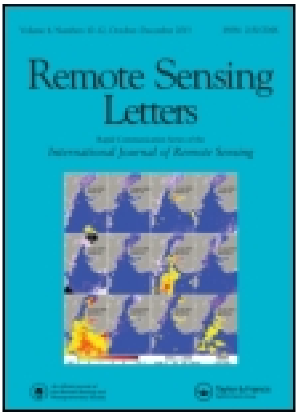

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Automatic land-cover update approach integrating iterative training sample selection and a Markov Random Field model

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Automatic land-cover update approach integrating iterative training sample selection and a Markov Random Field model

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Land-cover updating from remote-sensing data is an effective means of obtaining timely land-cover information. An automatic approach integrating iterative training sample selection (ITSS) and a Markov Random Field (MRF) model is proposed in this study to overcome the land-cover update problem when no previous remote-sensing data corresponding to the land-cover data are available. A case study in the Beijing region indicates that ITSS can effectively select reliable training samples based on historical land-cover data and that ITSS with MRF can achieve satisfactory land-cover update results (overall classification accuracy: 83.1%). The MRF model can effectively reduce salt-and-pepper noise and improve overall accuracy by approximately 6%. The proposed approach is completely unsupervised and has no strict requirements for newly acquired remote-sensing data for land-cover updating.

1. Introduction

Global and regional land-cover status and changes are fundamentally important for climate and environmental change studies (Turner, Lambin, and Reenberg 2007; Jin et al. 2013). More importantly, accurate and timely land-cover information is an essential factor for improving the performance of ecosystem, hydrologic and atmospheric models (Bounoua et al. 2002; Jung et al. 2006; Miller, Guertin, and Goodrich 2007). Due to natural causes and human activities, land-cover is changing throughout the world. Therefore, it is important to quantify and monitor these land-cover changes to support global and environmental changes studies.

Remote sensing is an effective means for land-cover monitoring with its ability to provide quickly broad, precise, impartial and easily available information on the land surface (Hansen et al. 2000; Liu et al. 2003). Many global and regional land-cover data sets have been derived from remote-sensing data (Hansen et al. 2000; Friedl et al. 2002; Liu et al. 2010; Gong et al. 2013), but these data sets use only data acquired during one or several years and represent land-cover characteristics for a specific period, without long-term change information. Land-cover update using timely remote-sensing data to support global change studies is one feasible strategy. Furthermore, the large and growing satellite data archives make it possible to achieve this requirement.

Traditional land-cover updating approaches determine and classify changed areas based on co-registered multi-temporal remote-sensing data analysis (Yang et al. 2003; Chen et al. 2012; Jin et al. 2013). Spectral-based change-detection methods are commonly used for

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land-cover change detection; for example, Change Vector Analysis has been proposed to update the 2001 national land-cover database (Xian, Homer, and Fry 2009). Spectral-based change-detection methods can produce an accurate land-cover map, but have strict requirements for remote-sensing data, specifically that two sets of data acquired in different years should come from the same phenological period. Furthermore, nearly all current methods need historical remote-sensing data corresponding to the historical land-cover data for change detection. If only historical land-cover data are available and the corresponding remote-sensing data are missing, or if the land-cover data are not produced using remote-sensing data, change-detection-based land-cover updating methods will lose efficacy. Therefore, developing robust, efficient and accurate automated or semi-automated methods for cost-effective update of land-cover maps in this situation is a challenging work.

The primary goal of this research is to develop and evaluate an automatic land-cover updating approach using remote-sensing data in situations where no historical remote-sensing data are available. First, an iterated training samples selection (ITSS) procedure is used to select training samples automatically based on historical land-cover data. Then the samples are used to classify newly acquired remote-sensing data, and the map is refined based on comparison of the classification result with that of the last iteration until the difference between two successive classification maps achieves a satisfactory consistency. In addition, a Markov Random Field (MRF) model is integrated into the classification procedure to reduce salt-and-pepper noise which is usually apparent in pixel-based classification of remote-sensing data.

2. Study area and data

2.1. Study area

A rectangular subset region of Beijing is selected to validate the presented approach. The study area is located between latitude 39º58′N and 40º9′N and longitude 116º11′E and 116º30′E, with an area of about 500 km^2. Beijing is located in the northern part of the North China Plain and belongs to the temperate climatic zone. The average annual temperature and precipitation is about 12ºC and 664 mm, respectively. The numerous land-cover types in this area, including forest, cropland, built-up areas and water, have made land-cover updating in this region a representative of the difficulties encountered. Furthermore, Beijing has undergone rapid urbanization and economic growth in recent years, especially after the 29th Olympic Games. Therefore, a land-cover map update experiment in this region is a suitable choice.

2.2. Data and processing

A Landsat 8 Operational Land Imager (OLI) data set (path/row: 123/32) of the study area on 12 May 2013 was downloaded from the United State Geological Survey website (http://glovis.usgs.gov/). The OLI data was not affected by cloud, and the quality of the multispectral data was good. OLI data processing mainly included radiance calibration and subset selection. Radiance calibration was performed to convert the digital numbers (DN) value to surface spectral reflectance. Atmospheric correction was done using FLAASH tools provided by ENVI version 5.0 (Exelis, Visual Information Solutions, Boulder, CO, USA). Subset selection was done to extract the data covering the study area for land-cover map updating.

The finer-resolution global land-cover data set produced by Gong et al. (2013) was selected as the historical land-cover, which was based on classification of Landsat TM/

ETM+ data using manually selected training samples and a support vector machine classifier, and the overall classification accuracy was 71.5% based on the validation samples. The Landsat data used for classification in this land-cover map was acquired on 22 September 2009. According to the class type distribution in the subset region, five land-cover types were selected as the final classification types, including water, crops, forest, impervious surfaces and bare land.

3. Method

3.1. *Classification method*

The Maximum-likelihood classifier (MLC) is selected for land-cover map updating in this study because MLC offers high calculation speed with large training samples, unlike some non-parametric classification methods. 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 (Jia et al. 2011). The unknown pixel is considered to belong to the class with the maximum probability of membership.

3.2. *Markov random field model*

The MRF model is usually used to reduce salt-and-pepper noise in pixel-based remote-sensing data classification (Bruzzone and Prieto 2000; Chen et al. 2012). In the MRF model, the probability of a pixel belonging to a given class (C_l) is determined both by the spectral information and by its neighbouring pixels.

$$P(C_l(i,j)) = \frac{1}{Z}\exp[-U(C_l(i,j))] \tag{1}$$

$$U(C_l(i,j)) = U_{\text{context}}(C_l(i,j)) + U_{\text{spectrum}}(C_l(i,j)) \tag{2}$$

where Z is a normalizing factor and U, U_{context} and U_{spectrum} are the total energy, energy of the context and energy of the spectrum. U_{spectrum} is the log function of the posterior probability

$$U_{\text{spectrum}}(C_l(i,j)) = -\ln(P_{\text{spectrum}}(C_l(i,j))) \tag{3}$$

where P_{spectrum} is the posterior probability derived from the MLC classifier. The energy of the context is calculated based on the labels of the neighbouring pixels (Bruzzone and Prieto 2000).

$$\begin{aligned} U_{\text{context}}(C_l(i,j)) &= U_{\text{context}}(C_l(i,j)/\{C_l(g,h),(g,h)\in N(i,j)\}) \\ &= \sum_{(g,h)\in N(i,j)} \beta\delta_k(C_l(i,j),C_l(g,h)) \end{aligned} \tag{4}$$

where β is a constant set to 1.6 in this study, $N(i,j)$ is a set of neighbouring pixels set to a second-order neighbourhood with $N(i,j) = \{(i \pm 1, j), (i, j \pm 1), (i + 1, j \pm 1), (i\text{-}1, j \pm 1)\}$, and δ_k is expressed as:

$$\delta_k(C_l(i,j), C_l(g,h)) = \begin{cases} -1, & if\ C_l(i,j) = C_l(g,h) \\ 0, & if\ C_l(i,j) \neq C_l(g,h) \end{cases} \tag{5}$$

Land-cover mapping based on the MRF model classify an image by minimizing the total energy function in Equation (1) using an optimization algorithm. In this study, the commonly used iterated conditional modes (ICM) approach is used to optimize the energy function because ICM has acceptable efficiency and accuracy in the classification of remotely sensed images (Bruzzone and Prieto 2000; Liu et al. 2008). For all changed pixels, $C_l(i, j)$ is updated to the class that minimizes the total energy function in Equation (1), and this process is repeated until convergence is reached. Finally, isolated pixels are more likely to be replaced by their neighbouring class type, thereby improving the spatial consistency of the classification map.

3.3. Iterative training sample selection

Automatic training sample selection is performed under the hypothesis that land-cover changes occur only in small areas, and then the training samples are selected in the unchanged areas based on historical land-cover data. An iterative procedure has been developed to refine the unchanged area to select the training samples, which includes the following steps: (1) all pixels in the historical land-cover map are initially selected as the training sample; (2) the training samples are used to train the MLC classifier for newly acquired remote-sensing data classification and to calculate the posterior probability which is used for the MRF model; (3) the classification result is refined using the MRF model; (4) the refined classification result is compared with that from the last iteration to detect the changed and unchanged pixels, and the changed pixels are removed from the training samples to obtain the refined pixels; (5) the consistency rate, which is defined as the ratio of the number of unchanged pixels to the total number of pixels, is calculated. If the consistency rate reaches 99% compared to the map produced at the previous iteration, the iteration stops, and the classification result of the last iteration is confirmed as the final updated land-cover map. Otherwise, the refined training samples are used to classify the remote-sensing data; (6) steps (2)–(5) are repeated until the consistency rate reaches 99% compared to the map produced at the previous iteration.

This iterative procedure is expected to refine the training samples to improve classification accuracy by selecting the unchanged areas at every iteration step. A higher consistency rate indicates that changes in the training samples have less influence on remote-sensing data classification and that the final training samples have been refined to classify the remote-sensing data. Consequently, the final updated land-cover map is obtained by classifying the remote-sensing data using the final refined training samples.

3.4. Classification accuracy assessment

To validate the performance of land-cover map updating by the ITSS and MRF approaches using Landsat OLI data, the classification results were assessed by visual observation and quantitative classification accuracy indicators. Randomly selected sample pixels were used to assess land-cover classification accuracy quantitatively. Each validation sample was identified by visual interpretation with the help of GoogleEarth and the researchers' knowledge and experience. The final numbers of sample pixels for classification accuracy estimation were 47 pixels for water, 216 pixels for crops, 255 pixels for forest, 586 pixels for impervious surfaces and 85 pixels for bare land. The overall classification accuracy, producer's accuracy and user's accuracy were then estimated for quantitative classification performance analysis (Congalton and Green 1999; Tso and Mather 2001; Foody 2009, 2002).

4. Results

4.1. Land-cover updating using ITSS and the MRF model

Figure 1 shows the relationship between consistency rate and number of iterations. ITSS with or without the MRF model algorithm rapidly reaches the 99% consistency rate by the fifth or sixth iteration. The results indicate that the ITSS process can effectively refine the training samples and achieve a stable classification result. Furthermore, ITSS with the MRF model reaches the 99% consistency rate more quickly than without the MRF model, which suggests that the MRF model has a significant effect on the land-cover updating approach.

The land-cover updating results using ITSS with and without the MRF model are shown in Figure 2. From the visual perspective, each class type could be identified effectively using ITSS with or without the MRF model based on expert knowledge,

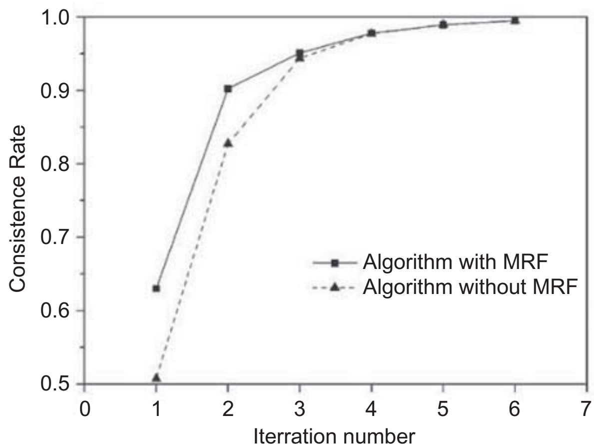

Figure 1. Relationship between consistency rate and number of iterations.

Figure 2. Land-cover updating using the ITSS with (left) and without (right) the MRF model.

indicating satisfactory land-cover updating results using the proposed approach. Forest was distributed mainly in the western mountain regions of Beijing and the Beijing Olympic Forest Park region. Crops and bare land were distributed mainly in the northern plain regions of the study area, while impervious surfaces were distributed mainly in urban regions. The main difference in the land-cover updating results using ITSS with and without the MRF model was that ITSS with the MRF model could effectively reduce salt-and-pepper noise in the classification map and achieve a smoother result, although some thin linear objects could also be mistakenly removed. In general, the distribution of land-cover types in the updated map was consistent with the actual situation, and ITSS with the MRF model achieved smoother land-cover classification results.

4.2. *Classification accuracy of land-cover updating*

The confusion matrixes of land-cover updating using ITSS with and without the MRF model are shown in Table 1. Satisfactory land-cover updating results were achieved using ITSS both with and without the MRF model. The overall performance of ITSS with the MRF model approach (overall accuracy 83.1%) was better than that without the MRF model (overall accuracy 77.3%). In other words, the MRF model improved the overall classification accuracy by approximately 6%. These results suggested that the MRF model could significantly improve classification accuracy when using the ITSS approach.

Bare land had the lowest user and producer accuracy and showed the maximum confusion with impervious surfaces and crops (Table 1). Other class types all showed better separation from each other, with higher user and producer accuracy. The confusion of bare land and impervious surfaces was caused mainly by the similar spectral features of these two class types, or perhaps by mislabelling in the historical data set. In addition, bare land did not always remain bare throughout the year, because bare land could later be planted with crops. The different phenological periods of the acquired OLI data and the remote-sensing data used for historical land-cover classification brought about errors in training sample selection and resulted in misclassification of bare land and crops. Overall,

Table 1. Confusion matrixes for land-cover update using the ITSS with and without MRF model.

	Ground truth (pixels)							
Mapped class	Water	Crop	Forest	Impervious	Bare land	Total	User accuracy (%)	Producer accuracy (%)
ITSS with MRF model								
Water	43	0	1	4	0	48	89.6	91.5
Crop	0	199	28	48	25	300	66.3	92.1
Forest	2	11	213	0	0	226	94.3	83.5
Impervious	2	5	13	486	13	519	93.6	82.9
Bare land	0	1	0	48	47	96	48.9	55.3
ITSS without MRF model								
Water	39	1	4	4	0	48	81.3	83.0
Crop	0	199	47	66	22	334	59.6	92.1
Forest	4	6	195	4	0	209	93.3	76.5
Impervious	4	8	9	429	6	456	94.1	73.2
Bare land	0	2	0	83	57	142	40.1	67.1
Total pixels	47	216	255	586	85	1189		

the integration of ITSS with the MRF model showed satisfactory performance in land-cover updating when no previous remote-sensing data corresponding to the historical land-cover map were available.

5. Discussion

The proposed approach is completely automatic without any human interaction, which overcomes the problems of time cost and labour intensiveness in traditional supervised classification depending on manual training sample selection. The automatic approach also avoids training sample selection error arising from different interpreters. The ITSS process can select reliable training samples and achieve satisfactory land-cover update results, while the iterative process converges in no more than six iterations, keeping computational cost low.

Traditional land-cover update methods usually detect changed areas first through comparison between newly acquired and historical remote-sensing data and then re-classify the changed areas to complete the update process. However, sometimes the historical remote-sensing data corresponding to the historical land-cover data are missing, or the historical land-cover data were not produced by classifying remote-sensing data, for example, from ground survey mapping. The proposed approach has been developed precisely to overcome the problem of missing historical remote-sensing data corresponding to historical land-cover data. This approach can extend the land-cover data source selection range and use older land-cover data which were not produced using remote-sensing data.

The proposed approach has no strict requirements for newly acquired remote-sensing data. The only condition is that the newly acquired remote sensing and historical land-cover data must have the same spatial resolution. Compared to some change-detection methods which need two sets of remote-sensing data which were acquired at the same phenological period in different years or from the same sensor, the proposed approach can greatly extend the remote-sensing data-source selection range (Chen et al. 2003; Xian, Homer, and Fry 2009). The approach thus overcomes the difficulty in acquiring remote-sensing data from the exactly same phenological period, free of cloud influence. Furthermore, spectral attenuation caused by an aging satellite sensor may lead to errors in change-detection processes using spectral change analysis, but the proposed approach avoids the spectral change-detection process. Therefore, much more newly acquired satellite remote-sensing data can be used to update historical land-cover data.

The proposed approach has some potential limitations. First, it assumes small land-cover changes between the newly acquired data period and the historical data period. If large land-cover changes have occurred, the initial selection of training samples in the ITSS process will select large incorrect samples, leading to misclassification in large areas and loss of efficacy in the training sample refinement process. This phenomenon can also occur when historical land-cover data are of poor quality, because error propagation is complex and small errors in training samples may be a source of major MIS-interpretations as found by Foody (2010, 2013). In addition, if one of the land-cover types represented by a very small number of pixels in the historical land-cover data, this class type may have low classification accuracy in the updated land-cover map because the small number of pixels may be classified into other types. Moreover, if a new class has appeared between data acquisitions, the proposed method cannot recognize the new class type. Furthermore, the MRF model may remove linear or small objects, and therefore the proposed approach is not suitable for situations where the land surface exhibits a high degree of fragmentation or where the land-cover update objective is to examine small or linear land-cover objects, such as roads.

In this study, MLC is selected as the classification method because it is popular and easily implemented, and the MLC classifier is also suitable for large training samples. However, at present, many more advanced non-parametric classification methods have been developed for land-cover classification to improve accuracy, such as support vector machine, neural networks and design trees (Lu and Weng 2007). Non-parametric classifiers will be investigated to improve the performance of the proposed approach in future research. In addition, in this research, only one temporal remote-sensing data set is used to update the historical land-cover map. Multi-temporal information, which can be helpful to improve classification accuracy, is not involved in this study, but will be in future work to improve land-cover update accuracy.

6. Conclusions

This paper presents an automatic approach integrating ITSS and a MRF model for land-cover update in situations where no previous remote-sensing data corresponding to the land-cover map are available. A case study in Beijing using OLI data indicates that the proposed method can achieve satisfactory land-cover updating results, and that the MRF model can effectively reduce salt-and-pepper noise and improve classification accuracy. The proposed approach is simple and easy to use for updating land-cover without corresponding historical remote-sensing data. Further research will focus on involving advanced non-parametric classifiers in the remote-sensing data classification step and using multi-temporal remote-sensing data to improve the land-cover update accuracy.

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