RESEARCH PAPER

PREDICTION OF WILDFIRES BASED ON THE SPATIO-TEMPORAL VARIABILITY OF FIRE DANGER FACTORS

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ABSTRACT. Most methods in the field of wildfire prevention are based on expert assessment of fire danger factors. However, their weights are usually assumed constant for the entire application area despite the geographical and seasonal changes of factors. This study aimed to develop a wildfire prevention method based on partial and general fire danger ratings taking into account their spatio-temporal variability. The study was conducted for Krasnoyarsk territory, Orenburg region and the Meschera lowland as the most forest, steppe and peat fire dangerous regions of Russia respectively. Surface temperature, moisture, vegetation structure, anthropogenic load, topography and their variation over subzones and in time were used as fire danger factors. They were evaluated by measuring parameters such as radiobrightness temperature, Normalized Difference Water Index (NDWI), Normalized Difference Vegetation Index (NDVI), Soil-Adjusted Vegetation Index (SAVI), distance to settlements and roads, elevation, slope and aspect. Materials from the Terra/Aqua, Sentinel-3, Landsat-8, Sentinel-2 satellites, ASTER Global Digital Elevation Model and Open Street Maps vector layers were used in the study. Correlation between these parameters and the actual fires in 2016-2018 was analyzed. Linear relationships were established, and correlation coefficients, equations of partial ratings and prevention 90%-threshold values were identified. On their basis, the parameter weights were computed to integrate them into the general fire danger rating. The developed method was validated using data over 2019. The results showed 67% confidence and 61% reliability of fire prevention along with the spatio-temporal patterns of fire danger factors. The method is recommended for preventing wildfires within the study areas and can be extend to similar regions.

KEYWORDS: wildfire prediction, remote sensing, fire danger

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INTRODUCTION

Fire danger is a key indicator in the prevention of wildfires. It is estimated based on weather variables influencing the fire conditions (Camia and Amatulli 2009) and the health of vegetation, which acts as the main fuel (Yebra et al. 2013; Sofronova and Volokitina 2017). With methodological advances, various national fire danger rating systems were developed, including American National Fire Danger Rating System (Deeming et al. 1972; Burgan 1988), Canadian Fire Weather Index (Van Wagner 1987), Russian Nesterov (Nesterov 1949) and Australian (McArthur 1967) Fire Danger Index, etc. These systems mainly use ground meteorological observations at weather stations and forest inventory data.

The development of remote sensing technologies has led to the use of satellite datasets with larger spatial coverage and higher temporal resolution. Estimation of fire danger based on remote sensing data is performed using visible and infrared imagery, which characterize major fire danger factors (Chuvieco and Congalton 1989). It is commonly used to assess live and dead fuel moisture content (Chuvieco et al. 2003; Arganaraz et al. 2016), temperature (Chuvieco et al. 2004), topography (Eskandari et al. 2020), and anthropogenic load (Suresh Babu et al. 2016). The usual practice is to define fire prevention zones by assigning certain weights to the classes of all fire danger factors according to their influence on fire probability (Jaiswal et al. 2002; Xu et al. 2005). Combining all factors into a general fire danger parameter is usually conducted using GIS operations such as overlay and raster algebra (Akbulak et al. 2018; Yankovich et al. 2019), with the recent addition of machine learning, neural networks (Bui et al. 2018) and big data (Piralilou et al. 2022) technologies. Modern methods have advanced to using ensembles of different techniques with the selection of the most optimal and accurate results (Rosadi and Andriyani 2021).

In Russia, methods for fire prevention and fire danger assessment are currently developed for three major areas:

– Institute of Space Research of the Russian Academy of Sciences (RAS) developed technologies for improving the Remote Monitoring Information System of the Russian Federal Forestry Agency, which is aimed at predicting pyrogenic tree mortality (Bartalev et al. 2017), stochastic simulation of fire ignition and propagation (Khvostokov et al. 2016) and mapping of fire danger classes based on remote sensing products (Plotnikova and Ershov 2015) for the Central and European parts of Russia as well as its entire territory;

– The Siberian branch of RAS devoted its studies to enhancing fire danger classes and developing local and regional scales for Siberian forests (Sofronova et al. 2008; Volokitina et al. 2016);

– Far-Eastern branch of RAS developed methods for predicting fires based on vegetation combustibles (Zubareva 2018) and evaluating grass fire danger (Glagolev 2018) for Far-Eastern regions.

However, despite the great number of methods and their regional and local corrections, almost all of them have a major shortcoming – the key parameters describing fire danger factors (threshold values, weights, etc.) are assumed to be constant for large territories, while in fact they are characterized by significant spatial (geographical and scale) and temporal (seasonal) variability. This leads to a rough and inaccurate assessment of fire danger: for example, one temperature threshold value for a large meridional territory can perform well for the middle part of the area, overestimate the danger in the south and underestimate it in the north. Another shortcoming concerning Russian territory is that the Nesterov index, which mainly uses ground meteorological data and ignores the huge potential of remote sensing and other spatial products, is usually applied at the official level.

The aim of this study was thus to develop a method for preventing wildfires based on fire danger estimation, which would rely on the general principles of existing systems (Gizatullin et al. 2019) and take into account the spatio-temporal variability of fire danger factors. The study was conducted in the most fire dangerous regions of Russia – Krasnoyarsk Territory, Orenburg Region and the Meschera lowland, using Terra/Aqua, Sentinel-2,3 and Landsat-8 images, ASTER GDEM elevation model and OpenStreetMap layers.

MATERIALS AND METHODS

The study area

The study areas were selected based on the number of fire cases and the spatial variability of fire conditions and fuels in Russia, which is characterized by the type of wildfire: forest, steppe and peat. Sample analysis included an overlay of landcover maps (Ogureeva and Kotova 2013) with FIRMS hotspot (fire points) layers (Hanston et al. 2014, https://firms.modaps.eosdis.nasa.gov/). It was demonstrated that during the last decade (in 2010-2018), the largest number of forest, steppe and peat fires was observed in the Krasnoyarsk territory, Orenburg region, and the Meschera lowland respectively. The study areas were divided into zones of homogeneous vegetation (Fig. 1) corresponding to different types of forests, steppes and peatland which determine the possible fuel (based on Furaev et al. 2016; Pavleychik 2016; Medvedeva et al. 2019).

Krasnoyarsk territory is characterized by a high forest cover – more than 70% of the region area or 160 million hectares. The forests of the region have a large meridional extent and can be divided into seven forest zones (Fig. 1a) with different natural pyrological conditions. The area is characterized by the prevalence of coniferous tree species along with fire dangerous moss and lichens, lowland (0-200m) and tableland (500-700m) topography, and a heavy continental climate with the maximum temperature (+25…40°C) and consequently the largest number of fires observed in summer due to lightning ignition (based on Sofronov and Volokitina 1990 with authors' updating). In addition, the region has a population of about 2.8 million people, concentrated in its southern part. However, the middle and northern parts are also characterized by a high anthropogenic fire load due to the development of oil and gas fields and pipelines installation. Under these conditions, several million hectares of forest burn annually within the region as more than 700 thousand MODIS hotspots were registered here from 2010 to 2018.

In Orenburg region, the main pyrological factors include the dominance of dry steppe vegetation (sheep fescue, needlegrass, artemisia, etc.), heavily continental arid climate with a shortage of liquid precipitation and significant variation in topography (segments of the Southern Urals). Anthropogenic factors of fire ignition are a population of 1.9 million people, agriculture development and a great number of grass fires in the spring during a sharp temperature increase by 10-20°C. From 2010 to 2018, about 140 thousand MODIS hotspots were registered in the region.

The Meschera lowland is located within Moscow, Ryazan and Vladimir regions and is characterized by a continuous

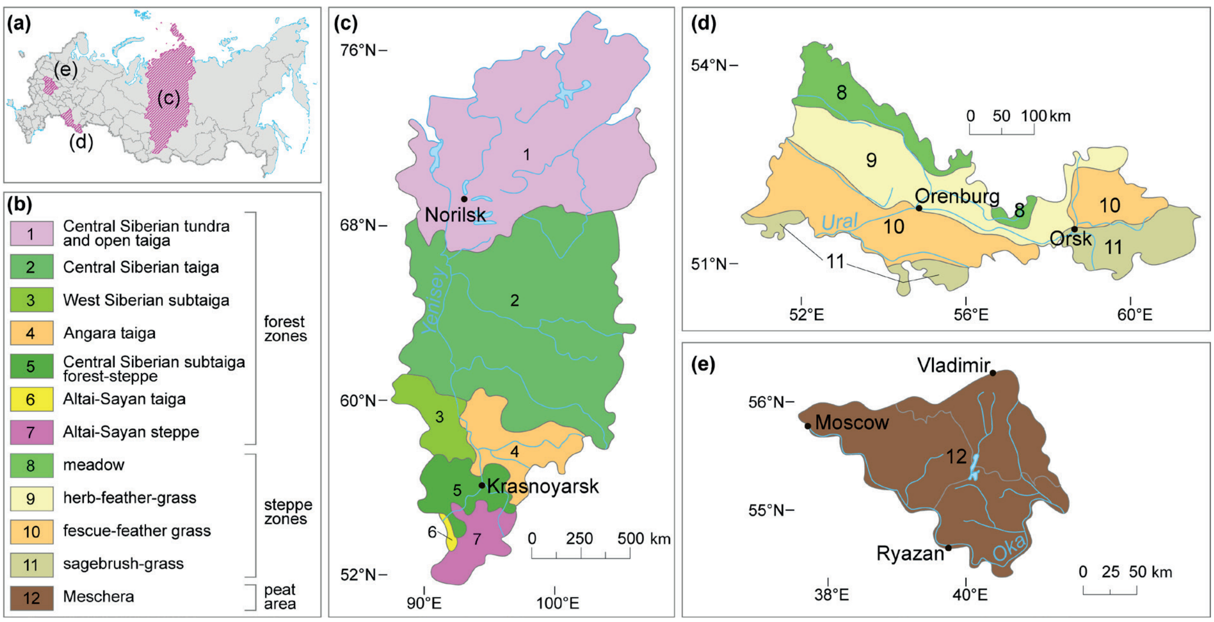

Fig. 1. Spatial units of the study areas: (a) Overview map (b) Legend (c) Krasnoyarsk territory (d) Orenburg region (e) Meschera peat area

spread of dry peatlands. The fire vulnerability of the region is determined by its high population density (more than 150 people per km^2) and consequently great anthropogenic load, as well as the presence of drained peatland locations with low moisture. The region is known for the fires of 2010 during the summer heat wave, while 7.4 thousand MODIS hotspots were also determined here from 2010 to 2018.

Data

In the study, we used only data that met the requirements of spatial reference, regular updating and open access, which makes it possible to reproduce the developed method for further studies and use it for similar purposes.

Fire data. Previously mentioned FIRMS MODIS and VIIRS hotspots with confidence values greater than 95% were used as a reference sample of fires from 2010 to 2019. This sample was divided into several parts:

– 2000-2018 – to select the regions of Russia with the most fires in the last decade for further study (as was mentioned in the Study areas section);

– 2016-2018 – for estimating fire danger parameters based on the available remote sensing data of the selected satellites;

– 2019 –to test and validate the developed fire prevention method in near-real-time conditions.

For Krasnoyarsk territory, 2016-2019 ground data from the regional forest fire center (http://www.lpcentr.ru/) was additionally applied.

Remotely sensed data. To identify the changes in fire danger factors during the considered period, we used atmospherically corrected satellite products over 2016-2019 with different spatial and temporal resolution: MODIS (Moderate Resolution Imaging Spectroradiometer, Aqua/Terra, 250/500 meters, 0.5-2 days), SLSTR (Sea and Land Surface Temperature Radiometer, Sentinel-3, 500/1000 meters, 1.5 days), OLI/TIRS (Operational Land Imager/Thermal Infrared Sensor, Landsat-8, 30/100 meters, 16 days) and MSI (Multispectral Instrument, Sentinel-2, 10/20/60 meters, 5 days). Satellite data were derived from the USGS EarthExplorer service (https://earthexplorer.usgs.gov/). During the processing, they were divided into two complementary spatial levels: regional (MODIS and SLSTR, resampled to a base resolution of 500 m, available 1-2 times a day for all the study areas) and local (OLI/TIRS and MSI, resampled to a base resolution of 30 m, more accurate sensors, but available only once every 5-14 days).

Digital elevation model. The ASTER GDEM (Advanced Spaceborne Thermal Emission and Reflection Radiometer Global Digital Elevation Model) Version 3 was also obtained from the USGS EarthExplorer service to characterize the topography of the areas, including elevation, slope and aspect parameters. Its spatial resolution is 1″ (~30 meters), vertical accuracy (RMSE) – 8.52 meters, and it covers the area between 83°N and 83°S, which is crucial for the territory of Russia.

Map layers. Feature layers for settlements and roads located in the study areas were extracted from OpenStreetMap (https://www.geofabrik.de/data/download.html) to estimate the anthropogenic load.

METHODS

To achieve the main goal of the study, a mixed methodological approach was used. Quantitative methods of GIS, raster algebra and mathematical statistics were applied to process the input spatial data, calculate fire danger parameters, investigate their correlation with the observed fires and evaluate the applicability of the developed method. But to interpret the results and make some conclusions, qualitative expert methods were included in the study.

Fire danger parameters. Fire danger parameters were defined in this study as parameters that are related to the fire danger factors and can be used to quantify them. The structure of the forest, steppe and peat vegetation was described using vegetation indices – Normalized Difference Vegetation Index (NDVI; Rouse 1973) and Soil Adjusted Vegetation Index (SAVI; Huete 1988), which were applied for complete and partial projective cover respectively. These parameters are calculated based on two stable spectral bands – red (R) and near-infrared (NIR). Normalized Difference Water Index (NDWI; Gao 1996) was also used to evaluate surface moisture based on the near-infrared and shortwave infrared (SWIR) bands. These indices were computed using the following formulas:

$$NDVI = (B_{NIR} - B_R) / (B_{NIR} + B_R) \tag{1}$$

$$SAVI = (B_{NIR} - B_R) / (B_{NIR} + B_R = 0.5) \times (1 + 0.5) \tag{2}$$

$$N_{DWI} = (B_{NIR} - B_{SWIR}) / (B_{NIR} + B_{SWIR}) \tag{3}$$

where B_R, B_{NIR} and B_{SWIR} correspond to reflectance in channels 1, 2 и 5 of MODIS, 2, 3, 4 of SLSTR, 4, 5, 9 of OLI and 4, 8a, 10 of MSI.

The surface temperature was derived from the MO/YD11 (MODIS) and LST (SLSTR) thermal products and was also calculated from the thermal channels 10 and 11 of TIRS using QGIS (Quantum Geographic Information System). Topography was expressed in terms of morphometric parameters – true altitude, slope and aspect, derived from ASTER GDEM.

The anthropogenic load was determined as a normalized back-weighted function of the distance to settlements and roads. One of the main causes of fires is an anthropogenic factor. Therefore, a simple assumption was used: lower distance to settlements and roads as places of possible human presence corresponds to the higher fire danger. The weights of normalized distance values were calculated for different features using the ranked method: 0.91 for settlements and 0.09 for roads. Finally, the anthropogenic load (*AL*) was computed by the following formula:

$$MML = 0.91 \times D_S / D_{Smax} + 0.09 \times D_R / D_{Rmax} \tag{4}$$

where D_S – distance to settlements, D_R – distance to roads, D_{Smax} and D_{Rmax} – maximal values of distance to settlement and roads respectively, for normalization.

All fire danger parameters were divided into two types according to their variability:

– variable – NDVI, SAVI, NDWI and surface temperature, which vary within a day and over longer time intervals and were estimated using remotely sensed data for 2016-2018 and 2019;

– constant – topography parameters and anthropogenic load, which are characterized by negligible temporal changes and were determined once using the elevation model and feature layers.

Correlation of variable fire danger parameters with the actual fires. 4,590 actual fires were extracted from the fire data for 2016-2018, when all the used satellites were operational. To analyze the occurrence of these fires, we introduced the conditional probability of ignition P as a linear function of time. The zero probability was fixed at the time T1: 7 days before the fire at the regional level (when using frequent MODIS and SLSTR data) and 30 days at the local level (rare OLI/TIRS and MSI). **These time intervals allowed to gain a sufficient number of points and analyze trend lines.** The threshold probability of 90%, characterizing a potential fire, was defined as the value of the maximum difference in the parameter before the fire – at the time T2. As a result, the conditional probability of ignition P was found by interpolating between (T1, 0) and (T2, 90).

To determine the correlation between variable parameters V (NDVI, SAVI, NDWI and surface temperature t) and the value of P, we built their regional 7-day and local 30-day time series and established linear relationships between them (example in Fig. 2). To take into account the spatio-temporal variability of the fire danger factors, the analysis was performed in each of the 12 spatial units (seven forest zones, four steppe zones and one peat area) of the study areas for each of the 7 fire season months, from April to October. Finally, the linear transition equations P(V), correlation coefficients r and 90%-threshold values Vthreshold were derived for each variable parameter and 84 space-time units on two spatial levels. All these values were published at https://preventfires.github.io/.

Correlation of constant fire danger parameters with the actual fires. The constant fire danger parameters (C) within the study areas were divided into 8 equal topography (true altitude, slope, aspect) and anthropogenic load (L) classes. Based on these classes, the statistical probability of ignition S, which was defined as the ratio of the number of fires in the current class to the total number of fires, was calculated for the 84 space-time units and two spatial levels mentioned above (the values are presented on https://preventfires.github.io/).

RESULTS

The derived transition equations and 90%-threshold values of variable parameters can be used to prevent wildfires in the study areas over the fire season: if at least one indicator is greater than its threshold value, then this location can be interpreted as a fire point. For example, the temperature threshold value for the Meschera peat area in July is 51.5°C on a regional level and 55.1°C on a local level, while in June it is 41.5°C and 42.3°C respectively. Thus, the conditional probabilities *P* of NDVI, SAVI, NDWI and surface temperature represent partial ratings of fire danger.

However, the main principle of the existing systems is the weighted combination of partial ratings into a general fire danger rating. In our case, variable and constant parameters were combined at the highest hierarchical level. As the significance of variable parameters is larger compared to constant parameters due to the temporal updatability, their weights were ranked as 0.66 and 0.33 respectively. At the next level, the NDVI, SAVI, NDWI and temperature weights were established based on the correlation coefficient *r*, while statistical probability was used to determine the weights for topography and anthropogenic load factors. As a result, the equation of the general fire danger rating *G* within each space-time unit was as follows:

$$G = 2/3\sum_{i=1}^{n}\frac{r_i}{\sum r_{V-P}} \cdot P(V_i) + 1/3\sum_{j=1}^{m}\frac{S_j}{\sum S(C)} \quad (5)$$

where *n, m* – the number of significant (*r > 0.7*) variable and constant parameters. For example, for the Altai-Sayan taiga May unit this equation was as follows:

$$G = 0.28P(NDVI) + 0.39P(t) + 0.33S(L) \quad (6)$$

The weights of fire danger parameters that were used to generate equations for other space-time units as well as other result values from this study were published at https://preventfires.github.io/. The obtained general fire danger rating was used to divide the territory into 2 classes: fire points and no-fire area. If the value of the rating was greater than 0.9 or 90%, then the pixel was attributed to the fire point class, otherwise – to the no-fire class.

The workflow of the wildfire prevention method is shown in Fig. 3. It was validated by monitoring the study areas from April to August 2019. The fire points obtained using the developed method were compared with the reference FIRMS fire data of the same period (Table 1). To evaluate the applicability of the method, two metrics were used:

– reliability – the ratio of truly prevented (observed) fire points to all prevented (potential) fire points, this metric demonstrates the plausibility of the method results;

– confidence – the ratio of observed fire points, registered by the method, to all observed (real) fire points, this metric indicates how much the method results relate to the real situation.

Overall, the reliability of the method was 61%, and its confidence was 67%. These values were reached due to the spatio-temporal sampled variability of threshold values, equations and weights of fire danger partial and general parameters. It was also improved by combining the results of two spatial levels: regional data has large territorial coverage and high temporal resolution, but local data is more spatially detailed and accurate in identifying the fire danger parameters. There were common cases, when fires were not prevented by MODIS/SLSTR data, but prevented by OLI/TIRS/MSI data, and cases, when a fire was prevented on both levels.

However, the one weakness of the method is a sufficiently great number of falsely prevented points. It is planned to correct this in further studies.

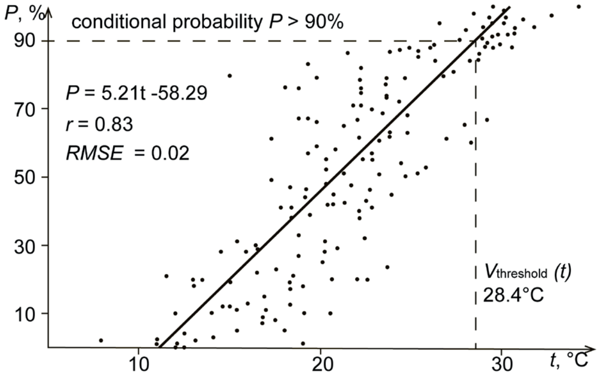

Fig. 2. Correlation between surface temperature t and conditional probability of ignition P in the case of the Altai-Sayan taiga forest area in May

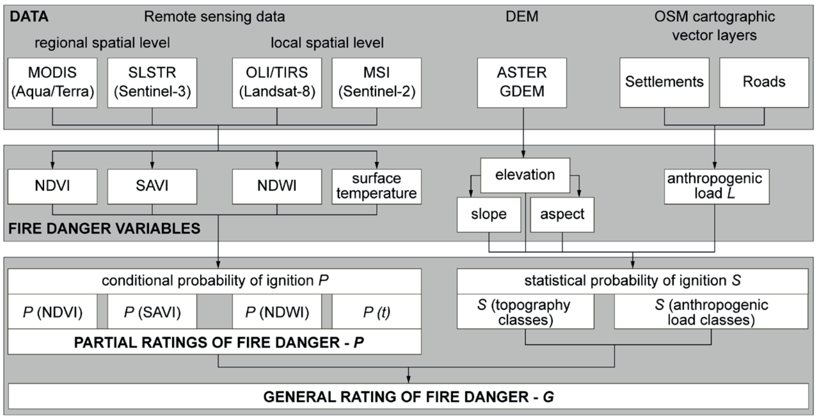

Fig. 3. Wildfire prevention by computing partial and general fire danger ratings

Table 1. Results of the fire prevention method validation

Parameter	Krasnoyarsk territory	Orenburg region	Meschera lowland	In total
Number of potential fires	201	60	41	302
Occured of them	119	37	29	185
Reliability, %	59	62	71	61
Number of occured fires	98	25	20	143
Prevented of them	64	15	17	96
Confidence, %	65	60	85	67

DISCUSSION

The proposed method is based on the spatio-temporal variability of fire danger factors, which was achieved by dividing the study areas into space-time units. To confirm that, changes in the threshold values of variable fire danger parameters were analyzed.

In Krasnoyarsk Territory, it was found that informative parameters with $r > 0.7$ were NDVI and surface temperature (Fig. 4a, b). The threshold values reached a maximum in June and July, during the flowering phenological phase and the highest surface heating. In Orenburg region, SAVI, NDWI and surface temperature were found to be informative. The time variation of SAVI showed a maximum in May, which corresponds to the phenological season in the steppes (Fig. 4c). Temperature threshold variation (Fig. 4d) was similar to the trend in the Krasnoyarsk forests. The NDWI changes (Fig. 4e) were inversely related to the temperature curve with a negative peak displacement towards August, when the surface moisture is minimal. The largest number of informative parameters (NDVI, SAVI, NDWI and surface temperature) was found in Meschera. Their variation (Fig. 4f) corresponded to the general trends described above with a difference only in values. Spatially, threshold values varied monotonically from North to South, which indicates the zonal variability of surface temperature, vegetation and consequently fire danger factors.

These trends led to the following conclusions. The dependence of fire danger on vegetation indices is complex. The higher index value usually corresponds to more live green vegetation, which limits the fire ignition. However, in our case, the inverse quantitative trend was identified as the higher index value indicates a larger amount of available fuel, which changes both zonally and seasonally. Surface temperature and moisture are inversely proportional and change in accordance with the air temperature curve, which creates conditions for ignition.

The significance of constant fire danger parameters represented by statistical probabilities was also great. The largest number of wildfires were observed in areas with slightly sloping surfaces (1…3°), southern aspect (South, South-East, South-West) and high anthropogenic load. These patterns allow to prevent fires in areas with these classes of constant parameters. It proves that the inclusion of constant fire danger factors in the analysis is crucial, particularly when variable parameters do not reach threshold values.

To summarize, we had the following policy implications. The revealed spatial and temporal trends of threshold values, especially zonal and seasonal, justified the relevance of the discrete approach to fire danger assessment based on space-time units (zones and months). The obtained values of correlation coefficient (in most cases higher than 0.7) and statistical probability allowed to establish the relations between fire danger factors and integrate them in the general fire danger parameter for the study areas.

CONCLUSIONS

As a result of the study, we developed the wildfire prevention method that is distinguished by original and advantageous features:

– the method involves multidimensional discrete adaptive modelling of significant fire danger factors – NDVI and SAVI as vegetation fuel factor; NDWI as water content factor; surface temperature as thermal factor; elevation, slope and aspect as topography factor; and distance to settlements and roads as anthropogenic load factor;

– the identification of possible fire points was performed both analytically, based on partial ratings (each variable factor has a threshold value and can independently characterize a potential fire), and synthetically by normalized-weight integration of parameters into the general rating;

– the fire prevention was enhanced by the use of heterogeneous regional and local data, which complement each other at two different spatial levels;

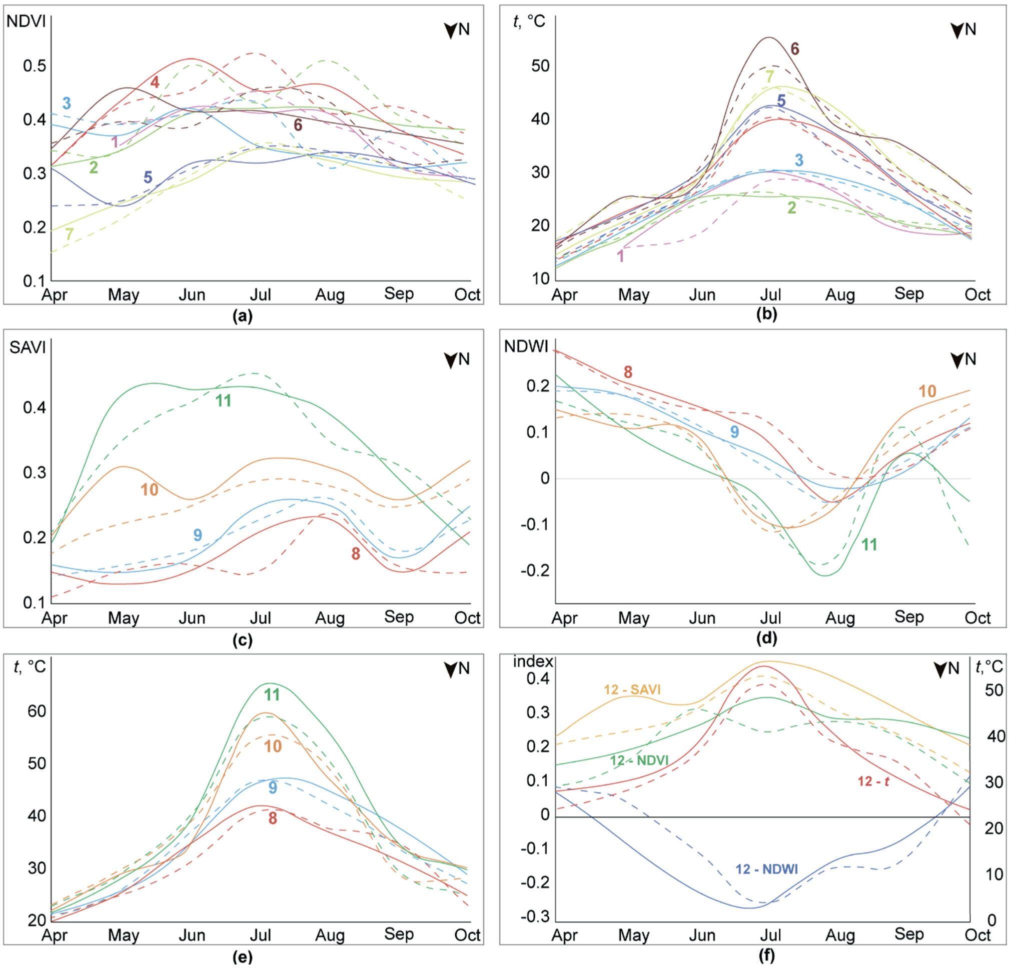

Fig. 4. Temporal variation in threshold values of variable fire danger parameters: (a) NDVI, (b) surface temperature in Krasnoyarsk, (c) SAVI, (d) NDWI, (e) surface temperature in Orenburg region, (f) in Meschera. The subzones are presented in Fig. 1, solid lines reperesent OLI/TIRS and MSI values, dashed lines – MODIS and SLSTR

– the main feature is the establishment of the key parameters (threshold values, equations and weights) for different space-time units (forest, steppe and peat zones and months), which makes it possible to improve fire prevention based on the spatio-temporal differentiation of fire danger factors.

All of this indicates the validity of the method for solving scientific and practical problems in similar study regions, which was confirmed by the relevant validation results with the confidence and reliability values above 60%. Further studies will be devoted to improving the prevention by extending fire danger parameters for the study areas by including deviation spring, relative greenness (Cheret and Denux 2011), etc.

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