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RESEARCH

A novel multi-spectral index for burned area detection using high-resolution satellite imagery

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Abstract
The limitations of existing indices, heavily depend on the shortwave infrared (SWIR) band for identifying burned areas—a band not available in SuperDove satellite imagery. The study offers the novel SuperDove burned area index (SBAI) for burned area identification using high-resolution SuperDove satellite imagery as existing indices fail to use available SuperDove spectral bands. SuperDove satellite imagery with 3.7-m resolution was used to perform the analysis and the study area was the burned region in Goizha Mountain in Sulaymaniyah, Iraq. Nine established indices and K-nearest neighbor (KNN), support vector machine (SVM), random forest (RF), and maximum likelihood (ML) machine learning techniques for burned area detection were compared to the performance of the SBAI. The investigations showed that SBAI underscored high accuracy with 80.7% in detecting areas burned by fire, which outperformed 8 out of 9 traditional indices and all used machine learning algorithms. SBAI showed lower noise and false detections compared to the established techniques. The difference normalized burn ratio dNBR was the only index among all techniques which slightly surpassed the performance of SBAI, with 83.4% accuracy, while the majority of indices showed poor performance when applied to SuperDove images. The research also underscored that well-designed indices could outperform advanced machine learning techniques in specific conditions of earth observation applications. The developed novel index significantly contributes to monitoring fire events and post-fire assessment by using high spatial and temporal resolution multispectral imagery, which offers valuable insights to geospatial analysts and land managers for accurate fire event mapping. This novel index fills the gap in using SuperDove satellite imagery accurately to detect burned areas, which previously was challenged by existing indices.

Keywords Burned area index · Earth observation · Multi spectral · SuperDove

Introduction

Millions of hectares burn annually which leads to severe environmental and economic damages. Around one-thousandth of the world's green areas are affected by fires each year globally, making wildfires a significant global issue (Zhang et al. 2020). Due to the change in climate conditions and human activities, wildfires have significantly increased in recent years. The mountainous terrain and increasing drought conditions in the region, contributed significantly to the rapid spread of fires, leading to substantial damage to the ecosystems and the loss of biodiversity (Skinner et al. 2022). The wildfire also threatens local citizens due to the proximity to settlement areas and farming areas. In the Kurdistan region, significant economic losses were recorded which significantly affected the local communities because they rely on the resources. Addressing the wildfire challenges in the Kurdistan region of Iraq is significant for sustainable development and understanding the environmental impacts better by accurate and efficient mapping of fires (Garcês and Pires 2023). Limited researches have been done for burned area detection using the Normalized difference vegetation index (NDVI) and Normalized Burned Ratio (NBR) (Mustafa and Habeeb 2016; Rasul et al. 2021). Additionally, multiple researches have been conducted to identify vulnerable areas to fire in the Kurdistan region of Iraq in recent years using remote sensing and Geographic

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information system technologies (Salar 2019; Khwarahm 2022). Mapping burned areas accurately contributes significantly to assessing the air quality, fire emissions and post-disaster analysis, which offers significant information for climate change studies and resource management (Neves et al. 2024). Having accurate maps of affected areas by fires allows researchers and policymakers to better analyse the source of fires and develop strategic planning for reducing the effects of wildfires on ecosystems and human health (Sali et al. 2021; Liu et al. 2023).

There are multiple spectral indices that have been used to map and detect burned areas using different types of satellite imagery. Burned areas have unique spectral signatures that could be captured by satellite imagery using spectral bands, and the unique spectral signatures would be used by these indices to identify the burned areas accurately. The Normalized Burn Ratio (NBR) and Burned Area Index (BAI) are the two most commonly used methods to classify burned and unburned areas using both the near-infrared and shortwave infrared bands. However, there are limitations and challenges within the existing indices in the context of accuracy and applicability across different environments and burn degrees (Roy et al. 2002; Chuvieco et al. 2019). Liu, Maeda et al. indicated that the BAI can detect burned areas with 90–95% accuracy (Liu et al. 2021). Moreover, a study used near-infrared and short-wave infrared bands to identify burned areas using Normalized Burn Ratio (NBR) with an accuracy of 85–95% (García and Caselles 1991). Moreover, researchers developed a burned area detection index (BADI) with 92.15% accuracy, which is specifically designed for sentinel 2 imagery (Farhadi et al. 2023). Holden, Smith et al. used the enhanced normalized burn ratio using thermal bands in normalized burn ratio thermal 1 (NBRT1) with an accuracy of 90–95% (Holden et al. 2005). However, another research used the analytic Burned Area Index (ABAI) to detect forest fire severity by using Landsat and Sentinel imagery with 80–90% accuracy (Guo et al. 2024). Additionally, Key and Benson integrated multiple factors to identify the burned areas using the Composite Burn Index (CBI) with an accuracy of 80–85% (Key and Benson 2005).

There are multiple researches that used advanced machine learning techniques to detect fire events and burned areas using satellite imagery, showing different classes of accuracy. The K-nearest neighbors (KNN) and random forest (RF) machine learning classifiers were used effectively to assess the burned areas using multispectral imagery of Landsat 8, Sentinel 2 and MODIS datasets, showing excellent performance between 93 and 96% accuracy (Pacheco et al. 2021). Moreover, Support Vector Machine (SVM) accurately classified and differentiated land covers with burned areas in different researches. Additionally, more advanced techniques such as deep learning tools of Uni-Temporal were used as an effective approach to detect burned areas with 97% accuracy using Sentinel 2 satellite imagery. There are also specific tools and models designed for burned areas which showed reliable results, such as the Burnt-Net model (Seydi et al. 2022). Using advanced techniques of artificial intelligence technology, substantially changed the fire monitoring in both accuracy and reliability of the mapped areas.

The majority of existing indices primarily depend on shortwave infrared (SWIR) to identify burned areas, which is a band not available in SuperDove satellite imagery, failing to use the existing indices for SuperDove datasets. The gap highlighted the necessity of developing a new effective and useful index specifically designed for burned areas using SuperDove available bands. The study offers the novel SuperDove burned area index (SBAI) for burned area identification using high-resolution SuperDove satellite imagery to fill the gap. Additionally, increasing the frequency and intensity of wildfires globally underscores the urgent need for a new and more accurate spectral index that addresses the challenges and limitations. With the limitations of current indices which cannot be used for SuperDove imagery, this new index provides enhanced capabilities and offers more detailed and precise burn detection. By developing a novel multi-spectral index that considers the before and after the event and uses multiple ranges of spectral bands including near-infrared, red, green, yellow, red edge, coastal blue, and blue, we aim to improve the accuracy and reliability of the burned area mapping, which this approach significantly contribute in better management and restoration strategies (Sali et al. 2021).

Materials and methods

Study area

Goizha Mountain is one of the valuable places in Sulaymaniyah, Kurdistan region of Iraq, which is near to the urbanized areas. Located at an elevation of 1500 m and known for its rich biodiversity and recreation significance for the city. However, there were several fires that caused severe damage to the ecosystem. The mountain has diverse cover types, with the majority of oak trees alongside grasslands. 600 different plant species have been registered in recent years in the mountain. Emphasizing the ecological significance of the mountain. However, urbanization and land cover changes lead the mountain to face significant environmental challenges, resulting in threatening its natural habitats (Muhamad and Rasul 2024). Recently, on July 29, 2024, a critical fire caused substantial damage to the ecological diversity and valuable region, burning around 100 hectares and more than 20 thousand trees. Using high-resolution SuperDove satellite imagery with its 3.7 m spatial resolution and daily revisit capability, it's a significant study site for burned area detection using multiple indices. Planet imagery was used in this study which provides imagery with very high spatial and temporal resolution, offering valuable insights for assessing the extent and severity of the damaged places. 12 field surveys were used to assess the accuracy of the results by providing ground truth data. The ecological significance and biodiversity of Goizha Mountain make it a critical resource which needs protection for a more sustainable environment (Fig. 1).

Burned area detection approaches

Multiple spectral indices by different studies having different characteristics and applications, which significantly facilitated the process of burn area detection in the past (Table 1, Fig. 2). NBR is one of the most common indices which utilize the near-infrared (NIR) and shortwave infrared (SWIR) bands. The main application of this index is that used effectively for large fire zones, to classify the burned areas with unburned areas using before and after data. The idea of the

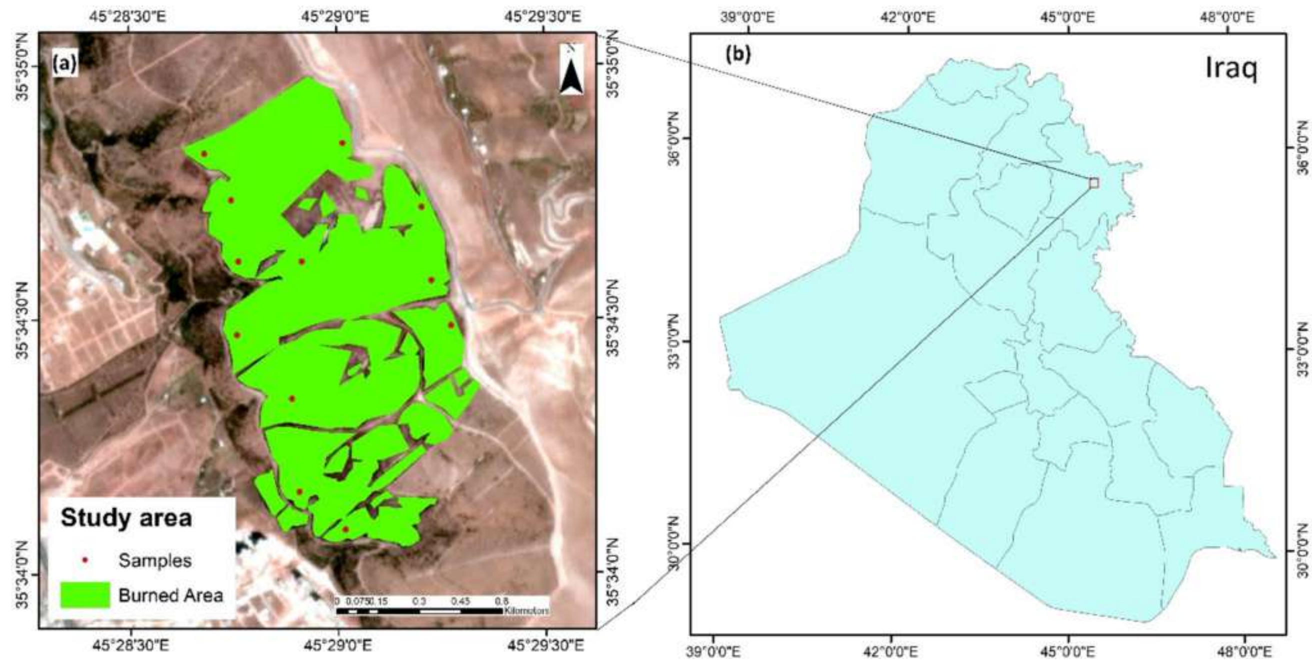

Fig. 1 Burned area of the study area in Sulaymaniyah (**a**), Iraq (**b**)

Table 1 Common burned area indices from literature

Index	Formula	Used Bands	Reference
NBR	NBR = (NIR—SWIR) / (NIR + SWIR)	NIR, SWIR	(Tichouiti 2024)
Differenced Normalized Burn Ratio (dNBR)	dNBR = NBR_pre—NBR_post	NIR, SWIR (pre and post-fire)	(Ramayanti et al. 2024)
Relative differenced Normalized Burn Ratio (RdNBR)	RdNBR = dNBR / $\sqrt{(\text{NBR pre fire})}$	NIR, SWIR (pre and post-fire)	(Gupta et al. 2024)
BAI	BAI = 1 / ((0.1—RED)^2 + (0.06—NIR)^2)	RED, NIR	(Suresh Babu et al. 2024)
Mid-Infrared Burn Index (MIRBI)	MIRBI = 10 * SWIR2—9.8 * SWIR1 + 2	SWIR1, SWIR2	(Zhang et al. 2024)
Char Soil Index (CSI)	CSI = NIR / SWIR	NIR, SWIR	(Novo et al. 2024)
Normalized Difference Moisture Index (NDMI)	NDMI = (NIR—SWIR) / (NIR + SWIR)	NIR, SWIR	(Mofokeng et al. 2024)
Burned Area Index Modified (BAIM)	BAIM = 1 / (NIR * SWIR)	NIR, SWIR	(Han et al. 2024)
Global Environmental Monitoring Index (GEMI)	GEMI = η(1—0.25η)—(RED—0.125) / (1—RED), where η = (2(NIR^2—RED^2) + 1.5NIR + 0.5RED) / (NIR + RED + 0.5)	NIR, RED	(Fan et al. 2024)

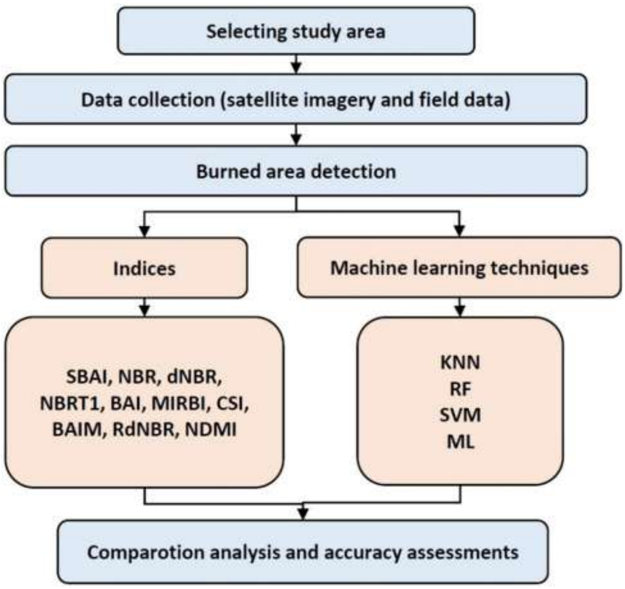

Fig. 2 The flowchart of the study

NBR formula is similar to the NDVI but uses different bands (Liu et al. 2021).

$$NBR = \frac{\text{Near Infrared} - \text{Short Wave Infrared}}{\text{Near Infrared} + \text{Short Wave Infrared}} \tag{1}$$

BAI is also one of the commonly used index in literature which calculates the spectral distance of pixels in burned areas. Red and near-infrared are the only two bands that need to calculate the BAI, which proved its performance in detecting burned areas (Liu et al. 2021).

$$BAI = \frac{1}{(0.1 - \text{RED})^2 + (0.06 - \text{Near Infrared})^2} \tag{2}$$

NBRT1 is another index that was developed to enhance the NBR index by adding a thermal band in the formula to improve the classification of burned areas more accurately. Thermal infrared (TIR) offers more reliability, especially for landscapes with complex structures where temperature differences can offer effective information for detecting burn areas accurately. The near-infrared (NIR) and short-wave infrared (SWIR) are also two other bands that are used in the NBRT1 index for burn area calculation (Liu et al. 2021).

$$NBRT1 = \frac{\text{NIR} + (\text{SWIR} * \text{TIR}/10000.0)}{\text{NIR} - (\text{SWIR} * \text{TIR}/10000.0)} \tag{3}$$

Besides the most commonly used indexes, there are various studies that used other spectral indices for burn area assessments, such as Soil Adjusted Vegetation Index (SAVI) and the Modified Normalized Difference Water Index (MNDWI), which showed effective performance in identifying burned areas. Near-infrared, red bands and soil brightness correction factors are the parameters needed for SAVI calculation, however, green and short-wave infrared are only two bands needed for MNDWI calculation (Fornacca et al. 2018).

$$NBRT1 = \left(\frac{\text{Near Infrared} - \text{RED}}{\text{Near Infrared} + \text{RED} + \text{SB}}\right) * (1 + \text{SB}) \tag{4}$$

where SB is Soil brightness correction factor

$$MNDWI = \frac{\text{Green} - \text{short wave infrared}}{\text{Green} + \text{short wave infrared}} \tag{5}$$

The literature showed the effective performance of traditional indices like NBR and BAI, however, there are limitations in specific environments or conditions. The accuracy and reliability of these indices face challenges and fluctuate based on the types of vegetation, burn levels, and the time passed since the fire event. There are researches that indicated that using the average of multiple spectral indices significantly improves the accuracy and reliability of burn area mappings compared to individual indices.

The improvement and generating the new spectral indices for burn area extraction still are the significant field for researchers. Understanding the strengths and limitations of previously developed indices offers scientists valuable insights to enhance the performance of indices and develop new approaches of burn area detection and fire monitoring. Furthermore, the integration of indices with advanced analytical techniques, such as fuzzy classification methods, provides more accuracy and reliability to monitor burned area and offers valuable information for better sustainable management (Kavzoglu et al. 2016).

There are limitations of existing indices such as soil, water and atmospheric effect sensitivity which significantly reduce the accuracy of detected burned area (Liu et al. 2021). Also, the characteristics of the vegetation have an impact on the spectral responses to the fire, which some indices like NBR could not perform well in different environments, resulting in less accurate mapping of burned areas. Moreover, the majority of the indices were developed based on specific temporal and spectral conditions or post fire assessments, which may not be possible for all conditions. The temporal resolution of satellite imagery since fire-events may significantly change the response of the burned (Kavzoglu et al. 2016).

Additionally, four different advanced machine learning techniques from ArcGIS Pro were used for burned area detection in this research, such as K-nearest neighbor (KNN), Random Forest (RF), Support Vector Machine (SVM), and Maximum Likelihood (ML). The machine learning techniques alongside the existing indices were compared together with the novel index to assess the accuracy and performance of each technique.

SuperDove burned area index (SBAI)

7 out of 9 indices analysed in this study, were relying primarily on shortwave infrared (SWIR) to identify burned areas, which is a band not available in SuperDove satellite imagery, failing to use the existing indices for SuperDove datasets. Having the limitations in previous indices, there is a necessary need for a new index which more accurately detects burned areas effectively and integrates more spectral bands, such as green, red edge and coastal blue and blue bands. The objective of this comprehensive method is to develop a new burned area detection index specifically for SuperDove satellite imagery using the available bands, resulting in capturing more characteristics and details which existing indices may overlook. SBAI is the proposed new index which utilizes additional spectral bands which is more sensitive to unique spectral signatures of burned regions and offers more accuracy. The SBAI offers valuable insights for policymakers which contributes significantly to fire management ecological studies and post-fire recovery strategies. Developing a novel multi-spectral index for detecting accurately burned areas is critical to face the challenges of existing indices. The SBAI improves the accuracy and reliability of burned area mapping which offers valuable insights for better fire management and ecological restoration planning.

The SBAI index uses multispectral bands primarily designed for SuperDove planet satellite imagery (Fig. 3). Spectral bands used in this index are: Near-Infrared (NIR), Red (R), Green II (G2), Coastal Blue (CB), and Blue (B). SBAI is based on the pre and post-fire assessment to accurately differentiate the changed spectral details after the fire (Eq. 6).

$$SBAI = \left(\left(\frac{NIRpost}{NIRPre} - \frac{Rpost}{Rpre} \right) + \left(\frac{Rpost}{RPre} - \frac{GIIpost}{GIIpre} \right) + \left(\frac{CBpre}{CBpost} - \frac{Rpost}{Rpre} \right) \right) * \left(1 - \frac{Bpost}{Bpre} \right) \tag{6}$$

The ArcGIS Pro and Google Earth Engine (GEE) were used to detect burned areas using multiple indices and performing the comparison analysis between them. Two images from before and after fire of both SuperDove and Sentinel 2 were used for the analysis (Fig. 4, Table 2). SBAI results were compared with 13 other burned area detection techniques using geographic information techniques (GIS).

The components used in SBAI were selected based on the ability to detect unique spectral characteristics that contributed to burned areas. The NIR band is one of the commonly used bands in previous indices also, which is crucial for vegetation health detection, as healthy vegetation reflects significant amounts of NIR light. In contrast, after burning there would be a substantial decrease in NIR reflectance due to the loss of chlorophyll and structural changes. The difference of the post-fire to pre-fire reflectance of NIR band provides valuable information and can be used as a main indicator of occurred damages by fire, making it a significant parameter of the SBAI. Moreover, multiple researches showed the effectiveness of NIR in burned area detection.

Moreover, the red band is also another significant spectral band which significantly used for vegetation assessment. By the comparison of post and pre-fire reflectance values of the red band, SBAI can identify regions effectively where vegetation has been significantly reduced due to fire. The Green II band offers valuable information

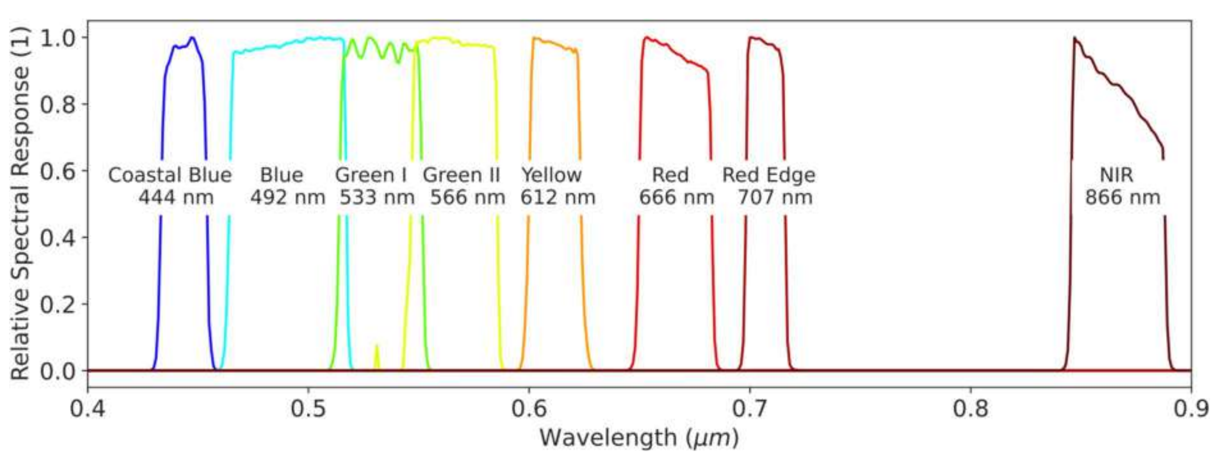

Fig. 3 8 bands of multispectral PlanetScope SuperDove imagery (Vanhellemont 2023)

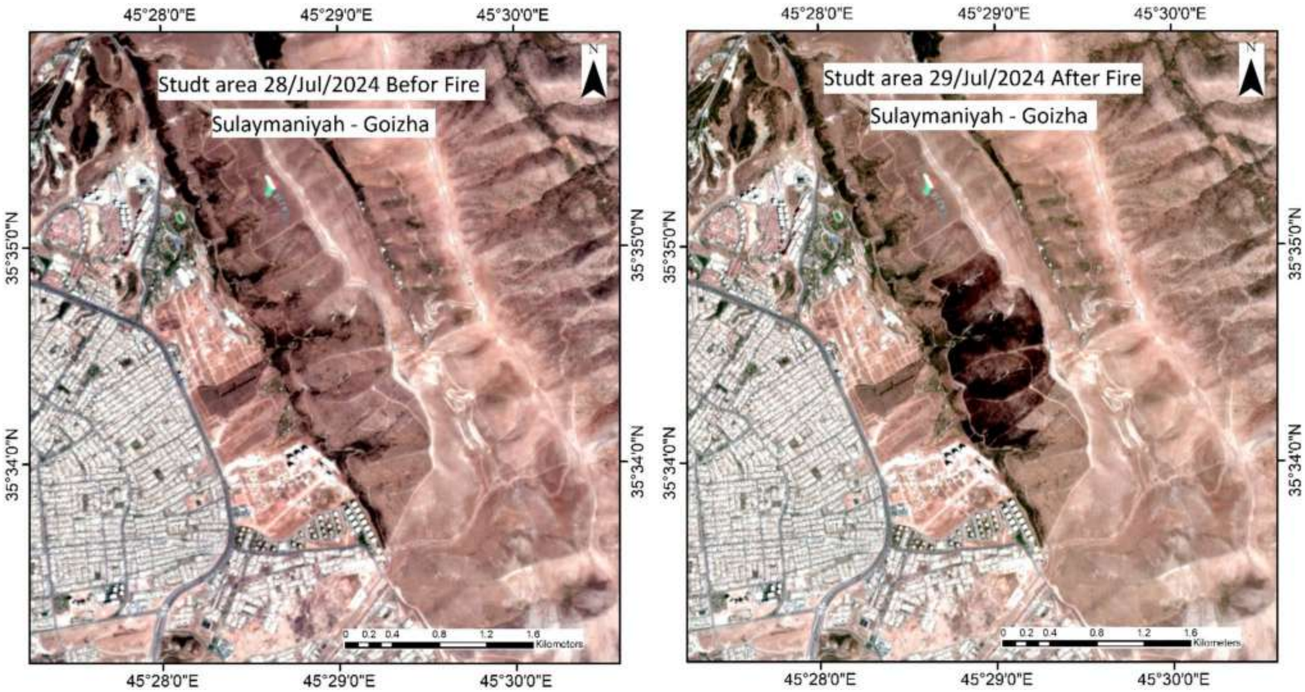

Fig. 4 Before and after fire SuperDove imagery in Goizha mountain, Sulaymaniyah

Table 2 Satellite imagery used for burned area detection

Satellite	Bands	Resolution (m)	Time
Sentinel 2	Red	10	Pre-fire: 26-Jul-2024 Post-fire: 31-Jul-2024
	Near infrared		
	Shortwave infrared	60	
Planet (SuperDove)	Coastal Blue Blue Green I Green II Yellow Red Red Edge NIR	3.7 – 4.1	Pre-fire: 28-Jul-2024 Post-fire: 29-Jul-2024

about the density and health of vegetation. Using post and pre-fire assessment using green II bands increases the sensitivity of the index to subtle changes in vegetation that may not be as apparent in the Red band alone (Guo et al. 2024). Additionally, the Coastal Blue band is included in the index which offers significant detail of the moisture content or specific soil types in the region. Using coastal blue helps to differentiate the land covers which have similar spectral characteristics (Martín et al. 2005). The limitation of the SBAI is that in specific regions there is noise and some areas which are not burned are identified as burned areas, using blue band significantly reduces the noise and makes the index more accurate and reliable by using the difference in pre and post fire. The blue band used in the term $\left(1-\frac{Bluepost}{Bluepre}\right)$ is effective for identifying the impact of fire on soil and ash, specifically in regions with sparse vegetation (Kavzoglu et al. 2016).

The SBAI offers a novel approach for detecting burned areas by integrating the multispectral high-resolution bands which significantly increase the accuracy and reliability. The index addressed the challenges faced by the limitation of existing indices, contributing to enhanced detection of various environmental and ecological conditions. SBAI primarily utilized high-resolution satellite imagery from PlanetScope SuperDove satellites, which provide frequent and detailed earth observations. The constellation of PlanetScope consists of 240 microsatellites providing the daily

Table 3 The accuracy of indices and machine learning algorithms for detected burned areas

Actual burned area = 108.56 hectare					
Type	Burned area (hectare)	False burn area (hectare)	Area discrepancy (hectare)	Accurate detected area (hectare)	Accuracy %
dNBR	104.3	2.1	−4.3	90.5	83.4
SBAI	102.3	9.7	−6.3	87.7	80.7
KNN	82.8	8.9	−25.8	77.4	71.3
SVM	81.3	7.1	−27.3	76.6	70.6
RF	79.7	11.6	−28.8	75.0	69.1
ML	70.0	0.6	−38.6	67.8	62.5
CSI	71.9	18.3	−36.7	64.4	59.3
BAIM	83.1	261.4	−25.5	64.2	59.2
NBRT1	61.1	13.4	−47.5	59.2	54.5
RdNBR	38.5	32.7	−70.1	57.9	53.4
NDMI	49.8	5.7	−58.8	51.6	47.6
BAI	46.2	11.3	−62.4	43.4	40.0
NBR	43.4	5.8	−65.2	41.7	38.4
MIRBI	43.1	82.5	−65.5	39.8	36.6

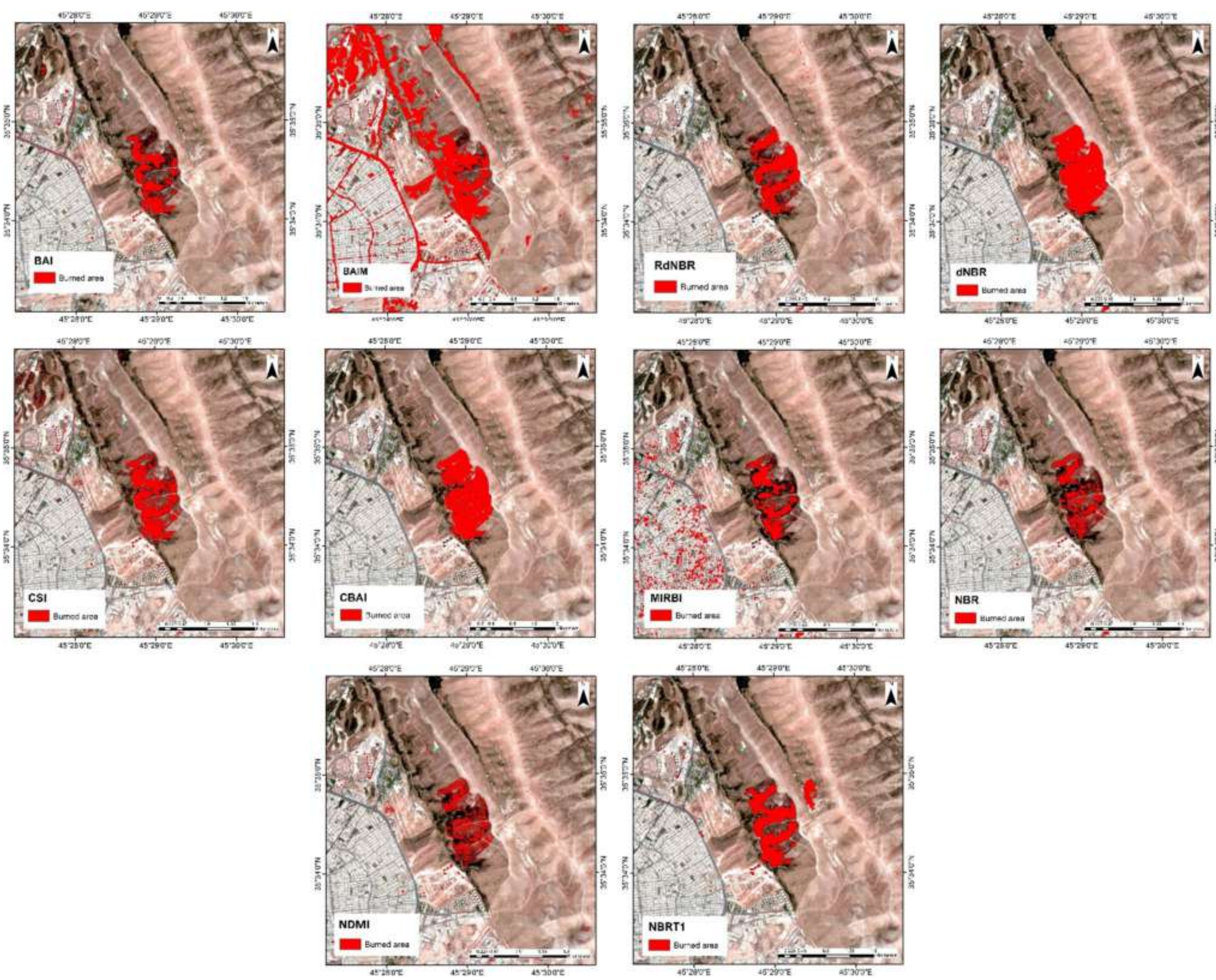

Fig. 5 Detected burned areas using multiple indices: BAI, BAIM, RdNBR, dNBR, CSI, SBAI, MIRBI, NBRT1, NDMI, and NBR

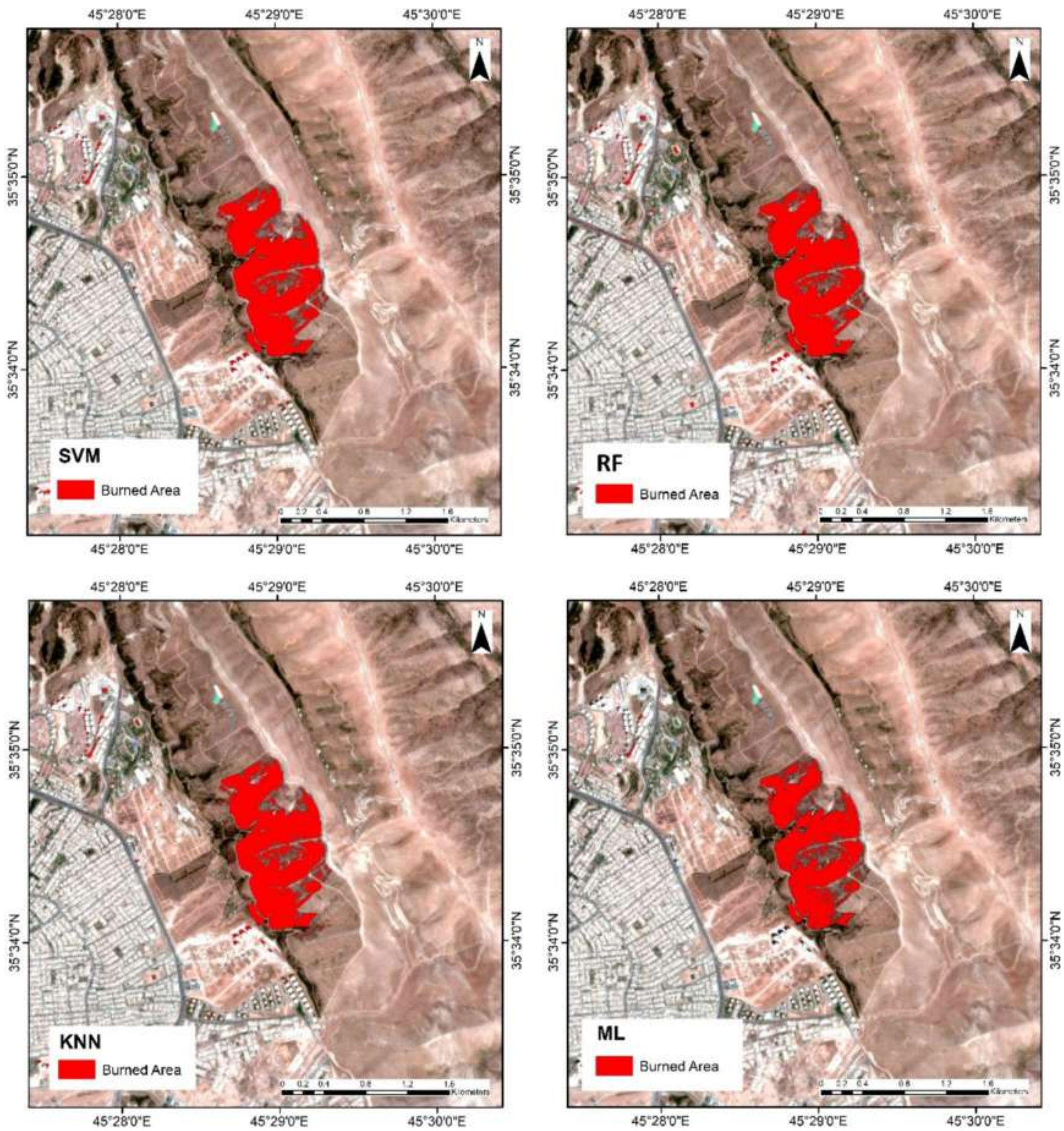

Fig. 6 SVM, RF, ML, and KNN

revisit which covers the majority parts of the world. The SuperDove offers imagery with daily temporal resolution and a spatial resolution of up to 3.7 m. The high temporal and spatial characteristics and free availability of the imagery are significantly helpful for different types of applications and provide detailed information on ground features. The SuperDove satellites have eight multi-spectral bands, including blue, green, red, near-infrared (NIR), coastal blue, and red edge, which improves the reliability and accuracy of identifying the detailed changes in vegetation and land features caused by fires (Apollo 2024). These characteristics provide valuable insights for SBAI to detect burned areas with detail using multiple bands.

Results and discussions

In this study, 9 commonly used indices and 4 machine learning techniques were compared with the proposed novel SBAI, the result showed that the SBAI index was more accurate than machine learning techniques and 8 out of 9 indices with 80.7% accuracy. The outcome indicated that dNBR is the most accurate index to detect the burned areas and it has the smallest discrepancy between the detected area with actual areas which was 108.56 hectares. Moreover, the study emphasized that among the machine learning techniques, KNN were the most accurate and all machine learning techniques showed better performance than all indices except

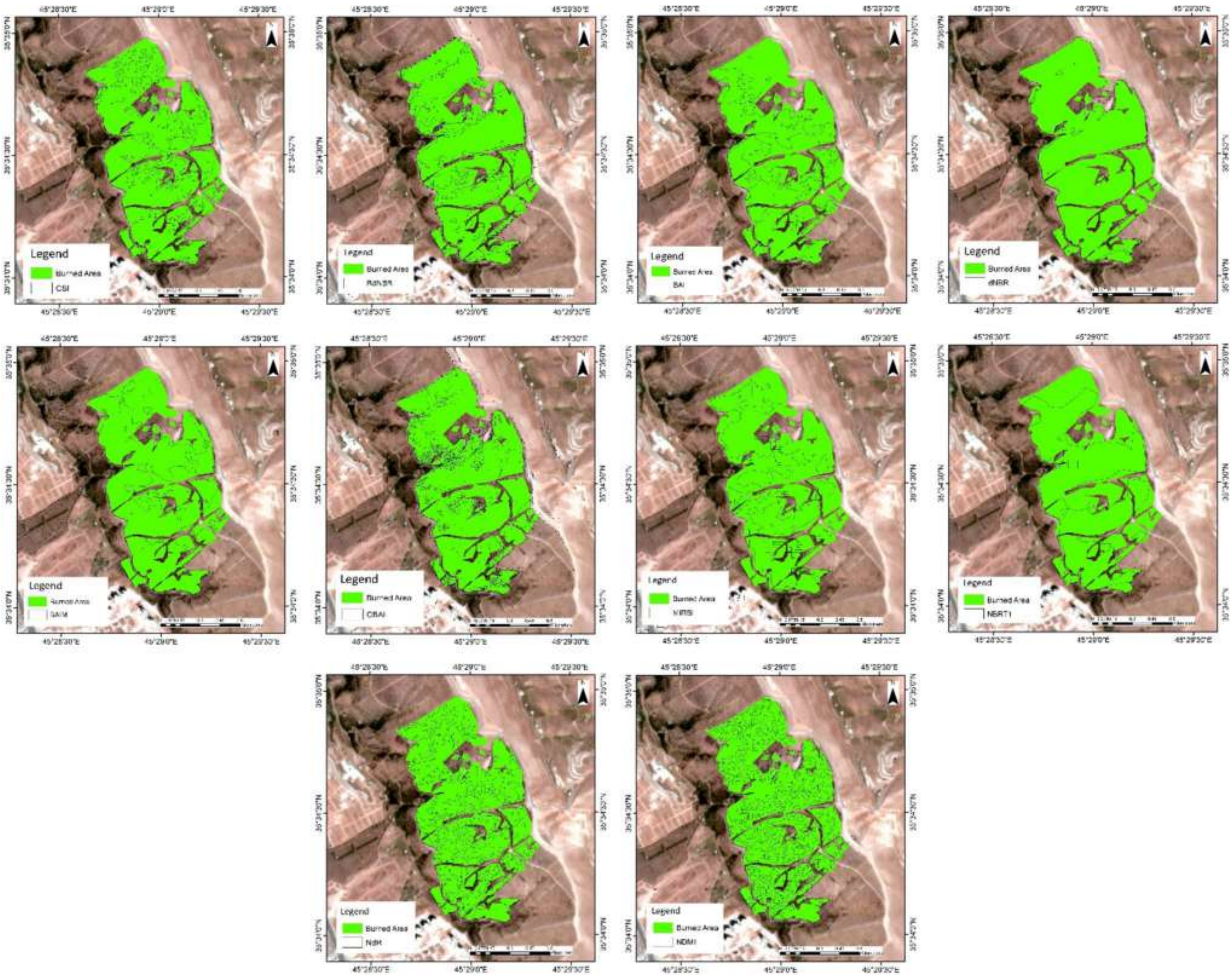

Fig. 7 Comparisons between detected burned areas (black) with actual burned areas (green): BAI, BAIM, RdNBR, dNBR, CSI, SBAI, MIRBI, NBRT1, NDMI, and NBR

dNBR and SBAI. MIRABI, NBR, BAIM, BAI, and NDMI were the indices which showed the least accurate results with very high noise of areas detected as burned which were not burned, and the outcome showed that they are not suitable for accurate burned area detection using SuperDove imagery. However, KNN, dNBR, SBAI, and RdNBR showed the least amount of noise and detected the burned areas with reliable results, specifically the intense burned areas.

In this study, 9 commonly used indices and 4 machine learning techniques were compared with the proposed novel SBAI. The assessments were conducted using SuperDove satellite imagery of the Goizha mountain area in Sulaymaniyah, Kurdistan region of Iraq, comparing pre and post-fire images (28–29-July-2024). We mapped the actual burned area manually and generated the burned area using ArcGIS Pro and SuperDove high-resolution satellite imagery. The actual burned area for the region of interest was 108.56 hectares. The SBAI index showed high accuracy ranking second among all utilized techniques with an accuracy of 80.7%. SBAI detected 103.3 hectares of areas burned by fire, with only 9.7 false positive hectares, showing a relatively small discrepancy of −6.3 hectares compared to the actual burned area of 108.56 hectares. However, the Differenced Normalized Burn Ratio (dNBR) indicated the highest accuracy with 83.4% slightly outperforming SBAI. SBAI was better than 12 out of 13 other traditional approaches of burned areas detections including indices such as NBR, BAI, NDMI, MIRBI, CSI, BAIM, NBRT1, and RdNBR, also KNN, SVM, RF, and ML machine learning techniques. The MIRBI, NBR, BAIM, BAI, and NDMI indices performed poorly in detecting

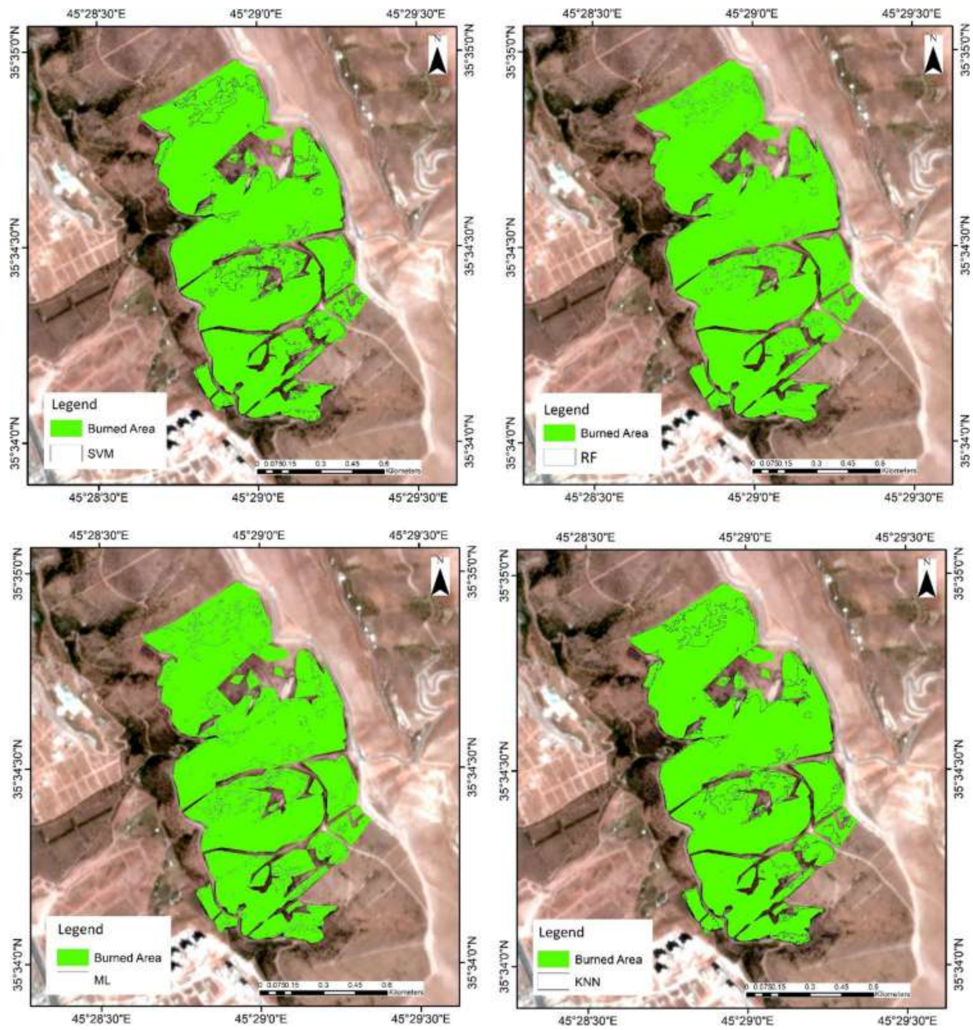

Fig. 8 Machine learning techniques: SVM, RF, ML, and KNN

burned areas, showing a high level of noise and false detection using SuperDove imagery (Table 3, Fig. 5).

The outcome indicated that dNBR is the most accurate index to detect the burned areas and it has the smallest discrepancy of detected area with actual areas which was 108.56 hectare. Moreover, the study emphasized that among the machine learning techniques, KNN were the most accurate and all machine learning techniques showed better performance than all indices except dNBR and SBAI. MIRABI, NBR, BAIM, BAI, and NDMI were the indices which showed the least accurate results with very high noise of areas detected as burned which were not burned, and the outcome showed that they are not suitable for accurate burned area detection using SuperDove imagery. However, KNN, dNBR, SBAI, and RdNBR showed the least amount of noise and detected the burned areas with reliable results, specifically the intense burned areas Fig. 6.

The investigation showed that SBAI outperformed all four machine learning techniques that have been tested: KNN, SVM, RF, and ML. Moreover, among the machine learning approaches, K nearest neighbors (KNN) indicated the best accuracy with 71.3%, followed by support vector machine (SVM) with 70.6%. Additionally, according to the false detection and having noise, SBAI along with dNBR KNN and RdNBR showed the least amount of noise, however, traditional indices such as MIRBI, NBR, BAIM, BAI, and NDMI detected very large areas as burned which actually not affected by the fire, showing a high level of noise. Among all 14 indices, dNBR was the most accurate which effectively detected 104.3 hectares out of 108.56 hectares, followed by SBAI with 102.3 hectares (Fig. 7). The substantial performance of SBAI compared to the most commonly used technique for burned area detection can be the contribution of the integration of multispectral bands of SuperDove imagery with its high spatial resolution, which offers more detailed information about the features on earth before and after fire, addressing the limitation of traditional approaches. Moreover, the performance of dNBR and SBAI over machine learning techniques is substantial, showing that having effective and well-designed indexes can provide accurate results and outperform complex algorithms in specific conditions and applications.

However, KNN and SVM performance showed that using machine learning in burned area detection can be significant and useful to address specific challenges in diverse ecosystems. The research results emphasized the SBAI index as a valuable tool for detecting affected areas by fires using multi-spectral imagery from SuperDove. Future studies may use the SBAI and test for more complex and diverse environments. Moreover, the integration of SBAI and advanced machine learning techniques could significantly reduce the noise and enhance the accuracy and reliability of burned area mapping, contributing significantly to fire management and ecological restoration strategies Fig. 8.

Conclusion

A novel multi-spectral index, the SBAI, was offered in this research to detect burned areas using high-resolution SuperDove satellite imagery. 7 out of 9 indices assessed in this research, were primarily based on shortwave infrared (SWIR) to detect burned areas, which this band is not available in SuperDove satellite imagery, highlighting the unsuitability of the existing indices for SuperDove imagery. The study compared the performance of SBAI with 9 traditional indices and 4 advanced machine learning algorithms, for Goizha Mountain in Sulaymaniyah, Kurdistan region of Iraq for a fire event from 28-Jul-2024. The analysis of the study demonstrated that SBAI showed a great performance with 80.7% accuracy in detecting burned areas, which outperformed 8 out of 9 traditional and established indices and all four machine learning techniques tested in this study. SBAI multi-band methodology, using near-infrared, red, green II, coastal blue and blue bands, showed substantial performance by identifying the unique characteristics of the burned areas. However, other indices showed poor performance using SuperDove imagery which was inaccurate with a high level of noise. While dNBR slightly was better than SBAI, the new novel index's performance showed valuable potential for accurate and effective mapping of burned areas.

The process of generating the SBAI provides valuable insights into the field of earth observation for fire monitoring and management. Some of the limitations of traditional indices were addressed with the novel indices in which high-resolution imagery was used to assess the post-fire accurately. The superior performance of SBAI over multiple approaches underscores the potential significance of the index for policymakers and remote sensing analysts which critically enhances the accuracy of burned area mapping and better understanding of the impact of fire events on the environment. Future studies could be focused on using SBAI on various fire intensities and environmental conditions and different satellite platforms to investigate its efficiency. Moreover, the integration of machine learning with SBAI could enhance the precision mapping of burned areas. The SBAI offers promising advancement in the methodology of burned area detection, which significantly contributes to the enhancement of tools to better monitor the environment due to increased fire frequency and intensity because of climate change impacts.

Author contribution K. C: Writing – original draft, Conceptualization, Investigation, Methodology, data collection.

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Data availability No datasets were generated or analysed during the current study.

Declarations

Conflict of interest The authors declare no competing interests.

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