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Land-cover mixing and spectral vegetation indices

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Vegetation indices have been widely used as indicators of seasonal and inter-annual variations in vegetation caused by either human activities or climate, with the overall goal of observing and documenting changes in the Earth system. While existing satellite remote sensing systems, such as NASA's Multi-angle Imaging SpectroRadiometer (MISR) and Moderate Resolution Imaging Spectroradiometer (MODIS), are providing improved vegetation index data products through correcting for the distortions in surface reflectance caused by atmospheric particles as well as ground covers below vegetation canopy, the impact of land-cover mixing on vegetation indices has not been fully addressed. In this study, based on real image spectral samples for two-component mixtures of forest and common nonforest land-cover types directly extracted from a 1.1 km MISR image by referencing a 30 m land-cover classification, the effect of land-cover mixing on the Normalized Difference Vegetation Index (NDVI) and the Enhanced Vegetation Index (EVI) has been quantitatively evaluated. When the areal fraction of forest was lower than 80%, both NDVI and EVI varied greatly with mixed land-cover types, although EVI varied less than NDVI. Such a phenomenon can cause errors in applications based on use of these vegetation indices. This study suggests that methods that reduce land-cover mixing effects should be introduced when developing new spectral vegetation indices.

1. Introduction

Vegetation indices derived from satellite remotely sensed data are related to the amount of vegetation on the ground in a pixel area (NASA 2003). They have been widely utilized to study the properties and dynamics of terrestrial ecosystems and other vegetation-related environmental issues in the global change research community (Foody and Curran 1994, Goetz 1997, Justice *et al.* 1998, Ferreira *et al.* 2003). For example, carbon cycle research is applying them in inferring Leaf Area Index (LAI), percent green cover, Fraction of Photosynthetically Active Radiation (FPAR), biomass, and evidencing carbon sinks in the northern hemisphere forests (Sellers *et al.* 1994, DeFries *et al.* 1999, Myneni *et al.* 2001); climate change research is using them to identify the effects of global warming on vegetation and correlating vegetation greenness levels with regional climate variability (Lim and Kafatos 2002, Boelman *et al.* 2003). Undoubtedly, these applications will be affected by the accuracy of vegetation indices in representing the real amount of vegetation.

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Typically, vegetation indices are some functions of the reflectance in the visible and reflective infrared wavelengths (Tucker 1979). Many factors, such as atmospheric condition, ground cover underneath vegetation canopy, illumination and observation geometry, and moisture condition in the ground soil, influence the reflected radiation in these wavelengths and, in turn, the accuracy in vegetation indices (Huete *et al.* 1985, Chen *et al.* 2004). In the past decades, great efforts in vegetation indices research have been focused on correcting for the distortions caused by atmospheric particles, under-canopy covers, and soil backgrounds (Elvidge and Lyon 1985, Huete *et al.* 1985, Huete 1988, Qi *et al.* 1994), while studies in spectral mixing have been largely focused on developing linear or nonlinear spectral mixing models for the sole purpose of resolving areal fractions of component land-cover types (Adams *et al.* 1986, Borel and Gerstl 1994, Hall *et al.* 1995, Ray and Murray 1996, Roberts *et al.* 1998, 2002). Little attention has been paid to the potential impact of land-cover mixing on vegetation indices. Because the number of mixing pixels in a satellite remotely sensed imagery can be very large (Crapper 1984, Foody and Curran 1994) and the mixed land-cover types may be of different varieties, this issue is very important, especially for coarse spatial resolution satellite remote sensing, which is mainly designed for global change research.

In this Letter, using land-cover mixtures of forest and several common nonforest land-cover types directly extracted from MISR (Multi-angle Imaging Spectroradiometer) imagery, the effect of land-cover mixing on vegetation indices has been quantitatively evaluated based on the most widely used vegetation indices—the Normalized Difference Vegetation Index (NDVI) and the Enhanced Vegetation Index (EVI).

2. Study area and data

The study area is located in the southern Maryland in the eastern United States temperate ecosystem region, and its total extent is around 3146 km^2 (figure 1). Various common land-cover types, such as forest, grassland, cropland, water, urban and residential area, are extensively distributed in this area.

The basic data used in this study include: (1) one satellite remotely sensed MISR image acquired at 1.1 km spatial resolution; (2) one land-cover classification image at 30 m spatial resolution. The MISR image was collected at the nadir viewing position on 6 September 2002, including four spectral bands at 446.4 nm (Blue), 557.5 nm (Green), 671.7 nm (Red) and 866.4 nm (Near-infrared) wavelengths. The terrain effect on MISR radiances was corrected by NASA Langley Atmospheric Sciences Data Center. All pixel values were transformed to top of atmosphere (TOA) reflectance by applying the conversion factors included in the original image files. As the final step of data pre-processing, MISR TOA reflectance was converted into surface reflectance using the method specified by Richards and Jia (1999).

The 30 m spatial resolution classified image was produced by combining the visible, near-infrared and short infrared bands of one Landsat Enhanced Thematic Mapper Plus (ETM+) image and one Radarsat C-band HH Synthetic Aperture Radar (SAR) image, both collected at the beginning of October 2000 (Liu *et al.* 2003). Classes on this classification image were Forest, Grassland/Cropland, Residential Area, Water and Wetland. By checking with ground data collected in the field (figure 1) and referencing another land-cover map separately produced by

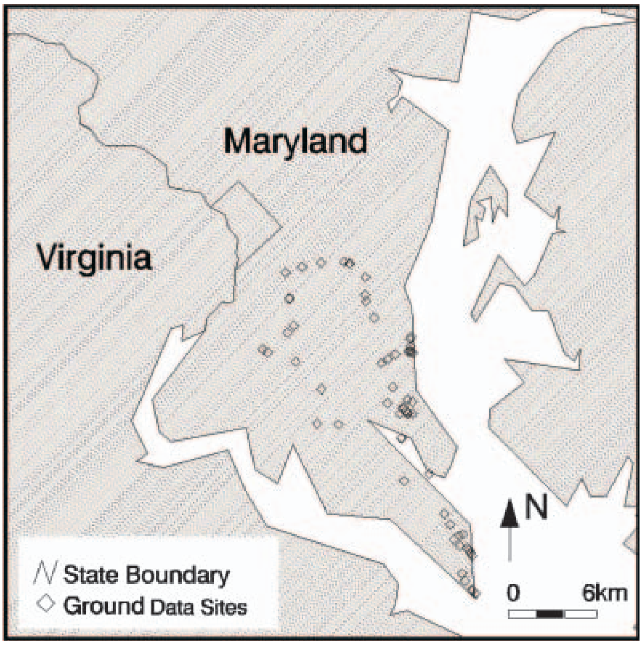

Figure 1. The study area; diamond symbols indicate the ground data sites.

the state of Maryland, the overall accuracy in this 30 m spatial resolution land-cover classification was approximately 81% correct for all the involved land-cover types.

3. Methods

Identifying mixed pixels on the MISR image was the prerequisite to conducting this study. So first the MISR image was registered against the already georeferenced 30 m ETM + image by carefully selecting control points on both images; secondly, a geographic link between the two images was set up. Based on this link and visually choosing 1.1 km × 1.1 km windows (approximately the area of 37 30 m pixels) with different land-cover components and areal fractions on the 30 m classified image, mixed pixels on the MISR image were identified. For each of these mixed MISR pixels, the areal fractions of its component land-cover types were calculated through counting the numbers of 30 m pixels by land-cover types; and its spectral signature sample (actually at four discrete bands) was collected by extracting a spectral profile directly from the MISR image.

If the 30 m land-cover classification was not 100% correct, neither were the collected spectral samples. By plotting all the spectral samples together and visual inter-comparison, apparently incorrect spectral samples were identified and removed from the sample set. For example, if a mixture spectral signature of 20% Residential Area and 80% Forest is not placed between the signatures of 10–30% Residential Area and 90–70% Forest, it is very possible to be an error, and should be removed from the sample set.

In reality, land-cover mixing cases are numerous, so mixtures of two, three or more components with varied land-cover types are all possible. To exhaust analysing all these cases of land-cover mixings in one study is unrealistic. Besides, forests are believed to be one of the most important terrestrial components of the Earth's climate system affecting the dynamics of both carbon cycle and water cycle sub-systems, this analysis was only limited to two-component mixtures, consisting of Forest and several common nonforest land-cover types.

4. Results and analyses

Based on the methods above, a total of 70 mixed spectral samples were collected. After removing the incorrect ones and averaging the spectral samples approximately representing same mixtures, 26 mixed spectral samples standing for different areal fractions of forest between 0 and 100% were obtained from the MISR image: seven samples for Forest and Residential Area mixtures; nine samples for Forest and Water mixtures; and 10 samples for Forest and Cropland/Grassland mixtures.

For each mixture spectral sample, the reflectance at the red and near-infrared bands were used to calculate its NDVI value by the common formula (NIR−Red)/(NIR+Red). The results were shown in figure 2.

It can be seen from figure 2 that, for any given areal fraction of Forest cover (hence a given areal fraction of the other land-cover component), NDVI varies much with mixed nonforest land-cover types if the areal fraction of Forest cover is less than 80%. For example, at the fraction of 60% Forest cover, NDVI varies between 0.575 and 0.825. When the areal fraction of Forest cover is over 80%, however, NDVI varies little. This implies, when areal fraction of Forest cover is over 80%, it dominates the spectral characteristics of the pixel and the spectral effect from other nonforest land-cover components is minor.

Based on the same spectral sample dataset used for the NDVI case, EVI was also calculated using the following formula (Justice *et al.* 1998)

$$\mathrm{EVI} = 2.5(\mathrm{NIR} - \mathrm{Red})/(L + \mathrm{NIR} + C_1\mathrm{Red} - C_2\mathrm{Blue}) \quad (1)$$

where L is the canopy background adjustment term, C_1 and C_2 are the coefficients of the aerosol resistance terms. The values of these coefficients used in this study, are $L=1$, $C_1=6$, $C_2=7.5$, the same as those used in the Moderate Resolution Imaging Spectroradiometer (MODIS) EVI algorithm. The results are shown in figure 3.

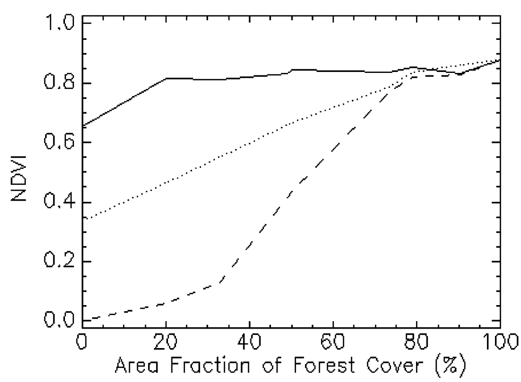

Figure 2. NDVI for two-component mixtures of Forest and other land-cover types: (1) ——, Forest mixed with Cropland/Grassland; (2) ·······, Forest mixed with Residential Area such as urban areas, roads, etc.; (3) – – – –, Forest mixed with Water such as lakes, rivers and coastal waters.

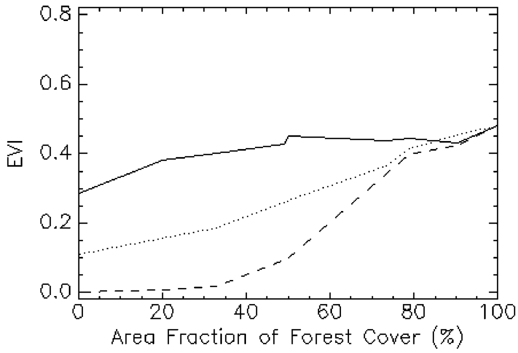

Figure 3. EVI for two-component mixtures of Forest and other land-cover types: (1) ——, Forest mixed with Cropland/Grassland; (2) ·······, Forest mixed with Residential Area such as urban areas, roads, etc.; (3) – – – –, Forest mixed with Water such as lakes, rivers and coastal waters.

In figure 3, the same phenomenon as shown in the NDVI case was observed, that is, for any given fraction of Forest cover (hence a given fraction of the other nonforest land-cover component), EVI still varies much with mixing nonforest land-cover components if the areal fraction of Forest cover is less than 80%. For example, at the fraction of 60% Forest cover, EVI varies between 0.2 and 0.45. When the areal fraction of Forest cover is over 80%, EVI also varies little. However, based on the comparison between figure 2 and figure 3, under the same areal fraction conditions, EVI varies less than NDVI (table 1).

5. Discussion and conclusions

Spectral vegetation indices particularly those derived from coarse-resolution satellite remotely sensed systems, such as NOAA AVHRR and NASA MODIS/MISR, are being widely used as important inputs to many global change analyses and simulation models (Chen *et al.* 2004). They are assumed to be able to represent the real amount of vegetation in any pixel area on the land surface. Therefore, their accuracy in reflecting this variable is very important to the associated global change applications.

This study, based on two-component mixtures of forest and several common nonforest land-cover types, preliminarily evaluated the potential effect of land-cover mixing on spectral vegetation indices, particularly the most widely used—NDVI and EVI. This study has revealed, for both NDVI and EVI, that if the areal fraction of forest cover is less than 80%, any given areal fraction of forest cover may correspond to a range of vegetation index values when the mixed land-cover type changes. This means that a given vegetation index value may correspond to a range of areal

Table 1. Comparison of NDVI and EVI for range of variations (range of variation is defined as the difference between the maximum and minimum index values at any given areal fraction of forest cover).

Forest cover (%)	Range of NDVI variation	Range of EVI variation
20	0.754	0.374
40	0.575	0.350
60	0.250	0.250

fractions of forest cover in not-high-density forest cover conditions, which will cause errors in quantifying vegetation and analysing the dynamics of vegetation change. This study has also revealed that, under the same mixture conditions, EVI varied less than NDVI. This means EVI is stronger than NDVI in resisting the negative effects from land-cover mixing.

A large percentage of the Earth's land surface is not covered by high density forests, so pixels with areal fraction of forest cover lower than 80% may occur frequently on coarse resolution satellite remotely sensed imagery. Although the number of component land-cover types in a pixel area may not be only two, and the mixing land-cover types may not be only limited to the above four land-cover types, the mixing cases discussed above are typical and common in real remote sensing situations. Therefore, this study suggests that methods that can reduce land-cover mixing effects should be introduced when developing new spectral vegetation indices.

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