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Original Empirical Research

Development of an Algorithm for Semantic Segmentation of Earth Remote Sensing Data to Determine Phytoplankton Populations

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Abstract

Introduction. Computer vision is widely used for semantic segmentation of Earth remote sensing (ERS) data. The method allows monitoring ecosystems, including aquatic ones. Algorithms that maintain the quality of semantic segmentation of ERS images are in demand, specifically, to identify areas with phytoplankton, where water blooms— the cause of suffocation — are possible. The objective of the study is to create an algorithm that processes satellite data as input information for the formation and checking of mathematical models of hydrodynamics, which are used to monitor the state of water bodies. Various algorithms for semantic segmentation are described in the literature. New research focuses on enhancing the reliability of recognition — often using neural networks. This approach is modified in the presented work. To develop the direction, a new set of information from open sources and synthetic data are proposed. They are aimed at improving the generalization ability of the model. For the first time, the contour area of the phytoplankton population is compared to the database — and thus the boundary conditions are formed for the implementation of mathematical models and the construction of boundary-adaptive grids.

Materials and Methods. The set of remote sensing images was supplemented with the author's augmentation algorithm in Python. Computer vision segmented areas of phytoplankton populations in the images. The U-Net convolutional neural network (CNN) was trained on the basis of NVIDIA Tesla T4 computing accelerators.

Results. To automate the detection of phytoplankton distribution areas, a computer vision algorithm based on the U-Net CNN was developed. The model was evaluated by the calculated values of the main quality metrics related to segmentation tasks. The following metric values were obtained: Precision = 0.89, Recall = 0.88, F1 = 0.87, Dice = 0.87, and IoU = 0.79. Graphical visualization of the results of CNN learning on the training and validation sets showed good quality of model learning. This is evidenced by small changes in the loss function at the end of training. The segmentation performed by the model turned out to be close to manual marking, which indicated the high quality of the proposed solution. The area of the segmented region of the phytoplankton population was calculated by the area of one pixel. The result obtained for the original image was 51202.5 (based on information about the number of pixels related to the bloom of blue-green algae). The corresponding result of the modeling was 51312.

Discussion and Conclusion. The study expands theoretical and practical knowledge on the use of convolutional neural networks for semantic segmentation of space imagery data. Given the results of the work, it is possible to assess the potential for automating the process of semantic segmentation of remote sensing data to determine the boundaries of phytoplankton populations using artificial intelligence. The use of the proposed computer vision model to obtain contours of water bloom due to phytoplankton will provide for the creation of databases — the basis for environmental monitoring of water resources and predictive modeling of hydrobiological processes.

Keywords: environmental monitoring of water resources, phytoplankton boundaries, water bloom contour, blue-green algae bloom, space image data segmentation

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Оригинальное эмпирическое исследование

Разработка алгоритма семантической сегментации данных дистанционного зондирования Земли для определения фитопланктонных популяций

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Аннотация

Введение. Компьютерное зрение широко используется для семантической сегментации данных дистанционного зондирования Земли (ДЗЗ). Метод позволяет контролировать экосистемы, в том числе водные. Востребованы алгоритмы, обеспечивающие качество семантической сегментации снимков ДЗЗ, в частности, для выявления областей с фитопланктоном, где возможно цветение воды — причина заморов. Цель исследования — создание алгоритма, обрабатывающего спутниковые данные как входную информацию для формирования и верификации математических моделей гидродинамики, по которым отслеживается состояние водных объектов. В литературе описаны различные алгоритмы семантической сегментации. Новые исследования сосредоточены на повышении надежности распознавания — чаще с помощью нейросетей. Этот подход совершенствуется в представленной работе. Для развития направления предлагаются новый набор сведений из открытых источников и синтетические данные для улучшения обобщающей способности модели. Впервые область контура фитопланктонной популяции сравнивается с базой данных — и так формируются граничные условия для реализации математических моделей и построения гранично-адаптивных сеток.

Материалы и методы. Набор снимков ДЗЗ дополнили с помощью авторского аугментационного алгоритма на языке Python. Компьютерное зрение сегментировало области фитопланктонных популяций на снимках. Сверточную нейронную сеть (СНС) U-Net обучили на базе ускорителей вычислений NVIDIA Tesla T4.

Результаты исследования. Для автоматизации обнаружения областей распространения фитопланктона разработан алгоритм компьютерного зрения, основанный на СНС U-Net. Модель оценили по вычисленным значениям основных метрик качества, относящихся к задачам сегментации. Получены следующие значения метрик: Precision = 0,89, Recall = 0,88, F1 = 0,87, Dice = 0,87 и IoU = 0,79. Графическая визуализация результатов обучения СНС на обучающем и валидационном наборах показала хорошее качество обучения модели. Об этом свидетельствуют малые изменения функции потерь в конце обучения. Выполненная моделью сегментация оказалась близка к ручной разметке, что говорит о высоком качестве предложенного решения. По площади одного пикселя рассчитали площадь сегментированной области фитопланктонной популяции. Полученный результат для исходного изображения — 51202,5 (по информации о количестве пикселей, относящихся к цветению сине-зеленых водорослей). Соответствующий итог моделирования — 51312.

Обсуждение и заключение. Исследование расширяет теоретические и практические знания о применении сверточных нейронных сетей для семантической сегментации данных космических снимков. Учитывая итоги работы, можно оценить потенциал автоматизации процесса семантической сегментации данных ДЗЗ для определения границ фитопланктонных популяций с помощью искусственного интеллекта. Применение предложенной модели компьютерного зрения для получения контуров цветения воды из-за фитопланктона позволит создать базы данных — основу для экологического мониторинга водных ресурсов и прогностического моделирования гидробиологических процессов.

Ключевые слова: экологический мониторинг водных ресурсов, границы фитопланктона, контур цветения воды, цветение воды из-за сине-зеленых водорослей, сегментация данных космических снимков

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Introduction. Automated algorithms for processing information received from satellites are needed in various fields of activity. Solving fundamental and applied problems of ecology requires segmentation of regions in accordance with the focus of attention of researchers. This optimizes the process of studying and modeling hydrobiological processes. An example of such local interest is the bloom of water due to the spread of phytoplankton. The phenomenon is important for current and complex monitoring of water resources. It is clearly visible from satellites during remote sensing of the Earth (ERS).

Water bloom affects significantly its quality in surface sources used for domestic water supply systems [1]. The reaction of phytoplankton populations in the hydrological environment can reliably assess the general state of the aquatic ecosystem [2]. The negative consequences of uncontrolled algae growth are mass death of fish (suffocation), increased load on water purification plants [3], and pollution of shores and beaches [4].

Systematic measurements at automatic water quality monitors, as well as obtaining data from research expeditions, are labor-intensive and expensive activities. An additional source of information on the state of the phytoplankton community is modern satellite systems equipped with survey instruments. They allow remote recording of the state of the algae biomass, tracking its dynamics in a given time period.

A significant advantage of satellite data as a tool for monitoring water resources is the possibility of full-scale and operational control at any point on Earth. A wide view of the water area, as a rule, gives researchers a significant amount of useful information. But, despite the active development of systems based on computer vision algorithms, the problem of identifying the contours of regions of interest in remote sensing data has not yet been fully solved.

Good results are obtained by various algorithms of semantic segmentation on images. With their help, it is possible to identify and clarify the boundaries and structure of natural objects. In [5], the efficiency of the LBP method (local binary patterns) for recognizing objects consisting of curvilinear contours is shown. LBP provides high edge sharpness and detail of Earth satellite sensing data. In [6], it is noted that to increase the reliability of recognition, it is required to combine artificial intelligence algorithms and such classical methods of image edge detection as Sobel, Kirsch and Laplace operators. In [7], a comprehensive approach is proposed for semantic processing of satellite images of unlimited size using U-Net neural network models, which showed an F1-score value from 0.78 to 0.91 when detecting objects.

Paper [8] provides an overview of intelligent methods for solving the problem of semantic segmentation of data on satellite images. The authors conclude that in this case, neural network algorithms are the most effective and productive. As an example, a convolutional neural network (CNN) is given, trained on several thousand satellite images of Massachusetts (USA). The accuracy of the model was 85.31%. In [9], semantic segmentation, instance segmentation, and panoptic segmentation are considered. The advantages of using deep learning methods implemented in the architectures of such CNN as SegNet, U-Net, and DeepLab are specified. In [10], automated processing of satellite images is based on a combination of the SpaceNet dataset and progress in computer vision which are made possible by deep learning. This paper presents five approaches based on improvements to the U-Net and Mask R-Convolutional Neural Networks models. The metric values for the best models are as follows: average precision (AP) and average recall (AR) are 0.937 and 0.959, respectively. An effective application of CNN for detecting contrails on satellite images is described in [11]. It is proven that in large-scale monitoring of contrails with measurement of their impact on climate, the approach based on CNN of U-Net architecture demonstrates F1-score equal to 0.52, with an overall average detection probability of 0.51.

The 2023 models Segment Anything (SAM), Language-Segment-Anything (Lang-SAM), and HQ-SAM are of particular interest. These are dynamic deep learning tools that can predict object masks from images using input hints. Several researchers have already applied this approach to the analysis of aerial photographs and ERS data. The accuracy of identifying areas of interest has proven to be high [12]. In [13], the F1- score value reaches 86.5%±4.1%. In the future, models of similar architecture with various modifications (Polyp-SAM, Grounding DINO, etc.) will provide for both interactive (requiring user intervention) and automatic segmentation.

Intelligent technologies are increasingly being introduced to process remote sensing data. High accuracy of models is noted. Particular attention is paid to methods based on such CNN as SegNet, U-Net, DeepLab in combination with classical methods of image preprocessing. A generalized approach to segmentation is actively developing.

This paper considers the solution to a problem in the ERS data assimilation using computer vision. The application of U-Net CNN for segmentation of areas containing phytoplankton populations is shown. The algorithm created by the authors provides for the segmentation of regions of interest and calculation of their areas, which is required for further analysis when solving problems of hydrodynamics and hydrobiology.

The following four points describe the scientific novelty of the presented study.

1. A data set was formed from open sources.

2. Synthetic data were generated to improve the generalizing ability of the model. For this purpose, the authors' own augmentation algorithm was used to make the model more resistant to noise in practical use [14].

3. An intelligent model based on the U-Net CNN architecture was implemented in the high-level Python language. Its key hyperparameters were optimized using the Optuna library and checked on a test dataset.

4. The areas of the found contour containing phytoplankton populations were compared to the existing database. In this way, boundary conditions have been formed for the subsequent implementation of mathematical models and the construction of boundary-adaptive grids.

To achieve the set goal, it is required to solve a number of problems:

– to prepare an ERS database containing regions of interest segments of water bloom;

– to validate and describe the topology of the U-Ne SNS;

– to perform data augmentation to create an extended representative set;

– to implement, optimize, debug and test the CNN of U-Net architecture;

– to determine values of key metrics of the model quality for segmentation;

– to calculate the areas of the segmented contour given the scale of the original image.

The theoretical significance of the study is due to the expansion of ideas about the possibilities of using computer vision technology in the field of water resources monitoring. The practical significance consists in the development of an applied cross-platform and scalable tool for analyzing remote sensing images to record regions of interest in aquatic ecosystems.

Materials and Methods. For geospatial analysis, we use open-source software that is often applied to solve environmental problems [15].

The study is based on current satellite data. The authors focus on the state of water bodies during the bloom of blue-green algae. Analysis of this information allows:

– predicting the volume and distribution of phytoplankton in the water area [16];

– checking physical and biological processes that determine the rate of phytoplankton growth and biomass accumulation [17];

– analyzing climate change based on the forecast of the dynamics of the bloom process [18];

– studying in detail the process of CO_2 exchange between a water body and air [19].

To automate the process of detecting regions of phytoplankton populations and calculating their areas, it is proposed to develop a computer vision algorithm based on the U-Net CNN architecture.

As a training sample for the deep learning algorithm, 20 space images of water bodies such as the Black, Caspian, Azov Seas, etc., were taken. The photos were obtained at different points on the earth's surface.

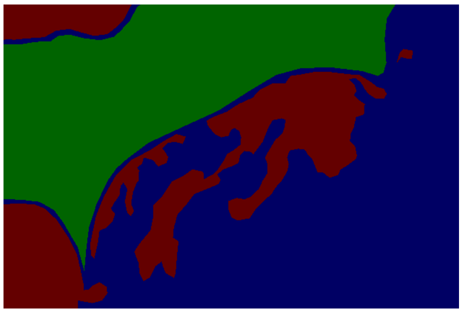
The first step was to label the images to transform the information into a format that could be understood by the computer vision algorithm for performing the segmentation. There were two common approaches to providing annotations:

– creating a pixel-level mask;

– selecting polygon boundaries for the region of interest.

We have used the first option, where the pixel-level mask files represent regions of interest for the algorithm. The marked masks are files with the extension jpeg or png. The proportions correspond to the image they annotate. Figure 1 shows an example of the original image and its mask, where green indicates land, blue indicates water surface, and red indicates the region of the phytoplankton population.

a)



b)

Fig. 1. Image mapping: *a* — original image; *b* — image mask

To increase the number of images in the data set, we used the authors' augmentation code, supplemented with noise effects. When creating the extended data set, we used the following modifications of the original images:

– rotation by an arbitrary angle;
– display along the OX and OY axes;
– cropping;
– scaling;
– color correction.

All changes were made taking into account the noise that may appear on real images obtained through remote sensing, and were segmented using the developed algorithm.

Let us note the advantage of the authors' algorithm for creating additional source data. Under conditions of a limited set of real images, the use of artificially created images for training will allow for a more fine-tuning of the developed model, optimizing its parameters and making it more resistant to distortion in practical application.

The U-Net CNN architecture is designed to solve the problem of biomedical data segmentation. The determining factor in its selection is the relatively small size of the initial data, with which U-Net shows satisfactory results in practice.

The U-Net CNN architecture is based on the interaction of convolution layers + pooling, which first reduce the spatial resolution of the image (encoder), and then increase it, having previously combined it with the image data and passed it through other convolution layers (decoder) (Fig. 2).

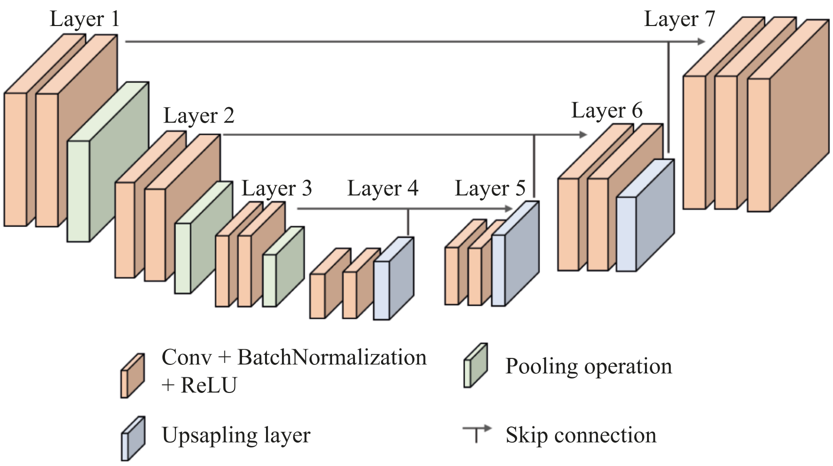


Fig. 2. Architecture of U-Net SNN

The convolutional blocks of the decoder and encoder are linked by end-to-end connections, or skip connections. This solves the problem of vanishing gradient, which is a challenge for computer vision [20]. In this study, we used the encoder from the ResNet–50 neural network, pre-trained on the ImageNet dataset.

To select the hyperparameters of the U-Net CNN that affect the architecture and training process, the Optuna library was used. This made it possible to automate the model tuning to achieve better results.

Research Results. Table 1 shows the model parameters specified under training.

Table 1

Parameters for Training the U-Net Convolutional Neural Network

No.	Parameter	Value
1	Number of images in training set	700
2	Number of images in validation set	200
3	Number of images in test sample	100
4	Batch size	10
5	Learning rate	1st-4
6	Overfitting detector	Early stopping
7	Solver	Adam

The model was trained using optimization of the Dice loss function (2) based on the Dice coefficient (1).

$$DSC = \frac{2|X \cap Y|}{|X|+|Y|}, \tag{1}$$

$$Dice\ Loss = 1 - \frac{2|X \cap Y| + Smooth}{|X|+|Y|+Smooth}. \tag{2}$$

Here, X — a set of pixels defined during the mapping as a scope of a specific class; Y — a set of pixels assigned to a specific class according to the conclusions of the developed segmentation model. The Smooth coefficient is used to smooth the calculation result in the case when the values X and Y are close to zero.

The Adam method for stochastic optimization was used to train the model. Early stopping was used as an overfitting detector. In machine learning, this is one of the most widely used regularization methods to prevent overfitting. The training process was performed on the basis of NVIDIA Tesla T4 computing accelerators, it was implemented in 100 epochs and took 55 minutes.

Figure 3 shows the graph of CNN training on the training and validation sets. The OX axis shows the training epochs, and the OY axis shows the values of the loss function. Analyzing the graph, we can conclude that the quality of model training is good, since at the end of training on the training sample, small changes in the loss function are observed.

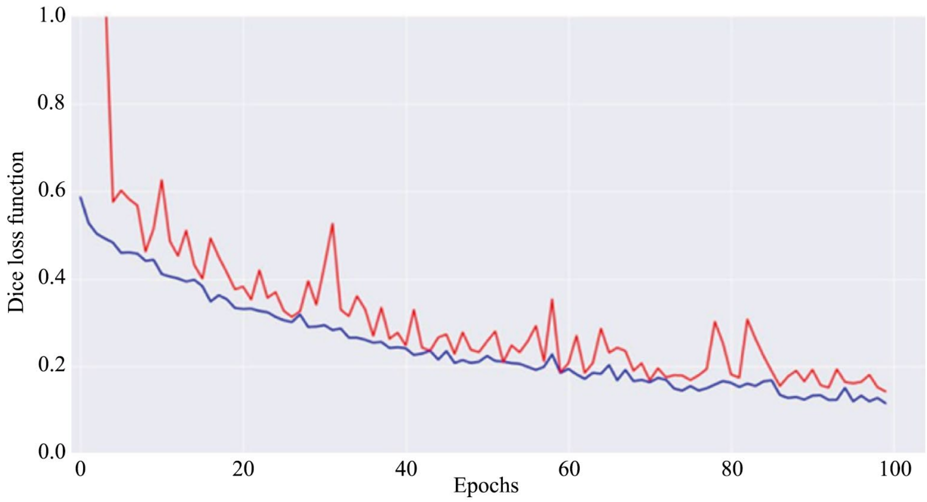


Fig. 3. Training U-Net CNN: — on training sample; — on validation sample

When assessing the quality of segmentation models, the Dice coefficient and the metric of the degree of intersection between two bounding rectangles (Intersection over Union — IoU, Jaccard index), determined form the following formula, are used:

$$IoU = \frac{X \cap Y}{X \cup Y}, \tag{2}$$

where X — a set of pixels defined under the mapping as a scope of a concrete class; Y — a set of pixels assigned to a concrete class according to the conclusions of the developed segmentation model.

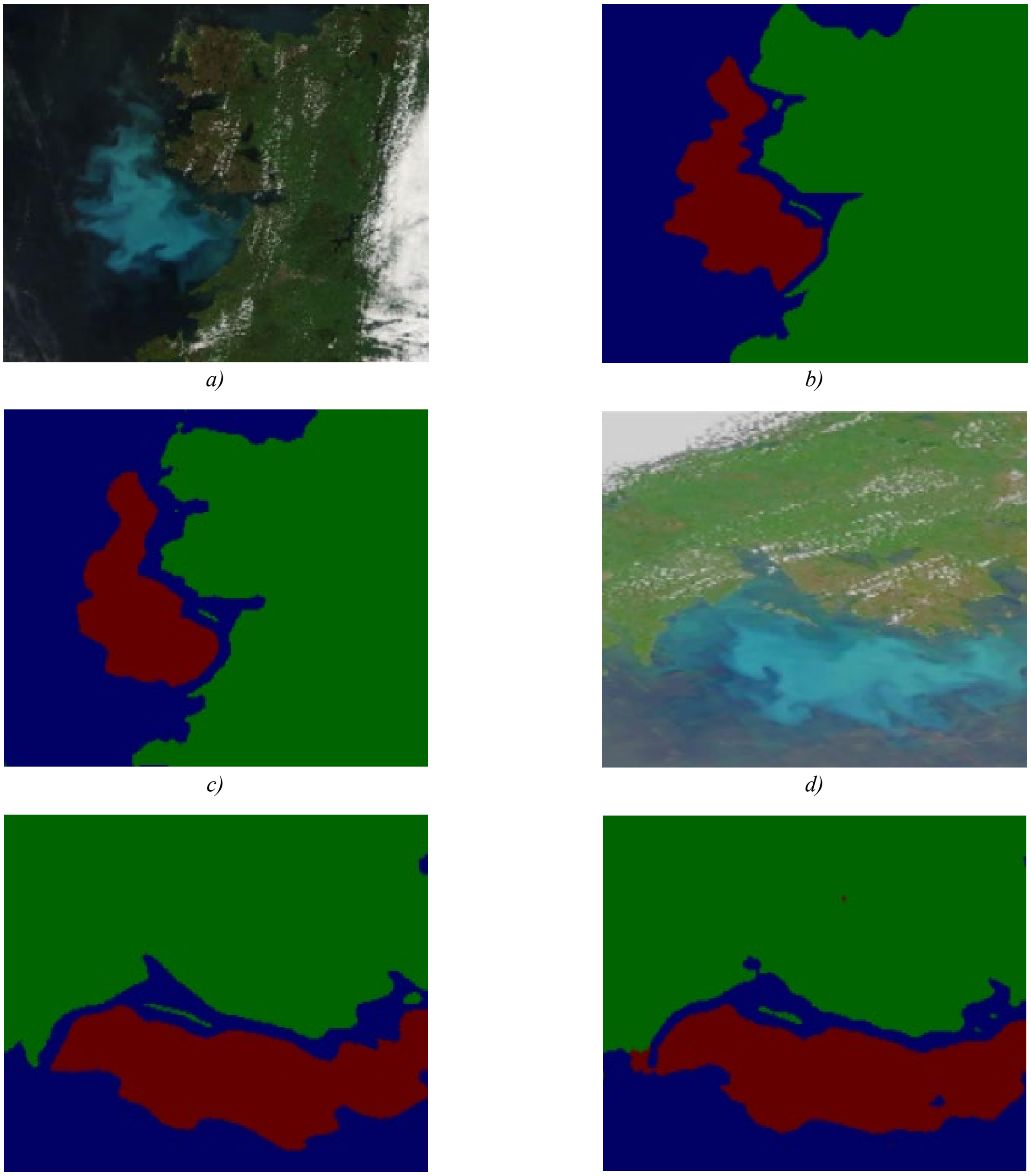
Table 2 presents the values of per-pixel precision, recall, F1-score, Dice coefficient, and IoU. To obtain the final IoU value, the weighted average is calculated for the values of this metric for each class.

Table 2

Results of Model Quality Assessment on the Test Sample

Metric	Precision	Recall	F1	Dice	IoU
Average value for test sample	0.89	0.88	0.87	0.87	0.79

Figure 4 shows the results of the algorithm's work on segmenting regions of water resources, land and phytoplankton populations. The results obtained satisfy the tasks of water resource monitoring and have practical value.



a) *b)* *c)* *d)* *e)* *f)*

Fig. 4. Algorithm results for segmenting areas of water resources, land and phytoplankton populations:
a, *d* — original image; *b*, *e* — manual mapping; *c*, *f* — model result

The segmentation result in Figures 4 *c* and 4 *f* is visually close to manual mapping, which indicates the high quality of the model. The area of the segmented region of the phytoplankton population was calculated by estimating the area of one pixel. Each image provided has additional metadata indicating the image scale and its resolution. Based on this value, the area occupied by each pixel is calculated. In the case considered for Figure 4 *a*, the final value is 51202.5. This figure was obtained according to information on the number of pixels related to blue-green algae blooms from a set of segmented images of phytoplankton populations in coastal systems [21]. The calculation result for Figure 4 *c* is 51312.

Discussion and Conclusion. When assessing the state of water resources, computer vision and other machine learning algorithms allow specialists to become free from monotonous operations. They are performed by intelligent systems. In this case, monitoring can be carried out round-the-clock. The algorithm will adequately predict risks, model the development of situation, and support the adoption of operational decisions. Stored and replicated knowledge in the form of databases and registers can be used to create long-term sources of information that researchers can use to analyze the state of water bodies and build climate models.

Processing ERS data in the form of semantic contours will provide verifying complex mathematical models through refining boundary and initial conditions, increasing the accuracy, speed and reliability of predictive modeling of hydrobiological processes.

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