

Analysis of Hyperspectral Images of River Waters

I. Novikov^a, A. Makarov^{b, c, *}, A. Pirogov^b, V. Podlipnov^{b, c}, A. Nikonorov^{b, c}, R. Skidanov^{b, c},
V. Platonov^b, V. Lobanov^d, Yu. Pridanova^b, Yu. Vybornova^b,
O. Kalashnikova^b, and T. Podladchikova^a

^a Skolkovo Institute of Science and Technology, Moscow, 121205 Russia

^b Samara National Research University, Samara, 443086 Russia

^c Image Processing Systems Institute, NRC “Kurchatov Institute”, Samara, Russia

^d Adyghe State University, Maykop, Adyghe Republic, 385000 Russia

*e-mail: andre.makar1999@gmail.com

Received June 7, 2024; revised September 25, 2024; accepted September 30, 2024

Abstract—This article proposes an approach to the analysis of high-resolution hyperspectral images in the applied problem of analyzing the state of river waters. This method allows you to detect blooming or contamination of water by foreign substances. High-resolution hyperspectral images were obtained using a hyperspectrometer mounted on a small unmanned aerial vehicle. The difference between the spectra of river areas with different intensity of algal blooms is demonstrated. Samples of river water were taken, chemical analysis was carried out, which confirmed the different content of magnesium and calcium in all samples, corresponding to the intensity of algal blooms in the water. The effectiveness of using machine learning algorithms and the construction of index images for the classification of water areas with different intensity of algal blooms is shown.

Keywords: hyperspectrometer, spectral analysis, hyperspectral images, index images, machine learning

DOI: 10.3103/S1060992X24700668

1. INTRODUCTION

Pollution control of coastal waters is a current issue in industrial regions. One of the tools for detecting pollution hotspots is remote sensing of the Earth, which is already being used for monitoring water quality parameters (for example, suspended sediments (turbidity), chlorophyll, and temperature) [1–3]. It is possible to obtain information about the spectral component of the water with the help of specialized devices, such as a hyperspectrometer [4–14], UAV [15–18] and including appropriate dispersing optical elements [19–24], which allows you to compare the obtained spectra with the mineral water composition. This will allow the use of earth sensing data to predict environmental changes and integrate results into monitoring systems [25]. The article [26] contains information about the possibilities of applying hyperspectral image analysis of water pictures for environmental monitoring and may be useful for researchers and specialists in the environmental protection field. The article [27] focuses on harmful algal blooms and the need to protect aquatic ecosystems and human health. The study describes the spatial and temporal distribution of cyanobacterial blooms to identify the relationship between blooms and environmental factors in Baekje Reservoir. Two years of cyanobacterial cell data at one fixed station and four remotely measured hyperspectral image (HSI)-based phycocyanin (PC) concentration distributions were used to describe the relationship between spatial and temporal changes in blooms and the influencing factors.

2. EXPERIMENTAL

2.1. Hyperspectral Data

Hyperspectral data collection of river waters took place on the Chapayevka River at locations with varying intensities of algal blooms (see Figs. 1 and 2). The locations were: “Gorki”, “Prichal”, “Mayak”, “Maloe Tomylovo”.

The shooting was carried out with a slit hyperspectrometer built according to the Offner scheme [4, 5].



Fig. 1. Chapaevka river at the “Gorki” and “Prichal” locations.



Fig. 2. Chapaevka river at the “Mayak” and “Maloe Tomylovo” locations.

As a result of the shooting from a small UAV, hyperspectral images (HSI) were obtained formed from a video sequence of spectra. A spectrum example from the video is presented in Fig. 3. The video corresponds to telemetry data. A telemetry data example is presented in Fig. 4.

After assembling the HSI, an RGB shooting locations synthesis was formed. The RGB synthesis is presented in Fig. 5.

2.2. Statistical Data Analysis

Two analyses of water samples were carried out: chemical and spectral. Chemical analysis revealed the presence of calcium and magnesium. The sections of the rivers in which the samples were taken were at different distances from the dam, from where foreign substances were discharged into the river. Accordingly, what got into the water served as food for microorganisms. The closest point to the dam and the area of intense flowering of the river was the “Prichal”, and the farthest from the dam was the “Mayak”.

Visually, the water that was closer to the dam appeared greener, and the color saturation gradually decreased as the sampling point moved away from the dam. Samples from areas with low levels of water



Fig. 3. A video sequence of the spectra captured on a UAV.

rostime;latitude;longitude;altitude;compass_hdg;rel_alt;timing;cam_ID;x;y;z					
1678188758.949390;53.241583;50.361675;64.837846;-1.275164;25.100000;2023-03-07-11-32-38;Hypercam start point					
1678188794.955330;53.241039;50.362211;64.808143;-0.879108;25.072000;2023-03-07-11-33-14;Hypercam end point;					
1678188798.835146;53.241059;50.362313;64.788087;0.275074;25.052000;2023-03-07-11-33-18;Hypercam start point;					
1678188798.885039;53.241060;50.362314;64.787087;0.275074;25.051000;;Hypercam frame;46.967339;-77.198929;25.					
1678188798.899616;53.241060;50.362314;64.787087;0.275074;25.051000;;Hypercam frame;46.967339;-77.198929;25.					
1678188798.916545;53.241060;50.362314;64.787087;0.275074;25.051000;;Hypercam frame;46.967339;-77.198929;25.					

Fig. 4. Example of flight telemetry data.



Fig. 5. An example of image by RGB synthesis from HIS at the “Gorki” and “Prichal” locations.

bloom showed lower concentrations of calcium and magnesium, while in areas with high levels of water bloom, the concentration of calcium and magnesium was higher. The results of the chemical analysis are presented in Table 1. The sampling points and the dam are shown in Fig. 6.

Samples for chemical analysis were taken from the center of the river at all points from a depth of 30–40 cm. One sample corresponds to one sampling point. The central part of the river was also considered as a research area using a hyperspectral thermal imager. This eliminates the influence of the riverbed on the water reflection spectrum and allows you to cover the section of the river where samples were taken for chemical analysis. It was necessary to confirm equal lighting conditions for the HSI to validate the spectral analysis results. Vegetation areas with yellow grass were selected in two HSIs. The spectra of the selected objects are presented in Figs. 7 and 8. The t-statistic was used to check the similarity of the spectra, with a significance level of 0.05. To check the similarity of the spectra, t-statistics with a significance level of 0.05 were used. The significance level of 0.05 (or 5%) is often used in statistical tests as a threshold for deciding whether to reject the null hypothesis. This means that the researcher is willing to accept a 5% risk of making an error and reject the null hypothesis when it is actually true (Type I error). In our case, if the significance level is greater than 0.05, it indicates that the two samples are similar to each other. If the significance level is less than 0.05, it means that the two samples are different from each other. The p-value was 0.113 when comparing two spectra of yellow grass on the HSI “Gorki” and HSI “Prichal” was made and was 0.092 on the HSI “Mayak” and HSI “Maloe Tomylovo”. This means that the spectra of yellow grass are similar on the HSI “Gorki” and HSI “Prichal”, HSI “Mayak” and HSI “Maloe Tomylovo”, which confirms equal lighting conditions.

An average spectra comparison of river sections on the HSI at the points “Gorki” and “Prichal”, “Mayak” and “Maloe Tomylovo” was made. The spectra of the selected river areas are presented in Figs. 9 and 10. The t-statistic was also used to check the similarity of the spectra, with a significance level of 0.05. The p-value was 2.37×10^{-17} when comparing two spectra of water areas on the HSI “Gorki” and HSI “Prichal” was made. The p-value was 0.0018 when comparing two spectra of water areas on the HSI

Table 1. Chemical analysis of water

Locations	Substance	
	calcium	magnesium
	concentration, Mg/L	
Gorki	66.49	23.44
Prichal	83.88	30.38
Mayak	63.43	21.77
Maloe Tomylovo	68.36	24.18

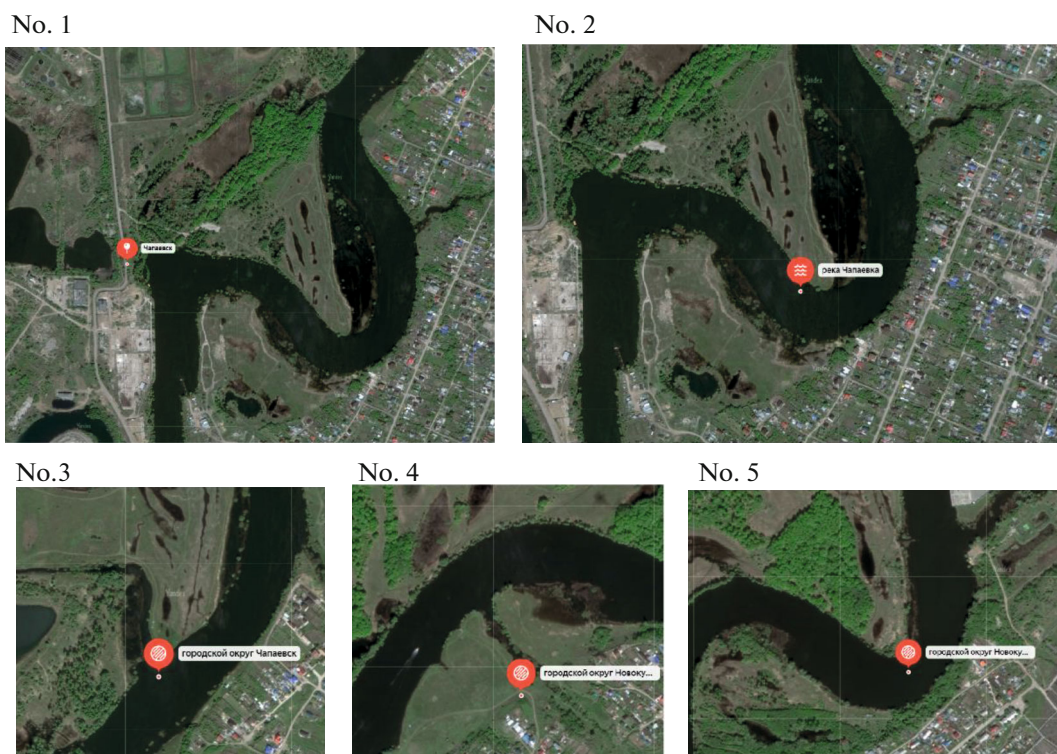


Fig. 6. Survey points and location of the dam.

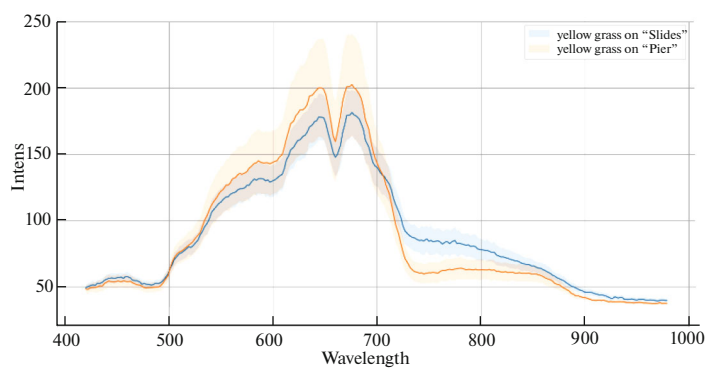


Fig. 7. Reflectance spectra of yellow grass in the “Gorki” and “Prichal” under solar lighting.

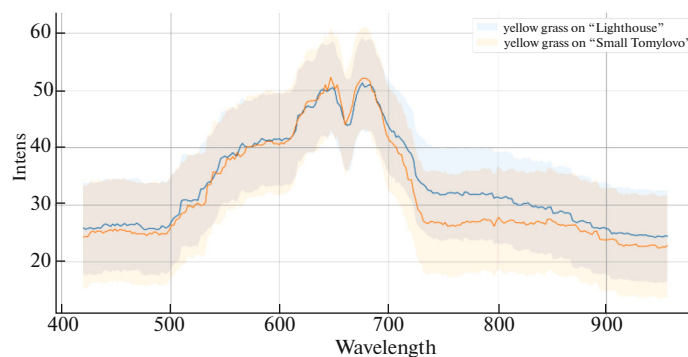


Fig. 8. Reflectance spectra of yellow grass in the “Mayak” and “Maloe Tomylovo” under solar lighting.

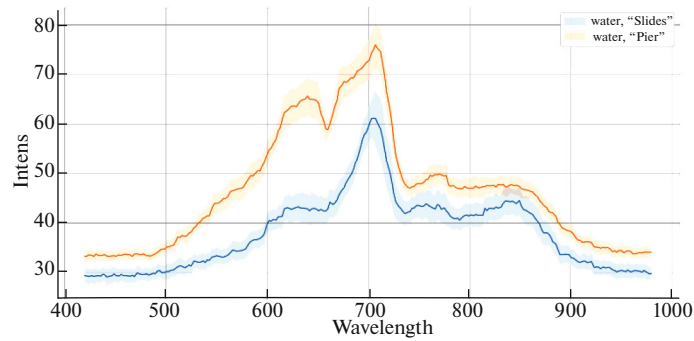


Fig. 9. Water reflectance spectra of yellow grass in the “Gorki” and “Prichal” under solar lighting.

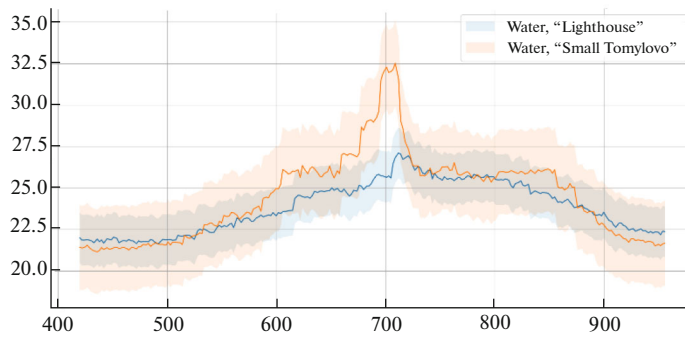


Fig. 10. Water reflectance spectra of yellow grass in the “Mayak” and “Maloe Tomylovo” under solar lighting.

“Mayak” and HSI “Maloe Tomylovo” was made. The p -values are very small compared to the set significance level when comparing the average spectra of river water was made. The difference in spectra of water areas on the HSI “Gorki” and HSI “Prichal”, HSI “Mayak” and HSI “Maloe Tomylovo” is statistically significant.

2.3. Index for Classification

To determine the presence of vegetation, there are specialized indices such as NDVI [28] and OSAVI [29]. For quantitative assessment of chlorophyll and its potential ability to absorb sunlight, indices TCARI [29] and ChlRI [29] are used. The NDWI index [30] can be used to assess moisture content in plant cover and measure the extent of coverage by surface waters. These indices can be used to determine the intensity of algae bloom in the areas of the water body that interest us.

An optimal index was selected for classifying waters by the intensity of algal blooms in the water. After forming the hyperspectral image, an index image is calculated according to the formula:

$$Ind = \frac{I_{635} - I_{851}}{I_{635} + I_{851}}, \quad (1)$$

where Ind is the index image, I_{635} is the brightness of the reflected spectrum at a wavelength of 635 nm, I_{851} is the brightness of the reflected spectrum at a wavelength of 851 nm. The index image is shown in Fig. 11.

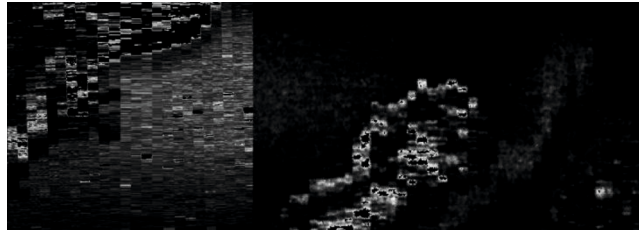


Fig. 11. Contrasting index image of waters.

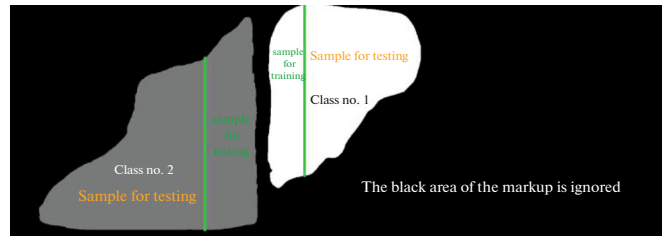


Fig. 12. Marking for GPS survey points “Gorki” and “Prichal”.

3. RESULTS AND DISCUSSION

3.1. Classification of River Waters

In this work, a comparison was made between the nearest neighbor method (as a basic algorithm), the spectral deep convolutional neural network M1D-CNN [31], the normalized spatially spectral convolutional network N3DCNN [32], the maximum likelihood method [33], the support vector machine method [34]. Figures 12 and 13 show the selection of HIGH markup into training and test samples. The HSI layers are shown in Figs. 14 and 15.

KNN is a machine learning method used for classification and regression. In the context of classification, the KNN algorithm works as follows: for a new object to be classified the distance to each of the objects of the training sample is calculated, k objects of the training sample are selected, the distance to which is minimal. The new object belongs to the class that is most common among the k nearest neighbors. Formally, this can be written as follows:

Let X be the space of objects and Y be the space of answers. A training sample is provided $X' = \{(x_i, y_i)\}_{i=1}^l$, where $x_i \in X$, $y_i \in Y$. The number k and the distance metric are also given

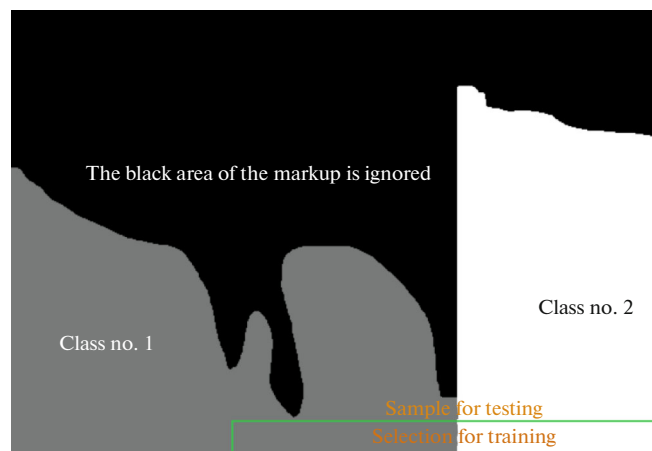


Fig. 13. Marking for GPS survey points “Mayak” and “Maloe Tomylovo”.

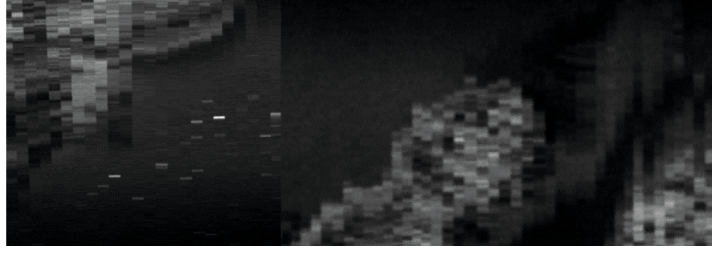


Fig. 14. HIS layer “Gorki” and “Prichal”.

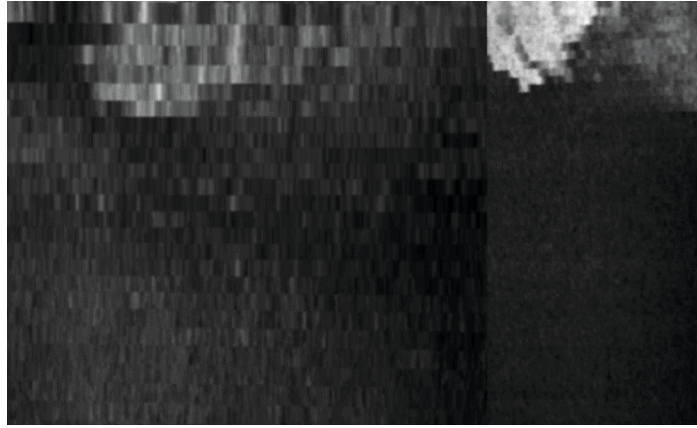


Fig. 15. HIS layer “Mayak” and “Maloe Tomylovo”.

$\rho : X \times X \rightarrow [0, +\infty)$. The KNN algorithm binds an object $u \in X$ to that class $y \in Y$, for which the total weight of the nearest training objects is $x_i : y_i = y$ maximum:

$$a(u; X^l, k) = \arg \max_{y \in Y} \sum_{i: y_i = y} w(i, u), \quad (2)$$

where $w(i, u)$ —the weight function is equal to one if the object x_i is among the k nearest neighbors for u , and zero otherwise.

MLC calculates the probability of an individual pixel belonging to a certain class and is based on an estimated probability density function obtained from certain reference classes [35]. MLC is a popular classifier [36]. To utilize spectral profiles using this method requires ROIs based on multiple pixels. Following this method, the classification is based on the selection of the most representative spectral profiles in the ROI of the same class on different flight lines. The MLC classifier assumes a Gaussian distribution for each input training class [36], and this can be expressed by the following equation:

$$g_i(x) = \ln p(\omega_i) - \frac{1}{2} \ln \left| \sum_l \right| - \frac{1}{2} (x - m_i)^T \sum_l^{-1} (x - m_i), \quad (3)$$

where i is a given spectral class, x is equal to n —dimensional data, $p(\omega_i)$ —the probability that the class ω_i occurs in the image and is assumed to be the same for all classes, $\left| \sum_l \right|$ —the determinant of the covariance matrix of data in a class ω_i , $\sum_l^{-1}$ the inverse matrix, and m_i —is the mean vector. The advantage of MLC as a parametric classifier is that it takes into account variance and covariance in class distributions, and for normally distributed data MLC performs better than other known parametric classifiers [37]. However, for data an abnormal distribution, the results may be unsatisfactory.

SVM (Support Vector Machines) is a machine learning algorithm used for classification and regression tasks. SVM works by searching for the hyperplane that best divides the data into classes. The hyperplane is chosen in such a way as to maximize the gap between the nearest points (support vectors) of each class.

Table 2. The structure of the modified neural network NM3D-DCNN

Filter	Number of filter cores	The dimension of the filter core (H, W, B)	The step of moving $\Delta(H, W, B)$
Conv1	16	3, 3, 11	1, 1, 3
Conv2_1	16	1, 1, 1	1, 1, 1
Conv2_2		1, 1, 3	
Conv2_3		1, 1, 5	
Conv2_4		1, 1, 11	
Conv3_1	16	1, 1, 1	1, 1, 1
Conv3_2		1, 1, 3	
Conv3_3		1, 1, 5	
Conv3_4		1, 1, 11	
Conv4	16	2, 2, 3	1, 1, 1
BatchNorm3d	16	—	—
Pooling	—	2, 2, 3	2, 2, 3
Dropout	—	—	—
Linear	5	—	—

This is known as the gap maximization principle. In the case of linearly inseparable data, SVM uses the core function to move to higher dimensions where the data can be linearly separated. This is called a “nuclear trick”. Mathematically, SVM solves the following optimization problem:

$$\min_{w,b,\xi} \frac{1}{2} \|w\|^2 + C \sum_{i=1}^n \xi_i, \quad (4)$$

provided that

$$y_i (w^T x_i + b) \geq 1 - \xi_i, \quad \xi_i \geq 0, \quad (5)$$

where, w is the vector of weights, b —is the offset, ξ_i —variables representing classification errors C —is the regularization parameter controlling the balance between maximizing the gap and minimizing classification errors, x_i and y_i —are training examples and their class labels, respectively.

NM3DCNN is the architecture of the proposed classifier containing five layers with weights, which are the input layer, the convolutional layer, the maximum union layer, the full connection layer and the output layer. These five layers are implemented for each spectral signature to distinguish it from the others.

The NM3DCNN network is a combination of convolutional layers for the analysis of 1D and 2D slices of a hyperspectral image, thereby allowing you to switch to the analysis of 3D sections. A hypercube is fed to the network input, the dimensions of which are determined by the number of channels B and spatial coordinates (height and width) H and W , respectively. This approach allows not only to identify the features of a single hyperpixel, but also to find its interdependencies with its neighbors.

The numerical results of the classification are presented in Table 2. A visual representation of the classification results is shown in Fig. 16. Classification quality assessment indicators: mean accuracy, F-score. The description of the classification quality assessment indicators is presented in [38].

Table 3 shows a significant difference in classification for the HSI “Gorki and Prichal” and “Mayak and Maloye Tomylovo”. The high classification results by all algorithms for the location “Gorki and Prichal” can be explained by the high light intensity at the location and the separability of the observed algae bloom. The decline in classification results for the location “Mayak and Maloye Tomylovo” occurs due to the low light intensity at the site and the more ambiguous separability of the observed objects.

Figure 15 shows that the closer the pixels of different classes are to each other, the better the classification algorithms handle their separation. The models perform better in classifying pixels that correspond to

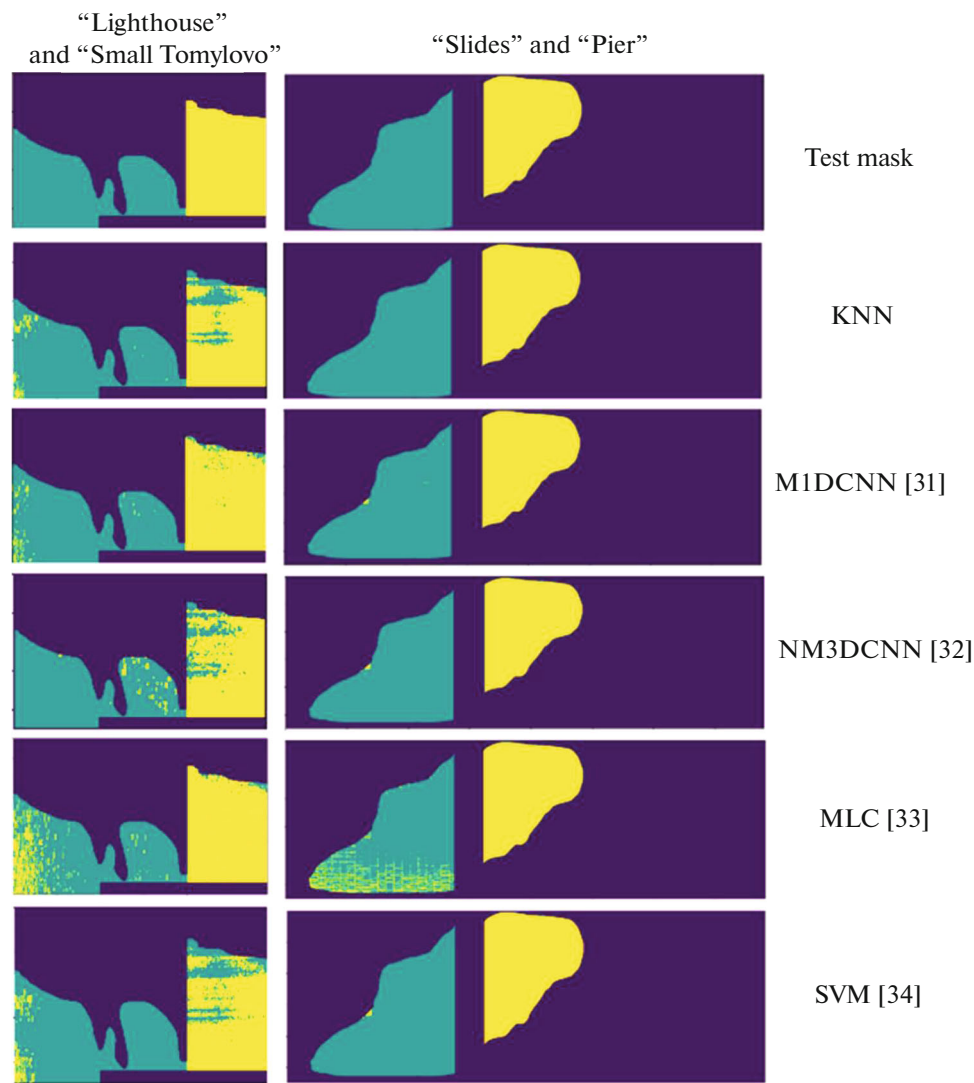


Fig. 16. Visual representation of the classification results.

areas with higher intensity of algae bloom (in both locations, this is class N.2). Table 3 demonstrates greater resilience of classification algorithms, especially those based on neural networks, to changes in environmental parameters compared to vegetation indices. For the location “Gorki and Prichal”, all algorithms showed high classification results. In cases of deteriorating environmental conditions, the best classification accuracy was achieved by the convolutional neural networks M1DCNN and NM3DCNN.

Table 3. Numerical classification results

Locations	Classification algorithms									
	KNN		M1DCNN [31]		NM3DCNN [32]		MLC [33]		SVM [34]	
	Acc.	F-1	Acc.	F-1	Acc.	F-1	Acc.	F-1	Acc.	F-1
Gorki and Prichal	0.99	0.99	0.99	0.99	0.99	0.99	0.93	0.94	0.99	0.99
Mayak and Maloe Tomylovo	0.90	0.92	0.98	0.96	0.95	0.92	0.91	0.92	0.90	0.91

4. CONCLUSIONS

Thus, the hyperspectral image analysis of water showed the difference in the river areas average spectra with different intensities of algal blooms. The effectiveness of constructing index images and applying machine learning methods to detect river water blooms is demonstrated. These methods can be used for regular state monitoring of water. Further research in this area can help develop more effective methods for detecting water resource pollution.

ABBREVIATIONS AND NOTATION

PC	phycocyanin
HIS	hyperspectral images
UAV	unmanned aerial vehicle
SVM	support vector machine
MLC	maximum likelihood classification
KNN	k-Nearest Neighbors

FUNDING

The theoretical part of the work was supported by the Russian Science Foundation, grant no. 22-19-00364, the experimental part of the work was supported by the State assignment of NRC “Kurchatov Institute”.

CONFLICT OF INTEREST

The author of this work declares that he has no conflicts of interest.

REFERENCES

1. Ritchie, J.C., Zimba, P.V., and Everitt, J.H., Remote sensing techniques to assess water quality, *Photogramm. Eng. Remote Sens.*, 2003, no. 69, pp. 695–704.
<https://doi.org/10.14358/PERS.69.6.695>
2. Chen, Y., Rongshuang, F., Xiucheng, Y., Jingxue, W., and Aamir, L., Extraction of urban water bodies from high-resolution remote-sensing imagery using deep learning., *Flood Forecasting Using Machine Learning Methods* (Special Issue), 2018, vol. 10, no. 5, p. 585.
<https://doi.org/10.3390/w10050585>
3. Yigit, A., Z., Gordana, K., Serdar, G., and Ugur, A., Monitoring the water quality of small water bodies using high-resolution remote sensing data, *ISPRS Int. J. Geo-Inform.*, 2019, vol. 8, no. 12, p. 553.
<https://doi.org/10.3390/ijgi8120553>
4. Podlipnov, V., Shchedrin, V., Babichev, A., Vasilyev, S., and Blank, V., Experimental determination of soil moisture on hyperspectral images., *Comput. Opt.*, 2018, vol. 42, no. 5, pp. 877–884.
<https://doi.org/10.18287/2412-6179-2017-42-5-877-884>
5. Karpeev, S.V., Khonina, S.N., Murdagulov, A.R., and Petrov, M.V., Alignment and study of prototypes of the offner hyperspectrometer, *VESTNIK Samara Univ. Aerospace Mech. Eng.*, 2016, vol. 15, no. 1, pp. 197–206.
<https://doi.org/10.18287/2412-7329-2016-15-1-197-206>
6. Kazanskiy, N.L., Kharitonov, S.I., Karsakov, A.V., and Khonina, S.N., Modeling action of a hyperspectrometer based on the Offner scheme within geometric optics, *Comput. Opt.*, 2014, vol. 38, no. 2, pp. 271–280.
<https://doi.org/10.18287/0134-2452-2014-38-2-271-280>
7. Kazanskiy, N.L., Kharitonov, S.I., Khonina, S.N., Volotovskiy, S.G., and Strelkov, Yu.S., Simulation of hyperspectrometer on spectral linear variable filters, *Comput. Opt.*, 2014, vol. 38, no. 2, pp. 256–270.
<https://doi.org/10.18287/0134-2452-2014-38-2-256-270>
8. Skidanov, R.V. and Blank, V.A., Diffraction axicon as the dispersive element for imaging hyperspectrometer, *Proc. SPIE*, 2016, vol. 9807, p. 98070G.
9. Kazanskiy, N.L., Kharitonov, S.I., Doskolovich, L.L., and Pavelyev, A.V., Modeling the performance of a spaceborne hyperspectrometer based on the Offner scheme, *Comput. Opt.*, 2015, vol. 39, no. 1, pp. 70–76.
<https://doi.org/10.18287/0134-2452-2015-39-1-70-76>
10. Kazanskiy, N.L., Modeling diffractive optics elements and devices, *Proc. SPIE*, 2018, vol. 10774, p. 107740.O.
<https://doi.org/10.1117/12.2319264>
11. Rastorguev, A.A., Kharitonov, S.I., and Kazanskiy, N.L., Modeling of image formation with a space-borne Offner hyperspectrometer, *Comput. Opt.*, 2020, vol. 44, no. 1, pp. 12–21.
<https://doi.org/10.18287/2412-6179-CO-644>

12. Kazanskiy, N., Ivliev, N., Podlipnov, V., and Skidanov, R., An airborne Offner imaging hyperspectrometer with radially-fastened primary elements, *Sensors*, 2020, vol. 20, no. 12, p. 3411.
<https://doi.org/10.3390/s20123411>
13. Rastorguev, A.A., Kharitonov, S.I., and Kazanskiy, N.L., Numerical simulation of the performance of a space-borne Offner imaging hyperspectrometer in the wave optics approximation, *Comput. Opt.*, 2022; vol. 46, no. 1, pp. 56–64.
<https://doi.org/10.18287/2412-6179-CO-1034>
14. Ivliev, N., Podlipnov, V., Petrov, M., Tkachenko, I., Ivanushkin, M., Fomchenkov, S., Markushin, M., Skidanov, R., Khanenko, Y., Nikonorov, A., Kazanskiy, N., and Soifer, V., 3U CubeSat-based hyperspectral remote sensing by Offner imaging hyperspectrometer with radially-fastened primary elements, *Sensors*, 2024, vol. 24, no. 9, p. 2885.
<https://doi.org/10.3390/s24092885>
15. Bibikov, S.A., Kazanskiy, N.L., and Fursov, V.A., Vegetation type recognition in hyperspectral images using a conjugacy indicator, *Comput. Opt.*, 2018, vol. 42, no. 5, pp. 846–854.
<https://doi.org/10.18287/2412-6179-2018-42-5-846-854>
16. Nikonorov, A.V., Petrov, M.V., Bibikov, S.A., Yakimov, P.Y., Kutikova, V.V., Yuzifovich, Y.V., Morozov, A.A., Skidanov, R.V., and Kazanskiy, N.L., Toward ultralightweight remote sensing with harmonic lenses and convolutional neural networks, *IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens.*, 2018, vol. 11, no. 9, pp. 3338–3348.
<https://doi.org/10.1109/JSTARS.2018.2856538>
17. Kazanskiy, N.L., Skidanov, R.V., Nikonorov, A.V., and Doskolovich L.L., Intelligent video systems for unmanned aerial vehicles based on diffractive optics and deep learning, *Proc. SPIE*, 2020, vol. 11516, p. 115161Q.
<https://doi.org/10.1117/12.2566468>
18. Ivliev, N., Evdokimova, V., Podlipnov, V., Petrov, M., Ganchevskaya, S., Tkachenko, I., Abrameshin, D., Yuzifovich, Y., Nikonorov, A., Skidanov, R., Kazanskiy, N., and Soifer, V., First earth-imaging cubesat with harmonic diffractive lens, *Remote Sens.*, 2022, vol. 14, no. 9, p. 2230.
<https://doi.org/10.3390/rs14092230>
19. Soifer, V.A., Doskolovich, L.L., and Kazanskiy, N.L., Multifocal diffractive elements, *Opt. Eng.*, 1994, vol. 33, no. 11, pp. 3610–3615.
<https://doi.org/10.1117/12.179890>
20. Doskolovich, L.L., Golub, M.A., Kazanskiy, N.L., Khramov, A.G., Pavelyev, V.S., Seraphimovich, P.G., Soifer, V.A., and Volotovskiy, S.G., Software on diffractive optics and computer-generated holograms, *Proc. SPIE*, 1995, vol. 2363, pp. 278–284.
<https://doi.org/10.1117/12.199645>
21. Doskolovich, L.L., Kazanskiy, N.L., Soifer, V.A., Perlo, P., and Repetto, P., Design of DOEs for wavelength division and focusing, *J. Mod. Opt.*, 2005, vol. 52, no. 6, pp. 917–926.
<https://doi.org/10.1080/09500340512331313953>
22. Doskolovich, L.L., Bezus, E.A., and Kazanskiy, N.L., Multifocal spectral diffractive lens, *Comput. Opt.*, 2018, vol. 42, no. 2, pp. 219–226.
<https://doi.org/10.18287/2412-6179-2018-42-2-219-226>
23. Kazanskiy, N.L. and Skidanov, R.V., Technological line for creation and research of diffractive optical elements, *Proc. SPIE*, 2019, vol. 11146, p. 111460W.
<https://doi.org/10.1117/12.2527274>
24. Doskolovich, L.L., Skidanov, R.V., Bezus, E.A., Ganchevskaya, S.V., Bykov, D.A., and Kazanskiy, N.L., Design of diffractive lenses operating at several wavelengths, *Opt. Express*, 2020, vol. 28, no. 8, pp. 11705–11720.
<https://doi.org/10.1364/OE.389458>
25. Popandopulo, G., Illarionova, S., Shadrin, D., Evteeva, K., Sotiriadi, N., and Burnaev, E., Flood extent and volume estimation using Remote Sensing Data, *Remote Sens.*, 2023, vol. 15, no. 18, p. 4463.
<https://doi.org/10.3390/rs15184463>
26. Fan, C., Spectral analysis of water reflectance for hyperspectral remote sensing of water quality in Estuarine Water, *J. Geosci. Environ. Prot.*, 2014, vol. 02, no. 02, pp. 19–27.
<https://doi.org/10.4236/gep.2014.22004>
27. Park, Y., Pyo, J., Kwon, Y.S., Cha, Y., Lee, H., Kang, T., and Cho, K.H., Evaluating physico-chemical influences on cyanobacterial blooms using hyperspectral images in inland water, *Water Res.*, 2017, vol. 126, pp. 319–328.
<https://doi.org/10.1016/j.watres.2017.09.026>
28. Francois, B. and Bhaskar, J.C., Relative sensitivity of normalized difference vegetation index (ndvi) and microwave polarization difference index (mpdi) for vegetation and desertification monitoring, *Remote Sens. Environ.*, 1988, vol. 24, pp. 297–311.
29. Victor, S., Alexandr, K., Konstantinova, A., Balashov, I., Krashenninnikova, Yu., Vladimir, T., Maklakov, S., and Evgeny, S., Capabilities of hyperspectral indices analysis of the vega-constellation remote monitoring information systems, *Curr. Probl. Remote Sens. Earth Sace*, 2016, vol. 13, pp. 28–45.

30. Stuart, K., The use of the normalized difference water index (ndwi) in the delineation of open water features, *Int. J. Remote Sens.*, 1996, vol. 17, pp. 1425–1432.
31. Hu, W., Huang, Y., Wei, L., Zhang, F., and Li, H., Deep Convolutional Neural Networks for hyperspectral image classification, *J. Sens.*, 2015, vol. 2015, pp. 1–12.
<https://doi.org/10.1155/2015/258619>
32. Firsov, N.A., Podlipnov, V.V., Ivliev, N.A., Nikolaev, P.P., Mashkov, S.V., Ishkin, P.A., Skidanov, R.V., and Nikonorov, A.V., Neural network-aided classification of hyperspectral vegetation images with a training sample generated using an adaptive vegetation index, *Comput. Opt.*, 2021, vol. 45, no. 6, pp. 887–896.
<https://doi.org/10.18287/2412-6179-co-1038>
33. Diruit, W., Le Bris, A., Bajjouk, T., Richier, S., Helias, M., Burel, T., and Ar, G.E., Seaweed habitats on the shore: Characterization through hyperspectral UAV imagery and field sampling, *Remote Sens.*, 2022, vol. 14, no. 13, p. 3124.
<https://doi.org/10.3390/rs14133124>
34. Awad, M. and Khanna, R., *Support Vector Machines for classification*, *Efficient Learning Machines*, 2015, pp. 39–66.
https://doi.org/10.1007/978-1-4302-5990-9_3
35. Foody, G.M., Status of land cover classification accuracy assessment, *Remote Sens. Environ.*, 2002, vol. 80, no. 1, pp. 185–201.
[https://doi.org/10.1016/s0034-4257\(01\)00295-4](https://doi.org/10.1016/s0034-4257(01)00295-4)
36. Mariani Colombo, P. and Orsenigo, M., Sea depth effects on the algal photosynthetic apparatus II. an electron microscopic study of the photosynthetic apparatus of *Halimeda Tuna* (Chlorophyta, Siphonales) at –0.5 m and –6.0 m sea depths, *Phycologia*, 1977, vol. 16, no. 1, pp. 9–17.
<https://doi.org/10.2216/i0031-8884-16-1-9.1>
37. Xiuping Jia and Richards, J.A., Efficient maximum likelihood classification for Imaging Spectrometer Data Sets, *IEEE Trans. Geosci. Remote Sens.*, 1994, vol. 32, no. 2, pp. 274–281.
<https://doi.org/10.1109/36.295042>
38. Meysam V., Mohammad G., and Masoumeh R., Performance Analysis and Comparison of Machine and Deep Learning Algorithms for IoT Data Classification.

Publisher’s Note. Allerton Press remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

AI tools may have been used in the translation or editing of this article.