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Land cover classification of finer resolution remote sensing data integrating temporal features from time series coarser resolution data

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ABSTRACT

Land cover classification of finer resolution remote sensing data is always difficult to acquire high-frequency time series data which contains temporal features for improving classification accuracy. This paper proposed a method of land cover classification with finer resolution remote sensing data integrating temporal features extracted from time series coarser resolution data. The coarser resolution vegetation index data is first fused with finer resolution data to obtain time series finer resolution data. Temporal features are extracted from the fused data and added to improve classification accuracy. The result indicates that temporal features extracted from coarser resolution data have significant effect on improving classification accuracy of finer resolution data, especially for vegetation types. The overall classification accuracy is significantly improved approximately 4% from 90.4% to 94.6% and 89.0% to 93.7% for using Landsat 8 and Landsat 5 data, respectively. The user and producer accuracies for all land cover types have been improved.

1. Introduction

Land cover refers to the physical and biological cover over the earth surface, including water, vegetation, bare soil, wetland, snow/ice and artificial structures. Land cover patterns reflect the underlying natural and social processes, thus providing essential information for modeling and understanding many phenomena on the earth, including climate change, ecosystem, hydrologic, atmospheric models and the complex interactions between human activities and global change (Bounoua et al., 2002; Gong et al., 2013; Jung et al., 2006; Liang, 2008; Miller et al., 2007; Running, 2008). Therefore, timely and accurate regional and global scales land cover information is critical and serves as the basis for geoscience and global change studies.

Remote sensing has long been an important and effective means for monitoring land cover with its ability to quickly provide large scale and easily available information regarding the spatial variability of the land surface (Gong et al., 2013; Hansen et al., 2000; Jia et al., 2014; Liu et al., 2003; Mutanga et al., 2012; Zhou et al., 2013). 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 products (Friedl et al., 2002), and the finer resolution global land cover (Gong et al., 2013). However, most of the land cover products are at coarser spatial resolution except for the finer resolution global land cover product. Because a substantial proportion of land cover changes have been shown to occur at resolutions below 250 m (Townshend and Justice, 1988), coarser spatial resolution (refers to data with spatial resolution lower than 250 m in this study) remote sensing data is not enough for catching the accurate land cover changes information. Recent advances in medium resolution data acquisition and accessibility make Landsat-like spatial resolution remote sensing data being a suitable choice for deriving finer resolution (refers to data with spatial resolution like Landsat or higher than it in this study) land cover maps.

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Landsat-like resolution remote sensing data with high temporal resolution is very significant for monitoring land cover, because temporal or phenological information contained in time series remote sensing data is very useful for land cover mapping, especially for vegetation cover classification (Jia et al., 2013; Xiao et al., 2002). Time series vegetation index (e.g., NDVI and EVI) data are approved to well descript vegetation growth and the shape of vegetation growing profiles depicted by time series vegetation index contain vegetation type information (Brown et al., 2013; Xiao et al., 2002). However, duo to the frequent cloud contamination and tradeoff in sensor designs which balance spatial resolution and temporal coverage, it is difficult to acquire time series high temporal resolution Landsat-like spatial resolution remote sensing data (Zhang et al., 2013). Thus, land cover classification using time series remote sensing data are usually focus on coarser spatial resolution data, whereas finer resolution land cover products are usually obtained from classification of single or fewer temporal Landsat-like spatial resolution remote sensing data (Gong et al., 2013). Therefore, it has great potential to improve land cover classification accuracy if temporal features involved in classifying finer resolution remote sensing data.

The main issue comes to how to extract temporal information from time series coarser resolution remote sensing data to improve land cover classification accuracy of finer resolution single or fewer temporal remote sensing data. Fusing observation from multiple sensors with different characteristics is considered as a feasible way to solve the problem. Several fusion methods have been developed to generate high temporal resolution Landsat-like surface reflectance data (Gao et al., 2006; Zhang et al., 2013; Zhu et al., 2010), but this data is rarely used to assist finer resolution data for improving land cover classification accuracy. In this study, finer resolution remote sensing data integrating temporal features from time series coarser resolution data is investigated for improving land cover classification accuracy. The specific objective is to investigate the potential of temporal features from coarser resolution time series vegetation index data on improving land cover classification accuracy of finer resolution remote sensing data.

2. Study area and data

2.1. Study area

Beijing is selected as the study area, which is located between latitudes 39°26′N and 41°03′N and longitudes 115°25′E and 117°30′E, covering an area of approximately 16,800 km^2 (Fig. 1). Beijing belongs to a temperate climatic zone and locates in the northern extent of the North China Plain. The climate in Beijing has four distinct seasons with hot and humid summers and cold, windy, and dry winters. The average annual temperature is approximately 12 °C and the average annual precipitation is approximately 664 mm. Beijing is characterized by alluvial plains in the south and east with hills and mountains dominating the north, northwest and west regions. The highest point above sea level in the study area is 2303 m and the lowest is 10 m. The abundant land cover types, including forest, grass, cropland, urban regions and water, have made land cover classification in Beijing a representative choice. Furthermore, the complex vegetation composition is very suitable to investigate the proposed classification method integrating finer resolution remote sensing data and time series coarser resolution data derived temporal features which are sensitive to vegetation types.

2.2. Landsat data and preprocess

The Landsat 8 satellite was successful launched on February 11, 2013, from Vandenberg Air Force Base in California, providing the continuity in the Landsat earth observation mission (Lulla et al., 2013). Operational Land Imager (OLI) on board Landsat 8 was the main sensor for land cover monitoring, which had nine bands including the high-resolution panchromatic band. Two Landsat OLI data (path/row: 123/32 and 123/33) covering the study area on May 12, 2013 were downloaded from the United States Geological Survey (USGS) website (http://glovis.usgs.gov/) for land cover classification in this study. The quality of the Landsat OLI multispectral data were good and cloud was nearly absent in the acquired data. In order to further validating the effectiveness of the proposed method, two Landsat 5 TM data (path/row: 123/32 and 123/33) covering the study area on June 5, 2010 were also downloaded from USGS for land cover classification. The Landsat data processing mainly included radiance calibration, mosaic and subset. Radiance calibration was conducted to convert the DN value to surface spectral reflectance and the atmospheric correction was conducted using FLAASH tools provided by ENVI version 5.0. Mosaic and subset process was used to extract the Landsat data covering the study area for land cover classification.

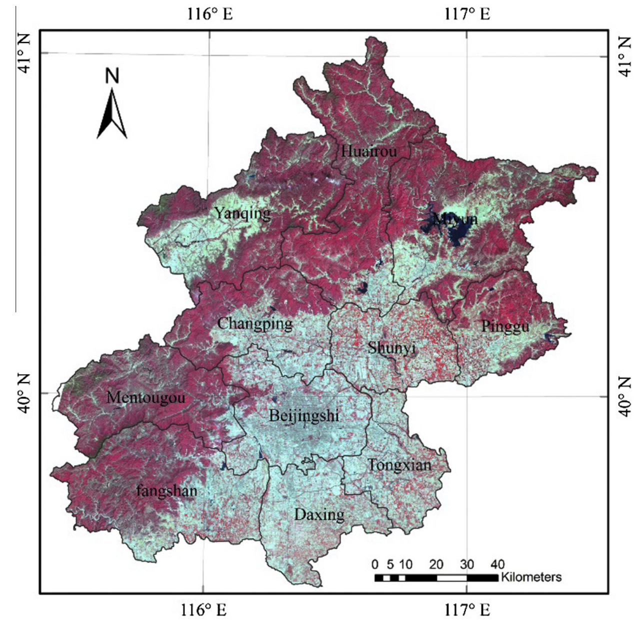

Fig. 1. The geographical region of the study area and the background information is the false color image (R: NIR, G: red, B: green) of Landsat OLI data acquired on May 12, 2013. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

2.3. Time series MODIS NDVI data

MODIS MOD13Q1 products (vegetation indices 16-day L3 Global 250 m version 5) covering the study area and spanning one year from October 2012 to September 2013 and from October 2009 to September 2010, for assisting land cover classification of OLI and TM data, respectively, 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). Firstly, the daily MODIS vegetation indices data were computed from atmospherically corrected bi-directional surface reflectances that had been masked for water, clouds, heavy aerosols, and cloud shadows. Then, every 16-day daily vegetation indices data were composited to generate MOD13Q1 products.

MOD13Q1 product provided 16-day composited vegetation indices data at a spatial resolution of 250 m in the sinusoidal projection. The NDVI data was extracted from the MOD13Q1 datasets for land cover classification in this study.

The Savitzky–Golay (S–G) filter was used to smooth the time series MODIS NDVI data, specifically the noise 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. The smoothed MODIS NDVI data was re-projected to the same projection with Landsat data and the spatial resolution was resampled to 30 m. Finally, the same columns and lines of MODIS NDVI data were extracted to keep consist with Landsat data for further analysis.

3. Method

A flowchart of land cover classification of finer resolution remote sensing data integrating temporal features from time series coarser resolution data was presented in Fig. 2. All the remote sensing data were firstly preprocessed to have good quality and the same processing area. Then the MODIS NDVI data was fused with Landsat data derived NDVI using the Spatial and Temporal Adaptive Reflectance Fusion Model (STARFM) (Gao et al., 2006). The temporal features were extracted from the fused time series finer resolution NDVI data, and combined with Landsat spectral bands for finer resolution land cover classification using supervised classifier. Finally, accuracy assessment was conducted to investigate the effect of temporal features extracted from coarser resolution data on improving land cover classification accuracy of finer resolution data. The proposed approach hypothesized that land cover classes were not changed in the Landsat image across the temporal MODIS NDVI data, because changed land cover would brought inaccurate temporal features and influence the classification accuracy.

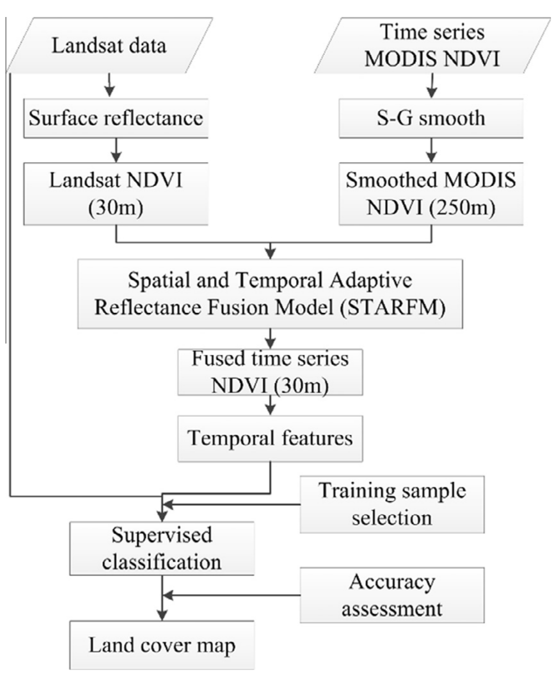

Fig. 2. The flowchart of land cover classification of finer resolution remote sensing data integrating temporal features from time series coarse resolution data.

3.1. Fusion of Landsat NDVI with MODIS NDVI data

STARFM is firstly developed to blend MODIS and Landsat surface reflectance by fusing high temporal resolution 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). In this study, Landsat NDVI data was scaled to 0–10,000 and assigned as the Landsat T1-scene data. The same scaled and spatial resampled (30 m) MODIS NDVI data acquired on the date which was nearest to Landsat data was assigned as the MODIS T1 data. The time series MODIS NDVI data was then scaled to 0–10,000 and used to produce Landsat-like NDVI data using STARFM. Finally, the time series 16 day interval 30 m spatial resolution fused NDVI data was generated for further land cover classification.

3.2. Temporal features extraction from fused time series NDVI data

Using all of the fused time series NDVI data for land cover classification was not a judicious choice, because the time series data had much redundancy information and might reduce the precision of model estimation of these parametric classifier (Vaiphasa et al., 2007). Features selection was the better strategy for reducing redundancy and improving computational efficiency. Therefore, four temporal features included the maximum, the minimum, the mean and the standard deviation value of the fused time series NDVI data were extracted for further land cover classification. These temporal features could represent the vegetation growth characteristics and provided phenological information for improving vegetation type identification. The four temporal features were composited with Landsat spectral data for further land cover classification. The combined data contained not only the spectral features of Landsat data, but also the temporal information extracted from the time series MODIS NDVI data.

3.3. Supervised classification

The maximum likelihood classifier (MLC) was selected for the land cover classification of Landsat data integrating temporal features extracted from time series MODIS NDVI data. The MLC was the traditional parametric classifier used for remote sensing data classification, which assumed that a hyper-ellipsoid decision volume could be used to approximate the shape of the data clusters (Foody et al., 1992; Jia et al., 2011). Moreover, for a given unknown pixel, the probability of membership in each class was calculated using the mean feature vectors of the classes, the covariance matrix and the prior probability (Duda and Hart, 1973). The unknown pixel was considered to belong to the class with the maximum probability of membership.

Coastal aerosol and blue bands of the Landsat OLI data were significantly correlated and the coastal aerosol band was designed for monitoring coastal waters and aerosol, therefore the coastal aerosol band was removed in the classification process. The cirrus band of OLI data, which was designed for cloud identification and contained limited land surface information, was also removed in the land cover classification. Finally, bands 2, 3, 4, 5, 6, 7 of OLI data, the composited OLI spectral bands with temporal features, bands 1, 2, 3, 4, 5, 6 of TM data and the composited TM spectral bands with temporal features, were separately used for land cover classification to investigate the effect of temporal features on classification accuracy improvement.

Based on the characteristics of land cover type distribution in the region, six classes were identified as the final class types of the regional land cover classification experiment, which included water, crop, bare land, impervious, grass and forest. Samples were randomly selected in the Landsat data from known areas using the 'region of interest' (ROI) tools provided by ENVI version 5.0 software with the help of ground knowledge and the Google Earth tool. The characteristics of the sample ROIs for training and validating the classifier using Landsat data and MODIS NDVI data were summarized in Table 1. These homogeneous sample areas were easily identified on the Landsat image and Google Earth map by visual observation. The distribution of the sample pixels was uniform and well represented the entire study area. Half of the sample pixels were randomly selected as training samples, and the remaining half as validating samples.

3.4. Accuracy assessment

To assess the land cover classification performance using Landsat data integrating temporal features extracted from time series MODIS NDVI data, the classification results of the MLC classifier by using only Landsat data and Landsat data integrating temporal features were assessed via visual observations and quantitative classification accuracy indicators. Randomly selected sample pixels were used to quantitatively assess the land cover classification accuracy using the indicators including the overall classification accuracy, producer accuracy, user accuracy, and Kappa statistics (Congalton and Green, 1999; Foody, 2009; Tso and Mather, 2001). The total validation sample pixels for classification of OLI data and OLI data integrating temporal features were 3023 pixels for water, 3430 pixels for crop, 3961 pixels for bare land, 3523 pixels for impervious, 6695 pixels for forest and 2365 pixels for grass. Meanwhile, the validation sample pixels for classification of TM data and TM data integrating temporal features were 2898 pixels for water, 3199 pixels for crop, 3107 pixels for bare land, 3626 pixels for impervious, 6293 pixels for forest and 2190 pixels for grass. In order to access statistical differences between the accuracy measurements of classification results using only Landsat data and Landsat data integrating temporal features, a Z-test was performed to see if they were significantly different (Foody, 2009; Thenkabail, 2010; Thenkabail et al., 2004).

4. Result

The land cover classification result of MLC using only Landsat data and the composited Landsat spectral bands with temporal features extracted from time series MODIS NDVI data were shown in Figs. 3 and 4. In the visual aspect, each land cover types could be identified effectively in each classification map based on the visual observation of the Landsat data under expert's knowledge. Forests and grasses were mainly distributed in the north, northwest and west mountain regions of Beijing, accounting for more than half the area of Beijing. Crops were primarily distributed in the south and east plain regions and plain regions in Yanqing County. The impervious class was primarily distributed in urban regions. Furthermore, classification result of combined Landsat spectral data with temporal features extracted from time series MODIS NDVI data performed better than that using only Landsat spectral data. The main difference in the classification results of using temporal features or not was that Landsat data integrating temporal features could better classify each land cover type, especially the vegetation types, and reduce the misclassification between each class types, indicating a more satisfactory land cover classification results.

The quantitative classification accuracy assessment and kappa statistics were estimated based on the validation samples. The confusion matrices of the classification results using only Landsat spectral data and combined Landsat spectral data with temporal features were shown in Tables 2 and 3. The land cover classification performances were all satisfactory, and Landsat spectral data integrating temporal features achieved better classification accuracy (overall accuracy 94.6% and 93.7%, kappa coefficient 0.93 and 0.92 for OLI data integrating temporal features and TM data integrating temporal features, respectively) than that using only Landsat spectral data (overall accuracy 90.4% and 89.0%, kappa coefficient 0.88 and 0.86 for OLI and TM data, respectively), which was similar with the visual observation. The four temporal features extracted from time series MODIS NDVI data improved the overall classification accuracy approximately 4%, and the kappa coefficient value approximately 5%. It was also shown that user accuracy and producer accuracy for all land cover types had improvement when using temporal features, especially for grass which had accuracy improvement more than 10%.

The Z-test was used to compare the error matrices to determine whether the classification accuracies were significantly different. $Z > 1.96$ or $Z < -1.96$ would indicate the difference of the two error matrices being significant at the 5% significance level (Foody, 2009). If the two error matrices were not significantly different, when given the choice of whether using temporal features extracted from time series coarser resolution data, one should use only finer resolution remote sensing data to obtain the easier, quicker or more efficient approach because the accuracy would not be the deciding factor (Thenkabail et al., 2004). The Z-test value for comparison between the error matrices of classification result using temporal features or not was 17.53 and 17.55 for OLI and TM data, respectively, both larger than 1.96, and indicated that the error matrices was significantly different and temporal features extracted from time series coarser resolution data could significantly improve land cover classification accuracy of finer resolution data.

The grass having lowest user and producer accuracy was mainly caused by the fact that grass always co-existed with forest and had smaller areas in the forest gaps and boundaries. In addition, dense grass might have similar spectral characters with crops (mainly wheat in this period); sparse grass typically had lower coverage, which might be confused with bare land and impervious classes. These phenomena had leading to difficulty in grass identification using only one temporal Landsat data. Temporal information contained vegetation growth characteristics and provided valuable information for vegetation type discrimination, which was also seen in the classification accuracy assessment in this study. It was therefore concluded that temporal features extracted from time series coarser resolution data had great effect on significantly improving land cover classification accuracy of finer resolution remote sensing data.

Table 1
Number of ROIs and pixels in each land cover type used for training and validating the MLC.

	Water	Crop	Bare land	Impervious	Forest	Grass
ROIs used for OLI data						
Number of ROIs	22	86	51	33	107	81
Number of pixels	6046	6860	7922	7046	13,390	4730
ROIs used for TM data						
Number of ROIs	21	93	88	38	106	86
Number of pixels	5796	6398	6214	7252	12,586	4380

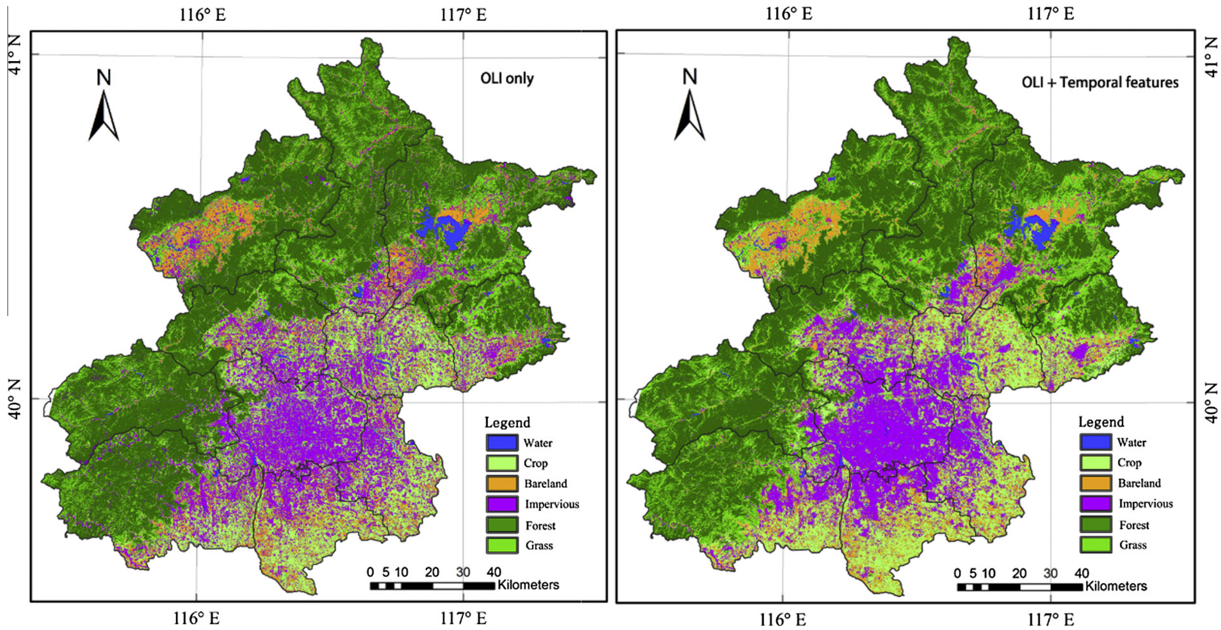

Fig. 3. Land cover classification results of MLC using only OLI spectral data (left) and the composited OLI spectral data and temporal features from MODIS NDVI data (right).

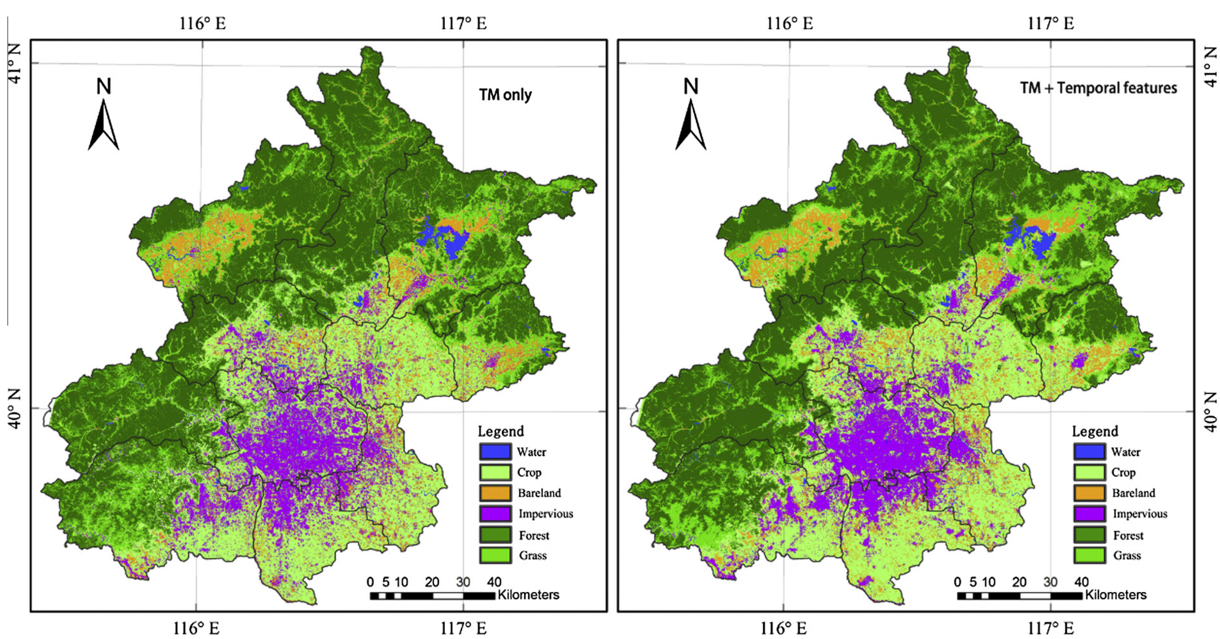

Fig. 4. Land cover classification results of MLC using only TM spectral data (left) and the composited TM spectral data and temporal features from MODIS NDVI data (right).

5. Discussion

Temporal features are important information for land cover classification using remote sensing data, especially for vegetation type discrimination (Gu et al., 2010). Because different vegetation types usually have different phenology characteristics, and show different growth profiles in time series remote sensing data which are always described by vegetation index profiles, thus providing valuable information for land cover type classification. However, the temporal features are only widely used in classification of coarser resolution remote sensing data (Brown et al., 2013; Xiao et al., 2002), because high temporal and finer spatial resolution remote sensing data acquiring is very difficult (Zhang et al., 2013). This study involved temporal features contained in time series coarser resolution NDVI data to improve land cover classification accuracy of finer resolution remote sensing data. The study provided a data fusing strategy of integrating temporal features from coarser resolution data with land cover classification of finer resolution remote sensing data and solved the problem of difficulty in acquiring finer resolution temporal features. The temporal features contained vegetation variation characteristic information and can weak the influence of cloud, terrain and shadow on classification of single or fewer temporal finer resolution remote sensing data, thus significantly improving land cover classification accuracy, especially for vegetation type classification.

The proposed method is easily operated and only the time series coarser resolution MODIS NDVI data is added, which is free and leading to no data acquiring cost increasing. Along with more and

Table 2
Confusion matrixes for land cover classification using Landsat 8 OLI data and temporal features extracted from time series MODIS NDVI data.

	Ground Truth (Pixels)							User acc. (%)	Pro. acc. (%)
	Water	Crop	Bare	Imp	Grass	Forest	Total		
Mapped class (pixels)									
Using only Landsat OLI data									
Water	2927	0	0	0	0	0	2927	100.0	96.8
Crop	1	3173	14	39	43	187	3457	91.8	92.5
Bare	0	5	3837	257	2	0	4101	93.6	96.9
Imp	86	28	110	3223	3	15	3465	93.0	91.5
Grass	4	126	0	4	1503	372	2009	74.8	63.6
Forest	5	98	0	0	814	6121	7038	87.0	91.4
Using Landsat OLI data and temporal features									
Water	2933	0	0	0	0	0	2933	100.0	97.0
Crop	6	3309	18	8	20	130	3491	94.8	96.5
Bare	2	5	3895	120	0	0	4022	96.8	98.3
Imp	77	26	48	3395	0	2	3548	95.7	96.4
Grass	3	22	0	0	1973	303	2301	85.6	83.4
Forest	2	68	0	0	372	6260	6702	93.4	93.5
Total	3023	3430	3961	3523	2365	6695	22,997		

Notes: Bare, bare land; Imp, impervious; Pro. acc., producer accuracy; User acc., user accuracy.

Table 3
Confusion matrixes for land cover classification using Landsat 5 TM data and temporal features extracted from time series MODIS NDVI data.

	Ground Truth (Pixels)							User acc. (%)	Pro. acc. (%)
	Water	Crop	Bare	Imp	Grass	Forest	Total		
Mapped class (Pixels)									
Using only Landsat TM data									
Water	2841	0	0	0	0	0	2841	100.0	98.0
Crop	11	2936	11	73	170	226	3427	85.7	91.8
Bare	0	28	2873	246	0	0	3147	91.3	92.5
Imp	43	7	223	3307	0	0	3580	92.4	91.2
Grass	3	103	0	0	1245	299	1650	75.5	56.9
Forest	0	125	0	0	775	5768	6668	86.5	91.7
Using Landsat TM data and temporal features									
Water	2842	0	0	0	0	0	2842	100.0	98.1
Crop	14	3136	11	17	128	208	3514	89.2	98.0
Bare	6	23	2982	119	0	0	3130	95.3	96.0
Imp	33	0	114	3490	0	1	3638	95.9	96.3
Grass	3	34	0	0	1718	278	2033	84.5	78.5
Forest	0	6	0	0	344	5806	6156	94.3	92.3
Total	2898	3199	3107	3626	2190	6293	21,313		

Notes: Bare, bare land; Imp, impervious; Pro. acc., producer accuracy; User acc., user accuracy.

more finer resolution remote sensing data becoming available, e.g., GF-1, HJ-1 A/B CCD, and SPOT 6 data, the proposed method have great potential in improving land cover classification accuracy of these finer resolution remote sensing data and will play an important role in regional land cover mapping. The proposed approach also has potential in classifying more detailed vegetation types, such as coniferous and broad-leaf forest in forest category, wheat and corn in crop category. Further studies will focus on using more types of finer resolution remote sensing data and classifying more detailed land cover types. Another interesting topic is the spans of the temporal data influencing the land cover classification accuracy if high-quality higher temporal resolution time series NDVI data being available, because larger temporal interval will weaken the temporal characteristics.

There are also some potential limitations regarding the proposed method. Firstly, the temporal features used in this study are only the basic statistic variables, more significant features should be developed for land cover classification, such as the phenological features, the shape features extracted from the time series vegetation index data. In addition, land cover in Landsat image should not be changed across the temporal MODIS data, because changed land cover would change the NDVI temporal profiles and derive inaccuracy temporal features. The inconsistency in the temporal features would influence the final classification result. Moreover, the traditional and easily conducted MLC is selected as the classification method which is also suitable when there are large training samples. However, many more advanced non-parameter classifiers have been developed for land cover classification to improve accuracy, such as support vector machines, neural networks and design tree (Lu and Weng, 2007). And non-parameter classifiers usually can achieve more satisfactory classification results (Mountrakis et al., 2011). This study is designed to investigate the effect of temporal features extracted from time series coarser resolution data on improving land cover classification accuracy using finer resolution remote sensing data. Therefore, only MLC is used in this paper and non-parameter classifiers will be used to improve the performance of the proposed approach in the future work.

6. Conclusion

This study proposed a land cover classification method of finer resolution remote sensing data integrating temporal features from time series coarser resolution data. The results indicated that temporal features extracted from time series coarser resolution remote sensing data contained abundant vegetation growth information and had significant effect on improving land cover classification accuracy of finer resolution data. The land cover classification in Beijing region shown that temporal features extracted from time series MODIS NDVI data could significantly improve the overall classification accuracy approximately 4% compared to that only using a single temporal Landsat data. User accuracy and producer accuracy for all land cover type had a great improvement, especially for vegetation types. The proposed method had great potential for using on regional land cover classification of finer resolution remote sensing data.

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