Multi-spectral multibeam imaging of palaeo-ice stream landforms in the Baltic Sea

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Abstract: *This research presents the preliminary results of the Baltic STREAMBAL project. In this project imaging and mapping of the seafloor was conducted using multibeam echosounder to identify palaeo-ice streams activity and their geomorphic traces in Central and Southern Baltic Sea. Recognition and classification of bottom morphological forms was carried out through parametrization of the bathymetric model. The Digital Elevation Model was subjected of two-dimensional Fourier Analysis allowing calculation of spectral parameters including spectral width, spectral skewness and spectral moments. In addition, the fractal dimension was calculated using the slope of the spectrum to quantify bottom roughness and assess the regularity of glacial relief. The selected parameters were the input set for the object-based image analysis (OBIA) algorithm enabling automatic separation of palaeo-ice stream landforms on the use of the theory of moments with invariants. The values of moments with invariants, determined on the basis of the available maps, create a new, valuable set of data, which are the geometrical parameters of the scene representing the landforms. The obtained data sets are used in deep machine learning method, the result of which is a map of classified bottom morphological forms.*

Keywords: *Multibeam echosounder, Baltic Sea bottom, palaeo-ice streams, 2D FFT DEM parametrization, OBIA, deep machine learning*

1. INTRODUCTION

The results of studies conducted in areas covered by modern ice sheets prove that ice movement has the highest speed within areas known as ice streams. Ice streams cause the formation of very regular landforms with a shape that is significantly elongated in the direction of the ice flow. The STREAMBAL project has the goal to reconstruct ancient ice streams, which most likely functioned in the central and southern Baltic area during the last glaciation and intensively relief its bottom. One of the effects of this activity are the elongated glacial forms that are perfectly visible in some areas of the bottom of the Baltic Sea.

Identification of subglacial formations of the Baltic Sea bottom was carried out on the basis of DEM analyses with a horizontal resolution of 2 m obtained as a result of multibeam echosounder measurements. The study area was located in the south-central Baltic Sea with coordinates of a rectangular area with corners – south-west 55°33'20", 16°43'30" and north-east. - 55°41'38", 17°0'50". The area is approximately 17×16 km (272 km^2) with depths ranging from 27.33 m to 52.80 m (Fig.1.).

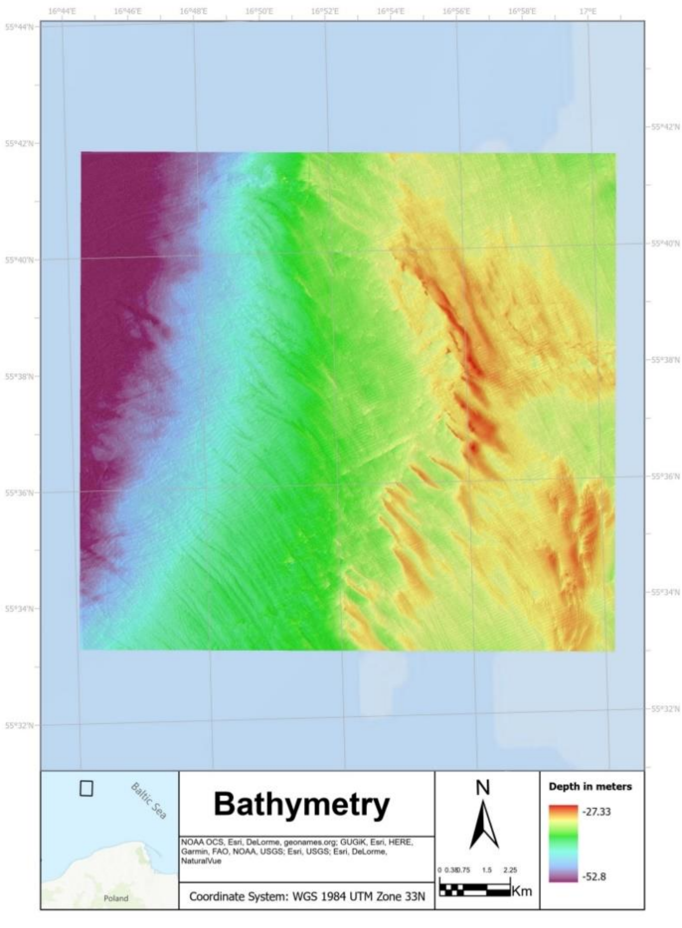

Fig.1: Bathymetric map of studied area in the Baltic Sea.

The 2D FFT method was used to analyse the seabed surface. A novelty for recognizing subglacial landforms is the calculation of spectral parameters [1, 2] as the input to Object Based Image Analysis (OBIA) and artificial intelligence methods through machine learning, which were applied for segmentation and classification of DEMs. After segmentation, a few supervised classification approaches were introduced and tested to generate predictive outcomes based on ground-truth samples (points inserted manually in localisations with interpreted type of landform) and relevant features selected in the previous step.

Segmentation and classification of DEM with OBIA were used to extract characteristic, streamlined landforms and automatically identify their spatial distribution and planar shape.

2. METHODOLOGY

Two-dimensional Fourier analysis was used for morphometric analysis of the bottom surface, the coefficients of which were calculated in a sliding square window with a dimension of 400 m and an overlap of two consecutive sliding windows of 90%. Before the analysis, each surface extracted by the sliding window was multiplied by a three-dimensional Slepian function to remove the effect of spectral leakage, and then the value of the average slope (trend) of the surface was subtracted [1].

The 2D FFT is defined as follows:

$$P(K_x, K_y) = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} s(x, y)\, e^{-i2\pi(K_x x, +y)} dxdy \tag{1}$$

where:
K_x, K_y – spatial frequencies, values of wave vectors in x, y [m^{-1}] directions,
$s\ (x, y)$ – corrugated surface in sliding window,
x, y – distance in the x and y directions.

Next, the two-dimensional spectrum was cross-sectioned every 5° from the central point to the edge of the window, determining the one-dimensional spectra. For each one-dimensional spectrum obtained in this way, the eight spectral parameters were calculated [2]. There are zero-order spectral moment (m0), second-order spectral moment (m2), spectral width (ν2), mean frequency (ω0), quality factor (Q-factor), spectral skewness (γs,), spectral skewness, defined for central moments (γs_centr), and fractal dimension (Dfft) from the slope of the spectrum. The parameters calculated in each window were averaged. An example of the results of calculations of the four spectral parameters are shown in the form of maps of their values in Figure 2.

A geographically referenced graphic maps of 8 spectral parameters were obtained in Matlab and visualized in ArcGIS. Artificial intelligence methods were then used using machine learning based on image attribute enhancement.

The calculations were performed in Matlab software, using Graphical Toolbox, Deep Learning Toolbox [3] and an author's script [4]. The calculated parameters of the script provide a set of search/missing input data for the OBIA algorithm, which allows automatic separation of geomorphological bottom forms based on the theory of moments of shape with invariants. The values of moments with invariants, determined using available maps, form a new data set, which are geometric parameters of the scene representing bottom forms in the absence of other input data.

The OBIA (object recognition centroid) algorithm used in the script integrated the map cells into groups. The result of the algorithm is a grouping that allocates cells to given objects. The innovation of the author's solution compared to standard solutions of this type [3] is that the relationships between objects were also analysed. These invariants are an original feature of the author's work. They describe the relationships of graphical features between objects [4].

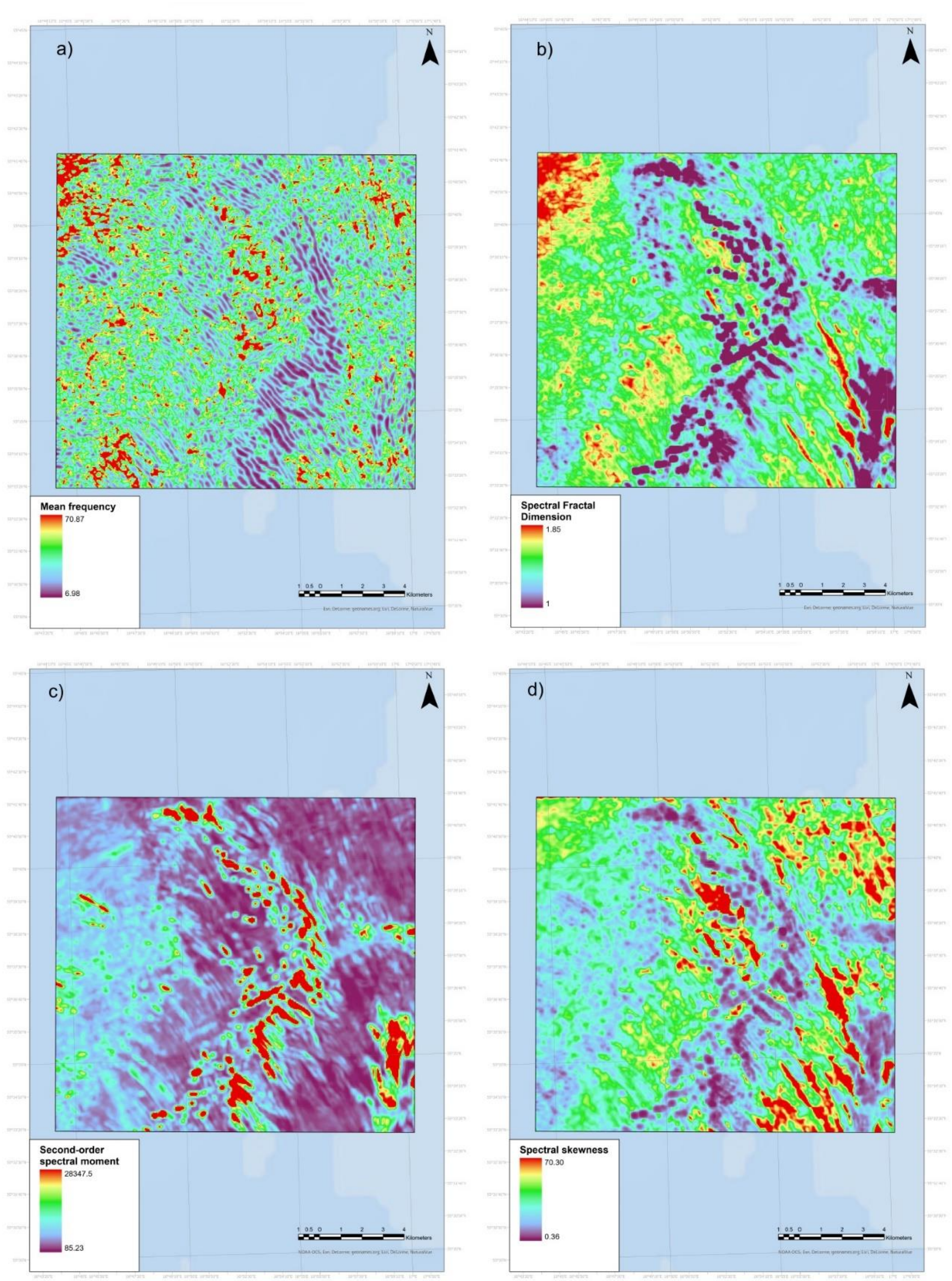

Fig.2: Maps of spatial distributions of spectral parameters a) mean frequency, b) fractal dimension, c) spectral moment of second order, d) spectral skewness.

The way to define it was to create a graphical centre of gravity of the group in the script and add it to the object. The algorithm involves collecting a group of cells with their centroids (i.e., points associated with the groups, lying inside and representing their geometric centres of gravity) on the plane of the learning map. The distances between the nearest centroids of the groups in Euclidean space on the map plane are then determined. The centroids are then moved based on the arithmetic average of the distances between all points in the group (no point is rejected or added to the group). The steps of the algorithm were repeated until the convergence criterion is met (i.e., a state is reached in which the affiliation of points to groups and objects does not change). Using image variables, Artificial Intelligence evaluates the movement of neighbouring objects (or more precisely, their centroids) by analysing the spatial relationships of a sequence of artificially generated features that follow each other with step $dt \rightarrow 0$.

The information given to the algorithm was a so-called gain signal based on positive gain and negative attenuation. In subsequent rounds, the system learned from previous runs, each time changing the gain characteristics of the image. In our case, the data proved to be quite stable and the system did not show much change (it learned) after only 4 passes. The system used feedback from its own actions and experiences. Note the very possible over-learning of the system – drawing false conclusions from artificially created artefacts, such as statistical ones.

3. RESULTS AND CONCLUSIONS

The result of using artificial intelligence algorithms to distinguish glacial forms in the study basin is shown in Figure 3. The algorithm accurately identified line forms and determined the direction of the movement of the ice sheet and the outflow of glacial waters.

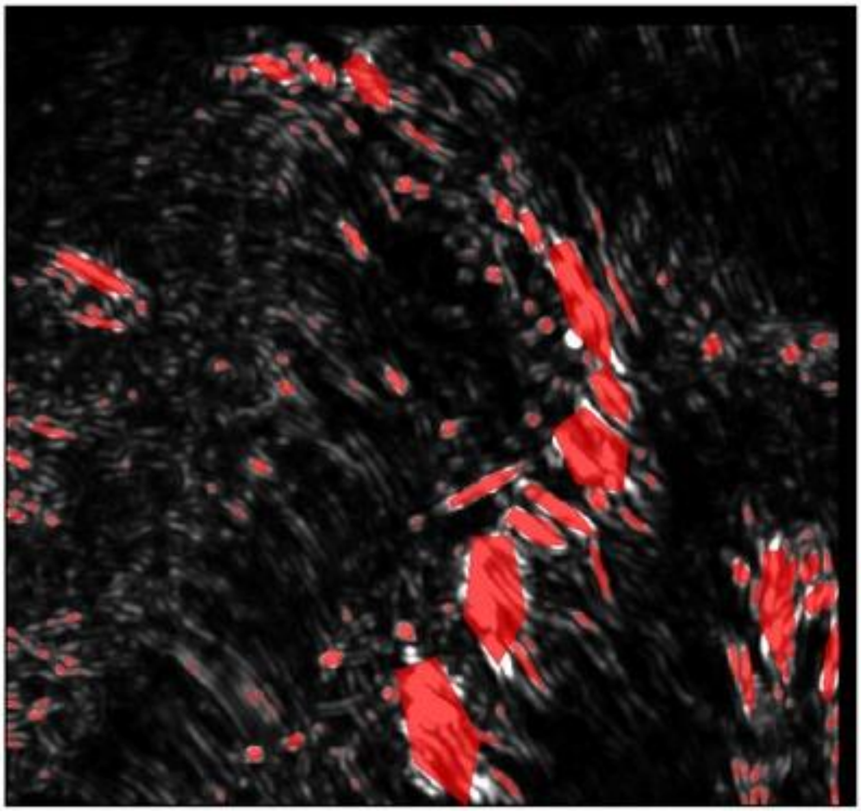

Fig.3: Map showing distinguished linear geomorphological forms with the directions and forces of the movement of the ice sheet and the outflow of glacial waters.

The obtained results of the average direction 168 [deg] and average velocity 149 [m s^{-1}] of the determined objects, do not relate in any way to real physical characteristics only to artificially created geometric features of the image and should be considered only as an illustration of the script's capabilities. Providing more real parameters will help drive the algorithm to produce more real results. Providing more real parameters will help drive the algorithm to produce more real results.

The presented image analysis method using DEM spectral parametrization and deep machine learning can be very helpful in recognizing and classifying bottom geomorphological forms recorded with multibeam echosounder. Large bottom areas of hundreds and thousands of square kilometres scanned with high resolution require automated methods for their geomorphological analysis. The method we present is an attempt to address such a challenge.

4. ACKNOWLEDGEMENTS

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