

A Simple Approach for Guiding Classification of Forest and Crop from Remote Sensing Imagery: A Case Study of Suqian, China

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Abstract. Basic scientific research of land cover in Suqian is fundamental to ensure the sustainability of land resource management. The major study is to monitor the confusable land cover types according to the remote sensing, and the integrated information. It supplies a new direction for integrating date sets and improves the monitor on land cover. It presents a simple fusion approach for integrating time series of the MODIS Vegetation Index products and Landsat TM data. The fusion supplies the prior probability to distinguish forest with crop for guiding supervised classification which served in monitoring forest quantities-increasing in future. The entire operation just uses primarily the fusion method from the fuzzy mathematics to achieve various kinds of information with some simple parameters. However, the fusion is a spatial feature classification conducted remote sensing training mask data blending the advantages of the phonological information, the feature characteristics and the spatial-temporal data.

Keywords: Forest and crop cover masks · Feature extraction · Fusion operator · Classification · Sustainability

1 Introduction

Knowledge of the changes in land uses and present land cover is crucial to be able to determine which areas require more attention from conservation and restoration programs. The construction of informational society and ecological city is the object of urban development and harmonious society. It established completing the classification and evaluation of land using status by taking advantage of all kinds of geographic information resources, which has a very important significance to establish a type of ecological and livable city, and to realize the sustainable development of land using. In view of China's state policy, collecting and classifying the geographic space information of land using, analyzing and evaluating the regional ecological environment, providing the suggestion and guidance for land using and regulating by 3S technology, and then achieving the development of land using is starting point of this paper [1–4].

In recent years, the forestry development in Jiangsu Province of China has made considerable progress. In order to improve efficiency and expand the extent of these investigations, remote sensing technology (RS) has begun with utilizing the characteristics by monitoring the covering forest resources, which is used to the real outside survey data with interpretation of supplementary Thematic Mapper (TM) imagery. Because remote sensing technology can decrease a lot of manpower, material and costs for the economic and social development on monitoring forest dynamically.

Firstly, extracting the boundary of forest is the principal task which should be operationalized by withdrawing the real location of forest from the existing data fully. The time-series high spatial resolution satellite data sets have been studied to quantify forest in an early form [5]. The Landsat products for Earth observation have provided invaluable information on the Earth's surface characteristics over the past four decades [6]. The analysis time has been chose by the phenological key period of every vegetation types [7, 8].

Secondly, high resolution satellite data has not only coarser temporal resolution which can easily be confounded efforts of rainy climate and cloud cover contaminated, but also it has high costs that not any researcher could afford [9–12]. The homogeneity of time series of satellite images is crucial when they has been studied abrupt or gradual changes from vegetation types via remote sensing data.

The Moderate Resolution Imaging Spectroradiometer (MODIS) Vegetation Index products can solve the above limitations of Landsat data sets. Hansen et al. [10] and Potapov et al. [13] uses the regression tree to integrate Landsat and MODIS imagery, which can monitor deforestation in Africa and North America except the problem of mixed sub-pixels. Gao et al. [14] introduces the Spatial and Temporal Adaptive Reflectance Fusion Model (STARFM) to blend Landsat and MODIS data. It can generate synthetic Landsat-like imagery with a spatial resolution of 30 m on a daily basis. Hansen et al. [10] demonstrates that can be used regional/continental MODIS to derive forest cover products from calibrating Landsat data for exhaustive high spatial resolution mapping of forest cover and clearing in the Congo River Basin. However, such data-fusion approaches are often based on spatially integrating reflectance observations and specifically being designed by the sub-pixel ranges of the coarse-spatial-resolution [15, 16]. But it is arguable due to high data costs and the difficulties of combining disparate resolution data.

This paper presents a fusion approach based on the fuzzy mathematics. That explains that it derive the masks of forest and crop locations from time series of the MODIS Vegetation Index products and Landsat TM data on the same which is addressed an antecedent feature extraction classification method. We are aware of only few studies about the problem of land-cover class spatial variability [17]. Feature extraction is implemented as a fast algorithm for segmenting TM imageries utilized homogeneous regions according to elements of the neighboring pixel like brightness, the texture, the color and the saturation [18]. However, the fusion approach focuses on the intersection operation of forest and crop masks and TM spatial feature classification which equivalently corrects the weight or likelihoods of the forest or crop cover types. The method provides a way of thinking by remote sensing, which serves in evaluating forest quantities-increasing in future.

2 Algorithm

In Fig. 1 we present an overview of the processing steps implemented in this methodology, which are described in detail below. The aim of the proposed procedure is to provide the guidance of classification and users' interpretation. To the Landsat data, the plants have the difficulty to be discerned due to Landsat spatial and temporal resolution limitations. First of all, it should prepare the dataset of MODIS products in 2006, which covers the same lands with Landsat images and the phenology data. At the same time, these images need the pre-processing procedure and atmospheric correction operation to decrease the cloud and shadow contamination. Secondly, it reconstructs the high-quality NDVI time series derived from the MODIS Vegetation Index Products by the filter method. Thirdly, the two sets of forest and crop cover masks must extract respectively with one of which derived from analyzing the time series of the phenology and other segments. Finally, the two sets of data are operated by implementation of fusion operator to extract samples included information as much as possible. It can serve for the further classification.

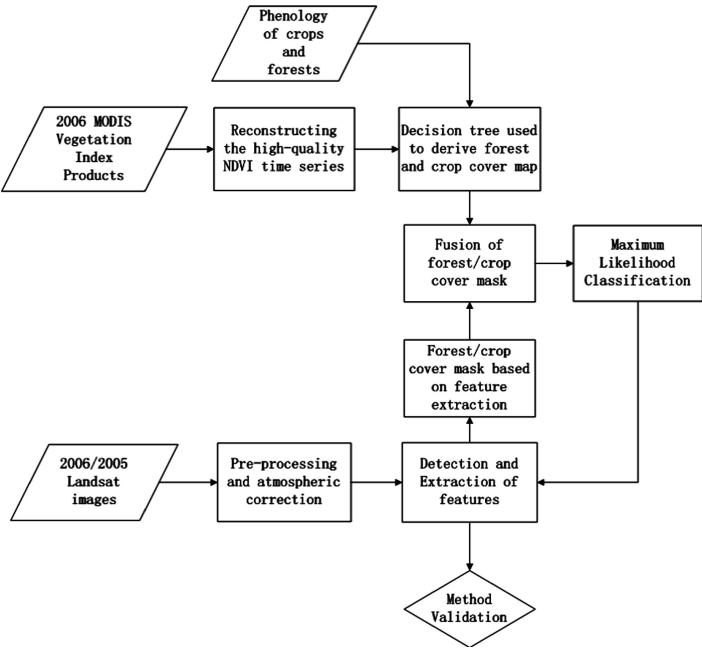


Fig. 1. It presents an overview of the processing steps. First of all, the dataset of MODIS products and Landsat images in 2006 have done the pre-processing procedure and atmospheric correction operation. Secondly, it reconstructs the high-quality MODIS Vegetation Index Products. Thirdly, it extracts the two sets of forest and crop cover masks which derived from analyzing the time series of the phenology and other segments. Finally, the two sets of data are operated by implementation of fusion operator to extract samples included information as much as possible.

2.1 Reconstructing NDVI Time-Series Data

The methodology smoothes noises out in NDVI time-series. Specifically the noises can be caused primarily by cloud contamination and atmospheric influence. Although the most often-used NDVI dataset are 16-day Maximum Value Composite (MVC) products [19], these still include a lot of noises caused by cloud contamination, atmospheric influence, and bi-directional effects. The prototype of the filter method is proposed by Savitzky and Golay [20] and improved by Chen et al. [21] as a simplified least squares-fit convolution for smoothing and computing derivatives of consecutive values. The general equation can be given as follows:

$$Y_j^* = \frac{\sum_{i=-m}^{i=m} C_i Y_j}{2m + 1} \quad (1)$$

Y_j^* and Y_j are represented the resultant and the original NDVI value. C_i is the coefficient for the its NDVI values of the smoothing window which can be obtained directly from Steinier et al. [22] as a corrected version of Savitzky and Golay's work [20]. It is calculated from the equations presented by Madden [23]. C_i includes the degree of the smoothing polynomial, which is a range selected by the NDVI observation, and m . m is a half-width of the smoothed window to filter $2m + 1$ points.

Now it only sets the selection value of polynomial. Afterwards it does not stop iteration until it determined the best filtering results. Through continuous iteration until new NDVI value is the maximum and the fitting-effect parameter is the minimum, the new NDVI is the real Y_j^* .

2.2 Classification and Decision Tree

Decision tree classification has got a wide studied application. The decision tree is a hierarchical classifier. It predicts the class memberships by recursively partitioning a data set into more homogeneous subsets, referred to nodes [24]. This method is carried out with the combination of phenology and time-series on the basis of the vegetation time series curves. These pixels of other classes are discriminated until the tree's growth is terminated. Nodes of the classification tree can be obtained from either categorical data by summarizing from the phenology data or continuous data by performing the percent of the sub-pixel percent cover estimations.

2.3 Segmentation of Imageries

Image segmentation is a key stage which defects crop and forest land cover types in images [25]. The algorithm is a general one based upon Mumford-Shah function [26, 27]. The function is summarized by the following equation.

$$E(\mu, K) = \sum_{i=1}^n \|\mu(i) - g(i)\|^2 + \lambda I(K) \quad (2)$$

K is a discerned factor of the dataset. The boundary of K is a set of pixel edges which separate the regions and its length (K) is a number of edges of the Landsat data. $u(i)$ is an expectation of $g(i)$ from every segmented region which includes the information of region A , values of pixels DN (such as brightness, DN et al.) and texture T . Continued iterations cannot stop dividing and merging regions of homogeneous objects until the value of the function $t(A, DN, T)$ equals to a threshold λ . The smaller the λ is, the more fragmented images we will get.

As λ is man-made, the result of segmentation is based on the nature of the expert experiences. Due to 30 m resolution of TM, an appropriate λ can be selected to achieve the fine segmentation without any redundant information.

2.4 The Fusion of the Cover Mask

In order to obtain the training data for the further classification, it should adequately use the guidance of the forest and crop cover masks. If a region of interests of forest covers is not a real forest mask, it will greatly affect the accuracy because of the false ROIs. To decrease the probability of false circumstances, this method is a traditional intersection of the two dataset which is defined based on the fuzzy mathematics.

$$St = \left\{ t \mid \Phi S_{MODIS}(P, NDVI_i) \cap S_{TM}(B_m, DN_m, T_m, NDVI_j), i \in \Phi S_{MODIS}, j \in \Phi S_{TM}, t > 0 \right\} \quad (3)$$

t is the dataset of results St . St includes crossing values of S_{TM} and S_{MODIS} . S_{TM} is the TM vegetation cover masks derived from phenology of vegetations P and time-series NDVI values $NDVI_i$. S_{MODIS} is derived from brightness B_m (m is an original pixel of TM), the values of DN DN_m , the texture data T_m and the NDVI values $NDVI_j$. St is blending information to fill with some missing information and reduce a data volume of higher spatial resolution and costly time series data such as TM. It generates the class labels independently for each Landsat training data as a dependant variable and the Landsat cover masks as an independent variable. If the area of one sample from MODIS fully covers that of Landsat, the data of Landsat is selected in St . Contrary to the rule, the data of MODIS is selected so that TM data has different objects in the same spectrum. The overlap parts can be selected to reduce the length of the sample and make the forest or crop cover mask precise likelihoods if the extent of two fusion samples is these ones.

3 Materials and Methods

3.1 Study Area

The test area covers a surface of about 8555 km² located at northwest of Jiangsu Province, which is known as a ‘pure land’ and ‘greatest oxygen bar’ in the east of China (Fig. 2). It is a representative forestry and agricultural ecological city in Jiangsu. The main crops in Suqian are winter wheat, spring corn and summer rice, etc. in rotation.

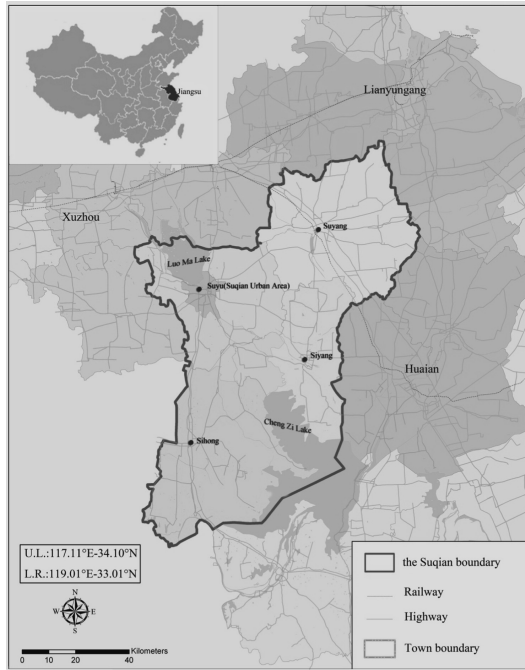


Fig. 2. This is the location figure of the study area, Suqian in Jiangsu province.

3.2 Satellite Data and Pre-Processing

There are four scenes of Landsat satellite data to cover all areas of Suqian. TM data are available in $185 \text{ km} \times 185 \text{ km}$ per scene defined in a Universal Transverse Mercator projection, 50 N, and the datum is WGS-84. The dates of TM data sets show in Table 1. The images were atmospherically corrected using the FLAASH atmospheric correction algorithm [28].

Table 1. Landsat data used in this study: Due to the humid climate during the flourish stage of vegetation in rich soil in Jiangsu, Landsat data are selected by being visually identified small cloudy and little shadowy areas. Although the TM data come different time, they have little influence to the further processing because they are some difficult changes of places where trees are planted during one year.

Acquisition	Path/row
09/09/2006	120/37
09/09/2006	120/36
12/08/2005	121/36
12/08/2005	121/37

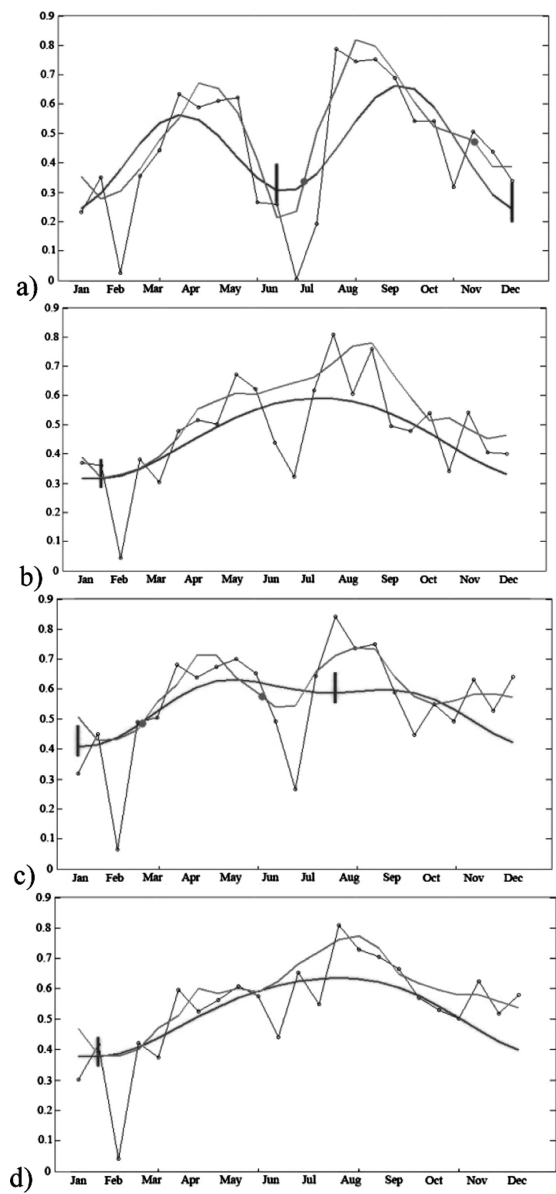


Fig. 3. The NDVI time-series curves of 4 vegetation types of land cover are generated using the SG method. The rule curve is depicted by hard lines with big dots, and the hard line with small dots delegates the original NDVI time-series curve. Seasonal fit is smoothly lines. (a) two crop annually (mainly are winter wheat and summer rice in rotation in Suqian); (b) broadleaf forest; (c) two crop mixed with forest; (d) evergreen forest.

The twenty-three 250 m 16-days composite MODIS Vegetation Index Products (MOD13Q1) when the acquisition year is 2006. It selected cloud contaminated pixels by fixing an arbitrary threshold on Quality Assurance values if Usefulness Index > 3 . MODIS images are re-projected from the native sinusoidal map projection to the Universal Transverse Mercator reference system. It can be corrected into registration with the Landsat data set and resized the 1:250,000 vector boundary map.

4 Results

4.1 MODIS Forest and Crop Cover Masks

In Fig. 3, the final NDVI time-series are obtained. Due to the limitation of the spectral resolution, only the results of 3 classes of pixels are shown in the figure. Using SG analysis method and important information of phenology, the important phenological parameters could be extracted to serve the further classification. The beginning of a season is defined from the point in time for which the value had increased by a certain value. It sets 20 % of the value the distance which is the base level to the maximum. The end of the season was defined by the same way.

According to the temperature, winter wheat begins with gradually turning green to joint in February. Due to a relatively low temperature, it delayed to grow than that in the past slightly. When the NDVI of winter wheat is rising, the NDVI of forest begins to growing up in March. Rice begins to be transplanted in July and gradually to tiller and joint when the NDVI value has started rising. To distinguish the spectrum of forest and crop, the suitable time of classification is March. From in July to in October, it has maintained a high value and it can reach to 0.6 contrasted with the crops.

4.2 TM Forest and Crop Cover Masks

After the atmospheric correction and other preprocessing method, it should ideally choose the highest Scale Level that delineates the boundaries of features as well as possible. Good segmentation can ensure the more accurate results of classifications. Since TM data are segmented to some objects instead of pixels, a classification approach has been used to per-vegetation class likelihoods for each object of Landsat acquisition. According to the National Bureau Investigation, some objects are selected as the ROIs.

4.3 Implementation of Fusion and Classification

Figure 4 shows the result of the fusion operator, and it is the forest and crop cover samples respectively. The procedure generates training data independently for each Landsat vegetation types. In Table 2, it is the comparison of the Landsat cover masks operated with the MODIS cover masks. The results of the masks what we wanted are composited above the methodology described. This figure reveals that most of these samples fit closely with the boundary of some land cover classes. The patterns of human settlement and road infrastructure through the masks are excluded.



Fig. 4. The result of the fusion operator is derived from MODIS and Landsat forest or crop cover masks. The procedure is based on the raster mask data which is represented the precise likelihoods of land cover types. Then the result has been transferred to the vector mask data showed above.

Table 2. Confusion matrix indicated the samples extraction

	Original cover	Landsat forest cover	Landsat crop cover	Percent agreement
Original cover	/	18120	18726	/
MODIS forest cover	3110	838	/	26.95 %
MODIS forest cover	3437	/	2450	71.28 %
Percent agreement	/	4.62 %	13.08 %	/

In circumstance of the software ENVI, every part of the training samples is classified by the MLC classifier. Mentioned in Sect. 4.2, the pre-classification based on the feature extraction is used to compare with the method. The results are shown in Fig. 5 and the comparison of these contributions is shown in Table 3. We use training samples to add with the experimental area. Those are chosen as ROIs according to the visual inspection.

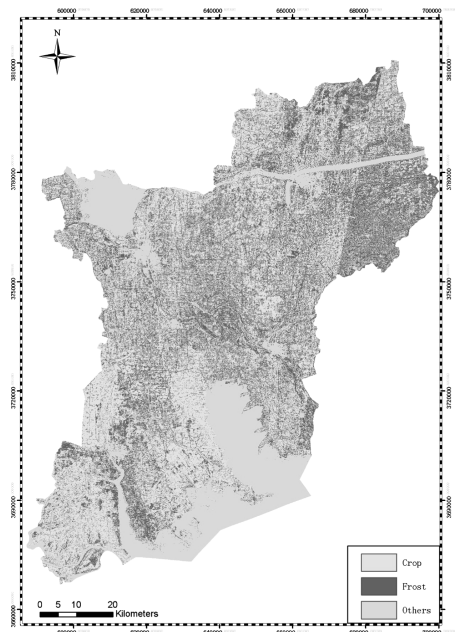


Fig. 5. Landsat derived classification result by the fusion cover mask of the Landat scene covering overall Suqian. The vegetation classification image was based on the MLC approach.

Table 3. The comparison of the accuracy assessment result from MLC and pre-classification

Class	Forest	Crop	/
Forest	73.97 %/66.72 %	24.84 %/33.08 %	/
Crop	24.89 %/30.04 %	74.41 %/69.95 %	/
Overall Accuracy	/	/	97.17 %/93.35 %
Kappa	/	/	0.8912/0.6915

Remark 1: The samples data derive the classification confusion matrix, and the overall accuracy and the Kappa coefficient are assessed by 3 classes (Crop, Forest, Others). The front number respects the result of MLC and the later one is pre-classification, which the percentage of each class is labeled as the percentage of the class.

Viewing the precision, the accuracy of the forest and crop classification achieves more than 70 % which shows a fine result. Comparing with the pre-classification, it plays a guiding role of the method.

5 Discussion

By relying on MODIS NDVI time series as the reference information, several limitations of the distinguishing procedures has been addressed, as the Landsat data allowed for vegetation masks with the fusion. The Landsat dataset derive vegetation cover

masks from successfully the segmentation. Image segmentation is based on a preview of the results what you wanted. Certain texture could bring the bias, so it is the key stage to select an appropriate λ for segmentation of TM images. The MODIS products derive the vegetation masks with the phenology information. The filter is a simple and robust method comparing with the BISE algorithm, Gauss and Flourier methodology, which only sets a window size to derive the seasonal information. The masks served the further classification of Landsat data.

Finally, the maximum likelihood classification is based on the vegetation mask derived from the fusion operator. We select the validation from segmentation compared with the pre-classification. When the training data is labeled from the cover masks data, we have considered the center pixels on the samples. These pixels can bring some influence to the results of classification. The purpose of this paper found a simple, robust and economically affordable method to serve the earlier stage of the higher classification, which improves the phenomenon having the same spectrum from different field categories.

6 Conclusion

Basic scientific research of land cover in Suqian is fundamental to ensure the sustainability of land resource management. This paper presents a multi-resolution methodology to extract forest and crop masks from the scale of Landsat data, covering 8552 km² of Suqian. Typical Landsat scale studies use a time series of good quality image to class many kinds of vegetations for one given year or decade. This can decrease the high resolution data costs and the difficulty of combining multi-temporal Landsat acquisitions. The paper describes a method to supply the basis for the supervised classification by processing multi-resolution and time-series imageries per year. Initial results indicate that Suqian has the tremendous changes in rural and urban greening. Also the area of forest has increased. However, the fusion of vegetation cover masks, integrating phenology, texture, brightness, NDVI etc., provides the higher accuracy greatly for the effective guidance of the classification and saves the manpower and costs. The training data from the new method provides the sample likelihoods at a certain extent which can be used to class.

The method is a simple and robust one that it is an operational alternative for large area vegetation cover to monitor at data-lacking satellite imageries. The full operation is just primarily an operation of the input data contained various kinds of information with simple parameters. When various types of vegetation had no start time, this method might represent a feasible approach. Thanks to minimize data costs, it is the better way to ensure accuracy monitoring for mining the information from imageries and improving the operating method.

Acknowledgements. This study is supported partly by National Natural Science Foundation of China (41201485), Scientific Research Startup Foundation of Chuzhou University (2012qd17) and the Doctorate Fellowship Foundation of Nanjing Forestry University and the Graduate Education Innovation Project of Jiangsu Province.

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Geo-Informatics in Resource Management and
Sustainable Ecosystem

Third International Conference, GRMSE 2015, Wuhan,
China, October 16-18, 2015, Revised Selected Papers

Bian, F.; Xie, Y. (Eds.)

2016, XIX, 988 p. 443 illus., Softcover

ISBN: 978-3-662-49154-6