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STRUCTURE AND DYNAMICS OF BOREAL ECOSYSTEMS: ANOTHER APPROACH TO LANDSAT IMAGERY CLASSIFICATION

ABSTRACT. An alternative approach to information extraction from Landsat TM/ETM+ imagery is proposed. It involves transformation the image space into visible 3D form and comparing location in this space the segments of the ecosystem types with expressed graphically typology of forest and mire cover (biogeocenotic scheme). The model is built in LC1-LC2-MSI axis (the two first principal components of the image matrix in logarithmic form and moisture stress index). Comparing to Tasseled Cap, this transformation is more suitable for study area (north taiga zone of Eastern Fennoscandia). The spectral segments of mature and old-growth forests line up from the ecological optimum (moraine hills) along two main environmental gradients: i) lack of water and nutrition (fluvioglacial sands bedrock) and ii) degree of paludication (lacustrine plains). Thus, the biogeocenotic complexes are identified. The succession trajectories of forest regeneration through spectral space are also associated with the type of Quaternary deposits. For mire ecosystems spectral classes accurately reflect the type of water and mineral nutrition (ombrotrophic or mesotrophic). Spectral space model created using measured by the scanner physical ecosystem characteristics can be the base for developing objective classification of boreal ecosystems, where one of the most significant clustering criterions is the position in the spectral space.

KEY WORDS: boreal ecosystems, geoinformation modeling, multispectral imagery classification, Quaternary deposits

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INTRODUCTION

At present, forest cover mapping is moving from regional to international levels. Data sets from the various countries differ greatly, and development of unified methods is required (Tomppo and Czaplewski 2002; Pekkarinen et al. 2009). The basic data source (Landsat imagery) is used worldwide; thus, it is possible to use the scanner as a tool for unification. The main approach to extracting information from imagery, i.e., supervised classification, is also universal. It is based on the extrapolation of ground truth data to the entire image. Training sites are set according to a previously developed classification scheme which reflects a researcher's understanding about vegetation typology. It depends on the tasks that should be solved (ecology, forestry, geobotany, etc). However, on the one hand, the vegetation is the holistic environmental system with intrinsic laws of functioning; on the other hand, the scanner is a technical device with its own "vision." Therefore, the complete correspondence between the classification scheme and the image information cannot be achieved.

The maximum likelihood classifier (MLC) is thought to be one of the most accurate methods of supervised classification. It has been widely used in forest mapping since the emergence of the multispectral imagery (Hirata and Takahashi 2011). MLC is based on probability and requires normal distribution in each band of ground data, which can be achieved with a large number of training sites. Artificial neural networks (ANN) are also the commonly applied algorithm for the classification of remotely sensed data (Kanellopoulos and Wilkinson 1997; Zhou and Yang 2008). Their application also requires a careful selection of training sites. However, any number of plots is useless if the classification scheme poorly conforms to the capabilities of the scanner for categories recognition. Thus, these methods of information extraction can hardly be used as the base for data sets unification. Uncertainty at the regional level is carried to the global.

The process of image classification using techniques such as MLC and especially ANN, is almost a "black box." The researcher cannot estimate the real size and location of the categories in spectral space, their relative spatial position, i.e., actually acts blindly. Commonly used bi-band scatterplots (feature space images) are only a partial solution to the problem. Long term studies of the taiga landscapes structure and dynamics using remote sensing data (Litinsky 1997, 2007) suggested that the natural space structure of ecosystems can be much better revealed using another approach, which can be named "spectral space modeling" (Litinsky 2011, 2012). It includes three key components: i) creation of graphical expression of forest and mire cover typology (biogeocenotic scheme); ii) transformation of image spectral space into a visible 3D form, and iii) comparison of the positions of the ecosystem signatures in spectral space with the biogecenotic scheme. An example of this approach is briefly described below.

MATERIALS AND METHODS

Study area

The area encompasses about 10 million ha in north taiga of Eastern Fennoscandia (Fig. 1). The altitude ranges from 0 to 350 m a.s.l., mean annual temperature is about 0ºC, long-term mean annual precipitation is 500-550 mm. The area is a sample of continental glaciation. The Quaternary cover is formed by the glacial (moraine) and fluvioglacial (delta, sandur) deposits that cover Precambrian bedrock of the Fennoscandian Shield. They are locally overlain by lacustrine and marine sand-clay material and peat deposits. The

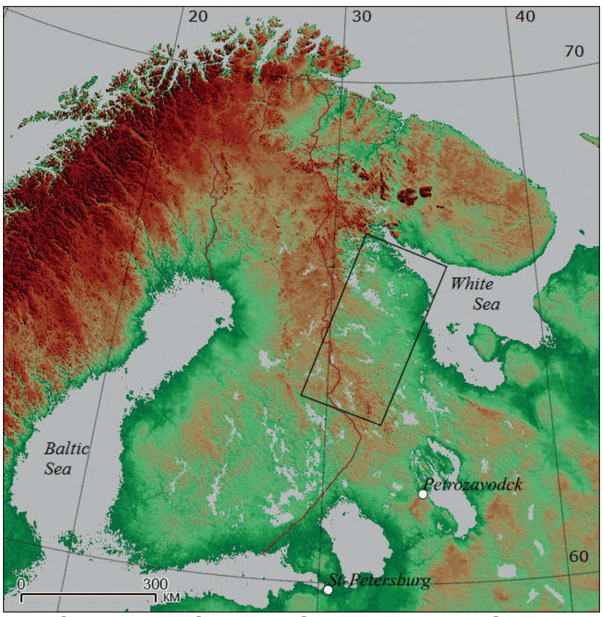

Fig. 1. The study area – the Landsat scene path 186, rows 13-15

exposures of ancient crystalline rocks are very common in denudation-tectonic relief prevailing here. The lake surface/drainage area ratio is remarkably high, 12% (Biotic diversity... 2003).

The area includes all main north taiga ecosystem types. There are three forest forming species here: Scots pine (Pinus silvestris L.), Finnish spruce (Picea x fennica (Regel) Kom.), and white birch (Betula pubescens Ehrh.). Due to intensive cuttings since the early 1960s, more than two-thirds of forests are currently younger than 50-60 years. The large fragments of old growth forests have remained only along the Finnish-Russian border.

More than 80% of the forest land is covered with pine forests that occur in almost all types of habitats, formed on different Quaternary deposits (Volkov et al, 1995). Their diversity can be represented in the axes of the edaphic coordinates diverging from the ecological optimum (Fig. 2). Spruce-dominated stands (12% of the forest land) occur mostly on the slopes of moraine hills and wet depressions. Birch is an accompanying species in stand composition.

Due to excessive moistening and little evaporation, open mires occupy about one-third of the area. The largest mire systems are located on sea and lacustrine plains. Significant parts of forests are the ecotones between open mires and terrestrial ecosystems. The area is sparsely populated, with only one industrial center there – Kostomuksha ore-dressing mill. Agricultural lands (mostly meadows) occupy about 1.5%.

Image Data and processing

Landsat ETM+ images from path 186 rows 13-14 acquired 2000.07.28 and row 15 (2002.06.16) were used for model creation. Landsat TM images from the same path, row 14 (1992.06.12) and row 15 (1990.06.23) were taken as time series, all obtained at ftp://ftp.glcf.umiacs.umd.edu.

The spectral space model is built in LC1-LC2-MSI axis: the two first principal components

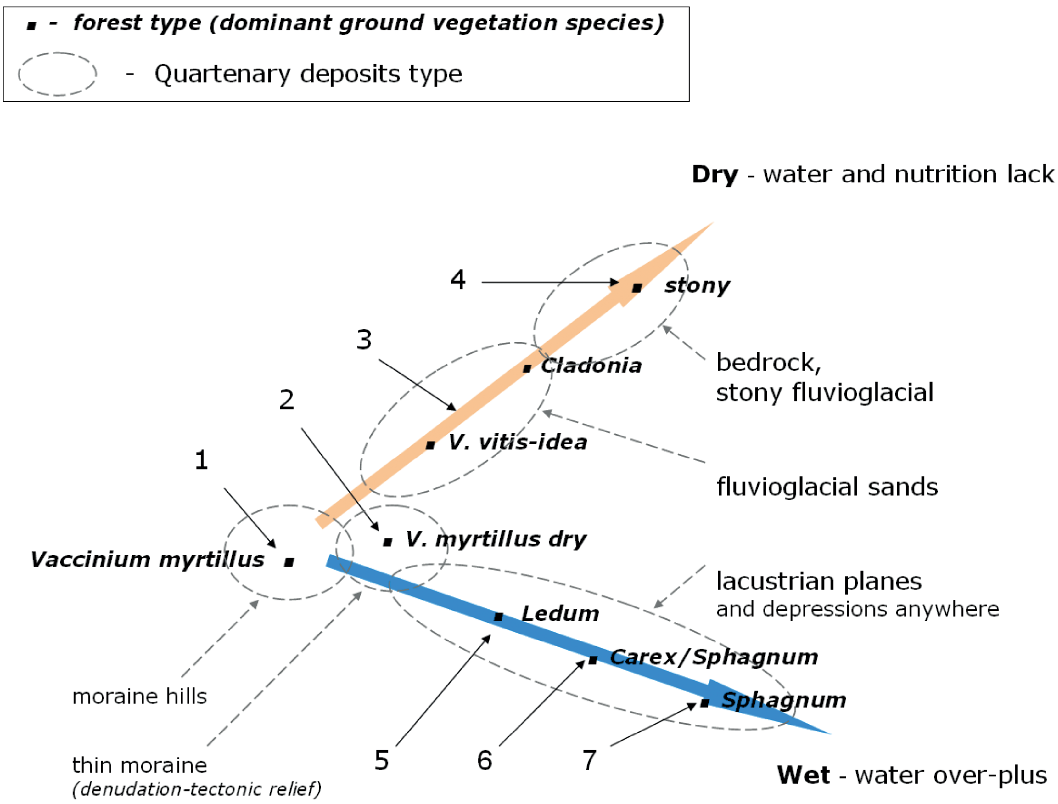

Fig. 2. The biogeocenotic scheme of north taiga pine forests. "Dry" and "Wet" are the automorphic and hydromorphic axes, respectively. Digits 1–7 are the reference points for comparison with the spectral space model shown in Fig. 4.

of the image matrix in logarithmic form, and Moisture Stress Index. LC1 accounts for general scene brightness, LC2 correlates with quantity of green biomass, but not orthogonal to brightness (Litinsky, 2011). Thus, in physical terms this transformation is the gnuplot plotting utility was used for 3D visualization and analyzing the spectral space model. Localization of spectral classes within the model space was made using aerial images, forest inventory maps, landscape transects, and other ground data.

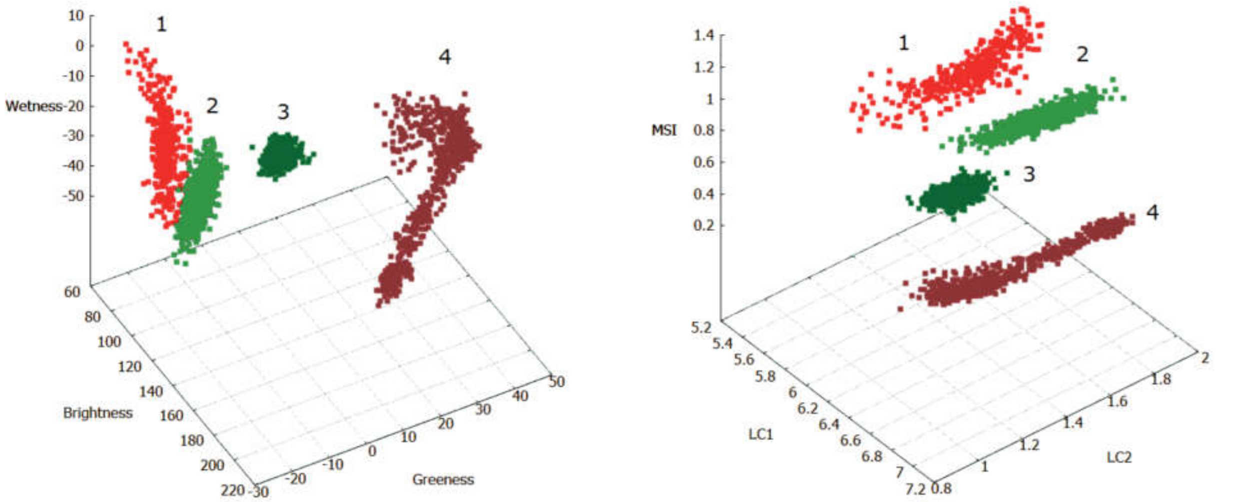

Fig. 3. Signature clouds of the same mire (1 and 4) and forest (2 and 3) plots in Tasseled Cap (left) and LC1-LC2-MSI space.

similar to Tasseled Cap (Kauth and Thomas, 1976; Huang et al, 2002), but it makes space more "compact", understandable, and suitable for analyzing (Fig. 3).

The lightest categories (cuttings, mires) are represented significantly in spectral space not due to their heterogeneity, but only to the largest value of albedo. The logarithm equalizes the values of the dark forest and bright non-forest categories, with open water zone being scattered. MSI is opposite to "wetness" and it makes space visually closer to human perception: dry and poor vegetation is at the hill top, rich and wet in the valley. Three minimally mutually correlating bands were used for the axes LC calculation:

$LC1 = 0.2793 \times \ln(R) + 0.7786 \times \ln(NIR) + 0.5619 \times \ln(SWIR2)$;

$LC2 = 0.5887 \times \ln(R) - 0.6012 \times \ln(NIR) + 0.5404 \times \ln(SWIR2)$;

$MSI = SWIR1/NIR$;

where R, NIR, SWIR1, SWIR2 - Landsat ETM+ bands 3, 4, 5, 7 digital numbers, respectively; ln - natural logarithm.

Free RS/GIS packages QGIS, SAGA, and GRASS, were used for image processing;

RESULTS

Any of more or less homogeneous category of an ecosystem (e.g., even-aged stand forest canopy or meadow surface) is represented in the model as a lenticular object (oblate ellipsoid) tilted to the plane of LC1-LC2, e.g., cloud 3 in Fig. 3 ("oblate" means that variation in the MSI value is significantly less than in LC1 and LC2). For illustration purposes only, the centers of classes forming "molecule" ball-and-stick segments are shown. The most essential features of the 3D model are shown below step by step: a) mature and old growth forests: b) pine forest regeneration after cutting; c) open mires, and d) destroyed categories, starting with forest ecosystems located in the central, "core" part of spectral space. These categories include the vast majority of vegetation types of the territory, more than 95% of the area.

Mature and old growth forests

The biogeocenotic scheme shown in Fig. 2 is an "imaginary" construction, based on ground observations, while the spectral space model is real, albeit virtual. Nevertheless, the location of reference points 1-7 in Fig. 2 almost completely coincides with the position of the mature and old-growth pine forest classes in spectral space (Fig. 4).

Both gradient lines, dry and wet, go along axis LC1 from dark to bright parts of spectral space due to reduction of radiation absorption by canopy caused by decreasing leaf area index (LAI), which, in turn, is a result of edaphic conditions deterioration. Besides, along the dry gradient the moisture stress grows, and line goes up. There is no moisture lack along the wet gradient, and the line remains almost horizontal. Due to their wide ecological amplitude, pine stands occupy all the forest zone of spectral space. Class 1 is the most productive mixed pine-spruce-birch forest with spruce undergrowth. Dominant ground vegetation species are Vaccinium myrtillus and V. vitis-idaea; the soils are Ferric and Ferric-Carbic Podzol. Class 3 is pure pine stands on fluvioglacial sands, with pine undergrowth, the soil is sandy shallow Podzol. Wet concave spots are of the V. vitis-idaea type, while dry convex ones are of the Cladonia type. Class 4 represents low productive pine stands growing on bedrock or boulder fluvioglacial sediments with primitive soils (Leptosol). The ecosystems located along the wet gradient line are the ecotones between automorphic habitats and open mires. Class 5 is formed by mixed pine-birch-spruce stands at an intermediate stage of paludifcation with a thin peat layer (up to 0.3-0.5 m); the ground vegetation is a dwarf shrubs (Ledum palustre, Vaccinium uliginosum). Classes 6 and 7 are pure sparse pine stands of Sphagnum and Carex-Sphagnum type, respectively.

Classes 5 and 6 occupy large areas at the periphery of mesotrophic mires; class 7 is commonly a narrow strip alone the edge of ombrotrophic mires. The strip width is often less than 30 m, so the scanner is unable to register it. Thus, in most cases, the location of pine forests in spectral space coincides with their location in the axis of edaphic and phytocenotic coordinates, and the biogeocenotic complexes (quaternary deposits + vegetation) can be identified. Obviously, the scanner registers not the type of Quaternary sediments as such, but the conditions of water and mineral nutrition, most typical for specific type of habitats.

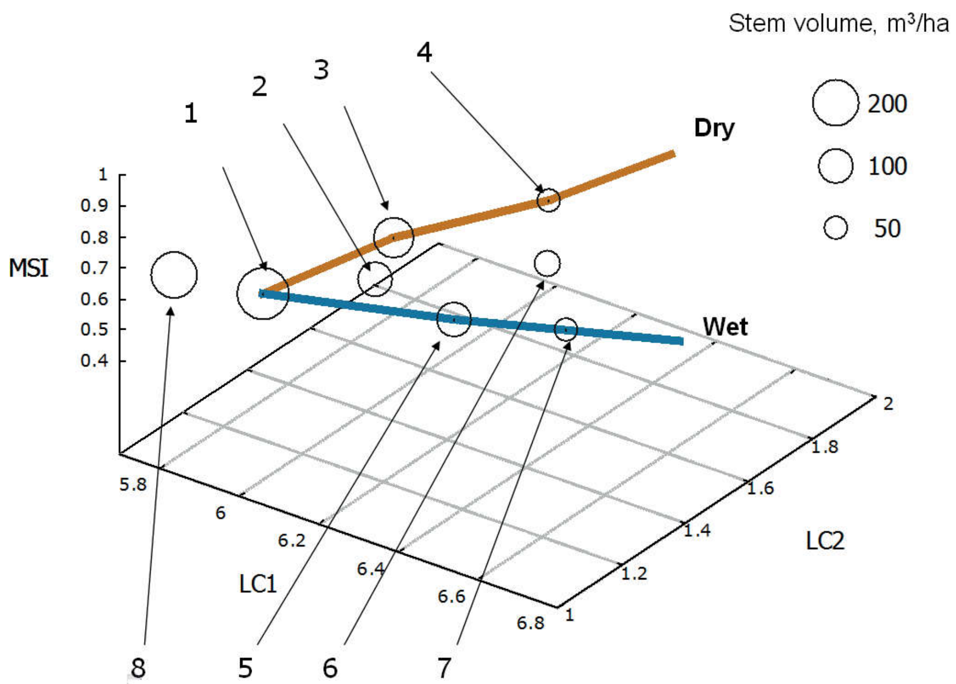

Fig. 4. A spectral segment of mature forests. Points 1–7 are the same forest classes as in Fig. 2. Class 8 is closed canopy spruce stands. Mean stem volumes are calculated from forest inventory data.

Class 2 is relatively ambiguous; it can be marked as the "open canopy conifer stands." Due to pixel size 30x30 m, the scanner registers mixed signal from crowns, ground vegetation, and tree shadows, which makes it impossible to determine the tree species composition, and even dominant species. In some cases, this is possible by using the landscape context; e.g., in denudation-tectonic relief, this class includes pine-dominated, or pine-spruce stands of the dry myrtillus type, while on abraded, smoothed drumlins of sea plane (the White Sea lowland) one can find spruce stands of the wet myrtillus type. If a sufficiently detailed digital elevation model (DEM) existed, then the discrimination of these classes could have been made with the use of some geomorphometric indexes (Wood 1996). Thus, the two types of habitats above have rather different values of fractal dimension. It should be noted that these classes are rather similar types of vegetation in terms of the mass and energy exchange (without account of tree species composition).

Class 8 is represented by spruce-dominated stands with closed canopy growing on the slopes of moraine hills (myrtillus type), and more wet variants (Sphagnum/myrtillus) occupying gentle slopes at the foot of hills and depressions. Stands of this type have high LAI; most solar energy is absorbed, making them difficult targets for discrimination of classes (Cohen et al 1995). Thus, class 2 is ambiguous due to low canopy density, while class 8 – owing to high density. In both cases discrimination is possible using DEM.

A more or less significant proportion of spruce in stand composition is observed in classes 1, 2, and 5, closest to the optimal edaphic condition. In these classes, the share of birch may reach 20-30%. All forest classes have a few parts with different canopy density, so the total number of mature forest categories exceeds 20.

Pine regeneration

The cutting in this territory is carried out in the most productive habitats (classes 1 and 3 in Fig. 4). The locations of new clearcut class is almost the same for both habitats, but the succession trajectories of forest regeneration through spectral space are sharply different depending on the type of Quaternary deposits (Fig. 5).

The exact position of the trajectory end point (pine or spruce domination), as well as succession velocity, especially at last stages, depends on local conditions: landscape context, details of edaphic features, and the

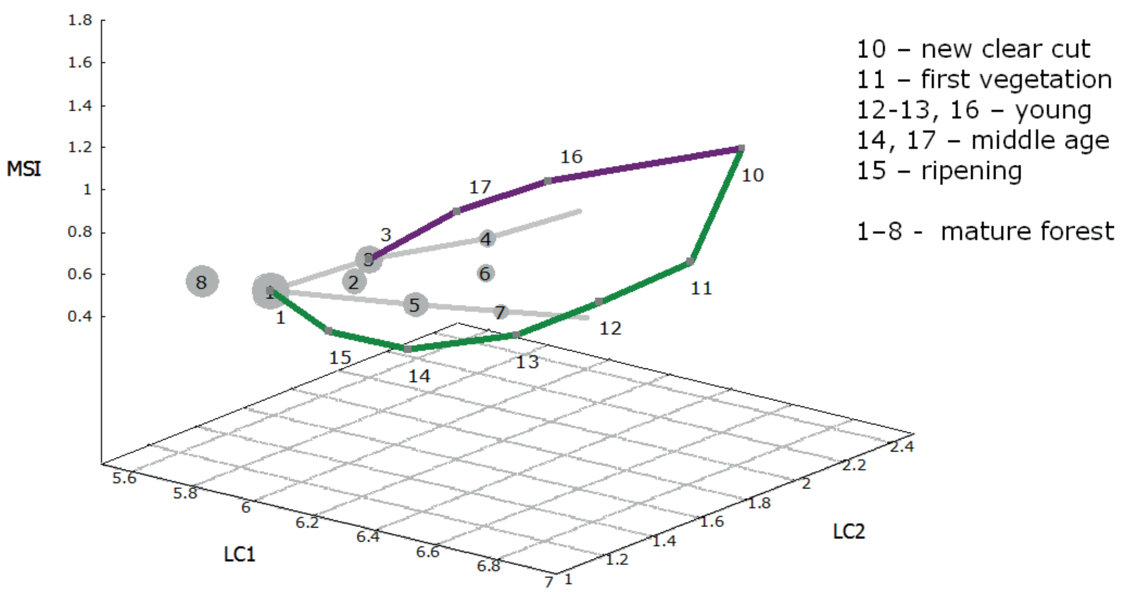

Fig. 5. Trajectories of pine forest regeneration on moraine (green) and on fluvioglacial deposits (purple). Light grey is mature forest segment (classes 1-8).

availability of spruce and/or pine seeds. On fluvioglacial sands, the trajectory is almost a straight line, age stages are less visible than on the moraine. Multi-temporal images are required for better discrimination.

Open mires in this territory are presented by two main types of water-mineral nutrition: ombrotrophic (oligotrophic) and mesotrophic. These mires have significantly different microrelief and vegetation cover; dominant species are Sphagnum and Carex, respectively. Due to differences in reflectance, in spectral space mires encircle the forest zone from opposite sides (Fig. 6). Different types of mires form wide "blades" of complex shape; only the main centerlines are shown here. Position in spectral space also reflects the level of water table, from inner lakes and pools in the dark part of space to the dried plots occupying the brightest part.

Deeply transformed ecosystems (shrubs, meadows, crops) are located in the right, lightest part of space (Fig. 7). The trajectory of forest recovery after the fire moves from the dark side in the direction of a new clearcut. Non-vegetation categories, such as sands and ore careers, roads and settlements, occupy the zone with the maximum MSI value.

Ecosystem map

The simplest way to transform the spectral space model into the map is to use LC1-LC2-MSI coordinates of the points in Figures 4–7 as class centers for the minimum distance classification. Obviously, this method is rather illustrative. For more accurate modeling of the space structure and further mapping, the full voxelization is required. This is especially the case for complex mire systems and forest-mire ecotones. The vectorized classification result is shown in Fig. 7. Two-step generalization was applied: "mode" filtering to the classified raster and the cleaning topology tool "remove small areas" after vectorization.

The position in spectral space defines a type of the biogeocenoic complex (Quaternary deposits/vegetation), which, in turn, determines the soil type, biological productivity, tree species composition, undergrowth, and ground vegetation, i.e., qualitative, intrinsic biogeocenotic characteristics. Specific quantitative values of such parameters as stem volume, average height, dbh, etc., can be calculated using forest inventory data. These values compose the attribute data of the vector layer. So, the ecosystem model can produce a set of thematic maps: land use categories, Quaternary deposits, forest inventory, soil and mire types, biological productivity, anthropogenic disturbance, etc.

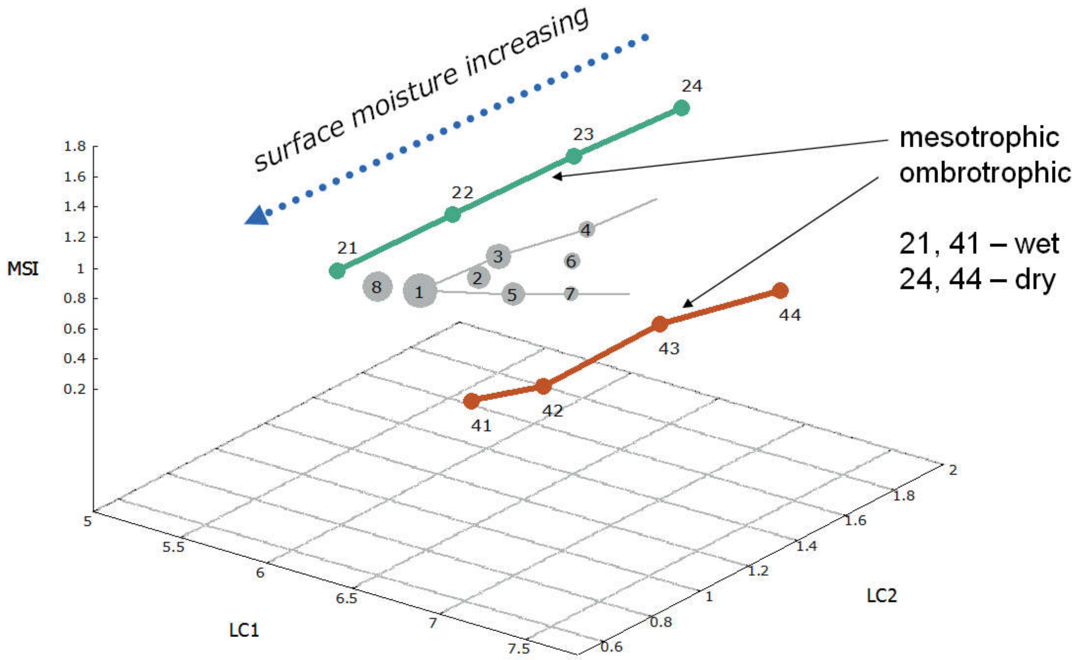

Fig. 6. Segments of open mires.

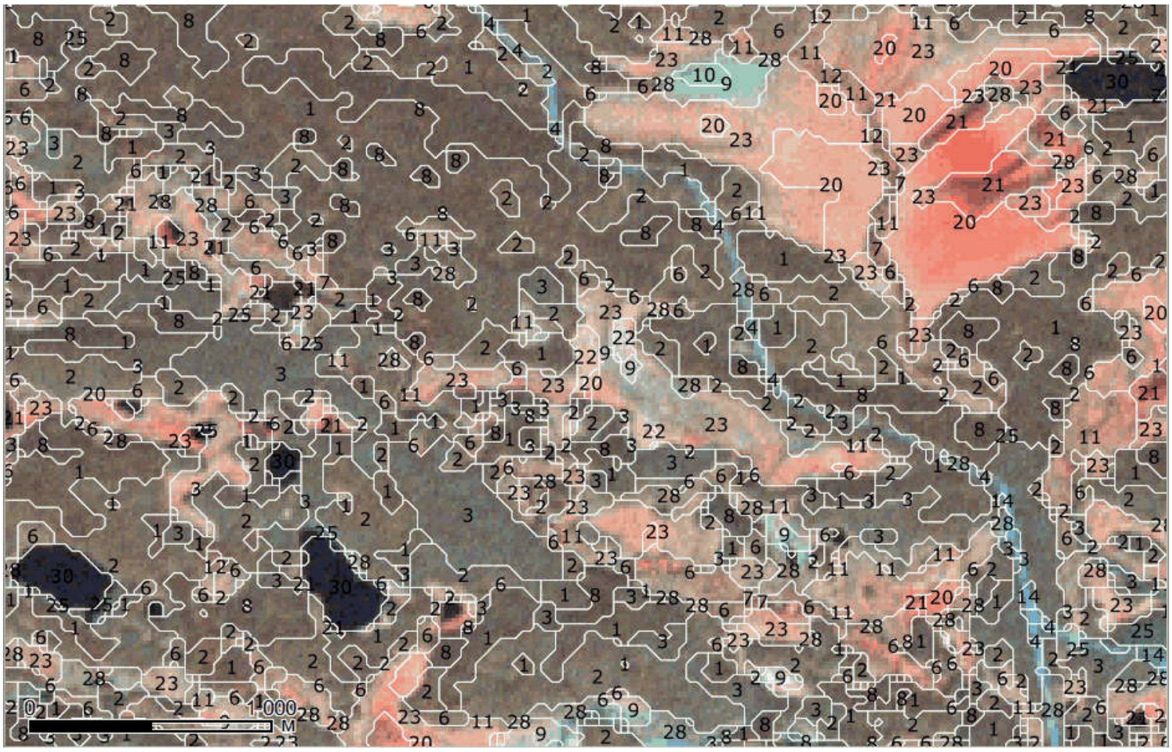

Fig. 7. A fragment of the vector layer of vegetation model. Background RGB-synthesis of infrared channels (4-5-7). Coordinates of the center 64.4752 N, 30.6894 E

DISCUSSION

Figures 4–6 show that spectral space of the scanner image is a complicated system of zones and trajectories. However, it can be easily interpreted in ecological terms. The investigation of these patterns to create a vegetation map is thought to be much more reasonable, effective, and interesting than "blind" supervised classification. The process starts with the biogeocenotic scheme creation (Fig. 2) by studying published materials on Quaternary deposits and vegetation typology of the study area. At this stage, the visible scanner image of the area is created (RGB-synthesis from infrared channels). As a result of the analysis of all the data available, the first variant of the classification scheme is obtained. The next step is to build the spectral space model. Protected areas are believed to be ideal as reference objects: their ecosystems are undisturbed (this facilitates the localization of spectral classes) and usually well studied and mapped. The procedure of taking training sites signatures is conventional.

After preliminary localization of the main ecosystem classes in spectral space and its visualization with the gnuplot utility, the model refinement begins and the advantages of 3D modeling become apparent. The capability to examine the whole spectral space from any side, as well as the location and relative position of different categories are fundamentally important as it involves human intuition into analysis. Two bi-dimensional scatterplots Brightness/Greenness and Brightness/Wetness (e.g. Cohen et al 1995; Krankina et al 2008) are much less informative.

The spectral space model makes it possible to purposefully correct the position of class centers in space by editing the statistical table for the minimum distance classification and to find optimal classification variant by the trial-and-error method. The supervised classification is one-directional, i.e., it goes from training sites to the entire image. In 3D space, interpolation becomes possible. It is logical to assume that the categories with intermediate characteristics can be found in the space span between classes with known properties. To test this hypothesis we can simply add a new line with space coordinates into the statistical table. We can also determine where the category occupying a specific part (LC1-LC2-MSI) of spectral space is located in the map. And, most importantly, there is the possibility to see the classification results both in geographical and spectral space, e.g., as a set of voxels, or points clouds. To conclude, the classification can be transformed from supervised to manageable one, thus allowing to extract a greater amount of information from the image.

These new opportunities improve our understanding of the way the scanner recognizes different types of vegetation, and provide a much more effective feedback mechanism of training sites selection, as compared to the accuracy assessment by the kappa statistics. In some cases, classes discrimination by non-visual methods is practically impossible, but is very simple in visible 3D space. This can be applied to forest edges at the borders with mires and lakes, as well as to any types of narrow ecotones. Preliminary results have shown that the proportion of such categories is remarkably high.

The spectral space model is a link between technical image information and human understanding of ecosystems typology. It plays the role of interactive, mobile classification scheme. Creating the spectral space model is a long-term research process. As a result, the first detailed digital map of the biogeocenotic structure for the study area has been compiled. The model includes all basic classes of primary ecosystems, and some variants and stages of their natural and anthropogenic disturbances. The number of detail is constantly increasing. Accuracy assessment was carried out by comparing with the georeferenced database "CORINE-biotopes" (Söderman 1997). Taking into account the level of generalization, the degree of identity was almost 100% (Kryshen and Litinsky 2013). Such accuracy is quite explicable. Plants and environment are interacting as a physico-chemical system (Pignatti et al 2002). The scanner registers the physical characteristics of biogeocenosis. This allows allocating a relatively small number of generalized ecosystem classes with an almost absolute certainty.

The biophysical base of such a classification makes it independent of local (forestry, geobotanical) typologies and, thus, provides an opportunity for creating an internally consistent vegetation map for large areas. It should be noted that currently the main barrier to increase the map detail is the lack of high resolution DEM. The ideal variant would be the use of LiDAR data, which would also allow receiving the information on canopy architecture. Decomposition of the spectral classes by these parameters could increase the total number of recognized classes of vegetation several times.

CONCLUSIONS

The spectral space model reflects the continual structure and dynamics of vegetation cover in space and time in a clearly visible form. The model analysis substantially facilitates the classification process and allows extracting much more information from the image that was previously unavailable. Maps derived from spectral space models can be useful for forest management and the monitoring of landscape mosaic dynamics on the regional level and will help investigate landscape structure with quantitative methods. However, its mission seems to be more fundamental. Perhaps, the spectral space model can serve as the foundation for objective classification of ecosystems, where one of the most significant clustering criteria is the mathematically expressed position in spectral space. Practically, it will help reduce uncertainty in forest mapping at the global level. An internally consistent ecosystem map can be a spatial frame for integration of discrete fragmentary data (phytocenotic, geobotanical, landscape ecological) into the holistic space-time continuum, i.e., a comprehensive structural and functional model.

Preliminary analysis has shown that spectral models are rather similar in TM/ETM+ images of Fennoscandia, Siberia and Canada. Free web-enabled imagery and software are used for the approach implementation, so it could be applied right now. In our opinion, it is likely to be of interest to the unconventionally minded researchers and students. It would be beneficial to test this approach in similar natural conditions and in other boreal territories.

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