Significance of Vegetation Indices for Vegetation Mapping in Hyperspectral Imagery

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***Abstract*—** Hyperspectral imaging has become an essential tool for vegetation mapping through remotely sensed data since it contains abundant spectral information and can detect the indistinct features to accurately monitor the vegetation status. Mapping vegetation through these remotely sensed images involves various considerations, processes and techniques. The Increasing availability of hyperspectral remotely sensed images due to the rapid advancement of remote sensing technology expands the perception of making choices of imagery sources. Imagery from different sources contains differences in spectral, spatial and temporal characteristics and thus they are suitable for different purposes of vegetation mapping. This paper presents an overview of how hyperspectral imagery is used for mapping vegetation cover. The paper also focuses on the advantages and disadvantages of different vegetation indices used in vegetation mapping and also showcases the various applications of vegetation mapping.

Index Terms - Remote sensing, vegetation mapping, hyperspectral images, agriculture, vegetation indices.

I. INTRODUCTION

Assessing, observing and monitoring the state of the earth's surface is a key requirement for global change research (Committee on Global Change Research, National Research Council, 1999) [1], [2]. Vegetation mapping and its classification is essential for managing the technical task of natural resources as vegetation provides a base for all living beings and plays an important role in affecting global climate change, such as influencing terrestrial CO2 [3]. Vegetation mapping also gives us valuable information for understanding the natural and man-made environments through the process if quantifying vegetation cover from local to global scales at a given time point or over a continuous period. It is critical to obtain current states of vegetation cover in order to initiate vegetation protection and restoration programs [4], [5]. Traditional methods (e.g. field surveys, literature reviews, map interpretation, and ancillary data analysis), however, are not effective to acquire vegetation covers because they are time-consuming, date lagged and often too expensive. Remote sensing is regarded as a technology that offers practical and economical means to study large areas of vegetation- cover change [6], [7]. Due to the potential capability for systematic and accurate observations at various scales, remote sensing technology extends attainable information from the present time to over several decades back.

Urban vegetation study is a key feature in landscape monitoring; it provides a base for the ecological regulator and serves to many ecosystem services. Accurate mapping is required for the conservation and management of green vegetation spaces, which is carried out by field inspection, aerial photography interpretation, and many different money-consuming methods. The existing solutions of urban vegetation records may be significantly improved by introducing more advanced remote sensing techniques without a remarkable increase in costs [8]. Monitoring and mapping of vegetation in an urban context by remote sensing techniques, of course, remains a challenging issue because the vegetation spectral response is sensitive to chlorophyll content at the plant level, which tends to increase the spectral variation and fluctuation in respect of individual species. Many misclassifications between species could be therefore expected depending on the seasonality of data with its spectral/ spatial resolution [9]. An important aspect is to provide reliable vegetation maps that could aid as the basis for urban planners [10], municipalities [11], and decision-makers [12].

A. Hyperspectral Imagery for Vegetation Mapping

Nowadays, the hyperspectral imagery is studied increasingly for vegetation mapping as compared to the multispectral imagery. Multispectral imagery only contains a dozen of spectral bands, whereas the hyperspectral imagery includes hundreds of spectral bands. Hyperspectral sensors are well adapted and suitable for vegetation studies as the reflectance spectral signatures from individual species as well as more complex mixed pixel communities can be effectively differentiated from the much wider spectral bands of hyperspectral imagery [13]. Consider an example, the hyperspectral imagery from AVIRIS is commonly used in the realm of earth remote sensing.

An optical sensor known as AVIRIS is capable of delivering the calibrated images of upwelling spectral radiance in 224 contiguous spectral channels (bands) with wavelengths ranging from 400 to 2500 nm. The information within those bands can be used to identify, measure and monitor constituents of the earth's surface (e.g. vegetation types). AVIRIS imagery was studied for the classification of salt marshes in China and in San Pablo Bay of California, USA [14]. The study showed a satisfactory result that succeeded in classifying two main marsh vegetation species, Spartina and Salicornia, that covered approximately 93.8% of the total marsh, although further work was required to analyze and make the correction for false detection of other marsh vegetation species. Similar work was also conducted by monitoring vegetation dynamics that aimed at proposing sustainable management of wetland ecosystems in the study of the structure of wetlands in San Francisco Bay of California [15].

Hyperion instrument on board the Earth Observing-1 (EO-1) satellite acquired the hyperspectral data which was evaluated for the discrimination of five important Brazilian sugarcane varieties [16]. The results showed that the five Brazilian sugarcane varieties were discriminated using EO-1 Hyperion data. This imply that hyperspectral imagery has the potential of separating plant species, which may be very difficult by using multispectral images. The procedure for pre-processing and classification of hyperspectral and multispectral images are similar, the processing of hyperspectral data remains a challenge. Specialized, cost-effective and computationally efficient procedures are required to process hundreds of bands [13]. To extract vegetation communities or species from hyperspectral imagery, a set of signature libraries of vegetation is usually required [17].

B. Vegetation Indices for Vegetation Mapping

The most important goal of remote sensing projects is to characterize the variety, quantity and condition of vegetation present within a particular scene. The amount of energy reflected from a surface is determined by the amount of solar irradiance that strikes the surface, and the reflectance property of the surface. Solar irradiance changes with time and atmospheric conditions. A simple measure of energy reflected from a surface is not sufficient enough to characterize the surface in a repeatable manner. This problem can be evaded by combining data from two or more spectral bands that is commonly known as a vegetation index. Vegetation Indices (VIs) are defined as the integration of surface reflectance at two or more wavelengths that are designed to highlight a specific property of vegetation. It is a number that is produced by different combinations of remote sensing bands and may have some relationship to the amount of vegetation in a given image pixel. They are designed to intensify the vegetation reflected signal from estimated spectral responses by combining two (or more) wavebands, often in the red (0.6 - 0.7 nm) and near-infrared (NIR) wavelengths (0.7-1.1 nm) regions [18].

When light strikes a surface, it gets reflected, transmitted or absorbed. The relative amount of reflected, transmitted and absorbed light serves as a function of the surface and varies with the wavelength of the light. For example, the majority of light striking soils are either reflected or absorbed, with very little being transmitted and relatively little change with wavelength. With vegetation, however, most of the light in the near infrared wavelength is transmitted and reflected, with little absorbed, in contrast to the visible wavelengths where absorption is predominant, with some reflected and little transmitted [17].

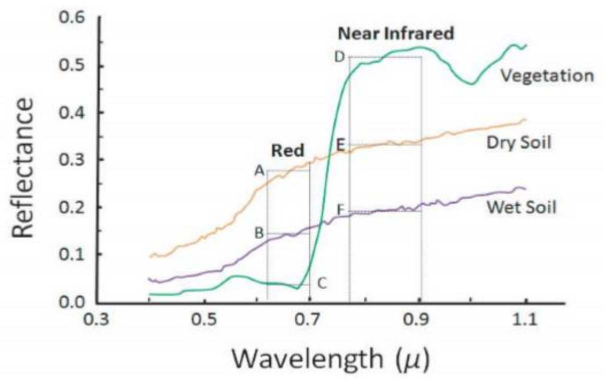

Figure 1: A generic scheme of HSI spectral signature for dry soil, vegetation and wet soil
Source: http://remote-sensing.net/concepts.html

II. DIFFERENT VEGETATION INDICES

A. Ratio Vegetation Index (RVI)

In 1969, Jordan proposed Ratio Vegetation Index (RVI), following the principle that leaves absorb relatively more red than infrared light [19]. RVI can be expressed mathematically as-

$$RVI = \frac{R}{NIR}$$

where *NIR* is the near-infrared band reflectance and *R* is red band reflectance. With respect to the spectral characteristics of vegetation, bushy plants usually contain a low amount of reflectance on the red band and have shown a high correlation with LAI, Leaf Dry Biomass Matter (LDBM), and chlorophyll content of leaves [20]. As the RVI is extremely sensitive to vegetation and has a good correspondence with plant biomass, it is immensely used for green biomass measurement and monitoring at high-density vegetation coverage. However, when the vegetation cover is dispersed or scattered (less than 50% cover), RVI is sensitive to atmospheric effects, and their representation of biomass is weak.

B. Difference Vegetation Index (DVI)

After Ratio Vegetation Index (RVI), The Difference Vegetation Index (DVI) was proposed. The DVI is very sensitive to changes in soil background and can be applied for monitoring the vegetation's ecological environment. It is also called Environmental Vegetation Index (EVI) [21]. DVI can be expressed mathematically as-

$$DVI = NIR - R$$

where NIR is the near-infrared band reflectance and R is the red band reflectance.

C. Perpendicular Vegetation Index (PVI)

The Perpendicular Vegetation Index (PVI) was proposed by Richardson and Wiegand in 1977. This VI is the parent index from which the entire group of distance-based VIs is derived. The PVI makes use of the perpendicular distance from each pixel coordinate to the soil line.

The main purpose of PVI is to cancel the effect of soil brightness in different scenarios where vegetation is sparse and pixels contain a mixture of green vegetation and soil background. This technique is specifically important in arid and semi-arid environments. The entire process for PVI is based on the soil line that is later obtained through the technique of linear regression of the near-infrared band against the red band for a sample of bare soil pixels. Pixels that are away from the soil line are considered as vegetation while those pixels that are near the soil line are considered as soil [22]. PVI can be expressed mathematically as-

$$PVI = \sqrt{(P_{soil} - P_{veg})R^2 - (P_{soil} - P_{veg})NIR^2}$$

where, NIR is the near-infrared band reflectance, R is red band reflectance, P_{soil} is the soil reflectance and P_{veg} is vegetation reflectivity.

D. Normalized Difference Vegetation Index (NDVI)

The Normalized Difference Vegetation Index (NDVI) was introduced by Rouse et al. (1974). It was intended to produce a spectral VI that would be capable of separating green vegetation from its background soil brightness using Landsat MSS digital data. The range of NDVI values is between 0 and 1 because the index is calculated through a normalization procedure that has a sensitive response to green vegetation even for low vegetation-covered areas. NDVI is usually used in research related to regional and global vegetation assessments and was considered to be related not only to canopy structure and LAI but also to canopy photosynthesis [23], [24]. NDVI can be expressed mathematically as-

$$NDVI = \frac{(P_{NIR} - P_R)}{P_{NIR}} + P_R$$

where P_{NIR} is the near-infrared band reflectance, P_R is red band reflectance.

E. Atmospherically Resistant Vegetation Index (ARVI)

Due to the limitations of NDVI under atmospheric effects, the Atmospherically Resistant Vegetation Index (ARVI) was proposed by Kaufman and Tanr´e [25]. ARVI is based on the principle that the atmosphere affects significantly 'R' compared to the 'NIR'. Thus, Kaufman and Tanr´e modified the radiation value of R by the difference between the blue (B) and R. Therefore, ARVI is capable of reducing the dependence on atmospheric effects, which is expressed as-

$$ARVI = \frac{(NIR - RB)}{(NIR + RB)}$$

where RB is the difference between B and R. NIR is the near-infrared reflectivity related to the molecular scattering and gaseous absorption for ozone corrections, and represents the parameters for air conditioning.

F. Soil Adjusted Vegetation Index (SAVI)

Soil Adjusted Vegetation Index is the dissimilarity and divergence of vegetation from the soil background. This VI was originally proposed by Richardson and Wiegand [26] by evaluating the soil line, which is considered as a linear relationship on the 2D plane of the soil's spectral reflectance values between the NIR and R. Therefore, it can be considered as a detailed description of a large number of soil spectral information from a number of different environments [27]. SAVI was established to improve the sensitivity of NDVI to soil backgrounds. Many VIs that are based on the effect of soil background has been based on this principle. SAVI can be expressed mathematically as-

$$SAVI = \frac{(P_N - P_R)(1 + L)}{(P_N + P_R + L)}$$

where L is defined as soil conditioning index, that is used to improve the sensitivity of NDVI to soil background. The range of L is from 0 to1. In various fields of applications, the values of L are considered and determined according to the specific environmental conditions. It can be assumed that when the degree of vegetation coverage is high, L is close to 1, indicating that the soil background has no effect on the extraction of vegetation information.

III. AREAS OF APPLICATION

Agriculture plays a key role in economies of both developed and undeveloped countries. Vls are used as took to classify crop types, to assess crop conditions and to estimate crop yield, as well as to map soil characteristics and soil management practices.

Applications of Vls for monitoring crop condition and predicting crop yield at the regional scale have been substantially studied over last decades [28], [29]. An operational application for agriculture is the land use map obtained by the multitemporal crop classification at the high spatial resolution, extracting the classes in the image by their eon1 time evolution of the VI. Traditionally, a known approach based on statistical regression models were used. Studies based on light use efficiency models have shown that the cumulative seasonal NDVI values were significantly correlated with reported crop yields [30]. In these models, the VI estimates the fAPAR which provides, in combination with the light use efficiency and the PAR integrated over time, the estimate of the net primary production [31].

The rapid degradation of forest environments is of important international concern [32]. Among the forestry applications where V1s have been used, that can be used to highlight land cover and land use changes, forest fire detection forest fire risk assessment, and vegetation regeneration.

Land cover changes appear as one of the major large-scale environmental perturbations grouped under the term Global Change [33]. Those changes play an active role in the surface energy and water balance, as well as in the carbon cycle [34]. There is a variety of methodologies to assess vegetation dynamics based on the analysis of long-time series of PIS. Certain algorithm make use of NDVI time series to derive parameters related to vegetation phenology and production that are necessary for modelling vegetation distribution and dynamics [35]. Land cover change is often detected by analyzing time series of coarse-resolution AVHRR data [36], [37]. With the availability of MODIS NDVI 250 m data, time-series data analysis has been adapted to higher resolution applications [38].

Regarding burned area detection and mapping, spectral FZs, and specially NDVI, have proved a simple and fast method to map vegetation abundance using the NOAA-AWRR and the Landsat m. Other indices widely used for free mapping includes the shortwave-infrared (SWIR) instead of red wavelengths, such as the Normalized Difference Infrared Index (NDII) [39], the Normalized Difference Moisture Index (NDMI) [40] and the Normalized Difference Water Index (NDWI) [41] because of their ability to estimate the water content in the vegetation. In addition to this, due to the ability of the NOAA-AVHRR sensor to cover a wide area and its high temporal frequency, the NDVI has often been used in the prediction of fie risk [42]. A link between a NDVI decrement to vegetation water stress, vegetation photosynthetic activity and to fie risk has been found [43]. Another relevant application where the indices have a direct application is the hydrology. Different applications of remote sensing, particularly forestry, agriculture and land cover, the field of hydrology plays an important role since water is a vital component in each of these disciplines. The remote sensing data are inputs in the hydrological models such as the crop coefficient map, land use [44], etc.

IV. CONCLUSION

Combination of the visible and NIR band with simple VIs have notably improved the sensitivity of detecting the green vegetation. Different environments have their own variable and complex characteristics, which need to be considered when using different vegetation indices (VIs). As a result, each VI has its specific expression of green vegetation, its own suitability for specific uses, and some limiting factors. Therefore, for practical applications, the choice of using a specific VI needs to be made with caution by comprehensively considering and analyzing the advantages and limitations of existing VIs and then integrate them so that it can be applied in a specific environment. In this way, the usage of VIs can be altered to specific platforms, instrumentation used, and applications. With the development of hyperspectral and multispectral remote sensing technology, new VIs can be developed, which will broaden research areas accordingly.

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