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Forest cover classification using Landsat ETM+ data and time series MODIS NDVI data

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ABSTRACT

Forest cover plays a key role in climate change by influencing the carbon stocks, the hydrological cycle and the energy balance. Forest cover information can be determined from fine-resolution data, such as Landsat Enhanced Thematic Mapper Plus (ETM+). However, forest cover classification with fine-resolution data usually uses only one temporal data because successive data acquirement is difficult. It may achieve mis-classification result without involving vegetation growth information, because different vegetation types may have the similar spectral features in the fine-resolution data. To overcome these issues, a forest cover classification method using Landsat ETM+ data appending with time series Moderate-resolution Imaging Spectroradiometer (MODIS) Normalized Difference Vegetation Index (NDVI) data was proposed. The objective was to investigate the potential of temporal features extracted from coarse-resolution time series vegetation index data on improving the forest cover classification accuracy using fine-resolution remote sensing data. This method firstly fused Landsat ETM+ NDVI and MODIS NDVI data to obtain time series fine-resolution NDVI data, and then the temporal features were extracted from the fused NDVI data. Finally, temporal features combined with Landsat ETM+ spectral data was used to improve forest cover classification accuracy using supervised classifier. The study in North China region confirmed that time series NDVI features had significant effects on improving forest cover classification accuracy of fine resolution remote sensing data. The NDVI features extracted from time series fused NDVI data could improve the overall classification accuracy approximately 5% from 88.99% to 93.88% compared to only using single Landsat ETM+ data.

1. Introduction

Forest is at the core of terrestrial ecosystems and covers approximately 31% of the global land surface (FAO, 2011; Liu et al., 2006). Forest cover and forest cover changes have widespread effects on the provision of ecosystem services, affect biodiversity, and provide important feedbacks to human welfare (Bonan, 2008; Kuemmerle et al., 2009). In addition, forest cover changes influence the climate by alerting the energy, water and carbon cycles (Bonan, 2008; Malmer et al., 2010). As the pressure rises of human on climate change, monitoring forest cover from global to regional scales is becoming an important component of global change studies (Hansen et al., 2008).

National inventory is the most frequently way to get forest cover information. However, the uneven quality in time and space, inconsistent survey methods, and intensive labor makes national inventory not the optimal way to quickly acquire forest cover information at a large regional scale. Remote sensing has long been an effective means of monitoring land cover with its ability to quickly collect information at large scale, and becomes the effective method to obtain forest cover information (Jia et al., 2012; Townshend et al., 2012). Many land cover maps at global and regional scales have been produced in recent years using remote sensing data, and the popular products include the University of Maryland land cover map (Hansen et al., 2000), International Geosphere Biosphere Programme (IGBP) global land cover dataset (Loveland et al., 2000), European Commission Joint Research Centre Global land cover for the year 2000 (Bartholome and Belward, 2005), the MODIS global land cover map (Friedl et al., 2002), and the finer resolution global land cover (Gong et al., 2013). In addition, many efforts have been to make global and regional thematic forest cover maps, such as

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MODIS Vegetation Continuous Fields (VCF) product (Hansen et al., 2003), the Japan Aerospace Exploration Agency (JAXA) forest cover map (Shimada et al., 2011), the United Nations Educational Scientific and Cultural Organization (UNESCO) implemented Reducing Emissions from Deforestation and Forest Degradation (REDD+) project (Caplow et al., 2011), forest cover change map made by University of Maryland (Huang et al., 2008).

However, most of the land cover datasets are at coarse spatial resolution, whereas a substantial proportion of land cover changes have been shown to occur at resolutions below 250 m (Townshend and Justice, 1988). Therefore, coarse spatial resolution remote sensing data is not enough for catching the accurate forest cover changes information. Landsat-like resolutions remote sensing data are essential for forest cover mapping and change detection because of forest cover changes from anthropogenic factors are usually at a small scale (Townshend et al., 2012). Present Landsat-like resolution land cover or forest cover datasets are usually obtained from classification or automatic change detection of single Landsat-like resolutions remote sensing data (Gong et al., 2013; Huang et al., 2008; Shimada et al., 2011). The temporal information or phonological information are not involved in the classification because of the successive acquirement of the Landsat-like resolutions remote sensing data are very difficult, but these information is very useful for land cover mapping, spatially for vegetation cover classification (Jia et al., 2013; Xiao et al., 2002). Time-series vegetation index data are approved to well descript vegetation growth and the shape of vegetation growing profiles depicted by time series vegetation index contained vegetation type information (Brown et al., 2013; Xiao et al., 2002). For example, Xiao et al. investigated multi-temporal SPOT-4 Vegetation sensor data for characterization of temperate and boreal forests in Northeastern China, and found temporal data was useful for achieving accurate forest cover map (Xiao et al., 2002). However, these forest or vegetation cover classification studies using time series remote sensing data are usually focus on coarse spatial resolution satellite data. The main issue comes to how to integrate temporal information of coarse resolution time series remote sensing data with high spatial resolution data for a better forest cover classification.

At present, the study on using time series coarse resolution data to assist high resolution data improving forest cover classification is rare. In this paper, Landsat ETM+ data appending with time series MODIS NDVI data is investigated for improving forest cover classification accuracy. The specific objectives of this study are to investigate the potential of time series NDVI features on improving the forest cover classification accuracy, and provide a demonstration of forest cover classification integrating spectral feature of high resolution data with corresponding coarse resolution time series NDVI features.

2. Study area and data

2.1. Study area and ground survey

The study area is selected in North China region, corresponding to path 123 and row 31 of Landsat ETM+ data. To weaken the influence of Landsat ETM+ gaps on classification accuracy, a rectangle region is subset as the final study area, which lies between approximately 40°6′ N to 42°4′ N, and 116°3′ E to 117°7′ E (Fig. 1). The study area mainly consists of Weichang, Fengning, Longhua, Duolun and Luanpin counties of China. It belongs to semi-humid and semi-dry climate region at temperate zone. The annual precipitation is about 500 mm, of which 80% falls in the period of July to September. The annual average temperature is about −1.4 to 4.7 °C, and the annual accumulated temperature above zero is 2000–2200 °C. Four seasons are evident, and wet and hot in the summer, cold in the winter. The main vegetation types in this region are forest and grassland, whereas cropland occupied a little part. Therefore, the complex vegetation composition is very suitable to investigate the present method of forest cover classification. The main tree species include Siberian elm (*Ulmus Pumila* L.), larches (*Larix* spp.), Chinese pine (*Pinus tabulaeformis* Carr.), Birch (*Betula piatyphylla* Suk.), and Populus davidiana (*Populus davidiana* Dode.). Grass species mainly consists of Achnatherum (*Achnatherum splendens* Nevski.), Agriophylli (*Agriophyllum squarrosum* Moq.), and spear grass (*Stipa capillata* Linn.).

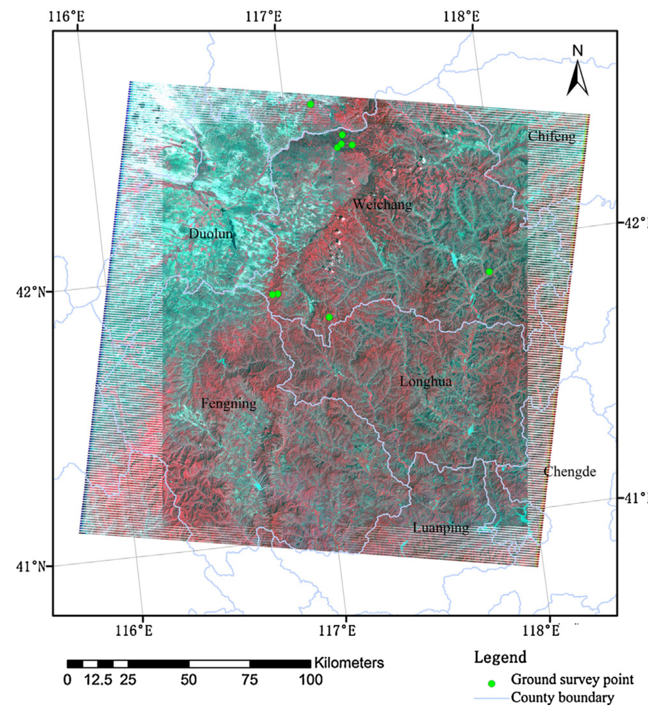

Fig. 1. The study area and the ground survey point in this study. The original whole scene of Landsat ETM+ data is shown as base map. A rectangle subset of the whole scene is selected as the final data for forest cover classification which is shown in false color (the NIR, red, and green bands of ETM+ data are assigned to red, green, and blue color bands). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of the article.)

In order to determine the actual forest distribution in the study area and assist to select training and validating samples, a ground survey was carried out from August 7 to 12, 2011. During the ground survey, the details of the representative land cover were recorded, and the position had been recorded with the help of a handheld global positioning system receiver with positioning accuracy approximately 3 m.

2.2. Landsat ETM+ data

One Landsat 7 ETM+ SLC-off data of the study area on August 18, 2005 was downloaded from USGS website (http://glovis.usgs.gov/) for forest cover classification. This data was selected because of many land cover products were provided in 2005 and the classification result could be compared with the existed products. Furthermore, the vegetation in August was at exuberant growth stage in this study area and the ETM+ data was nearly not affected by cloud. For the scan-line corrector of the Landsat 7 ETM+ sensor failed in 2003, it was resulted in about 22% of the pixels per scene not being scanned (Chen et al., 2011). To fill in the data gaps, another Landsat data in August 21, 2006 was downloaded from Global Land Cover Facility Website of Maryland University (http://glcf.umd.edu/). The data gaps was filled using the method

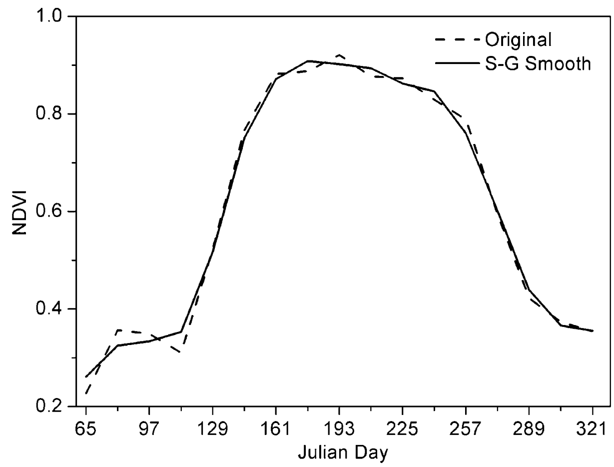

Fig. 2. Time series MODIS NDVI profile before and after S-G filtering.

developed by (Chen et al., 2011), which was based on the assumption that the same class neighboring pixels around the un-scanned pixels had the similar spectral characteristics and these neighboring and un-scanned pixels exhibit similar patterns of spectral differences between dates. The projection of the data was converted to Albers Equal Area projection with World Geodetic System 84 (WGS-84) datum to keep the forest cover area in the data consisted with the actual ground surface. Finally, a rectangle subset consisted of 5013 columns × 5542 lines × 6 visible-NIR bands were extracted as the final data for forest cover classification to reduce the influence by the gaps (Fig. 1).

2.3. Time series MODIS NDVI data

MOD13Q1 products (vegetation indices 16-Day L3 Global 250 m version 5) spanning the vegetation growing season from March to November were downloaded from the National Aeronautics and Space Administration (NASA) of the United States (US) Warehouse Inventory Search Tool (WIST). These data were distributed by the Land Processes Distributed Active Archive Center (LP DAAC), located at the US Geological Survey (USGS) Earth Resources Observation and Science (EROS) Center (https://lpdaac.usgs.gov). MOD13Q1 data were provided every 16 days at a spatial resolution of 250 m in the sinusoidal projection. It included red, NIR, blue and SWIR reflectance bands, NDVI and Enhanced Vegetation Index (EVI) from the MODIS onboard of Terra platform. The NDVI data was extracted for forest cover classification in this study.

The Savitzky–Golay (S-G) filter was used to smooth out noise in the time series MODIS NDVI data, specifically that caused primarily by cloud contamination and atmospheric variability (Chen et al., 2004; Savitzky and Golay, 1964). The algorithm made data approach the upper NDVI envelope and to reflect the NDVI pattern of change. It used a moving window, and noisy values were approximated by polynomial regression within the moving windows. An original NDVI profile and the S-G filtered NDVI profile at a randomly selected pixel was presented in Fig. 2. It was seen that S-G filter could effectively eliminate data noise and improve the quality of time series MODIS NDVI data. Projection of the smoothed MODIS NDVI data was converted to the same projection with Landsat ETM+ data. The spatial resolution of MODIS NDVI data was resampled to 30 m, and the same columns and lines were extracted to keep consist with Landsat ETM+ data for further analysis.

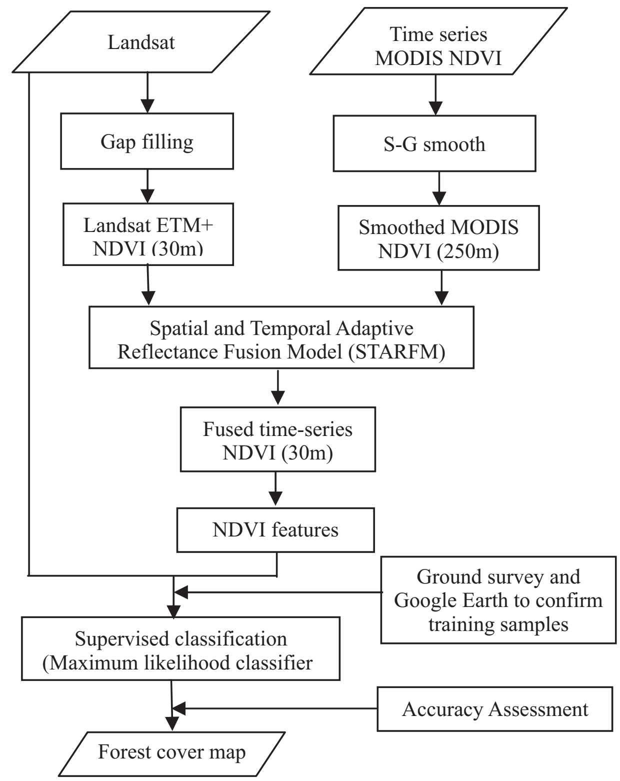

Fig. 3. The flowchart of classification of Landsat ETM+ data appending with time series MODIS NDVI features to improve forest cover mapping accuracy.

3. Method

Fig. 3 presents a flowchart of forest cover classification using Landsat ETM+ data appending with time series MODIS NDVI data. Before implementing the forest cover classification, all the data should be preprocessed to have good data quality and the same processing area. The Landsat ETM+ NDVI data is calculated using Red and NIR bands, and then the ETM+ NDVI data is fused with MODIS NDVI data using Spatial and Temporal Adaptive Reflectance Fusion Model (STARFM) (Gao et al., 2006). The NDVI features are extracted from the fused time series NDVI data, and combined with Landsat ETM+ spectral data as the final data for forest cover classification. Finally, supervised classification and accuracy assessment is conducted to analysis the accuracy improvement for forest cover classification.

3.1. Fusion of Landsat ETM+ NDVI with time series MODIS NDVI data

STARFM is developed for blending Landsat and MODIS surface reflectance by fusing high-frequency temporal information from MODIS and high spatial resolution information from Landsat data. STARFM predicts pixel values based upon a spatially weighted difference computed between the Landsat and the MODIS data acquired at T1, and the Landsat T1-scene and one or more MODIS scenes of prediction day (T2), respectively (Gao et al., 2006). A moving window technique is used to minimize the effect of pixel outliers thereby predicting changes of the center pixel using the spatially and spectrally weighted mean difference of pixels within the window area (Gao et al., 2006). The STARFM was also extended for blending NDVI data of different spatial and temporal resolutions to produce high temporal and spatial resolution NDVI dataset, and satisfactory results were achieved (Meng et al., 2011). Therefore, Landsat ETM+ NDVI data acquired on 18 August, 2005 which was

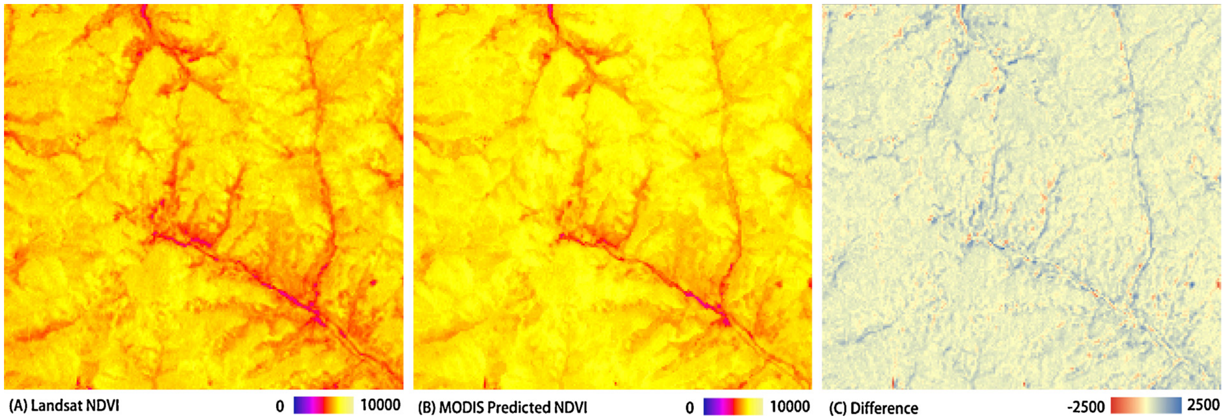

Fig. 4. Comparison between predicted NDVI and Landsat ETM+ NDVI.

scaled to 0–10,000 was assigned as the Landsat T1-scene data, and the same scaled and spatial resampled MODIS NDVI data acquired on 13 August, 2005 which was nearest to ETM+ data was assigned as the MODIS T1 data. The same scaled and spatial resampled MODIS NDVI data acquired at other date were used for prediction of Landsat-like NDVI data. Finally, the 30 m spatial resolution 16-day temporal resolution fused time series NDVI data was generated for further analysis.

3.2. *Temporal features extraction from fused time series NDVI data*

To analyze the effect of time series NDVI data on improving forest cover classification accuracy, and avoid adding too much redundancy information of high dimension data, four temporal features were extracted from the fused time series NDVI data for the forest cover classification. The four temporal features included the maximum, the minimum, the mean and the standard deviation value of the fused time series NDVI data. Finally, a new composited data combining the four temporal features bands and six spectral bands of Landsat ETM+ data (bands 1, 2, 3, 4, 5, and 7) was generated for forest cover classification. The combined data included not only the spectral features of Landsat ETM+ data, but also the high spatial resolution vegetation growth information contained in the fused time series NDVI data.

3.3. *Classification and accuracy validation*

The traditional maximum-likelihood classifier (MLC) is selected for forest cover classification in this study. MLC classifier assumes that a hyper-ellipsoid decision volume can be used to approximate the shape of the data clusters. For a given unknown pixel, described by a vector of features, the probability of membership in each class is calculated using the mean feature vectors of the classes, the covariance matrix and the prior probability (Duda and Hart, 1973). The unknown pixel is considered to belong to the class with the maximum probability of membership. In this study, six bands (1, 2, 3, 4, 5, and 7) of the Landsat ETM+ data and the composited ETM+ spectral bands with temporal features extracted from time series NDVI features bands were separately provided as the input data for MLC to analyze the accuracy improving effect of NDVI features.

Representative sample collection is the most time consuming process in the classification effort. In this study, samples were randomly selected from known areas using the 'region of interest' (ROI) tools provided by ENVI version 4.8 (ITT industries Inc., Boulder, CO, USA) with the help of ground survey and Google Earth tool. Finally, 70 and 138 ROI regions were selected for forest and non-forest class samples, respectively. The total sample pixels for forest and non-forest class were 13,212 and 15,824 pixels. The distribution of the sample pixels was uniform, which made it well representative for the whole study area. Half of the sample pixels were randomly selected as training samples, and the remaining half as validating samples. The training and validating samples had no overlap.

Accuracy validation of the classified maps was based on the independent validation samples as presented above. For each class, validation samples were easily identified and located within the study area from the remote sensing images and Google Earth map. The overall classification accuracy and kappa statistics estimated from the confusion matrix using the validation samples (Congalton and Green, 1999; Foody, 2009) were selected for evaluating the forest cover classification results.

4. Results analysis

In order to demonstrate that STARFM algorithm was applicative to the NDVI series fusion, a square region containing approximately 200 × 200 pixels was randomly selected to compare the predicted NDVI on Julian data 241 of 2005 with actual acquired Landsat ETM+ NDVI data on Julian date 246 of 2005 (Figs. 4 and 5). The general spatial distribution of predicted NDVI was consistent with the corresponding period of Landsat ETM+ NDVI, and the difference value between these two NDVI data were mainly distributed around

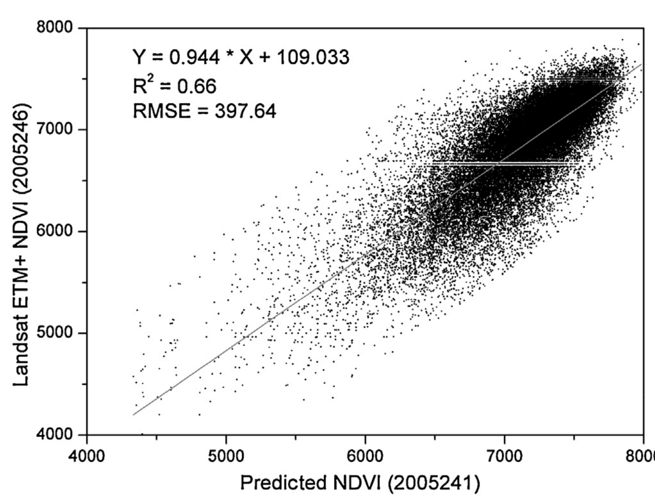

Fig. 5. Scatter plot of predicted and Landsat ETM+ NDVI data.

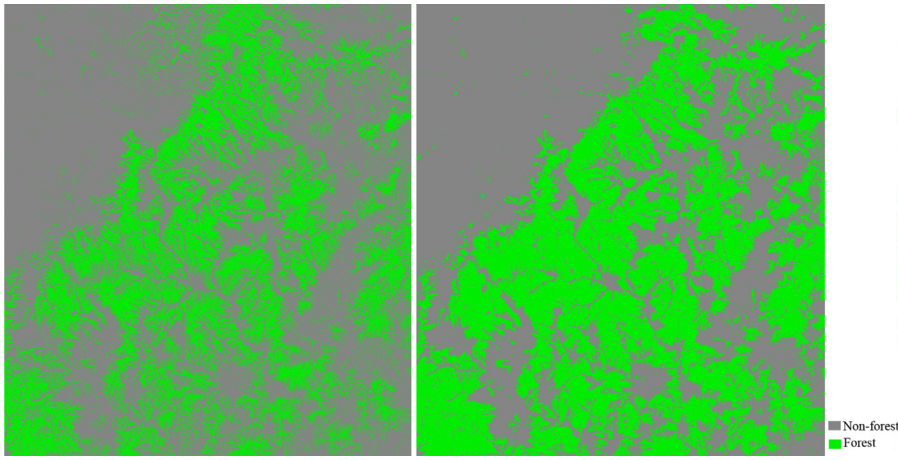

Fig. 6. Forest cover classification of MLC using only Landsat ETM+ data (left) and the composited ETM+ spectral bands with time series NDVI features bands (right).

zero (Fig. 4). This result indicated that the temporal information of MODIS and the spatial information of Landsat ETM+ data were effectively integrated in the predicted NDVI dataset which could describe a more detailed spatial variation of NDVI at the resolution of 30 m. From the scatter plot of predicted and Landsat ETM+ NDVI data (Fig. 5), it could be seen that most of the scatter points were concentrated along the line of $x = y$. The determination coefficient (R^2) was 0.66 at the 0.05 significant level, and the Root Mean Square Error (RMSE) was 397.64 which meant approximately 4% estimation error of predicted NDVI data (the NDVI data was scaled to 0 to 10,000). Additionally, predicted NDVI data was slightly larger than Landsat ETM+ NDVI data, which might be responsible for the 5 date interval of data acquisition. Based on the comparison of predicted NDVI and Landsat ETM+ NDVI, it was indicated that STARFM in this study could effectively fuse the MODIS and Landsat ETM+ NDVI data, and the fused NDVI dataset could be used for improving forest cover classification accuracy of Landsat ETM+ data.

The classification results of MLC using the Landsat ETM+ (MLC-TM) and the composited ETM+ spectral bands with time series NDVI features bands (MLC-All) were shown in Fig. 6. In the visual aspect, forest cover could be identified effectively in each classification map based on the visual observation of the Landsat ETM+ data. The classification results of MLC-All performed better than the MLC-TM result, and the main difference in the two classification results was misclassification in the forest region borders and small parcels in the interior of forest region. In the borders of forest regions, forest was always mixed with small proportion of other vegetation type or soil in the ETM+ pixel for its moderate spatial resolution. The mixed pixels phenomenon was also presented in some small parcels in forest regions. Furthermore, terrain, small cloud and shadows influence on the forest cover classification would be weaken by appending the fused time series NDVI data. Single Landsat ETM+ spectral data might not contain enough information to identify these forest pixels and lead to misclassification in these regions. When fused time series MODIS NDVI data which contained more vegetation growth information involved to the classification, the possibility of identifying these pixels increased.

The quantitative classification accuracy assessment had shown the same results with visual observation. The overall performance of the MLC-All shown evident improvement compared to the MLC-TM result based on the overall classification accuracy and kappa coefficient calculated from the confusion matrix (Tables 1 and 2). The four temporal features extracted from fused time series NDVI data improved the overall classification accuracy from 88.99% to 93.88%, and the kappa coefficient from 0.775 to 0.875. The results indicated that moderate or high spatial resolution multi-spectral data appending with time series coarse spatial resolution vegetation index data could provide more valuable information for forest cover classification. The main reason for classification accuracy improvement was that time series vegetation index data contained phonological and vegetation growth information, and different vegetation types had different growth features. Vegetation type might be difficult to identify in single temporal remote sensing data, but time series growth information could provide valuable information for vegetation type discrimination.

Table 1
Confusion matrix for the forest cover classification result of MLC using only Landsat ETM+ data.

Mapped class	Ground truth		
	Forest	Non-forest	Total
Forest	5255	247	5502
Non-forest	1351	7665	9016
Total	6606	7912	14,518

There were also some reasons might lead to mis-classification of this study: (1) the gaps in Landsat ETM+ original data was filled using other data instead of the observation of the actual earth surface reflectance; (2) a little cloud in the Landsat ETM+ data; (3) the fusion method of Landsat ETM+ NDVI data with MODIS NDVI data might bring out some uncertainty because STARFM was designed for reflectance fusion. Though the MLC-All method might bring out uncertainty in forest cover classification, the positive effect of time series MODIS NDVI data on improving classification accuracy of Landsat ETM+ data was confirmed. This method unlocked the issue about lower classification accuracy using single high spatial resolution data and difficult of acquiring of multi-temporal high spatial resolution data.

The time series NDVI data contained much vegetation growth information and temporal vegetation variation characters, thus weaken the influence of cloud, terrain and shadow on classification of single high spatial resolution data in a certain extent. The

Table 2
Confusion matrix for the forest cover classification result of MLC using the composited ETM+ spectral bands with time series NDVI features.

Mapped class	Ground truth		
	Forest	Non-forest	Total
Forest	5740	23	5763
Non-forest	866	7889	8755
Total	6606	7912	14,518

proposed method achieved encouraging forest cover classification result, and it also could be used for more land cover types classification using remote sensing data, such as grass, crop and even the more detailed vegetation types. Along with more and more fine spatial resolution data become available, such as HJ-1 A/B multispectral data, RapidEye data, and the coming GF satellite data of China, this method would play an important role in regional forest cover mapping and land cover mapping.

There were also some limitations in the proposed method and improvement should be conducted in the future work. Firstly, the time series NDVI data features used in this study were the basic statistic variables, more significant factors should be invested for the classification, such as the phonological features and the shape features extracted from the time series vegetation index data. Furthermore, the fusion method of coarse and high spatial resolution NDVI data was another important way to improve the classification accuracy. Moreover, the traditional MLC was selected as the classification method because this study was mainly designed to investigate the effect of time series NDVI data features on improving forest cover classification accuracy using Landsat ETM+ data. However, many more non-parameter classifiers had been developed for remote sensing data classification and usually could achieve more satisfactory classification results (Lu and Weng, 2007; Mountrakis et al., 2011). Therefore, advanced classifiers should be used to improve the classification performance in the future work.

5. Conclusion

This study presented a method for forest cover classification using Landsat ETM+ data appending with time series MODIS NDVI data, and confirmed that time series NDVI features had significant effort on improving classification accuracy of fine resolution remote sensing data. The forest cover classification in North China region shown that NDVI features extracted from time series fused NDVI data could improve the overall classification accuracy approximately 5% compared to only using a single Landsat ETM+ data. This study provided an illustration of forest cover classification method integrating temporal and spatial information from different resolution remote sensing data, and this method could be expanded to more complex study of land cover classification using remote sensing data.

However, only basic statistic features of time series fused NDVI data were investigated for forest cover classification, more significant features would be investigated in the future work. The fusion strategy between coarse and high spatial resolution NDVI data was another issue to further study. In conclusion, time series vegetation index data contained abundant vegetation growth information which was a helpful complementary data for land cover classification using high spatial resolution remote sensing data, especially for vegetation type classification.

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