Investigation of fire risk zones using heat–humidity time series data and vegetation

Javad Rabiei1 · Mahboube Sadat Khademi2 · Sahar Bagherpour3 · Negin Ebadi4 · Akram Karimi5 · Kaveh Ostad-Ali-Askari6

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Abstract
Forest fires destroy these areas and have devastating and harmful socio-economic and environmental effects. One of the methods of preventing and managing the hazards created in the field of forest fires is to determine the range of fire risk. The purpose of this study is to determine the high-risk areas of fire in the forests of Golestan province using remote sensing data and field information. For this purpose, the data of MODIS satellite during the years 2005 to 2020 for the middle of November to mid-February, which is the peak of the fire occurrence, were prepared. (NDVI) vegetation index, (NDMI) plant moisture stress index and (LST) land surface temperature were extracted as a 15-year average in these months. Then, using precipitation data from meteorological stations, precipitation index (SPI) was calculated as an average to estimate the amount of drought for the mentioned years. By combining the mentioned indices, the areas with fire risk were extracted. Then, previous fire reference data were used to validate the obtained results of the study. The results of fire potential map evaluation showed that about 6.39% of the area has very high potential, indicating that about 65.78% of fire risk points have been located in this area and about 56.32% of the area is in moderate-fire-risk position, encompassing about 23.16% of the areas with fire risk. Finally, a low-risk zone encompassing 36.34% of the area, which about 11.06% of the high-fire-risk areas are located in this area. Also, the indices of NDMI, NDVI, SPI and LST precipitation have a degree of correlation of 74.58%, 60.1%, 47.11% and 41.02% with the map of fire points, respectively.

Keywords Fire risk · Vegetation index · MODIS satellite · Precipitation index · Remote sensing · Plant moisture stress index · NDVI · SPI · NDMI · LST

Introduction
Forest as one of the most important natural and renewable assets plays a very important role in the sustainability of natural ecosystems (Talebmorad et al. 2022; Yuan et al. 2015). One of the dangers that threaten forests and cause irreparable damage to forest plant and animal life is fire (Chaparro et al. 2016). Fire is one of the most important natural hazards that always threaten the vital ecosystems (Abdollahi et al. 2021; Ghashghaie et al. 2022; Ostad-Ali-Askari 2022a, b; Marozas et al. 2007). According to the FAO, about 6% of Iran’s forests are destroyed by the fire every year (Gholami et al. 2013). Natural fires have active and inactive cycles, including normal or extinguishing times. At this time, the forest is not endangered by significant fires and this can be considered as the forest calmness period against the fire crisis. The time period when fires occur in highlands or shrub forests with large areas and
grassland fuel can be called semi-critical time or standby period. Crisis or standby time inside and outside the organization is the time when the highest number of fires and burned surfaces occurs (Vanani et al. 2022; Karimi et al. 2018). Fire risk assessment at the crisis time is one of the basic tasks for fire control and management in the forest areas and areas with forest fire risk and can be a useful guide for the forest fire management (Karimi et al. 2018). In this regard, Çolaka and Sunarb (2020) used remote sensing technology and geographical information system in the Izmir region of Turkey to determine the areas with high risk of fire and the results of this study indicate a very high impact of the surface temperature factor on determining the areas at risk of fire. In a study, using temperature and vegetation satellite data from Landsat and Sentinel sensors in the eastern Himalayas (Bar et al. 2020) surveyed areas under fire change over the years. In a study, Konkathi and Shetty (2021) evaluated fire areas, using Landsat satellite data. The findings of this study indicate acceptable results in determining fire zones, using the Landsat satellite. With useful information, but it requires a lot of time and money. In contrast, the use of remote sensing techniques and satellite images have a high capability in monitoring fire areas due to fast and easy access, wide visibility and cost and time savings. Therefore, in order to obtain accurate results, it is necessary to combine remote sensing data and field information to identify high-risk areas of fire using new technologies and time series analysis. Finally, the location of fire-prone areas in the forest lands in the east of the Caspian Sea is presented. In this regard, using remote sensing techniques and examining the time series of land surface temperature, vegetation and plant moisture stresses and also by reviewing groundwater rainfall data, we first calculated the drought index and then zoned the fire risk in forest areas. Finally, the degree of correlation and the effect of each of the studied factors in increasing the incidence of fire have been studied separately. Then, using 2658 fire risk points from field visits, the accuracy of fire zones has been evaluated.

Materials and methods

Study area

Golestan province is located in the southeast of the Caspian Sea. The area of this province is 20,387 square kilometers and covers about 1.3% of the total area of the country. The province is located between 36 degrees and 30 min and 38 degrees and 8 min of north latitude and 53 degrees and 51 min and 56 degrees and 22 min of east longitude. Golestan Province is bounded on the north by the Republic of Turkmenistan, on the east by North Khorasan Province, on the south and southeast by Semnan Province, and on the west by Mazandaran Province, Gorgan Bay and the Caspian Sea. Golestan province consists of 14 cities, 29 cities, 27 districts, 60 villages, 1004 residential villages. The area of the province is 20,438 square kilometers, equivalent to 1.3% of the total area of the country and the 21st province in terms of area.

One of the important geographical features that affect the climatic conditions of the province is the existence of a mountainous region in the southern part of the province and the spread of Alborz Mountains throughout this part and also its northern proximity to the low and arid lands of the Caspian Sea and Turkmen desert (Turkmen Sahara). Shah Kooh, Siah Marzkuh, Chah Bid and Korkhod mountain ranges have surrounded the south and east of this province. The southern parts are affected by mountainous conditions and the northern parts are affected by dry and desert conditions. Golestan province is divided into three parts: mountainous, slope and plain. This province was separated from Mazandaran province in 1997, and the name Golestan is taken from the natural landscapes of the province as well as Golestan National Park. The climate of this province is highly varied due to various factors such as latitude, altitude and length of Alborz wedges, distance from the sea, Turkmen desert and Siberian plain in northern Russia, local and regional winds and dense forest cover.

The location of the study area is shown in Fig. 1 in relation to Iran.

Research data

The data used in this study include telemetry time series data and field data. In order to monitor the effect of temperature, humidity and vegetation changes in Golestan province during a 15-year study period and to investigate fire risk areas, NDMI plant moisture stress indices, NDVI advanced vegetation index and LST surface temperature index extracted from MODIS satellite and TERA sensor was used. The reason for choosing the MODIS sensor in this research is its high spectral resolution, suitable temporal resolution and lack of spectral absorption of water vapor in the infrared band that, as a result, the error caused by the absorption of water vapor is greatly reduced.

Time to select images

To evaluate the monitoring time of satellite images, it is necessary to know the fire behavior during different time periods in different seasons. A statistical study of fires that have occurred in recent years shows that the severity of the crisis during the year is as follows:
Fire normal or extinguishing time

According to a 20-year study of fire-related statistics in the forests and pastures of the province in April, May, June, October, the first half of November, the second half of February and March, there are no significant fires and six months of the year can be considered as the calmness time of forest against the fire crisis.

Semi-crisis or standby time within the organization

July, August and September can be called semi-critical times due to fires in highlands or shrub forests that sometimes cover large areas and grassland fuel.

Time of crisis or preparedness inside and outside the organization

From the second half of November to the end of the first half of February, the highest number of fire occurrence and burned surfaces has occurred for three months.

Methodology

The procedures of conducting this research have been done in four stages, which are shown in Fig. 2. In the first stage, data preparation was done to calculate the remote sensing indices by preparing the required data such as land surface temperature maps, plant moisture stress and normal differential vegetation index, using different bands for an average of 15 consequent years from 2005 to 2020 (to prevent environmental fluctuations and reduce possible errors). Then, the total 15-year average for each index was calculated. In the second stage, the drought rate map was calculated using field data from meteorological stations in the years 2005 to 2020 and the 15-year average map of the index was generated again. In the third stage, by combining the indicators obtained from the first and second stages, a fire hazard map was obtained. In the fourth stage, the actual results were evaluated.

First stage

The information received from MODIS sensor includes MOD13Q1 (with spatial resolution of 500 m and 16-day temporal resolution) for obtaining NDVI vegetation index and NDMI moisture stress index and involves MOD11A1 product (with spatial resolution of 1000 m and 8-day temporal resolution) for obtaining LST land surface temperature index with hdf format. Due to the need for time matching (accommodation) of the analyzed images, MOD11A2 products were also prepared for sixteen days. Also, for the reduction in annual fluctuations, each index was used as an average for a 15-year period from 2005 to 2020. Of these products, 85 MOD13Q1 images and 85 MOD11A1 images were prepared as time series images during the fire incident seasons occurring between the second half of November and the first half of February in the years 2005 to 2020 to reduce annual impacts and error rates. After preparing the time series images, the average of the obtained indicators was processed. Relevant calculations were also performed in TERR SET software.

Fig. 1 Geographical location of Golestan province in the country and location of the fire points
Second stage

Using land statistics and calculating the SPI precipitation index, it is possible to understand the relationship between the drought severity and fire risk areas.

Synoptic station data (ground data)

To conduct the study, rainfall statistics of ten synoptic stations located in Golestan province was used (Table 1). The stations cover the whole area based on the appropriate spatial coverage and have been prepared by the Meteorological Department from 2005 to 2020 according to the statistical period of the study.

The third stage

Using the results of the previous two stages, a fire risk zoning map was prepared.

The fourth stage

Another data used in this study are fire data collected during the fire years in the region. These data were received from
Golestan Province Environment Organization and were, then, evaluated. The images of the fire zones were, then, validated and evaluated using these spatial data. The general research process is shown in Fig. 3.

**Calculation of standardized precipitation drought index (SPI)**

The SPI is an index that depends on the probability of precipitation for each timescale and can be calculated for different timescales Labedzki (2007). This method was proposed by McKay et al. (1993), members of the Colorado Climate Center, with respect to the different effects of rainfall on groundwater, surface water sources, soil moisture and watercourse. The SPI is obtained from Eq. (1) (McKee et al. 1993):

$$\text{SPI} = \frac{P_i - \overline{P}}{S}$$  \hspace{1cm} (1)

where $P_i$ is the amount of rainfall in the intended period, $\overline{P}$ is the long-term average of precipitation for the desired period and $S$ is the standard deviation of the precipitation amount. To calculate this index, the gamma distribution is used to fit the precipitation data. Then, the necessary calculations and determination of variables related to SPI are performed. After calculating the SPI value in each time period, the moisture status is divided into different classes (Table 2) (McKee et al. 1995). Satellite data determine vegetation, plant moisture stress and land surface temperature. One of the most important capabilities of satellite imagery in natural resource surveys is the use of images related to different time periods of measurement and their comparison. In this study, in order to monitor the environmental changes in Golestan province, NDMI and LST NDVI resulting from satellite and MODIS sensor information were used.

**Normalized difference vegetation index (NDVI)**

The NDVI is used as the most important vegetation index in remote sensing. This index is suitable for areas with medium and high vegetation density, because it is less sensitive to light background soil and atmospheric effects. But, it is not suitable

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**Table 1  Characteristics of the studied synoptic stations**

| Station name       | Longitude | Latitude | Height |
|--------------------|-----------|----------|--------|
| Airport            | 269199.850 | 4087684.022 | 2      |
| Marvtape           | 407514.872 | 4184329.625 | 450    |
| Hashem Abad—Gorgan | 256295.677 | 4081720.322 | 3.13   |
| Gonbad Kavous—Gonabad | 340397.046 | 4125973.598 | 2.37   |
| Kalalah            | 363640.850 | 4138634.425 | 127    |
| Ali Abad           | 313542.356 | 4086040.043 | 182    |
| Turkmen port       | 238028.193 | 4088372.251 | 10.7   |
| Gaz                | 763889.640 | 4074454.198 | 16.7   |
| Inche              | 298282.141 | 4147606.057 | 10.7   |
| Minoudasht         | 356657.512 | 4121548.938 | 21     |

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**Fig. 3  Average drought zoning using SPI in Golestan province in November to February 2005 to 2020**
for low-vegetation areas. It is used to estimate the frequency of vegetation and study its relationship with surface temperature, which is based on red and infrared band data. The NDVI indicates the biophysical properties of vegetation such as leaf area index, photosynthetic capacity (chlorophyll content) and vegetation abundance. The NDVI not only has the ability to map the presence of vegetation on a pixel basis, but also has the capability of determining the vegetation density in a pixel (Zhang et al. 2009). The NDVI, as the most well-known vegetation index, is used to assess the health and density of vegetation by measuring changes in plant chlorophyll uptake (Thenkabail et al. 2004). In recent years, this index has been used extensively to determine and assess the drought in different parts of the world. This plant index is one of the most famous, simplest and most practical plant indexes, which was first presented by Rouse et al. (1973). The normalized difference vegetation index (NDVI) is expressed as Eq. (2):

$$\text{NDVI} = \frac{(P2-P1)}{(P2 + P1)}$$  \hspace{1cm} (2)

where P2 and P1 are the reflection rates in bands two and one, respectively. This index has values between +1 and -1.

**Normalized difference moisture index NDMI**

The computational algorithm of NDMI is the same as vegetation index, but its relation is defined to reflect the thermal response of vegetation. During drought, the earth’s surface temperature rises due to the lack of water for evaporation and, consequently, the reduced evaporation. Therefore, the inclusion of land surface temperature as drought can affect drought assessment indices (Kogan 1995). The Normalized Moisture Difference Index (NDMI) is an index that is used along with NDVI and LST indices to estimate soil moisture and study its spatiotemporal variations. This index determines the soil moisture content for the elements of the landscape, especially for soil, rocks and vegetation and is an excellent indicator for drought. Values greater than 0.1 (light colors) indicate high humidity, and low values (close to −1 (dark colors)) indicate low humidity.

This index is obtained from NIR and SWIR bands. The index calculation Eq. (3) is as follows (Jin and Sader. 2005) (Eq. 3):

$$\text{NDMI} : \frac{(\text{NIR} - \text{SWIR})}{(\text{NIR} + \text{SWIR})} \hspace{1cm} (3)$$

**Land surface temperature index LST**

With the development of thermal remote sensing technology, land surface temperatures can be calculated throughout the region. Land surface temperature can be calculated, using various satellite images Cardil et al. (2014). Here, 31 and 32 heat bands of MODIS sensor were used to estimate it. Equation (4) shows the land surface temperature index formula, where BT is the luminosity temperature, and $BT_{max}$ and $BT_{min}$ are the maximum and minimum luminosity temperature values for a particular period in the long run as follows (Eq. 4):

$$\text{LST} = \frac{BT_{max} - BT_j}{BT_{max} - BT_{min}} \times 100$$  \hspace{1cm} (4)

The present research was conducted over a period of 15 years in order to reduce the errors and environmental fluctuations of these indicators.

**Results**

In this section, first the results obtained from meteorological drought extracted from data obtained from meteorological stations and, then, maps extracted from satellite data are presented, and finally, by combining these maps, a fire hazard zone map in Golestan province has been obtained. Then, using land fire data, the zoning map of fire risk was verified.

**Results of SPI**

The SPI was calculated using Excel software on a monthly basis during the season of natural fires peak, from 2005 to 2020 in ten meteorological stations. Then, using logistic regression method, interpolation and, then, averaging and classification were performed.

**Results from the NDVI**

According to the vegetation index classification Fig. 4, the amount of vegetation in the region has been strengthened from north to south, respectively. In the area, four vegetation categories including poor, medium, good and very good have been differentiated and most of the vegetation in
this region is displayed in light green and dark green and is located in good and very good vegetation floors.

**LST index**

The land surface temperature index is LST, where $BT$ is the luminosity temperature and $BT_{\text{max}}$ and $BT_{\text{min}}$ are the maximum and minimum luminosity temperature for a particular long-term period. As shown in Fig. 5, according to the LST index map, the area has a high temperature, and in the central part, in some areas, temperature decrease can be observed.

**NDMI**

**Preparation of a fire hazard zoning map**

To prepare the fire potential map in the region, surface temperature layers, plant moisture stress and vegetation related to high-risk periods during different years were used. Then these layers were combined, and finally, zoning of fire risk areas was done. According to the potential map and zoning of fire risk in the region and its comparison with the integrated layers of the map such as surface temperature, plant moisture stress, rainfall index and vegetation, we zoned fire-prone areas. Then it was observed that areas with high-fire-risk zone are mostly in areas with medium to high vegetation, low humidity (high moisture stress) and surface temperature in the highest zone (23.9 to 32) and drought index due to rainfall amount in severe to very severe drought group. Considering that all the factors evaluated in this study have been studied as an average of fifteen years evaluation during the months of fire risk, so zoning during this 15-year period can also be cited for fires that occurred during this period (Figs. 6 and 7).

**Accuracy assessment**

In this study, ground fire risk data were used to evaluate and classify the output results. In this research, in the layer of fire danger points obtained from the ground monitoring of the region for many years, 2658 ground points of the high-risk land area of fire have been identified. After placing these points on the fire risk zoning map, resulting from
summarizing the results, about 65.78% of the points were placed in the high-risk category. About 23.16% of the points were placed in the zone of moderate fire risk, and about 11.06% of these points were located in low-fire-risk areas (Table 3). In the non-hazardous level, we did not observe any fire risk points, indicating the high accuracy of the model in zoning fire risk areas. In the next step, the correlation of each of the indicators used to create a fire zoning map was investigated. The results show a high correlation between plant moisture stress index (NDMI), then vegetation index (NDVI), then drought index from precipitation data (SPI) and, finally, land surface temperature (LST) index (Table 4) (Fig. 8).

Discussions and conclusions

Forest fires are destructive phenomena that, due to the complexity of the phenomenon, incomplete knowledge of the causative processes of the phenomenon, variability of influential climatic factors and the difficulty of good extraction and collection of data (Glasa and Halada 2008). It seems that climatic factors such as drought, low humidity, decrease in relative humidity, increase in average annual temperature and decrease in rainfall have had a significant impact on providing favorable conditions for fires. As in 2010, there were the most favorable climatic conditions for fire. Considering that many forest fires have been related to climatic factors in recent years, it is possible to determine fire risk areas to some extent by examining climatic factors. On the other hand, the complexity of the phenomena and the extent of the areas related to the occurrence of the fire prevent the full field studies of the factors related to it. Therefore, in order to monitor fire zones through time series data, in high-fire-risk months (mid-November to mid-February during a 15-year period), meteorological station data over a 15-year period in Golestan province located in the northeast of Iran have been used. The present study shows the factors involved in the occurrence of fire in the form of indicators based on NDMI, SPI, LST and NDVI time series in Golestan province in the time period between 2005 and 2020. The NDMI, indicating the amount of moisture stress in plants, is calculated, as the vegetation index, for the desired period. Which has the highest correlation with fire zoning map with 74.58%? In
similar studies such as Serra-Burriel et al. (2021) to estimate the effects of fire using telemetry data or studies conducted by Karimi et al. (2021), the NDMI by revealing the amount of moisture changes in plants can detect fire hazards with high accuracy. The high correlation between the NDMI and the fire risk zoning map shows the importance of winter vegetation stress and drought on the fire generation process in this season. The NDVI time series index in this study indicates the average vegetation of the period over 15 years. The resulting map is 60.1% correlated with the fire hazard map. In a similar study in 2021, Michael et al. (2021) used the NDVI vegetation index to predict fire risk, and acceptable results were obtained for fire risk zoning maps. The LST time series index was also used to observe the average land surface temperature in the three high-risk months. The correlation of this index with the final zoning plan of fire risk is 41.2%. In a similar study used the NDVI and SPI for 2021 fire risk zoning in the Mediterranean region of Algeria and calculated the correlation of these indices with fire risk zones, which achieved similar results. After collecting and combining the above maps, a fire risk zoning map in the area was obtained. Fire hazard points were also used to evaluate the accuracy of the results.

According to the zoned fire risk map in Golestan province, areas with high fire risk are located in the middle strip from the west to the east of the province. This zone with an area of about 07.07989 square kilometers occupies about 6.39% of the area, devoting to itself about 2084 fire risk points, equivalent to 65.78% of the total study area. In terms of vegetation, this group is often located in the middle to high category. In terms of plants moisture stress, it is often located in the category of low humidity and, therefore, high moisture stress. Also, most of the area of this category in terms of rainfall drought index is located in the severe to very severe drought class. Finally, by examining the land surface temperature index, it is revealed that this zone has

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**Fig. 6** NDMI of Golestan province in winter from 2005 to 2020
been located at the maximum temperature of the region during the months under study. Moreover, areas with moderate fire risk are located in the southern part of the province from the west to the east of the province. This zone with an area of about 4900.3 square kilometers occupies about 65.32% of the area, devoting to itself about 434 fire risk points, equivalent to 23.16% of the total study points. Low-risk zone has an area of 36.34% of the total province, devoting to itself about 134 fire risk points, equivalent to 11.06% of the total area. Finally, the safe zone with an area of about one percent has no fire hazard points. During the overhaul of the fire hazard map with the map of previous fire critical points, it was found that about 66% of the high-risk points that have already been affected by fire are consistent with the very high-risk and high-risk areas obtained in the final map. Demonstrates use in estimating fire risk areas. These results are similar to the results obtained from other studies (Vadrevu et al. 2009; Mohammadi et al. 2010; Salamati et al. 2011).

**Suggestions**

Possibility of deploying firefighting units in stressful times in the high-risk area is estimated in the research to prevent the spread of fire. Due to the importance of the two factors of moisture stress and vegetation, by the timely examination of these two factors with the help of remote sensing during high-risk months, an alarm and preparedness state can be provided to prevent fires.
Table 3 Assessing the accuracy of fire risk areas

|                     | Fire points | Safe zone | Low-risk zone | Medium-risk zone | High-risk zone |
|---------------------|-------------|-----------|---------------|------------------|----------------|
| Number of points    | 2658        | 0         | 136           | 434              | 2084 point     |
| Percentage of points| 100         | 0         | 11.06%        | 23.16%           | 65.78%         |
| Area of category    | 45/8        | 7432/7    | 4900/3        | 7989/07          |
| Percentage of area of each floor | 1.04%   | 36.34%    | 56.23%        | 6.39%            |

Fig. 8 Fire risk zones based on fire points

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Availability of data and materials Some or all data, models or code generated or used during the study is available from the corresponding author by request.

Declarations

Conflict of interest There is no conflict of interest.

Ethical approval The present study and ethical aspect was approved by the Department of Environment and Planning, University of Aveiro, 3810-193 Aveiro, Portugal, and Department of Geography, Faculty of Literature and Humanities, Islamic Azad University Central Tehran Branch, Iran, and University of Malayer, Iran, Department of Environmental Health Sciences, Faculty of Communication, Arts and Sciences, Canadian University Dubai, Dubai, P. O. Box 117781, Dubai—United Arab Emirates and Department of Irrigation, College of Agriculture, Isfahan University of Technology, 8415683111 Isfahan, Iran.

Consent to participate All authors designed the study, collected data, wrote the manuscript and revised it.

Consent to publish All authors agree to publish this manuscript. There is no conflict of interest.

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