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Supervised classification of Łobez forest area in Landsat images

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In the paper, we analyse spectral information content of a satellite picture of 728 square kilometres terrain in the northwestern Poland. Our aim is to classify forest areas on the basis of combined information from the multispectral Landsat image and ground truth data. The classification procedure chosen is the maximum likelihood method with equal a priori probabilities of the presence of particular classes in the image. The forest stands are classified to 13 and the other grounds to 23 classes.

1. Introduction

In practical applications of image processing techniques two main approaches are employed: the frequency space and the image plane processing. The frequency space processing is based on Fourier transform realised either optically by means of a lens or numerically by means of the fast Fourier transform algorithm. A possibility of manipulations on an image spectrum leads to pattern recognition based on correlation operation. Correlation techniques in optical pattern recognition are possible on relatively small images limited by the size of existing spatial light modulators illuminated with coherent light. Recognition can be based on either discrimination of a correlation signal obtained in a single filter operation or discrimination decision made in feature space when a few, *e.g.*, circular harmonic filters are sequentially employed [1]. Pattern recognition in the frequency space takes into account information content of the whole image, such as edges, lines and shapes but not that of a single pixel.

The image plane processing is based on local operations carried out either optically or numerically. Optical imaging can be described as a convolution operation of an input object function with a point spread function of the objective. Optical imaging system realises a convolution integral in parallel for the whole object plane. Numerical image plane processing consists in iterative local convolutions of neighbourhood of subsequent image pixels with a filter window. Local convolution sums combine information content of the pixels in the neighbourhood. As a result, morphological image modifications are possible [2].

Spectral satellite images are usually analysed using the image plane processing. Recognition is replaced by classification for two reasons. First, resolution of geographical information or meteorological satellites is too poor (at most 20×20 m)

T a b l e 1. Main types of forests observed in the region under investigation [1].

Forest type	Sub-type	Forest stand		
		Main species	Additional species	Undergrowth layer species
Coniferous forest – weak forest sites, with strong acid soil made of sands and highmoore peat, coniferous fleece, main species in the forest stand: pine	young coniferous forest – not influenced by the ground water, dry to moderate moist (ground water level approx. 3-5 m);	pine or birch	birch or pine	juniper, rowan, non-petiole oak
	bog coniferous forest – moist meliorated (ground water level approx. 0.5 m)	pine or birch	spruce, birch	bushy willow
Mixed coniferous forest – weak forest sites, with acid soil and low level of alkaline saturation, made of sands and transitional peat, species in the forest stand: pine (dominates) and non-petiole oak, beech, spruce, fir, birch.	young mixed coniferous forest – moderate moist, not influenced by the ground water (ground water level below 5 m)	pine	beech, oak, larch, birch, spruce	juniper, rowan, hazel
	mixed moist coniferous forest – with mineral soil, moderately influenced by the ground water (ground water level approx. 2 m)	pine, spruce	oak, birch, spruce	bushy willow, hazel
	bog mixed coniferous forest – moist meliorated (ground water level approx. 0.5 m)	pine	birch, spruce	bushy willow

Forest – fertile forest sites, moderate, weak acid or neutral soil, with moderate or high level of alkaline saturation, species in the forest stand: petiole oak, beech, fir, alder, ash.	young forest – not influenced by the ground water (ground water level approx. 5 m)	beech, petiole oak	maple, juniper, lime, larch, spruce	hazel, hawthorn, lilac, rowan
	moist forest – with mineral soil, influenced by the ground water (ground water level approx. 2 m)	petiole oak	ash, maple, lime, spruce	lilac, currant
Mixed forest – moderate fertile forest sites, fertile soil, moderate acid soil, with moderate level of alkaline saturation, species in the forest stand: pine, non-petiole and petiole oak, beech, spruce, fir larch, birch.	young mixed forest – with moderate moist soil, not influenced by the ground water (ground water at a low level)	pine, beech, petiole oak, non-petiole oak, lilac	larch, birch, lime, spruce	hazel, juniper, rowan
	mixed moist forest – with mineral soil, moderately influenced by the ground water (ground water level approx. 2 m)	pine, spruce, petiole oak	spruce, birch, lime, beech	hazel, rowan
	bog mixed forest – moist meliorated (ground water level approx. 0.5 m)	spruce, pine	birch	rowan, juniper
Alder forest – forest sites with bog peat organic-mineral soil	moist meliorated forest sites – strongly influenced by the ground water (ground water level approx. 0.5 m)	alder	birch, ash	

to recognise useful shapes. Second, information content of each pixel recorded in several spectral bands is crucial. As a result, each pixel separately is considered and assigned to a class [3]–[6].

In this paper, we present a supervised classification of terrain photographed on a multispectral satellite image. Oversight of classification decisions is possible due to additional information on the analysed terrain, such as description made by the local forester office and data collected by one of the authors during the forest reconnaissance. The limited amout of additional information available in the digital form has made us choose the maximum likelihood classification method with an assumption that all classes may appear with the same probability.

2. Source data

The analysed region is located in the northwestern part of Poland, in the neighbourhood of Węgorzyno, which is in the southern part of the Łobez forest inspectorate. It is a lowland with the various kinds of vegetation. The main types of forests present in the area are listed in Tab. 1, according to data obtained from the Institute of Forestry Research in Warsaw [7].

Classification of data from a multispectral satellite image is made. The image was taken on February 4th, 1995 by a geophysical satellite Landsat TM with the resolution of 30×30 m. The area covered by the image is 24.180×30.540 m (806×1018 pixels). An additional multispectral image recorded by SPOT XS satellite on October 26th, 1995 was used to help in visual discrimination of regions. This additional image has the resolution of 20×20 m.

In the Landsat image recorded in February, deciduous tree stands are not enough diversified for visual assessment. Therefore, the following spectral bands are chosen: band 1 (0.45–0.52 μm) in the visible part of the spectrum and bands 5 (1.55–1.75 μm) and 7 (2.08–2.35 μm) in infrared. Figure 1 presents the inspected area in pseudocolours, where red corresponds to band 7, green to band 5, and blue to band 1. For computer classification six wavebands are used, that is, apart from the above mentioned we use band 2 (0.52–6.00 μm), band 3 (0.63–0.69 μm) and band 4 (0.76–0.90 μm). Thus, the supervised classification of the terrain is made in six-dimensional (6-D) feature space.

Apart from the remote sensing images, we use topographical maps of Poland (1:50000) made in 1994, review maps of Łobez forest inspectorate made by the Regional Management of National Forests in Szczecin [8] and data acquired during the local reconnaissance in October, 1997 to choose the training areas.

3. Classification methods

Multispectral classification consists in dividing a group of pixels into a finite number of separate classes on the basis of their multidimensional numerical values (vectors). Supervised classification is a kind of multispectral classification in which a user selects typical pixel vectors that represent area types one wants to identify in an

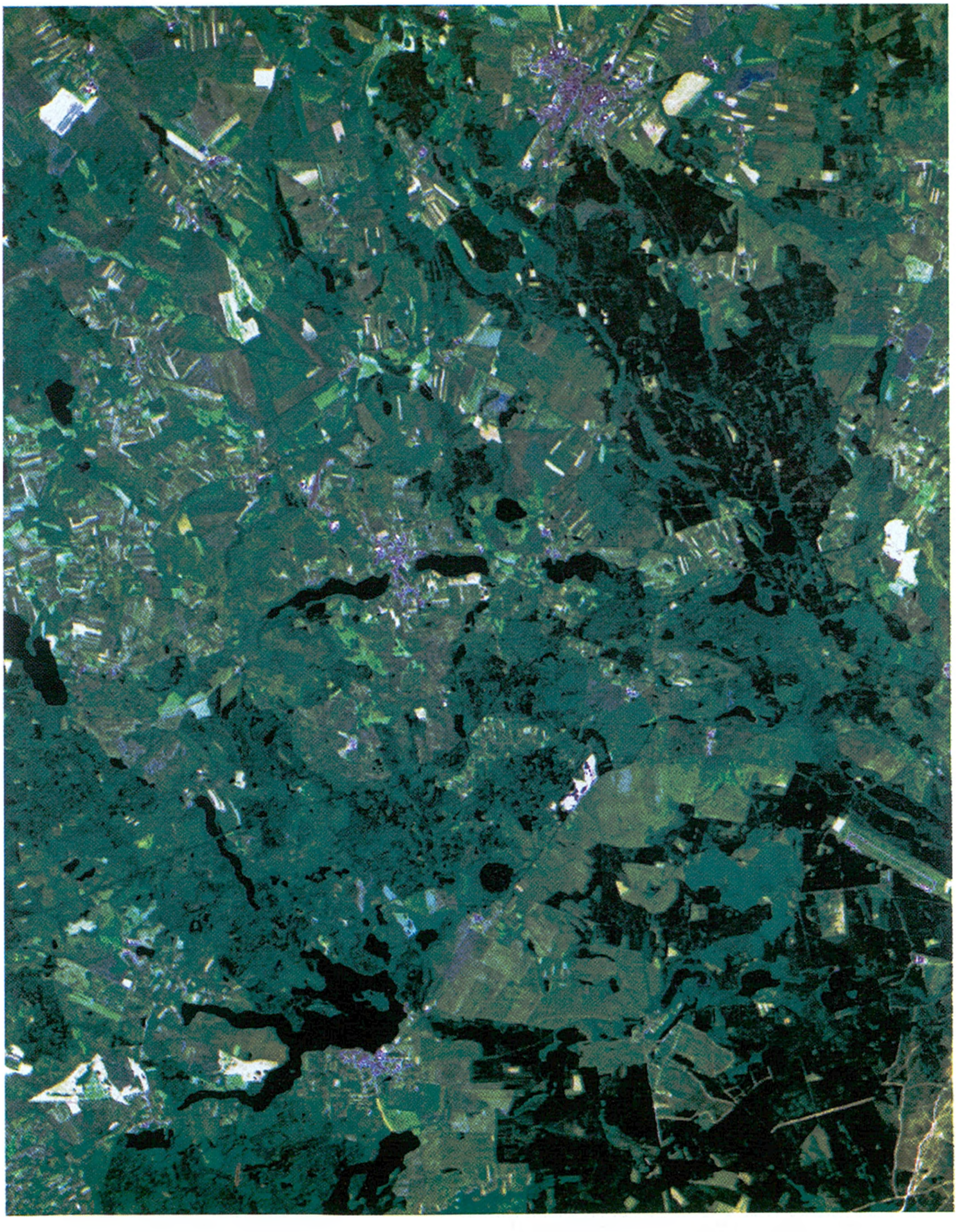


Fig. 1. Source Landsat TM image with pseudocoloured three bands (R = TM7, G = TM5, B = TM1).

image. The selection of these pixel vectors is made before the classification, with the help of data from other sources, such as aerial photos, maps and ground truth data. In this way, one can train a computer to recognise pixel vectors of similar characteristics [3]–[6].

Pixel vectors which group in certain regions of a multidimensional feature space can be assigned to separate classes according to several criteria. The simplest one, a parallelepiped criterion accepts pixel vectors which end between predefined minimum and maximum data values in each dimension. Another criterion, a minimum distance one excludes all pixel vectors which are separated from the class-mean by a distance bigger than a predefined threshold given in units of standard deviation. The third classification criterion, called the Mahalanobis distance, takes into account the directional spread of pixel vectors and is given in terms of particular classes k

$$MD = (\mathbf{x}-\bar{\mathbf{x}}_k)^T C_k^{-1}(\mathbf{x}-\bar{\mathbf{x}}_k). \tag{1}$$

Covariance matrix C for the whole image is defined as

$$C = \begin{bmatrix} c_{11} & c_{12} \ldots & c_{1n} \\ c_{21} & c_{22} & \\ c_{n1} & \ldots & \ldots c_{mn} \end{bmatrix} = E\{(\mathbf{x}-\bar{\mathbf{x}})(\mathbf{x}-\bar{\mathbf{x}})^T\} \tag{2}$$

where n is the number of spectral bands and equals 6 in our case; the diagonal elements of the matrix $c_{ii} = \sigma^2(x_i) = E\{(x_i-\bar{x}_i)^2\}$ are variances of subsequent bands $i = 1, \ldots n$; the other elements $c_{ij} = \mathrm{cov}(x_i, x_j) = E\{(x_i-\bar{x}_i)(x_j-\bar{x}_j)\}$ are covariances for pairs of random variables x_i and x_j, where i and j are numbers of spectral bands; $E\{\mathbf{x}\} = \bar{\mathbf{x}}$ denotes the expected value calculated for the whole image; and vectors

$$\mathbf{x} = \begin{bmatrix} x_1 \\ x_2 \\ \cdot \\ \cdot \\ x_n \end{bmatrix}, \quad \mathbf{x}^T = [x_1, x_2 \ldots x_n] \tag{3}$$

correspond to 6-D intensity values recorded in each image pixel.

The covariance matrix expressed in terms of the mean vector value $\bar{\mathbf{x}}$ that is calculated for the whole image is not useful in classification tasks. The situation changes when the mean vector value $\bar{\mathbf{x}}_k$ is calculated for a uniform group of pixels, which form a class k. Then, the covariance matrix C_k calculated for this class k becomes more sensitive to directional spread of pixel vectors in the 6-D spectral space.

Finally, the most popular criterion is called the maximum likelihood. It has several versions connected with the prior probability that a pixel vector neighbourhood may influence the assignment.

In this work, we choose the equal prior-probability maximum-likelihood classification criterion for reasons:

– Polish forests are diversified and the most typical stands contain a nonuniform mixture of the main species with several additional species.

– Polish forests usually preserve uniformity over small areas corresponding to a small number of pixels.

– We had no access to numerical information about the structure and area of uniform forests in the region analysed.

The main part of the work, including multivariate classification and calculation of the area statistics, is made using ER Mapper 5.1 commercial software. The rest of the work, that is, spectral profile visualisation, calculation of spectral distances, distributions, *etc.*, is made using a spreadsheet program.

The main steps of supervised classification process are shown in Fig. 2.

At the beginning, data used to select training areas are gathered and studied in all spectral channels. In our case, information collected during the forest reconnaissance played a supporting role. Then, initial training regions are selected. In the next step, statistical parameters of the training regions, *i.e.*, distributions, means, and standard deviations are calculated. The training regions for which mean values are too close (a distance between region mean values is smaller than a given value) or standard deviations are too large (above a given value) are rejected. Then, the supervised classification is carried out by means of the ER Mapper algorithm. If the result contains significant errors, for example, bad assignments in areas that are known to be of a certain type, then the training regions are modified, and the procedure of classification is iteratively repeated. The result is an image in which pixels are assigned to one of several classes corresponding to different types of land.

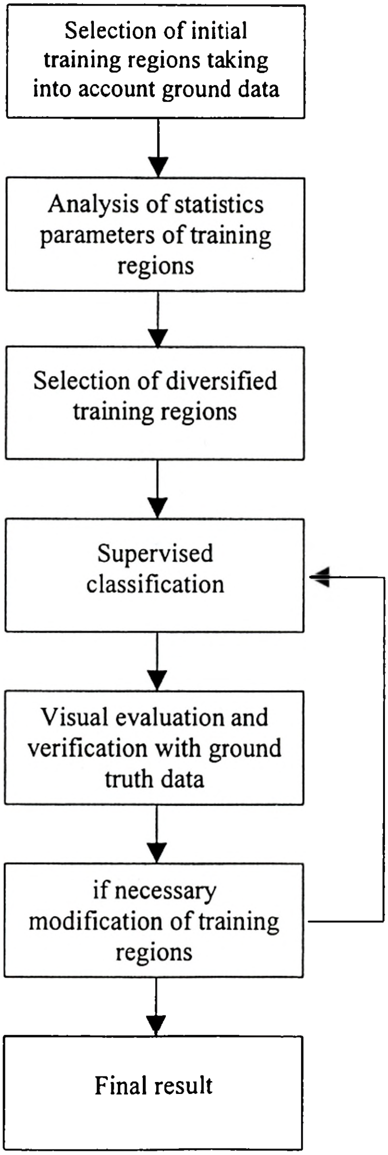


Fig. 2. Block diagram of supervised classification procedure.

3.1. Multispectral space

A multispectral space is a discrete limited Euclidean space. The number of its dimensions is the same as the number of spectral bands used. The coordinate values are given in intensity units. A spectral space is equivalent to a *feature space*, which serves to represent object properties and is frequently used in pattern recognition applications [1]. In this case, properties of an object correspond to intensity of light recorded in given spectral channels.

Every pixel in an image has its representation in the spectral space. Pixels of similar spectral signatures form clusters, which represent pixel classes. Training areas can be chosen on the basis of these clusters. An example of a 3-D spectral space is shown in Fig. 3.

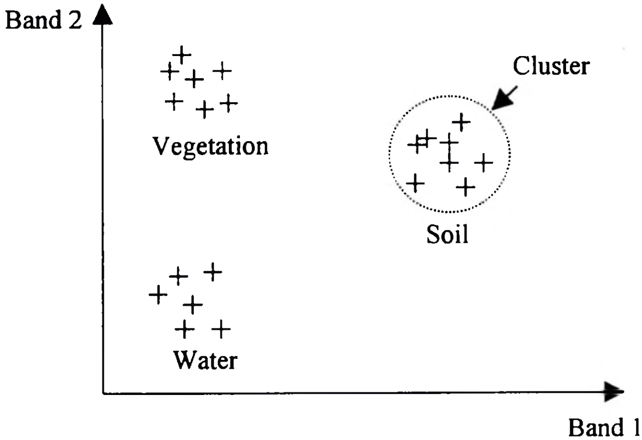


Fig. 3. Example of 2-D spectral space.

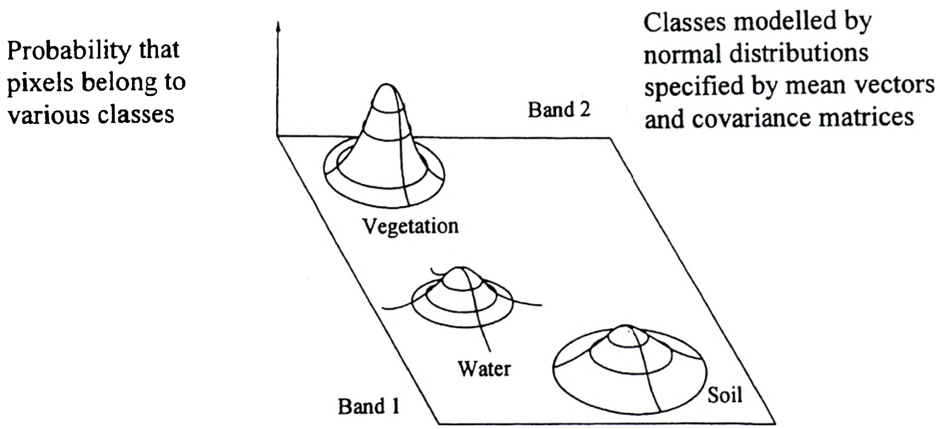


Fig. 4. Example of a 2-D spectral space with classes modelled by normal probability distributions.

The spectral classes can be described by multivariate probability density functions (pdfs) in the spectral space. The pdfs determine the probability of finding a pixel that belongs to a certain class at any point in the spectral range. Figure 4 shows an example of a 2-D spectral space with classes modelled by normal probability distributions.

In the case of images made by Landsat TM, the spectral space has 7 dimensions. Increasing the number of spectral channels used may give better results, but using a large number of channels is not always effective. In our case we do not take into account data from band 6 (10.4 – 12.5 μm).

3.2. Maximum likelihood classification

From several possible distance measures which can be taken for classification algorithm we choose the distance function. It is used to calculate a distance between mean vector values in the 6-D spectral space for each pair of classes

$$D_{kl} = \sqrt{\sum_{i=1}^{6} (\bar{x}_{ki} - \bar{x}_{li})^2} \tag{4}$$

where k, l are class numbers, and $i = 1, \ldots 6$ stands for chosen spectral channels.

The distance function is used to determine which classes of training are as overlap and should be merged together. The minimum distance between class-means can be found after analysis of all distances between means of initial training regions.

The supervised classification is done according to maximum likelihood decision rule, which assumes that the histograms of the band values of each class have normal distributions.

Every pixel in the 6-D spectral space represented by a vector $\mathbf{x} = [x_1 \ x_2 \ \ldots \ x_6]$, should be assigned to one of the spectral classes ω_k, $k = 1, \ldots K$, where K is the number of classes a priori taken into account during the classification. To find the proper class we calculate the conditional pdf $p(\omega_k|\mathbf{x})$, $k = 1, \ldots K$. The classification condition is

$$\mathbf{x} \in \omega_k \quad \text{if} \quad p(\omega_k|\mathbf{x}) > p(\omega_l|\mathbf{x}) \quad \text{for each} \quad l \neq \mathrm{k}. \tag{5}$$

It means that x is assigned to the class ω_k, if for this pixel vector the conditional pdf $p(\omega_k|\mathbf{x})$ is the highest.

The conditional pdf $p(\omega_k|\mathbf{x})$ is not a priori known, however, its value can be estimated from the following Bayes probability equation:

$$p(\omega_k|\mathbf{x}) = p(\mathbf{x}|\omega_k)\,\frac{p(\omega_k)}{p(\mathbf{x})}. \tag{6}$$

Values of $p(\omega_k)$, which describe the pdf of finding pixel of this class in the image, should be known a priori. If it is not possible, then we assume that they are equal. This assumption is not very realistic in the case of diversified mixed forests of the area, however, exact calculation of $p(\omega_k)$ values is difficult.

Let us define a discriminating function $g_k(\mathbf{x})$ as follows:

$$g_k(\mathrm{x}) = \ln\{p(\mathrm{x})|\omega_k)p(\omega_k)\} = \ln p(\mathrm{x}|\omega_k)+\ln p(\omega_k). \quad (7)$$

From Equations (5) and (7) the modified classification condition is derived

$$\mathrm{x}\in\omega_k \quad \text{if} \quad g_k(\mathrm{x}) > g_l(\mathrm{x}) \quad \text{for each } l \neq k. \quad (8)$$

We assume that the conditional pdf $p(\mathrm{x}|\omega_k)$ for each spectral class is given as a multidimensional normal distribution and for n spectral channels is expressed as

$$p(\mathrm{x}|\omega_k) = (2\pi)^{-n/2}|C_k|^{-1/2}\exp\left\{-\frac{1}{2}(\mathrm{x}-\bar{\mathrm{x}}_k)^T C_k^{-1}(\mathrm{x}-\bar{\mathrm{x}}_k)\right\}. \quad (9)$$

The factor $(2\pi)^{-n/2}$ in Eq. (9) is constant and can be neglected. Thus the discriminating function can be rewritten as

$$g_k(\mathrm{x}) = \ln p(\omega_k)-\frac{1}{2}\ln|C_k|-\frac{1}{2}(\mathrm{x}-\bar{\mathrm{x}}_k)^T(C_k^{-1}(\mathrm{x}-\bar{\mathrm{x}}_k). \quad (10)$$

In our case, the first component $\ln p(\omega_l)$ is constant for all classes and can be neglected in calculations. Finally, the discriminating function can be written as [3]

$$g_k(\mathrm{x}) = -\ln|C_k|-(\mathrm{x}-\bar{\mathrm{x}}_k)^T C_k^{-1}(\mathrm{x}-\bar{\mathrm{x}}_k). \quad (11)$$

The discrimination function of this form is used in the following classification procedure.

4. Supervised classification

4.1. Training regions

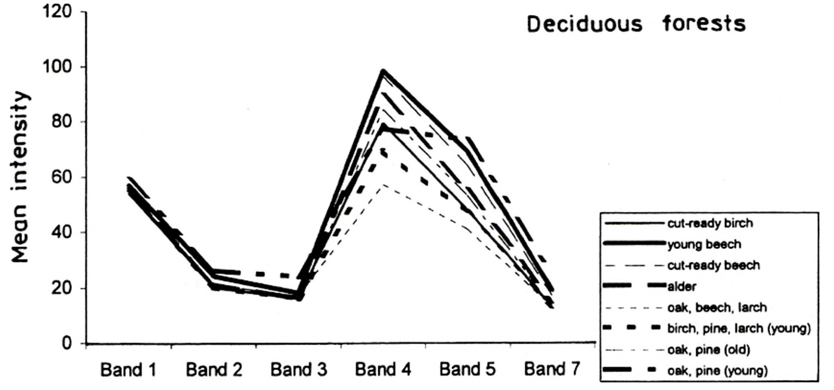
The main and time-consuming task during the classification is the proper choice of training regions. The training regions should well represent modelled classes. The quality of classification depends on this choice. In the first stage of the process, we selected 52 classes and the total number of training regions was 148.

4.1.1. Spectral intensity profiles

The analysis of spectral intensity profiles is made to check the intensity variability between distinct classes and inside classes. Afterwards we reject classes that overlap or have too large standard deviations. In Figure 5, examples of spectral intensity profiles of forest classes are shown. The lines connecting intensity mean values have not any physical sense; they only help to visualise profiles. Below we use the following classes of age of tress: young (1 – 20 years), cut-ready (up to 85 for pine, 65 for spruce, 90 for beech, 65 for birch, 125 for oak, 85 for larch, and 60 for alder), and old (over cut-ready age).

– **Moist deciduous forest and moist mixed deciduous forest**: young forest stands reflect more radiation than older ones. This may result from the fact that when trees are young and small, the undergrowth layer has an important influence on the total reflectance value. Deciduous forest stands reflect more radiation than coniferous or mixed ones. It is difficult to distinguish a moist old spruce forest from a moist old mixed pine/oak one.

– **Moist coniferous forest and moist mixed coniferous forest**: young forest stands reflect more radiation than cut-ready and old ones. It is hard to distinguish young pines from old pines in moist forests, because they have almost the same spectral intensity profiles.



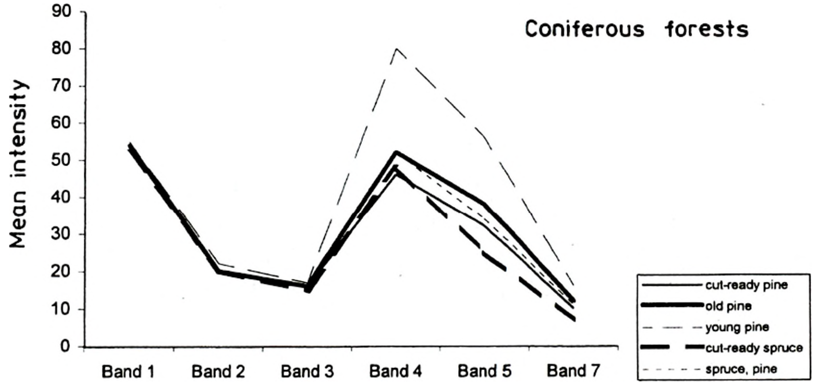


Fig. 5. Spectral intensity profiles calculated for forest classes.

– **Moist young forest**: young moist deciduous forest stands reflect more radiation than coniferous forest stands. It is difficult to distinguish a young moist mixed birch/pine forest from a moist coniferous larch forest, because its spectral intensity profiles overlap in the visible channels TM1, TM2 and TM3.

– **Cut-ready deciduous and coniferous forests**: deciduous forest stands reflect more radiation than coniferous ones. Several pine-dominated forest stands have similar spectral intensity profiles in spite of the additional species. There is no difference between such forest stands in the channels TM1, TM2 and TM3. Classification cannot be done on the basis of these spectral channels data.

— **Old forest**: spruce-dominant stands are dense, therefore reflect less radiation because the undergrowth layer gives less contribution to the total radiance factor.

— **Pine-dominant forest**: the biggest reflectance has a young mixed pine/oak forest stand in moist sites. Other additional deciduous species give less reflectance than oak. The reflectance of cut-ready pine-dominated forest stands does not strongly depend on additional species. The same holds for old pine-dominated forest stands.

— **Sites with different forest stands**: it is difficult to distinguish between the following pairs of classses:

a) a moist cut-ready mixed birch-dominated forest stand and a moist cut-ready birch forest,

b) a moist deciduous forest stand with old birch and a moist deciduous forest stand with cut-ready birch,

c) a moist cut-ready mixed oak-dominated forest stand from a moist forest stand with old oak and pine.

— **Open ground**: different kinds of open ground have different spectral intensity profiles and can be easily distinguished from each other.

4.1.2. Band intensity distributions

Standard deviations of spectral intensity profiles of forests are smaller than those of cities and open grounds. The main differences between different kinds of forest appear in the infrared bands TM4 and TM5. Radiance reflection and dispersion in these wavelength ranges occur in *parenchyma*. Chloroplasts are transparent to these wavelengths and do not reflect radiance. Thus, it is internal structure of leaves, thickness of cuticle, and mezophyll that mainly influence the recorded spectral intensity values. The mezophyll of different species has various structures, which results in various reflection factors. The more diversifed the species appearing in a training region, the bigger the standard deviation of recorded intensity values. The rejection criterion, that is, the maximum acceptable standard deviation for a class is 8.25.

The supervised classification requires that pixel intensity values within one class have normal distribution. Table 2 shows means and standard deviations for one of the training regions, and the corresponding distributions (histograms) are given in Fig. 6. It appears that pixel intensity values recorded in the channels TM1, TM2, TM3 and TM7 have normal distributions, while those recorded in TM4 and TM5 are composed of several normal distributions.

Table 2. Mean and standard deviation values for one of the training regions.

Channel No.	Mean	Standard deviation
TM1	54.299	0.854
TM2	20.237	0.524
TM3	16,742	0.572
TM4	45.175	2.289
TM5	33.015	2.012
TM6	11.052	0.856

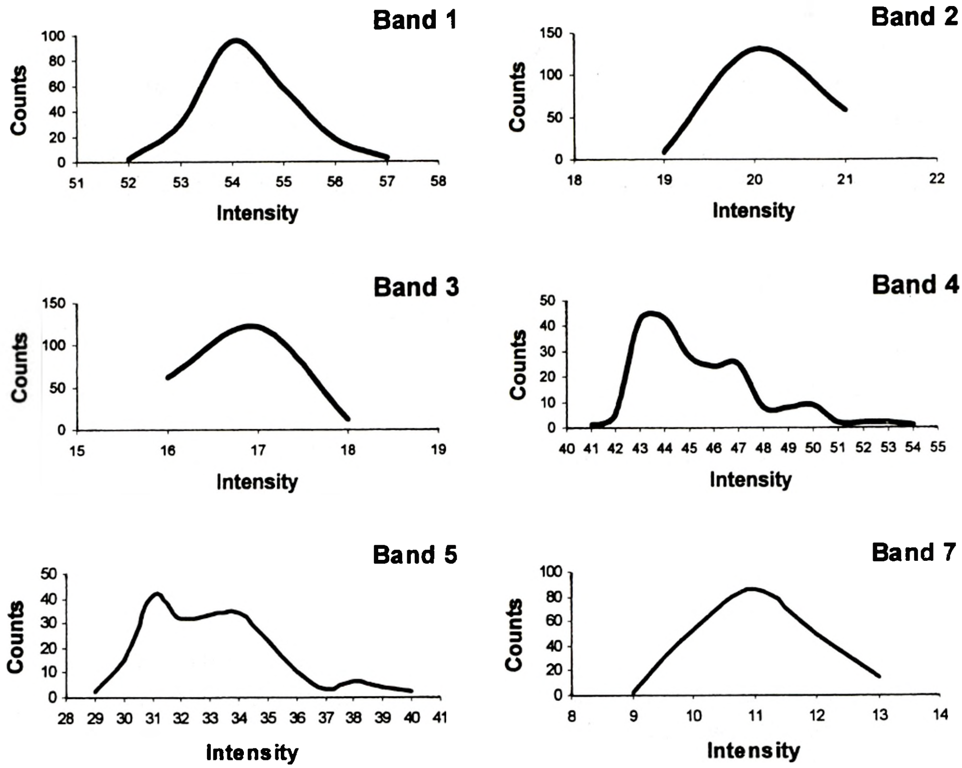


Fig. 6. Intensity distributions (histograms) calculated for one of the training regions.

In our case, we assume that pixel intensity values in the channels TM4 and TM5 can be approximated by normal distributions and possible misclassifications can be corrected at a stage of verifying the procedure. Formed in this way, the 6-D normal distributions of clusters of intensity values do not overlap with distributions of other clusters. Since the classes finally calculated are well separated, the assumption is justified.

4.2. Results

The terrain under study is assigned to 36 classes and 13 of them are forests. Forests are divided to 5 coniferous and 8 deciduous classes. Large areas of open ground cannot be precisely classified as cultivated agricultural terrain because the Landsat image covers areas which formerly belonged to state farms. A considerable part of this terrain should be forested. All the classes are listed in Tab. 3. Figure 7 presents the false colour map of classes, which can be compared with the original Landsat image shown in Fig. 1. The calculations are listed below:

– Almost all assignments are consistent with the ground truth data.

– In some cases, areas of moist mixed coniferous forest with young pine (40% or 50% of all trees) were wrongly assigned to the class 2.5, which is a forest with pine and spruce.

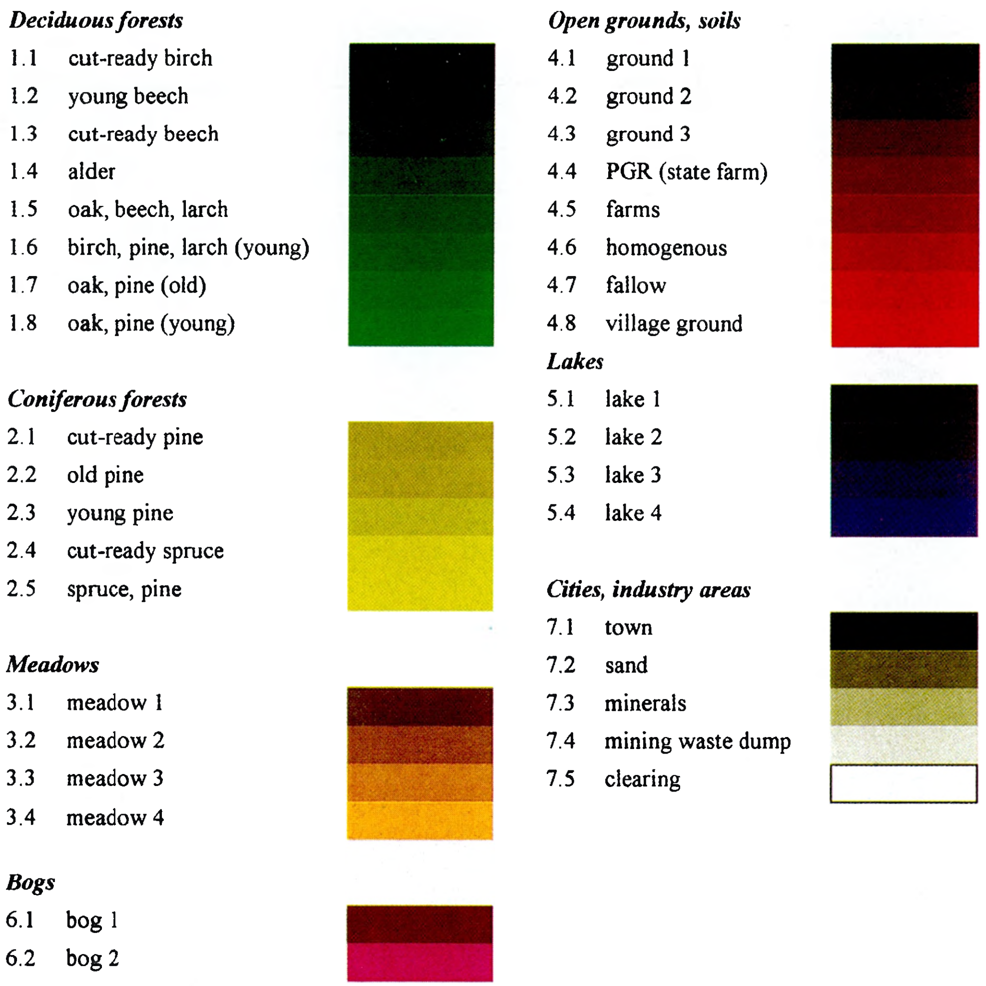


Fig. 7a. Result of supervised classification – list of pseudocolours.

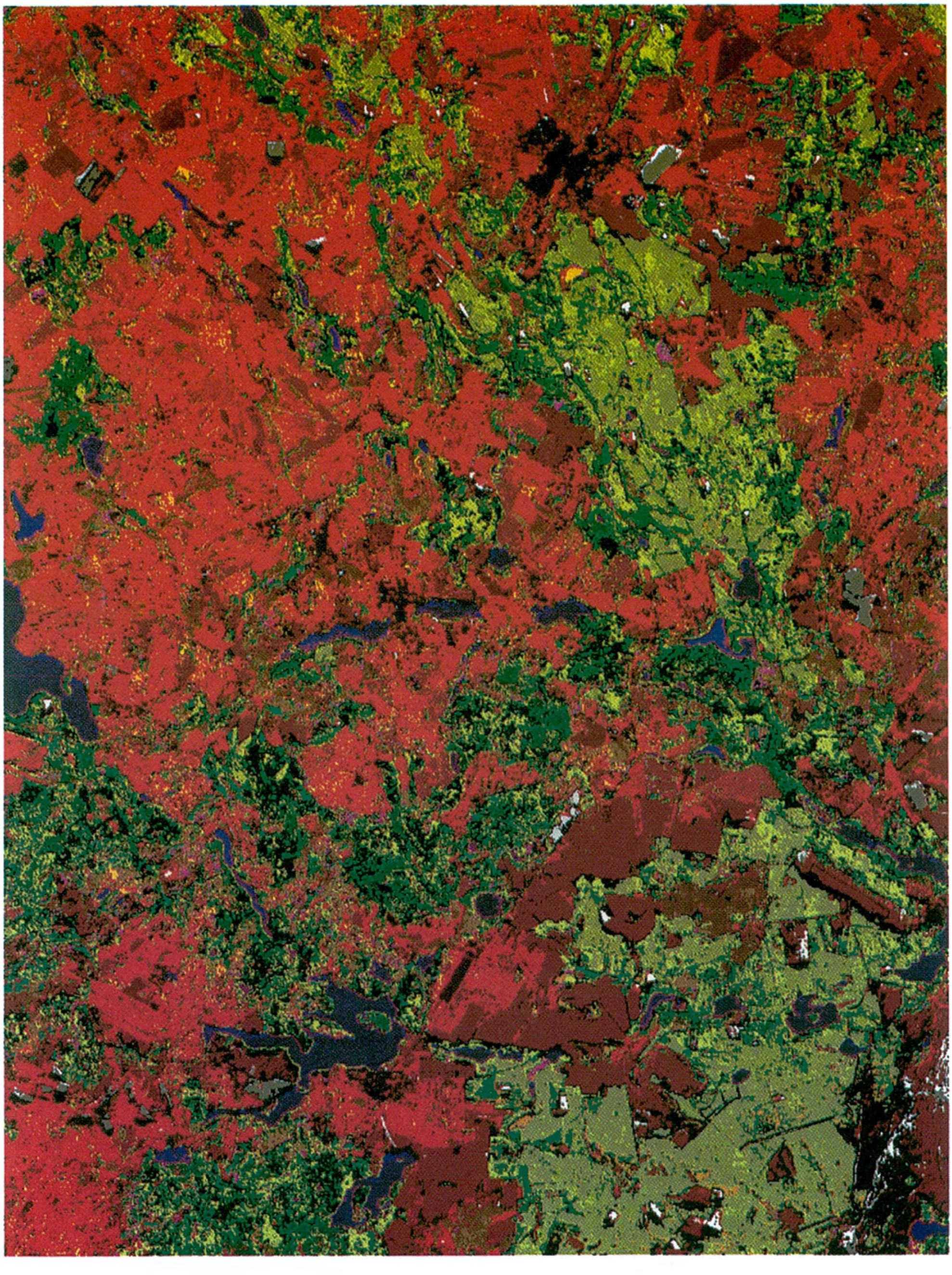


Fig. 7b. Result of supervised classification – classified image.

– Several pixels belonging to the airport and military areas (shown in the right-bottom corner of the image) were wrongly assigned to the class 7.1, which is a town.

Table 3. Classes finally taken into account.

No.	Class name	Number of training regions	Total number of pixels in a class
1.1	Cut-ready birch	17	1185
1.2	Young beech	2	49
1.3	Cut-ready beech	2	114
1.4	Alder	9	367
1.5	Oak, beech, larch	8	280
1.6	Birch, pine, larch (young)	4	129
1.7	Oak, pine (old)	4	194
1.8	Oak, pine (young)	2	60
2.1	Cut-ready pine	20	2247
2.2	Old pine	6	526
2.3	Young pine	5	613
2.4	Cut-ready spruce	2	26
2.5	Spruce, pine	12	969
3.1	Meadow 1	3	1606
3.2	Meadow 2	2	205
3.3	Meadow 3	1	74
3.4	Meadow 4	1	81
4.1	Ground 1	1	243
4.2	Ground 2	1	559
4.3	Ground 3	1	290
4.4	PGR (state farm)	7	4642
4.5	Farms	2	482
4.6	Homogeneous	1	730
4.7	Fallow	2	615
4.8	Village ground	3	4387
5.1	Lake 1	5	2044
5.2	Lake 2	1	194
5.3	Lake 3	1	213
5.4	Lake 4	1	257
6.1	Bog 1	3	48
6.2	Bog 2	3	182
7.1	Town	4	1230
7.2	Sand	2	578
7.3	Minerals	2	12
7.4	Mining waste dump	3	64
7.5	Clearing	4	69

5. Conclusions

In supervised classification tasks, a good average classification accuracy varies from 80 to 95% depending on the number of bands considered and on diversity of analysed area. In our study, verification of the classification is not possible: we used images taken in 1995 and accomplished our work three years later. Forests had changed during those years and we could not estimate the obtained classification accuracy. Efficient supervised classification is to be made using recent images, in close collaboration with offices of Regional Management of National Forests.

To achieve good classification accurcay the following conditions should be fulfilled:

– Different class pdfs $p(\omega_i)$ should be calculated on the basis of estimation description.

– Two or more images of the same region made in different seasons are to be employed to increase the number of dimensions of the spectral space.

– Images with higher spatial resolution are to be used. However, we are not able to state what the optimum resolution of images is for the purpose of classification of forest area.

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