Assessment of the universal pattern decomposition method using MODIS and ETM+ data

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The universal pattern decomposition method (UPDM) is a sensor-independent method in which each satellite pixel is expressed as the linear sum of fixed, standard spectral patterns for water, vegetation and soil. The same normalized spectral patterns can be used for different solar-reflected spectral satellite sensors. Supplementary patterns are included when necessary. The UPDM has been applied successfully to simulated data for Landsat/ETM+, Terra/MODIS, ADEOS-II/GLI and 92-band CONTINUE sensors using ground-measured data. This study validates the UPDM using MODIS and ETM+ data acquired over the Three Gorges region of China. The reduced \( \chi^2 \) values for selected area D, that with the smallest terrain influences, are 0.000409 (MODIS) and 0.000181 (ETM+), and the average linear regression factor between MODIS and ETM+ is 1.0077, with root mean square (rms) value 0.0082. The linear regression factor for the vegetation index based on the UPDM (VIUPD) between MODIS and ETM+ data for area D is 1.0089 with rms 0.0696. Both UPDM coefficients and VIUPD are sensor independent for the above sensors.

1. Introduction

Multi-temporal and multi-sensor satellite data supply a wealth of information for monitoring environmental changes at regional, continental and global scales. Past studies have focused on terrestrial land cover, vegetation classification (Muchoney et al. 2000) and natural calamities. In addition, satellite data are frequently used in studies in oceanography, hydrology, geology, forestry and meteorology. Larger volumes of multi-spectral data have become available from Landsat/TM (ETM+), Terra (Aqua)/MODIS, ADEOS-II/GLI and other sensors. The characteristics of each sensor differ, as the number of bands, band wavelengths and position of the

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central wavelength of each band vary (Zhang et al. 2006a). Thus, multi-sensor products must incorporate sensor dependencies. Such dependencies are extremely disadvantageous for global change research (Teillet et al. 1997).

The universal pattern decomposition method (UPDM) is a sensor-independent method that is tailored for satellite data analysis (Zhang et al. 2003, 2006a). Sets of spectral reflectance measured by a sensor are transformed by the UPDM into three or four coefficients with three or four fixed spectral reflectance patterns. Spectral reflectance patterns are determined in the spectral region between 350 and 2500 nm and are called the ‘universal standard spectral patterns’. Sensor wavelength values are selected from these universal standard spectral patterns to analyse the spectral region of each sensor. The coefficients are known as ‘pattern decomposition coefficients’. This method has been applied successfully to simulated data with wavelengths observed by Landsat/ETM+, Terra/MODIS, ADEOS-II/GLI and 92-band CONTINUE sensors (Zhang et al. 2003). The resulting pattern decomposition coefficients are independent of the sensor; that is, regardless of the sensor, the four coefficients are nearly the same for the same samples. The average estimation error of reduced $\chi^2$ values for Landsat/TM (ETM+), Terra/MODIS, ADEOS-II/GLI and CONTINUE sensors is 0.025 (Zhang et al. 2006a).

The conventional pattern decomposition method (PDM) can be explained using both linear spectral mixing analysis (Adams et al. 1986) and multi-dimensional analysis (Harsanyi and Chang 1994). The linear spectral mixture analysis approach uses a physically based model that transforms radiance values into physical variables linked to the subpixel abundances of endmembers within each pixel (Tompkins et al. 1997). The technique divides each pixel into its constituent materials or components using endmembers that represent the spectral characteristics of key landcover types (Adams et al. 1986, Smith et al. 1990, 1994). In the most general approach to spectral mixture analysis, a set of endmembers is selected from an image data set that best accounts for the $n$-dimensional spectral variance within a constrained, least-squares mixture model (Adams et al. 1993, 1995). Ideally, these image endmembers can be compared to ground-based reference spectra. The UPDM removes the non-negative constraint for the coefficient solution because the fourth pattern is difficult to select using spectral mixing analysis. For this reason, the UPDM is considered a multi-dimensional analysis in which standard patterns are interpreted as an oblique coordinate system, and coefficients are the coordinates of a pixel’s reflectance. Therefore, in the UPDM, each pixel in a multi-spectral image is an observation vector that can be projected to a subspace consisting of standard water, vegetation and soil patterns. Supplemental patterns can be included when necessary. However, the three decomposition coefficients $C_w$, $C_v$ and $C_s$ (for water, vegetation and soil, respectively) resulting from the same pixel computed using three and four components would have almost the same value; that is, with the supplemental pattern included or not, the influences of $C_w$, $C_v$ and $C_s$ are negligible (Zhang et al. 2005c). This approach includes an orthogonal independent space; any data in the multi-dimensional space can be approximated as a vector in this three- (or four-) dimensional standard subspace.

The UPDM is mathematically and practically almost identical to the spectral unmixing method (Roberts et al. 1993, 1998, Vikhamar and Solberg 2003a, 2003b). Linear spectral unmixing is a technique used to divide each pixel into its component or endmember spectra (Ustin et al. 1998). The method assumes that the reflectance from each pixel is a linear combination of each endmember, and the fractional
abundances are computed on a pixel-by-pixel basis (Okin and Roberts 2000). Standard patterns of the UPDM are standard vector components in \( n \)-dimensional space that represent the main features of objects on the land and form nearly orthogonal vectors with each other. UPDM solutions are similar to those of the spectral mixture method and the orthogonal subspace projection (OSP; Harsanyi and Chang 1994), but the underlying concepts differ. In the UPDM, the same pattern (endmember), which is called the standard pattern, is used even for different sensors, and the sum of the coefficients is almost the same as the spectrally averaged reflectance of the spectral region from 350 to 2500 nm.

The ultimate goal is to apply the UPDM to satellite data. UPDM analyses using satellite data are more complicated than those using ground-measured data because of the presence of the atmosphere. Previous UPDM studies used about 600 ground samples (Zhang et al. 2006a). However, even this number of samples cannot cover all ground objects. This study validated the sensor-independent characteristics of the UPDM using MODIS and ETM+ satellite data from above the Three Gorges region in China, and assessed the independence of a vegetation index based on the UPDM (VIUPD; Zhang et al. 2006b) using MODIS and ETM+ data.

2. The universal pattern decomposition method (UPDM)

Previous studies have discussed PDM (Fujiwara et al. 1996, Muramatsu et al. 2000, Daigo et al. 2004) and UPDM (Zhang et al. 2003, 2006a) algorithms. The UPDM decomposes reflectance values at each pixel into a linear sum of standard spectral patterns for water, vegetation and soil and any supplemental patterns using the following formula (Zhang et al. 2006a):

\[
R_i = C_w P_{iw} + C_v P_{iv} + C_s P_{is} + C_4 P_{i4}
\]

Here \( R_i \) is the reflectance of band \( i \) measured on the ground (or by satellite sensor), \( C_w, C_v \) and \( C_s \) are the decomposition coefficients for water, vegetation and soil, respectively, \( C_4 \) represents the supplemental coefficients, and \( P_{iw}, P_{iv} \) and \( P_{is} \) are the respective standard spectral patterns for water, vegetation and soil for some typical sensor, which is captured from the same standard pattern normalized in the same wave region of 350 nm to 2500 nm for any sensor, and is therefore related to the properties of each sensor. \( P_{i4} \) is the supplementary standard pattern for \( i \) bands and is an optional component that is also controlled for the purpose of the study. For example, for MODIS and ETM+, \( P_{iw}, P_{iv}, P_{is} \) and \( P_{i4} \) are different, as described in the following section, but they are all captured from the same normalized standard spectral pattern, namely the sensor-independent standard spectral pattern. In this case, a yellow-leaf spectrum is used, but the supplemental pattern is not fixed. Rather, it depends on the purpose of the study.

Equation (1) can be expressed using matrix notation as follows:

\[
\begin{pmatrix}
R_1 \\
R_2 \\
\vdots \\
R_n
\end{pmatrix} = 
\begin{pmatrix}
P_{i1w} & P_{i1v} & P_{i1s} & P_{i14} \\
P_{i2w} & P_{i2v} & P_{i2s} & P_{i24} \\
\vdots & \vdots & \vdots & \vdots \\
P_{inw} & P_{inv} & P_{ins} & P_{in4}
\end{pmatrix} 
\begin{pmatrix}
C_w \\
C_v \\
C_s \\
C_4
\end{pmatrix} + 
\begin{pmatrix}
r_1 \\
r_2 \\
\vdots \\
r_n
\end{pmatrix}
\]

or
\[ \mathbf{R} = \mathbf{PC} + \mathbf{r} \]  

(3)

where \( \mathbf{R} = [R_1, R_2, \ldots, R_n]^T \) is the column vector of observations, \( n \) is the number of spectral bands, \( \mathbf{P} = [\mathbf{P}_W, \mathbf{P}_V, \mathbf{P}_S, \mathbf{P}_4] \) is the \( n \times 4 \) matrix of which the row vector is the standard spectral pattern for band number \( n \), \( \mathbf{C} = [C_W, C_V, C_S, C_4]^T \) is the column vector of UPDM coefficients and \( \mathbf{r} \) is the residual column vector for band \( i \). Inverting (3) and minimizing the sum-of-squared-error criterion function (Duda et al. 2001) yields

\[ J_s = \| \mathbf{R} - \mathbf{PC} \|_2^2 \]  

(4)

This function can be solved by a gradient search procedure:

\[ \nabla J_s(\mathbf{C}) = \frac{\partial (\mathbf{R} - \mathbf{PC})^T (\mathbf{R} - \mathbf{PC})}{\partial \mathbf{C}} \]  

(5)

and setting it equal to zero. The unique solution of \( \mathbf{C} \) is

\[ \mathbf{C} = (\mathbf{P}^T \mathbf{P})^{-1} \mathbf{P}^T \mathbf{R} \]  

(6)

where \( \mathbf{R} \) is a vector known from satellite data, and \( \mathbf{P} \) is a standard spectral pattern matrix as described above. The spectral pattern matrix is derived from normalized standard spectral patterns of water, vegetation, soil and supplementary data, which in this case is yellow-leaf (Zhang et al. 2006a).

Spectral reconstruction precision was evaluated using reduced \( \chi^2 \) values that satisfied the expression

\[ \chi^2 = \sum_{i=1}^{n} r(i)^2 / (n-4) \]  

(7)

where \( n \) is the number of bands, and \( r \) is the error of band \( i \).

3. Data processing

3.1 Data used in this analysis

Landsat/ETM+ standard product data (path 125/row 39) observed over the Three Gorges region of China on 2 April 2002 were acquired from the Beijing Remote Sensing Ground Station. Data were georeferenced with a spatial resolution of 28.5 m. The solar zenith angle was 35.3°, and the observation time was 10.00 am.

Terra/MODIS data acquired over the same region on 2 April 2002 at 11.18 am were provided by the MODIS Receiving Station at Wuhan University. MODIS bands 1 and 2 have horizontal resolutions of 250 m, and bands 3–7 have horizontal resolutions of 500 m; the average solar zenith angle is around 34.0°. MODIS L1B data contain geometric distortions that are reduced by geometric correction using the common nearest-neighbour approach described in many studies. In this method, digital number (DN) values are not changed, although a half-pixel shift in the output image space can occur (Lillesand and Kiefer 2000). Each corrected pixel in the output image is geometrically similar to ETM+ data. This study used MODIS bands 1 to 7 resampled to a spatial resolution of 484.5 m, 17 times the resolution of ETM data (28.5 m). Figure 1 shows reflectance images for (a) MODIS and (b) ETM+ data for selected areas A, B, C and D, where terrain conditions vary by area.
ETM+ data are standard products that have better georeferencing and geometric corrections. Thus, spatial resampling was applied to the data to match resampled MODIS data (at 484.5 m resolution).

The MODIS and ETM data covered the same region, between 29.35° and 31.28° N and 109.52° and 112.00° E, on the same observed date. Observation times differed by about an hour and the solar zenith angle was similar. Periodic noise from
a mechanical sensor is present every 20 lines in MODIS band 5 (1230.0–1250.0 nm) but this was ignored; this noise had little effect on the results of the analysis.

3.2 Radiometric correction and reflectance retrieval

Radiometric corrections to surface reflectance allow quantitative comparisons with spectral target signatures. Satellite sensors record total reflected energy and output the value as an electric signal that is called a DN value. The calibration task is to retrieve satellite radiances. Radiance values for each ETM+ pixel in each band can be derived from the DN according to Joachim and Boris (1991):

$$L_{(ETM)} = a_{0(ETM)} + a_{1(ETM)}DN \tag{8}$$

MODIS radiances are given by (Toller and Issacman, 2003):

$$L_{(MODIS)} = a_{1(MODIS)}(DN - a_{0(MODIS)}) \tag{9}$$

Here, $L$ is the total radiance for the ETM+ and MODIS sensors at the satellite, in mW cm$^{-2}$ sr$^{-1}$ μm$^{-1}$; calibration constants $a_0$ and $a_1$ are offsets and gains for the ETM+ and MODIS sensors, and are provided by data distribution agencies.

Radiation is scattered as it passes through and interacts with the atmosphere. Typically, total radiance is the sum of target-reflected radiance and Rayleigh scattering path radiance (Muramatsu et al. 2000). Radiometric correction in this case means removing the effects of Rayleigh scattering. Various atmospheric correction methods can be applied (Zhang et al. 1998). More precise techniques use a statistical analysis of automatically masked invariant scene elements to derive a linear band-to-band transformation function (Schott et al. 1988). However, statistical methods give no quantitative measure of actual properties, so the present study used a simplified Rayleigh scattering correction that ignores environmental scattering. Atmospheric Rayleigh scattering path radiance is approximated by

$$L_r = \frac{1}{4\pi} \cdot \frac{\mu_0}{\mu + \mu_0} \left\{ 1 - e^{-\tau_r \left( \frac{1}{2} + \frac{1}{2\mu_0} \right) \frac{P_r(\varphi)}{d^2} \right\} E_0 \tag{10}$$

where $L_r$ is the Rayleigh scattering path radiance, in mW cm$^{-2}$ sr$^{-1}$ μm$^{-1}$, and $\mu_0$ and $\mu$ represent the cosines of the sun zenith angle $\theta_0$ and satellite zenith angle $\theta$, respectively. $E_0$ is the solar irradiance at the top of the atmosphere, in mW cm$^{-2}$ μm$^{-1}$, and $d$ is the earth–sun distance in astronomical units. $P_r(\varphi)$ is the Rayleigh scattering phase function and can be written as

$$P_r(\varphi) = \frac{3}{4} (1 + \cos^2 \varphi) \tag{11}$$

with backscattering angle

$$\varphi = 180 - \theta_0. \tag{12}$$

$\tau_r$ is the molecular optical thickness for a standard Rayleigh atmosphere (Joachim and Boris 1991):

$$\tau_r = 0.00879 \lambda^{-4.09}. \tag{13}$$
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Solving for path radiance yields an equation for ground-target reflectance $\rho_{\lambda}$:

$$\rho_{\lambda} = \frac{\pi d^2 (L - L_t)}{E_0 \cos \theta_0}.$$ \hspace{1cm} (14)

For MODIS reflectance at the top of the atmosphere, we can also compute ground-target reflectance using reflectance gain and offset in the MODIS L1B products (Zhang et al. 2005b):

$$\rho_{\lambda, \text{MODIS}} = \frac{m_{R, \lambda} (DN_{\lambda} - b_{R, \lambda})}{\cos \theta_0}.$$ \hspace{1cm} (15)

Here, $m_{R, \lambda}$ and $b_{R, \lambda}$ are reflectance gain and offset, respectively. The path reflectance value computed by the Rayleigh scattering path radiance is then removed. Table 1 shows the Rayleigh scattering reflectance values for the MODIS and ETM+ sensors. Figure 2 shows spectra of MODIS and ETM+ data using values listed in table 1 band by band. Blue represents the logarithmic value of reflectance for each pixel. Green represents the reflectance frequency.

3.3 UPDM subspace projection

Reflectance values for each pixel in multi-dimensional space were projected onto four-dimensional UPDM space to transform the standard spectral pattern from the normalized standard spectral pattern at wavelengths between 350 and 2500 nm. For the MODIS sensor, the standard spectral vector is

$$P_w = \begin{bmatrix} 3.336933 \\ 2.878424 \\ 1.542390 \\ 0.797594 \\ 0.230624 \\ 0.264724 \\ 0.114276 \end{bmatrix}, \quad P_v = \begin{bmatrix} 0.163671 \\ 0.465862 \\ 0.188812 \\ 2.327511 \\ 1.909090 \\ 1.035108 \\ 0.358373 \end{bmatrix}, \quad P_s = \begin{bmatrix} 0.517848 \\ 0.758124 \\ 0.918608 \\ 0.972886 \\ 1.080348 \\ 1.253452 \\ 1.255247 \end{bmatrix}, \quad P_4 = \begin{bmatrix} -1.771638 \\ 0.568648 \\ 2.501290 \\ 0.015900 \\ 0.208386 \\ -0.634276 \\ -1.124477 \end{bmatrix}

Table 1. Rayleigh scattering correction values for MODIS and ETM+.

<table>
<thead>
<tr>
<th>Band</th>
<th>MODIS Wavelength (nm)</th>
<th>E_0 (W m(^{-2}) sr(^{-1}) μm)</th>
<th>Rayleigh scattering</th>
<th>ETM+ Wavelength (nm)</th>
<th>E_0 (W m(^{-2}) sr(^{-1}) μm)</th>
<th>Rayleigh scattering</th>
</tr>
</thead>
<tbody>
<tr>
<td>1*</td>
<td>459.0–479.0</td>
<td>2088.039</td>
<td>0.060</td>
<td>450.0–515.0</td>
<td>1969.0</td>
<td>0.055</td>
</tr>
<tr>
<td>2*</td>
<td>545.0–565.0</td>
<td>1865.903</td>
<td>0.033</td>
<td>525.0–605.0</td>
<td>1840.0</td>
<td>0.031</td>
</tr>
<tr>
<td>3</td>
<td>620.0–670.0</td>
<td>1607.099</td>
<td>0.019</td>
<td>630.0–690.0</td>
<td>1551.0</td>
<td>0.017</td>
</tr>
<tr>
<td>4</td>
<td>841.0–876.0</td>
<td>992.098</td>
<td>0.006</td>
<td>775.0–900.0</td>
<td>1044.0</td>
<td>0.007</td>
</tr>
<tr>
<td>5</td>
<td>1230.0–1250.0</td>
<td>474.399</td>
<td>0.001</td>
<td>1550.0–1750.0</td>
<td>225.7</td>
<td>0.000</td>
</tr>
<tr>
<td>6*</td>
<td>1628.0–1652.0</td>
<td>240.205</td>
<td>0.000</td>
<td>2090.0–2350.0</td>
<td>82.1</td>
<td>0.000</td>
</tr>
<tr>
<td>7</td>
<td>2105.0–2135.0</td>
<td>90.336</td>
<td>0.000</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

*In this study, for convenience, we changed the MODIS bands 1, 2 to bands 3, 4 according to the wavelength value; for ETM+, we changed band 7 to band 6, respectively. The earth–sun distance on 2 April was 0.999910 (Zhang et al. 2005b) in astronomical units (149.6 x 10^6 km); the Rayleigh scattering value is expressed by the reflectance value.
The vector for the ETM+ sensor is

\[
P_w = \begin{bmatrix} 3.277077 \\ 2.672011 \\ 1.449789 \\ 0.817368 \\ 0.219794 \\ 0.205009 \end{bmatrix}, \quad P_v = \begin{bmatrix} 0.175195 \\ 0.384025 \\ 0.171269 \\ 2.311455 \\ 0.961035 \\ 0.332513 \end{bmatrix}, \quad P_s = \begin{bmatrix} 0.545911 \\ 0.786754 \\ 0.925836 \\ 0.979686 \\ 1.251477 \\ 1.164075 \end{bmatrix}, \quad P_4 = \begin{bmatrix} -1.259582 \\ 0.957375 \\ 2.589210 \\ 0.023746 \\ -0.604368 \\ -1.392741 \end{bmatrix}
\]

Figure 2. MODIS and ETM+ ground-target reflectance histogram with respect to figure 1: (a) MODIS; (b) ETM+. Blue represents the logarithmic value of reflectance for each pixel. Green represents the reflectance frequency.
UPDM coefficient vectors were computed for each pixel using equation (6). Multispectral data in multi-dimensional space were projected to four UPDM dimensional space. The UPDM vector in the new dimensional space has lower band-by-band correlation coefficients than the original dimensional space. Figure 3 shows MODIS and ETM+ data in UPDM space. For convenience, four-dimensional space is expressed by two-dimensional space of $C_w, C_v$ and $C_s$, respectively, in figure 3. The long tail represents clouds that differ between MODIS and ETM+ data because of the 1-hour difference in observation times. Figure 1 shows more cloud in the

![Figure 3. MODIS and ETM+ multi-spectral reflectance data expressed in the UPDM dimensional space. Upper rows from left to right are MODIS data expressed by $C_s-C_v, C_v-C_w, C_v-C_w$ two-dimensional spaces; lower rows are ETM+ data.](image)

UPDM coefficient vectors were computed for each pixel using equation (6). Multispectral data in multi-dimensional space were projected to four UPDM dimensional space. The UPDM vector in the new dimensional space has lower band-by-band correlation coefficients than the original dimensional space. Figure 3 shows MODIS and ETM+ data in UPDM space. For convenience, four-dimensional space is expressed by two-dimensional space of $C_w, C_v$ and $C_s$, respectively, in figure 3. The long tail represents clouds that differ between MODIS and ETM+ data because of the 1-hour difference in observation times. Figure 1 shows more cloud in the

![Figure 4. Relationship between UPDM coefficients computed using ETM+ data with different spatial resolutions. The horizontal axis represents the UPDM coefficients computed from pixels with 484.5 m resolution, and the vertical axis represents the average values of UPDM coefficients using $17 \times 17$ pixels, which were computed from 28.5 m resolution ETM+ data.](image)
MODIS data than in the ETM + data. Cloud-free regions are almost the same in the sensor-independent UPDM space.

4. Results and discussion

4.1 Linear relationship of UPDM coefficients as a function of spatial resolution

UPDM coefficients show a linear relationship with data computed using different spatial resolutions. In this study, we computed UPDM coefficients using ETM + data that were resampled to a horizontal resolution of 484.5 m. Of course, we could have used data with a horizontal resolution of 28.5 m and then computed the average value of the UPDM coefficients using $17 \times 17$ pixels ($28.5 \times 17 = 484.5$). Figure 4 shows the linear relationship between these two UPDM coefficients. The horizontal axis represents the UPDM coefficients computed from pixels with...
484.5 m resolution, and the vertical axis represents the average values of UPDM coefficients using $17 \times 17$ pixels, which were computed from 28.5 m resolution ETM+ data.

### 4.2 Sensor independence of UPDM coefficients

Because UPDM is a sensor-independent method, UPDM coefficients derived from different sensors should have the same approximate values, at least theoretically. Previous studies using ground-measured data support this statement (Zhang et al. 2006a). UPDM coefficients computed in this study used MODIS and ETM+ data acquired over the Three Gorges region on 2 April 2002. The relationship between the coefficients was compared in four selected areas (A, B, C and D) where topography varied from mountainous to hilly, as shown in figure 1. Figure 5 shows the comparison. Linear regression equations are (a) $f(x)=1.0103x$, (b) $f(x)=0.9963x$, (c) $f(x)=1.0057x$ and (d) $f(x)=1.0077x$. Region D shows a linear relationship and the smallest root mean square (rms) value. Area D is the most sensor independent because it is the area in which terrain has the least influence.

Table 2 shows details of the UPDM coefficients for the two satellite sensors in each of the four areas. The table includes correlations, linear regression coefficients and vegetation index correlations. Of the four UPDM coefficients, $C_v$ and $C_s$ show linear behaviour, whereas $C_w$ and $C_4$ do not, because their values are very small. A minor change caused by a pixel shift or topographic influence may cause a relatively large shift in value. Figure 5 shows $C_w$ and $C_4$ values clustered around zero; a small

<table>
<thead>
<tr>
<th>UPDM coefficients</th>
<th>Linear regression function</th>
</tr>
</thead>
<tbody>
<tr>
<td>Coefficients</td>
<td>Coefficient values</td>
</tr>
<tr>
<td>Area A</td>
<td></td>
</tr>
<tr>
<td>$C_w$</td>
<td>0.4808</td>
</tr>
<tr>
<td>$C_v$</td>
<td>1.1496</td>
</tr>
<tr>
<td>$C_s$</td>
<td>0.9705</td>
</tr>
<tr>
<td>$C_4$</td>
<td>0.3088</td>
</tr>
<tr>
<td>$\Sigma$</td>
<td>1.0103</td>
</tr>
<tr>
<td>Area B</td>
<td></td>
</tr>
<tr>
<td>$C_w$</td>
<td>0.3247</td>
</tr>
<tr>
<td>$C_v$</td>
<td>1.1432</td>
</tr>
<tr>
<td>$C_s$</td>
<td>0.9414</td>
</tr>
<tr>
<td>$C_4$</td>
<td>0.3923</td>
</tr>
<tr>
<td>$\Sigma$</td>
<td>0.9963</td>
</tr>
<tr>
<td>Area C</td>
<td></td>
</tr>
<tr>
<td>$C_w$</td>
<td>0.4320</td>
</tr>
<tr>
<td>$C_v$</td>
<td>1.0870</td>
</tr>
<tr>
<td>$C_s$</td>
<td>0.9356</td>
</tr>
<tr>
<td>$C_4$</td>
<td>0.2468</td>
</tr>
<tr>
<td>$\Sigma$</td>
<td>1.0057</td>
</tr>
<tr>
<td>Area D</td>
<td></td>
</tr>
<tr>
<td>$C_w$</td>
<td>0.5696</td>
</tr>
<tr>
<td>$C_v$</td>
<td>1.0427</td>
</tr>
<tr>
<td>$C_s$</td>
<td>0.9540</td>
</tr>
<tr>
<td>$C_4$</td>
<td>-0.0693</td>
</tr>
<tr>
<td>$\Sigma$</td>
<td>1.0077</td>
</tr>
</tbody>
</table>
shift in values will move the linear regression coefficients away from the line $f(x) = x$. Figure 5 also shows somewhat larger rms values because of the resampling method for MODIS data. MODIS pixels may include a half-pixel shift, so pixels in MODIS and ETM+ data may not be identical. Such an effect is reduced by comparing $3 \times 3$ pixel averages of UPDM coefficients. Figure 6 shows the results of that comparison.

### 4.3 Sensor independence of vegetation index

A new vegetation index has been proposed based on the UPDM (VIUPD) (Zhang et al. 2006b) and derived from sensor-independent UPDM coefficients. Previous studies have shown that the VIUPD is sensor independent. Table 2 compares the three vegetation indices, VIUPD, the normalized difference vegetation index (NDVI) and EVI (Enhanced Vegetation Index), and figure 7 shows the three vegetation indices computed from MODIS and ETM+ data. VIUPD images from MODIS and ETM+ show more detailed information than NDVI and EVI images.

![Figure 6. Correlation of the UPDM coefficients computed using average values of $3 \times 3$ pixels between MODIS and ETM+ sensors: (a) area A with 200 pixels, (b) area B with 256 pixels, (c) area C with 256 pixels, (d) area D with 256 pixels.](image-url)
and the VIUPD images derived from MODIS and ETM+ data are similar. Figure 8 shows correlations between vegetation indices using data in the selected areas in figure 1. Columns in the figure are for areas A, B, C and D as noted in figure 1; rows denote the vegetation indices VIUPD, NDVI and EVI. Two points stand out,

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Figure 7. Vegetation index images computed from MODIS and ETM+ data. (a), (c) and (e) are the vegetation indices using VIUPD, NDVI and EVI for the MODIS sensor, and (b), (d) and (f) are the vegetation indices using VIUPD, NDVI and EVI for the ETM+ sensor.
Figure 8. Correlations of MODIS and ETM+ vegetation indices. Columns denote values computed from selected areas (A, B, C and D) in figure 1; rows refer to the vegetation index (VIUPD, NDVI and EVI) obtained from data in the same areas.
Figure 9. Correlations of MODIS and ETM + 3 × 3 averaged vegetation indices. Columns denote values computed from selected areas (A, B, C and D) in figure 1; rows refer to the vegetation index (VIUDP, NDVI and EVI) obtained from data in the same areas.
namely the linear correlation and the smaller rms values. From area A to area D, VIUPD increases in independence: area D has an rms of 0.0696 and a regression function of \( f(x) = 1.0089x \), a function that has the most linear relationship found in this study. Values with even smaller rms values are shown in figure 9, which shows vegetation indices computed with 3 × 3 pixel averages.

5. Conclusion

Four UPDM coefficients were computed using Landsat/ETM+ and Terra/MODIS data observed over the Three Gorges region in China. Vegetation indices were computed in the same multi-dimensional space. UPDM coefficients computed with six-band ETM+ data, with wavelengths between 350 and 2500 nm (the solar reflected wavelength region), were compared to coefficients computed with MODIS data in bands 1 to 7. Both datasets were resampled to a spatial resolution of 484.5 m. The DN value was converted to a reflectance value by considering radiometric calibration and atmospheric correction. Reflectance values were the input vector for calculating UPDM coefficients. Data processing precision depends on the algorithm selected. Because the aim of the present study was to assess the sensor independence of the UPDM, an easy and fast method was selected to preprocess the data. Such a preprocessing method may impact the representativeness of the UPDM coefficients and the vegetation indices derived.

The four UPDM coefficients were independent of the sensor. The independence of \( C_s \) and \( C_v \) is better than \( C_w \) and \( C_4 \), because both \( C_w \) and \( C_4 \) have values near zero. Consequently, any small bias will move them away from a linear relationship. The fitted errors of reduced \( \chi^2 \) calculated from equation (7) for MODIS data were 0.000698, 0.000549, 0.000475 and 0.000409 for areas A–D, respectively, and the respective fitted errors for ETM+ data were 0.000339, 0.000296, 0.000228 and 0.000181. UPDM coefficients and vegetation indices (VIUPD, NDVI and EVI) were computed using 3 × 3 pixel averages to evaluate the effect of pixel spatial location errors. Coefficients and vegetation indices computed this way showed smaller rms values. ETM+ gave smaller fit errors than MODIS, because ETM+ standard products have more precise geometry. The results also suggest that the VIUPD is sensor independent, especially in areas with little topographic influence, such as areas C and D.

Theoretically, hyper-multi-dimensional spectral data observed by different solar-reflected spectral sensors can be projected to a universal three- (or four-) dimensional UPDM space. In a previous paper, we presented the concept behind the UPDM and verified results using simulated data (Zhang et al. 2006a); we further verified the UPDM using ETM+ and MODIS data in this paper. The results demonstrate that both UPDM coefficients and the vegetation index VIUPD are sensor independent for specific pairs of sensors. We can thus expect UPDM techniques to reduce spectral features, decrease data amount requirements, and allow sensor-independent operations including landcover classification and the calculation of a sensor-independent vegetation index. However, the validations are insufficient, and further validation using data derived from other spectral sensors is required.

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