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Land Cover Land Use Mapping & Classification Model (Mapping Of Land Cover Land Use Using Multispectral Space Born Image)

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Abstract

Measurement of land use and land cover is costly and time-consuming by imperial technique. Remote sensing plays important role in the mappings and classification of land cover features. Indigenous space-born images can be used for identification and mapping. Remote sensed imagery is most popular method to capture data on Land Use Land Cover. Multispectral imaging is one of the most widely used technologies for LULC mapping and monitoring.This paper proposes a model which will help to classify and map land cover land use using remote sensing imagery.It also increase accuracy in the mapping and classification of land area land cover.

Keywords: Classification; Remote Sensing; Land cover land use, Satellite Image;

INTRODUCTION

Identification of Land cover land use and measurement of land cover land use is a very important task. However, techniques available for the above mention purpose are labor incentives, time-consuming and costly. Images were taken with the help of Space born remote sensing platforms (Satellite) can be very helpful for the Identification and measurement of land cover land. Furthermore, this method is cost-effective and consumes a lesser amount of time.As we struggle to comprehend the influence of anthropological activities on our earth, concerns over global land use and land cover change are rising [1]. For years remote sensing has been used as an instrument to generate land use/land cover maps [2]. Many studies have been carried out to produce land cover maps of several ecosystems using broadband multispectral data [3]– [7]. Landsat TM imagery is predominantly used in the classification studies of forest growth stages [8], [9]. Arroyo-Mora [10] has studied different successional stages of dry deciduous forest with the help of a combined Landsat TM and IKONOS data set. Asner et al. [11]attempted to monitor forest degradation and deforestation over different types.

Remote Sensing plays an important role in providing the land coverage mappings and classification of land cover features. Characteristics of land cover land use, the difference of spectral reflectance of different land use, and difference in feature characteristics such as shape and texture are important parameters that should be considered while working land cover land use areas with remote sensing. Therefore, image classification is an important tool for examine and assessing satellite images.

1. LITERATURE REVIEW

ANN classifier gave the highest OAA values of 81%. The image classification done with the help of SVM showed OAA of 71% and SAM showed the lowest OAA of 66%. SVM showed the highest OAA of 80% in classifying spectra coming from 165 processed bands[12]. Used SVM classification into land cover and land-use sectors. Pre-processing contains Gaussian filtering & RGB to Labcolorspace image translation. Segmentation is done using the fuzzy incorporated hierarchical clustering technique. The cluster centroids are subjected to the trained SVM to obtain the land use and land cover sectors [13]. Correctness and consistency of Support Vector Machine (SVM) classifier and compare its performance with Artificial Neural Network (ANN) classifier for multispectral Landsat- 8 images of Hyderabad region. Overall precisions of Land used and land cover classification approximately 93% for SVM and 89% for ANN According to experiment results SVM has the better classification accuracy [14]. Artificial Neural Network classifier and Principal Components Analysis have been used. After performing the tests, according to the Kappa index, the Artificial Neural Networks are capable of being employed as pattern classifiers in multispectral images [15]. Collected image data from Landsat ETM+ and Terra ASTER images. Maximum Likelihood (ML) and Artificial Neural Network (ANN) classifiers are used. Image band combinations are given to the neural network for training and the success of the classification. According to the results, the ANN classifier yielded more accurate results than the ML classifier [16]. SMA (Spectral Mixture Analysis) to map coconut land-cover. SMA was executed and assessed based on Landsat-8 ETM (Enhanced Thematic Mapper Plus) data [17].

2. Land use/Land coverMapping &Classification Model

The proposed model for classification and accurate mapping of land use land cover using remote sensing images or space-born images. Indian remote sensing satellite images will be acquiredfrom archives of ISRO and preprocessed. After geometric corrections GCPs will be laid down on images to perform supervised classification. An inherent supervised classification mechanism was used to cluster pixels in the dataset into classes corresponding to defined training classes. Non-linear classifications algorithms (ANN, SAM, and SVM) were used to classify the image. Hits from all correctly classified pixels were used for accuracy assessment. Two measures of classification accuracy (user's and producer's accuracy), overall accuracy (OAA), and kappa coefficient were calculated.

The Model is intended to perform the following task.

2.1 Data Acquisition

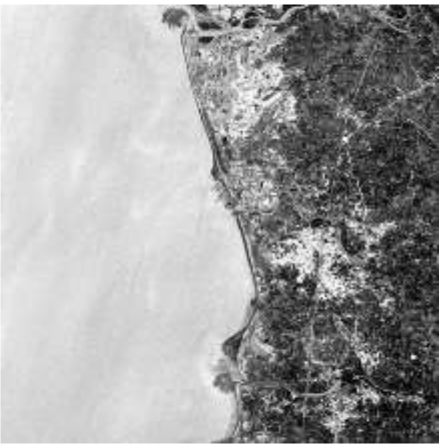
2.2 Data Pre-processing

2.3 Identification and classification

Figure 1:Land use land covers Mapping & Classification Model

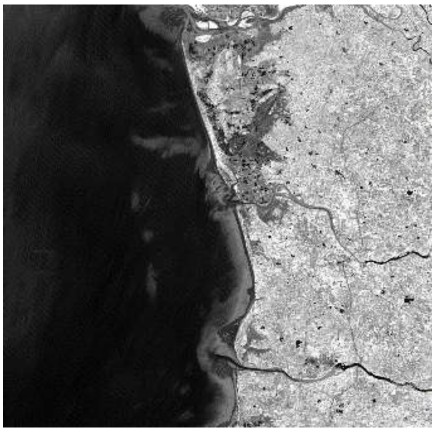
3.1 Data Acquisition

It is a process of gathering information or procedure of collecting related information. An extensive field survey was done to record ecological features and distribution patterns of different land use. Eight distinct land use classes have been identified in the study area. Quadrats of 30m×30m size (corresponding with a spatial resolution of satellite sensor 30m) were laid down across the marked study area. The numbers of points taken for each class were dependent on the distribution of identified land use classes within the study area. Ground control Points (GPS) locations of all the quadrats were recorded within an error of ±4m.Imageswere taken from IRS (LISS III) platform (Spatial Resolution 30 m). The numbers of points taken for each class were dependent on the distribution of identified land use classes within the study area.

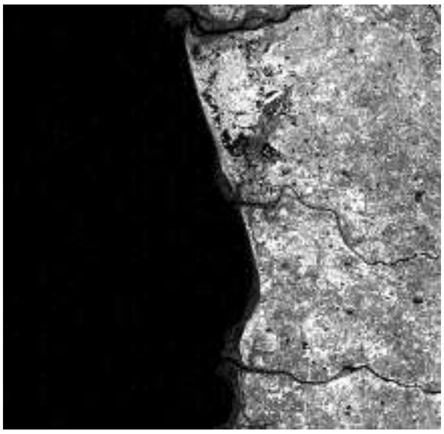


Band 2 (Blue)

Band 3(Green)



Band 4 (Red)



Band 5 (Infrared)

Figure 2: LISS – III Image

3.2 Data Pre-Processing

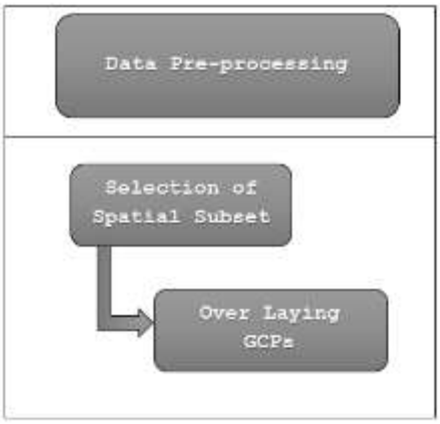


Figure 3: Data Pre-Processing

3.2.1 Selection of Spatial Subset

In this section, the image is processed and converted into a rectangular shape. Input the x and y coordinates of the upper left and lower right. Subset your data into a rectangle that contains the selected ROIs. The rectangle is the smallest rectangle that will fit the ROI. You can mask the pixels in the rectangle that do not fall within the ROI.

3.2.2 Over Laying GCPs (Ground Control Points)

The Ground Control Points (Ground Control Points, GCPs) is an important baseline data of Remote Sensing Image correction [19]. The quantity, distribution, and accuracy of GCPs play an important role in correcting Remote Sensing Images.

Figure 4Pre-Processing (False Color Composition (FCC)) Image

3.3 Identification and classification

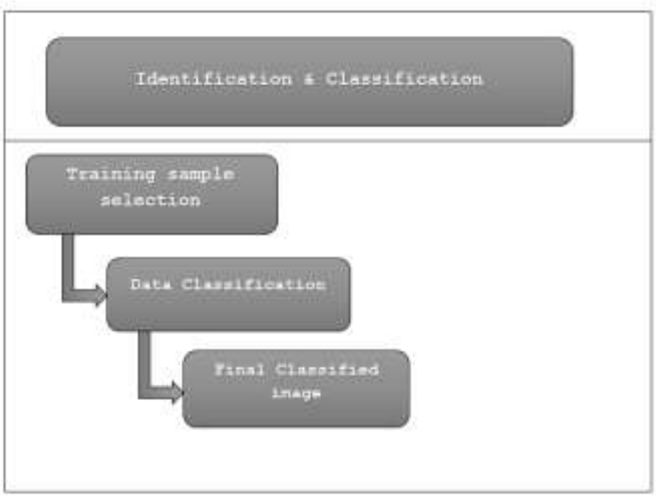


Figure 5 Identification and classification

3.3.1 Training Sample Selection

It is the most important component of remote sensing classification and measuring the quality of the region of interest (ROI). Accurate classification accuracy is dependent upon good training sample selection. . Classification correctness is mainly determined by ROI separability. High-quality classification training samples (with high ROI reparability) determines the classification accuracy to a certain extent [20].

3.3.2 Data Classification

To obtain correct as well as quick land cover detail remote sensing classification is very useful and widely applied in the area like a disaster or environment monitoring, Land Cover /Land Use, etc. Proposed model designed to work with supervised classification. Supervised classification algorithms include classification methods based on machine learning, including artificial neural network (ANN), support vector machine (SVM), and decision tree.

3.3.3 Final Classified Image

The final classified image contains different classes of land use/land cover classification. The final image is classified into the classes like water bodies, agricultural land, residential areas, grasslands, mangroves, etc. with different value pixels.

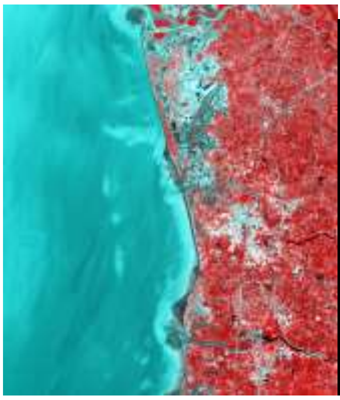
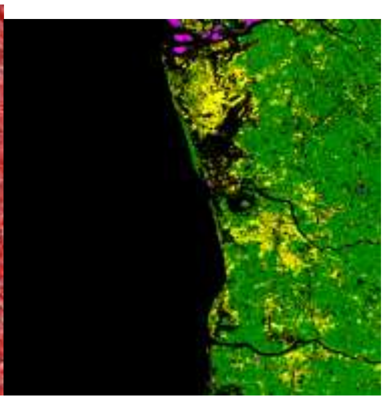
 

Figure 6 : FCC Image **Final classified image (SVM)**

3. CONCLUSION

The proposed model is concerned with the findingof different land cover land use. It helps various government agencies to survey an area and future planning. That will increase accuracyin the mapping and classification of land area land cover.

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