CHANGE DETECTION OF FOREST CROWN CLOSURE USING AN INVERTED GEOMETRIC-OPTICAL MODEL AND SCALING

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ABSTRACT:

The physical based Li-Strahler geometric-optical model can be inverted to retrieve forest canopy structural variables. One of the main input variables of the inverted model is the fractional component of sunlit background (K_g). K_g is calculated by using pure reflectance spectra (endmembers) of the viewed surface components. To detect the forest canopy changes by the inverted geometric-optical model combined with the scaling approach in large areas at high temporal frequency is the main objective of this paper. We firstly extract the viewed surface components endmembers from the low spatial resolution MODIS data in two different years by a regional scaling-based linear unmixing model using the corresponding medium spatial resolution Landsat TM images; secondly, derive and map one of the forest structural properties, crown closure (CC), by inverting the Li-Strahler geometric-optical model based on the extracted endmembers; thirdly, complement prediction deficiencies of the inverted Li-Strahler model CC by using a spatial interpolation algorithm (regression kriging) in the infeasible regions; finally produce the spatially continuous CC maps and representing CC changes in two years. This methodology is illustrated with an example application in the Three Gorges region of China.

1. INTRODUCTION

Forest is one of the most important components of the biosphere, which directly influences the global atmospheric cycles and human well-being. Detecting forest conditions as well as monitoring the changes of various forest structural, biophysical or biochemical variables can enable accurate understanding of forest ecosystem services. Crown closure (CC), defined as the percentage of ground covered by the vertical projection of tree crows, is an essential forest structural variable that indicates the distribution, density and growing status of trees. CC is also a forest property that is most commonly mapped using remote sensing techniques (Ustin, 2004).

At local, regional and global scales, remote sensing has become an effective tool in inventory, planning and management of forest resources. Methods applied for deriving the forest structural variable CC include traditional classification and spectral mixture, statistically based regression analysis and inversion of physically based canopy reflectance (CR) models. A main advantage of inverting CR models as compared to empirical methods is their physical foundation and their better general applicability to different sites and sampling conditions (cf., Schaepman et al., 2005; Schlerf and Atzberger, 2006).

Among the CR models, geometric-optical model, treating the surface as an assemblage of discrete geometric objects with the reflectance modeled as being a linear combination of viewed sunlit and shaded components, has been used commonly for monitoring forests and also has been successfully inverted to estimate forest structural attributes in various studies (Franklin and Strahler, 1988; Woodcock, 1994; Hall et al., 1995; Woodcock et al., 1997; Gemmell, 1999; Peddle et al., 1999; Scarth and Phinn, 2000; Scarth et al., 2001; Peddle et al., 2003). Zeng et al. (2007) derived pixel-based CC by inverting the Li-Strahler geometric-optical model (Li and Strahler, 1985; 1992). For the inversion of the Li-Strahler model, an essential input variable is the areal fraction estimate of the sunlit background component, which usually is calculated based on the pure reflectance spectra of the viewed surface components, i.e., endmembers.

The most convenient approach of endmember extraction is estimating the pure spectrum directly from the remote sensing image. For high spatial resolution imagery, such as Landsat Thematic Mapper (TM) and SPOT, the inherent pixel size (≤30 m) renders it possible to identify pure pixels representing each endmember. However, the use of these images is less suitable for monitoring forest structural changes over large areas (Chambers et al., 2007). Moreover, the significant time requirement of multi-temporal image collection renders these types of images less suitable. Moderate and low spatial resolution imagery (≥250 m), like the MODerate-resolution Imaging Spectroradiometer (MODIS), providing daily observations with large coverage, are more suitable to investigate temporal changes of forest conditions at larger scales. Nevertheless, using an image-based endmember extraction method, the detected "pure" pixels may still 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. Zeng et al. (2008) up-scaled QuickBird data to EO-1 Hyperion image using linear spectral unmixing, and the results demonstrated that the scaling-based endmembers were more feasible for monitoring forest crown closure by

* Corresponding author. More information about this work is presented in the PhD thesis of Zeng (2008) entitled: Quantitative remote sensing for monitoring forest canopy structural variables in the Three Gorges region of China.

inverting the Li-Strahler model than using image-based endmembers. This method provides an avenue to up-scale the information from local to regional scale. We subsequently call this method the regional scaling-based endmember extraction.

Additionally, in very densely forested regions, crowns touch each other and almost no sunlit background component can be derived, thus no estimation from the Li-Strahler model inversion is obtained. With regard to increasing the applicability of the Li-Strahler model inversion for mapping CC on a per-pixel basis, finding ways, such as spatial interpolation, to solve missing estimations in densely forested regions is extremely important.

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 and a spatial interpolation technique to derive forest crown closure over larger areas and to map changes in crown closure within a time span of 2 years.

2. STUDY SITE AND DATA

The Three Gorges region of China is chosen as study site in this work. This region refers to a special area associated with the Three Gorges Dam and Reservoir project along the Yangtze River and it is also called the Three Gorges Reservoir region. The total acreage of this region is about 58,000 km^2 (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). This study area belongs to the temperate climate zone (Koeppen: Cwa–Subtropical monsoon (McKnight and 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 investigation of 2002, 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 mainly dominated by coniferous, deciduous broadleaved and subtropical evergreen broadleaved species.

The field data were collected in September 2006. With help of 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. For each sample site, we first determined a homogeneous forest area with acreage above 500 m x 500 m. According to information from the yearly local forest investigation, 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 (±15 m spatial accuracy). At every sample site, at least 2 sample plots (100 m x 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).

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. Both TM images cover the eastern part of the Three Gorges region. The moderate spatial resolution data covering the whole Three Gorges region are based on MODIS images, 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. Due to the importance of the image viewing angle in the model inversion and scaling approach used in this study, we use the Aqua-MODIS, which has an observation direction (nadir), located closer to the Landsat TM images. In addition, 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. Other ancillary data needed for modelling are the digital elevation model (DEM) with 25 m spatial resolution over the Three Gorges region and the MODIS Global Geolocation Angle product, which contains information on solar illumination and instrument viewing geometry.

3. METHOD

3.1 Inverted Geometric-Optical Model

The Li-Strahler geometric-optical model (Li and Strahler, 1985; 1992) is based on the assumption that the Bidirectional Reflectance Distribution Function (BRDF) is a purely geometric phenomenon resulting from a scene of discrete 3-dimensional objects being illuminated and viewed from different positions in the hemisphere. For modelling a forest scene, three components have to be estimated: sunlit canopy–C, sunlit background–G and shadow–T (Li and Wang, 1995; Peddle et al., 1999; Peddle et al., 2003). This model also assumes that the resolution of the remote sensing image is larger than the size of individual crowns but smaller than the size of forest stands, and that the individual trees are ‘Poisson’ distributed within the pixel (Woodcock et al., 1994).

To derive CC by inverting Li-Strahler model, the fraction of sunlit background (K_g) is required as input (Strahler and Jupp, 1990; Li and Strahler, 1992; Woodcock et al., 1997; Zeng et al., 2007; 2008). Based on the field measurements in the forest area of the Three Gorges region, the crown shape can be modelled as an ellipsoid. Therefore, the measured values of tree height from ground to mid-crown, crown radius in vertical direction and crown radius in horizontal direction are the necessary inputs of model inversion. Moreover, 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.

3.2 Endmember Extraction

Traditionally, the linear unmixing model has been widely used to calculate the percentages of several individual surface components contained in each pixel of a remote sensing image (Peddle et al., 1999; Goodwin et al., 2005). The model assumes that the reflectance (S) of each pixel is a linear combination of endmembers (R), which are the pure reflectance spectra for each component. The general equations are:

$$S_j = \sum_{i=1}^{m} K_i R_{i,j} + v_j \qquad j = 1,2...,p \tag{1}$$

$$1 = \sum_{i=1}^{m} K_i \qquad K_i >= 0 \tag{2}$$

Where m is the number of components, in this case, m is the 3 components of C, G and T; p is the number of image bands; K is the fractional abundance of each component within the pixel and v is the residual for each band.

In this study we unmix the MODIS pixels, so the pixel-based reflectance (S) is provided by the MODIS image. However, we now consider that the fractions (K) are known and estimated from the TM fractional images. Then we can calculate each endmember (R) by solving equation (1) simultaneously for a series of equations using a least squares approach (Haertel and 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 and T) being the MODIS endmembers is assumed to be valid for the whole Three Gorges region.

3.3 Spatial Interpolation

In areas where the Li-Strahler model inversion is infeasible, CC values will be obtained by a hybrid spatial interpolation technique, i.e. regression kriging. Regression kriging employs regression analysis to model the trend of a target variable with one or more (*p*) exhaustively sampled auxiliary variables and spatial interpolation (kriging) of observed residuals to predict local departures from that trend (Hengl et al., 2007). The method is also referred to as universal kriging (Pebesma, 1997; Pebesma and Wesseling, 1998) or kriging with external drift (Deutsch and Journel, 1998). For CC interpolation, it can be expressed as:

$$CC(x_0) = \mathbf{q}_0^{\mathbf{T}} \cdot \boldsymbol{\beta}_{\mathbf{GLS}} + \boldsymbol{\lambda}_0^{\mathbf{T}} \cdot (\mathbf{CC} - \mathbf{q} \cdot \boldsymbol{\beta}_{\mathbf{GLS}}) \tag{3}$$

Where $CC(x_0)$ denotes the predicted CC at location x_0; $\mathbf{q_0}$ is a vector with 1 as the first element, followed by the *p* auxiliary values at the location to be predicted; $\boldsymbol{\beta}_{\mathbf{GLS}}$ is a vector of regression coefficients obtained by generalized least squares (GLS) fitting; $\mathbf{CC} - \mathbf{q} \cdot \boldsymbol{\beta}_{\mathbf{GLS}}$ are *n* observed residuals in the neighborhood of x_0; and $\boldsymbol{\lambda}_0$ is the vector of *n* kriging weights. Estimation of the regression coefficients by GLS requires prior knowledge of the covariance matrix of the residuals (Cressie, 1993):

$$\boldsymbol{\beta}_{\mathbf{GLS}} = (\mathbf{q}^{\mathbf{T}} \cdot \boldsymbol{\Sigma}^{-1} \cdot \mathbf{q})^{-1} \cdot \mathbf{q}^{\mathbf{T}} \cdot \boldsymbol{\Sigma}^{-1} \cdot \mathbf{CC} \tag{4}$$

Where $\boldsymbol{\Sigma}$ is the covariance matrix of the residuals and **CC** is the vector of estimated CC by the Li-Strahler model inversion. In geostatistics it is common practice to derive $\boldsymbol{\Sigma}$ from a (semi) variogram which describes spatial dependence as a function of the distance between locations (Isaacs and Srivastava, 1989). Typically, it suffices to approximate this function from the residuals of a drift model obtained by ordinary least squares (OLS) fitting of the target variable on the secondary variable(s), in a single iteration (Kitanidis, 1993).

We adopt this approach using the Gstat software (Pebesma, 1997; Pebesma and Wesseling, 1998), with a single secondary variable that is selected from the commonly used vegetation indices (i.e. the normalized difference vegetation index (NDVI), the simple ratio (SR), the reduced simple ratio (RSR) (Brown et al., 2000), and also a single near-infrared (NIR) band) as the one having the highest linear correlation with CC. The choice for these variables is based on their expected correlation with CC while they are also readily derived from the both MODIS images.

4. RESULTS AND DISCUSSION

Since the TM fractional images are re-sampled to 25 m, each MODIS pixel corresponds to 20 x 20 TM pixels. When applying the linear unmixing model in the overlapping area (excluding clouds) of the MODIS image and the TM fractional images (G, C and T) for both years, the extracted spectral reflectance can be used as the regional scaling-based MODIS endmembers. Then, the fractions of sunlit background (K_g) from the both MODIS images are derived for inverting the Li-Strahler model to estimate CC on a per-pixel basis.

After a correlation analysis, NDVI shows the highest linear correlation with the model estimated CC in the Three Gorges region for both 2002 (R=0.61) and 2004 (R=0.57), which is then selected to be the secondary variable used in the regression kriging. The final CC maps of 2002 and 2004 (Figure 1) display that the percentage of pixels with feasible CC values in the forested areas of the Three Gorges region increases from 70% (without interpolation) to current 95%. Only the cloud covered areas can not be estimated. Based on the 25 sample sites, validations show that for both years this method yields similar accuracies (R^2_{2002} = 0.614; $RMSE_{2002}$ = 0.060; R^2_{2004} = 0.631 and $RMSE_{2004}$ = 0.052).

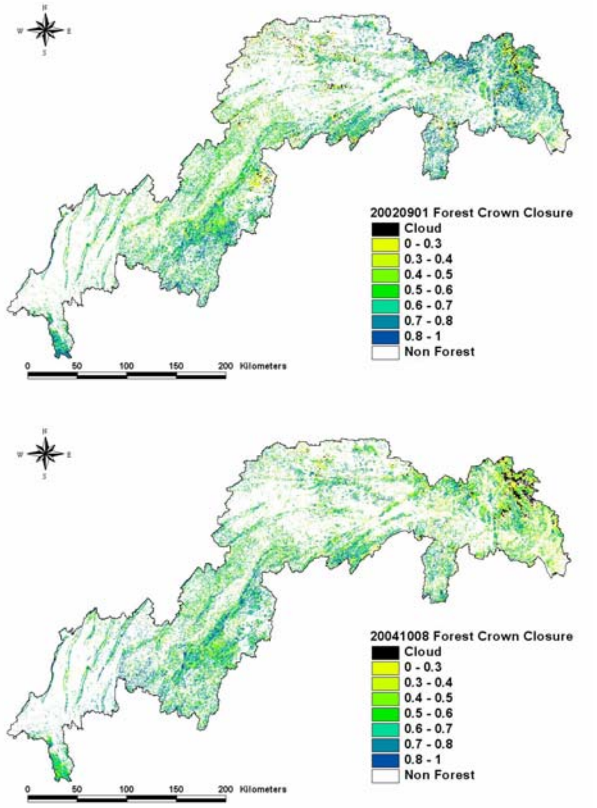

Figure 1. Mapping results of forest crown closure for 2002 (up) and 2004 (down) in the Three Gorges region.

We plot absolute trend differences of CC between the two years (i.e. $CC_{2004} - CC_{2002}$). This histogram approximates a normal distribution, but the mean (μ) is slightly negative (-0.057) instead of 0. We therefore use statistics to obtain the standard deviation (σ = 0.22) and the following thresholds for 5 differential classes: severe decrease (-1 to μ-2σ), slight decrease (μ-2σ to μ-σ), indifferent (μ-σ to μ+σ), slight increase (μ+σ to μ+2σ) and severe increase (μ+2σ to 1).

The spatial change of the derived CC between 2002 and 2004 in the forested area of the Three Gorges region is mapped in Figure 2. It clearly shows that areas with an increasing and decreasing CC are not randomly distributed. As a result, most of the forest areas show an increase of CC between 2002 and 2004. In some counties of Chongqing reservoir region, like the range from Wuxi in the east to Shizhu in the west, more than 5% coverage with the class of severe increase are detected. This general increasing trend of the forest CC 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. However, due to the rural resettlement and urban relocation in the Three Gorges region resulted from the Dam project, an increase in resource needs is observed, such as the demand of arable farmland and wood removal, which directly leads to forest destruction and therefore decreasing CC. This is particularly visible in two counties, Xingshan and Yichang. The identified 'severe decrease' regions are the most important areas requiring a solid and sustainable forest resource protection in the Three Gorges region.

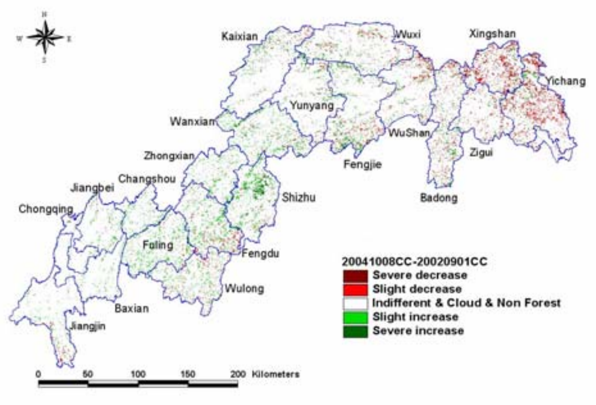

Figure 2. Change map of CC between 2002 and 2004 in the Three Gorges region.

5. CONCLUSION AND OUTLOOK

This study indicates that: (1) The Li-Strahler geometric-optical model can be successfully inverted for estimating the forest crown closure (CC) and the pixel-based fraction of sunlit background scene component (K_g) is the most important input parameter that influences the accuracy of the Li-Strahler model inversion; (2) The regional scaling-based endmember extraction method can upscale the information from high spatial resolution data to low spatial resolution data by means of inverting a linear unmixing model in the overlapping region for two images. It can also expand the information from local to regional. The inverted Li-Strahler model combined with the scaling method makes it possible to estimate CC in large areas. By using multi-temporal data, a change detection can be carried out; and (3) Spatial interpolation techniques can properly deal with the missing estimates resulting from the Li-Strahler model inversion based on the endmembers calculated by the scaling approach. With the support of a statistical based interpolation, the inverted Li-Strahler model combined with the scaling method can finally yield spatially continuous maps representing CC in the whole study area.

Although this method contains several uncertainties, it provides a remotely sensed technique to detect changes of the forest structure. This study gives the basis for understanding the changes of the forest between 2002 and 2004 in the Three Gorges region. It also points out important issues for further work in an effort to develop a forest monitoring and change detection protocol for the Three Gorges region based on multi-temporal 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.

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