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Review of Rice Crop Identification and Classification using Hyper-Spectral Image Processing System

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ABSTRACT

Digital image processing is collection of techniques for the manipulation of digital images by computer and its applications. This collection of methods in remote sensing is dominantly treated as Satellite Digital Image Processing (SDIP). A spaceborne Multispectral Image Processing System (MIPS) has been used since 1960 as a traditional satellite image processing system for data analysis and extraction of meaningful information from/in the earth surface. The MIPS system provides limited information due to the small number of spectral channels. Over the past two decades, advances in satellite imaginary system have made it possible for the collection of several hundred spectral bands for processing. This is commonly referred to as Hyperspectral Image Processing System (HIPS). This study details the differences between MISP and HISP; and focuses on the application of HIS for Rice crop-classification, plant growth, plant biophysical, biochemical, physiology properties in different spectral regions and their mapping.

Keywords: Multispectral, Hyperspectral, Classification, Maximum Likelihood, Hyperion.

1. INTRODUCTION

The conventional method of compiling statistics on rice-crop acreage is for staff from the appropriate Government Ministry to make ground surveys, during which selected farmers or village officials are interviewed regarding their crops. By comparison with the results of previous years, this information is then extrapolated to generate data and predictions on a regional basis. This means that these traditional surveys are both time-consuming and expensive that's why farmer's eye estimates are remarkably close to actual crop production figures [1]. In addition, the information collected is often imprecise and unreliable, leading to inaccurate crop-yield forecasts and subsequent difficulties for agricultural planners and managers on both regional and national scale.

The satellite image processing is becoming increasingly available for vegetation mapping and to decision makers for future growth and development. Remote sensing identified as a tool to assess performance more than a decade ago [2] but the actual applications have been very few so far. Remote sensing data and some GIS tools has been used to develop the crop yield models [3]. The multi-date satellite spectral data is examined for crop yield modelling [4]. In the last decade, remote sensing has been increasingly identified an objective, standardized, possibly cheaper and faster methodology for crop production surreys than conventional field investigation [5].

2. MULTISPECTRAL IMAGE PROCESSING DATA AND LIMITATIONS

The advantage of satellite remote sensing systems was to provide both the synoptic view space provides and the economies of scale, since data over large areas could be gathered quickly and economically from such platforms [6]. Multispectral imagery has been used as the data source for water and land observational remote sensing from airborne and satellite systems since the 1960s [7].

Multispectral airborne and satellite systems have been employed for gathering data in the fields of agriculture and food production, geology, oil and mineral exploration, geography and urban to non-urban localities [7]. But a Multispectral data is processed into a limited number of bands. Multispectral data is collected in two or more spectral bands (less than 20) of the EMS. The bands may be located in VNIR, SWIR and TIF parts of the spectrum and frequently are not contiguous. Multispectral data is not a great dimensionally data, and so it is not able to detect materials more accurately. A material may display distinct spectral properties over a particular narrow wavelength range, making it distinguishable from other materials only in images recorded over that wavelength range. A Multispectral scanner may not cover this spectral range, particularly if the range is outside the range for detection of the principal materials known to be present at the scene. Two distinct objects may absorb and reflect radiation almost same in a small part of spectrum and show the same spectral signatures; therefore it becomes so difficult to differentiate them. To make them differentiable few spectral bands are not sufficient i.e. multispectral data is not sufficient to differentiate the two different objects with different properties in the limited (same) numbers of bands or using same wavelength. Therefore more bands are needed to increase the object distinguishing. To identify a large range of surface cover features that can not be identified with broad band, low spectral resolution imaging system such as Landsat MSS, TM or SPOT [8]. Due to the spectral resolution limitations and to obtain data of a higher spectral resolution compared to multispectral data, hyperspectral sensors on board satellites or airborne hyperspectral imagers are used [9].

3. USE OF MULTISPECTRAL REMOTE SENSING IN RICE-BASED AGRICULTURE

Robert N. Colwell stresses the possibilities of the "multi" concept in remote sensing which he identified as: Multidate, Multispectral, Multistation, Multistage, Multipolarization, Multidirectional, Multienhancement, Multidisciplinary and Multithematic. NASA has conceived, designed, and utilized systematically Multispectral scanner instruments to sense the earth remotely. Certainly the capability to carry out "multi" remote sensing has increased more rapidly that the depth of our knowledge about the limits of these concepts.

The most multispectral satellite systems measure between three and six spectral bands within the visible to middle infrared region of the electromagnetic spectrum [10]. Multispectral remote sensing allows for the discrimination of different types of vegetation, rocks and soils, clear and turbid water, and selected man-made materials [10].

The study in Bhadra Project in the state of Karnataka in India is an attempt to use of satellite remote sensing applications to assess agricultural system performance of Rice-base irrigation system [11]. In this project multi-year satellite data have been analyzed to provide irrigated area, cropping pattern and Rice productivity. In this observation high resolution multi-date data from Landsat 5, IRS IA and IB with LISSI data and Thematic Mapper data were selected for analysis. In this project, NDVI has been used to correlate with Rice yield.

For developing a Rice mapping and monitoring capability, RADARSAT in particular and Synthetic Aperture Radar (SAR) satellite systems in general, are very promising tools [12].

In an observation RADARSAT-simulated imagery of Zhaoqing, ground truth information provided by the Institute of Remote Sensing Application was used to classify land use and identify Rice crops [13]. In a study multi-temporal and multi-parameter RADARSAT dataset with multi-frequency and multi-polarization is used to develop a Rice-type distribution map with different Rice growing stages in Zhaoqing, China. In this study neural network classifier algorithm is used to separate the different type of Rice. The classification accuracy (91%) of Rice was examined using PCI software package and checked by ground truth verification [14].

In a study of Rice mapping a RADARST (Standard 5) imagery data is merged with ground truth information provided by Institute of Remote Sensing Application, Beijin, China then a Rice cropping calendar is developed using this interpreted imagery data that makes the potential for Rice crop monitoring strong, at Sihui County, in the province of Guangdong, and located in the southeast corner of China. This region is suitable for early-Rice (March-July) and late-Rice (July-November) cropping system. Manipulation of the imagery was performed using PCI's EASI/PACE software on a Sun SPARC Station 20 [15].

A study was carried out to evaluate the capabilities of ERS-l SAR data for monitoring of Rice planting acreage and its growth, in Thailand. Number of stalk density, length of leaf, width of leaf, diameter of stem, plant height above water, net weight, dry weight and yields were selected as the data parameters. GPS was used to locate and register test site boundaries and calculate the area of each test site. Supervise classification with Maximum Likelihood method was performed with 7 different classes. Finally it was found that the Rice mapping accuracy was 78% while the over all accuracy was 79% [16].

In a study six multi-temporal ERS-2 (SAR) and Landsat-5 (TM) imagery data set has been used to identify the Rice crop, general terrain types and land use classes in Thailand. Classification has done using maximum likelihood classifier in which the seven classes of Rice are identified with 84.7% accuracy [17].

To investigate the land use patterns for Rice in Thailand, Landsat 2 multispectral data has been used. The maximum likelihood classifier has been utilized to classify the 4 Rice classes out of 11 classes in the entire data set with 93.2% of accuracy [18].

4. SPECTRAL SIGNATURE (SPECTRAL REFLECTANCE CURVES)

The property that is used to quantify spectral signatures is called spectral reflectance. This is a ratio of the reflected energy to incident energy as a function of wavelength [9]. The graph of the spectral reflectance of an object as a function of wavelength is termed the spectral reflectance curve [19]. These reflectance curves are known as spectral signatures and stored in a spectral database-Spectral Library. It has been suggested the need to build spectral signatures such that they can account for intra-species variability and unique discrimination of various types vegetation species [20]. The configuration of the spectral reflectance curves is important in the determination of the wavelength region(s) in which remote sensing data is acquired as the spectral reflectance curves give insight into the spectral characteristics of an object [19].

5. HYPERSPECTRAL IMAGINARY DATA AND ADVANTAGES

The barrier of limitation of Multispectral imagery data is broken with Hyperspectral imagery data. The "Hyper" in Hyperspectral means "over" as in "too many" and refers to the large number of measured wavelength bands therefore Hyperspectral imagery data is an over-determined data. Hyperspectral data is often not as readily available as other (Multispectral) types of remotely sensed data. In particular, there are few spaceborne Hyperspectral sensors. One important feature of hyperspectral data is its large data volume, data redundancy and band correlation. Hyperspectral imagery provides opportunities to extract more detailed information than is possible using traditional Multispectral data.

Hyperspectral sensors are passive sensors that simultaneously record hundreds of narrow bands from the electromagnetic spectrum, and group the bands in what is called a Hyperspectral data cube [21] and provide spectroscopic information in relatively narrow contiguous spectral bands throughout visible, near and short-wave infrared regions of EMS [22]. A Hyperspectral remote sensing system has four basic parts: the radiation source, the atmospheric path, the imaged surface, and the sensor. Hyperspectral imaging sensors are basically advanced digital color cameras with fine spectral resolution at given wavelengths of illumination. Instead of measuring three primary colors-red, green, and blue-these sensors measure the radiation reflected by each pixel at a large number of visible or invisible frequency (or wavelength) bands. The Hyperspectral imagery is a good source to provide the information of some objects of interest implementing the both physical processing techniques and statistically based exploration techniques. A Hyperspectral imager provides information on scene content that is not obtainable from broad or single band data i.e. Multispectral Imaginary Data. Hyperspectral data will be the mantra for the next generation of optical satellite sensors [23]. Hyperspectral imagery provides an opportunity for more detailed image analysis. To fulfil this potential, new image processing techniques have been developed. In this series a sequence of algorithms were developed and commercialized specifically to extract detailed information from Hyperspectral imagery [24]. These tools, applicable to a variety of applications, distinguish and identify the unique materials present in the scene and map them throughout the image [25]. They remain the most widely used image analysis tools for working with Hyperspectral imagery. In the present scenario the Hyperspectral imaging systems are receiving increasing attention for a wide variety of military, intelligence, civil and commercial systems, identify vegetation species, stress, disease, forest species, soil properties, minerals and materials and toxic wastes world wide. Still is expected that hyperspectral spectral data permits the unique identification of most surface types like rocks, soils and vegetation, provided that the spatial resolution of the data is sufficient to represent a single surface type for each spectrum [26].

5.1 Applications of Hyperspectral Data for Surface Properties

Hyperspectral imagery has also been used to study details of surface properties that are undetectable using other types of imagery like multispectral. For example, Hyperspectral images have been used to detect soil properties including moisture, organic content, and salinity [27]. Hyperspectral images have found many applications in water resource management, agriculture and environmental monitoring [10]. A project in Sydney, Australia provides another example of material identification and mapping. In this application, Hyperspectral imagery was used to identify roofs susceptible to hail damage [28]. Material mapping is also performed with Hyperspectral imagery when the materials present in the scene are known beforehand. In a study Hyperspectral images have been used by geologists for mapping economically interesting minerals [29]. They have also been used Hyperspectral image to map heavy metals and other toxic wastes within mine tailings in active and historic mining districts including superfund sites [30].

5.2 Applications of Hyperspectral Data for Vegetation Classification & Identification

Hyperspectral remote sensing technology demonstrates the capacity of accurate vegetation identification and estimate biochemical content, which is mainly because of narrow and contiguous bands that make it possible to distinguish the variations of absorption features that can not be done by multispectral sensors. It is demonstrated that using hyperspectral image to make quantitative classification and identification of crop or vegetation characteristics is successful. The simplest way to identify different vegetation is to use reflectance curve due to chlorophyll absorption in blue and red regions and high reflectance in green and near infrared regions, or use different vegetation index [31]. Measures of plant physiology and structure such as leaf area index, water content, plant pigment content, canopy architecture and density have been investigated extensively over the past decade ([32]; [33]; [34]; [35]; [36]; [37]; [38]; [39]; [40]; [41]; [42]; [43]) using hyperspectral imagery. Vegetation scientists have also successfully used Hyperspectral imagery to identify vegetation species ([44]; [45]) and to detect vegetation stress and disease identification [46].

In a study Hyperspectral data has been used to develop the spectral signatures and variability of the six forest species-Teak, Chir Pine, Tropical Pine, Eucalyptus, Ficus and Grass [47].

In a study EO-1 Hyperion hyperspectral data acquired on March 28, 2005 at 03:32:29 UTC over Menghai County, Xishuangbanna tropical vegetation area in Yunnan province, China to make agriculture land classification. It is located at 21º33′ 50″– 22º25′ 24″ N latitudes and 100º9′ 39″–100º25′ 46″ E longitudes. Spectral Angle Mapper (SAM) a physically based hyperspectral classification algorithm is used to classify the image. Two hundred randomly selected reference pixels on the classified image were used. The classified image was equipped with ten classes-water, building, crop (sugarcane and corn), pine tree, bare soil, bamboos, chestnut, shanmahuang, crop (paddy field) [48].

A comparative analysis of accuracy of classified images in the respect of crop varieties (Cotton, Rice, Sugarcane and Chilly) has been carried out using EO-1 Hyperion imaginary data, in-situ hyperspectral data using field spectroradiometer and other ancillary data like crop type, cultivar, date of sown/transplant, plant height, soil type etc. The study area is part of Guntur district, Andra Pradesh state of India lying between 16°7′31″– 16°50′55″ N latitude and 79°40′37″– 79°44′49″ E longitude. The spectral library is build using field spectroradiometer data. Image processing has been done using ERDAS IMAGINE-8.6 and ENVI 4.3 software [49].

In a study presented in 2002, the extension of areas of rice fields in Zhejiang Province has been estimated. In this study MODIS hyperspectral satellite data analysis is integrated with GIS tool and the presence of GPS increased the classification accuracy of rice fields. MODIS data have been used because it has higher spatial resolution than NOAA/AVHRR with similar temporal resolution, GIS defined the location of paddy fields and after training samples were selected by GPS, the areas of rice fields were then extracted by the classification of MODIS data [50]. The software packages used for image processing and geo-information analyses were ENVI 3.4 and ARC/INFO 8.1. The supervised approach of Minimum Distance Classification was conducted to extract the Rice field. Thus two classes the irrigated land and the land of rainfed agriculture were extracted from the digital land use map for rice cultivation. The quantitative accuracy of this method was enhanced up to 95.7%, and the spatial accuracy of rice location was also enhanced.

5.3 Ground Based Hyperspectral Image Processing (HIP)

A ground based hyperspectral data analysis is a supporting tool for remote sensing technology. The chlorophyll a, chlorophyll b, and carotenoids are interrelated to the physiological function of the plant leaves and act as a very important role in growth. Continuous removal method is used to extract the absorption features for chlorophyll a, chlorophyll b (400-550nm), and carotenoids (550-770nm) pigment contents in rice leaves and panicles [51]. In this study the reflectance curves of leaves and panicles at different stages were measured with a ground based hyperspectral analysis using ASD (Analytical Spectral Device) 2500 spectroradiometer that obtains continuous spectra from 300nm to 2500 nm.

The benefits of EO-1 Hyperion hyperspectral data to agriculture have been studied in Australia. In this study airborne and ground-based hyperspectral data have been used to find indexes most sensitive to plant nitrogen, water, chlorophyll, lignin, cellulose and soil (clay composition and chemical substances). A digital spectral library also built for nine sampling sites like Rice, Green Rice, Yellow Rice, Stubble and Soil using a field spectroradiometer. Hyperspectral indexes derived from Hyperion were compared with the same indexes derived from ground-measured spectral using spectroradiometer device (ASD), for this six indexes selected [52].

In a study a method is evolved to estimate the concentration of three biochemical variables of corn, i.e., Nitrogen (N), Crude Fat (EE) and Crude Fiber (CF). A ground based hyperspectral analysis is carried out to acquire the spectral signatures using ASD and the first derivative reflectance at fresh leaf scale. The correlations between spectral signatures, first derivative reflectance and three biochemical variables were established using curve-fitting analysis. For the optimum estimation of the concentration of three biochemical variables in the crop, the coefficient of determination (R2), root mean square error (RMSE) and relative error of prediction (REP) were calculated to develop a qualitative model. Resultant the first derivative reflectance at 759nm, 1954nm and 2370nm were most suitable to develop the estimation model of N, EE and CF [53].

6. CONCLUSION

In general this review illustrates the enhanced capability of hyperspectral technologies in the field of agriculture, its development stages and chemical variables. Till today neither multispectral nor hyperspectral library is available for Rice and its attributes for Haryana and Uttaranchal regions. The aim of this study is to evolve some methods and algorithms for the development of such spectral library using multispectral (ASTER) and hyperspectral (EO-1, Hyperion) satellite data in place of ground-based tools. Resultant we can develop a classified image for mapping the rice crop in the remote area and allows researchers to make decisions with the relevant detail in an efficient timeframe. Since during this period there may be crop mixing of rice crop with others crops due to their comical composition like chlorophyll, nitrogen, water etc. But we are using narrowband data in this study therefore the reflectance value of these components may be different in the different spectral regions. Therefore different vegetation indices may be used to differentiate the rice crop and its verities among the different crops on the bases of chemical variables and their composition. This data source will be frequently used in the future.

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