

THE DEFINITION OF THE AREA OF FELLING FORESTS BY HIGH RESOLUTION SATELLITE IMAGES

Khrystyna Burshtynska, Bogdan Polishchuk, Judith Madyar

Summary

The paper presents a hybrid classification method based on the determination of the optimal number of classes according to uncontrolled classification followed by image processing techniques of controlled classification.

A criterion for determining the optimal number of classes is proposed based on the definition of averaged values differences of average spectral brightness among the classes. Space images from satellites Ikonos (2002, 2007) and QuickBird (2010) were used to study different time cuttings in the forests of the Carpathian region.

A significant amount of ground observation was held for getting test information.

A Hybrid Classification Method is used for different time cuttings by QuickBird satellite images and implemented in a software environment of ERDAS Imagine. In order to obtain acreage of cuttings made for the period of 2002–2007 and 2007–2010, a comparative analysis of cuttings is introduced in these time intervals and their area is determined on the basis of the digital images of polygons in the ArcGIS software environment.

Keywords

remote sensing of the Earth • space image • forest monitoring • classification • method of maximum probability • Mahalanobis's method • method of minimum distance • deforestation

1. Introduction

In modern cartographic and information technology, solving problems of forest research is performed using space information, which is a priority in conducting forest monitoring, developing prediction methods, detecting changes and in general ensuring effective forest exploitation. In the practice of forest study, the materials for distance Earth investigation are used for forest inventory, fulfillment of phenological observations, monitoring of environmental violations and the state of the environment.

The priorities for the development and conservation of forests are: 1) conservation of forests and the need for rational use of forest resources, 2) increase of productivity and improvement of the species composition of forests, 3) improvement of the sustainability of forest ecosystems to the negative factors caused by anthropogenic disturbances and global climate changes [Lang et al. 2006].

The expediency of using satellite images for studying the Earth's forest resources is determined by their advantage over traditional methods, and the presence of infrared range of modern surveying systems increases their information content [Swain and Davis 1978, Лялько et al. 2006].

Having studied special literature [Havlon 2007, Kovacs 2007, Sakhatsky et al. 2002] we have identified the following main tasks of forestry: monitoring of deforestation, including cuttings; inventory of forests; mapping of forests; monitoring of forest resources.

Forest monitoring using Earth observation data includes: acquisition, accumulation and preprocessing of generic space information; acquisition and accumulation of ground test information containing forestry parameters; compatible processing of satellite and ground data using GIS technology and software such as ERDAS Imagine; computer modeling of ecosystems to predict the direction of the development and intensity of ecological processes; managerial decision-making and the development of measures to create optimal conditions for forest exploitation.

Frequency of making images during forest monitoring varies, depending on the objectives of the research, from several years to several hours [Лялько et al. 2006].

Determining the type of species, age characteristics, areas of forests incidence and their ecological condition is commonly realized by the use of multi-and hyper-spectral surveying systems.

In ERDAS Imagine software environment, classification algorithms are implemented using the methods of controlled and uncontrolled classification [Кохан and Востоков 2009.].

The process of forests classification is an iterative one. Vector measurement of each pixel is compared to each signature, according to the algorithm. The following solutions are the most commonly used for parametric methods: the minimum distance; Mahalonobis's distance; maximum probability.

Basic dependences of mathematical methods are presented in Swain and Davis [1978] and Лялько et al. [2006].

The development of geo-information systems and remote sensing methods provide forest monitoring with access to a new level for solving various problems of evaluation of forests condition and forestry activities. Assessment of unauthorized felling and design of clearing bands are particularly relevant among the tasks of forestry.

2. Objectives of the study

The objective of this research was to: develop a hybrid classification method based on the controlled and uncontrolled classification, and analyze its effectiveness to identify different time of forests cuttings; work out a criteria for determining the optimal number of classes; assess the effectiveness of the hybrid classification technique for detecting forest cuttings of different years; identify the areas of cuttings by high fragmentation satellite images obtained in different years.

3. Characteristics of initial materials

Space images from optical-electronic surveying systems from satellites Ikonos (March 2002), Ikonos (June 2007), QuickBird (June 2010) served as starting material for the detection and classification of forest cuttings in Yavoriv district of Lviv region (Carpathian region).

These space systems provide images in five spectral ranges: panchromatic, blue, red, green and near infrared. Resolution ability of Ikonos is 1 m in panchromatic mode and 4 m in the spectral ranges of QuickBird – 0.46 m and 2.44 m respectively.

Coniferous and deciduous forests dominate in the area of study. Cuttings were observed there. The part of the area near the village of Lepekhivka, located in the north, is occupied by agricultural land. The plot is flat, so the impact of the relief on the image can be ignored.

The data obtained by the field studies with the division of the image into ranges and the corresponding description of each one with temporal interpolation of changes was used as test information. It was obtained in 2011. Selection of testing sites is shown in Figure 1.

Data is collected according to the following parameters: general description of the polygon (e.g. mature coniferous forest, uncontrolled growth etc.), the percentage of dominant species breed, the average height of trees, the average thickness of trunks, the average distance between trees.

In general, the picture selected 229 polygons, which were then combined into 17. It is noted that vegetation of cuttings is different, which indicates that cuttings were carried out at different times.



Source: authors' study

Fig. 1. Selection of polygons for the establishment of educational standards

The following main types of cuttings were selected: fresh cuttings not overgrown with vegetation, cuttings covered with grassy vegetation, cuttings with deciduous trees planted in rows, cuttings overgrown with bushes, cuttings with coniferous plantations.

4. Methodology

The process of distribution of pixels into classes is carried out in spectral space. If a pixel meets specific conditions, it is credited to the selected class. Difficulties in classification relate primarily to the variability of signs, reflectivity varies depending on the time, day, season, etc., that is why rules of classification for different images may differ.

Classification is often uncertain and inaccurate because the values of the spectral brightness of the pixels may belong to several classes at once, and the raster pixel itself can be an integral feature of the objects of different classes, the so-called mixed pixels. However, the uncertainty in the classification is ignored, and each pixel is credited to one of the classes [Swain and Davis 1978].

According to the area of object recognition, the space of features for classification should be divided into closed areas, each of which contains the value of attributes specific to one of the classes and each pixel of the image should be credited to the class which area its attributes vector got into. The method of classifying the image pixels to objects classes defines the so-called decision rule, the rule of classification, the implementation of which is provided by an appropriate computer algorithm. Grading is based on the characteristics of typical objects, which belong to a known class (e.g. characteristics of sample objects at the test plots). Computer analysis algorithms that implement different rules for classification are divided into two types: algorithms of controlled and uncontrolled classification.

In the literature [Кохан and Востоков 2009, Лялько et al. 2006.] it is pointed out that controlled classification by means of the minimum distance, Mahalanobis distance and maximum probability leads to different results. The most accurate way to determine the classes of trees is to use the method of maximum probability, while methods of Mahalanobis and minimum distance give less accurate results. That is the reason why we used this method in our research.

In some works, in particular Кохан and Востоков [2009], Лялько et al. [2006], it is mentioned that the priority for the classification of forests can be so-called hybrid classification, which combines methods of uncontrolled and controlled classifications. In the method of uncontrolled classification, it is principal to determine the optimal number of classes that would allow creating quite a homogeneous image of class surface. Block diagram of a hybrid classification is presented in Бурштинська et al. [2014].

The main stages of the scheme are: uncontrolled classification, determination of the optimal number of classes by a given criterion, development of training standards by test information, implementation of controlled classification by the method of maximum probability and the analysis of results.

For the correct performance of uncontrolled classification, it is necessary, first of all, to find the right combination of channels as uncontrolled classification is performed automatically and depends on the image data.

The first step is to configure combinations of channels. To interpret woods, infrared, red and green channels are selected, according to the reflectivity of objects.

Uncontrolled classification. Uncontrolled classification makes it easy to distinguish many classes (groups of pixels) and can be useful to create a thematically defined set of classes using the following controlled classification.

Algorithms for uncontrolled classification implement commonly used in various multidimensional studies clustering methods, which are based on the so-called limit procedures. Their use provides that the amount of initial information is sufficient for the division of classes and that is why the standards are not used. During image processing the algorithms use various measures of classes resolution in the space of objects attributes and constitute mathematical basis of their formal clustering.

ISODATA algorithm classification is based on the use of the smallest spectral distance formula: dependence (4). This method of classification is used in the case of the similarity of the spectral features of different classes and the overlap of classes' values ranges.

Thus, a pixel belongs to the class, distance to the aggregate average values of which was the smallest. The process takes place in several stages – iterations. At each iteration all pixels are reclassified and new mean values for clusters are selected, distances to which are defined. As a result, all the pixels of the image are distributed between classes.

The criterion for choosing the optimal number of classes may be expression (1)

$$\frac{\Delta M_{(i+1)-i}}{\Delta M_{1-n}} \leq \varepsilon, \quad (1)$$

where:

$\Delta M_{(i+1)-i}$ – the average differences of average spectral brightness between classes of channels,

n – number of classes,

ΔM_{1-n} – averaged total difference of spectral brightness.

The choice of a set value of the criterion ε depends on the classification task: arrays integrated by the types of trees (e.g. pine, deciduous, mixed), more structured (birch, oak, etc.).

In general, the choice of value ε depends on the difference in spectral brightness ΔM_{1-n} and the average difference between the classes $\Delta M_{(i+1)-i}$.

That is:

$$\Delta M_{(i+1)-i} = \frac{\sum_{l=1}^L [\Delta M_{(i+1)-i}] l}{L}, \quad (2)$$

$$\Delta M_{1-n} = \frac{\sum_{l=1}^L [\Delta M_{1-n}] l}{L}, \quad (3)$$

where:

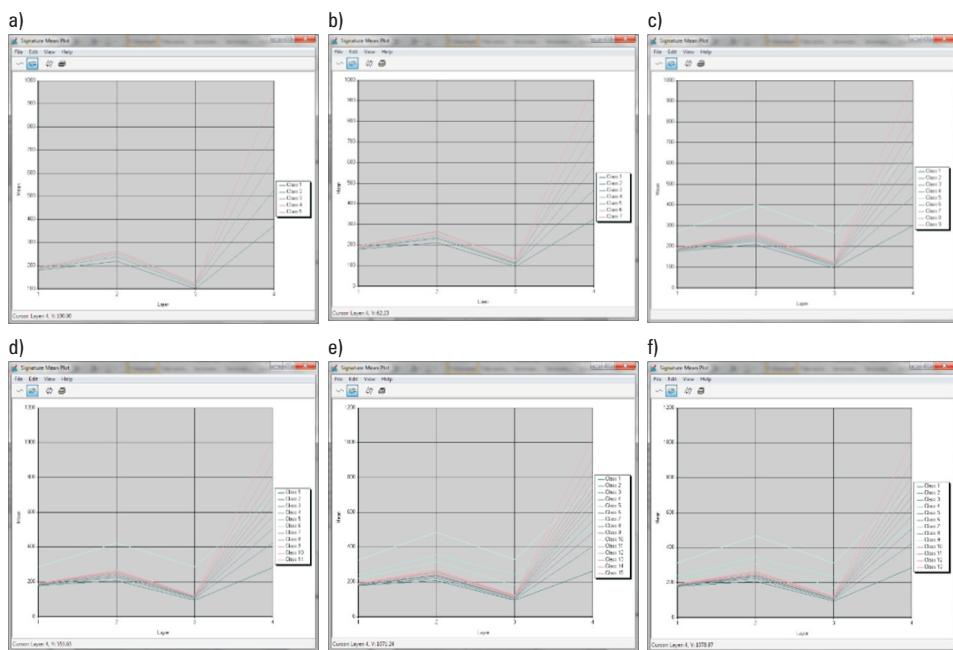
L – the number of channels.

Hybrid classification is performed by the satellite image of OuickBird [June, 2010]. To investigate the optimal number of classes in the region, the division into 5, 7, 9, 11, 13 and 15 classes is made with obtaining statistical characteristics: the mathematical expectation of the spectral brightness of classes and histograms of images.

Figure 2 presents the average values of the spectral brightness of classes in four channels. The average differences in spectral brightness, which are shown in Table 1, are calculated by formula (2). In the last line of the table, the average values of the total spectral brightness differences are calculated by the formula (3).

Table 2 presents the results of calculations by formula (1). If you specify the value $\varepsilon \leq 0,1$, the optimal number of classes will be 9–10.

The greatest focus is on cuttings, which, as shown by field studies, were carried out at different time.



Source: authors' study

Fig. 2. Plotting graphs of the mean values of the spectral brightness of classes: a) 5 classes, b) 7 classes, c) 9 classes, d) 11 classes, e) 13 classes, f) 15 classes

Table 1. Mean differences in spectral brightness

No. of a class	5	7	9	11	13	15
1–2	50	46.25	41.75	49	41	41
2–3	35.75	28.5	28.75	38	29	25.5
3–4	37	34	22.5	19.25	72.25	18
4–5	46.5	28.25	110	16	84.75	85.75
5–6		35.75	98	120	17.75	101.75
6–7		40.75	25.25	107.75	48.75	63.5
7–8			24.75	23.75	41.75	50
8–9			35.75	28.25	153.25	13
9–10				27.5	135.75	167
10–11				34.75	35	151.5
11–12					40.25	13.75
12–13					36.25	13.5
13–14						21.25
14–15						33.5
1–n	163.75	186.5	199.25	208.25	207.25	217.5

Table 2. Selection of the optimal number of classes

No. of a class	5	7	9	11	13	15
1–2	0.31	0.25	0.21	0.24	0.20	0.19
2–3	0.22	0.15	0.14	0.18	0.14	0.12
3–4	0.23	0.18	0.11	0.09	0.35	0.08
4–5	0.28	0.15	0.55	0.08	0.41	0.39
5–6		0.19	0.49	0.58	0.09	0.47
6–7		0.22	0.13	0.52	0.24	0.29
7–8			0.12	0.11	0.20	0.23
8–9			0.18	0.14	0.74	0.06
9–10				0.13	0.66	0.77
10–11				0.17	0.17	0.70
11–12					0.19	0.06
12–13					0.17	0.06
13–14						0.10
14–15						0.15

Further study by the method of controlled classification is performed by dividing the image into 9 classes.

Key dependences of controlled classification. The following main ways (rules) are distinguished in controlled classification: minimum distance, Mahalanobis distance and maximum probability [Anwar 2012, Kozak et al. 2007].

Classification by the rule of minimum distance consists in calculation of the spectral Euclidean distance:

$$SD_{xyl} = \sqrt{\sum_{l=1}^L (\mu_{li} - X_{xyl})^2}, \quad (4)$$

where:

L – the number of channels,

l – channel number,

μ_{li} – mean value of class i in the channel l ,

i – number of the class,

X_{xyl} – pixel values for channel l ,

SD_{xyl} – spectral distance of the pixel at a point with coordinates x, y .

The equation used for classification by the method of Mahalanobis distance is:

$$D_M = (X - M_i)^T \times (K_i^{-1}) \times (X - M_i), \quad (5)$$

where:

D_M – Mahalanobis distance,

i – a defined class,

X – vector of a classified pixel measurement,

M_i – the average brightness value of class i ,

K_i – covariance matrix of brightness class pixel i ,

K_i^{-1} – inverse matrix to K_i ; its dimension corresponds to the number of channels.

Classification according to the rule of maximum probability is performed to the following algorithm:

$$D = \ln(a_i) - [0.5 \ln(|K_i|)] - [0.5 D_M], \quad (6)$$

where:

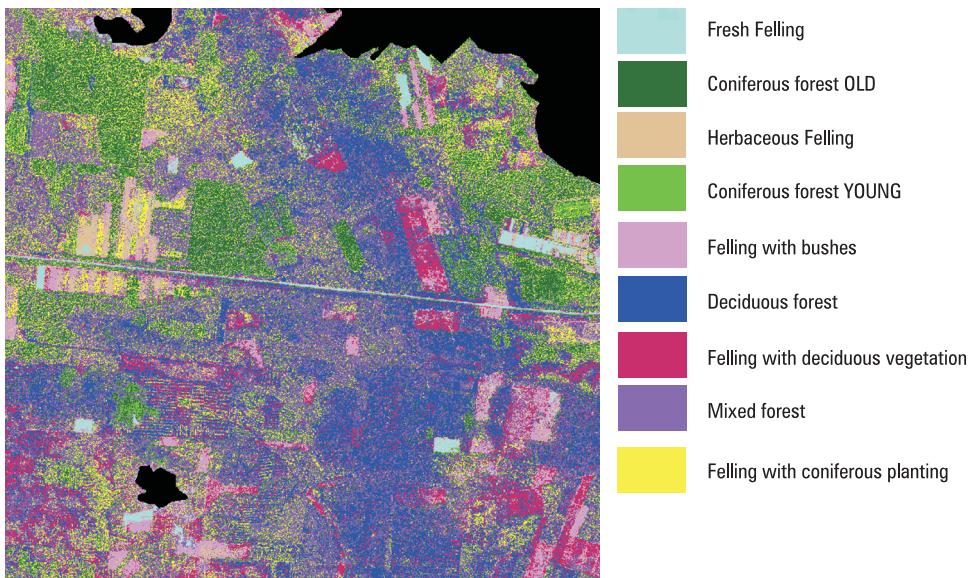
D – weight distance (probability),

a_i – the percentage of probability of classified pixel's belonging to class I (equal to 1.0 or introduced on the basis of a-priori information),

$|K_i|$ – the determinant of the matrix K_i .

In special literature, there are no clear guidelines as to the size of the reference samples. In Лялько et al. [2006] it is indicated that the sample can start with one pixel, increasing its size. The size of selected for study standards was about 100 pixels. We found that this selection gives more accurate results than smaller size samples.

Classified images with the division into nine classes according to the method of maximum probability are presented in Figure 3.



Source: authors' study

Fig. 3. Classified space image from QuickBird satellite

Table 3 presents differences of different type areas of cuttings obtained from the classification, and test areas defined by the results of digitizing the cutting plots in ArcGIS.

The results of identification of different time cuttings by the method of maximum probability indicate a slight deviation from the areas determined by test measurements for fresh cuttings. The difference is about 4%.

From the definition of the cutting area according to the results of the classification for the areas covered with grassy vegetation, shrubs and deciduous trees the difference is about 18–28%. As for conifer plantations accuracy is much lower due to the influence of underlying surface.

In addition to the study of different time cuttings by satellite images of high resolution (QuickBird), areas are determined by different time images: Ikonos (2002, 2007) and QuickBird (2010). Figure 4 shows cutting elements, which are clearly identified and give the opportunity to see how cuttings are carried out at certain time intervals. Cuttings for the period of 2002 – 2007 are shown in red in Figure 4a, and for the period of 2007–2010 – in blue in Figure 4b. Cutting areas are defined in ArcGIS software environment.

Table 3. Differences of cutting areas

Types of different time cuttings	Areas calculated by the decryption of the image [ha]	Areas calculated by the method of controlled classification using the algorithm of maximum probability [ha]	Differences of areas [ha]	Difference of areas [%]
Fresh felling	18.89	19.64	0.75	3.97
Felling with bushes	77.91	63.14	14.77	18.96
Felling with coniferous plantings	27.35	13.67	13.68	50.02
Felling with deciduous plantings	120.97	87.29	33.68	27.84
Herbaceous felling	23.16	17.82	5.34	23.05

a)



b)



Source: authors' study

Fig. 4. Identification of cuttings in images: a) Ikonos 2002 – Ikonos 2007, b) Ikonos 2007 – QuickBird 2010

Forest roads, specially laid for the removal of the wood are well identified in the pictures. Table 4 presents the total area of cuttings (without division into classes) carried out during the period of 2002–2007 and 2007–2010.

Table 4. Cutting areas at different time

Year	The area of cuttings [ha]	The area of cuttings for the period [ha]	The area of cuttings for the period [%]
2002	134.76	74.47	35.59
2007	209.23		
2010	268.28	59.05	22.03

Apparently, the presence of satellite images of high resolution gives the opportunity to identify cuttings, set the time of cuttings and determine their area.

5. Conclusions

Hybrid classification method based on the combination of controlled and uncontrolled classification is processed.

Criteria for determining the optimal number of classes are proposed based on determination of the average values of the spectral brightness differences between the classes.

It is stated that different time cuttings are effectively identified in the satellite images of high resolution of QuickBird by the available vegetation: grass, shrubs, deciduous or coniferous plantations.

Method of comparing different time satellite images is effectively used to identify cuttings and determine their areas.

References

- Anwar S. 2012. Detection and spatial analysis of selective logging with geometrically corrected Landsat images. Stein Alfred. Int. J. Remote Sens., 33, 24, 7820–7843.
- Havlon L. 2007. Vyuzitie fotogrametrickych metod pri vyhodnotení poskodenia lesných porastov. Geod. a kartogr. obz., 53, 7–8, 133–136.
- Kovacs F. 2007. Assessment of regional variations in biomass production using satellite image analysis between 1992 and 2004. Trans. GIS, 11, 6, 911–926.
- Kozak J., Estreguil C., Vogt P., Eur. J. 2007. Forest cover and pattern changes in the Carpathians over the last decades. Forest Res., 126, 1, 77–90.
- Lang M., Jürjo M., Adermann V., Korjus H. 2006. Integrated approach for quantitative assessment of illegal forest felling in Estonia. Forest., 12, 1, 103–109.
- Sakhatsky A.I., McCallun J., Khodorovsky A.Ja., Bujanova I.Ja. 2002. Classification of space image for forest state identification within the Siberia region. Pt. 1 IIASA, Laxenburg, Austria, IR-02-09, 45.

- Swain P.H., Davis S.M.** (eds.) 1978. Remote sensing – the quantitative approach. New York, 396.
- Бурштинська Х.В., Поліщук Б.В., Фіковська О.А.** 2014. Гібридна класифікація лісів за космічними знімками високого розрізnenня. Сучасні досягнення геодезичної науки та виробництва, I, 27, 156, 86–93.
- Кохан С.С. Востоков А.Б.** 2009. Дистанційне зондування Землі: теоретичні основи. Вища шк., 511.
- Лялько В.І., та інш.** 2006. Багатоспектральні методи дистанційного зондування Землі в задачах природокористування: Наукова думка, 360.

PhD, Professor Khrystyna Burshtynska
Lviv National Polytechnic University
Department of Photogrammetry and Geoinformatics
Ukraine, 79013 Lviv, Bandera Street, 12
e-mail: bursht@polynet.lviv.ua

PhD student Bogdan Polishchuk
Lviv National Polytechnic University
Department of Photogrammetry and Geoinformatics
Ukraine, 79013 Lviv, Bandera Street, 12
e-mail: bogdan.polishchuk@gmail.com

Student Judith Madyar
Lviv National Polytechnic University
Department of Photogrammetry and Geoinformatics
Ukraine, 79013 Lviv, Bandera Street, 12
e-mail: judith.madyar@gmail.com