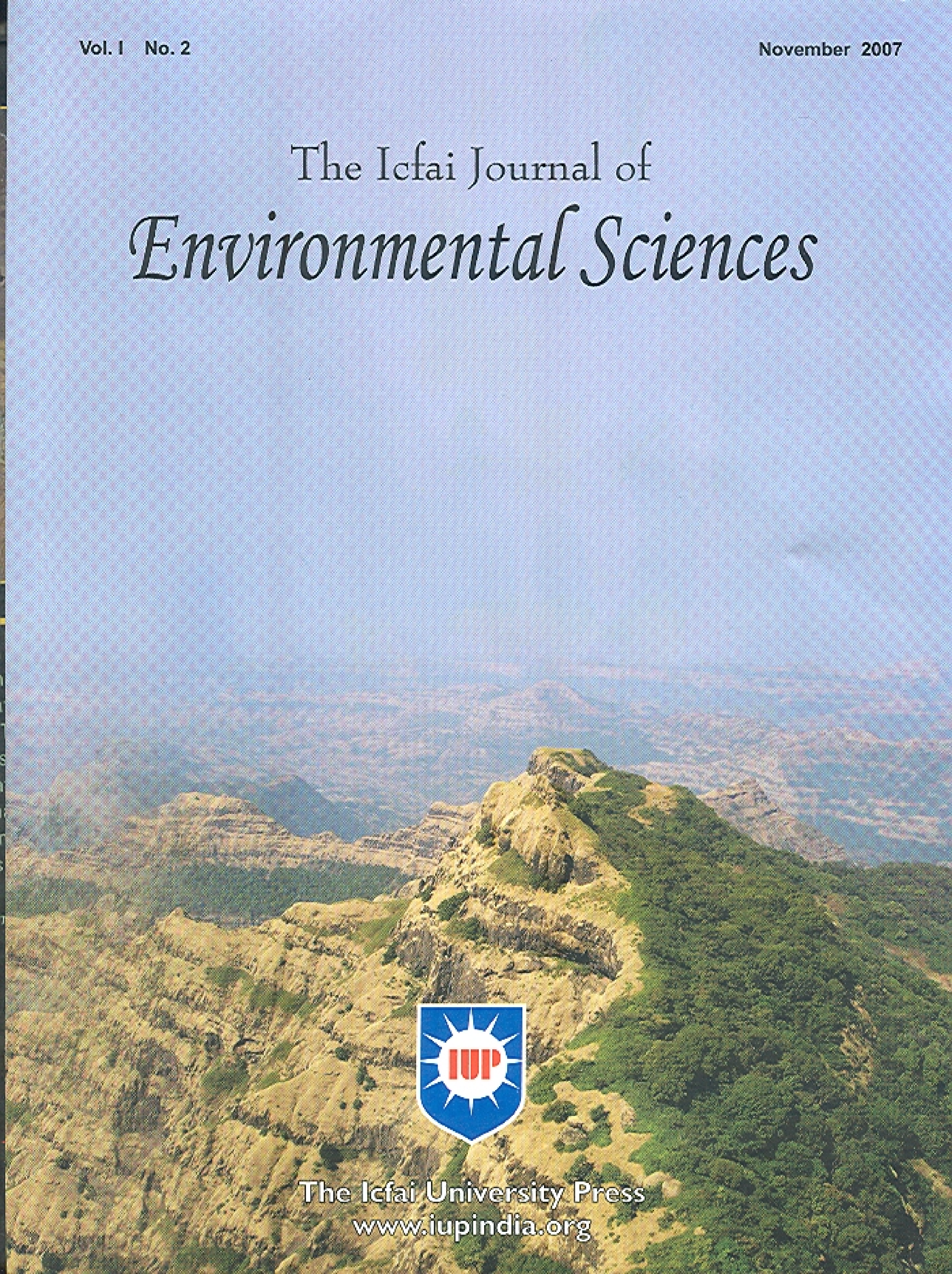
Vol. I No. 2 November 2007

The Icfai Journal of
Environmental Sciences



The Icfai University Press
www.iupindia.org

Focus

Very few ideas have ignited such a contentious debate in the history of scientific world than James Lovelock's Gaia hypothesis—a postulation that the global ecosystem sustains and regulates itself like a biological organism rather than an inanimate entity. Controversies aside, the Gaia hypothesis and the Daisy world model—an imaginary planet, which maintains conditions for its survival simply by following its own natural process—developed by Lovelock and Andrew Watson to prove their argument, incidentally have highlighted an important idea—the idea of 'hysteresis' which states that damage once done to the ecosystem is very difficult to undo. This idea obviously brings forth an argument: "We are just one part of a larger system and are reliant on that system for our continued existence." This whole thought process has only intensified the global concern for sustaining the 'eco-balance'.

Interestingly, the articles that are included in the current issue air similar ideas and underscore the attempts made at weathering the consequences of our abusing the ecosystem. The first article in the series – *Comparative Assessment of Techniques for Bioresource Monitoring Using GIS and Remote Sensing* – avers that in developing economies such as India, biomass is the cheap source of energy. For instance, 70% of India's population depends on biomass for its energy requirements. Indeed in many regions, there is no alternative to biomass for catering to the energy needs of rural households. And it is increasing day by day. This is resulting in depletion of forests, loss of vegetation and erosion of top soil. As against this growing menace, sustainable management of land demands for a synoptic ecosystem approach in the management of natural resources. Against this backdrop, the author of the article, Ramachandra T V has carried out a detailed field investigation using spatial tools such as GIS and Remote Sensing data for bioresource assessment of Kolar district in Karnataka state. His assessment has shown that 45.93% of area is under vegetation while the rest is with no vegetation. Land use analysis carried out using Gaussian Maximum Likelihood Classifier revealed that 43.78% of land is under agriculture, 6.11% under plantation, 5.7% is covered by forests, 4.12% is built-up area, and 1.02% is covered by water while the remaining is waste land. The author has also studied the coverage of land under different plant species using pixel level mapping and identified that 2.44% of land is covered by Eucalyptus, 0.7% by Mango plantation, 0.20% by *Prosopis juliflora* and 0.17% by *Acacia nilotica*. Population density analysis revealed that more than 90% of villages have 0-4 persons per hectare and not surprisingly the density is high in towns. The competition of bioresource status revealed that more than 95% of villages in the district have acute resource scarcity. The author, based on the estimated bioresources and the demand for energy, has opined that Kolar can be classified as bioresources deficit district. He recommends tree plantation in waste land and exploration of alternative resources for cooking as a means to maintain the eco-balance in the district. Over and above all this, the study revealed that among the techniques tested, Gaussian Maximum Likelihood Classifier has least errors.

In the recent past the exploitation of groundwater has reached alarming heights in the country. This overexploitation sans right management techniques has resulted not only in

Comparative Assessment of Techniques for Bioresource Monitoring Using GIS and Remote Sensing

*Ramachandra T V**

Growing concern over the status of global and regional bioenergy resources has necessitated the analysis and monitoring of land cover and land use parameters on spatial and temporal scales. The knowledge of land cover and land use is very important in understanding natural resources utilization, conversion and management. Land cover, land use intensity and land use diversity are land quality indicators for sustainable land management. Optimal management of resources aids in maintaining the ecosystem balance and thereby ensures the sustainable development of a region. Thus, the sustainable development of a region requires a synoptic ecosystem approach in the management of natural resources that relates to the dynamics of natural variability and the effects of human intervention on key indicators of biodiversity and productivity. Spatial and temporal tools such as Remote Sensing (RS), Geographic Information System (GIS) and Global Positioning System (GPS) provide spatial data at regular intervals with the functionalities of a decision support system to help in visualization, querying, analysis, etc., which would aid in sustainable management of natural resources. RS data and GIS technologies play an important role in spatially evaluating bioresource availability and demand. This paper explores various land cover and land use techniques that could be used for bioresources monitoring considering the spatial data of Kolar district, Karnataka, India. Slope and distance-based vegetation indices are computed for qualitative and quantitative assessment of land cover using remote spectral measurements. Different-scale mapping of land use pattern in Kolar district is done using supervized classification approaches. Slope-based vegetation indices show area under vegetation which range from 47.65% to 49.05%, while distance-based vegetation indices show its range from 40.40% to 47.41%. Land use analyses using maximum likelihood classifier, indicate 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 water bodies. The comparative analysis of various classifiers indicate that the Gaussian maximum likelihood classifier has least errors. The computation of taluk-wise bioresource status shows that Chikballapur taluk has better availability of resources compared to other taluks in the district.

Key words: Bioresource monitoring, Global Positioning System (GPS), Kolar district, Land use, Vegetation Indices

Introduction

Biomass was the chief source of fuel in the pre-industrial revolution world, and is still a major source of energy in many developing countries including India. Although biofuel

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accounts for only 12% of the global energy requirements in terms of total energy content, it caters to the largest section of energy users. It is estimated that two-thirds of households in the developing countries still depend on bioresources for domestic activities such as cooking, water heating and space heating—during winter and monsoon (USAID capsule Report,1999). Bioresource inventory helps in describing the quality, quantity, change, productivity and condition of bioresources in a given area. These inventories may be for regional or national level assessment (Ramachandra *et al.*, 2004).

India with a geographical area of about 3.28 mn sq. km, accounts for 2.47% of the total geographical area and has 16.1% of the human population and 15.1% livestock population. 70% of India's population depends on biomass to meet their basic energy needs, i.e., fuel, food and fodder. Studies reveal that 85-90% of regional energy consumption in most States in India comes from bioresources. Bioresources ensure provision of energy to the poor and more vulnerable groups. In many regions, there is no realistic alternative to biomass fuels for the poorest portions of the population, and bioresource consumption is also growing. The procurement of energy from biomass is responsible in varying degrees for the ongoing deforestation, and loss of vegetation and topsoil (Ramachandra *et al.*, 2000a). This necessitates prudent planning of bioresources to ensure its availability to meet the growing demand. The production of biomass in all its forms for fuel, food, and fodder, demands environmentally sustainable land use and integrated planning approach. Detailed planning would be required from national, to State, to District, to Taluk and village levels (Ramachandra *et al.*, 2000b).

Currently available bioresources in Kolar district are under threat of deterioration due to short-term perspectives and narrow sectoral approaches in planning process through indiscriminate pursuit of developmental activities. The changes driven by human activities are directly related to land cover and land use, and have the potential to significantly affect food security and the sustainability of the world agricultural and forest product supply systems. Appropriate policy formulation and planning require the assessment and forecasting of the demand and supply of all forms of energy. This is required to identify problems and for appropriate intervention options. For this purpose, data on several factors that have an impact on an energy system is needed. A regional database on bioresources is needed to support the information requirements of the regional energy planning for sustainable development. However, for most parts of India these data are not available for planning. The production, distribution and consumption of bioresource occur usually at the local level, on a small scale and often outside the monetary economy. The environment, the level of income, the type of settlement and the existence and accessibility of resource vary among areas, the supply of biomass and energy consumption varies spatially. Likewise, within an area, the pattern of energy demand and supply can vary by sub-area, town, or village, depending on cultural, social, geographic, agro-ecological and climatic conditions. The bioresource assessment is based on detailed field investigations to estimate the available bioresources and demand spatially in Kolar district of Karnataka state, India for evolving better management strategies and ensure renewability of resources. In this regard, spatial tools such as Geographic Information System (GIS) and Remote Sensing (RS) data help immensely in providing geographically referenced spatial distribution of potential and demand.

Remote Sensing and Geographic Information System

Remote sensing is the practice of deriving information about the earth's land and water surface using images acquired from an overhead perspective, using electromagnetic radiation in one or more regions of the electromagnetic spectrum, reflected or emitted from the earth's surface (James, 2002). Remote sensing systems offer four basic components to measure and record data about an area from a distance. These components include the energy source, the transmission path, the target and the satellite sensor. The energy source, electromagnetic energy, is very important. It is the crucial medium required to transmit information from the target to the sensor.

Remote sensing sensors (airborne or space borne) aid in acquiring the spatial data of the earth or its parts at frequent intervals, which are required for sustainable management of natural resources. It provides synoptic coverage of resources at regular intervals, which help in mapping and classification of land cover features, such as vegetation, soil, water and forests. It helps in assessing the extent and diversity of vegetation. Also, it aids in estimating how factors such as moisture, latitude, elevation above sea level, length of the growing season, solar radiation, temperature regimes, soil type and drainage conditions, topographic aspect and slope, prevailing winds, etc., influence vegetation (Deekshatulu and Rajan, 1984).

Remote sensing technology has emerged to support data collection and analysis methods of potential interest and importance in resource sustainable management so as to satisfy the expressed desire or goal that resource management succeeds in maintaining the ecosystem in a sustainable condition (Steven and Franklin, 2001). Sustainable development of a region requires a synoptic ecosystem approach that relates to the dynamics of natural variability and the effects of human intervention on key indicators of biodiversity and productivity (Ramachandra and Subash, 2002). Inventory and mapping of resources are today facilitated by remotely sensed imageries. The multispectral images are used for quantification and monitoring of resources and analyze changes over a period of time. An important aspect of remote sensing data is that it helps in quantitatively deriving the biomass variation from the high dimensional data collected from multi-frequency (multi spectral), dual-polarized, multi-day, multi-angle, and passive sensors. GIS helps in archiving, analysis and visualization of remote sensed data along with other collateral data (spatial as well as statistical). RS data along with GIS and GPS (Global Positioning System) help in land cover and land use analyses as well as species level mapping (using higher spatial and spectral resolution data).

Land cover refers to the physical characteristic of the earth's surface, captured in the distribution of vegetation, water, desert, ice, and other physical features of the land including those created solely by human activities (Xavier and Gerard, 1998). Land use is defined as the use of land by humans, usually with emphasis on the functional role of land in economic activities. In a much broader sense, land cover designates the visible evidence of land use, to include both vegetative and non-vegetative features (James, 2002). The analysis of vegetation and detection of changes in the vegetation pattern on spatial and temporal scales are keys to the natural resource assessment and monitoring. Thus, the detection and quantitative assessment of vegetation is one of the major applications of remote sensing for environmental resource management and decision-making. Land cover analysis is done using Vegetation Indices (VIs) and land use analysis using classification techniques.

Objectives

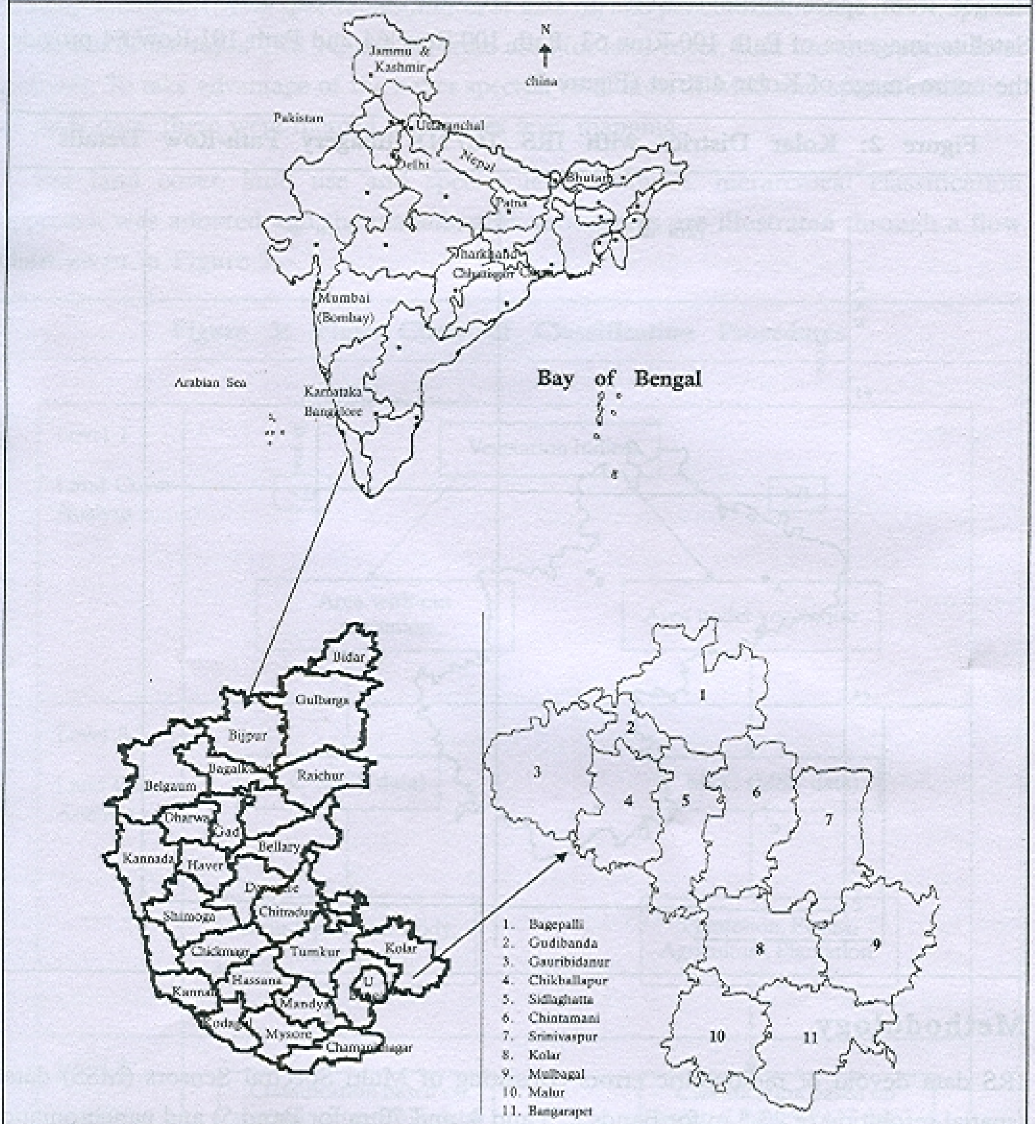
The primary goal of this investigation is to explore and assess the various techniques that could be adopted for land cover and land use analysis for regional bioresource monitoring. Land use analysis helps to gain insight into the data for area-based energy planning and problems related to the resources availability, collection, etc. The objectives are:

- Land cover and land use analyses;
- Analyses of spatial distribution of bioresource and specie level mapping;
- Identification of the availability of resource at different levels with the help of remote sensing data;
- Estimate energy demand with the help of field data and data from government agency or other organization; and
- Estimate village-wise bioresource status.

Study Area

Kolar district is located in the southern plains of Karnataka, India. It lies between 77° 21' to 78° 35' East Longitude and 12° 46' to 13° 58' North Latitude and extends over an area of 8,225 sq. km (Figure 1). The population was 2.523 million in 2001. For administrative purposes, the district has been divided into 11 Taluks. There are 15 towns and 3,325 inhabited villages in the district. Kolar belongs to the semi-arid zone of Karnataka. In the semi-arid zone apart from the year-to-year fluctuations in the total seasonal rainfall, there are also large variations in the time of beginning of rainfall, adequate for sowing as well as in the distribution of drought periods within the crop-growing season. Kolar district depends on the rainfall during the southwest and northeast monsoon. Out of

Figure 1: Study Area

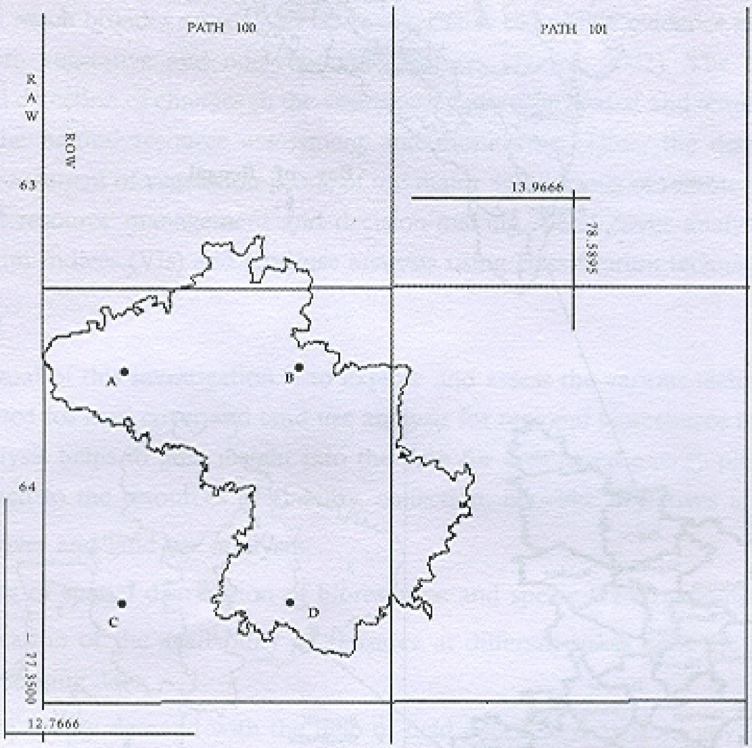


about 2,800 sq. km of land under cultivation, 35% is under well and tank irrigations. There are about 951 big tanks and 2,934 small tanks in the district.

Data

The data sets needed to develop the vegetation database, which included village maps, Survey of India toposheets (1:50000, 1:250000), satellite images (multispectral and panchromatic sensor data) and information from field surveys (training data) using GPS. In order to take into account the variation in spectral values due to climatic factors (seasonality), remote sensing data at different time intervals were considered. Cloud-free images from space borne sensors of IRS 1C and ID were used for this purpose. Satellite imageries of Path 100-Row 63, Path 100-Row 64 and Path 101-Row 64 provide the entire image of Kolar district (Figure 2).

Figure 2: Kolar District with IRS 1C/1D Imagery Path-Row Details



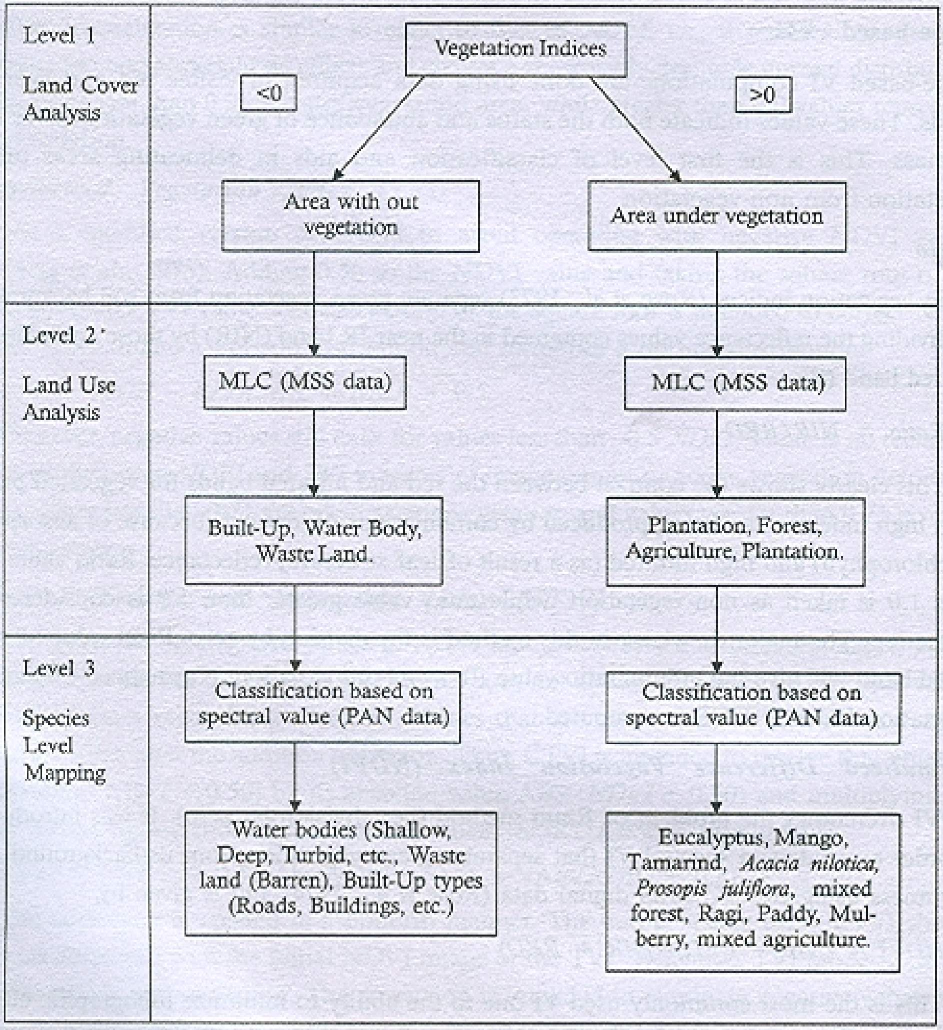
Methodology

IRS data devoid of radiometric errors consisting of Multi Spectral Sensors (MSS) data (spatial resolution of 23.5 m for Bands 2, 3 and 4, and 70 m for Band 5) and panchromatic data (spatial resolution of 5.8 m) for two seasons for the district was procured from National Remote Sensing Agency, Hyderabad. MSS data supplied by NRSA was in BIL (band interleaved by lines) format and individual bands were extracted using band extraction algorithm (written in C++).

Accurate mapping or inventory of natural resources requires ground control points (GCP), which are necessary to fit details extracted from satellite images. Cadastral map (1:6000) of villages was considered for pixel level mapping (during the field visits). These maps were digitized and geo-registered. GPS values corresponding to individual trees, plantations, water bodies and forest areas were transferred to the digitized village maps. Multispectral data (MSS, spectral resolution of 23.5 m) and panchromatic data (PAN, spatial resolution of 5.8 m) of IRS 1C and ID were used for land cover, land use and species level analyses. To take advantage of the better spectral resolution of MSS and spatial resolution of PAN data, these were merged for species level mapping.

For land cover, land use and species level analyses, hierarchical classification approach was adopted and the classification procedures are illustrated through a flow chart given in Figure 3.

Figure 3: Flow Chart of Classification Procedures



Land Cover Analysis

Land cover analysis was done using different slope and distance-based vegetative indices (VIs). This helps in identifying observed physical cover including vegetation (natural or planted). VI is computed based on the data grabbed by space-borne sensors in the range 0.6-0.7 (red band) and 0.7-0.9 (Near-IR band), which helps in delineating the area under vegetation and non-vegetation areas.

It is found that vegetation is sparsely distributed in Kolar district because of its semi-arid environment and the pixels contain a mixture of green vegetation and soil background. Hence, in addition to slope-based vegetation indices, distance-based vegetation indices have been computed. This would cancel the effect of soil brightness in case where there is a mixture of green vegetation and soil background.

Slope-based VIs

Slope-based VI computations are done using data acquired in visible red and near IR bands. These values indicate both the status and abundance of green vegetation cover and biomass. This is the first level of classification and aids in delineating areas under vegetation from non-vegetation.

Ratio

Ratio vegetation indices (Rose *et al.*, 1973) separate green vegetation from soil background by dividing the reflectance values contained in the near IR band (NIR) by those contained in the red band (R).

$$Ratio = NIR/RED \quad \text{...(1)}$$

This clearly shows the contrast between the red and infrared bands for vegetated pixels with high index values being produced by combinations of low red (because of absorption by chlorophyll) and high infrared (as a result of leaf structure) reflectance. Ratio value less than 1.0 is taken as non-vegetation, while ratio value greater than 1.0 is considered as vegetation. The major drawback in this method is the division by zero. Pixel value of zero in red band will give the infinite ratio value. To avoid this situation, Normalized Difference Vegetation Index (NDVI) is computed.

Normalized Difference Vegetation Index (NDVI)

NDVI overcomes the problem of Ratio method (i.e., division by zero). It was introduced in order to produce a spectral VI that separates green vegetation from its background soil brightness using IRS 1C MSS digital data (Rose *et al.*, 1974) and is given by,

$$NDVI = (NIR - RED)/(NIR + RED) \quad \text{...(2)}$$

This is the most commonly used VI due to the ability to minimize topographic effects while producing a linear measurement scale ranging from –1 to +1 .The negative value represents non-vegetated area while positive value represents vegetated area.

Ratio Vegetation Index (RVI)

The ratio vegetation index is the reverse of the standard simple ratio (Richerdson and Wiegand, 1977),

$$RVI = RED/NIR \quad \text{...(3)}$$

The range for *RVI* extends from 0 to infinity. The ratio value less than 1.0 is taken as vegetation while value greater then 1.0 is considered as non-vegetation area.

Normalized Ratio Vegetation Indexes (NRVI)

Normalized ratio vegetation index is a modification of the RVI (Baret and Guyot, 1991) where the result of $RVI - 1$ is normalized over $RVI + 1$.

$$NRVI = (RVI - 1)/(RVI + 1) \quad \text{...(4)}$$

This normalization is similar in effect to that of *NDVI*, i.e., it reduces topographic, illumination and atmospheric effects and creates a statistically desirable normal distribution. Ratio value less than 0.0 indicates vegetation area, while greater than 0.0 values represents non-vegetation.

Transformed Vegetation Index (TVI)

TVI is a modified version of NDVI to avoid operating with negative NDVI values (Deering et al., 1975). Adding 0.50 to the NDVI value and taking the square root of the result computes TVI value. The calculation of the square root is intended to correct NDVI values approximate a Poisson distribution and introduce a normal distribution.

$$TVI = \sqrt{}(NIR - RED/NIR + RED) + 0.5 \quad \text{...(5)}$$

However, negative values still exist for values less than –0.5 *NDVI*. There is no technical difference between *NDVI* and *TVI* in terms of image output or active vegetation detection. Ratio values less than 0.71 are taken as non-vegetation and values greater than 0.71 give the vegetation area.

Corrected Transformed Vegetation Index (CTVI)

CTVI suppresses the negative values in NDVI and TVI (Perry and Lautenschlager, 1984). Adding a constant of 0.5 to all NDVI values does not always eliminate all negative values as NDVI values range from –1 to +1. Values that are lower than –0.50 will leave small negative values after the addition operation. Thus, CTVI is intended to resolve this situation by dividing ($NDVI + 0.50$) by its absolute value ABS ($NDVI + 0.50$) and multiplying the result by the square root of the absolute value {SQRT[ABS($NDVI + 0.50$)]}.

$$CTVI = (NDVI + 0.5)/\mathrm{Abs}(NDVI + 0.5) \times \sqrt{}\mathrm{Abs}(NDVI + 0.5) \quad \text{...(6)}$$

The correction is applied in a uniform manner. The output image using CTVI should have no difference with the initial NDVI image or the TVI. Whenever TVI properly carries out the square root operation. The correction is intended to eliminate negative values and generate a VI image that is similar to, if not better than, the NDVI. Ratio value less than 0.71 is taken as non-vegetation and value greater than 0.71 gives the vegetation area.

Thiam's Transformed Vegetation Index (TTVI)

The CTVI image is very noisy due to an over-estimation of the greenness, which can be avoided by ignoring the first term of the CTVI, and it provides better results (Thiam, 1997). This is done by simply taking the square root of the absolute values of the NDVI in the original TVI expression to have a new VI called as TTVI. It can be defined as:

$$TTVI = \sqrt{\text{abs}\{(NIR - RED)/(NIR + RED)\}} + 0.5 \quad \text{...(7)}$$

Ratio value less than 0.71 is taken as non-vegetation and value grater than 0.71 gives the vegetation area.

Distance-based VIs

The main objective of the distance-based VI is to cancel the effect of soil brightness in cases where vegetation is sparse and pixels contain a mixture of green vegetation and soil background. This is particularly important in arid and semi-arid environment such as, Kolar district of Karnataka.

Distance-based VIs are evaluated on the basis of soil line intercept concept. The soil line is a hypothetical line in spectral space that describes the variation in the spectrum of bare soil in the image. The soil line represents a description of the typical signatures of soils in red/near-infrared bi-spectral plot. It is obtained through linear regression of the infrared band against the red band for sample of bare soil pixels. Pixels falling near the soil line are assumed to be soils, while those far away are assumed to be vegetation. Equations of the soil lines are given below:

$$Y\,1 = 0.841333x + 10.781234 \text{ (red band independent variable)} \quad \text{...(8)}$$

$$Y\,2 = 0.985684x + 9.501355 \text{ (infra-red band as independent variable)} \quad \text{...(9)}$$

The procedure requires that a set of bare soil pixels as a Boolean mask (value '1' is assigned to pixels representing soil while '0' for others). Analysis is done by regressing the red band against infrared band and *vice versa*. This provides slope and intercept of soil line. Distance-based VIs using the soil line require the slope (b) and intercept (a) of the line as inputs to the calculation. Unfortunately, there has been a remarkable inconsistency in the logic with which this soil line has been developed for specific VIs. For evaluating PVI2, PVI3, TSAVI1, TSAVI2, it requires red band as independent variable for the regression, while for evaluating PVI, PVI1, DVI, WDVI and MSAVI, it requires infrared band as independent variable for regression.

Perpendicular Vegetation Index (PVI)

PVI uses the perpendicular distance from each pixel coordinate to the soil line and this was derived to define vegetation and non-vegetation for arid and semi-arid region (Richerdson and Wiegand, 1977). The pixels, which are close to the soil line, are considered as non-vegetation, while pixels away from soil lines represent vegetation. PVI values for data taken at different dates require an atmospheric correction of data, as PVI is quite sensitive to atmospheric variations. This can be defined as:

$$PVI = \sin(a)NIR - \cos(a)RED \quad ...(10)$$

where, a is the angle between the soil line and the NIR axis.

$$PVI = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2} \quad ...(11)$$

where, (x_1, y_1) is the coordinate of the pixel; and (x_2, y_2) is the coordinate of soil line point that is perpendicular to pixel coordinate.

Perpendicular distance less then 7.0 is taken as non-vegetation area, while grater than 7.0 is taken as vegetation area.

Perpendicular Vegetation Index 1 (PVI1)

It was noticed that the original PVI equation is computationally intensive and does not discriminate between pixels that fall to the right or left of the soil line (i.e., water from vegetation). Given the spectral response pattern of vegetation in which the infrared reflectance is higher than the red reflectance, all vegetation pixels will fall to the right of the soil line. In some cases a pixel representing non-vegetation (e.g., water) may be equally far from the soil line but it will fall on the left side of the soil line.

In PVI the water pixel will be assigned a high vegetation index value. PVI1 assigns negative values to those pixels, which can be delineated from vegetation. The mathematical equation for PVI1 (Perry and Lautenchlager, 1984) is written as:

$$PVI\,1 = (b\,NIR - RED + a)/\sqrt{(b^2 + 1)} \quad ...(12)$$

where, NIR is the reflectance in the near infrared band; RED is reflectance in the red band, a is intercept of the soil line; and b is slope of the soil line.

Infrared band is taken as the independent variable and the red band as dependent variable for regression analysis. Perpendicular distance less then 6.5 is taken as non-vegetation area while greater than 6.5 is taken as vegetation area.

Perpendicular Vegetation Index 2 (PVI 2)

In PVI2, Red band is taken as independent variable over infrared dependent variable for regression analysis (Bannari *et al.*, 1996), and importance is given to the red band with the intercept of soil line. Mathematically, PVI2 can be represented as:

$$PVI\,2 = \sqrt{\{(NIR - a \times RED + b)/\sqrt{(a^2 + 1)}\}} \quad ...(13)$$

where, a is intercept of the soil line, and b is slope of the soil line.

Here, pixels having less than –95.0 are grouped as non-vegetation area.

Perpendicular Vegetation Index 3 (PVI 3)

PVI3 is an improved version of PVI, where red band is taken as independent variable on regression analysis and special attention was given to avoid the negative results (Qi *et al.*, 1994). PVI3 can be defined as,

$$PVI\ 3 = apNIR - bpRED \quad ...(14)$$

where, a is intercept of the soil line; b is slope of the soil line; $pNRI$ is reflectance in the near infrared band; and $pRED$ is reflectance in the visible red band.

Difference Vegetation Index (DVI)

DVI weighs up the NIR band by the slope of the soil line (Richerdson and Wiegand, 1977) and is given as:

$$DVI = gNIR - RED \quad ...(15)$$

where, g: the slope of the soil line.

Similar to the PVI1, with DVI, a value of zero indicates bare soil, values less than zero indicates non-vegetation, and greater than zero indicates vegetation.

Ashburn Vegetation Index (AVI)

AVI (Ashburn, 1978) is presented as a measure of growing green vegetation. Scaling factor is required for evaluating AVI. For IRS 1C data scaling factor of 1 was chosen, as all bands are 7-bit. AVI can be represented as,

$$AVI = sNIR - RED \quad ...(16)$$

where, s is scaling factor.

AVI was evaluated for Kolar district using scaling factor as 1 for 8-bit MSS data set.

Soil Noise

Soil reflectance spectra depend on type of soil. The vegetation indices computed earlier assume that there is a soil line, where there is a single slope in red-NIR space. However, it is often the case that there are soils with different red-NIR slopes in a single image. Also, if the assumption about the isovegetation line (parallel or intercepting at the origin) is not exactly right, changes in soil moisture (which move along isovegetation lines) will give incorrect answers for the vegetation index. The problem of soil noise is most acute when vegetation cover is low. The following groups of indices like SAVI, TSAVI1, TSAVI2, MSAVI1, MSAVI2 attempt to reduce soil noise by altering the behavior of the isovegetation lines. All of them are ratio-based, and the way that they attempt to reduce soil noise is by shifting the place where the isovegetation lines meet. These indices reduce soil noise at the cost of decreasing the dynamic range of the index. These indices are slightly less sensitive to changes in vegetation cover than NDVI (but more sensitive than PVI) at low levels of vegetation cover. These indices are also more sensitive to atmospheric variations than NDVI (but less so than PVI).

Soil Adjusted Vegetation Index (SAVI)

SAVI is intended to minimize the effects of soil background on the vegetation signal by incorporating a constant soil adjustment factor L in the denominator of the NDVI equation (Huete, 1988). L varies with the reflectance characteristics of soil (i.e., color and brightness). The L factor chosen depends on the density of the vegetation. For very low vegetation L factor can be taken as 1.0 while for intermediate it can be taken as 0.5 and for high density 0.25. The best L value to select is where the difference between SAVI values for dark and light soil is minimal. For $L = 0$, SAVI equals NDVI. For $L = 100$, SAVI approximates PVI. Mathematically SAVI is defined as,

$$SAVI = \{(NIR - RED) / (NIR + RED + L)\} \times (1 + L) \quad \text{...(17)}$$

where, NIR is near-infrared band; RED is visible red band; and L is soil adjustment factor.

Multiplicative term $(1 + L)$ present in SAVI (and MSAVI) is responsible for vegetation indices to vary from –1 to +1. This is done so that both vegetation indices reduce to NDVI when the adjustment factor L goes to zero. Soil adjustment factor (L) of 0.5 was considered for Kolar district, as vegetation density is medium.

Transformed Soil Adjusted Vegetation Index (TSAVI 1)

The SAVI concept is exact only if the constants of the soil line are $a = 1$ and $b = 0$, where a is slope of the soil line and b is y-intercept of the soil line. As it is not generally the case, some modification was needed in SAVI. By taking into consideration the PVI concept (Baret *et al.*, 1989), SAVI is modified as TSAVI1. This index assumes that the soil line has arbitrary slope and intercept, and it makes use of these values to adjust the vegetation index and is written as:

$$TSAVI\,1 = a\,(NIR - a \times RED - b)/(RED + a \times NIR - a \times b + X(1 + a^2)) \quad \text{...(18)}$$

where, NIR is reflectance in near infrared band; RED is reflectance in red band; a is slope of the soil line; b is intercept of the soil line; and X is adjustment factor which is set to minimize soil noise.

Red band is taken as independent variable for regression analysis. Ratio value less than –9.0 is taken as non-vegetation while greater than –9.0 is taken as vegetation. With some resistance to high soil moisture, TSAVI1 could be very good candidate for use in semi-arid regions, and was specifically designed for semi-arid region and does not work well in areas with heavy vegetation.

Transformed Soil Adjusted Vegetation Index (TSAVI 2)

TSAVI2 is modified version of TSAVI which was readjusted with an additive correction factor of 0.08 to minimize the effects of the background soil brightness (Baret *et al.*, 1989) and is given by:

$$TSAVI\,2 = a\,(NIR - a \times RED - b)/(RED + a \times NIR - a \times b + 0.08(1 + a^2)) \quad \text{...(19)}$$

Red band is taken as independent variable for regression analysis and is given preference with soil line intercept.

Modified Soil Adjusted Vegetation Index 1 (MSAVI 1)

The adjustment factor L for SAVI depends on the level of vegetation cover being observed which leads to the circular problem of needing to know the vegetation cover before calculating the vegetation index, which is what gives the vegetation cover. MSAVI is the Modified Soil Adjusted Vegetation Index (Qi *et al.*, 1994) and provide a variable correction factor L. The correction factor used is based on the product of NDVI and WDVL. This means that the isovegetation lines do not converge to a single point. MSAVII is written as,

$$MSAVI\ 1 = \frac{NIR - RED}{NIR + RED + L} \times (1 + L) \qquad \text{...(20)}$$

where, $L = 1 - 2 \times s \times NDVI \times WDVI$; s is slope of the soil line, $NDVI$ is Normalized Difference Vegetation Index; $WDVI$ is Weighted Difference Vegetation Index used to increase the L dynamic range, range of $L = 0$ to 1.

Modified Soil Adjusted Vegetation Index 2 (MSAVI 2)

MSVI2 was derived based on a modification of the L factor of the SAVI (Qi *et al.*, 1994). SAVI and MSVI2 are intended to correct the soil background brightness in different vegetation cover conditions. Basically, this is an iterative process and substitute 1-MSAVI $(n - 1)$ as the L factor in MSAVI (n) and then inductively solve the iteration, where $MSAVI\ (n) = MSAVI\ (n - 1)$. MSVI2 uses an inductive L factor to:

- Remove the soil "noise" that was not cancelled out by the product of NDVI by WDVI; and
- Correct values greater than 1 that MSAVII may have due to the low negative value of $NDVI \times WDVI$. Thu,s its use is limited for high vegetation density areas.

The general expression of MSAVI2 is,

$$MSAVI2 = (2NIR + 1 - \sqrt{\{(2NIR + 1)^2 - 8(NIR - RED)\}})/2 \qquad \text{...(21)}$$

where, NIR is reflectance of the near infrared band; and RED is reflectance of the red band.

Pixel value less than 0.0 are under non-vegetation and pixel having greater than 0 are under vegetation.

Weighted Difference Vegetation Index (WDVI)

Like PVI, WDVI is very sensitive to atmospheric variations (Richerdson and Wiegand, 1977) and can be presented as,

$$\mathrm{WDVI} = \mathrm{NIR} - \gamma\,\mathrm{RED} \qquad \text{...(22)}$$

where, NIR is reflectance of near infrared band; RED is reflectance of visible red band; and γ is slope of the soil line.

Although simple, WDVI is as efficient as most of the slope-based VIs. The effect of weighing the red band with the slope of the soil line is the maximization of the vegetation signal in the near-infrared band and the minimization of the effect of soil brightness.

Land Use Analysis

Land use analysis is done through classification of remotely sensed data. It 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, and each of the classes has varying spectral patterns. There is substantial variation in the distribution of the pixel reflectance values (depending upon the sample's location within a cover type). The spectral information contained in the original and transformed bands is then used to characterize each class pattern, and discriminate between the classes. There are two approaches to classify an image, namely unsupervized and supervized classification techniques. The unsupervized classification technique intends to uncover the major land cover classes that exist in the image, without prior knowledge or field data. This is based on cluster analysis, considering clusters of pixels with similar reflectance characteristics in a multi-band image.

With supervized 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 investigated. Once a statistical characterization has been achieved for each information class, the image is then classified by examining the reflectance for each pixel and making a decision about which of the signatures it resembles most. There are several techniques for making these decisions, and these are often termed classifiers (hard and soft classifiers). Among the hard classifiers, three approaches (Parallelepiped (PP), Minimum Distance to Mean (MD), and Maximum Likelihood Classification (MLC)) were used to classify the images. The classified images were then reclassed into final six land use types. Different hard classification procedures are described below.

Minimum Distance-to-Means Classification (MD)

The Minimum Distance classification approach is commonly used when the number of pixels used to define the signatures is very small or when training sites are not well defined. By characterizing each class by its mean band reflectance only, it has no knowledge of the fact that some classes are inherently more variable than others, which in turn can lead to misclassification. Unknown pixels are classified based on their distance from the mean vector.

Parallelepiped Classification (PP)

The parallelepiped procedure characterizes each class by the range of expected values on each band. This range may be defined by the minimum and maximum values found in the training site data for that class or by some standardized range of deviations from the mean with multi-spectral image data, which ranges from an enclosed box-like polygon of expected values known as a parallelepiped. However, the performance of this classifier is very poor.

Maximum Likelihood Classification (MLC)

Maximum likelihood classification (MLC) is one of the most widely used methods in classifying remotely sensed data. The MLC procedure is based on Bayesian probability theory. This technique generally yields higher accuracy in classification, but it is highly computationally intensive and time-consuming. It was found that the MLC approach is the best of all the hard classifiers based on the accuracy assessment matrices (confusion matrices) generated for all the three classified images. Also MLC has generally been proven to be the one that obtains best results for classification of remotely sensed data. Hence, the MLC approach was adopted for land use analysis. This provides classified information at both macro and micro levels. For macro level classification, training sites were selected so as uniformly distributed all over the taluk and about 375 training sites (GCP) were chosen for an area of 750-1,000 sq. km and remotely sensed MSS data were used. In case of micro level classification village-wise training, data at pixel level were collected and high resolution PAN data was used.

This classification is based on probability density function associated with a particular signature (training site). Pixels are assigned to the most likely class based on a comparison of the posterior probability, that it belongs to each of the signatures being considered. Mean and standard deviation for each training set is calculated. Probability density function is derived from mean and standard deviation and probability of each pixel belonging to each category is computed.

$$\text{Mean } (\mu) = (\Sigma f(i) \times i) \;/\; \Sigma f(i) \qquad \text{...(23)}$$

$$\text{SD } (\sigma) = \sqrt{(\;\Sigma f(i) \times (\mu - i)^2)/\; \Sigma f(i)} \qquad \text{...(24)}$$

where, i is spectral value; and $f\ (i)$ is number of pixels.

Probability density function for Normal distribution is given as:

$$f(x) = \frac{e^{-(x-\mu)^2} \;/(2\sigma^2)}{\sigma\sqrt{2\pi}} \qquad \text{...(25)}$$

where, μ is Mean; σ is Standard Deviation; and $f\ (x)$ is density function defined as,

$$P(a < x < b) = \int_a^b f(x)dx \qquad \text{...(26)}$$

where, a and b are minimum and maximum spectral values of training site, respectively. The pixel is assigned to that training site, where its probability is found maximum. Further, species level classification was done on the basis of spectral response pattern of different species, which is based on pixel level mapped field data.

Accuracy Assessment

The final stage of the classification process usually involves an accuracy assessment. The purpose is to estimate the accuracy of quantification of mapping using remote sensing data to the ground conditions. This is useful in comparing classification techniques, and determining the level of error that might be contributed by the land cover image in further analyses in which it is incorporated. Accuracy of each classification is expressed as an error matrix. An error matrix is a square array of numbers in which the columns express the informational categories, and the rows represent the classes in which those informational categories have been classified. The overall agreement of the classification is therefore expressed by the sum of main diagonal entries. An omission error happens when a test area that should have been classified into its informational category is not classified. On the other hand, the commission error occurs when a test area is classified in a class different from its true informational category. Information about these types of errors is given by the user's and producer's accuracies, respectively. Test areas of the same size as the training areas were used to determine the agreement of classification with the ground reference data. The majority rule was used to determine the class in which a test area is classified. With this rule, a test area is classified into the class that presents the highest frequency of pixels within the test area. The agreement of the classification with ground truth was measured by means of the overall accuracy, and the Kappa statistic.

Traditionally, accuracy assessment is done by generating a random set of locations to visit on the ground for verification of the true land cover type. A simple values file is then made to record the true land cover class (by its integer index number) for each of these locations. This values file is then used with the vector file of point locations to create a raster image of the true classes found at the locations examined. This raster image is then compared to the classified map using ERRMAT, which tabulates the relationship between true land cover classes and the classes as mapped. It also tabulates errors of omission and errors of commission as well as the overall proportional error. This information is used to assess the accuracy of the classification procedure that was undertaken, and the results of all supervized classifications.

The size of the sample (n) to be used in accuracy assessment can be estimated using Equation 3, as follows:

$$n = z^2\ p\ q / e^2 \qquad \text{...(27)}$$

where, z is the standard score required for the desired level of confidence (i.e., 1.96 for 95% confidence, 2.58 for 99%, etc.) in the assessment; e is the desired confidence interval (e.g., 0.01 for 10%); and p is the prior estimated proportional error and $q = 1–p$.

Bioresource Availability Estimation

Bioresource availability was computed considering the extent of land use in each category (like agriculture, forests, etc.) and productivity. Overlaying a vector layer with taluk boundaries on the classified image of the district provides taulk level estimates. In order to assess the bioresource stock species-wise, pixel level mapping was done using digitized cadastral maps of villages and GPS.

Species Level Mapping

The area under different species was noted along with their location coordinates, vegetation types, etc. When two or more species coexisted, it was taken as mixed vegetation. Agriculture, plantation, forest and built up area were mapped at pixel level on the village maps. While, mapping areas under forest and plantation, parameters such as species type, canopy cover, girth at breast height (135cm), height and density were also noted down (these parameters would be useful to assess the standing biomass). This field data (vector layer of villages) is compared with the corresponding geo-referenced remote sensing data of spatial resolution 5.8m (by overlaying these two layers). This helped in obtaining the spectral response pattern for species.

Bioresource mapping software was developed in C++ for finding the spectral range of each species and their corresponding spectral response pattern.

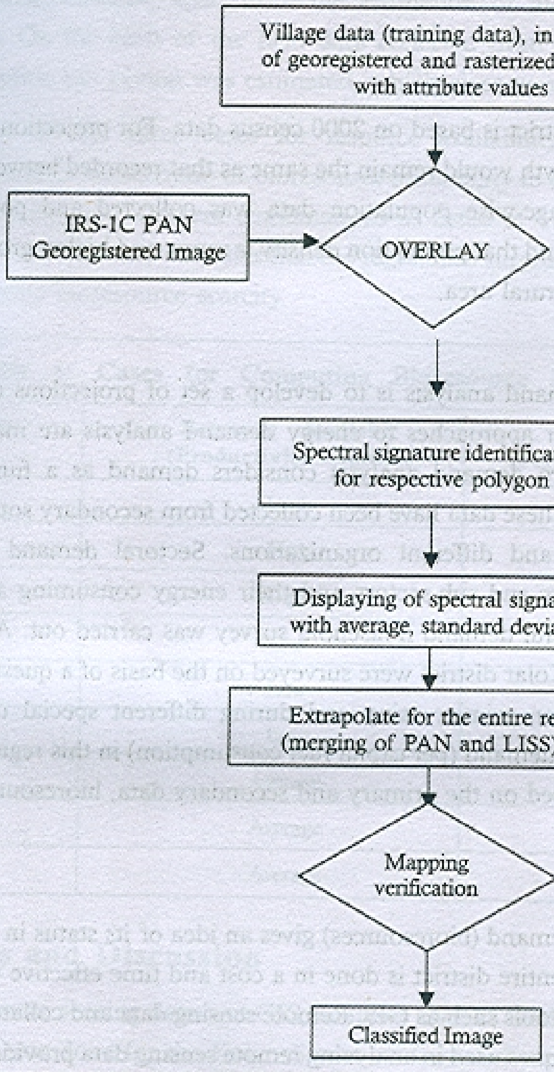
Bioresource Mapping Software

Bioresource Mapping Software developed as illustrated in Figure 4 provides spectral response range of each species. This classification depends on probability density function associated with spectral signatures (spectral response pattern) of a particular species training site (micro level MLC). With the help of this software, the geo-registered vector layer of training data collected from sample villages (village level pixel mapping) was overlayed to its corresponding geo-registered PAN image. Training data in the form of polygons (each polygon representing a type of species) is overlayed to PAN image and the corresponding pixel values for the entire region is found out. The histogram is plotted for the dominant specie and probability density function was found out.

Histogram plays an important role in species level mapping. Vector layer of species (based on field data) was overlaid on raster image and corresponding spectral value was recorded and histogram generated for those species, which provides spectral range of the species. This can be narrowed down through statistical analyses (and considering parameters such as density or spatial spread of species, age of species, etc.). On the basis of the variability, new spectral range for the training site was selected. Based on these parameters, probability density function was determined which helps in classification.

Histogram analysis along with bioresource mapping software provides the spectral range for individual species. However, there is variation in spectral values due to seasonal aspects. It is found that spectral value of eucalyptus was 94-95 on November 17, 1998, while on January 30, 1999 the value changed to 86-88. Hence, season wise PAN scene classification has been done. Spectral range for each species was determined through probability density function. This information was used to classify the image and the result is extrapolated for the entire taluk and then to the district. This study maps the resources available in different levels—village, taluk and district.

Figure 4: Flow Chart of Bioresource Mapping Software



Mapping of *Prosopis juliflora* – Fuel Wood Species

Field survey in Kolar district indicates that rural people depend on species such as *Prosopis juliflora*, *Acacia nilotica*, and *Acacia auriculiformis* to meet fuel wood requirement for domestic activities. A detailed study was carried on for fuel wood species *Prosopis juliflora*—its spectral response pattern was determined with the help of a bioresource software. Training data for *Prosopis juliflora* was taken from Iragasandra and Huttoor villages of Kolar taluk. Bioresource software provided its spectral range is 98-99. This spectral range was mapped in Kolar taluk, and subsequently, in Gauribidanur taluk (where training data was not collected) and cross verification was done in both taluks.

Gauribidanur taluk, was chosen for mapping and verification of *Prosopis juliflora, which* lies in the northwestern side of the district, has basic soil and allows the growth of *Prosopis juliflora*.

Population Density

Population data for the Kolar district is based on 2000 census data. For projections, it was assumed that average annual growth would remain the same as that recorded between 1980 and 1990, and 1990-2000. Village-wise population data was collected and population density was calculated. It was found that population density is more, and higher growth was observed in towns compared to rural area.

Energy Demand Estimation

The objective of the energy demand analysis is to develop a set of projections of future energy consumption. Two major approaches to energy demand analysis are macro and sectoral demand analysis. Macro demand analysis considers demand as a function of population, income and prices. These data have been collected from secondary sources like different government agencies and different organizations. Sectoral demand analysis examines the structure of sectors and sub-sectors and their energy consuming activities. For purpose of evaluation, sectoral demand household survey was carried out. A total of 2,070 houses from all taluks of Kolar district were surveyed on the basis of a questionnaire in different seasons like summer, winter, rainy and during different special occasions (like festivals). It was found that demand (per capita fuel consumption) in this region varies from 1.3-2.5 kg/person/day. Based on the primary and secondary data, bioresource status was calculated for each village.

Bioresource Status

The ratio of availability to the demand (bioresources) gives an idea of its status in a region. The resource availability to the entire district is done in a cost and time effective way with the help of spatial and temporal tools such as GIS, Remote sensing data and collateral data. Hierarchical classification techniques used in analyzing remote sensing data provided details about land use and area under each vegetation (at species level). Based on the productivity value ranges for forest/plantation, bioresource availability is computed as Resource (average), Resource (high) and Resource (low) categories. Bioresource productivity in each type of landuse is computed based on field sampling techniques. Based on randomly selected quadrant in all types of land use, the productivity ranged from 3.6 to 6.5 ton/hectare/year for evergreen, 13.5 to 27 ton/hectare/year in deciduous patches and 0.8 to 1.5 ton/hectare/year for scrub jungle.

Bioresource demand estimation is based on randomly selected sample households (2,070 houses using standard questionnaire). These houses were selected from 154 villages, which are situated all over Kolar district covering different community and category of people (stratified random sampling). A seasonal survey was carried out to determine the season-wise variation apart from the estimation of fuelwood demand during different festivals. On the basis of the field data collected from different seasons, average energy consumption per person was estimated, which gives an average demand value.

Based on the three cases for resource availability and three cases for demand, the bioresource status (ratio of bioresource availability to demand) for the Kolar district was computed for nine different combinations as listed in Table 1. The value of bioresource status greater than one indicates that the region has surplus resources, while values less then one indicate bioresource scarcity.

Table 1: Cases for Computing Bioresource Status of Kolar District

Cases	Resource Available (Productivity Values)	Demand (Per Capita Energy Demand)
1	High	High
2	High	Low
3	High	Average
4	Low	High
5	Low	Low
6	Low	Average
7	Average	High
8	Average	Low
9	Average	Average

Results and Discussion

Using remote sensing data and GIS, analyses such as land cover, land use and species level mapping was done for the Kolar district as discussed earlier.

Land Cover Analysis

In slope-based vegetation indices, area under vegetation in Kolar district ranges from 47.65% to 49.05%, while in distance-based vegetation indices it ranges from 40.40% to 47.41%. Table 2 provides area under vegetation considering slope and distance-based vegetation indices. Comparative analyses of vegetation indices indicate that slope-based vegetation index NDVI (Figures 5) is appropriate for the regions with a good vegetation cover (such as Chikballapur Taluk). While distance-based vegetation index TSAVI 1 (Figures 6) is suitable for semi-arid regions with scanty vegetation cover.

Table 2: Land Cover Analysis of Kolar District with Different VI Aspects

Vegetation Indices	Area in sq. km		Area in %	
	Non-Vegetation	Vegetation	Non-Vegetation	Vegetation
Slope-based VIs				
RATIO	4312.92	4152.29	50.95	49.05
NDVI	4312.92	3888.34	52.59	47.41
RVI	4576.87	3888.34	54.07	45.93
NRVI (-NDVI)	4312.92	3888.34	52.59	47.41
TVI	4599.14	3866.07	54.33	45.67
CTVI	4599.14	3866.07	54.33	45.67
TTVI	4599.14	3866.07	54.33	45.67
Distance-based VIs				
PVI	4666.95	3798.26	55.13	44.87
PVI1	4783.66	3681.55	56.51	43.49
PVI2	4728.17	3737.04	55.85	44.15
PVI3 (less veg)	4976.69	3488.49	58.79	41.21
DVI	4825.18	3640.03	57.00	43.00
AVI	4312.92	3888.34	52.59	47.41
SAVI	4312.92	3888.34	52.59	47.41
TSAVI1	4576.87	3888.34	54.07	45.93
TSAVI2	5045.25	3419.96	59.60	40.40
MSAVI	4312.92	3888.34	52.59	47.41
WDVI	4671.59	3793.62	55.19	44.81

Figure 5: NDVI of Kolar District

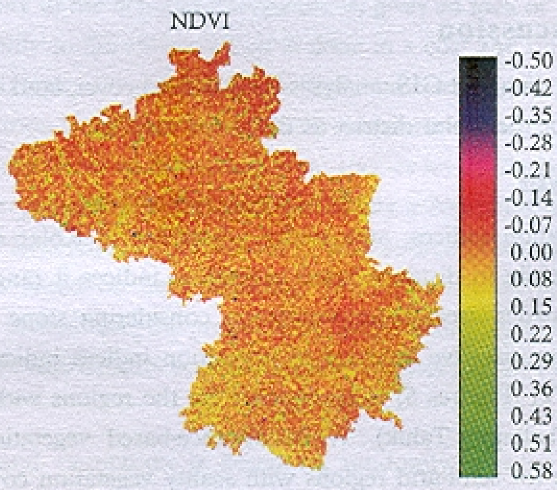
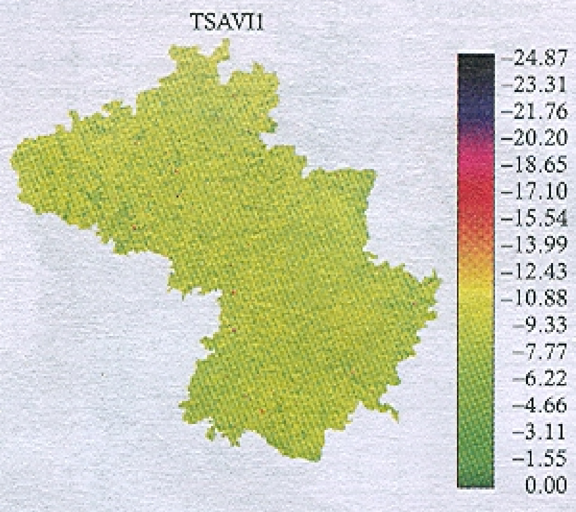


Figure 6: TSAVI1 of Kolar District



Based on the extent of vegetation cover (land cover) and agroclimatic conditions, two representative taluks namely Kolar and Chikballapur were selected for training data collection for land use analyses.

Land Use Analysis

Supervized classification approaches were tried for land use analysis. In order to select the training sites (or ground control points) for supervized classification, a composite image (of G, R and IR bands) with false color assignment was generated. Composite image was generated using linear contrast stretch method by saturating 2.5% from each end of the gray scale. Figure 7 shows false color composite (FCC) image of Kolar district. This helps in identifying heterogeneous patches, which aid in the selection of training polygons. Also homogenous patches are distinguishably visible. Figure 8 displays the selected training sites in Kolar taluk and supervized classification techniques were tried and the results are tabulated in Table 3. Land use analyses using maximum likelihood classifier indicate that 46.69% is agricultural land, 42.33% is wasteland (barren land), 4.62% is built up, 3.07% of plantation, 2.77% natural forest and 0.53% water bodies. Accuracy assessment reveals that MLC is superior compared to MD and PP as it has least errors (due to commission and omission). Contingency (error) is tabulated in Table 4 for all the classifiers. Figure 9 represents the classified image of Kolar district indicating major landuse categories: built up, agriculture, plantation, forest, wasteland and water body.

Figure 7: False Colour Composite Image of Kolar District

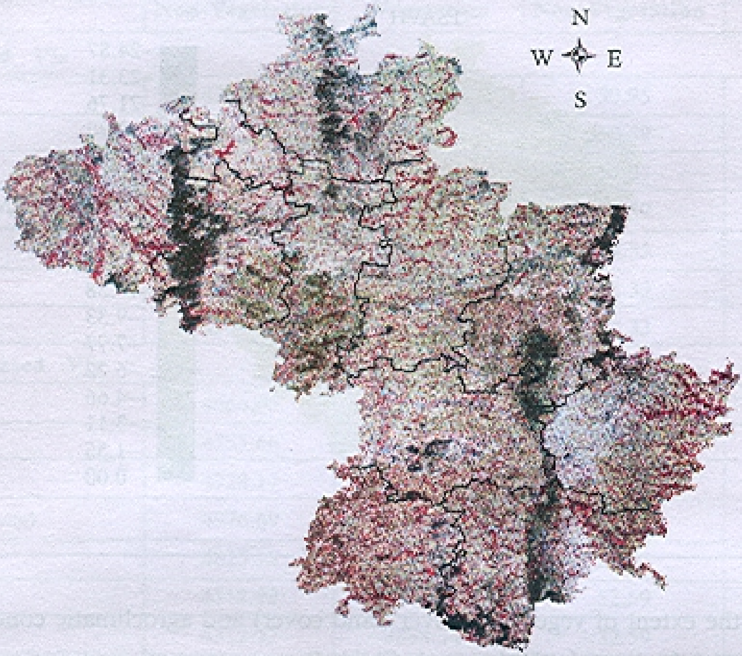


Figure 8: Training Sites in Kolar District

Table 3: Taluk-wise Land Use Pattern Computed using Hard Classifiers of Supervized Classification Techniques							
Taluk	Classifiers	Land Use (in sq. km)					
		Built-up	Agriculture	Plantation	Vegetation	Wasteland	Water Body
Bagepalli	MLC	78.260	302.590	1.651	9.058	541.04	6.725
	MD	197.300	187.350	10.110	18.520	518.77	5.271
	PP	38.470	268.170	4.307	7.854	538.45	7.575
Bangarpet	MLC	23.040	495.750	37.290	50.560	258.31	9.125
	MD	86.190	364.530	63.530	59.640	290.64	6.931
	PP	14.390	472.910	50.440	34.030	266.71	8.295
Chikballapur	MLC	18.010	314.450	15.460	30.600	252.46	8.665
	MD	68.890	218.220	21.890	52.320	265.47	5.316
	PP	8.882	287.590	19.710	21.900	243.34	8.922
Chintamani	MLC	50.740	428.910	4.983	1.048	409.68	2.989
	MD	189.600	259.260	14.020	1.670	426.38	2.626
	PP	27.130	372.300	5.641	0.884	441.38	2.056
Gauribidanur	MLC	51.580	325.850	0.715	5.231	511.82	2.924
	MD	151.000	321.990	6.377	12.070	492.20	1.867
	PP	27.670	293.410	2.107	4.550	488.97	3.305
Gudibanda	MLC	8.027	62.343	0.109	1.028	154.36	1.538
	MD	36.720	39.202	0.793	2.445	147.12	1.202
	PP	4.666	52.757	0.358	1.020	149.58	1.399
Kolar	MLC	25.780	406.980	17.400	14.500	330.18	3.233
	MD	15.510	370.730	18.460	11.700	332.74	0.683
	PP	110.700	270.900	33.740	14.240	362.24	3.321
Malur	MLC	10.760	414.670	47.110	3.530	168.51	4.283
	MD	57.080	306.080	61.390	5.435	212.28	3.610
	PP	6.020	387.390	43.950	3.031	170.84	3.558
Mulbagal	MLC	49.810	428.680	15.270	6.358	321.25	4.720
	MD	127.100	288.110	37.160	10.750	355.98	3.901
	PP	27.220	434.020	18.840	6.451	322.12	3.402
Sidlaghatta	MLC	33.950	320.400	35.150	4.731	276.30	2.080
	MD	16.440	297.590	31.400	4.228	283.12	0.667
	PP	105.200	232.040	45.970	4.997	280.82	1.887
Srinivasapur	MLC	32.940	480.400	32.520	57.450	262.81	3.118
	MD	96.940	334.240	61.920	60.750	310.82	1.910
	PP	17.160	455.790	37.240	44.180	293.73	3.057

Figure 10: Villages Surveyed in Kolar Taluk

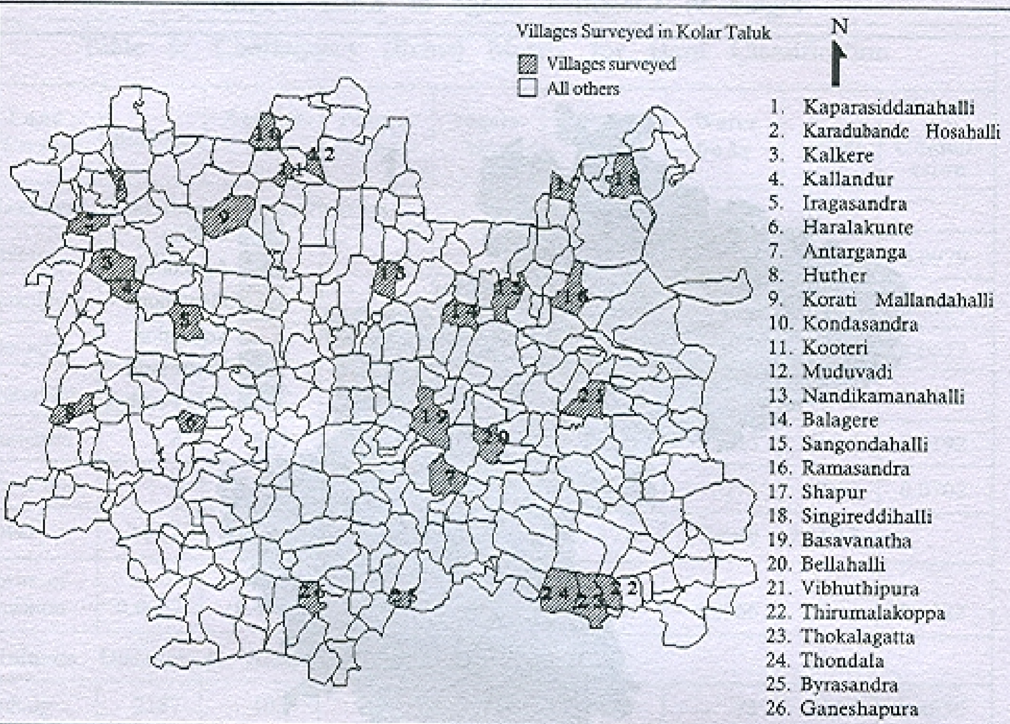
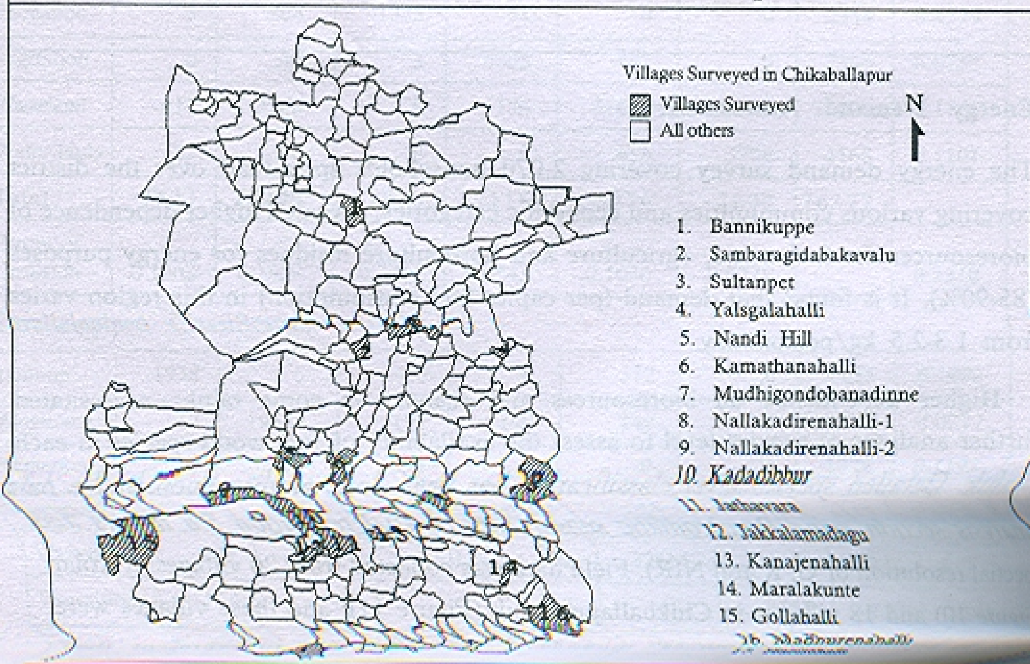


Figure 11: Villages Surveyed in Chikkaballapur Taluk



Figures 12 and 13 represent pixel level mapping in geo registered cadastral village maps of Bannikupe and Jathavara Hosahali villages in Chikballapur taluk and its corresponding panchromatic village maps and histogram of a dominant species. Similar exercise has been done on 26 villages of Kolar taluk. Figures 14 and 15 represent digitized vector layer of Antaragange and Iragasandra-1 villages and its corresponding Panchromatic village maps and spectral response curve of the dominant species. Training sites were selected on the basis of their girth, height, density etc. Adult plants having high density were taken as training data set for image classification. However, there is variation in spectral values due to seasonal aspects. Hence, season wise PAN scene classification has been done.

Figure 12: Digitized Vector Layer of Bannikupe Village in Chikballapur Taluk and its Corresponding Panchromatic Village Map and Histogram of Dominant Species

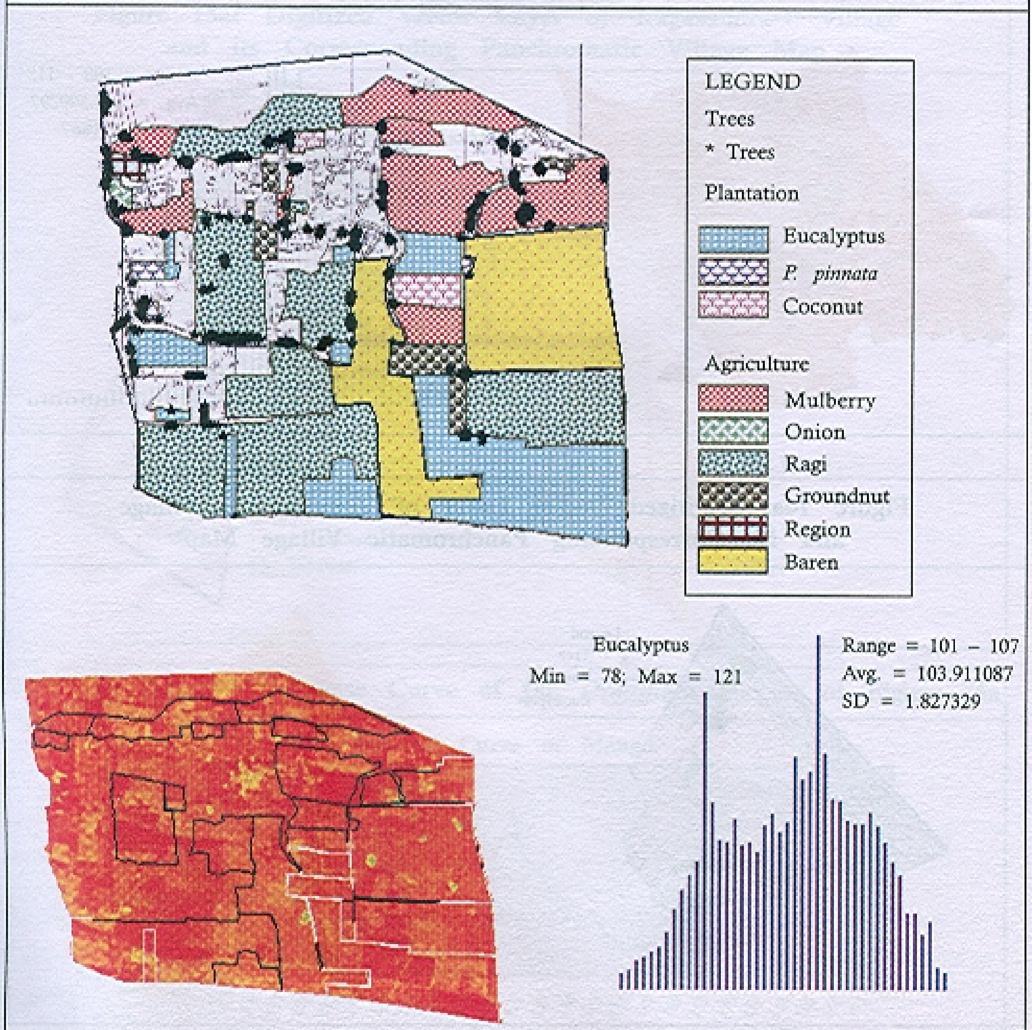


Figure 13: Digitized Vector Layer of Jathavara Hosahali Village in Chikballapur Taluk and its Corresponding Panchromatic Village Mapand Histogram of Dominant Species

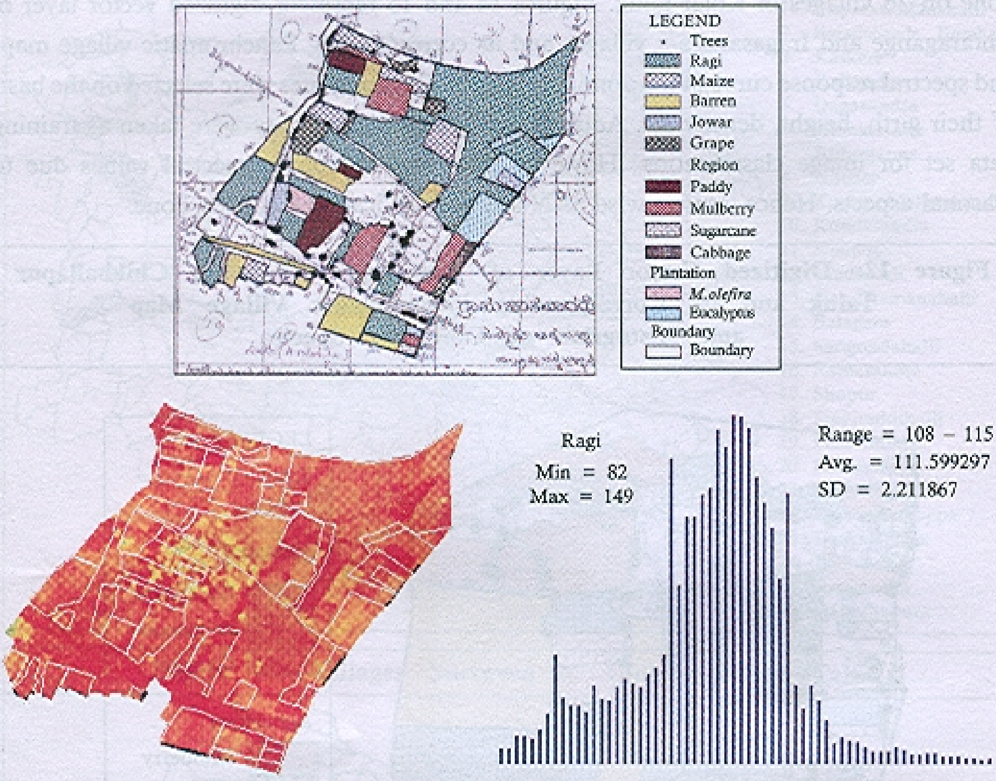


Figure 14a: Digitized Vector Layer of Antaragange Village and its Corresponding Panchromatic Village Map

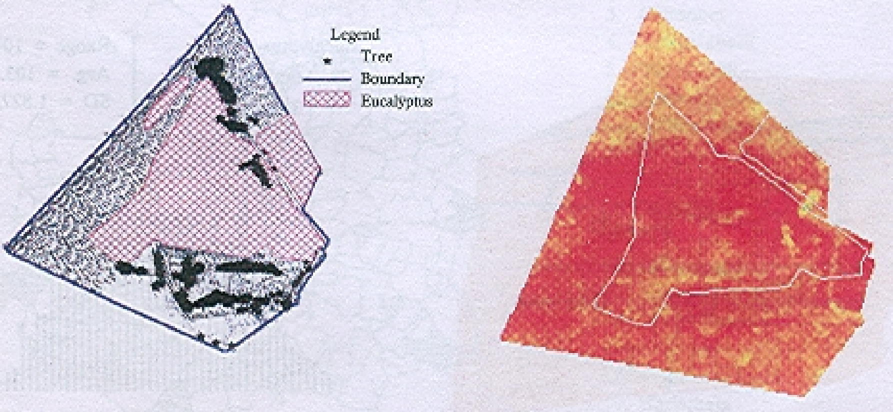


Figure 14b: Spectral Response Curve of the Dominant Species of Figure 14a

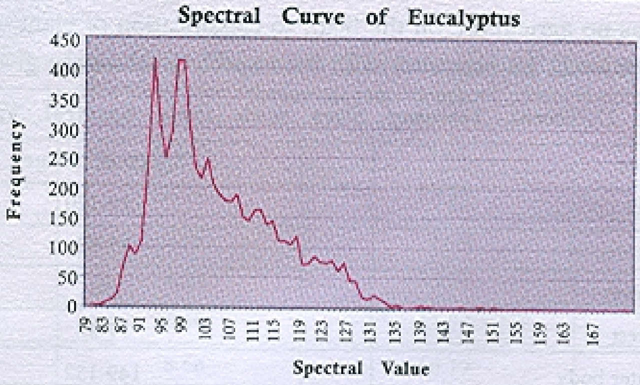


Figure 15a: Digitized Vector Layer of Iragasandra-1 Village and its Corresponding Panchromatic Village Map

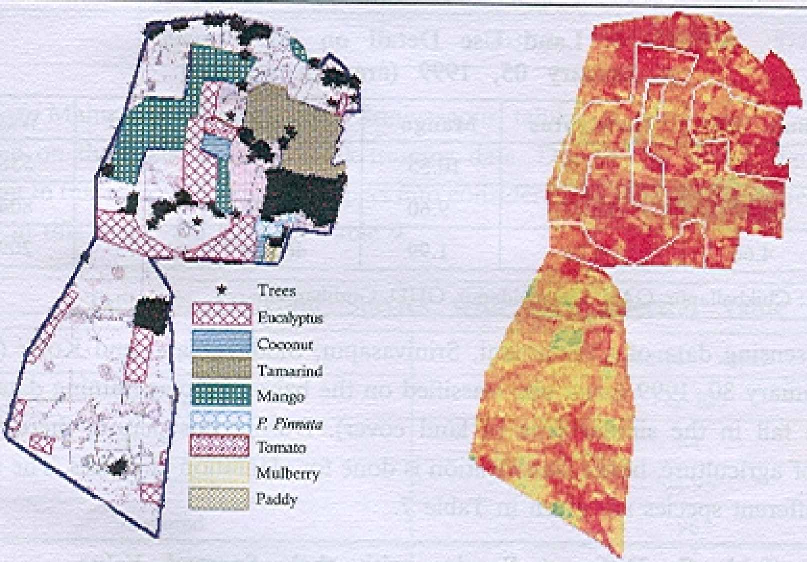
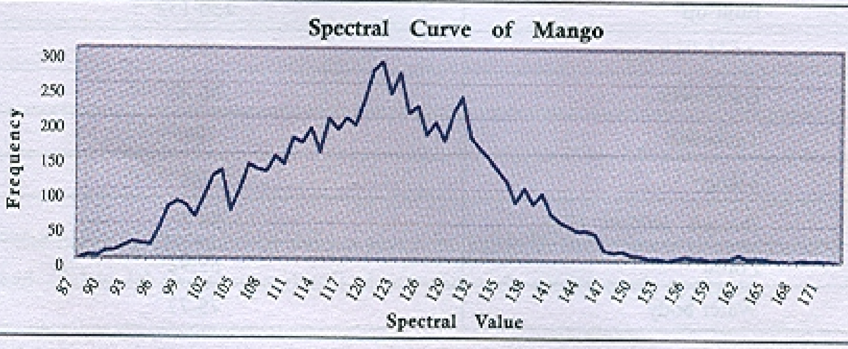


Figure 15b: Spectral Response Curve of the Dominant Species of Figure 15a



PAN images of Chikballapur, Gauribidanur and Gudibanda were taken on January 05, 1999. Based on the training data of Chikballapur, these three taluks are classified. During this period, there was no agriculture on the field, so classification of plant was taken into consideration. The different training sites with their spectral values are given in Table 5.

Table 5: Different Training Sites with their Spectral Value

Sites	Spectral value
Built up	119-120
Eucalyptus	85-87
Mango	90
Forest	77-82
Water body	149-152

Based on the spectral values given in Table 5, taluk level classification was carried out and the results are presented in Table 6.

Table 6: Land Use Detail on PAN Image of January 05, 1999 (area in sq. km)

Taluks	Built Up	Eucalyptus	Mango	Forest	Water	Waste
CHK	17.92	27.09	10.55	3858.21	3.11	538.12
GAU	18.82	17.77	9.60	2406.80	5.12	804.77
GUD	4.66	4.03	1.99	463.36	1.75	209.41

Note: CHK: Chikballapur, GAU: Gauribidanur, GUD: Gudibanda.

Remote sensing data of Chintamani, Srinivasapur, Siddhlaghata, and Kolar (partial) taluks of January 30, 1999 scene was classified on the basis of Kolar training data (as all these taluks fall in the similar type of land cover). During this period, there was no cultivation of agriculture, hence classification is done for plantation and trees. The spectral values of different species are given in Table 7.

Table 7: Different Species with their Spectral Value

Species	Spectral Value
Built up	130-132
Acacia nilotica	79-80
Eucalyptus	86-88
Tamarind	94
Mango	98
Prosopis juliflora (PJ)	84-85
Forest	89-92
Water body	75-77

On the basis of the spectral values given in Table 7, the respective taluks were classified and the results are presented in Table 8.

Table 8: Land Use Detail on PAN Image of January 30, 1999 (area in sq. km)			
Taluk	**CHN**	**SRI**	**SID**
Built-up	34.29	22.87	22.05
Acacia nilotica	0.99	5.14	1.16
Eucalypts	9.55	35.89	17.05
Tamari	6.60	13.70	8.35
Mango	8.56	16.17	9.69
Prosopis juliflora	5.05	7.24	3.98
Forest	20.93	46.03	21.23
Water	2.79	8.18	1.83
Waste	797.22	703.10	577.42

Kolar, Malur, Chintamani, and Srinivasapur taluks of November 17, 1998 were classified on the basis of Kolar taluk training data. During this period, agriculture was prevalent in this region. Taking this aspect into consideration, the spectral values of different species in this image are given in Table 9.

Table 9: Different Species with their Spectral Value		
	Species	**Spectral value**
	Built up	122-123
	Acacia nilotica	84
	Eucalyptus	94-95
	Tamarind	96
	Mango/PJ	98
	Forest	88-92
	Water body	85-86
	Ragi	110-113
	Paddy	102-105
	Mulberry	105-107
	Mixed agri	114-118

On the basis of the spectral values given in Table 9, the values of species and taluks are classified. Table 10 shows the detail about the area under each species.

Table 10: Land Use Detail on PAN Image of November 17, 1998 (area in sq. km)						
Taluk	BAG	BAN	KOL	MAL	CHN	SRI
Built up	29.56	13.35	25.64	18.90	35.51	22.92
Acacia nilotica	1.20	2.66	1.58	1.24	1.25	4.36
Eucalyptus	8.29	27.12	27.96	27.33	8.51	35.73
Tamarind	8.88	13.97	15.16	13.82	7.11	13.27
Mango/PJ	11.33	15.13	18.92	16.82	12.12	23.59
Forest	6.76	38.13	36.24	26.67	15.02	51.16
Water	3.58	3.40	4.60	4.13	3.25	6.69
Ragi	84.35	67.22	98.71	79.33	129.58	116.35
Paddy	41.51	56.87	99.48	81.53	81.39	98.80
Mulberry	48.40	40.83	54.83	44.49	54.06	69.89
Mix agri	80.40	70.53	118.21	90.95	150.13	100.29
Waste	428.00	209.85	287.41	236.44	388.53	366.43

Note: BAG: Baagepalli, BAN: Bangarpet, KOL: Kolar, MAL: Malur, CHN: Chintamani, SRI: Srinivasapur.

Classification was done for Bagepalli taluk (for 70% of Bagepalli area, in the scene of path 100 and row 63) and Bangarpet taluk with the help of remote sensing data (PAN data) of November 17, 1998. Table 11 gives details about the classification result of plantation and forest area of all taluks.

Table 11: Land Use Pattern on PAN Image (Species Level) for All Taluks (area in sq. km)							
Taluk	*Acacia nilotica*	Eucalyptus	Mango	Tamarind	Mango/PJ	Forest	*Prosopis juliflora*
BAG (98)	1.20	8.29		8.88	11.33	6.76	
BAN (98)	2.66	27.12		13.97	15.13	38.13	
CHK (99)		27.09	10.55			38.58	
CHIN (98)	1.25	8.51		7.11	12.12	15.02	
CHIN (99)	0.99	9.55	8.56	6.60		20.93	5.05
GAU (99)		17.77	9.60			24.06	
GUD (99)		4.03	1.99			4.63	
KOL (98)	1.58	27.96		15.16	18.92	36.24	
MAL (98)	1.27	27.33		13.82	16.82	26.67	
SID (99)	1.16	17.05	9.69	8.35		21.23	3.98
SRI (98)	4.36	35.73		13.27	23.59	51.16	
SRI (99)	5.14	35.89	16.17	13.70		46.03	7.24

Note: BAG: Bagepalli, BAN: Bangarpet, CHK: Chikballapur, CHN: Chintamani, KOL: Kolar, GAU: Gauribidanur, GUD: Gudibanda, MAL: Malur, SID: Siddhlaghata, SRI: Srinivasapur, PJ: *Prosopis juliflora*.

Mapping of *Prosopis juliflora*, a commonly used fuel wood species, was done in Iraghasandra and Huthur villages of Kolar taluk, where the growth was more due to the favorable edaphic factors. 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 neighboring Gauribidanur taluk (Figure 16) with the help of merged remote sensing data (LISS III MSS and PAN) in Kolar district. Figure 17 depicts the fused image of MSS and

Figure 16: PAN Image of Gauribidanur Taluk with *Prosopis juliflora* Mapped

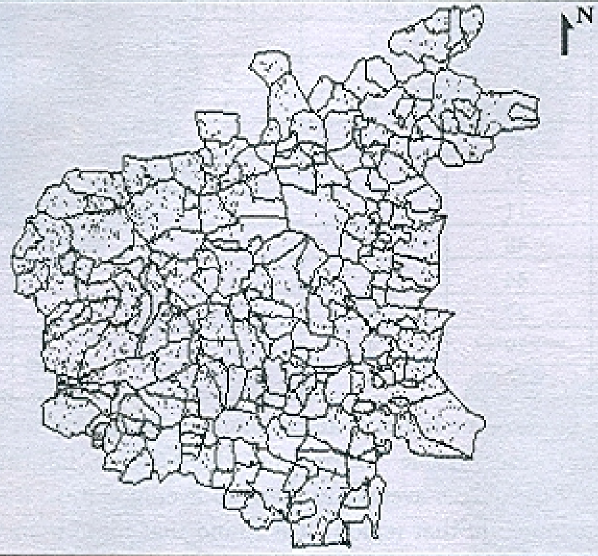


Figure 17: LISS III and PAN Fused Image of Gauribidanur Taluk

PAN data. The map of *Prosopis juliflora* was verified (field visit) using GPS. The accuracy of mapping is 88% as 44 polygons out of 50 mapped polygons correlated with the species.

Table 12 provides village-wise population density data. It is observed that population density is less in villages compared to towns. It is found that 80-90% villages have population density less than 5 persons per hectare while 1-2% villages (towns) have high population density of more than 20 persons per hectare.

Table 12: Taluk-wise Population Density (persons per hectare)

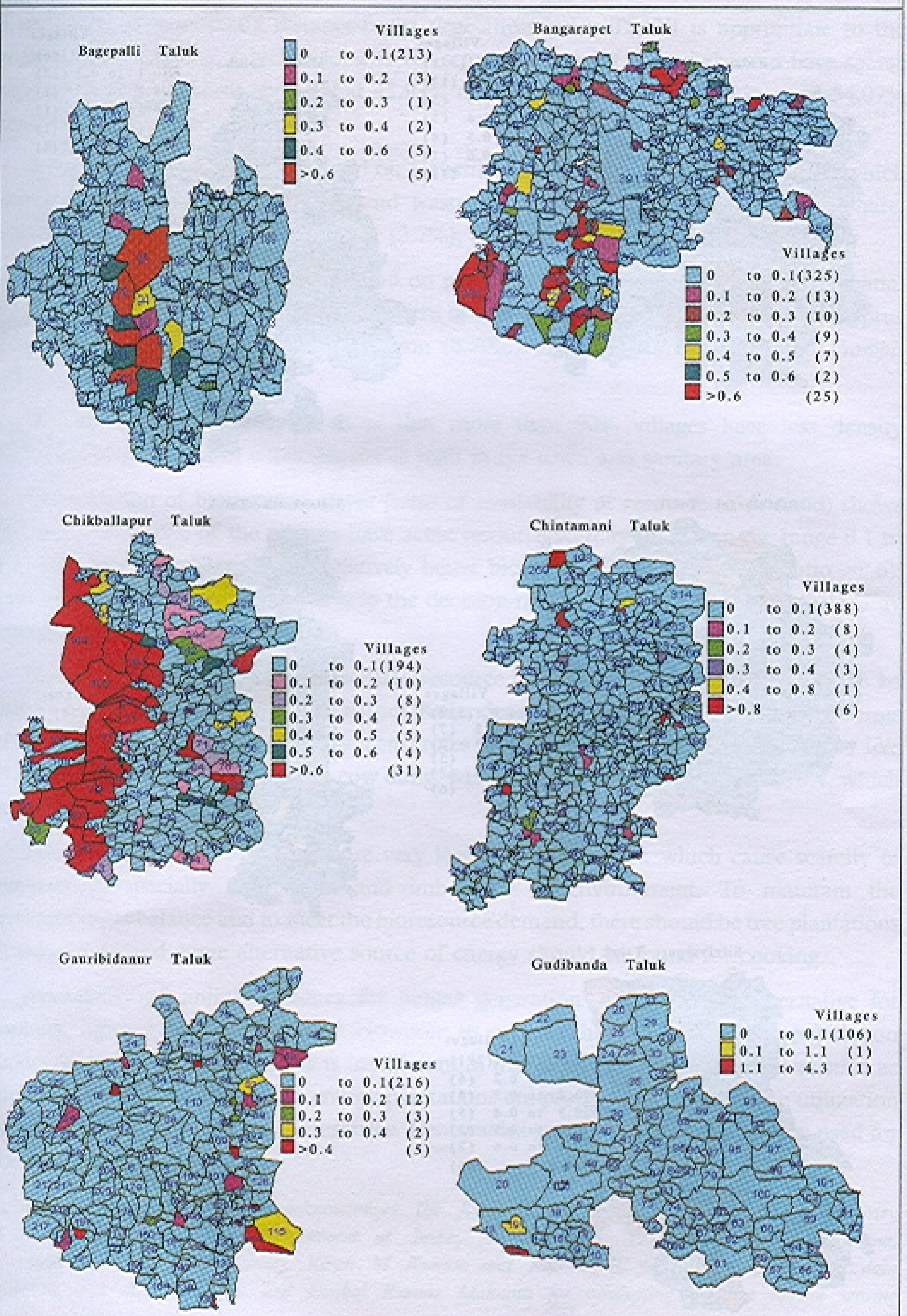
Taluk	0-4	4-8	8-12	12-16	16-20	>20
Bagepalli	211	15	2			1
Bangarpet	315	61	7	5	1	2
Chikballapur	200	41	9	3		1
Chintamani	362	42	3	2		1
Gauribidanur	198	32	5		2	1
Gudibanda	96	11				1
Kolar	308	48	3	2	1	2
Malur	319	44	2			1
Mulbagal	309	27	6	2	1	1
Sidlaghatta	253	29	4	1	1	3
Srinivasapur	319	20	5	2	1	2

Figure 18 illustrates the bioresource status of all the taluks in Kolar district for Resource (average)/Demand (average) cases. Table 13 presents the detailed information about bioresource status for Case 9 (resources average to demand average ratio). Ratio less than 1 gives the scarcity of bioresource in that region. It is found that more than 90% villages have potential to meet up to 20% of total population energy demand. This means there is scarcity of bioresource in most of the villages of Kolar district. It is found that Gauribidanur and Gudibanda taluks have least bioresource, whereas in more than 95% villages, bioresource option can meet the domestic energy requirement of only 0-20% population. Chikballapur, Srinivasapur, Malur taluks have healthy vegetation compared to other taluks. In 20% of the villages of these taluks, bioresource option can meet the domestic energy requirement of more than 60% population.

Table 13: Taluk-wise Bioresource Status for Case 9

Taluks	0-20%	20-40%	40-60%	>60%
Bagepalli	216	3	5	5
Bangarpet	338	19	9	25
Chintamani	396	7	1	6
Chikballapur	204	10	9	31
Gauribidanur	228	5	1	4
Gudibanda	106			2
Kolar	340	8	5	11
Malur	358	3	1	4
Mulbagal	331	7	2	6
Sidlaghatta	282	6		3
Srinivasapur	297	13	4	35

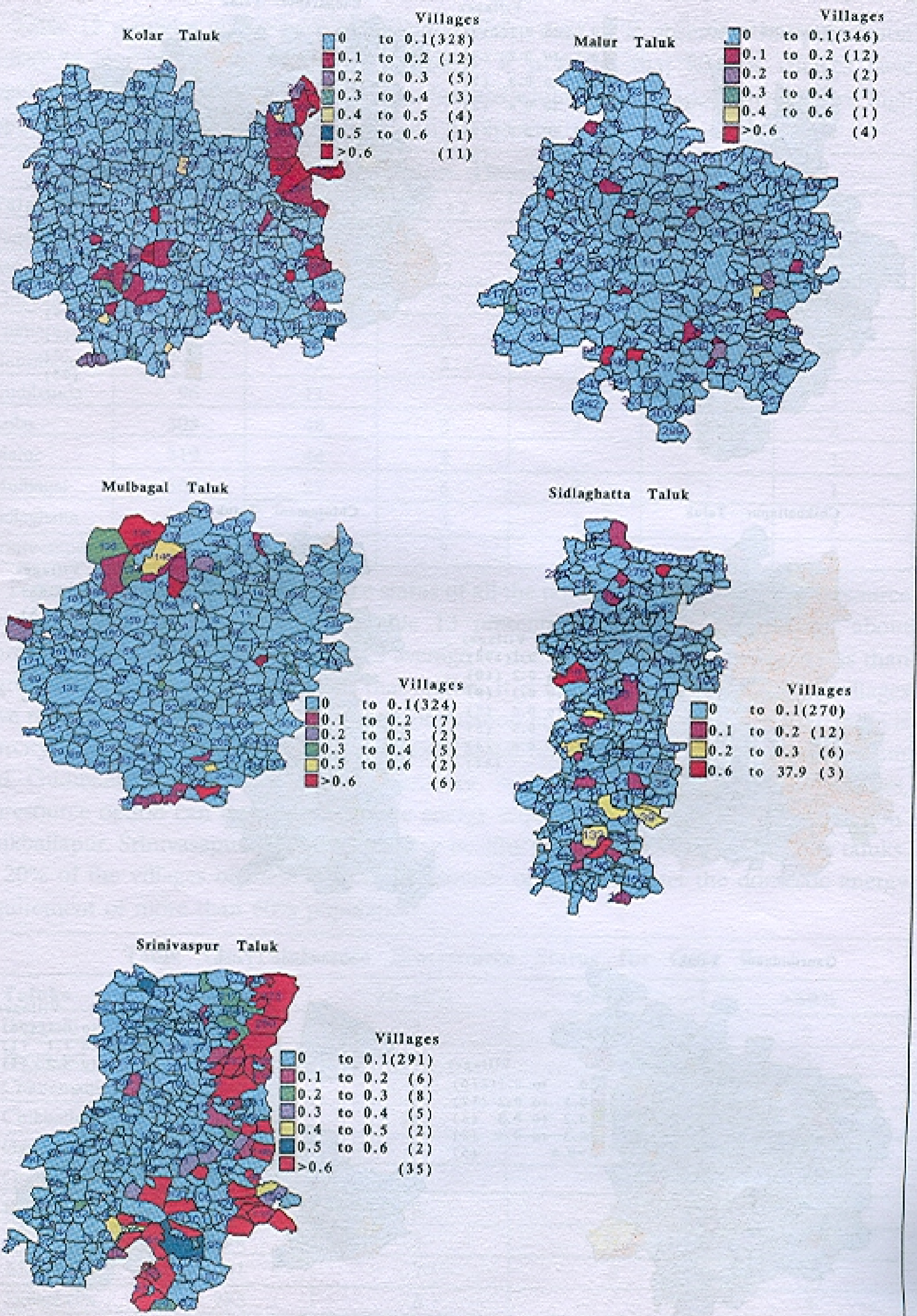
Figure 18: Bioresource Status of All the Taluks in Kolar District



(Contd...)

Figure 18: Bioresource Status of All the Taluks in Kolar District

(...Contd)



Conclusion

Land cover analysis using distance-based vegetation index TSAVI is appropriate to the regions, such as Kolar, which belong to the semi-arid zone of Karnataka and have sparse vegetation. This analysis shows that 45.93% of the area is under vegetation and 54.07% under non-vegetation.

Land use analysis was done based on Gaussian Maximum Likelihood Classifier, which indicates that agriculture (43.78%) and wasteland (38.70%) constitute the major share, followed by plantation (6.11%), forest (5.7%), built up (4.12%) and water (1.02%).

Species level land use analyses based on pixel level mapping (considering higer spatial resolution data) and spectral response pattern of each species give the area under eucalyptus (2.44%), forest (3.18%), mango plantation (0.70%), *Acacia nilotica* (0.17%) and *Prosopis juliflora* (0.20%).

Population density analyses show that more than 90% villages have less density (0-4 persons per hectare) while density is high in the town and sanitary area.

Computation of bioresource status (ratio of availability of resource to demand) shows that more than 95% of the villages have acute resource scarcity (values in the range 0.1 to 0.3) and very few villages have relatively better bioresource status (with the ratio >0.6). This area-based resource analyses help the decision-makers in selecting villages for energy interventions.

Based on this investigation of biomass resource availability and demand, Kolar can be categorized as a bioresource deficit district. Kolar depends mainly on non-commercial forms of energy. Non-commercial energy constitutes 84% and is met mainly by sources like firewood, agricultural residues and cow dung, while commercial energy share is 16%, which is met mainly by electricity, oil, etc.

The plantation and forest area are very less in Kolar district, which cause scarcity of bioresource, specially fuel wood and imbalance of environment. To maintain the environmental balance and to meet the bioresource demand, there should be tree plantations in waste area and some alternative source of energy should be found for cooking.

Availability of animal residues for biogas generation gives a viable alternative for cooking, lighting fuel and fertilizer. However, to support the present livestock population fodder from agricultural residues is insufficient in this district. Various alternatives such as fuel-efficient stoves, biogas, and energy plantations are proposed to improve the utilization of bioresources and enhance bioresource. Renewables such as solar energy can be used for cooking and lighting.

Acknowledgment: *The author acknowledges the financial assistance provided by the Ministry of Science and Technology, Government of India, for this work. He thanks Lakshminarayana, Jagadeesh K, Madhu M Kumar, Kiran M Kumar and Rao G R for their help in field data collection and data analyses; and Pankaj Kumar Mohanta for conducting the the remote sensing data analysis.*

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Reference # 57J-2007-11-01-01