A comparison of multi-resource remote sensing data for vegetation indices

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Abstract. With the development of the satellite sensor, multi-resource observation systems have become widely used. However, there is a huge difference between quantitative remote sensing products because of the different sensing observations and the quantitative retrieval algorithms. In this paper, the quantitative relationships between the normalized difference vegetation index (NDVI), the soil-adjusted vegetation index (SAVI) and the vegetation index based on the universal pattern decomposition method (VIUPD) of Landsat ETM+ and ASTER sensors are investigated. The difference in observations was examined between the two sensors, based on a pair of images. The results showed that: 1) There was a strong correlation between the different vegetation indices for the same sensor, with the coefficient of determination being greater than 0.9. 2) Whether for ASTER or Landsat, the information of VIUPD was richer than that of NDVI and SAVI. Furthermore, in dense vegetation areas, the values of NDVI and SAVI could easily reach saturation. 3) The values of SAVI were higher than NDVI in the areas of water or bare soil, while this was the opposite in areas of lush vegetation.

1. Introduction

Each remotely sensed image source has its own specifications, such as orbital altitude, spatial and spectral resolutions, wavelength band limits, relative spectral response of the sensor, etc. The information in remote sensing images is affected by the sensor type, observation angle, atmosphere and terrain conditions. There is therefore a huge variance in the value of the multi-source observation system products because of the different sensor observation systems and the quantitative inversion algorithms, and the value of these multi-source products is difficult to apply collaboratively. Therefore, it is important to analyze the interactions and the quantitative relationships between multi-sensor products to unify the quantitative parameters of the remote sensing products.

Vegetation plays an important role in the global ecological environment. Spectral vegetation index data have been used to investigate the interactions between climate and landscape ecosystems, to assist with land management and sustainability, and to investigate climate change and carbon sequestration. In recent years, many different vegetation indices have been proposed for different purposes. An interactive comparison between the vegetation indices for different sensors was found to be an effective method to achieve calibration between the sensors [1]. In this study, significant differences were found, and the authors established conversion factors for AVHRR, Landsat MSS, TM and ETM+, SPOT-2 and SPOT-4 HRV, IKONOS, MODIS and QuickBird sensors. Soudani et al. [2] tested the...
sensitivity of NDVI, SAVI and the atmospherically resistant vegetation index (ARVI) to the spectral and spatial characteristics of ETM+, SPOT and IKONOS sensors. The results showed that the values of the three vegetation indices for IKONOS were lower than those of the ETM+ and SPOT sensors. Yoshioka et al. [3] compared the NDVI simulated from MODIS and AVHRR and found the transformation of the relationship between NDVI for the different sensors. Miura et al. [4] analyzed the NDVI, simple ratio (SR), SAVI and the enhanced vegetation index (EVI) derived from ASTER and MODIS, and the results showed that there was a strong correlation between these vegetation indices; however, there were discrepancies in the values of the vegetation indices when selecting different infrared and near-infrared bands. Gao et al. [5] compared MODIS composite NDVI values from several sensors (AVHRR not included) and found that there was good agreement in response to the phenology of the land-cover types being examined.

Landsat and ASTER have a lot of similarities in terms of resolution and spectral response characteristics. Therefore, there is great significance in comparing Landsat and ASTER data in order to expand the application of the data sources [6]. In this paper, our study aims to investigate the response of the different vegetation indices for different sensors, and the values of NDVI, SAVI and VIUPD are estimated from ETM+ and ASTER data.

2. Materials and methods

2.1. Study site and data acquisition

The test site is situated at Gaoligong Mountain, on the railway from Dali to Ruili, Yunnan province, China (figure 1). An ASTER image (Feb 28, 2007) and a Landsat ETM+ image (Feb 17, 2003) are used in this research. The ASTER bands include three visible bands of 15 m resolution and six near-infrared bands of 30 m resolution. The solar elevation and azimuth angle of the ASTER data are 51.23° and 144.55°, respectively. All the bands of ETM+ have a spatial resolution of 30 m. The solar elevation and azimuth angle of the ETM+ data are 43.32° and 138.48°, respectively. The data from both ASTER and ETM+ were rectified to a UTM coordinate system, WGS-84.

![Figure 1. Images of ASTER and ETM+. (a) ASTER (b) Landsat ETM+](image-url)

2.2. Data pre-processing

A. Geometric correction

The visible and near-infrared bands of ASTER are 15 m resolution. In order to unify the spatial resolution, geometric registration was used to obtain 30 m resolution data.

B. Radiometric correction

1) Radiometric terrain correction
In mountainous areas, the irregular terrain significantly affects the spatial variations of the climatic variables, and also the reflectance of the pixels in a remote sensing image. Therefore, a C-correction model [7] was used for radiometric terrain correction. The resolution of the DEM was 30 m and the elevation resolution was 0.1 m. A total of 6000 samples evenly distributed in the study area were selected in order to ensure the accuracy of the fit.

2) Reflectance inversion

Radiation calibration is often combined with the specific sensor calibration records of the calibration parameters corresponding to the different data formats and the different response coefficients for each sensor. The following equation was used to convert the digital number (DN) into an at-satellite spectral radiance value \( W \cdot m^{-2} \cdot sr^{-1} \cdot \mu m^{-1} \) [8]:

\[
L = \text{Gain} \times DN + \text{Bias}
\]  

where the gain and offset can be obtained from the header file of the images. \( \text{Gain} = \frac{(L_{\text{max}} - L_{\text{min}})}{255} \), and \( L_{\text{max}} \) and \( L_{\text{min}} \) (also given in the header file of the images) are, respectively, the max. and min. spectral radiance in \( W \cdot m^{-2} \cdot sr^{-1} \cdot \mu m^{-1} \).

The at-satellite spectral radiance value was then converted to an at-satellite reflectance value using the following equations [1]. For Landsat ETM+:

\[
\rho = \frac{\pi \cdot L \cdot d^2}{ESUN \cdot \cos \theta}
\]  

where \( \rho \) is the at-satellite reflectance, \( ESUN \) is the mean solar atmospheric irradiance in \( W \cdot m^{-2} \cdot \mu m^{-1} \), \( \theta \) is the solar zenith angle in degrees, and \( d \) is the earth–sun distance in astronomical units.

For ASTER:

\[
\rho = \frac{\pi \cdot (Q - 1) \cdot UCC \cdot d^2}{ESUN \cdot \cos \theta}
\]  

where \( UCC \) is the transformation coefficient in \( W \cdot m^{-2} \cdot sr^{-1} \cdot \mu m^{-1} \), and \( Q \) is the quantized calibrated pixel value in DN. The values of the parameters in the equations are shown in table 1.

|               | Properties and parameters of the ASTER and Landsat ETM+ images |
|---------------|---------------------------------------------------------------|
| **Band**      | **ASTER**          | **ETM+**           |
| **Sun azimuth**| **UCC**            | **ESUN**          |
| 1             | 1.69               | 1845.99           |
| 2             | 1.42               | 1555.74           |
| 3             | 0.87               | 1119.47           |
| 4             | 0.22               | 231.25            |
| 5             | 144.55             | 0.07              |
| 6             | 0.06               | 79.81             |
| 7             | 0.06               | 138.48            |
| 8             | 0.04               | 225.7             |
| 9             | 0.03               | 56.92             |

2.3. Vegetation indices
Three vegetation indices are used in this study. NDVI and SAVI are the two commonly used vegetation indices, computed using the red and near-infrared bands. VIUPD is a sensor-independent index, which is expressed as a linear sum of the decomposition coefficients.

1) NDVI
NDVI is the most widely used vegetation index for a variety of remote sensing applications. Here, it is used as the principal basis for comparison between the sensors:

\[
NDVI = \frac{\rho_{\text{NIR}} - \rho_{\text{red}}}{\rho_{\text{NIR}} + \rho_{\text{red}}}
\]  

where \(\rho_{\text{NIR}}\) and \(\rho_{\text{red}}\) are the reflectances for the NIR and R bands, respectively.

2) SAVI
SAVI can overcome the effect of the soil background noise by introducing a soil brightness correction factor \(l\). SAVI is calculated using the following relationship [10]:

\[
SAVI = \frac{(\rho_{\text{NIR}} - \rho_{\text{red}})(1 + l)}{\rho_{\text{NIR}} + \rho_{\text{red}} + l}
\]  

When \(l\) is 0.5, the influence of the soil background noise can be weakened greatly.

3) VIUPD
This vegetation index is a kind of spectral signature measurement which can describe the earth’s surface vegetation condition. The index is based on the universal pattern decomposition method (UPDM) and is a function of the linear combination of the pattern decomposition coefficients \((C_w, C_v, C_s)\). The VIUPD can reflect biomass, degree of coverage and chlorophyll content. VIUPD is defined as follows [11–12]:

\[
VIUPD = \frac{(C_w - 0.10 \times C_v - C_s)}{C_w + C_v + C_s}
\]  

where, \(C_w, C_v,\) and \(C_s\) are the UPDM coefficients of water, vegetation and soil. \((C_w + C_v + C_s)\) represents the sum of total reflectance, and \(C_w + C_v + C_s = \frac{\int R(\lambda)d\lambda}{\int d\lambda}\).

3. Results and discussion

3.1. Characteristics of the different vegetation indices
Figures 2 and 3 are the distribution images of NDVI, SAVI and VIUPD for ASTER and Landsat ETM+ in the study area. The results shows that no matter what the data source, each vegetation index can effectively respond to the vegetation growth patterns. The vegetation index values of ASTER are, however, clearly lower than those of Landsat ETM+.

There are big differences between the vegetation indices, especially in the areas of lush vegetation, and the SAVI values are significantly lower those of NDVI and VIUPD. Due to the nonlinear change in NDVI, the result of the calculation is enhanced at the low values and inhibited at the high values. Therefore, compared to VIUPD, the values of NDVI can more easily reach saturation for each sensor. As VIUPD takes advantage of all the band information, the distribution of VIUPD adequately and accurately reflects the vegetation density and vegetation coverage.
3.2. Relationships between the vegetation indices

Table 2. Mean and standard deviations of NDVI, SAVI and VIUPD for the two sensors

|       | NDVI  |       | SAVI  |       | VIUPD |       |
|-------|-------|-------|-------|-------|-------|-------|
|       | mean  | std   | mean  | std   | mean  | std   |
| ASTER | 0.1947| 0.1683| 0.1207| 0.1064| 0.2215| 0.1812|
| Landsat| 0.4503| 0.1509| 0.2364| 0.0789| 0.4110| 0.2200|

Table 2 shows the mean and standard deviation values of the ASTER and Landsat ETM+ vegetation indices in the study area. Each of the mean values of the vegetation indices of ASTER are less than those of Landsat. This result is in accordance with the distributions shown in figure 2 and figure 3. On the other hand, the standard deviation values of VIUPD are higher than those of NDVI and SAVI for
both sensors. Overall, VIUPD adequately reflects the difference between the lush vegetation areas and the non-vegetated regions.

Figures 4 and 5 are the scatter plots of the different vegetation indices for the two sensors. The results show that: 1) the NDVI values are lower than those of SAVI when the NDVI value is negative, while the values are higher than those of SAVI when NDVI is positive; 2) the values and the range of VIUPD are slightly higher than those of NDVI; 3) the values and the range of VIUPD are significantly higher than those of SAVI; and 4) the values of NDVI and SAVI are the same in the bare soil regions. According to figure 2 and figure 3, these areas are the exposed ridges, where the values of both NDVI and SAVI are 0. For the different vegetation indices of ASTER and Landsat, there is a strong correlation between each vegetation index, with \( R^2 > 0.9 \). This result agrees with the results obtained in another experimental study [11], where the ASTER vegetation index correlations were higher than those of Landsat, and the values of \( R^2 \) were greater than 0.95.

Figure 4. The relationships between the NDVI, SAVI and VIUPD of ASTER

Figure 5. The relationships between the NDVI, SAVI and VIUPD of ETM+

4. Conclusions
In this paper, NDVI, SAVI and VIUPD were used to estimate the vegetation conditions using the data from both ETM+ and ASTER sensors. After a comprehensive analysis of the distributions of the different vegetation indices for both sensors, the results can be summarized as follows: 1) there was a strong correlation between the different vegetation indices for the same sensor, with the coefficient of determination being greater than 0.9; 2) whether for ASTER or Landsat, the information of VIUPD was richer than that of NDVI and SAVI in the dense vegetation areas, and the NDVI and SAVI values could more easily reach saturation; and 3) the values of SAVI were higher than those of NDVI in the non-vegetated areas, while the values in the areas of lush vegetation were the opposite.
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