Classification of Landsat 8 OLI Image Using Support Vector Machine With Tasseled Cap Transformation

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Abstract—Landsat represents the world's longest continuously acquired collection of space-based moderate-resolution land remote sensing data. Compared with the other earlier Landsat satellites, Landsat 8 has several new characteristics in spectral bands, spectral range and radiometric resolution. Therefore, there is a strong requirement to analyze the characteristics of the Landsat 8 for land cover classification, global change research. In this paper, Landsat 8 OLI image was used with Support Vector Machine (SVM) and Tasseled Cap Transformation (TCT) for land cover classification. Firstly, the Top of Atmospheric (TOA) reflectance based TCT was developed based on Landsat 8 OLI images. Then comparison of ISODATA, K-Means and SVM of all original 8 Landsat 8 OLI bands and both of TCT Greenness and Wetness in land cover classification was done. The present results showed that compared with using the original 8 Landsat 8 OLI bands, the classification results from ISODATA and K-Means based on both of TCT Greenness and Wetness had better robustness and accuracy, and the classification using SVM with TCT had better efficiency and accuracy.

Keywords-classification; Landsat 8 OLI; support vector machine; tasseled cap transformation

I. INTRODUCTION

Land cover information has been identified as one of the crucial data components for many aspects of regional planning, global change research and environmental monitoring applications. Over the last four decades or so, remote sensing has increasingly become a prime source of land cover information. The derivation of land cover information from satellite remote sensing images has been the subject of intense interest and research in the remote sensing community. One of the major approaches to derive land cover information from remote sensing images is classification. Numerous classifiers have been in use in remote sensing researches including the ISODATA, K-Means unsupervised classifiers, the Maximum Likelihood (ML), minimum distance, mahalanobis distance, parallelepiped, spectral angle mapper, neural network and decision tree classifiers, and most of them have been integrated in the remote sensing image processing software such as PCI, ERDAS and ENVI. In spite of this, there is still considerable scope for study for further increases in accuracy to be obtained and maximizing the degree of land cover information derivation from remote sensing images, and a strong desire to simplify the classification procedure and improve the classification efficiency. Thus, new sensors and research into new methods of classification has continued. Landsat represents the world's longest continuously collection of space-based moderate-resolution land remote sensing data. Four decades of imagery provides a unique resource for those who work in agriculture, geology, forestry, regional planning, education, mapping, and global change research. On May 30, 2013, data from the Landsat 8 satellite (launched on February 11, 2013) became available. As with previous partnerships, this mission continues the acquisition of high-quality data that meet both NASA and USGS scientific and operational requirements for observing land use and land change. Compared with the other earlier Landsat satellites, Landsat 8 has several new characteristics in spectral bands, spectral range and radiometric resolution. Therefore, there is a strong requirement to analyze the characteristics of the Landsat 8 for land cover classification, global change research. One of new classification methods, support vector machine (SVM) have recently attracted the attention of the remote sensing community.

SVM is derived from statistical learning theory. It discriminates the classes with a decision surface, called optimal hyper-plane, which enhances the margin between the classes. The data points closest to the hyper-plane are called support vectors [1]. In the recent years, SVM has been successfully used to classify images [2-8]. However, the general SVM doesn’t take the high dimensions and redundancy of multispectral remote sensing images into account, classification accuracy based on general SVM still needs to be improved [9]. To overcome these problems, combining feature extraction and image classification algorithms such as Principal Component Analysis (PCA), Independent Component Analysis (ICA) and Tasseled Cap Transformation (TCT)) with SVM were developed and used [9-12], which showed that a quite effective and high accuracy classification could be achieved.

The Tasseled Cap Transformation (TCT) has been widely used in the remote sensing community. Compared with the PCA, TCT can compress multispectral data into a few bands which can be directly linked to physical scene characteristic which are easier to be understood. However, TCT is sensor dependent and affected with acquisition season and geographic...
location of images, for a new sensor or a new application (different set of relevant scene classes) a reworking of the tasseled cap transformation is required starting with analysis of the data structures of images [13]. Thus, TCT parameters have been derived based on Landsat MSS, Landsat 4 TM, Landsat 5 TM, Landsat 7 ETM+, JERS-1 OPS, ASTER, MODIS, SPOT 5, IKONOS, QUICKBIRD 2, CBERS-02 and HJ-1 satellite images [14-27]. Therefore, it is also necessary to derive the TCT parameters for the new images from the Landsat 8 satellite. In this paper, firstly the Top OF Atmospheric (TOA) reflectance based TCT was developed based on Landsat 8 OLI images. Then, the original Landsat OLI bands and the TCT components were analyzed from a view of discussing their implication for land cover classification.

II. MATERIALS AND METHODS

A. Remote Sensing Data

Landsat 8 carries two instruments: the Operational Land Imager (OLI) and the Thermal Infrared Sensor (TIRS). OLI will collect image data for nine shortwave bands (Band1, 433-453 nm; Band2, 450-515 nm; Band3 525-600 nm; Band4, 630-680 nm; Band5, 845-885 nm; Band6, 1560-1660; Band7, 2100-2300 nm; Band8, 500-680 nm; Band9, 1360-1390 nm. The pixel size of Bands 1-7 and 9 is 30 meters and the pixel size of Band8 is 15 meters). TIRS will collect data for two long wave thermal bands (Band10, 10300-11300 nm; Band11, 11500-12500 nm). The Band10 and 11 collected at 100 meters every 16 days which are resampled to 30 meters to match OLI multispectral bands.). OLI provides for compatibility with the historical Landsat data, while also improving measurement capabilities. A set of 5 clear and near cloud-free OLI scenes for the Yellow River Delta, China were used in this study (Table I). Huang et al. (2002) demonstrated the necessity to convert digital number to at-satellite reflectance when atmospheric correction is not feasible, and a Tasseled Cap Transformation based on at-satellite reflectance is more appropriate for regional applications where atmospheric correction is not feasible [18]. Raw Digital Number (DN) was converted to the Top of Atmosphere (TOA) reflectance using radiometric rescaling coefficients provided in the product metadata file (MTL file), as described from the Landsat website [28].

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<tr>
<th>Bands</th>
<th>TCT Components</th>
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<td></td>
<td>Brightness</td>
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<tr>
<td>Band1</td>
<td>0.0568</td>
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<td>Band2</td>
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<td>Band6</td>
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B. Tasseled Cap Transformation

Tasseled Cap Transformation is from its cap shape. In general, the Brightness Component (TCTB), Greenness Component (TCTG) and Wetness Component (TCTW) derived from TCT can explained over 90% of the spectral variance of individual scenes. TCTB responds to the physical properties that influence total reflectance. TCTG is responsive to the characteristic of healthy green vegetation that is the combination of high absorption of chlorophyll in the visible bands and high reflectance of leaf structure in the near-infrared band. TCTW responds to the amount of moisture being held by the vegetation or soil.

The TOA reflectance based tasseled cap transformation was derived using the method described in Jackson (1983) [29]. More than 2000 random samples of dry soils, wet soils, dense vegetation and water were respectively selected from the images acquired on May 30, 2013 and Oct. 5, 2013 according to the two dimension scatter plot between the Normalized Difference Moisture Index (NDMI, \( \frac{\rho_4 - \rho_6}{\rho_4 + \rho_6} \)) and Normalized Difference Vegetation Index (NDVI, \( \frac{\rho_4 - \rho_3}{\rho_4 + \rho_3} \)). Firstly, the first dimension of the Tasseled Cap Transformation, Brightness, was derived with the differences between the dry (salt-affected soils and fallow fields) and the wet soil (muddy tidal flat) points. Then, with the orthogonal to the Brightness preserved through the Gram-Schmidt process, the second dimension of the Tasseled Cap Transformation, Greenness, was derived with the differences between the dense green vegetation (healthy forest) and the dry soil points. Finally, the third dimension of the Tasseled Cap Transformation, Wetness, was derived with the differences between the dense green vegetation and the water body points (reservoir, ponds, river and sea).

Fig. 1 suggested that the Tasseled Cap Transformation parameters derived from the image from October (called as the autumn TCT) can differentiate among the dry soils, wet soils, vegetation and water in the Greenness-Wetness space better than the Tasseled Cap Transformation parameters derived from the image from May (called as the spring TCT). Considering the dynamic changes of landscapes represented by the five scene images and discrimination power, the Tasseled Cap Transformation parameters derived from the image from October (Table II) likely is applicable to clear and near cloud-free images for the spring, summer and autumn across the Yellow River Delta, China. The image from May 30, 2013 was most appropriate for regional land cover classification.

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<td>Band7</td>
<td>0.6582</td>
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<td>Band9</td>
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The Greenness-Wetness scatter plot calculated with the spring TCT, and (b), (d), (f), (h) and (l) was the Greenness-Wetness scatter plot image calculated with the autumn TCT based on the May 30, June 15, September 3, October 5, November 6, 2013 respectively.

C. Support Vector Machine

SVM functions by nonlinearly projecting the training data in the input space to a feature space of higher (infinite) dimension by use of a kernel function. This results in a linearly separable dataset that can be separated by a linear classifier. The implementation of SVM includes generating the regions of interesting as the training data, selecting kernel functions (linear, polynomial, radial basis function and sigmoid) and a penalty parameter, which affect the classification results. The radial basis function is often selected as kernel which gets better classification results [3]. The SVM method integrated in ENVI 5.0 was used in this paper, and the radial basis function was selected as kernel.

D. Classification Experiments

The classification experiments were divided into two groups: the original 8 bands, and TCT Greenness and Wetness with the image from May 30, 2013 over the Yiqianer Natural Reserve. For each group, two unsupervised classifiers (ISODATA and K-Means) and SVM method were used to compare the classification results separately. As training data, fallow fields, tidal flats, vegetation and water samples were chosen according to the scatter plot between the TCT Greenness and Wetness components derived from the image of May 30, 2013, presenting the main land cover classes over the Yiqianer Natural Reserve of the Yellow River Delta (shown in Fig. 2).

III. RESULTS AND DISCUSSION

Fig. 3a and 3b were the false color composite images RGB Band6 and Band5 and Band4, and the TCT Brightness and Greenness. Fig. 4a and 4b were the classification results from ISODATA based on the original 8 bands, and the TCT Greenness and Wetness components of the image from May 30, 2013. Fig. 5a and 5b were the classification results...
from K-Means based on the original 8 bands, and the TCT Greenness and Wetness components of the image from May 30, 2013. Fig. 6a and 6b were the classification results from SVM based on the original 8 bands, and the TCT Greenness and Wetness components of the image from May 30, 2013.

From the Fig. 4a and 4b, Fig. 5a and 5b, water could be detected very well on all the derived land cover maps. Compared with the classification results from the original 8 Landsat 8 OLI bands, the classification results from ISODATA and K-Means based on both of TCT Greenness and Wetness components had more aesthetic accuracy. The land cover maps from ISODATA and K-Means based on the original 8 Landsat 8 OLI bands (shown in Fig. 4a and Fig. 5a) could detect the fallow fields, while it was almost impossible to distinguish between vegetation and tidal flats. The land cover maps from ISODATA and K-Means based on the TCT Greenness and Wetness components (shown in Fig. 4b and Fig. 5b) could detect the fallow fields, dense vegetation and tidal flats but there were confusions between the fallow fields and sparse vegetation. There were large differences between the land cover maps from ISODATA and from K-Means based on the original 8 Landsat 8 OLI bands, while the land cover maps from ISODATA and from K-Means based on the TCT Greenness and Wetness components expressed less differences, which indicated that the classification based on the TCT Greenness and Wetness had better robustness, independent of the unsupervised classifiers.

As could be seen in Fig. 6a and 6b, it was very well to classify the image into fallow Fields, tidal flats, vegetation and water from both the original 8 Landsat 8 OLI bands and the TCT Greenness and Wetness components based on SVM. However, the SVM with the TCT Greenness and Wetness components approach exhibited high performance in computation speed, and got better classification results for visual effectiveness. The classification result from the SVM with the original 8 Landsat 8 OLI bands underestimated water at where water was small and very dark, while the classification result from the SVM with the TCT Greenness and Wetness components overestimated fallow fields at where water had high suspended materials. Analyzing the accuracy components carefully, it was easy to find that there were worse results in the areas around ponds and salt pans, which were a composite of water bodies, bare soils and sparse vegetation, and where there were more spectral confusion pixels. The field validation demonstrated that overall classification accuracy of SVM in both based on the original 8 Landsat 8 OLI bands and based on the TCT Greenness and Wetness components was quite close, being 91.2% and 93.1% respectively. This result indicated that Landsat 8 OLI data were good data source for land cover classification.

IV. CONCLUSIONS

The classification results showed that Landsat 8 OLI data were suitable for land cover studies. Considering the discrimination power on land cover, the Tasseled Cap Transformation parameters derived from the October image likely is applicable to clear and near cloud-free images for the spring, summer and autumn over the Yellow River Delta, China. Compared with the original 8 Landsat 8 OLI bands, the
classification result from ISODATA and K-Means classifiers based on the Tasseled Cap Transformation Greenness and Wetness components had more aesthetic accuracy, and better robustness, independent of the unsupervised classifiers. The field validation demonstrated that overall classification accuracy of SVM in both based on the original 8 Landsat 8 OLI bands and based on the TCT Greenness and Wetness components was quite close. However, compared with the original 8 Landsat 8 OLI bands, the SVM with the TCT Greenness and Wetness components approach exhibited high performance in computation speed.

Future work would test the classification potential of using the different band composites of Landsat 8 OLI images based on the different kernel of SVM with the Tasseled Cap transformation over the different seasonal and geographic location areas.

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