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LAND COVER CHANGES AND DYNAMICS OF YUNTOLOVSKY RESERVE

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ABSTRACT

In this study, the land cover types of the Yuntolovsky reserve were analyzed on the basis of the classification results acquired using pixel-based image analysis approaches. Aerial images were used to carry out the image classification and ground truth data was collected from the available maps (Soil map, Topographic maps), field observation and from personal knowledge. In pixel-based image analysis supervised classification was performed using the minimum distance, Mahalonobis distance, box-classifier through ILWIS 3.31, maximum likelihood classifier. On the other hand, pixel-based image analysis unsupervised classification was evaluated through ILWIS 3.31 software. During the implementation, several different sets of parameters were tested for image segmentation and the standard nearest neighbour was used as the classifier. The results of the classified images have shown that the Maximum Likelihood approach gave more accurate results, including the overall accuracy, higher producer's and user's accuracy for most of the land cover classes in the studied region than those achieved by pixel-based classification algorithms, such as: minimum distance, Mahalanobis distance, box-classifier and cluster analyses.

Key words: landscape, remote sensing, image processing, natural heritage.

INTRODUCTION

Land cover change is one of the most important indicators in understanding the interactions between human activities and the environment. Although both natural and anthropogenic factors are responsible for land cover change, the human modification in land cover round the world has recently appeared as unprecedented, profoundly affecting the earth's ecological systems [13]. This phenomenon is particularly common in developed countries, such as Russia, where widespread land cover change driven by socio-economic development results in pervasive environmental degradation, particularly landscape fragmentation.

Remote sensing techniques have been used to monitor land use changes. This has an important role in urban development and the determination of ecosystem quality parameters. Remote sensing is also very useful for the production of land use and land cover statistics which can be useful to determine the distribution of land use/land cover types in protected areas.

Remote sensing methods and techniques have been proven to be a very useful tool for creating thematic maps [12]. A thematic map displays the spatial variation of a specified phenomenon, such as land cover type, soil type or vegetation type. Using remote sensing techniques to develop land use classification mapping is a useful and detailed way to improve the selection of areas designed to agricultural, urban and/or industrial areas of a region. The reliability of thematic maps depends on how we analyse remotely sensed images. Remotely sensed image analysis is a challenging task. One popular and commonly used approach to image analysis is digital image classification. The purpose of image classification is to label the pixels in the image with meaningful information of the real world [11]. Through classification of digital remote sensing image, thematic maps bearing information such as land cover type; vegetation type etc. can be obtained [19]. The evolution in the technology of remote sensing has caused it to become one of the most commonly used techniques in the world.

In this study two different classification methods were used: supervised and unsupervised classification. Supervised classification is the process of using training samples, samples of known identity to classify pixels of unknown identity. Unsupervised classification is the identification of natural groups, or structures, within multispectral data.

Considering the above facts, the objectives of this paper are: to use remote sensing techniques to identify the land use of the Yuntolovsky reserve in accordance with their actual use; to detect and monitor the changes in land use/cover from 1990 to 2012; to compare the classification method and to decide which one provides a better based assessment of the overall accuracy of land use classification; to examine the effect of land use change on landscape structure in terms; and to determine the major driving factors of land use/cover change.

The main objective of this study is to identify the changes of land protected areas of St. Petersburg due to the negative impact of the megacity on natural ecosystems and to predict their dynamics. Because of the knowledge of historical trends of land cover change, not only how much has changed but also where and when changes have occurred can help land managers identify the key resource and ecosystem stressors, as well as prioritize management efforts.

STUDY AREA

Protected areas (PAs) are founded in many countries around the world today. They are protected by law, scientists are studying these areas, and people visit them. However, wrong economic activity can lead to a violation of the natural landscape, the destruction of links between its constituent components. To prevent this from happening in these areas, conservation measures should be carried out, aimed at protecting the natural environment, through better monitoring and control systems. Environmental protection measures provide land use planning, to study the dynamics of land use/cover and its changes, as well as the biodiversity of natural systems.

Rapid urban expansion due to large scale land cover change has become a matter of concern since urbanization has been driving environmental change on multiple scales. St. Petersburg, the cultural capital of Russia and the second largest city in the country, has been experiencing break-neck urban growth in the last few decades that resulted in many adverse impacts on the environment.

Protected natural areas of St. Petersburg have regional significance. They are classified into two categories: reserves and natural parks, which have a complex biological profile. At present there are thirteen protected areas, seven natural reserves and six natural parks. These PAs – are the “fragments” of the natural ecosystems within the boundaries of St. Petersburg. The total area of them is 5978.7 hectares, equivalent to 4.15% of the whole territory of St. Petersburg [23]. Of the seven protected areas six are located on the Gulf of Finland. Each of these distinctive areas is not only a well-preserved valuable natural complex, but also a rich history. Natural parks “Dudergofskie height” and the Park “Sergievka” are on the list of UNESCO World Heritage sites in the historic centre of St. Petersburg and Related Groups of Monuments.

The object of this research is the natural complex of Yuntolovsky reserve. The reserve was founded in 1990. It is one of the protected natural areas of St. Petersburg. The study area is located at the north part of St. Petersburg in the Primorsky region. Its territory is washed by the Lakhta Bay – the gulf of the Neva River. There is an enormous forest area of the Yuntolovo forest summer residence in the north part of the lake. The Lakhta Bay and the Yuntolovo forest summer residence are considered to be the territory of the reserve. There are 337 species of vascular plants and 69 species of mosses in its area. Not only are some species of plants but all kinds of flora and fauna in its territory is protected. It is famous for its various worlds of flora and fauna [21].

BACKGROUND AND PREVIOUS WORK

Previous investigations were carried out in the Yuntolovsky nature reserve under the name project FORECAST. The main objective of the project was to evaluate the acuteness of forest disease by combining the use of advanced technologies (remote-sensing and cartography engineering) together with the results of current ground observations. Forecast had been elaborated to increase the efficiency of the ecological survey over large forested area.

The studies of land use/cover were conducted in a joint project between the Division of International Baltic and Arctic projects in St. Petersburg State University (SPbGU Division) and partners from the French National Geographic Institute (IGN-FI). Satellite images corresponding to part of St. Petersburg in several bands of the spectrum were obtained for studying land use/cover in the Yuntolovsky reserve. These satellite images Landsat TM (channels 2–6, the spatial resolution – 30 m) were transferred to the Office of the partners, IGN-FI. Raster system IDRISI 2.0 (IDSRI Geographic Analysis System, Window NT), MAP II 1.5 (MAP II Map Processor, MacOS) were used to work with satellite images; the vector system MapGrafix 3.5 (MapGrafix Mapping System, MacOS) was used to work with cartographic information. Sample plots representing the study area were identified on the satellite images in 1990 and 1997, and 3-component RGB composite images of band 3, 4, and 5 have been received [22].

The received raster images have been combined with the vector layers of previously digitized map-scheme reserve after its geographical binding. The main types of land use in 1990 and 1997 were identified from the preliminary automatic classification. The research was done in 1990 and 1997 in the area of the Yuntolovsky reserve as well as in its observing buffer zone. 3-component composite images and automatic classification results of land use in the Yuntolovsky reserve in 1990 and 1997 can be uploaded [22].

MATERIALS AND METHODS

Data Collection and Preparation

Recognition of types of land cover based on spectral reflectance characteristics of satellite data is one of the fundamental tasks of remote sensing. The resulting spatial information data about the types of land cover based on remote sensing allows to create thematic maps and required digital databases, in particular, for optimal control of territories, the organization of environmental and land use/cover management, environmental protection and basic research in Earth sciences. Remote sensing is a cost-effective and an increasingly used technique to characterize urban land use/cover [10].

Aerial photos and satellite images are made in programs for Aerospace Survey. Then this data is properly processed and stored. In the U.S. and Russia archives for such information data are managed by governments. Earth Resources Observation Systems (EROS) Data Center is one of the major archives of its kind in the United States. Archives are reported to the Department of the Interior U.S.

About 5 million aerial photographs, approximately 2 million Landsat satellite images from satellites as well as a lot of copies of all aerial photographs and remote sensing data is stored in the National Aeronautics and Space Administration (NASA) archive. This information is publicly available. But in Russia, extensive aerial photos and satellite images archives are only available for a variety of military and intelligence agencies. These archives have special access secrecy.

Authors were confronted with difficulties of the input data when carrying out research. The satellite images to the territory of research are available on the Internet. However, these images are not good enough in their resolution and quality (a lot of satellite images were taken under clouded sky). In addition, most satellite images were obtained in late autumn or early spring, but at this time land cover is not yet fully formed.

The following information was available for this research: aerial images of Yuntolovsky reserve (Primorsky District of St. Petersburg) (scale 1: 5000, made in 2005 and 2012, flat country); topographical maps (scale 1: 2000, made in 2002 and 2004; scale 1: 5000, made in 2005 and 2011); thematic geobotanical map and description (made in 2005). Table 1 shows the properties of the aerial image.

Table 1. Aerial image characteristics

Type of characteristics	Property value
Number of bands	3 (RGB)
Cell size (X, Y) [m]	0.5×0.5
Pixel depth [bit]	8
Band Wavelength [µm]	Blue: 0.45–0.51 Green: 0.51–0.58 Red: 0.655–0.69
Resolution [m]	0.5
Project size [pixels]	32 000×48 000
Color coding	28=(23×23×22)=256
NoData Value	256

Image processing: Before work with non-metric aerial image began, images were georeferenced. For geometric correction, an aerial image was registered in the Local Coordinate System 1964 (rectangular coordinate system) via projective transformation with the use of the Nearest Neighbor resampling method using ArcGIS 10.0. The image was adjusted to a topographic map with the use of reference points (in this case its lake outline, meadows outline) acquired by digitization. Fourteen adjustment points were used. The accuracy of adjustment was approximately 0.3–1.0 meters and was accepted as adequate because the topographical map was created in 2011 and the image was taken in 2012. The spatial resolution of pixel was 0.5 m. On account of computational complexity of the process of recognition, the mosaic was divided into squares [20] of 100×100 m spatial dimension in accordance with the grid on the topographical map, which constituted the data for classification.

It should be noted that there is a problem with the reception of satellite imaginary of Russian territory. There are no images which are freely available on open-access servers on the study area with the necessary resolution better than 15 m. Satellite imagery which was uploaded for free access, had been unsatisfactory for the task, because it was made through clouds of 25–35% and more.

Land cover classification scheme: The next step of research was to create anomenclature of land cover. The land cover classification was carried out during the visual study of image and literature review. A modified scheme of Anderson land use/cover classification level was adopted to examine multi-temporal land use/cover changes in the study area since this classification system is suitable and can efficiently be mapped from aerial imagery [1]. Five separable land use/cover types have been identified in this study as forest and vegetation, water bodies, wetland/lowlands, artificial surface, and cultivated land (Tab. 2). In addition to ancillary information obtained from various sources, the authors' priori knowledge was also utilized to document spatio-temporal characteristics of land use/cover.

Table 2. Generally land cover classification scheme

Types of the land cover	Description
Forest and Vegetation	Deciduous forest, mixed forest lands, palms, conifer, scrub and others
Water bodies	River, permanent open water, lakes, ponds and reservoirs
Wetlands/lowlands	Permanent and seasonal wetlands, low-lying areas, marshy land, rills and gully, swamps
Artificial surface	Residential, commercial and services, industrial, transportation, roads, mixed urban, and other urban
Cultivated land	Agricultural area, crop fields, fallow lands and vegetable fields, pasture

This land cover classification scheme indicates major categories (abstract to a greater or lesser degree) of land cover. This is the first level of land cover classification for all categories of protected areas in St. Petersburg [2].

The basic types of St. Petersburg protected areas land cover are established by the classification scheme. Only the first level of classification scheme which is characteristic for all the existing protected areas in St. Petersburg is used for research. This is due to the fact that the received result will be compared with land cover classification data made in 1990 and 1997 [7] for detecting land cover changes and the dynamics of the Yuntlovsky reserve and its analysis.

Land cover classification using remote sensing methods

Supervised and Unsupervised classification

Normally, multispectral data is used to perform the classification and, indeed the spectral pattern present within the data for each pixel is used as the numerical basis for categorization. These are different feature types with different combinations [14, 16]. The pixel based approach is based on conventional statistical techniques. In this study two different classification methods were used: supervised and unsupervised classification.

In the supervised classification the pixel categorization process is done by specifying, a numerical description of various land cover types present in a scene. There is a set of data samples that have class labels associated with them. This set is called the training dataset and is used to estimate the parameters of the classifier. The classifier is then tested on an unknown dataset referred to as the test dataset. An important underlying assumption is that the test dataset is similar in terms of distribution of features to the training dataset (i.e. the classifier must have observed similar features in the training in order to perform a good classification). Each pixel in the data set is then compared numerically to each category in the interpretation key and labeled with the name of the category it looks more alike to.

Unsupervised classification is the categorization of digital image data by a computer processing based solely on the image statistics without the availability of training samples or a-priori knowledge. The classification creates natural groupings in the image values, called spectral clusters. In this fashion, values with similar grey levels are assumed to belong to the same cover type. The analyst must then determine the identity of these spectral clusters. Two methods of classification are commonly used: Unsupervised and Supervised. The flow diagrams (Fig. 1a and 1b) present the logic or steps.

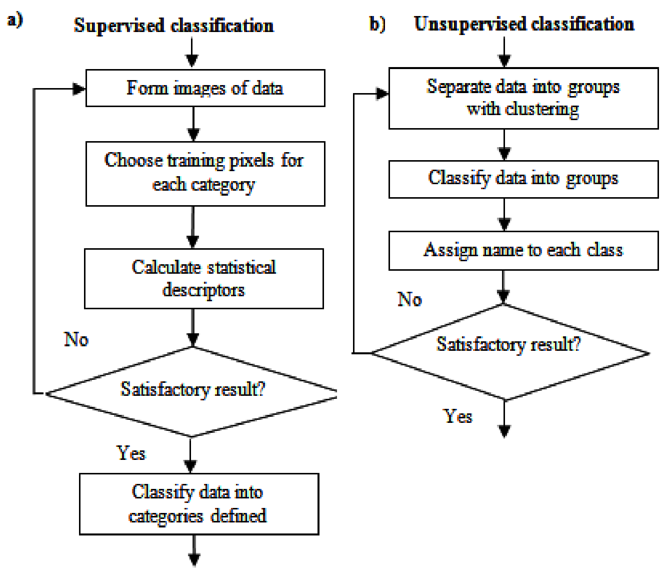


Fig. 1. The logic or steps of Supervised (a) and Unsupervised (b) classification

There are different methods and approaches of deciphering aerial and satellite images. Some algorithms of automatic interpretation remote sensing data will be discussed in detail.

Supervised classification was performed using RGB composition. Supervised classification of remote sensing data includes the following steps:

1. Select training samples which are representative and typical for that information class;
2. Perform classification after specifying the training samples set and classification algorithms;
3. Assess the accuracy of the classified image through analysis of a confusion matrix which is generated either through random sampling or using test areas as reference data (ILWIS 2001).

ILWIS academic version 3.31 was used for minimum distance classification, minimum Mahalanobis distance classification, box-classifier algorithm, test area production and accuracy assessment. Maximum likelihood classification was performed using a self-implemented algorithm. In this case, the accuracy assessment was calculated using Adobe Photoshop 9.2 and MS Excel 10.0.

Training samples are selected according to the ground truth. These homogenous areas are identified in the image to form the training samples for five information classes.

The classifying operation performs a multi-spectral image classification according to training pixels in a sample set. The algorithms for performing the supervised classification are selected. The following classification methods are available:

- minimum distance, optionally using a threshold value;
- box classifier, using a multiplication factor;
- binimum Mahalanobis distance, optionally using a threshold value;
- maximum Likelihood, optionally using a threshold value.

In case of minimum distance, the spectral distance of a feature vector towards a class mean is thus a simple Euclidian distance in *n*-dimensions, as demonstrated above. For the minimum Mahalanobis distance or the maximum likelihood classifier however, the calculation of the spectral distance towards a class mean involves the variance-covariance matrix of the class; this implies a non-Euclidian distance concept [6].

Minimum distance is one of the simplest and most commonly used in digital photogrammetry. The input data is the mean vector obtained during training for each class and each spectral band.

The brightness value for each pixel (*BVijk*), not related to the training sample is calculated Euclidean distance *D* to the mean vector in accordince with the formula [4]:

$$D = \sqrt{(BV_{ijk} - \mu_{ck})^2 + (BV_{ijl} - \mu_{cl})^2} \quad (1)$$

where:
BV_{ijk} and BV_{ijl} – brightness values for each pixel per band *k* and *l,*
μ_{ck} and μ_{cl} – standard deviation brightness values for each pixel per band *k* and *l.*

The shortest Euclidian distance to a class mean is found. If this shortest distance to a class mean is smaller than the user-defined threshold, then this class name is assigned to the output pixel. Else the undefined value is assigned.

The advantage of this method is that it is easy to realize, relatively fast, fairly easy to implement (class means, not thresholds), robust for normally distributed data. Disadvantages of the method are: it does not take into account the statistical differences between the classes, and does not take into account the correlation between the different bands of the spectrum (considering all spectral differences as equally important).

Box-classifier (parallelepiped) algorithm based on the conventional Boolean logic (and/or) and statistics of the training set in "*n"* spectral bands. First, for each class, and with a range of "*k"* the average brightness in the training set is calculated and after that, the following rules apply for the classification of image pixels: a pixel belongs to the class *C* if and only if its brightness *BVijk* satisfies the following condition [4]:

$$\mu_{cx} - \sigma_{cx} \le BV_{ijk} \le \mu_{cx} + \sigma_{cx} \quad (2)$$

where:
μ_{ck} – standard deviation brightness values for each pixel per band *k,*
BV_{ijk} – brightness values for each pixel per band *k,*
$c = 1, 2, 3, \ldots, m$ – number of classes,
$k = 1, 2, 3, \ldots, n$ – number of bands.

The set of points which obey this condition, form a box in *n*-dimensional space of spectral features. For each class, a multi-dimensional box is drawn around the class mean. If a feature vector falls inside a box, then the corresponding class name is assigned. If a feature vector falls within two boxes, the class name of the box with the smallest product of standard deviations is assigned, i.e. the class name of the smallest box. If a feature vector does not fall within a box, the undefined value is assigned.

The advantages of this method are: it is fast, more realistic than Minimum Distance to Mean.

Disadvantages: mixtures unclassified pixels, overlapping classes, thresholds difficult to establish.

Box algorithm is more realistic than the minimum distance algorithm.

For each feature vector, ***the Mahalanobis distance*** towards class means are calculated. The Mahalanobis distance is used in multi-dimensional statistical analysis; in particular, for testing the hypotheses and the classification of observations. The Mahalanobis distance of an observation $x=(x1, x2,\ldots,xN)^T$ from a group of observations with mean $m=(m_1, m_2,\ldots,m_N)^T$ and variance-covariance matrix V for each class i is calculated as:

$$d_i(\boldsymbol{x}) = \boldsymbol{y}^T V_i^{-1} \boldsymbol{y} \qquad (3)$$

where:
d_i – distance between feature vector $\boldsymbol{x}$ and a class mean m_i based on probabilities,
V_i^{-1} – the inverse of the the n×n variance-covariance matrix V_i of class i,
n – the number of input bands,
$x=(x_1, x_2,\ldots,x_N)^T$ – a (random) vector that contains the measurements made on a given individual or entity under study,
$y=(x - m_i)$ is the difference between feature vector $\boldsymbol{x}$ and class mean vector m_i [15].

The Mahalanobis distance depends on the distances towards class means and the variance-covariance matrix of each class. For each feature vector $\boldsymbol{x}$, the shortest Mahalanobis distance to a class mean is found. If this shortest distance to a class mean is smaller than the user-defined threshold, then this class name is assigned to the output pixel. Else the undefined value is assigned.

According to ***maximum likelihood algorithm***, for each feature vector, the distance towards class means is calculated. This includes the calculation of the variance-covariance matrix V for each class i. The formula used in Maximum Likelihood reads:

$$d_i(\boldsymbol{x}) = \ln|V_i| + \boldsymbol{y}^T V_i^{-1} \boldsymbol{y}. \qquad (4)$$

For an explanation of the parameters equal Mahalanobis distance classifier. For each feature vector $\boldsymbol{x}$, the shortest distance d_i to a class mean m_i is found. If this shortest distance to a class mean is smaller than the user-defined threshold, then this class name is assigned to the output pixel. Else the undefined value is assigned [6].

Using methods of ***unsupervised classification*** of the interpreter almost do not need to introduce any input. All operations on the classification of land cover are performed automatically, the program analyzes the space of spectral parameters and on the basis of certain criteria separates the pixels into classes, hoping for secondary characteristic values and covariance matrix. To explain the basic principles of cluster analysis, we consider the example of a very simple, but not always effective, algorithm, called CLUSTER [8].

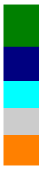
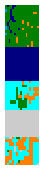
The algorithm is realized in two consecutive phases: the first – phase identified clusters, and the second – each pixel data is related to a particular cluster (class) in accordance with the criterion of the minimum distance based algorithm CLUSTER. Since the selection of clusters and classification was carried out in pixel space of spectral features, the decoder must match the spectral classes of information.

However, it may be that for one data class it is needed to combine two or more spectral characteristics. The size of the resulting cluster may be too large and this cluster will need to be divided into two. Unfortunately, the algorithm CLUSTER provides only the possibility of merging clusters, but there is no algorithm to separate them [4].

The next stage of the research is a preliminary processing aerial photos, creation of training sets in Maximum likelihood classifier (Tab. 3) and the GIS ILWIS 3.31 in order to define: which method produced results reflect the most current and the real situation of the distribution of land cover types in the Yuntolovsky reserve in St. Petersburg.

Table 3. Visualization of the test vectors classification for classes 1 to 5 using the maximum likelihood algorithm

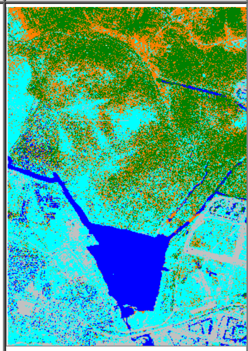
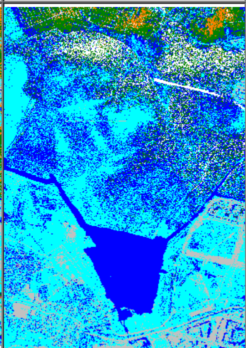
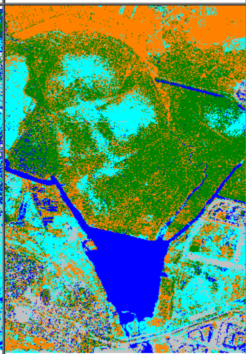
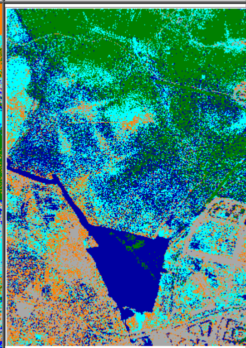
Types of land cover	Feature vector	Expected result	Achieved result
Forest and Vegetation Water bodies			

Wetlands/lowlands Artificial surface Cultivated lands			

Later the automatic classification formed the training set according to the methods of supervised classification: maximum likelihood algorithm, the minimum distance, parallelepiped, minimum Mahalanobis distance, andunsupervised classification method based on the algorithm CLUSTER in the software product GIS ILWIS 3.31 is carried out.

The classification of images using the maximum likelihood algorithm was conducted in self-implemented application in .NET environment. The statistical method of maximum likelihood created a classifier, which is necessary to determine the type of distribution, the parameter estimates the distribution based on the training set and a priori probabilities of classes of land cover. Table 4 shows the results of the research for the year 2005.

Table 4. Comparison of image classification using different supervised and unsupervised classification algorithms

Result	Name of automatic classification algorithm				
	Minimum Distance	*Box-classifier*	*Minimum Mahalanobis Distance*	*Maximum Likelihood Classifier*	*CLUSTER*
Land cover map of study area					
Overall accuracy [%]	55,7	27,2	66,7	71,5	36,1
Legend	– forest and vegetation, – water bodies, – wetlands/lowlands, – artificial surface, – cultivated land.				

Accuracy assessment: Another area that is continuing to receive increased attention by remote sensing specialists is classification accuracy [14]. ILWIS supplies a method to assess the accuracy by error matrix based on test areas (ground truth). By defining the ground truth mask, ILWIS generates an error matrix automatically. Table 5 and Table 6 show the error matrix for land cover classification 2005 and 2012 year by Maximum likelihood classification.

Table 5. Confusion matrix for pixel-based image classification, 2005

Remote sensing classification [pixels]	**Ground referencing information [pixels]**					**Accuracy criteria**		
	Water bodies	Forests and vegetation	Wetlands/Lowlands	Cultivated land	Artificial surface	**Row total [pixels]**	**Producer accuracy [%]**	**Omission error [%]**
Water bodies	**446719814**	10638995	19573229	218145	3138051	**480288234**	93,0	7,0
Forests and vegetation	15762970	**185437482**	6205003	33839888	3601810	**244847154**	75,7	24,3
Wetlands/Lowlands	23847248	11154462	**122364597**	21310307	28880734	**207557348**	59,0	41,0
Cultivated land	168052	110096789	8074583	**139433203**	6794801	**264567429**	52,7	47,3
Artificial surface	0	465375	87031630	46485814	**204757017**	**338739836**	60,4	39,6
Column total	**486498084**	**317793103**	**243249042**	**241287356**	**247172414**	**1536000000**	**1098712113**	**K=63,7%**
User accuracy [%]	91,8	58,4	50,3	57,8	82,8	**T=71,5%**	***MPA=68,2%***	***MUA=68,2%***
Commission error [%]	8,2	41,6	49,7	42,2	17,2	–	–	–

Table 6.Confusion matrix for pixel-based image classification, 2012

Remote sensing classification[pixels]	**Ground referencing information [pixels]**					**Accuracy criteria**		
	Water bodies	Forests and vegetation	Wetlands/Lowlands	Cultivated land	Artificial surface	**Row total [pixels]**	**Produceraccuracy [%]**	**Omission error [%]**

Water bodies	240897159	55168945	1400652	122450	0	297589205	80,9	19,1
Forests and vegetation	21677887	270551460	10717568	730402	0	303677316	89,1	10,9
Wetlands/Lowlands	14614475	22530738	302278812	24539342	6445	363969813	83,1	16,9
Cultivated land	4296	5297559	19972185	229691940	489799	255455779	89,9	10,1
Artificial surface	0	487650	0	607952	314212284	315307886	99,7	0,3
Column total	277193817	354036352	334369218	255692086	314708528	1536000000	1357631655	**K=85,5%**
User accuracy [%]	86,9	76,4	90,4	89,8	99,8	**T=88,4%**	***MPA=88,5%***	***MUA=88,7%***
Commission error [%]	13,1	23,6	9,6	10,2	0,2	–	–	–

In order to assess the accuracy of land cover maps extracted from satellite data, stratified random sample strategy was employed, which is a measure of unbiased assessment [9]. A total of 1 536 000 000 pixels were produced and used for the aerial imagery of 2005 and 2012. Then using the geographical locations of features available on historical land use maps, high resolution images, original images, survey of St. Petersburg topographic maps and field data, accuracy assessment of the land use/cover maps was carried out and the results were derived in error matrix. A non-parametric Kappa test was used to measure the classification accuracy as its accounts for all the elements in the confusion matrix rather than the diagonal elements [4].

We can calculate the Kappa-coefficient according to the formula:

$$\hat{K} = \frac{N \sum_{i=1,\ j=1}^{m} D_{ij} - \sum_{i=1,\ j=1}^{m} R_i \cdot C_j}{N^2 - \sum_{i=1,\ j=1}^{m} R_i \cdot C_j} \qquad (5)$$

where:

$\hat{K}$ – the Kappa-coefficient,
N – total number of pixels,
m – number of classes,
$\sum_{i=1}^{m} D_{ii}$ – total diagonal elements of an error matrix (the sum of correctly classified pixels on all images),
R_i – total number of pixels in row i,
C_j – total number of pixels in column j.

The overall accuracy for land cover maps of 2005 and 2012 were 71.5 and 88.4% with corresponding kappa statistics of 63.7 and 85.5%, respectively. A standard total accuracy for land cover mapping studies has been set between 85% and 90% [1]. Examining the total accuracy of the derived maps showed that they met the minimum requirement, hence the application of rule-based post-classification refinement found to be effective improved the accuracy by 15–17%.

According to the results of land cover automatic classification of Yuntolovsky reserve for the period of 2005 it can be concluded that the most accurate classification result gives the maximum likelihood algorithm (T=71.5%), while the lowest – the box-classifier algorithm (T=27.2%). Minimum Mahalanobis distance algorithm showed classification accuracy equal to T=66.7%. Satisfactory results showed the minimum distance method – T=55.7%. Methods based on the box-classifier and cluster analysis showed low overall accuracy (the precision is 27.2% and 36.1% respectively).

A supervised maximum likelihood classification technique was subsequently applied to each image which has generally been proven to generate superior result from remotely-sensed data, if each class has a Gaussian distribution [3]. In further studies for supervised classification images used the maximum likelihood algorithm, because it gave the best results (the overall classification accuracy was 71.5% for the 5 types of land cover). Figure 2 shows the automatic classification results of aerial photos of Yuntolovsky reserve in 2012, made according to the maximum likelihood method.

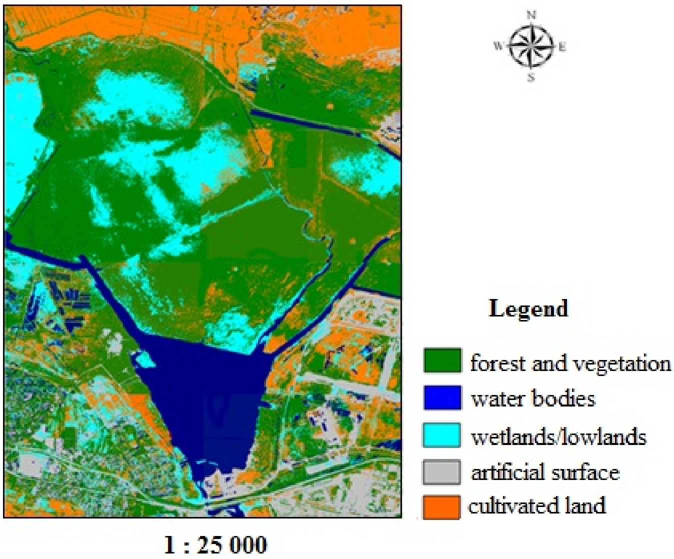


Fig. 2. Land cover map of Yuntolovsky reserve, 2012 year

However, it is safe to say that spatial data given by remote sensing contains information on the types of land cover. Such data will allow to create thematic maps and databases of PAs, which can be used for optimal management of territories, the organization of the natural environment and land cover.

Remote sensing is economically effective. Remote sensing data, in particular, has been widely used in classifying land cover protected areas. It is based on the research results and it studies the technique of digital image classification of the technology of aerospace monitoring of the land protected area in St. Petersburg, as shown in Figure 3.

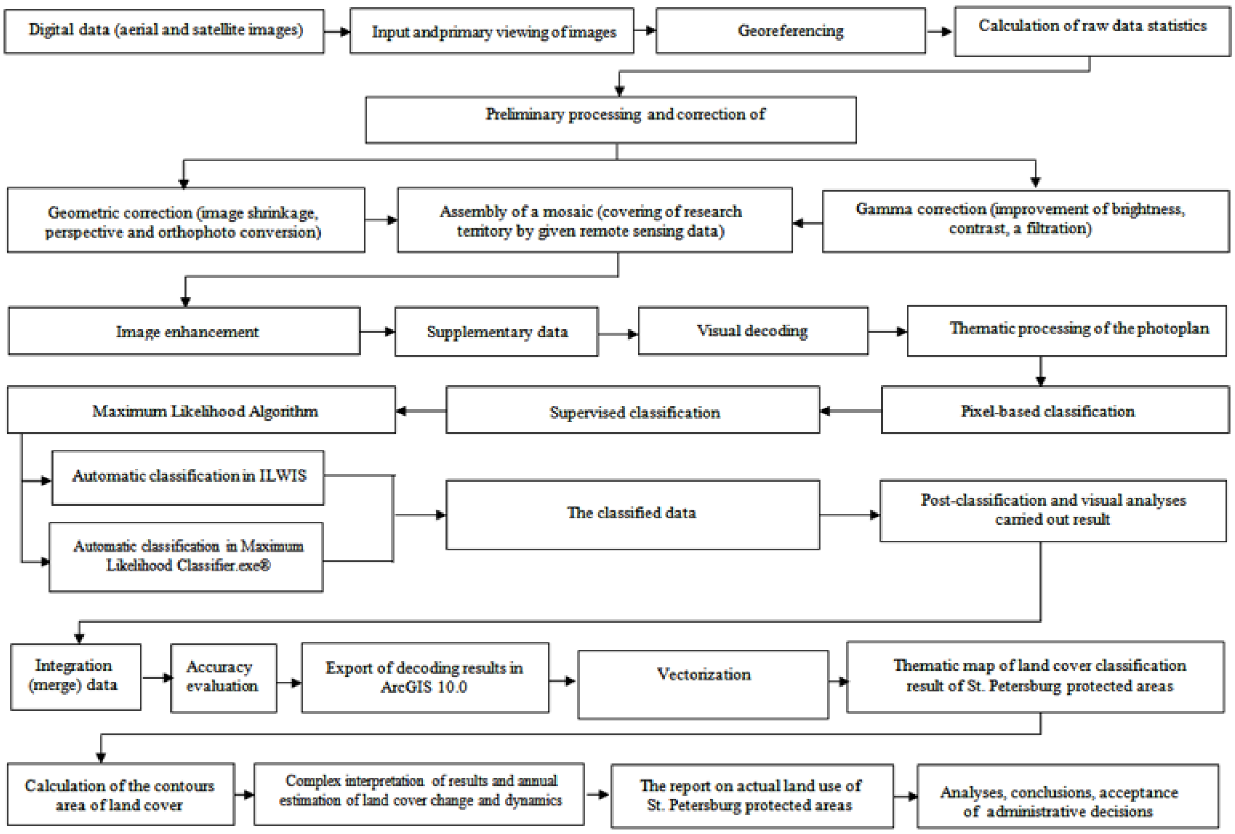


Fig. 3. Aerospace monitoring technology of land cover protected areas of St. Petersburg

The proposed aerospace monitoring technology of land cover St. Petersburg protected areas is based on the automated interpretation technique of aerial and satellite images by maximum likelihood algorithm. This technology will allow conducting real-time monitoring changes in the land area of protected areas in the shortest possible time, without the cost of a field survey, and the opportunity to set borders on the types of land cover.

RESULTS

The study of land cover structure and dynamics of the Yuntolovsky reserve and its ‘buffer zone’ was conducted by scientists from St. Petersburg State University, working in the “International Baltic and Arctic projects SPbGU” (Branch Office) [22]. The field observations in 1990 and 1997 in the Yuntolovsky reserve were conducted by staff of Branch Office for the international project 'FORECAST'. The result of these observations was a digitized map diagram of the study area. In addition, the staff of the Branch Office conducted the study of satellite images of territory reserve and its buffer zone. These satellite images were later used to study the land cover distribution in the Yuntolovsky reserve.

The land cover changes (during 7 years) were identified after analyzing previous satellite images and results. The greatest reduction in size area was marked on the land under forest phytocenoses. Reasons of area reduction of the forest land are:

1. forest cutting of main use, though forbidden by the law [18] in the protected areas;
2. low productive forests exposed to swamping, during which the lands occupied by forests, become swamps.

It is established that the total area in 2012 was 1025.4 hectares but it contradicts the operating law of the Saint-Petersburg governor [21] according to the law its territory is demanded to be equal 976.8 hectares. The following types of land cover are located in the area of Yuntolovsky reserve, for example: forests and vegetation; water bodies; wetland/lowland; artificial surface; and cultivated land (Tab. 7).

Table 7. Proportions of the land cover area according to Yuntolovsky reserve, from 1990 to 2012 years

Types of the land cover	Area							
	1990		1997		2005		2012	
	[ha]	[%]	[ha]	[%]	[ha]	[%]	[ha]	[%]
Forests and vegetation	587,1	60,1	470,8	48,2	422,7	41,5	384,5	37,5
Water bodies	90,8	9,3	97,7	10,0	186,4	18,3	136,4	13,3
Wetlands/ lowlands	171,9	17,6	299,9	30,7	258,7	25,4	346,6	33,8
Artificial surface	127,0	13,0	79,1	8,1	146,7	12,1	147,5	14,4
Cultivated land	0,0	0,0	29,3	3,0	27,5	2,7	10,4	1,0
Total area:	976,8	100	976,8	100	1018,6	100	1025,4	100

Forests occupy about a half of the reserve area. There are birch, pine forests and mixed plantings and original forests in fir groves in the given district. Besides that there is a renewal process of pine spruce in some deciduous and mixed coniferous-broad-leaved forest. As a result the replacement derivatives of the radical woods by the original ones are possible if no other changes happen.

The meadows occupy the western part of the reserve. They are basically used for haymaking and as grassland. The anthropogenous lands are located on the perimeter of the reserve, mainly in the buffer zone. They are presented by the cuttings down, haymakings, vegetable gardens and lands under construction, for example, the village Kamenka.

The land cover dynamics of the Yuntolosky reserve according to its various types of land use/cover was composed by the researching results conducted in 1990, 1997, 2005 and 2012. One of the aims of our study was the comparison of land cover thematic maps of the actual land use the Yuntolovsky reserve for 2005 and for 2012 years with the geobotanical maps 1990 and 1997 that the researchers of Branch Office SbGU had created. By monitoring observations based on the data of four periods of time a diagram of land cover changes of the Yuntolovsky reserve for the last 22 years was made up (Fig. 4).

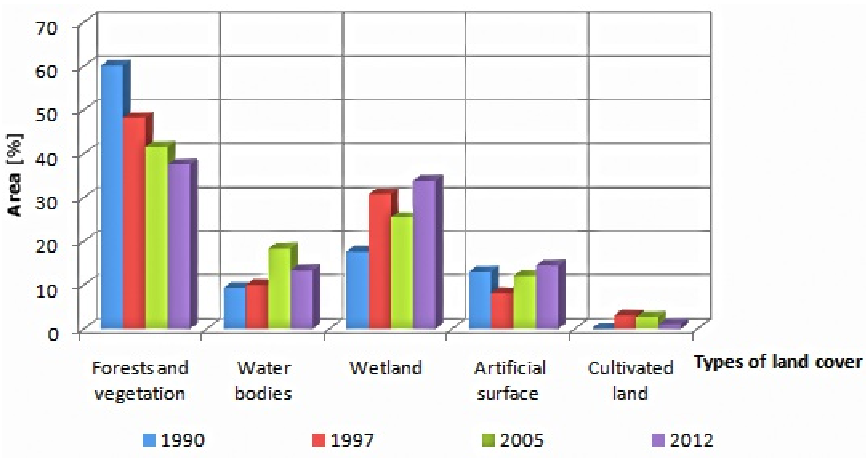


Fig. 4. Land cover dynamic of Yuntolovsky reserve (1990, 1997, 2005 and 2012 years)

The bar chart shows that there has been a 22.6% reduction of forest lands within 22 years. We can make a conclusion that lumbering is held in the reserve [5]. But lumbering is forbidden there according to law, as well as agricultural activity according to the local government statement [21]. Moreover, areas used for agricultural aims have been increased lately. The illegal gardens of local people have appeared on the reserve outskirts.

The areas classified in 1990 as "built-up" have been changed into "wetlands" (in the western part) and "cultivated" (in the eastern part) in 1997. The construction area has increased in the eastern outskirts of the reserve's buffer zone. Figure 5 shows the spatial pattern of land use/cover change in the study area for 1990 (Fig. 5a [22]), 1997 (Fig. 5b [22]), 2005 (Fig. 5c) and 2012 (Fig. 5d).

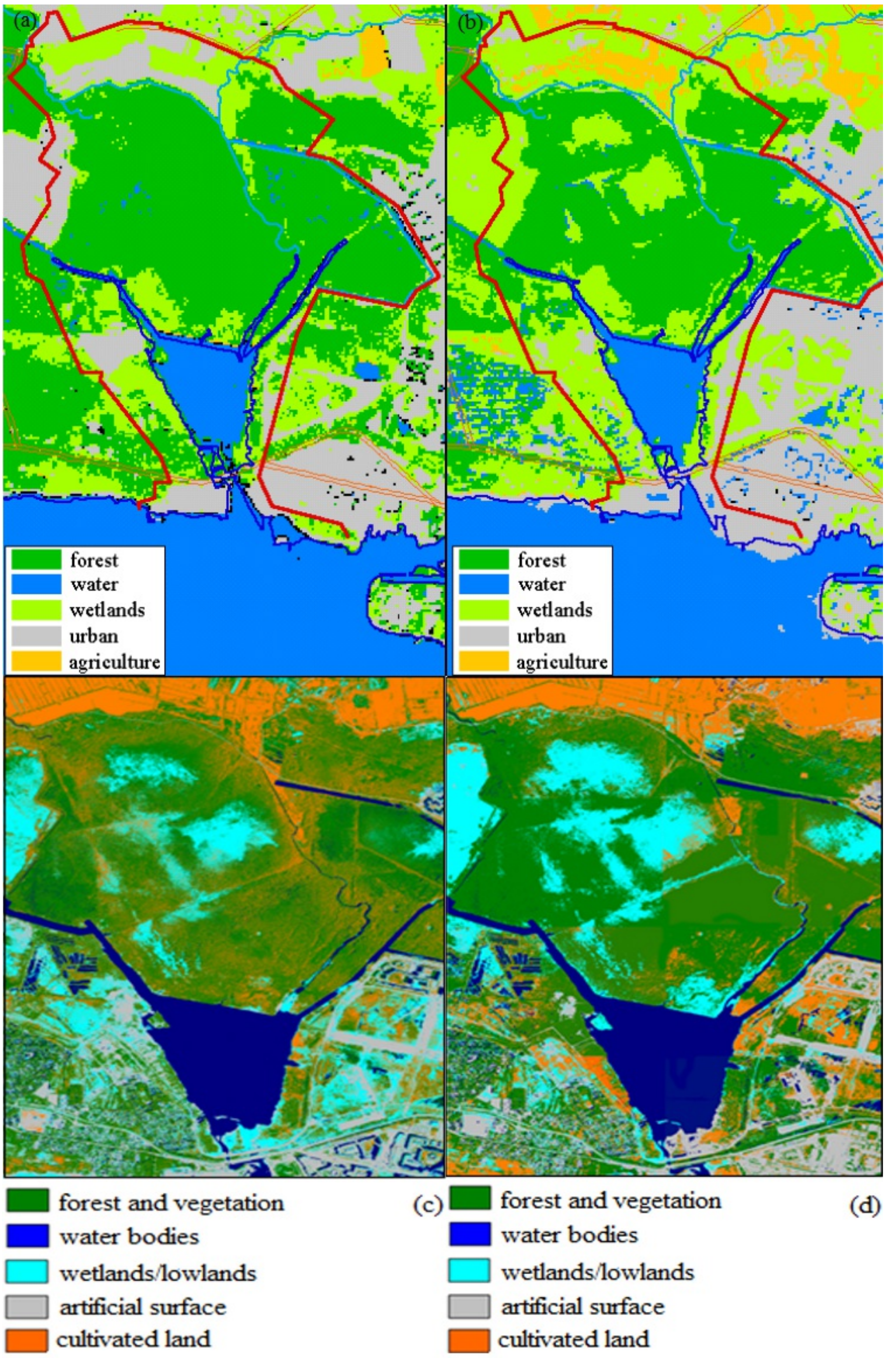


Fig. 5. The spatial pattern of land use/cover change in the study area for 1990 (a), 1997 (b), 2005 (c) and 2012 (d)

CONCLUSIONS AND DISCUSSIONS

Significant changes in land cover were noticed in the Yuntolovsky reserve over the research period in 1990–2012. Rapid urbanization was manifested by a large reduction of forests and vegetation from 587.1 ha in 1990 to 384.5 ha in 2012. At the same time, the artificial surface and wetlands increased to about 20.5 and 174.4 ha, respectively. Consequently, sharp changes in landscape pattern and composition were observed. The total area of reserve increased to approximately 48.6 ha during 22 years. Areas under the cultivated land almost have not changed; they are characterized by relatively stable performance (when comparing 1990 and 2012.)

The landscape became highly fragmented as a result of rapid increase in the surrounding built-up and developing areas. Landscape diversity declined, urban dominance amplified, and the overall landscape mosaics became more continuous, homogenous and clumped. In order to devise sustainable land use planning and to determine future landscape changes for the natural resource of the Yuntolovsky reserve management strategies, the present research is expected to have significant implications in rapidly urbanizing cities of the world in delivering baseline information about long term land use change and its impact on landscape structure.

After reviewing the present state protected area in St. Petersburg (on example of the Yuntolovsky reserve) we can conclude, that an enlarged during last year's recreational load on their land and large-scale construction of border areas leads to a significant degradation of the health of the natural resources of protected areas.

We need constant monitoring of land cover protected areas, which should contain information about all the changes of natural areas, the number and condition. It should be noted that the development cadastre of land protected areas need timely monitoring of these facilities in order to assess the state of the recovery and the information about them the land cadastre in the state real estate cadastre.

In our opinion, special attention should be given to annual land cover monitoring of protected areas and timely comparison of the current information with the data of previous years to identify the dynamics of natural resources and eliminate the causes that led to the change. Development of aerospace monitoring technology of land cover is an important step in the study of the land cover dynamics of protected areas, identifying and removing the causes of their degradation.

Adoption of new technology will save time and money on operational aerospace monitoring of land cover protected areas. Finding results that give the opportunity for rational planning costs on the recovery and routine maintenance of their natural resources.

Summarizing the information given above it is necessary to fix the reserve buffer zone legislatively. It demands to get the status of specially natural protected areas in order to reduce the anthropogenous impact on the reserve land cover and the natural environment. It is required to regulate natural protection and the recreational role of the reserve to save the ecological balance of the territory.

Long-term tendency study of natural complex changes of the Yuntolovsky reserve is required to develop the management plan and take measures for the safety of rare plants and animals' population. Getting the reliable data of landscaping dynamic trends and vegetation demands realization of long-term monitoring on the experimental area in different types of location and plant clusters.

One thing is doubtless today: the largest among the existing naturally protected areas of the St. Petersburg complex - Yuntolovsky reserve, can survive in a five million city if nature protection and recreational functions are combined. Nevertheless, the problem of area protection can be solved by means of a complex study of its natural features.

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