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ORIGINAL ARTICLE

Experience in Applying Probabilistic Approaches in Predicting the Level Regime of the Marmarik River

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Abstract—The possibility of short-term and long-term forecasting of water levels, including those associated with dangerous hydrological phenomena on the Marmarik River, using various probabilistic approaches, including regression dependencies, an integrated moving average autoregression model, and multilayer perceptron models, is considered. To evaluate the effectiveness of prognostic methods, the statistical parameters of a random process are calculated, while recommendations are given using the classical criteria for the effectiveness of issued forecasts. For long-term forecasting, the expediency of using the integrated moving average autoregression model was assessed, while it is noted that these models in the classical representation are not applicable due to time gaps, and therefore it is recommended to focus on the mathematical expectation of a random process. For short-term forecasting one or two steps ahead, the method of training artificial neural networks was used. The analysis carried out in the work revealed that in the case of short-term forecasting of water levels for one period in advance (12 h), it is most expedient to focus on the value of the water level attributable to the date of issue of the forecast, the standard error of such a forecast is 5 cm. For a 24-h water level forecast forward, it is expedient to develop neural network forecasting models, taking into account the development of the situation on Gomraget-Meghradzor. A further increase in the quality of the outputs is possible when using data for a longer observation period and a whole year. At the same time, as an alternative to neural network forecasting models, physical and mathematical (hydraulic) models of the formation of water levels can be used.

Keywords: forecasting, artificial neural networks, water level, short-term forecasts, long-term forecasts

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INTRODUCTION

Different sectors of the economy, and primarily such as hydropower and agriculture, need forecasts of water conditions with different lead times. Forecasts make it possible to use the country's water resources most rationally, as well as to prepare in advance for dangerous hydrological phenomena and thereby prevent or significantly reduce the damage they cause to the national economy [1, 2]. The most complex river catchments, from the point of view of forecasts, include the catchments of mountain and semi-mountain rivers, which differ in the specificity of runoff formation associated with altitudinal zonation, properties of the underlying surface, slope catchments and river network.

Existing ontological approaches to forecasting the flow of mountain and semi-mountain rivers can be divided into the following groups [3]: methods based on determining the components of the water balance; methods based on conceptual models of river flow formation; methods using physical and statistical dependencies of river flow characteristics on hydrometeorological factors; methods based on solving mathematical models.

In the practice of operational forecasting of mountain river flow, various methods are common. They can be based either on conceptual models of runoff formation, where the main processes of runoff formation are described using simplified semi-empirical equations, or on physical and statistical dependencies of flood runoff characteristics on meteorological and hydrological factors [4]. An example of a conceptual model is given in [5], in which this model is used for short-term forecasting of the runoff of small high-mountain tributaries of the Kuban. The works [6, 7] show the effectiveness of using physical and statistical methods of forecasting on mountain rivers. Methods

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Table 1. Water levels, the increase of which lead to unfavorable hydrological phenomena

Hydrological station	Gomraget R.—Megradzor post	Marmarik R.—Ankavan post	Marmarik R.—Agavnadzor post
Water level, cm	234	123	36

based on mathematical models are not widespread enough to predict the flow of mountain rivers, as they are relatively difficult to obtain and use.

In [8], the possibility of predicting water flow (Q) of the Marmarik River using the kinematic wave equation was considered. The results obtained during verification forecasts indicate a fairly high quality of the produced water flow forecasts.

It is worth noting the advisability of predicting not only flow rates, but also water levels (H), as the main characteristic of possible flooding of the territory. Forecasting water levels can be accomplished by a variety of methods depending on the desired forecast lead time and the data available for the forecast. A fairly large number of forecasting techniques, especially for higher water levels, are based on the relationship between flow discharges and water levels. However, water flows, in real conditions, are determined at the end of the year according to the annual dependence $Q = f(H)$ and their use in operational forecasting practice is rarely advisable; only in conditions of a stable channel can water levels be predicted from the values of the forecast water flow using long-term dependence of expenses on levels.

In real conditions, it is extremely rare to construct long-term dependences $Q = f(H)$. Therefore, it is preferable to predict water levels directly, as this reduces the final error of the forecast values and facilitates the use of this technique. As predictors, you can use water levels that are measured directly at the post, as well as water levels at higher posts. Another equally pressing problem of forecasting is the selection of optimal, most stringent quality criteria that meet the requirements of the Hydrometeorological Center of Russia.

Thus, the goal of this work is to develop a methodological approach to predicting water levels of various genesis and approaches to assessing the quality and effectiveness of methods for predicting water levels measured with different time resolutions. To achieve the stated goal of the study, it is necessary to use a specific example to consider a methodological approach to forecasting urgent water levels with different lead times, show an algorithm for determining the optimal lead time of issued forecasts, test various mathematical approaches to forecasting and, finally, develop a methodological approach to assessing the quality of issued forecasts.

The basin of the semi-mountain river was chosen as an object for testing the proposed approaches. Marmarik. For this object there are series of observations of urgent values of water levels and water flows.

The Marmarik River basin is a strategically important object in terms of the water reserves contained in the river for use in the agricultural and energy sectors [9]. In addition, the river valley Marmarik has great recreational opportunities; in its valley there is a deposit of the Hankavan mineral water [10, 11].

MATERIALS AND METHODS

This work uses two-term water level observation data (series No. 1) from April 1 to June 30 (182 values per year) at hydrological stations (Table 1) for the period from 2011 to 2022 [8] in the river basin Marmarik. Based on urgent water levels, their maximum values for the year were also determined (row No. 2). The initial information (series No. 1) is a time series that can be considered as a non-stationary periodically correlated random process [12, 13]. A random process is understood as such a process, each of the sections of which is a random variable [12]. A random process is represented in the form of sections and realizations. The cross section of a random process is understood as the random variable into which the random process turns at time t; the realization of a random process is understood as the non-random function $x(t)$ into which the random process $X(t)$ turns as a result of experiment. In this case, each observation period is a cross section of a random process, and each year is a realization, so each of the 182 sections contains 11 values for each realization. Row number 2 is a random variable.

The quality criterion in this case can be the ratio of the standard error of forecasting to the standard error of the "natural" forecast. By "natural" we mean such a forecast when the next step is given the value of the characteristic at the current moment in time.

Also, as quality criteria, the Hydrometeorological Center of Russia recommends using the ratios S/σ and S/σ_Δ [14] (where S is the standard error; σ is the standard deviation calculated from the actual series; σ_Δ is the standard deviation of the predicted value for the lead time period). The applicability of these criteria for predicting random processes is not specified in the instructions.

Abroad, the Nash-Sutcliffe criterion is also used. In the classical representation, the Nash-Sutcliffe coefficient is calculated using the formula [15]:

$$NSE = 1 - \frac{\sum_{t=1}^{T}\left(Q_m^t - Q_0^t\right)^2}{\sum_{t=1}^{T}\left(Q_0^t - \bar{Q}_0\right)^2}; \tag{1}$$

where Q_m^t – predictive value of any characteristic, Q_0^t – actual value of any characteristic, $\bar{Q}_0$ – its arithmetic mean value.

Despite the understatement in the guidance documents, this coefficient in the given form (as well as the criteria proposed by the Hydrometeorological Center) can only be used when forecasting or modeling random variables, despite their widespread use for any purposes related to forecasting and modeling. The impossibility of their use is due to the fact that the standard (mean square) deviation of a random process, unlike a random variable, is not a fixed number, but a non-random function, which is calculated separately for each of the sections of the random process (in this case, for each observation period) [12]. In this work, the results obtained are analyzed using various classical criteria [14], including combined ones. When predicting random variables, it is proposed to use the ratios S/σ and S/σ_Δ and the Nash-Sutcliffe criterion (1); when predicting a random process, the values σ and σ_Δ should be calculated relative to the mathematical expectations of the random process, which should also be used in the Nash-Sutcliffe criterion. In this case, the values of the ratios S/σ and S/σ_Δ should be less than 0.80, however, in a number of cases, models for which the given ratios are less than 1.0 are accepted as satisfactory [16].

At the preliminary stage of the study, it was also found that constructing a long-term relationship $Q = f(H)$ is not possible, so it is advisable to predict levels directly depending on the levels at the target post (Marmarik river – Agavnadzor village) and upstream sections.

RESEARCH RESULTS

The level regime of the rivers of this basin is quite complex, as it is determined by various formation factors, including such as an increase in water flow due to floods, floods and melting glaciers, which can maintain relatively high water levels for quite a long time. During the presented observation period, water levels several times exceeded unfavorable levels (Table 1).

Exceeding these marks at the Agavandzor target post was observed three times during the period under review, with the greatest duration and magnitude of the excess of the given marks observed in 2011, when unfavorable levels were observed from April 30 to May 8, and the highest water level was 396 cm, while note that on the river Gomraget-Meghradzor village also observed an excess of marks, but the excess of unfavorable marks along the inflow began later than along the main river. The low frequency of unfavorable hydrological phenomena, as well as the atypical timing of their formation (for hydrological forecasting it is necessary that the predicted phenomena develop from top to bottom downstream) leads to the impossibility of establishing water levels at upstream sections at which the formation of unfavorable hydrological phenomena occurs at the target section.

To assess the effectiveness of predictive methods, it is necessary to calculate the statistical parameters of the random process for 182 sections, which correspond to 91 days and, accordingly, 182 observation periods and 11 realizations, which correspond to the analyzed years. The mathematical expectation and standard deviation of a random process are non-random functions, the values of which were calculated separately for each of the sections (Fig. 1).

The given graph shows the characteristic values of water level for each observation period from April 1 to June 30, this graph also shows the standard deviation, which characterizes the mean square error when focusing on the average values of water levels. It is possible to note the coherent course of the two graphs, that is, as the water level increases, its scatter also increases, while the maximum values of the standard deviation reach only 31 cm, which indicates a relatively small variability of the predicted value and the possibility of focusing on the average value for long-term forecasting. The calculated standard errors in determining the mathematical expectation reach 9%, on average they amount to 5% of the average value of the water level for specific measurement periods, thus, the error in determining the mathematical expectation does not exceed 10%, which indicates high reliability and the possibility of using these values for long-term forecasting of water level in the Marmarik River in the village of Agavnadzor.

Speaking about short-term forecasting, we can mean forecasting water levels one or several steps ahead with a fixed forecast lead time (in this case, the problem of forecasting a random process represented as a time series is solved), or forecasting the highest or extreme water levels that represent is a random variable. In the first case, one of the most stringent criteria (assuming relatively low water level variability) is the so-called "natural" forecast. The standard error of such a forecast increases with increasing lead time, reaching 39 cm at its peak, due to the presence of interannual data connectivity; after the peak, the error begins to decrease, reaching a minimum with a shift that is a multiple of seasonality (Fig. 2).

Thus, when making long-term forecasts of water levels, one can rely not only on the mathematical expectation of a random process, but also on the water levels of the previous year for the same observation periods, while the standard error decreases by 2 cm and amounts to 28 cm. When short-term forecasting water levels for 12 h ahead, the standard error of the

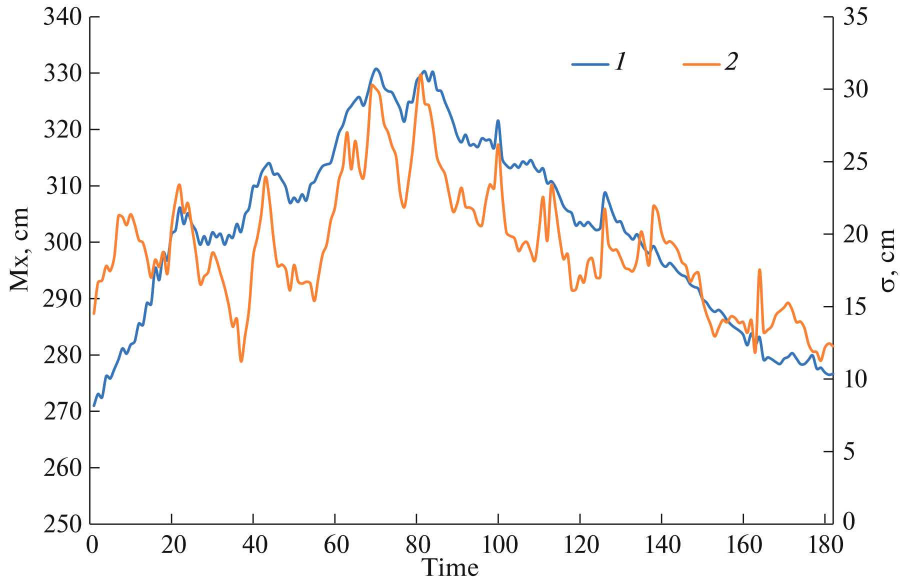

Fig. 1. Estimation of the mathematical expectation (*1*) and standard deviation (*2*) of the urgent water levels Marmarik-Aghavnadzor for the observation period 2011–2022.

natural forecast is 5 cm, for 24 h ahead—7 cm. Thus, when assessing the quality of forecasts issued using the developed models, the standard error of forecasting with a lead time of one year should be less than 22 cm, and when forecasting 12 h ahead, less than 4 cm.

Long-term Forecasting of Water Levels

The main task that must be solved when developing any predictive model is assessing its effectiveness, that is, how much better this or that approach is than statistical ones. When developing long-term forecasting methods, currently, as a rule, two approaches are used: the Autoregressive Integrated Moving Average (ARIMA) method and the method of training artificial neural networks. A comparison of these methods was presented in [17], the analysis showed comparable effectiveness of both approaches.

In this case, however, such models are practically inapplicable due to the time gap: to build a model, data without period breaks is needed, since the essence of autoregression is to link previous and future values of the predicted value. Thus, none of the ARIMA model parameter sets can describe this series with sufficient accuracy. In this work, several forecasting models were initialized with approximately the same quality of the forecasts produced; the models were tested using data from 2022, and all models showed a significantly lower quality compared to focusing on the mathematical expectation of a random process (Fig. 3).

By analyzing this graph, one can come to an unambiguous conclusion about the presence of a systematic error, the cause of which is a break in the observation period (the model perceives the series as continuous). This problem can be corrected by issuing a forecast on the 3rd day after the start of a new period, when the correct input data has appeared, after which the model can give a much more accurate forecast for 3 months ahead. However, in this case, for 2022, the quality of the model turned out to be insufficient compared to focusing on the mathematical expectation of a random process, since when focusing on the mathematical expectation in 2022, the standard deviation from it was 10 cm, and when using the ARIMA model, the standard error of the forecast was 14 cm, which indicates the ineffectiveness of the model, therefore, for the purpose of long-term forecasting, it is recommended to focus on the mathematical expectation of a random process, subject to clarification of its values using historical and future results of water level observations.

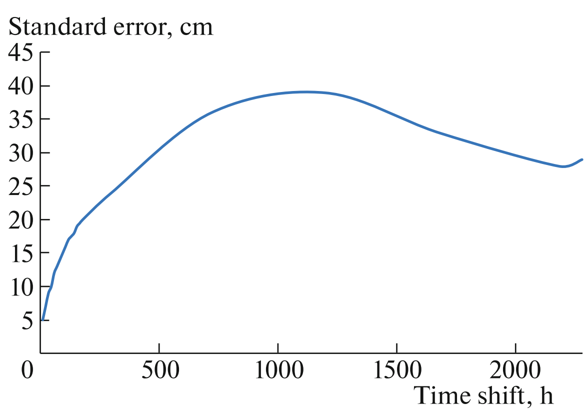

Fig. 2. Change in the standard error of the “natural” forecast depending on the increase in lead time.

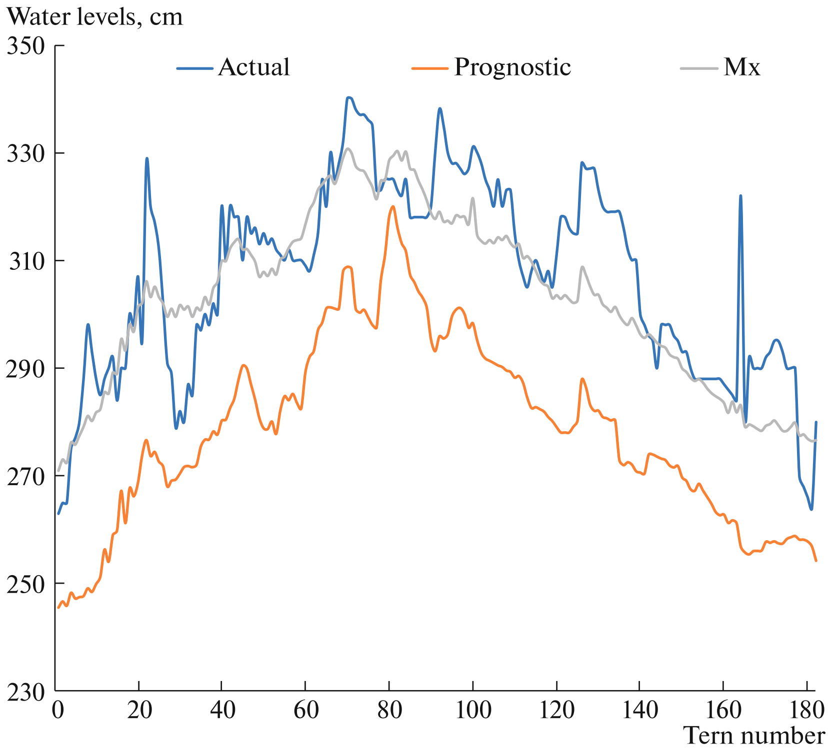

Fig. 3. Comparison of actual and predicted water levels with a lead time of one year using the ARIMA.

Thus, we can conclude that the development of long-term forecasting methods for rivers, especially with flood regimes, is impractical due to the relatively low autocorrelation of data and in the vast majority of cases one should focus on the mathematical expectation of a random process; the standard error of forecasting when using this approach is the standard deviation of the random process.

Short-term Forecasting

For short-term forecasting one or two steps ahead, you can use the method of training artificial neural networks. The large inertia of the process of forming water levels in any case requires the use of data for the previous period at the target point, while data from overlying posts should be used as additional predictors. In this case, data on the Marmarik River-Hankavan village and the Gomraget River—Meghradzor village can be used as such predictors. In this case, one of the intermediate tasks is to determine the optimal lead time of such a forecast.

To determine the travel time between posts (and, therefore, the lead time), it is necessary to analyze the paired correlation coefficients between the predictant (target post) and two predictors; accordingly, the travel time will be equal to the time shift at which the correlation coefficient is greatest; it is also advisable to analyze the dates of formation of higher water levels at all three posts. The result of the analysis of the dates of formation and correlation coefficients showed that the highest water levels are formed almost during the same observation periods at the Ankavan and Agavnadzor posts, however, the highest water levels at the tributary are formed earlier than at the main post by 24 h, which makes it possible to use the given data when developing a short-term forecasting techniques with a given lead time of 24 h. For shorter lead times, it is most appropriate to focus on the actual value of the water level at the time the forecast is issued, since water levels practically do not change during the day. Thus, to predict urgent water levels of the Marmarik River-Agavnadzor village with a 24-h lead time, the following predictors should be used: water level of the target post 24 h earlier than the forecast release date, water levels along the river Gomraget-Meghradzor village, also due to the fact that water levels have a pronounced seasonality, the observation period number should be added as a predictor. It is worth noting that this dependence will be complex, which predetermines the need to use the training capabilities of artificial neural networks.

In this work, it is proposed to use the capabilities of the *Statistica* 12 software package [18], which allows you to automatically select the best neural network architecture and configure internal parameters. The analysis showed that the best results are obtained by multilayer perceptron (MLP) neural networks containing 13–15 hidden neurons. The best results were shown by the MLP 3-13-1 neural network, which uses

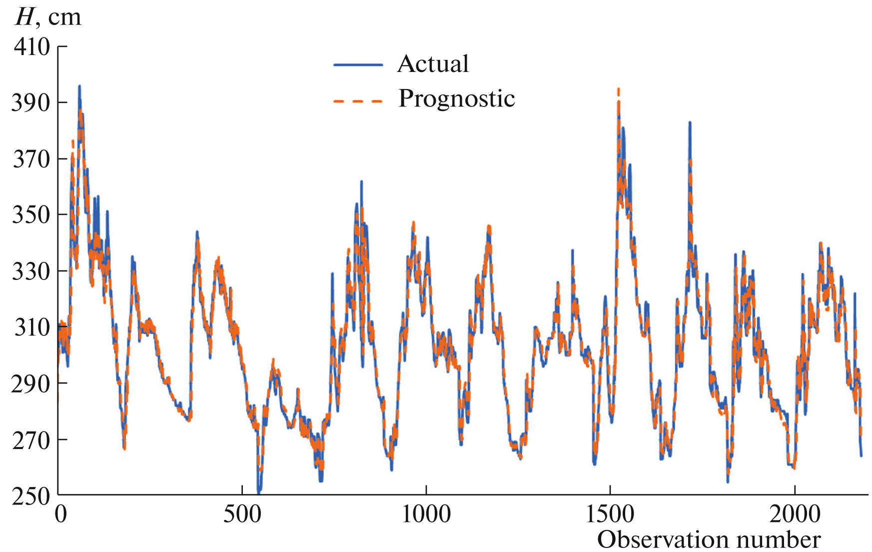

Fig. 4. Comparison of actual and predicted urgent water levels of the Marmarik River—v. Aghavnadzor for the observation period 2011–2022.

the hyperbolic tangent as an activation function. A comparison of actual and predictive data when using this neural network is shown in Fig. 4.

Analysis of the given graph indicates a fairly high degree of correspondence between actual and forecast data, which indicates the possibility of using this model for short-term forecasting. The Nash-Sutcliffe coefficient, calculated using formula (1), for this model was 0.93, which should indicate the extremely high quality of the forecasts produced. However, as mentioned above, the predicted value is a random process, therefore, the arithmetic mean is not a fixed number, but a function presented in Fig. 2, so the formula for calculating the Nash-Sutcliffe coefficient should be rewritten:

$$NSE^* = 1 - \frac{\sum_{t=1}^{T}\left(Q_m^t - Q_0^t\right)^2}{\sum_{t=1}^{T}\left(Q_0^t - \bar{\bar{Q}}_0\right)^2}; \qquad (2)$$

where $\bar{\bar{Q}}_0$ – assessment of the mathematical expectation of a random process calculated from 182 sections.

Thus, the NSE^* was 0.88, which still indicates the high quality of the forecasts produced. An analysis of the S/σ ratio gives a similar estimate.

Calculation of average changes for each observation period and derivation of the average change in water level for the lead time period as a function is not advisable due to its complexity and absolute conditionality (in this case, the average change for the lead time period, due to the period of rise and fall of water levels, calculated over a long-term period is equal to zero). Therefore, as the most stringent quality criterion, it is proposed to choose the value of the water level at the target point at the time the forecast is issued, under the assumption that it will not change over the lead time; it was calculated above that the standard error of such a forecast is only 7 cm. Standard error of the forecast model was 6 cm, and the ratio of two errors was 0.86, which is slightly more than 0.80 and indicates the relatively low efficiency of the model. Since the predicted value is a random process, the analysis of its errors should also be carried out for each of the sections, however, the effectiveness of the method is always most indicative when predicting extreme values, therefore the effectiveness of such methods is also recommended to be checked without fail at the maximum values of the predicted value.

To assess the quality of forecasting the highest water levels (Fig. 5) for the year, it is necessary to select the highest water levels for the year, calculate their average value and standard deviation, as well as the average change over the lead time period. It can be noted that the average value of the highest water levels for the year is 351 cm, and the standard deviation from the average is 28 cm, the average change over the lead time (24 h) was 15 cm, the standard error of the model when predicting the highest water levels is 20 cm (model natural forecast for higher water levels has a standard error of 25 cm). Thus, the ratio S/σ and S/σ_Δ can be calculated, which are equal to 0.71 and 1.33. The model effectively predicts high water levels compared to focusing on their average value and a natural forecast model, but is ineffective compared to focusing on the average change in level over the lead time. However, it must be taken into account that the forecast from the model is issued continuously, and in order to focus on the average change in level over the lead time,

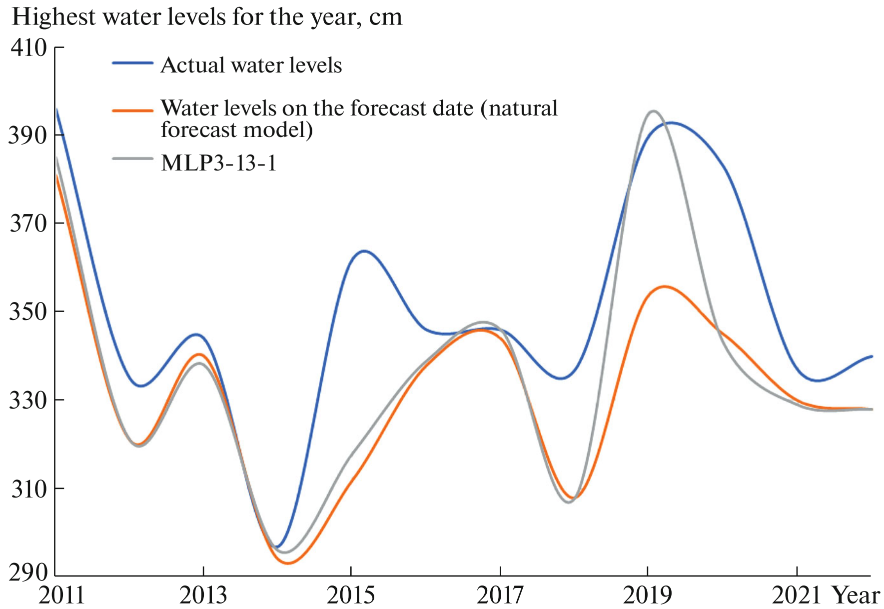

Fig. 5. Actual and predicted highest water levels for the year of the Maramarik River for the settlement Aghavnadzor.

it is necessary to determine the date of issue of the forecast, which, due to the lack of markers, is impossible (it is not known in advance how long after the highest water level will form), therefore the criterion S/σ_Δ is fictitious and cannot indicate the effectiveness of such methods when used to predict extreme values of quantities.

It can be concluded that the foregoing forecasting technique is quite effective in short-term forecasting of urgent water levels of the Maramarik River in the village of Agavnadzor, including in forecasting higher water levels. The forecasting approach presented in this work is universal and tested on many rivers of the Russian Federation [19, 20].

CONCLUSIONS

The analysis presented in this work showed the features and nuances of developing time series forecasting models, while considerable attention was paid to the issue of the correct application of certain criteria for the effectiveness of forecasting methods.

It can be concluded that when long-term forecasting water levels on Maramarik in the village of Agavnadzor, it is most advisable to focus on assessing the mathematical expectation of a random process, and it is recommended to clarify its values taking into account historical and future values of water levels. The standard error should be on average 19 cm. When short-term forecasting water levels for one period in advance (12 h), it is most advisable to focus on the water level values attributable to the date of issue of the forecast; the standard error of such a forecast is 5 cm. For forecasting water levels for 24 h ahead, it is advisable to develop neural network forecasting models taking into account the development of the situation on the river Gomraget—Meghradzor village. In this case, further improvement in the quality of issued forecasts is possible by using data for a longer observation period and the whole year.

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CONFLICT OF INTEREST

The authors of this work declare that they have no conflicts of interest.

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