

Hard- and software system of airborne hyperspectral sensing of natural and man- made environment

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Hyperspectrometers NPO Lepton

2007



2009



2010



Functional scheme of hyperspectrometer

Input objective:

$F = 17 \text{ mm};$
 $D = 6 \text{ mm}$

Spectral slit:

Width - $H = 10 \text{ mkm};$ Length - $L = 4.9 \text{ mm}.$

Output objective:

$F = 34.75 \text{ mm};$
 $D = 13 \text{ mm}$

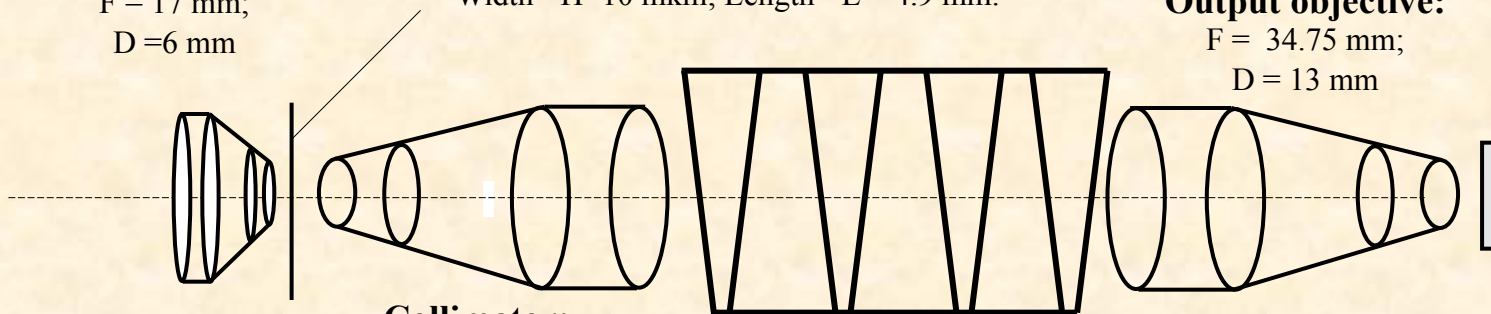
Collimator:

$F = 34.48 \text{ mm};$
 $D = 15 \text{ mm}$

Dispersive device:

number of prisms – 7

Charge-coupled device:
SONY "ICX-255"

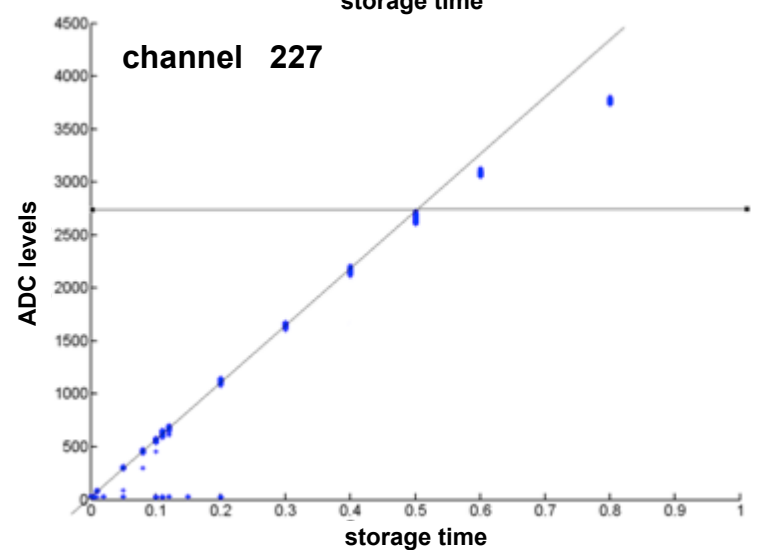
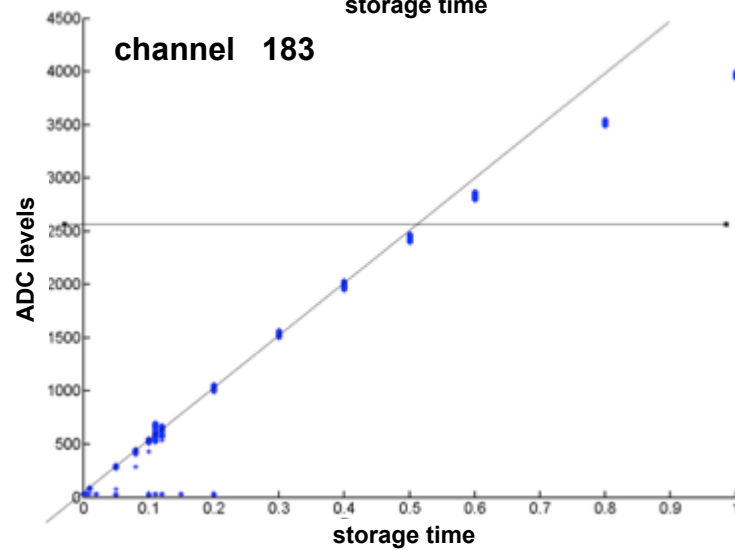
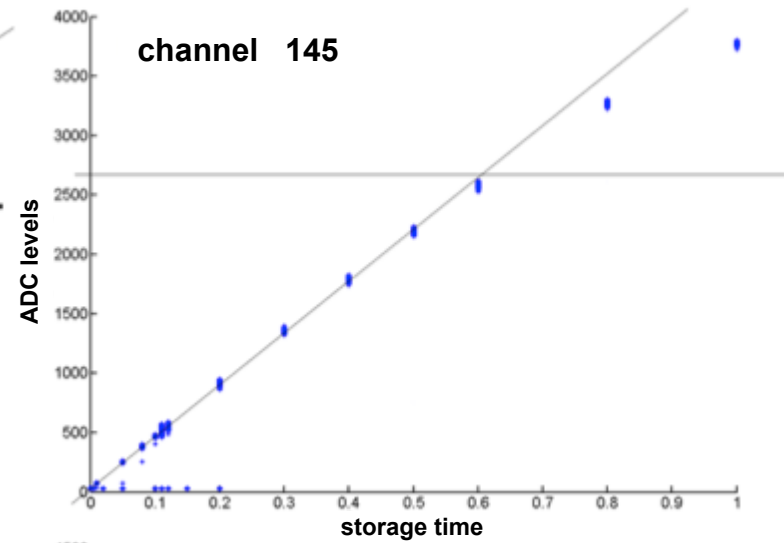
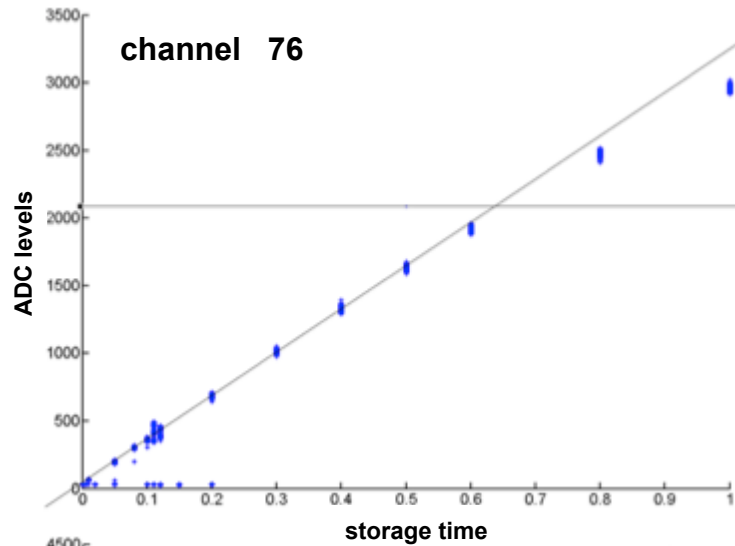


Comparison with the existing airborne hyperspectral sensors

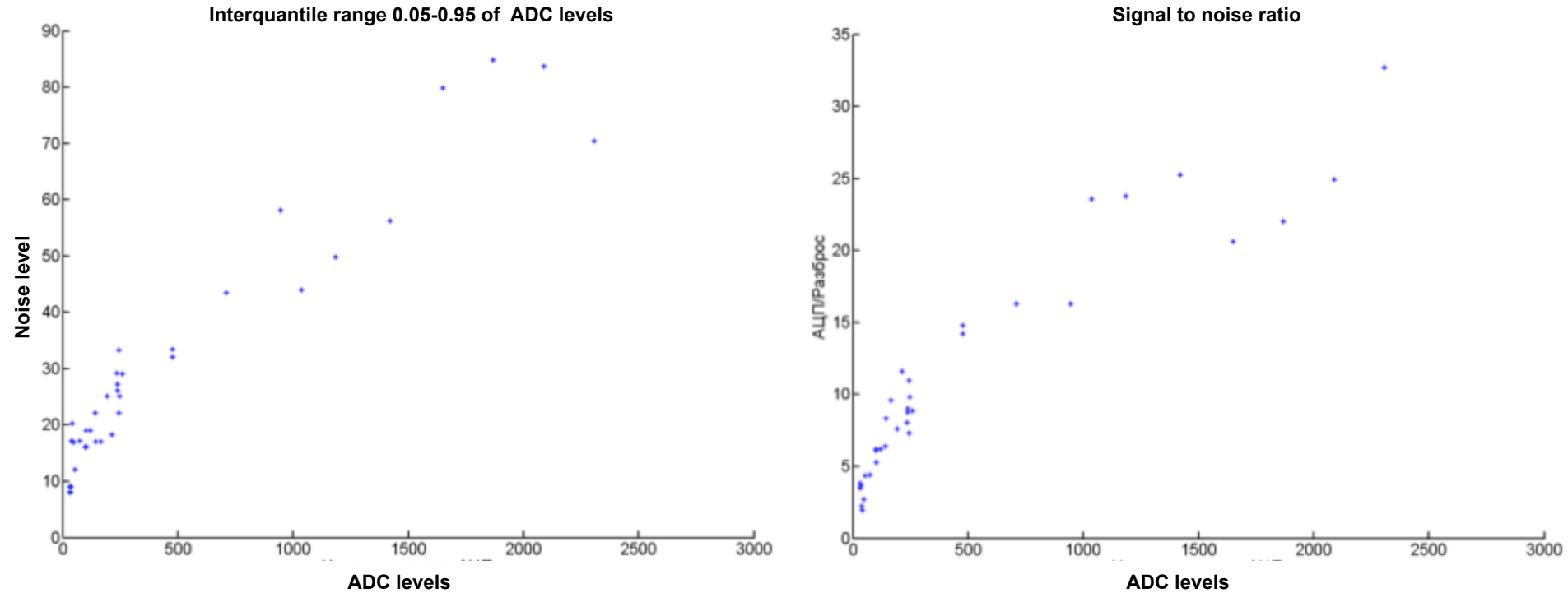


Sensor name	AisaEAGLET	CASI1500	Sokol-GCP (Сокол-ГЦП)	Reagent (Реагент)	Fregat (Фрегат)	RNKP.64.00. 00.00
Developer	Spectral Imaging Ltd., Finland	ITRES Research Ltd, Canada	FNCP OAO Krasnogorsky plant S.A.Zverev	ZAO Reagent, Moscow	NIU ITMO, S.Peterburg	NPO Lepton, Zelenograd, Moscow
Spectral range, nm	400-1000	380-1050	530-1000	450-900	400-1000	400-1000
Number of channels	410	288	105	106	70	287
Spectral resolution, nm	1.4	2.4	4.6-7.1	1.6-16	7	0.5-15
Binning	yes	yes	no	no	no	no
Calibration	yes	yes	yes		no	yes
Space resolution	0.33-0.4m/1km	0.4m/1km	0.75m/1km	1.4m/1km	1m/1km	0.56 m/1km
Span (pixels)	1600	1500	?	250	?	500
Bit capacity	12	14	14	14	?	12
Weight, kg	3.5 (10.5 all)	25 (43 all)	(50 all)	?	8	4.5
Power, W	100	?	250	?	10	7

Linearity range of the calibration

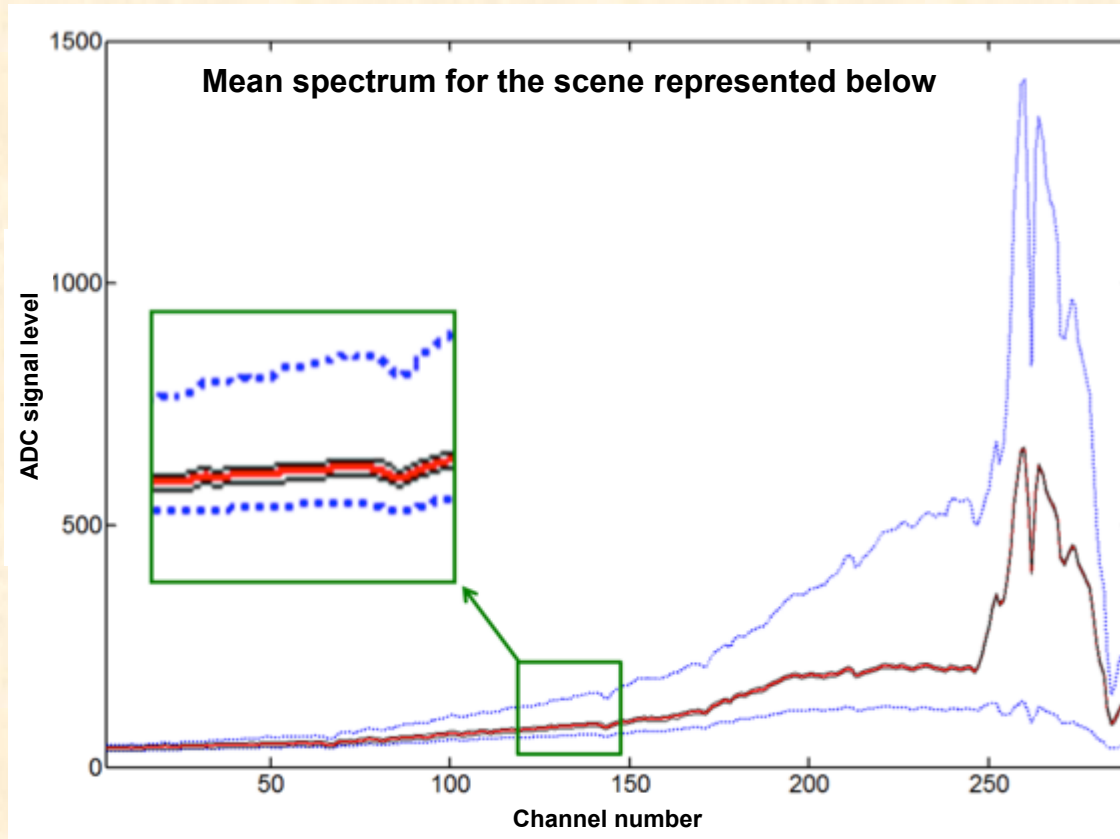


Effective number of grayscale levels



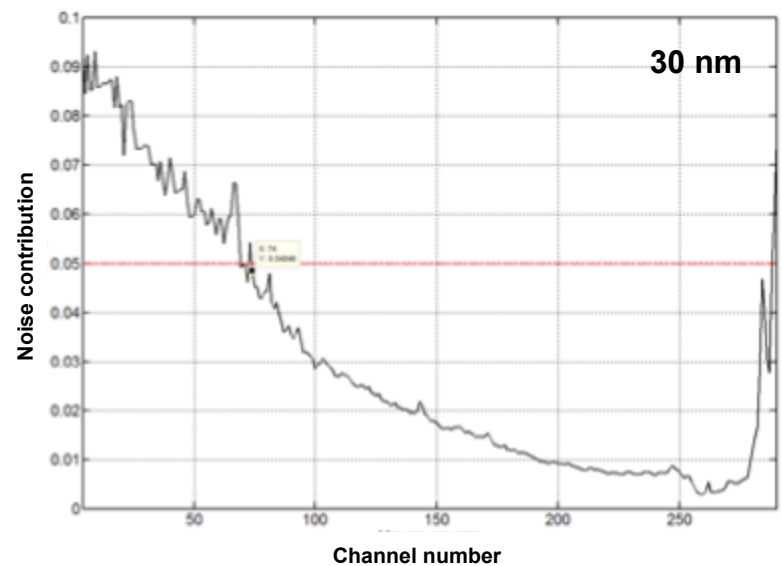
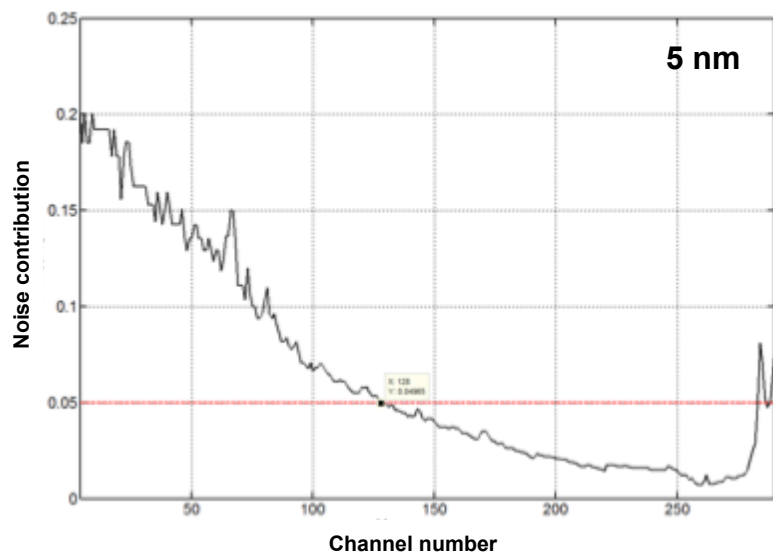
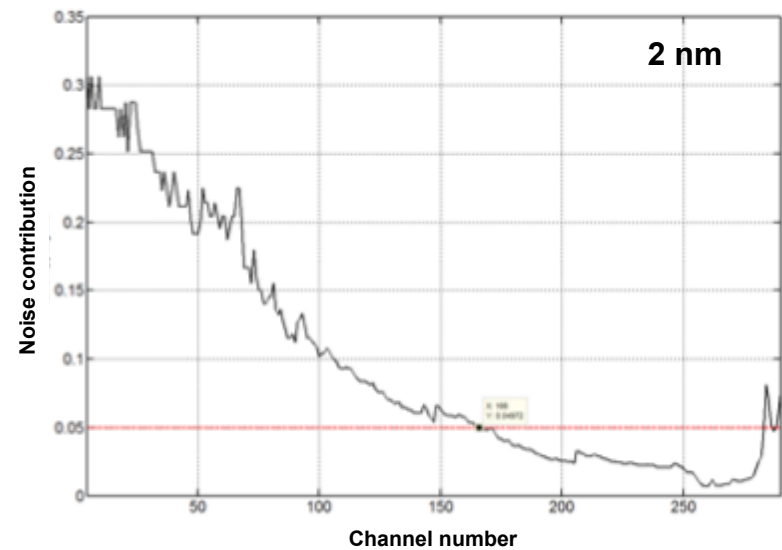
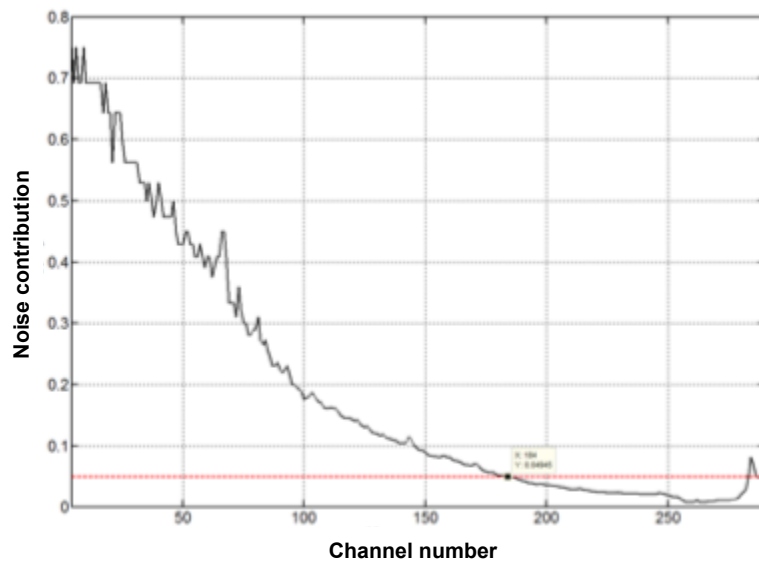
$N \sim 30$

Signal and noise ranges



Choice of the binning intervals

(reduction of the spectral resolution)



Software programs

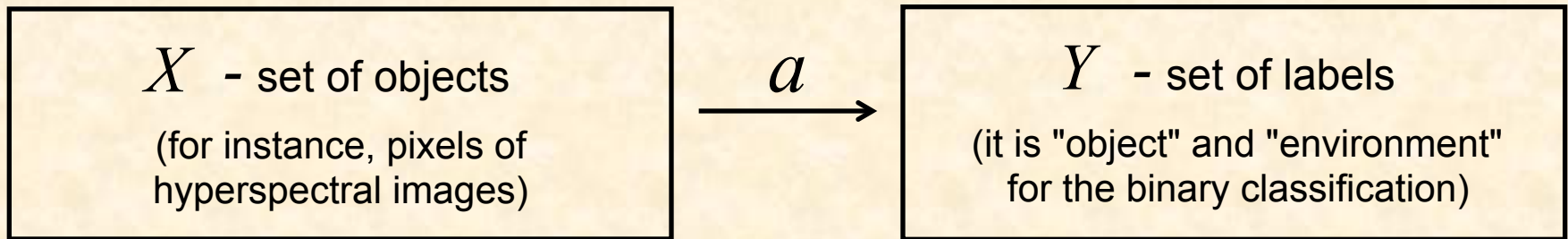
The developed software programs are designed for hyperspectral data processing using Matlab.

The main problems:

1. Access to 0-level data and primary digital correction.
2. Transformation of hyperspectral data.
3. Visualization and primary analysis.
4. Creating training sets.
5. Classification and pattern recognition.
6. Retrieval of biological and forest taxation parameters.

Pattern recognition: problem statement

(supervised version)



Our purpose is to create an algorithm $a : X \rightarrow Y$ performing a minimum of errors

In the case of the supervised classification, the algorithm is based on the minimizing error for the set $X^N = \{x(i), y(i)\}_{i=1}^N$ of known pairs of objects and labels.

In practice it is better to work with **features** - characteristics of objects, than directly with objects.

Probabilistic approach

Maximum likelihood principle

$$(x, y) \in X \times Y \longrightarrow p(x, y) = P(y)p(x | y)$$

The optimal algorithm corresponds to a minimum of the average risk function

$$R(a) = \sum_{y \in Y} \sum_{s \in Y} \lambda_{ys} P_y P(A_s | y)$$

where $A_s = \{x \in X \mid a(x) = s\}$, λ_{ys} - the loss function

As a rule the loss function has the form

$$\lambda_{ys} = \begin{cases} 0, & s = y, \\ \lambda(y, s) > 0, & s \neq y. \end{cases}$$

In particular, if $\lambda_{ys} = \begin{cases} 0, & s = y, \\ 1, & s \neq y, \end{cases}$ then $R(a)$ is the total probability of error of the algorithm $a(x)$

Bayesian decision rule

from general to specific

Bayesian classification algorithm (general form)

$$a(x) = \arg \min_{s \in Y} \sum_{y \in Y} \lambda_{ys} P_y p_y(x)$$

Classical form of Bayesian algorithm

$$\lambda_{ys} = \begin{cases} 0, & s = y, \\ \lambda(y), & s \neq y. \end{cases} \longrightarrow a(x) = \arg \max_{y \in Y} \lambda_y P_y p_y(x)$$

Principle of the maximum of *a posteriori* probability

$$\lambda_y \equiv 1 \longrightarrow a(x) = \arg \max_{y \in Y} P(y | x)$$

Due to the optimality property the Bayesian decision rule can be useful as a benchmark to test classifiers in the simulated data. Any other method can't be better than the Bayesian. The question is how worse is it.

Parzen window method

(non-parametric approach)

$$a(x) = \arg \max_{y \in Y} \lambda_y P_y p_y(x)$$

Normalized histogram

$$\hat{p}_h(x) = \frac{1}{m} \sum_{i=1}^m \prod_{j=1}^n \frac{1}{h_j} \delta \left(|x^j - x_i^j| < \frac{h_j}{2} \right)$$

where $\delta(A) = \begin{cases} 1, & \text{if } A \text{ occurs;} \\ 0, & \text{otherwise} \end{cases}$ - the indicator function.

Parzen-Rosenblatt estimate

$$\hat{p}_h(x) = \frac{1}{m} \sum_{i=1}^m \prod_{j=1}^n \frac{1}{h_j} K \left(\frac{x^j - x_i^j}{h_j} \right)$$

K - kernel: any continuous, limited in L_2 , even function, satisfying the condition $\int_X K(z) dz = 1$

Approximation of the probability density function

Examples of the kernel function ordered in ascending of smoothness

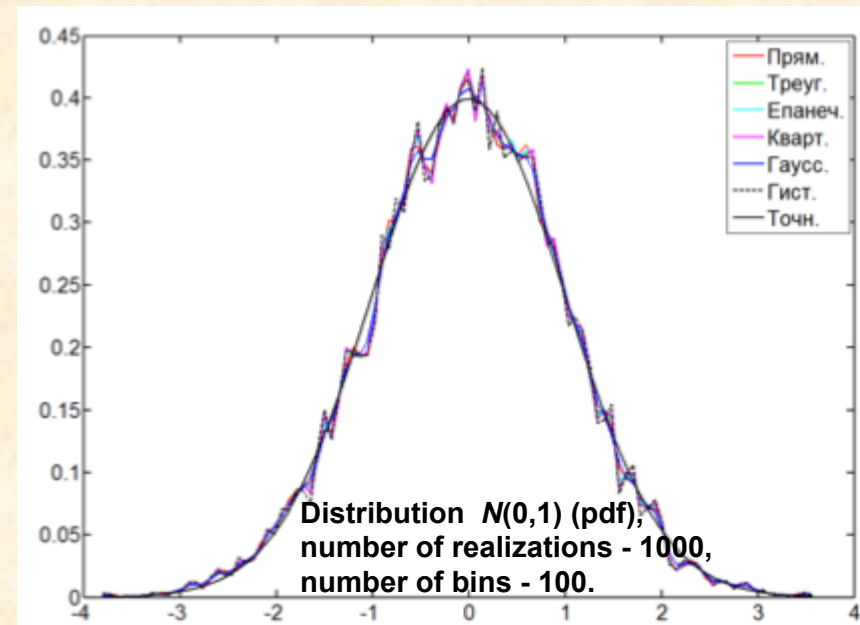
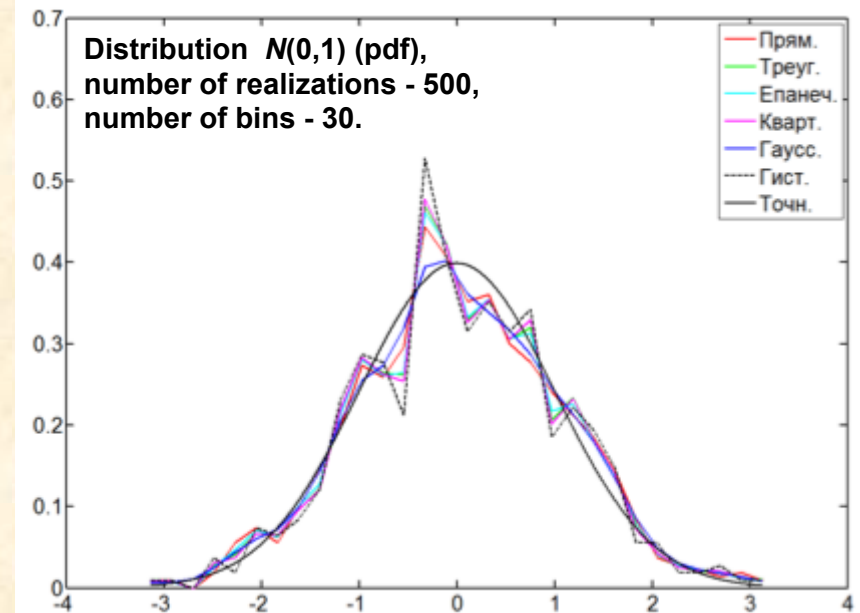
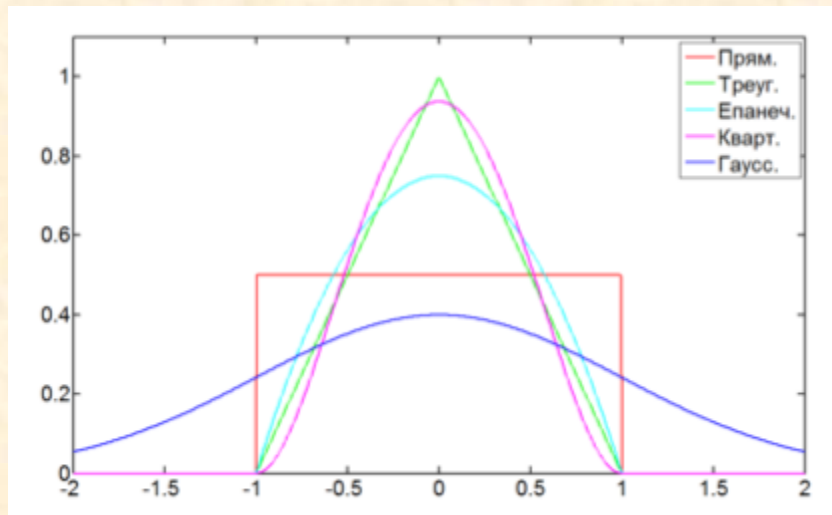
$$K(z) = \frac{1}{2} \delta(|z| \leq 1) \quad - \text{rectangular}$$

$$K(z) = (1 - |z|) \delta(|z| \leq 1) \quad - \text{triangular}$$

$$K(z) = \frac{3}{4} (1 - z^2) \delta(|z| \leq 1) \quad - \text{Epanechnikov}$$

$$K(z) = \frac{15}{16} (1 - z^2)^2 \delta(|z| \leq 1) \quad - \text{quartic}$$

$$K(z) = \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{z^2}{2}\right) \quad - \text{Gaussian}$$



Normal Bayesian classifier

(parametric approach)

Multiclass algorithm

$$a(x) = \arg \max_i \left(\ln(P(x \sim D_i)) - \frac{1}{2}(x - m_i)^T C_i^{-1}(x - m_i) - \frac{1}{2} \ln(\det(C_i)) \right) \quad \begin{matrix} D_i = N(m_i, C_i), \\ i \in 1, 2, \dots, n \end{matrix}$$

Likelihood ratio test

$$D_1 = N(m_1, C_1) \Leftrightarrow D_2 = N(m_2, C_2)$$

$$\delta_c(x) = \begin{cases} T(x) < t & \rightarrow x \sim D_1, \\ T(x) \geq t & \rightarrow x \sim D_2, \end{cases}$$

$$T(x) = \ln \left(\frac{f_2(x)}{f_1(x)} \right) \quad t = \ln \frac{P(x \sim D_1)}{P(x \sim D_2)}$$

quadratic $C_1 \neq C_2$

$$F = x^T Q x + Lx + K$$

$$Q = C_2^{-1} - C_1^{-1} \quad L = 2(m_1^T C_1^{-1} - m_2^T C_2^{-1})$$

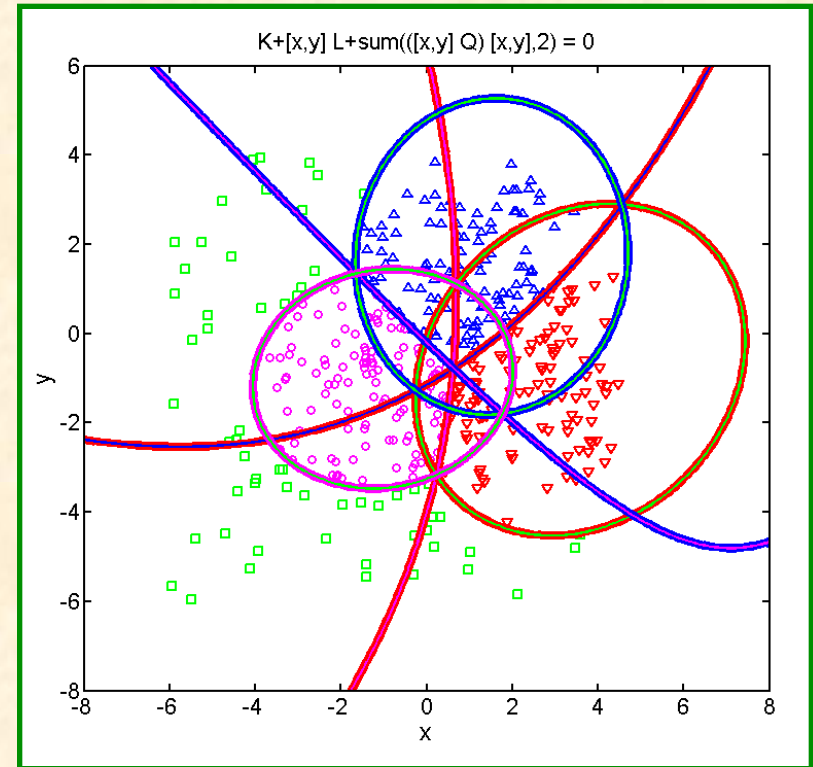
$$K = 2t + \ln \left(\frac{\det C_2}{\det C_1} \right) + m_2^T C_2^{-1} m_2 - m_1^T C_1^{-1} m_1$$

linear $C_1 = C_2 = C$

$$F = Lx + K$$

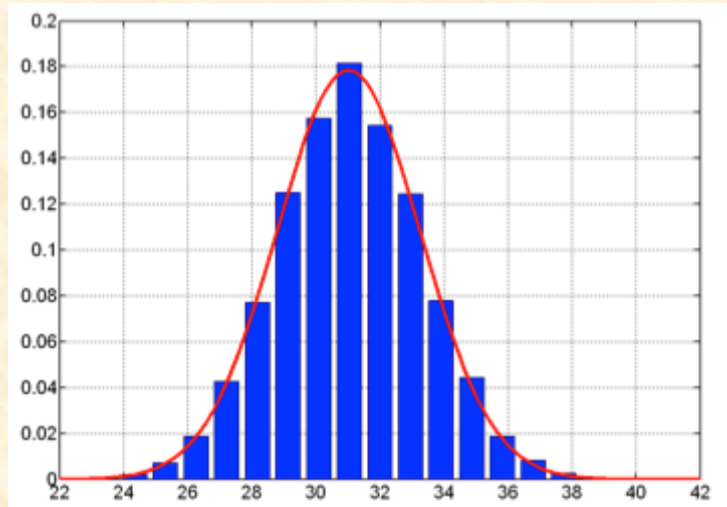
$$Q = 0 \quad L = 2(m_1 - m_2)^T C^{-1}$$

$$K = 2t + m_2^T C^{-1} m_2 - m_1^T C^{-1} m_1$$

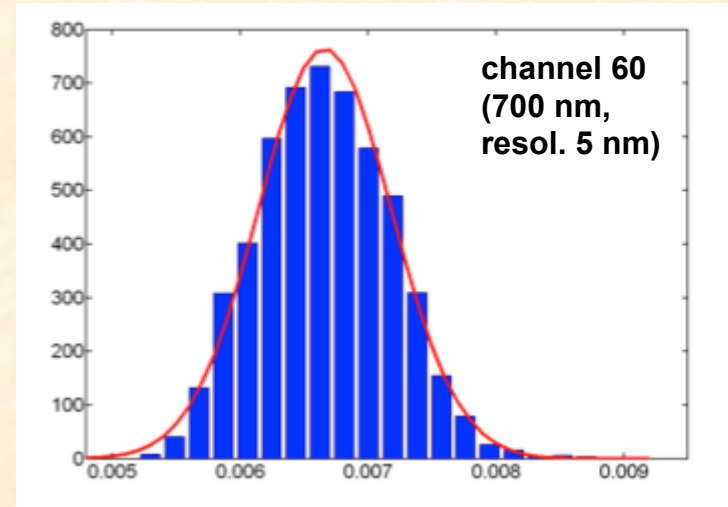


Histograms of the spectral radiance

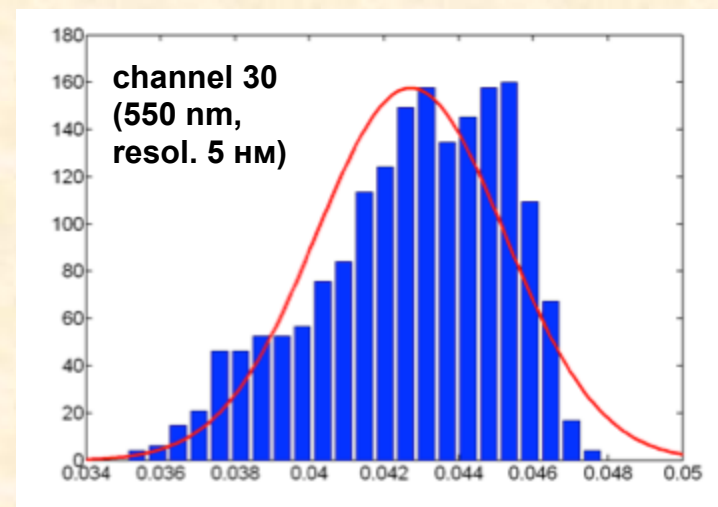
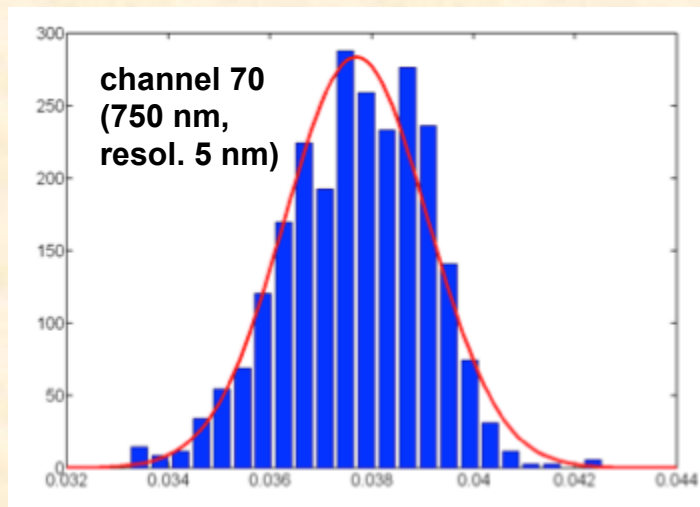
Noise of the instrument



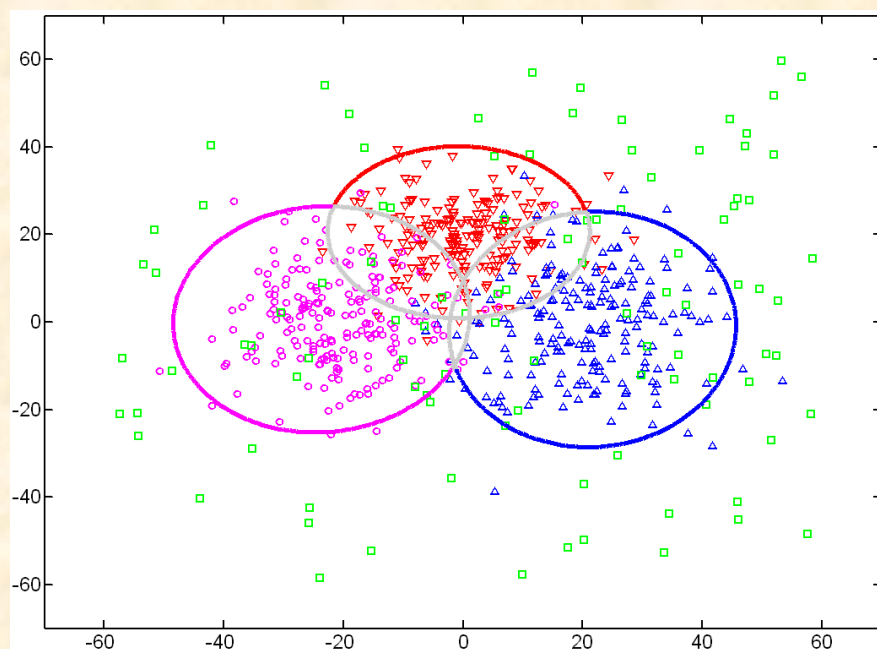
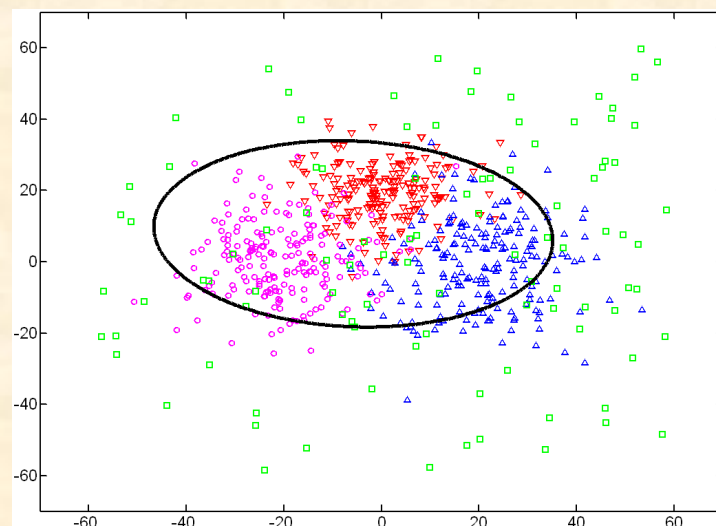
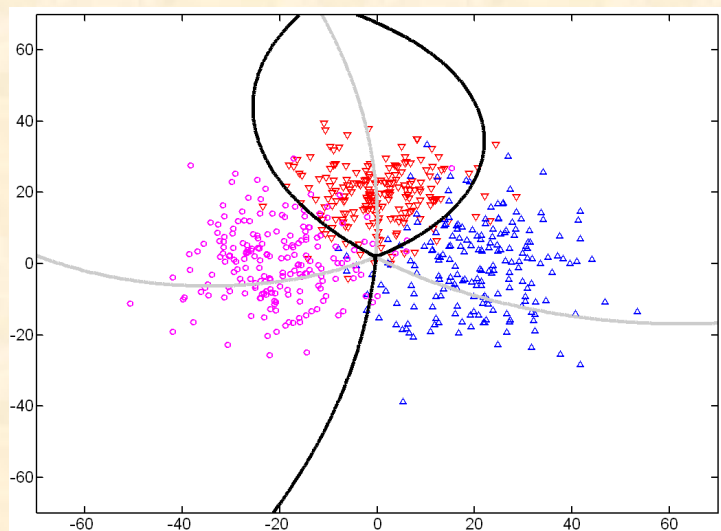
Water surface, Tvertza



Asphalt surface (Zmeevo airport)

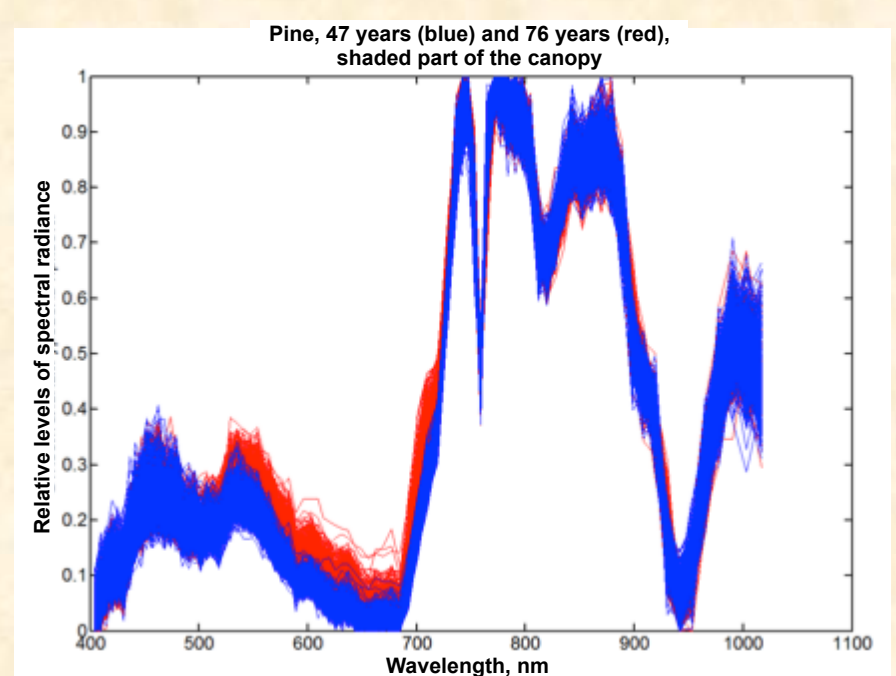
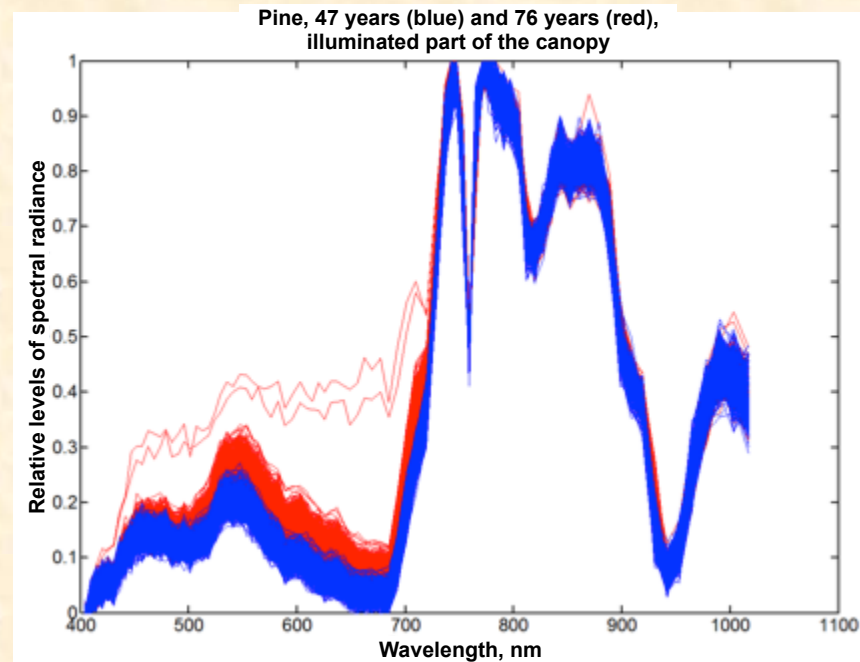
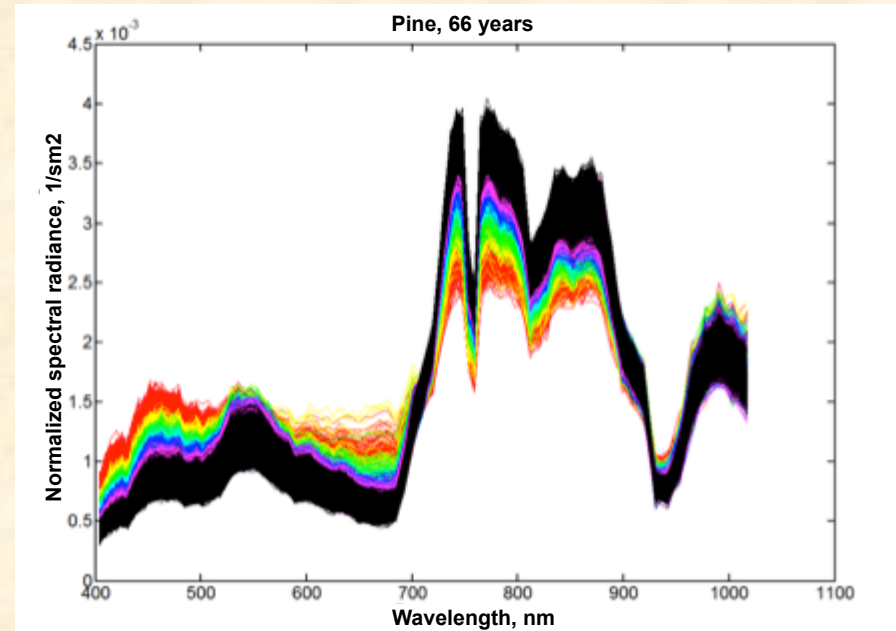
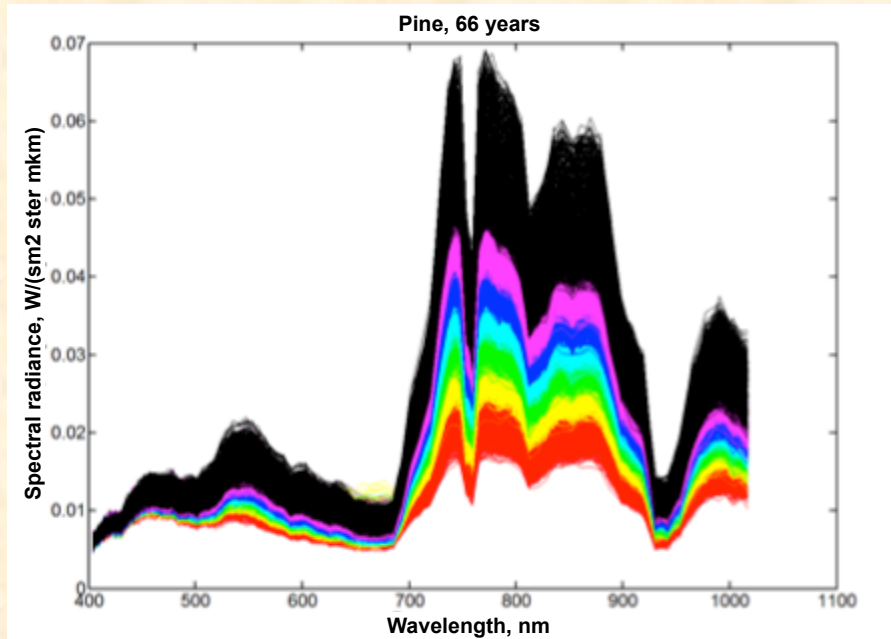


Processing of compound classes



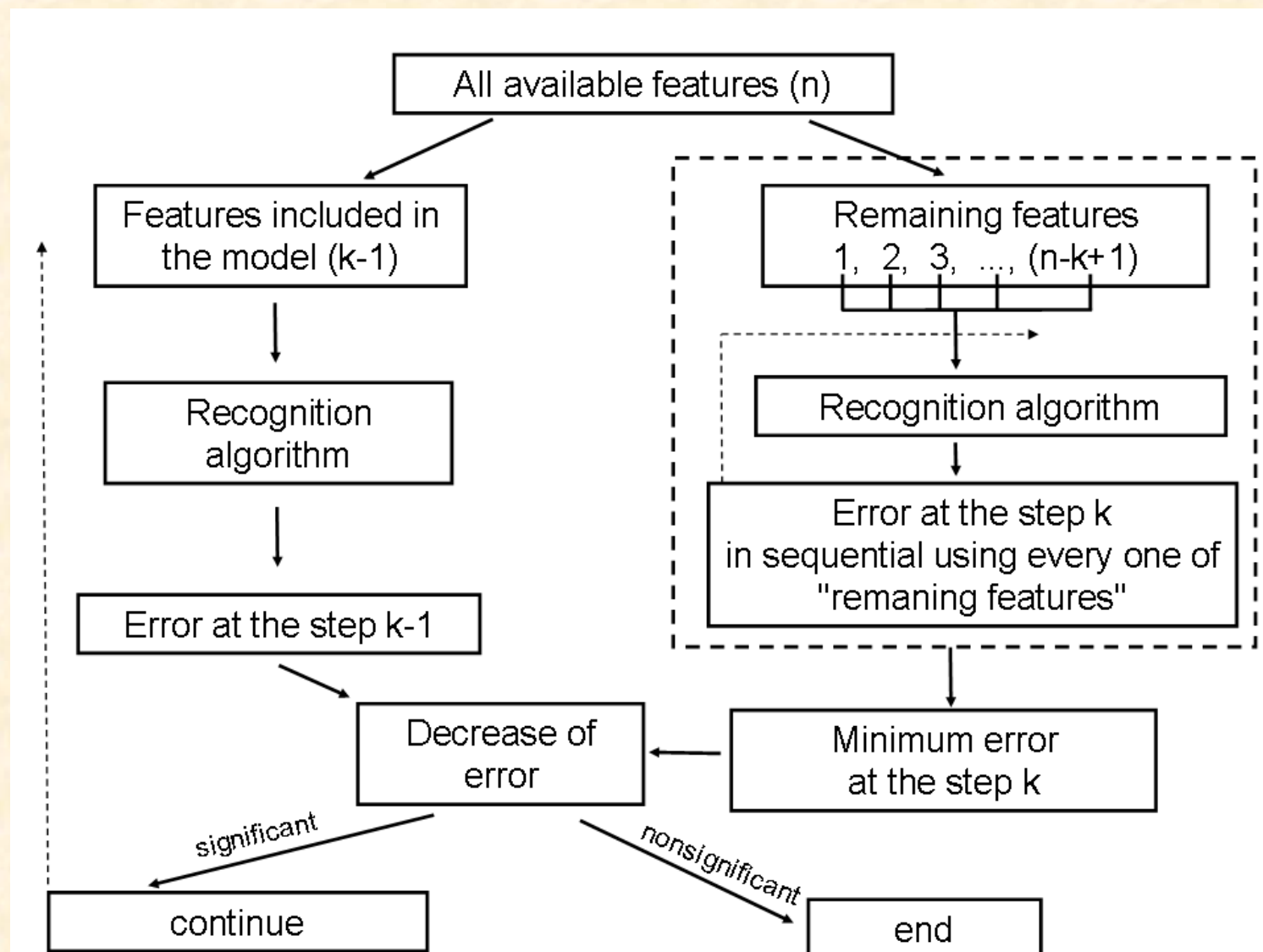
□ - uniform random
number generator

Clustering spectral radiances of the forest canopy



Finding informative features (1)

(step up algorithm)



Finding informative features (2)

Removing channels with strong
radiometric perturbations

Channels for well distinguished objects: water, soil,
vegetation
(classification accuracy ~ 0)

Channels for the classification of types the objects:
water types (open water, rivers, pit, soil...)
soil types (sandy, clayey, chernozem, peaty,...)
vegetation type (grass, conifer, deciduous...)

Channels for classification of the parameters badly
distinguished from spectral feature:
age of forest trees

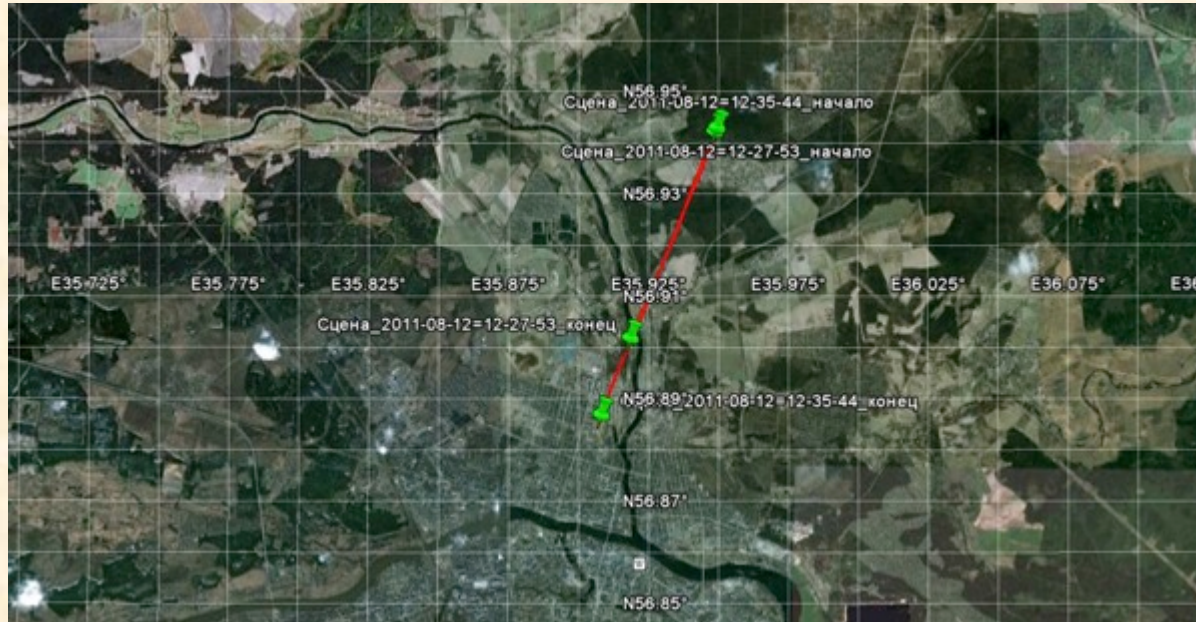
Most informative spectral channels

water	55	42	10	32	6	50	34	48	39	61							
soil	55	4	53	1	23	5	32	42	81	33	3	52	11	8	34	24	44
asphalt	55	22	3	52	51	75	20	81	24	7	1	74	25				
grass	55	36	15	20	81												
forest species, illuminated canopy	55	7	36	52	51	38	81	47	41	53	86	37					
forest species, half-shaded canopy	55	2	36	3	53	29	28	35									
forest species, shaded canopy	55	66	37	53	52	57	31	79	29	21							
age, pine, illuminated canopy	55	51	81	17	44	27	53	52	57	68	46	18	79	1	74	24	2
age, birch, illuminated canopy	55	27	18	46	52	49	33	6	69	68	35	66	44				

Number of channel	2	3	4	7	10	15	18	22	27	36	37	42	55	66	81
Wavelength, nm	409.45	414.73	420.01	436.09	451.81	478.95	495.93	518.35	547.41	602.89	609.12	636.71	736.58	804.37	941.27

Stability of the recognition results

(processing of two different overlapping hyperspectral images, Zmeevo airport zone, Tver region)



Zmeevo1 : 2011-08-12 12-27-53



Zmeevo2 : 2011-08-12 12-35-44

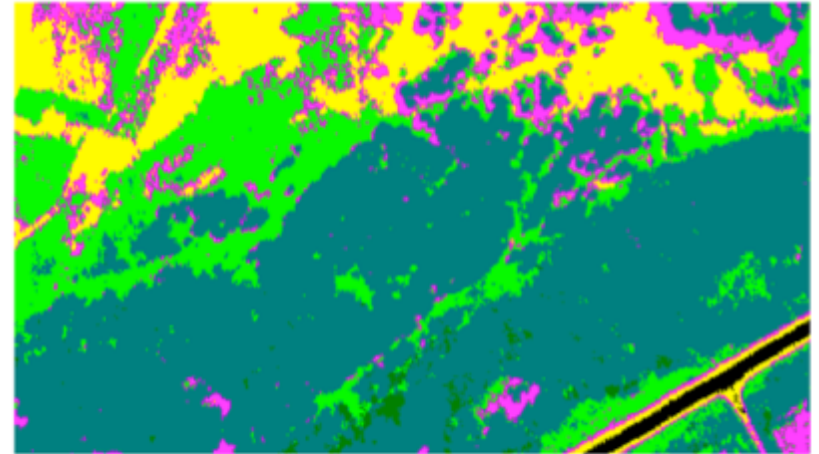


Classification of overlapping images (1)

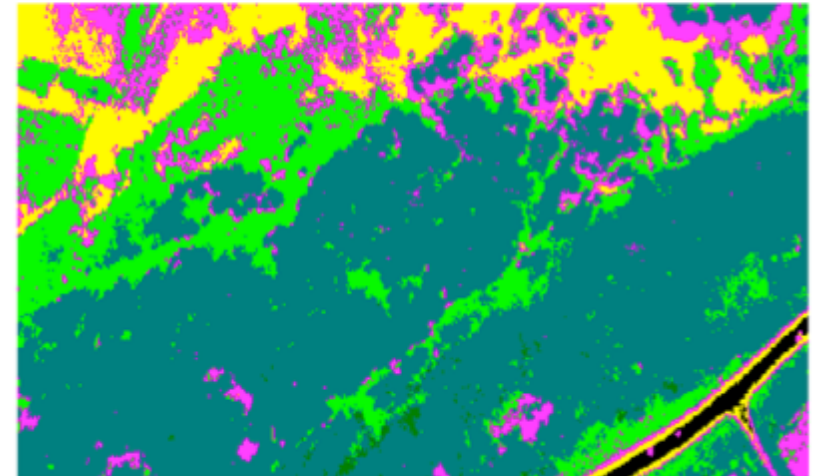
scene containing open soils, grassland and forest vegetation



Zmeevo1



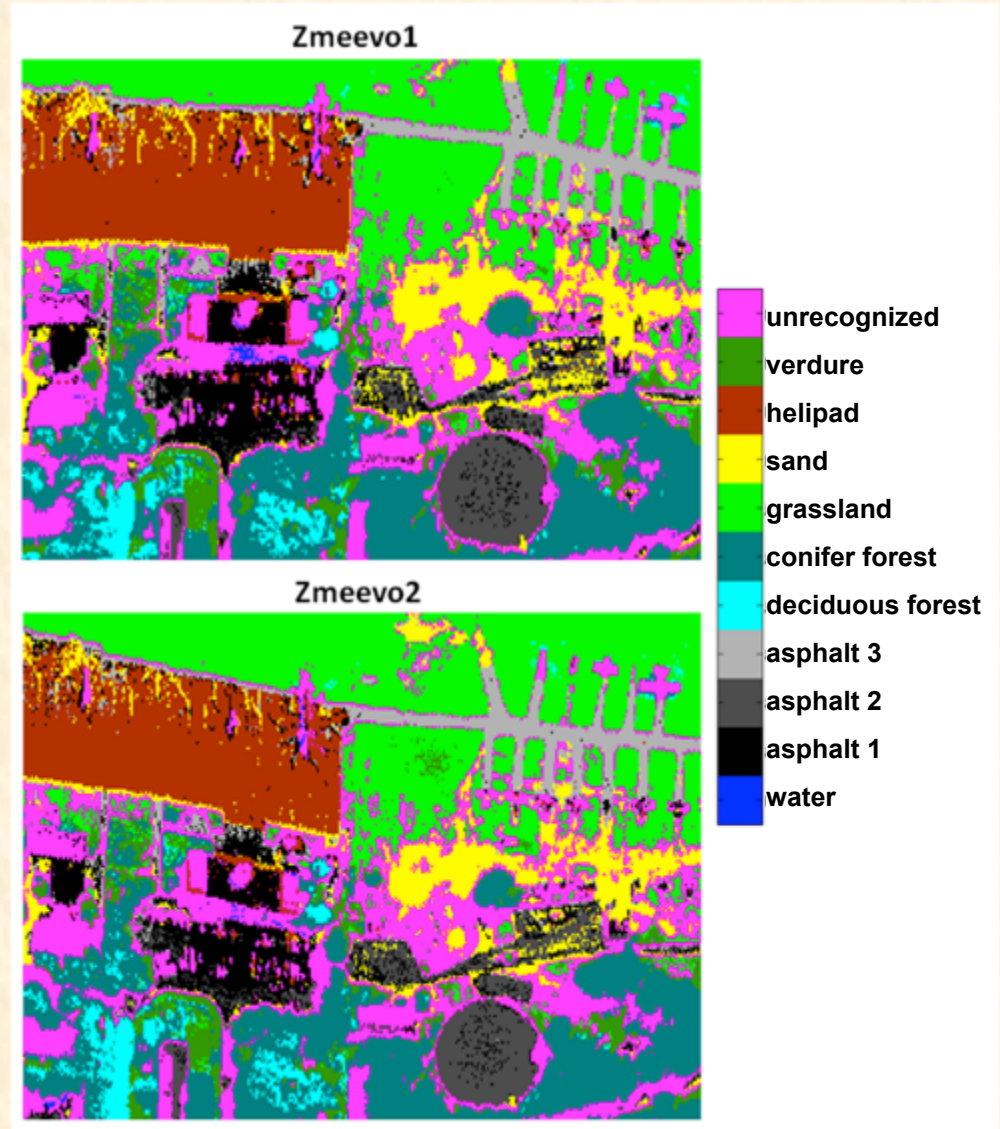
Zmeevo2



water	asphalt	forest	grassland	sand	verdure	unrecogn.
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Classification of overlapping images (2)

scene containing a variety of man-made objects (airport zone)

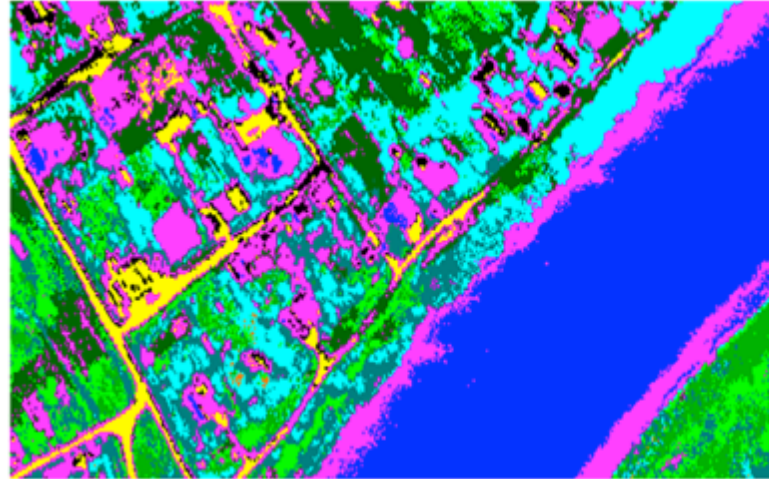


Classification of overlapping images (3)

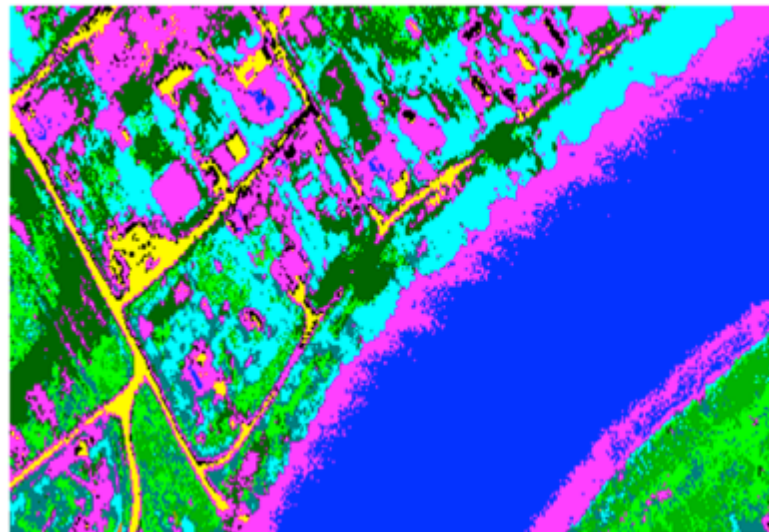
scene containing water object (Tvertza)



Zmeevo1



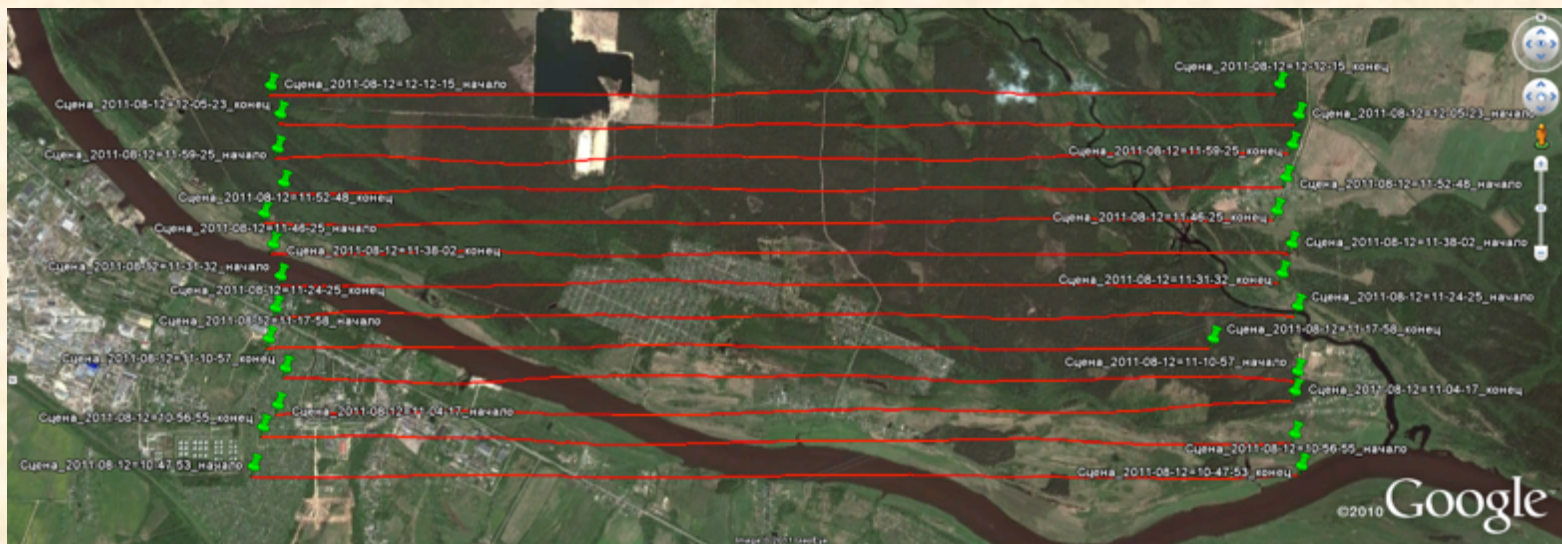
Zmeevo2



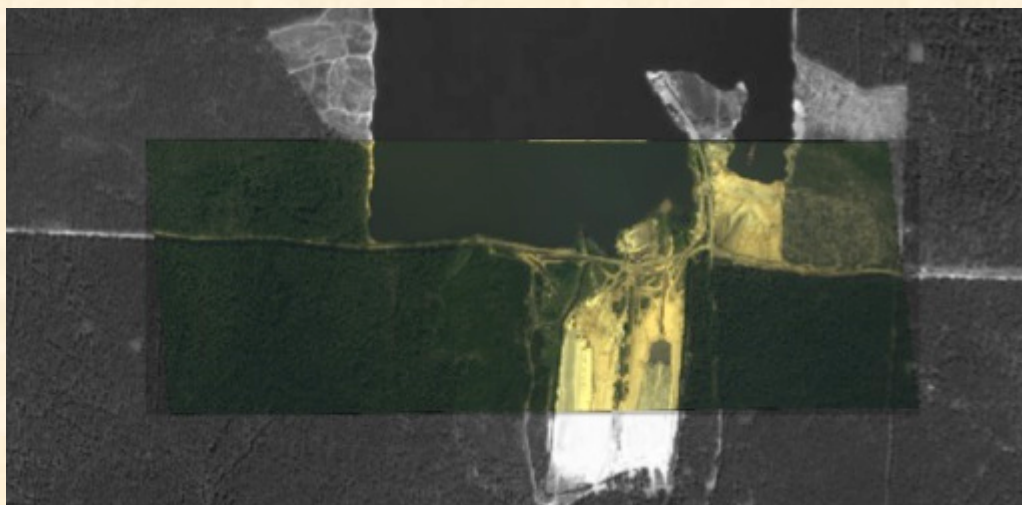
- unrecognized
- verdure
- sand
- grassland 3
- grassland 2
- grassland 1
- conifer forest
- decid. forest
- asphalt
- water

Series of flights over Savvatyevskoe forestry

RGB



Registration with Google Earth images



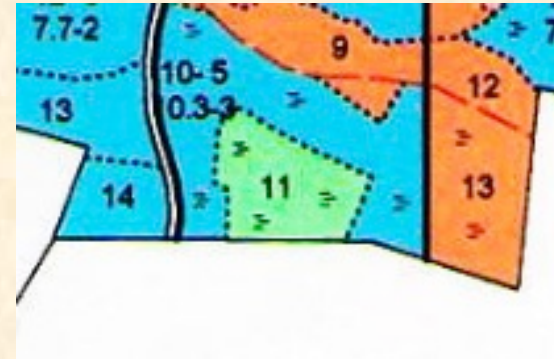
Recognition of tree species (1)

Savvatyevskoe forestry (area near gardens)

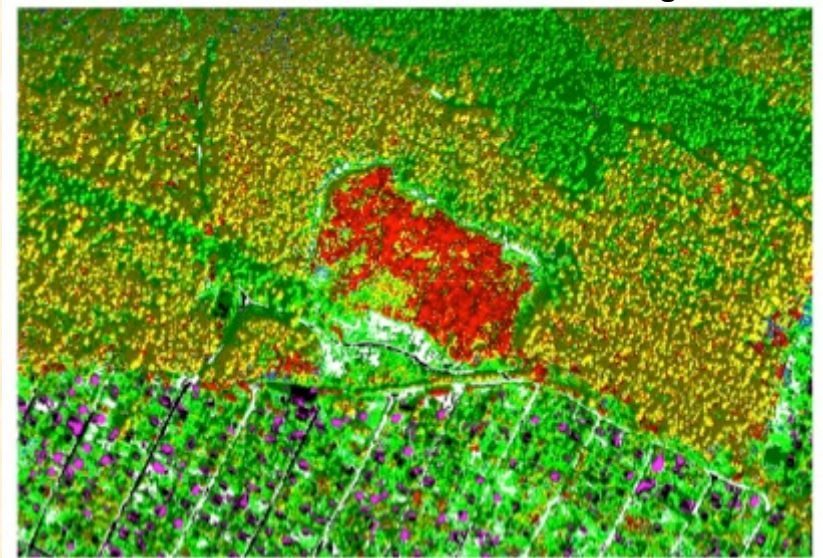
RGB



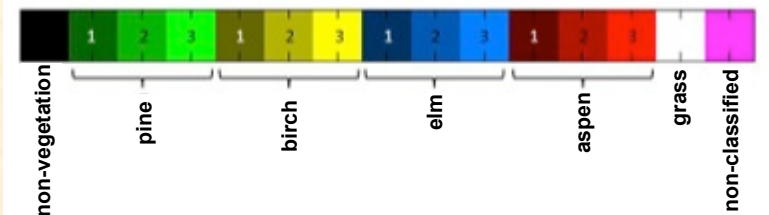
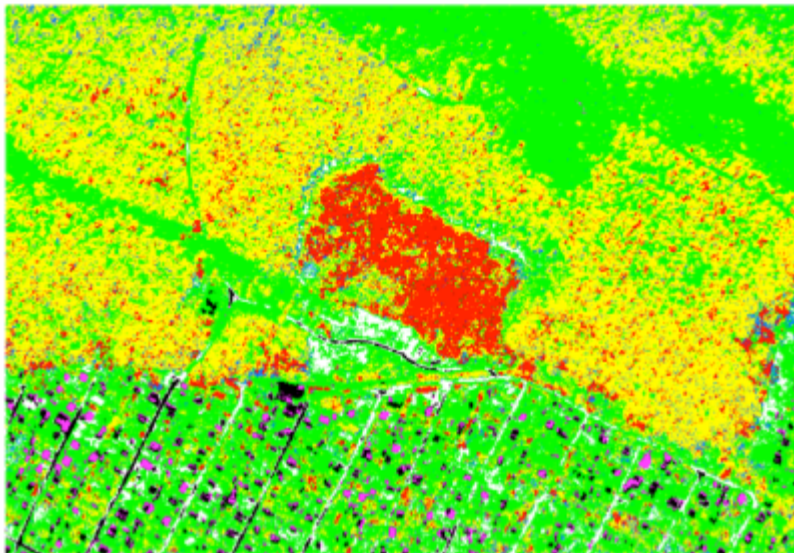
Forest taxation map



Classification with the use of illumination gradation



Tree species recognition results



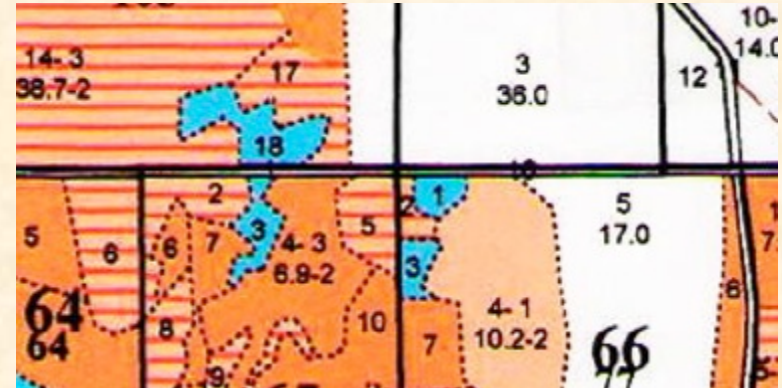
Recognition of tree species (2)

Savvatyevskoe forestry (area near sandpit)

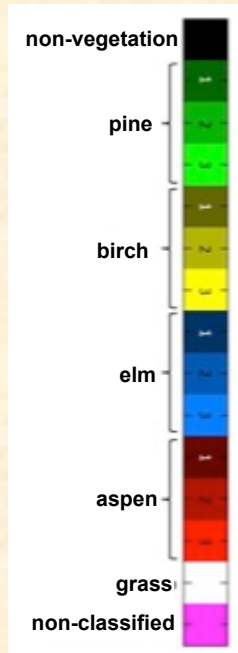
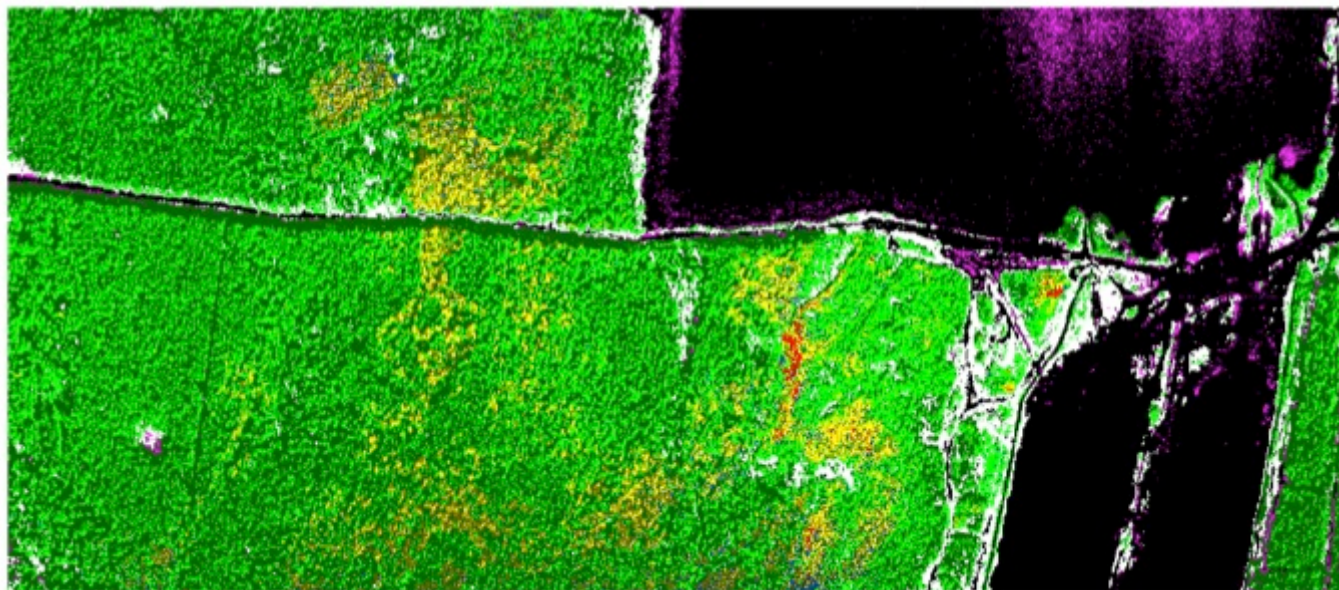
RGB



Forest taxation map



Classification with the use of illumination gradation



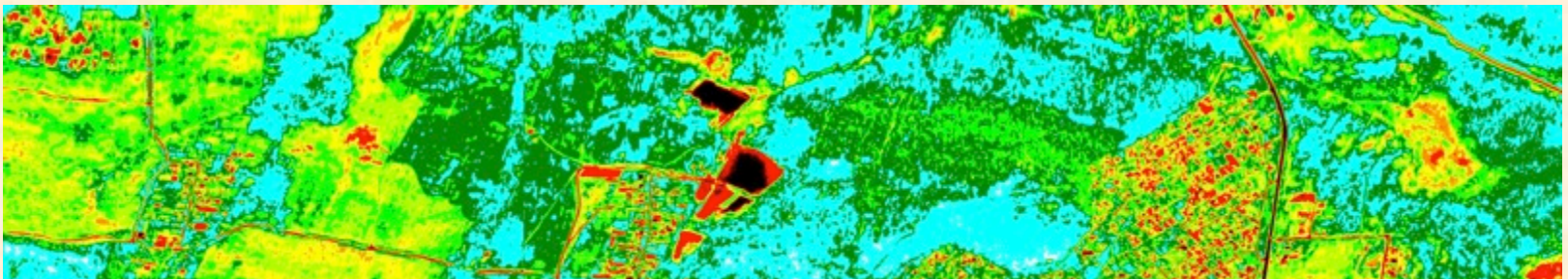
Retrieval of biological productivity parameters

(Why do we need something more than vegetation indexes?)

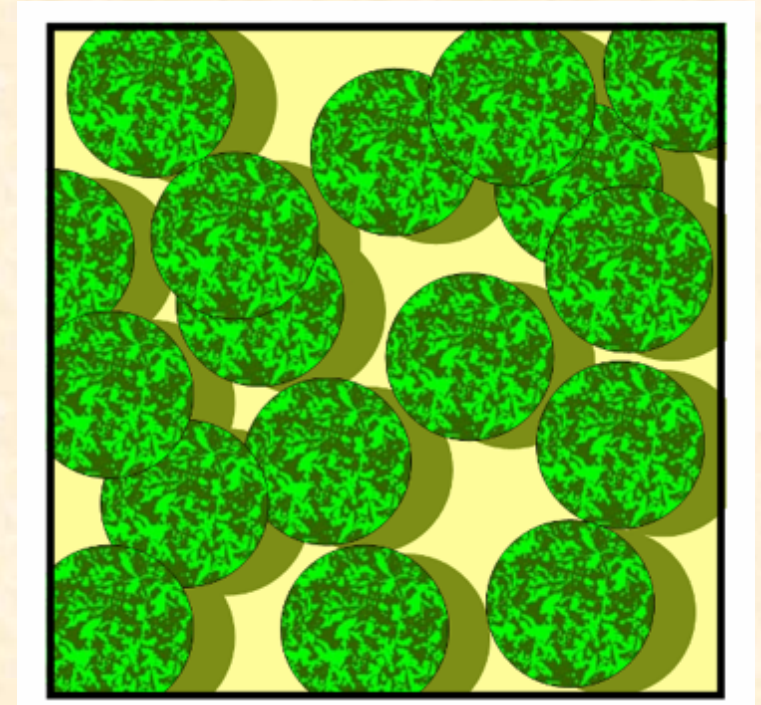
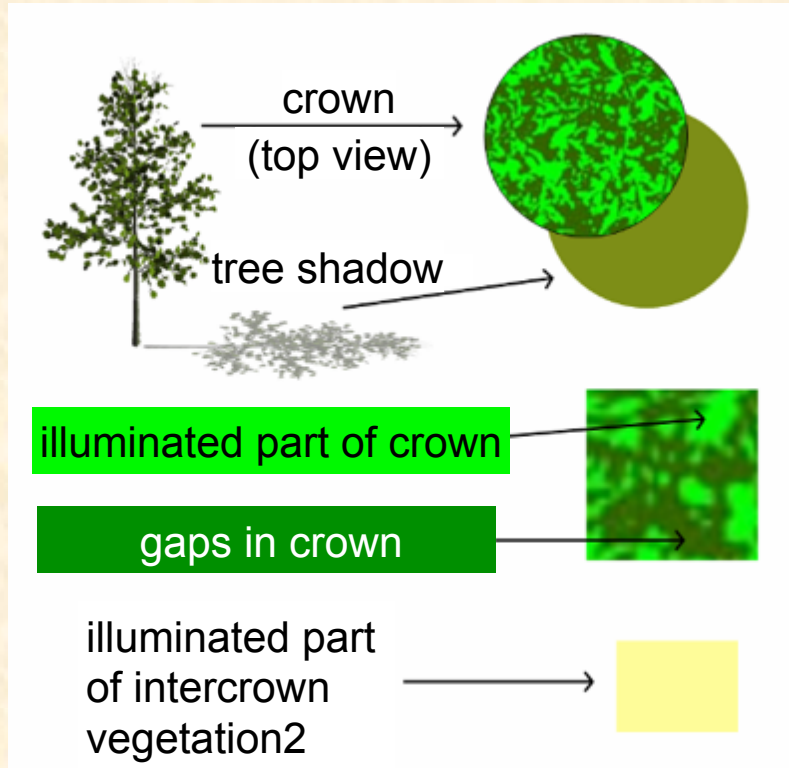
RGB



$$NDVI = \frac{NIR - RED}{NIR + RED}$$

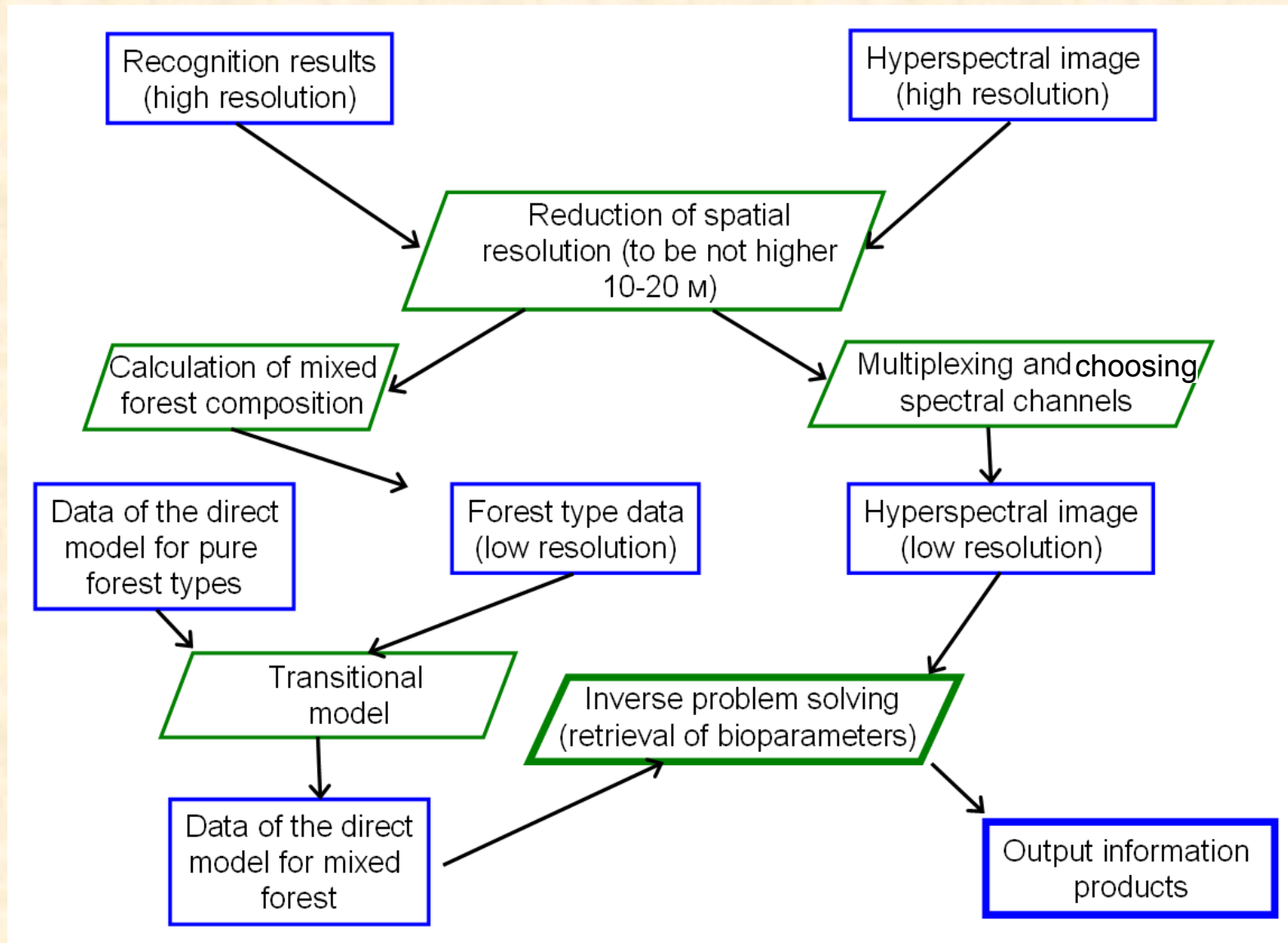


Modeling reflected spectral radiance (forest)



$$L(\lambda, D_{canopy}, D_{crown}) = \left\{ \left[E(\lambda)(1 - D_{canopy} - \delta_1) + H(\lambda)\delta_1 \right] \rho_1(\lambda) + \right. \\ \left. + \left[E(\lambda)(D_{canopy}D_{crown} - \delta_2) + H(\lambda)\delta_2 \right] \rho_2(\lambda) + E(\lambda)D_{canopy}(1 - D_{crown})\rho_3(\lambda) \right\} \tau_a(\lambda) + L_b(\lambda),$$

Scheme of retrieval of bioparameters from hyperspectral data



User interface of the software for retrieval of biological productivity parameters

Retrieval of bioparameters

Hyperspectral data

Channel order (BSQ format)

Swath order (BIP format)

Information file

Central wavelengths

Spectral radiance modeling

☒ use standard data

Solar angle: zenith azimuth

☐ use external data

Viewing angle

zenith azimuth

☐ load angle distribution file

Forest type classification

☒ NDVI classification

☐ Green-Red-NIR classification

☐ External classification data

Tree species

Select all

Unselect all

birch
maple
aspen
ash
pine
spruce

Data adjustment

☒ adjust model data

Folder with tree species samples

Atmospheric correction

☐ Auto

☒ Manual (type)

☐ Manual (parameters)

Atm. transp.

Haze

Inverse problem solving

Partial solution (search method)

Global solution (joining method)

Scale

Visualization of the results

Color bar setting

min max

number of colors

Param. name

Scale H Scale V

☐ Flip UD ☒ Flip LR ☒ Show axes

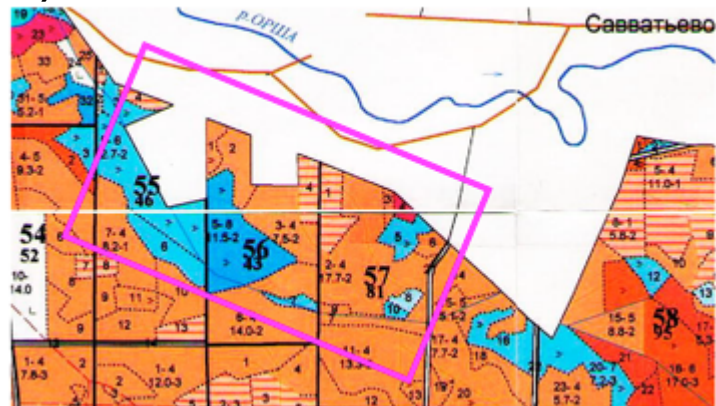
other objects

Recognition using different spectral resolution (quadratic discriminant)

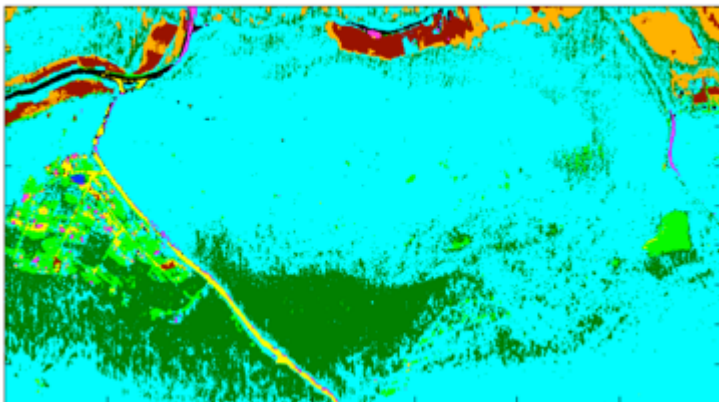
a)



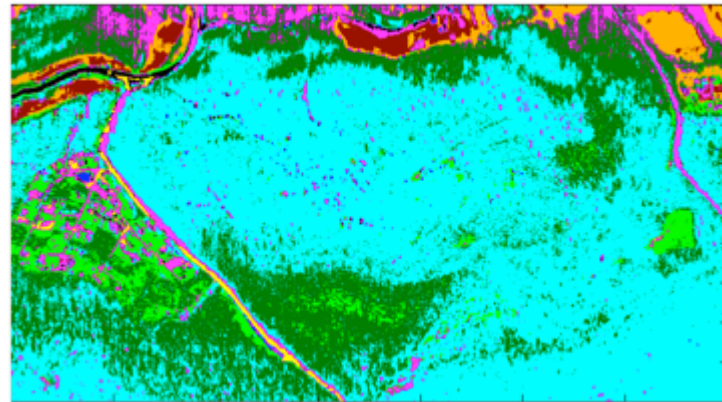
b)



c) hyperspectral

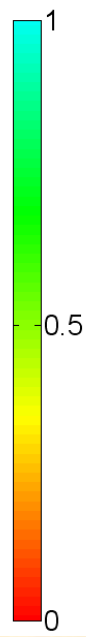
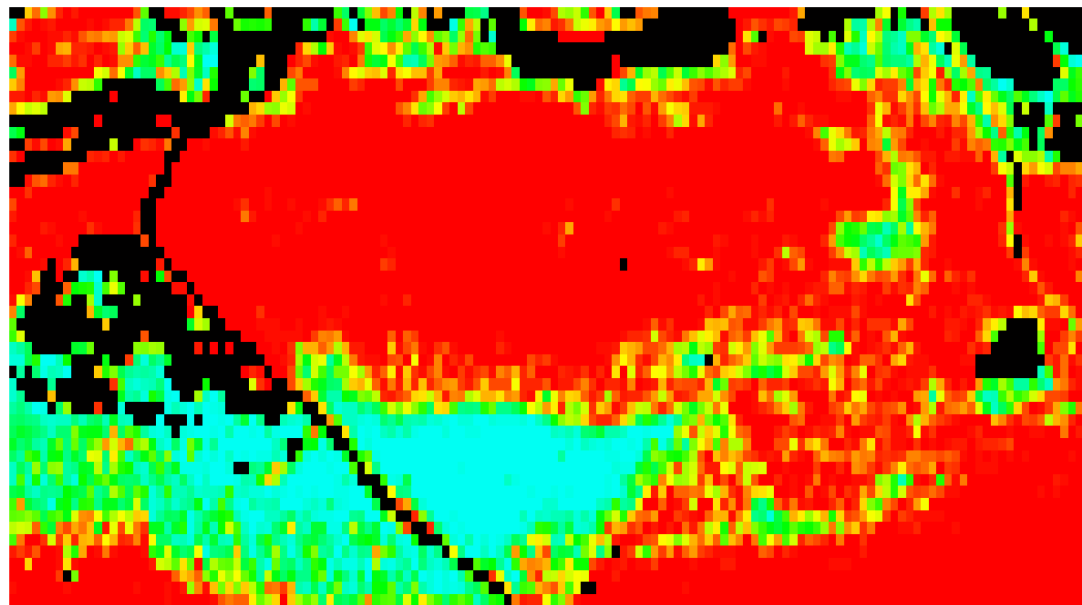


d) multispectral



(a) – RGB; (b) – forest taxation map, blue – predominance of birch, orange – predominance of pine; (c) – results of recognition, 48 channels (resolution 10 nm); (d) – results of recognition 6 channels (resolution 100 nm). Colours for (c) and (d): blue – water, black – asphalt, yellow – sand, dark red – open soils, orange – grass, light green – young birch forest, dark green – mature birch forest, cyan – mature pine forest, violet – others.

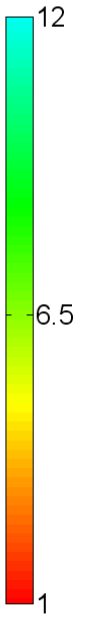
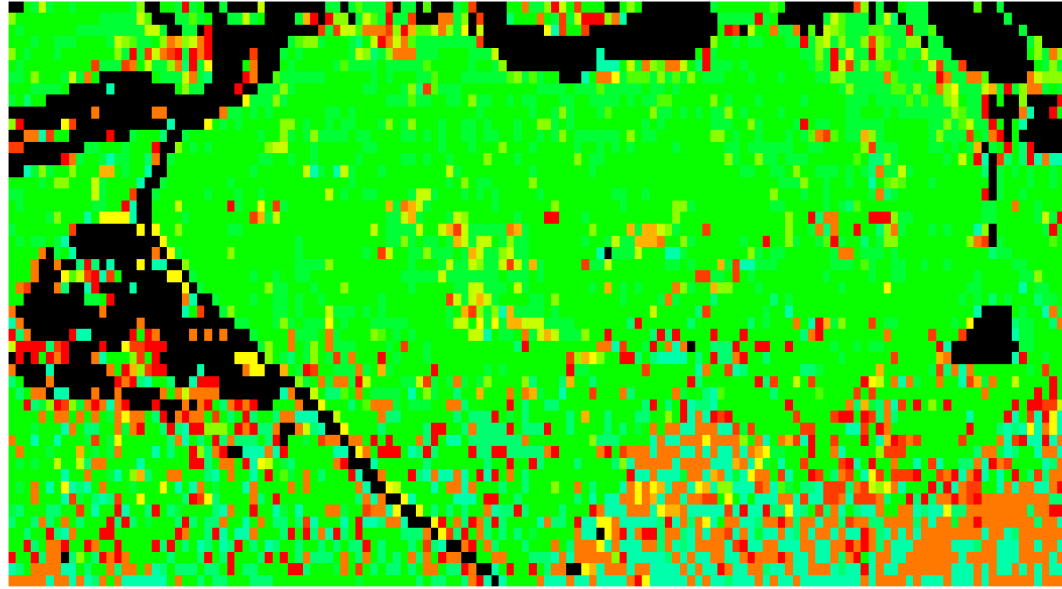
Forest type



conifer

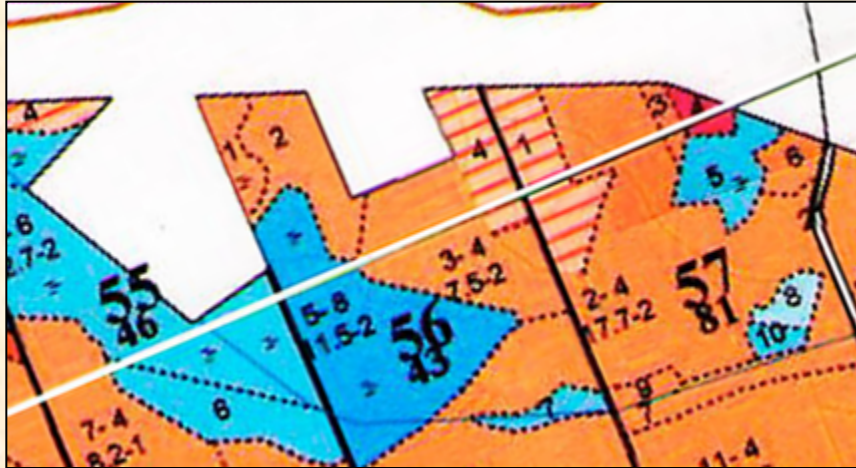
deciduous

Intercrown vegetation type

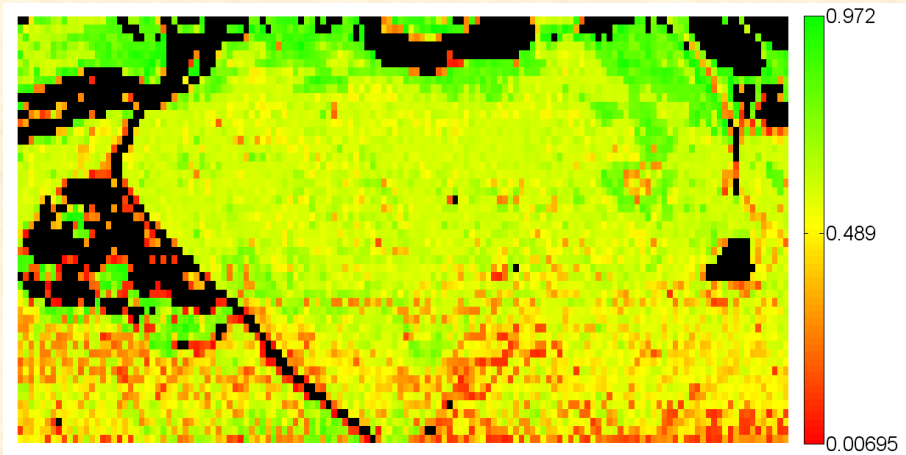


Growing density characteristics retrieval

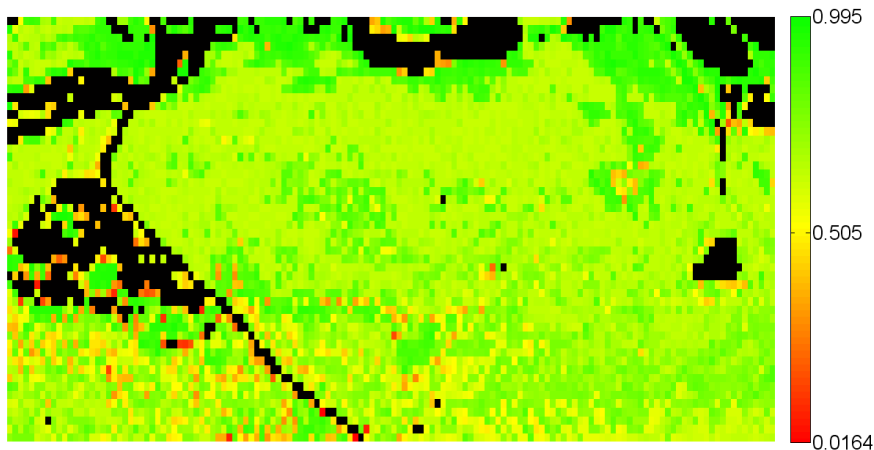
Forest taxation map



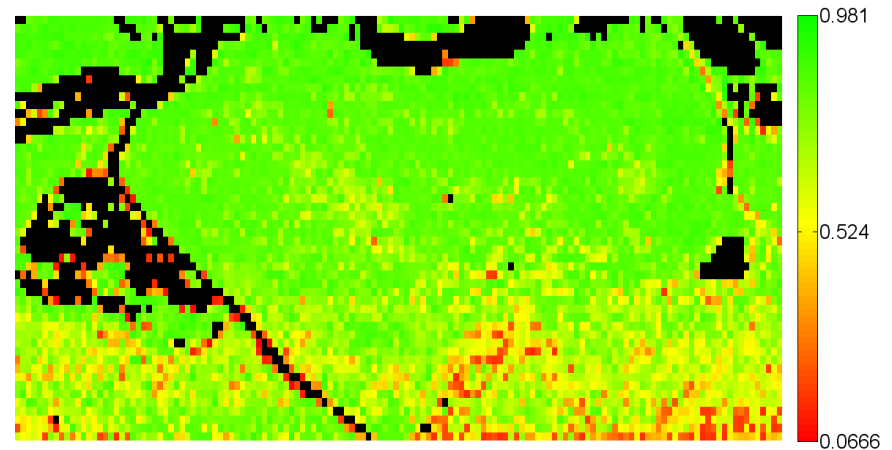
Projective cover



Density of canopy



Density of crown



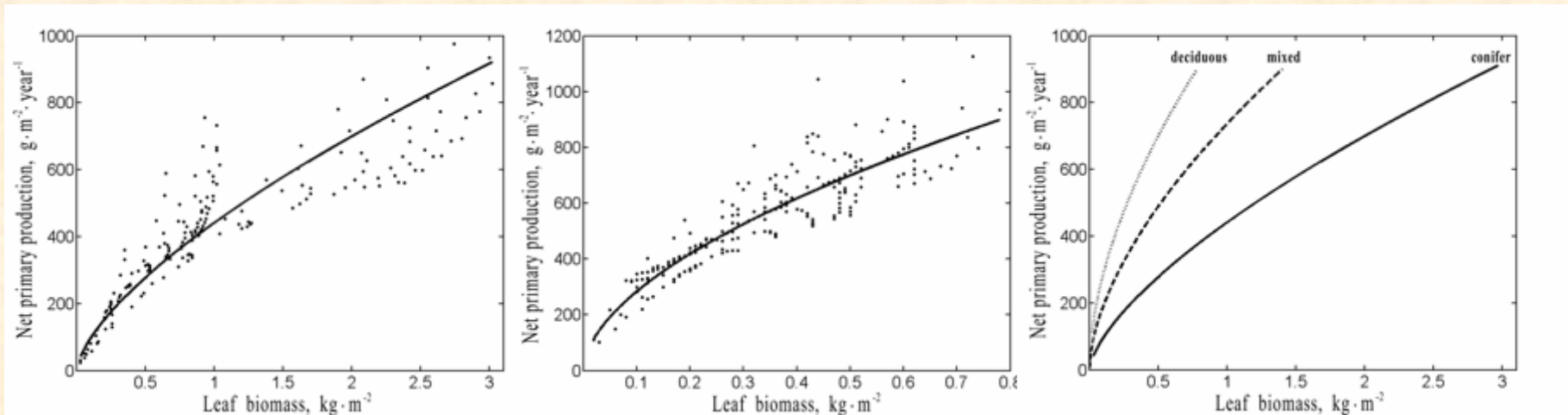
Black color means not-forest objects

Net Primary Production (NPP) is a mass of carbon absorbed by plants from the atmosphere in a unit area in unit time less the respiration.

Parameterization of NPP as a function of leaf biomass

$$Y = (1 - W) \left(\frac{X}{B_{deciduous}} \right)^{A_{deciduous}} + W \left(\frac{X}{B_{conifer}} \right)^{A_{conifer}}$$

Y – NPP (g/m²/year), X – biomass (t/ha), W – portion of conifer trees in the forest, A and B – fitted parameters (A<1). The parameterization is constructed using the data provided by Moscow State University of Forest. The data are specific for the vegetation of East European part of Russia.



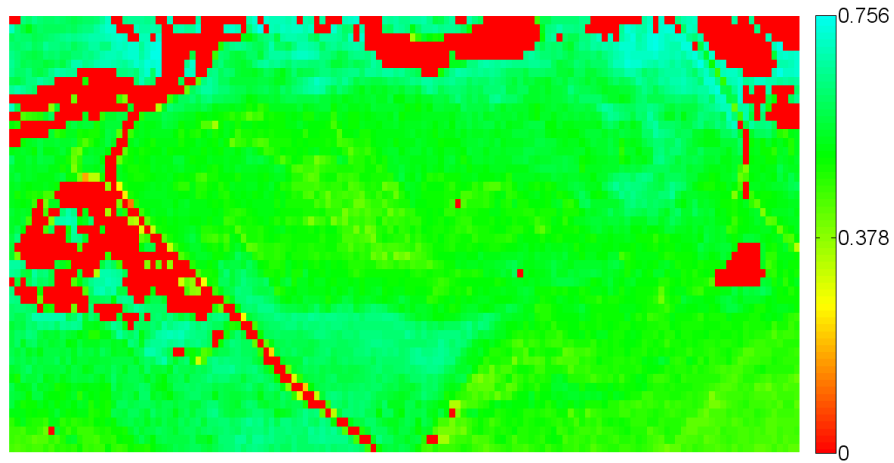
Estimating of **Fraction of Absorbed Photosynthetically Active Radiation (FAPAR)**

$$FAPAR = A * F * [1 + R * (1 - (1 - T) * F)]$$

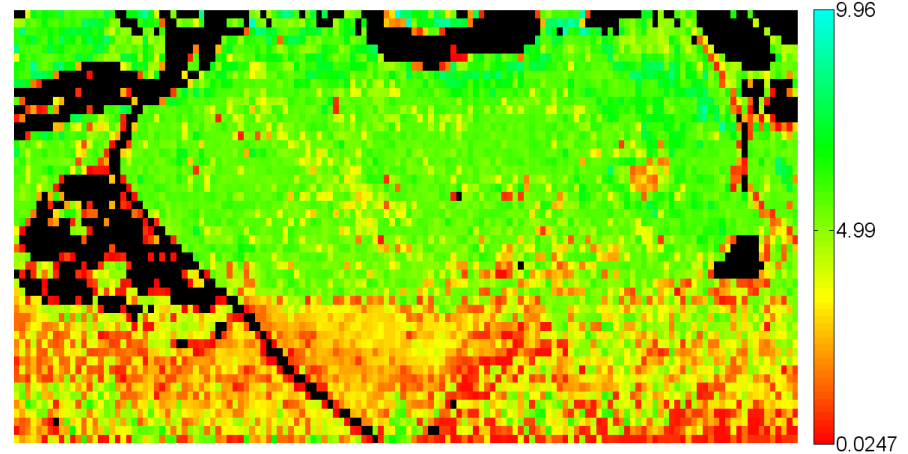
A – the absorption coefficient by tree leaves, F – the projective cover of soil by green phytoelements, R – reflectance of inter-crown vegetation, T – transmission coefficient of tree leaves.

Biological productivity

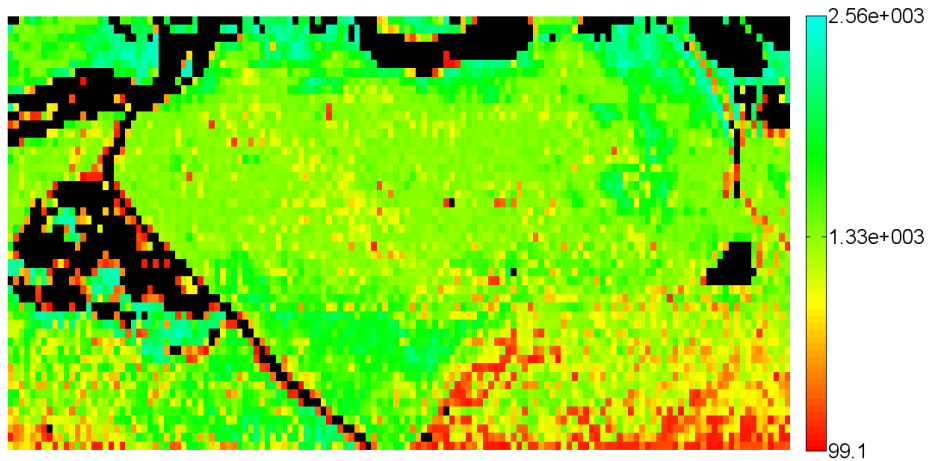
NDVI



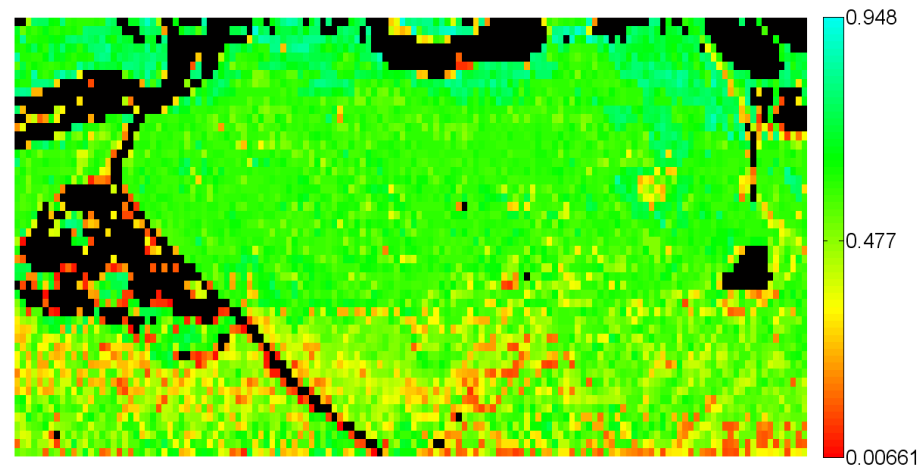
Biomass of leaves, t/ha



NPP, g C/m²/year



FAPAR



Ground-based measurements of projective parameters

Dividing into 2 classes with the use of k-means clustering

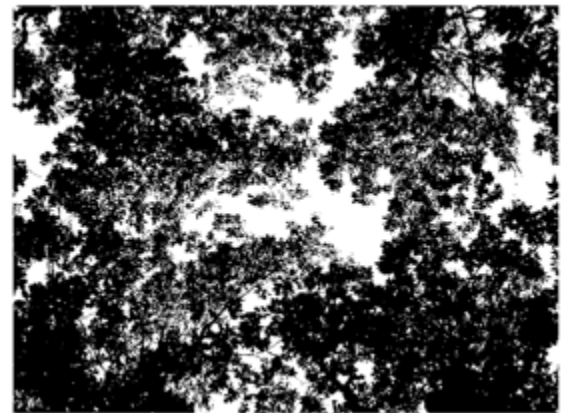
Ground-based photo of the forest canopy



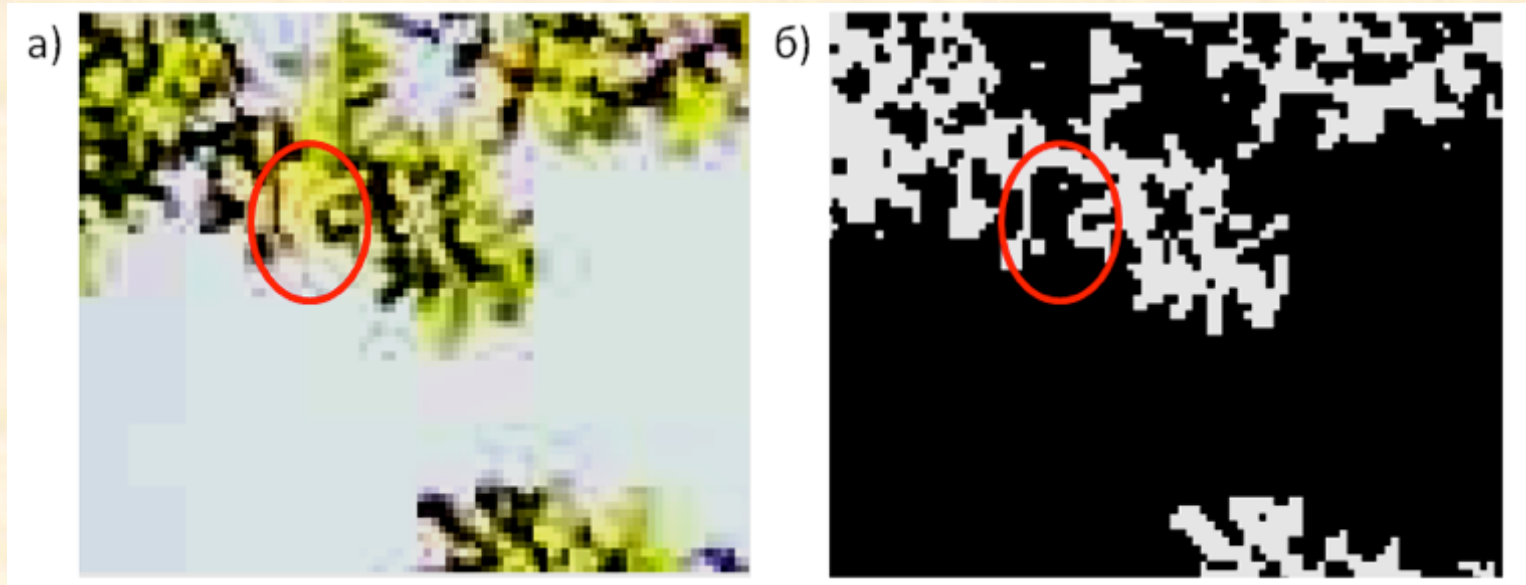
a)



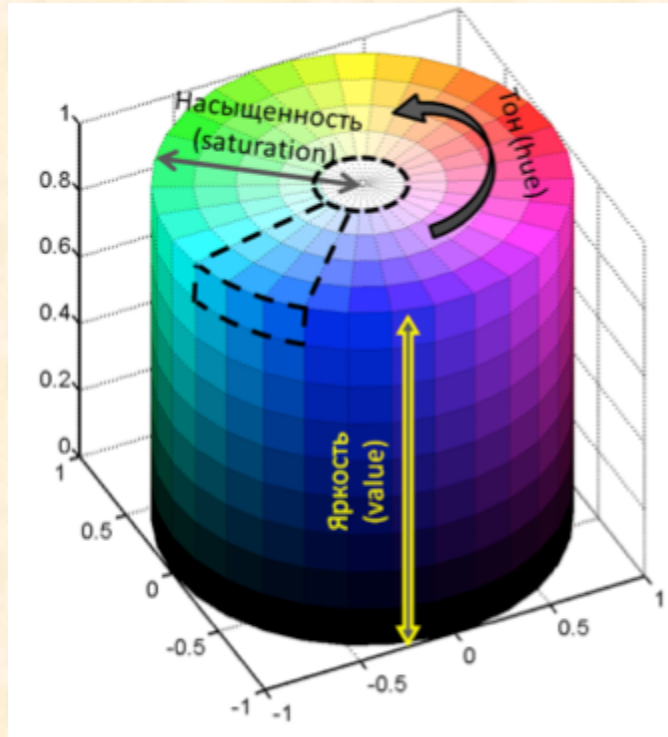
6)



Problems of k-means clustering with the classification of "sky" and "vegetation"



Recognition of the sky from ground-based photos of the forest canopy using HSV space and calculation of the projective parameters



Central cylinder: Hue – from 0 to 1 (all possible), Saturation – from 0 to 0.2, Value – from 0.85 to 1.
Sector of cylinder: Hue – from 190/360 to 240/360 (central color is blue), Saturation – from 0 to 1 (from 0.2 if the cylinder defined above is taken into account), Value – from 0.7 to 1.

Projective cover area

$$S_{ProjCov} = \frac{S_{foliage}}{S}$$

Sky pixels $S_{sky} = S_{big} + S_{little}$ are divided into clearances between crowns S_{big} and between leaves inside a crown S_{little} .

Density of canopy

$$D_{canopy} = \frac{S_{crown}}{S} = 1 - \frac{S_{big}}{S}$$

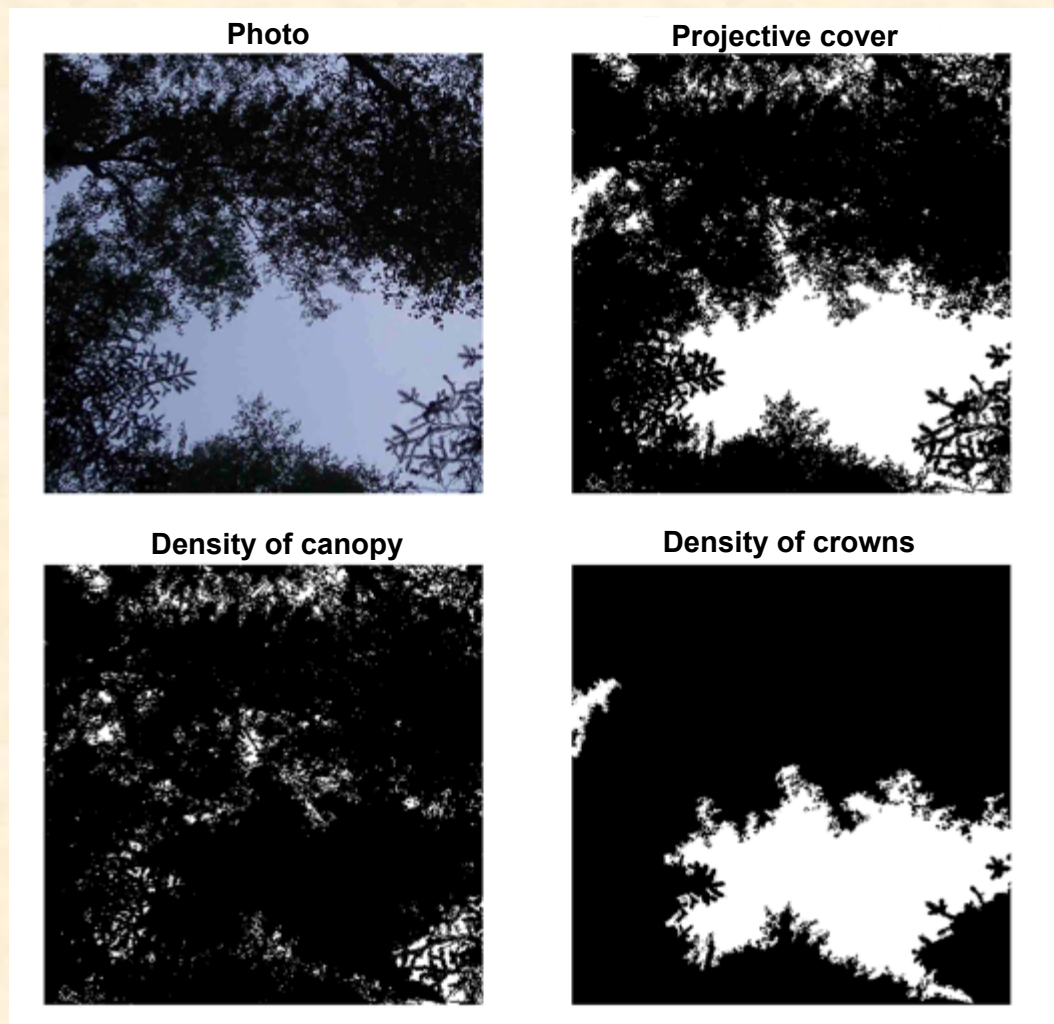
Density of crowns

$$D_{crown} = \frac{S_{foliage}}{S_{crown}} = \frac{S_{foliage}}{S - S_{big}}$$

Relation between the projective parameters

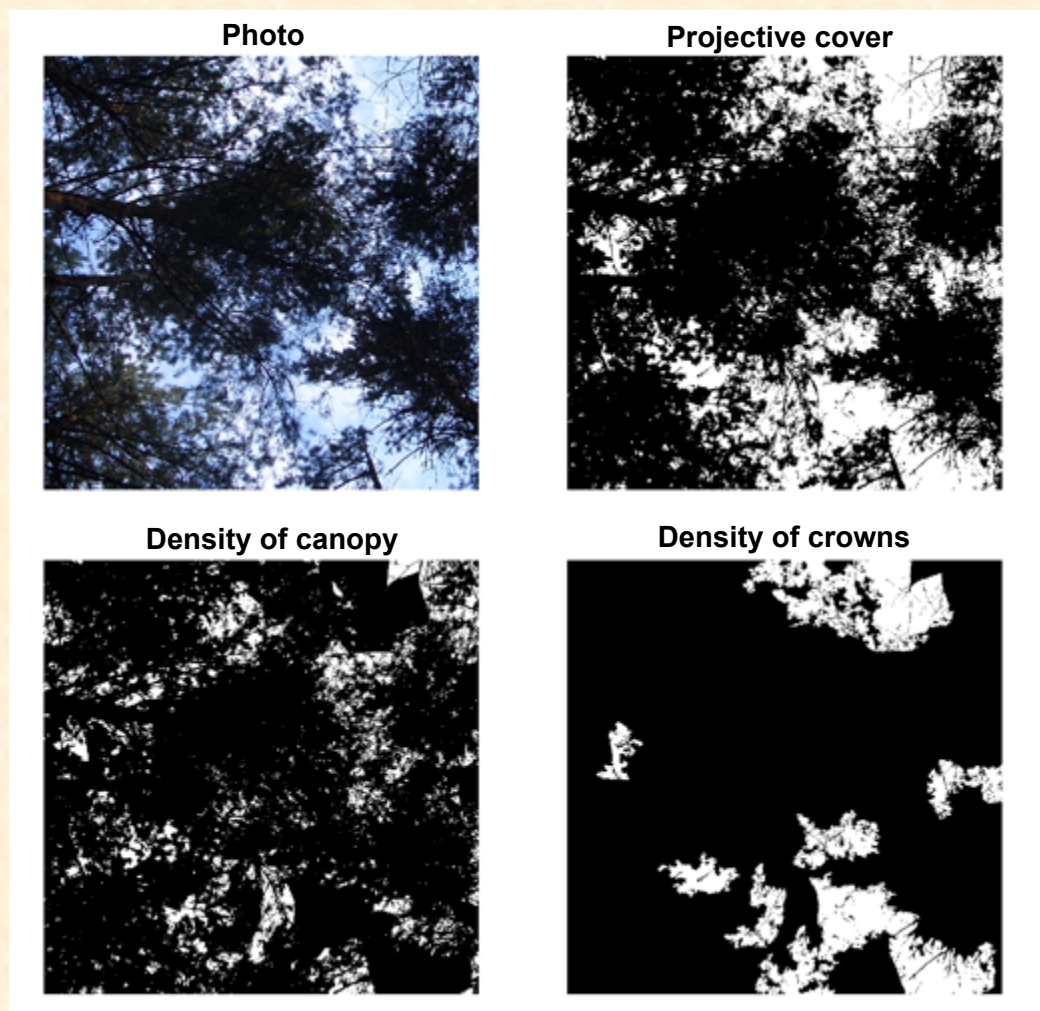
$$S_{ProjCov} = D_{canopy} \cdot D_{crown}$$

Estimation of the projective parameters (1)



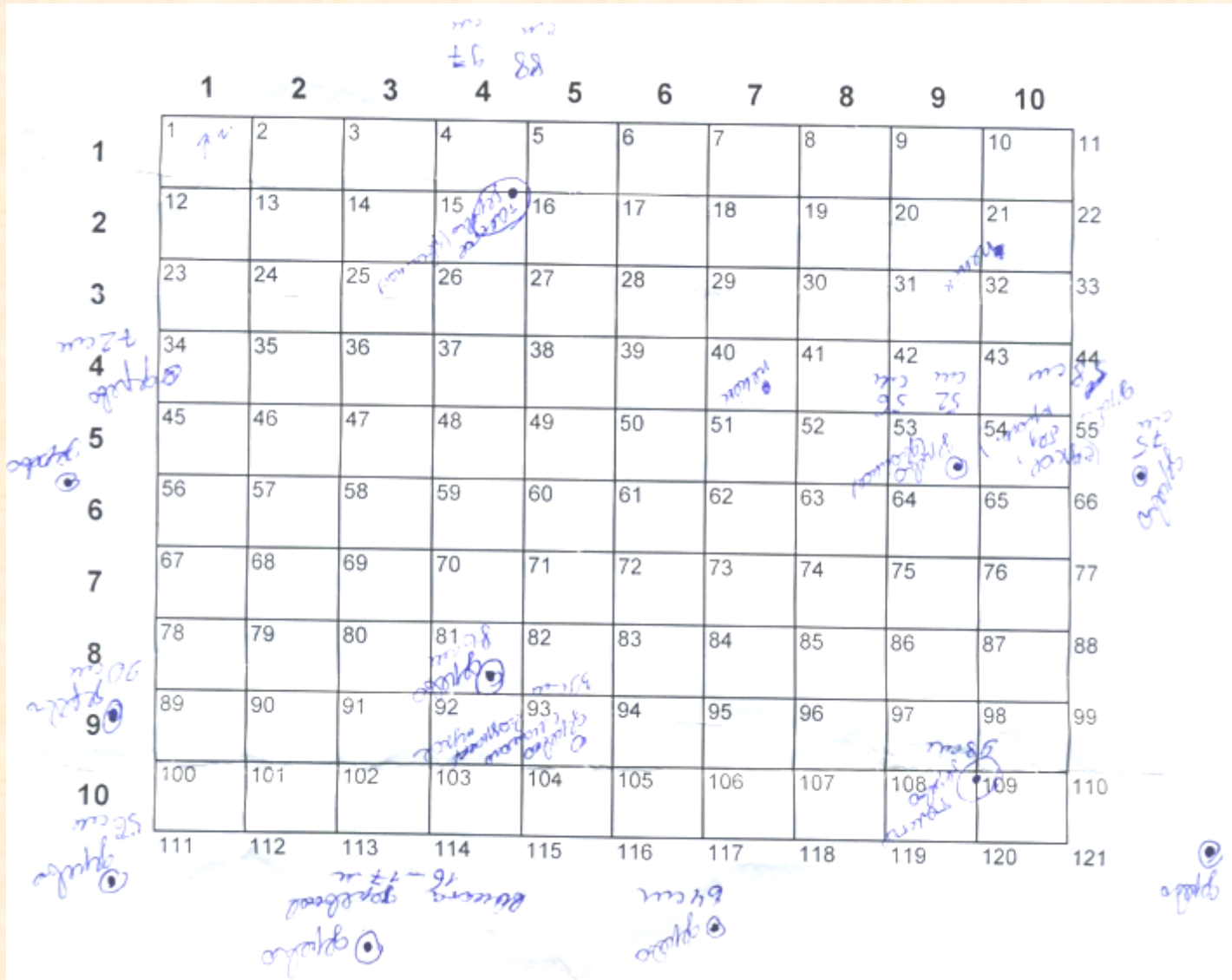
Forestry	N quarter	N apportio nment	Forest composition	Date	Projective cover	Density of canopy	Density of crowns
Савватьевское	54	2	8C2E	4082010	0.713048	0.776792	0.917939

Estimation of the projective parameters (2)



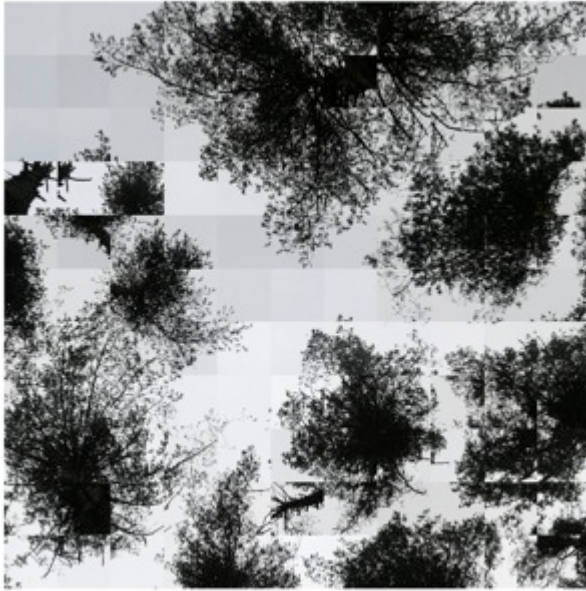
Forestry	N quarter	N apportionment	Forest composition	Date	Projective cover	Density of canopy	Density of crowns
Савватьевское	79	18	10С	26072010	0.725744	0.845073	0.858794

Grid method of the measurement of projective parameters of the forest canopy

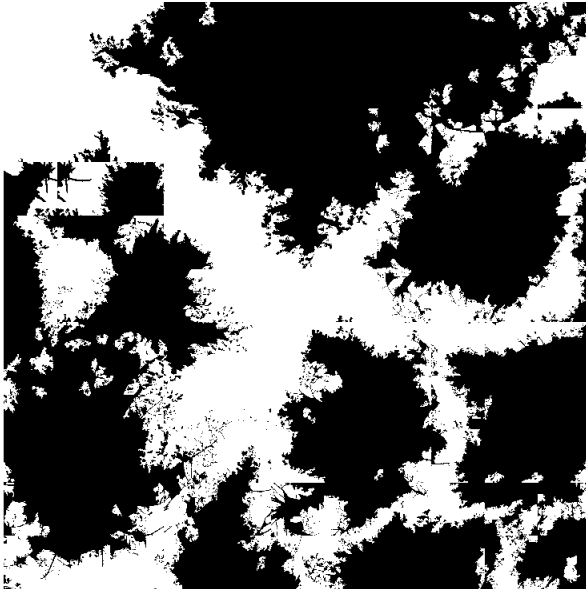


Processing of grid ground-based photos

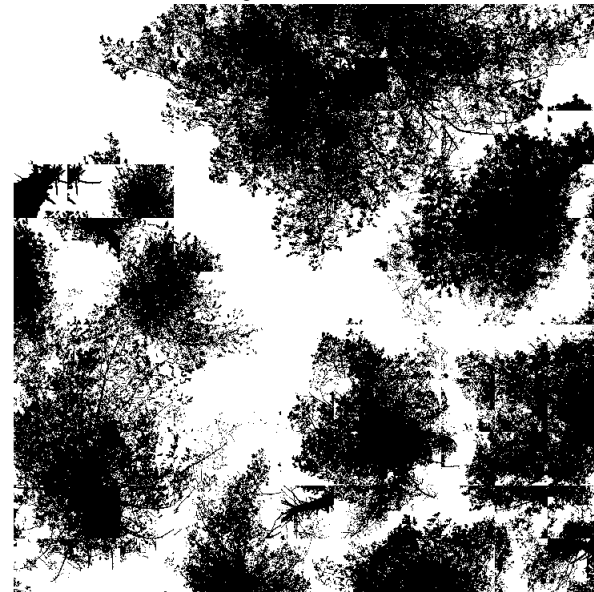
Photo



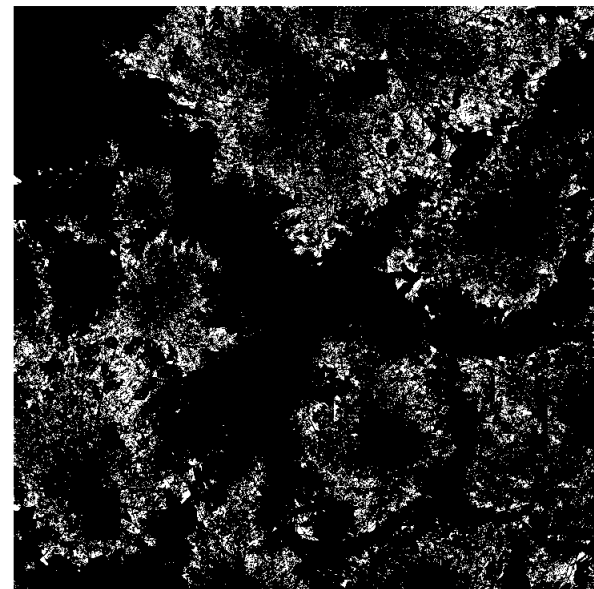
Density of canopy 0.60



Projective cover 0.51



Density of crowns 0.84



Conclusions

1. The current state of the development of the hard- and software system of airborne hyperspectral sensing consisting of:
 - videospectrometer of visible and near infrared spectral range;
 - algorithms and software for processing hyperspectral imageryis represented.
2. The method used for recognition of ground objects is based on the Bayesian classification and optimization of binning and selection of spectral channels of the hyperspectrometer.
3. Examples of recognition results demonstrate the stability of training of the classifier used and capability of reliable classification of species of the forest vegetation.
4. The method of retrieval of biological parameters of forest vegetation such as phytomass of fractions and net primary production is represented.
5. The method of ground-based measurements of projective characteristics of the forest canopy is proposed.