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Forest Fire Assessment and Estimation Using Landsat 8 and Sentinel 2 Satellite Images in Google Earth Engine

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ABSTRACT

Different natural hazards which are sometimes caused by climatic processes such as fires, have put human life at stake throughout the course of history. Forest fire which is said to be one of the major causes of deforestation has been recognized as a major crisis in recent years. Satellite imagery and remote sensing techniques can effectively contribute to investigation of forest and rangeland fires. In the present study, the GEE system was used to assess the severity of fire in the Arasbaran Protected Area. For this purpose, Landsat 8 and Sentinel 2 satellite images as well as NBR (normal burning ratio) and dNBR indices were used for this purpose. According to the results, the map of areas with high fire risk can effectively contribute to forest fire management across the region.

1. Introduction

During the previous 100 years, the growth of the planet's population has led to the uncontrolled exploitation of natural resources, and forests are without doubt one of the most critical environmental and economic resources for humans (Cencerrado et al. 2012). Fire is one of the most important ecological elements in forests, with unpredictable occurrences. This devastating ecological phenomenon is directly linked to environmental and human factors. The distinction between forest fires and calamities such as floods and earthquakes is that, on the one hand, the time and location of their occurrence are almost foreseeable. On the other hand, they rarely happen, allowing damage and losses to be reduced throughout their occurrence (Nuthammachot and Stratoulias 2021). No event will certainly harm forest life as much as fire, since hundreds of hectares of forests are destroyed in a tiny fire in a single day. As a result, the presence of a fire warning system to prevent the occurrence and progression of fire appears to be essential. In general, the causes of forest fires around the world are numerous and are due to natural (environmental) and artificial (man-made) factors. The environmental factors that affect the occurrence of forest fires are numerous and of varying importance. These factors include biological, physiological and climatic factors. Vegetation is one of the most important biological factors affecting forest fires, in terms of species and density, influencing the occurrence of fires (Zarekar et al. 2012). Rising temperature, diminishing relative humidity and decreasing rainfall are also climatic factors that affect forest fires. In Iran, the high temperature in the hot season and the resulting drought, coupled with combustible substances with high drought coefficients in forest areas,

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are the leading causes of forest fires (Arnett et al. 2015; Bendixsen et al. 2015; Chen et al. 2013). The extent and propagation of wildfires make it challenging for managers to monitor and use reliable data (Wu et al. 2011; Zhang et al. 2013). Further information on the pre, post, and while forest fires may be made available through Remote Sensing and the necessary satellite data (Azari and Mohammadzade, 2016). The primary and most crucial benefit of satellite photographs over other methods is the broad coverage of space and time of these images, and satellites can provide numerous photos per day and send them to the earth, depending on their orbit from a large area. By receiving these images and processing them, it is possible to deal with how the fire is progressing and apply the necessary facilities to deal with the spread of the fire. The fire monitoring project in the United States, which has been carried out by significant organizations such as NOAA, NDMC, and USDA, and in which the fire situation in the United States has been researched, is one of the most fascinating projects in this field (Dolat yar, 2018). In 2013, Eskandari et al. used a fuzzy hierarchical analysis method to model fire risk in the forests of Mazandaran's Seh Neka-Zalamrud area. The findings revealed that man-made, biological, meteorological, and topographic factors all significantly impacted fire danger. Furthermore, the adaptation of high-risk points to fire areas showed the high validity and accuracy of the model (Eskandari et al., 2013). Zarekar et al. developed a fire capability map using fuzzy hierarchical analysis in the Gilan province forests in 2013. The model's map has a 66 percent overlap with high and very high-risk locations. The main causes of fires in this study were the vicinity of roadways and residential areas (Zareh Kar et al., 2013). Stroppiana et al. (2012) used TM and ETM photos, as well as aggregation of MIRBI, NBR, EVI, SAVI, and NDVI indices, to extract fire areas in southern Europe in 2012. A multi-criteria approach based on spectral indices, computational techniques, and growth zone algorithm was introduced in this research. The method used revealed that the sensitivity and accuracy of the maps of the burned areas to the accumulation of different indicators and defined thresholds is considerable. In 2012, Adab et al. In a study modeled the fire risk in Golestan forests using MODIS images and GIS (Adabet al., 2012). The variables were categorized based on the fire risk coefficient, and the data were analyzed in a GIS environment to produce three risk classifications for the region: low, medium, and high. Chang et al. (2004) used logistic regression to generate a fire hazard map in Heilongjiang Province, China. They used topographic parameters, sort of cover, climatic conditions, and human activities, and the results revealed that this strategy had an overall accuracy of 87.3 percent. In the Zagros forest of Kermanshah province, Dolat Yar used satellite data and spectral indices BAI, NBR, NBRT, and NDVI to identify forest fire-prone zones in 1396. The results show that the BAI index outperformed other indicators in identifying fire-affected areas (Dolat yar, 2018). Parks et al. (2018) analyzed 18 fires in the western United States, using the GEE platform and TM and ETM + data, to compare the three criteria dNBR, RdNBR, and RBR. According to the findings, the RdNBR indicator has a stronger association and accuracy with the occurrence of fire in the environment. As a result, given the importance of the research region as a protected area, we attempted to reduce damage to our country's forests and natural areas by forecasting and determining fire-prone areas in this study.

2. Materials and Methods

2.1. Study area

The Arasbaran Protected Area covers an area of 80676 hectares. It is located between 38 degrees and 40 minutes and 39 degrees and 9 minutes north latitude and 46 degrees and 42 minutes and 47 degrees and 3 minutes east longitude (Figure 1). The research area is in the north of East Azarbaijan province, within the city of Kaleybar, and leads from the north to the Aras river, from the east to the Qarasu river, from the west to the Ilgene Chay river, and from the south to the Saigram and Qaramut mountains. Because of the abundance of plants and animals, this region joined the global network of biosphere reserves in 1976 by UNESCO. The mountainous unit has the largest size in the region, accounting for 63,354 hectares or more than 78 percent of the total area, followed by the hill unit, which has an area of 10,278 hectares.

Fig 1. Arasbaran region

The remainder of the site is made up of upper plateaus and terraces, as well as sedimentary, alluvial, and flood plains (Dolat Yar et al., 2017). In terms of vegetation, in the Arasbaran region, 1334 plant species belong to 493 genera and 97 families (Najafi, 2015). Oak, wild cherry, yew, and juniper are valuable and unique species of the region. Cornelian cherry shrub, as a landmark of the area and wild cherries and yaw, are considered important plants of the Mediterranean region plains (Dolat Yar et al., 2017). The main wood species of this region include hornbeam, maple, oak, wild cherry, Scots elm, ash, apple, fig, ailanthus, walnut, hazelnut, juniper, and pistachio. Other wood species unique to the Arasbaran region include juniper, smoke tree, and white oak. Shrub species include almond, hackberry, Cornelian cherry, forest pomegranate, mahlab, cranberry, and barberry (Najafi, 2015).

2.2.Data used

Due to the fact that the fire in the Arasbaran forest area occurred from August 12 to September 26, 2019, the images before the fire were dated 15/02/2019 to 28/03/2019 and after the fire on 27/08/2019 to 09/23/2019 in Google Earth Engine (GEE) system for Landsat 8 and Sentinel 2 sensors. Landsat 8 The eighth satellite in the Landsat series has 11 bands. Bands 1 to 4 and 8 are visible, whereas the remaining bands are not. Band 5 is the near-infrared band (NIR), which is crucial for ecology and reveals plant health. Bands 6 and 7 are in the infrared short wave range (SWIR). These bands are used to differentiate wetlands from dry and fire-prone areas. Sentinel series satellites have been created and designed by the European Union, and five series of these satellites have been launched into space so far. The second series of Sentinel satellites began their mission on June 23, 2015. The satellite consists of 13 spectral bands, 8 NIR bands, and 11 and 12 bands in the SWIR range. Figure 2 shows the steps of the proposed method.

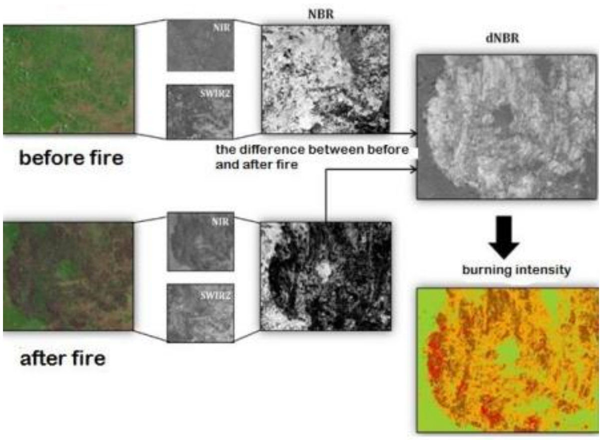

Fig 2. Proposed method

In this study, a map of fire intensity and the quantity of destroyed area was created using Landsat 8 and Sentinel 2 satellite pictures and the dNBR index. Various classifications can be established using the dNBR fire index in conjunction with the discussion of fire intensity in satellite photos; nevertheless, this index, like most other indices, has uncertainties, and rich and relevant ground data are required for better calibration. The United States Geological Survey (USGS) has proposed a table of seven classes to interpret burn intensity (Table 1), which was used in this study to interpret the results.

Table 1. Intensity level obtained by calculating dNBR, proposed by USGS.

	Severity level	dNBR Rang (scaled by 10^3)	dNBR Rang (not scaled)
	Enhanced Regrowth high	-500 to -251	-0.500 to -0.251
	Enhanced Regrowth low	-250 to -101	-0.250 to -0.101
	Unburned	-100 to +99	-0.100 to +0.99
	Low Severity	+100 to +269	+0.100 to +0.269
	Moderate- low Severity	+270 to +439	+0.270 to +0.439
	Midrate-high Severity	+440 to+659	+0.440 to +0.659
	High Severity	+660 to +1300	+0.660 to +1.300

The dNBR burn index can be expressed as follows.

NBR is an indicator designed to identify burned areas. This index is similar to the NDVI index, except that the NBR uses both NIR and SWIR wavelengths. Low NBR levels imply burned areas, while high NBR values suggest healthy vegetation. The NBR index is calculated for photos taken before and after a fire. The two photos utilized in these processes must be referred to each other. After applying the index to both photos before and after the fire, a simple fluxion between the two images may be used to identify the fire-affected area; this index is known as dNBR.(Keeley (2009) Table 2 shows the Landsat 8 and Sentinel 2 band combinations for the production of NBR and dNBR indices.

Table 2. Landsat 8 and Sentinel 2 band combinations to produce NBR and dNBR indices

Row	Satellite	Fire index	Formula
1	Landsat 8	NBR	(B5-B7)/(B5+B7)
2	Sentinel 2	NBR	(B8-B12)/(B5+B7)
3	-	dNBR	NBR_{pre} - NBR_{post}

3.Results and discussion

Figure 3 depicts the map created by using the dNBR index, and Table 3 depicts the area of fire classes in hectares.

In Figure 3, purple shows the areas with the highest risk probability and pink indicates the areas with average probability, and yellow has the lowest probability.

In the achieved results in the study area, it is observed that due to the decreasing trend of vegetation cover and the decrease in its density in the area, the corresponding fire risk has also shown a decreasing trend. It is worth mentioning that in the zoning of fire potential, the greatest impact will be related to plant mass in the study area. Even though human factors can increase the risk of fire on their own, personal carelessness can lead to large-scale forest fires, which have been witnessed in many cases around the world.

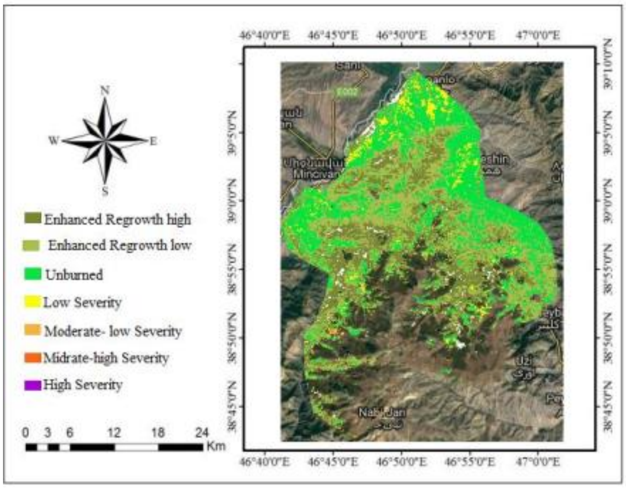

Fig 3. DNBR index map

Table 3- Area of fire classes

Fire intensity class	area (hectares)
Enhanced Regrowth, high (post-fire)	19836.9
Enhanced Regrowth, low(post-fire)	21673.89
unburned	27582.21
Low severity	4258.8
Moderate-Low severity	621.27
Midrate-high severity	97.11
High severity	25.9

4. Conclusion

The proposed method in this research is a quick and low-cost way to identify regions with high fire risk to help prepare for fires in these forest areas, which occur every year at the start of the warm months, and to detect and take the required safeguards to prevent fire damage. In the future, the image obtained can be overlaid over the region's DEM, and the processed results can be displayed in three dimensions. Furthermore, the fire layer can be categorized as a classified layer or a threshold can be used to indicate hazardous locations with a high fire risk (for example, more than 80 percent). In this situation, the fire risk classification layer can be transformed to vector polygons before being imported into the GIS system. Before proceeding, a median filter should be used to remove any small regions of the image. The median filter eliminates very small isolated hazardous areas while retaining only big polygons with a high fire risk.

5.References

1. *Adab, H., Devi Kanniah, K. and Solaimani, K., 2012. Modeling forest fire risk in the northeast of Iran using remote sensing and GIS techniques, Natural Hazard, 65(3): 1723-1743.*
2. *Azari, O. & Mohammadzade, A. 2016. Fire Identification in Remote Sensing from the Perspective of Some Satellite Sensors, Geospatial Engineering Journal, 7 (3): 15-23.*
3. *Arnett, J.T., Coops, N.C., Daniels, L.D. & Falls, R.W. 2015. Detecting forest damage after a low-severity fire using remote sensing at multiple scales. International Journal of Applied Earth Observation and Geoinformation, 35, pp.239-246.*
4. *Bendixsen, D.P., Hallgren, S.W. &Frazier, A.E. 2015. Stress factors associated with forest decline in xeric oak forests of south- central United States. Forest Ecology and Management, 347, pp.40-48.*
5. *Cencerrado, A., Rodriguez, R., Cortes, A. and Margalef, T., 2012, Urgency versus accuracy: Dynamic Data Driven, application system for natural hazard management, International Journal of numerical analysis and modeling, 9, 432-448.*
6. *Chang, Y., Zhu, Z., Bu, R., Chen, H., Feng, Y., Li, Y., Hu Y. and Wang, Z., 2013, Predicting fire occurrence patterns with logistic regression in Heilongjiang Province, China. Landscape Ecology 28(10): 1989-2004.*
7. *Chen, W., Sakai, T., Moriya, K., Koyama, L. & Cao, C. 2013. Estimation of vegetation coverage in semi-arid sandy land based on multivariate statistical modeling using remote sensing data. Environmental Modeling & Assessment, 18(5), pp.547-558.*
8. *Dolat yar Fariba, 2018, Identification of forest fire prone areas using satellite images in Heli Zagros forest of Kermanshah province, Master's thesis, Amol non-profit university.*
9. *Dolat Yar Fariba, Soleimani Karim, Naji Sadegh and Zand Karimi Arash, 2017, Preparation of Forest Fire Risk Map Using Fire Risk Model in GIS Environment, Case Study: Kermanshah Forests, 5th Scientific Conference on New Horizons in Science Geography and Planning of Architecture and Urban Planning of*

Iran, Tehran, Association for the Development and Promotion of Basic Sciences and Technologies.

10. *Eskandari Saeedeh, Oladi Ghadiklaei Jafar, Jalilvand Hamid and Serajian Mohammad Reza, 2013, Modeling and Predicting the Risk of Fire in the Forests of Seh Neka-Zalmrud Using Geographic Information System, Quarterly Journal of Forest and Poplar Research Iran, 21 (2): 203-217.*
11. *Nuthammachot, N. & Stratoulias, D. 2021. A GIS-and AHP-based approach to map fire risk: a case study of Kuan Kreng peat swamp forest, Thailand. Geocarto International, 36(2), 212-225.*
12. *Najafi Ahmad, Irannejad Mohammad Hossein, Sotoudeh Ahad, Mokhtari Mohammad Hossein and Kiani Bahman, 2015, Modeling and preparing a forest fire risk map using remote sensing and GIS) Case study: Bagh Shadi Protected Area Yazd (, Applied Ecology, 4 (14): 13-26.*
13. *Keeley, J.E., 2009, Fire intensity, fire severity and burn severity: A brief review and suggested usage, International Journal of Wildland Fire, 18(1): 116–126.*
14. *Parks, S.A., Holsinger, L.M., Voss, M.A., Loehman, R.A., 2018, Mean Composite Fire Severity Metrics Computed with Google Earth Engine Offer Improved Accuracy and Expanded Mapping Potential, Remote Sensing 10(6): 1-15.*
15. *Stroppiana, D., Bordogna, G., Carrara, P., Boschetti, M., Boschetti, L. and Brivio, P.A., 2012, A method for extracting burned*
16. *Wu, Z.W., He, H.S., Chang, Y., Liu, Z.H. & Chen, H.W. 2011. Development of customized fire behavior fuel models for boreal forests of northeastern China. Environmental management, 48(6), pp.1148-1157.*
17. *Zarekar, A., Vahidi, H., Kazemi Zamani, B., Ghorbani, S. & Jafari, H. 2012. Forest fire hazard mapping using fuzzy AHP and GIS. Study area: Gilan Province of Iran. International Journal on "Technical and Physical Problems of Engineering"(IJTPE), 4(3), pp.47-55.*
18. *Zareh Kar Azadeh, Kazemi Zamani Bahareh, Ghorbani Sara, Ashegh Maala Maryam and Jafari Hamid Reza, 2013, Preparation of spatial distribution map of forest fire risk using multi-criteria decision making method and GIS (Case study: three forest areas In Gilan province), Iranian Journal of Forest and Poplar Research 21 (2): 218-230.*
19. *Zhang, H., Han, X. & Dai, S. 2013. Fire occurrence probability mapping of northeast China with binary logistic regression model. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 6(1), pp.121-127.*