POLISH ASSOCIATION FOR SPATIAL INFORMATION
ANNALS OF GEOMATICS 2009 ❍ VOLUME VII ❍ NUMBER 2(32)

LAND COVER CLASSIFICATION USING MULTI-TEMPORAL MODIS SATELITE DATA

KLASYFIKACJA FORM POKRYCIA TERENU NA PODSTAWIE WIELOCZASOWYCH ZDJĘĆ SATELITARNCYH MODIS

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Keywords: MODIS, land cover, multi-temporal classification
Słowa kluczowe: MODIS, pokrycie terenu, klasyfikacja wieloczasowa

Introduction

A good understanding of the Earth system is one of the most important goals in natural science today. The acquisition and analysis of data obtained from monitoring the terrestrial ecosystem enables us to comprehend natural patterns and cycles. Knowledge of these processes and its influence on global-scale patterns allows us to build models and make predictions.

For many years, all land cover and land use data for analysis were obtained from maps and atlases and was the cause for the model's low accuracy output. Since the 1970's, remote sensing techniques enabled monitoring of the entire Earth system. This made it possible to observe and map even the most dynamic processes on either the global or local scale. The most essential opportunity for global land use and land cover monitoring began in the 1970's, with the introduction of the Landsat program and the series of NOAA Polar-Orbiting Operational Environmental Satellites with AVHRR (Advanced Very High-Resolution Radiometer) on board (Jensen, 2000).

The very first global land cover map was created using AVHRR data by DeFries and Townshend (1994) in the early 1990's. During the following years, the algorithms and classification strategies were improved. The real change started in December 1999 when NASA launched the EOS Terra Satellite, followed in 2002 by Aqua, both equipped with MODIS (Moderate Resolution Imaging Spectroradiometer). Thanks to the technical specification, MODIS provided data on land, atmosphere, and ocean, which are used in many models of the Earth's global dynamics (Guenther et al., 2002). Constant improvements, validation, and development of products cause great popularity. However, despite MODIS' rather low spatial resolution (250 m, 500 m and 1000 m), it is also applied for many local scale research projects.

In this paper I would like to present my results of land cover classification using MODIS data performed for a study area of 22,100 square kilometres situated in western Poland. The main objective of this research is to analyse the multi-temporal approach which is believed to increase the overall accuracy of the classification. Unlike other algorithms, the final classification result was elaborated on the basis of four land cover classifications of one day reflectance MODIS data acquired for the year 2007. The main concept is subpixel time sequence analysis of change in land cover classes, during the vegetative season.

Data and study area

The study area of 22,100 square kilometres (130 km x 170 km) is situated in western Poland. Its geological history is quite complex and is represented in a variety of landforms. The ground altitude ranges from approximately 50 to 400 m above sea level. The whole area is in the moderate maritime climate zone with a long growing season (lasting approximately 210–220 days). The geography disturbs the air circulation and annual precipitation is in the range of 450–600 mm (Starkel, 1999). Agricultural areas dominate land use and occupy over 55% of the area. 25% of the ground is devoted to forests of which over 64% is coniferous forest. Almost 10% of the country is occupied by pastures and areas of natural vegetation (European Environment Agency, 2004). Beside some small cities and villages, two big agglomerations of Poznań and Wrocław are situated in the study area.

Because of the characteristics of MODIS, only data acquired from bands 1 to 7 were used in this study. They were designed mainly for land analysis and have spatial resolution of 250 m for channels 1 and 2 and 500 m for channels 3 to 7 (Guenther et al., 2002). In order to represent land cover classification changes, the study relies on one day reflectance data. Although multi-temporal compositions have an advantage of the absence of cloud cover, which is a serious problem in medium latitudes, they were rejected because of the heterogeneity of the vegetation present in one scene.

Two MODIS products were used in this analysis: *MODIS/Terra/Aqua Surface Reflectance Daily L2G Global 250m SIN Grid V005* and *MODIS/Terra/Aqua Surface Reflectance Daily L2G Global 1km 500m SIN Grid V005.* For the period from March 2007 to October 2007 the best (i.e. without significant cloud cover and registration errors) data sets for h18v03 and h19v03 MODIS sinusoidal grid were chosen and downloaded from the WIST (Warehouse Inventory Search Tool) website. The selection of data was based on the data quality and date of registration. Finally four sets of images were chosen (Table 1).

Table 1. MODIS data sets used in the research (registration date, satellite and comment)

Date of registration	Satellite	Comment
31 March 2007	Terra	Minor errors of data registration – fill value
16 July 2007	Terra	Minor errors of data registration – fill value
2 August 2007	Terra	Minor errors of data registration – fill value; lightly clouded with cirrus clouds
13 October 2007	Aqua	Minor errors of data registration – fill value

Additionally, two Landsat ETM+ scenes (p191r024 registered at 13 June 2000 and p190r024 from 24 May 2001) with a resolution of 30 meters were collected from USGS as reference material for training sites and reclassification processes. The Corine Land Cover 2000 database, used as reference data, was downloaded from European Environment Agency (EEA) website.

Methods

Before the data sets could be used in classification some preprocessing was needed. Because the study relies on MODIS products from the second level of processing, geocoding and atmospheric correction were already done. The main objective of preprocessing was to obtain one file instead of four files for each data set. With this end in view, 500 m resolution data was resampled to 250 m and united with the corresponding files with a resolution of 250 m. Next the appropriate data sets for h18v03 and h19v03 MODIS sinusoidal grid were mosaiced to obtain one image from the seven bands. Finally the data was reprojected from Integerized Sinusoidal (ISIN) projection to the Polish National Coordinate Reference System '1992'. The histogram was checked for every study polygon clipped from these data sets, which enables us to find the number of pixels with an incorrect value (so called 'fill value') which are the result of minor registration errors. Having in mind the future problems with the classification of these pixels, they were replaced with values obtained by median filters (5x5) performed for copied data sets. Preprocessing of Landsat ETM+ data include automatic mosaic of both scenes, reprojection to the '1992' Coordinate Reference System and clipping to the study area.

The low resolution of MODIS data and specific Polish land use conditions caused only a small number the image's pixels to have a homogeneous spectral response. The value of the majority is an average calculated for all spectral responses of the components included into the area represented by that pixel. This fact caused problems with the recognition of small and spread land cover classes. In order to establish the training sites for supervised classification it is essential to know which land cover classes are possible to recognize using MODIS data. The selection of classes for this study was elaborated as a visual comparison of (6, 2, 1) and (7, 2, 1) MODIS RGB composition with ETM+ (4, 5, 3) RGB images. Because CORINE Land Cover 2000 is a reference dataset, new land cover classes were established on the basis of a third level of the CLC legend (Table 2).

This approach allows us to adopt the CLC legend and find all the land cover classes which are possible to detect in MODIS data sets. Althoughr the spectral response of artificial areas like mineral extraction sites, dump sites, and construction sites differs from agricultural areas, the number of pixels occupied by these classes is too small to assign them as independent land forms. Moreover, visual analysis of all four MODIS data sets prove agricultural areas change during the growing season. Because of this, four sub-classes of agricultural area land cover were established: areas of bare soil, areas of green crops, areas of rope crops, and agricultural areas briefly after harvest. It increases the number of land cover classes to 10, but the actual number recognised on each image differs accordingly to the season.

Bearing in mind my subpixel time sequence analysis, rules for classification can now be defined. I decided to perform supervised classification instead of unsupervised classification mainly due to the prior knowledge of the number and type of land classes. This is essential during the analysis of the pixel change sequence because hetrogenous classes lead to unexpected results.

Table 2. Relation between classified MODIS land use classes and CLC Level 3 legend. MODIS' agricultural areas are presented with four subclasses established according to the growing season changes. Some CLC classes are not classified due to MODIS resolution

MODIS		CLC class with code and description
Code	Class name	
1	Urban area	1.1.1. Continuous urban fabric 1.1.2. Discontinuous urban fabric 1.2.1. Industrial or commercial units 1.2.2. Road and rail networks and associated land
2	Agricultural areas: 2.1. areas of bear soil 2.2. areas of green crops 2.3. areas of rope crops 2.4. areas briefly after harvest	1.3.1. Mineral extraction sites 1.3.2. Dump sites 1.3.3. Construction sites 2.1.1. Non-irrigated arable land 2.4.2. Complex cultivation patterns 3.3.3. Sparsely vegetated areas
6	Grasslands	1.2.4. Airports 2.2.2. Fruit trees and berry plantations 2.3.1. Pastures 2.4.3. Land principally occupied by agriculture, with significant areas of natural vegetation 3.2.1. Natural grassland 4.1.1. Inland marshes
7	Broad-leaved forest	3.1.1. Broad-leaved forest 1.4.1. Green urban areas 1.4.2. Sport and leisure facilities
8	Coniferous forest	3.1.2. Coniferous forest
9	Mixed forest	3.1.3. Mixed forest 3.2.4. Transitional woodland/shrub
10	Water bodies	5.1.1. Water courses 5.1.2. Water bodies

Knowing the actual number of land cover classes which are recognisable, the training sites were set for each image. To ensure the accuracy, the Landsat ETM+ data and agricultural knowledge were used during this procedure. Because the data sets registered on the 2nd of August 2007 had partial cirrus cloud cover, those areas were selected using a mask and classified separately from the rest of the scene. The separability of classes was tested for all data sets with Battacharrya Distance (Richards, 1986). Results show general low separability of mixed forest with broad-leaved and coniferous forests. Also, outcomes for grasslands and agricultural areas of green crops were a bit disappointing, as expected according to the similar spectral response of both landforms. Maximum likelihood supervised classification was conducted for all data sets with a bias of 0.01, set for the urban area class. Visual analysis of results exposed a tendency to mis-classify coniferous forests as mixed forests. Another problem was that the broad-leaved forests occupied too large an area. More precise analysis proved that this was caused by forest borders and grasslands with a significant number of shrubs. The last main problem classifying results are urban areas mis-classified on the boundaries of forests and fields, caused by MODIS pixel size and the average of the spectral response of land cover.

Overall classification accuracy was checked with the Corine Land Cover 2000 database using 4200 randomly distributed points (the number of points for each class is proportional to the area occupied by this class). To ensure the association between data sets, CLC was firstly reclassified using the previously presented legend (Table 2) and resampled using the nearest neighbour algorithm to a resolution of 250 m. Additionally, agricultural subclasses for classifying results were united into one agricultural class. The accuracy of classifications are presented in Table 3.

Table 3. Classifications accuracy for training sites and overall accuracy estimated using 4200 randomly distributed check points

Data set	Number of recognized classes	Classification accuracy			
		Training sites		4200 check points	
		Overall	Kappa statistic	Overall accuracy	Kappa statistic
31 March	8	91.50%	0.902	73.24%	0.577
16 July	9	93.91%	0.931	75.33%	0.588
2 August	10	93.10% 93.55% *	0.922 0.927 *	76.91%	0.615
13 October	9	88.34%	0.866	73.67%	0.579

* Masked area of cirrus clouds in data registered on the 2nd of August

The analysis of time sequence pixel values is a widely known method for detecting changes (Lunetta et al., 2006), monitoring vegetation phenology (Zhang et al., 2003), or studying soil erosion (Marquinez et al., 2008). Multi-temporal analysis is also very useful in land cover classification and has the potential to increase overall classification accuracy.

Using logical processes, all four classifications results with different numbers of classes were overlaid in order to obtain existing pixel sequences. Out of 6480 possible combinations only 3696 occurred. Statistical analysis proved that 394 sequences appeared for 100 pixels or more occupying over 87% of the polygon and as many as 2253 combinations concerned 10 or less pixels. Precise analysis of pixel sequences allowed us to develop 4 general reclassification rules:

- The same four, three or two class values in the sequence determine the outcome of the dominating class.
- Intermingle of agricultural subclasses determine the outcome of agricultural class.
- The draw, when two class values appeared in the sequence twice, determines the outcome of the class with higher significance (set according to the area occupied by the class).

In addition some exceptions from these general rules were set:

- Intermingle of agricultural areas of green crops and grasslands determine the outcome of the grassland class.
- For intermingled forest classes the final class depends on the existing sequence of classes (for example, the sequence of mixed and coniferous forest determine the outcome of the coniferous forest class, while the sequence of broad-leaved and mixed forests led to the mixed forest class).

- Intermingled broad-leaved forest and agricultural areas of green crops and grasslands determine the outcome of the grassland class.

On the basis of these rules, the reclassification program was written in an EASI script for PCI Geomatica software.

Results and discussion

The final outcome of the reclassification is presented in Figure, with reference data from the CLC2000 database. Visual comparison shows that MODIS based outcomes are more generalised and class boundaries are less precise than CLC. The main difference is the mis-classification of broad-leaved forest classes which occupies a larger area than they should. Also, water bodies and urban areas seem to be larger. Another difference is the mis-classification as mixed forest instead of coniferous forest. Despite these problems the general accuracy appears to be good.

The accuracy assessment was checked the same way as it was for single classifications, using 4200 randomly distributed points. In Tables 4 and 5 the error matrix and accuracy report are presented. Overall accuracy of the final outcome is estimated at 81.21% and 0.697 Kappa statistic, an improvement over the single classification's accuracy (Table 3). The best results include coniferous forests, agricultural areas and water bodies. Statistics for urban areas are also good with the producer's and user's accuracy above 71%. Grasslands obtained rather good results, but the mis-classification of agricultural areas was significant and determined a 0.598 Kappa statistic. Definitively, the lowest accuracy occurred for mixed and broad-leaved forests. The main reason of this situation is an unclear differentiation between forest types and heterogeneity in species contribution. Problems with the proper classification of broad-leaved forests can also be caused by spectral similarity with scrubs, which are common on the boundaries of forests and fields.

Conclusion

This analysis proved that a multi-temporal approach allowed us to obtain better results than single term classification. The general improvement of accuracy is at the level of 4-8% depending on which single classification is used. Analysis of class sequence changes and a good understanding of phenology changes allows us to better define final classes. Results are very promising despite some problems with forest classes; the general detection of landforms is satisfactory. As a result of the spatial resolution of MODIS data, some inaccuracy of borders and generalisation are expected and cannot be excluded. The presented approach showed also that MODIS data can obtain good results for local studies of areas with complex agriculture.

Acknowledgments

This study was carried out using PCI Geomatics Geomatica 10.1 software. Access to a one-year license would not be possible without support from Iain MacInnes of PCI who provided the software.

I would also like to thank MSc Edyta Woźniak (Warsaw University) for our discussions.

References

European Environment Agency, 2004: Corine Land Cover 2000 database. http://www.eea.europa.eu. 10/02/2009.

DeFries R.S., Townshend J.G.R., 1994: NDVI derived land cover classifications at a global scale. *International Journal of Remote Sensing*, 5: 3567-3586.

Guenther B., Xiong X., Salomonoson V.V., Barnes W.L., Young J., 2002: On-orbit performance of the Earth Observing System Moderate Resolution Imaging Spectroradiometer; first year of data. *Remote Sensing of Environment*, 83: 16-30.

Jensen J.R., 2000: Remote Sensing of the Environment An Earth Resource Perspective. Prentice Hall, New Jersey, United States of America.

Lunetta R.S., Knight J.F., Ediriwickrema J., Lyon J.G., Worthy L.D., 2006: Land-cover change detection using multi-temporal MODIS NDVI data. *Remote Sensing of Environment*, 105: 142-154.

Marquinez J., Wozniak E., Fernandez S., Martinem R., 2008: Analysis of the evolution of soil erosion classes using multitemporal Landsat imagery. *International Journal of Wildland Fire*, 17: 549-558.

Richards J.A., 1984: Remote Sensing Digital Image Analysis. Springer-Verlag, Berlin, Heidelburg, New York, London, Paris, Tokyo.

Starkel L. (ed.), 1999: Geografia Polski: Środowisko przyrodnicze, Wydawnictwo Naukowe PWN, Warszawa.

Zhang X., Friedl M.A., Schaaf C.B., Strahler A.H., Hodges J.C.F., Gao F., Reed B.C., Huet A., 2003: Monitoring vegetation phenology using MODIS. *Remote Sensing of Environment*, 84: 471-475.

Streszczenie

Od lat siedemdziesiątych dwudziestego wieku możliwe jest pozyskiwanie aktualnych danych satelitarnych o pokryciu i użytkowaniu terenu. Informacje te pozwalają na lepsze poznanie środowiska naturalnego Ziemi, a ich analiza w skali globalnej, regionalnej i lokalnej jest celem wielu programów badawczych.

W ramach programu EOS, w grudniu 1999 roku Narodowa Agencja Aeronautyki i Przestrzeni Kosmicznej NASA umieściła na orbicie ziemskiej satelitę Terra, a trzy lata później Aqua. Oba satelity zostały wyposażone w skaner MODIS (Moderate Resolution Imaging Spectroradiometer), który ze względu na swoje parametry techniczne oraz dostępności danych, jest obecnie uważany za jeden z ważniejszych skanerów środowiskowych. Choć został on zaprojektowany przede wszystkim z myślą o analizach wielkoobszarowych, MODIS wykorzystywany jest także w opracowaniach regionalnych. Niniejszy artykuł jest prezentacją wyników klasyfikacji wieloczasowych zdjęć MODIS, wykonanej dla poligonu badawczego o powierzchni 22 100 km^2, położonego w zachodniej Polsce. W analizie wykorzystano cztery zestawy jednodniowych zobrazowań o rozdzielczości 250 i 500 m, zarejestrowanych w różnych okresach wegetacyjnych 2007 roku. Ostateczny wynik klasyfikacji został opracowany na podstawie analizy sekwencji zmian klas pokrycia terenu dla wszystkich czterech terminów. W ocenie dokładności klasyfikacji, jako materiał referencyjny wykorzystano bazę danych Corine Land Cover 2000. Na podstawie analizy 4200 losowo rozmieszczonych punktów, dokładność całkowitą oceniono na poziomie 81%. Przedstawiona metoda postępowania, w porównaniu z klasyfikacjami wykonanymi dla pojedynczych zdjęć, pozwoliła na uzyskanie znacznej poprawy wyników.

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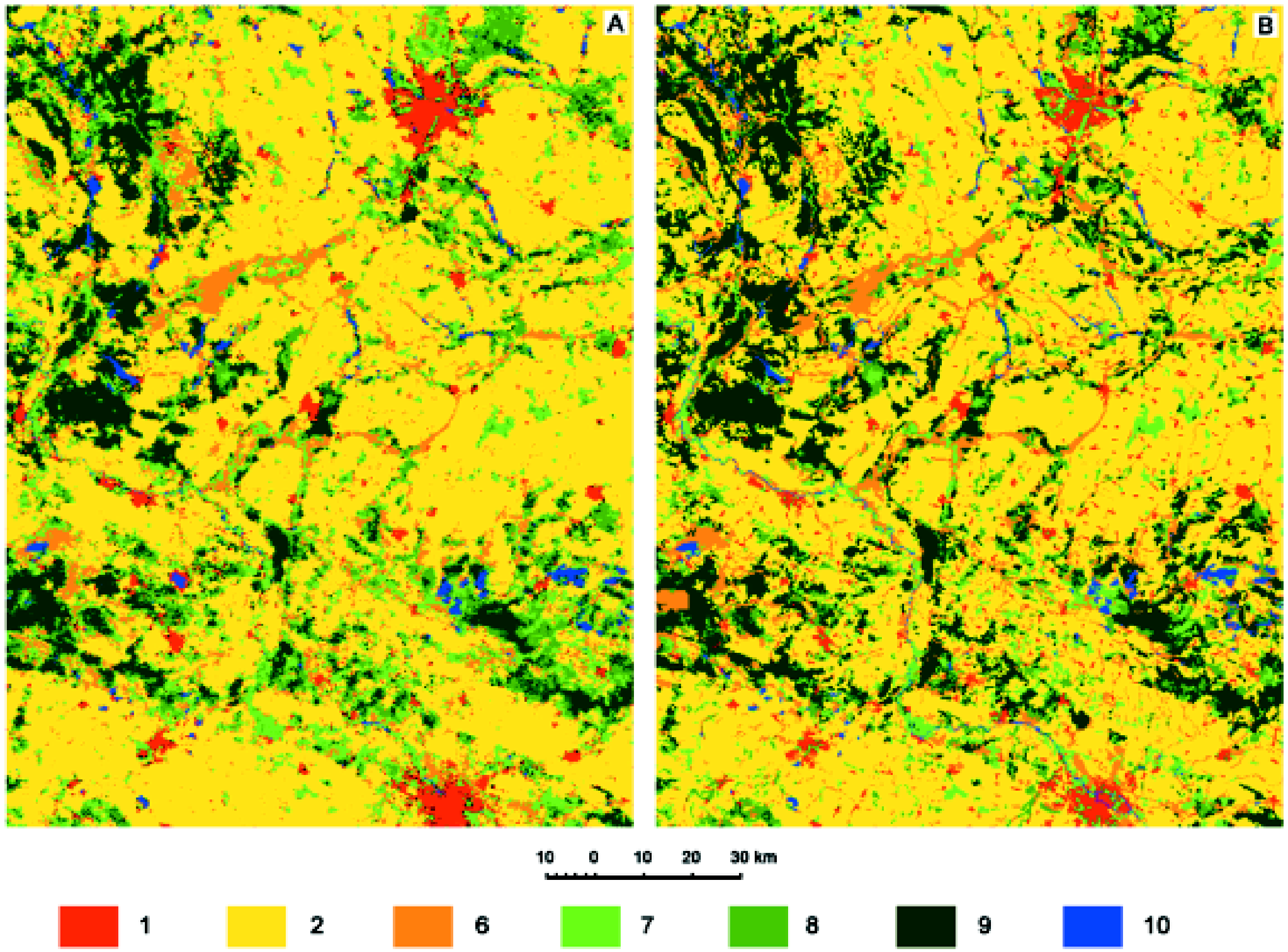

Figure 1. A – Final classification result, B – reference CLC2000 database after class aggregation and resampling to MODIS resolution

Table 4. Error matrix for final classification result

Class code	1	2	6	7	8	9	10	Sum
1	**98**	20	5	4	2	3	2	134
2	26	**2283**	113	6	10	14	1	2453
6	3	95	**222**	12	9	7	0	348
7	5	33	64	**132**	28	78	3	343
8	5	16	7	3	**490**	22	2	545
9	0	2	5	20	153	**148**	4	332
10	0	2	3	1	0	1	**38**	45
Sum	137	2451	419	178	692	273	50	**4200**

Table 5. Accuracy report for final classification result

Classification accuracy report: Overall Accuracy: 81.21% 95% Confidence Interval (80.02% ; 82.41%) Overall Kappa Statistic: 0.697 Overall Kappa Variance : -0.000%					
Class code	Producer's accuracy	95% Confidence interval	User's accuracy	95% Confidence interval	Kappa Statistic
1	71.53%	(63.61% ; 79.45%)	73.13%	(65.26% ; 81.01%)	0.722
2	93.15%	(92.13% ; 94.17%)	93.07%	(92.04% ; 94.09%)	0.834
6	52.98%	(48.09% ; 57.88%)	63.79%	(58.60% ; 68.99%)	0.598
7	74.16%	(67.45% ; 80.87%)	38.48%	(33.19% ; 43.78%)	0.358
8	70.81%	(67.35% ; 74.27%)	89.91%	(87.29% ; 92.53%)	0.879
9	54.21%	(48.12% ; 60.31%)	44.58%	(39.08% ; 50.08%)	0.407
10	76.00%	(63.16% ; 88.84%)	84.44%	(72.74% ; 96.15%)	0.843