Remote Sensing of Environment 171 (2015) 83–97

Contents lists available at ScienceDirect

Remote Sensing of Environment

journal homepage: www.elsevier.com/locate/rse

A new vegetation index for detecting vegetation anomalies due to mineral deposits with application to a tropical forest area

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ARTICLE INFO

Article history:
Received 22 June 2015
Received in revised form 15 September 2015
Accepted 15 October 2015
Available online xxxx

Keywords:
Vegetation index
Geobotany
Reflectance spectra
Metal content
Landsat ETM+ image

ABSTRACT

This study aimed at developing a geobotanical remote sensing method to explore mineral deposits in areas covered by thick vegetation. For this, a new vegetation index (VI) is proposed using reflectance data from five bands in the visible green to shortwave infrared region. This index is called VIGS (Vegetation Index considering Greenness and Shortwave infrared), developed so that the VI can accurately detect vegetation stress caused by metal contamination of soils. A set of laboratory experiments was conducted to demonstrate the capability of VIGS, which investigates change in reflectance spectra based on the concentration of four selected metals (Cu, Pb, Zn, and Cd) in soils. The results show that VIGS values are more sensitive to vegetation stress than the Normalized Difference Vegetation Index and can amplify the stress difference, depending on soil metal contents. The VIGS is further examined for a mineralized area containing hydrothermal copper deposits in Jambi, central Sumatra, Indonesia, for which a set of geochemical data of the top layer composed of weathered rocks and soils were systematically obtained. Through kriging of point content data, the spatial distributions of Cu, Pb, and Zn in soil are found to be strongly correlated with the geology and controlled by faults. Using one Landsat ETM+ scene image after atmospheric correction, VIGS values are calculated by a combination of reflectances in bands 2, 3, 4, 5, and 7. The effectiveness of VIGS is proven by this case study, because VIGS anomalies appeared in high-content zones common to the three metals. This concordance probably originated from the fact that plant formations (mainly primary forest) in the high metal zones are closely related to the geological units.

1. Introduction

Remote sensing optical sensors onboard satellites have been used effectively in geological fields to identify minerals and rocks, produce geologic maps, and detect manifestations of mineral, hydrocarbon deposits, and groundwater outflows via reflectance and emissivity spectral characteristics of earth surface materials (Koide & Koike, 2012; Sabins, 1999; van der Meer et al., 2012). In addition, geometrical features appearing on satellite imagery have been used to characterize large geological structures such as folds and faults (Fernandes da Silva, Cripps, & Wise, 2005; Fraser, Huggins, Rees, & Cleverly, 1997), and estimate fracture systems in terms of distribution, direction, and size (Koike & Ichikawa, 2006; Koike, Nagano, & Kawaba, 1998). However, for spectral applications, the applicability of geological remote sensing is limited to arid and semiarid areas where vegetation is sparse or absent. Because reflectance spectra of vegetation conceal the spectra of underlying soils and rocks, vegetation is the most critical barrier for geologic identification and mapping. Therefore, exploration and potential assessment of mineral deposits by optical remote sensing is very difficult for thickly vegetated areas.

Several studies have tried to separate or remove vegetation spectra from non-vegetation components by techniques of spectral unmixing or directed principal component analysis (Asner & Lobell, 2000; Carranza & Hale, 2002; Fraser & Green, 1987; Guerschman et al., 2015), and by the forced invariance method for vegetation suppression without considering non-vegetation component spectra (Crippen & Blom, 2001; Yu, Porwal, Holden, & Dentith, 2011). These methods basically assume that reflectance spectra at image pixels are mixtures of vegetation, soil, rock, and other features; contributions of soil and rock reflectances are more or less included. However, in densely vegetated areas such as tropical forest, this mixing assumption cannot hold. Source materials of the reflectance spectra are almost entirely vegetation, which requires development of an unconventional method.

One key factor of geobotanical remote sensing (GBRS) for mineral exploration is the presence of unusual vegetation over mineralized areas, which can be identified from the reflectance spectral pattern of plants. This idea has been used since the early stage of satellite remote sensing, and change in reflectance spectra of plants with metal absorption (particularly heavy metal) has been investigated (Horler, Barber, & Barringer, 1980; Rencz & Watson, 1989; Sabins, 1999). This absorption induces vegetation stress by interfering with chlorophyll activity and inhibiting water suction from soils and water supply to leaves

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http://dx.doi.org/10.1016/j.rse.2015.10.006
0034-4257/

(Barceló & Poschenrieder, 1990; Slonecker, 2011). Additionally, understanding of the relationship of plant formations to geologic conditions and metal contents in soils is essential (Bruce & Hornsby, 1987). The wavelength range from visible to near infrared (VNIR; 400–1400 nm), in which the effect of metal absorption on reflectance spectra is readily apparent, has generally been used for GBRS (Curran, Dungan, Macler, & Plummer, 1991; Dunagan, Gilmore, & Varekamp, 2007; Kooistra et al., 2004; Milton, Ager, Eisworth, & Power, 1989). The effect is also discriminable in a longer wavelength range, shortwave infrared (SWIR; 1400–2400 nm), as vegetation stress (Horler et al., 1980; Sridhar, Han, Diehl, Monts, & Su, 2007).

Based on this background, this study aimed to develop a Vegetation Index (VI) using reflectance data from several bands in the VNIR and SWIR regions so that the VI was sensitive to vegetation stress by metal absorption. VI is a measure emphasizing the change in reflectance at selected bands for estimating stress magnitude. To this end, a set of laboratory experiments was undertaken to clarify the relationship between metal contents in soils and reflectance spectra of a selected plant species. Four types of metals were prepared for the experiment to investigate VI differences with metal content. After verifying the new VI, it was applied to a Landsat ETM+ image of a case study area in central Sumatra, Indonesia, where there are porphyry copper deposits and mineralized zones in places, to characterize the vegetation reflectance spectra. A set of soil geochemical data was used as ground truth to evaluate positional agreement of VI anomalies derived from the imagery with soils of high metal content. Through this case study, the applicability of GBRS using the new VI to mineral exploration in densely vegetated areas is addressed.

2. VI and laboratory experiment

2.1. Definition of new VI

VI is one of the most discussed techniques and applications of remote sensing (Slonecker, 2011). For areas covered almost entirely by plants with a small fraction of exposed soils, the Normalized Difference Vegetation Index (NDVI; Rouse, Haas, Schell, & Deering, 1973) is the most representative VI, which can quantify vegetation stress by metal absorption (Boluda, Andreu, Gilabert, & Sobrino, 1993; Dunagan et al., 2007; Gallagher, Pechmann, Bogden, Grabosky, & Weis, 2008). NDVI is formulated simply as:

$$\mathrm{NDVI} = \frac{N-R}{N+R} \tag{1}$$

where N and R are amounts of surface reflectances in the NIR and visible red regions, respectively. NDVI is especially useful for multispectral imagery covering wide areas with a small number of bands, such as Landsat and ASTER (Advance Spaceborne Thermal Emission and Reflection Radiometer) imagery. The wavelength range of each band of these satellite data is broad. As a recent advance, VIs other than NDVI have been derived from a more limited wavelength range of hyperspectral imagery and have successfully detected vegetation stress by metals, and these VIs are red edge position, photochemical reflectance index, and normalized pigment chlorophyll index (Curran et al., 1991; Gamon, Peñuelas, & Field, 1992; Peñuelas, Gamon, Fredeen, Merino, & Field, 1994). However, hyperspectral imagery does not cover all land on the earth. Landsat and ASTER imagery are more versatile, because they provide global coverage of the land's surface.

Common to NDVI and other VIs, including the above and listed in Slonecker (2011), is the main use of VNIR reflectances only. However, SWIR reflectances are sensitive to leaf water content and thus can be used to detect vegetation stress by water supply interference. Therefore, a VI derived from reflectance data in the VNIR and SWIR regions is expected to enhance detection accuracy of vegetation anomalies. Based on this expectation, a new VI, the Vegetation Index considering Greenness and Shortwave infrared (VIGS), is proposed. This index is aimed at wide availability to general multispectral satellite imagery by integrating visible green, red, NIR, and SWIR reflectances as:

$$\mathrm{VIGS} = w_1\left(\frac{G-R}{G+R}\right) + w_2\left(\frac{N-R}{N+R}\right) + w_3\left(\frac{N-S_1}{N+S_1}\right) + w_4\left(\frac{N-S_2}{N+S_2}\right) \tag{2}$$

where G, S_1, and S_2 denote reflectances in the visible green and two SWIR regions, respectively, and w_1, w_2, w_3, and w_4 are weights for emphasizing each term. For Landsat ETM+ imagery, S_1 and S_2 correspond to bands 5 and 7 (B5 and B7). Considering reports on the variability of reflectances induced by vegetation stress in the selected regions (Carter, 1991; Horler et al., 1980; Sridhar et al., 2007) and using the data sets in the latter two references, a weights set, $w_1 = 1.0$, $w_2 = 0.5$, $w_3 = 1.5$ and $w_4 = 1.5$, was obtained as the most suitable because the VIGS from this combination greatly enhanced the difference in stress. Three normalized difference spectral indices are incorporated into VIGS and combined using the above weights, which are green-red-based normalized difference index (Motohka, Nasahara, Oguma, & Tsuchida, 2010) to detect chlorosis-related phenomena, NDVI, and a SWIR-based normalized difference index (Ji, Zhang, Wylie, & Rover, 2011) that is sensitive to water contents of leaves, partly controlled by the metal-induced stress.

2.2. Laboratory experiment

The purpose of the set of laboratory experiments was to clarify change in reflectance spectra of plants depending on metal concentration in soils and different types of metal. For this, the Japanese mustard spinach (*Brassica rapa* var. *perviridis*) was selected because of its relatively short lifetime (~2–4 months) and easy cultivation from seed under laboratory conditions (Fig. 1). Soils in a pot of volume 400 cm^3 were composed of minerals and organic matter (humus and plant debris), whose sizes were classified as clay through sand in the aggregate.

Four types of metal, Cu, Pb, Zn, and Cd, were selected for simulating contaminated soils for the following reasons. Cu, Pb, Zn are common metals in mineralized soils around metal deposits, and therefore the experimental results can be used to verify NDVI and VIGS results of the study area. Although Cd contamination is generally limited to soils rich in greenockite (CdS), Cd has been recognized as a metal with strong biological toxicity (Woolhouse, 1983). Another aspect of Cu and Zn is as a micronutrient of plants through a certain content level of tolerance, which differs from the physiological function of Pb and Cd (Alloway, 2013).

The four metals were sourced from standard metal solutions of $Cu(NO_3)_2$, $Pb(NO_3)_2$, $Zn(NO_3)_2$, and $Cd(NO_3)_2$, respectively. Solutions were mixed with HNO_3, NaOH, and K-phosphate buffers to preserve the composition of the non-metallic elements and pH at a normal level (6–7). The solutions were classified into three levels based on their metal concentrations, i.e., low (20 ppm), medium (100 ppm), and high (200 ppm). Soil in each pot was uniformly mixed with 150 ml of metal solution and equilibrated for one week at room temperature. In total, 26 pots were prepared: there were two pots for each metal and concentration level, giving a total of 24, and two of normal soils without addition of metals to provide reference data. Seeds were germinated in the normal soils for 2 weeks, and then sprouts were transplanted to the pots of metal-contaminated soils. The plants were placed under lights and in darkness for 16 and 8 h per day, respectively, at ~20 °C for daytime and 15 °C for nighttime, and supplied with distilled water daily to maintain the moisture level.

Reflectance spectra from 400 to 2400 nm and total leaf chlorophyll were measured by a spectroradiometer, FieldSpec3 (Analytical Spectral Devices, Boulder, Colorado USA), and a chlorophyll meter, atLEAF (FT Green LLC, Wilmington, Delaware USA). The measurements commenced when the plants bore four or more leaves 60 days after sowing and continued the next 20 days with 5-day intervals. Four 100 W