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HYDROLOGICAL PROBLEMS OF WATER-SCARCE REGIONS

Forecasting Catastrophic Floods in Crimean Territory

A. S. Lubkov[a], E. V. Vyshkvarkova[a,] *, E. N. Voskresenskaya[a], and A. E. Shchodro[a]

[a] *Institute of Natural and Technical Systems, Sevastopol, 299011 Russia*

**e-mail: aveiro_7@mail.ru*

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Abstract—The catastrophic situations of recent years—in June 2021 near Yalta and in January 2024 in Sevastopol—associated with abundant precipitation, water level rise in rivers, and the formation of mudflows—once again showed the need for advance forecasting of events with extreme precipitation in Crimean territory for prompt response and minimization of economic losses. The region of the mountain Crimea with its complicated relief and considerable slopes is especially susceptible to the formation of dangerous situations after heavy (often multi-day) rains. Daily data on precipitation from the Ai-Petri weather station were used to calculate and analyze the cases with total precipitation ≥40 mm within three consecutive days. Such conditions were used in the analysis as a threshold of extreme precipitation leading to channel erosion in mountainous Crimea rivers and the formation of debris flows. The catastrophic flood on the Chernaya River in January 2024, which was due to three days of extreme precipitation in the Sevastopol region, is considered. This situation was analyzed to determine the possibility to forecast it up to 3 months in advance with the use of the developed artificial neural network model. The obtained results showed that the quality of the developed neural network is satisfactory to forecast with a lead time of 3 months 2–3-day long extreme precipitation, which intensifies the erosion processes in the mountainous Crimea.

Keywords: extreme precipitation, Crimean rivers, neural network, seasonal forecast

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INTRODUCTION

An important problem of Crimea has long been and remains now the water problem associated with the uneven distribution of runoff due to the physical–geographic features of the peninsula [4]. The runoff of Crimean rivers differs significantly from that of continental rivers. They belong to a specific category of rivers with a flood regime of a Crimean subtype [10]. Floods in Crimea occur mostly in winter and spring and account for up to 80% of the surface runoff [3]. At the same time, a deficiency in runoff forms in summer, and some rivers dry up [9]. Such a regime forms due to irregularity of precipitation and the geomorphological structure of river basins. Clearly, the geological conditions remain practically unchanged; therefore, the formation of both the regime of precipitation and its climatic anomalies become the focus of the study. No doubt, both floods and water shortages cause important environmental and economic effects, which have aggravated in recent decades.

In making managerial decisions, of great practical importance is the analysis of extreme precipitation values, which lead to some adverse effects, such as floods and underflooding [6, 12]. During heavy rains, mudflows often form in rivers and ravines. They cause considerable damage: they destroy bridges, erode roads, wash out fertile soil layer or deposit thick sediments in gardens, vineyards, etc. Mudflows can form in almost any river or ravine in the mountainous Crimea [12].

Illustrative catastrophic situations in the recent years include the following. The first formed in June 2021, when 2–3 monthly amounts of precipitation fell onto Yalta and Ai-Petry within two days. As a result, the Vodopadnaya and Derekoika rivers overflowed their banks, flooding many streets, houses, and passages; power lines were cut off. Several towns near Bolshaya Yalta and segments of roads on the Southern Coast of Crimea suffered from large mudflows, which caused considerable damage to the recreational structure of the region.

Mudflows and discharge of considerable amounts of sedimentary material occurred in many regions of Greater Yalta, which inflicted considerable damage to the recreational infrastructure. At the same time, mudflows and multiple collapses of slopes with export of collapse products into the Baidarskaya and Chernorechenskaya valleys caused underflooding of many households (almost 70) in this part of Crimea. A different situation formed in January 2024. Then, after three days with extreme precipitation, a technogenic catastrophe occurred in the Chernaya River basin, resulting in an interruption of municipal water supply to Sevastopol City for a week. Rains caused a rapid rise in water level in rivers, resulting in underflooding of almost 70 households; water intake structures were out of order.

The described critical situations were caused by heavy rains. Such rains are the main formation factor of erosion processes, which, along with steep slopes and small drainage areas of Crimean mountain rivers, contribute to a rapid concentration of water flow in river channels [6].

Note that the southern part of Crimean Peninsula is characterized by the highest heterogeneity of precipitation events over time and the extreme precipitation volumes [26]. According to the most recent IPCC report, the frequency of extreme precipitation events tendв to increase in many regions of the Earth against the background of surface air temperature rise [17]. Positive trends in the frequency and intensity of extreme precipitation were also found in the Russian territory, including Crimean Peninsula [1, 27]. Forecasting such situations is an important task in hydrometeorology, both from a scientific point of view and in the applied aspect for minimizing the adverse effects of such situations. To prevent and minimize such effects, a reliable and early precipitation forecast is required.

One of the modern methods for precipitation forecast is the use of artificial neural networks (ANN). Studies in the recent decade apply models for such forecasts at a monthly and seasonal scale in individual regions of the Earth. In particular, various NNs were used for forecasting monsoon precipitation in India [24, 25] and Sri Lanka [23], forecasting precipitation in Australia [14, 15, 21], Jordan [13], China [19], and Greece [22]. Studies [15, 19, 24, 25, 29] were made using several NN structures. In this case, a unidirectional heteroassociative NN with one or more hidden layers (such an NN scheme is often called a multilayer perceptron) showed competitive results.

The models for forecasting monthly and seasonally averaged precipitation based on NN can be conventionally divided into two groups by their input data: (1) using regional meteorological characteristics over some previous period (precipitation, minimal and maximal temperature, moisture content, various precipitation indices); (2) using global climate signals (El Niño Southern Oscillation (ENSO), Pacific Decadal Oscillation (PDO), Atlantic Multidecadal Oscillation (AMO), Indian Ocean Dipole (IOD), etc.). In these cases, acceptable simulation quality was obtained obtained both in the first, e.g., in [13, 14, 24], and the second case [15, 21, 24].

In this study, long-term observation data and artificial NN are used to study the potential of forecasting extreme atmospheric precipitation events as causes of river channel erosion and slope collapses.

MATERIALS AND METHODS

The study used daily data on precipitation from Ai-Petri weather station over 1950–2020 and data on Sevastopol over 1950–2024. The Ai-Petri weather station was chosen for analysis since both the Chernaya River and the rivers of Yalta originate from the slopes and foot of the Ai-Petri Yaila.

The criterion of a hazardous phenomenon was taken to be a precipitation threshold of 40 mm within 3 consecutive days. Each such phenomenon was regarded as an independent hydrological situation, and the artificial intelligence system was trained based on recording such phenomena.

The NN-based model from [8, 20] was used; it is schematized in Fig. 1. The first step (Fig. 1, stage 1) in the proposed model was decomposing the forecasted series into a low-frequency and a high-frequency component. The decomposition was made with the use of 9-year running-average filter. The series smoothed by the filter was taken as the low-frequency component, and the series of the difference between the source and smoothed values, as the high-frequency component. Since the low-frequency component in different months explains, on the average, 10% of the variance, it was simulated by the simplest multiple linear regression.

At the next stage, the predictors to be used in modeling were chosen and sorted (Fig. 1, stage 2). The domains in which the predictors were calculated are similar to those presented in [8, 20]; however, some changes were made in the set of predictors for the geopotential field on the isobaric surface of 500 mbar. All domains chosen for this study are given in Fig. 2.

The main difference from the earlier configuration of model [8] at this stage is the use of Hoeffding's nonlinear nonparametric method for the search for statistical relationships (Hoeffding's D correlation) [16]. The Hoeffding method partly reproduces the Kendall rank correlation [18], where agreement/disagreement between two observations is considered. A distinctive feature is the use of not only a pair of observations, but also two isolated series of this pair. If there exists a relationship between the series, the obtained joint distribution will differ from that for independent series, indicating that the ranks in one series are systematically related with the ranks in the other series. In essence, the Hoeffding method determines, whether the observed joint distribution of ranks differs from that corresponding to independent series.

The core of the model (Fig. 1, stage 3) uses a unidirectional heteroassociative multilayer NN, represented by a perceptron with one hidden layer (also called a multilayer perceptron). The output layer is represented by one neuron. The activation function of NN neurons is sigmoidal bipolar $f(x) = \tanh(\beta x)$. The proposed scheme of the model implies a learning (38 years—1950–1987), test (19 years—1988–2006), and check (14 years—2007–2020) samples. Four years

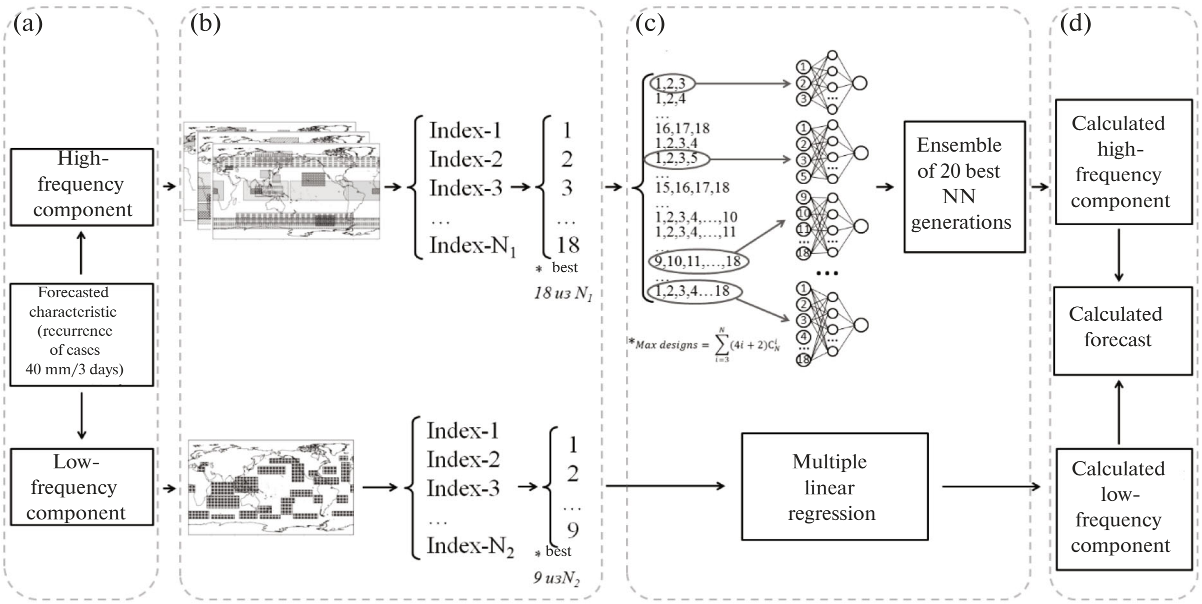

Fig. 1. Scheme of the proposed model: (a) decomposition of the simulated series; (b) data preprocessing; (c) modeling; (d) modeling results and verification.

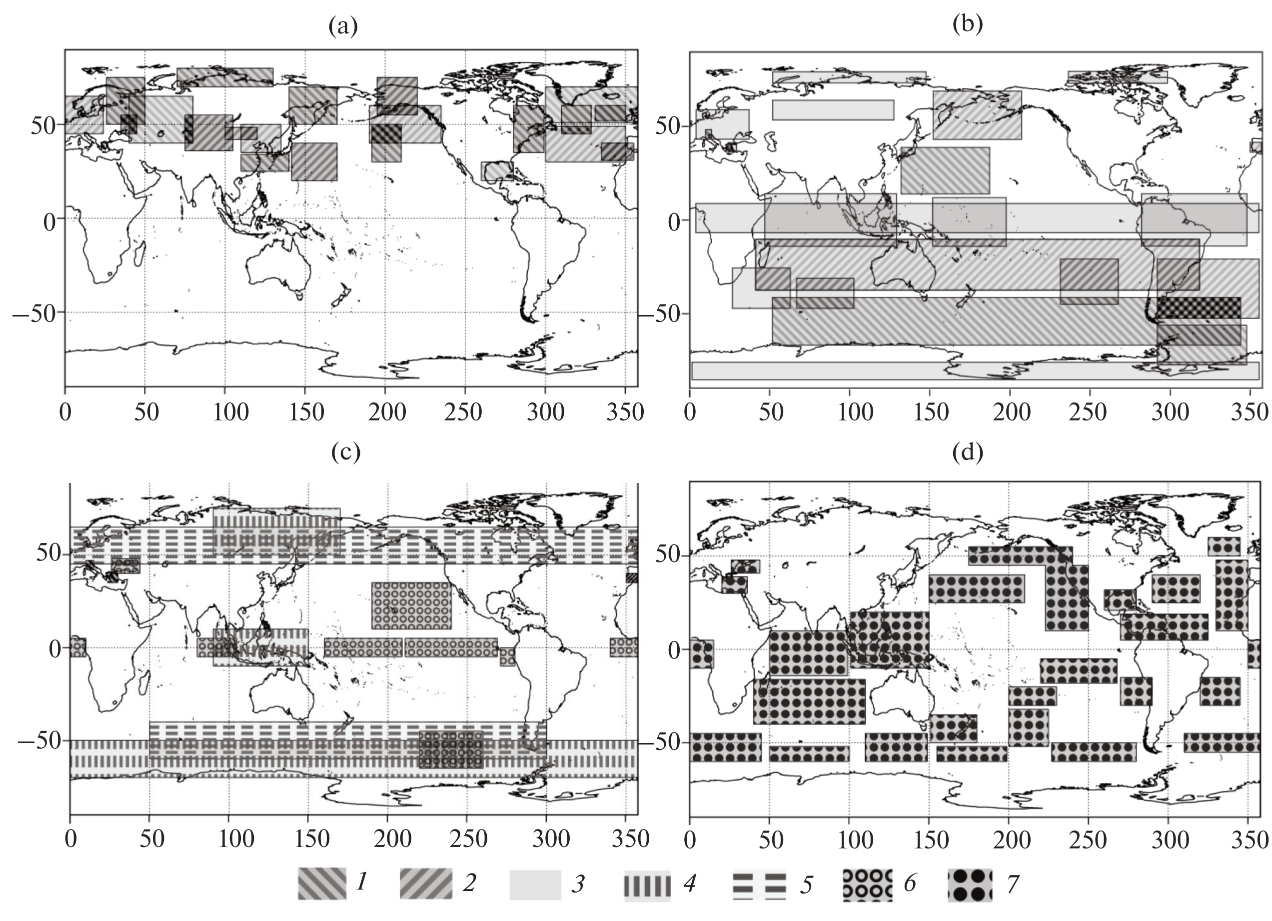

Fig. 2. Localization of the spatial distribution of indices. Domains of indices of geopotential altitude on the isobaric surface 500 mb are marked by shading *1*, *2*, and *3*; meridional and zonal wind components—*4* and *5*, respectively; TPO—*6*; and TPO series smoothed by a 9-year running average filter TPO series—*7*.

more (2021–2024) were simulated without comparison with the actual series.

The simulation was implemented by multiple enumeration of input signal combinations, resulting in the formation of a vector of solutions with different NN designs. The test sample was used to choose the best 20 NN structures. The further analysis of the calculation data was made with the use of the mean calculated values for 20 best NN constructions, represented by block diagrams.

The predictive ability of the model was evaluated in comparison with a control sample (2007–2020) with the use of the following parameters:

— Pearson correlation coefficient:

$$r = \frac{\mathrm{cov}(x_i y_i)}{\sigma_x \sigma_y},$$

where σ_x and σ_y are root mean square deviations of the samples x and y, representing the simulation results and the observed values. A result of calculation will be considered statistically significant if $r > 0.5$ (for 14 values of the check period, at a level $\alpha = 0.001$).

— the ratio of the root mean square error of the model relative to the observed values (RMSE) to the standard deviation of the observed series (SD or σ):

$$\mathrm{RMSE}/\sigma = \frac{\sqrt{\dfrac{\sum (x_i - y_i)^2}{n}}}{\sqrt{\dfrac{\sum (y_i - \bar{y})^2}{n-1}}} = \sqrt{\frac{(n-1)\sum (x_i - y_i)^2}{n \sum (y_i - \bar{y})^2}},$$

where n is the length of the test sample series, x_i is the model, y_i is the observed value, $\bar{y}$ is the mean of the observed series, i is the year of the check sample. The result is significant if $\mathrm{RMSE}/\sigma < 1$ (i.e., $\mathrm{RMSE} > \sigma$).

RESULTS AND DISCUSSION

An increase in surface air temperature in the Crimean Peninsula contributes to changes in the regime of average precipitation and its extreme characteristics [5]. The precipitation regime in the mountainous Crimea shows pronounced seasonality; the largest amount of precipitation falls in winter [12]. The Ai-Petri area is a part of the southwestern subregion with a precipitation peak in winter; the weather station lies at an elevation of 1180 m above sea level. In the period 1950–2020, the mean annual precipitation depth at the Ai-Petri weather station was 1009 mm. The series shows a negative trend (19 mm/10 years), though not statistically significant. The months with maximum precipitation amount were January and December (139 and 148 mm, respectively), and minimums of precipitation were recorded in July and August (52 and 55 mm, respectively). The largest sums of extreme precipitation were recorded at weather stations of the mountainous Crimea; for example, the 95% percentile value for winter at Ai-Petri weather station was 29 mm, and the 99% percentile was 64 mm [2]. A typical feature of the mountainous Crimea is the highest irregularity in the precipitation distribution over time, when periods of long droughts give place to intensive precipitation events [28]. The formation of extreme hydrological/ecological phenomena is due to a combination of several processes: heavy rainfall over several days (at least three); snowfall and its intensive melting at the end of a period of heavy precipitation; washout of sediments from the surface of slopes; the formation of mountain creeks merging into larger streams; sediment transport by these streams; the formation of mudflows and the transport of large amounts of sediment by them.

The formation of the catastrophe in January 2024 was preceded by the following conditions. The two previous months (November and December), were characterized by rains lasting for many days, which resulted in soil oversaturation with moisture. The snow that fell on January 12–13 at a negative air temperature in the drainage areas of Sevastopol rivers, melted rapidly during the following warmer period. Since January 14 to 19, 37 mm of precipitation fell in Sevastopol (13 mm on January 14, 11 mm on January 16, and 13 mm on January 19). Note that the average precipitation rate in January in Sevastopol over the recent climatic period (1991–2020) was 38.3 mm.

Note that the situations described above are not unique, as can be seen from the plot of monthly precipitation for January over period 1950–2024 by data of Sevastopol weather station (Fig. 3). To identify similar situations over the historical period, the RX5day index was used, which is calculated as the maximal amount of precipitation over 5 consecutive days (mm) in the period of interest (in this case, one month) [30].

An analysis of the series of total monthly precipitation in January in Sevastopol in different years shows that such cases have been observed before. In 1951, 43 mm of precipitation fell from January 20 to 23; in 1953 and 1957, >60 mm fell in January; in 1959, ~80 mm fell; in 1960, >48 mm fell from January 9 to 12; in January 1968, >117 mm fell, in that period, 25 days in January were rainy. As can be seen from Fig. 3, the situations when the amount of precipitation over several days in January was near the norm or more are not rare, and should be forecasted.

Mean monthly forecasts in the Black Sea region, including Crimea, have been already made with the use of a unidirectional heteroassociative NN with one hidden layer [8, 20]. Predictors for the model were sets

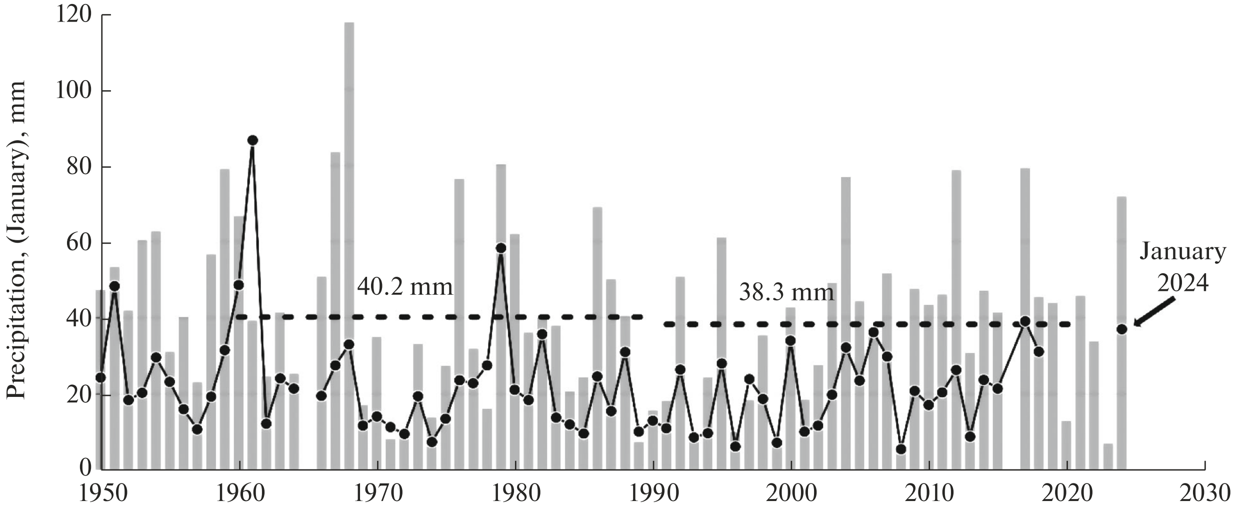

Fig. 3. Long-term variations of (gray columns) precipitation totals and (full black line) RX5day index in January by weather data on Sevastopol over 1950–2024. The dashed line shows the mean annual precipitation over periods 1961–1990 and 1991–2020.

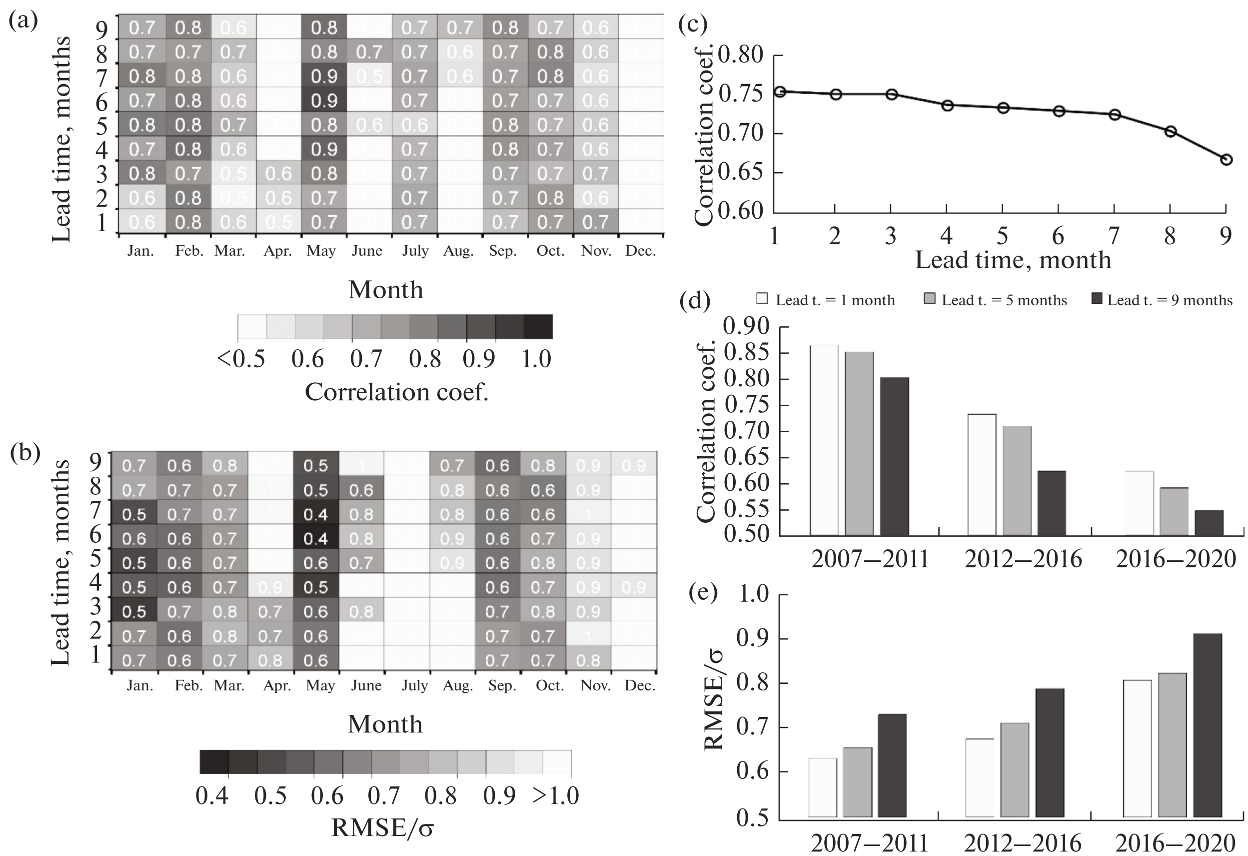

Fig. 4. Estimates of the model ability to forecast cases with extreme precipitation with the use for the test period of 2007–2020 of (a, b) diagram of the dependence of the simulation quality on the simulated month and the forecast lead time; (c) variations of the correlation coefficient as a function of the lead time; (d, e) variations of the simulation quality for three time periods in the test sample for the case of the lead time of 1, 5, and 9 months.

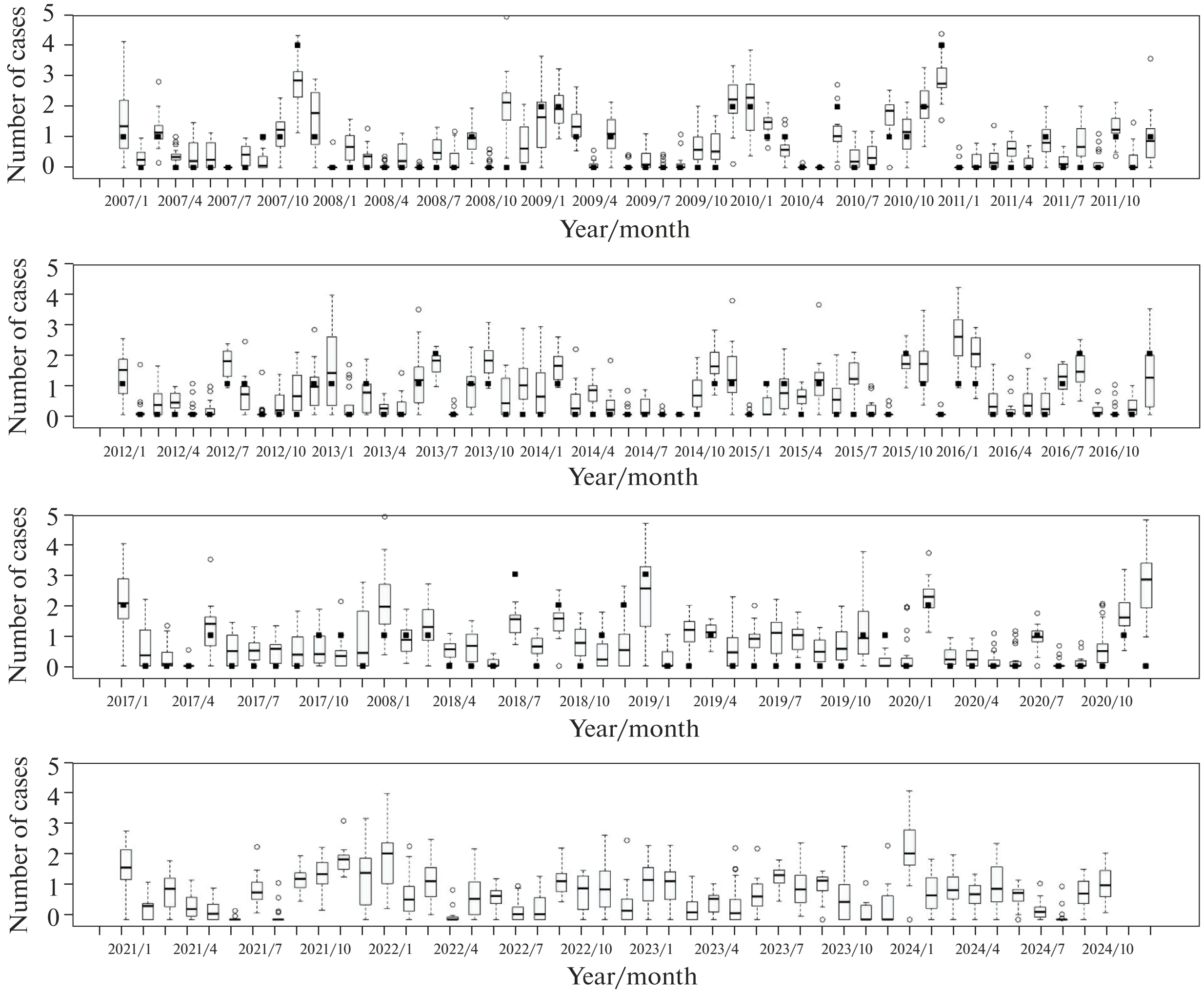

Fig. 5. Block diagrams for 20 best simulation results with a forecast lead time of 3 months on a test smple of 2007–2024. The cases with precipitation above 40 mm over three consecutive days are given by black dots (for 2020).

of indices of global climate signals of the ocean–atmosphere system. Maslova et al. [20] used such a model to forecast the frequency of intense cyclones in the Black Sea region with a lead time of up to 6 months, and Lubkov et al. [8] used it to forecast precipitation in Ai-Petri area. In this study, we will apply the architecture of a model based on NN from studies [8, 20] with changes in configuration described below.

Figure 4 gives estimates of the model's ability to forecast cases with precipitation >40 mm over three consecutive days with a lead time of up to 9 months over a reference period 2007–2020. As can be seen from Figs. 4a, 4b, only for December, the modeling results are not statistically significant with any lead time. A regular feedback can be seen on the plot of the dependence of the correlation coefficient on the forecast lead time (Fig. 4c). It is also worth mentioning that the coefficient of correlation decreases and RMSE/σ increases (Fig. 4d, 4e) with the distance from the test sample (1988–2006), which was involved in the simulation process for determining the moment of maximum learning (the procedure is described in detail in [8]). Therefore, we note that the model is non-stationary and, therefore, requires recalculation every 5 years.

Figure 5 gives the results of simulation of cases with precipitation >40 mm over three successive days in the form of block diagrams over period 2007–2024, including the check sample, which have been constructed based on 20 best NN structures. In most cases, the model finds extreme months, when there were not less than 2 cases of excess of 40-mm precipitation threshold over 3 consecutive days. Thus, in November 2007, 4 cases were recorded, while the average model estimation is 3; in December 2010, 4 cases were recorded, and the model showed 3; in July 2018, 3 cases were recorded, and the model showed variation from 1 to 2 (at the long-term mean of 0.3 cases); in January 2019, 3 cases were recorded, and the model showed scatter from 1 to 3. At the same time, in 2007–2024, there were 14 months in which 2 cases of excess over the threshold of 40 mm were recorded in 3 consecutive days. For 10 out of 14 months, the model adequately reproduces the case of exceeding of the precipitation threshold. For four months, the number of simulated cases was underestimated.

An event that occurred in the Sevastopol region in January 2024 attracted special attention of the authors of the study. The proposed model could forecast the emerged climate anomaly. An advance model forecast showed the occurrence in January 2024 of two cases of exceedance of the threshold of 40 mm of precipitation over 3 consecutive days. In the described cases, extreme precipitation that fell over a short time period led to the rapid filling of mountain river beds, water level rise, and, as a consequence, intensification of erosion processes. As the river channels of the mountainous Crimea have considerable slopes, their flows have a high eroding capacity and can transport large amounts of sediments of different sizes [6, 11].

CONCLUSIONS

The complex orographic conditions in the Crimean Peninsula, the observed rise of air temperature and the characteristics of extreme precipitation in the Mountainous Crimea form favorable conditions for the formation of floods having a catastrophic character.

The catastrophic hydrological–environmental situation that formed in January 2024 in the Sevastopol Region as a result of three days of abundant precipitation preceding the formation of strong erosion processes is not unique. Such conditions recur on an interannual–interdecadal scale and require high-quality forecasting.

A study of the possibility to forecast extreme precipitation in the Mountainous Crimea with the use of an artificial NN model showed the following: all anomalous months with ≥3 cases of exceedance of a 40-mm precipitation threshold in 3 consecutive days were correctly forecasted with a ≥3 months lead time on the test sample. Ten out of the fourteen months, when two cases of exceedance of 40-mm precipitation threshold within 3 consecutive days were recorded, were successfully forecasted with a 3 months lead time. The correlation coefficient and the forecast lead time are inversely correlated. The coefficient of correlation decreases and RMSE/σ increases on the control sample as its difference from the test sample increases, which indicates the non-stationarity of the model. This implies the need to update the data of the training control sample by recalculation for the next 5 years.

The results of studying the model on a check sample suggest the conclusion that it can be used for control and prevention of hazardous natural phenomena (floods, mudflows), caused by extreme precipitation falling within 2–3 successive days, with a need to recalculate the computation block every 5 years.

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CONFLICT OF INTEREST

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

REFERENCES

1. Aleshina, M.A. and Semenov, V.A., Variations of precipitation characteristics in the Russian territory in the XX–XXI centuries based on data of CMIP6 model ensemble, *Fundam. Priklad. Klimatol.*, 2022, vol. 8, no. 4, pp. 424–440.
2. Voskresenskaya, E. and Vyshkvarkova, E., *Ekstremal'nye osadki v Ukraine i global'nye klimaticheskie protsessy* (Extreme Precipitation in Ukraine and Global Climate Processes), Saarbrucken: LAP LAMBERT Acad. Publ., 2014.
3. *Gidrogeologiya SSSR* (USSR Hydrogeology), vol. VIII, *Krym* (Crimea), Sidorenko, A.V., Ed. in Chief, Moscow: Nedra, 1970.
4. Zemlyanskova, A.A., Makar'eva, O.M., Nesterova, N.V., and Fedorova, A.D., Modeling the runoff formation of the Derekoika mountain river (Crimean Peninsula), *Sbor. dokl. mezhdunarod. nauch. konf. pamyati Yu.B. Vinogradova "Chetvertye Vinogradovskie chteniya. Gidrologiya ot poznaniya k mirovozzreniyu"* (Collection of Reports of International Scientific Conference in Memory of Yu.B. Vinogradov "Fourth Vinogradov Readings. Hydrology from Knowledge to Worldview"), St. Petersburg, 2020, pp. 78–83.
5. Kovalenko, O.Yu., Bardin, M.Yu., and Voskresenskaya, E.N., Changes in the characteristics of air temperature extremity in the Black Sea region and their variations in the context of large-scale climate processes of interannual scale, *Fundam. Priklad. Klimatol.*, 2017, vol. 2, pp. 42–62.
6. Kuksina, L.V., Golosov, V.N., Zhdanova, E.Yu., and Tsyplenkov, A.S., Hydrological-climatic formation factors of extreme erosion events in the Mountain Crimea, *Vestn. Mosk. Univ. Ser. 5, Geografiya*, 2021, no. 5, pp. 36–50.
7. Lubkov, A.S., Voskresenskaya, E.N., and Marchukova, O.V., A new approach to neural network use for long-term forecast of El Niño and La Niña, *Fundam. Priklad. Klimatol.*, 2023, vol. 9, no. 4, pp. 432–466. https://doi.org/10.21513/2410-8758-2023-4-432-466
8. Lubkov, A.S., Voskresenskaya, E.N., and Sukhonos, O.Yu., Forecast of precipitation in Ai-Petri

area based on artificial neuron network model, *Water Resour.*, 2022, vol. 49, no. 4, pp. 671–679.

9. Mikhailov, V.N. and Dobrolyubov, S.A., *Gidrologiya* (Hydrology), Moskva; Berlin: Direkt-media, 2017.
10. Oliferov, A.N. and Timchenko, Z.V., *Reki i ozera Kryma* (Rivers and Lakes of Crimea), Simferopol: Dolya, 2005.
11. Pavlov, I.N., Crimean rivers: channel processes and their environmental estimate, *Vestn. Mosk. Univ.*, Ser. 5, *Geografiya*, 1994, no. 3, pp. 76–82.
12. *Sovremennoe sostoyanie beregovoi zony Kryma* (The Current State of the Crimean Coastal Zone), Goryachkin, Yu.N., Ed., Sevastopol: EKOSI-Gidrofizika, 2015.
13. Aksoy, H. and Dahamsheh, A., Artificial neural network models for forecasting monthly precipitation in Jordan, *Stoch. Environ. Res. Risk Assess.*, 2009, vol. 23, pp. 917–931.
14. Deo, R.C. and Şahin, M., Application of the artificial neural network model for prediction of monthly standardized precipitation and evapotranspiration index using hydrometeorological parameters and climate indices in eastern Australia, *Atmos. Res.*, 2015, vol. 161–162, pp. 65–81.
15. Haidar, A. and Verma, B., Monthly rainfall forecasting using one-dimensional deep convolutional neural network, *IEEE Access.*, 2018, vol. 6, pp. 69053–69063.
16. Hoeffding, W., A non-parametric test of independence, *Ann. Math. Stat.*, 1948, vol. 19, pp. 293–325.
17. *IPCC 2021. Climate Change 2021: The Physical Science Basis. Contribution of Working Group I to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change*, Masson-Delmotte, V., Zhai, P., Pirani, A., Connors, S.L., Péan, C., Berger, S., Caud, N., Chen, Y., Goldfarb, L., Gomis, M.I., Huang, M., Leitzell, K., Lonnoy, E., Matthews, J.B.R., Maycock, T.K., Waterfield, T., Yelekçi, O., Yu, R., Zhou, B., Cambridge: Cambridge Univ. Press, 2021. In Press.
18. Kendall, M.G., A new measure of rank correlation, *Biometrika*, 1938, vol. 30, pp. 81–93.
19. Lu, W., Chu, H., and Zhang, Z., Application of generalized regression neural network and support vector regression for monthly rainfall forecasting in western Jilin Province, China, *J. Water Supply: Res. Technol.-Aqua*, 2014, vol. 64, no. 1, pp. 95–104.
20. Maslova, V.N., Voskresenskaya, E.N., Lubkov, A.S., Yurovsky, A.V., Zhuravskii, V.Y., Evstigneev, V.P., Intense cyclones in the Black Sea Region: change, variability, predictability and manifestations in the storm activity, *Sustainability*, 2020, vol. 12, no. 11, p. 4468.
21. Mekanik, F., Imteaz, M.A., Gato-Trinidad, S., and Elmahdi, A., Multiple regression and artificial neural network for long-term rainfall forecasting using large scale climate modes, *J. Hydrol.*, 2013, vol. 503, pp. 11–21.
22. Moustris, K.P., Larissi, I.K., Nastos, P.T., and Paliatsos, A.G., Precipitation forecast using artificial neural networks in specific regions of Greece, *Water Resour. Manage.*, 2011, vol. 25, pp. 1979–1993.
23. Nagahamulla, H.R.K., Ratnayake, U.R., and Ratnaweera, A., Monsoon rainfall forecasting in Sri Lanka using artificial neural networks, *Proc. 6th Int. Conf. Ind. Inf. Syst.*, 2011, pp. 305–309.
24. Shukla, R.P., Tripathi, K.C., Pandey, A.C., and Das, I.M.L., Prediction of Indian summer monsoon rainfall using Niño indices: A neural network approach, *Atmospheric Res.*, 2011, vol. 102, nos. 1–2, pp. 99–109.
25. Singh, P. and Borah, B., Indian summer monsoon rainfall prediction using artificial neural network, *Stoch. Environ. Res. Risk Assess.*, 2013, vol. 27, pp. 1585–1599.
26. Voskresenskaya, E. and Vyshkvarkova, E., Extreme precipitation over the Crimean Peninsula, *Quaternary Int.*, 2016, vol. 409, pp. 75–80.
27. Vyshkvarkova, E., Changes in extreme precipitation over the North Caucasus and the Crimean Peninsula during 1961–2018, *IDŐJÁRÁS*, 2021, vol. 125, no. 2, pp. 321–336.
28. Vyshkvarkova, E., Voskresenskaya, E., and Martin-Vide, J., Spatial distribution of the daily precipitation concentration index in Southern Russia, *Atmos. Res.*, 2018, vol. 203, pp. 36–43. https://doi.org/10.1016/j.atmosres.2017.12.003
29. Zhang, M., Su, B., Nazeer, M., Bilal, M., Qi, P., and Han, G., Climatic characteristics and modeling evaluation of pan evapotranspiration over Henan Province, China, *Land*, 2020, vol. 9, no. 7, p. 229.
30. Zhang, X. and Yang, F., *RClimDex (1.0) User Guide*, Climate Research Branch Environment. Ontario: Climate Res. Branch Environ. Canada, 2004.