Comparative Analysis of the Multispectral Vegetation Indices and the Radar Vegetation Index

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Abstract

RVI (Radar Vegetation Index) has shown some promise in the vegetation fields, but its relationship with MVI (Multispectral Vegetation Index) is not known in the context of various land covers. Presented herein is a comparative analysis of the MVI values derived from the LANDSAT-8 and RVI values originating from the RADARSAT-2 quad-polarimetric SAR (Synthetic Aperture Radar) data. Among the various multispectral vegetation indices, NDVI (Normalized Difference Vegetation Index) and SAVI (Soil Adjusted Vegetation Index) were used for comparison with RVI. Four land covers (urban, forest, water, and paddy field) were compared, and the patterns were investigated. The experiment results demonstrated that the RVI patterns of the four land covers are very similar to those of NDVI and SAVI. Thus, during bad weather conditions and at night, the RVI data could serve as an alternative to the MVI data in various application fields.

Keywords : Multispectral Vegetation Index, Radar Vegetation Index, Quad-polarimetric SAR, Comparative Analysis

1. Introduction

Lately, the trend in the area of spaceborne satellites has been satellite constellations. A satellite constellation is composed of various satellites, including the electro-optical and SAR satellites. Thus, more frequently, data acquisition is possible on the same AOIs (Areas Of Interest) (McNairn et al., 2009). Likewise, the KOMPSAT constellation consists of the KOMPSAT-2 & 3 (electro-optical), KOMPSAT-5 (SAR), and KOMPSAT-3A (electro-optical & thermal IR) satellites. Accordingly, recent researches report that the integration or fusion of optical and SAR data might be beneficial due to their distinct features (Zhou et al., 2012) because optical data allows the measurement of the reflectance of the land-covers and SAR data deliver useful geometric information without affected by weather conditions (Vaglio Laurin et al., 2013). In addition, multispectral data provide information on the chemical composition vegetation while the SAR scattering process is influenced by the structural elements of the vegetation. Therefore, comparative study of these data could be effective for various land-cover studies.

Among the various application fields of remote sensing, vegetation indices derived from multispectral satellite data are the primary sources of information for operational vegetation monitoring (Baig et al., 2014; Zhou et al., 2014). MVI is a key information source about vegetation
conditions and is very useful for the environmental issues. The use of MVI has been proposed for providing the vegetation conditions from different portions of the multispectral spectrum. Among the various MVIs, NDVI is a very popular and standard index (Gao, 1996; Rouse et al., 1974). It takes normalization forms that are the bases of most current indices, and is obtained by dividing the difference by the sum of the NIR (Near-InfraRed) and red reflectances (Jones and Vaughan, 2010). NDVI is increasingly being used for the indirect study of biophysical plant canopy properties (Teillet et al., 1997). It has some problems, however, due to external-factor effects such as soil background variations (Qi et al., 1994). To reduce the soil background effect, Huete (1988) proposed the use of soil adjustment factor $L$ to account for the first-order soil background variation. This index is SAVI, and adjustment factor $L$ varies with the vegetation density.

With regard to radar remote sensing, Kim and Van Zyl (2009) introduced an index for volume scattering media, such as vegetation canopies: RVI. They evaluated RVI by modeling a vegetation canopy as a collection of randomly oriented cylinders with different lengths and diameters. RVI has been proposed as a method for monitoring the level of vegetation growth, particularly when time series data are available (Kim et al., 2012). Also, RVI would be less sensitive to both the incident angle and the changes in the environmental conditions. Recently, some researches demonstrated that RVI is a robust index for characterizing vegetation canopies and for the retrieval of the biophysical parameters of crops (Kim et al., 2014; Kim et al., 2012). Despite the good results of RVI, it has to be considered that the backscatter recorded from a vegetated surface is a function of several physical properties: vegetation type, surface roughness, soil moisture, vegetation structure, and plant moisture content as well as sensor configuration (Koppe et al., 2013). Also, most of the RVI researches were conducted using a scatterometer rather than satellite sensors, and as such, there can be some uncertainties in the applicability of satellite-based RVI.

As mentioned earlier, two main sensor-type indices have been developed to estimate vegetation conditions. While the two approaches are quite complementary, the relationship between MVI and RVI in the context of various land covers is not known. Also, due to the limited multi-sensor data, their relationship remains ambiguous. Additionally, the apparent similarity of seasonal trends in SAR signatures and MVI values does not imply a real relationship but an indirect or superficial relationship. One reason for the ambiguity using SAR sensors was the low spatial resolution but the latest C-band RADARSAT-2 can achieve the required high spatial resolution. This study did not aim to find accurate models to link MVIs to RVI data but to provide a base study comparing satellite-based C-band RVI with MVI. Therefore, the objectives of this paper are as follows: (1) to provide MVI and RVI data for comparison; (2) to explore the MVI and RVI data patterns in the four land covers; and (3) to investigate the possibility of using the RVI data as an alternative to the MVI data. Towards these ends, the MVI data obtained from the LANDSAT-8 satellite and the RVI data obtained from the C-band quad-polarimetric RADARSAT-2 satellite, were compared. This paper is organized as follows. In section 2, the MVIs are briefly introduced, and in section 3, RVI is explained for comparative analysis. In section 4, the analysis results of four land covers are presented, and the patterns are discussed. Finally, conclusions are drawn in section 5.

2. Multispectral Vegetation Indices

The MVIs are usually dimensionless measures derived from radiometric data that are primarily used to indicate the amount of green vegetation. In this section, NDVI and SAVI are reviewed, and their characteristics are concisely discussed. Ideally, satellite-based MVIs should always be calculated based on the corrected surface reflectance. Thus, to calculate the vegetation index, the digital numbers of the data were converted to surface reflectance using atmospheric correction module. In this study, to reduce the atmospheric effects and extract surface reflectance, the model QUAC (QUick Atmospheric Correction) was used for LANDSAT-8 imagery (Bernstein et al., 2012). QUAC code performs atmospheric correction on multi- and hyperspectral imagery spanning all or part of the visible and near infrared-short wave infrared spectral range.
This is based on that empirical finding which the average reflectance of diverse material spectra is essentially scene-independent. QUAC depends less on the atmospheric parameters and relatively easy to achieve the corrected surface reflectances.

2.1 Normalized difference vegetation index

One important method of extracting biophysical characteristics from satellite sensors involves the use of vegetation indices. NDVI, which is the difference between the NIR and red bands divided by their sum, has been the most widely used index in various applications. NDVI (Rouse et al., 1974) is defined as

\[ NDVI = \frac{\rho_{\text{NIR}} - \rho_{\text{RED}}}{\rho_{\text{NIR}} + \rho_{\text{RED}}} \] (1)

where \( \rho_{\text{NIR}} \) and \( \rho_{\text{RED}} \) are the reflectance values of the NIR and red bands, respectively.

NDVI is a basis form for most of the current indices applicable to both reflectance and radiance. Note that the sum of the NIR and red bands represents the average reflectance in this wavelength range. Division by this factor reduces the effect of non-uniform illumination and thus helps make for better comparability of the vegetation index across an image (Jones and Vaughan, 2010).

2.2 Soil-adjusted vegetation index

Huete (1988) found that the vegetation biophysical isolines in an NIR-red reflectance space are neither parallel to a soil line nor converge at the origin. SAVI was subsequently developed based on this general vegetation biophysical isoline behavior. Also, to reduce the soil background effect, SAVI uses soil adjustment factor \( L \) to account for the first-order soil background variation. SAVI (Huete, 1988) is defined as

\[ SAVI = \frac{\rho_{\text{NIR}} - \rho_{\text{RED}}}{(\rho_{\text{NIR}} + \rho_{\text{RED}} + L)} \] (2)

where \( \rho_{\text{NIR}} \) and \( \rho_{\text{RED}} \) are the reflectance values of the NIR and red bands, respectively, and \( L \) is the soil adjustment factor. In this study, \( L=0.5 \) was used.

SAVI minimizes the soil brightness influences, which are prominent in ratio-based vegetation indices such as NDVI (Jiang et al., 2006). Huete (1988) suggested that SAVI with \( L=0.5 \) successfully minimized the effect of soil variations in green vegetation compared to NDVI.

3. Radar Vegetation Index

In the microwave region of the electromagnetic spectrum, the intensity of the incident energy scattered by vegetation is primarily a function of the canopy architectures, such as the size, shape, and orientation of the canopy components and the dielectric properties. Also, the backscattered microwave is affected by the sensor configuration, such as the frequency, polarization, and incidence angle (Koppe et al., 2013).

To apply the index in various fields, an index should attempt to minimize the impact of the crop structure, incidence angle, and environmental conditions. RVI would be less sensitive to both the incidence angle and the changes in the environmental conditions. This polarimetric index is most suitable for monitoring the level of growth using time series observations. Few studies, however, have attempted to establish a relationship between RVI and the biophysical parameters (Kim et al., 2012). RVI generally ranges between 0 and 1 and is a measure of the randomness of the scattering. RVI is near zero for a smooth bare surface, and increases as a vegetation grows. RVI can only be calculated using the quad-polarimetric SAR or scatterometer and RVI (Kim and Van Zyl, 2009) is given by

\[ RVI = \frac{8\sigma_{\text{HH}}}{\sigma_{\text{HH}} + 2\sigma_{\text{HV}} + \sigma_{\text{VV}}} \] (3)

where \( \sigma_{\text{HH}} \) and \( \sigma_{\text{VV}} \) are the co-polarization backscattering cross-sections, and \( \sigma_{\text{HV}} \) is the cross-polarization backscattering cross-section represented in power units.

Speckle noise is an inherent consequence of the coherent nature of radar. It arises due to electromagnetic interactions with multiple scattering centers within a single resolution element of the radar rather than actual variations. In this study, the 7x7 Enhanced Lee filter was used to reduce the speckle noise (Lopes et al., 1990).
4. Comparative Analysis

The flowchart of this study is shown in Fig. 1. First, geocoding of the LANDSAT-8 and RADARSAT-2 was conducted, and co-registration was performed. Thereafter, surface reflectance and sigma-naught data were generated, and the vegetation indices were calculated. Finally, four land covers were selected, and comparative analysis was conducted.

4.1 Test area

The study area is in Dangjin city. The test site mainly covers a large number of agricultural fields, as well as several forested areas, urban and water body. The selected test area shown in Fig. 2 was the LANDSAT-8 image and the RADARSAT-2 data are shown in Fig. 3. The RADARSAT-2 data were acquired on May 6, 2013, and the LANDSAT-8 data were taken on May 13, 2013. Thus, the timelag between these data is very short. The timelag is the most important point in the field of multi-sensory applications. The NDVI, SAVI, and RVI results are shown in Fig. 4, 5, and 6, respectively. In all the three indices, the forest areas show high values all over the index. In NDVI and SAVI, high values mean that the vegetation has high vegetation vitality. Also, high RVI values mean that there is high volume scattering. The darker areas in the image are mostly agricultural fields and bodies of water.
4.2 Results and analysis

4.2.1 Comparative analysis
The main land covers of the test area were urban areas, forests, bodies of water, and paddy fields. In each land cover, four AOIs were selected, and 1,200 pixels were picked up by visual inspection. Selected AOIs can be seen in Fig. 2. In the four AOIs, the mean values and standard deviation values were calculated and Fig. 7 shows the mean values of the four land covers. It can be seen in such figure that the NDVI, SAVI, and RVI patterns are very similar for all the four land covers. In the MVIs, the forest areas showed the highest values because of the high NIR reflectance values. Also, the bodies of water showed the lowest values because of high red reflectance and low NIR reflectance values. The paddy fields and urban area land covers showed similar values. This implies that there are no live green plants. In RVI, the forests indicated the highest values because of the volume scattering. The bodies of water showed the lowest values due to the surface scattering or odd-bounce scattering. The urban areas showed the slightly higher values than water bodies due to the double scattering. Also, the paddy fields had similar values or slightly higher values than water bodies. This is because the paddy fields were flooded to irrigate the fields. Korean farming system is irrigated lowland rice. Thus, the scattering characteristic of both the bodies of water and the paddy fields was surface scattering. Fig. 8 shows the standard deviation values of the four land covers. Predictably, the standard deviation values of RVI were much higher than those of MVI. Basically, this is because there was inherent speckle noise in the SAR data. In addition, the standard deviation of the urban area was the highest. This is because the selected AOI of the urban area was a complex shape and this is also due to the vertical structure of buildings. In other words, the selected urban features were not homogeneous land cover.
Fig. 9 and Fig. 10 show the all pixels of extracted four land-covers. As you can see, forest covers are well separated from other AOIs. In case of NDVI, more than 0.6 are the forest areas and more than 1.0 are the forest areas in SAVI data. Also, the bodies of water are well distinguished from others AOI. Less than 0.1 NDVI and less than 0.2 SAVI dataset can be classified into bodies of water. However, it is difficult to discern the urban and paddy fields. In the NDVI, the urban areas are distributed from 0.1 to 0.25 and also ranged from 0.2 to 0.5 in the SAVI data. In the class of paddy fields, NDVI are ranged from 0.25 to 0.4 and distributed from 0.3 to 0.7 in the SAVI data. This implies that the separability between urban and paddy fields is very low, but this is natural because the MVIs and RVI were developed to enhance the vegetation features. In Fig. 9 and Fig. 10, the RVI data still showed very high speckle noise level. Thus, to compare the RVI with MVIs, we have applied the second speckle filter to reduce the noise level. In the next subsection, this study focuses on the relation between RVI and SAVI for simple comparisons that directly estimate the RVI from the SAVI data.

### 4.2.2 Error analysis and validation

As mentioned before, after first comparison, we found that main error source is the speckle noise. Although Enhanced Lee filter was applied, RVI data still have some speckle noise. Thus, to reduce the speckle noise, second Enhanced Lee filter applied and the filter size ranged from 3x3 to 11x11. Accordingly, six RVI and SAVI data were compared. For quantitative analysis, correlation coefficient, R-square and RMSE (Root Mean Squared Error) were used and these are shown in Table 1. Correlation coefficient is a measure of the strength of the linear relationship between two variables and R-squared is a statistical measure of how close the data are to the fitted regression line. Also, the RMSE is a measure of the difference between values predicted by a linear regression model. As increased the filter size, the RVI and SAVI show better relationship in the all statistics. In other words, as reduced speckle noise, the linearity of these variables was increased. Finally, the total pixels of the data were compared and Fig. 11 shows the density plot of SAVI and filtered RVI (11x11). The density plot function produces a two dimensional plot of two variables where color is used to provide information about the frequency with respect to the two variables. Thus, the higher value implies that the located point frequency is very high.

<table>
<thead>
<tr>
<th>Data Type</th>
<th>Correlation Coefficient</th>
<th>R²</th>
<th>RMSE</th>
</tr>
</thead>
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<tr>
<td>First RVI</td>
<td>0.5957</td>
<td>0.3548</td>
<td>0.2328</td>
</tr>
<tr>
<td>Filtered RVI (3x3)</td>
<td>0.7052</td>
<td>0.4972</td>
<td>0.1724</td>
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<tr>
<td>Filtered RVI (5x5)</td>
<td>0.7292</td>
<td>0.5317</td>
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<tr>
<td>Filtered RVI (7x7)</td>
<td>0.7434</td>
<td>0.5526</td>
<td>0.1494</td>
</tr>
<tr>
<td>Filtered RVI (9x9)</td>
<td>0.7532</td>
<td>0.5673</td>
<td>0.1422</td>
</tr>
<tr>
<td>Filtered RVI (11x11)</td>
<td>0.7585</td>
<td>0.5753</td>
<td>0.1371</td>
</tr>
</tbody>
</table>

Fig. 10. SAVI and RVI plot of four AOIs

Fig. 11. SAVI and filtered RVI (11x11) density plot of total pixels
As can be seen in the figure, high linearity between SAVI and RVI was found and Table 1 also approves the results. Increased filter size causes the loss of spatial resolution, but lead to high correlation between RVI and SAVI data. In the filtered RVI (11x11), the correlation coefficient is close to 0.8 and R-square value is almost 0.6. This indicates that the RVI data of C-band SAR sensor can effectively monitor the trend of surface and it approves the conclusion drawn by Kim et al. (2012). In addition to all pixel comparison, this study compared uniformly selected samples. Sample size was range from 50 to 400 pixels. Table 2 shows the statistics of extracted samples. As can be seen in the Table 2, the correlation coefficients ranged from around 0.8 and R-square values distributed from around 0.7. Also, the RMSE was close to 0.1. In the case of R-square, it means that the almost 70% of the total variation in RVI can be explained by the linear relationship between SAVI and RVI. However, the other almost 30% of the total variation in RVI remains unexplained. Lastly, the RVI and MVI were developed to enhance the vegetation vitality; thus, we compared the vegetation class of RVI and SAVI data. To extract the vegetation land-covers, mean value of forest AOI was used. By thresholding the data, we have extracted the forest class and the density plot was shown in Fig. 13. As can be seen in the figure, point density is very high in the vicinity of near 1.3 SAVI and 0.9 RVI. In other words, this implies that there is low dispersion between forest class of RVI and SAVI data. Therefore, we conclude that the RVI could be an effective alternative of MVI.

Fig. 12. SAVI and RVI plot of randomly samples
5. Conclusions

It is important to determine the relationship among the complementary data obtained from SAR and multispectral satellites. For this reason, in this study, to determine the relationship between the MVI and RVI, a comparative analysis was conducted to find the patterns in four land covers. In the experiment results using the LANDSAT-8 and RADARSAT-2 data, the RVI pattern was very similar to the MVI pattern. Thus, at night and during bad weather conditions, RVI could be an alternative of MVI but further studies are required for assessing its applicability in various land-covers. In the future, our research will focus on more detailed comparison of each land-cover. Such research will increase our understanding of multi-sensor remote sensing and will lead to more effective method in vegetation fields.

Acknowledgements

This research was supported by an NRF (National Research Foundation) grant funded by the South Korean government (NRF-2014R1A1A1001995).

References


