Investigation of the dependence of small rivers on the state of bottom sediments by mathematical methods

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Abstract. Emergency inflow of contaminants into river waters, construction of various hydraulic engineering structures can have an adverse impact on the river ecosystem. Water quality assessment is necessary for operative water resources management, development of engineering solutions for water streams rehabilitation. In this work, application of genetic algorithms for selection of significant indicators of bottom sediments quality for water quality indicators of small rivers in the Republic of Bashkortostan (Russia) has been tested. Selection of significant parameters for indicators of water quality of small rivers was conducted from input parameters: hydrochemical indicators of bottom sediments.

1. Introduction

One of the main aspects of life safety is rational water resources management, the key task of which is to predict the quality of river water under intensively changing anthropogenic load on the watershed. Prediction of hydrochemical indicators of river water quality is used in planning environmental activities in the watershed. One of the most informative objects in the environmental assessment of the hydroecosystem is bottom sediments (BS). By accumulating pollution, which comes into the water body over a long period of time, BS are an indicator of the environmental condition of the territory, a kind of integral indicator of pollution levels. Bottom sediments are an inseparable unity of a complex of minerals and aqueous solution that impregnates the sediments. In the aqueous solution and at the interface (mineral phases and organic residues) lives the bottom microbial flora, which has an important influence on the chemical processes in BS and life activities of zoobenthos organisms.

In recent decades, the use of artificial neural networks (ANN) has become widespread in water resources management. In the present work selection of the significant hydrochemical parameters influencing parameters of the bottom sediments of anthropogenically loaded small rivers flowing in the western part of Chelyabinsk region and in the east of Bashkortostan Republic (Russia) is executed: Kydish river, Aikreelega river, Tanychau river, Erekl river, Buydy river, Yamelga river, Suyaska river, Uy river. The hydrological scheme for the zoning of the small rivers under study is shown in figure 1.
2. Analysis of the problem of preparation and selection of input parameters of the neural network in forecasting the quality state of watercourse

At forecasting of geoecological processes of a watercourse by means of elements of artificial intelligence at a stage of preparation of the data there are the difficulties connected with data passes and selection of significant input parameters. Widely used statistical methods imply replacement of omissions with the average value of this indicator or deletion of missed data from time series. Similarly, statistical methods solve the problem of restoring missed hydrometeorological data. There are known works that estimate statistical methods of interaction between bottom sediments and water quality [1-3].

However, the use of statistical methods leads to a loss of information or significant distortion of information, which may subsequently lead to incorrect predictions. In addition, the changing anthropogenic load makes it impossible to use these methods to estimate also non-constant hydrological parameters.

The choice of input variables is an important step in ANN predicting, and is complicated by a number of features [4-6]:

- the number of indicators that can be used as input parameters to the neural network is measured in dozens: water consumption, water levels, air temperature, precipitation, chemical oxygen consumption, biological oxygen consumption in 5 days, etc;
- not all potential input variables are equally informative. Some of them may be correlated (have a good relation to each other), noisy (distorted by random factors) or have a weak relation to the output parameters of the neural network;
- the specificity of hydrological and hydrochemical processes leads to the presence of a time lag of input parameters, that is, an indicator reflecting the lag or advance of one process over another, complicating the modelling of water quality.

Different methods of selecting input parameters determine different reliability of the forecast model of geoecological processes. The lack of a uniform methodology for selecting input parameters leads to inaccuracies in the results and, as a result, limits the use of ANN for water resources management.

The review of methods for determining the input parameters of the model in water resources management has shown that in many cases, the lack of methodology for determining the input parameters limits their application. In some cases, input parameters are selected arbitrarily, in other cases; a priori knowledge and trial and error method are used for selection [7-8].
The main methods used to determine the input parameters of the model in water resources management can be classified as follows (figure 2).

![Methods for selecting significant parameters](image)

**Figure 2.** Main methods used to determine the input parameters of the model in water resources management.

Thus, we can conclude that the use of traditional methods for optimal selection of input parameters is not an easy task, as each of them has disadvantages. The synthetic method is the most efficient (but also the most time consuming). As a result, it is necessary to use artificial intelligence technologies, such as genetic algorithm (GA), which simulates the processes of natural selection in the selection of input parameters of the predicted model of dangerous natural and technological processes in the watercourse with further prediction using neural networks.

### 3. Methods of artificial intelligence elements

Genetic algorithms are designed to analyze complex non-formalizable tasks that either exceed the capabilities of conventional algorithmic methods or require too much material and time expenditure.

In the present work GA are used for selection of significant parameters of bottom sediments quality affecting hydrochemical parameters of small rivers water (Republic of Bashkortostan, Russia). The realization of genetic analysis of significant data on quality of bottom sediments on parameters of water quality of small rivers was carried out in software product Statistica 12.0. The parameters set in the present work for genetic algorithm are presented in table 1.

**Table 1.** The parameters of the genetic algorithm.

| Parameter         | Value | Parameter designation                                                                 |
|-------------------|-------|---------------------------------------------------------------------------------------|
| Population size   | 100   | Defines the volume of the population of individuals                                     |
| Number of generations | 100   | Determines how many times the selection-evaluation cycle will be repeated               |
| Crossing probability | 0.8   | This probability should be high enough (0.9 at best)                                    |
A sufficiently low probability of mutation should be set (0.01 at best)

This parameter is multiplied by the number of selected input variables and added to the error. Typical values are in the range (0.001-0.005)

At the end of the algorithm’s work, a table was opened in Statistica 12.0 program, which indicated which variables were significant (Y) and which were not (–), as well as the standard error.

Experimenting with different values of the fine for the element, were distributed sequentially according to the degree of importance to the result of the forecast of hydrochemical parameters of water and bottom sediments, i.e. the sequential increase of this parameter makes the algorithm turn off the least significant of the already selected parameters.

Thus, the GA was used to select significant hydrochemical parameters of water and bottom sediments of small rivers, which can later be used as input parameters for the predicted neural network.

4. Selection of significant indicators of bottom sediments for indicators of water quality in small rivers by means of artificial intelligence elements

With the help of GA in [9-11] attempts were made to combine GA and ANN to optimize the process of learning ANN, aimed at reducing the amount of calculations while maintaining the accuracy of the solution at the required level.

This paper has tested the use of GA to select meaningful indicators of sediment quality for small rivers. The process of finding the “optimal” set of input variables was carried out by constructing bit masks that indicate which of the variables should be left at the input and which should be removed.

Selection of significant parameters for small rivers water quality indicators through GA was carried out from input parameters (selected from 34 hydrochemical parameters of the State Water Cadastre Collection):

- hydrochemical indicators of water quality: content of dissolved oxygen, chemical oxygen consumption, biological oxygen consumption in 5 days, nitrites, nitrates, ammonium ion, chlorides, sulfates, iron, copper, zinc, manganese, mercury, cadmium;
- quality parameters of bottom sediments: pH, nitrates, chlorides, sulphates, iron, copper, zinc, nickel, manganese, mercury, cadmium, percentage of particles with a diameter of <0.25 - 1 mm.

Table 2. Results of selection of genetic algorithm of quality parameters of bottom sediments for hydrochemical parameters of water quality in small rivers.

| Input of BS / water quality output | Nitrates | Chlorides | Sulphates | Iron | Copper | Zinc | Nickel | Manganese | Mercury | Cadmium |
|-----------------------------------|----------|-----------|-----------|------|--------|------|--------|------------|---------|---------|
| Nitrates                          | Y        | -         | -         | Y    | Y      | -    | Y      | Y          | Y       | -       |
| Chlorides                         | -        | Y         | -         | -    | -      | -    | -      | Y          |         |         |
| Sulphates                         | -        | Y         | Y         | -    | -      | -    | -      | -          | -       | -       |
| Manganese                         | -        | -         | -         | Y    | Y      | -    | Y      | Y          | -       | -       |
Experimenting with different values of the "fine for the element", there was an ordering of input parameters by the degree of significance for the results of forecasting, i.e. the sequential increase of this parameter forced the algorithm to disable the least significant of the already selected indicators. The results of GA selection of the impact of quality indicators and bottom sediments (BS) and water on BS in small rivers for the period 2000-2017 are presented in table 2.

The analysis of GA selection of input parameters of bottom sediments quality for water quality indicators of small rivers showed that:

- for indicators of water quality: iron, copper, zinc, nickel from the whole set of data on sediment quality there are no identified influences, which may be due to unstable anthropogenic load, hydrological seasonality or the influence of complex hydrometeorological values of the river catchment;
- important indicators of sediment quality are: nitrates, iron, copper, nickel, manganese and mercury;
- important for chloride content are indicators of quality of bottom sediments: chlorides, copper, cadmium;
- important for sulfate content are indicators of quality of bottom sediments: chlorides, sulfates;
- important for manganese content are quality indicators of bottom sediments: iron, copper, nickel, manganese;
- the quality of bottom sediments: nitrates, chlorides, sulfates, iron, copper, zinc, nickel, mercury;
- important for cadmium content are indicators of quality of bottom sediments: chlorides, sulfates, copper, zinc, nickel, mercury, cadmium.

For a qualitative selection of significant sediment indicators affecting watercourse conditions using GA, a sufficiently representative data set is needed, and hydrometeorological parameters and hydrogeological features of the catchment, as well as hydrological seasonality, should also be investigated. For example, works [6-8] show that the qualitative composition of the watercourse is also influenced by hydrometeorological parameters of the watercourse and catchment area: water discharge and water levels, current velocity, air temperature, water temperature, precipitation, etc., and the amount of precipitation in the watercourse and catchment area.

It should also be noted that, based on the identified dependencies between the quality indicators of BS watercourses and the relationships within the time series of BS indicators, it is possible to restore the quality indicators of bottom sediments missed.

5. Conclusion

Experimenting with different values of the "fine for the element", there was an ordering of input parameters by the degree of importance on the results of the forecast, that is, a sequential increase in this parameter forced the algorithm to disable the least significant of the already selected indicators. The results of GA selection of the impact of quality indicators and BS and water on BS in small rivers for the period 2000-2017 are presented in table 2.
The analysis of GA selection of input parameters of bottom sediments quality for water quality indicators of small rivers showed that for water quality indicators: iron, copper, zinc, nickel from the whole set of data on sediment quality there are no identified influences, which may be due to unstable anthropogenic load, hydrological seasonality or the influence of complex hydrometeorological values of the river catchment; important indicators of sediment quality are: nitrates, iron, copper, nickel, manganese and mercury; important for chloride content are indicators of quality of bottom sediments: chlorides, copper, cadmium; important for sulfate content are indicators of quality of bottom sediments: chlorides, sulfates; important for manganese content are indicators of bottom sediment quality: iron, copper, nickel, manganese; important for the mercury content of bottom sediments are: nitrates, chlorides, sulphates, iron, copper, zinc, nickel, mercury; important for cadmium content are indicators of quality of bottom sediments: chlorides, sulfates, copper, zinc, nickel, mercury, cadmium.

For the qualitative selection of significant indicators of bottom sediments that affect the state of the watercourse with the help of GA, a sufficiently representative set of data is needed, it is also necessary to study hydrometeorological parameters and hydrogeological features of the catchment, as well as hydrological seasonality. For example, works [12-13] show that the qualitative composition of the watercourse is also influenced by hydrometeorological parameters of the watercourse and catchment area: water discharge and water levels, flow velocity, air temperature, water temperature, precipitation, etc. The results of the study are presented in the paper.

It should also be noted that, based on the identified dependencies between the quality indicators of BS watercourses and the relationships within the time series of BS indicators, it is possible to restore the quality indicators of bottom sediments missed.

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