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Mapping of fuelwood trees using geoinformatics

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ABSTRACT

Rural population of India constitutes about 70% of the total population and traditional fuels account for 75% of the rural energy needs. Depletion of woodlands coupled with the persistent dependency on fuel wood has posed a serious problem for household energy provision in many parts. This study highlights that the traditional fuels still meet 85–95% of fuel needs in rural areas of Kolar district; people prefer fuel wood for cooking and agriculture residues for water heating and other purposes. However, rapid changes in land cover and land use in recent times have affected these traditional fuels availability necessitating inventorying, mapping and monitoring of bioresources for sustainable management of bioresources. Remote sensing data (Multispectal and Panchromatic), Geographic Information System (GIS), field surveys and non-destructive sampling were used to assess spatially the availability and demand of energy. Field surveys indicate that rural household depends on species such as *Prosopis juliflora*, *Acacia nilotica*, *Acacia auriculiformis* to meet fuel wood requirement for domestic activities. Hence, to take stock of fuel wood availability, mapping was done at species level (with 88% accuracy) considering villages as sampling units using fused multispectral and panchromatic data.

Contents

1. Introduction . . . 642
2. Literature review . . . 644
3. Objectives . . . 645
4. Study area . . . 645
5. Data and methods . . . 645
6. Data analysis, results and discussion . . . 647
7. Conclusion . . . 653
Acknowledgements . . . 653
References . . . 653

1. Introduction

Energy is an integral part of a society and the state of economic development of any region can be assessed from the pattern and consumption quality of its energy. Energy demand increases as the economy grows, bringing along a change in the consumption pattern, which in turn varies with the source and availability of its energy, conversion loss and end use efficiency. The burgeoning population coupled with developmental activities based on ad-hoc decisions have led to resource scarcity in many parts of India. Through the different stages of development, humankind has experimented with various sources of energy ranging from wood, coal, oil and petroleum to nuclear power. However, indiscriminate exploitation of resources and unplanned developmental activities has led to serious ecological and environmental problems. A

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judicious choice of energy utilisation is required to achieve growth in a sustainable manner. With 70% population in rural areas, there is tremendous demand on resources such as fuel wood, agricultural residues, etc. to meet the daily fuel requirements [1]. Analysis of the distribution of different energy forms in rural India reveals that out of 11.42×10^{14} kcal, the share of non-commercial energy is 65%, human energy 15% and commercial energy 20% [2]. This clearly shows that 80% of rural energy is met from traditional sources firewood, agricultural residues and animal residues. According to the report of the Fuel wood Study Committee in India (1982), the total requirement of fuel wood is calculated to be about 133 million tonnes/annum whereas the annual availability is estimated to be about 49 million tonnes [3,4]. A recent survey conducted [2] on energy sources and sector wise consumption in Karnataka State, India reveals that traditional fuel such as firewood (7.44 million tonnes of oil equivalent—43.62%), agro residues (1.510 million tonnes of oil equivalent—8.85%), biogas conditioning (0.250 million tonnes of oil equivalent—8.85%), account for 53.2% of total energy consumption. Dependence on bioresources to meet the daily requirement of fuel, fodder, etc. in rural areas is more than 85% while in urban areas the demand is about 35%. India with its not so huge landmass of 320 million hectares, when compared to its one billion human population, biomass energy thus continues to be a major source of energy and fuel. In order to meet the growing demand for energy, it is imperative to focus on efficient production and uses of biomass energy to meet both traditional (as a heat supplier) and modern fuel (electricity and liquid fuel) requirements. Inventorying of bioresources for sustainable management and conservation has emerged as an important scientific challenge in recent years [5].

Biomass refers to solid carbonaceous material derived from plants and animals. Plant biomass provides the primary energy source by absorbing solar energy through photosynthesis and acts as the foundation for all life forms. Information about biomass is necessary for estimating and forecasting ecosystem productivity, carbon budgets, nutrient allocation, and fuel accumulation. Biomass is also considered a useful indicator of structural and functional attributes of forest ecosystems across a wide range of environmental conditions [6–8]. The production of biomass in all its forms for fuel, food, and fodder demands environmentally sustainable land use and integrated planning approach [5].

Sustainable energy management requires a detailed planning from National to State to District (a region marked off for administrative or other purposes) to taluk (A taluk is an administrative subdivision or tier of local government/A taluk is typically a part of a district, and contains villages and/or municipalities) and village levels. For national-level studies, which are best suited to promote policy formulation, the analysis should be carried out at the lowest administrative level for which demographic, social and economic parameters are available, i.e. a village. The disaggregated level of analysis helps to avoid the aggregations and generalisations that so negatively affect energy management strategies. Inappropriate management strategies involving the selection of sites and species can have adverse effects and lead to degradation and abandonment of land. However, the correct selection of plant species can allow the economic production of energy crops in areas previously capable of only low plant productivities. Simultaneously, multiple benefits may accrue to the environment. Such selection strategies allow synergistic increases in food crop yield and decreased fertiliser applications while providing the local source of energy and employment.

Under this situation, it is necessary to estimate spatially available bioresources and evolve better management strategies to ensure the renewability of resources. In this regard, spatial tools such as GIS and remote sensing data help immensely in providing geographically referenced and spatial distribution of bioresources availability and demand. GIS offers possibilities for combining, or integrating, statistical and spatial information about the availability (supply side) and consumption (demand side) of bioresources (fuel wood, charcoal and other biofuels). This accessible, user-friendly technology aids as the decision support system through visualisation of the results of spatial analysis in easily understandable ways and querying. Multi-scale analyses make it possible to show local situations throughout an entire country or region. Satellite remote sensing is well adapted to complement existing strategies for mapping this type of information while also providing important advantages, particularly for large areas.

Remote sensing techniques help in acquiring spatial data at various time intervals (temporal data) of earth resources, which aid in inventorying, mapping and sustainable management of resources [9]. It offers a quick and efficient approach to analyse the drivers responsible for land-use changes, which has implications on energy availability, especially energy from bioresources. The multispectral temporal data are being used effectively for quantification and monitoring of natural resources. This helps in demarcating areas of deforestation, changes in crop productivity, location of groundwater, mineral, oil and other metals, which are required for managing the resources. Remote sensing data and GIS have immense value in mapping of resources and assessment of energy demand on spatial scale. Major application includes,

- Land-cover analysis.
- Land-use classification and evaluation of land resources.
- Monitoring and management of natural resources.

The terms land use and land cover are often used in natural resources management, meaning types or classes of geographical determinable areas. Land-cover analysis is done to discern vegetation, hydrological or anthropogenic features on the land surface. Land cover provides the ground cover information for baseline thematic maps. The land-cover features can be classified using the data of different spatial, spectral and temporal resolutions. Broadly speaking, land cover describes the physical state of the Earth's surface and immediate surface in terms of the natural environment (such as vegetation, soils, groundwater, etc.) and the man-made structures (e.g. buildings). In contrast, land use refers to the various applications and the context of its use. This involves both the manner in which the biophysical attributes of the land are manipulated and the intent underlying that manipulation (the purpose for which the land has been used). Land-use and Land-cover information play an important role at local and regional as well as at macro level planning. The land-cover changes occur naturally in a progressive and gradual way, however sometimes it may be rapid and abrupt due to anthropogenic activities. The planning and management task is often hampered due to insufficient information on the rates of land-cover and land-use change. Identifying, delineating and mapping land cover on temporal scale provides an opportunity to monitor the changes, required for sustainable management of natural resources. Thus, GIS and Remote Sensing allow spatial analysis approach to address the problem of regional energy planning.

The use of remote sensing data to monitor natural resources has advanced rapidly in recent years, allowing the determination of forest structural properties ranging from species-specific distribution, leaf area index to tree height or biomass at the landscape level [10–12]. Multi-resolution analysis plays an important role in image processing, it provides a technique to decompose an image and extract information from coarse to fine scales [13,14]. MSS data with the better spectral resolution allows identification of materials in the scene, while better spatial resolution data is required to locate those materials. It can extract features from source image, and provide more information than one image can. IRS-1C satellite provides both high-resolution panchromatic (5.8 m spatial resolution covering the spectral range of 0.4–0.90 m) and low-resolution (23.5 m) multispectral (G, R and NIR bands corresponding to 0.5–0.6, 0.6–07, 0.7–0.9 m) images. It is possible to have several images of the same scene providing different information although the scene is the same. Processing and synergistic combinations of information provided by various sensors would provide high-spatial-spectral-resolution remote sensing data required for inventorying and mapping bioresources on regional scale.

The present study was undertaken to identify and delineate various land-use categories and types of tree species present in a particular area to meet the bioenergy demand. The resource base in Kolar under each sector such as forests, agriculture, horticulture and animal residues are analysed spatially. Most parts of Kolar experience severe bioresource scarcity and immediate policy interventions are needed to restore the ecological balance of the region. Hence, this study is aimed to determine the supply and demand situation of biofuels of the region and spatially link this database to determine the energy surplus and deficit areas. The vegetation map for Kolar was prepared based on supervised classification of multispectral sensor (MSS) data of IRS-1C (Indian Remote Sensing Satellite-1C series). The base maps of the study site are prepared using the Survey of India (SOI) toposheets of scale 1:50,000. This includes administrative boundaries, road and drainage networks, contours and boundaries of vegetative areas (areas under forest department). MSS and PAN data were classified with ground data (collected using Global Positioning System, GPS). Image fusion technique was used to integrate the geometric detail of a high-resolution panchromatic (PAN) image and the spectral information of a low-resolution MSS image, particularly important for understanding land-use dynamics at a larger scale (1:25,000 or lower) and in determining the spectral response patterns of the vegetation. Fused images can extract features such as trees, etc. from source images and provide more information than one scene of MSS image. Merging helps in retaining the spectral advantage of multispectral bands while taking an advantage of PAN's spatial resolution. The spectral patterns of different vegetation were determined with a detailed mapping of 30 villages in Kolar taluk using GPS. This also helped in arriving at spectral response pattern of predominant tree species in Kolar taluk. This information was extrapolated to other taluks. This paper discusses an attempt in to map *Prosopis juliflora* (Mesquite), a fuel wood species that grows in basic soil (black soil) and has the ability to lower soil pH.

2. Literature review

Biomass is considered a useful indicator of structural and functional attributes of forest ecosystems across a wide range of environmental conditions [7]. It is therefore important to accurately estimate biomass to assess the role of forests in meeting the region's energy demand or in the global carbon (C) cycle, particularly when defining its contribution toward sequestering carbon. For an assessment of forest biomass, forest inventory is most commonly used and it differs depending on scope and purpose. Inventories are being designed to obtain information on other uses of the forest like recreation, grazing, wildlife and water conservation. It is designed to measure forest biomass rather than or in addition to traditional volume. The forest inventory area is usually one or more management units, each ranging in size from a few hundred to many thousand hectares. Each unit may be divided into forest-based strata or administrative subpopulations for which separate estimates are required. The attribute of primary interest is merchantable wood volume, with stem frequency. Basal area data are of secondary importance. These attributes are usually given by tree size classes and by a number of forest and administrative classes that are described in a classification system. Above ground standing biomass of trees is the weight of trees above ground, in a given area, if harvested at a given time. The change in standing biomass over a period of time is called productivity. The standing biomass helps to estimate the productivity of an area and also gives information on the carrying capacity of land. It also helps in estimating the biomass that can be continuously extracted. Various studies have estimated forest biomass at regional and national levels based on forest inventory data, such as forest species, area, stem volume, age class, and site class [15–19]. The standing biomass is computed agroclimate zonewise for a federal state in India using the remote sensing data along with the field data [15]. Archer [20] provides a sound sampling frame for energy analysis at the national level using Advanced Very High Resolution Radiometer (AVHRR) data. Agro ecological zonation was done to create the link between supply and demand and provided a valid basis for extrapolating the result of the supply survey to the national level in Pakistan using GIS and remote sensing. Automated selection of sampling units from digitally classified remote sensing data was effective, with overall 93% of woody biomass primary sampling units containing measurable woody vegetation. The results indicated a reasonable consistency between zones, the forest/highlands indicate an expected wood surplus and the semi arid zone indicates a large deficit [20].

Remote sensing methods have proved to be successful in mapping and monitoring forest health and distribution when a sufficiently small ground resolution is used. Supervised, unsupervised and hybrid classification methods were evaluated for their accuracy in discriminating dead and dying tree crowns from bare areas and the surrounding forest mosaic utilising 1-m resolution remote sensing data and the hybrid classifier significantly outperformed the other methods, producing low omission and commission errors among information classes [21]. Spectral class differences are related to leaf nitrogen, soil water content, soil organic matter and plant biomass evident from the effort to identify corn and soybean crops at various growth stages using high-spatial resolution (1-m) data. Maximum distinction between corn and soybeans was achieved using the near-infrared bands when the crops were mature, while the visible bands were more useful when the soybeans were senescing [22]. High spatial ($\leq$1 m) but low spectral resolution remote sensing data were used for mapping with accuracies $>$ 95% of Chinese tallow trees in dominant environments found in coastal and adjacent upland landscapes. Airborne colour-infrared photography (CIR) (1:12,000 scale) was used to map localised occurrences of the widespread and aggressive Chinese tallow, an invasive species [23]. Mapping multiple vegetation types at large scale, determining appropriate plot size and spatial resolution is very difficult because of spectral mixtures, low correlation of remote sensing and field data, and high cost to collect field data at a high density. The within-support and regional semi-variograms modelling technique was adopted based on field data and geostatistics theory accounting simultaneously for within-support and regional spatial variability. The range parameters of the within-support semi-variograms implied the maximum range of the appropriate plot sizes. Using the regional semi-variograms the support size was considered appropriate when the ratio of the nugget variance to sill variance stabilised [24]. The distribution of *Melaleuca quinquenervia*, an aggressive exotic species targeted for eradication at a site in the East Everglades was mapped using 1:7000-scale colour-infrared (CIR) aerial photographs, GPS and GIS, with an overall accuracy of 94% [25]. A pre field forest cover map was generated for two seasons based on field knowledge, experience, and the standard visual interpretation of Landsat TM data with an overall accuracy of 91%. The forest cover type boundaries were delineated based on various elements of interpretation. Accuracy assessment was done using bivariate matrix between map and ground observation [26]. The hybrid approach using Decision Tree (DT) and Adaptive Resonance Theory MAP (ARTMAP) neural network with confidence or uncertainty information via majority voting and other rules seems suitable to tackle a variety of classification problems in remote sensing and may ultimately aid map users in making more informed decisions. The classifier was tested with Advanced Very High Resolution Radiometer data to mapping land cover of North America [27]. Knowledge-based, post-classification processing considerably improves the accuracy of mapping evident from the incorporation of spatial knowledge with spectral knowledge of mangroves in the interpretation of SPOT data that has enhanced the accuracy level to 96.7% from 83.3%. Earlier parametric classification approaches had failed due to the spectral similarity of mangroves to other coastal vegetation despite their habitat being inside coastal waters [28].

Remotely sensed data, with synoptic coverage, allows for a means to collect data over an entire landscape. Its applications in the estimation of biomass for large-area forest inventory at the stand level have been successfully reported using remote sensing data sources [29–31]. The relative error of volume estimates using visual aerial photo interpretation has been reported to be 14–45% and the corresponding error using satellite image interpretation has been reported between 20 and 65% [32–34]. The approach presented in this paper has been developed to aid in the generation of biomass values from available or currently collected data.

3. Objectives

Fuel wood tree inventory data is collected in sample villages, which helps in estimating biomass from, i) forest inventory coverage only, ii) combining the forest inventory results with remotely sensed estimates of biomass, and iii) using the remotely sensed estimates of biomass to populate the entire study area. Main objective of this study is to map spatially available bioresources on a regional basis to examine the fuel availability and demand, and also mapping at species level (of dominant fuel wood species—*P. juliflora*) to aid regional decision makers with management decisions which are largely a function of monitoring tree (forest, plantation, etc.) stand volume by species. The technique involves:

1 Land-cover analyses—to distinguish regions under vegetation and non-vegetation through the computation of slope-based and distance-based vegetation indices (depending on the level of vegetation cover or aridity).
2 Land-use analyses—supervised classification approach, to delineate land-use pattern in the district.
3 Village level land-use analysis to determine spectral response patterns of predominant species.
4 Mapping of dominant fuel wood species used by the local people and validation of mapping at species level.

4. Study area

Kolar district is located in the southern plain region of the Karnataka State (Fig. 1). It lies between 77°21′ and 77°35′ east longitude and 12°46′ and 13°58′ north latitude and extends over an area of 8225 sq. km and divided into 11 taluks (for administrative purposes). The average population density of the district is 2.09 persons/ha (rural) and 2.69 persons/ha (rural and urban). The population density ranges from 1.44 (Bagepalli), 1.69 (Gudibanda), 1.70 (Srinivasapur) to the maximum of 2.55 (Kolar). While, the population density in taluks are—Bangarpet (2.52), Malur (2.38), Gauribidanur (2.36), Sidlaghatta (2.16), Chintamani (2.10), Mulbagal (2.04), and Chikballapur (1.92). The tree species predominant in the district are *Acacia nilotica* (Indian gum Arabic), *Acacia auriculiformis* (Earpod wattle), *Albizia amara* (Chigarae), *Albizia lebbek* (East Indian Walnut Tree), *Azardirachta indica* (Neem Tree), *Eucalyptus sp.* (Eucalyptus), *Mangifera indica* (Mango tree), *Pongamia pinnata* (Indian Beach Nut Tree), *P. juliflora*, *Tamarindus indicus* (Tamarind Tree), etc. Among these, the fuel wood trees preferred by local people are *P. juliflora*, *A. nilotica*, *A. auriculiformis*, and *Eucalyptus sp.* Due to scarcity of fuel wood in some parts of the district, a section of the population meets its cooking and heating energy requirement from shrubs and weeds like *Lantana camara* (Lantana) and *Cassia auriculata* (Tanner's Cassia).

P. juliflora—Fuel wood Tree: These are spiny shrubs and trees, very variable, small to medium sized, aggressively fast growing tree, semi-evergreen to evergreen, large crowned, with drooping low branches, with bipinnate leaves, greenish-yellow flowers cylindrical or flat and flowering almost throughout the year. The species include several varieties and forms; two important and well-known varieties besides *var. chilensis* are: *var. velutina and var. glandulosa.* Six species are reported in India; *Prosopis cineraria* (Mesquite) are indigenous and others have been introduced *Prosopis chilensis* (Mesquite), an American species, and *var. glandulosa* has run wild in many parts. When the growth of *P. juliflora* is disturbed through hacking or cutting its auxiliary bud becomes more active than the terminal bud and starts producing innumerable number of branches. So the tree attains a more bushy form or becomes shrub like instead of a tree. But if left undisturbed it can grow to a tree form even with a girth at breast height of more than 100–200 cm [35]. *P. juliflora* grow well in basic soils like the black cotton soil and hence, it is widely distributed in black soils of Andhra Pradesh and northern Karnataka. It prefers plain land soils instead of hilly soils as the latter have less surface soil volume. It prefers soils well drained with water but cannot survive in deep standing waters. In many villages of Kolar district, *P. juliflora* is used as fuel wood due to its easy accessibility, availability, calorific value, growth rate, short cycling period, coppicing capability, etc. Gauribidanur taluk, which lies in northwestern side of the district where the growth of fuel wood species *P. juliflora* is profuse, was considered for validation of mapping.

5. Data and methods

An integrated approach involving compilation of both spatial and non-spatial data from government agencies and institutions, application of spatial and temporal analyses using remote sensing data, GIS techniques and conventional field survey (ground truthing) were adopted in this study. The main sources of primary data were from field (using GPS), the Survey of India toposheets of 1:50,000, 1:250,000 scale and multispectral sensors (MSS) digital data of the IRS (Indian Remote Sensing satellites)-1C and IRS-1D (1998, 2002, 2006). LISS-III MSS data scenes corresponding to the district for path-rows [(100, 63) (100, 64) and (101, 64)] and cloud cover less than 2% were procured from the National Remote Sensing Agency, Hyderabad, India (http://www.nrsa.gov.in). LISS-III (band-2, band-3, and band-4) and PAN images provide a spatial resolution of 23.5 m and 5.8 m respectively. The secondary data was collected from the government agencies (Directorate of census operations, Agriculture department, Forest department and Horticulture department). Multispectral sensor data (G, R and NIR bands) was used for land-cover and land-use analyses. Panchromatic data of 5.8 m spatial resolution (IRS-PAN) was used for village level fuel wood species mapping. Primary data for supervised classification of MSS data was collected through

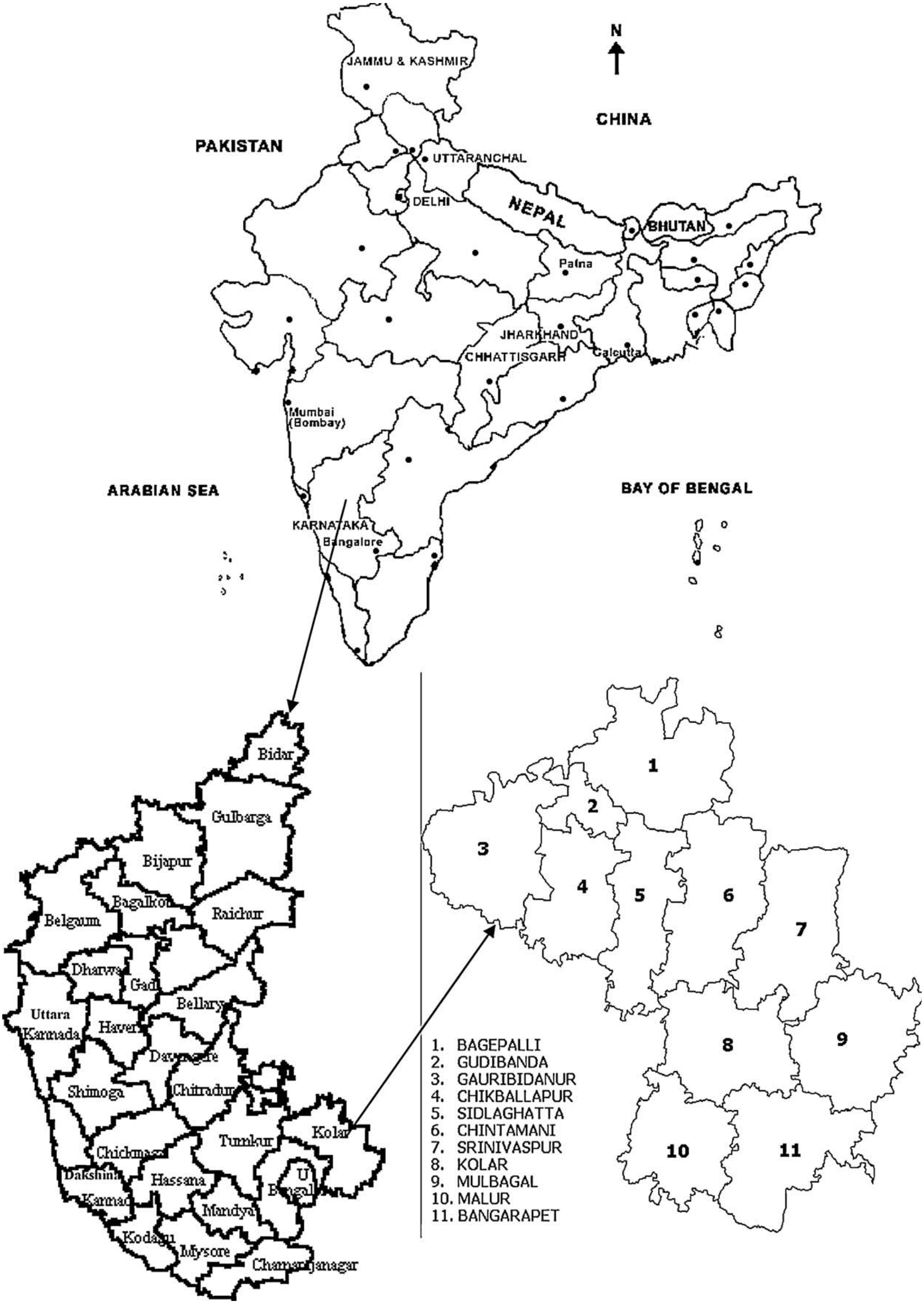

Fig. 1. Study area.

stratified random sampling using GPS. This collection of primary data (ground control points, GCPs) helped to correlate the ground information (attribute information) with the remote sensing data. This entailed:

i) Generation of geo-referenced base layers like district boundary, district with taluk and village boundaries, road network, drainage network, contours, mapping of waterbodies, etc. from the SOI toposheets of scale 1:250,000, 1:50,000 and revenue maps of scale 1:6000.
ii) Extraction of bands (LISS III with resolution 23.5 m and PAN with resolution 5.8 m) from the data (in BIL and BSQ format) respectively procured from NRSA.
iii) Geo-correction of bands through resampling using ground control points (GCPs). GCPs were chosen such that they can be easily identified in the image (like road and railway crossings, edges of large fields and approximate middle points of small lakes). It was taken care that the GCPs are of adequate number and equally spread throughout the image.
iv) Cropping and mosaicing of data corresponding to the study area–Kolar district.
v) Histogram generation, Bi-spectral plots, Regression analysis.
vi) Computation and analysis of various vegetation indices.
vii) Generation of FCC (False Colour Composite) by saturating 2.5% from each end of the gray scale using linear contrast stretch method and identification of the heterogeneous patches regions for training data collection (ground truthing).
viii) Collection of attribute information from field corresponding to the chosen training sites using GPS.
ix) Classification of remote sensing data–land-use analyses (both district wise and taluk wise), statistical analysis and report generation.
x) Fusion of LISS III and PAN data using fusion algorithm such as IHS (Intensity, Hue, Saturation).
xi) Village wise vector layers of species wise tree distribution was prepared using calibrated Global Positioning System (GPS) through an extensive field survey, taking the village as a sampling unit. Villages were selected so as to represent the entire taluk/district. The pilot surveys were undertaken to ascertain the sample size—the number of villages needed to be surveyed in order to obtain a reliable picture of bioresources in the region and their growing stock (wood volume in case of trees). The villages to be surveyed in different taluks were decided based on the extent of vegetation cover in respective taluks.
xii) Stratified (based on land holding) random sampling of households in select villages to assess the fuel wood demand.

6. Data analysis, results and discussion

Remote sensing data provides the most useful data on the condition and extent of resources on Earth. This spectral reflectance data in digital form allows the analysis using computers (Digital Image Processing). It involves image restoration (to geometrically correct the images), enhancement (to improve the contrast of images), transformation (such as Principal Component Analysis (PCA)—to reduce the dimensionality of data sets, Normalised Difference Vegetation Index (NDVI)—to carry out land-cover analysis) and classification (to derive information related land uses) [14]. Bioresource Assessment using the remote sensing data involves:

- Restoration of satellite images in its correct geometric position.
- Interpretation of satellite images to delineate various geomorphic units and land-use classes.
- Field verification of interpreted units.

The process of obtaining useful information from remotely sensed data requires the agglomeration of the data into meaningful groups that can be represented as a map of numerous but relatively homogenous classes. Decision-making and resource monitoring are based on the information provided by these maps. This data can be directly input in GIS to allow spatial analysis of the classified images. Other ancillary data can be used to either improve the training stage of the classification or refine the classification output. The use of a GIS also permits integration of all the information contained in the different ancillary map layers with classifications obtained from satellite imagery, and generation of new levels of information through its overlay capability.

Energy Scenario: Kolar depends mainly on non-commercial forms of energy. Non-commercial energy constitutes 84%, met mainly by sources like firewood, agricultural residues and cow dung, while commercial energy share is 16%, met mainly by electricity, oil, etc. The efficiency of conversion of the biomass to useful energy is between 5% and 15%.

Estimation of Bioresources: Forests provide both tangible and non-tangible benefits towards amelioration of soil, protection of environment besides economic benefits through timber, and minor forest produce, fuel and other products. Both conventional (quadrat sampling techniques) and recent method of usage of satellite imagery (remote sensing) is used to assess bioresources available in the region. Secondary data collected from the forest department shows that 7 taluks have forest cover less than 10%, 2 taluks are in the range 10–20% (Gudibanda and Srinivasapur) while, the remaining two taluks (Bagepalli and Chikballapur) have forest cover greater than 20%. Woody biomass annual availabilities in taluks of Kolar were computed taking into account woody biomass productivity of 3.6 t/ha/yr (evergreen, semi-evergreen), 3.9 t/ha/yr (deciduous) and 0.9 t/ha/yr (Scanty and Scrub vegetation).

Land-Cover Analysis—Kolar District: The analysis of vegetation and detection of changes in vegetation pattern are keys to natural resource assessment and monitoring. Healthy green vegetation has different trends in interaction with the energy in visible and near-infrared regions of the electromagnetic spectrum. This strong contrast between the amount of reflected energy in the red and near-infrared regions forms the basis to develop quantitative indices of vegetation condition using remotely sensed data. Various vegetation indices (VIs) have been developed for qualitative and quantitative assessment of land cover. The slope-based and the distance-based vegetation indices help in land-cover analysis depending on the extent of vegetation and soil in a region. In particular, the sensors with spectral bands in the RED and NIR lend themselves well to vegetation monitoring since the difference between the red and near-infrared bands have been shown to be a strong indicator of the amount of photosynthetically active green biomass. NDVI separates green vegetation from its background soil brightness. It is expressed as the difference between the near-infrared and red bands normalised by the sum of those bands, i.e.

$$\mathrm{NDVI} = \left(\frac{(\mathrm{NIR}-\mathrm{RED})}{(\mathrm{NIR}+\mathrm{RED})}\right) \tag{1}$$

This is the most commonly used VI as it retains the ability to minimise topographic effects while producing a linear measurement scale. In addition, divisions by zero errors are significantly reduced. The index normalises the difference between the bands so that the values range between -1 and +1. The negative value represents non-vegetated area while positive value represents vegetated area. NDVI computed for Kolar district is given in Fig. 2. In Kolar district, as per NDVI analysis 52.5% land is under vegetation while 47.5% land is under non-vegetation.

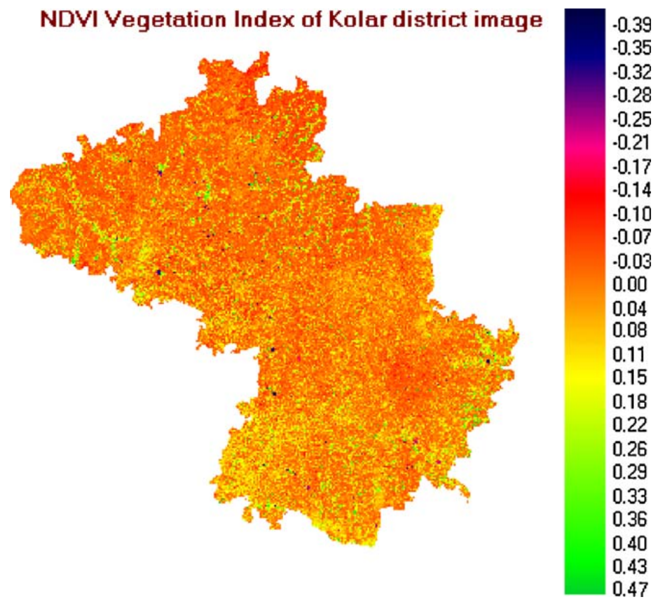

Fig. 2. Land cover of Kolar district.

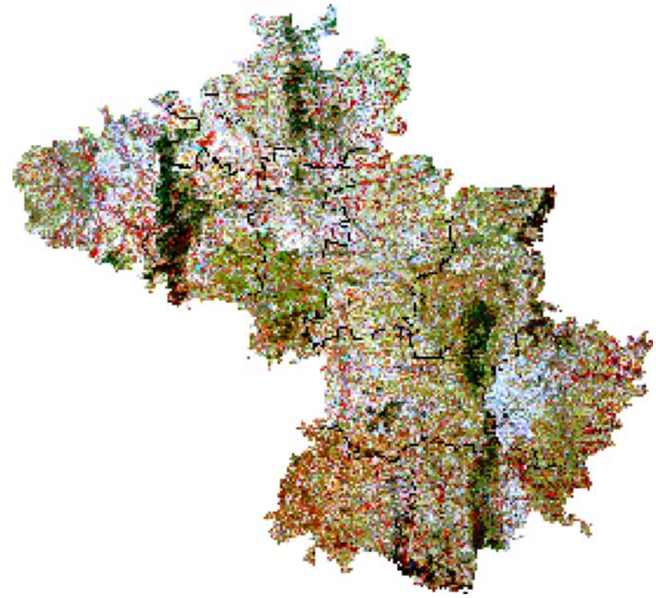

Fig. 3. False Colour Composite (FCC) of Kolar district.

Compared to this, the distance-based group measures the degree of vegetation present by gauging the difference of any pixel's reflectance from the reflectance of bare soil. The scatter plot of the two bands (Red and NIR) and regression analysis was performed by taking red band as the independent variable and NIR band as the dependent variable which helped in obtaining the slope, intercept and the correlation coefficient (Eqs. (2)–(5)).

$$y = 0.6347x + 34.762 \tag{2}$$

$$R^2 = 0.8903 \tag{3}$$

When the NIR band was treated as the independent variable the following results (Eqs. (4) and (5)) were obtained:

$$y = 1.4025x - 33.004 \tag{4}$$

$$R^2 = 0.8903 \tag{5}$$

Computation of Transformed Soil-adjusted Vegetation Index using TSAVI = $a(\text{NIR-}a \times \text{RED-}b)/(\text{RED} + a \times \text{NIR} - a \times b + 0.08(1 + a^2))$, where b: the slope and a: intercept (from Eq. (2) above), gave the output comparable to NDVI.

Land-Use analysis: The land-use map for Kolar district (taluk wise) was prepared based on the interpretation of MSS data of IRS-1C satellite. Six major land-use categories (i.e.: Built-up, Agriculture, Plantation, Vegetation (forests), Wasteland and Waterbodies) were obtained based on the information, which could be obtained from LISS III MSS imageries of 23.5 m spatial resolution. False Colour Composite (FCC) was generated with the band-2 (green), band-3 (red) and band-4 (near-infrared). FCC generated for Kolar district is given in Fig. 3. The vector polygons of different land-use categories were extracted from the FCC and field visits using GPS were made to collect attribute information corresponding to polygons in the heterogeneous patches of the image. Both supervised and unsupervised classification approaches were tried to identify land-use categories. For some of the land-use classes adequate sub classes were made to avoid range overlapping (for example, agriculture class was further divided into three classes for different types of crops). A total of eleven classes were finalised and adequate numbers of pixels were chosen for each of the class. The FCC image was used to create one or more vector files of training site polygons, i.e. vector outlines of training site areas by the use of the on-screen digitise feature. The training site polygons for Kolar taluk are shown in Fig. 4. A total of eleven classes were taken. Classification of remotely sensed data requires the assignment of each of the pixels on an image to a class. The classification approach is based on the assumption that each of the classes on the ground has a class-specific spectral response with each of the classes varying in spectral patterns. There is substantive variation in the distribution of the pixel reflectance values depending upon where the samples are drawn within a land-use type. The spectral information contained in the original and transformed bands is then used to characterise each class pattern, and to discriminate between classes. Fig. 5 depicts land-use map of the district classified using Gaussian Maximum Likelihood Classifier (GMLC). The level of accuracy in GMLC is 94.67 compared to unsupervised

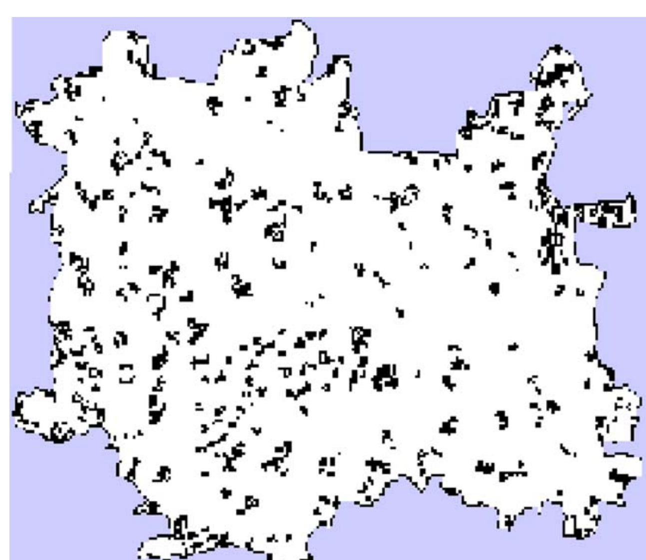

Fig. 4. Training site polygons of Kolar taluk.

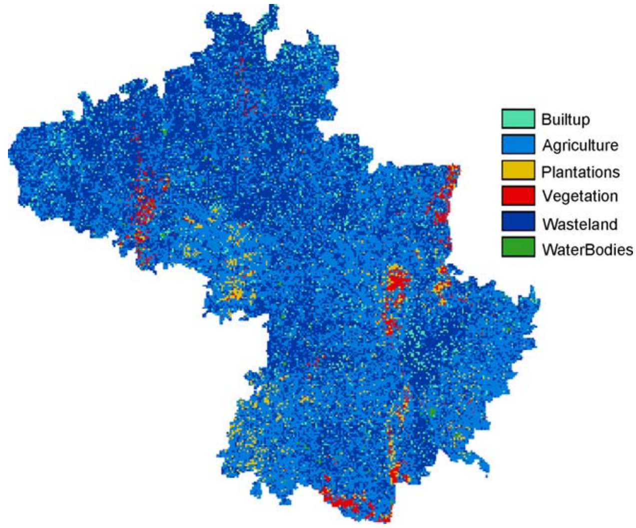

Fig. 5. Land use in Kolar district.

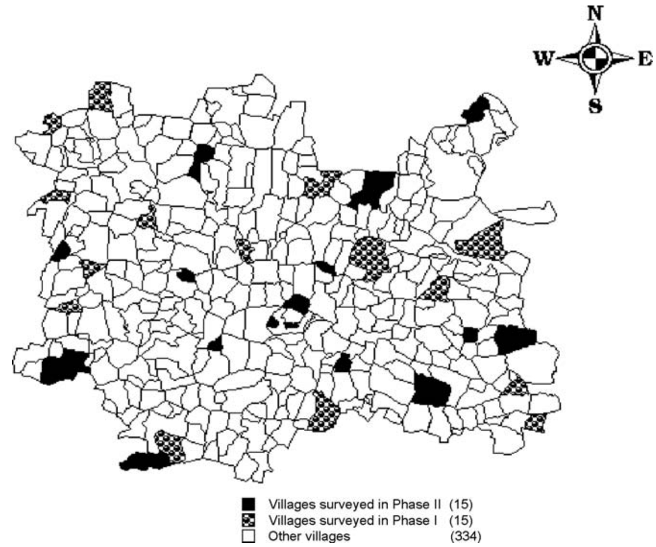

Fig. 6. Villages surveyed in Kolar taluk.

classifier (58.07%). Accuracy estimation in terms of producer's accuracy, user's accuracy, overall accuracy and k Kappa coefficient were subsequently made after generating confusion matrix. The producer's accuracy, user's accuracy corresponding to the various categories and overall accuracy results obtained are summarised in Table 1. A KHAT k value (0.931577) obtained from supervised classification matrix indicated that an observed classification is 93 percent better than one resulting from a chance.

With supervised classification one provides a statistical description of the manner in which expected land-use classes should appear in the imagery, and then the likelihood that each pixel belongs to one of these classes is to be investigated. Once a statistical characterisation has been achieved for each information class, the image is then classified by MLC with a better accuracy of 94.67% (compared to other supervised classification approaches: Minimum Distance to Mean (MD)—76% and Parallelepiped (PP)—70%)by examining the reflectance for each pixel and making a decision about which of the signatures it resembles most. Overlaying district layer with taluk boundaries on the classified district image, taluk wise land-use details were obtained. Land-use analysis for the Kolar district by MLC technique indicates that 46.69% is agricultural land, 42.33% is wasteland (barren land), 4.62% is built up, 3.07% is plantation, 2.77% is natural forest and 0.53% is waterbodies. Recursive soil erosion was reported in Kolar, leading to the loss of productive topsoil, which is evident from the extent of the wasteland (about 42%) in the district. The loss of topsoil degrades arable land and eventually renders it unproductive. The area under vegetation (Agriculture, Plantation and Forests) ranges from 27.91% (Gudibanda), 33.35% (Bagepalli), 36.94% (Gauribidanur), 48.41% (Chintamani), 52.66% (Kolar), 53.56% (Sidlaghatta), 54.51% (Mulbagal), 56.36% (Chikballapur), 65.62% (Srinivasapur), 66.76% (Bangarpet), and Malur (71.71%).

Table 2
Taluk wise bioresource status in Kolar district.

Taluk	Bioresource status
Bagepalli	0.15
Bangarpet	0.15
Chikballapur	0.42
Chintamani	0.12
Gauribidanur	0.16
Gudibanda	0.16
Kolar	0.33
Malur	0.21
Mulbagal	0.18
Sidlagatta	0.17
Srinivasapur	0.39

Improved Spatial Resolution: IHS fusion technique was adopted to convert a colour image from the RGB (Red, Green, Blue) space into the IHS (Intensity, Hue, Saturation) colour space. IHS transformation can enhance image features, improve spatial resolution, and integrate disparate data. The Intensity (I) band resembles a PAN image and was replaced by a high-resolution PAN image in the fusion. A reverse IHS transform is then performed on the PAN together with the Hue (H) and Saturation (S) bands, resulting in an IHS fused image. The general IHS procedure uses three bands of a lower spatial resolution dataset and transforms these data to IHS space. A contrast stretch is then applied to the higher spatial resolution image so that the stretched image has approximately the same variance and average as the intensity

Table 1
Producer's accuracy, user's accuracy and overall accuracy.

Category	Supervised Classification			Unsupervised Classification		
	Producer's Accuracy (%)	User's accuracy (%)	Overall accuracy (%)	Producer's accuracy (%)	User's accuracy (%)	Overall accuracy (%)
Agriculture	95.45	97.67	94.67	80.49	97.06	78.07
Built-up	94.11	100.00		68.00	80.95	
Forest	90.90	86.96		88.37	74.51	
Plantation	91.89	94.44		65.16	100.00	
Waste land	100.00	93.75		85.71	56.60	

Table 3
Spectral ranges of fuel wood tree species (in the remote sensing data) (based on December 2006, MSS data fused with PAN).

Village	Tree species						
	Eucalyptus	*Prosopis Juliflora*	*Mangifera indica*	*Pongamia Pinnate*	*Acacia nilotica*	*Acacia auriculiformis*	*Tamarindus indica*
Huttoor	83–92	98–105		106–108	76–80		93–96
Ganeshpura	85–96	98–104	107–110	103–107			94–96
Ramasandra	86–92		106–108		78–82		
Kondasandra			107–109			90–100	93–97
Kaparasiddanahalli	88–94					92–96	
Nandikamanahalli	84–93		106–110	104–106		89–96	
Iragasandra	87–96	99–104	109–111	103–108		89–95	88–95
Antaragange	83–95						
Sangondahalli	84–88						

component image. Then, the stretched, higher resolution image replaces the intensity component before the image is transformed back into the original colour space [36]. The IHS colour coordinate system is based on a hypothetical colour sphere. The vertical axis represents intensity, which ranges from 0 (black) to 255 (white). The circumference of the sphere represents hue, which is the dominant wavelength of colour. Hue ranges from 0 at the midpoint of red tones (through green, blue and black) to 255. Saturation represents the purity of the colour and ranges from 0 as the center of the colour sphere to 255 at the circumference [37]. The IHS values can be derived from the RGB values through transformation equations. The following equations (Eqs. (6)–(8)) are used to compute IHS values for a RGB image (BV_1, BV_2, and BV_3). The IHS values can also be converted back into RGB values using the inverse

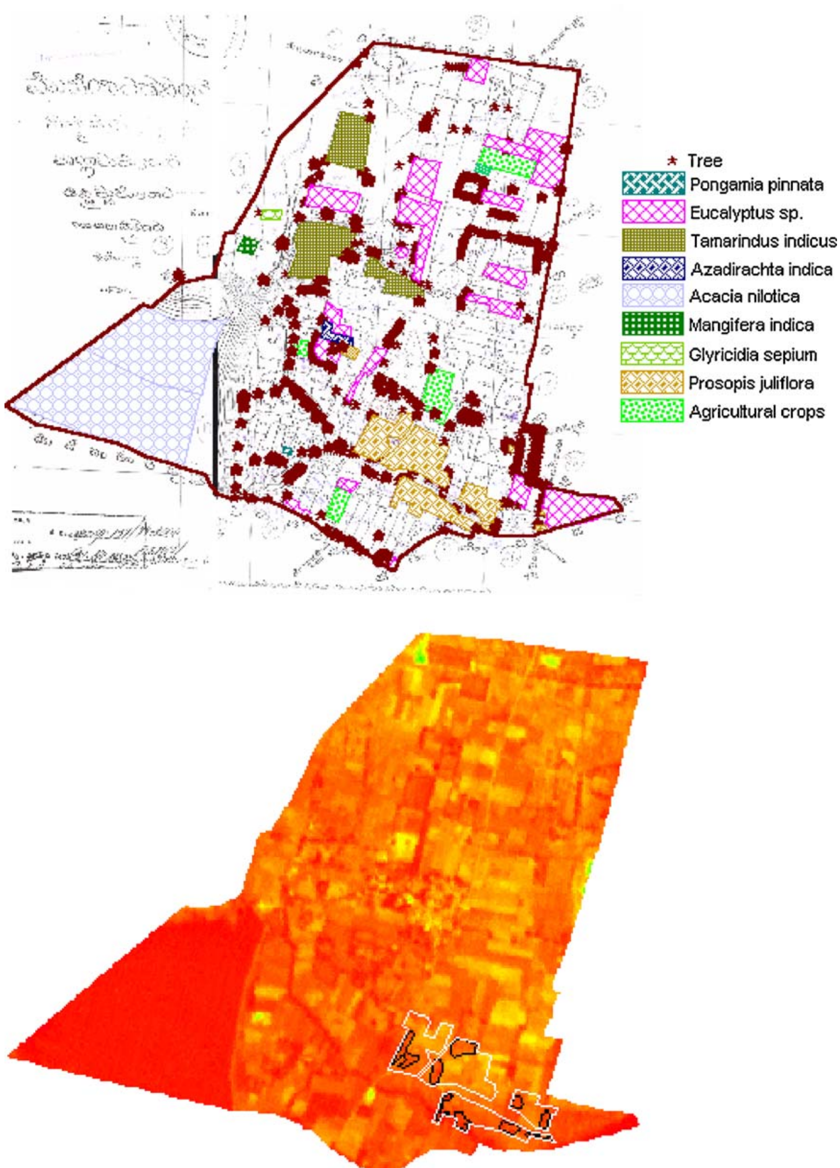

Fig. 7. (7.1) Vector layer of fuelwood species in Iragasandra village. (7.2) Remote sensing data (5.8 m spatial resolution) of Iragasandra village.

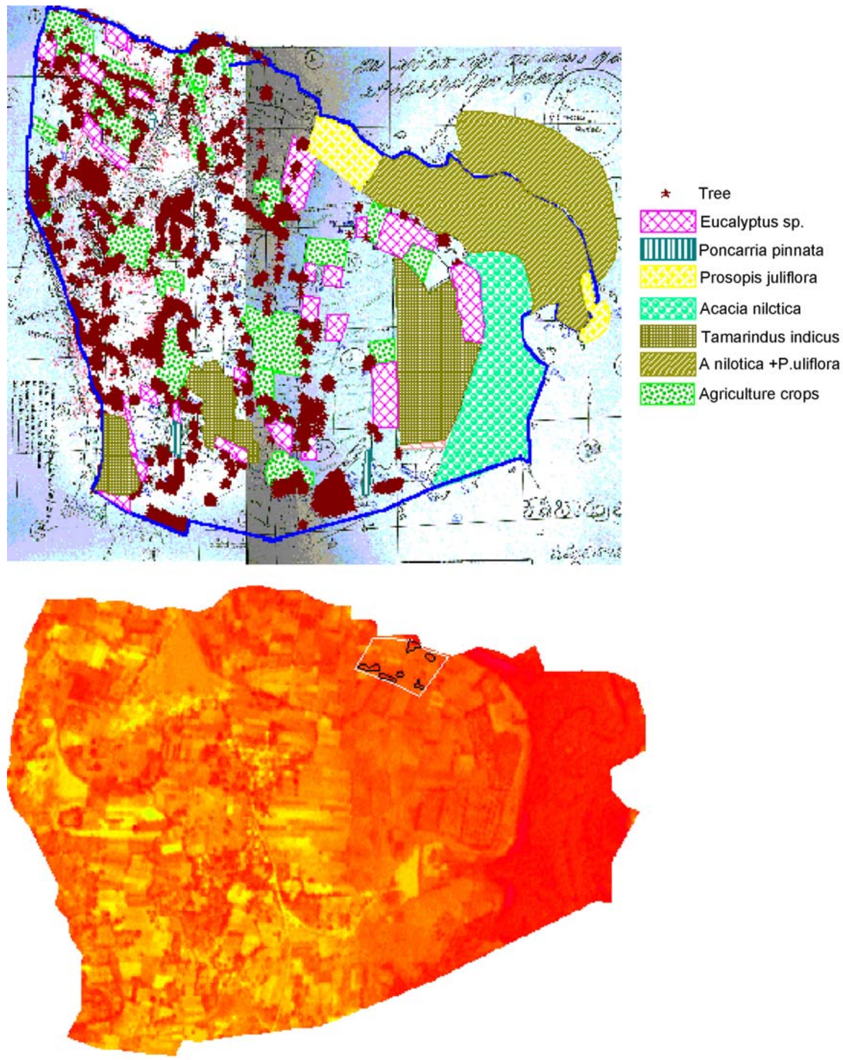

Fig. 8. (8.1) Vector layer of fuelwood species in Huttor village. (8.2) Remote sensing data (5.8 m spatial resolution) of Huttor village.

equations [38].

$$I = \frac{(BV_1 + BV_2 + BV_3)}{3} \tag{6}$$

$$H = \left[\frac{\arctan(2BV_1 - BV_2 - BV_3)}{\sqrt{3}(BV_2 - BV_3)}\right] + C \tag{7}$$

$$S = \frac{\sqrt{6}(BV_1^2 + BV_2^2 + BV_3^2 - BV_1BV_2 - BV_1BV_3 - BV_2BV_3)^{-0.5}}{3} \tag{8}$$

where $C = 0$, if $BV_2 \geq BV_3$; $C = \pi$, if $BV_2 < BV_3$.

Status of Bioresource: Biomass availability was computed taluk wise considering the spatial extent of bioresources and the productivity. The average fuel wood demand was considered as 1.3 kg/person/day based on the household survey of 2500 sample households covering all categories of households in the district. The ratio of availability to the demand (bioresources) gives an idea of its status in a region. This is computed taluk wise and it is listed in Table 2. Ratio less than one gives the scarcity of bioresource in that region. The availability to demand ratio ranges from 0.12 (Chintamani) to 0.42 (Chikballapur). The ratio being less than one indicates that there is bioresource scarcity and Kolar district can be categorised as a bioresource deficit district. Bioresource status ratio (resource to demand) showed that more than 95% of the villages have very less value (0–0.2), while very few villages have average value (>0.6).

Kolar depends mainly on non-commercial forms of energy. Non-commercial energy constitutes 84%, met mainly by sources like firewood, agricultural residues and cow dung. Availability of animal residues for biogas generation gives a viable alternative for cooking and lighting fuel and fertiliser. However, fodder from agricultural residues is insufficient to support the present livestock population in this district. Various alternatives such as fuel-efficient stoves, biogas and energy plantations are proposed for improved utilisation of bioresources and to enhance bioresources. Renewables such as solar energy can be used for cooking and lighting. To maintain the environmental balance and to meet the bioresource demand there should be tree plantations in wastelands and some alternative energy source should be found for cooking need.

Mapping of Tree Species: Field surveys in Kolar indicate that rural household depends on species such as *P. juliflora*, *A. nilotica*, *A. auriculiformis* to meet fuel wood requirement for domestic activities. Hence, to take stock of fuel wood availability, mapping was done considering villages as sampling units and villages were selected randomly. Training data through field surveys for *P. juliflora* and other fuel wood species in Kolar taluk covering 30 villages (Fig. 6) were collected. In order to take stock of fuel wood

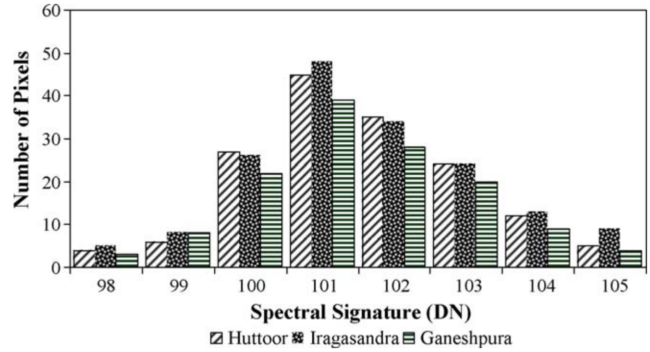

Fig. 9. Histogram: Spectral signatures of *Prosopis juliflora*.

availability in a village, detailed mapping of trees (pixel level mapping) was carried out wherein all the scattered trees in both cultivated and non-cultivated fields were considered including some of them growing in arduous geographical locations like the steep hill ranges and other such localities (except some small totally inaccessible regions like along rock boulders uphill the Antaragange range reserve forest) were mapped using GPS. The survey counts and measures all trees with a diameter of 10 cm and above (dbh). The parameter such as tree type, girth at breast height (GBH), height, and soil type along with the position (in three dimensional) was done for each tree. In case of a patch, a quadrat was taken. The quadrat dimension depends on density of trees and the type of patch (homogenous or heterogeneous). Counting the number of trees in the quadrat and extrapolating it to the whole of the patch area, the trees in the whole village were mapped. In case of homogenous plantations covering a large area, 10 m $\times$ 10 m quadrat was laid and the total number of trees in it was counted, which was later extrapolated to its spatial extent. Then, this information was converted into digital format using GIS (a vector map of respective village using GIS with attribute database). Vector layers of the villages were generated with individual trees marked on the village layer and the corresponding tree information was recorded in the database. These layers were generated for all surveyed villages (Figs. 7.1 and 8.1 for Iragasandra and Huttor villages). These layers were then overlaid onto the fused image of PAN and LISS (Figs. 7.2 and 8.2). Spectral response patterns of the dominant species, covering a large aerial extent were determined by linking ground data with the image data. Large plantations and grooves are depicted in polygons and an individual tree is shown with a symbol, and colours were assigned for various species (Figs. 7.1 and 8.1).

Spectral Signature Analysis: The vector layer of a particular species is overlaid to its corresponding remote sensing data to get the respective spectral signatures. Frequency distribution and histogram analyses of spectral values were done and Fig. 9 provides the histogram for *P. juliflora*. Frequency distribution of spectral values helped in delineating the reasons for variations. The range where the highest peak occurs corresponds to a spectral value of adult species. Average value of the selected range was taken as spectral value of that species and its standard deviation gives the range for spectral signature. Spectral value depends on the type of species, its girth, canopy and density. Considering these parameters, training sites for each species was mapped. Then their corresponding spectral signature is found out by overlaying field data with remote sensing data. Table 3 shows the spectral signature ranges for various tree species dominant in the villages of Kolar taluk.

Mapping of P. juliflora: Mapping of *P. juliflora* using GPS was done in Iragasandra and Huttor villages of Kolar taluk. The study was done in two phases. In first phase, all the areas with *P. juliflora* were

Fig. 10. Mapped *Prosopis juliflora* trees in Gauribidanur taluk (based on the training data collected from neighbouring Kolar taluk).

identified and marked as quadrats. Then the imageries of the particular quadrats were studied to get the spectral signatures and spectral response pattern. In the second phase, sub quadrat was taken within the quadrat with thick patches (density of trees, age of the plantation—juvenile and adult, etc.). With the results of second phase the spectral pattern was still narrowed down based on the density (spatial spread of trees in a quadrat) and age of the trees.

The knowledge of spectral response pattern of select species (considering density and age), helped in mapping those select species for the entire Kolar taluk as well as for the neighbouring Gauribidanur taluk with the help of PAN and LISS III fused data in Kolar district. Fig. 10 depicts fused image. The map of *P. juliflora*

Fig. 11. Fused remote sensing data of Gauribidanur taluk.

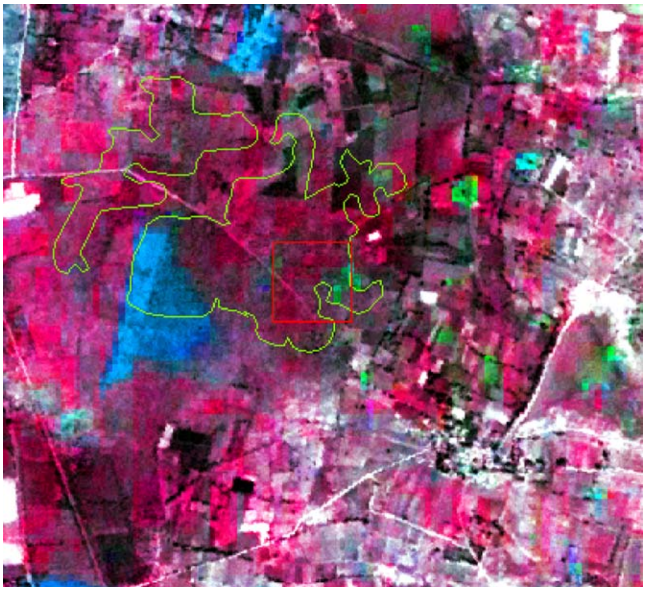

Fig. 12. Verification sites of *Prosopis juliflora* patches in Gauribidanur taluk.

was verified using GPS. Polygons chosen for verification are given in Fig. 11. The spectral pattern of *P. juliflora* (adult plantation) is in the range of 100–102 (whereas Juvenile ones are in the range 98–99 while trees which are sparsely spread constitute the range 103–105) and the field verification indicated the mapping accuracy of 88% and errors due to omission and commission contributed to 12% (Fig. 12).

7. Conclusion

The role of fuel wood in meeting a region's requirement in the form of energy has increased the interest in mapping the extent of fuel wood availability in a region. In addition to environmental benefits, fuel wood offers many economic and energy security benefits. The mapping of fuel wood has continually been refined over the past decade or so as the methodologies, knowledge and the technology available for such methods and for such mapping have improved. The possibility of quickly accessing and processing large spatial databases offers a tremendous improvement. In spite of rapidly advancing computer technology and the proliferation of software for decision support, GIS and Remote Sensing can be used for fuel wood mapping.

Fuel wood mapping shows that Kolar is a bioresource deficit district. Kolar depends mainly on non-commercial forms of energy. Non-commercial energy constitutes 84%, met mainly by sources like firewood, agricultural residues and cow dung, while commercial energy share is 16%, met mainly by electricity, oil, etc. NDVI computation considering NIR and R bands of MSS data shows that 52.5% land cover in Kolar district is under vegetation and 47.5% is under non-vegetation (such as soil, water, etc.). MLC is the best for classifying the remote sensing data with an accuracy of 94.67% which indicates that 46.69% is agricultural land, 42.33% is wasteland (barren land), 4.62% is built up, 3.07% plantation, 2.77% natural forest and 0.53% water bodies. This is based on the accuracy assessment matrices (confusion matrices). The area under vegetation (Agriculture, Plantation and Forests) ranges from 27.91% (Gudibanda), 33.35% (Bagepalli), 36.94% (Gauribidanur), 48.41% (Chintamani), 52.66% (Kolar), 53.56% (Sidlaghatta), 54.51% (Mulbagal), 56.36% (Chikballapur), 65.62% (Srinivasapur), 66.76% (Bangarpet), and Malur (71.71%).

Mapping of fuel wood tree *P. juliflora* was carried out considering village as a sampling unit. Sub-sampling units were selected such that it includes variability in *P. juliflora* cover. Overlaying this field data with the remote sensing data corresponding to the same region helped in identifying the spectral response pattern of the species. With the identification of spectral response pattern for the species (considering density and age), mapping was done for the entire Kolar taluk as well as for the neighbouring Gauribidanur taluk with the help of merged remote sensing data (LISS III MSS and PAN) in Kolar district. The spectral pattern of *P. juliflora* was in the range of 98–105. The map of *P. juliflora* was verified using GPS and the accuracy of mapping was 88% and error due to omission and commission was 12%. The technique used in this work would aid regional energy planners and foresters in management decisions which are largely a function of monitoring forest stand volume by species.

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