Available online at www.sciencedirect.com
SciVerse ScienceDirect
Physics Procedia 25 (2012) 1055 – 1062
Physics Procedia

2012 International Conference on Solid State Devices and Materials Science

Spectral Unmixing Approach in Remotely Sensed Forest Cover Estimation: A Study of Subtropical Forest in Southeast China

Liming Bai , Hui Lin, Hua Sun, Dengkui Mo, Enping Yan

Center of Forestry Remote Sensing Information Engineering
Central South University of Forestry and Technology
Changsha Hunan Province, 410004, China

Abstract

Addressing the problem of spectral mixing in remotely sensed forest cover mapping, a linear spectral unmixing approach was employed in the study to assess if sub-pixel method would improve forest cover estimation accuracy in the context of complex subtropical forest ecosystem. After masking out water bodies using Modified Normalized Difference Water Index (MNDWI), the TM imagery of Pingnan County, Guangxi Zhuang Autonomous Region, China, was processed with Minimum Noise Fraction (MNF) Rotation transform and Pixel Purity Index (PPI), thus "pure" spectral endmembers of woody cover, herbaceous vegetation and bare ground were extracted as input into the spectral unmixing algorithm and produced forest map. The forest percentage is 55.7%, overestimated by 0.8% when compared with the National Continuous Forest Inventory 2004 statistics, reporting a fair agreement with ground truth. The approach also shows a better performance than Spectral Angle Mapper (SAM) classification (overall RMSE of 9.2 compared with 10.7 for latter).

Keywords: forest cover, TM, linear spectral unmixing, SAM, forest inventory

1 Introduction

Remote sensing (RS) has become a generally adopted approach in forest inventory and mapping, as is proved effective in forest extent identification and forest area estimation. However, spectrum of an image

 doi:10.1016/j.phpro.2012.03.199

pixel is often a mixture of information from several spectrally distinct surface components [1]. This inherent problem affects the estimation accuracy of conventional image classification techniques.

An alternative approach for reducing classification error is spectral mixture modelling, which assumes a pixel can be divided into components. Previous studies have succeeded in vegetation mapping [2-3]. The advantage of mixture modelling for coarse resolution satellite image (e.g., AVHRR, MODIS, and SPOT VEGETATION) may be more significant. It is meaningful to investigate if the method is effective as well for medium resolution data, especially in the case of highly fragmented or complex surface condition. Therefore, this study intended to assess the usefulness of mixture modelling in forest cover estimation of subtropical forest in southeast China.

To simplify the calculation, the mixing of surface reflectance spectrums is often deemed as linear, although nonlinear algorithms have been reported [4].

2 Methodology

2.1 Study Area

The study area is Pingnan County, situated at latitude 23° 2'19"-24°2'19" and longitude 110°3'54"-110°39'42", southeast of the Guangxi Zhuang Autonomous Region, China. With a total area of 2988 km^2, the county has more than half of territory covered by subtropical coniferous/broadleaf forest and dense shrubs.

2.2 Satellite Data and Ancillary Data

Imagery from the Thematic Mapper (TM) onboard the Landsat7 satellite was selected as the reference satellite data. The target year was 2004. The reason for choosing the year was the abundance of ground reference data, which enabled the validation of research results. The forest cover interpretation map and the imagery plot data from the National Continuous Forest Inventory 2004 were used as the ground reference data. The images reflected the most stable stage of the growing season when the leaves are fully developed. The methodology design was shown in Fig. 1.

2.3 Preprocessing

The TM imagery acquired was radiometrically and geometrically corrected. Therefore, the image mosaic was compiled using the calibrated data. The image of study area was clipped according to the vector county boundary from the image mosaic.

To eliminate the impact of the water body reflectance on endmember selection and image interpretation, the Modified Normalized Difference Water Index (MNDWI) [5] was applied to mask out water bodies before the unmixing procedure. The MNDWI and its threshold are as follows:

$$(TM2-TM5)/(TM2+TM5)>k. \quad \textbf{(1)}$$

In (1), TM2 and TM5 refers to TM band2 and band5; k is threshold constant, here, it was defined interactively as 0.02. Water body masked image was used as input for spectral unmixing and land cover mapping.

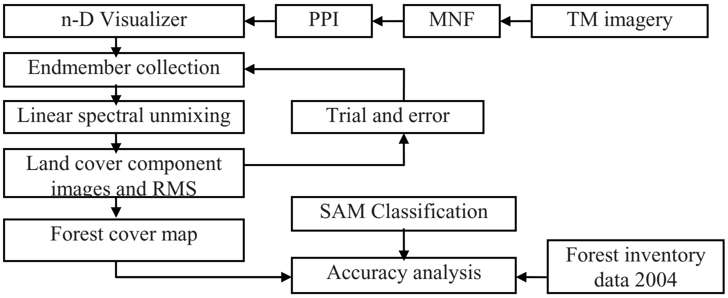


Fig. 1. Working Flow Chart.

2.4 Spectral Endmember Selection

The performance of mixture model requires pure 'endmembers', representing spectral values of land covers. To ensure the function matrix can be solved, the maximum number of variables to be estimated should be less than the number of spectral bands.

Similar to [2], this study initially determined 3 land cover spectral endmembers in terms of woody cover, herbaceous vegetation and bare ground. And referring to the IGBP land cover classification and re-classification of [6], woody cover referred to forest, including coniferous forest, broadleaf forest, mixed forest and closed shrub lands, with bamboo grove added; Herbaceous vegetation includes grasslands and croplands; while bare ground includes bare soil and urban/built-up.

2.5 Image Interpretation

The image interpretation algorithm took the water body masked image mosaic as input, and it proposed a value of forest cover of the study area as target variable.

MNF Rotation. Minimum Noise Fraction (MNF) Rotation transform was used to examine the inherent dimensionality of image data and to separate noise from the data [7]. It was applied to the post-masking TM spectral subset of 6 bands except thermal band (band6). Examination of the transformed images and Eigenvalues (Fig. 2 (a)) showed that band1 and band2 contained most of the information of the data (Eigenvalue for band1 is 72.87, and for band2 is10.61).

PPI. The Pixel Purity Index (PPI), which was used to determine the most spectrally pure (extreme) pixels in remote sensed images, was run on the MNF transform output image to select spectral endmembers (Fig. 2 (b)). A Pixel Purity Image was created, and by setting Region of Interest (ROI) threshold as PPI value between 90 and 254, a group of 2 733 pure endmembers were extracted as input into ENVI's n-D Visualizer.

After refinement and class merge, predefined endmembers of woody cover, herbaceous vegetation and bare ground were collected for Linear Spectral Unmixing and the comparing Spectral Angle Mapper (SAM) classification. Fig.3 demonstrated the spectral curves of all endmembers.

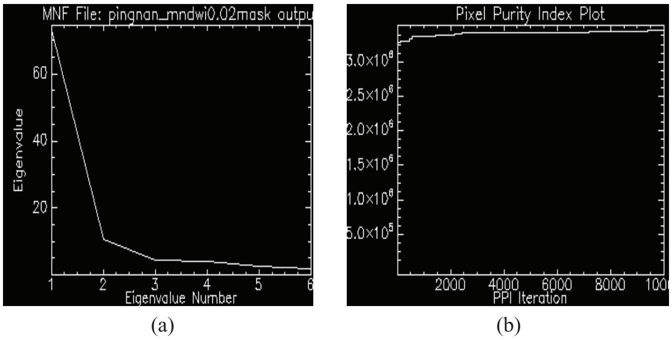


Fig. 2. MNF Eigenvalue plot and PPI plot of TM image. (a) MNF Eigenvalue plot, (b) PPI plot. The number of PPI iterations is 10000; PPI Threshold Value is 2.5.

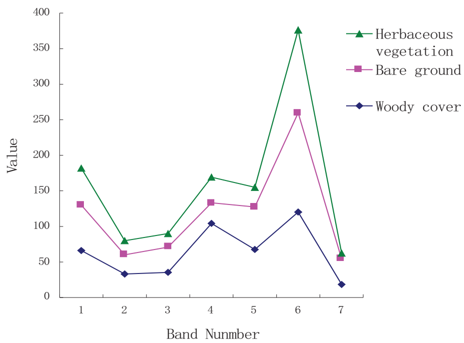


Fig. 3. Spectral curves of required endmembers

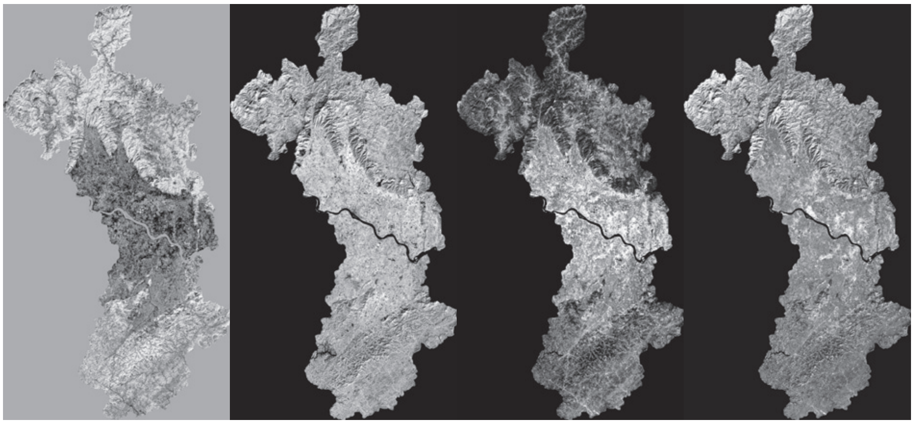
Linear Spectral Unmixing. In linear mixture model, the reflectance of each pixel at each spectral band is presented as a linear combination of the reflectance of each endmember and its relative abundance [8]:

$$v_i = \sum_{j=1}^{n} \left(a_{ij} x_j \right) + e_i \qquad \textbf{(2)}$$

In (2), i =1,2,3, …m, j =1,2,3,…n, v_i is the reflectance of mixed pixel, a_{ij} is the reflectance of the endmember j at band i , x_j refers to the abundance of the endmember j in the pixel, and e_i is error for band i .

The linear spectral unmixing approach was applied to the post processed TM image to solve for the abundance of each endmember (Fig.4).

For instance, bright pixels in Fig.4 (a) represented the abundances of forest unmixed from the other land cover classes, a pixel value of 0.30 from the abundance image indicated that 30% of the pixel was consisted of forest. It was ideal that fraction value for each endmember fell between 0-1, and the mean RMS was 0.9%.



(a) (b) (c) (d)

Fig. 4. Endmember fraction images from linear spectral unmixing. (a) woody cover (b) herbaceous vegetation (c) bare ground (4) RMS image.

Computation of Forest Cover. The forest cover was estimated based on woody cover abundance image. After stretching the image by setting a [0, 1] value range, the image was slice into 3 forest density strata and produced forest cover map. The percent tree cover of a pixel was estimated as the area proportion of the pixel content classified as forest. The final forest cover was computed as the sum of the output area of pixel units for the density strata and the whole county.

3 Results

3.1 Distribution Characteristics of Forest Cover

The forest cover map produced by linear spectral unmixing was shown as Fig. 5. To report statistics, the forest cover was measured in percentage, referred to proportion of forest area of the total land area. As is shown in Table I, the forest cover of study area from linear spectral unmixing is 55.7%. Among the 3 forest percentage strata, the 0.00-0.30 range took 19.9%, the 0.31-0.60 range took 23.2% and the 0.61-1.00 range took 12.6% of the area of county territory. Dense forest mainly distributed in northern and southern mountainous regions, while central area was fragmented.

3.2 Evaluation

To assess the effectiveness of the linear spectral unmixing towards TM imagery, accuracy analysis was carried out using the National Continuous Forest Inventory 2004 map as ground truth data. In this phase, an automatically selected training sample consisting of the spectral means of 2*2 pixels (60m*60m) was used, the sample size was 80. The pixel group was assumed to represent homogeneous ground targets.

Furthermore, a supervised classification through Spectral Angle Mapper (SAM) technique was performed using the same endmembers as input.

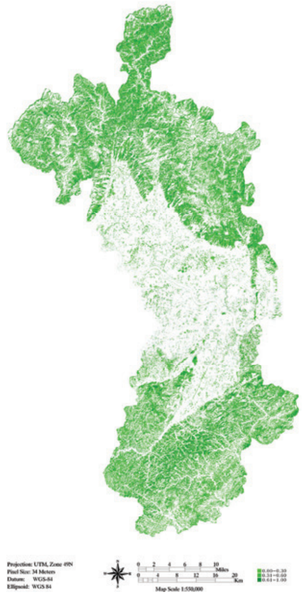


Fig. 5. Forest cover map of Pingnan produced by linear spectral unmixing

Table 1. Forest cover of study area

Forest cover strata	Linear Spectral Unmixing (%)	SAM (%)
0.00-0.30	19.9	11.8
0.31-0.60	23.2	25.6
0.61-1.00	12.6	14.7
Overall percentage	55.7	52.1
Overall RMSE	9.2	10.7

It can be drawn from Table1, through the linear spectral unmixing method, the forest area of Pingnan County was overestimated by 0.8% compared to the official statistics from the National Continuous Forest Inventory 2004, while the SAM classification underestimated by 2.8% compared to the same statistics.

Further comparison of the forest cover map of this study to the inventory map found a slight underestimation of forest area in some mountainous region. The reason for this was thought to be the shade, which featured similar to water body and inevitably lost in water body masking and spectral unmixing procedures. Meanwhile, an overestimation occurred in the central area, where residence and farmland were predominated land classes. The overestimation was likely due to some non-forest vegetation was mistaken as forest.

To carry out accuracy analysis, comparison of the root mean square errors (RMSE) for county-wide forest percentage was computed for both methodologies, as listed in Table I. The average RMSE values yielded from linear spectral unmixing (9.2%) model indicated a more robust result to the SAM classification (10.7%). It suggested that forest cover estimation from spectral unmixing might be more successful than conventional classification techniques.

4 Conclusion and Discussion

This study was to examine the capability of Linear Spectral Unmixing technique for improving the accuracy of forest cover estimation, particularly in a context of complex ecosystem composition and fragmented land cover condition of subtropical forest in southeast China.

The Landsat TM imagery of Pingnan County, Guangxi Zhuang Autonomous Region, China was chosen as target data, and forest inventory data were utilized as ground reference data. After masking out water bodies using MNDWI, the TM image of the study area was processed with MNF, PPI and n-D visualizer endmember selection procedures, resulting in 3 "pure" spectral endmembers, namely, woody cover, herbaceous vegetation and bare ground. The endmember spectral characteristics and a Linear Spectral Unmixing algorithm were then applied over the image, outputting land cover component images and corresponding forest cover map. The estimated forest area and percentage were then compared with those extracted using SAM classification method and the official forest inventory statistics.

The spectral unmixing mapping resulted in fair agreement with the official data sets and showed a better performance than conventional SAM classification. The forest percentage of the county was 55.7%, underestimated by 0.8% when compared with forest inventory statistics. Although in general the forest area was close to the ground truth, a slight underestimation of forest area was found in some mountainous region, and an overestimation occurred in the central area.

The most critical difficulty in spectral unmixing approach is the accurate selection of endmembers. Atmospheric correction, mosaicking, seasonal effect, and the skill of the performer may impact the endmember selection and the image interpretation. The rationales behind spectral unmixing procedures, as well as more physical-based approach for producing consistent result are research focus.

Moreover, in the future research, more ground-sampling techniques will be tested to improve the reliability of the using of reference data.

Acknowledgments

This work is partially supported by National Science and Technology Support Program #2006BAC08B03 to H. Lin, National Science and Technology Support Program #2006BAD23B-01 to H. Lin, NSF Grant #30871962 to H. Lin and Doctoral Program of Higher Specialized Research Fund #200805380001 to H. Lin.

References

[1]Foody, G., Campbell, N., Trodd, N., Wood, T.: Derivation and applications of probabilistic measures of class membership from the maximum-likelihood classification. Photogrammeng Rems, 58, 1335--1341 (1992)

[2]DeFries, R., Hansen, M., Townshend, J.: Global continuous fields of vegetation characteristics: a linear mixture model applied to multiyear 8 km AVHRR data. Int J Remote Sens, 21, 1389--1414 (2000)

[3]Tuomas, H. et al.: AVHRR-based forest proportion map of the Pan-European area. Remote Sens Enronn, 77, 76--91(2001)

[4]Foody, G., Lucas, R., CurranJ, P., Honzak, M.: Nonlinear mixture modelling without end-members using an artificial neural network, Int J Remote Sens, 18, 937--953 (1997)

[5]Xu H.: A Study on Information Extraction of Water Body with the Modified Normalized Difference Water Index (MNDWI). J Remote Sen, 9, 589--594 (2005) (In Chinese)

[6]Wade, T., Riitters, K., Wickham, J., Jones, K.: Distribution and causes of global forest fragmentation. Conservation Ecolog, 7, 7 (2003)

[7] Boardman, J., Kruse, F.: Automated spectral analysis: a geological example using AVIRIS data, north Grapevine Mountains: in: ERIM Tenth Thematic Conference on Geologic Remote Sensing, Environmental Research Institute of Michigan, Ann Arbor, MI, I-407 -- I-418., Nevada (1994)

[8] Charles, I., Arnon, K.: A review of mixture modeling techniques for sub-pixel land cover estimation. Remote Sens Rev, 13, 161--186 (1996)