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Estimating Maximum Water Levels During Winter Flooding at Some Segments of the Lena River

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***Abstract* – The Sakha Republic (Yakutia) has a large territory that covers various climatic zones and a network of water bodies and thus is exposed to a wide range of natural emergencies. The most typical of them is spring-summer floods that cause flooding of vast territories, facilities and infrastructure, thus causing enormous damage to the economy; it determines relevance of developing and perfecting flood prediction methods to reduce the hazard level and possible damage. This research presents application of multiparametric models and neuron networks for development of a predictive model that allows forecasting the spring flooding hazard from statistical data accumulated through 44 years of observation and regressive modeling. The proposed methods allow evaluating the spring flood water levels as a function of various factors (thickness of ice, temperature, etc.) with sufficient accuracy, as confirmed with the results of predicting maximum water levels for two segments of the Lena River. Selection of the river course segments was determined by nearby location of potentially hazardous facilities whose flooding may cause significant property loss. Factors influencing spring flood levels have been determined.**

Key words – spring floods; prediction; regression modeling; statistical approach; neural networks.

I. INTRODUCTION

The most typical natural emergencies in Yakutia are spring-summer floods. The scope of damage caused by the floods depends on effectiveness of flood proofing performed with considerations for timely predictions of ice jamming and ice-jam water levels. During the 13 years from 2001 to 2013, spring flooding of rivers within the territory of the republic caused damage to the amount of 16 billion rubles [1]. The main waterway of Yakutia is the Lena River. The length of the river is 4400 km, area of its basin is 2,490,000 km^2, average duty of water is 16500 m^3/s. By the nature of its flow, the The Lena river is usually divided into three large segments: upper – from origins to the creek of Vitim (1690 km), middle – from the creek of Vitim to the inflow of Aldan (1400 km), lower – from the creek of Aldan to the Stolb island (1310 km) [2]. Freeze-up lasts for about 7 months, flooding takes place between early May and the second decade of June. Breakup of river ice is often accompanied with multiple ice jams and floods.

Features of the Lena's water regime match the nature of its feed, primarily snow-related, which reflects in the height of flooding, whose size increases due to ice jams. The highest levels of spring flooding on the Lena are seen during the ice

breaking or in case of ice jams. A specific feature of the annual movement of water levels of rivers is high intensity of change. Fast rising of water levels during spring floods is due to accelerated melting of snow in the basin and meridional direction of the river course. The floodwater is supported and further reinforced with local melt waters from tributaries. The Lena and its tributaries are characterized with increased intensity of flooding lower down the course of the river, however, in parts where rivers flow through broad valleys with significant flood plains, flood rises significantly slower.

The average duration of spring flooding is 75 days. The spring flooding on the Lena ends in the second decade of June on average. Segments of the Lena that have multiple islands sometimes experience simultaneous breaking of river ice by the flood wave in several creeks. River discharge, being divided between several creeks, grows weak, which it its own tern facilitate appearance of a massive jam that completely or almost completely blocks the river corridor at the confluence. Such jams often cause catastrophic flooding.

Selecting segments to be used in solution of the prediction task. Jam-associated water levels are formed under the influence of factors common for the Lena as a whole: 1) intensity of increment and height of spring flood; 2) ice and meteorological situation during formation and breaking of the ice cover. The segments considered here were selected due to nearby location of potentially hazardous objects that may happen to be in the flooding zone during spring flood.

Segment near the village of Tabaga. In the vicinity of Tabaginskii promontory, somewhat upstream and with a connection to the Pokrovsk – Yakutsk road, near the gas pipeline passing Khatassy village, a bridge across the Lena is planned. At that, frequency of jam formation and flooding during the period considered in this study is 0.8 at this segment. Studying this segment will allow resolving the issue of ensuring the safety of the bridge construction, as well as a submerged crossing that is being in operation since 2004. During this period, there were 3 emergency situations at the crossing.

In the vicinity of the village of Solyanka there is a trenched submerged crossing of the East Siberia – Pacific (ESP) oil pipeline under the Lena with a diameter of 1200 mm and operating oil pressure of 10 MPa. A high probability of the ESP oil pipeline emergency at this crossing near Solianka is due to the fact that the Olekma river disgorges into the Lena 4 km upstream, causing a major hazard of ice jamming, which may expose the oil pipeline and remove it from its trench under the hydrodynamic action of water flow and pressure of jammed ice. The bed underneath the oil pipeline may get washed away and resulting pipeline dip may lead to beyond design deformations and loads in the pipeline [3, 4].

A large contribution into development of probabilistic methods for description of river discharge as a stochastic process were made by S.N. Kritskii, M.F. Menkel, D.Ia. Ratkovich, V.A. Rumiantsev, N.I. Koronkevich, D.A. Burakov, N.A. Kartvelishvili, V.A. Lobanov and others. The works [5-14] built models with accounts for and using the results from research into stochastic properties of long-term changes in the main components of water balance of reservoirs and water collections; extreme hydrological situation in the territory of Russia and other countries were considered, analyzed and classified, roles of natural and anthropogenic factors in their formation were identified; possibility of prediction and mitigation of expected negative consequences was analyzed.

Neural networks were applied to prediction of residual rainfall in a research performed by K. Hsu, S. Sorooshian, H.V. Gupta, X. Gao and B. Imam, while A. Joorabchi, H. Zhang and M. Blumenstein analyzed application of neural network to predict flooding on Australian rivers.

D.A. Burakov [5] obtained prognostic models for the Yenisei river, using the most significant hydrometeorological parameters as inputs, namely, ice thickness, water discharge as of ice breaking, maximum water level at the beginning of ice cover formation, average air temperatures before ice cover breaking and water equivalent of snow cover. Using this approach, hydrological date covering the period from 1970 to 2014 were used to produce statistical multiparametric models of maximum water level at two segments of the Lena: in the vicinity of the village of Tabaga near Yakutsk, and in the vicinity of the village of Solianka near Olekminsk. Long-term observations show that these segments of the Lena are potencially prone to ice jams during the spring period.

II. MATERIALS AND METHODS

The data analysis has shown that the possibility of extreme spring floods depends on the following natural factors: Maximum water level (at the time of spring flood); water discharge on the date of breakup of river ice; sum of positive air temperatures from the date of crossing into positive temperatures to the date of breakup of river ice; maximum ice thickness; water level at the beginning of freeze-up; water equivalent in snow cover determined from April snow survey (April average); average air temperature in April – May (April and the first decade of May);

The available prognostic methods for spring flooding hazard are based on predictive dependences linking the water level to various factors that may be used to predict the water level from the known characteristics (ice thickness, temperature, etc.) from 3 to 8 days ahead.

Fixed observations covering the period from 1970 to 2008 were used to develop a model, then for the last six years (2009-2014) a retrograde prediction of the maximum water level in the Lena river at the segments in question was produced.

1. Vicinity of Tabaga**.** Let us consider the regression model that takes into account the main factors influencing the spring flooding process.

The maximum water level prediction is computed with the equation:

$$H_{\max} = 0.279 \cdot N_{ldc} + 0.006 \cdot Q + 0.644 \cdot d + 2.759 \cdot S + \\ + 2.192 \cdot t_4 + 530.906$$

where $H_{\max}$ is the maximum water level; N_{ldc} is the water level at the beginning of freezing-over; Q is the water discharge as of the breakup of river ice date; d is the maximum ice thickness; S is the water equivalent of snow cover averaged for April, t_4 is the average air temperature in April and the first decade of May. Data were sourced from Yakutsk meteorological station and gaging station in Tabaga (at a distance of approximately 20 km).

Breaking-up of Lena in the vicinity of Tabaga starts on May 15th-20th, while the maximum water level is usually reached on May 20th-24th. In the vicinity of Solianka, the breaking-up of river ice takes place on 10-15 of May, the highest water level is observed on 15-18 of May [15].

This method may be recommended for use, on condition of being controlled with independent data and conforming to conditions of accuracy and quality. Criterion of applicability and quality of the method is taken as a ratio between mean square errors of revision predictions to the square deviation of the predicted value. Allowable error is 64 cm. Criterion of applicability of the technique is 0.5, correlation coefficient is 0.8, meaning that this technique is a good one. Distribution of residuals is normal that is the model is valid and suitable for further analysis.

Table 1 shows a characteristic of retrograde prediction for water level in the vicinity of Tabaga. Prediction for the vicinity of Tabaga may be obtained starting from the first decade of May, 3-8 days in advance.

2. Vicinity of Solianka, near Olekminsk. Let us consider the regression model that takes into account the main factors influencing the water level during spring flooding.

The maximum water level prediction is computed with the equation:

$$H_{\max} = 0.27 \cdot d + 0.003 \cdot Q - 0.198 \cdot N_{ldc} + 3.481 \cdot S + \\ + 2.952 \cdot t_4 + 834.369$$

where $H_{\max}$ is the maximum water level; N_{ldc} is the water level at the beginning of freezing-over; Q is the water discharge as of the breakup of river ice date; d is the maximum ice thickness; S is the water equivalent of snow cover averaged for April, t_4 is the average air temperature in April. Data for calculations were sourced from meteorological station and gaging post in Solianka.

Breakup of river ice in the vicinity of Solianka happens on the May 10th-15th, the highest water level is observed on the May 15th-18th. Allowable error is 66 cm. Criterion of applicability of the technique is 0.6, correlation coefficient is 0.7, meaning that this technique is a satisfactory one. Table 2 shows results of retrograde prediction for water levels in the vicinity of Solianka obtained by regression modeling method. Flooding starts in late April – early May, the highest levels of spring flooding on the Lena are seen during the ice breakup or in case of ice jams in the first decade of May. Prediction for the vicinity of Solianka may be obtained starting from the beginning of May, 3-8 days in advance.

Unlike statistical methods of analysis, artificial neural networks (ANNs), are based upon parallel processing of information and are capable of automatic learning. Let us consider an ANN-based predictive model with considerations for optimal amount of input parameters training set.

The role of a neural network during the solution of the predictive problem is in predicting a future reaction of a system from its previous behavior. Having information about values of variable x in moments preceding the prediction $x(k-1), x(k-2), \ldots, x(k-N)$, the network develops a solution, what will be the most probable value of the sequence $x(k)$ in the current moment k. In order to adapt weight coefficients, actual prediction error $\varepsilon = x(k) - x(k-1)$ and the values of its error in preceding moments are used, where ε is the prediction error.

When selecting network architecture, several configurations of varying number of elements are usually tested. Proceeding from the position that the prediction problem is a special case of regression, it follows that the following types of neural networks may be used to solve it: multilayer perceptron (MLP), radial basis function network (RBF), generalized regression neural network (GRNN), Volterra network and Elman network.

When applying a neural network to solving a prediction problem, the time series is divided into three sets: training, testing and control sets, which are then supplied to the network's input. The result of a prediction is a value of the time series in a desired moment of time.

For prediction of maximum water level, the optimal structure of the neural network was selected with the following parameters: the strategy is automated neural network; the data was divided into subsets as follows: 70% training, 15% testing and 15% control; the type is MLP; three-layered: 5 input neurons, 5 hidden layer neurons, 1 output neuron. Criterion of applicability of the technique is 0.5, correlation coefficient is 0.9, meaning that this technique is a good one. (Subset sizes covered: 32 years for training, 4 years for testing and 4 years for control). Table 1 shows results of a retrograde prediction of water level in the Lena river obtained by INS method in the vicinity of the Tabaga village.

Let us also consider modeling the maximum water level with artificial neuron networks (ANN) and regression analysis for the period from 1970 to 2008 for the segment of Lena in the vicinity of Solianka, near Olekminsk.

For prediction of maximum water level, the optimal structure of the neural network was selected with the following parameters: The type is MLP; three-layered structure: 5 input neurons, 3 hidden layer neurons, 1 output neuron. Criterion of applicability of the technique is 0.5, correlation coefficient is 0.8, meaning that this technique is a good one.

TABLE I. COMPARATIVE CHARACTERISTICS OF RETROGRADE PREDICTION RESULTS FOR THE WATER LEVEL IN THE LENA RIVER IN THE VICINITY OF THE TABAGA VILLAGE

Regression analysis						
Year	2009	2010	2011	2012	2013	2014
Water level, cm						
prediction	837	977	979	993	936	799
observed	823	956	935	943	903	736
Error,						
absolute, cm	14	21	44	50	33	63
relative, %	2	2	5	5	4	8
INS						
Water level, cm						
prediction	810	939	961	968	938	791
observed	823	956	935	943	903	736
Error,						
absolute, cm	13	17	26	25	35	55
relative, %	2	2	3	3	4	7

Let us consider an ANN-based predictive model with considerations for optimal amount of input parameters training set for Solianka neighborhood; the results of relevant calculations are given in Table 2.

TABLE II. COMPARATIVE CHARACTERISTICS OF RETROGRADE PREDICTION RESULTS FOR THE WATER LEVEL IN THE LENA RIVER IN THE VICINITY OF THE SOLIANKA VILLAGE

Regression analysis						
Year	2009	2010	2011	2012	2013	2014
Water level, cm						
prediction	1940	1182	1323	1088	1127	933
observed	1021	1236	1385	1135	1191	868
Error,						
absolute, cm	19	54	62	47	64	65
relative, %	2	4	4	4	5	7
INS						
Water level, cm						
prediction	1044	1203	1336	1186	1238	931
observed	1021	1236	1385	1135	1191	868
Error,						
absolute, cm	23	33	49	51	47	63
relative, %	2	3	4	4	4	7

III. RESULTS AND DISCUSSION

From Tables 1 and 2 (regression model) it is evident that the constructed regression model to a sufficient degree reflects the actual water level, prediction errors (1-4)% reflect adequate validity of the statistical models selected. Preliminary analysis of variables has shown weak correlation between predictors, while analysis of residues has shown that they are normally distributed, confirming validity and adequacy of the model. Taking into account the fact that the length of the initial series is short, additional evaluation of the technique's quality has been performed using the excluded point method. Obtained values of relative mean square error, 11% for Tabaga and 12% for Solianka confirm satisfactory quality of the technique.

From Tables 1 and 2 (ANN) it is evident that the constructed model to a sufficient degree reflects the actual water level, prediction errors (1-8)% reflect adequate validity of the statistical models selected. Predictions obtained with the ANN method were compared to those produced with the regression method for the two segments, Tables 1 and 2. Relative errors of the predictions made with ANN and linear regression diverge insignificantly, thus witnessing to possibility of applying either of the methods.

IV. CONCLUSION

It should be noted that solving the prediction problem is more efficient in case the neural network is trained on a larger volume of data.

The proposed approaches will allow obtaining estimates of water level increase during spring flood if a data base is available covering water levels for previous years, thus allowing evaluating the situation for planning of protecting measures. It may be also used to predict flood hazard when constructing industrial facilities.

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