Review of methods for effective forecasting of river runoff characteristics in mountain and semi-mountain areas

E V Gaidukova\textsuperscript{1}, V G Margaryan\textsuperscript{2}, N V Myakisheva\textsuperscript{1}, M R Pavlov\textsuperscript{1} and V A Khaustov\textsuperscript{1}

\textsuperscript{1} Russian State Hydrometeorological University, 79, Voronezhskaya st., St. Petersburg, 192007, Russia
\textsuperscript{2} Yerevan State University, 1, Alek Manukyan st., Yerevan, 0025, Armenia

E-mail: oderiuut@mail.ru

Abstract. Methods for forecasting river runoff characteristics are considered and analyzed: a method based on identifying regression dependencies, methods using autoregressive moving average models (autoregressive model, mixed models, an integrated moving average autoregressive model), a forecasting method using artificial neural networks, a method based on dynamic and stochastic modeling. The following, important for practical purposes, features of the considered approaches are revealed: regression dependences are quite simple to obtain but require complete current information about all predictors in the model; autoregressive moving average models can be applied, having retrospective series of observations of river runoff without knowledge of the meteorological leaving, but there is a possibility of obtaining unsatisfactory results due to the peculiarity of the conditions of runoff formation from year to year; forecasting using artificial neural networks requires a sufficient amount of retrospective information and knowledge of computational algorithms to obtain an effective model; dynamic and stochastic modeling of the processes of river runoff formation allows obtaining reliable results due to the variation of the model values, as well as the possible change in their number.

1. Introduction

Water resources are the basis of energy and agriculture in mountainous regions of Russia and countries whose territories are located in mountainous areas. These industries need early forecasts of the water regime including the maximum runoff values, as well as the runoff during the spring flood. The determination reliability of the river flow characteristics depends on the effectiveness of methods and techniques.

There are various methods for forecasting the runoff of mountain and semi-mountain rivers. Most of them are based on the use of actual observations of river flow characteristics for the period preceding the forecast date. There are approaches based on water balance methods that take into account the impact of climate change on runoff. The methods used in the practice of operational forecasting of the mountain rivers runoff are based on conceptual models of runoff formation which are based on semi-empirical equations, or on the physical and statistical dependence of the river runoff characteristics on hydrometeorological factors.

The purpose of the paper is to analyze methods for efficient prediction of the river runoff characteristics during high water and floods in mountainous and semi-mountainous regions. The following approaches have been considered and analyzed: regression dependencies, ARMA theory.
methods (autoregressive model, mixed models, integrated moving average autoregressive model), forecasting by means of artificial neural networks, dynamic and stochastic modeling.

2. Materials and methods

2.1 Regression dependencies

The development of reliable models for forecasting river flow and hazardous hydrological processes is an urgent task of the present and future. In conditions when the application of conceptual and physical and mathematical models is impossible for various reasons, and the need for forecasting hydrological characteristics is great, models based on empirical dependencies are used. A number of requirements, stipulated by both general laws and experience in the development of predictive models, and the current state of the hydrometeorological observation network, can be imposed on such dependencies: the number of predictors should be minimal; predictors must be uniquely identified; predictors should be measured directly on the observational network; the lead time of forecasts should be no less than that of existing methods; the quality of the issued forecasts must be satisfactory.

Thus, the prognostic equations developed to date are based on the methods of mathematical statistics and regression analysis due to the peculiarities of the current stage in the evolution of the hydrological forecasts practice. The most common forecasting approach is to identify regression relationships between the predicted value and the factors that affect it.

For example, the work [1] demonstrates the problem solution of forecasting the flow rates and water levels for eight river sections located on six rivers of the Black Sea coast of the Caucasus on the southern slope of the Greater Caucasus Range. The regression model to obtain a forecast of the maximum water discharge per day ($t+1$) took into account the following predictors: maximum water consumption ($Q_{\text{max}}(t)$) per day of forecasting; maximum water consumption ($Q_{\text{max}}(t-1)$) for the previous day; precipitation layer at the weather station ($P(t)$) per day of forecasting; mean surface air temperature at the meteorological station ($T(t)$); daily precipitation forecast ($P(t+1)$) at the weather station; forecast of average daily surface air temperature ($T(t+1)$). Calculation of the average daily forecasted water consumption was carried out according to the formula:

$$
\hat{Q}(t+1) = a_0 + a_1Q(t) + a_2Q(t-1) + a_3[T(t+1)-T_{\text{min},S}]^2 + a_4[T(t+1)-T_{\text{min},P}] + 
+a_5P(t+1)[T(t+1)-T_{\text{min},P}]^2 + a_6P(t+1)[T(t+1)-T_{\text{min},P}] + a_7P(t+1) + 
+a_8[T(t)-T_{\text{min},S}]^2 + a_9[T(t)-T_{\text{min},S}] + a_{10}P(t)[T(t)-T_{\text{min},P}]^2 + a_{11}P(t)[T(t)-T_{\text{min},P}] + a_{12}P(t).
$$

Formula (1) made it possible to obtain practically the minimum forecast error for all river sections and throughout the year. The formula parameters were estimated by the least squares method for each month. Thus, the differences in the soil and vegetation cover state of the catchments were taken into account during the year, as well as the influence of meteorological elements on the runoff.

The work [2] notes that the use of satellite information facilitates the process of analyzing snow melting and the conditions for the formation of spring floods and has a practical focus in terms of forecasting water content.

2.2 ARMA theory methods

In the conditions of the existing deficit of initial information, the use of time series of actual observations which are considered as random processes with the application of methods based on extrapolation opens up wide opportunities for forecasting hydrometeorological processes.

ARMA theory methods (autoregressive models of moving average) were developed and brought to practical application by J. Box and G. Jenkins [3]. They allow not only describing the correlation and spectral structure of time series in terms of ARMA processes model and reflecting their statistical relationship in terms of transfer function models, but also making a forecast since the above mentioned models are actually a predictive function. The main difficulty in applying these methods for solving
practical issues of hydrometeorology is in identifying a model for a specific time series, that is, in choosing an appropriate model equation for it.

The generalization of the ARMA model to the case of non-stationary time series is the autoregression model of the integrated moving average ARIMA \((p, d, q)\), where \(p\) – autoregressive parameter, \(d\) – difference operation order, \(q\) – moving average parameter.

### 2.2.1. Autoregression model (AR)

In this model, the current values of a random process are expressed as a finite linear combination of its previous values and white noise:

\[
\hat{X}_t = \phi_1 \hat{X}_{t-1} + \phi_2 \hat{X}_{t-2} + \ldots + \phi_p \hat{X}_{t-p} + \epsilon_t,
\]

where \(\hat{X}_t\) – centered random process, \(\hat{X}_t = \hat{X}_t - m_t\); \(\epsilon_t\) – white noise with zero mean square deviation of \(\sigma_\epsilon\).

The model contains \(p+2\) parameters: \(\phi_1, \phi_2, \ldots, \phi_p, m_t, \sigma_\epsilon\), where \(m_t\) – mathematical mean value of a random process \(X(t)\); \(\phi_1, \phi_2, \ldots, \phi_p\) – model coefficients (constants). The model is called the \(p\)-th order autoregressive model and is denoted as AR \((p)\).

### 2.2.2. Moving average model (MA)

The moving average model can be obtained from the so-called general linear model (GLM), if we assume that the GLM contains a finite number of terms. In this model, the current values of the process \(X(t)\) are expressed in terms of the previous values of white noise \(\epsilon_{t-1}, \epsilon_{t-2}, \ldots, \epsilon_{t-q}\):

\[
\hat{X}(t) = \epsilon_t - \psi_1 \epsilon_{t-1} - \psi_2 \epsilon_{t-2} - \ldots - \psi_q \epsilon_{t-q}.
\]

The model contains \(q+2\) parameters: \(\psi_1, \psi_2, \ldots, \psi_q, m_t, \sigma_\epsilon\), where \(\psi_1, \psi_2, \ldots, \psi_q\) – model coefficients (constants). The expression is called the \(q\)-th order moving average model and is denoted by MA \((q)\).

### 2.2.3. Mixed models (ARMA)

Sometimes it is advisable to combine AR and MA models. Mixed ARMA model is obtained in this case \((p, q)\), where \(p\) – autoregressive order, \(q\) – moving average order. The expression for ARMA \((p, q)\) is:

\[
\hat{X}_t = \phi_1 \hat{X}_{t-1} + \phi_2 \hat{X}_{t-2} + \ldots + \phi_p \hat{X}_{t-p} + \epsilon_t - \psi_1 \epsilon_{t-1} - \psi_2 \epsilon_{t-2} - \ldots - \psi_q \epsilon_{t-q}.
\]

Such a model may be suitable, for example, when the observed time series is the sum of two or more independent components each of which is described by either the AR model or the MA model but they are not directly measured.

### 2.2.4. Autoregressive integrated moving average model (ARIMA)

The models AR, MA and ARMA considered above belong to the class of stationary models that describe processes for which the mathematical mean value and variance are constants. However, in nature there is an unlimited number of different manifestations of nonstationarity.

Studies by J. Box and G. Jenkins have showed that it is possible to get rid of nonstationarity by replacing the original series with a series of differences \(Y_t = X_t - X_{t-1}\). It is advisable to take the difference again \(Z_t = Y_t - Y_{t-1}\), if it was not possible to get rid of nonstationarity.

ARMA model can be applied after the transformations to the original series.

The model obtained on the basis of such reasoning is called the Box-Jenkins model or the autoregression model of the integrated moving average – ARIMA \((p, d, q)\). In this model: \(p\) is autoregressive order, \(d\) – difference order, \(q\) – moving average order.

Consider some examples of forecasting time series of monthly discreteness. Lakes of different types Ladoga and Ilmen were selected as research objects. The predicted characteristic is the water level for years specific to water content (low-water, high-water, average). The time series of water
levels of Lake Ladoga has duration of 117 years (1881 – 1997), Lake Ilmen – of 44 years (1945 – 1988). Note that the level regime of Lake Ilmen is similar in its features to the regime of river inflow into the reservoir.

The generation of forecasts was carried out in two ways. The first way included the ARIMA model application which takes into consideration both evolutionary and seasonal nonstationarity. Forecasting was carried out 12 months ahead of time (from January to December). The model comprised one regular and one seasonal moving average parameter. The original series was transformed three times in the course of logarithm taking the difference with a step of 1 (to eliminate evolutionary nonstationarity) and taking the difference with a step of 12 (to eliminate seasonal nonstationarity).

The outcomes of applying the ARIMA, AR (1) and SS (1) models for Lake Ladoga (1920) and Lake Ilmen are shown in Figure 1. Forecasts based on the ARIMA model are categorized as “excellent” for Lake Ladoga, and the AR (1) and CC (1) models are categorized as “good.” Forecasts based on the ARIMA model are classified as “good” for Lake Ilmen, and the AR (1) and CC (1) models are classified as “excellent.”

![Figure 1](image.png)

**Figure 1.** Actual and prognostic values of intra-annual fluctuations in the levels of Lake Ladoga for 1920 year (a) and Lake Ilmen for 1985 year (b)

### 2.3 Forecasting with artificial neural networks

Artificial neural networks (ANN) are increasingly used as an alternative way to solve a wide range of hydrological problems [4].

ANN training methods, along with regression methods and autoregression methods of integrated moving average, are referred to “black box” models. The main difference between ANN training methods and standard regression models is the possibility of nonlinear transformations within the model, and when forecasting time series – the opportunity of using additional predictors. Besides, one of the advantages of neural networks is the ability to reduce the number of predictors directly within the model.

The idea of artificial neural networks boils down to the fact that a neural network is a multilayer structure of layers of neurons, and each neuron of the previous layer, as a rule, is connected with each neuron of the subsequent layer. In the case when there are no feedbacks, such a neural network is called a feedforward network. In the simplest case, a neural network consists of an input layer, that is, a layer of predictors the number of which can be unlimitedly many; a hidden layer with a certain amount of hidden neurons where the initial information is transformed by means of an activation function and weight coefficients (multiple hidden layers can be in a more complex case), and the output predictor layer.

As an example, consider the results of ANN training in order to predict the highest water level for the period of ice drift on the Pechora River near the village of Oksino. The maximum ice-moving water level in the village of Ermitsy, located upstream of the river, and the maximum pre-ice water level at the post in Oksino were used in the development of the forecasting model as predictors. The average lead time of the forecast was 4 days. A model containing 3 and 5 hidden neurons on each hidden layer, respectively, then Seq 2-3-5-1, was created in the Python 3 programming environment. The function of automatic learning of neural networks was used in the Statistica 12 program. Best
artificial neural network $MLP_{2-8-1}$ contains 8 hidden neurons; hyperbolic tangent is used as activation function. The ratio of the standard error of the predictive model ($S$) to the root-mean-square deviation of the predicted variable from the norm ($\sigma$) is used as a criterion for the quality of issued forecasts. It can be noted that neural networks trained in the Statistica 12 program have proven best in solving this problem (Fig. 2).

![Figure 2](image-url)  

**Figure 2.** Outcomes of predicting the maximum ice-drifting water level at the section of the hydrological station in Oksino (1) using neural network models of $MLP_{2-8-1}$ (2), $Seq_{2-3-5-1}$ (3) and multiple linear regression model (4); training and test samples are separated by a conditional line (5).

Analyzing the applied models, we can come to the conclusion that $MLP_{2-8-1}$ indicated the best results on all subsamples, however, the quality of the model dropped slightly on the test subsample, almost equal to $Seq_{2-3-5-1}$.

The use of artificial neural network methods of training often affords a tangible improvement in the quality of produced forecasts in comparison with regression dependences. For example, the works [5, 6] prove a higher efficiency of neural network modeling in predicting runoff from various catchments, including mountain ones, than when applying regression dependences. Forecasting outcomes using artificial neural networks in 38 out of 40 applications outperformed autoregressive methods within 5% [6]. Work [7] presents the results of using ANN to predict rainfall runoff on the Apura River in Venezuela. The authors note that the assessment of the produced forecasts quality based on independent material during ANN training turned out to be 10% higher than that of the calibrated conceptual model of runoff formation. The work [8] considers the flood flow forecasting of the Shoor Ghayen River located in Iran the basin of which has an altitude of about 1420 meters above sea level. The work outcomes indicate the optimal performance of artificial neural networks for predicting flood runoff. The forecasting accuracy in the research was assessed using both standard forecast errors and correlation coefficients between the predicted and actual values of water discharge. The maximum correlation coefficient when testing an artificial neural network on an independent material was 0.99 in April and September, and the minimum 0.93 in August. Artificial neural networks of various configurations, including recurrent ones, were used in the work devoted to forecasting the river flow of the Tunxi small river in China. The superiority of all artificial neural networks has been revealed over regression methods while LSTM networks are the best for short-term time series forecasting [9].

In domestic hydrological practice, the application of neural networks is not widespread but it is already showing good results. For instance, the work [10] considers the possibility of predicting the maximum water discharge for the spring flood and the average monthly water discharge of the Northern Dvina River. The superiority of artificial neural networks is shown over similar predictors using linear regression models by 10–20%. The work [11] demonstrates the application of the neural network apparatus for the analysis and ultra-short-term forecast of surface temperature using the
created meteorological data base obtained from the automatic meteorological station of RSHU. The work [12] shows the problem solution to assessing the situation in the near sea zone for choosing routes or areas for safe ships maneuvering taking into consideration various territorial factors: ice conditions, wind, currents, environmental restrictions, economic activity, social factors, and etc. The work [13] works out an integrated model for forecasting hydrological processes in a changing climate and anthropogenic load using elements of artificial intelligence (artificial neural networks and genetic algorithm). Models for predicting hydrological indicators have been tested on the example of the Belaya River, the largest waterway in the Republic of Bashkortostan. The outcomes obtained in the above works are considered satisfactory.

One of the specific problems when using neural networks in the practice of hydrological forecasting is the choice of the correct network architecture and the optimal number of hidden neurons. An insufficient number of neurons will not allow solving a complex problem, and too many of them will greatly slow down the learning process and lead to overfitting. A large number of neurons will allow the network not to approximate the dependence between input and output but only to remember all the supplied data to the input and compare the corresponding outputs to them. This approach turns out to be erroneous which manifests itself when testing a neural network on an independent material.

2.4 Dynamic and stochastic modeling
A technique based on the use of dynamic models for the formation of daily water flow rates in the form of differential equations of the first and second order has been developed and successfully used at RSHU for background forecasting of the process of changing flow modules with the provision of predictive information in the form of appropriate maps which allow predicting trajectories of displacement of the runoff extreme values (for example, [14]). Figure 3 shows the results obtained by the background forecasting method of water content.

![Figure 3](image_url)

Figure 3. Predicted changes in the runoff module distribution in the North-West region for eight days, the diagrams are presented after two days

Models of the first and second order, respectively, are the most suitable for short-term forecasting of river water availability:

\[
\frac{dQ}{dt} = -\frac{1}{k\tau}Q + \frac{\dot{X}}{\tau},
\]  

(2)
\[ \tau_2 \frac{d^2 Q}{dt^2} + \left( \frac{\tau_2}{k \tau_1} + 1 \right) \frac{dQ}{dt} + \frac{1}{k \tau_1} Q = \frac{1}{\tau_1} \dot{X}, \]  

where \( Q \) – flow rate (module, layer) of runoff; \( \dot{X} \) – precipitation intensity; \( k \) – runoff coefficient; \( \tau \) – river basin relaxation time; \( \tau_1 \) – runoff time; \( \tau_2 \) – underground runoff time.

The forecast algorithm scheme is as follows:

- 15 days (or 30 days) preceding the day of the forecast release are taken to parameterize the model;
- the parameters of the model are considered optimal if the root-mean-square error ratio of the verification predictions to the standard deviation of the predicted value for the lead time \( S/\sigma_\Delta \) is minimal, and the number of justified verification predictions \( P(\%) \) is maximum;
- fractal diagnostics based on the calculation of the correlation dimension is carried out over the parameterization period and shows the number of phase variables necessary for a reliable forecast, that is, the predictive model dimension of the first or second order (it is assumed that the order of the model will be preserved for the forecast lead time);
- a forecast is given with a lead time, for example, a day, then the parameterization period is shifted to the forecast release date after a day, namely, dynamic parameterization is applied [14].

For instance, the article [14] shows the dynamic models use of the formation of daily water discharges in the form of differential equations of the first and second order to predict the process of changing river runoff from the catchments of Columbia which are located in a semi-mountainous area and for which short-term floods of rain origin are typical. It was experimentally proved that the differential equation (model) of the first order demonstrated more reliable results for the conditions of the daily runoff formation of Columbia rivers in the course of performing verification forecasts of water discharge.

The background stochastic forecasting technique is based on the use of differential equations system for the initial moments of the probability density distribution of daily runoff modules. This technique makes it possible to obtain operational forecasts of the water bodies’ state; a forecast of the probabilistic characteristics of water flows (levels) is issued.

Meteorological forecast of changes in precipitation and air temperature (in the case of forecasting spring floods), and standard network hydrometeorological observations are required to implement the method of background stochastic forecasting.

The dynamic forecast is limited to pointing specific values of costs (levels) at the nodes of the computational grid. Such a strictly deterministic approach ignores random factors of runoff formation, as well as errors in setting the initial data, model parameters, and external influences (the course of predicted precipitation). Knowing the curves of the probability density distributions of expenditures \( p(Q) \) or levels \( p(H) \) (or predicted distributions) makes it possible to ascribe to any predicted value of the expenditure (level) the likelihood of its occurrence in the case of a process stochastic description. This expands the risk assessing opportunities of making erroneous decisions for the economy.

The Fokker-Plank-Kolmogorov equation (FPK) is approximated for predictions by a system of ordinary differential equations [15]:

\[
\begin{align*}
\frac{dm_1}{dt} &= -(\bar{e} - 0.5G_e)m_1 + \bar{N} - 0.5G_{\bar{e}}N; \\
\frac{dm_2}{dt} &= -2(\bar{e} - G_{\bar{e}})m_2 + 2\bar{N}m_1 - 3G_{\bar{e}}m_1 + G_N; \\
\frac{dm_3}{dt} &= -3(\bar{e} - 1.5G_{\bar{e}})m_3 + 3\bar{N}m_2 - 7G_{\bar{e}}m_2 + 3G_Nm_1; \\
\frac{dm_4}{dt} &= -4(\bar{e} - 2G_{\bar{e}})m_4 + 4\bar{N}m_3 - 4 \cdot 3.5G_{\bar{e}}m_3 + 6G_Nm_2,
\end{align*}
\]

where \( m_i \) – initial statistical moments of the \( i \)-th order; \( c = 1/k \tau \), \( N = \bar{X} / \tau \), \( k \) – runoff coefficient; \( \tau \) – river basin relaxation time; \( \bar{X} \) – precipitation intensity; \( G_{\bar{e}}, G_N \) – intensity of white Gaussian noise. The first three equations are sufficient to obtain the evolution of asymmetric probability distributions.
Various options for the system parameterisation are possible (4). Given that \( c = 1/k\tau \), \( N = \bar{X}/\tau \) and \( k \) and \( \tau \) are known from the model optimization but \( \bar{X} \) – from weather forecast, it is necessary to determine the intensities \( G_c, G_R \) and \( G_{cR} \) from the first three equations of the system (4) with the acquainted \( m_1, m_2 \) and \( m_3 \). They can be defined on the basis of 30-day observations of the runoff at the section for which the forecast is given.

Changes in water flow rates, which are not measured or recorded, occur during the day. Only daily average values are used in practice, making a kind of statistical generalization of intraday variations in water discharge. The solution of the equation systems for the initial moments (4) is the predicted value \( s \) of the first three moments which characterize the daily average value, the variation of the water flow rate within the day, and the deviation of the average value from the modal.

3. Conclusion

The following features, significant for practical purposes, were identified as a result of the analysis of considered approaches to predicting the characteristics of river runoff:

- regression dependencies are quite simple to obtain but they require complete current information about all predictors in the model;
- ARMA theory methods (autoregressive model, mixed models, integrated moving average autoregressive model) can be applied with retrospective series of river runoff observations without knowledge of the meteorological leave but there is a possibility of obtaining unsatisfactory outcomes due to the peculiarity of runoff formation conditions for the year the forecast is issued;
- forecasting using artificial neural networks requires a sufficient amount of retrospective information and knowledge of computational algorithms to obtain an effective model;
- dynamic and stochastic modeling of the processes of river runoff formation allows obtaining reliable results due to the variation of the model values, as well as the possible change in their number [16]; the outcomes of stochastic modeling are predictions in the probability form of the phenomenon occurrence.

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