A comprehensive model for the forest fire consequences assessment

V F Mochalov

Laboratory of Information Technologies in System Analysis and Modeling, St. Petersburg Institute for Informatics and Automation of the Russian Academy of Sciences St. Petersburg Federal Research Center of the Russian Academy of Sciences (SPC RAS), 14th Line of Vasilievsky island 39, St. Petersburg 199178, Russian Federation

Corresponding email: vicavia@yandex.ru

Abstract. A model for the forest fire consequences assessment based on integrated processing of multispectral space imagery and ground survey data is presented. The focus is on the following steps: initial data gathering for further automated clustering of landscape elements; clustering; and cross-validation of the results of the forest fire consequences assessment. The modelling assesses the following indicators: the burned area size, forest fire type, and the main burned plant community types.

1. Introduction

One of the popular areas of natural object analysis, including that of forests prone to fires, is clustering of landscape elements and parameter estimation based on the processing of multispectral imagery materials from satellites of the family Sentinel-2 [1-3]. Geographically referenced and power calibrated materials from satellite imagery in 13 spectral channels of the visible and near infrared spectral ranges are in the public domain. The frequency of filming with a spatial resolution of 10 to 60 m is five days. The capabilities of the system allow, taking into account the limitations caused by cloudiness, to process the survey materials before and after the fire. The main condition for the initial data accumulation is the availability of reliable preliminary information about the approximate location and time of the forest fire in question. The urgency of solving the problem is confirmed by the fact that the forest fire consequences assessment, especially in large inaccessible areas, is a time consuming task. The output should be presented in a visual form that ensures selective quality control of the parameters evaluated.

To solve the problem under consideration, technologies for processing multi- and hyperspectral aerospace imagery materials are widely used [1-10]. At the same time, the tasks of initial data gathering, choosing spectral-brightness features for clustering landscape elements, and controlling the quality of clustering are, as a rule, non-systematic. Difficulties arise when choosing the boundary values of the calculated clustering features, primarily due to the seasonal variability of the spectral reflective characteristics of landscape elements, a wide variety of plant communities and their growing conditions.

For this reason, the proposed model focuses on gathering the input data for assessing the consequences of each specific forest fire and control (cross-validation) of the output.
2. Methods and Materials

2.1. The structure of a comprehensive model of the forest fire consequences assessment process

Figure 1 shows a generalized integrated model of the forest fire consequences assessment process. The process is performed regularly to monitor forest regeneration. An important role is assigned to the initial data gathering, on which the quality of the steps shown in the figure depends. In the course of clustering, a set of landscape elements is divided into groups, taking into account the formed features. In parallel with clustering, cross-validation of spectral-brightness clustering features and clustering results is performed.

![Figure 1. The steps of the forest fire impact assessment process.](image)

It is important to note that the clustering features of landscape elements are preliminarily formed as part of the initial data gathering, and then their cross-validation is carried out. Informative features that reflect the properties of landscape elements, which are common in the processing of multispectral and hyperspectral imagery materials, are selected. For cross-validation, training sites are used that are not involved in training, but for which the values of the estimated parameters are known. Thus, the complexity of the modeled process is taken into account [10]. To detect errors of the first and second type, testing sites are selected within and outside the contour of a burned area. The process of gathering the initial data and their composition are shown in Figure 2.

![Figure 2. The sequence of the initial data gathering for assessing the forest fire consequences.](image)
The well-proven random subsampling method is used in the selection of training and testing sites [11]. This ensures an independent selection of the clustering feature boundary values. The quality of informative features and the accuracy of clustering results are assessed on an appropriate set of testing sites. The advantage of the described method is the ability to maintain proportions between training and testing sites. When performing cross-validation, the quality of clustering is analyzed using a previously selected set of testing sites. The key components of the proposed model are discussed below.

2.2. Clustering of the burned area contour

To cluster the burned area contour, a feature is used based on the widely applied vegetation stress index [1]. Its maximum and minimum values are calculated within the training site:

$$\text{NDVI} = \frac{(B8 - B12)}{(B8 + B12)}$$

Hereinafter, the numbered letter $B$ denotes the values of the energy brightness of a signal reflected from the landscape elements within the corresponding spectral channels of the Sentinel-2 spacecraft. Further, based on the analysis of boundary values, a rule for clustering landscape elements within a burned area contour is formed.

The preliminary boundary values of a feature based on the NDVI index, as well as on all the characteristics considered below, are determined during the initial data gathering. Further, when performing cross-validation, it is possible to verify their boundary values.

2.3. Clustering of plant community types

Clustering of plant communities within the burned area is the most laborious task in the framework of the process considered. Clustering features are selected on the basis of the analysis of the properties of training sites using the “before the fire” survey materials. The number of clusters is determined expertly based on the analysis of the available initial forest inventory data and survey materials. One should bear in mind that the reflective spectral characteristics of coniferous and deciduous trees may differ significantly from the values of previous years. Seasonal variations in reflectivity are also age dependent for both broadleaf and coniferous species. Nevertheless, clustering of coniferous and deciduous species based on clustering features which take into account the reflective characteristics in the near infrared region of the spectrum at wavelengths of 0.9...1.7 microns is relatively reliable. A significant contribution to the automation of clustering of plant community types can be made by the creation of a library of spectral reflective characteristics of vegetation, taking into account its properties (type, age, crown density, etc.)

For the clustering of vegetation types within a burned area, training sites on the territory with similar spectral characteristics, but with no exposure to the fire, are selected based on the survey materials obtained before the fire. They are examined during field work. Next, the Enhanced Vegetation Index is calculated [5]

$$\text{EVI} = 2.5 \times \frac{[(B8 - B4)/(B8 + 6 \times B4 - 7.5 \times B2 + 1)]}{}$$

2.4. Clustering of burned area types

Burned area types are determined based on the calculation of the burning index and the difference between its values before and after the fire [14]:

$$\text{NBR} = \frac{(B8 - B12)}{(B8 + B12)},$$

$$\text{DNBR} = \text{NBR}_{\text{prefire}} - \text{NBR}_{\text{postfire}}$$

Table 1 shows different ranges of DNBR values suggested by the United States Geological Survey (USGS) to categorize burn severity [1].
### Table 1. The DNBR burn severity categories, according to the USGS categorization.

| DNBR       | Burn Severity                |
|------------|------------------------------|
| <0.25      | High post-fire regrowth      |
| -0.25….-0.1| Low post-fire regrowth       |
| -0.1…..+0.1| Unburned                    |
| 0.1 – 0.27 | Low-severity burn            |
| 0.27 – 0.44| Moderate–low severity burn   |
| 0.44 – 0.66| Moderate–high severity burn  |
| >0.66      | High-severity burn           |

### 2.5. Clustering of burned areas with forest regeneration of varying degrees

The special burning index is calculated annually within the agreed vegetative period [2, 3]

\[
BAIS2 = \left(1 - \sqrt{\frac{B6+B7+B8A}{B4}}\right) \cdot \left(\frac{B12-B8A}{\sqrt{B12+B8A}} + 1\right). 
\]  

(5)

Assessment of the fire consequences is carried out by calculating the area of landscape elements based on the results of their clustering, as well as by analyzing the dynamics of changes in the special fire index.

### 3. Results and Discussion

The proposed model was tested using an assessment of the consequences of a forest fire that occurred in 2019 in the Leningrad Region as an example. Fragments of the burned area survey report are shown in figure 3. From the report provided by the operating organization, initial data were extracted, including the date and geographical coordinates of the burned area. We obtained data from the Sentinel-2 spacecraft immediately before and after the fire.

### Figure 3. Fragment of the forest fire report, where, (a) - the first page, (b) - the map of the area affected by the forest fire (dark outline), and (c) - a ground photo of the burned area.

When compiling the initial dataset, preliminary boundary values of clustering features were selected and refined in the course of cross-validation. The results of the relevant operations are shown in table 2.

### Table 2. Clustering features and their values.

| Estimated parameter       | Clustering feature | Preliminary value of the feature when compiling the initial dataset | Refined feature value based on cross-validation results |
|---------------------------|--------------------|---------------------------------------------------------------------|--------------------------------------------------------|
|                           |                    | min | max   | min | max   |
| Burned area size          | NDVI               | 0.055 | 0.067 | 0.059 | 0.067 |
| Coniferous forest area size | EVI1            | 0.320 | 0.342 | 0.320 | 0.343 |
| Sparse forest area size   | EVI2               | 0.220 | 0.250 | 0.218 | 0.255 |
| Moderate–low severity burn | DNBRlsb          | 0.27 | 0.44  | 0.27 | 0.44  |
| Moderate – high severity burn | DNBRhsb         | 0.44 | 0.66  | 0.44 | 0.66  |
As a result of calculations described above, data were obtained for assessing the consequences of the forest fire. The results of clustering the contours of the burned area, burned area types, and plant community types exposed to the fire are shown in figure 4.

![Figure 4](image)

**Figure 4.** Results of clustering of landscape elements, where, (a) -contour of the burned area (gray color), purple color indicates a contour of the burned area from a fire report; (b) - coniferous forest is shown in red, and sparse forest, in green; (c) - a contour of high (top) and low intensity burns.

The boundary values of clustering features given in table 2 are typical for coniferous forests of Northwest Russia at the end of summer. When running the model, the boundary values can be adjusted and used for other regions and seasons. In this case, a database of accumulated clustering features is formed.

The contours of landscape elements shown in figure 4 are used to create digital maps reflecting the state of forest vegetation.

In the course of ground-truthing, it was confirmed that due to cross-validation, a high reliability of the results was ensured, and the information presented in the fire report was verified. On the basis of these parameters, the economic damage from a fire can be estimated. An important area is the ability to assess the state of forest regeneration, which will facilitate informed management decisions. By using the proposed model, it is possible to significantly reduce the labor intensity of data collection for a fire report during ground surveys.

It is important to note that taking into account the spatial resolution of the Sentinel-2 onboard imaging equipment, the tasks of assessing the consequences of forest fires with an area of at least one hectare are being solved. To achieve a higher spatial resolution, data from multispectral aerial imagery or imagery from unmanned aerial vehicles can be used as survey materials, provided they are geometrically referenced and power calibrated.

4. **Conclusion**

On the basis of the integrated model developed, the possibility of solving a complex practical problem of assessing the state of vegetation under anthropogenic impact has been demonstrated. It has been confirmed that, on the basis of preliminary processing of multi- and hyperspectral aerospace imagery materials, highly informative, stable within a particular season and region, spectral-brightness features were formed for automated clustering of landscape elements. The requirements for the initial data in terms of the use of survey materials before and after the fire have been systematized. The role of training and testing sites, both within the burned area and outside it, as the basis for performing cross-validation has been demonstrated. The list of clustering features and the accuracy of their boundary values for monitored landscape elements can be increased through the artificial neural networks training using data from the Sentinel-2 spacecraft [10]. It is understood that in this case the multispectral survey materials must undergo atmospheric correction and ensure presentation of the results of measuring the spectral reflective characteristics of landscape elements. Supervised learning of the neural network will be accompanied by a decrease in the required number of ground surveys when gathering initial data and an increase in the quality of solving urgent practical problems.
In general, the presented model for the forest fire consequences assessment is universal in nature and can find practical application in the activities of national operating organizations.

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