FLOOD PREDICTION AND SUSCEPTIBILITY MAPPING USING DEEP LEARNING AND GEOSYSTEM APPROACH

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ABSTRACT

The article is devoted to solving the problem of flood prediction and susceptibility mapping. A test site on the territory of Russia, including the flood plain of the Pechora River, was chosen as the study area. The relevance of the approach presented in the article lies in the application of deep machine learning technologies and the geo system approach to the analysis of geo spatial data. The task of collecting historical data necessary to predict the susceptibility of the territory to flooding during the spring flood was solved, which makes it possible to predict flooding of territories in order to make decisions necessary to ensure the safety of life and health of the population, as well as territories from flooding. The presented Flood NET model takes as input data about the territory during the low-water period and historical meteorological observations and predicts the susceptibility of the territory to flooding. The model achieves an accuracy of 92%, its increase is influenced by the informativeness of the analyzed geo informational model and the quality of the model fine-tuning.

KEYWORDS: Deep Learning, Flooding, Flood Susceptibility, Geosystems, Machine Learning, Natural-Social-Production Systems

INTRODUCTION

Currently, one of the necessary conditions for making effective decisions in managing complex objects is the timely development of advanced management decisions based on predictive assessments of the state of this object. One of the important tasks of managing complex objects of great economic and social importance is to prevent the negative consequences of floods. The main difficulties in solving the problems of forecasting the passage of a flood are associated with the complexity of collecting initial data, their insufficient availability, insufficient knowledge of the mechanisms that determine the dynamics of changes in water levels in different parts of the region, as well as a number of other reasons. The purpose of this article is to solve the problem of predicting the susceptibility of an area to flooding based on spatial and temporal data, including retrospective meteorological observations, digital elevation models, and Earth remote sensing data.

In modern conditions, the solution to the problem of forecasting floods is possible on the basis of an experimental study of systemic relationships and regularities of the functioning and development of natural-social-production systems (NSPS) with the subsequent development of new high-precision algorithms for predicting the development of spatio-temporal processes based on the analysis of large arrays of retrospective, current and expert digital SDI data with complex application of deep neural networks.
The test site bounded by coordinates 66.596935N and 67.628850N from the south to north, 51.046486E and 53.278371E from the west to east was chosen as the object of research. The key object under analysis is the Pechora, a river in the Komi Republic and the Nenets Autonomous Okrug of Russia, which originates in the Northern Urals, in the southeastern part of the Komi Republic, and flows mainly to the southwest. Length - 1809 km, basin area - 322 thousand km². The height of the source is 675 m above sea level. From the source to the mouth of the river Unya Pechora has a mountainous character. The river is fed by mixed, with a predominance of snow. High water begins in late April - early May, maximum - in mid-May in the middle and lower reaches until early June. Summer and winter - low water. Summer low-water period – from mid-July to August, is often interrupted by rainfloods. The average annual water discharge at the mouth is 4100 m³/s. Freezes in late October; the opening occurs from the head waters and is accompanied by ice jams.

RELATED WORK

The development and experimental substantiation of new geoinformation methods and algorithms for automated analysis of spatial data (space images, digital models and maps, attributive spatio-temporal information) for the purpose of analyzing the state of lands and predicting natural and man-made emergencies is an urgent challenge of our time. Algorithms for automated analysis of large arrays of spatio-temporal data and software systems functioning on their basis are becoming an integral component of digital infrastructures of spatial data.

In the past two decades, the practical role of deep machine learning, methods and principles that use multiple layers of nonlinear data processing to extract and transform features, analyze and classify patterns, have been strengthened. Using deep learning allows you to reduce the cost of research due to the possibility of accurate interpolation and extrapolation of measurements [Bengio et al., 2007]. While in the analyzed problem area the largest number of publications is devoted to the use of recurrent and convolutional neural networks, as well as autoencoders, other deep models are also used to solve many problems [Kim et al., 2019]. A good result can be obtained only with the parallel improvement of deep model architectures and algorithms for the optimal enrichment of training data sets. The actual direction is the solution of this problem on the basis of the geosystem approach, which is based on the hypothesis that the geographic envelope, landscape sphere, population and environment, economic sectors, territorial-production complexes are intertwined with internal, deep relationships, on the basis of which conclusions about the origin are drawn and the state of the object [Yamashkin, 2018].

From the standpoint of the geosystem approach, the state and properties of each territorial unit are determined by: the peculiarities of its interaction with neighboring objects of the same hierarchical level, the characteristics of the enclosing geospatial system of a higher hierarchy level, as well as the interaction of objects of a lower hierarchy level that make up the analyzed territory [Sochava, 1982].

Based on this, it is possible to formulate a hypothesis that the accuracy of land classification based on remote sensing data can be increased if the classifying model takes into account and analyzes not only the properties of a particular territory, but also the characteristic features of geosystems with which it interacts, and, in particular, in which she enters. From the standpoint of the geosystem approach, the properties of the territory are significantly influenced by the enclosing geosystem (neighborhood). Remote sensing data are an informative source of information about it [Schowengerdt et al., 2006]. Not only remote sensing data of a certain scale can characterize geosystems of different hierarchical levels; this role can be successfully assigned to digital elevation models, meteorological maps, and spatial models of glaciation.
METHODS OR METHODOLOGY

To effectively solve the problem of predicting water levels during the spring flood, the following tasks were set and consistently solved: revision and data collection, preliminary preparation, development of a deep neural network model, analysis and assessment of the accuracy of the generated model, creation of a hierarchical model of the resulting raster in order to visualize the results within the framework of responsive web interfaces. The study was carried out on the basis of the hypothesis that the task of predicting the flooded area during the spring flood can be effectively solved by working out 3 control points: information about solar activity and permafrost, etc.; 2) development of a deep neural network model for analyzing data on the geosystem model of the territory; 3) the introduction of geoportal systems for visualizing the results of machine analysis in order to provide information support for making balanced management decisions in the field of organizing sustainable development of territories and predicting natural processes. Analysis of the problem area showed that for effective forecasting of the susceptibility of a territory to flooding in northern latitudes, it is advisable to form a geoinformation model based on the following data layers: digital elevation model, data on permafrost and ground ice conditions, Earth remote sensing data, meteorological and climatic observations (Table 1).

<table>
<thead>
<tr>
<th>ID</th>
<th>Data Category</th>
<th>Data Source</th>
<th>Data Role</th>
</tr>
</thead>
<tbody>
<tr>
<td>E1</td>
<td>Digital Elevation Model</td>
<td>ASTER Global Digital Elevation Map</td>
<td>The source of information about the terrain is the main geomorphometric component. Formation of the surface model.</td>
</tr>
<tr>
<td>E2</td>
<td>Digital Elevation Model</td>
<td>USGS.gov (United States Geological Survey)</td>
<td></td>
</tr>
<tr>
<td>E3</td>
<td>Rosreest data: topographic maps (Interpolated raster model)</td>
<td></td>
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<tr>
<td>G1</td>
<td>Data on permafrost and ground ice conditions</td>
<td>National Snow and Ice Data Center</td>
<td>Identifying patterns between permafrost conditions and the potential for flooding an area</td>
</tr>
<tr>
<td>R1</td>
<td>Remote Sensing Data</td>
<td>United States Geological Survey</td>
<td>Revealing the relationship between the type of vegetation and flood resistance, the formation of target values</td>
</tr>
<tr>
<td>R2</td>
<td>Remote Sensing Data</td>
<td>Copernicus Open Hub</td>
<td></td>
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<tr>
<td>M1</td>
<td>Meteorological and Climatic Data</td>
<td>Meteorological station data, open internet portals</td>
<td>Revealing the relationships between the accumulation of precipitation and snow cover, changes in solar activity, climatic transformations and the potential of the territory to flooding</td>
</tr>
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</table>

We collected data on the test site under study for three years of observations. Sentinel-2 satellite imagery data was taken on the dates of maximum river flooding: 2020-05-25, 2019-05-31, 2018-06-05. We also took a survey of the territory during the low water period (2019-08-21). The channels of the red, green and blue spectrum, as well as the near infrared range, were selected for analysis. These ranges are most informative when analyzing vegetation cover, the outer visible part of the landscape envelope.

Due to the fact that the investigated test site is located in northern latitudes, data from the National Snow and Ice Data Center were collected on the conditions of permafrost and ground ice. ASTER Global Digital Elevation Map data was selected as a digital elevation model. Since these data are not characterized by sufficient spatial resolution, they were detailed by means of biharmonic spline interpolation, in which unknown points of the surface are reconstructed using the formula:
Impact Factor (JCC): 8.8746  SCOPUS Indexed Journal  NAAS Rating: 3.11

\[ s(x) = \sum_{j=1}^{N} c_j g(x, x_j) \]  

(1)

Where \( g(x_i, x_j) \) – Green’s function, which can be calculated as:

\[ g(x_i, x_j) = |x_i - x_j|^2 (\ln |x_i - x_j| - 1) \]  

(2)

The N parameter indicates the number of points used for interpolation. Finally, retrospective data on meteorological conditions (temperature and precipitation) of the test site were collected with a time resolution of one week.

Thus, it was decided to design a Flood NET deep learning model that has three inputs. The first input is the data on the analyzed point of the territory during low-water periods - its spectral characteristics, data on the height, and the content of ground ice. A three-dimensional matrix is fed to the second input, which characterizes, under the same conditions, a neighborhood with a side of 31 pixels at a spatial data resolution of 20 meters per 1 pixel. The geoinformation model of the host geosystem is built on the basis of the layers presented above. Finally, the third input of the model is a time series of weather observations. All data were normalized before training the deep neural network model; in total, 20,000 training samples were prepared. The general structure of the Flood NET model with decomposition into blocks of the top level of the hierarchy is shown in Figure 1.

![Figure 1: The General Structure of the Deep Flood NET Model.](image)

To generate target data that will be used in training the Flood NET model to predict the susceptibility of an area to flooding, satellite imagery of the area during the flood period was used. First, NDWI - Normalized difference water index was calculated using the Sentinel-2 database by means of the following formula:

\[ NDWI = \frac{\alpha x_{\text{green}} - \beta x_{\text{NIR}}}{\alpha x_{\text{green}} - \beta x_{\text{NIR}} - \text{bias}} \]  

(3)

Where \( \alpha, \beta, \text{bias} \) – calibration coefficients, \( x_{\text{green}} \) – reflective characteristic of the territory in the green spectrum, \( x_{\text{NIR}} \) – near infrared. Then the class of the territory during the flood is determined by the formula:

\[ \text{class} = (NDWI > 0) \? 1 : 0 \]  

(4)

After the automated calculation of the binary target coefficient, a manual expert adjustment of the result was carried out. Let's move on to decomposing the Flood NET model. Figure 2 shows Feed forward and Completive Units representing feed forward neural networks using fully connected layers [Hu et al., 2009]. The first module solves the problem of analyzing data about the point under study, and the second one makes the resulting solution after combining the outputs of the previous modules. The number of fully connected layers of a multilayer perceptron and their power are selected according to the principle of minimizing these parameters while maintaining sufficient classification accuracy. In addition, to solve the problem of retraining, it was decided to use batch normalization and dropout to the outputs of the
fully coupled layer. To activate the output of the input and hidden layers, a rectified linear unit is selected, for the output layer – sigmoid for the binary classification solved in our problem.

To extract features from data about the neighborhood, the Conv Unit block was introduced, which separates hierarchical features of various levels from the analyzed matrix (Figure 3). The structure of each block represents a chain of layers. The first layer, performing the operation of deep separable convolution [Chollet et al., 2017], allows you to extract features from the original image and, in contrast to using a conventional convolutional layer, allows you to make the deep model more compact and, accordingly, resistant to overfitting [LuCun et al., 2015].

The underlying operation of the layer is a two-dimensional convolution operation with a kernel $W$ of size $K$ represents a linear transformation in which each value $y_{i,j}$ of the output matrix $Y$ is calculated based on the $x$ values of the original matrix $X$ according to the following expression:

$$y_{i,j} = W * X = \sum_{a=0}^{K-1} \sum_{b=0}^{K-1} W_{a,b} x_{i+a,j+b}$$  (5)

The batch normalization layer made it possible to achieve regularization and model stability. A rectified linear unit was selected to perform the activation. At the end of the feature extraction block is a subdecritization layer that reduces the size of the resulting representations by taking a maximum. Figure 4 shows the module for analyzing historical data on meteorological conditions. It has a similar structure to the Conv Unit, but it uses a one-dimensional, depth-separable convolution, and the resulting processing is done by a fully connected layer.
The final decision on predicting the coefficient of the territory's susceptibility to flooding is made by the Complete Unit shown in Figure 2. When training the Flood NET model, the Root Mean Square Propagation algorithm based on the stochastic gradient descent method is used as an optimizer, and cross entropy is used as a loss function. From the point of view of the black box, the deep Flood NET model based on the application of the geosystem approach is a functional element that accepts data on the territory and its surroundings during the low-water period and predicts the susceptibility of the territory to flooding under specific historical meteorological observations. Point-to-point analysis of the test area allows you to build a Flood susceptibility map of the study area (Figure 5). The designed model made it possible to achieve an accuracy of 92% when solving the problem described above, and the integrated use of all layers from Table 1 made it possible to increase the accuracy by 8% relative to the indicators achieved using only traditional space survey materials. Flexible tuning of the Flood NET model hyper parameters provided an initial increase in accuracy of 6%.

The software implementation of the model is written in Python, the initial data were prepared using the SNAP 7.0 software package.

RESULTS

Based on the research presented in the article, the following conclusions can be drawn.
The main value of the approach presented in the article to the analysis of geospatial data by means of deep machine learning for predicting the susceptibility of an area to flooding is to use the geosystem approach to form a capacious geosystem model of the area and develop a deep Flood NET model that can effectively analyze this data.

The task of collecting historical data necessary to predict the resilience of the territory to flooding during the spring flood was solved, which makes it possible to predict flooding of territories in order to make decisions necessary to ensure the safety of life and health of the population, as well as territories from flooding.

The Flood NET model accepts data on the territory and its surroundings during low-water periods as input and predicts the susceptibility of the territory to flooding under specific historical meteorological observations. The model achieves an accuracy of 92%, its increase is influenced by the informativeness of the analyzed geo information model of the territory and the quality of setting the model hyper parameters.

ACKNOWLEDGEMENTS

The reported study was funded by RFBR, project number 20-37-70055.

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