A system for visualization and prediction of floods on lowland rivers

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***Abstract*—A system for visualizing and forecasting floods on lowland rivers is presented, combining a geometric approach to calculate a flood zone and a complex of four neural networks to predict water levels. The modular architecture of the system allows independent implementation and interchangeability of elements both at the subsystem level and at the level of processing individual input variables involved in system analysis.**

Keywords*—*neural network, flood, forecast, lowland rivers

I. INTRODUCTION

A set of rivers located within a river basin generally is a complex hierarchy of watercourses. The flow of water in each of the watercourses is characterized by its own water discharge (the volume of water passing through the cross section of the riverbed per unit of time). The high water level *h* is important for assessing the flooding of an area and is uniquely determined by the water flow in the watercourse. The terrain relief *R* of the river floodplain is another factor, in addition to the water flow rate, that determines the contour of the flood zone:

$$z=f(h, R) \tag{1}$$

In general, the river flow not only experiences the influence of the relief, but also participates in its formation [1].

Obviously, a change in water flow in the feeder of any river channel (so-called higher-order streams) directly affects the change in water flow in a given channel. In turn, the change in the value of water flow Δq in the watercourse under consideration is influenced (in addition to the previous values of flow *q*) also by a number of climatic factors: precipitation *c*, air temperature *t*, the amount of previously accumulated snow reserves *s*:

$$\Delta q=f(q, c, t, s) \tag{2}$$

Three different scenarios can be distinguished, in which precipitation affects water flow in very different ways. When the air temperature is positive, precipitation directly affects water flow by flowing into the river bed. At negative temperatures they accumulate in the form of snow cover, which then affects the spring flood. In this case, the contribution of precipitation to water consumption occurs with losses due to evaporation and infiltration into the soil. In the case of water contained in the snow cover, the magnitude of these losses is significantly influenced by the temperature regime. In the presence of a large volume of precipitation with a subsequent transition of air temperature to negative values, the soil saturated with water freezes and significantly loses its ability to absorb further; as a result, water infiltration is significantly reduced.

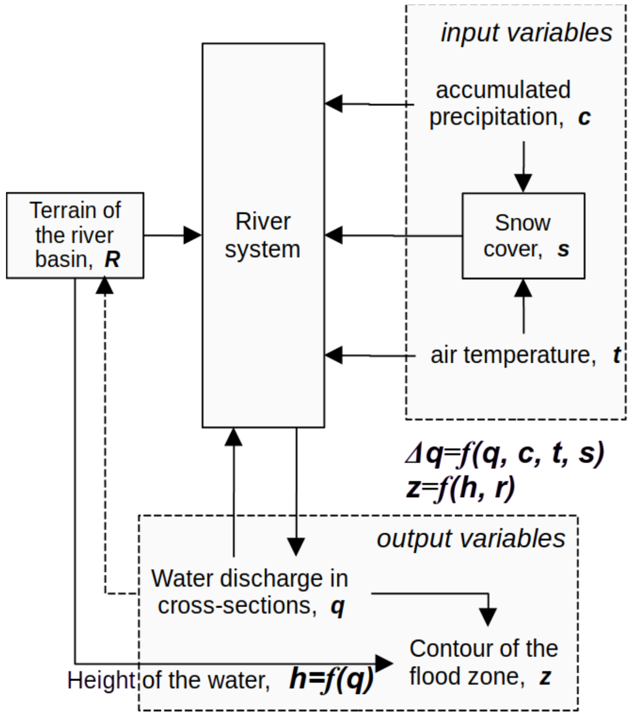

Fig. 1. A set of rivers in the river basin as a complex system

Therefore, when considering a set of rivers within a river basin as a complex system (see Figure 1), flood forecasting tasks must take into account the temporal dynamics of climate impacts over the previous period, and the system memory effect in this case extends to time intervals that can reach, in depending on the time of year, several months.

II. FLOOD VISUALIZATION AND PREDICTION

Figure 2 presents the general structure of the presented software system, which includes the following independent parts.

- Flood zone calculation subsystem uses information about water discharge in control points of the watercourses (i.e. the water level in specific river cross-sections) and digital elevation map (DEM) of the terrain to calculate contour of the flood zone [1].
- The prediction subsystem estimates future values of the water discharge based on the current values and

hydrometeorological data (input variables on Fig. 1) [2].

- Data visualization and interpretation sybsystem combines online geographical maps and calculated contour of the flood zone to show flooded regions. Based on this information the subsystem allows to estimate socio-economic riscs caused by flood on an anthropogenically transformed area [1, 3].

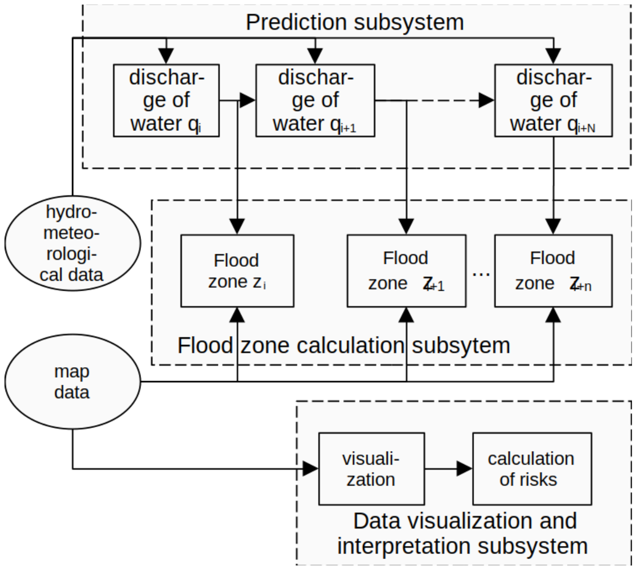

Fig. 2. A set of rivers in the river basin as a complex system

The prediction of water discharge is done iteratively, obtaining a predicted q_{i+1} value based on a (supposedly measured) q_i one, then obtaining q_{i+2} value based on q_{i+1}, and so on. In the same way, flood zone z_i calculation done for the current situation is followed by z_{i+1} , z_{i+2}, ... predicted flood zones. This iterative approach allows to show flood dynamics with a series of static images of the flooded zones.

To figure out socio-economic riscs, the magnitude of socio-economic damage per unit area is estimated depending on the depth of water and weight coefficients, determined by the expert estimates method from preliminary physical, technical and economic analysis of the effect of the water depth on the territory. Also, the duration of flooding of the territory is taken into account in the same way as in the case of the depth of water on the territory, based on weighting factors. Thus, a quantitative risk assessment is represented as a product of combinations of the probabilities of flooding events and their duration by an assessment of the socio-economic significance of the territory fragment [1, 3].

III. Flood Zone Calculation Subsystem

There are two main approaches to calculating the flood area: geometric and hydrodynamic ones. An integral part of both is the terrain model – a digital elevation map, or DEM. The hydraulic approach involves solving a system of differential equations of hydrodynamics in partial derivatives. Its advantages include physical validity and calculation of the distribution of the velocities of water masses over the area of the flood zone. Its disadvantages are the critical dependence of the calculations adequacy on the quality of determining the hydraulic characteristics of the relief, as well as significant increase in computational complexity at the increase in the resolution of the modeling zone area.

Hydrodynamic approach can be either one-dimensional or two-dimensional. If it is sufficient to predict the time course of changes in the water level in the river channel, it is recommended to use a hydrodynamic model that solves the system of hydraulic equations in a one-dimensional approximation. The initial data for a one-dimensional hydrodynamic model is information about the terrain in the form of river cross-sections. When performing calculations, the heights of the water surface level along the section of the river bed are used as initial conditions. The result of the simulation is the change in time of the levels of the height of the rise of the surface of the water and the rates of flow of the volume of water along the section of the river channel.

The geometric approach involves the creation of a three-dimensional model of the water surface and its subsequent intersection with the DEM to determine the contour of the flood area boundary. The disadvantages of the geometric approach include the following three:

- oversimplification of hydrological and hydrodynamic processes;
- limiting the calculation of the area by the width of the cross sections of the river valley;
- non-triviality of the choice and location of these sections (especially if it is necessary to calculate the flooding of the river system).

The advantages of the geometric approach include its low demands to computing resources, satisfactory quality of forecasting the flooding area in the presence of a dense network of hydrological measuring stations, and inaccessibility of the hydrodynamic characteristics of the river valley.

So, from the point of view of a compromise between accuracy (taking into account the natural relief and technogenic elements of the territory) and the use of computing resources, we can recommend geometric approach when flood zones are calculated for lowland rivers, and the whole flooding process shows relatively low dynamics [1, 4, 5].

IV. Prediction Subsystem

A block diagram illustrating the presented method of neural network flood forecasting is presented in Fig. 3. Due to the fact that high and low floods have very different flow patterns, their prediction is carried out by separate artificial neural networks (ANN), trained on phenomena of the corresponding class.

The forecast of water flow values up to the maximum during high floods is carried out by the forecasting ANN 1, which simultaneously processes the values of two time series using the sliding window method: the average daily water flows recorded at the hydrological observation post, and the total values of water accumulation in the snow cover in the studied catchment area. The calculation of the amount of water accumulation in the snow cover was carried out by a separate ANN based on the results of a daily assessment of the water content in the snow cover based on data from passive radio-thermal scanning of the catchment area from an artificial Earth satellite (AES), with optional filtering of the generated time series.

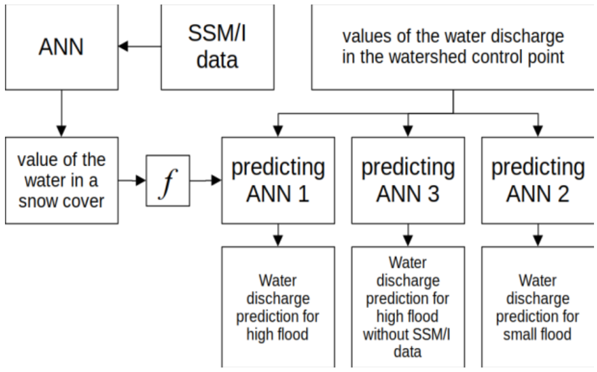

Fig. 3. The predicting subsystem diagram

The existing approach to determining the water equivalent of snow cover from radio-thermal satellite measurements is based on the use of empirical regression dependencies, which often give significant discrepancies compared to direct measurements on snow-measuring routes [6, 7].

In order to increase the accuracy of calculating the water content in snow, the possibility of replacing regression dependencies with an ANN was studied using the example of a large climatically heterogeneous territory. To carry out the research, we used data obtained from the microwave scanning radiometer-polarimeter SSM/I for the period from 1987 to 2014. The territory of the Russian Federation was chosen as the territory with the required size and climatic heterogeneity [6]. During the experiments, meteorological stations with differentiation of snow-measuring routes according to landscape characteristics were used to train the ANN: forest, field, and forest/field. The architecture of the ANN was a classic multilayer perceptron with one intermediate layer, and the hyperbolic tangent was used as the activation function of neurons in the hidden layer (fig. 4).

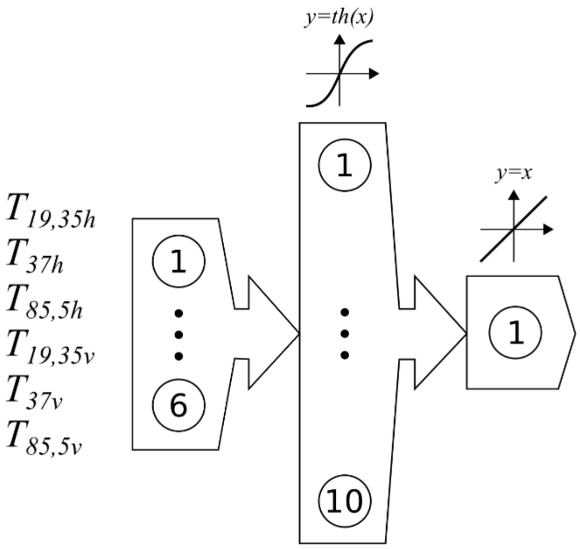

Fig. 4. ANN architecture used to find out the amount of water in a snow cover

As a result, ANNs, individually trained for each snow-measuring route, for data with an expanded set of used radio frequency channels (19.35; 37.0; 85.5 GHz of both horizontal and vertical polarization) made it possible to achieve a maximum value of the Pearson correlation coefficient r equal to 0 .79, which allows us to conclude that it is preferable to use an ANN to estimate the value of the water equivalent of snow cover [6].

In case there is no access to the results of microwave scanning of the catchment surface (for example, due to a malfunction of satellite equipment), a forecasting ANN 2 is provided, which is capable of forecasting high floods using a single time series. A real example of the limited availability of such data is the technical malfunction of the 37 GHz vertical polarization channel of the SSMIS sensor, located on the DMSP F-17 satellite, registered starting from 04/05/2016 [8].

Finally, minor floods occur when the soil significantly absorbs water released as a result of snow melting, and for them there is no significant dependence of the water flow in the area on the accumulated snow reserves. For phenomena of this class, a predictive ANN 3 is provided, which takes into account only a number of flow rates.

A sign that allows us to determine that not a low, but a high flood is coming, is precipitation in the fall followed by winter freezing of the soil (i.e., a significant decrease in its infiltration capacity) and the presence of a sufficient amount of accumulated snow reserves. Due to the fact that the microwave radiation recorded by the orbital sensor complex is completely absorbed by the layer of water in the thickness or on the surface of the snow (appearing as a result of melting and/or precipitation), it is possible to reliably and timely detect the moment of the beginning of intensive melting of the snow cover.

The determination of the expected flood category is based on the results of a preliminary accounting of the amount of autumn precipitation for the October-November period and the proportion of days with negative average daily air temperature for the December-January period. The necessary characteristic values of the considered quantities for a specific area are determined based on the analysis of meteorological time series accumulated over the corresponding time periods immediately preceding the recorded high floods.

In the case when data on autumn precipitation and winter average daily temperatures indicate an upcoming minor flood, a third ANN trained on hydrological data characteristic of minor floods is used for forecasting.

The architecture of predictive ANNs is similar to that shown in Fig. 4 (a classic multilayer perceptron with one hidden layer is used). The activation function in the hidden and output layers is the hyperbolic tangent. In accordance with the chosen activation function, the elements of the training and testing samples are scaled to the range [-1, 1].

The size of the sliding window for processing input data by predictive ANNs is determined empirically in order to minimize the error of the trained neural network on the test sample. The data sets used for training and testing the ANN must cover the period including the peak of the average daily water flow - the latest recorded during spring floods at the selected river section.

The size of the forecast horizon must correspond to the lead time of the medium-term meteorological forecast (from 7 to 10 days). To assess the nature of the water decline when the peak of the flood reaches, it is advisable to also forecast the descending branch of the hydrograph (no more than twice the forecast horizon).

V. Computational experiments

In the conducted computational experiments, the architectures of artificial neural networks with the following changes in the size of the hidden layer were studied: the number of neurons in the hidden layer corresponds to the number of neurons in the input layer, the size of the hidden layer is half the size of the input layer, and the size of the hidden layer is half the size of the input layer (see Table 1) . The consequences of changes in the results of the ANN operation when the size of the sliding window is reduced to 23 days are also studied.

TABLE I. ANN ARCHITECTURE EXAMINED TO PREDICT WATER DISCHARGE IN THE RIVER CONTROL POINT

	Layesrs structure	Size of a training sample	Size of a testing sample	Number of training iterations	MSE of the training	MSE of the prediction
ANN 1	92-92-7	18300	732	1000	0,0002	0,0007
	92-46-7	9150			0,0003	0,0012
	92-184-7	36478			0,0003	0,0011
	46-46-7	5040	1008		0,0002	0,0005
ANN 2	46-46-7	5002	122		0,0004	0,0011
	46-23-7	2440			0,0004	0,001
	46-92-7	9760			0,0004	0,0011
	23-23-7	1428	168		0,0003	0,001
ANN 3	46-46-7	5002	1968		0,0004	0,0008
	46-23-7	2460			0,0008	0,0011
	46-92-7	9758			0,0004	0,0012
	23-23-7	1470	2520		0,001	0,0009

As a result of the studies, based on the lowest achieved values of the root mean square error of the forecast, the following architectures were considered optimal for ANN 1, ANN 2 and ANN 3: 46-46-7, 23-23-7 and 46-46-7, respectively. When assessing the quality of forecasting water flow at the control river section during spring floods, the developed ANNs obtained high values of Pearson correlation coefficients, namely: 0.99, 0.94 and 0.74. Figure 5 shows an example of the water discharge prediction (dashed line shows ANN-generated values, while bold line is a hydrographer obtained via real measuremets).

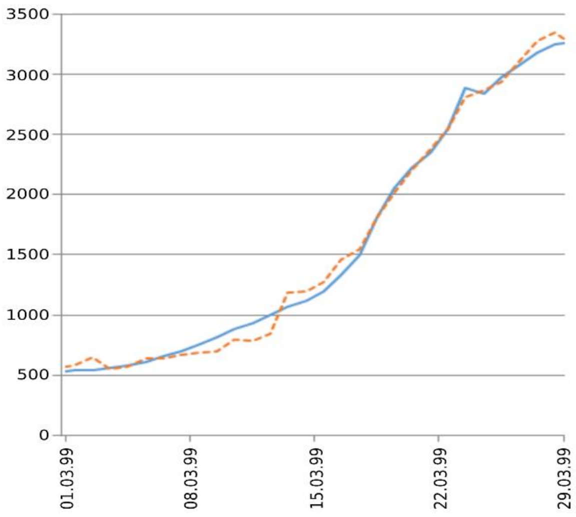

Fig. 5. Example of the water discharge prediction

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