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

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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.

Keywords: vegetation index, geobotany, reflectance spectra, metal content, Landsat ETM+ image

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 et al., 2005; Fraser et al., 1997), and estimate fracture systems in terms of distribution, direction, and size (Koike & Ichikawa, 2006; Koike et al., 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 et al., 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 et al., 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 (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 et al., 1991; Dunagan et al., 2007; Kooistra et al., 2004; Milton et al., 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 et al., 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; Pearson & Miller, 1972) is the most representative VI, which can quantify vegetation stress by metal absorption (Boluda et al., 1993; Dunagan et al., 2007; Gallagher et al., 2008). NDVI is formulated simply as:

$$NDVI = \frac{N - R}{N + R} \quad (1)$$

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, et al., 1992; Peñuelas et al., 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:

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

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 et al., 2010) to detect chlorosis-related phenomena, NDVI, and a SWIR-based normalized difference index (Ji et al., 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 cm³ were composed of minerals and organic matter (humus and plant debris), whose sizes were classified as clay through sand in the aggregate.

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141 **Fig. 1.** Growth of Japanese mustard spinach (*Brassica rapa* var. *perviridis*) in metal-contaminated and normal soils
 142 in an experimental room. Height of a pot was 10 cm.

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

151 The four metals were sourced from standard metal solutions of $\text{Cu}(\text{NO}_3)_2$, $\text{Pb}(\text{NO}_3)_2$,
 152 $\text{Zn}(\text{NO}_3)_2$, and $\text{Cd}(\text{NO}_3)_2$, respectively. Solutions were mixed with HNO_3 , NaOH , and K-
 153 phosphate buffers to preserve the composition of the non-metallic elements and pH at a normal
 154 level (6–7). The solutions were classified into three levels based on their metal concentrations,
 155 i.e., low (20 ppm), medium (100 ppm), and high (200 ppm). Soil in each pot was uniformly
 156 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 hours 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 quartz-tungsten-halogen lights were used as an illumination source for spectral measurement at 45° incident angle in darkroom conditions, to block light from the outside. A fiber optic sensor was placed at a distance ~5 cm from the leaves. The reflectance spectrum of a specimen was the average of measurements on two to four leaves with 10 repetitions for each leaf. Total chlorophyll content of a specimen was also from averaged values of leaves, measured along the adaxial direction by inserting a leaf into the device aperture. To convert reflectance spectra to VNIR and SWIR band reflectances of Landsat TM and ETM+ sensors, original reflectances were averaged over the wavelength range of each band using ENVI software.

3. Materials for study area

The study area in Jambi, central Sumatra (western Indonesia) was of 50×50 km size, within 101.73° – 102.18° E longitudes and 1.64° – 2.09° S latitudes (Fig. 2). This area is mostly mountainous with thick vegetation cover, and is a part of the Sumatra tropical rain forests.

Fig. 2. Location of study area in central Sumatra, sampling sites of geochemical data, and mineral occurrences superimposed on subscene of true-color composited Landsat ETM+ image. This image, acquired on 15 August 2002, was used for VI analyses.

3.1. Geologic setting

The main geological features of the study area are portrayed in Fig. 3 and summarized as follows, based on references for preparing regional geological maps (Pardede et al., 1992; Rosidi et al., 1996; Simandjuntak et al., 1994; Suwarna et al., 1992). The study area is mainly overlain by block-shaped NW–SE trending Permian intrusions belonging the Palepat Formation and composed of lava, crystal lithic tuff, and lithic tuff of andesitic composition with some propylite.

This block, the oldest geology in the study area, is the most important to mineral exploration because many mineralized regions have been found in this formation. The subordinate lithology is Triassic–Cretaceous granitoid, with the same trend as the Permian block. In the middle and southwest parts, Jurassic–Cretaceous metasedimentary rocks composed of compact quartzite and weakly deformed pelitic shale and siltstone are distributed along a NW–SE thrust and bounded by Tertiary intrusions. Quaternary volcanic rocks are partially distributed in the west and northeast parts, and Quaternary sediments are only on the plains near the southern and southeast edges of the study area. The distribution of the lithologic units is controlled by faults that mostly strike along NW–SE and (a few) E–W directions. The valleys are deep and their directions are also controlled by the fault strikes.

Fig. 3. Simplified geologic map of study area (after Pardede et al., 1992; Rosidi et al., 1996; Simandjuntak et al., 1994; Suwarna et al., 1992).

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The study area is characterized by joint or separate occurrences of precious and base metals in places (Crow et al., 1993). Three zones of significant Cu mineralization are present in the Permian intrusions in the Rantau Kelayang, Ngaol, and Sengering regions (Fig. 3). In Rantau Kelayang, low-grade Cu mineralization of disseminated chalcopyrite, a typical feature of porphyry copper deposit, occurred via hydrothermal alterations, propylitization, and silification. In addition, there are many small-scale Au mines operated by local people along rivers in the Lontar region, where sizeable nuggets have been found occasionally on the riverbanks.

Vegetation condition is usually influenced by hydraulic properties of topsoils, particularly permeability, which controls the amount and velocity of water infiltration to deeper soils. Permeability in the study area is strongly correlated with the general geology; it is low in the areas of Permian intrusions and granitoid, moderate in fractured and weathered zones, and moderate to high in the Quaternary sediments. From the productivity map of aquifers (i.e., near-surface permeability for groundwater flow) modified from a hydrogeological map of Indonesia (Setiawan et al., 2013; Sukiban, 2005; Yudhanagara, 2005; Zahirdin & Hendra, 1982), nearly all the study area has low permeability (non-exploitable groundwater and poorly productive aquifers only for local use), and there are a few locally productive aquifers near faults in the Ngaol region and in the Quaternary sediments (Fig. 4).

Fig. 4. Productivity map of aquifers (near-surface permeability for groundwater flow) superimposed on fault and river distributions, following a hydrogeological map of Indonesia (Setiawan et al., 2013; Sukiban, 2005; Yudhanagara, 2005; Zahirdin & Hendra W, 1982).

3.2. Geochemical data

Geochemical data of near-surface rocks and soils in the study area are quoted from a report of regional geochemical investigation of southern Sumatra, undertaken systematically at scale 1:250,000 by the Indonesian Directorate of Mineral Resources between 1980 and 1992 (British Geological Survey, 2007). The investigation followed a traditional method using stream sediments, which originate from surrounding upstream rocks and soils, with sampling density one every 10 km². Content data of three metals (Cu, Pb, and Zn) at 282 sampling points were selected and transformed into natural logarithms to reduce bias of statistical distribution and approximate it with a normal distribution for subsequent geostatistical analyses. Geostatistics has been a common method to build regional-scale geochemical models using point sample data (e.g.,

Conradsen et al., 1992). Histograms and Q-Q plots of the log-transformed data show that they roughly follow a normal distribution (Fig. 5).

Fig. 5. Histograms and Q-Q plots of log-transformed contents of Cu, Pb, and Zn at 282 sampling sites.

Spatial correlation of the log-transformed content data was clarified by a semivariogram, $\gamma(\mathbf{h})$, by assuming that data of each metal were stationary and intrinsic random variables, $Z(\mathbf{x})$:

$$\gamma(\mathbf{h}) = \frac{1}{2} E[Z(\mathbf{x} + \mathbf{h}) - Z(\mathbf{x})]^2 \quad (3)$$

where $\mathbf{x}$ and $\mathbf{h}$ denote a sampling coordinate in space and a vector connecting two locations, respectively, and E means expectation. After approximating experimental $\gamma(\mathbf{h})$ by a model, simple kriging (SK) and ordinary kriging (OK) were used for estimating metal contents across the study area. The choice of SK or OK was dependent on cross-validation of which method yielded higher estimation accuracy (see Zirschky (1985) for details on SK and OK). Then, the concentration-area (C-A) model (Cheng et al., 1994) was used to extract anomaly zones in the interpolated metal content map. The C-A model is expressed by

$$A(r > r_i) = cr_i^{-D} \quad (4)$$

where $A(r > r_i)$ denotes the cumulative area of content r greater than or equal to a cutoff r_i , and c and D are a constant and scaling component, respectively, of a regression line fitted to $A(r > r_i)$ versus r_i in log-log plots. The optimal threshold to separate background and anomaly was determined by an inflection on the regression line, i.e., the metal content at which the D value changes abruptly.

3.3. Image data and preprocessing

A subscene of a Landsat ETM+ image (path 126 and row 61) of the standard level-one terrain-corrected product (L1T) was selected for the VI analysis. This image, acquired on 15 August 2002 in the dry season with low humidity and under nearly 0% cloud cover, i.e., only a few clouds in the study area, was the best quality that satisfied the three conditions. The other Landsat images were inferior in quality for the study area. Cloud-covered pixels were excluded from the analysis. Reflectance of each pixel was derived from the original image by an atmospheric correction using the Fast Line-of-sight Atmospheric Analysis of Spectral Hypercubes (FLAASH) module of ENVI software and a topographic correction. The topographic correction was intended to correct brightness distortion caused by change in the sun illumination effect with the gradient (θ_p) and aspect (ϕ_o) of slope. A digital elevation model (DEM) of the Shuttle Radar Topographic Mission (SRTM) with 90-m spatial resolution (Jarvis et al., 2008) was used to compute the incident angle (γ_i) for the illumination (IL) condition modeled by Civco (1989):

$$IL = \cos \gamma_i = \cos \theta_p \cos \theta_z + \sin \theta_p \sin \theta_z \cos(\phi_a - \phi_o) \quad (5)$$

where θ_z and ϕ_a are the solar zenith and azimuth angles, respectively. Using IL , horizontal reflectance (ρ_H) was calculated by the following C-correction method, a non-Lambertian technique (Teillet et al., 1982):

$$\rho_H = \rho_T \left(\frac{\cos \theta_z + c_k}{IL + c_k} \right) \quad (6)$$

where ρ_T is reflectance at an inclined surface. c_k is a coefficient to relate ρ_T at band k to IL by linear regression; $\rho_T = b_k + m_k IL$, where b_k and m_k are the regression coefficients, and $c_k = b_k / m_k$. Furthermore, to reduce overcorrection under low IL conditions, a modified C-correction by Riaño et al. (2003), which smoothes IL values, was adopted. This method was demonstrated as the most effective for mapping vegetation types.

Using the corrected reflectance, a land-cover map was produced to delineate the vegetation zone and identify plant formation using a maximum likelihood supervised classifier of the Landsat image and DEM. Training datasets for each category were selected in the image by referring to the land-use map (Bakosurtanal, 1986) and a central Sumatra vegetation map (Blasco et al., 1986). As a result, the image was classified into eight categories, submontane forest, primary forest at low-to-medium altitude, secondary forest, plantations, and others unrelated to vegetation (paddy field, urban area, bare soil, and water), as shown in Fig. 6. All forest types were composed of dense, moist, and evergreen vegetation (Blasco et al., 1986).

Fig. 6. Land-cover map of plant formations and other categories produced by maximum likelihood supervised classification of the Landsat ETM+ image in Fig. 2.

Next was VI calculation and recognizable display of the result following the procedure of Lyon et al. (1998):

- The VI values were calculated at all image pixels using the corrected reflectance, and values $< 0.2\%$ and $> 99.8\%$ of the cumulative distribution were removed as outliers.
- The remaining values were normalized to a Gaussian distribution with range 0 to 1 and mean 0.5. By this normalization, the NDVI and VIGS values could be compared.

4. Results

4.1. Experimental change in VI

The mature plant heights ranged from 10 cm to 20 cm with the leaves of ca. 8–12 cm in width. The effect of metal soil contamination clearly appeared in the rate of plant growth, in that

higher metal contents reduced plant height; this finding was the same among the four metals (Fig. 7). This symptom of vegetation stress by metal contamination is the same found in other studies (Horler et al., 1980; Slonecker, 2011). Another common symptom of high metal content was leaf chlorosis, which decreased the photosynthetic rate and caused insufficient chlorophyll in the leaves. The most typical chlorosis appeared in a specimen with high Cd content.

Fig. 7. Difference in growth of Japanese mustard spinach with metal content level in soils (L = low, M = medium, and H = high). Selected metals were Cu, Pb, Zn, and Cd. This photo shows a mature condition of the plants, 70 days since sowing.

Although chlorosis was not discriminated visually in the specimens with low metal contents, it was suggested by the total leaf chlorophyll content, which generally decreased with metal content except for Pb (Fig. 8). The effect of metal content on total chlorophyll content was strongest in the Cd specimens. Values of high Cd content-specimens were half those of the reference specimen over the elapsed days. The Cu and Zn specimens had similar values and trends of total chlorophyll content with the variation of content and days. Therefore, Cu, Zn, and Cd were confirmed to affect photosynthetic activity of the Japanese mustard spinach. On the

contrary, this effect was weak in the Pb specimens, in which there was no significant difference of total chlorophyll content despite change in Pb content.

Fig. 8. Changes in total chlorophyll content of leaves with metal content and days since sowing. Each chlorophyll (Chl) content is an average of two specimens at each metal content level in soils and two reference specimens.

The results elucidated the featured changes in reflectance spectra to be dependent on the metal type and content in soils. Reflectances in the visible region (400–700 nm and Landsat B1–B3) were dominated by pigments composed of chlorophylls, carotenoids, and anthocyanins (Sims & Gamon, 2002). Coincident with the magnitude of decrease in total chlorophyll content, reflectances of Cu and Zn specimens slightly increased with metal content, with the greatest increase in the Cd specimens (Fig. 9). In common to these metals, the reflectances increased the most in the visible green (B2) region, caused by chlorophyll degradation. Another notable common feature was a red edge shift to shorter wavelengths with increasing metal content, similar to Sridhar et al. (2007). No clear reflectance change was observed in the Pb specimens, as readily estimated from the total chlorophyll content data.

In the NIR (B4) and SWIR (B5 and B7) regions, reflectance change with metal content was classified into two groups, (i) Cu and Zn, and (ii) Pb and Cd (Fig. 9). Group (i) shows reflectance decrease in the three bands with increasing metal content, whereas reflectances of Group (ii)

increased. The cellular structure of leaves and water content in the tissues dominate reflectances in the NIR and SWIR regions, respectively (Grant, 1987). Deformation and collapse of mesophyll cells must have occurred in Group (i), which reduce the spongy mesophyll air volume and consequently reduce the scattering of electromagnetic (EM) waves (Grant, 1987; Knipling, 1970; Rosso et al., 2005). This is the most rational mechanism for reflectance decrease in the NIR region. Cd strongly and Pb slightly increase leaf moisture stress, which is a cause of plant dehydration. This phenomenon enlarges the reflective surface area of cells and consequently the NIR reflectance through intensification of the scattering of EM waves by the cells (Ripple, 1986). In addition, decreased water content enhances SWIR reflectance by reducing the water absorption of EM waves.

Fig. 9. Average reflectances (× symbols) measured between 60 and 80 elapsed days for each metal and content level, converted to reflectances in Landsat bands (visible B1–B3, NIR B4, and SWIR B5 and B7). Bars above and below averages indicate standard deviations.

Using the Landsat band reflectances, NDVI and VIGS were calculated, and their changes with metal content and elapsed days are compared in Fig. 10. The two VIs show opposite trends; i.e., NDVI decreases with metal content whereas VIGS increases. The NDVI changes align with total chlorophyll content, which is confirmed by an absence of NDVI change for Pb despite the

difference in metal content. On the contrary, VI change is reflected by the VIGS for the Pb specimens, and more remarkable changes are shown by the VIGS for the Cd and Zn specimens. Another noteworthy point is that VIGS magnitudes correctly followed the order of metal content for nearly all elapsed days, i.e., VIGS values increased in the order of reference, low, medium, and high contents. This feature verifies the effectiveness of using SWIR for VI.

Fig. 10. Comparison of NDVI and VIGS change with metal contents and days since sowing. As with total chlorophyll content of leaves (Fig. 8), each VI value is an average of two specimens at each metal content in soils and two reference specimens without metal addition.

4.2. Spatial distribution of metal contents

All experimental $\gamma(h)$ of three metals fit well the spherical model (Fig. 11). The $\gamma(h)$ of Cu and Pb contents showed orthogonal anisotropic behavior with the major and minor axes along E–W and N–S, respectively, whereas the $\gamma(h)$ of Zn contents was isotropic. Details of the $\gamma(h)$ model and kriging method for each metal are summarized in Table 1.

Table 1. Semivariogram models and parameters of Cu, Pb and Zn content data (OK: ordinary kriging; SK: simple kriging).

Metal	Method	Model	Nugget	Sill	Azimuth of major/ minor axes	Range (km) along major/minor axes
Cu	OK	Spherical	0.335	0.84	E–W/N–S	55/24
Pb	OK	Spherical	0.195	0.15	E–W/N–S	45/14
Zn	SK	Spherical	0.171	0.31	–	34.5

Fig. 11. Experimental semivariograms of log-transformed Cu, Pb, and Zn content data and approximation with the spherical model. Cu and Pb data are along the minor axes.

Spatial distributions of Cu and Pb contents were estimated by OK and Zn by SK (Fig. 12). It is obvious that these metal contents are strongly correlated with the geology and controlled by the faults. For the three metals, high contents were mainly in the Permian intrusions and around an E–W fault in the central area. The high Cu and Pb contents showed clear continuity along the strike of major NW–SE faults. This trend was weak for the Zn contents, which were high along the N–S direction. The similarity of the Cu and Pb content distributions suggests that these metals originated from the same source in the Permian and Triassic-Cretaceous intrusive rocks. The contrasting trend of Zn content can be explained by secondary enrichment that occurred jointly with gold placer deposits (Crow et al., 1993). Including the Permian intrusions, the high content zones mostly originated in the intrusive rocks, associated with past volcanic activities.

Fig. 12. Distributions of metal contents estimated by ordinary kriging (OK) for Cu and Pb and simple kriging (SK) for Zn. Black lines and circles here and in Fig. 14 show faults and metalliferous mineral occurrences, respectively.

To categorize content distributions (Fig. 12), C-A models of kriged metal contents were constructed, which are characterized as bi-fractal because C-A plots of all metals can be approximated by three segments with different gradients (Fig. 13). Using intersections of adjacent two segments as thresholds, the contents were separated into three categories, low, medium, and high. The C-A models are reasonable because the three categories are related to the geological units. The first segment corresponding to the low-content category is overlapped mainly by sediments and metasediments, whereas the other two segments (medium and high content categories) are in the Permian intrusion area (Fig. 14).

Fig. 13. C-A models of kriged metal contents in Fig. 12 and three segments for approximating the curves. Values at bottom indicated thresholds for three content categories, low, medium and high.

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Fig. 14. Distributions of low, medium, and high content categories defined by C-A models in Fig. 13.

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425 4.3. Relationship between VIs and control factors of vegetation stress

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Distributions of NDVI and VIGS values from the Landsat ETM+ image were overlain on the geological boundaries and faults (Fig. 15). Although the two distributions are similar, there are small differences, in that large NDVI values (> 0.5) almost completely overlap the vegetation area (Fig. 2), whereas VIGS values are more variable, even in the vegetation area, probably because of intrinsic factors other than vegetation. The factors are identified as follows.

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Fig. 15. Comparison of two maps showing (a) NDVI and (b) VIGS from Landsat ETM+ image in Fig. 2,

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superimposed on geologic boundaries and faults.

The reflectance spectra of a plant canopy has been known to be similar to that of a single leaf, but changeable by several factors such as plant tissue optical properties, canopy biophysical attributes, soil reflectances, and solar illuminations (Asner, 1998; Knipling, 1970). These factors can be related to several controls on vegetation activity, which are classified as internal factors such as leaf geometry and plant physiology, and external factors such as climatic conditions, solar illumination intensity, mineral nutrient supplies related to geology, and water supply (Bruce & Hornsby, 1987; Koide & Koike, 2012). Therefore, the influence of each factor on the reflectance spectra must be examined over the study area.

First, to examine the effect of internal factors, the NDVI and VIGS are characterized by the relationship between their statistics (averages and standard deviations) and land-cover type (Fig. 16). The two VI averages are almost identical, except that VIGS can enhance the difference between submontane forest and primary forest at low-medium altitude. From this figure, applicability of the VIGS as a VI can be confirmed in addition to the NDVI, because it satisfies the conditions that VI values should not be saturated in heavily vegetated areas and should be sensitive to land cover of green vegetation (Koide & Koike, 2012).

Fig. 16. Changes in NDVI (blue) and VIGS (red) for land-cover types, shown by averages (×) and standard deviations (bars above and below the average): (a) submontane forest; (b) primary forest at low-medium altitude; (c) secondary forest; (d) plantations; (e) paddy field; (f) bare soil; (g) urban area.

The average NDVI and VIGS were also related to elevation, slope gradient, and slope aspect, to examine the effect of the representative external factors climatic conditions and solar illumination, by selecting the three natural forest types, submontane, primary, and secondary. NDVI and VIGS show almost the same trends and values for all three types in terms of elevation (Fig. 17a); i.e., their values form gentle convex curves and have a maximum at 300 m a.s.l. This trend can be interpreted from the fact that plant formations of the Sumatra rain forest generally vary with elevation. The low elevation range below 300 m a.s.l. is occupied by mixed dipterocarp rain forests with trunk diameters > 30 cm, with 60% dominance across all plots. The dominance of the dipterocarp families decrease with elevation, but are still the most abundant in the medium elevation range 300–1,000 m a.s.l., coexisting with Fagaceae and Burseraceae (Laumonier, 1997). Despite the difference in dominance, plant formations in the low and medium elevations are traditionally grouped into the same type, primary forest. In the high elevation range over 1000 m a.s.l., submontane forest composed of Fagaceae, Lauraceae, and Myrtaceae families is dominant.

A trend in which the NDVI and VIGS increase with slope gradient (Fig. 17b) may be caused by the crown shape of plants on slopes, because that shape can enhance the apparent crown density. For detailed characterization of the effect of aspect by considering the trend of slope gradient, the gradient was separated into gentle and steep groups, 0–15° and > 15°. Except for the submontane VIGS, NDVI and VIGS values tended to be smaller on the eastern aspects (N, NE, E, and SE) than those on the western aspects (S, SW, W, and NW) (Fig. 17c), which may be caused by solar azimuth. However, changes in the NDVI and VIGS with slope gradient and aspect were small, even smaller for VIGS for all forest types. This fact signifies that these effects

on the reflectance spectra can be mitigated by the aforementioned topographic corrections, and this mitigation is more effective for the VIGS.

Fig. 17. Relationships of average NDVI and VIGS with (a) elevation, (b) slope gradient, and (c) slope aspect for three natural forest types.

Because the primary forest is the most common type, covering 54.6% of the study area, it was selected for analysis of the influence of geology on the reflectance spectra. Box plots of the NDVI and VIGS divided by the seven geological units (see Fig. 3 for their distributions) reveal that change of VIGS averages was less than that of NDVI. The VIGS averages for sedimentary and volcanic units (a, b, c, and e) were nearly identical and slightly smaller than the values for intrusive rocks (units d, f, and g) (Fig. 18a). The NDVI averages were more variable and inconsistent with the geological units. Therefore, the effect of geological unit on VI was more apparent in the only VNIR-based VI. However, this might conceal the effect of metal content in the soils. VIGS can avoid this risk.

Permeability of the top layer (Fig. 4) is also a possible external factor of VI. The NDVI and VIGS in the primary forest show a similar trend, in which their averages increase with decreasing permeability (Fig. 18b: the c aquifer type has the lowest permeability). Although the differences in averages among the three categories were small, the change was smaller in VIGS than NDVI, as with the geological unit result.

Fig. 18. Relationships of NDVI and VIGS of primary forest with (a) geological units and (b) three categories of aquifer productivity, shown as box plots.

All the above external factors were confirmed to affect the VIs. Because the difference of VI values affected by the factors was small, a suitable categorization is necessary to minimize the effect of those factors and emphasize the effect of metal content, as examined in the next section.

4.4. Correlation of VIs with metal contents

To accurately evaluate the effect of soil metal content on VI by comparing NDVI and VIGS, an appropriate domain for the evaluation and comparison was defined from the aforementioned results of external factors elevation, slope gradient, slope aspect, and aquifer productivity. The factor geological unit was excluded here, because metal distributions were found to be strongly related with those units. Vegetation structures such as canopy heights and shapes were not considered because of an insufficiency of their data. Stability of VI values and the following featured parts of the factors were assumed to define the conditions for establishing the domain. One featured part is the area higher than 300 m a.s.l. and occupied by the primary forest, because NDVI and VIGS averages in that area were about the same, with patterns similar to those at low elevations and for the other forest types. This area was further limited to regions without exploitable groundwater, which is the most widespread (64.2 % of the study area) among the categories of aquifer productivity (Fig. 4). Finally, four subdomains were defined from the two categories of slope gradient and aspect (Table 2). The total area of the subdomain is 836.2 km², which is 33.4 % of the study area.

Table 2. Conditions of VI control factors for selecting domain to correlate VI values with soil metal content in study area.

Plants formation	Elevation	Aquifer	Slope gradient	Slope aspect
Primary forest at low–medium altitude	>300 m a.s.l.	Regions without exploitable groundwater	0–15°	N, NE, E, and SE
			>15°	S, SW, W, and NW

Using the corrected Landsat ETM+ reflectances in the selected domain, average reflectances in the six bands were correlated with the three metal contents (low, medium, and high) in Fig. 14 (Table 3). Low Pb contents were not included because of a lack of data.

Although the differences were small among the three contents of the three metals, reflectance increases with metal content generally appeared in the visible region, particularly in the visible green (B2) region, which is sensitive to chlorophyll conditions. Additionally, the increase of reflectance in the SWIR region (B4, B5, and B7) concurs with the experimental result that suggested plant water stress from metal absorption. It is common for water stress as a secondary effect when a metal alters mineral nutrition, which may affect the photosynthesis system of plants after long exposure times (Poschenrieder & Barceló, 1999).

Table 3. Average reflectances of Landsat ETM+ bands after atmospheric and topographic corrections (B1–B5 and B7) and area for each metal content category. Details of the low, medium, and high categories are shown in Figs. 13 and 14. The selected area for this reflectance characterization is based on the domain classification listed in Table 2.

Slope gradient	Slope aspect		Eastern aspect (N, NE, SE, SE)							Western aspect (S, SW, W, and NW)						
	Metal	Category	B1	B2	B3	B4	B5	B7	Area (km ²)	B1	B2	B3	B4	B5	B7	Area (km ²)
0–15°	Cu	Low	0.008	0.025	0.016	0.276	0.113	0.042	36.14	0.008	0.024	0.015	0.270	0.111	0.041	85.93
		Medium	0.008	0.025	0.015	0.276	0.114	0.042	114.31	0.008	0.024	0.015	0.276	0.113	0.042	122.96
		High	0.010	0.026	0.016	0.283	0.117	0.044	49.00	0.009	0.026	0.016	0.283	0.116	0.043	67.57
	Pb	Medium	0.008	0.025	0.016	0.277	0.114	0.043	110.41	0.008	0.024	0.015	0.274	0.113	0.042	175.03
		High	0.009	0.025	0.016	0.279	0.115	0.043	80.93	0.009	0.025	0.016	0.281	0.115	0.043	85.33
	Zn	Low	0.009	0.025	0.016	0.280	0.116	0.044	22.91	0.008	0.025	0.016	0.277	0.114	0.043	46.41
		Medium	0.008	0.025	0.015	0.276	0.114	0.042	142.32	0.008	0.024	0.015	0.273	0.112	0.042	194.03
		High	0.010	0.026	0.016	0.286	0.116	0.043	34.22	0.009	0.026	0.016	0.290	0.116	0.044	36.02
>15°	Cu	Low	0.008	0.025	0.016	0.280	0.114	0.042	24.97	0.007	0.024	0.015	0.275	0.111	0.041	70.27
		Medium	0.008	0.024	0.015	0.279	0.114	0.042	70.46	0.007	0.023	0.015	0.273	0.110	0.041	106.39
		High	0.009	0.025	0.016	0.284	0.116	0.043	37.57	0.008	0.024	0.015	0.280	0.114	0.042	50.61
	Pb	Medium	0.008	0.025	0.016	0.281	0.115	0.043	77.56	0.007	0.023	0.015	0.275	0.111	0.041	156.35
		High	0.009	0.025	0.015	0.280	0.114	0.042	50.36	0.008	0.024	0.015	0.277	0.112	0.042	60.55
	Zn	Low	0.008	0.024	0.016	0.277	0.114	0.042	14.77	0.007	0.024	0.015	0.276	0.112	0.041	40.26
		Medium	0.008	0.025	0.015	0.279	0.114	0.042	94.46	0.007	0.023	0.015	0.273	0.111	0.041	162.27
		High	0.010	0.026	0.016	0.289	0.115	0.043	23.78	0.009	0.025	0.015	0.290	0.114	0.042	24.73

Finally the NDVI and VIGS averages for low, medium, and high metal contents were compared for the selected area using the conditions in Table 2. As a result, the superiority of VIGS is confirmed from Fig. 19, because the VIGS of every metal increased appropriately with metal content in all four classifications. Both the NDVI and VIGS values are the smallest for the

low metal contents, which may be due to a geological control because the low categories are mostly overlain by the sedimentary rocks. When focusing only on the medium and high metal contents, the NDVI values decrease all classifications of Cu, two of Pb, and two of Zn. This part of the NDVI results and the increase of VIGS with metal content agrees with the result of laboratory experiments. Additionally, VI variation with metal content is more conspicuous for VIGS than NDVI, for all metals. It is noteworthy that VIGS can discriminate high and medium contents more clearly than the NDVI. However, the present analysis was based on only the best quality Landsat image for the study area. More images with different seasons will be necessary to generalize the superiority of VIGS.

Fig. 19. Comparison of average NDVI and VIGS for each metal content category, low (L), medium (M) and high (H) in the selected area covered by the primary forest, higher than 300 m a.s.l. and without exploitable groundwater. Metals are (a) Cu, (b) Pb, and (c) Zn. The area is further separated into four domains by slope gradients (1) 0–15° and (2) >15°, and aspect (3) dip toward east side (N, NE, E, and SE) and (4) west side (S, SW, W, and NE). Combinations of gradient and aspect in the four domains are (I) 1 and 3, (II) 1 and 4, (III) 2 and 3, and (IV) 2 and 4, respectively.

5. Discussion

5.1. Evaluating metal stress in plants

Vegetation stress is known to be caused by absorption of any metal type, which manifests as physiological declines in growth rate, photosynthetic activity, and chlorophyll content. Physiological declines are also caused by many other factors such as salinity, drought, disease, nutrient deficiency, and senescence (Boluda et al., 1993; Chapin, 1991; Woolhouse, 1983). However, the magnitude of stress, which manifests as change in reflectance spectra, varies with metal and vegetation type (Karr & Mouat, 1990; Horler et al., 1980; Slonecker, 2011).

Vegetation type varied between the laboratory experiment and case study; i.e., the Japanese mustard spinach and tropical forest mainly composed the primary forest. However, a common result was obtained in that vegetation stress appeared in the reflectance spectra over a wide wavelength range, from the VNIR to SWIR regions. A noteworthy feature found by the experiment is that there were two change patterns in the NIR reflectance spectra (the reflectance decrease in Group (i) and increase in Group (ii), see Section 4.1), associated with the metal contents. These patterns are similar to the initial stage, Group (ii), and the advanced stage, Group (i), of plant senescence (Grant, 1987).

In addition to the above chloroplast-related phenomena, the effect of metal absorption imposes the water stress and change in the SWIR reflectance spectra. To confirm this stress, an inner leaf structure was observed using a scanning electron microscope (SEM). The most remarkable feature of a leaf with high Cd content is stomatal closure (Fig. 20a), which may be caused by the hydropassive or hydroactive mechanism that induces turgor pressure change or abscisic acid signaling, respectively (Poschenrieder & Barceló, 1999). These mechanisms reduce photosynthesis activity and consequently decrease transpiration and water-use efficiency of the

plants (Osakabe et al., 2014). The closure did not occur in the reference plant, which had no addition of metal to the soil (Fig. 20b).

Fig. 20. SEM photomicrographs showing the effect of metal absorption on stomatal closure in: (a) leaf with high Cd content in soil; (b) reference leaf without addition of metal, with open stomata. These leaf samples were prepared by a simple air-drying method.

Based on these results, it is concluded that the use of VNIR only is inadequate to accurately detect vegetation stress by metal absorption, because it does not address water stress whose effect appeared in the SWIR region. VIGS considers both chloroplast-related and water stresses. Another point is that the NDVI tended to decrease while VIGS increased with metal content. The essential function of the VI is to enhance the difference in vegetation activity, which is associated with plant type, amount, and condition, and minimize the effects of solar irradiance and soil background (Jackson & Huete, 1991). Because non-vegetation pixels typically have small VI values, values actually related to vegetation anomalies are desired to be large so they can easily be distinguished from non-vegetation values. The VIGS can satisfy this requirement.

5.2. Applicability of VIGS to mineral exploration

Pixel-by-pixel comparison between VIs and metal content generally yields weak correlation, because metal content at each pixel results from interpolation of irregularly spaced sample data in the drainage system (e.g., Carranza & Hale, 2001). Vegetation stress induced by both edaphic and external factors also makes stress assessment difficult (Section 4.3). To improve the VIGS applicability to mineral exploration by a method other than pixel-to-pixel correlation, the following method is proposed.

Because the VIGS data were transformed into a Gaussian distribution, those exceeding the mean plus one standard deviation (1.0σ) were regarded as anomalous, related to metal enrichment based on the results above. Thus, 490,990 pixels (17.7% of the total) satisfying this condition were extracted, which were scattered across the image. To characterize the anomaly distribution by converting the scatter to a simple pattern, a point density map of anomalous pixels was constructed. After gridding the study area with 1×1 km grid size, this density was defined by the number of anomalous pixels within each grid cell.

Finally, the C-A model was applied to the density of VIGS anomalous values, to clearly distinguish large-value zones (Fig. 21a) in which the anomaly densities were categorized as I: low, II: medium, and III: high. High-density areas are mainly covered by the primary forest (Fig. 6). Furthermore, the spatial distribution of Cu contents classified as low, medium, and high was correlated with the density of VIGS anomalies (Fig. 21a). The reason for selecting Cu is that it is the major metal in the study area for characterizing mineralization, with twice the average for the Sumatra region. In contrast, the Pb and Zn averages are nearly identical to that of the region (British Geological Survey, 2007). Obviously, the high Cu-content data are in the high-density category in the northern half of the study area (marked by “A” in Fig. 21a). This relationship did

not appear in the Ngaol region, where high Cu-content data are within a low-density category. This may be because that region is covered by the secondary forest and paddy fields (Fig. 6) which generally have small VIGS values. Inconsistency in the other regions was mainly caused by the submontane forest, which also tends to have small VIGS values.

Fig. 21. Spatial characterization of density of VIGS anomaly values (greater than mean + standard deviation) with metal content. (a) Distribution of (I) low, (II) medium, and (III) high density categories of VIGS anomaly values from the C-A model, overlaid by Cu content data classified as low (1–19.8 ppm), medium (19.8–36.6 ppm), and high (36.6–70.1 ppm). The content classifications follow the C-A model in Fig. 14. (b) Relationships of Cu, Pb, and Zn contents with VIGS categories, shown by box plots.

VIGS validity can be confirmed from another aspect of geologic correspondence. High densities are found in the Tertiary intrusive rocks (Fig. 3) as shown by the “B” in Fig. 21a, whereas there are low densities in the Jurassic–Cretaceous metasedimentary rocks. This is a reasonable tendency, because metal contents are generally higher in intrusive or volcanic units than sedimentary and metasedimentary units. The C-A model was also used to correlate the values with the metal content data in detail. This correlation focused on the area covered by the primary forest, where 131 content data were sampled, because the effect of metal soil contamination has accumulated in this natural land cover as mentioned above. As a result, average metal contents increase with category, for all three metals (Fig. 21b); large VIGS values are associated with high metal contents, and small values with low contents. This trend confirms the satisfactory VIGS correspondence to metal soil contamination and the applicability of VIGS to mineral exploration in areas with thick vegetation, using the C–A model and area segmentation with control factors of VI.

6. Conclusions

This paper proposed the new vegetation index VIGS, combining reflectances in the VNIR and SWIR regions, for detecting vegetation stress caused by metal soil contamination in densely vegetated and mineralized areas. The effectiveness of VIGS was examined through a set of laboratory experiments and Landsat image analysis of a Cu mineralized area in Jambi, central Sumatra. The main results are as follows.

- In one experimental result using specimens of Japanese mustard spinach, symptoms of vegetation stress caused by metal absorption clearly appeared in the low rate of plant growth

and chlorosis of leaves, for all four metals (Cu, Pb, Zn, and Cd). These symptoms were exacerbated by increasing metal contents.

- In consonance with the magnitude of decrease in total chlorophyll content of the specimens, reflectances in the visible region increased with metal content. In the NIR and SWIR regions, two patterns of reflectance spectra change were clarified, depending on whether the change was caused by cell deformation or increase in reflective surface area of the cells. The changes in reflectance spectra were more clearly revealed by the VIGS than NDVI, because the former can consider both chloroplast-related and water stresses, which appeared in the VNIR and SWIR regions, respectively.
- Although vegetation type varied between the laboratory experiment and the case study area (mainly covered by the primary forest type), vegetation stresses from three metals (Cu, Pb, and Zn) in the soils frequently appeared in the reflectance spectra, in both the VNIR and SWIR regions. By correlating metal content categories in the top layer, which were prepared by kriging interpolation and the C-A model and using NDVI and VIGS values, VIGS superiority was confirmed. This was because VI change with metal content was more discriminable by VIGS than NDVI, for all metals.
- To simplify spatially scattered VIGS values, a method for characterizing VIGS anomaly values was proposed. This method used the C-A model of the density of points whose VIGS values were greater than the mean plus standard deviation. High-density zones were generally correspondent with those of high metal content, which verifies VIGS applicability to mineral exploration in areas thickly covered by vegetation.
- A limitation of this study is that the analysis was based on only the best quality Landsat image for the study area. More images with different seasons and a consideration of

vegetation structures such as canopy heights and shapes will be necessary to generalize the superiority of VIGS in future work.

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Figure 1. Growth of Japanese mustard spinach (*Brassica rapa* var. *perviridis*) in metal-contaminated and normal soils in an experimental room. Height of a pot was 10 cm.

Figure 2. Location of study area in central Sumatra, sampling sites of geochemical data, and mineral occurrences superimposed on subscene of true-color composited Landsat ETM+ image. This image, acquired on 15 August 2002, was used for VI analyses.

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