Scaling-based forest structural change detection using an inverted geometric-optical model in the Three Gorges region of China

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1. Introduction

Ecologically sustainable development and optimal management of natural resources is an essential ingredient for socio-economic development. Forest is the most widely distributed ecosystem and natural resource on Earth, affecting the lives of human beings on a daily basis, either as an economic good or as an environmental regulator (Wulder, 1998). Reliable information on forest structure is therefore critical for many aspects of forest management, including timber inventory and harvest, wildlife habitat modeling, and fire management (Franklin et al., 2000). The timely and accurate availability of forest structural properties, such as stem density, stem diameter at breast height, tree height, crown closure, crown size and age, are important throughout a range of ecological, biogeochemical and atmospheric science disciplines (Kalacska et al., 2007; McRoberts & Tomppo, 2007). Forest structural conditions constantly show changes that may be either subtle or abrupt, and can be the result of natural and/or anthropogenic forces (Hayes & Cohen, 2007). A method to quantitatively monitor forest structural properties over large areas would enable accurate assessments of changes in forest ecosystem services and provide insight into processes that can be of influence. One of the regions where major changes are taking place in a forest ecosystem is the Three Gorges region in China, which is widely known due to the Three Gorges Dam project (Qian, 2006). This hydroelectric dam construction is situated in Yichang (Hubei province) and located in the middle section of the Xiling Gorge of the Yangtze River. The Three Gorges Dam project is expected to have a positive impact on issues such as flood control, electrical power generation, shipping, and water supply; it may also exert far-reaching and profound impacts on the natural environment, including local climate, forest structure, water quality, aquatic life, sediment deposition and soil erosion (Li, 1990; Wu et al., 2002). The Chinese government also puts great importance to the eco-environmental aspects of the Three Gorges Dam project and has therefore implemented a long-term investigation (Huang et al., 2006), intending to monitor the changing environment. Over the past half century, a range of airborne and space-borne sensors have acquired remotely sensed data, whereby the number of sensors and their capability steadily increased over time (Rosenqvist et al., 2003). Remote sensing techniques can be used for estimating forest conditions and monitoring changes in forest structure at local, regional and global scales.
regional and global scales. Traditionally, quantitative retrieval methods for assessing forest structural properties by remote sensing can be grouped into two major categories: statistical and physical approaches. Statistical approaches are mainly based on a wide variety of vegetation indices and they use empirical regression models to infer forest properties. Physical approaches usually rely on inverting or assimilating canopy reflectance models (Liang, 2004). While forest canopy architecture and multiple scattering present major challenges to the empirical, statistical models, they are a core focus in physically based canopy reflectance modeling studies (Wulder & Franklin, 2003).

Canopy reflectance models have been used to derive many forest structural properties. In particular, geometric-optical models (GOM) have been used for forests (Chopping et al., 2006). They treat the surface as an assemblage of discrete geometric objects with the reflectance modeled as a linear combination of viewed sunlit and shaded components. GOM provide methods to analyze the interaction between forest structural properties and forest reflectance (Franklin & North, 1997). GOM have also been successfully inverted to estimate forest structural attributes in various studies (Franklin & Strahler, 1988; Gemmell, 1999; Hall et al., 1995; Peddle et al., 2003, 1999; Scarth & Phinn, 2000; Scarth et al., 2001; Woodcock, 1994, 1997). Zeng et al. (2007) derived pixel-based forest structural variables (crown closure and crown diameter) from EO-1 Hyperion data in the Longmenhe forest nature reserve (located in the Three Gorges region) by inverting the Li-Strahler geometric-optical model (Li & Strahler, 1985, 1992). The results indicate that the model predicts forest crown closure more reliably than crown size. For the inversion of a geometric-optical model, the essential input variable is the areal fraction of sunlit background, which usually is calculated based on pure reflectance spectra of the viewed surface components (endmembers). Therefore, the accuracy of forest structural properties derived from such an inverted model is primarily determined by the feasibility of methods for endmember extraction.

The most convenient approach of endmember extraction is estimating the pure spectrum directly from the remote sensing image. The usability of this approach depends upon the availability of pure pixels for every viewed surface component across the image. Hence, the quality of the endmembers is a function of both spatial resolution and ecosystem fragmentation. For very high spatial resolution imagery, such as QuickBird and IKONOS, and high spatial resolution imagery, such as Landsat Thematic Mapper (TM) and SPOT, the inherent pixel size ($\leq 30$ m) renders it possible to identify pure pixels representing each endmember in the scene properly. However, the use of these systems is usually constrained to small areas or regions of a few hundred square kilometers and are therefore less suitable for monitoring forest structural changes over large areas (Chambers et al., 2007). Moderate and low spatial resolution imagery ($\geq 250$ m), like the MODerate-resolution Imaging Spectroradiometer (MODIS), providing daily observations with large coverage, are more suitable for investigating temporal changes of forest conditions at larger scales. However, using an image-based endmember extraction method, the detected “pure” pixels probably contain mixtures of components due to the low spatial resolution.

In order to solve the mixture problem, an up-scaling endmember extraction approach using the linear unmixing model can be applied (Haertel & Shimabukuro, 2005; Zhukov et al., 1999; Zurita-Milla et al., 2006). When the fractions of components from a co-registered high spatial resolution image are available, e.g., from a classification, the linear unmixing model can be applied to unmix the low spatial resolution data and obtain the required endmembers. Zeng et al. (in press) used QuickBird data to an EO-1 Hyperion image using linear spectral unmixing in the Longmenhe study area. The results demonstrate that the scaling-based endmembers are more feasible for monitoring forest crown closure by inverting the Li-Strahler model than using image-based endmembers. This method provides a way to up-scale the information from local to regional scale. Subsequently, we call this the regional scaling-based endmember extraction method. Another approach is up-scaling the fractions of scene components from the high spatial resolution data to each pixel detected directly from the low spatial resolution image. Then the purest single pixel may be determined for every component. This pixel scaling-based endmember extraction method can be used to evaluate the purity of the image-based extreme pixels and select the purest one as the endmember.

In summary, the major goal of this study is to use an inversion of the Li-Strahler geometric-optical model combined with a scaling-based endmember extraction method to detect forest structural changes over large areas. The Three Gorges region of China is chosen as study area due to its expected changes over recent years. The Li-Strahler model is used to derive forest structural property, namely crown closure, in this region and to map changes in crown closure within a time span of 2 years.

2. Study area and data

2.1. Study area

The Three Gorges region refers to a special area associated with the Three Gorges Dam and Reservoir project along the Yangtze River of China (Fig. 1). It is also called the Three Gorges Reservoir region. The total area of this region is about 58,000 km² (28°32′–31°44′ N, 105°44′–111°39′ E), which includes 20 counties in Hubei province (ranging from Yichang in the east to Badong in the west) and Chongqing (ranging from Wushan in the east to Jiangjin in the west). The study area is characterized by a temperate climate zone (Koeppe: Cwa–Subtropical monsoon (McKnight & Hess, 2000)). The average annual precipitation is about 1000–1300 mm and the rainy season is between spring and summer (April–October). Based on a land cover inventory performed in 2002, it is found that the Three Gorges region is occupied by about 43% cropland, 30% forest, 20% shrub and 3% grassland (Huang et al., 2006). The forested areas are dominated by coniferous species (dominant species are Pinus massoniana and Cupressus funebris), deciduous broadleaved species (dominant species are Platycarya strobilacea and Betula luminifera) and subtropical evergreen broadleaved species (dominant species are Quercus spinosa and Cyclobalanopsis oxyodon).

2.2. Field data

The field data were collected in September 2006. Using 1:50,000 topographic maps and a land cover map of 2002, a total of 25 sample sites within the forest area of the Three Gorges region were selected (Fig. 1). For each sample site, we first determined a forested region with an acreage exceeding the MODIS pixel size of 500 m $\times$ 500 m. According to information originating from yearly local forest inventories, the sample sites were chosen to be in areas without severe logging and replanting activities between 2002 and 2006. The central location of each sample site was recorded by a GPS ($\pm 15$ m spatial accuracy). At every sample site, at least 2 sample plots (100 m $\times$ 100 m) were selected and forest structural properties were measured. These include forest crown closure (CC), crown diameter (CD), stem diameter at breast height (DBH), tree height (H), trunk height (TH) and stem density (SD).

Crown closure (CC), also known as crown cover, is the percentage of ground covered by a vertical projection of the outermost perimeter of the crowns in a stand (Brack, 1999). Crown diameter (CD), also called crown width, is the span of a crown and it is used to describe the crown size (About, 2007). CD for each tree with a DBH $\geq 5$ cm was measured in the field by taking twice the average radius of the projected outer boundary of the crown. Based on the crown map with stem positions of all measured trees in a sample plot, the CC was determined. Tree height (H) and trunk height (TH) were estimated by
performing angular measurements using a compass clinometer. Stem density (SD) was measured by counting the number of trees in each sample plot. The final forest measurements for the 25 field sample sites used for validation are the average values of several sample plots within each sample site.

2.3. Satellite images

Two Landsat TM images (Path 125/Row 39), acquired on September 1, 2002 and October 8, 2004 respectively, are used in this study as high spatial resolution data (30 m). The images have been geometrically corrected and converted from digital numbers (DNs) to top-of atmosphere (TOA) reflectance using the approach of Chander (Chander & Markham, 2003). Both TM images cover the eastern part of the Three Gorges region, including the Three Gorges Dam and the Longmenhe forest reserve (Fig. 2).

The moderate spatial resolution data covering the whole Three Gorges region are based on MODIS images (Fig. 2), which were collected at the same dates as the Landsat TM images. We use the daily ‘surface reflectance’ product of MODIS (MODIS-09, collection-4) with 7 spectral bands and 500 m spatial resolution in this study. In addition, for each required date, two MODIS-09 products are available, namely one from Terra-MODIS and one from Aqua-MODIS with about 2 h time difference in acquisition. Due to the importance of the image viewing angle in the model inversion and scaling approach used in this study, we use Aqua-MODIS images, which have an observation direction (nadir) located closer to the Landsat TM images. On the other hand, the use of MODIS Albedo products has also been considered. However, even though the MODIS BHR (bi-hemispherical reflectance, see Schaepman-Strub et al., 2006 for terminology) is more appropriate, a direct comparison with the Landsat data will only be possible by applying a directional correction of Landsat data as well. Detailed parameters of the images used (Landsat TM and Aqua-MODIS) are shown in Table 1.

2.4. Ancillary data

A land cover map of the Three Gorges region from 2002 is used for identifying the forest region. This map is derived from field investigations...
combined with a remote sensing classification (Zhang et al., 2007). The forest change detection between 2002 and 2004 in this study is only focused on the forest area present in the 2002 land cover map (Fig. 1). Other ancillary data used for monitoring the forest is a digital elevation model (DEM) with 25 m spatial resolution over the Three Gorges region, which was created by digitizing topographic maps (Huang et al., 2006). Additionally, the MODIS Global Geolocation Angle product contains information on solar angle and instrument viewing geometry that is also needed for modeling.

3. Methods

3.1. Overview of methodology

The methodology used in this study is presented as a flowchart in Fig. 3. The inverted Li-Strahler geometric-optical model is applied to retrieve one of the forest structural properties, crown closure (CC). This model requires three scene components as input variables: the sunlit background (G), the sunlit canopy (C), and the shadow (T). The endmembers of these three components are extracted from the two MODIS images combined with the matching Landsat TM data using two different scaling approaches:

- Regional scaling-based linear unmixing model: Invert the linear spectral unmixing model in the overlapping region of Landsat TM and MODIS. For each pixel of the MODIS image, the fractions of the three components are provided by the Landsat TM image; and
- Pixel scaling-based purest-pixel selection: Evaluate the purity of the extreme pixels derived automatically from the MODIS image based on the Landsat TM fractions of the three components, and then use the spectrum of the purest extreme (singular) pixel to represent the three components.

For both years, the forest CC is estimated from the inverted Li-Strahler model by integrating: (1) the fractional image of sunlit background \( K_g \) obtained by forward linear spectral unmixing of the MODIS data using the extracted endmembers (G, C and T) by the two tested scaling methods; (2) the slope and aspect images derived from DEM data using a general topographic analysis model, and (3) the mean parameters calculated from the field measurements for describing the shape of the forest canopy. Finally, we use the field measured CC from 25 sample sites to validate the model estimations for both years and evaluate the influence of the two scaling-based endmember extraction methods. The changes of the forest CC between 2002 and 2004 are detected and quantified in 20 counties of the Three Gorges region using the CC mapping.

3.2. Geometric-optical model

Zeng et al. (2007, in press) have shown that the Li-Strahler geometric-optical model can be inverted to retrieve forest canopy variables like CC using very high and high spatial resolution images. This model represents the forest as a collection of 3-dimensional geometrical objects with a Poisson distribution. For modeling a forest scene, three components have to be estimated: sunlit background (G), sunlit canopy (C) and shadow (T) (Hall et al., 1995; Li & Wang, 1995; Peddle et al., 1999, 2003). In order to apply this model to individual pixels in a remote sensing image, the pixel size should be much larger than the tree size, but smaller than the size of a forest, and the individual trees should be randomly distributed within the pixel (Woodcock et al., 1994).

To derive CC by inverting the Li-Strahler model, the fraction of sunlit background ($K_g$) is required as input (Li & Strahler, 1992; Strahler & Jupp, 1990; Woodcock et al., 1997). Based on the field measurements in the forest area of the Three Gorges region, the crown shape can be modeled as an ellipsoid. Therefore, the measured mean values of tree height from ground to mid-crown ($h=7.21$ m), crown radius in vertical direction ($b=2.01$ m) and crown radius in horizontal direction ($r=1.22$ m) are all required input parameters for the model inversion. In addition, the slope and aspect images re-sampled to 500 m spatial resolution and the solar and viewing angles are also required for model inversion (Schaaf et al., 1994; Zeng et al., 2007). Since $K_g$ is the most critical input, accurate extraction of the G, C and T endmembers from the MODIS images of the Three Gorges region for both years is very important.

3.3. Endmember extraction

Both scaling-based endmember extraction methods presented hereafter require the fractional images of the three scene components (G, C and T) from the Landsat TM data. The spatial resolution of TM (30 m) allows the selection of pure pixels representing each endmember. With the support of extensive field measurements in the study area covered by the TM images, pure pixels indicating the G, C and T endmembers are selected from the TM images at the same locations for both years. A forward linear spectral unmixing model is performed using these endmembers to obtain the TM fractional images of G, C and T for both years. These TM fractional images are then re-sampled to 25 m and used as the reference images to spatially co-register the corresponding MODIS image.

3.3.1. Regional scaling-based method

In Zeng et al. (in press) a scaling-based linear unmixing model was successfully applied to the Longmenhe forest natural reserve using a fusion of Quickbird and Hyperion images. In this study, this method will be extended to a larger region by using Landsat TM and MODIS images.
Originally, the linear spectral unmixing model is designed to estimate the fractions of components in each pixel of a remote sensing image (Adams et al., 1986; Goodwin et al., 2005; Peddle et al., 1999; Settle & Drake, 1993). The pixel reflectance \( S_j \) is defined as a linear combination of the endmembers \( (R) \), i.e. the pure reflectance spectra of components.

\[
S_j = \sum_{i=1}^{m} K_i R_{ij} + v_j \quad j = 1, 2, \ldots, p \tag{1}
\]

where \( m \) is the number of endmembers; \( p \) is the number of image bands; \( K \) is the fraction of each endmember within the pixel and \( v \) is the residual for each band.

In this study, we unmix MODIS pixels, so the pixel-based reflectance \( S \) is provided by the MODIS image. However, we now assume that the fractions \( (K) \) are known and estimated from the TM fractional images. Then we can calculate each endmember \( (R) \) by solving Eq. (1) simultaneously for a series of equations using a least squares approach (Haertel & Shimabukuro, 2005).

The overlapping area between the MODIS and TM images is used for this, and subsequently the obtained spectral reflectance of the three components \((G, C, T)\), being the MODIS endmembers, is assumed to be valid for the whole Three Gorges region.

### 3.3.2. Pixel scaling-based method

In order to compare the regional scaling-based method with one that is commonly used, we selected the pixel purity index (PPI) approach (Boardman, 1993). The PPI is implemented to identify a number of extreme pixels in each MODIS image. Due to the low spatial resolution of the MODIS image, up-scaling the pixel-based fractions of \( G, C \) and \( T \) from TM data and evaluating the purity of these extreme pixels are required. After calculating the mean fractions of the three components for every PPI derived MODIS extreme pixel based on the TM fractional images, the purest pixel representing the \( G, C \) and \( T \) endmembers of the MODIS image can be selected.

### 3.4. Validation and change detection

For validating the model inversion, we use 25 field sample sites and calculate the mean value of CC for each field sample site for comparison with the corresponding pixel from the CC image. The root mean square error (RMSE) between estimated and measured CC and also the coefficient of determination \( (R^2) \) from a linear regression between estimated and measured CC are used to evaluate the suitability of the two scaling-based methods for deriving endmembers as input to the model inversion. The best result is then used as final CC map for both years.

In order to detect the spatial distribution of CC change between 2002 and 2004, we use an algebra-based change detection method, which is relatively simple, straightforward and easy to interpret (Lu et al., 2004). We assume that the frequency of the CC difference in the study area is normally distributed. When fitting the histogram of the CC difference with a Gaussian function \( (3) \) and \( (4) \), the mean \( \mu \) and standard deviation \( \sigma \) can be calculated (where \( x \) represents the physical increase of pixel-based CC between 2002 and 2004).

\[
f(x) = \frac{1}{\sigma \sqrt{2\pi}} \exp \left( -\frac{(x-\mu)^2}{2\sigma^2} \right) \tag{3}\]

\[
x = CC_{2004} – CC_{2002} \tag{4}\]

Statistically, about 68% of the values fall within the interval defined by one standard deviation difference from the mean \((\mu \pm \sigma)\) and these are considered as regions where there is not enough evidence that CC has changed and are thus called indifferent regions. The regions with a slight increase or slight decrease in CC are defined by a CC difference in the ranges \((\mu + \sigma \rightarrow \mu + 2\sigma)\) and \((\mu - \sigma \rightarrow \mu - 2\sigma)\). These regions combined with the indifferent region include about 95% of the total pixels. For labeling a pixel as a severe increase or severe decrease, the difference in CC between the two years should deviate significantly from the mean. Therefore, these pixels are defined by values between \((\mu + 2\sigma \rightarrow \text{maximum})\) and \((\mu - 2\sigma \rightarrow \text{minimum})\), which represent the regions with obvious changes in CC.

### 4. Results and discussion

#### 4.1. Signatures of the endmembers

The signatures of the endmembers \( G \) (sunlit background), \( C \) (sunlit canopy) and \( T \) (shadow) extracted directly from the TM image in terms of TOA reflectance are presented in Fig. 4a and b for 2002 and 2004, respectively. Using these three endmembers, the TM image is unmixed in order to derive the TM fractional images of \( G, C \) and \( T \) for both years.

Since the TM fractional images are resampled to 25 m, each MODIS pixel corresponds to 20x20 TM pixels. When applying the linear unmixing model in the overlapping area (excluding clouds) of the MODIS image and the TM fractional images of \( G, C \) and \( T \) for both years, the spectral reflectances after the unmixing of the MODIS image finally can be used as the regional scaling-based MODIS endmembers (Fig. 4c and d).

In addition, the PPI method is also applied in the overlapping area to extract the extreme pixels from the MODIS image. We iterated 10,000 projections, finally resulting in 11 extreme pixels \((C: 4 \text{ extreme pixels}; G: 3 \text{ extreme pixels}; T: 4 \text{ extreme pixels})\) which are selected for both years. Overlaid every MODIS extreme pixel with a window of 20x20 pixels of the TM fractional images, mean fractions of \( G, C \) and \( T \) are calculated. These are listed in Table 2 for both years. The results indicate that most of the extreme pixels automatically detected by the PPI method are still mixtures. This is not unexpected, since at 500 m spatial resolution the derivation of the pure pixels of \( C \) and \( T \) becomes increasingly unfeasible compared to \( G \). Thus, the fractions of \( G \) and \( T \) are almost intermixed in each \( C \) and \( T \) extreme pixel for both years. After comparing the purity of all extreme pixels, the purest pixels are chosen to be the pixel scaling-based MODIS endmembers. They are the pixels G4, C1 and T3 for the 2002 MODIS image, and G2, C3 and T2 for the 2004 MODIS image (Fig. 4e and f).

When comparing the MODIS endmembers extracted by the two scaling-based methods, the regional scaling-based endmembers have consistently higher \( G \) values and lower \( C \) values than the pixel scaling-based endmembers for both years (Fig. 4). The extracted \( T \) endmembers for both methods are quite similar. The uncertainties of these two scaling-based methods are affected by the accuracy of the TM fractional images, the quality of the co-registration between the MODIS and TM images, and the representativeness of the overlapping region for the whole study area.

#### 4.2. Crown closure mapping

For retrieving the CC map using the inverted Li-Strahler model, first the forward linear spectral unmixing is used to derive the fractions of sunlit background \( K_G \) from the MODIS image based on the extracted endmembers for both years. For some pixels the model produces a negative \( K_G \). This is a result of limitations in the unmixing approach and particularly occurs in areas consisting of a mixture of sunlit canopy and shadow only. The missing sunlit background fraction is then forcing the unmixing to negative results. In some very dense forest regions, it is also difficult to derive the fraction of sunlit background. In our analysis, those non-CC areas as well as cloud covered areas have been marked as “infeasible” regions in the final CC map.

The inversion of the Li-Strahler model is implemented at the MODIS pixel level using input derived by the two endmember extraction methods for 2002 and 2004, respectively. The scatter plots in Fig. 5 indicate the relationship between the model-estimated CC and the ground measurements of CC for the 25 sample sites in the study area. Results show that for both years the regional scaling-based endmembers ($R^2_{2002} = 0.614$; RMSE$_{2002} = 6\%$; $R^2_{2004} = 0.631$ and RMSE$_{2004} = 5.2\%$) perform better than the pixel scaling-based endmembers ($R^2_{2002} = 0.428$; RMSE$_{2002} = 7.2\%$; $R^2_{2004} = 0.502$ and RMSE$_{2004} = 8.3\%$) for CC retrieval. Therefore, we decide to limit our further analysis to the use of endmembers extracted using the regional scaling-based method in the Three Gorges region for both 2002 and 2004. Excluding the “infeasible” regions, the CC mapping performed on MODIS 2002 data predicts values for about 89% of the forest area and for 2004 about 75% of the forest pixels get a CC value. All pixels with an estimated CC value in both years are finally identified. This results in a prediction of CC for about 70% of the forest area in the whole Three Gorges region (Fig. 6).

4.3. Estimating changes

The histograms of the model derived CC for both years (2002 and 2004) are shown in Fig. 7a. A clear trend, expressed as a shift in CC

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**Table 2**

<table>
<thead>
<tr>
<th>Extreme pixels of 02 MODIS</th>
<th>02 TM fraction-G</th>
<th>02 TM fraction-C</th>
<th>02 TM fraction-T</th>
<th>04 TM fraction-G</th>
<th>04 TM fraction-C</th>
<th>04 TM fraction-T</th>
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<tbody>
<tr>
<td>G1:</td>
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<td>0.19363</td>
<td>0.00539</td>
<td>G1:</td>
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<td>0.17752</td>
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<td>G2:</td>
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<td>0.19116</td>
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<td>G3:</td>
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<td>0.22983</td>
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<tr>
<td>G4:</td>
<td>0.94416</td>
<td>0.17421</td>
<td>0.00000</td>
<td>G4:</td>
<td>0.73823</td>
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<tr>
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<td>T3:</td>
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</tr>
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</table>

The purest pixel for each component is shown in bold.
retrieval frequency, can be observed from the two histograms. Trends may be caused by model errors of the inverted Li-Strahler approach and the linear spectral unmixing. Trends may also be explained by inaccurate atmospheric correction and by differences in solar and viewing angles of the MODIS images for both years. Finally, a real increase and/or decrease of CC can cause this trend. We plot absolute trend differences of CC between the two years (i.e. CC$_{2004}$−CC$_{2002}$) (Fig. 7b). This histogram approximates a normal distribution, but the mean (μ) is slightly negative (−0.057) instead of 0. Since it is impossible to isolate the above trends individually and we are interested in CC trends only, we assume the general trend to be of a systematic origin. As a result, we assume the histogram to be normal distributed around the mean. The assignment of systematic errors as discussed above leads consequently to a loss of the pure physical meaning of changing CC. We therefore use statistics to obtain the thresholds defined in Section 3.4 and attribute non-symmetric values around 0 in the following 5 classes (μ=−0.057, σ=0.22): severe decrease (−1 to −0.497), slight decrease (−0.497 to −0.277), indifferent (−0.277 to 0.163), slight increase (0.163 to 0.383) and severe increase (0.383 to 1).

The spatial change of the model derived CC between 2002 and 2004 in the forest area of the Three Gorges region is mapped in Fig. 8. It clearly shows that areas with an increasing and decreasing CC are not randomly distributed. The statistical differences of the CC change between 2002 and 2004 in the 20 counties of the Three Gorges region are quantified by the percentages of increase and decrease in coverage and these are listed in Table 3.

Table 3 indicates relative change classes, that reliably can identify hotspot areas of severe CC changes. In the Chongqing reservoir region, the ‘severe increase’ is particularly visible in the counties of Shizhou to Wuxi (from west to east), with Kaixian county being affected the most. This general increasing trend of the forest structural parameter (crown closure) in the observed period is not only due to an expected natural increase of CC in trees but also because of some policies implemented in the Three Gorges region. To prevent soil erosion, pollution and geological disasters, the Chinese government issued a reforestation policy in 2000 (Duan & Steil, 2003). This policy has been adopted gradually by converting cultivated land (especially on slopes greater than 25°) to forest and pasture land. It benefits from rehabilitation of the environment in the Three Gorges region on a long-term basis. Another policy of constructing a green belt was approved and carried out in 2004. This green belt mainly covers the region surrounding the Three Gorges reservoir, where the existing forest is being rehabilitated through ceasing logging activities and replanting trees (Tan & Yao, 2006).

However, due to the rural resettlement and urban relocation in the Three Gorges region as a result of the Dam project, an increase in resource needs is observed, such as the demand of arable farmland and the removal of wood, which directly leads to forest destruction and therefore decreasing CC. This is particularly visible in two counties, Xingshan with 9.79% coverage of severe decrease and Yichang with 7.47% coverage of severe decrease (Fig. 8 and Table 3). Both counties possess the highest forest coverage, especially natural broadleaved forest. Additionally, the most affected areas of CC loss...
between 2002 and 2004 are located around Yichang where the Three Gorges Dam itself is being constructed. It seems that forest eco-environmental disturbance and decline are associated with the Three Gorges Dam project and are existing despite the above mentioned reforestation and green belt construction policies implemented. The identified ‘severe decrease’ regions are the most important areas requiring a sustainable forest resource protection in the Three Gorges region.

5. Conclusions and outlook

This study demonstrates that the inverted Li-Strahler geometric-optical model combined with the scaling approach, used at a local scale in the Longmenhe study area with QuickBird and Hyperion images (Zeng et al., in press), can also be applied at the regional scale of the Three Gorges region with Landsat TM and MODIS images allowing to monitor severely affected areas. A main advantage of this methodology as compared to commonly used empirical methods is its physical basis and its better general applicability to different study areas. Furthermore, based on the collected 2002 and 2004 data, the model derived forest structural properties can well be compared to detect changes. After validating the model results for both years using 25 field samples, it can be concluded that the regional scaling-based endmembers extracted from the linear unmixing model are the most suitable ones to be used in combination with the inverted Li-Strahler model for monitoring the forest crown closure. For both years this methodology yields similar accuracies.

Although this methodology contains several uncertainties, it provides a technique based on satellite data to detect changes of the forest structure. This study offers the basis for understanding the
changes of the forest between 2002 and 2004 in the Three Gorges region. The results and analyses highlight the severely changed regions where sustainable efforts in ecosystem restoration will have most impact. At present, scaling-based remote sensing approaches provide the only large scale means for monitoring ecosystem changes, especially in areas where validation data are sparse.

Currently scaling is one of the important issues in quantitative remote sensing. We demonstrate in this study that scaling gaps between typical spatial resolutions of Landsat TM and MODIS can be successfully bridged by applying a scaling-based endmember extraction method using the linear unmixing model. This is in particular true, as long as the corresponding fine and coarse spatial resolution data satisfy the fractional cover retrieval constraints (sufficient sunlit and shaded canopy fraction present) of the model. If this requirement is fulfilled, a quantitative derivation of CC is feasible. However at larger spatial scales (>1 km spatial resolution), the canopy heterogeneity may be higher, no longer allowing a clear separation of the fractions. The proposed methodology provides therefore the possibility to carry out change detection at larger scales than previously, and finally will allow the integration of remote sensing data in process models (Schaepman, 2007).

This study also points out important issues for further work in an effort to develop a forest monitoring and change detection protocol for

Table 3

<table>
<thead>
<tr>
<th>County name</th>
<th>% Forest cover by 2002 land cover map</th>
<th>% Forest pixels with modelled CC value</th>
<th>%Severe decrease in CC region</th>
<th>%Slight decrease in CC region</th>
<th>%Indifferent in CC region</th>
<th>%Slight increase in CC region</th>
<th>%Severe increase in CC region</th>
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<td>8.47</td>
<td>75.14</td>
<td>13.76</td>
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<td>25.74</td>
<td>62.41</td>
<td>3.38</td>
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<td>63.34</td>
<td>0.53</td>
<td>11.40</td>
<td>73.84</td>
<td>12.79</td>
<td>1.43</td>
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<td>5.91</td>
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<td>16.39</td>
<td>70.13</td>
<td>6.99</td>
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<tr>
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<td>18.09</td>
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</tr>
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Fig. 7. (a) Histograms of the model derived CC for 2002 and 2004 and (b) the pixel-based difference between the two years (i.e. CC_{2004} - CC_{2002}).

Fig. 8. Change map of the model derived CC between 2002 and 2004 in the forest area of the Three Gorges region. The colored pixels indicate the obvious changes of CC increase (green) and CC decrease (red). For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.
the Three Gorges region based on multimodal satellite observations. The Three Gorges Dam is expected to be fully operational in 2009. The eco-environmental impact resulting from the construction of the dam will require a long-term monitoring approach, beyond the one presented here. In addition, besides the forest crown closure, other forest structural and biophysical properties, such as tree height, age, leaf area index, and canopy chlorophyll will be of future research interest for forest monitoring in this region.

Acknowledgments

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References

