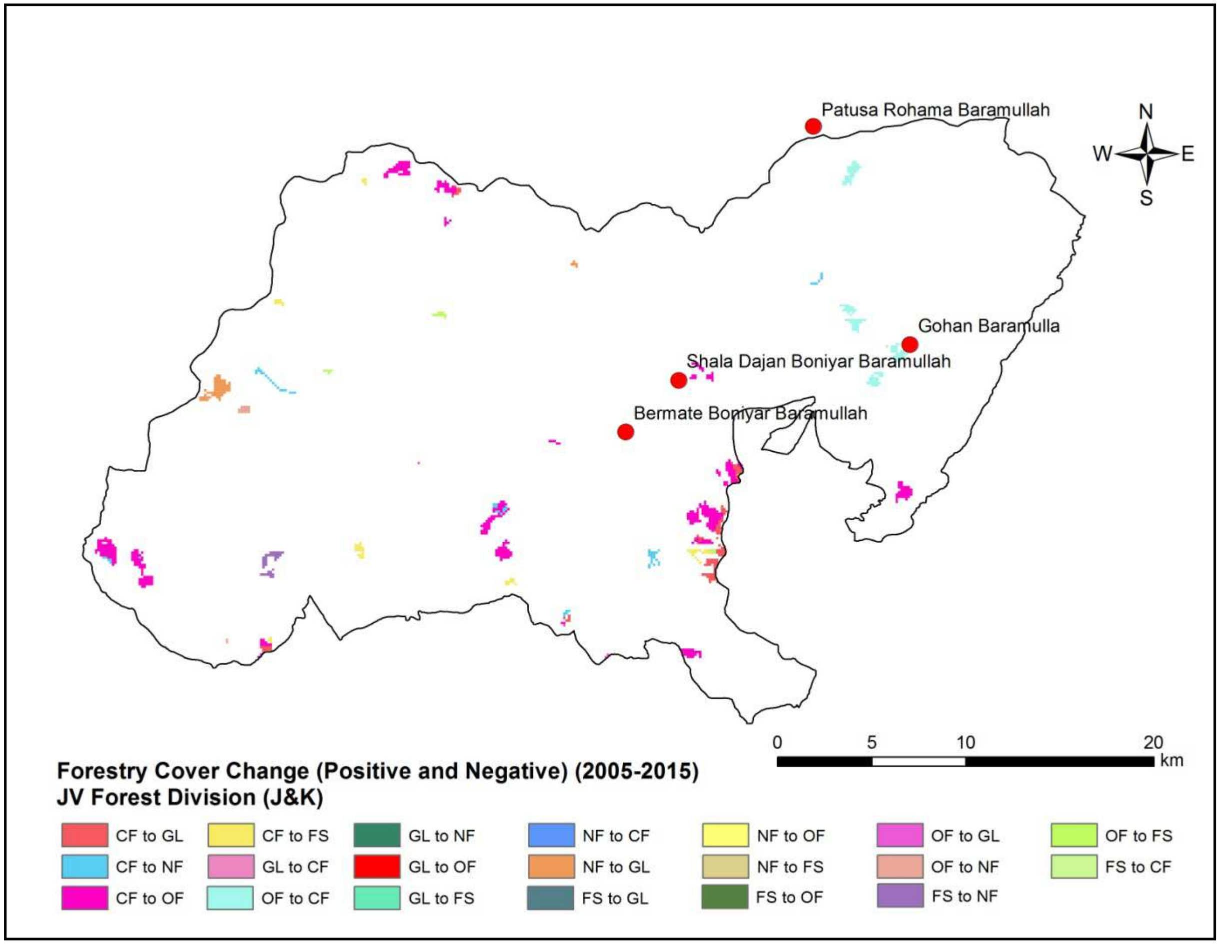

Fig. 19: Location of the villages witnessing negative and positive change from forest cover mapping.

Table-13: Analytical results for drivers of change adjoining villages witnessing negative changes from mapping

Type	S. No	Drivers of change	Frequency against each score 1	2	3	4	5	6	N	Weighted mean score	Variance	Std deviation	Range	Rank
Direct drivers	1	Expansion for agriculture	0	3	4	9	4	0	20	3.70	10.49	3.24	2-5	**8**
	2	Illicit felling for timber	11	9	0	0	0	0	20	1.45	12.15	3.49	1-2	**2**
	3	Excessive fuel wood extraction	10	6	4	0	0	0	20	1.70	8.25	2.87	1-3	**4**
	4	Excessive grazing/ fodder extraction	8	9	3	0	0	0	20	1.75	9.74	3.12	1-3	**5**
	5	Plantation/Afforestation measures by the SFD*	0	1	5	4	4	6	20	4.45	3.04	1.74	2-6	**9**
Indirect drivers	1	Population growth	10	7	3	0	0	0	20	1.65	8.66	2.94	1-3	**3**
	2	Subsistence	9	8	2	1	0	0	20	1.75	8.34	2.89	1-4	**5**
	3	Poverty/Lack of employment	18	2	0	0	0	0	20	1.10	15.45	3.93	1-2	**1**
	4	Lack of awareness about importance of forests	6	4	3	5	2	0	20	2.65	4.08	2.02	1-5	**7**
	5	Degree of forest protection*	0	0	0	2	9	9	20	5.35	18.16	4.26	4-6	**10**
	6	Increasing demand for timber leading to smuggling	9	3	8	0	0	0	20	1.95	10.94	3.31	1-3	**6**

(1= Strongly agree; 2 = Moderately agree; 3= Slightly agree; 4 = Slightly disagree; 5 = Moderately disagree; 6 = Strongly disagree), ' Positive drivers of change*

Table-14: Analytical results for drivers of change adjoining villages witnessing positive changes from mapping

Type	S. No	Drivers of change	Frequency against each score						N	Weighted mean score	Variance	Std deviation	Range	Rank
			1	2	3	4	5	6						
Direct drivers	1	Expansion for agriculture	0	0	0	0	8	12	20	5.60	29.41	5.42	5-6	**8**
	2	Illicit felling for timber	0	0	0	0	7	13	20	5.65	32.62	5.71	5-6	**9**
	3	Excessive fuel wood extraction	0	0	0	3	6	11	20	5.40	19.40	4.40	4-6	**6**
	4	Excessive grazing/ fodder extraction	0	0	0	1	7	12	20	5.55	26.39	5.14	4-6	**7**
	5	Plantation/Afforestation measures by the SFD*	12	8	0	0	0	0	20	1.40	11.74	3.43	1-2	**1**
Indirect drivers	1	Population growth	0	0	0	4	7	9	20	5.25	13.57	3.68	4-6	**4**
	2	Subsistence	0	0	0	3	6	11	20	5.40	19.40	4.40	4-6	**6**
	3	Poverty/Lack of employment	0	0	0	3	7	10	20	5.35	16.86	4.11	4-6	**5**
	4	Lack of awareness about importance of forests	0	0	0	7	3	10	20	5.15	16.85	4.11	4-6	**2**
	5	Degree of forest protection*	12	8	0	0	0	0	20	1.40	11.74	3.43	1-2	**1**
	6	Increasing demand for timber leading to smuggling	0	0	2	3	4	11	20	5.20	17.01	4.12	3-6	**3**

(1= Strongly agree; 2 = Moderately agree; 3= Slightly agree; 4 = Slightly disagree; 5 = Moderately disagree; 6 = Strongly disagree), ' Positive drivers of change*

Statistical analysis of drivers of forest cover change for J V forest division in the villages witnessing negative change from forest cover mapping (Bernate and Shala Dajan) revealed that weighted mean was lowest (1.10) for “Poverty/Lack of employment” hence ranked as number 1 driver with “Illicit felling of timber” having second lowest weighted mean score of 1.45 ranked as number 2 driver. Similarly population growth, excessive fuelwood extraction, excessive grazing/fodder extraction, subsistence, increasing demand for timber leading to smuggling, lack of awareness about importance of forests and expansion of agriculture with weighted mean scores of 1.65, 1.70, 1.75, 1.75, 1.95, 2.65, 3.70 and 5.35 respectively were ranked in the increasing order of geometric mean of their corresponding frequencies (Table 13).

. Similarly in villages witnessing positive change from forest cover mapping (Gohan and Patusa) the top drivers was afforestation done by State Forest Department and degree of forest protection with weighted mean scores of 1.40 each (Table 14).

Chapter-5

DISCUSSION

In the light of available literature from different source, the results obtained from the present study are discussed under the following headings.

5.1 Landuse/Landcover (LULC) maps and Forest cover density maps of 2005 and 2015

Landsat images (OLI) and (TM) of 2015 and 2005 were used to generate Landuse/Landcover maps and Forest cover density maps of 2015 and 2005 in the present study. Several researchers in the past have widely used Landsat imageries, with appropriate spectral and spatial resolutions to identify and calculate vegetation cover changes (Mohamed, 2017; Ochege and Okpala-Okala, 2017; Akike and Samanta, 2016; Jiya *et al.*, 2016; Okoro *et al.*, 2016; Wani *et al.*, 2016; 2014; 2013; 2009; Bhatt *et al.*, 2015; Sajjad *et al.*, 2015; Banerjee *et al.*, 2014). Batar *et al.* (2017) in a similar type of study used Landsat 5 Thematic Mapper (TM) and Landsat 8 Operational Land Imager (OLI) to generate LULC maps for the year 1998 and 2015 in the Garhwal Himalayan region.

The study area was delineated via visual image interpretation technique into 10 LULC classes viz., forest, forest scrub, agriculture, grassland, snow, habitation, waterbody, horticulture, wasteland and agroforestry respectively. Landuse/Landcover maps of 2005 and 2015 have been shown in Fig. 2 and Fig. 3 while as Forest cover density maps of 2005 and 2015 have been shown in Fig. 4 and Fig. 5 respectively. The mapping was done using ArcGIS software. The LULC/forest cover density mapping was carried out using visual interpretation at 1:50,000 scale as employed by several workers in the past (Basavarajappa *et al.*, 2017; Miheretu and Yimer, 2017; Chaudhary and Kumar, 2017; Kumar, 2017; Wani *et al.*, 2016; 2014; 2013; 2009).

Landuse/Landcover map (2015) reveals that there has been a considerable change in Landuse/Landcover from 2005-2015 in J V forest division. In LULC, agriculture has recorded a sharp decline in its area primarily in Baramulla and Doabgah Ranges from 2005 to 2015 which can be mainly ascribed to increased conversion of agricultural land to horticulture and habitation. These results are very much parallel with the investigations carried out by Shafiq *et al.*, 2017; Chaudhary and Kumar, 2017; and Mohamed, 2017. The conversion of agricultural land into horticulture can be attributed mainly to increased dependence of people on horticulture than any other sector as it provides comparatively more economic profit. On the other hand, conversion of agricultural land into habitation can be ascribed to utilization of this land for residential and commercial purposes due to increased population. Forests have also registered a severe decline during the decade due to conversion into other LULC categories like grassland, habitation and agriculture. These changes can be attributed to various factors like deforestation, agricultural expansion and increased built up land which are putting remarkable burden on the forest resources. These observations are in harmony with studies conducted by Shafiq *et al.*, 2017; and Wani *et al.*, 2012.

5.2 Forest cover density dynamics (2005 to 2015)

Forest cover density map was classified into three classes on the basis of crown density viz., Closed Forest, Open Forest, Forest Scrub (FSI, 2005). Furthermore, two additional classes Grassland and Non Forest were also delineated. The forest cover density change matrix (2005-2015) as shown in Table 12 reveals forest degradation because of conversion of closed forest into open forest (851.48 ha) and forest scrub (104.77 ha), similarly conversion of an area of 33.26 ha from open forest to forest scrub signifies transformation from higher forest category to lower one. Furthermore, conversion of 111.42 ha, 59.87 ha and 26.61 ha of land from closed forest, forest scrub and open forest into non forest indicates deforestation. These observations are very much akin with the work conducted by Chaudhary and Kumar (2017) in Koshalya-Jhajhara watershed, Shafiq *et al.* (2017) in Lolab watershed, Debnath *et al.* (2017) in Baramura hill range, Batar *et al.* (2017) in Rudraprayag district (Uttarakhand), Kumar (2017) in Kamrup district (Assam), Amin (2016) in Pirpanjal forest division, Wani *et al.* (2016) in Anantnag forest division and Farooq and Rashid (2010) in Doodhganga watershed respectively.

5.3 Accuracy assessment and conditional kappa

The total number of reference points (ground truth points) for accuracy assessment and map validation was 133 at various places of the study area (Fig. 10). The overall classification accuracy of forest density map of 2015 came out to be 92.48%. The overall classification accuracy of forest density map 2015 was calculated on the basis of producer's accuracy and user's accuracy as shown in Table 10.

The conditional kappa for each category was calculated using Kappa formula. The overall Kappa statistics was calculated as 0.8757 as shown in Table 11. Azizi *et al.* (2008) got overall accuracy of 84.4% and kappa 78.3% while as Ismail and Jusoff (2008) got overall accuracy equal to 83.5% and kappa 75% for a similar type of study.

5.3 Drivers of change

Statistical analysis of drivers of forest cover change for J V forest division in the adjacent villages witnessing negative change from forest cover mapping as shown in Table 13 reveals poverty/lack of employment, illicit felling for timber and population growth as the top most ranked drivers. The same has been reported by various workers like Makunga and Misana (2017) and Amin (2016).

A small positive change at certain places around forest areas was also observed as a result of two positive drivers viz., plantation/afforestation measures by the SFD and degree of forest protection (Table 14). This is akin with the results obtained by FAO (2015); Antonio *et al.* (2012) and Amin (2016).

Chapter-6

SUMMARY AND CONCLUSION

Forest cover estimation of any area is always in great demand by various parties namely the policy makers, the local population, environmentalists, manufacturers and the consumers. The absence of fitting information collected and exhibited in a logical way has been a noteworthy shortcoming in the forest policy and administration all through India particularly in Jammu and Kashmir and this articulates the need of forest cover assessment. Forests around the globe are confronting colossal pressure and the Jammu and Kashmir forests are no special case. Thus, there is a huge need of analysis of the forest cover in our state. The management policy for the present assets and for restoring the forest cover could be framed on the outcome of forest cover dynamics. Having exact information on amount and degree forest wealth would quicken the way toward building cutting edge techniques towards preservation and environmental change.

In the current investigation, J V forest division has been mapped for the first time using the present system of categorization of forest classes based on forest cover density classes using remote sensing and GIS. Visual image interpretation technique of satellite data has been used in the current investigation. Extensive ground truth checks were performed in the study area. The maps acquired through visual image interpretation of satellite data are highly accurate. The maps generated in the current studies are accurate with overall classification accuracy being 92.48% and kappa equal to 0.8757 which is considered highly accurate.

In Landuse/Landcover, agriculture has recorded a sharp decline in its area mostly in Baramulla and Doabgah ranges of the J V forest division from 2005 to 2015 which can be mainly ascribed to increased conversion of agricultural land to horticulture and habitation, therefore increasing the area under horticulture and habitation categories. Forests have also recorded a decrease in area during the decade due to conversion into other LULC categories like grassland, habitation and agriculture.

The results of forest cover change matrix (2005-2015) as shown in Table 10 reveals conversion of closed forest into open forest (851.48 ha), closed forest into forest scrub (104.77 ha), and open forest into forest scrub (33.26 ha) designates transformation from higher forest category to lower one which can be ascribed to forest degradation. Furthermore, conversion of 111.42 ha, 59.87 ha and 26.61 ha of land from closed forest, forest scrub and open forest into non forest can be attributed to deforestation. Top drivers of change in adjoining villages witnessing negative change from mapping were identified to be poverty/lack of employment and illicit felling of timber. Similarly positive drivers of change were identified to be plantation/afforestation measures and degree of protection by State Forest Department

The conclusion of whole study is as under:

- The area under agriculture has shown a decline of 0.87% (863.11 ha) during the decade.
- Habitation area has shown an increase of 1.08% (1067.67 ha) during the study period chiefly due to conversion of agricultural and horticultural land into habitation.
- Horticulture has shown an increase of 0.83% (370.86 ha) during the decade largely due to transformation of agricultural land into horticulture.
- The total forest area has diminished by 0.48% (472.3 ha) from 2005 to 2015 due to deforestation.

- The results from change matrix signifies an elevated forest degradation of closed forest to open forest (851.48 ha) and forest scrub (104.77 ha); open forest into forest scrub (33.26 ha). Moreover, a high rate of deforestation is also indicated by change matrix through conversion of closed forest (111.42 ha), open forest (26.61 ha) and forest scrub (59.87 ha) into non forest category.
- The total area under grassland has shown a net increase of 0.32 % (310.98 ha) throughout the decade.
- Drivers of change indicate a negative change in forest cover and density mainly due to poverty/lack of employment and illicit felling of timber. Also, a small positive change in the forest areas at certain places has taken place mainly due to plantation/afforestation measures and degree of forest protection by State Forest Department.
- There is a need to supervise and follow up on the recognized drivers of forest cover by the concerned forest department to alter the course of deforestation and forest degradation in the investigation region.
- The areas having witnessed severe deforestation and forest degradation must be immediately protected and necessary silvicultural interventions be made based on severity.
- The identified drivers must be incorporated in the working plans and necessary technical and financial measures should be outlaid in annual action plans.
- Training programmes in areas having witnessed negative changes should be conducted to spread awareness about importance of forests.
- The state forest department should invest funds directed towards conservation and uplifting socio-economic status of people involved in such activities.

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Appendix- I

Preliminary details of villages adjoining forest witnessing negative forest cover change from mapping

Village 1

Preliminary details of village		Respondent No.	Name & Parentage	Profession (Agr/Employed/Daily wager/None)	No of family dependent family members	Average monthly family income (Rs.)	Altitude (m)	Dependence on forests (Timber, Fuel, Fodder etc.) %	Land holding (ha) Agri/Hort/unproductive	No. of livestock
Address (Village, Tehsil, District)	Bernate (Boniyar, Baramulla)	1	Farooq Ahmad Mir S/o Gh. Ahmad Mir	Employed	7	15,000	1790	25	0	0
Population	1961	2	Hafeezullah Mir S/o Gh. Rasool Mir	Labour	11	5000	1790	35	0	0
No of households	328	3	Gh. Mohd. Mir S/o Samad Mir	Labour	9	5000	1795	50	0.02	2
Location (Lat/Long)	E 74°12′11.1″ N 34°07′34.8″	4	Mohd. Sultan Sheikh S/o Gh. Rasool Sheikh	Labour	9	4000	1793	40	0.15	2
Altitude (m)	1782	5	Wali Mohd. Mir S/o Abdul Mir	Employed	10	10,000	1792	20	0.10	1
Distance from nearby forest	0.5 km	6	Atta Mohd. Mir S/o Habeeb Mir	Labour	9	5000	1792	30	0.05	4
Dominant changes in the nearby forest observed from mapping	Deforestation	7	Bashir Ahmad Mir S/o Ahmad Mir	Employed	7	4000	1780	40	0.10	4
Major profession of villagers	Labour	8	Jumma Sood S/o Sardara Sood	Labour	5	4000	1778	60	0.20	4
Connected to forest by kutcha/pucca road	Kutcha	9	Bilal Ahmad War S/o Wali Mohd. War	Shopkeeper	8	7000	1779	30	0.07	2
Distance from nearest forest check post	2.5 Km	10	Ali Mohd. Lone S/o Mohd. Rustom	Dailywager	9	8000	1780	20	0.02	1

Village 2

Preliminary details of village		Respondent No.	Name & Parentage	Profession (Agr/Employed/Daily wager/None)	No of family dependent family members	Average monthly family income (Rs.)	Altitude (m)	Dependence on forests (Timber, Fuel, Fodder etc.) %	Land holding (ha) Agri/Hort/unproductive	No. of livestock
Address (Village, Tehsil, District)	Shala Dajan (Boniyar, Baramulla)	1	Mohd. Iqbal Khan S/o Akbar Ali Khan	Labour	7	3000	1763	40	0.05	2
Population	692	2	Ab. Majeed Khan S/o Dilawar Khan	Labour	13	3000	1767	40	0.20	4
No of households	115	3	Mohd. Amin Khan S/o Mohd. Zaman Khan	Employed	7	15,000	1766	20	0.20	2
Location (Lat/Long)	E 74°14′00.3″ N 34°09′05.0″	4	Mohd. Sidiq Khan S/o Mohd. Zaman Khan	Employed	7	14,000	1764	10	0.20	2
Altitude (m)	1773	5	Mohd. Shabir S/o Mohd. Yaqub	Labour	8	3000	1789	50	0.15	7
Distance from nearby forest	0.4 km	6	Mohd. Saleem S/o Shah Zaman Khan	Labour	8	4000	1777	30	0.10	4
Dominant changes in the nearby forest observed from mapping	Deforestation	7	Mohd. Lateef S/o Laldin	Employed	8	15,000	1774	10	0.30	0
Major profession of villagers	Labour	8	Ab. Quyoom S/o Dilawar Khan	Labour	4	3000	1770	50	0.10	1
Connected to forest by kutcha/pucca road	Kutcha	9	Ali Bahadur S/o Gh. Mohd. Khan	Labour	12	4000	1762	40	0.10	7
Distance from nearest forest check post	3 km	10	Mohd. Azam S/o Kalu Khan	Labour	6	5000	1760	40	0.30	3

Appendix-II

Preliminary details of villages adjoining forest witnessing positive forest cover change from mapping

Village 1

Preliminary details of village		Respondent No.	Name & Parentage	Profession (Agr/Employed/Daily wager/None)	No of family dependent family members	Average monthly family income (Rs.)	Altitude (m)	Dependence on forests (Timber, Fuel, Fodder etc.) %	Land holding (ha) Agri/Hort/unproductive	No. of livestock
Address (Village, Tehsil, District)	Gohan (Baramulla, Baramulla)	1	Gh. Nabi Magray S/o Gh. Mohd. Magray	Employed	8	7000	1998	20	2.78	3
Population	1056	2	Mohd. Akbar Wani S/o Gh. Mohd. Wani	Labour	4	4000	1998	30	0.05	0
No of households	197	3	Meetwal Singh S/o Sewa Singh	Teacher	6	10,000	2014	10	3.03	2
Location (Lat/Long)	E 74°22′00.1″ N 34°10′09.0″	4	Javed Ahmad Checha S/o Gulabdin Checha	Teacher	6	10,000	2024	10	1.01	1
Altitude (m)	2048	5	Gh. Rasool Mir S/o Rahman Mir	Agr	10	5000	1999	30	1.51	3
Distance from nearby forest	1 km	6	Ali Mohd. Wani S/o Habibullah Wani	Employed	4	6000	2021	10	0.30	0
Dominant changes in the nearby forest observed from mapping	Afforestation	7	Bashir Ahmad Wani S/o Mohd. Wani	Agr	8	5000	2022	20	1.01	1
Major profession of villagers	Farming	8	Abdul Ahad Magray S/o AB. Gani Magray	Agr	4	5000	2040	20	0.50	1
Connected to forest by kutcha/pucca road	Pucca	9	Mohd. Yousuf Wani S/o Gh. Mohd. Wani	Dailywager	6	3000	2050	30	0.30	1
Distance from neaest forest check post	3 km	10	Wali Mohd. Mir S/o Mohd. Ramzan Mir	Agr	6	4000	2069	30	1.01	1

Village 2

Preliminary details of village		Respondent No.	Name & Parentage	Profession (Agr/Employed/Daily wager/None)	No of family dependent family members	Average monthly family income (Rs.)	Altitude (m)	Dependence on forests (Timber, Fuel, Fodder etc.) %	Land holding (ha) Agri/Hort/unproductive	No. of livestock
Address (Village, Tehsil, District)	Patusa (Rohama, Baramulla)	1	Mudasir Bashir Dar S/o Bashir Ahmad Dar	Dailywager	4	2000	1720	20	0.50	0
Population	1305	2	Tariq Ahmad Dar S/o Ab. Rashid Dar	Dailywager	10	2000	1720	20	0.20	3
No of households	171	3	Ab. Quyoom War S/o Khazir Mohd	Agr	4	3000	1715	10	0	0
Location (Lat/Long)	E 74°18′36.1″ N 34°16′24.9″	4	Mohd. Sultan Lone S/o Mohd. Maqbool	Agr	5	4000	1714	10	0.30	1
Altitude (m)	1705	5	Gh. Nabi Sheikh S/o Gh. Mohd. Sheikh	Agr	14	4000	1709	30	0.50	3
Distance from nearby forest	2 km	6	Ab. Hameed Dar S/o Gh. Rasool Dar	Agr	14	5000	1710	40	0.40	3
Dominant changes in the nearby forest observed from mapping	Afforestation	7	Gh. Hassan Dar S/o Ab. Subhan Dar	Agr	6	3000	1710	30	0.50	0
Major profession of villagers	Farming	8	Farooq Ahmad Dar S/o Gh. Hassan Dar	Agr	7	4000	1700	30	0	0
Connected to forest by kutcha/pucca road	Kutcha	9	Nazir Ahmad Bhat S/o Habibullah Bhat	Agr	8	5000	1699	40	0.25	2
Distance from neaest forest check post	4 km	10	Wali Mohd. Bhat S/o Ab. Jabbar Bhat	Agr	6	4000	1699	20	0.40	2

Interview Schedule for assessing drivers of change (Negative)

Close ended semi-structured interview (Villages adjoining negative forest cover change from mapping)
Perceived reasons for drivers of forest cover change by village respondents based on six dominant perceptions with an assigned score from 1 to 6
(1 = Strongly agree; 2 = Moderately agree; 3 = Slightly agree; 4 = Slightly disagree; 5 = Moderately disagree; 6 = Strongly disagree)

Village No.	Respondent No.	Expansion for agriculture (1-6)	Illicit felling for timber (1-6)	Excessive fuel wood extraction (1-6)	Excessive grazing/ fodder extraction (1-6)	Plantation /Afforestation measures by the SFD (1-6)	Population growth (1-6)	Subsistence (1-6)	Poverty/ Lack of employment (1-6)	Lack of awareness about importance of forests (1-6)	Degree of forest protection (1-6)	Increasing demand for timber leading to smuggling (1-6)
Village 1	1	5	1	1	1	6	1	1	1	1	6	1
	2	4	1	3	2	5	2	2	1	3	5	3
	3	4	2	2	2	5	2	4	1	4	5	3
	4	3	1	2	2	4	2	2	1	3	6	3
	5	5	1	1	1	6	3	1	1	1	6	1
	6	4	2	3	1	3	1	2	1	3	5	2
	7	5	2	1	3	4	2	1	1	1	6	1
	8	3	2	2	3	4	3	2	1	4	5	1
	9	4	1	1	2	5	1	3	1	2	4	2
	10	4	1	1	1	6	1	1	1	2	6	1
Village 2	1	4	2	2	2	5	1	2	2	4	5	3
	2	5	2	3	2	3	2	2	1	5	5	3
	3	4	1	1	1	6	1	1	1	1	6	1
	4	4	1	1	1	6	1	1	1	1	6	1
	5	3	2	2	1	3	2	2	1	5	6	2
	6	2	1	2	2	3	3	3	1	2	5	3
	7	4	1	1	1	6	1	1	2	1	6	1
	8	2	2	1	3	4	2	1	1	4	5	3
	9	3	2	1	2	2	1	2	1	4	5	3
	10	2	1	3	2	3	1	1	1	2	4	1

Interview Schedule for assessing drivers of change (Positive)

Close ended semi-structured interview (Villages adjoining negative forest cover change from mapping)

Perceived reasons drivers of forest cover change by village respondents based on six dominant perceptions with an assigned score from 1 to 6 (1 = Strongly agree; 2 = Moderately agree; 3 = Slightly agree; 4 = Slightly disagree; 5 = Moderately disagree; 6 = Strongly disagree)

Village No.	Respondent No.	Expansion for agriculture (1-6)	Illicit felling for timber (1-6)	Excessive fuel wood extraction (1-6)	Excessive grazing/ fodder extraction (1-6)	Plantation/Afforestation measures by the SFD (1-6)	Population growth (1-6)	Subsistence (1-6)	Poverty/ Lack of employment (1-6)	Lack of awareness about importance of forests (1-6)	Degree of forest protection (1-6)	Increasing demand for timber leading to smuggling (1-6)
Village 1	1	6	6	6	6	1	6	6	6	6	1	6
	2	6	5	5	4	2	5	5	5	4	2	4
	3	6	6	6	6	1	6	5	6	6	1	6
	4	5	6	5	6	1	6	4	6	6	1	6
	5	5	5	4	5	2	5	6	4	5	2	5
	6	6	6	6	6	1	6	6	6	6	1	6
	7	5	6	5	6	2	4	6	5	4	1	3
	8	5	5	6	5	2	4	4	5	4	2	4
	9	6	6	6	6	1	6	6	6	6	1	6
	10	5	5	6	5	1	5	6	4	4	2	3
Village 2	1	6	6	6	6	1	5	6	5	6	1	5
	2	6	6	6	6	1	5	6	5	6	1	6
	3	5	6	4	5	2	6	5	6	6	2	6
	4	6	5	4	5	2	6	4	4	5	2	5
	5	5	6	5	5	2	4	5	6	6	1	6
	6	6	6	6	5	1	6	5	6	4	2	5
	7	6	6	6	6	1	5	6	5	6	1	6
	8	5	6	5	6	2	6	6	6	4	1	6
	9	6	5	5	6	1	4	5	5	4	2	4
	10	6	5	6	6	1	5	6	6	5	1	6

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CERTIFICATE

Certified that all the corrections/amendments as suggested by External Examiner Dr. P. K Joshi, Professor, School of Environmental Sciences, Jawaharlal Nehru University, New Delhi during Viva-Voce examination held on November 24, 2017 have been incorporated in the manuscript entitled **" Decadal forest cover change in Jehlum Valley forest division of Kashmir Himalayas using remote sensing and GIS technique"** submitted by **Mr. Zaid Bashir Wani (Regd. No. 2015-For-50-M).**

(Dr.Akhlaq Amin Wani)
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