Interrelation of the Estimation of Social and Economic Development of the Region and Quality of Water Resources

L.G. Matveeva[2], N.A. Kosolapova[1], A.Y. Nikitaeva[2,*] and E.A. Likhatskaya[2]

[1]*Southern Federal University, Rostov-on-Don, Russia, 344002 M. Gorkogo t., 88, office 322*

[2]*Southern Federal University, Rostov-on-Don, Russia, 344002 M. Gorkogo t., 88, office 115*

Abstract: The paper validates the practicability of studying the problem of the quality of water at a regional level taking into account the mutual interaction between socio-economic and hydroeconomic systems of the territories. The research revealed the limitations of the existing methods of estimation of the quality of water in the light of creation of informational and analytical basis of making managerial decisions. Accordingly, the authors suggest using the analytical tools of fuzzy logic, cluster analysis and neural networks to build an integral estimation of degree of water pollution and to classify water bodies according to the degree of their pollution and similarity of conditions and parameters of pollution. On the basis of the data concerning the quality of water resources in the river basin neural network was built, allowing to determine clusters of regions according to the quality of water resources. As input variables we used the information on the volume of drawing and dropping of water for each region, the amount of wastewater, which is polluted. The suggested methods allow greatly increase the opportunities to make managerial decisions with the help of interrelated estimation of the quality of water resources and the indicators of social and economic development of regional economic systems.

Keywords: Social and economic development, Regional economic system, Water resources, Estimation of the quality of water, Hydroeconomic system, Machine Learning.

INTRODUCTION

In modern world social and economic processes in a significant degree depend on the quality of water resources. Water is the most relevant natural resource used in economy. The annual use of water resources greatly outmatches the use of all other extracted resources together. Taking into consideration the diversity of climatic, geographic, technologic, social and economic peculiarities of different territories, it is rational to deal with the question of providing water resources for economic systems at a regional level. If regional economy gets amount of water which is rational in its quality and quantity and is sufficient to achieve the social and economic aims of a region, it will facilitate normal implementation of economic processes, regional plans, programs, projects and support the stable operation of the economic system of a region and its subsystems both in current and strategic perspective [1]. Rational in its quality and quantity water delivery for the economy of a region is clearly targeted and due to this is among the factors of preserving of integrality and stability of a regional system. Alongside this, the relevance of studying the problem of the quality of water resources is provided by the fact that possibilities, directions and conditions of water usage in a regional economy directly depend on the qualitative parameters of water. At the same time, the parameters of the regional economy regulating measures and activities, connected to restoring and supporting the quality of water resources, directly influence the quality of water and possibilities of its cyclic usage. Most strategies, policies and regulatory actions dedicated to protection and preservation of water resources depend on efficient monitoring and estimation of the quality of water. So, there is an obvious interrelation and interdependence between the quality of water resources and social and economic development of a region. In defines the practicability of interrelated development of hydroeconomic and economic systems of regions taking into account their interdependence. Thus, the question of interrelated estimation of the quality of water resources and the indicators of social and economic development of regions and creating and applying necessary analytic tools becomes more essential.

Many researchers devoted their works to the questions of estimating the quality of water resources. A great number of academic papers are dedicated to the development of indicators and tools of estimating the quality of water resources and their classification according to a certain group of indicators. For example, Cadence Hsien, Jonathan Sze Choong Low, Si Ying Chung, Daren Zong Loong Tan suggest classifying the types of water according to the level of quality on the basis of a group of indicators, narrowing the set of indicators to those which are often gathered and fixed

*Address correspondence to this author at the Southern Federal University, Rostov-on-Don, Russia, 344002 M. Gorkogo t., 88, office 115;
Tel: +79282265711; Email: a_nikitaeva@list.ru

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in regulatory norms [2]. Different indexes, applied to estimate the quality of water (taking into consideration its source, function etc.), are used by governmental organizations or regulatory agencies of different levels [3-6]. Because the quality of water is estimated from the point of view of physical, chemical and biological parameters [7], the index approach is valid for solving the problem of estimation the quality of water. But the inequivalence of different strands which characterize the quality of water leads to the creation of new indexes. For example, Mansi Tripathi и Sunil Kumar Singal suggest using factor analysis to determine the weight the parameters of Water Quality Index (WQI) [8].

In recent years scholars have started to actively use intellectual technologies, especially, machine learning and artificial intelligence to prognosticate the quality of water within different contexts [9, 10].

There are attempts to create models of planning of regional development and control of water resources within the context of uncertainty with the usage of inexact fuzzy programming combined with water quality model [11], but at the same time they deal with a limited set of indicators.

The development of modern analytic tools allows broaden the existing models, for determining the optimal extent of regional water and wastewater treatment and wastewater diversion schemes in a river basin) [12], facilitating the growth of validity of the decisions concerning managing the hydroeconomic systems of river basins. There are solutions for the problem of creating an efficient (from the point of view of time and expenses) approach towards the prognosticating the class of the indicators of the quality of water on the basis of applying the model of decision tree to increase the quality of managing the water resources of rivers [13]. Statistical methods such as factor analysis, the analysis of main constituents and discriminant analysis are widely used as objective methods of analyzing the data concerning the quality of water [14-17]. Modern equipment used to measure the quality of water allows us to conduct a deeper analysis of the quality of water resources with the help of multivariate statistical HJ-Biplot approach [18]. The pilot projects may be, in which the monitoring of the quality of water is performed with the help of the method based on feedback self-correcting dense connected convolution network [19].

A great number of methods of estimation of the quality of water were suggested for particular branch and regional systems taking into account their specificity. But, we need to bear in mind not only the obvious effect on water ecosystems, but also little-known sidewise human impact on water resources via the soil, relief, biota – unirrigated farming, forestry, urbanization and other human activity on reception basis and the movement of water within products. Due to this, although the existing tools allow estimating the quality of water, there is an obvious lack of research to solve managing tasks of coordinated development of regional social and economic systems and hydroeconomic systems. It emphasizes the importance of solving the problem of interrelated estimation of the quality of water resources and the indicators of social and economic development of regions on the basis of using adaptive economic, mathematic, informational and technologic tools.

MATERIALS AND METHODS

Approaches and Methods to Water Quality Assessment

Nowadays the state of water bodies is estimated not from the point of view of the needs of particular water users, but from the position of preserving parameters and functional capability of the whole ecosystem. Due to this fact, there are many different approaches to the estimation of the quality of water resources within water bodies, which require the calculation of indicators, characterizing the physical and chemical peculiarities, the content of different substances. Analyzing these approaches, we can make conclusions concerning the difficulty of calculating the value of the complex estimation of the degree of water pollution. That is why apart from traditional integral estimation, which is usually based on maximum allowable concentration, environmental criteria or hydrochemical index of water pollution, the authors suggest using other methods of building the integral estimation of the quality of water in the areas of water bodies and the classification of water bodies according to the level of pollution and similarity of conditions and parameters of pollution. The suggested model is based on the modelling of qualitatively defined indicators with the usage of analytical tools of fuzzy logic, cluster analysis and neural networks. The advantage of such models is in their flexibility in terms of correction both the inference rules and the estimation based on individual indicators. The models allow us to change easily the inference rules and to improve them when the situation changes in what concerns the estimation of the quality of sources of water. The built models allow giving valid information about the level of pollution of a water source based on a complete set of hydrochemical indicators, whose values are determined with the help of the results of observations. The models can be adapted to the changes of the set of hydrochemical characteristics.

The estimation of the quality of the source of water can be given only on the basis of a subcollection of hydrochemical indicators, whose composition is also determined by experts. The model allows choosing the ingredient, which, according to an expert, is necessary to calculate the integrated index of the degree of pollution. Moreover, the suggested methods let us greatly broaden the possibilities of making managerial decisions thanks to the interrelated estimation of the quality of water resources and the indicators of social and economic development of regional economic systems.

In the Russian Federation the problem of estimation of the quality of water within the regions of water basin is especially relevant taking into account the size of the country and great difference of its territories both in the presence of resources and the level of their economic development against the context of the increasing scope of demographic, ecological and social problems on certain territories [20]. Due to this condition they compose and regularly update the Schemes of complex usage and protection of water objects (SCUPWB) which regulate the distribution of water resources within water basins and increase their quality, including the process of industrial and other usage.

The development of the hydroeconomic complex (HEC) of a region and realization of SCUPWB and the norms of allowed water consumption (NAW) is an important trait of not only the development of HEC itself but also the regions of the water basin and economy as a whole.

In the boundaries of the monetary means, provided according to the Federal programs to implement SCUPWB for the year 2018, the central regions of the Russian Federation completed the planned activities dedicated to the rational use and protection of water bodies only to the level of 20-50% (Figures **1**, **2**).

Conducting the cluster analysis for the members of the Russian Federation, taking into account such factors as “percentage of completed actions” and “percentage of actions completed according to value” led to the following results.

According to the analyzed parameters the best one was the clusterization with five clusters which include: 1 cluster of 2 observations; 2 cluster 13 observations; 3 cluster 20 observations; 4 cluster 28 observations; 5 cluster 20 observations.

Using the results of this segmentation it is possible to establish the regularity of dividing regions into clusters: the first class – regions with the highest indicators of all the input variables; the fourth class includes the regions with the lowest indicators both for the completion of actions and money allocated to complete the actions.

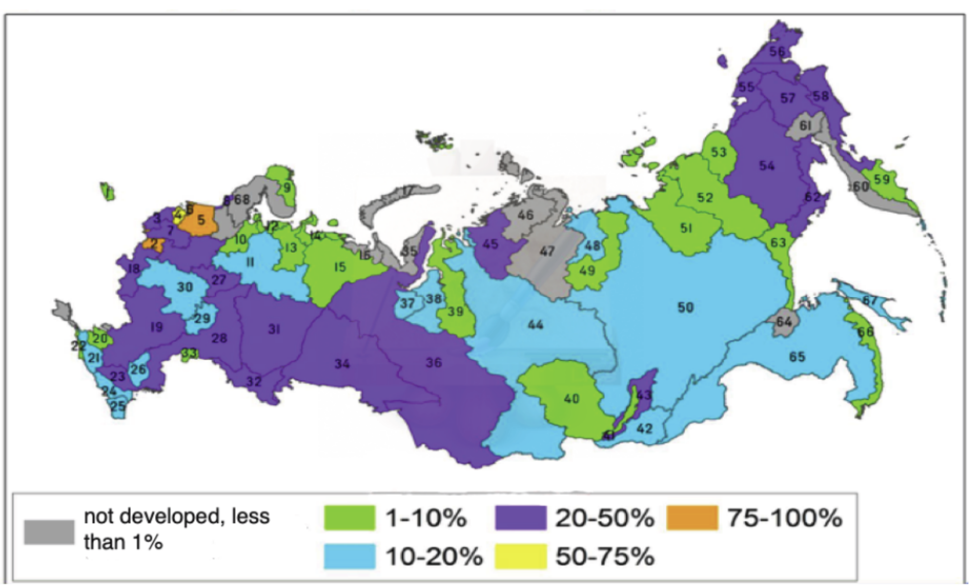


Figure 1: Grouping the regions of the RF according to the degree of realization of SCUPWB in numerical terms (2018).

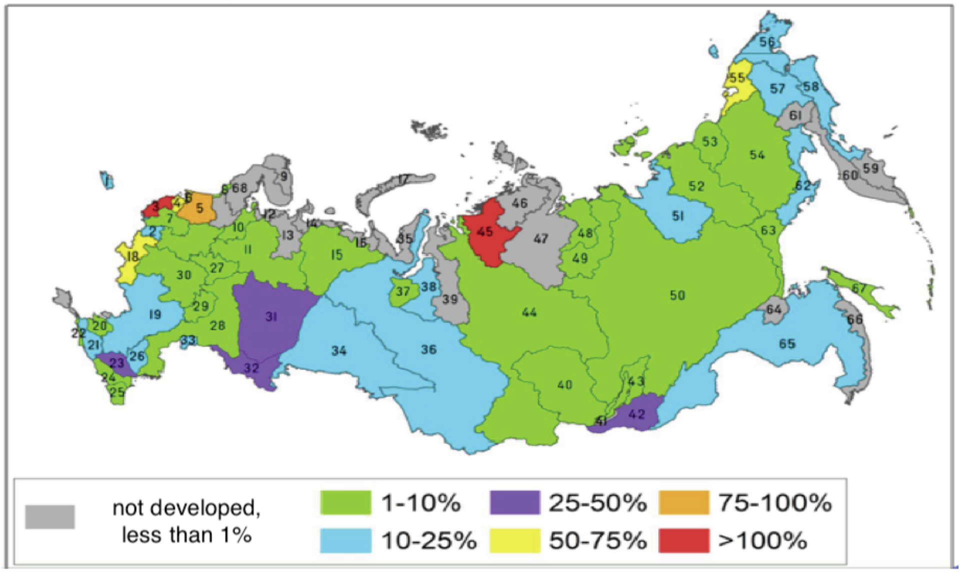


Figure 2: Groups of the regions of the RF according to the degree of realization of actions of SCUPWB in monetary terms (2018).

For example, Rostov region is in the fourth cluster, which is characterized by pretty low level of completion of the activities on allocation and usage of water resource of the basin both in terms of quantitative indicators and the monetary equivalent.

Neural Networks in the Estimation of Social and Economic Development of the Region and Quality of Water Resources

The complex analysis of the realization of SCUPWB in the Russian Federation in 2018 was carried out, and an analysis of strategic aims of the development of hydroeconomic systems (HES) and the level of the economic development of the regions was performed.

With the help of neuronal modeling, classes were built, which determine the degree of the concurrence of the development of hydroeconomic and economic systems of the analyzed regions.

The development of computers allows simplifying approaches towards modelling, thereby making technologies closer to the possibility of the educability of a system through the example of brain activity. But this approach does not exclude manual/human interference. Information technologies assimilate mental activity of a human brain, but in spite of all the abilities of information processing, they cannot excel humans.

The research in the field of building an artificial neural network (ANN) is conducted by programmers within the context of so-called neuro-computing. Such modeling uses the simplest models of a brain. But in fact it is a more complicated type of regressive or statistic model. An example of ANN is shown in Figure **3**.

In the left part of the neural network there are several crosspoints of the entrance level, in the right part – crosspoints of the exit layer. The middle part is the hidden layer. There can be many parts of this type. The number of hidden layers and crosspoints in every layer are the two parameters of creating a neural network.

The majority of projects, using neural network modelling, have at least three types of layers:

1. Entrance layer – crosspoints, which get information from outdoor environment. This information is not modified; its weighted values are studied and sent to the next hidden level.

2. A hidden level consists of crosspoints, which usually get transported weighted values from the entrance level or the previous hidden level. Here this information if modified in a certain way, and the results are sent to the next adjacent level, which can be another hidden level or the exit level.

3. Exit level consists of crosspoints which get the results from a hidden level and send them to the user of an artificial neural network.

The neural network in Figure **3** is a multilayer perceptron network or a feedforward network. There

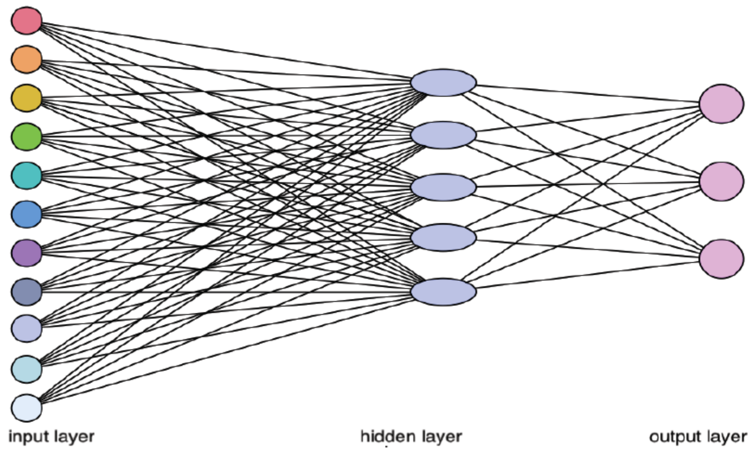


Figure 3: A multilayer artificial neural network.

are other architectures of ANN, which include recurring neural networks, maps of self-organizing functions, Hopfield networks, radical basis function networks, support vector machines etc.

The weight of a formation of data, received at the entrance, is the calculated parameter of a neural network. Values of the outcoming data, which leave crosspoint j at every possible exit, we will indicate as Qj . The net in Figure **3** is a typical neural network with ten entrances and a hidden layer and shows the entrance layer for ten different entrances, a hidden layer with the exits in the exit layer, which has three exits. Input value Ik for every crosspoint k in every middle and exit layer is a sum of each of its weighted entrances $wjQj$ from all crosspoints j, which provide entrances with crosspoint k. The input value for crosspoint k:

$$Ik = wjQj \tag{1}$$

It needs to be noticed that Ik is the argument of function $fk\left(Ik+\theta k\right)$ which changes the input value Ik (in every crosspoint k and the exit layer) into output value Qk Variable θk is a threshold member which influences the horizontal separation of the function. At the same time function fk can be linear or nonlinear.

So, the function can be represented as a logistic function (2), its graphical representation can be seen in Figure **4**.

$$Qk = 11 + e - \left(I \quad k + \theta k\right) \tag{2}$$

The process of transformation of entrances into exits in every hidden crosspoint of a layer is shown in Figure **5**. The same process takes place in every crosspoint of the exit layer.

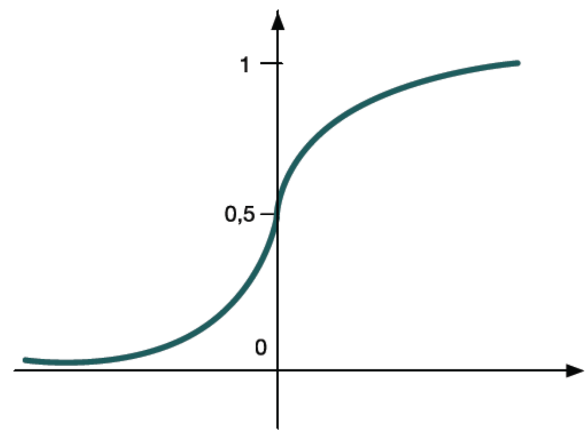


Figure 4: Sigmoid or logistic threshold function with threshold θk .

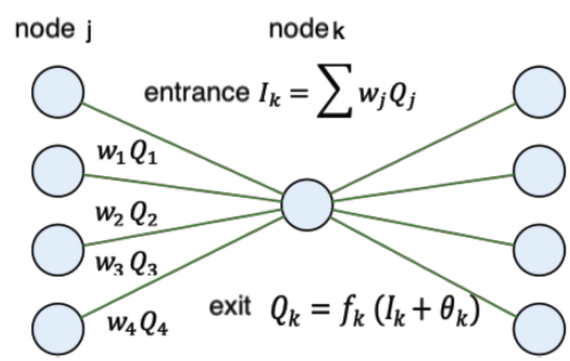


Figure 5: Transformations in a multilayer neural network.

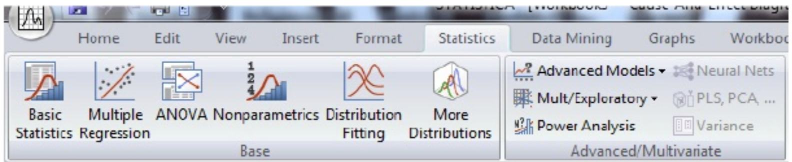
The number of crosspionts in entrance and exit layers is determined, depending on the problem, faced by the developers. The number of hidden layers is determined, depending on the calibration of parameters. Developer's task is to find the solution, which best corresponds to the observed and forecasted output data on the basis of initial input parameters.

The training of an artificial neural network is the main step for determining the weights and thresholds of every formation in the light of previously formed input and output data arrays.

Modern software packages (ASP STATISTICA 13.0) provide modules for building neural networks. It should be noted that depending on the construction of ANN changes the approach towards processing of data. As for today, there two topologies:

- Feedforward networks. In such a topology data moves straight from the entrance to the exit through hidden layers. So, all the output values are based on the current data array, received at the entrance.

- Recurring networks or feedback networks. Networks of this type send data from the entrance to the exit, but there is the reverse direction. In recurring networks the information about previous entrances is sent back and mixes with the entrances through recurring (backward) connections.



	1 water withdrawn from natural water bodies mln.m3	2 discharged water into natural water bodies	3 volume of wastewater requiring treatment	4 volume of wastewater with pollutants
Altai region	387,44	268,97	120,65	120,65
Amurskaya Oblast	104,51	73,24	73,14	73,14
Arkhangelsk region	723,42	667,08	356,02	356,02
Astrakhan region	712,6	211,21	52,06	52,06
Belgorod region	318,37	133,03	112,2	112,2
Bryansk region	106,33	61,25	55,31	55,31
Vladimir region	151,89	107,62	104,64	104,64
Volgograd region	955,28	245,09	105,87	105,87
Vologodskaya Oblast	262,49	223,43	187,11	187,11
Voronezh region	412,43	243,91	119,2	119,2
Moscow	668,69	1085,51	845,28	845,28
Saint Petersburg	953,52	1159,58	1041,07	1041,07
Sevastopol	96,49	63,3	23,22	23,31
Jewish Autonomous Region	22,79	13,54	13,54	13,54
Transbaikal region	296,85	214,07	90,6	91,4
Ivanovo region	123,55	97,1	72,99	72,99
Irkutsk region	1004,23	824,37	608,22	608,22
Kabardino-Balkarian Republic	738,16	98,93	29,28	29,28
Kaliningrad region	137,41	127	111,13	111,66
Kaluga region	138,22	77,93	77,34	77,34
Kamchatka Krai	167	121,36	33,21	33,21
Karachay-Cherkess Republic	2945,85	527,89	46,01	526,76
Kemerovo region	1995,82	1723,08	598,71	598,84
Kirov region	180,92	126,1	88,81	91,96
Kostroma region	1874,63	1874,34	51,19	51,19
Krasnodar region	6181,18	6308,85	841,61	841,61
Krasnoyarsk region	2191,27	1820,65	358,37	358,37
Kurgan region	66,57	36,22	36,22	36,22
Kursk region	224,48	93,08	40,95	40,95
Leningrad region	5576,9	5457,99	282,41	282,59
Lipetsk region	186,18	87,99	79,71	79,71
Magadan Region	77,51	40,08	19,91	19,91
Moscow region	3310,24	1874,25	1072,82	1072,82
Murmansk region	1613,37	1543,73	322,3	327,4
Nizhny Novgorod Region	802,99	793,54	395,93	395,93
	103,61	87,62	81,88	81,88
	628,3	520,98	256,85	256,85

Figure 6: A fragment of a database for building neural network models.

As a result of ANN training the best value for all the weights can be found. To achieve this, the training usually goes in a controlled mode, and the initial weights, determined in random manner, are correlated until at the exit the optimal value, close to the factual/desired output results, is obtained.

Any methods of adjusting the weights are aimed at the minimization of differences between observation and the data, calculated de facto. The training consists of providing input and output data in the network. For each entrance the desired array of exits is determined. Also it is necessary to understand that network training is a long process and its completion depends on whether the desired level of productivity is achieved or not. Thereunder we mean the statistical accuracy, because it produces the necessary output data for a certain succession of input data. When further training isn't considered necessary, the resulting weights are usually recorded.

As soon as the controlled network starts working well with training data, it is important to see, what it can do with the data it has never seen before. If the system does not provide reasonable output data for this set of tests, then the period of training must be prolonged. Testing has the defining meaning to make sure, that the net knows the common patterns, used in the application instead of just remembering an array of data.

Based on the information about the quality of water resources in the basin, it is possible to build neural network models that allow determining clusters of regions by the quality of water resources. As input variables we used the information about the volume of withdrawing and discharging of waste water, which require purification, and the volume of polluted waste water (Figure **6**).

The used software program is ASP STATISTICA 13.0 (Figure **7**).

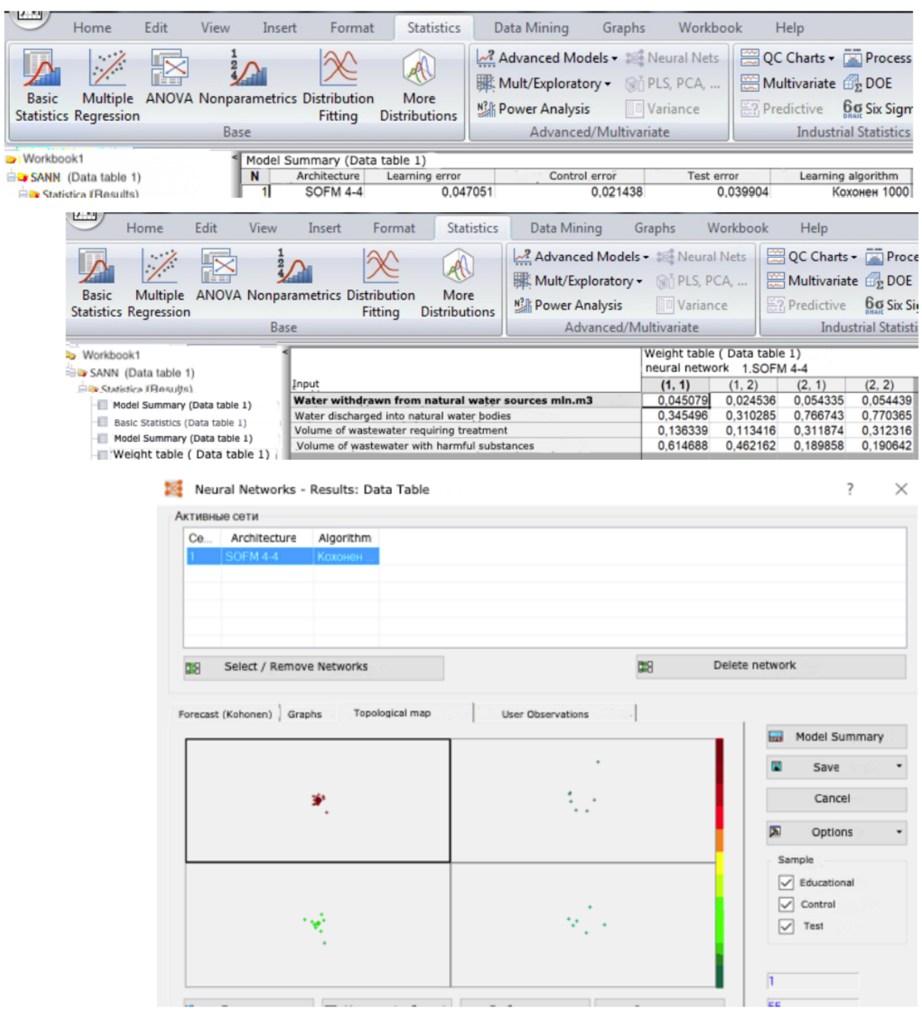


Figure 7: Dialog boxes in ASP STATISTICA with the results of clusterization.

Solving the problem of clusterization is premised on the usage of Kohonen's networks as an algorithm for searching the best structure of clusters. Unlike other types of neural network models, Kohenen's networks realize the principle of uncontrolled training, when the input data does not contain the values for output variables, *i.e*. the network "tries" to understand the structure of the initial data. Such networks have only two layers – the entrance one and the exit ones, which are also called a topology map. The training is implemented through sequential optimization of the structure of the data. We can make parallels between how such algorithms work and the method of k-averages in cluster analysis.

The neural network cluster algorithm is iterative in its character and takes place during several stages, in every of which first the best (winning) neural processing element which is the closest one to the original example, then it is corrected, basing on the weighted sum of the previous center of the cluster and the training example, to become closer to the input example.

RESULTS

The best one is the clusterization with four clusters (Figure **8**), which include:

1 cluster - 55 observations;

2 cluster - 7 observations;

3 cluster - 14 observations;

4 cluster - 6 observations.

According to the results of segmentation we can create a consistent pattern of division: the first class – regions with the lowest indicators of nearly all the input variables; the fourth class, on the other hand, includes regions with the highest indicators of water withdrawal and the pollution of wastewaters.

Rostov region is in the third cluster, which is characterized by pretty high volumes of withdrawal of water resources. But, at the same time, low indicators of the pollution of waste waters.

	Neuron position	Neuron ID	Activation
Altai region	(1, 1)	1	0,082556
Amurskaya Oblast	(1, 1)	1	0,036029
Astrakhan region	(1, 1)	1	0,070703
Belgorod region	(1, 1)	1	0,068097
Bryansk region	(1, 1)	1	0,033611
Vladimir region	(1, 1)	1	0,062199
Volgograd region	(1, 1)	1	0,124484
Vologodskaya Oblast	(1, 1)	1	0,167134
Voronezh region	(1, 1)	1	0,080887
Sevastopol	(1, 1)	1	0,060301
Jewish Autonomous Region	(1, 1)	1	0,079069
Transbaikal region	(1, 1)	1	0,040786
Ivanovo region	(1, 1)	1	0,032147
Kabardino-Balkarian Republic	(1, 1)	1	0,084949
Kaliningrad region	(1, 1)	1	0,071045
Kaluga region	(1, 1)	1	0,034625
Kamchatka Krai	(1, 1)	1	0,041731
Kirov region	(1, 1)	1	0,042795
Kostroma region	(1, 1)	1	0,374869
Kurgan region	(1, 1)	1	0,051889
Kursk region	(1, 1)	1	0,029984
Lipetsk region	(1, 1)	1	0,031577
Magadan Region	(1, 1)	1	0,066473
Novgorod region	(1, 1)	1	0,041918
Omsk region	(1, 1)	1	0,094140
Orenburg region	(1, 1)	1	0,174323
Oryol Region	(1, 1)	1	0,038626
Penza region	(1, 1)	1	0,044311
Pskov region	(1, 1)	1	0,038568
Republic of Adygea	(1, 1)	1	0,049372
Altai Republic	(1, 1)	1	0,091983
The Republic of Buryatia	(1, 1)	1	0,105433
The Republic of Ingushetia	(1, 1)	1	0,082052
Republic of Kalmykia	(1, 1)	1	0,068282
Republic of Crimea	(1, 1)	1	0,066689
Mari El Republic	(1, 1)	1	0,040410
The Republic of Mordovia	(1, 1)	1	0,060753
The Republic of Sakha (Yakutia)	(1, 1)	1	0,019204
Republic of North Ossetia-Alania	(1, 1)	1	0,118998
Tyva Republic	(1, 1)	1	0,078464
The Republic of Khakassia	(1, 1)	1	0,052070
Ryazan Oblast	(1, 1)	1	0,035495
Saratov region	(1, 1)	1	0,166254
Sakhalin Oblast	(1, 1)	1	0,039310
Smolensk region	(1, 1)	1	0,024374
Tambov Region	(1, 1)	1	0,038238
Tomsk region	(1, 1)	1	0,032567
Tula region	(1, 1)	1	0,131726
Udmurt republic	(1, 1)	1	0,057709
Ulyanovsk region	(1, 1)	1	0,056858
Khabarovsk region	(1, 1)	1	0,151079
Chechen Republic	(1, 1)	1	0,075434
Chuvash Republic	(1, 1)	1	0,053197
Chukotka Autonomous Okrug	(1, 1)	1	0,089533
[illegible]	(1, 1)	1	0,155273

	Neuron position	Neuron ID	Activation
Arkhangelsk region	(2, 1)	3	0,033623
Irkutsk region	(2, 1)	3	0,360118
Karachay-Cherkess Republic	(2, 1)	3	0,470549
Krasnoyarsk region	(2, 1)	3	0,280467
Murmansk region	(2, 1)	3	0,180903
Nizhny Novgorod Region	(2, 1)	3	0,079536
Novosibirsk region	(2, 1)	3	0,115708
Perm region	(2, 1)	3	0,203715
Primorsky Krai	(2, 1)	3	0,065575
Republic of Bashkortostan	(2, 1)	3	0,084241
Republic of Karelia	(2, 1)	3	0,199595
Komi Republic	(2, 1)	3	0,079407
Republic of Tatarstan	(2, 1)	3	0,066143
Samara Region	(2, 1)	3	0,103849

	Neuron position	Neuron ID	Activation
Leningrad region	(2, 2)	4	0,505067
The Republic of Dagestan	(2, 2)	4	0,386541
Rostov region	(2, 2)	4	0,216581
Stavropol region	(2, 2)	4	0,460929
Tver region	(2, 2)	4	0,194368
Tyumen region	(2, 2)	4	0,260935

	Neuron position	Neuron ID	Activation
Moscow	(1, 2)	2	0,277002
Saint Petersburg	(1, 2)	2	0,366702
Kemerovo region	(1, 2)	2	0,302429
Krasnodar region	(1, 2)	2	0,951085
Moscow region	(1, 2)	2	0,378473
Sverdlovsk region	(1, 2)	2	0,320974
Chelyabinsk region	(1, 2)	2	0,324786

Figure 8: Cluster created as a result of building a neural network.

Thereby, in this paper the possibility and efficiency of applying the neural network tools as a means of support of decision making in the sphere of water economy were clearly demonstrated.

DISCUSSION

The usage of the methods of clusterization and neural simulation allows us to build classes of regions according to the quality of water resources. From the managerial point of view it gives an opportunity to develop and implement regulatory actions (groups of actions), which take into account the specificity of the quality of water of given regional systems. In addition, the suggested methods also allow uniting within one estimation the resource and resulting aspects upon condition that the parameters of social and economic development of regions are included into the group of analyzed indicators. As an example of such indicators we can use gross regional product, infection rate among the population, different indicators of industrial development, directly or indirectly connected with the quality of water. In this case the results can be used in a broader way due to revealing common features of the regional systems and development of not scattered actions and measures, but complex programs of ecosystematic development of the regions, taking into account social and economic and hydroeconomic aspects. But to solve this problem it is necessary to establish an adequate information array and expand the indicators, included into statistical observations. The structure of such indicators, allowing to reveal the interrelation between the development of social and economic and hydroeconomic systems, methods and sources of getting adequate data characterize the direction of future research by the authors.

CONCLUSIONS

Thus, the assessment of the quality of water resources is now a very urgent problem. It is reasonable to carry out such an assessment at the regional level using intellectual analytical tools. At the same time it is important to estimate together the indicators of socio-economic development of the regions and the quality of water resources. In the presented research the expediency of using clustering and neural network modeling for solving this problem is proved. It is shown that neural networking and clustering allow to unite within one estimation the resource and resulting aspects of regional development and combine consideration of indicators of water quality and indicators of social and economic development of regions. From the managerial side it gives an opportunity to develop and implement effective regulatory actions.

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REFERENCES

[1] Kosolapov AE, Kosolapova NA, Matveeva LG, Chernova OA. Assessment of water resources use efficiency based on the GRP water intensity indicator. Regional Statistics 2018; 8 (2): 154-169. https://doi.org/10.15196/RS080201

[2] Hsien C, Low JSC, Chung SY, Tan DZL. Quality-based water and wastewater classification for waste-to-resource matching. Resour Conserv Recycl 2019; 151: 104477. https://doi.org/10.1016/j.resconrec.2019.104477

[3] Government of Newfoundland and Labrador, 2018. Drinking Water Quality Index. URL http://www.mae.gov.nl.ca/-waterres/quality/drinkingwater/dwqihtml (accessed Nov 1, 2019).

[4] Tyagi S, Sharma B, Singh P, Dobhal R, Water quality assessment in terms of water quality index. Am. J. Water Resour 2013; 1: 34-38.

[5] Raut S, GS A, Dharnaik A. Determination of wastewater quality index of municipal wastewater treatment plant using determination of wastewater quality index of municipal wastewater treatment plant using fuzzy rule base. Eur. J. Adv. Eng. Technol 2017; 4(10): 733-738.

[6] Vijayan G, Saravanane R, Sundararajan T. Wastewater quality index - a tool for categorization of the wastewater and its influence on the performance of sequencing batch reactor. Int. J Environ Eng Manag 2016; 7: 69-88.

[7] Sargaonkar A, Deshpande V. Development of an overall index of pollution for surface water based on a general classification scheme in Indian context. Environ. Monit. Assess 2003; 89: 43-67. https://doi.org/10.1023/A:1025886025137

[8] Tripathi M, Singal SK. Allocation of weights using factor analysis for development of a novel water quality index. Ecotoxicol Environ Saf. 2019; 183: 109510. https://doi.org/10.1016/j.ecoenv.2019.109510

[9] Ahmed AN, Othman FB, Afan HA, Ibrahim RK, Fai CM, Hossain MS et al. Machine learning methods for better water quality prediction. J Hydrol 2019; 578: 124084. https://doi.org/10.1016/j.jhydrol.2019.124084

[10] Maier HR, Dandy GC. Neural networks for the prediction and forecasting of water resources variables: a review of modelling issues and applications Environ. Model. Softw 2000; 15(1): 101-124. https://doi.org/10.1016/S1364-8152(99)00007-9

[11] Fu ZH, Zhao HJ, Wang H, Lu WT, Wang J, Guo HC. Integrated planning for regional development planning and water resources management under uncertainty: A case study of Xining, China. J Hydrol 2017; 554: 623-634. https://doi.org/10.1016/j.jhydrol.2017.08.022

[12] Vieira JMP, Lijklema L. Development and application of a model for regional water quality management. Water Res

1989; 23(6): 767-777.
https://doi.org/10.1016/0043-1354(89)90212-1

[13] Ho JY, Afan HA, El-Shafie AH, Koting SB, Mohd NS, Jaafar WZB et al. Towards a time and cost effective approach to water quality index class prediction. J Hydrol 2019; 575: 148-165.
https://doi.org/10.1016/j.jhydrol.2019.05.016

[14] Bu H, Meng W, Zhang Y, Wan J. Relationships between land use patterns and water quality in the Taizi River basin China. Ecol. Indic., 2014; 41: 187-197.
https://doi.org/10.1016/j.ecolind.2014.02.003

[15] Guo X, Zhang X, Yue H. Evaluation of hierarchically weighted principal component analysis for water quality management at Jiaozuo mine Int. Biodeterior. Biodegrad 2018; 128: 182-185.
https://doi.org/10.1016/j.ibiod.2017.11.012

[16] Kim SE, Seo IW, Choi SY. Assessment of water quality variation of a monitoring network using exploratory factor analysis and empirical orthogonal function. Environ. Model. Softw 2017; 94: 21-35.
https://doi.org/10.1016/j.envsoft.2017.03.035

[17] Singh VB, Tripathi JN. Identification of critical water quality parameters derived from principal component analysis: case study from NOIDA area in India Am. J. Water Res 2016; 4: 121-129.

[18] Carrasco G, Molina JL, Patino-Alonso MC, Castillo MDC, Vicente-Galindo MP, Galindo-Villardón MP. Water quality evaluation through a multivariate statistical HJ-Biplot approach. J Hydrol 2019; 577: 123993.
https://doi.org/10.1016/j.jhydrol.2019.123993

[19] Shuhong C, Shijun Z, Dianfan Z. Water quality monitoring method based on feedback self correcting dense connected convolution network. Neurocomputing 2019; 349: 301-313.
https://doi.org/10.1016/j.neucom.2019.03.023

[20] Dobrolezha EV. Resource support of development of the region's economy: evaluation, management, efficiency. Rostov State Economic University. Ltd 2011.

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