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Study and Analysis of HySi Data in 400 to 500 nm VNIR Spectrum for Precision Agriculture

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Abstract— *The ability to extract information about world and present it in way that our visual perception can comprehend is ultimate goal of imaging science in remote sensing .Hyperspectral imaging system is most powerful tool in the field of remote sensing also called as imaging spectroscopy, It is new technique used by researcher to detect terrestrial, vegetation and mineral. This paper reports analysis of hyperspectral images. Firstly the hyperspectral image analyzed by using supervised classification of Amravati region from Maharashtra province of India. The report reveals spectral analysis of Amravati region. We acquired satellite imagery to perform the classification using maximum like hood classifier. Analysis is performing in ERDAS to determine the spectral reflectance against the no of band. The analytical outcome of paper is representing the soil, water, vegetation index of the region.*

Keyword— Hypespectral images system, Vegetation index, Maximum like hood classifier.

I. INTRODUCTION

In hyperspectral remote sensing hyper mean too many wavelength band .This image provide the spectral information due to this identify the unique material is possible In the hyperspectral images there is high correlation between band .The image provide more accurate information[2][13].The aim of remote sensing is to extract the information from the object & present it in way that we easily analyzed it[8]. The hyperspectral imagery & multispectral imagery are both powerful tool in the remote sensing sector within the electromagnetic spectrum all spectral band is not available for purpose of remote sensing. Hyperspectral data set will be compare of 100 to 200 spectral band have narrow bandwidth & multispectral data set which possess 5-10 band of larger bandwidth [12]. The analysis of multispectral image depend upon shape ,texture and spectral property in few wavelength band in which image is acquired so it is not possible to identify the unique material or any element in soil [9][10].

For this purpose hyperspectral remote sensing is used which provide the spectral characteristic of the object .Hyperspectral image are spectrally over determine due to that it is easy to identify & distinguish the object which is spatially similar looking but having spectral changes [11][12][15].The hyperspectral remote sensing era began in 1970 .where AVIRIS was propose to NASA in 1983 .which on aircraft platform, where the first space born Hyperion sensor have 10 nm bandwidth & give the range of 400-2500 m[14].

A.Motivation

Hyperspectral sensors and analysis have provided more information from remotely sensed imagery than ever possible before. As new sensors provide more hyperspectral imagery and new image processing algorithms continue to be developed, hyperspectral imagery is positioned to become one of the most common research, exploration, and monitoring technologies used in a wide variety of fields motivated me to To Study and Analysis of Hyperspectral Images.

II. LITERATURE REVIEW

[1] Heng Dong, Chao Chen, Jinliang Wang, Qiming Qin, Hongbo Jiang, Ning Zhang, Mingchao Liu published paper on “Study On Quantitative Retrieval Of Soil Nutrients” This paper described Soil spectral reflection is affected due to soil chemical and physical nature and physical basis of remote sensing .The impact factor of soil spectrum feature are water organic , iron oxide and physical composition. In this paper study ASD FieldSpec Pro FR was used to collect the spectra of soil samples. Sensitive band which select for analyzed the relation between nutrient and soil spectral feature. The inversion model of nitrogen & organic matter established by linear regression The result show that nitrogen & organic matter retrieve from remote sensing.[2] B. Krishna Mohan and Alok Porwal published paper on “Hyperspectral image processing and analysis” This paper describes a general framework for working with hyperspectral imagery, including removal of atmospheric effects, imaging spectroscopy, dimensionality reduction and classification of imagery. The phenomenon of mixture modelling is briefly discussed, followed by a recent development in mapping the classes at sub-pixel level based on the principle of super resolution. [3] David Landgrebe published paper on “Some Fundamentals and Methods for Hyperspectral Image Data Analysis”This paper describes the study of data analysis methods for such

high dimensional data . They show that such data have substantially increased potential for deriving more detailed and more accurate information, but to achieve it, the primary limiting factor has become the precision with which a user can specify the analysis classes of interest. Some methods and procedures for mitigating this limitation in practical circumstances will be described.[4] Lin Qiu published paper on "In situ measurement of soil macropores by dye tracing and image analysis." This paper described Soil macropore are important migration passage for water and air in soil . The proper amount of soil macropore in soil increase soil permeability, improve rhizosphere environment & increase water tension capacity ,but excess of macropore waste in rainfall irrigation and pollution of ground water .To understand the monitoring of water quality ,mechanism of solution solute transportation .We need the know about spatial distribution of soil macropore .Measurement of soil pore is very difficult .So in this paper we study measurement of macropore by using dye tracing and image analysis.(DTIA) with paddy soil from the Tai Lake region as case study. Brilliant blue solution is used as dye solution was poured into soil study area .After one days dyeing vertical solution were dug & photograph .The photograph is taken by digital camera process software ERDAS IMAGINES 9.0 is used for analysis

[5] Heike Bach published paper on "Methods and Examples for Remote Sensing Data Assimilation in Land Surface Process Modeling". This paper described by using land surface parameter and variable land surface process model describe the energy nutrient ,water on local to regional scale ,so we required the series of spatial distribution input for the temporal & spatial variability of land process. So input taken from microwave and optimal sensor .New tech developed called 4DDA(four-dimensional data-assimilation) .it combine remote sense data and land surface model effectively .In this paper we describe 4DDA tech in land process moderately were two case study describe. Where the assimilation of soil moisture estimates from ERS (European Remote Sensing) radar data in flood forecasting which improve the accuracy of parameter are explained.[6] Lei Chen published paper on "Economic loss of soil erosion in Linyi City" This paper described both on-site and off-site impact causes due to soil erosion, that contribute the economic loss.On-site impact include sediments, soil nutrient and water, while off-site impact include detainment and saltation. By using remote sensing tech survey in Linyi city we determine various method to calculate soil erosion.The soil erosion in city reaches 327.7069x106 Yuan in 2008.The loss of sediment 37%of total loss. The result indicates that physical factor is also important to determine soil erosion, human factor also play important role.[7] Zheng hongbo published paper on "Study on the Spatial Variability of Farmland Soil Nutrient based on the Kiriging Interpolation"This paper described the spatial variability of nutrient including TN,AP,AK .Which provide management of farmland & protection of ecology & enviorment land. In this paper we take 100 sample of soil from Ninghai country Zhenjing province, China,which give the spatial variability of TN,AK,AP was study by kiring interpolation & geostatistic analysis.The ratio of Nug/sill of soil TN is 70.8% and AK is 81.86%.TN show moderate & AK show weak spatial autocorrelation. The spatial autocorrelation of soil TN,AP,AK show the factor such as fertilization ,soil management , land used spatial variability soil nutrient in study area .The use of kiring could successfully interpolate soil TN,AK,AP.

III. PROPOSED METHODOLOGY

A. Image acquisition

The satellite imagery of the selected study regions are acquired from the database of "Bhuvan". For study region, we have select one tile of amaravati region . Which taken by HySI sensor, having 17 band. The preprocessing step also includes resizing the image at a defined and standard format.

B. Image Classification

The aim of the classification process is to categorize all pixels in a digital image into one of several land cover classes. This categorized data may then be used to produce thematic maps of the land cover present in an image. Two main classification methods are *Supervised Classification* and *Unsupervised Classification*.

3.2.1Supervised Classification

With supervised classification, we identify examples of the Information classes (i.e., land cover type) of interest in the image. These are called *"training sites"*. The image processing software system is then used to develop a statistical characterization of the reflectance for each information class. This stage is often called "*signature analysis*" and may involve developing a characterization as simple as the mean or the rage of reflectance on each bands, or as complex as detailed analyses of the mean, variances and covariance over all bands. 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.

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3.2.1 Maximum Likelihood Classifier

The **maximum likelihood classifier** is one of the most popular methods of classification in remote sensing, in which a pixel with the maximum likelihood is classified into the corresponding class. The **likelihood** Lk is defined as the posterior probability of a pixel belonging to class k.

Lk = P(k/**X**) = P(k)*P(X/k) /Σ P(i)*P(**X**/i)

where P(k) : prior probability of class k

P(X/k) : conditional probability to observe **X** from class k, or probability density function

Usually P(k) are assumed to be equal to each other and Σ P(i)*P(**X**/i) is also common to all classes. Therefore Lk depends on P(**X**/k) or the probability density function.For mathematical reasons, a multivariate normal distribution is applied as the probability density function. In the case of normal distributions, the likelihood can be expressed as follows.

$$L_k(\mathbf{X}) = \frac{1}{(2\pi)^{\frac{n}{2}}|\Sigma_k|^{\frac{1}{2}}} \exp\left[-\frac{1}{2}(\mathbf{X}-\mu_k)\Sigma_k^{-1}(\mathbf{X}-\mu_k)^t\right]$$

where n: number of bands

X: image data of n bands

Lk(**X**) : likelihood of **X** belonging to class k

μk : mean vector of class k

Σk : **variance-covariance matrix** of class k

$|\Sigma_k|$: determinant of Σ_k

In the case where the variance-covariance matrix is symmetric, the likelihood is the same as the Euclidian distance, while in case where the determinants are equal each other, the likelihood becomes the same as the Mahalanobis distances.

IV. SIMULATION RESULTS

The methodology is simulated in ERDAS with machine configuration, i3 Intel Core CPU @ 3.30 GHz, 3GB RAM and 32 – bit windows operating system, and the analysis is done. According to the simulation we obtain spectral analysis of soil ,water ,vegetation index of the Amravati region. The graph show reflection curve against no the band. The analysis outcomes are illustrated in Figure a,b,c. After the supervised classification by using maximum likehood classifier firstly we get the classified image which respresent the area where the soil water is present , and the graph show the relectance curve of soil,water, vegetation index present in the region.

The following graph gives the analysis of the soil ,water, vegetation index of output image.

a) Soil Spectral Graph Give Reflection Against Wavelength

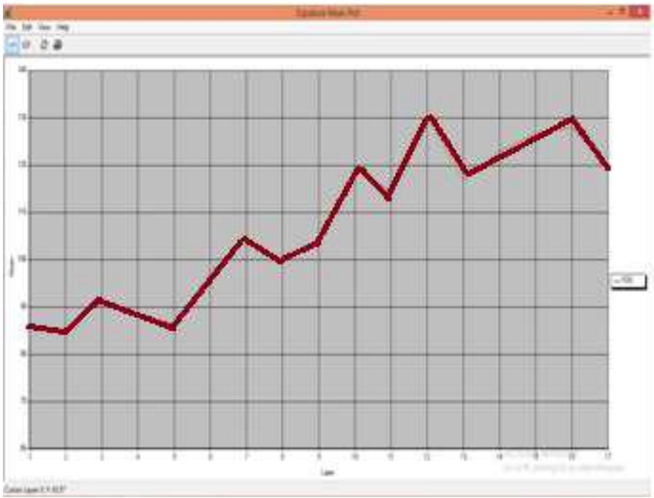

Fig.a: Soil Reflection

b) Water Spectral Graph Give Reflection Against Wavelength

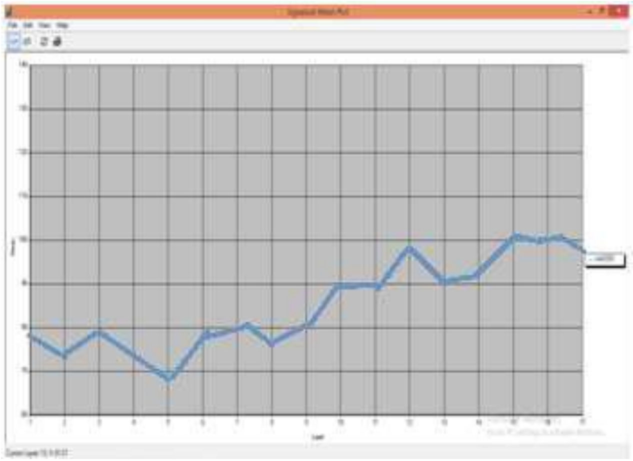

Fig. b: water reflection

c) Vegetation Index Spectral Graph Give Reflection Against Wavelength

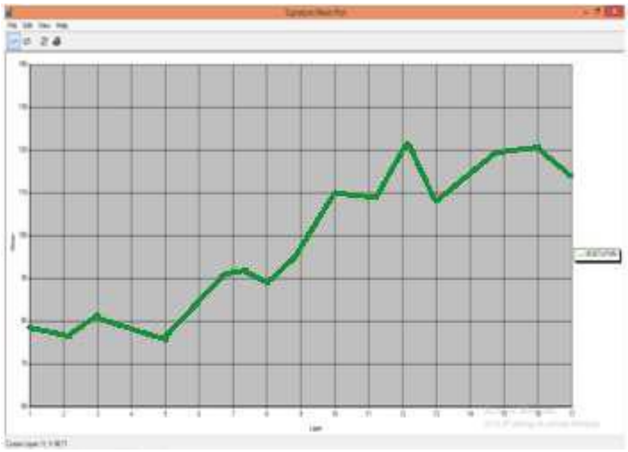

Fig.c: Vegetation Index reflection

V. CONCLUSION

This paper provides analysis of hyperspectal images by using supervised classification. Firstly with maximum likehood classifier is used for the classification purpose we get classified image. After that spectral analysis of the input image. Which represent existence of soil, water etc. depends upon the no of band in image. Spectral analysis represents an area where the soil, water & VI present in input image In Hyperspectral image analysis we have used the seventeen band data image which indicate only soil, water ,and VI present in image .In future work, we will improved the proposed work ,by selecting image of 220 band data .The Hyperion sensor have 220 band which is used to predict the carbon in soil Thus, increasing the number of band we can determine the presence of element or component in hyperspectral image.

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