Relevance of Hyperspectral Data for Sustainable Management of Natural Resources

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Abstract

Land cover mapping relates to identifying the types of features present on the surface of the earth. It deals with discerning the extent of land cover features namely vegetation, geologic, urban infrastructure, water, bare soil or others. Variations in land cover and associated physical characteristics do influence weather and climate of our earth and hence, it is considered an essential element for modelling and understanding the earth as a system for many planning and management activities. Thus, understanding of land cover dynamics plays an important role at the local/regional as well as global level. Identifying, delineating and mapping land cover on temporal scale provides an opportunity to monitor the changes, which is important for planning activities and sustainable management of the natural resources.

Land cover mapping can be done most effectively through space borne remote sensors of various spatial, spectral and temporal resolutions. Due to the spectral resolution limitations of conventional multispectral imageries, hyperspectral sensors, which collect numerous bands in precisely defined spectral regions were developed. Hyperspectral images have ample spectral information to identify and distinguish spectrally unique materials that allow more accurate and detailed information extraction. These imageries are classified into different land cover categories using various algorithms. The genesis and the underlying principle behind each of these algorithms are different and essentially produce different output maps. This paper discusses the various efforts made for land cover and land use mapping with an emphasis on the hard classification algorithms for hyperspectral image processing at a regional scale. Neural network algorithm for classifying MODIS data has been implemented for Kolar district, Karnataka. The accuracy assessment is done using ground truth data and classified multispectral map on a pixel to pixel analysis.

Keywords: Land cover, hyperspectral, MODIS, algorithms

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Introduction

Land cover is the discernible vegetation, geologic, hydrologic or anthropogenic features on the planet's land surface. 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). These land cover features can be classified using the data of different spatial, spectral and temporal resolutions acquired through remote sensors mounted on space borne platforms. Land cover changes induced by human play a major role in patterns of the climate and biogeochemistry at a regional scale [1].

Land cover mapping using high spectral resolution has several advantages, because it aids in numerous mapping applications such as soil types, species discrimination, mineral mapping, etc. Hyperspectral data processing poses both challenges and opportunities for land cover mapping. Land cover mapping can be performed using various algorithms by processing the remotely sensed data into different themes or classes.

The terms land use and land cover are often used in natural resources management, meaning types or classes of geographical determinable areas. Land cover provides the ground cover information for baseline thematic maps. 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). Identifying, delineating and mapping land cover on temporal scale provides an opportunity to monitor the changes, required for sustainable management of natural resources. .

Recent exercise on global LULC (Land Use Land Cover) for vegetation mapping was the use of MODIS data as one of the most critical global data sets. The classification included 17 categories of land cover following the International Geosphere-Biosphere Program (IGBP) scheme. The set of cover types includes eleven categories of natural vegetation covers broken down by life form; three classes of developed and mosaic lands, and three classes of non-vegetated lands [2].

In India, land use and land cover (LULC), an important study from national perspective on annual basis using data from the latest Indian Remote Sensing Satellite – Resourcesat has been initiated by ISRO (Indian Space Research Organisation) and NRSA (National Remote Sensing Agency), Department of Space in coordination with several RRSSCs (Regional Remote Sensing Service Centres). Spatial accounting and monitoring of land use and land cover systems was carried out on a national level on 1:250,000 scale using multi-temporal IRS (Indian Remote Sensing Satellites) AWiFS (Advanced Wide Field Sensor) datasets to provide on an annual basis, the net sown area for different cropping seasons and the integrated LULC map. The AWiFS data covered Kharif (August – October), Rabi (January – March) and Zaid (April – May) seasons to address spatial and temporal variability in cropping pattern and other land cover classes. Decision tree classifier method was adopted to account the variability of temporal datasets and bring out reliable classification outputs. Legacy datasets on forest cover, type, wastelands and limited ground truth were used as inputs for classification and accuracy assessment [2].

The most significant recent breakthrough in remote sensing has been the development of hyperspectral sensors. The ‘Hyper’ in hyperspectral means ‘too many’ and refers to the large number of measured wavelength bands. Hyperspectral images are spectrally over determined, which means that they provide ample spectral information to identify and distinguish spectrally unique materials. Hyperspectral imagery provides the potential for more accurate and detailed information extraction than is possible with any other type of conventional remotely sensed data.

Moderate Resolution Imaging Spectroradiometer (MODIS) is a major instrument on the Earth Observing System EOS-AM1 and EOS-PM1 (termed AQUA) missions [3]. The ‘heritage’ of the MODIS comes from several space-borne instruments. These include the Advanced Very High Resolution Radiometer (AVHRR), the High Resolution Infrared Sounder (HIRS) unit on the National Oceanic and Atmospheric Administration’s (NOAA) Polar Orbiting Operational Environmental Satellites (POES), the Nimbus-7 Coastal Zone Colour Scanner (CZCS), and the Landsat Thematic Mapper (TM). MODIS is able to continue and extend the databases acquired over many years by the AVHRR, in particular, and the CZCS/Sea Star-Sea WiFS series.

Hard Classification Algorithms

Gaussian Maximum Likelihood Classifier (GMLC): The maximum likelihood classifier quantitatively evaluates both the variance and covariance of the category spectral response patterns when classifying an unknown pixel. It is assumed that the distribution of the cloud of points forming the category training data is Gaussian (normally distributed). Here, the distribution of a category response pattern can be completely described by the mean vector and the covariance matrix. The probability density functions are used to classify an unidentified pixel by computing the probability of the pixel value belonging to each category. After evaluating the probability in each category, the pixel is assigned to the most likely class (highest probability value) or can be labelled as ‘unknown’ if the probability values are all below a threshold set by the analyst [4].

Spectral Angle Mapper (SAM): In N dimensional multi-(or hyper-) spectral space a pixel vector x has both magnitude (length) and an angle measured with respect to the axes that defines the coordinate system of the space [5]. In the Spectral Angle Mapper (SAM) technique for identifying pixel spectra only the angular information is used. SAM is based on the idea that an observed reflectance spectrum can be considered as a vector in a multidimensional space, where the number of dimensions equals the number of spectral bands. If the overall illumination increases or decreases (due to the presence of a mix of sunlight and shadows), the length of this vector will increase or decrease, but its angular orientation will remain constant. Smaller angles represent closer matches to the reference spectrum. If this angle is smaller than a given tolerance level, the spectra are considered to match even if one spectrum is much brighter than the other (farther from the origin) overall [4]. Pixels further away than the specified maximum angle threshold are not classified.

Neural Network: To overcome difficulties in conventional digital classification that uses the spectral characteristics of the pixel as the sole parameter in deciding to which class a pixel belongs to, new approaches such as Neural Networks (NN) are being used. Fully trained, neural networks can perform image classification relatively rapidly, although the training process itself can be quite time consuming. NN systems are 'self-training' in that they adaptively construct linkages between a given pattern of input data and particular outputs. A NN consists of a set of three or more layers, each made up of multiple nodes. Typically, these might include spectral bands from a remotely sensed image, textural features or other intermediate products derived from such images, or ancillary data describing the region to be analysed. The nodes in the output layer represent the range of possible output categories to be produced by the network [4]. Between the input and output layers are one or more hidden layers. These consist of multiple nodes, each linked to many nodes in the preceding layer and to many nodes in the following layer. These linkages between nodes are represented by weights, which guide the flow of information through the network. The number of hidden layers used in a neural network is arbitrary. An increase in the number of hidden layers permits the network to be used for more complex problems but reduces the network's ability to generalise and increases the time required for training. Applying a NN to image classification makes use of an iterative training procedure in which the network is provided with matching sets of input and output data. Each set of input data represents an example of a pattern to be learned, and each corresponding set of output data represents the desired output that should be produced in response to the input. During the training process the network autonomously modifies the weights on the linkages between each pair of nodes in such a way as to reduce the discrepancy between the desired output and the actual output [4].

Decision Tree Approach: Decision tree approach is a non-parametric classifier and an example of machine learning algorithm. It involves a recursive partitioning of the feature space, based on a set of rules that are learned by an analysis of the training set. A tree structure is developed where at each branching a specific decision rule is implemented, which may involve one or more combinations of the attribute inputs. A new input vector then 'travels' from the root node down through successive branches until it is placed in a specific class. The thresholds used for each class decision are chosen using minimum entropy or minimum error measures. It is based on using the minimum number of bits to describe each decision at a node in the tree based on the frequency of each class at the node. With minimum entropy, the stopping criterion is based on the amount of information gained by a rule (the gain ratio) [2].

Clustering: Clustering techniques fall into a group of undirected data mining tools [6]. The goal of clustering is to discover structure in the data as a whole. There is no target variable to be predicted and thus no distinction is being made between independent and dependent variables. Clustering partitions the image data into a number of spectral classes, and then labels all pixels of interest as belonging to one of those spectral classes, although the labels are purely nominal (e.g. A, B, C, …., or class1, class 2, …….) and are as yet unrelated to ground cover types [5]. The K-means algorithm is a simple, iterative procedure, in which a crucial concept is the one of '*centroid*'. Centroid is an artificial point in the space of records which represents an average location of the particular cluster. The coordinates of this point are averages of attribute values of all examples that belong to the cluster.

Data and Study Area

Band 1 to band 36 MODIS data "MOD 02 Level-1B Calibrated Geolocation Data Set" were downloaded from EOS Data Gateway [7]. This Level 1B data set contains calibrated and geolocated at-aperture radiances for 36 bands generated from MODIS Level 1A sensor counts (MOD 01). This data product [8], contains the radiometrically corrected, fully calibrated and geolocated radiances at-aperture for all spectral bands at 1km resolution [9]. Band 1 to band 7 MODIS product known as "MOD 09 Surface Reflectance 8-day L3 global" at 250 (band 1 and band 2) and 500m (band 1 to band 7) were also downloaded. The MOD 09 product is computed from the MODIS Level 1B land bands 1, 2, 3, 4, 5, 6, and 7 (centred at 648 nm, 858 nm, 470 nm, 555 nm, 1240 nm, 1640 nm, and 2130 nm, respectively) which is an estimate of the surface spectral reflectance for each band as it would have been measured at ground level if there were no atmospheric scattering or absorption [10]. These data are broken into granules approximately 5-min long and stored in Hierarchical Data Format (HDF).

The Indian Remote Sensing Satellites IRS - 1C/1D LISS 3 (Linear Imaging Self-Scanning Sensor 3) MSS (Multi Spectral Scanner) data having bands in Green, Red and Near-infrared part of the electromagnetic spectrum with a spatial resolution of 23.5 m procured from NRSA, Hyderabad was used as the high resolution image.

Kolar district in Karnataka State, India, chosen for this study is located in the southern plain regions (semi arid agro-climatic zone) extending over an area of 8238.47 sq. km. between 77°21' to 78°35' E and 12°46' to 13°58' N (Figure 1).

Kolar is divided into 11 taluks (or administrative boundaries/blocks/units) for administration purposes (taluks are Bagepalli, Bangarpet, Chikballapur, Chintamani, Gudibanda, Gauribidanur, Kolar, Malur, Mulbagal, Sidlaghatta and Srinivaspur). The distribution of rainfall is during southwest and northeast monsoon seasons. The average population density of the district is about 2.09 persons/hectare. The district is devoid of significant perennial surface water resources. The groundwater potential is also assessed to be limited. The terrain has a high runoff due to less vegetation cover contributing to erosion of top productive soil layer leading to poor crop yield. Out of about 280 thousand hectares of land under cultivation, 35% is under well and tank irrigation [11].

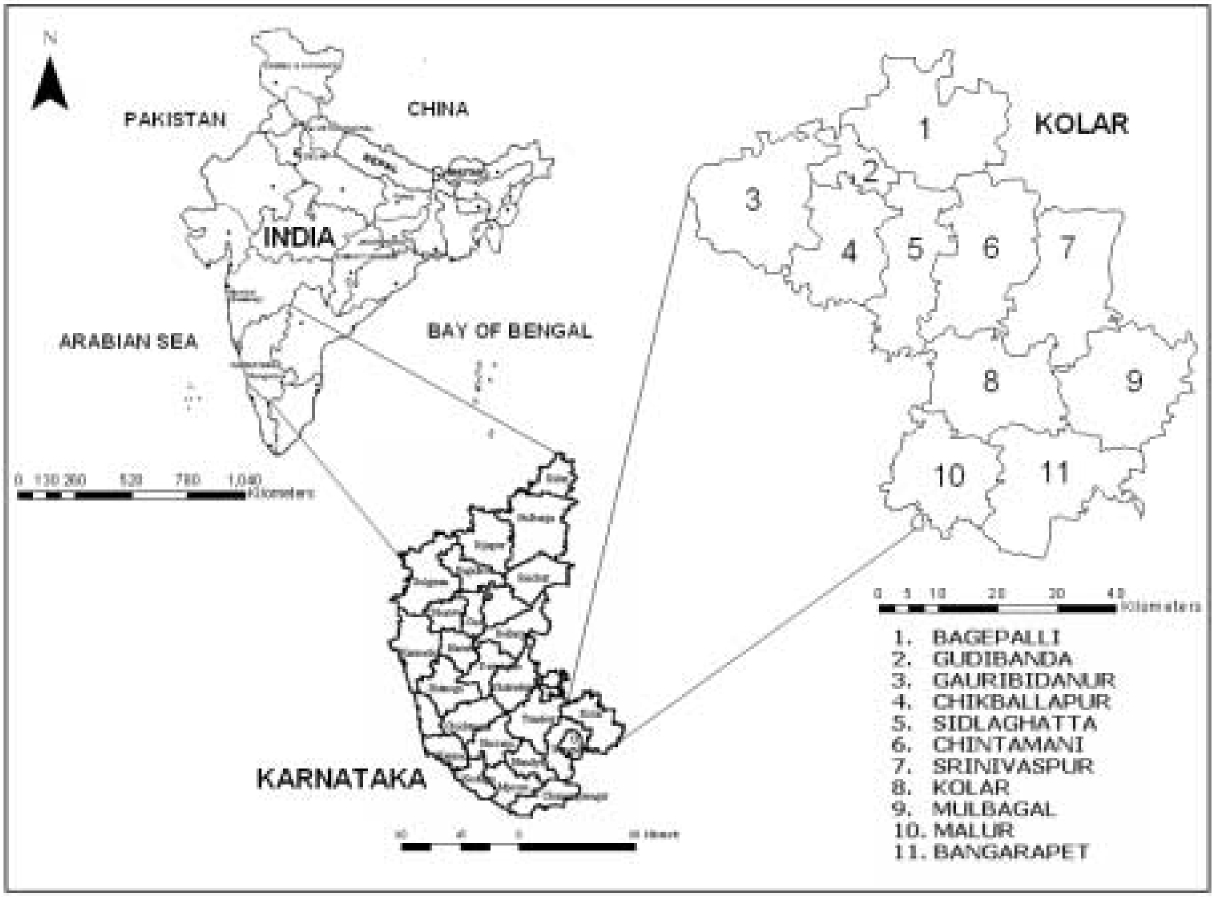

Figure 1: Study area – Kolar district, Karnataka State, India

Methodology

The methodology of the study involved -

1. Creation of base layers like district boundary, district with taluk and village boundaries, road network, drainage network, contours, mapping of waterbodies, etc. from the SOI topographical maps of scale 1:250000 and 1:50000.
2. Extraction of LISS-3 bands, identification of ground control points (GCP's) and geo-correction of the bands through resampling followed by cropping and mosaicing of data corresponding to the study area.
3. Generation of FCC (False Colour Composite) and identification of training sites on FCC.
4. Collection of attribute information from field corresponding to the chosen training sites using GPS.
5. Supervised Classification of LISS-3 MSS data.
6. Identification of ground control points (GCP's) and geo-correction of MODIS (MOD 09 Surface Reflectance 8-day L3 global Products) band 1 and 2 (spatial resolution 250 m) and bands 3 to 7 (spatial resolution 500 m) and MODIS L1B

product (MOD 02 Level-1B Calibrated Geolocation Data Set) with 36 spectral bands (of spatial resolution 1 km)
7. Resampling of MODIS bands 3 to 7 (MOD 09 Surface Reflectance 8-day L3 global Products) and MODIS bands 1 to 36 (MOD 02 Level-1B Calibrated Geolocation Data Set) to 250 m using nearest neighbourhood technique for easy processing, overlaying and comparison and for analysis consistency.
8. Reprojection of all MODIS bands from Sinusoidal to lat-long projection with Evrst 1956 as the datum, followed by masking of the study area.
9. Derivation of Principal Component Analysis (PCA) on the MODIS 36 bands.
10. Derivation of Minimum Noise Fraction (MNF) on the MODIS 36 bands.
11. Classification of MODIS data using Neural Network.
12. Accuracy Assessment of the classified maps.

Results and Discussion

Land Cover Analysis using LISS-3 MSS: NDVI was generated using LISS-3 data for land cover analysis ranging from 0.71 to -0.50. NDVI gave land cover (vegetation/green versus non-vegetation/non-green) information showing that 46.03% of the area has vegetation (agriculture, forest and plantations /orchards) and the remaining 53.98 % has non-vegetation (built up land, waste/barren rock/stony and water bodies).

Land Cover Analysis using MODIS data: Red (Band 1) and near-infrared band (Band 2) of the MODIS sensor at 250 m spatial resolution were used to compute NDVI, ranging from 0.35 to -0.54, indicating that 47.35% of the area under vegetation and the remaining 52.65 % under non-vegetation.

Classification of high resolution LISS-3 MSS data: The class spectral characteristics for the six land cover classes for LISS-3 MSS bands 2, 3 and 4 were generated to see the inter class seprability. The Transformed Divergence matrix also helped in distinguishing different classes indicating that the ROI pairs have a very good separability. Ground truth obtained from field and other ancillary data were used for the LISS-3 MSS classification. This was done in two steps: unsupervised classification and supervised classification.

False colour composite (FCC) was generated from the LISS-3 MSS data. The heterogeneous patches (training polygons) were chosen for the field data collection. Supervised classification using GMLC was performed with the ground truth data. Care was taken to see that these training sets are uniformly distributed representing/covering the study area. The supervised classified image shown in figure 2 (A) was validated by field visit and by overlaying the training sets used for classification. The land cover statistics are listed in Table 1.

Classification of MODIS data: The class spectral characteristics for the six classes defined in this study across the first seven bands, PCs and MNF components of the 36 bands of the MODIS sensor were determined showing their good separablity. The

Transformed Divergence Matrices were also computed which showed a similar pattern and helped in determining the separability among the various classes.

The MODIS data (bands 1 to 7), the first five PCs and the first five MNF components were classified using Neural Network as shown in figure 2 (B), (C), and (D). The process of training the neurons was time consuming. Although NN is considered to be one of the most robust techniques for classification of remotely sensed data, yet, controlling the training process in NN was difficult. The training process for training the neurons converged at 1000 iterations. The number of hidden layer was kept at 1 and the output activation function was kept at 0.001. The output activation function was increased in steps to see the variations in the classification. The training momentum was initially 0 and was increased gradually. The RMS error at the completion of the process was 0.09, 0.39 and 0.29 for the three different inputs. Table 1 shows the land cover statistics for the classification results.

Table 1: Percentage wise distribution of classes obtained from LISS-3 MSS (using MLC) and MODIS classification on Surface Reflectance Bands (1 to 7), Principal Components and MNF components of MODIS bands 1 to 36 using NN.

Classes	**LISS-3 MSS**	**MODIS Surface Reflectance bands (Bands 1 to 7)**	**MODIS derived PCs (36 bands)**	**MODIS derived MNF Components (36 bands)**
Agriculture (%)	19.03	21.88	21.49	19.38
Built up (Urban/Rural) (%)	17.13	26.44	15.78	17.55
Evergreen/ Semi-Evergreen Forest (%)	11.41	7.68	12.04	11.32
Plantation/ orchards (%)	10.96	19.31	09.45	10.84
Waste land/Barren Rock / Stony waste (%)	40.39	24.38	40.33	39.97
Water bodies (%)	1.08	00.31	0.91	00.94
Total (%)	100.00	100.00	100.00	100.00

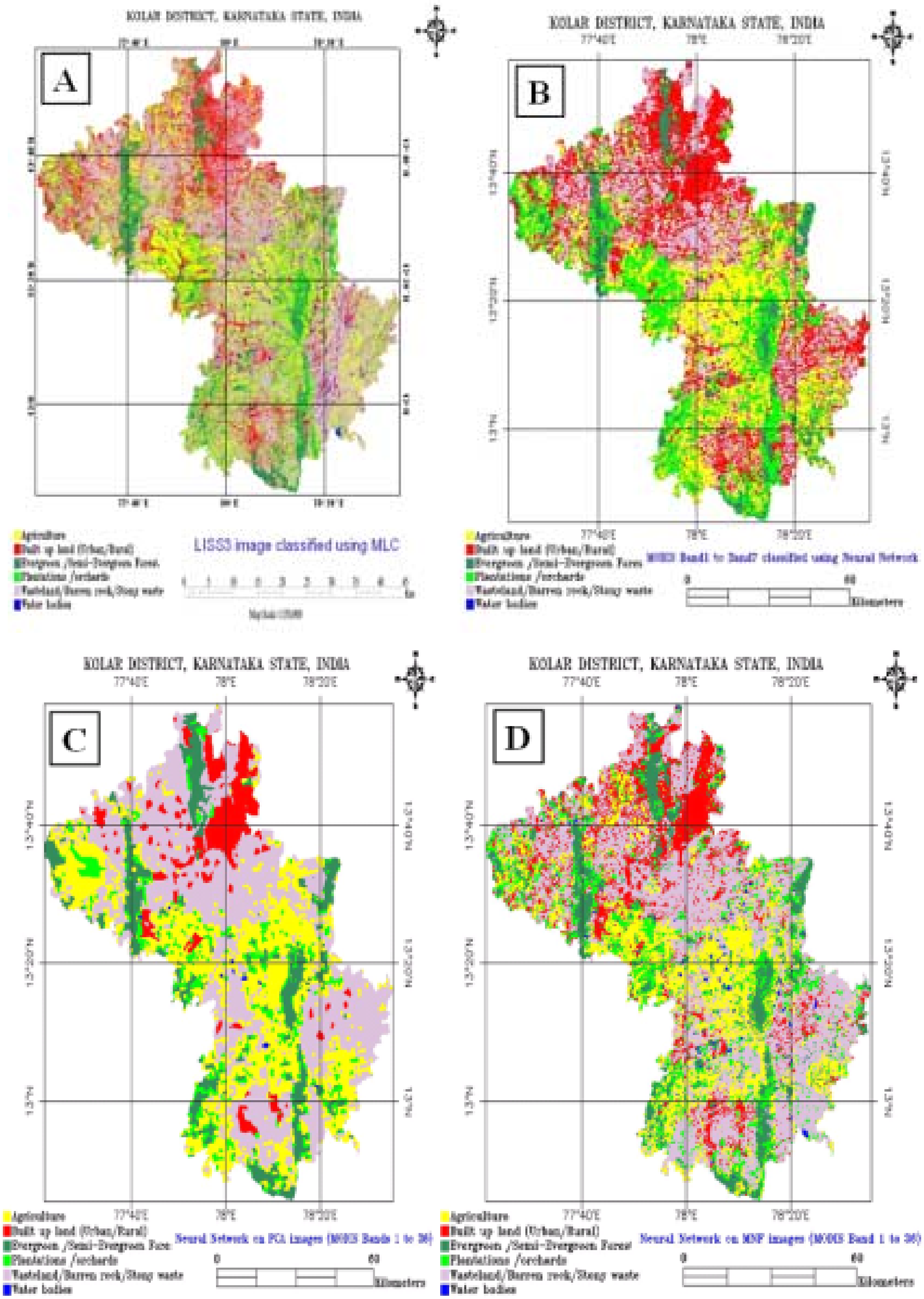

Figure 2: Supervised Classification using (a) MLC on LISS-3 MSS (b) NN on MODIS bands 1 to 7 (c) NN on PCs and (d) NN on MNF components.

Accuracy Assessment

Accuracy Assessment of LISS-3 classified map: The accuracy assessment was done with the collection of training sites data for the entire Chikballapur taluk The producer's, user's accuracy and overall accuracy corresponding to the various categories were computed, along with the error matrices for supervised and unsupervised classified MSS data of LISS-3, which is summarised in Table 2. The LISS-3 supervised classification accuracy assessment gave a *kappa* (k) value of 0.95 indicating that an observed classification is in agreement to the order of 95 percent.

Table 2: Producer's accuracy, user's accuracy and overall accuracy of land cover classification using LISS-3 MSS data for Chikballapur Taluk.

Supervised Classification				Unsupervised Classification		
Category	**Producer's Accuracy (%)**	**User's Accuracy (%)**	**Overall accuracy (%)**	**Producer's Accuracy (%)**	**User's Accuracy (%)**	**Overall Accuracy (%)**
Agriculture	94.21	84.54	95.63	94.47	83.39	90.22
Built up	96.47	83.11		89.68	80.30	
Forest	94.73	96.20		86.77	89.71	
Plantation	92.27	91.73		84.44	90.10	
Waste land	97.49	89.88		93.03	93.37	
Water	96.13	98.33		92.91	94.89	

Accuracy Assessment of MODIS classified Maps

Accuracy Assessment using Error matrix - User's, Producer's and Overall accuracy assessment of the MODIS classified maps (using hard classifier) was done for Chikballapur taluk with the ground truth data and the results are listed in Table 3, 4 and 5.

Table 3: User's Accuracy of classified MODIS Data of Chikballapur taluk.

Algorithms	Agriculture	Built up	Forest	Plantation	Waste land	Water bodies
NN (B1 to B7)	94.00	80.80	94.65	59.40	93.87	45.55
NN (PCA)	97.33	95.18	67.67	95.38	74.07	48.00
NN (MNF)	93.89	94.46	89.13	85.60	74.22	59.40

Table 4: Producer's Accuracy of classified MODIS Data of Chikballapur taluk.

Algorithms	Agriculture	Built up	Forest	Plantation	Waste land	Water bodies
NN (B1 to B7)	56.73	99.00	73.07	96.60	89.53	68.56
NN (PCA)	57.55	93.00	94.00	93.00	93.00	73.51
NN (MNF)	69.99	91.89	87.24	99.00	95.00	56.93

Table 5: Overall Accuracy of classified MODIS Data of Chikballapur taluk.

Techniques	Overall Accuracy
NN on MODIS Surface reflectance bands (B1 to B7)	68.88
NN on MODIS derived PCs (36 bands)	71.02
NN on MODIS derived MNF Components (36 bands)	86.11

Accuracy Assessment of MODIS classified maps was also performed at two spatial scales – at the administrative boundary level (Taluk) and at the pixel level.

Comparison based on land cover class percentage area - Land cover statistics were computed for all taluks pertaining to each classification algorithm at the taluk level.

Pixel to pixel analysis with LISS-3 MSS classified image - MODIS classified data were also compared with LISS-3 MSS classified data on a pixel by pixel basis for accuracy assessment of pure (homogenous) pixels. One pixel of MODIS spatially corresponds to 121 pixels (that is approximately equal to 258.5 m) of LISS-3. The error matrix was generated with user's accuracy, producer's accuracy and overall accuracy for the taluk and is listed in Table 6, 7 and 8.

Table 6: User's Accuracy obtained from pixel to pixel analysis with LISS-3 image comparison for Chikballapur taluk.

Algorithms	Agriculture	Built up	Forest	Plantation	Wasteland	Water bodies
NN (B1 to B7)	37	17	59	44	87	29
NN (PCA)	20	45	61	69	81	56
NN (MNF)	41	55	61	75	81	65

Table 7: Producer's Accuracy obtained from pixel to pixel analysis with LISS-3 image comparison for Chikballapur taluk.

Algorithms	Agriculture	Built up	Forest	Plantation	Wasteland	Water bodies
NN (B1 to B7)	46	**65**	19	41	60	45
NN (PCA)	61	29	38	69	78	45
NN (MNF)	59	41	55	76	**83**	65

Table 8: Overall Accuracy of classified MODIS Data of Chikballapur taluk from pixel to pixel analysis with LISS-3 image comparison.

Technique	Overall Accuracy
NN on MODIS Surface reflectance bands (B1 to B7)	51.34
NN on MODIS derived PCs (36 bands)	63.69
NN on MODIS derived MNF Components (36 bands)	69.87

The accuracy assessment showed that Neural Network classification on MNF components of MOFDIS bands 1 to 36 had highest overall accuracy followed by NN on PC's and NN on MODIS bands 1 to 7.

Conclusions

This paper gives an overview of the land cover mapping efforts and highlights the various hard classification algorithms being used for hyperspectral image processing. The experiment was conducted on MODIS 36 spectral bands with Neural Network classification technique. The results obtained from accuracy assessment showed that NN on Minimum Noise Fraction components was good for land cover mapping at regional scale.

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References:

[1] J.R. Jensen, Remote Sensing of Environment: An earth resource perspective, Pearson Education, 2003.

[2] Natural Resources Census, National Landuse and Land Cover Mapping Using Multitemporal AWiFS Data (LULC – AWiFS), Project Manual, Remote Sensing & GIS Applications Area, National Remote Sensing Agency, Department of Space, Government of India, Hyderabad, April 2005.

[3] Salomonson, V. V., Barne, W. L., Maymon, P. W., MODIS: advanced facility instrument for studies of the earth as a system. IEEE Transactions on Geoscience and Remote Sensing, 1989, vol. 27(4), pp. 145–153.

[4] Lillesand, T.M. and Kiefer. R. W., Remote Sensing and Image Interpretation, Fourth Edition, John Wiley and Sons, 2002, ISBN 9971-51-427-3.

[5] Richards, J.A., and Jia, X., Remote Sensing Digital Image Analysis - An Introduction, Third Edition, Springer, May 1996.

[6] Tso, B., Mather, P. M., Classification methods for remotely sensed data, New York: McGraw-Hill, Taylor and Francis, 2001.

[7] http://edcimswww.cr.usgs.gov/pub/imswelcome/

[8] Guenther, B., Godden, G. D., Pre-launch algorithm and data format for level 1 calibration products for the EOS-AM1 MODIS. IEEE Transaction on Geoscience and Remote Sensing, 1998, vol. 36(4), pp. 1142–1151.

[9] http://daac.gsfc.nasa.gov/MODIS/Aqua/product_descriptions_modis.shtml#rad_geo

[10] http://modis.gsfc.nasa.gov/data/dataprod/dataproducts.php?MOD_NUMBER=09

[11] Ramachandra T. V. and Rao G. R., 2005. Inventorying, mapping and monitoring of bioresources using GIS and remote sensing, *Geospatial Technology for Developmental Planning*, Allied Publishers Pvt. Ltd. New Delhi., pp: 49-76.