ШИНЖЛЭХ УХААНЫ АКАДЕМИ
ИНФОРМАТИКИЙН ХҮРЭЭЛЭН

Эрдэм шинжилгээний бүтээл №12

2012

Улаанбаатар хот

URBAN LAND COVER MAPPING USING OPTICAL AND MICROWAVE IMAGES

D.Amarsaikhan, Ts.Bat-Erdene, M.Ganzorig, D.Enkhjargal

Abstract: The aim of this study is to conduct urban land cover mapping of Ulaanbaatar, the capital city of Mongolia using high resolution satellite images. For the analysis, optical and microwave remote sensing (RS) images are used. To extract the reliable urban land cover information from the available RS data sets, a refined maximum likelihood classification (MLC) algorithm that uses spatial thresholds defined from the contextual knowledge is constructed.

Keywords: Urban mapping, RS, Refined method, Classification

1. Introduction

To prevent from the rapid urban expansion, especially from the unplanned urbanization process, urban planners and decision-makers need to regularly evaluate the current development procedures using updated urban planning maps. However, many city planners in developing countries have a lack of the updated maps and often they posses old data which is not relevant for current decision-making (Amarsaikhan *et al.* 2001, Amarsaikhan *et al.* 2009).

One of the possible solutions could be the use of space images, because present satellite RS has the huge potential of providing accurate spatial information over a large area in a short time sequence. Over the last years, the costs for the primary satellite data sets have considerably decreased. Meanwhile, massive archive of high resolution RS images with acceptable resolution has been available free of charge in different Internet sites. It means that it is possible to extract from RS images, different thematic information in a cost effective way and use it for different urban related studies.

The aim of this research is to perform urban land cover mapping of Ulaanbaatar city using optical and synthetic aperture radar (SAR) images. To extract the reliable urban land cover information from the selected RS data sets, a refined MLC algorithm that uses spatial thresholds defined from the contextual knowledge was used. Before applying the classification decision rule, some image fusion techniques were applied to the selected RS data sets, in order to define the most efficient fusion method that creates the best color image used for training sample selection as well as for defining the contextual knowledge.

2. Test site and data sources

As a test site, Ulaanbaatar, the capital city of Mongolia has been selected. Ulaanbaatar is situated in the central part of Mongolia, in the Tuul River valley, at an average height of 1350m above sea level. Although, the city is extended from the west to the east about 35km, and from the north to the south about 25km, the study area chosen for the present study covers an area of 28kmx20km. It covers the majority of the area belonging to the capital city, although there are some areas extending outside of the selected image frame. For the selected area, it is possible to define such classes as built-up area, ger area (Mongolian traditional dwelling), forest, grass, soil and water. The built-up area includes buildings of different sizes, while ger area includes mainly gers surrounded by fences.

As the data sources, Landsat TM data of September 2011 with a spatial resolution of 30m, and Envisat C-band HH polarization SAR image of January 2011 with a spatial resolution of 25m were used. In addition, topographic map of 1984, scale 1:50 000, and a general urban planning map were available. Figure 1 shows recent outlook of the test area in the Landsat TM image and some examples of its land cover.

Figure 1. 2011 Landsat TM image of the selected part of Ulaanbaatar city. 1-built-up area; 2-ger area; 3-forest; 4-grass; 5-soil; 6- water. The size of the displayed area is about 28kmx20km.

3. Radiometric correction and speckle suppression of the RS images

At the beginning, all the available images were thoroughly analyzed in terms of radiometric quality and geometric distortion. In case of the multispectral image, band 1 (i.e., blue band) of Landsat TM data had noise from the atmosphere and it was difficult to correlate its radiometric values with other bands. Therefore, it was excluded from the analysis. Moreover, as band 6 of TM and bands 61 and 62 of ETM are thermal bands, they were excluded from the further analysis, too.

In case of the SAR images, as they have a speckled appearance, radiometric correction should be based on the speckle reduction techniques. In this study, four different speckle suppression techniques such as local region, lee-sigma, frost and gammamap filters (ERDAS 1999) of 3x3 and 5x5 sizes were compared in terms of delineation of urban features and texture information. After visual inspection of each image, it was found that the 3x3 gammamap filter created the best images in terms of delineation of different features as well as preserving content of texture information. In the output image, the speckle noise was reduced with very low degradation of the textural information.

4. Image fusion

In the present study, the selected test site represents complex urban environment. In the area, the three main classes such as building area, ger area and soil have similar or mixed spectral characteristics. Therefore, in order to enhance the spectral and spatial variations of these statistically overlapping classes as well as to merge the images with different spatial resolutions, different image fusion techniques have been compared. Within the framework of the study, it was decided that the fused image should be used for determining the sites for the training sample selection and also for defining the contextual knowledge about the classes of objects.

The image fusion is a process, which integrates different images from diverse sources to obtain more information, considering a minimum loss or distortion of the original data. (Amarsaikhan *et al.* 2009). In the case of the present study, for the urban areas, the optical images provide the information about the spectral variations of different urban features, while the radar image provides structural information about buildings and street alignment due to the double bounce effect. Over the years, different data fusion techniques have been developed and applied, individually and in combination, providing users and decision-makers with various levels of information. Generally, image fusion can be performed at pixel, feature and decision levels (Pohl and Van Genderen 1998, Amarsaikhan *et al.* 2009). In this study, data fusion has been performed at a pixel level and the following rather common and more complex techniques were compared: (a) Brovey transform, (b) principal component analysis (PCA), (c) wavelet-based fusion, (d) Ehlers fusion.

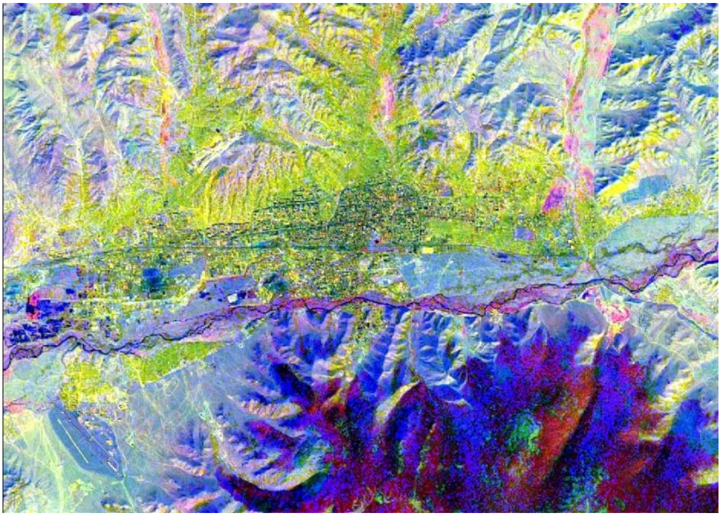

Figure 2. The result obtained by the wavelet-based fusion.

In order to obtain a reliable color image that can illustrate the spectral and spatial variations of the available urban classes, different band combinations have been used. Compared to all other results, the wavelet-based fusion gave the best result. On this image, it was possible to distinguish among all statistically overlapping classes and also observe the spread of the ger districts. Therefore, this image was selected for further analysis. Figure 2 shows the The result obtained by the wavelet-based fusion applied to 2011 images.

5. Classification of the images

For several decades, single-source multispectral RS data sets have been successfully used for land cover mapping and for the generation of thematic information, diverse supervised and unsupervised classification methods have been applied. Unlike single-source images, data sets from multiple sources have proved to offer better potential for discriminating between different land cover types. Many authors have assessed the potential of multisource images for the classification of different land cover classes (Benediktsson *et al.* 1997, Hegarat-Mascle *et al.* 2000, Amarsaikhan and Douglas 2004, Wu *et al.* 2009, Laurin *et al.* 2013). At present, the most commonly used RS data classification techniques are parametric and non-parametric methods, Dempster–Shafer theory of evidence, neural networks, decision tree classifier, and knowledge-based methods (Solberg *et al.* 1996, Franklin *et al.* 2002, Linderman *et al.* 2004, Amarsaikhan *et al.* 2007, Hu and Wang 2013).

In recent years, rapid and timely mapping of urban areas, specifically at regional and global scales has become an important task for many urban planners. This is associated with the rapid urbanization process, because the planners and decision-makers need to evaluation the related environmental and social problems (Cao *et al.* 2009). However, in most cases urban areas are complex and diverse in nature and many features have similar spectral characteristics and it is not easy to separate them by the use of common feature combinations or by applying ordinary techniques (Amarsaikhan *et al.* 2012). For the successful extraction of the urban land cover classes, reliable features and an efficient classification technique should be used. In the present study, for the classification of urban land cover types, a refined statistical MLC algorithm has been constructed.

5.1. The selected features and evaluation of the training signatures

Generally, in the classification process, it is desirable to include only the features in which the signatures of the selected classes are highly separable from each other in a multidimensional feature space. In case of the present study, as the features, the first four PCs defined from data sets of 2011 have been selected because, they contained more than 98% of the total variance.

Initially, from the PC image, several areas of interest (AOI) have been selected for each available class (i.e., building area, ger area, forest, grass land, soil and water) using the contextual knowledge. The contextual knowledge was defined on the basis of the spectral variations of the land surface features as well as the texture information delineated on the fused images. The separability of the selected training signatures was firstly checked in feature space and then evaluated using Jeffries–Matusita distance (ERDAS 1999) and it revealed that high statistical overlaps exist between the classes: building area and ger area. It is obvious, because ger families usually have houses beside their gers. Therefore, these two classes have very similar spectral characteristics. Then, the samples which demonstrated the best possible separability were chosen to form the final signatures. The final signatures included about 126-498 pixels.

5.2. The refined MLC method

The MLC is the most widely used classification technique, because a pixel classified by this method has the maximum probability of correct assignment (Erbek *et al.* 2004). The decision rule assuming Bayes' rule can be written as follows:

$$P(Ci|x) = P(x|Ci)*P(Ci)/P(x) \qquad (1)$$

where P(Ci|x)-posterior probability, P(x|Ci)-conditional probability, P(Ci)-prior probability, P(x)-probability of finding a pixel from any class. The actual classification is performed according to P(Ci|x) > P(Cj|x) for all j#i.

Within the framework of this study, for all classes equal prior probabilities have been assigned. To conduct a classification decision rule, for each class label a conditional probability that is approximated by a multivariate probability density function, should be evaluated. For this purpose, the sample mean vectors, determinants and variance-covariance matrices for each class are estimated from the selected training signatures. Then, every pixel in the digital image is evaluated using the maximum likelihood and the class label is assigned to the pixel that has the maximum probability.

At the beginning, in order to check the performance of the standard method, the selected PC bands were classified using the statistical MLC. As could be seen from the result, on the classified image there were different mixed classes between the classes: building area and ger area. This should be apparent, because the previous signature analysis indicated that the signature distributions of these classes had significant overlaps in the multidimensional feature space. To separate the statistically mixed classes, the class specific features as well as spatial thresholds can be applied. The class specific features can be determined through a feature extraction process, however, the application of this approach would become difficult if there is a fewer number of bands. The spatial thresholds can be determined on the basis of historical thematic spatial data sets or from knowledge about the site.

In order to improve the traditional MLC, the constructed classification algorithm uses spatial thresholds defined from the contextual knowledge. The contextual knowledge is based on the spectral and textural variations of the selected classes in different parts of the selected fused images and the thresholds are applied to separate the statistically overlapping classes. It is obvious that a spectral classifier will be ineffective if applied to the statistically overlapping urban classes, because they have very similar spectral characteristics. For such spectrally mixed classes, classification accuracies should be improved if spatial properties of the classes of objects could be incorporated into the classification criteria. To determine the initial spatial thresholds, firstly the appropriate polygon boundaries related to the selected classes were defined from the historical GIS data sets. As these polygon boundaries represented old information, it was necessary to update them. For this purpose, new polygon boundaries were defined from the fused images (i.e. PC and wavelet-based) on the basis of the contextual knowledge (i.e., defining class boundaries in relation to its neighbourhood) and added to the initial spatial thresholds.

When thresholds apply only the pixels falling within the threshold boundary are used for the classification. In that case, the likelihood of the pixels to be correctly classified will significantly increase, because the pixels belonging to the class that overlaps with the class to be classified using the threshold boundary are temporarily excluded from the decision making process. In such a way, the image can be classified several times using different threshold boundaries and the results can be merged (Amarsaikhan *et al.* 2007, Amarsaikhan *et al.* 2012).

The results of the classifications using the defined spatial thresholds are shown in figure 3.

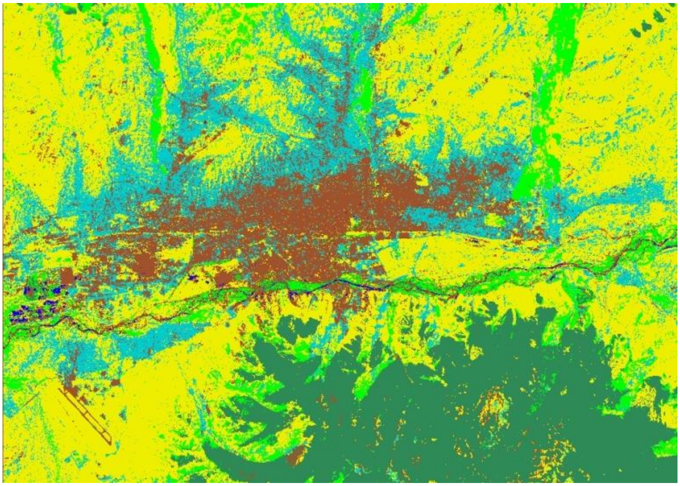

Figure 3. Classified image using the refined method.

For the accuracy assessment of the classification result, the overall performance has been used. This approach creates a confusion matrix in which the selected reference pixels are compared with the classes in the classified image and as a result, an accuracy report is generated indicating the percentages of the correspondence (ERDAS 1999). In this study, as ground truth information, different AOIs containing the purest pixels have been selected. The confusion matrix produced for the refined MLC classification method indicated the overall accuracy of 91.23%.

7. Conclusions

The overall purpose of the research was to classify urban land cover classes of the Mongolian capital city. For this aim, high resolution optical and microwave RS images as well as a topographic map were used. To extract the reliable urban land cover information from the selected multisource RS data sets, a refined maximum likelihood classifier that uses spatial thresholds defined from the contextual knowledge was constructed. Before applying the classification decision rule, some ordinary and advanced image fusion techniques were explored in order to define the most efficient fusion method that could create the best color image used for training sample selection as well as for defining the contextual knowledge. Of these methods, the image obtained by the wavelet-based fusion demonstrated better result than any other methods. It was seen from the classification result that the spatial thresholds defined from the contextual knowledge could considerably improve the performance of the classification and for the accurate classification, proper spatial thresholds should be applied.

8. References

1. Amarsaikhan, D. Ganzorig, M. and Saandar, M., 2001, Urban Change Study Using RS and GIS, *Asian Journal of Geoinformatics*, No2, Vol2. pp.73-79.
2. Amarsaikhan, D., Ganzorig, M., Ache, P. and Blotevogel, H., 2007, The integrated use of optical and InSAR data for urban land cover mapping, *International Journal of Remote Sensing, Vol.28, No.6*, pp.1161-1171.
3. Amarsaikhan, D., Blotevogel, H.H., Ganzorig, M. and Moon, T.H, 2009, Applications of remote sensing and geographic information systems for urban land-cover changes studies in Mongolia, *Geocarto-International, A Multi-Disciplinary Journal of Remote Sensing and GIS, Vol. 24, No. 4,* August 2009, pp.257–271.
4. Amarsaikhan, D., Ganzorig, M., Saandar, M., Blotevogel, H.H., Egshiglen, E., Gantuya, R., Nergui, B. and Enkhjargal, D., 2012, Comparison of multisource image fusion methods and land cover classification, *International Journal of Remote Sensing,* Vol.33(8), pp.2532-2550.
5. Benediktsson, J. A., Sveinsson, J. R., Atkinson, P. M., and Tatnali, A., 1997, Feature extraction for multisource data classification with artificial neural networks. *International Journal of Remote Sensing,* 18, pp.727–740.
6. Cao, X., Chen, J., Imura, H. and Higashi, O., 2009, A SVM-based method to extract urban areas from DMSP-OLS and SPOT VGT data, *Remote Sensing of Environment,* 10, pp.2205-2209.

7. Chinbat, B., Bayantur, M. and Amarsaikhan, D., 2006, Investigation of the internal structure changes of Ulaanbaatar city using RS and GIS, *Proceedings of the ISPRS Mid-term Symposium, ITC, Enschede*, The Netherlands, pp.wg04_1-6.
8. ENVI, 1999, User's Guide, Research Systems, USA.
9. Erbek, F.S., Zkan, C.O. and Taberner, M. (2004). Comparison of maximum likelihood classification method with supervised artificial neural network algorithms for land use activities, *International Journal of Remote Sensing*, 25, pp.1733–1748.
10. ERDAS, 1999, Field guide, Fifth Edition, ERDAS, Inc. Atlanta, Georgia.
11. Hegarat-Mascle, S.L., Quesney, A., Vidal-Madjar, D., Taconet, O., Normand, M. and Loumagne, M. (2000). Land cover discrimination from mutitemporal ERS images and multispectral Landsat images: a study case in an agricultural area in France, *International Journal of Remote Sensing*, 21, pp.435–456.
12. Hu, S. and Wang, L., 2013, Automated urban land-use classification with remote sensing, *International Journal of Remote Sensing,* Vol.34, pp.790–803.
13. Laurin, G.V., Liesenberg, V., Chen, Q., Guerriero, L., Frate, F.D., Bartolini, A., Coomes, D., Wilebore, B., Lindsell, J. and Valentini, R., 2013, Optical and SAR sensor synergies for forest and land cover mapping in a tropical site in West Africa, *International Journal of Applied Earth Observation and Geoinformation,* 21, pp.7-16.
14. Linderman, M., Liu, J. Qi, J., An, L., Ouyang, Z., Yang, J. and Tan, Y., 2004, Using artificial neural networks to map the spatial distribution of understorey bamboo from remote sensing data. *International Journal of Remote Sensing*, 25, pp.1685–1700.
15. Pohl, C., and Van Genderen, J.L., 1998, Multisensor image fusion in remote sensing: concepts, methods and applications. *International Journal of Remote Sensing*, 19, pp.823-854.
16. Solberg, A.H.S., Taxt, T. and Jain, A.K., 1996, A Markov random field model for classification of multisource satellite imagery, *IEEE Transactions on Geoscience and Remote Sensing*, 34, pp.100–112.