VEGETATION ESTIMATION FROM SATELLITE IMAGES USING HYBRID INTELLIGENCE SYSTEM: A CASE STUDY ON MEERUT CITY

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ABSTRACT

This paper deals with Image Analysis of Remote Sensing Data Integrating Spectral, and Spatial Features of land in the area of satellite image processing. We have used multi-spectral remote sensing data to analyze the pattern of surface change of the city of Meerut and explore the local economics and development this city.

The long-term objective of the paper is optimizing the city's function and operation, and more critically, secure a long-term economically and environmentally sustainable urban development. Some band combinations of remote sensed data are effective in the land cover classification. Here the hybrid method is use to obtain the final better result to estimate the agriculture land in Meerut. In hybrid method results by taking different samples of NDVI and trend the neurons by it, which provide us the better results then NDVI and Neural Network. Finally we gained the classified result as Hybrid Intelligence objects like vegetation, free land, urban area, roads and water resource area.

Keywords: Remote sensing, Data acquisition, Spectral resolution, Spectral wavelength, Sensors, LISS-IV, Vegitation, Solar zenith angle, Multi-spectral images, MX sensor, and Visible band. Artificial Neural Network and Hybrid Intelligence

I. INTRODUCTION

In the present scenario of the world, the information technology plays a major role in the world economics; if we get the timely information about the resources of the city then we could plan and manage the resources of the city in a better way, for the economically and environmentally sustainable urban development Land cover and the human or natural alteration of land cover play a major role in global scale patterns of climate. Rapid urbanization and urban sprawl have significant impact on conditions of urban ecosystems. Changes in land use and land cover are directly linked to many facets of human health and welfare, including biodiversity, food production, and the origin and spread of disease.

Basic aim of our study is to analyze the Remote Sensing Data that we have received from the national remote sensing agency (space department, government of India); Integrating Spectral, and Spatial Features of the Objects in the area of satellite image processing. Here the multi-spectral remote sensing data is used to find the spectral signature of different objects of the Meerut city for the land cover classification, how the use of land changes according to time and also performed the temporal analysis to analyze the impact of climate over the surface.

During the study following objectives were achieved:

1 Determination of NDVI images from the multi spectral images.
2 Determination of threshold values of NDVI for classified objects from the ground survey data.
3 Creation of the False Color Composite image for the classified objects such as (vegetation, structures, roads, free land and water)
4 ANN analysis of the multi spectral images
5 Creation of the False Color Composite image for the classified objects.
6 Finally training the neurons by samples obtained NDVI applying one method on the other to get hybrid intelligence data for better result.
7 Again creation of the False Color Composite image for the classified objects.

For efficient planning and management, we need the classified data in a timely manner, in order to get the classified data of the ground; satellites are the best resources to provide the data in a timely manner

Another significance is that our eyes can acquire and analyze the energy of the visible band only but satellites are capable of collecting data beyond the visible band also. This additional information helps us to analyze the new things, which are not possible in visible band.

II. REMOTE SENSING

Remote sensing is a technology used for obtaining information about a target through the analysis of data acquired from the target at a distance. It is composed of three parts, the targets - objects or phenomena in an area; the data acquisition - through certain instruments; and the data analysis - again by some devices. This definition is so broad that the vision system of human eyes, sonar sounding of the sea floor, ultrasound and x-rays used in medical sciences, laser probing of atmospheric particles, and are all included. The target can be as big as the earth, the moon and other planets, or as small as biological cells that can only be seen through microscopes. A diagrammatic illustration of the remote sensing process is as given below[7,8].

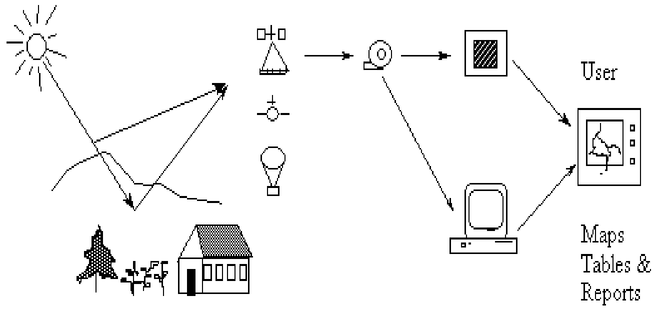

Figure1 The Flows of Energy and Information in Remote Sensing

Remote Sensing consists of the following elements: electro-magnetic energy, target (s), spectral response, sensors, platforms, and data/image.

2.1 Major Divisions of Spectral Wavelength Regions

The wavelength of electromagnetic energy has such a wide range that no instrument can measure it completely. Different devices, however, can measure most of the major spectral regions[5,6].

The division of the spectral wavelength is based on the devices, which can be used to observe particular types of energy, such as thermal, short-wave infrared and microwave energy. In reality, there are no real abrupt changes on the magnitude of the spectral energy. The spectrum are conventionally divided into various parts as shown below:

The optical region covers 0.3 - 15 mm where energy can be collected through lenses. The reflective region, 0.4 - 3.0 mm, is a subdivision of the optical region. In this spectral region, we collect solar energy reflected by the earth surface. Another subdivision of the optical spectral region is the thermal spectral range, which is between 3 mm to 15 mm, where energy comes primarily from surface emittance. Table 1 lists major uses of some spectral wavelength regions.

Table1. Major Uses of Some Spectral Wavelength Regions

Wavelength	Use	Wavelength	Use
g ray	Mineral	1.55-1.75 µm	Water content in plant or soil
X ray	Medical	2.04-2.34 µm	Mineral, rock types
Ultraviolet (UV)	Detecting oil spill	10.5-12.5 µm	Surface temperature
0.4-0.45 µm	Water depth, turbidity	3 cm - 15 cm	Surface relief, soil moisture
0.7-1.1 µm	Vegetation vigor	20 cm - 1 m	Canopy penetration, woody biomass

III. RESOURCESET-1 (IRS P6) AND ITS SENSORS

The main objectives of IRS-P6 mission are: To provide continued remote sensing data services on an operational basis for integrated land and water resources management at micro level with enhanced multi-spectral and spatial coverage with stereo imaging capability. To further carry out studies in advanced areas of user applications like improved crop discrimination, crop yield, crop stress, pest/disease surveillance, disaster management and urban management.

IV. SPECIFICATION

IRS-P6 is a three axes body-stabilized spacecraft launched by PSLV-C5 into a Sun Synchronous Orbit at an altitude 817 Km. descending node. And Repetevity 341 orbits / cycle (24 days). The spacecraft is designed for a nominal mission life of five years. IRS-P6 carries three optical cameras as payload [5].

4.1 Sensors Of Resourceset-1 (IRS P6)

4.2.1 Linear Imaging Self Scanning Sensor (LISS-IV) Camera

LISS-IV is a high-resolution multi-spectral camera operating in three spectral bands 0.52 to 0.59 m (Green (band 2)), 0.62 to 0.68 m (Red (Band 3)) and 0.76 to 0.86 m (NIR (Band 4)). LISSIV provides a ground resolution of 5.8 m (at Nadir) and can be operated in either of the two modes. In the multi-spectral mode (Mx), a swath of 23.9 Km (selectable out of 70 Km total swath) is covered in three bands, while in mono mode (Mono), the full Swath of 70 Km can be covered in any one single band, which is selectable by ground command (nominal is B3 – Red band). The LISS-IV camera can be tilted up to ± 26° in the across track direction thereby providing a revisit period of 5 days.

4.2.2 Linear Imaging Self-Scanning Sensor

The LISS-III camera is identical to the LISS-III flown in IRS-1C/1D spacecraft except that the spatial resolution of SWIR band (B5) is also 23.5 m (same as that of B2, B3, and B4). LISS-III covers a swath of 141 Km in all the 4 bands.

4.2.3 Advanced Wide Field Sensor (AWiFS)

AWiFS camera is an improved version compared to the WiFS camera flown in IRS-1C/1D. AWiFS operates in four spectral bands identical to LISS-III, providing a spatial resolution of 56 m and covering a swath of 740 Km. To cover this wide swath, the AWiFS camera is split into two separate electro optic modules, AWiFS-A and AWiFS-B. The IRS-P6 spacecraft mainframe is configured with several new features and enhanced capabilities to support the Payload operations.

4.2 Normalized Difference Vegetation Index

The Normalized Difference Vegetation Index (NDVI) is a simple numerical indicator that can be used to analyze remote sensing measurements, typically but not necessarily from a space platform, and assess whether the target being observed contains live green vegetation or not.

The researchers found that their ability to correlate, or quantify, the biophysical characteristics of the vegetation from the satellite spectral signals was confounded by these differences in solar zenith angle across this strong latitudinal gradient. With the assistance of a resident mathematician (Dr. John Schell), they studied solutions to this dilemma and subsequently developed the ratio of the sum of the red and infrared radiances over their difference as a means to adjust for or “normalize” the effects of the solar zenith angle[1,4].

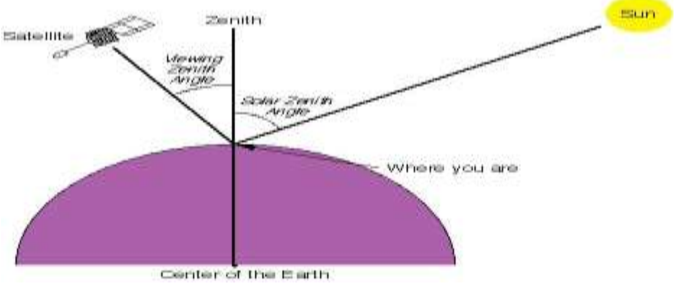

Figure 2 Solar Zenith Angle

Originally, they called this ratio the “Vegetation Index” (and another variant, the square-root transformation of the difference-sum ratio, the “Transformed Vegetation Index”); but as several other remote sensing researchers (e.g., Jim Tucker) were identifying the simple red/infrared ratio and other spectral ratios as the “vegetation index,” they eventually began to identify the difference/sum ratio formulation as the Normalized Difference Vegetation Index. The earliest formal reporting of the NDVI was in 1973 by Rouse et al. (Dr. John Rouse was the Director of the Remote Sensing Center of Texas A&M University where the Great Plains study was conducted).

Thus, NDVI was one of the most successful of many attempts to simply and quickly identify vegetated areas and their "condition," and it remains the most well-known and used index to detect live green plant canopies in multispectral remote sensing data. Once the feasibility to detect vegetation had been demonstrated, users tended to also use the NDVI to quantify the properties of the plant canopies[2].

4.3 Image Analysis Using Normalized Difference Vegetation Index

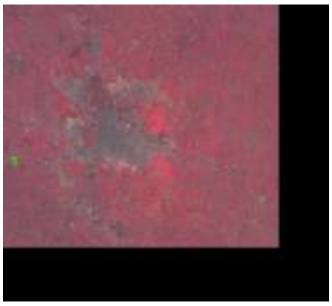

Figure 1(a) Original Image

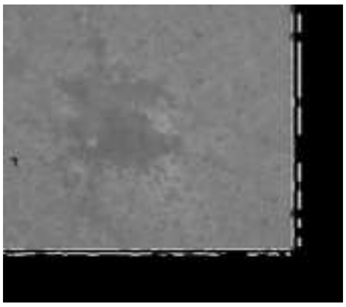

Figure 1(b) NDVI image

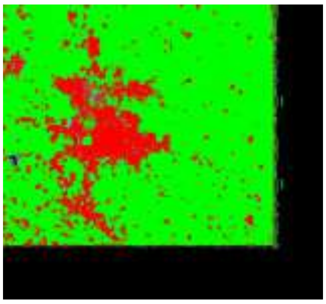

Figure 1(c) False color composite

V. ARTIFICIAL NEURAL NETWORK

A neural network, also known as a parallel distributed processing network, is a computing solution that is loosely modeled after cortical structures of the brain. It consists of interconnected processing elements called nodes or neurons that work together to produce an output function. The output of a neural network relies on the cooperation of the individual neurons within the network to operate. Processing of information by neural networks is characteristically done in parallel rather than in series (or sequentially) as in earlier binary computers or Von Neumann machines. Since it relies on its member neurons collectively to perform its function, a unique property of a neural network is that it can still perform its overall function even if some of the neurons are not functioning. In other words it is robust to tolerate error or failure. (see fault tolerant) Additionally, neural networks are more readily adaptable to fuzzy logic computing tasks than are Von Neumann machines.

Neural network theory is sometimes used to refer to a branch of computational science that uses neural networks as models to either simulate or analyze complex phenomena and/or study the principles of operation of neural networks analytically. It addresses problems similar to artificial intelligence (AI) except that AI uses traditional computational algorithms to solve problems whereas neural networks use 'networks of agents' (software or hardware entities linked together) as the computational architecture to solve problems. Neural networks are trainable systems that can "learn" to solve complex problems from a set of exemplars and generalize the "acquired knowledge" to solve unforeseen problems as in stock market and environmental prediction. I.e., they are self-adaptive systems.

Traditionally, the term neural network has been used to refer to a network of biological neurons. In modern usage, the term is often used to refer to artificial neural networks, which are composed of artificial neurons or nodes. Thus the term 'Neural Network' has two distinct connotations.

Biological neural networks are made up of real biological neurons that are connected or functionally-related in the peripheral nervous system or the central nervous system. In the field of neuroscience, they are often identified as groups of neurons that perform a specific physiological function in laboratory analysis.

Artificial neural networks are made up of interconnecting artificial neurons (usually simplified neurons) designed to model (or mimic) some properties of biological neural networks. Artificial neural networks can be used to model the modes of operation of biological neural networks, whereas cognitive models are theoretical models that mimic cognitive brain functions without necessarily using neural networks while artificial intelligence are well-crafted algorithms that solve specific intelligent problems (such as chess playing, pattern recognition, etc.) without using neural network as the computational architecture.

Please see the corresponding articles for details on artificial neural networks or biological neural networks. This article focuses on the relationship between the two concepts.

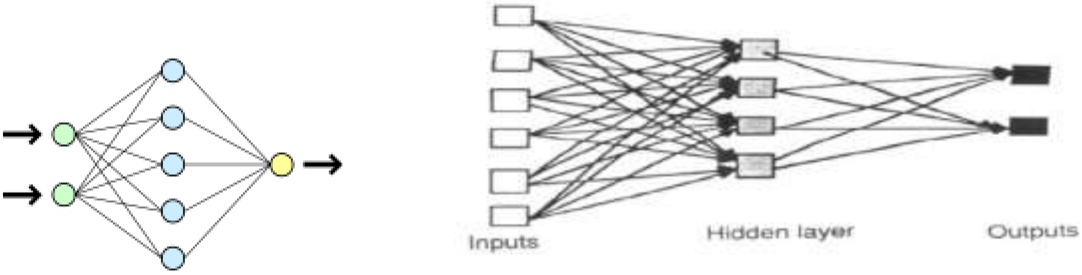

Figure2 Simplified View of an Artificial Neural Network

5.1 Characterization

In general, a biological neural network is composed of a group or groups of physically connected or functionally associated neurons. A single neuron can be connected to many other neurons and the total number of neurons and connections in a network can be extremely large. Connections, called synapses, are usually formed from axons to dendrites, though dendrodentritic microcircuits [Arbib, p.666] and other connections are possible. Apart from the electrical signalling, there are other forms of signaling that arise from neurotransmitter diffusion, which have an effect on electrical signaling. As such, neural networks are extremely complex. While a detailed description of neural systems seems currently unattainable, progress is being made towards a better understanding of basic mechanisms.

Artificial intelligence and cognitive modeling try to simulate some properties of neural networks. While similar in their techniques, the former has the aim of solving particular tasks, while the latter aims to build mathematical models of biological neural systems.

In the artificial intelligence field, artificial neural networks have been applied successfully to speech recognition, image analysis and adaptive control, in order to construct software agents (in computer and video games) or autonomous robots. Most of the currently employed artificial neural networks for artificial intelligence are based on statistical estimation, optimisation and control theory.

The cognitive modelling field is the physical or mathematical modelling of the behaviour of neural systems; ranging from the individual neural level (e.g. modelling the spike response curves of neurons to a stimulus), through the neural cluster level (e.g. modelling the release and effects of dopamine in the basal ganglia) to the complete organism (e.g. behavioural modelling of the organism's response to stimuli).

5.3 Image Analysis using Artificial Neural Network

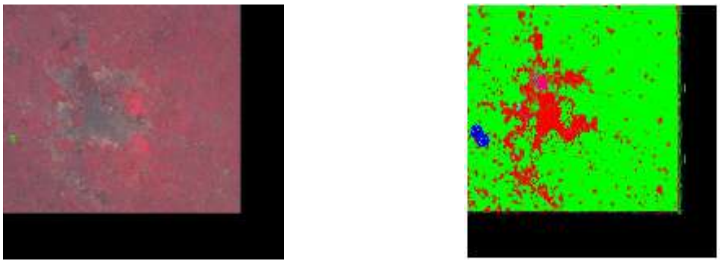

Figure 3(a) Original Image **Figure 3(b) ANN False color composite**

VI. HYBRID INTELLIGENCE

We have used a different hybrid system that combines NDVI system and neural networks. The hybrid neuro system is capable of performing neuro reasoning by using the trained neural network, which is constructed by learning from data. The results have shown that the fuzzy systems are fault tolerant, i.e., it can efficiently be trained from either well-defined initial neuro rules or ill-defined initial neuro rules; and the efficiency of the learning algorithm can be improved by choosing appropriate hybrid Intelligence. The classification results are best than other classifiers like NDVI, and ANN.

6.1 Image Analysis Using Hybrid Intelligence

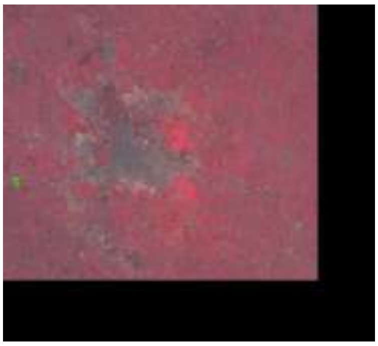

Figure 4(a) Original Image

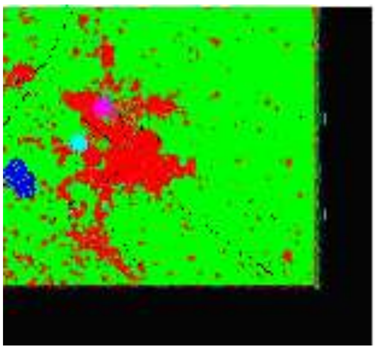

Figure4(c) Hybrid False color composite

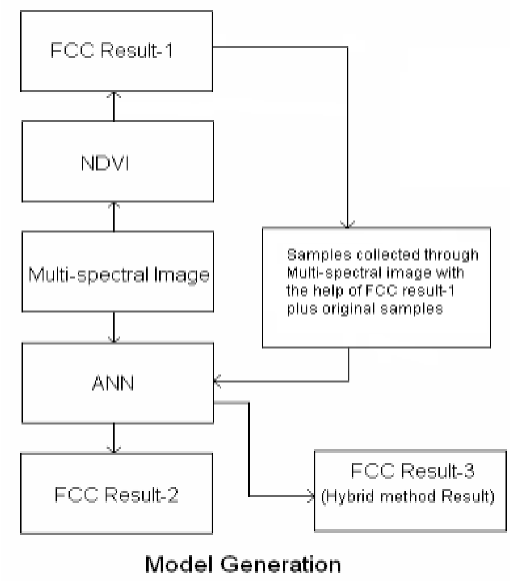

Figure 5 Hybrid Intelligence Systems

VII. CONCLUTION AND FUTURE SCOPE

In this paper we have analyzed the Remote Sensing Data that we have received from the national remote sensing agency (space department, government of India); to find the land cover classification of our city, and to know how the use of land changes according to time and also performed the temporal analysis to analyze the impact of climate over the surface. In order to analyze all these things, we have used the NDVI method of classification. This is a very fast and effective method of analysis. It is widely used for the crops classification in the world. But we have used this one for land covers classification because vegetation components are very dominant in the images. And our basic aim is also to preserve the greenery of the city for the healthy environment by which we obtained Result 1. But in case of result2, which is little bit better, then result1 we have used ANN. Though in case result3 we are in condition to get idea clearly about all types of classification in which we have gone through Hybrid Intelligence system.

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