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Integrated Geospatial Techniques for Land-use/Land-cover and Forest Mapping of Deciduous Munger Forests (India)

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Abstract:
The present study attempts to generate land-use/land-cover (LULC) and forest map using standard False-Colour composite (FCC) of satellite imagery of IRS P6 LISS III for a deciduous forest area of Munger in Bihar, India. The method adopted is an integration of geospatial techniques and field data to accurately map the LULC of the study area. Forest classification through unsupervised, supervised and visual interpretation is carried out to observe a corresponding gradual enhanced classification accuracy of the methods applied. Nearly 89% of the area is covered under forest out of which the dominant forest types are mixed *Shorea robusta* (Sal), *Acacia catechu* (Khair) and *Dendrocalamus* sp. (Bamboo) forests. The major constraint of the study is the inaccessibility of most of the area. The integrated geospatial approach overcomes this problem to a great extent and reveals its potential for gathering information from remote areas without directly intervening in the area. The study proposes the application of satellite remote sensing and geospatial techniques for future environmental monitoring and forest dynamics studies.

Keywords: Accuracy assessment, Forest strata, Geospatial, Land-use/land-cover, Supervised classification, Unsupervised classification, Visual interpretation

1.0 Introduction:
Satellite Remote Sensing is an important and convenient tool for monitoring and management of natural resources of the environment. Remotely sensed data are extensively and eficiently used in land-use/land-cover (LULC) classification (Brahabhatt *et al.,* 2000; Hyman *et al.,* 2000; Kumar *et al.,* 2010; Alaguraja *et al.,* 2010; Karwariya and Goyal, 2011; Gupta and Roy, 2012; Karwariya and Tripathi, 2012; Selvam, 2012) due to its repetitive data acquisition capabilities, digital format suitability for computer processing and lower cost than those associated with traditional methods (Karwariya and Goyal, 2011). Land-cover relates to the distinct features on Earth's surface (Lillesand *et al.,* 2007) with the composition and characteristics of Earth surface elements (Karwariya and Goyal, 2011) including natural and anthropogenic features, and thus describes the Earth's physical state in terms of the natural environment and the man-made structures (Karwariya and Tripathi, 2012) which can be mapped using suitable satellite imagery with spectral signatures. On the other hand, land-use deals with human uses or economic function of the landscape (Lillesand *et al.,* 2007) having no spectral basis for its unique identification. So it cannot be derived from image data unambiguously, however can be inferred by visual interpretation or assessed with object-based contextual analysis.

Land-use is constrained by environmental factors while it also reflects the importance of land as a major finite resource for human and act as an essential factor of production coupled with economic growth (Alaguraja *et al.,* 2010). Improper land-use practices cause environmental degradation impeding its sustainable use (Gupta and Roy, 2012). Hence, it is essential to know its characteristics, quality, productivity, suitability and limitations along with its extent and location. It is a product of interactions between a society's cultural background, state, and its physical needs with the natural potential of land (Hwang and Ku, 2004; Karwariya and Goyal 2011; Selvam, 2012). Land cover change, due to its dynamic nature (Sharma *et al.,* 2012a) is the most important regional anthropogenic disturbance to the environment (Roberts *et al.,* 1998). LULC change and land degradation are therefore driven by the same set of proximate and underlying factor elements central to environmental processes, change and management through their influence on biodiversity, heat and moisture budgets, trace gas emissions, carbon cycling, livelihoods and a wide range of socioeconomic and ecological processes (Desanker *et al.,* 1997; Verburg *et al.,* 2000; 2002; Fasona and Omojola, 2005; Selvam, 2012).

With the worldwide highest deforestation rate, India faces competing land uses that are causing a major decline in the forests (Selvam, 2012). In addition, increasing need for fuel-wood and charcoal is also contributing towards deforestation (Ademiluyi *et al.,* 2008). Agricultural encroachment and unfettered forest fire can cause many wild species to decline (Alaguraja *et al.,* 2010; Soundranayagam *et al.,* 2011). The reduction and/or degradation of this natural resource can exaggerate the competition specifically to stressed area. The precious environment and its inhabitants need to be conserved by proper management planning and not just keep them at the mercy of chance or evolution (Santhiya *et al.,* 2010; Karwariya and Goyal, 2011). Our study reveals the potential significance of certain LULC mapping and classification methods in deciduous forest set-up of Munger. The main objective of the study is to develop an effective method to enumerate both quantitatively and qualitatively the LULC features of the deciduous forest area with utmost accuracy. In addition, the study examines the need for proper geomanagement and geoinformation of the area.

2.0 Material and Methods:

2.1 Study Area and Datasets:

The study area of Munger situated in Bihar (India) is located in the south-west part of the Kharagpur district with geographic extent of 25º19'30''N-24º56'50''N latitudes and 86º33'33''E- 86º11'51''E (Figure 1). The notified area of the Munger Forest Division comprises of 257.50 km^2 of Reserved forests and 424.40 km^2 of Protected forests with heterogeneous tropical moist deciduous tropical forests. Soil colour is grey to dark grey with texture medium to heavy, moderately alkaline with average clay content throughout the profile. Maximum temperature during summer (March-May) touches 45^{o}C while it falls to nearly 3-9 ^{o}C during winter (October-February). The area receives rainfall from the south-west monsoon, which is active during the months of June–September with average annual rainfall of approx 1079 mm (IMD data). The area is highly rich in faunal and floral diversity. Satellite data of Indian Remote sensing Satellite (IRS) P6, linear image self-scanning (LISS) III of 2012 with a spatial resolution of 23.5m along with Survey of India (SOI) toposheets were used for the LULC feature classification.

2.2 Methodology:

The brief outline of the methodology is depicted in Figure 2. The georeferenced Survey of India (SOI) toposheet maps 72K/7, 72K/8, 72K/11 and 72K/12 were mosiacked on a scale of 1:50,000 using ERDAS Imagine (version 9.1) software. The mosiacked toposheet maps were digitized and features were extracted for the preparation of thematic maps using ArcGIS (version 9.3) software. Ground-based GPS (Global Positioning System) points of distinct identifiable objects on the toposheets were collected. Satellite image of IRS P6 LISS-III was co-registered and geometrically rectified in reference to the mosaicked SOI toposheet considering the analogous distinct identifiable objects on the toposheets, ground and image with an accuracy of RSME=0.4. The satellite image was geocoded with UTM projection, datum WGS-84, Zone 45 North having total 4 spectral bands on a 1:50,000 scales. LULC classification for various thematic data was carried out using three methods: unsupervised classification, supervised classification and visual interpretation.

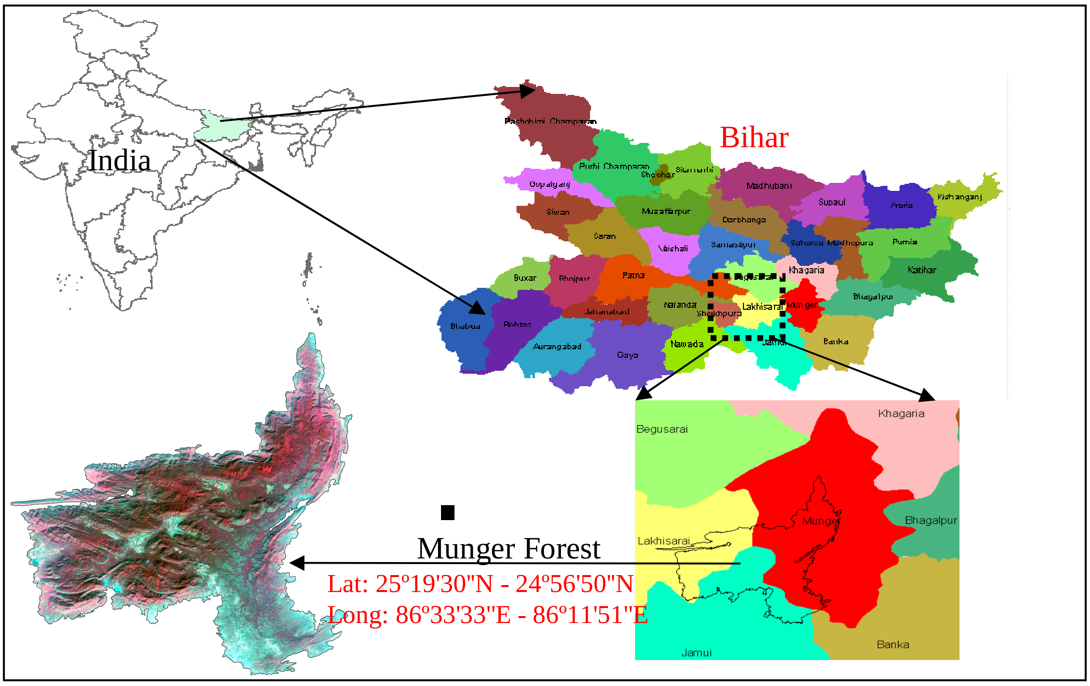

Fig. 1: Location of the study area

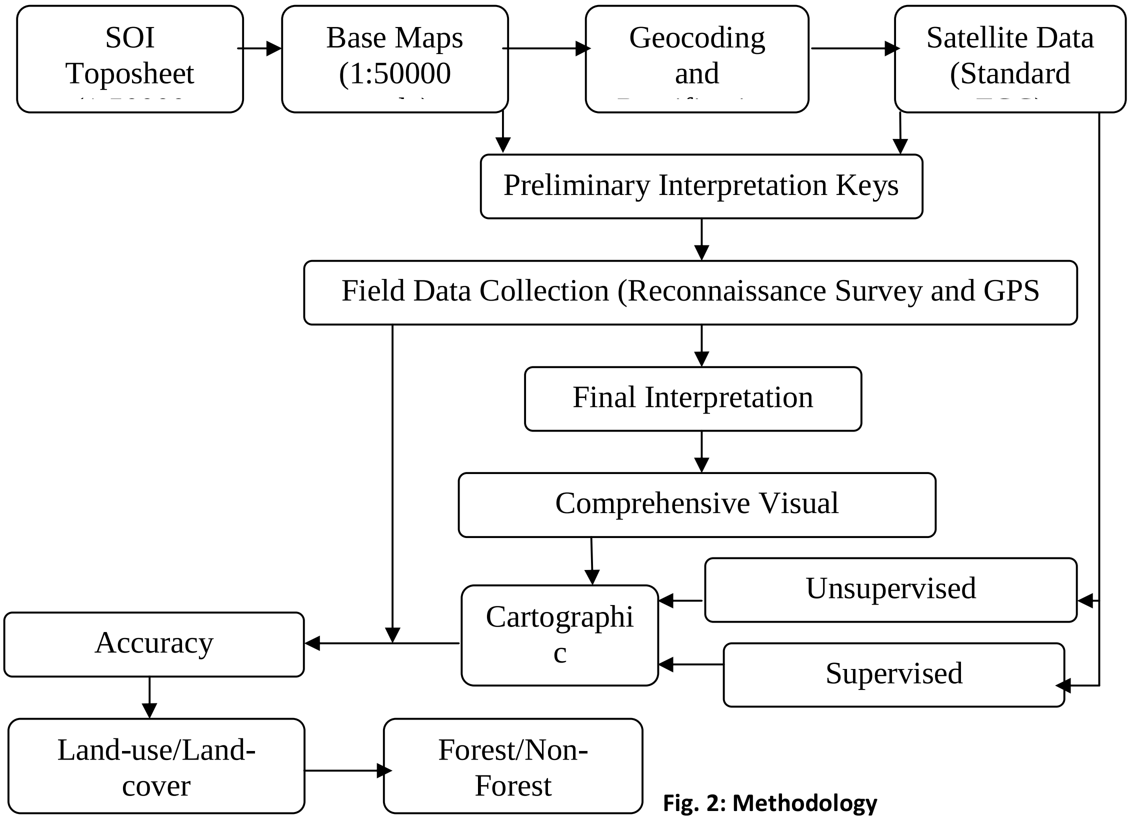

Fig. 2: Methodology

Unsupervised classification was performed in ERDAS Imagine (version 9.1) software using six iterations with a convergence threshold of 0.95. For supervised classification, training pixel sets were selected from the standard FCC (False-Colour Composite) image with Maximum Likelihood Classification (MLC) based on sample points depending on the spectral band information for respective LULC classes. Visual interpretation of the satellite imagery was carried out through preliminary interpretation keys like colour, tone, texture, association, pattern, shape, size, etc. wherein the forest was eco-floristically classified. Band spectral information was used to associate image characteristics and ground features as a standard visual technique. The spectral signatures for different LULC types were established and FCC was interpreted based on distinct image elements. An extensive field survey was conducted within the study area to determine the major LULC types. It was used for LULC classification by correlating the identifiable ground features of a specific LULC type with the appropriate imaging and spectral characteristics which was utilized in visual interpretation of the imagery. Simultaneously, ground data were used for accuracy assessment of the developed LULC maps.

3.0 Results and Discussion:

3.1 Land-use/land-cover:

Usually in optical range, infra-red (IR) band has been observed to be most valuable to discriminate vegetation cover along with other bands, specially the Red (R) band and hence, ratio images with a combination of IR and R bands have been used for distinguishing vegetative areas from non-vegetative regions (Kumar et al., 2013). Initially, the study area is classified into forest and non-forest areas. Non-forest cover types had close range of brightness values for majority of the classes; however, distinguishable. Topographically and ecologically dissimilar features nearly had a comparable reflectance pattern and therefore contributed to the intermixing of spectral signatures. However, this limitation was overcome using visual interpretation coupled with ground-truth survey data, as the most suitable and accurate classification technique among those adopted in this study. Among the forest types, Pure Sal, Sal mixed, Khair mixed, Bamboo-mixed, Sal-Bamboo, Sal-Mahua, plantation, scrub forest and degraded forests were identified. Built-up or settlement area, agricultural or crop land, fallow land, grazing land, mining areas, barren or unproductive infertile land, stony waste, rocky knob, exposed or uncovered land, water body and water logged areas were identified within non-forest cover types, which was not possible with the above-mentioned conventional pattern recognition techniques.

3.2 Forest classification and comparative study among different classification procedures:

Satellite image of Munger forest was classified using conventional pattern recognition techniques like unsupervised and supervised classification methods which were found ineffective. Possible factors responsible could be the acquisition of the satellite data in broad bandwidths in the optical region, analogous spectral signatures of the vegetation, high moisture content, shadow effects of the undulating terrain, the climax vegetation in the landscape, etc. hence, the use of narrower and more enhanced spectral bands could probably provide better results. It was observed that Khair-mixed; Sal-mixed, Sal-Bamboo and Sal-Mahua were only partially distinguishable from each other using the classification methods with higher number of clusters. Simultaneously, spectral similarity was observed for plantations, scrub land, agricultural land and fallow land. Scientific names of the different forest types based on the dominant floral species found in the study area is documented in Table 1.

Table 1: Scientific and common names of some dominant floral species

Scientific names	Common names
Shorea robusta	Sal
Madhuca longifolia	Mahua
Dendrocalamus strictus	Bamboo
Acacia catechu	Khair
Diospyros melanoxylon	Kendu
Terminalia tomentosa	Asan
Boswellia serrata	Sellai

With unsupervised classification, 7 vegetation type classes were recognized, namely Sal, Sal mixed, Khair-mixed, Sal-Mahua, Sal-Bamboo, plantation and degraded forest. The overall accuracy of the classification was 52.20% and kappa statistics were 0.44. As for supervised classification, an extra class of Bamboo-mixed in addition to the already mentioned 7 classes, were identified with an overall accuracy and kappa value of 65.40% and 0.6 respectively. Classification through visual interpretation provided better results as it was possible to categorize the same 8 vegetation type classes with enhanced overall accuracy of 93% and kappa coefficient 0.92. The ground-truth sample points collected recorded during the field survey with GPS were employed for the accuracy assessment of the classified outputs for the approaches.

Table 2: Accuracy assessment report for different classification methods for different vegetation type classes (including non-forest as a class)

Class	Producers Accuracy (%) in Unsupervised Classification	Users Accuracy (%) in Unsupervised Classification	Producers Accuracy (%) in Supervised Classification	Users Accuracy (%) in Supervised Classification	Producers Accuracy (%) in Visual Interpretation	Users Accuracy (%) in Visual Interpretation
Plantation	42.86	37.50	53.06	60.47	100.00	100.00
Sal-Mahua	48.78	43.48	58.33	47.46	87.50	100.00
Sal-mixed	50.00	58.06	78.02	71.72	100.00	84.62
Pure-Sal	52.83	47.46	77.55	65.52	100.00	100.00
Bamboo-mixed	0.00	0.00	56.86	67.44	100.00	100.00
Khair-mixed	51.32	50.00	57.63	60.71	100.00	100.00
Sal-Bamboo	48.24	57.75	54.02	67.14	80.00	100.00
Mixed Degraded	0.00	0.00	0.00	0.00	75.00	85.71
Non-Forest	67.47	68.29	81.82	75.00	90.91	90.91
Shrub Forest	0.00	0.00	0.00	0.00	100.00	83.33
Overall Accuracy	52.20		65.40		92.94	
Kappa Statistic	0.44		0.60		0.92	

Accuracy assessment report of every forest type class for all the classification methods are documented in Table 2, which prove the better classification potentials for the respective methods applied. Also, Figure 3 describes the graphical comparison of the accuracies obtained from the classification methods and this clearly reveals the better classification potential for the visual interpretation method than the aforesaid conventional pattern recognition techniques. Hence, classification of forest cover types which were inseparable due to comparable reflectance were classified by visual interpretation along with a reconnaissance survey with higher accuracy.

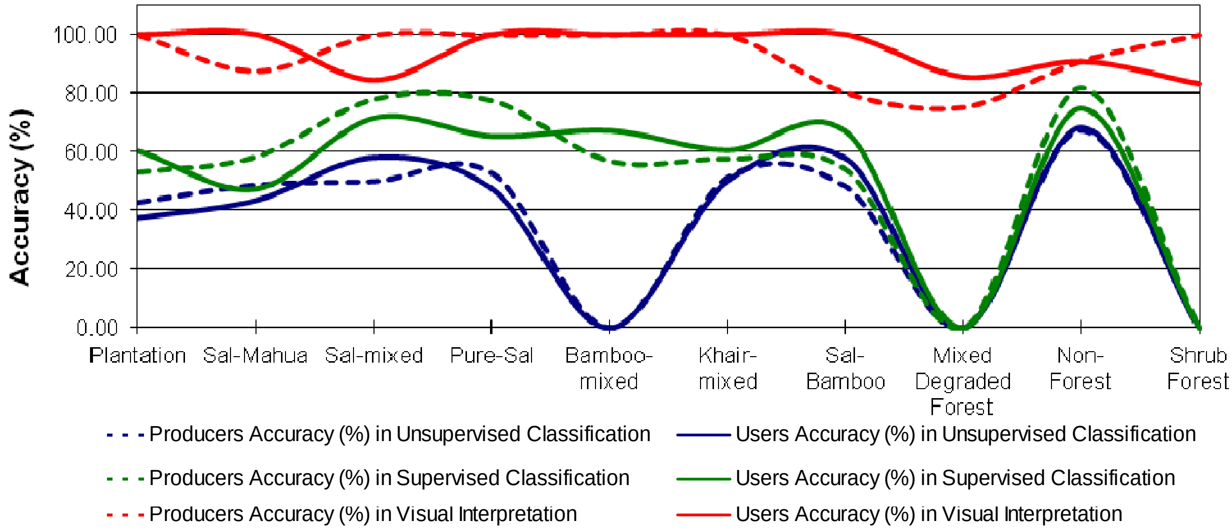

Fig. 3: Comparison of accuracies obtained from different classification methods

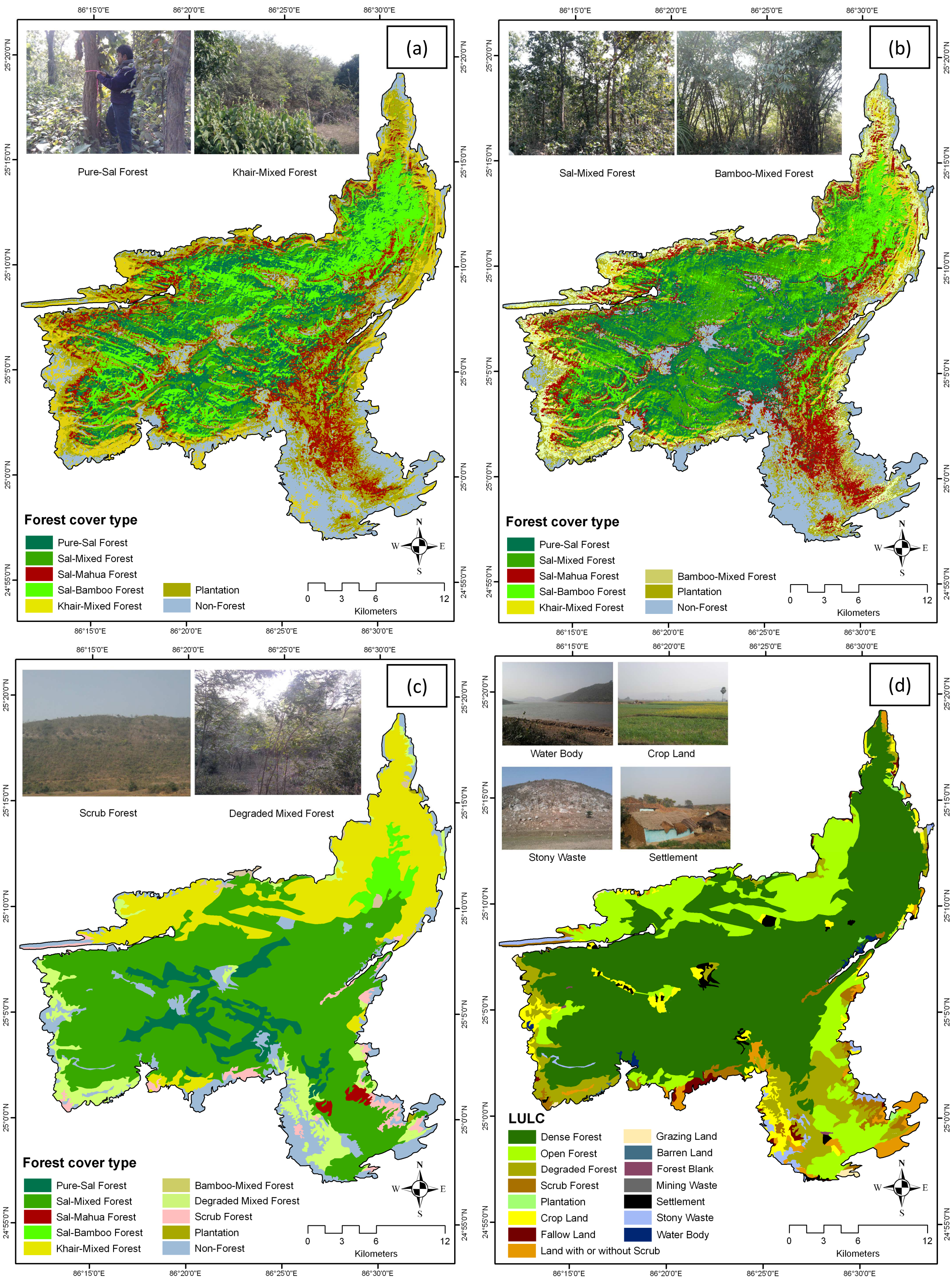

Fig. 4: Forest cover type map through (a) Unsupervised Classification, (b) Supervised Classification and (c) Visual Interpretation methods; (d) LULC map through Visual Interpretation method

Figures 4a and 4b show the unsupervised and supervised classification map respectively depicting the LULC features. Figures 4c and 4d illustrate the LULC and forest map respectively derived from visual interpretation method, which was found the most accurate out of the lot. Shrub forests and mixed degraded forests that are demarcated in visual interpretation method are mis-classified during supervised-unsupervised classification methods into non-forest, plantation and Khair-mixed classes. Bamboo-mixed is not identified during unsupervised classification and is mis-classified as Khair-mixed vegetation class. However, Bamboo-mixed is classified as a separate class while following supervised classification and visual interpretation, that was not possible with unsupervised classification. Table 3 illustrates the area statistics of the different LULC and forest classes derived from the visual interpretation method. More than 89% of the study area is covered under forests, the nature of which is moist-deciduous. Due to political disturbances, the forest suffers from limited human intrusion of forest natural resources; and the forest remained virgin and unexploited. Being a virgin forest with discrete anthropogenic interventions, the area under green cover is significantly higher than the non-vegetative cover. The non-forest areas include barren land, agricultural or crop land, fallow lands, grazing lands, mining waste, stony waste, plantation areas, water bodies, settlements, etc. Of the forest cover, dense forests extends for nearly 60% of the total area, while 18% and 9% correspond for open and degraded forests respectively, as observed in the study. Scrub forest is randomly distributed covering nearly 2%. *Shorea robusta* (sal) is the most dominant floral species and sal forests extends for over 59% (approx 400 km^2). This includes Sal-mixed, Sal-Mahua, Sal-Bamboo and Pure-Sal forests, of which Sal-mixed forests are most prevalent covering nearly 49%. Bamboo (*Dendrocalamus* sp.) is also extensively distributed that mostly occur along with other species, while mixed *Acacia catechu* (Khair) forests cover over 20%. The presence of virgin forests within the central part of the study area are predominantly dense and moderately dense forests, whereas, the outskirts are flanked by open and degraded mixed forests, with some human activities, like agriculture. Figure 4 also includes the field snaps of some of the major LULC classes of the study area. The information generated through the methodology in this study can be utilized in future prospect studies like forest biomass, biomass burning related to forest-fires, climate-change, wildlife habitat management, etc. in this study area. This work would serve as a benchmark for several related studies and future research in the field of forestry and allied branches.

Table 3: Area statistics in sq.km and percentage of total study area of LULC classes

LULC categories	Area (km^2)	Area (%)
Pure-Sal	45.385	6.75328
Sal-Bamboo	16.38178	2.437605
Sal-Mahua	3.582764	0.533115
Sal-mixed	333.9138	49.68632
Scrub Forest	14.03016	2.087685
Bamboo-mixed	3.379053	0.502802
Khair-mixed	138.8762	20.66475
Degraded Mixed Forest	46.08373	6.85725
Barren Land	0.447575	0.066614
Crop Land	24.16141	3.596027
Fallow Land	5.112403	0.760897
Forest Blank	0.365642	0.05442
Grazing Land	2.416277	0.359623
Land with or without Scrub	18.28284	2.721099
Mining Waste	0.291906	0.043445
Plantation	1.594108	0.237257
Settlement	6.499143	0.96729
Stony Waste	8.698701	1.294658
Water Body	2.383891	0.354803

4.0 Conclusion:

Integrated geospatial approach, incorporating remote sensing and GIS techniques, is a powerful technique for mapping and evaluating the LULC of inaccessible areas of the undulating terrain and the forest environment. This basic study shows three different approaches to classify land features from satellite imagery, where visual interpretation supported by field-based reconnaissance survey shows the best accuracy for forest classification in comparison to unsupervised and supervised classification methods. The observation is supported by the calculated overall and kappa accuracy values, along with the number of classes identified by the methods. Finally a complete LULC map was derived for the heterogenous tropical moist deciduous forest of Munger including the area statistics for the feature classes. Nearly 89% of the area is covered under forests with sal, khair and bamboo forests as dominant forest types, with the open and dense forests covering the maximum proportion of the forest area. A proper forest classification is essential for related studies in the future. Forests being the storehouse of biomass have a great prospect towards wildlife management and climate-change studies in the scope of REDD (Sharma *et al.,* 2013). It serves as an important parameter for wildlife habitat evaluation (Sinha *et al.,* 2011a,b; 2012), ecotourism development (Kanga *et al.,* 2011a), forest-fire risk analysis (Kanga *et al.,* 2011b; Sharma *et al.,* 2012b), etc. These are some of the application areas of utilizing forest information and the methodology adopted in this study provides an easy and effective approach for attaining relatively accurate means for forest and LULC classification. These records are particularly important for such undisturbed, virgin tropical deciduous forests, as these would harbor immense potential for wildlife habitat management, carbon storage and climate regulation.

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