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REMOTE SENSING FOREST PARAMETERS RETRIEVAL AS COMPARED WITH GROUND-BASED FOREST INVENTORY

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Abstract: Active and passive systems of optical remote sensing are considered as an alternative to the common-used ground-based forest inventory. The relevant laborious works of the forest inventory are outlined on the probe areas within Russian forest ranger stations. Imaging spectrometers with hundreds of spectral channels in visible and near infrared region are designed to enhance the information content of the hyperspectral imagery processing. Comparisons are given of these traditional techniques of forest inventory and the newly defined approaches of data processing for a selected test area. These approaches include pattern recognition methods of forest classification of different species and ages as well as the retrieval of such parameters of forests as the Net Primary Productivity (NPP) and similar other information products. The NPP products can be used for parameterization of forested environments in climate models.

Keywords: active and passive remote sensing systems, forest inventory, biological productivity retrival

1. Introduction

A typical work of ground-based forest inventory in Russia implies the use of normative indicators and the relevant instrumentation techniques based on any reference materials where general and regional characteristics of forest growth and forest productivity are taken into account [22]. This work has had a long history in Russia. Forest inventory maps are created in accordance with separate quarters and plots within them during specially arranged field campaigns. Prevailing species composition of trees, their area of growth, age and site index are among the related forest characterization parameters. The measurable parameters are wood stock (the trunk volume), the tree height and the stand density in a particular plot. Besides that, the forest stand typology contains many unique categories characterizing the inter-crown vegetation (fens, shrubs, various grasses, sphagnum, etc.). Additionally, geo-botanical descriptions could characterize the plots having in mind the relief of place and soil cover, clumping effect of grasses and shrubs due to their vertical distribution, different mosses and lichens, etc.

This routine work must be adapted to the current climate change impacts. A review is given by [9] as to multiple forms of knowledge and new approaches to forest management decisions in Europe. Partnerships integrating researchers from multiple disciplines with forest managers and local actors can facilitate improved decision making in the face of climate change. These adaptation options for forest management identified in this review by the Web of Science literature published between 1945 and 2013 serve to integrate traditional forest ecosystem sciences with social, economic and behavioral sciences to improve decision making.

The listed directions of the forest inventory are designed to enhance efficiency of the forest management while Net Primary Productivity (NPP) estimates for particular forest classes are conducted by researchers, including models of understanding processes of the forest exchange by substance and energy with the environment. NPP values represent the amount of chemical energy as biomass produced in a given length of time during the photosynthesis process minus respiration by the related plants as living organisms.

The NPP estimates are based on models of ratio of the phytomass fractions (leaves/needles, branches, etc.) to the forest yield as some functions (usually as an exponent function) from the site index [17], age and relative stand density index of an area by the stands. The models use the known tables of growth rates and productivity of the main Euro-Asian species. Some results of pattern recognition of forests of different species and ages within a test area using multispectral and hyperspectral airborne imagery processing as well as NPP estimates for the main species are given by [11].

In [18] different climate change scenarios at a large number of sites were modeled to assess NPP products in Europe and at the species level. Using scenarios is only a first stage of the studies. Hyperspectral remote sensing and the related classification techniques of imagery processing allows us to obtain more precise NPP estimates for different forest classes that looks attractive from the scientific point of view. Our main objective is to classify regional data using the imaging spectrometer to recognize forests of different species and ages and further to find NPP estimates. These ideas are realized in [12] based on an airborne instrument produced in Russia.

Retrieval procedures of forest stand attributes using optical airborne remote sensing data are given in [13].

This paper deals with comparisons of the common-used in Russia forest management practices and the newly defined techniques of remote sensing hyperspectral imagery processing. We consider main direction of the forest management issues as well as the aggregated models to estimate biomass of forest fractions within a climate model cell. After that main priorities of photonics and computers are reviewed to understand the proposed instrumentation of remote sensing and the forest applications for selected test sites. Pattern recognition of the forest classes of different species and ages and the forest stand parameters retrieval are the main directions of the relevant applications. As a result, the accuracy of the hyperspectral imagery processing is shown to be comparable with routine laborious works of ground-based forest inventory. This means that prospects are feasible to replace the laborious works by the more effective remote sensing monitoring of forest species and ages using the elaborated computational procedures.

2. Forest management in Russia

Ministry of Natural Resources and Environment of Russian Federation is the main body of the executive power that puts into practice the functions concerning state politics and legal regulation in the sphere of studying, use, reproducing and natural resources protection. These resources include mineral wealth, water bodies, forests, animals and their environment, land use objects, hunting and environmental protection incorporating environmental monitoring and waste product treatments. The ministry coordinates within its jurisdiction Federal Service on Hydrometeorology and Environmental Monitoring, Federal Service on Supervision in the sphere of Natural Resources Use, Federal Agency of Water Resources, Federal Agency of Forestry, etc.

Federal Agency of Forestry implements the control and supervision functions in the field of forest relations for all areas, excluding specially protected terrains. The main rights concerning use, protection and reproduction of forests authorized to the subjects of Russian Federation. The Agency realizes its activity via territorial bodies, including local organizations and communities. Forest ranger stations and parks are the main territorial units of the forest management. The state program adopted by the Russian government is directed to decreasing losses from forest fires, pests and illegal logging, creating conditions for rational forest use, supplying budgets between logging and forest restoration, efficiency enhancing of forest management.

Forest plans of each subject of Russian Federation are the main documents to enhance efficiency of use, protection and reproduction of forests within particular forest ranger stations and parks. These plans have been accepted by all subjects in 2008-2009 in accordance with Forest Charter. Forestry regulations are given by parameters of the complex forest use within these stations and parks. The state or municipal expertise of these plans is due to be carried out.

The state inventory of forests is arranged to outline development of possible negative impacts on forests, to assess efficiency of the accomplishments of use, protection and reproduction of forests as well as the relevant information supply of forest inventory. Special probe areas are created for these purposes based on statistical techniques of forest inventory to obtain reliable information about the forests. Analytical reviews are prepared for these probe areas to characterize the forests by their quantitative and qualitative parameters. More than 47 thousands of such probe areas have been laid down since 2007. Fig. 1 depicts formation of this laborious work. We consider in this paper an alternative of the forest inventory using more effective remote sensing techniques.

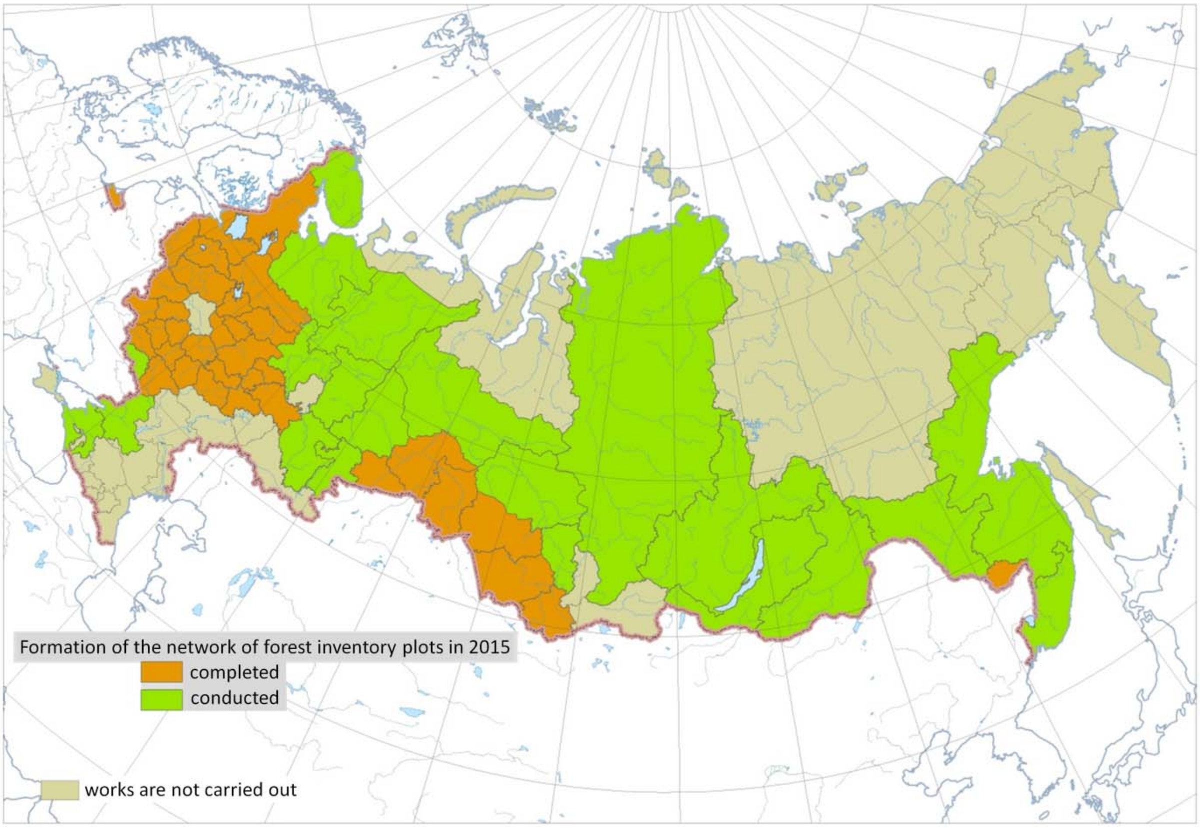

Fig. 1. *Formation of the national system of the forest inventory within the subjects of Russian Federation.*

Remote sensing monitoring is implemented to fix the following violation of the law in Russian Federation: illegal logging, violation in allowable observance of the cutting area, unlawful use of the forest areas. The forest management is the main information resource of sustainable forest use. Its main objectives are: projecting forest ranger stations and parks, projecting reserve forests, fixing the place of the stations and parks, forest inventory, projecting accomplishments of use, protection and reproduction of forests.

The state forest catalogue represents the document about the forests, their use, protection and reproduction, the forest ranger stations and parks. Besides that, the forest cadastre serves to identify boundaries between particular forests.

We present here the relevant categories of the common-used forest management to better understand the opportunities of updated forest monitoring using advances in photonics to create remote sensing devices and in computer means of data processing. Before that, however, we return to the main postulates of forest science, i.e. the growth rates and biological productivity of major tree's fractions (stem, bark, branches, leaves/needles, butts and roots) referring to initial data base on the Northern Eurasia level given by [19].

3. Aggregated models to estimate biomass of fractions within a climate model cell

Attempts are undertaken in [19] to extend the available materials concerning the biomass of fractions for particular species on a continental level. Their modeling applications need to be cleared up for particular calculation nodes of the modeling cell used. Existing tables of the tree's growth rates on the continental level are initial for NPP estimates of the related forest ecosystems. These tables were analyzed by us to unify the models for selected species. Our implication is to improve the related parameterization schemes of forests in climate models using hyperspectral remote sensing data processing.

Data sorting agrees with the biological parameters productivity calculations. Transition coefficients used for the conversion of forest yield to phytomass of separate fractions are defined by two types of equations with the common-used notations

$$R^i = C_0 \cdot SI^{C_1} \cdot A^{(C_2 + C_3 \cdot RS + C_4 \cdot RS^2)} \quad (1)$$

$$R^i = C_0 \cdot A^{C_1} \cdot SI^{C_2} \cdot RS^{C_3} \cdot \exp(C_4 \cdot A + C_5 \cdot RS) \quad (2)$$

where $C_1, \ldots, C_5$ are the regression coefficients, A – the age of the forest stands, RS – the relative stand density index within particular space of the corresponding plot, SI – the site index.

The existing comprehensive tables and their analytical approximation by (1-2) containing information about 35 parameters of the related fractions represent the growth rates and biological productivity of the main species. These are parameters of forest yield, site index, age of tree's stands, phytomass of stems, crowns, roots and particular plants, phytomass rates, net primary productivity of the canopy in general as well as productivity of stems, crowns and plants on specific soils, etc. The sets of parameters embed the known facts of observational studies in forest science.

Fig. 2 shows as an example of a scattering graph of the forest yield depending of the stem with bark phytomass on a unit area. We can see that a linear relationship is apparent in this case. This enables us (see [14]) to link the phytomass amount retrieved by hyperspectral imagery processing for a particular class of forests and the forest yield as the main forestry characterization. The Bayesian classifier of statistical decision making is used first to retrieve the composition of mixed forests for any scene under processing [15] and after that to retrieve the phytomass amount for the related forests.

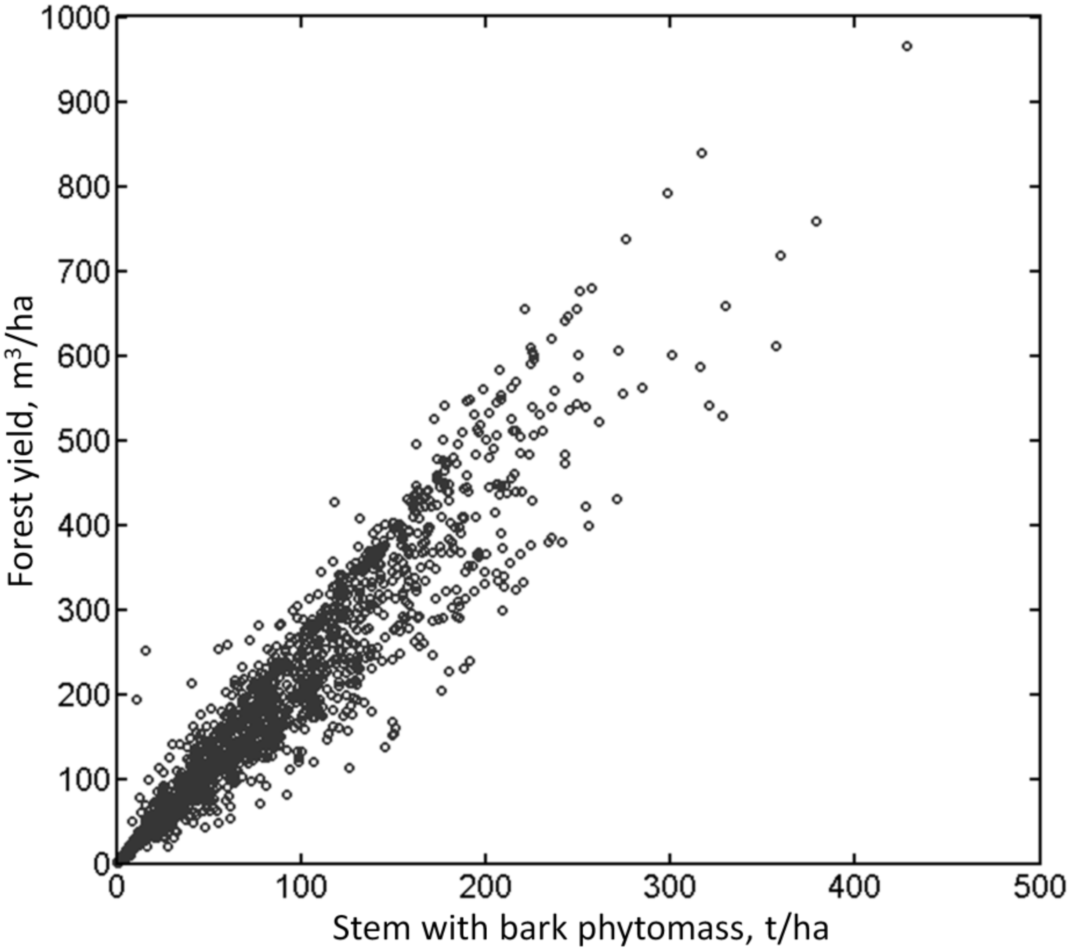

Fig. 2. *The forest yield as a function of the stem with bark phytomass on a unit area.*

A necessity has emerged to create data bases in the form of MATLAB structure we are operating with while hyperspectral imagery processing. A general scheme of the structure for the forest applications is given by Fig. 3. The *variable* branch contains the information about possible values of the variables SI, A and RS mentioned in formulae (1-2). The *name* branch contains names of the mentioned variables, the *value* branch contains the possible numerical values and the *str* branch – contains possible character values if they exist. The *parameter* branch contains the data about total and fractional phytomasses, carbon contents, losses and productivities of forest stands (35 different biological parameters in total) is given by the related functions of the mentioned 3 variables for different species. Codes of these parameters are presented by the *name* branch with their *description* and units in Russian (*unit-rus*) and English (*unit-eng*). The number of branches within the *tree types* group is determined by tree's species available (alder black, aspen, birch, lime tree, larch, oak seed, oak verdure, pine, spruce etc.). This structure allows us to find easily the values of biological productivity parameters for given age, relative stand density index and site index. As a result of these modeling constraints, a linear interpolation is used to merge remote sensing hyperspectral imagery processing with the modeling cells of the biomass fractions.

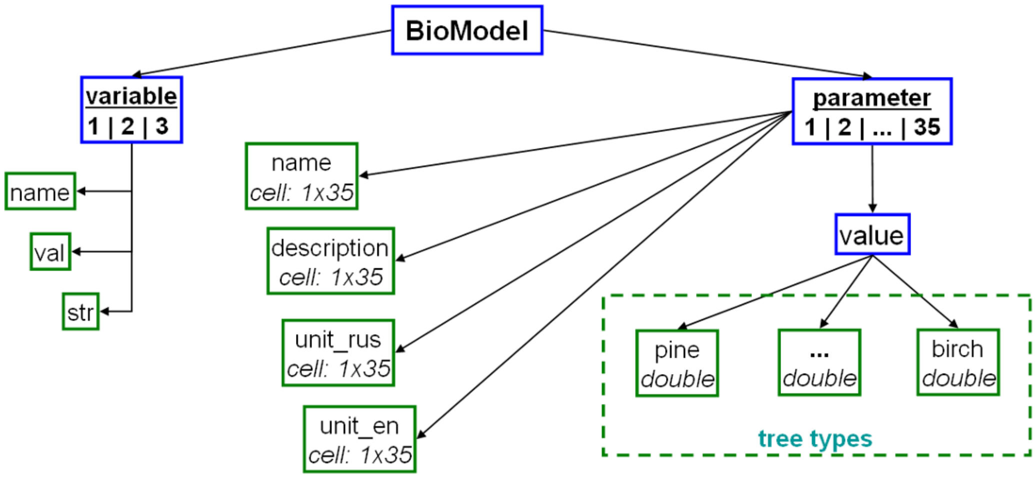

Fig. 3. Structure of modeling data for MATLAB system. Intermediate nodes of the tree structure within the modeling cell are shown by blue color while final nodes are shown by green color.

4. Measuring and data processing system

The measuring scheme used includes the modern achievements in photonics – the physical science dealing with different light manipulation applications and associated first of all with the laser invention. Coherent optics methods are important not only in laser construction, but in real-time communications and image transmission [2]. Information and communication technology applications such as sensors are among priorities integrating science and technology [20]. Not only the lidars (laser active optical systems), but the passive systems operating with the solar illumination conditions are important for remote sensing depending on radiometric, spectral and spatial properties of the related devices. Integration of photonic and information technologies connected with computer sciences is one of priorities in world markets.

In spite of advances in hyperspectral remote sensing imagery processing, the problem of the related applications is far from being solved using supercomputers. The main task of these computations is to find an objective function to optimize the vision problem. The optimization is needed due to various uncertainties in this problem. Machine-learning algorithms are common-used to improve the accuracy of the pattern recognition problem by combining spectral and texture feature selection on the processed images [7].

Unique technologies of remote sensing have emerged lately concerning precise determination of place and orientation in space of Unmanned Aerial Vehicles (UAV) to measure the related scenes. Scanning lidars and imaging spectrometers are used for obtaining these both types of images. The lidars serve to extract 3D structure of the forest canopy [3, 10] having in mind relief and other horizontal inhomogeneity of the land surface and forests. Imaging spectrometers are designed to build classifiers (computational procedures) using spectral and texture features of a scene under processing [16].

Typical classifiers are based on representation of any spectral measurement in multi-dimensional feature space given by the number of spectral channels. Each spectrum is given by a point in this space. Different points might be merged defining if they belong to the same class of objects. The problem of pattern recognition is to separate the boundaries between the classes encountered.

The following classifiers are the most often used in machine-learning algorithms of optical remote sensing imagery processing: the metrical classifier operating with Euclidean distance between any points of the multi-dimensional feature space given by registered spectra [1]; the K nearest neighbors classifier (K is a positive integer, typically small in comparison with the number of samples in the training set) based on a majority vote for neighboring pixels of the recognized objects [5]; the Bayesian classifier of statistical decision making [4]; the Support Vector Machine classifier dealing with stable solutions of the mini-max optimization problem [21] and their different modifications. Priorities and deficiencies of the listed classifiers are discussed in [16].

Fig. 4 reveals a schematic view of airborne passive and active remote sensing. Direct solar radiation and diffuse scattered radiation incoming from each place of the sky received by passive sensors and are the main sources of spectral information. The scattered echo-signals of the active scanning systems form the images reacting on the clumping effect of consequent receiving echo-signals from the ground level and other forest phyto-elements for neighboring pixels in the near to nadir view angles. As a result, both types of images (from these passive and active systems) are registered giving rise to new techniques of remote sensing data processing.

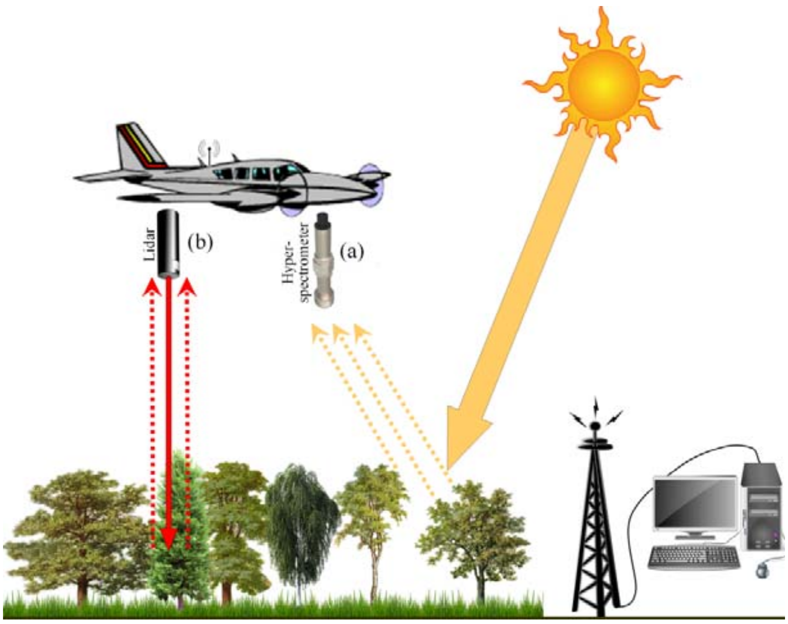

Fig. 4. *Schematic representation of passive (a) and active (b) remote sensing systems.*

5. Forest applications

We illustrate here some results of the passive remote sensing system given by the airborne imaging spectrometer produced in Russia as compared with the ground-based forest inventory. The entire test area of the size about 4x10 km was encompassed by 13 overlapped tracks obtained from the airplane equipped on the same gyro-stabilized platform by the imaging spectrometer and photo-camera [13]. The spatial resolution across the track is stable and amounts to 1.1 m at the flight altitude about 2 km above the ground level. The pixel size along the track depends on the flight speed and changes within 0.66-0.91 m. We show here some results for the small test area defined by the frame of yellow color at Fig. 5 containing the matrix of the relevant image of the size 120 x 50 pixels.

Fig. 5 represents this test area within the ground-based forest inventory map. The location of this small area is highlighted by the yellow frame. Typical in Russia forest inventory is given by this colored map in the form of the quarters (bold numbers 49-52, 60-65 at Fig. 5) and the plots within these quarters (convenient numbers). The colors of these plots correspond to the prevailing species: orange for pine, blue for birch, green for aspen. The darker color is consistent with the more age of the stands on the map. The former logging places are denoted by the horizontal red lines. Typical for each plot are the following four numbers: a conditional number of the plot, the average age of the forest stands on it (the upper part in the related numbers), area of the plot (m^2), its site index (the lower numbers at Fig. 5). In general, the more the value of site index, the less quality of the wood in the corresponding plot. Not for all plots these four numbers are presented at Fig. 5.

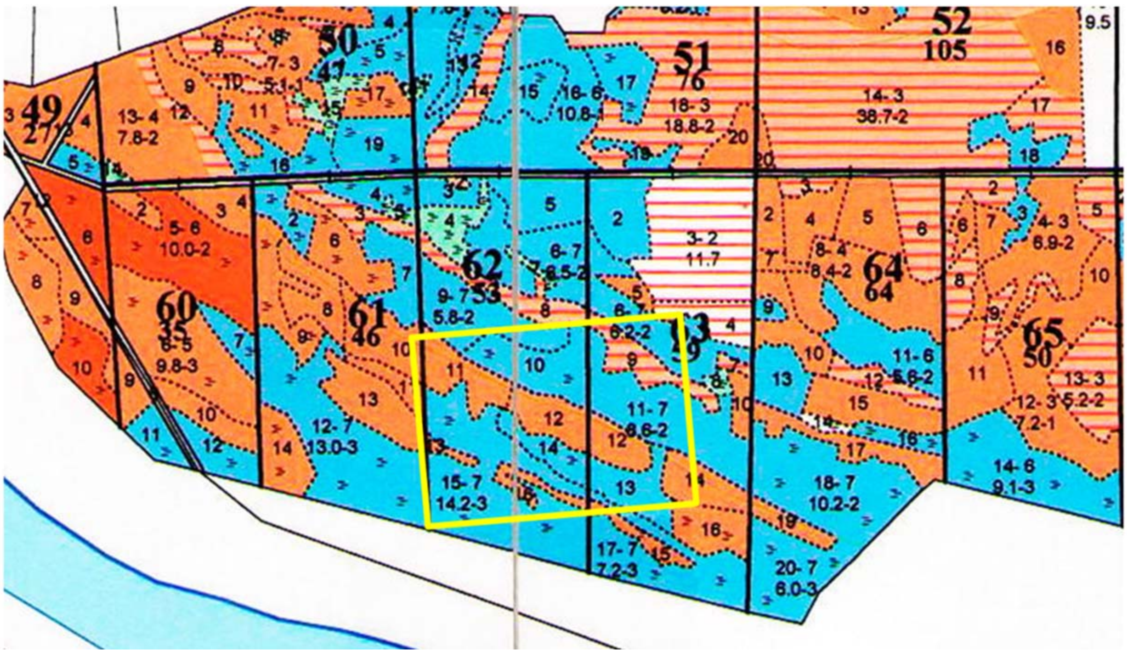

Fig. 5. *The test area (the yellow frame) within the ground-based forest inventory map.*

The recognition results of the forest stand composition within the yellow frame using the processed hyperspectral image are shown on Fig. 6 taking into account three levels of the Sun illumination of tree's crowns: the sunlit tops, the shaded background, the intermediate pixels of partly illuminated and partly shaded conditions. These three categories of the current optical state of the forest canopy on the image under processing, called as the canopy end-members [8], represent neighboring pixel's alternation for a particular class of forests containing different stands. Details of the recognition using Bayesian classifier and the mentioned three levels of the Sun illumination conditions remotely sensed by the airborne imaging spectrometer are given in [12, 15].

The recognition is based on the completely different spectra of the end-members: the availability of the red edge (a transitional zone between the chlorophyll absorption spectral band and maximum of spectral reflectivity) for the sunlit pixels and the background pixels illuminated by the diffuse scattered radiation of the Sun.

In this paper we used the supervised classification algorithm based on the technique of error correcting output codes (ECOC) [6] for solving the problem of recognition of the species composition of forest stands. This method uses several approaches from the information coding theory for the formalization of extending binary classifiers to the multiclass case. Feature space was reduced in accordance with the method and results of the selection of the most informative spectral channels represented in [13].

The plots counted from 1 to 13 are selected for the recognition. The comparison of these classification results with Fig. 5 of the ground-based forest inventory shows that the available inventory needs renewal. In particular, the pure pine species (denoted by 10P, P – pine, B – birch, S – spruce) numbered here as 2 and 3 (11 and 12 at Fig. 5) give in the place to 9P1B and 8P1B1S for the plots 11 and 13 (correspond to the second part of the plot 12 and 14 at Fig. 5), respectively. Besides that, the pine plot number 9 at Fig. 6 can be seen to consist now of pure pine species instead of the plot number 9 at Fig. 5 denoted as the logging place that has been re-growing from the time of the last inventory. Some details of the pine, birch and aspen species composition are reproduced at Fig. 6 for other plots.

Fig. 7 shows the results of retrieval of NPP values for the test area of Fig. 6 using models from [11, 14] for the image of the size 120 x 50 pixels. We can see that low NPP values (near to 15 g / (m^2 year)) correspond to the pure pine stands while for the mixed forest with prevailing birch stands has the higher values (such as 600 g / (m2 year)). The former logging places (such as the plot number 9 at Fig. 6) have the intermediate values (near to 300 g / (m^2 year)). These facts can be used to improve parameterization schemes of the forested environments in climate models. Detailed description of each plot by imaging spectrometer contributes to these improvements and enhances efficiency of remote sensing as compared with routine ground-based observations.

Additionally, values of stem with bark biomass (Fig. 8) given by the fraction models can improve the parameterization schemes and forest biodiversity. In particular, details can be seen on the selected plots: low values of these characteristics (near to 0.5 t/ha) are mainly on the upper left diagonal of Fig. 8, but higher values (near to 100 t/ha) for the birch stands, and very high values (near to 130 t/ha) characterize not only the former logging places grown-up at the time of survey, but some other places on the scene. The results of remote sensing imagery processing are new, thought-provoking and need to find coincidence with common-used forest science.

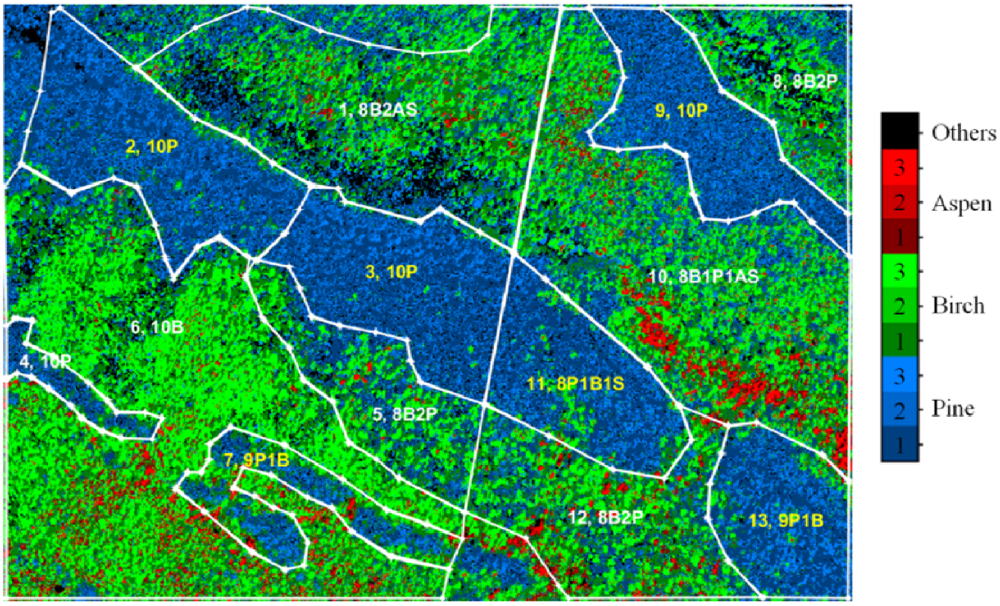

Fig. 6. Pattern recognition of the species composition for the selected 13 plots in accordance with the Sun illumination conditions for three types of the canopy end-members: sunlit tops, completely shaded background and partly illuminated and partly shaded phyto-elements.

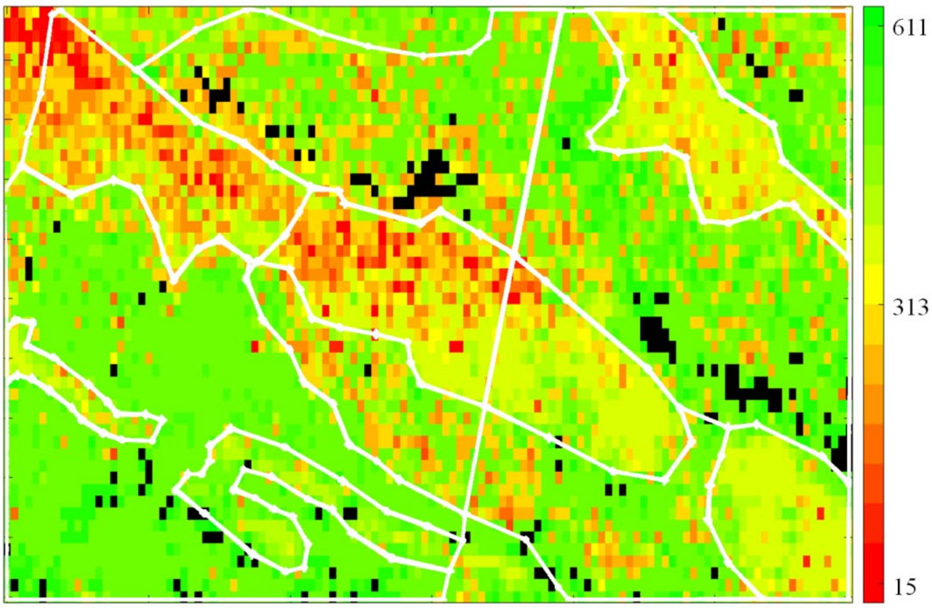

Fig. 7. NPP values (g / (m² year)) retrieved by the proposed models of the recognition and forest parameter estimates. Black color pixels correspond to unrecognized objects.

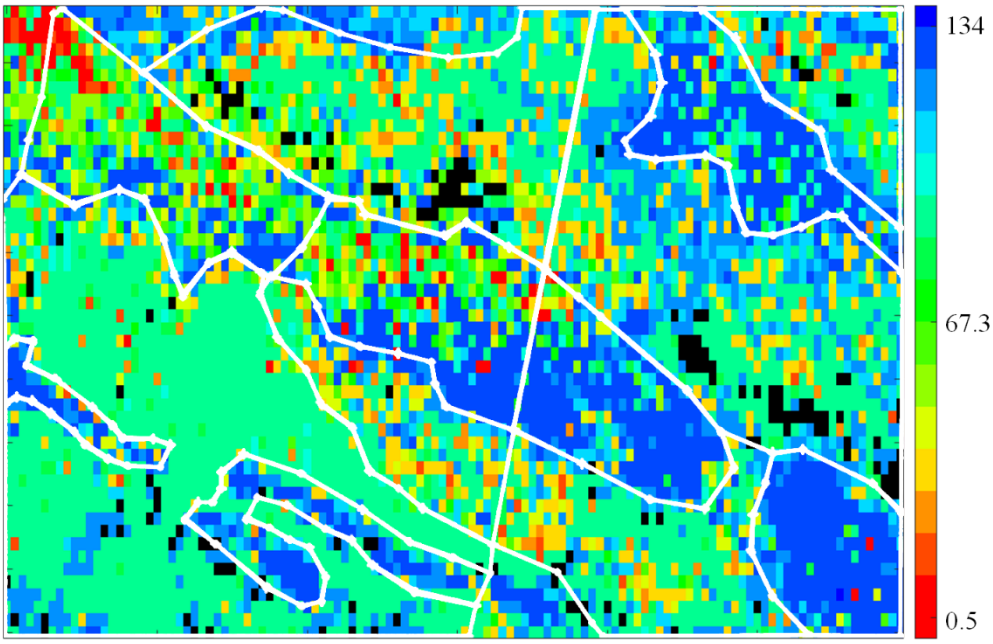

Fig. 8. *Retrieval of stem with bark biomass for the test area (t/ha). Black color pixels correspond to unrecognized objects.*

6. Conclusion

Existing plans to use the probe areas within Russian forest ranger stations for traditional ground-based forest inventory may have an alternative of aerial remote sensing provided proofs are given that the accuracy of these new techniques of imagery processing is comparable with that of the laborious works on the probe areas. Forest management in Russia is described with the emphasis on these traditional approaches. Besides that, aggregated models to estimate biomass of forest fractions within a climate model cell are given for enhanced parameterization of forested environments in climate models. Advances in photonics and computers can facilitate these new techniques. We have shown some results of imagery processing using the airborne imaging spectrometer produced in Russia as compared with the ground-based forest inventory. Pattern recognition methods are elaborated for classification of forest of different species and ages on a selected test area. NPP values as the main information products of the biological productivity of forests are then retrieved to demonstrate the recognition results and forest parameter estimates.

Acknowledgments

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