The use of convolutional neural networks to forecast the dynamics of spreading forest fires in real time[1]

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Abstract

This work focuses on the relevant task of increasing the efficiency of forecasting the dynamics of forest fires spreading in real time. To address the problem, it was proposed to develop a method for operational forecasting the forest fire spread dynamics in the context of unsteadiness and uncertainty based on some advanced information technologies, i.e. artificial intelligence and deep machine learning (the convolutional neural network). As part of the research, both domestic and foreign models for the spread of forest fires were evaluated, and the key limitations of using models in real fire conditions were identified (high degree of dynamism and uncertainty of input parameters, the need to ensure minimum collection time and input parameters, as well as minimum response time of the model). Based on the data obtained, the need to use artificial neural network tools to solve the problem of predicting the forest fire's spread dynamics was substantiated. A general logic diagram of the method for forecasting the forest fire dynamics in real time has been developed, the main feature of which is the construction of a tree of convolutional neural networks. To enhance the quality of learning convolutional neural networks that implement the function of predicting the spread of forest fires, we propose to create a database of forest fire dynamics.

Key words: forest fire; database; visual data; artificial intelligence; deep machine learning; convolutional neural network; big data; real-time forecasting.

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Introduction

The significant negative effect from forest fires for the Russian Federation is clearly confirmed by statistics from the Federal Forestry Agency (Rosleskhoz), as presented in the Unified Interdepartmental Statistical Information System(UISIS)[1]. According to the statistics from 2009 to 2017, there was a 27.92% increase in the forest land covered by forest fires. From 2013 to 2017, the growth of expenses related to the protection and restoration of forest area of the Russian Federation was 22.32%. At the same time, the aforementioned trend data comes against the background of a decrease in the total number of forest fires in the country.

According to the European forest fire statistics presented by the European Forest Fire Information System (EFFIS) [1], from 2009 to 2016 there was a 39.8% decrease in the total number of forest fires in the five southern member states of the European Union (Portugal, Spain, France, Italy and Greece). There was also a 4.6% decrease in the total forest area covered by forest fires in those countries. However, the total forest area covered by forest fires in 2016 was 316,866 hectares, which is higher than in previous years (from 2013 to 2015), and the number of forest fires was 31,751, which is lower than the long-term average values and is slightly lower than that in the previous year of 2015 (38,171 fires) but higher than in 2014 (23,425 fires).

According to the forest fire statistics in the United States of America, presented by the National Centers for Environmental Information of the National Oceanic and Atmospheric Administration (NCEI NOAA)[2], the number of fires decreased by 14.5% from 2009 to 2017, and the forest area covered by forest fires increased by 65.4%.

Although statistics vary considerably from year to year (which clearly shows how forest fires depend on seasonal meteorological conditions), the global forest fire statistics show similar dynamics, i.e. a decrease in the number of forest fires, an increase in the number of areas affected by forest fires, and an increase in the material expenses associated with forest fires.

Thus, it is extremely important for both the Russian Federation and other states to prevent, localise and eliminate forest fires.

One of the most important elements in addressing the problem is forecasting the forest fire spread in a real-time mode. Currently, it is not easy to use existing models for predicting the forest fire dynamics in difficult real fire conditions due to the limited functionality of models in the unstable and uncertain contexts.

The study is aimed at developing a method of forecasting of the forest fire dynamics in real time and in complex environments (with uncertainty and instability) by using artificial intelligence and deep machine learning. To achieve this goal it is necessary:

✦ to justify the need to use artificial neural network tools to predict the forest fire spread dynamics;

✦ to develop a common logic for the method of forecasting the forest fire dynamics in real time;

✦ to create a visual database on the forest fire dynamics.

This work is part of a research project to identify the fundamental dependencies of the influence of environmental factors, the nature of forest plantations and the type of fire on the forest fire dynamics.

[2] https://www.fedstat.ru/organizations/
[3] https://www.ncdc.noaa.gov/sotc/

1. Convolutional neural network as an advanced tool for the forest fires spread forecasting in real time

According to [2], it is quite a challenge to simulate a fire in a forest due to two main reasons: the extreme complexity of the physical phenomenon (fire) due to heterogeneous fuel and many influencing environmental factors (wind, relative humidity etc.), and the difficulty of carrying out real experiments to validate the models developed.

Currently, both domestic and foreign researchers representing various fields of science have developed an extensive set of models based on various methods for predicting the fire's behaviour in order to minimise the destructive consequences of this natural emergency [3–5].

In studying the models for forecasting the forest fire's spread, models are distinguished in terms of modelling into real-time, tactical and strategic models [6]. Since each modelling level is characterised by a specific goal and an appropriate level of management decisions, each level corresponds to its model type; e.g. real-time models are designed for the real-time level, tactical ones for the tactical level and strategic ones for the strategic level.

It is common to single out the following key areas of forest fire modelling. [3–6]:

✦ empirical and quasi-empirical models based on the statistical findings of experimentally obtained data to determine the statistical dependencies between the input and output parameters;

✦ physical and quasi-physical models based on the fundamental chemistry and/or physics methods for describing the processes occurring during a forest fire;

✦ mathematical models (including simulation and wave models) that use formulas to describe the fire dynamics, in some cases, with statistical data.

In addition, according to the method for displaying the forest fire modelling results, existing models can be divided into spatial and non-spatial ones. Also, depending on the availability or unavailability of random variables among the model parameters, they distinguish between deterministic and stochastic prediction models. Since forest fires are characterised by complex conditions (uncertainty and instability), stochastic models are most promising.

The works [3–5] present the results of analysing the key types of forest fire distribution models (empirical and quasi-empirical, physical and quasi-physical, mathematical and imitation) developed from 1990 to 2007. In the work [7] in-depth research was undertaken into a 3% model, the quasi-empirical Rothermel model, Balbi model and Balbi non-stationary model. The works [8, 9] focus on various models for forest fire forecasting, i.e. a mathematical model for the escalation of surface forest fire and/or scrub fire, in which complete trees burn, and a discrete forest fire model on the upper half-plane.

Some of the models considered are integrated into computer systems and are commonly used in practice. For example, in the Prometheus[4] and FlamMap[5] forest fire forecasting systems, wave fire models are applied, where the combustion process is described with the Huygens principle [6, 10], and the fire propagation rate is calculated with experimental data. The use of the Van Wagner model and the quasi-empirical Rothermel model is based on a fire forecasting system such as FARSITE[6] [2].

[4] http://firegrowthmodel.ca
[5] https://www.firelab.org/project/flammap
[6] https://www.firelab.org/project/farsite

However, despite the wide variety of models for predicting forest fire escalation dynamics, during analysis of the reference sources, which consider the features and functionality of all types of models [2–15], we see limitations, which significantly affect the forecast accuracy, as follows:

✦ a high degree of dynamic input parameters (the parameters dynamically changing in time are considered as constant);

✦ a significant degree of uncertainty of the input parameters (inability to obtain a series of data by direct measurement).

In addition, the time used to collect and enter the input data as well as the response time of the model have a significant impact on the ability to use models in a real fire environment. When minimised, these time characteristics pose a critical problem in developing and using models in practice.

The recent breakthrough in the field of information technology, which has promoted the emergence and active improvement of promising technologies – artificial intelligence, big data processing systems, and deep machine learning – have created unprecedented opportunities to improve the fire safety of forests.

Nowadays, both the models for forecasting the forest fire breaking-out and models for forecasting the fire spread dynamics based on neural network technologies already are available (for example, the works [16, 17]). Although models which use artificial neural networks can eliminate a number of drawbacks inherent in traditional models, the construction and practical application of models based on neural network technologies can be associated with some challenges. First of all, it should be noted that it is a challenge to collect a sufficient number of training examples in preparing test and training data sets. In addition, the network architecture construction can be characterised by complexity and labour intensity, and the network training procedure is time-consuming.

Taking into account the above disadvantages, we proposed to develop a method for forecasting the forest fire spread dynamics in real time in case of non-stationarity and uncertainty with a convolutional neural network (CNN). The convolutional neural network, being a multi-layered neural network, is part of the deep learning technology and addresses the problem of pattern recognition from visual data [18, 19]. The features of the construction and operation of convolutional neural networks are described in detail in the work [18, 19].

The choice of a convolutional neural network is due to the advantages of the type of networks revealed as a result of analysis of both domestic and foreign sources [18, 19]. They are highly accurate, resistant to changes and input data distortions, real-time, capable of performing self-tuning, allow for paralleling high performance computing etc. In addition, although convolutional neural networks are commonly used to solve recognition and classification problems (for the classification of images, automatic speech recognition etc.), they can also be used for forecasting due to their indisputable advantages.

The use of a convolutional neural network for forecasting the forest fire spread dynamics in real time makes it possible to generate a forecast in complex environments (with uncertainty and non-stationarity) and minimise time input due to paralleling high-performance computing. Thus, a convolutional neural network is an effective tool for obtaining a forest fire spread forecast in real time in the case of application in real environments.

2. Forecasting the forest fire dynamics in real time under non-stationary and uncertain conditions with a convolutional neural network

During the research, a method for forecasting the forest fire dynamics in real time under the conditions of non-stationarity and uncertainty was developed. A feature of the proposed method is to identify the dependencies of the influence of environmental factors, the nature of forest plantations and the type of forest fire on the forest fire dynamics with a convolutional neural network.

According to the works [18, 19], the idea of a CNN network is to implement a sequence of transitions from specific features of the visual input data to more abstract ones. The CNN network architecture can be characterised by alternating convolution layers and subsampling layers. The main purpose of the convolutional network layers is to implement the convolution operation with the subsequent creation of a feature map. Subsampling layers of the network can reduce the dimensionality of the previously created feature maps by selecting the maximum neuron from a number of neighbouring neurons of the map and replacing the given neuron with the entire considered set of neurons. Fully connected layers are used as the output layer of neurons in the CNN network, where a fully connected neural network is created.

To develop a convolutional neural network in order to generate a forest fire forecast in real time, CPython software is proposed to use. At the same time, the fire spread information obtained in real time for three hours from a satellite with a moderate-resolution spectroradiometer (36-channel spectroradiometer MODIS, Terra and Aqua satellites) and a visible infrared X-ray diffraction set (VIIRS) were used as the input visual data.

From 1999 to the present, MODIS has been one of the most widely used satellite tools for conducting global and regional research [20]. MODIS can be used to view the entire surface of the Earth every one or two days in 36 spectral bands at moderate resolutions ranging from 0.25 km to 1 km to obtain a data set (land and ocean surface temperatures, vegetation indices, land cover data, forest fires, volcanoes, clouds, aerosols etc.) [20]. VIIRS[7] is a 22-channel radiometer that collects images in the visible, infrared and ultraviolet ranges (0.45–12 μm) and performs radiometry of the land, atmosphere, cryosphere and oceans. The spatial resolution of the VIIRS data is in the range from 0.38–0.75 km (at nadir) to 0.8–1.6 km (at the edge of the zone) in the 3.000 km wide survey strip. The visual data on the fire spread is available in the NASA Fire Information for Resource Management System(FIRMS[8]).

The method developed for predicting the forest fire dynamics also includes using data on environmental factors (air temperature, air humidity and wind speed), data on the nature of forest plantations (type of forest stands) and data on the type of fire. The visual data on environmental factors are obtained with Ventusky InMeteo[9]; the data on the nature of forest plantations are obtained with the Land Cover Map[10] of the Institute for Climate Change and the European Space Agency.

The existing NASA Earth Observation System, as well as other global systems, provide sufficiently accurate information of various kinds in real time on the state of land, water and the planet's atmosphere [21]. The information is publicly available and, by enriching the global information space, is widely used to improve the accuracy of meteorological forecasts, environmental monitoring, pollution control etc.

Despite the advantages of the NASA Aerospace Earth Observation System and other global systems, countries are interested in

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[7] https://jointmission.gsfc.nasa.gov/viirs.html
[8] https://firms.modaps.eosdis.nasa.gov/
[9] https://www.ventusky.com/
[10] http://maps.elie.ucl.ac.be/CCI/viewer/

creating national satellite monitoring systems. For example, in Mexico in 1999, a hot spot detection system (as an indicator of possible forest fires) was introduced with day and night sensor images on NOAA satellites, and the possibility of creating a national system is under consideration [21].

This problem is also typical for the Russian Federation. Currently, Russia is planning to create a national aerospace earth observation system, the Multi-Purpose Aerospace Prediction Monitoring System[11]. However, at the moment, there is no real alternative to using sources other than those used in the research.

As an output, the proposed method provides for preparing a prediction of the fire escalation dynamics in real time in the form of a visual image, a map with a selected area with the coordinates of the fire's spread area over time.

The general logical pattern of the method developed for predicting the forest fire dynamics in real time with non-stationarity and uncertainty based on a convolutional neural network is shown in *Figure 1*.

The method for forecasting the forest fire dynamics in real time with non-stationarity and uncertainty based on a convolutional neural network includes the following steps:

Stage 1 (data input) – visual data input;

Stage 2 (preprocessing) – preprocessing of the input visual data to eliminate distorted elements of the input image;

Stage 3 (building and setting up a convolutional neural network) – building a network with subsequent training with the backpropagation method;

Stage 4 (a forest fire forecast in real time) – identification of dependencies of the influence of environmental factors, the nature of forest plantations and type of fire on the forest fire dynamics and (with the identified dependencies) creation of an operational forest fire dynamics forecast in real time.

The main feature of the proposed method is the construction of a tree of convolutional neural networks as a directed acyclic graph for analysing a significant amount of visual data. This graph includes one root node, a CNN, which performs the last stage of forecasting, and three intermediate nodes, CNNs, where dependences of the influence of environmental factors, the nature of forest plantations and the type of fire on the forest fire dynamics are created.

Thus, we developed a method for forecasting the forest fire dynamics in real time in the context of non-stationarity and uncertainty based on advanced information technologies, artificial intelligence and deep machine learning (convolutional neural network). This type of network allows analysis of visual data, determination of key dependencies of forest fire spread on environmental factors, the nature of forest plantations and the type of forest fires, and drafting a fire escalation forecast in real time. The main feature of the proposed method is the construction of a tree of convolutional neural networks.

3. Building a visual forest fire dynamics database

Since the quality of a convolutional neural network depends on the data set used to build the network and learn, it is necessary to create an appropriate database. To this end, an analysis of (hierarchical, network, relational, post-relational, object-oriented, multidimensional and object-relational) database models was performed with an expert ranking method and a modified hierarchy analysis method. On the basis of the database requirements created (large amount of data, visual data, the ability to quickly build/modify a database with the mini-

[11] http://russianspacesystems.ru/bussines/bezopasnost/maksm/

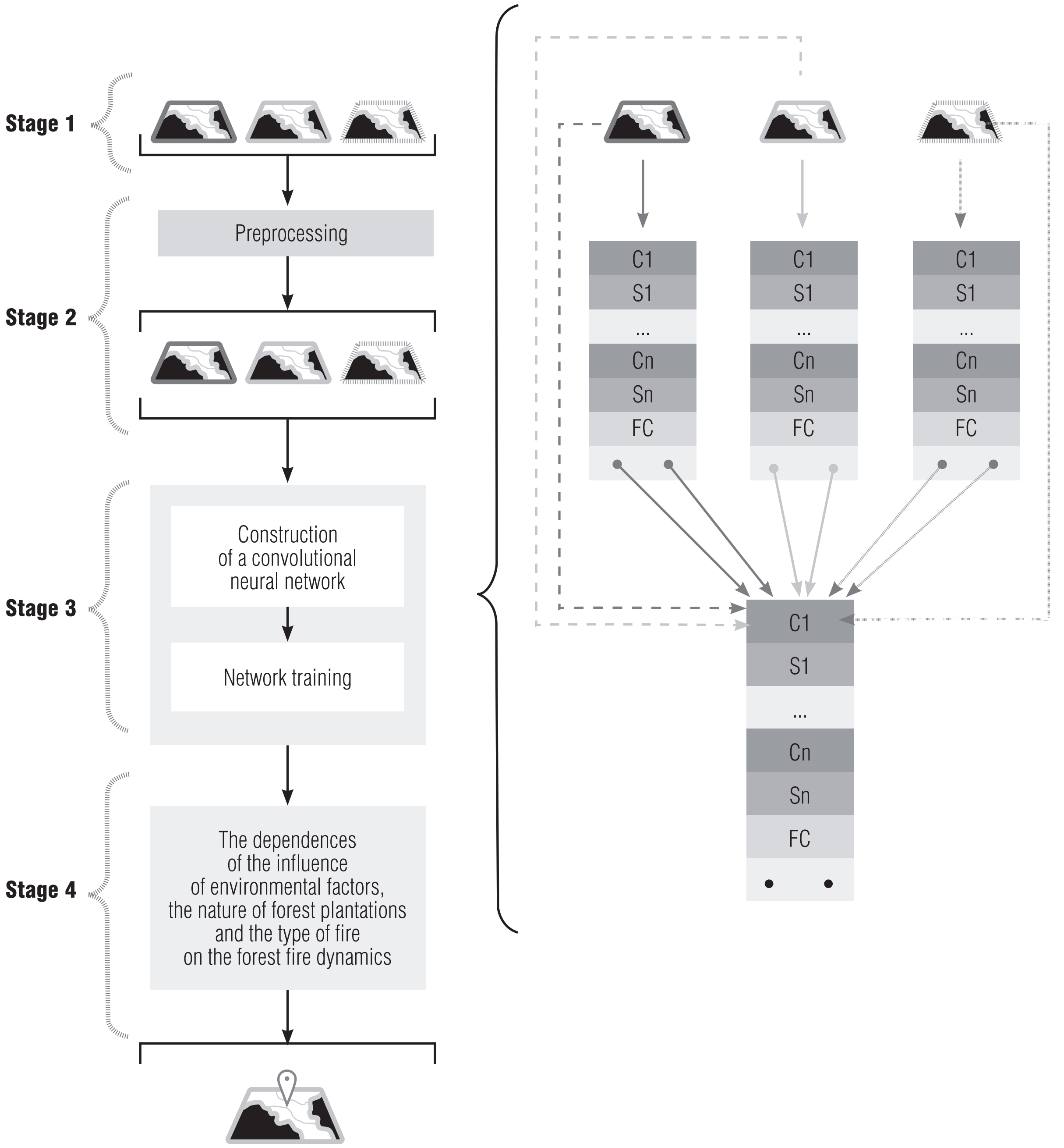

Fig. 1. General logical pattern of the method for forecasting forest fire dynamics
(C1, Cn – convolutional layers; S1, Sn – subsampling layers; FS – fully connected layer)

mal time and computational costs, the minimal time and computational costs when working with a database), we proposed to develop a relational database model on the forest fire dynamics.

A visual database on the forest fire dynamics was built. Its elements are the *Forest Fire*, *Environmental Factors* and *Nature of Forest Plantations* tables. The *Forest Fire* table is intended for storing and displaying in a user-friendly form

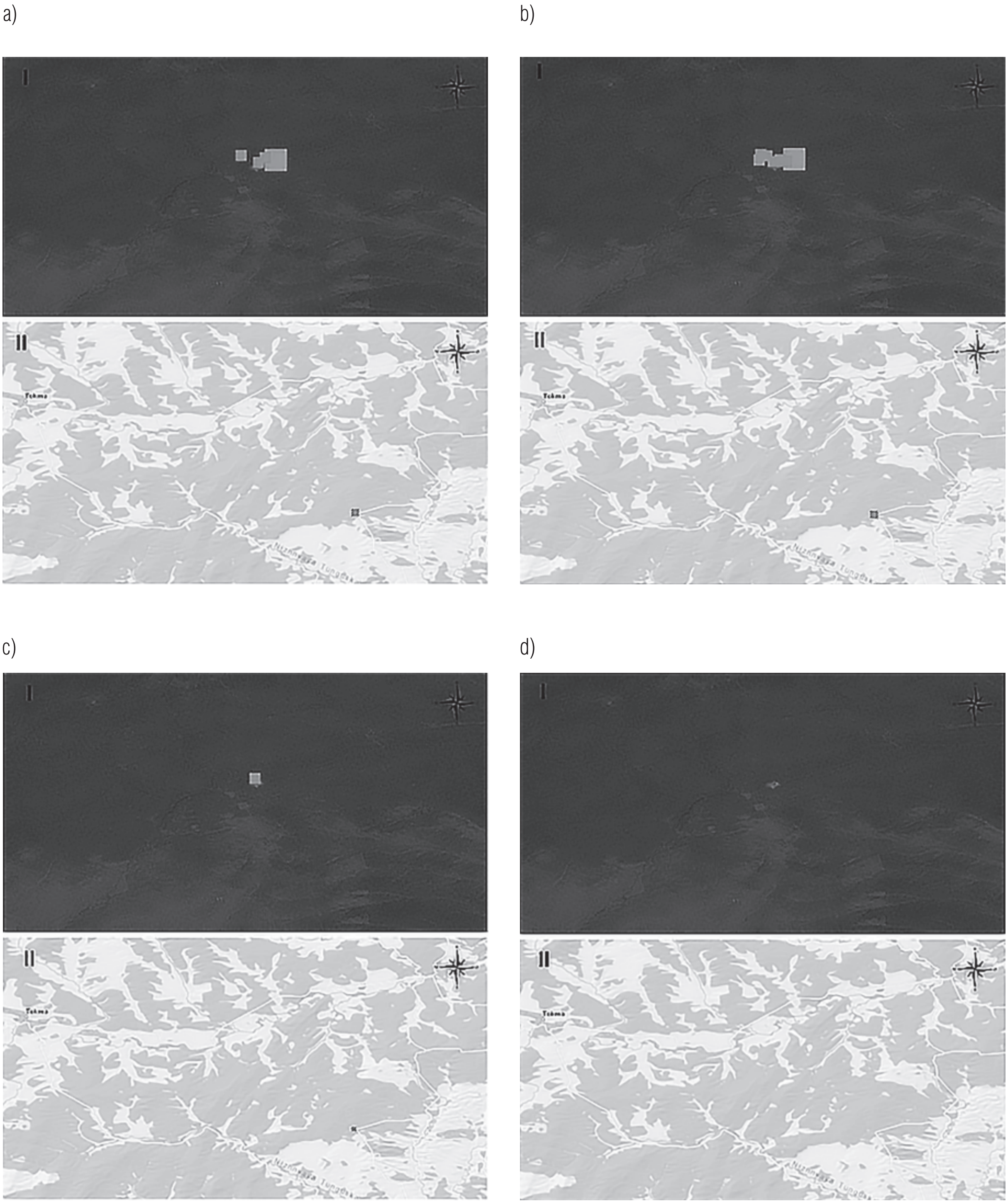

Fig. 2. Space images of the area covered by forest fire
(near the village of Tokma, Irkutsk Region, Russia, 58°15′36″ N 105°52′24″ E):

a) 16:00 GMT, 11.05.18; VIRS 375 m

b) 12:30 GMT, 12.05.18; VIRS 375 m

c) 13:48 GMT, 13.05.18; VIRS 375 m

d) 14:42 GMT, 21.05.18; VIRS 375 m

the visual data on the fire spread over time. The *Environmental Factors* table is for the visual data on environmental factors. Finally, the *Nature of Forest Plantations* table is for the visual data on the nature of the forest vegetation. The database created covers the period from 2018, and geographically all countries of the world. In addition, this database is constantly updated. To optimise the user experience with the database, the corresponding forms and requests were created.

An example of the fire history visual data is presented in *Figure 2*, which shows a visual change in the fire history over four days as space images of an area (2a, II; 2b, II; 2c, II; 2d, II) with the Blue Marble map (the image resolution is 1,000 m). For illustration purposes, space images of the area (2a, II; 2b, II; 2c, II; 2d, II) are shown with the Topographic map (the image resolution is 10,000 m) and a conventional symbol of space orientation is added.

In addition, to facilitate the user data handling experience, we intend to create a web application. Currently, the plan is to protect IP assets by filing an application for state registration of the database.

Conclusion

Our research provides insight into the existing domestic and foreign models for predicting the forest fire escalation. Based on the findings, the main constraints of the applied models under real fire conditions were identified, e.g. the highly dynamic and uncertain input parameters, the need to minimise the time of input parameter collection and entry as well as minimise the response time of the model. There are grounds for using artificial neural network (convolutional neural network) tools to make it possible to forecast the forest fire spread dynamics, i.e. the possibility of generating a forecast in complex environments of a real fire as well as the possibility of minimising time costs due to paralleling high-performance computing.

We developed a method for forecasting the forest fire dynamics in real time and in the conditions of non-stationarity and uncertainty using a convolutional neural network. The general logic pattern of the developed method is described (*Figure 1*). The main feature of the proposed method is the construction of a tree of convolutional neural networks as a directed acyclic graph for analysing a significant amount of visual data. This graph includes one root node, a CNN, which performs the last stage of forecasting, and three intermediate nodes, the CNNs, where dependences of the influence of environmental factors, the nature of forest plantations and the type of fire on the fire escalation dynamics are created.

An assessment of the existing database models was carried out and the preferred version of the forest fire behaviour database model was selected, a relational database. A visual forest fire behaviour database was built. Its elements are the tables *Forest Fire, Environmental Factors* and *Nature of Forest Plantations*. To optimise the user experience in handling the base, corresponding forms and requests were implemented. ■

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