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APPLICATION OF AUTOMATED GEOIMAGE ANALYSIS METHODS FOR AGRO-ECOLOGICAL ASSESSMENT OF LANDS

V. K. KALICHKIN and A. I. PAVLOVA
Siberian Branch of Russian Academy of Agricultural Sciences, Novosibirsk, Russia

Abstract

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Some approaches to the land cover mapping for agro-ecological assessment of lands are considered. For this purpose two algorithms for automated geoimage processing are compared: that of ISODATA and the algorithm for "object-oriented approach" by program complex ENVI. According to the research results the most reliable maps are made by the second algorithm. By implementing this algorithm the objects of the vegetation cover, overwet and arable lands are clearly identified, that allows for agro-ecological land groups mapping.

Key words: geoimage, GIS-technologies, agro-ecological assessment of lands, methods of automated processing, digital maps

Introduction

Agro-ecological assessment of the territory presupposes lands analysis by the most significant natural factors affecting landscape formation. The system of agro-ecological assessment is realized at global, regional and local levels. Different data are involved in agro-ecological estimation including those of topographic maps, soil maps, natural zoning and statistics. Better opportunities are given by satellite technologies (for data accessing and processing) and GIS. Geoimages (satellite images) have a number of advantages: extensive territories coverage, objective presentation of reality, the possibility of on-line data updating. At the same time GIS has a function of presenting different types of geographical information and the tools for manipulating thematic maps. The maps are still a powerful means for investigating spatially-referenced phenomena and objects (Berlyant, 2006; GIS for Earth Surface Systems, 1999; Remote Sensing and GIS, 2008).

Moreover geoimages may present natural complexes and their components, i.e. the relief, hydrography, vegetation, soil covering and landscape morphological structure within natural boundaries. These components investigation is one of the goals of lands agro-ecological assessment. In connection with the above the research of the land cover maps development using the earth remote sensing data seems to be important.

As the analysis of Russian sources revealed, in most of the works on agro-ecological assessment satellite images are interpreted visually. However the method is laborious and inefficient for large territories investigation. Automated or quantita-

tive methods cannot fully substitute traditional interpretation methods, but they have a number of advantages, i.e. the possibility of quantitative analysis, determination of a great number of the shades of gray, etc.

When realizing the procedures of automated analysis different techniques are applied which implement the algorithms of controllable and uncontrollable classifications. The controllable classification techniques require the standards for natural objects classes based on the terrestrial spectrophotometric measurements on testing sites, i.e. standard reflectance spectra. The class standards development is a difficult task. It takes considerable manpower and time resources due to the necessity of obtaining a representative sample, as thereafter interpolation of the whole territory under study is to be conducted (Adams and Gillspie, 2006; Konovalova et al., 2005; Mather, 2004).

Furthermore the traditional methods of pixel analysis do not always give the desired results, particularly, if the research is conducted for making small-scale maps of a large territory (Kitov, 2000; Andreyev and Chaban, 1999). Therefore most important for regional agro-ecological investigations are quantitative methods of satellite images identification.

The present research is aimed at the land cover mapping for agro-ecological estimation of lands by automated methods of geoimage analysis.

Materials and Methods

As the research materials Landsat-7 satellite images of a certain West Siberian territory, made by ETM radiometer, were used. Some additional sources were also used, i.e. digital maps: topographic (scale 1: 100 000), soil map (scale l: 400 000), that of natural and agricultural zoning (1: 400 000) and some pertinent literature. Application of cartographic materials and remote sensing data made it possible to specify the boundaries of natural-and-agricultural zones, to reveal main types of the relief, to make digital maps of : slopes (scale 1:100,000), the relief horizontal dissection (scale 1: 100 000) and local erosion basis depth (1: 100 000). Meteorological data allowed for making digital maps of mean long-term precipitations (1: 100 000); mean long-term accumulated air temperatures (1: 100 000) and others.

The present research involved brightness and geometric image transforms for facilitating visual interpretation, objectivity and reliability enhancement and images preparation for automated interpretation.

For automated image interpretation two algorithms were used: ISODATA and "object-oriented" one.

The first algorithm is per se a self-organizing one, used for classifying objects spectral images. It is based on computing statistical parameters of brightness distribution all over the image (minimal, mean, maximal, standard deviation). The essence of the algorithm comes to optimization of some of the indices, e.g. minimal error sum of squares ε. The error value is determined by formula:

$$\varepsilon = \sum_{k=1}^{K} \sum_{f \in Sk} \left\| f_k - \mu_k \right\| \qquad (1)$$

where K – the number of clusters; S_k – a set of pixels of k-cluster; μ_k – a vector of mean values for class k. In ISODATA algorithm the number of clusters (as starting points) is chosen arbitrarily. Clusterization is conducted by the minimum distance from these centers, using Euclidean metric. After that the mean values vectors are calculated and the error mean square ε is determined. In every consequent iteration clusterization is conducted by the minimum distances to mean values vectors μ_k.

The second algorithm, implementing "object-oriented' approach, gives rather good results when identifying different types of vegetation covering (Carlo and Paul, 1999; Yun, 2001; Ahmed et al., 2010; Gagnon et al., 2003; Kobzeva and Pozdina, 2008). The feature of this algorithm is that by

multilevel processing highlighted in the images are not the separate pixels, but the objects of the certain class.

Results

For agro-ecological assessment the map of the land cover is needed, which (when integrated with GIS) may be later used for making electronic maps of agro-ecological lands groups. In Russia it is common practice to differentiate between overwetted, saline, plaquor, erosive and other lands types, classified by the major limiting factor, affecting crop production.

Land cover maps were developed by special program complex ENVI. Figure 1 presents this map fragment. While interpreting the image by algorithm ISODATA the setups (the number of classes and iterations to be established) were specified. The given algorithm was applied for interpreting the synthesized images, created by combining Landsat image channels (Table 1).

In the process of work the raster map of vegetation indices was created by computing normalized differential vegetation index NDVI. This index is the most common one, often used for classifying land covers and forecasting crop-producing power (Ivanova et al., 2007; Chimitdorzhiyev and Yefimenko, 1998; Sudhanshu et al., 2010). Graphically it presents vegetation isolines with growing so called ***soil line*** angle. The index is calculated by differences in spectrum brightness in near infrared and red regions:

$$NDVI = \frac{f_2 - f_1}{f_2 + f_1}, \qquad (2)$$

where f_2, f_1 are image brightness in near infrared and red regions of the spectrum range.

The remote sensing data classification was followed by its accuracy estimation. The classification accuracy estimation was based on the comparison of two maps, i.e. the map, made as a result of geoimages analysis and the control one (digital topographic map was used for the purpose). It turned out that the most reliable classification was created on the basis of the processed synthesized images with added vegetation indices (classification # 5, with preset number of iterations – 14, number of classes – 6). The overall accuracy of the classification, developed by algorithm ISODATA, was 87.2 %. Forests, water objects, herbaceous vegetation, bogs, arable lands, meadow vegetation with sparse woods were used as identification classes (Table 2).

However, as the investigations revealed the given algorithm has disadvantages evident in classification quality decreasing with the growing number of identification classes. In the process of identification it was found out that hydrographic objects with smooth surface and small fluctuations of spectral brightness were more clearly identified. The identification percentage of errors was the lowest as opposed to the other classes.

When implementing the second algorithm the objects were identified according to the ***pixel-primitive-object*** principle. Compared with the traditional pixel classification method, ***the object-oriented*** algorithm allows for acquiring additional information on the image object structure, its shape, connection with the surrounding objects and their parts.

Different characteristics of the comparatively homogeneous primitives were obtained by seg-

Table 1

Combining Landsat image channels

Classification number	Spectral channels combinations	Classification number	Spectral channels combinations
1	04/03/2002	4	1/2/3/4/5/7
2	03/02/2001	5	1/2/3/4/5/7 + NDVI
3	04/05/2003		

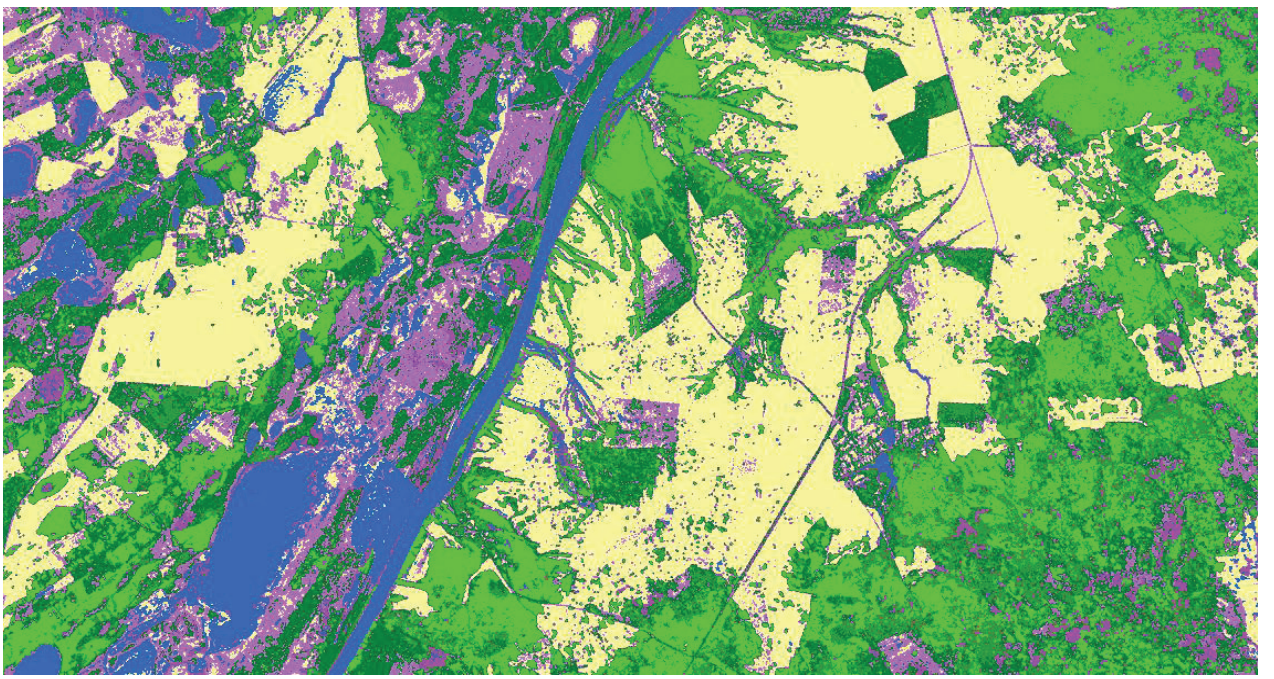


Fig. 1. The image received after cluster analysis using algorithm ISODATA

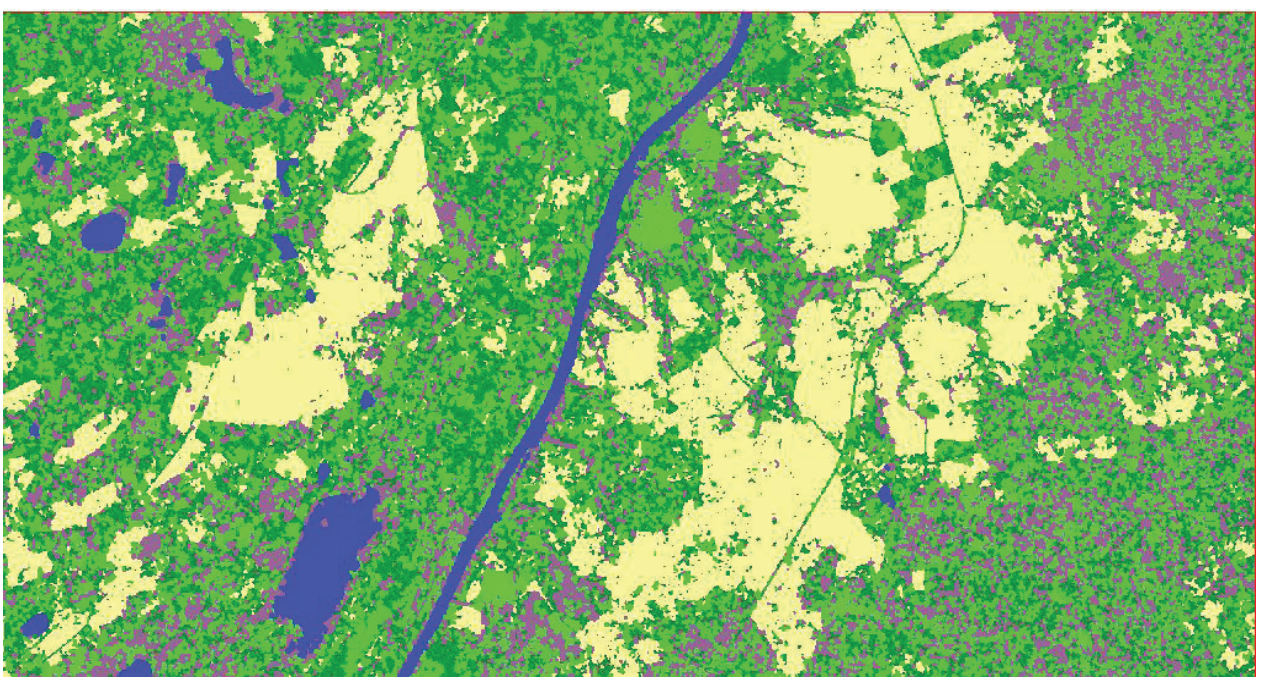


Fig. 2. The image received by the algorithm, implementing object-oriented approach

Bogs, wet lands
Hydrographic objects (lakes, rivers)
Herbaceous vegetation
meadow vegetation with sparse woods
forest
arable lands

Table 2

Classification error matrix, developed while identifying images by algorithm ISODATA

Actual class	Calculation class							Missing pixels	Percentage of errors
	Bogs, wet lands	Hydrographic objects	Herbaceous vegetation	Meadow vegetation with sparse woods	Forest	Arable lands	Total		
Bogs, wet lands	856	12	26	54	5	14	967	111	11.5
Hydrographic objects	34	813	0	0	0	0	847	34	4.0
Herbaceous vegetation	75	0	945	46	32	54	1152	207	18.0
Meadow vegetation with sparse woods	43	0	76	756	39	0	914	158	17.3
Forest	0	0	57	21	949	14	1041	92	8.8
Arable lands	17	0	83	44	36	1033	1213	180	14.8
Total	1025	825	1187	921	1061	1115	6134	782	

Table 3

Classification error matrix, developed while identifying images by *object-oriented* algorithm

Actual class	Calculation class							Missing pixels	Percentage of errors
	Bogs, wet lands	Hydrographic objects	Herbaceous vegetation	Meadow vegetation with sparse woods	Forest	Arable lands	Total		
Bogs, wet lands	976	8	16	32	0	16	1048	72	6.9
Hydrographic objects	13	756	0	0	0	0	769	13	1.7
Herbaceous vegetation	54	0	865	12	23	9	963	98	10.2
Meadow vegetation with sparse woods	18	0	24	843	31	0	916	73	8.0
Forest	0	0	57	21	911	23	1012	101	10.0
Arable lands	2	0	26	34	29	1234	1325	91	6.8
Total	1063	764	988	942	994	1282	6033	448	

menting objects images. For this purpose first the image segmentation was conducted. It was aimed at identifying homogeneous (as preset) segments. The homogeneousness here testifies to the region being of the certain class. In the process of the research segmentation was necessary for picking out the regions of approximately the same tone or colour and the homogeneous ones as concerns some more complex property (like texture).

Thereafter the classification by the nearest neighbor algorithm was derived using typical images for each identification class. They were obtained by means of the digital topographic map (Figure 2). The achieved identification results testified to the classification accuracy of the image received by the second algorithm being 92 % (Table 3). Comparing the results achieved by the two algorithms it was found out that the most efficient automated method for land cover map-

ping is the second algorithm. The objects outlines boundaries were more clearly defined, with vegetation cover objects (forest, herbaceous vegetation) being most identifiable.

Among the main advantages of the algorithm, implementing ***object-oriented*** approach, the following should be mentioned: the possibility of the classification results control and the possibility of texture analysis by introducing limitations for the contours forms and dimensions, extends, objects compactness and other characteristics. When identifying images by the given algorithm vector files may be received, which permit editing the obtained thematic maps and performing quantitative analysis.

Although the methods under consideration do not make it possible to completely automate the identification process, the "object-oriented approach" of geoimages interpretation allows for the land cover mapping necessary for agro-ecological assessment of lands at regional level.

Conclusion

It was found by the research that the "object-oriented" classification algorithm allows for a more reliable determination of the object boundaries and for making vector maps at once.

For the development of regional automated system of lands agro-ecological assessment the "object-oriented' algorithm may be applied for geoimage analysis , which makes it possible to take into account not only the spectral characteristics of the objects, but also their texture properties.

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