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MULTICRITERIA SELECTION OF A METHOD FOR PROCESSING MULTISPECTRAL EARTH REMOTE SENSING DATA

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The article is devoted to the use of qualimetry methods for models and polymodel complexes in order to solve one of the relevant engineering problems - automation of selecting methods for calculating Earth remote sensing (ERS) data processing when analysing the state of complex natural and technical systems. The proposed approach was discussed using the example of choosing methods for calculating forest sustainability indicators. A typical situation was considered when alternative methods and models can be applied at each stage of data processing. The essence of the proposed approach is to formulate and solve the task on multicriteria comparative analysis of processing methods based on a set of indicators, which include costs, required for implementation one or another method, efficiency, which refers to calculation duration of the analysed sustainability indicator, and an indicator reflecting the quality of the solution - accuracy of calculations result. The solution algorithm was illustrated within an example of choosing the method for assessing consequences of the forest fire. The selection results were presented in the form of a table, which allows the user to evaluate losses and gains in the values of partial indicators when moving from applying one method to another. The proposed algorithmization of the selection task determines possibility for its automation and, thereby, simplifying application of complex methods for processing ERS data for the end user. In addition, the possibilities and degree of validity for scaling the results of processing ERS data from individual areas to large forest areas are expanding.

Key words: qualimetry of models and polymodel complexes, multi-criteria selection, natural and technical systems, Earth remote sensing data, sustainability of forest vegetation

1 INTRODUCTION

Currently, one of the most prospective methods for studying complex natural and technical systems (NTS) including environmental problems is the use of Earth remote sensing data (ERS). Technologies for automated processing of multispectral aerospace ERS data are applied more and more often [1-6], that covers improvements in the field of artificial intelligence technologies. For example, a number of indicators for forest sustainability may be determined, including those characterizing the forests productive capacity, viability and their biological diversity. Species composition, age, crown density, biomass volume, characteristics of the forest fires consequences and others can be applied as specific assessed indicators.

In general, taking into consideration the variety of assessed indicators, in order to calculate them it is required to apply different types of NTS models and assessment methods, each can be used to calculate its own indicator or their combination [7-11]. While processing ERS data, methods, providing landscape elements identification and assessment of the NTS state can be used, in particular, classification methods, perceptron-based method, k-nearest neighbors, support vector machine method, “random forest” [12, 13] etc., as well as approaches based on clustering of landscape elements. Examples of clustering methods include the k-means method and the fuzzy C-means algorithm, or FCM algorithm [14].

One of the main advantages of remote sensing in analyzing NTS and the environmental state is the possibility to scale results of processing ERS data obtained on a specific scene (fragment of ERS data) with known NTS characteristics to large areas reflected in other survey fragments. As a basis for such scaling can serve, firstly, the stability of spectral-brightness and spatial-frequency characteristics over time for the considered scene [15], and secondly, a reasonable choice of the specific method for processing ERS data and determining the desired characteristics of the environmental state.

Currently, the task on selecting a method is most often solved by qualified researchers applying their own experience in a non-operative manner [16, 17, 18]. However, the widespread use of ERS data processing methods, expanding range of processing tasks and the necessity to introduce prospective methods for analyzing the NTS and environmental state into practical activities make it necessary to automate this stage of ERS data processing. Automation, in turn, is possible in case the algorithms for quantitative comparative analysis of the used models and methods are developed and applied. The use of approaches developed within the framework of a new scientific direction - qualimetry of models and polymodel complexes - can serve as a prospective direction for solving such problems [19]. Comparative analysis algorithms can be based on methods of complex objects multicriteria evaluation within a set of indicators. At the same time, according to the provisions of the theory on complex systems efficiency [20], it is advisable to use three groups of indicators as target functions of the task on comparative analysis and methods selection for calculating indicators of NTS and environmental state: the costs for implementing one or another method, efficiency, which refers to the calculation duration for a particular indicator of the environmental state based on a specific method, and a target indicator reflecting the quality of the solution obtained - reliability or accuracy of the modeling result.

It should be noted that in the considered context, the concepts of “calculation method” and “model” are different. The concept of “calculation method” includes not only the actual mathematical model used and the corresponding algorithm for estimating the studied indicator of environmental state, but also other components: procedures for preparing the initial data required to implement the mathematical model, as well as procedures for validating the results obtained within applying one or another calculation method. As will be demonstrated below, taking these components into account can significantly affect the duration and resource costs for performing calculations, and, accordingly, the selection of method for assessing the environmental state.

2 PROBLEM STATEMENT

In the general case, assessment of the NTS state is carried out by sequentially performing several stages (operations) of ERS data processing. Each of the operations can be implemented by one of the alternative methods. Such operations, for example, are: landscape elements identification at the level of defining known homogeneous surfaces; condition assessment or semantic qualitative description of a landscape element; assessing the dynamics of changes in the state of a landscape element over time. Let us consider the formulation of the task on selecting the best calculation methods precisely for this most general case.

To formalize the problem of multicriteria selection, suppose:

$A = \{A_i, i \in N\}, N = \{1, 2, ..., n\}$ is the set of calculation stages, each can use one of the possible alternative calculation methods (CM);

$B = \{B_j^i, j \in \{1, 2, ..., m_i\}, i \in N\}$ is the set of potentially possible calculation methods ($B_j^i - j$-th CM for the *i*-th stage);

$c_{ij}, i \in N, j \in \{1, 2, ..., m_i\}$ is the resource costs for implementation of *j*-th CM at the *i*-th stage of calculation;

$t_{ij}, i \in N, j \in \{1, 2, ..., m_i\}$ is the efficiency (implementation duration) of *j*-th CM at the *i*-th stage of calculation;

$p_{ij}, i \in N, j \in \{1, 2, ..., m_i\}$ is the performance target of *j* -th CM, applied at *i*-th stage of calculation – as noted above, this is an indicator of calculations accuracy;

$X = \|x_{ij}\|$ is the configuration of CMs for the calculation scheme as a whole, with $x_{ij} = 1$, if as A_i we use CM B_j^i and $x_{ij} = 0$, if otherwise. The specific configuration of calculation scheme is thus a set of CM used at all stages. Wherein $\sum_{j=1}^{m_i} x_{ij} \le 1, \forall i \in N$, as for each *i* -th stage only one method B_j^i can be used as a CM from the possible nomenclature. These restrictions determine the area Δ of acceptable solution options.

Taking into account the introduced notations, the task on determining the best calculation methods is a multicriteria selection problem on a discrete set of feasible alternatives of the following type:

$$\min_{X \in \Delta} C(X), \min_{X \in \Delta} T(X), \max_{X \in \Delta} P(X), \quad (1)$$

where $C(X)$ is the resource costs for calculations in the configuration *X*; $T(X)$ is the calculations duration; $P(X)$ is the modeling quality target.

In essence, the formulation of the selection task is interpreted as follows: it is necessary to determine such methods for calculating values of the required indicator for assessing the NTS state, that ensure minimization of resource costs for carrying out the calculations, minimizing the calculation duration and maximizing the target indicator of the modelling quality.

The general calculation scheme, commonly, may have a network structure. In this network, it is possible to form a set of shortest paths; for each path $k = 1, 2, ..., K$ we denote by Π_k set of CM numbers included in it. Thus, the analyzed indicators can be defined as follows:

resource costs for the calculation cycle:

$$C(X) = \sum_{i=1}^{n} \sum_{j=1}^{m_i} c_{ij} \cdot x_{ij} \quad (2)$$

duration of calculations:

$$T(X) = \max_{k=1,...,K} \sum_{i \in \Pi_k} \sum_{j=1}^{m_i} t_{ij} \cdot x_{ij} \quad (3)$$

target indicator:

$$\mathrm{P}(X) = \min_{k=1,\dots,K} \min_{i \in \Pi_k} \sum_{j=1}^{m_i} p_{ij} \cdot x_{ij} \qquad (4)$$

The substantial meaning of indicator (4) is as follows: the accuracy indicator for the entire calculation cycle is the worst accuracy value among all selected CMs for separate calculation stages.

As a rule, the algorithm for solving such problems includes identifying a set of non-dominated (Pareto-optimal) options for calculation schemes, and finding a unique solution based on the selected criterion on this set. In particular, a proven method is to find a compromise solution, which minimizes the maximum of the weighted relative deviations from the optimum for particular indicators [21]:

$$X^k = arg \min_{X \in \Delta} \max_{l \in L} \rho_l w_l(X), \qquad (5)$$

where: *L* is the set of individual quality indicators; ρ_l are the weighting factors of their relative importance, $\rho_l > 0, \sum_{l \in L} \rho_l = 1$; $w_l(X)$ are the relative deviations of indicator values from optimum,

$$w_l(X) = (f_l(\bullet) - f_l^0)/(f_l^* - f_l^0) \qquad (6)$$

where f_l^0 и f_l^* are the best and worst values of the *l*-th indicator respectively. In relation to the considered problem (1) the set *L* consists of three indicators: the indicator f_1 is *C(X)*, f_2 is *T(X),* and f_3 is *P(X).*

3 RESULTS AND DISCUSSION

Let us illustrate the solution to the selection problem applying example on the task of assessing consequences after a ground forest fire that occurred in the Leningrad region on August 30, 2019, using ERS data from the Sentinel-2 satellite.

Figure 1 shows the study area. This site has previously been covered by mixed pine-deciduous forest. Fire type is ground.

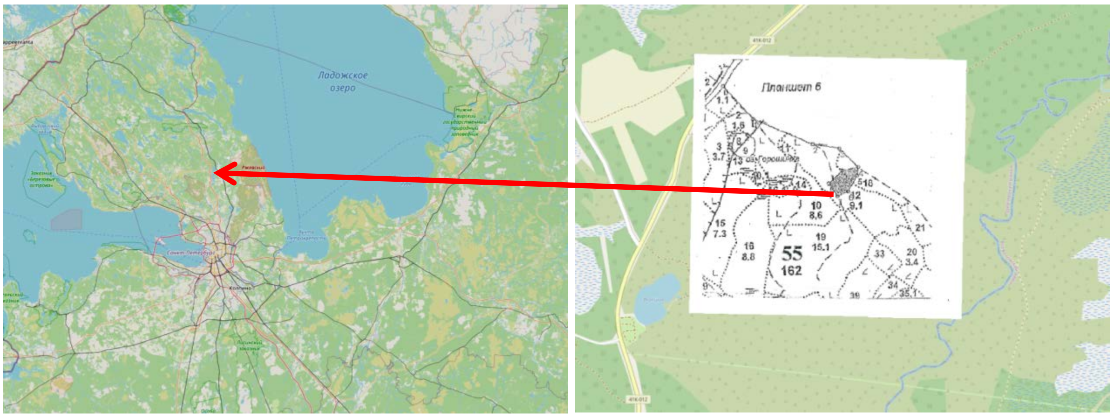


Fig. 1. Study area (latitude: 60° 26’ 54.7”, longitude: 30° 28’ 43.9”)

Two scenes of 12-band multispectral Sentinel-2 ERS data were used: dated August 27, 2019 (before the fire): S2A_MSIL1C_20190827T092031_N0208_R093_T36VUN_20190827T112253; and dated November 25, 2019 (two months after the fire): S2A_MSIL1C_20191125T092321_N0208_R093_T36VUN_20191125T092951.

Figure 2 shows ERS data on the study area map.

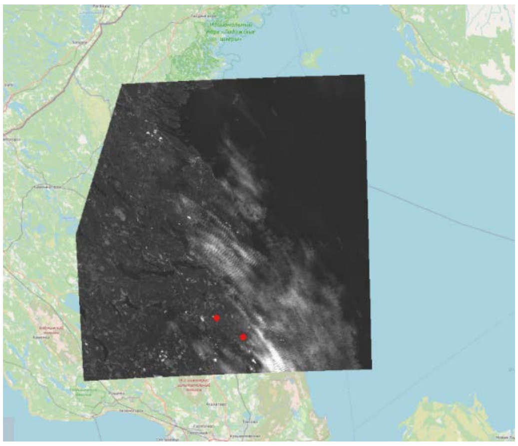


Fig. 2. Satellite image on the study area map

To simplify the presentation of selection procedure, the choice of CM in relation to one of the above-mentioned assessment stages is considering, precisely the stage of assessing a landscape element state.

The assessed indicators of the forest vegetation sustainability are the burnt area and types of burnt plant communities. Determination of these indicators' values can be performed using various methods and corresponding software for data processing and modeling [2].

The assessment accuracy of the considered indicators, time and other resources costs on performing the calculations depend on applied method. Possible alternative methods considered in the framework of this example include perceptron-based (PPN), support vector machine (SVM), random forest (RF); k-means and fuzzy c-means algorithm (FCM) clustering methods. [12] The initial data for choosing the best calculation method in terms of indicator (5) are the values of accuracy, duration, and resource costs for each of the methods under consideration.

To assess the calculations accuracy of the burnt area and the type of burnt plant community performed by alternative methods, ground surveys were carried out and a control sample similar to the training sample was formed. Ground surveys were performed after the fire, in parallel with satellite imaging.

Table 1 shows a fragment of the initial field data for forming a training sample using the first three methods mentioned. Each row of the table represents measurement results containing the values of the spectral brightness coefficients in twelve spectral channels of the Sentinel 2 satellite equipment for the corresponding image pixels as well as a class label. Measurements within the burnt contour are assigned with a class label "1". Class labels "2" and "3" are assigned to areas with forest vegetation types 1 and 2, respectively, in close proximity to the burnt area. The total number of records (image pixels) in the tables is 102 (34 rows for each class). The training sample included 70 pixels and the testing sample included 32 pixels. The sizes of the training sample were chosen to ensure the initial data representativeness in relation to the reflective characteristics general population of similar types vegetation within the scene. That is, the statistical characteristics of the surface reflective properties within the sample correspond to similar characteristics within the adjacent forest landscape.

Table 1. Initial data for forming a training sample

Measure ment №	Channel number						Class label
	1	*2*	*3*	*…*	*11*	*12*	
1	0.136	0.131	0.120		0.110	0.104	1
2	0.136	0.142	0.123		0.076	0.065	3
3	0.128	0.122	0.106		0.125	0.113	1
…							
100	0.140	0.110	0.122		0.081	0.066	3
101	0.140	0.132	0.129		0.092	0.075	3
102	0.125	0.118	0.099		0.087	0.075	2

Table 2 shows a fragment of the classification results performed using the compared methods.

In Table 2, the indicator referred to as "accuracy" characterizes the probability of correct classification, which means the ratio of correctly classified test measurements number to the total amount of measurements provided in the control sample. For a number of methods, the value of "accuracy" indicator turned out to be equal to 1.0, which is due to the insufficiently large volume of initial data (measurements) rather than the classification method quality. With an increase in the initial data volume, it is possible to obtain more accurate estimates. Table 3 presents results of clustering using k-means and FCM methods. To calculate the values of the "accuracy" metric, the resulting cluster labels were correlated with data from a similar control sample.

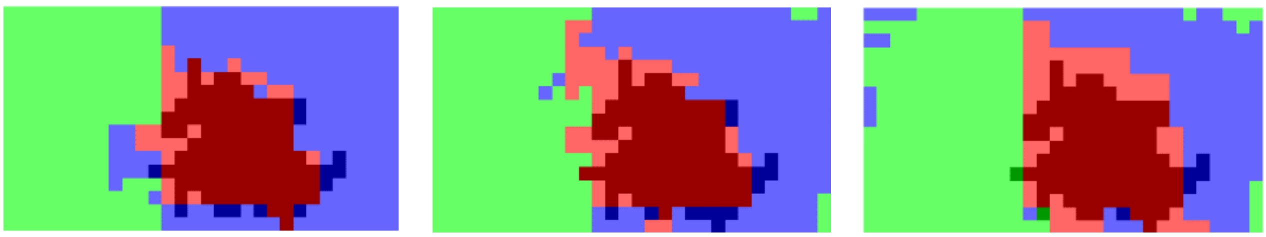
Table 2. Classification results

Measurement №	Class label	Methods		
		PPN	*SVM*	*RF*
1	1	1	1	1
2	3	3	3	3
3	1	1	1	1
…				
100	3	3	3	3
101	3	3	3	3
102	2	2	2	2
accuracy		1,0	1,0	0,98

Table 3. Clustering results

Measurement №	Class label	Clusterization methods				
		k-means	*FCM*			
			Affiliation measurements			*Class max.*
			1	*2*	*3*	
1	1	1	2,20e-4	0,99	4,45e-5	2
2	3	2	2,57e-3	2,20e-4	0,99	3
3	1	1	3,05e-6	0,99	3,76e-8	2
…						
100	3	3	0,79	6,18e-4	0,21	1
101	3	2	5,46e-7	2,59e-8	0,99	3
102	2	3	0,99	2,35e-4	1,23e-4	1
accuracy		0,87	0,90			

Figure 3 shows results of applying classification methods. The darkened area of the figure corresponds to the burnt forest territory; pink and dark blue colors indicate forest types 1 and 2, respectively. Blue and light green colors reflect unidentifiable surfaces.

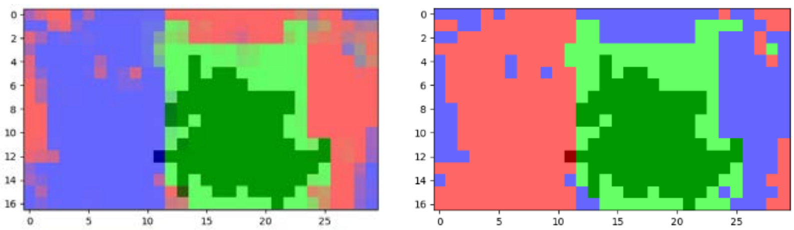


a) b) c)

Fig. 3. Results of applying classification methods

a) – RF; d) – SVM; e) – PPN.

Figure 4 shows the results of the considered clustering methods work.



a) k-means method б) FCM method

Fig. 4. Results of applying clustering methods

The dark green area corresponds to the burnt territory. To display the results of k-means and FCM methods operation when clustering adjacent forest vegetation species, light green and dark blue colors were used.

Analysis of the data content presented in Tables 2 and 3, and in Figures 3 and 4, allows us to draw conclusions about the accuracy of assessing indicators based on the calculation methods under consideration. To ensure a justified method selection, it is necessary to carry out a multi-criteria comparison, which covers an analysis of not only the accuracy indicator, but also the efficiency and resource intensity (economic efficiency) indicators of the methods under consideration. It should be taken into account that the k-means clustering and FCM methods do not involve constructing a training sample. To use them, you only need to indicate the boundaries of the landscape element undergoing clustering and the number of clusters that are identified within landscape element boundaries. Thus, the requirements to initial data composition, which are formed mainly during ground-based surveys, are reduced, i.e., the costs for gathering them are reduced and, accordingly, this affects the methods' economic efficiency.

Table 4 shows an example of indicators summary values for the compared methods when solving a typical task on identifying several types of forest surfaces (two...four) based on Sentinel-2 data over an area of 3-5 hectares.

Table 4. Initial data for methods comparison

№	Calculation method (algorithm)	Calculation accuracy	Duration of training	Resource costs (taking into account the volume of ground surveys) – in conditional currency unit
1	PPN	1,0	110 -1110 min	10
2	SVM	1,0	140 min	10
3	RF	0,98	140 min	10
4	K-means	0,87	130 min	4
5	FCM	0,90	40 min	2

Table 5 shows results of weighted relative deviations calculations from the optimum for particular indicators in accordance with relations (5), (6). In this case, it is considered that the calculation accuracy indicator has the highest priority: the weighting coefficients of particular indicators take the following values: 0.8 for the accuracy indicator, 0.1 for the efficiency indicator, 0.1 for the cost indicator.

Table 5. Weighted relative deviations from optima 1

Indicator	Weighted relative deviations from optima for the methods:				
	PPN	SVM	RF	K-means	FCM
Accuracy	0,000	0,000	0,123	0,800	0,615
Duration	0,100	0,009	0,009	0,008	0,000
Costs	0,100	0,100	0,100	0,025	0,000
Max. deviation	0,100	0,100	0,123	0,800	0,615

As can be seen from the table, the PPN and SVM methods are the best in this case according to the selected criterion.

However, in case the priority of the calculation duration indicator increases (ρ_2 = 0.3, while ρ_1 = 0.6 and ρ_3 = 0.1), the RF method has the best characteristics (Table 6).

If the indicator of resource costs for implementing the method is important, and its weight coefficient ρ_3 = 0.4, and at the same time ρ_1 = 0.4 and ρ_2 = 0.3, then FCM becomes the most preferable (Table 7).

In some cases, different methods may provide the same maximum deviation value, for example, as shown in Table 6. It is a pretty rare event indicating a lack of initial data. In this case, the final decision is made on the basis of additional information resulting from interactive interaction with the user, in accordance with the methodology of multi-criteria decision making [19, 21].

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Table 6. Weighted relative deviations from optima 2

Indicator	Weighted relative deviations from optima for the methods:				
	PPN	SVM	RF	K-means	FCM
Accuracy	0,000	0,000	0,092	0,600	0,462
Duration	0,300	0,028	0,028	0,025	0,000
Costs	0,100	0,100	0,100	0,025	0,000
Max. deviation	0,300	0,100	0,100	0,600	0,462

Table 7. Weighted relative deviations from optima 3

Indicator	Weighted relative deviations from optima for the methods:				
	PPN	SVM	RF	K-means	FCM
Accuracy	0,000	0,000	0,062	0,400	0,308
Duration	0,300	0,028	0,028	0,025	0,000
Costs	0,400	0,400	0,400	0,100	0,000
Max. deviation	0,400	0,400	0,400	0,400	0,308

Generally, the presented results show that the proposed method makes it possible to formalize and automate the process of selecting the most appropriate calculating method based on several criteria. This differs from the known descriptions of ERS data processing technologies using several types of algorithms without their reasonable choice or known approaches to evaluate algorithms by one indicator [18, 22-24]. That is, the proposed method can be used to complement these approaches and increase the efficiency of analyzing the NTS state.

4 CONCLUSIONS

Thus, based on the proposed approach, the best method for calculating indicators of the state of forest vegetation, or a set of methods for a multi-stage calculation scheme, can be selected according to the introduced criterion. The final choice is influenced by both accuracy and resource characteristics of the methods. The decision on methods selection is presented in the form of a table, which allows the user to evaluate losses and gains in the values of partial indicators when moving from using one method to another.

Algorithmization of the selection problem determines possibility of its automation and, thereby, simplifying the use of complex methods for processing remote sensing data for the end user. In addition, the possibilities and validity degree are expanding for scaling the results of processing multispectral ERS date for individual territories to large areas of forests.

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6 REFERENCES

[1] Semek, F, et al. Airborne remote sensing. Theory and practice in assessment of terrestrial ecosystems. (2014). Global Change Research Centre AS CR, v.v.i., Brno.

[2] Brovkina,O., Stojanović, M., Milanović, S., Latypov, I., Marković, N. & Cienciala, E. (2020). Monitoring of post-fire forest scars in Serbia based on satellite Sentinel-2 data. Geomatics, Natural Hazards and Risk, vol. 11, no. 01, 2315–2339, https://doi.org/10.1080/19475705.2020.1836037.

[3] Anushree, B., Santosh, K. Panda, Dar, A. Roberts, Christine, F. Waigl, Uma, S. Bhatt, Christopher, W. Smith and Rand,i R. Jandt. (2021)/ Hyperspectral Data Simulation (Sentinel-2 to AVIRIS-NG) for Improved Wildfire Fuel Mapping, Boreal Alaska. Remote Sens, vol. 13(9), 1693, https://doi.org/10.3390/rs13091693.

[4] Kourosh, Ahmadi, Bahareh, Kalantar, Vahideh, Saeidi, Elaheh, K. G. Harandi, Saeid Janizadeh and Naonori, Ueda. (2020). Comparison of Machine Learning Methods for Mapping the Stand Characteristics of Temperate Forests Using Multi-Spectral Sentinel-2 Data. Remote Sens, vol. 12(18), 3019, https://doi.org/10.3390/rs12183019.

[5] Mochalov, V., Grigorieva, O., Zhukov, D., Markov, A., Saidov A. (2020). Remote Sensing Image Processing Based on Modified Fuzzy Algorithm. Silhavy, R. (eds) Artificial Intelligence and Bioinspired Computational Methods. CSOC 2020. Advances in Intelligent Systems and Computing, vol 1225. Springer, Cham. https://doi.org/10.1007/978-3-030-51971-1_46

[6] Mochalov, V.F. (2020) Assessment of vegetation state based on modified fuzzy algorithm. Informatization and Communication, vol. 5, p.169-174. DOI: 10.34219/2078-8320-2020-11-5-169-174.

[7] Poluektov, R. A., Pikh, Y. A., Shvitov, I. A. (1980). Dynamic models of ecological systems. Gidrometeoizdat, Leningrad.

[8] Semevsky, F.N., Semenov, S.M. (1982). Mathematical Modeling of Ecological Processes. Gidrometeoizdat, Leningrad.

[9] Khomyakov, P.M., Ivanov, V.D., Iskandaryan, R.A., et al. Geoecological modeling for environmental management purposes in condition of the change of natural environment and climate. USSR, Moscow.

[10] Frelich, L.E. (2002). Forest Dynamics and Disturbance Regimes. Cambridge University Press, Cambridge.

[11] Kuznetsov, V.I., Kozlov, N.I., Khomyakov, P.M. (2005). Mathematical modeling of forest evolution for forestry management. URSS, Moscow.

[12] Rashka, S. (2017). Python and Machine Learning. Translation from English A.V. Logunova. DMK Press, Moscow.

[13] Aurélien, Géron.(20190). Hands-On Machine Learning with Scikit-Learn, Keras, and TensorFlow. O'Reilly Media, Inc.

[14] Terebizh, V. Yu. (2005). Introduction to statistical theory of inverse problems. Fizmatlit, Moscow.

[15] Shovengerdt, R. A. (2010). Remote sensing. Methods and models of image processing. Tekhnosphere, Moscow.

[16] Shestakova, T.A., Mackey, B.; Hugh, S., Dean, J., Kukavskaya, E.A., Laflamme, J.; Shvetsov, E.G., Rogers, B.M. (2022). Mapping Forest Stability within Major Biomes Using Canopy Indices Derived from MODIS Time Series. Remote Sens, vol.14, 3813. https://doi.org/ 10.3390/rs14153813.

[17] Brovkina, O, Navr´atilov´a, B., Novotný, J., Luk´aˇs Slez´ak, J A., Cienciala, E. (2022). Influences of vegetation, model, and data parameters on forest aboveground biomass assessment using an area-based approach. Ecological Informatics, vol. 70, 101754, DOI: 10.1016/j.ecoinf.2022.101754..

[18] Ghayour, L., Neshat, A., Paryani, S., Shahabi, H.; Shirzadi, A., Chen, W., Al-Ansari, N., Geertsema, M., Pourmehdi Amiri, M., Gholamnia, M. et al. (2021). Performance Evaluation of Sentinel-2 and Landsat 8 OLI Data for Land Cover/Use Classification Using a Comparison between Machine Learning Algorithms. Remote Sens. 2021, 13, 1349. https://doi.org/ 10.3390/rs13071349.

[19] Mikoni, S.V., Sokolov, B.V., Yusupov, R.M. (2018). Qualimetry of Models and Polymodel Complexes. RAS, Moscow.

[20] Petukhov, G.B. (1989). Fundamentals of the theory of task-oriented process effectiveness Pt. 1. Methodology, methods, models. MO SSSR, Moscow.

[21] Mikhalevich, V. S., Volkovich, V. L. (1982). Computational methods for the study and design of complex systems. Nauka, Moscow.

[22] You, H.; Gu, J.; Jing, W. (2023). Multi-Label Remote Sensing Image Land Cover Classification Based on a Multi-Dimensional Attention Mechanism. Remote Sens., vol.15, 4979. https://doi.org/10.3390/rs15204979.

[23] Yuting, Wan, Chao, Chen, Ailong, Ma, Liangpei, Zhang, Xunqiang, Gong, Yanfei, Zhong. (2023). Adaptive Multistrategy Particle Swarm Optimization for Hyperspectral Remote Sensing Image Band Selection. IEEE Transactions on Geoscience and Remote Sensing, vol.61, 1-15, doi: 10.1109/TGRS.2023.3305545.

[24] Ayna, C.O.; Mdrafi, R.; Du, Q.; Gurbuz, A.C. (2023). Learning-Based Optimization of Hyperspectral Band Selection for Classification. Remote Sens., vol. 15, 4460, https://doi.org/10.3390/rs15184460.

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