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Geospatial analysis of wildfire patterns and temporal trends in Kohat Division, Pakistan, using remote sensing and GIS

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Abstract. This study analyzes the spatial and temporal patterns of wildfires in the Kohat Division of Pakistan using Landsat satellite imagery from 2013 to 2022. Kohat Division falls in the extension of Hindukush and Sufaid Koh ranges, drained by Kurram and Kohat Toi rivers. The study area is an ecologically diverse region with a variety of tree species. The Normalized Burn Ratio (NBR) index and Delta Normalize Burn Ratio (dNBR) indices were applied to map burnt areas and assess wildfire intensity. The results revealed that wildfire incidents peaked in 2016 and 2020, causing extensive damage in the Kurram and Orakzai districts. Temporal analysis showed an increasing frequency of wildfire associated with higher pre-fire temperature and prolonged dry conditions. The findings highlight the growing vulnerability of forest ecosystems in Pakistan and underline the need for continuous satellite-based monitoring and proactive forest management strategies.

Key words: wildfire, remote sensing, GIS, NBR, dNBR, Kohat Division, Pakistan.

1. Introduction

Wildfires are among the most frequent and destructive natural hazards, spreading rapidly across diverse ecosystems worldwide. Wildfires leading to the destruction of forests, wildlife habits and human settlements. Globally, wildfires have been reported from many regions including Europe, North America and Australia, with the Australian continent recognized as one of the most fire-prone areas on Earth (Zhang et al., 2016). The intensification of global wildfire activity is closely linked to climate change, as rising temperature, declining humidity and extended droughts enhance vegetation dryness and fuel load, thereby facilitating ignition and propagation (Tariq et al., 2021). Forests are alos effected by anthropogenic activities different diseases which make it susceptible to fires (Colak & Sunar, 2022). In USA and Indonesia, extensive forest areas have been engulfed by the fire (Liu et al., 2010). It is a growing concern that the frequency of fire incidents is increasing over time and prolonged wildfire periods are now recorded all over the world (Weber & Yadav, 2020). The definition provided by Pakistan Forest Department suggests that wildfires are considered fires that erupt on forested land not for the purpose of agricultural production, conforming to a proposed plan (FAO, Global Forest Resources Assessment, 2010).

Wildfires may have both positive and negative impacts on the environment, as they can alter the forest structure;

however, it takes centuries for forests to recover from severe damage. Moreover, wildfire incidents disrupt ecological balance as they release harmful gases into the atmosphere, leading to air pollution. Various parameters contribute to wildfire incidents that describes the frequency of such catastrophes, which include humidity, temperature variations and other topographic characteristics of the area (Ma et al., 2022). According to Shi and Touge (2022), altering climatic conditions are playing a leading role in the rapid increase of wildfire incidents. Rise in temperature and aridity in different parts of Pakistan has been observed (Dawood et al., 2018; Rafiq et al., 2023), which escalate wildfire risk. Forests are one of the most precious natural resource for every region, but changes in climatic conditions make them more susceptible to fire incidents, which must be addressed as a priority (Bui et al., 2016). Wildfires are usually ignited through natural phenomena like lightning and thunderstorms, but anthropogenic activities also play a major role (Zhang et al., 2016). Currently, fire behavior differs from the historic fire incidents and the extent of damage remains difficult to predict (Roye et al., 2020). Apart from natural and human induced causes, fires may ignite depending upon the type of forest cover, as some species are more sensitive to fire than others. The changing climate scenario is also a leading cause behind the wildfires, as prolonged dry conditions support the wildfire incidents. Such fires have potential to change the composition of the forested areas. Many conditions contribute to wildfire occurrence, including prolonged droughts, high temperature, accumulation of the fuel load, topographic characteristics of the region and human activities like unattended campfires or discarded unextinguished cigarettes near forested zones (Liu et al., 2010). Forests maintain ecological balance and purify the environment; besides their ecological value, they serve as major economic resources (Yilmaz et al., 2023).

Forests are essential for economic growth in every country, yet Pakistan has one of the lowest forest cover percentages in South Asia and wildfires are further contributing to the depletion of this resource. Khyber Pakhtunkhwa (KP) accounts for approximately 40% of Pakistan's forested area, highlighting the province's environmental significance (Naseer & Chaudhary, 2025). Various forest types exist in Pakistan, including pines, dry deciduous, thorn woodlands and humid forests (Tariq et al., 2022). Pakistan spans an area of about 87.98 million ha, of which 4.57 million ha are forested. To meet the growing demands of an expanding population, approximately 2.6% of forest area is lost annually, with wildfire incidents contributing significantly to this decline as they burn nearly 50,000 ha each year (Wani, 2005). These incidents are reported from different parts of Pakistan; for instance, Swat valley experienced 20 wildfire incidents from 1993 to 2000, of which 4 occurred in 2000, mainly triggered by human activities (Nafees & Asghar, 2009).

Remote sensing technology provides environmental data efficientlyand cost-effectively. Satellite-based monitoring provides timely information, which is highly useful for assessing land use land cover (LULC) changes across time and space. Such data play important role in detecting and analyzing wildfire incidents (Syifa et al., 2020). Wildfires with temperatures between 800 to 1200 Kelvin can detected by satellite sensors, and active fire zones can reach up to 1800 K. These fires can be identified due to variations in reflectance within the mid-infrared (MIR) and thermal infrared (TIR) regions of the electromagnetic spectrum (Leblon et al., 2012). Multiple satellite systems are currently used for monitoring of environmental monitoring, including Light Detection and Ranging (LIDAR), Moderate Resolution Imaging Spectroradiometer (MODIS), Sentinel series and other advanced platforms (Yang et al., 2021).

Recent global studies have applied satellite-based indices such as the Normalized Burn Ratio (NBR) and Delta Normalized Burn Ratio (dNBR) to evaluate fire severity and temporal patterns (Ma et al., 2022; Shi & Touge, 2022; Yilmaz et al., 2023). However, in Pakistan, research on wildfire dynamics is still emerging and remains geographically limited and methodologically narrow. For instance, Tariq et al. (2021, 2022) investigated wildfire risk and drivers in the Margalla Hills using geospatial and machine learning models, while Naseer and Chaudhary (2025) developed a forest fire susceptibility model for KP using the MaxEnt algorithm. These studies, however, primarily focused on susceptibility mapping or short-term monitoring, rather than long-term spatio-temporal analysis based on multi-year satellite observations. Furthermore, few Pakistani studies have applied remote sensing–based indices such as NBR and dNBR for the quantitative assessment of wildfire severity over extended periods. Consequently, there is a pressing need for multi-year, region-specific analyses that can capture changing fire patterns in response to climatic and anthropogenic pressures. Despite the increasing frequency of wildfires in Pakistan—especially in KP's forested zones—there remains a critical lack of spatially explicit and long-term analyses of wildfire distribution and intensity. Most available data are scattered and limited, preventing a comprehensive understanding of decadal patterns and climatic influences.

The Kohat Division, with its diverse topography and ecological zones, frequently experiences wildfire incidents that are often undocumented or poorly mapped. Having experienced multiple fire events over the past decade, the Kohat Division presents an ideal case for assessing wildfire frequency, spatial distribution, and climatic associations using a geospatial framework. This lack of systematic monitoring and geospatial analysis impedes the ability of forest managers and policymakers to implement preventive strategies and assess fire impacts effectively. This study provides valuable insights into the spatial distribution, recurrence, and severity of wildfires over a ten-year period, offering a scientific basis for proactive forest management and mitigation strategies. Using remote sensing and GIS techniques, this research contributes to the national understanding of forest fire dynamics, supports climate adaptation planning, and informs early warning systems for sustainable ecosystem management. The primary aim of this study is to assess wildfire dynamics in the Kohat Division of Pakistan over the last decade by integrating remote sensing and GIS techniques. Specifically, the study focuses on mapping and quantifying burnt areas using Landsat satellite imagery from 2013 to 2022, evaluating spatial and temporal variations in wildfire occurrence and intensity through NBR and dNBR indices, and identifying hotspot regions that have experienced the most frequent and severe fire activity. Furthermore, the study analyzes temporal trends of wildfire occurrence in relation to climatic conditions and provides geospatial evidence to support forest managers and policymakers in formulating strategies for effective fire prevention, monitoring, and sustainable forest management in Pakistan.

2. Methods and materials

2.1. The study area

Geographically, the Kohat division lies between 32° 48′ N to 34°3′N latitude and its longitudinal extent is from 69°27′ E to 72°1′ (Fig. 1). It covers an area of approximately 12,377 km^2 and consists of the districts of Kohat, Karak, Kurram, Orakzai and Hangu in Khyber Pakhtunkhwa. The region is surrounded by mountainous ranges, namely the Samana range, Shingarh and Karakh ghar, Khattak and Koh-e-Sufaid range. The temperature in the region varies significantly, with severe cold in winter reaching around 6°C, while summer temperatures often exceeds 40°C. Similarly, precipitation of Kohat division: Kurram receives up to 800 mm of average annual rainfall, Kohat receives 546 mm, Hangu receives up to 545 mm, Karak receives more than 110 mm in August and Orakzai receives between 250 and 500 mm annually. Various plant species thrive in the area, providing mulberries, nuts, wild olives, apples and other valuable fruits and nuts. Major crops contributing to the region's agriculture include groundnut, wheat, maize and barley (Government of Pakistan, 1998). Mountain peaks in the northwestern zone of Kurram district are snow-covered,

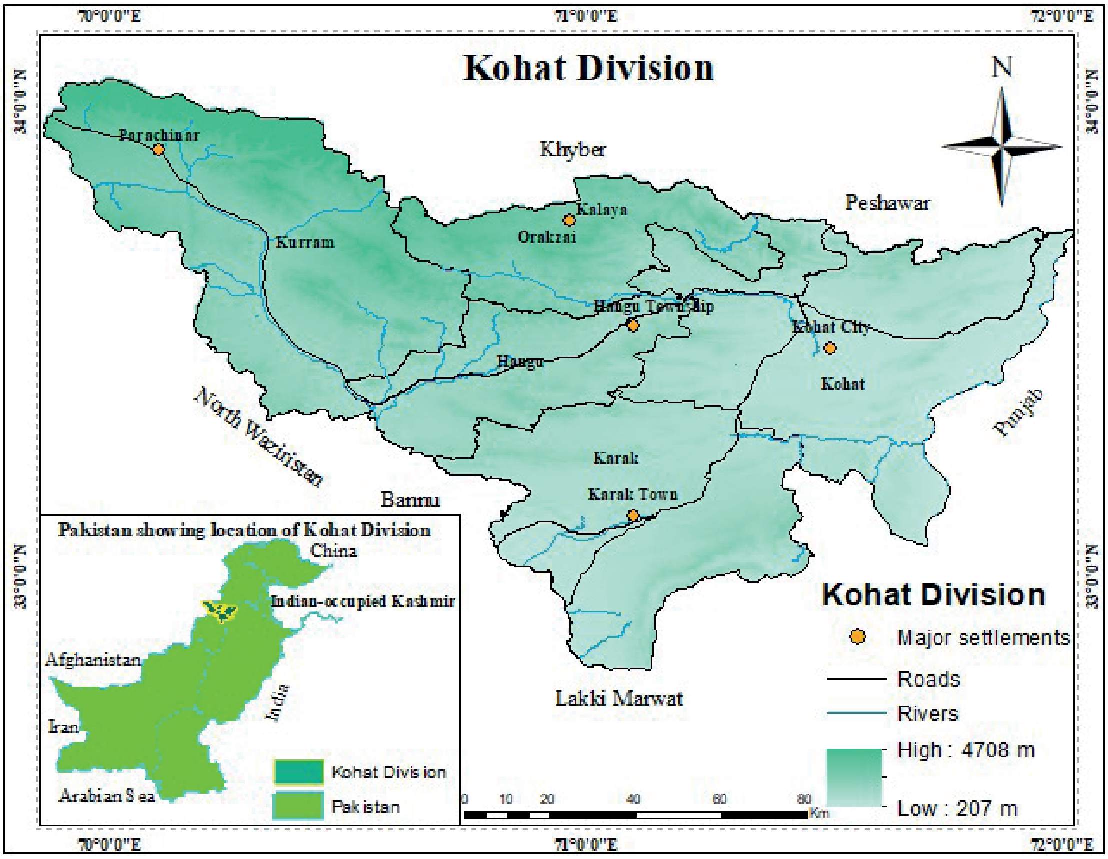

Figure 1. Location of the study area

while the southern zone features sandy terrain (Ilahi, 2008). Wildfire incidents occur every year in this region, making the assessment of the wildfire patterns a crucial component of wildfire-related studies.

2.2. Data acquisition and analysis

In order to achieve the study objectives, the Landsat 8 sensor data was preferred and selected. The study was conducted over a decade, from 2013 to 2022.Landsat 8 images were acquired through the USGS Earth Explorer website, a free data source (Fig. 2). Wildfire data were obtained from the Forest Department, which helped to identify the specific regions affected by fire. As the study area was covered by three Landsat scenes, three images were selected for each year. Pre-fire images were taken between March and June, while post-fire images were collected between September and November. Temperature data were obtained from Pakistan Meteorological Department (PMD) and monthly averages were calculated for each image acquisition month using Microsoft Excel. After image acquisition, atmospheric and radiometric corrections were performed. Quantum GIS (QGIS) software was used to apply corrections across all bands simultaneously. Since the study area spanned three Landsat scenes, each part was extracted and then merged using mosaicking tool in ArcMap. Following the mosaicking, the Normalized Burn Ratio (NBR) index was calculated for each image using the raster calculator tool. The NBR index utilized the Near-Infrared (NIR, band 5) and Shortwave Infrared (SWIR2, band 7) bands of Landsat 8. While the NBR index highlighted burnt regions, but the delta NBR (dNBR) index provided a more robust assessment by subtracting the post-fire NBR from the pre-fire NBR. However, these indices occasionally led to pixel mixing, which included unburnt regions. To address this issue, the raster-to-polygon tool in ArcMap was used to convert raster pixels into vector polygons. A specific burnt area composite was created to distinguish burnt from unburnt regions a color gradient from dark to light purplish tones. This composite was generated using Red (band 4), NIR (band 5) and SWIR1 (band 6) bands. Burnt area polygons were then extracted and analyzed to determine fire intensity based on area engulfed. A Digital Elevation Model (DEM) was used to visualize and highlight the burnt area polygons. The overall research process is illustrated in Figure 2.

2.3. Normalize Burn Ratio Index (NBR)

In order to assess the severity level of the wildfires, NBR index is widely adopted (Leal et al., 2008). NBR index ranges from -1 to 1, where higher values of NBR shows healthy vegetation while lower values mostly indicates burnt region or bare ground (Escuin et al., 2008). Although NBR has the ability to effectively distinguish burned areas from other land cover types, it could not differentiate between crop yields and barren land (Jin & Lee, 2022). Unburned region generally shows values close to zero. After a fire incident, lush green vegetation turns into a black powder-like substance that gives clear indication of fire damage (Yilmaz et al., 2023). Variations in the spectral reflectance of surface features following fire activity usually used to characterize the wildfire incidents (Jin & Lee, 2022). The NBR index was computed using the following formula (Eq. 1)

$$NBR = NIR - SWIR2 / NIR + SWIR2 \qquad \text{Eq. (1)}$$

As Landsat 8 imagery was used for this study, NIR and SWIR2 bands were applied to compute the NBR index across all images of the study area.

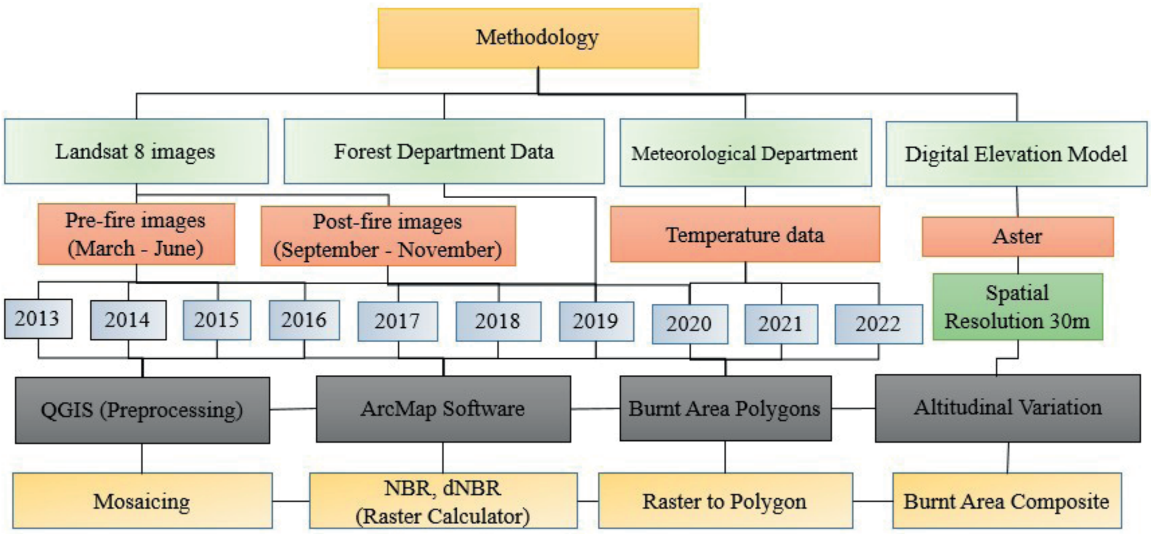

Figure 2. Research Process

2.4. Delta NBR (dNBR)

The NBR index works well in conjunction with delta NBR, which utilizes both pre-fire and post-fire NBR values to assess fire intensity. Variations in the spectral response of the NIR and SWIR regions observed after fire activity helps to identify burnt regions in the satellite imagery (Wang et al., 2008). The dNBR index value ranges from is –2 to 2 and was further classified into severity categories (Jin & Lee, 2022). The dNBR was computed using the following formula (Eq. 2)

$$dNBR = NBR_{\text{pre-fire}} - NBR_{\text{post-fire}} \qquad \text{Eq. (2)}$$

3. Analysis and Results

3.1. Spatio-Temporal assessment of Wildfire

Burnt area assessment helps to determine the intensity of fire and distinguish between old and recent burn scars based on their hue. Satellite imagery plays a crucial role in this regard. Burnt area composites utilize Red, NIR and SWIR band of satellite that highlight burn scars. Old scars appear in orange to brownish tones, while recent scars are reflect in purplish tones. Reduced reflectance in the NIR region after a fire incident is due to decreased in chlorophyll, which helps to identify vegetation cover. Conversely, reflectance increases in the SWIR region. Remote sensing technology enables the assessment of wildfire patterns and recurrence in a given area. The recurrence of wildfires depends on excessive heat and reduced moisture content in vegetated land. NBR and dNBR indices were used to determine wildfire patterns in the study area.

3.2. Wildfire assessment, 2013

NBR pre-fire and post-fire indices were calculated using the raster calculator tool in ArcMap, while dNBR was derived by subtracting the NBR pre-fire index from NBR post-fire index. The resultant dNBR was classified into five categories: unburnt area, moderately low burn area, moderately burn area, high burn area and severe burn area. NBR pre-fire values ranged from 0.95 to -0.91, while post-fire values ranged from 0.94 to -0.76. Higher pre-fire values were observed in Orakzai region and parts of Kurram, while lower values were found in Kohat and Karak districts. Hangu region exhibited mid to high NBR values. Post–fire NBR values were highest in the northern zone of Kurram district, with medium to low values in parts of Orakzai, Hangu and Kohat. Most of the lowest values were observed in Karak district. The delta NBR map showed severely burnt areas in Orakzai and Northern Kurram, while moderate to low burn regions were found in the other four districts. The dNBR index was categorized into five distinct classes, as shown in Figure 3.

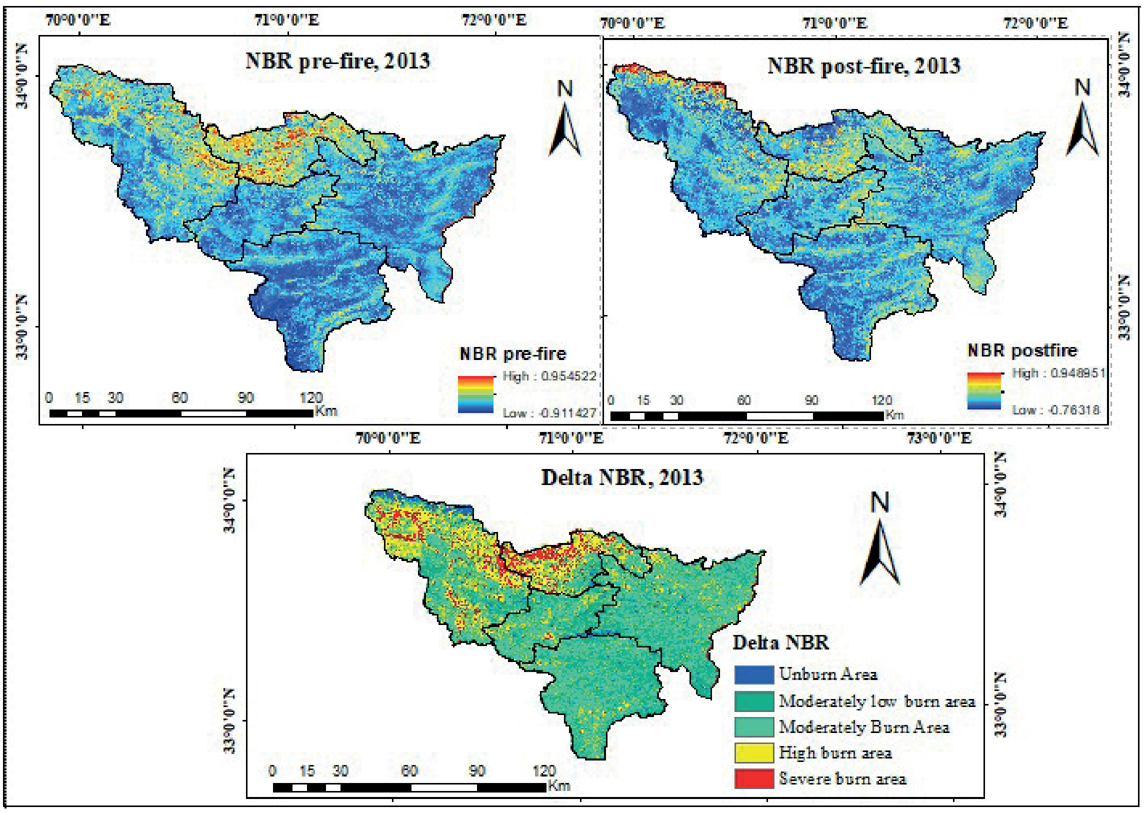

Figure 3. Wildfire assessment in Kohat Division, 2013

3.3. Wildfire assessment, 2014

NBR pre-fire values for 2014 ranged from 0.98 to -0.99, while post-fire values ranged from 0.90 to -0.91. Values close to +1 indicates healthy green vegetation while values close to -1 indicates barren land and burnt areas. Higher pre-fire values were observed in Orakzai district and parts of Kurram, representing lush green vegetation. Medium-range values were observed in parts of Hangu and Kurram, while lower values dominated Karak and Kohat districts. Post-fire NBR values were highest southern Orakzai and parts of upper Kurram, with medium values in Kohat and parts of Hangu. Lower values were observed in southern Karak and Hangu. The delta NBR index showed burnt regions in most of Orakzai and Kurram, moderately burnt areas in Hangu and Karak, and unburnt regions in Kohat. The color ramp used red for higher values and shades of blue for lower values, as shown in Figure 4.

3.4. Wildfire assessment, 2015

NBR pre-fire ranged from 0.94 to -0.99, while post-fire values ranged from 0.94 to -0.73. The dNBR was calculated by subtracting post-fire values from pre-fire values. The pre-fire map showed higher values in most of Orakzai and parts of Kurram, with medium to low values in Hangu, Kohat and Karak districts. Post-fire NBR values were highest in northern Kurram, withmedium values in Orakzai and parts of Kohat. Lower values were found in Hangu and most of Kohat. The delta NBR index indicated severely burnt burnt regions in Orakzai and Kurram, slightly burnt areas in Hangu, Kohat and parts of Kurram, and unburnt regions in northern Kurram. Outputs of NBR and dNBR are shown in Figure 5.

3.5. Wildfire assessment, 2016

Most of the fire incidents are reported in the year 2016 in Kohat division which shows remarkable rise from 2013. The value range of NBR pre and post fire ranges between 0.95 to -0.98 and 0.83 to -0.73. NBR pre-fire index shows higher values in the north of Kurram region while medium range values are shown in Orakzai and few parts of Kohat district. Lower values are recorded in Kohat and also in the few areas of Hangu district. Post fire scenario represent higher values in the south of Orakzai and also cover few portion of Kurram, mid-range values are observed in major parts of Kohat and Hangu while higher values are represented in Karak and Hangu district. Delta NBR shows severely burnt regions in the north of Kurram and mid zone of Hangu district while slightly bunt regions are covered in Orakzai, Karak, Kohat and few parts of Hangu also while unburnt regions are shown in Kurram district. dNBR is further reclassified into 5 groups of unburnt, moderately low burnt, moderately burnt, highly burnt and severely burnt regions as shown in Figure 6.

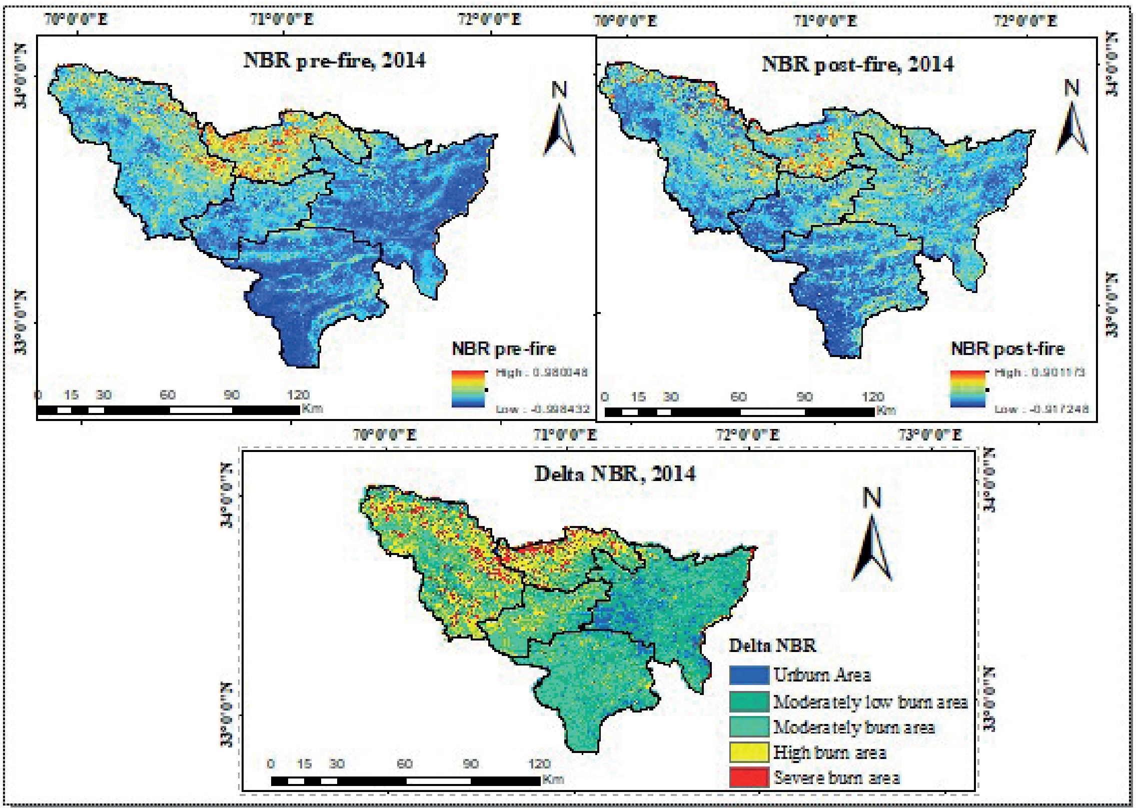

Figure 4. Wildfire assessment in Kohat Division, 2014

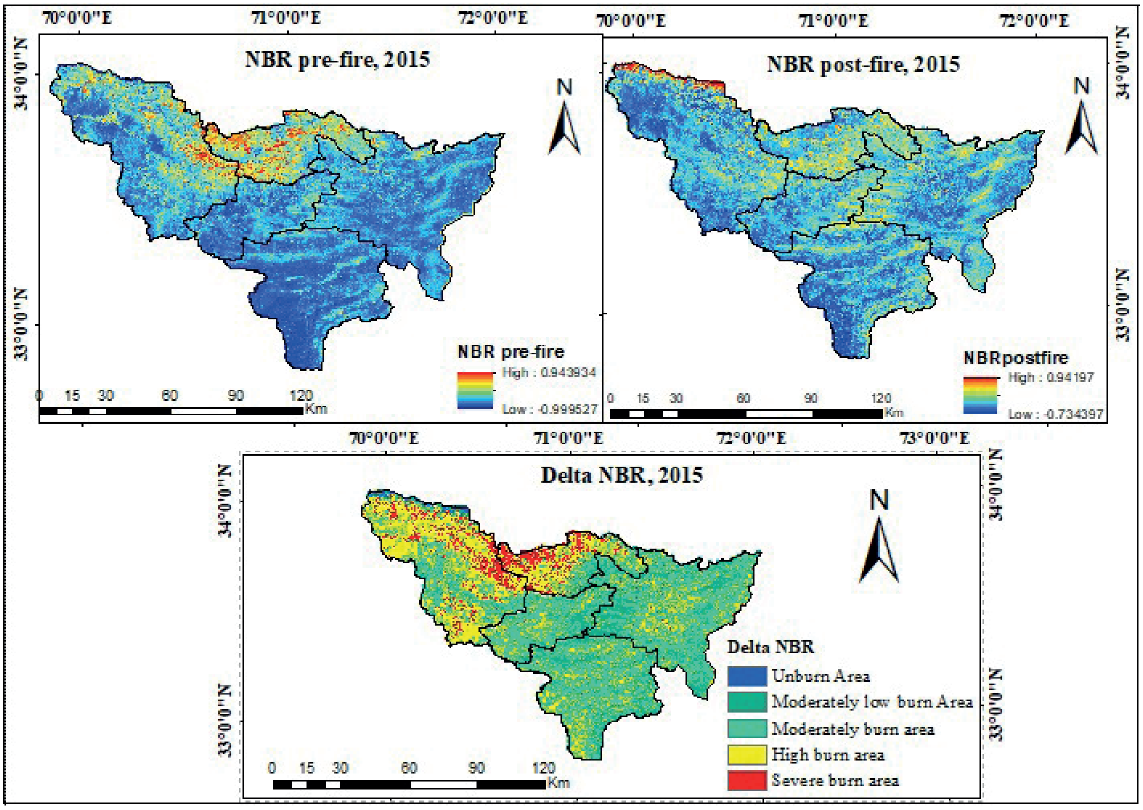

Figure 5. Wildfire assessment in Kohat Division, 2015

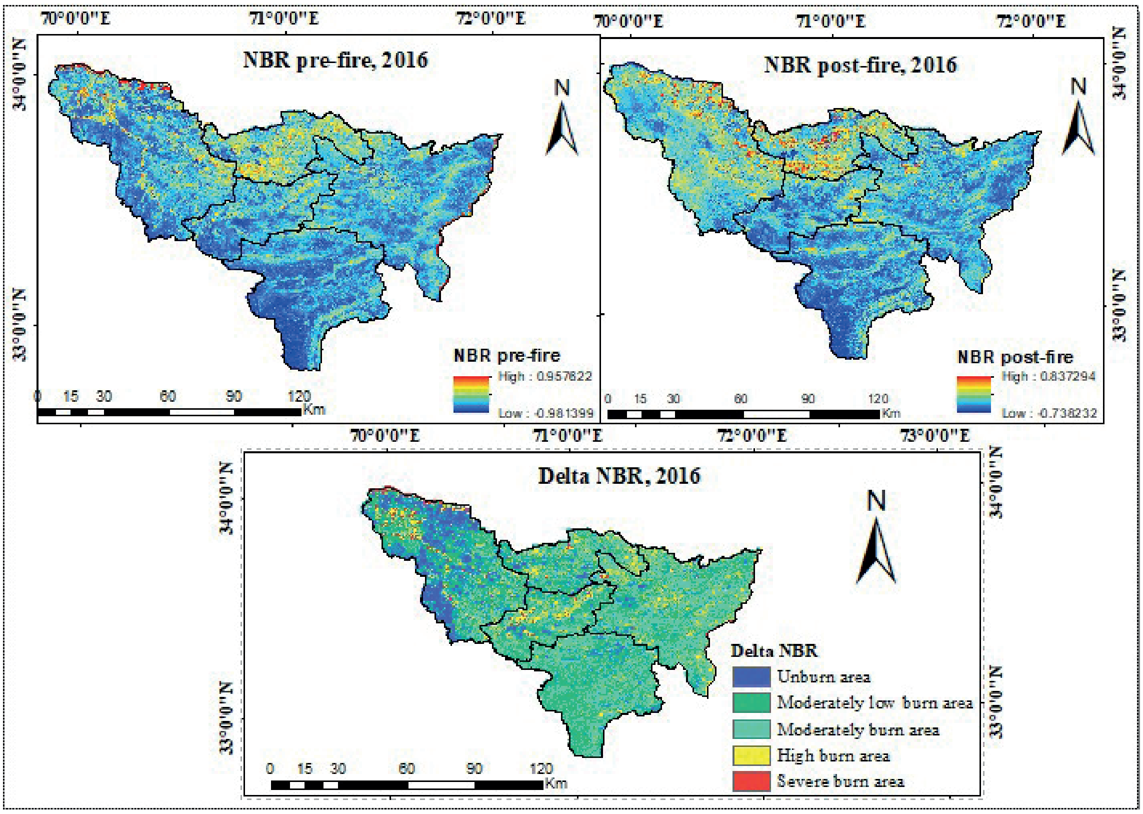

Figure 6. Wildfire assessment in Kohat Division, 2016

3.8. Wildfire assessment, 2017

The output of NBR pre- and post-fire is represented in terms of value ranges and maps. As for pre-fire scenario, values range from 0.97 to -0.99, while in the post-fire scenario, they range from 0.82 to -0.97. The pre-fire index indicates higher values in northern Kurram, medium values across major portions of Orakzai and Hangu districts and lower in Karak and Kohat districts. The post-fire map shows higher values in major parts of Orakzai and some areas of Kurram, while medium-range values are observed in Hangu district. Kohat and Karak districts covers show lower-range values. The dNBR index reveals severely burnt regions in northern Kurram, while moderately burnt areas are observed across the remaining four districts. Unburnt regions are also identified within Kurram district. The outputs of these indices are represented in Figure 7.

3.9. Wildfire assessment for the year 2018

These indices differentiate between burnt and unburnt regions, which can be interpreted through value ranges and maps. The obtained range of values for the year 2018 is 0.88 to -0.85, while the post-fire index varies from 0.91 to -0.85. In the pre-fire scenario, higher values are observed in northern Kurram, some parts of Orakzai and portions of Kohat district. Medium to lower values are observed in the Hangu, Karak and some parts of Kohat districts. The NBR post-fire map shows higher values in southern Orakzai and portions of Kohat, while medium values are shown in Kurram district. Lower values are represented in Karak, Kohat and some parts of Hangu districts. The delta NBR shows highly burnt regions in northern Kurram and central Kohat, while slightly burnt regions are distributed throughout the division and unburnt regions are mostly found in Orakzai and some parts of Kurram. The output of the calculated indices are shown in Figure 8.

3.10. Wildfire assessment, 2019

The NBR values for the year 2019 range from 0.97 to -0.99 for pre-fire images, while values from 0.91 to -0.65 are obtained for the post-fire index. In the dNBR index is calculated by subtracting the pre-fire index from the post-fire index. In the NBR pre-fire index, higher values are observed in northern Kurram, while medium-range values found in Orakzai and some parts of Kohat. Lower values are shown in southern Kurram, Hangu and Karak districts. In post-fire scenario, higher values are observed in Orakzai district and also some areas of Kurram and Kohat. Medium values are recorded in Hangu and portions of Kurram district, while lower values are predominantly found in Karak and Kohat districts. The delta NBR index shows severely bunt regions in northern Kurram while some burnt areas observed in central Kohat. Slightly burnt regions are found in Kohat, Karak and Hangu while unburnt regions are represented in Orakzai and some parts of Kurram district. The resulting raster is presented in Figure 9.

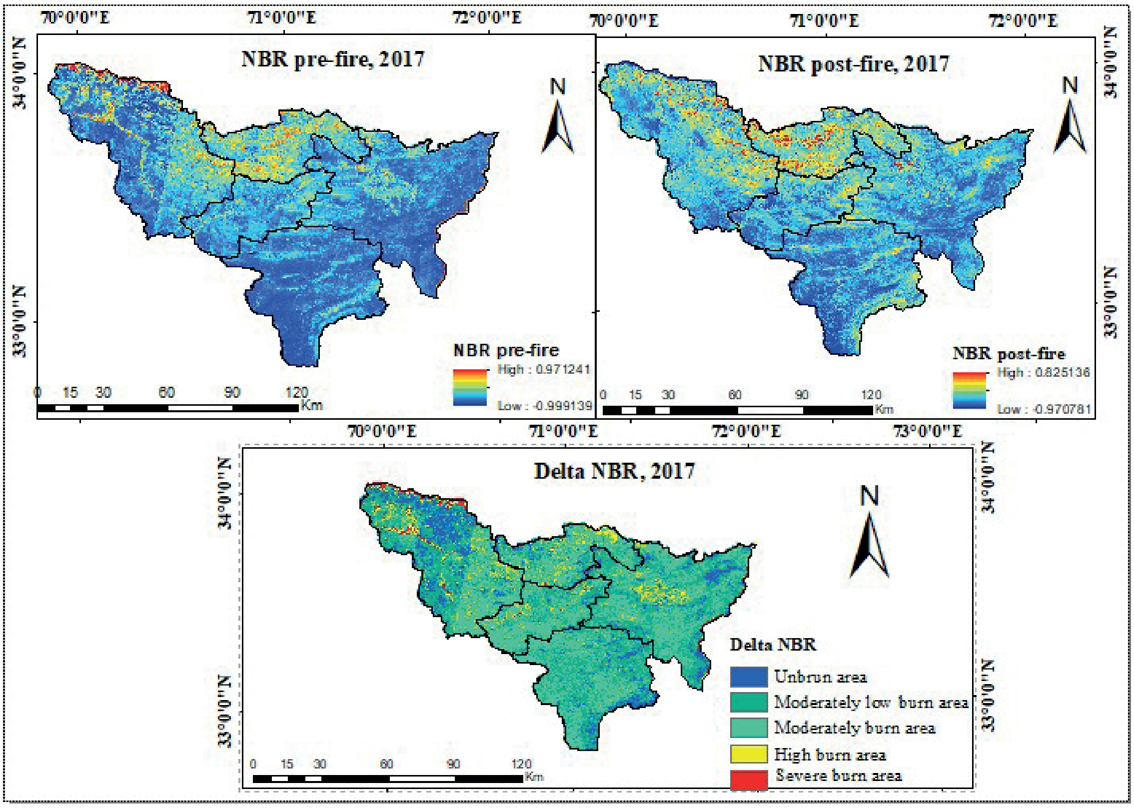

Figure 7. Wildfire assessment in Kohat Division, 2017

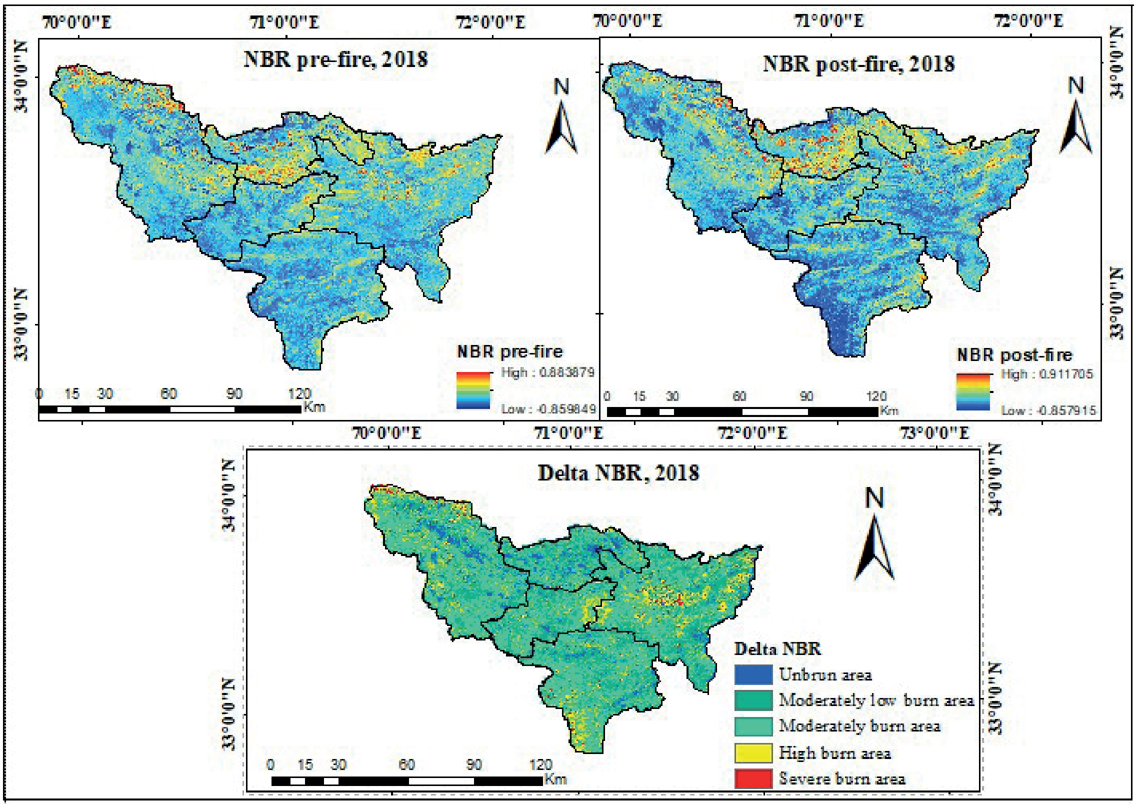

Figure 8. Wildfire assessment in Kohat Division, 2018

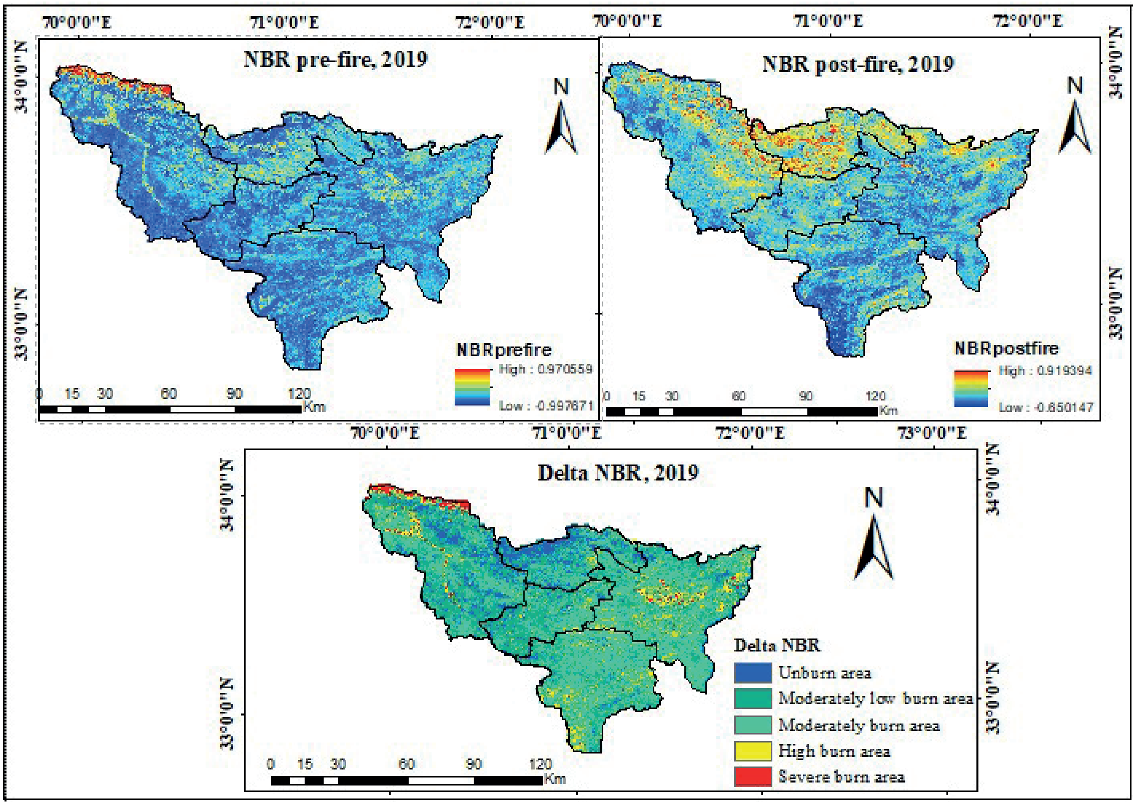

Figure 9.Wildfire assessment in Kohat Division, 2019

3.11. Wildfire assessment, 2020

The NBR pre-fire values in 2020, range from 0.97 to -0.98, while post-fire values range from 0.83 to -0.98. The pre-fire index shows higher value ranges in Orakzai district, while medium-range values are shown in Kurram and some parts of Hangu and Kohat districts. Lower values are predominantly found in southern Karak and some regions of Kohat and Hangu. The post-fire map shows higher values in portions of Orakzai and Kurram, while medium values are observed in Hangu district. Lower values are represented in Karak and Kohat districts. The delta NBR shows severely burnt regions in some parts of northern Kurram, while slightly burnt regions are shown in Orakzai, Hangu, Karak, and Kohat. Unburnt regions are observed in Kurram and Kohat districts. The dNBR is further classified into various categories, and an appropriate color scheme helps to differentiate between the classes as presented in Figure 10.

3.12. Wildfire assessment, 2021

In 2021, the NBR values for the pre-fire index range from 0.91 to -0.81, while post-fire values range from 0.84 to -0.79. The NBR pre-fire image shows higher values in northern Kurram, while mid-range values are shown in Orakzai and Kohat districts. Lower values of the index are found in Hangu, Karak, and some parts of Orakzai district. The post-fire map shows higher values in Orakzai district, medium values in Kurram and some parts of Kohat, and lower values in Karak district and portions of Kohat. The delta NBR index shows unburnt regions in Orakzai district and some areas of Kurram, while slightly burnt regions are shown in Hangu and Karak. Severely burnt regions are identified in northern Kurram and Kohat district. The delta NBR index is categorized into five distinct classes as presented in Figure 11.

3.13. Wildfire assessment, 2022

For the year 2022, NBR pre-fire values range from 0.79 to -0.67, and post-fire values range from 0.72 to -0.63. These indices are calculated using the raster calculator tool in ArcMap, while dNBR is reclassified using the reclassify tool in the ArcMap environment. The pre-fire index shows higher values in central Kohat district and some areas of Kurram district. Medium-range values are observed in regions of Kurram, Hangu, and Kohat, while lower values are shown in Karak district and portions of Orakzai. The post-fire scenario shows higher values in Orakzai and Kurram districts, which have good forest cover, while medium values are observed in parts of Kurram, Hangu, and Kohat. Lower values of the index are found in Karak and some areas of Kohat. The delta NBR shows severely burnt regions in central Kohat and portions of northern Kurram, while slightly burnt regions are distributed across the other districts. Unburnt regions are predominantly found in Orakzai and southern Kurram. The NBR pre-fire, post-fire, and dNBR outputs are presented in Figure 12.

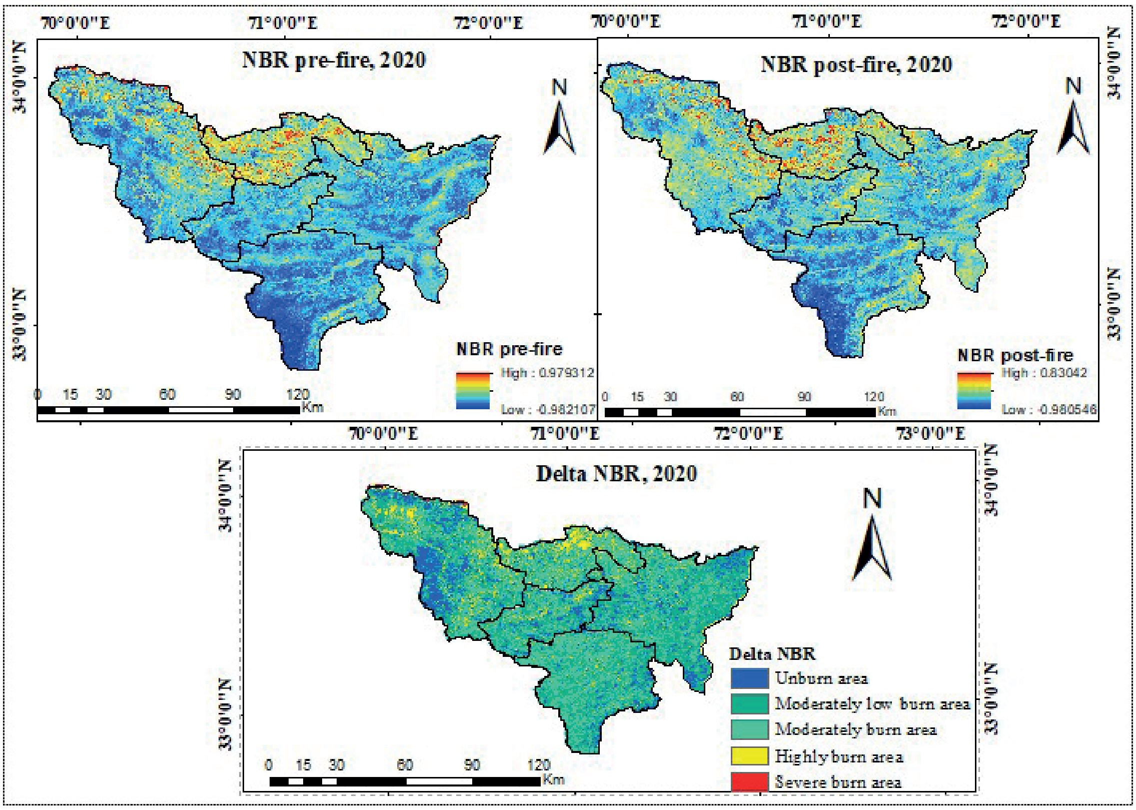

Figure 10. **Wildfire** assessment in Kohat Division, 2020

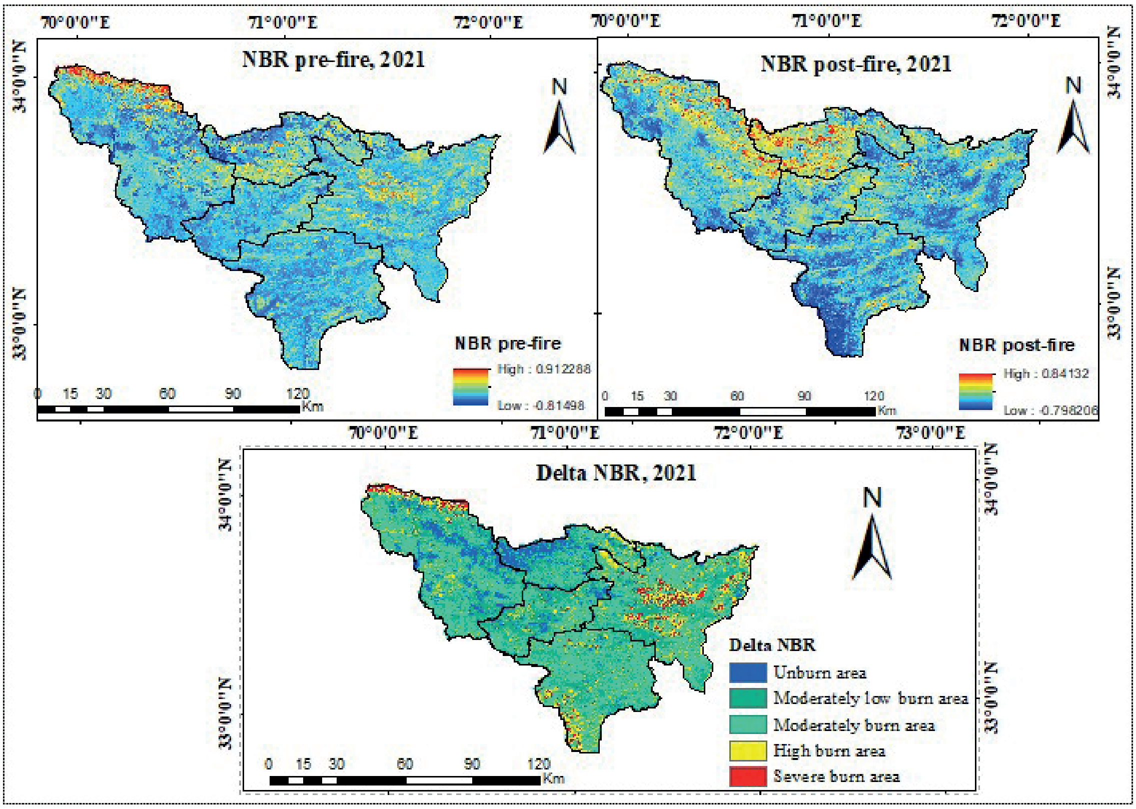

Figure 11. Wildfire assessment in Kohat Division, 2021

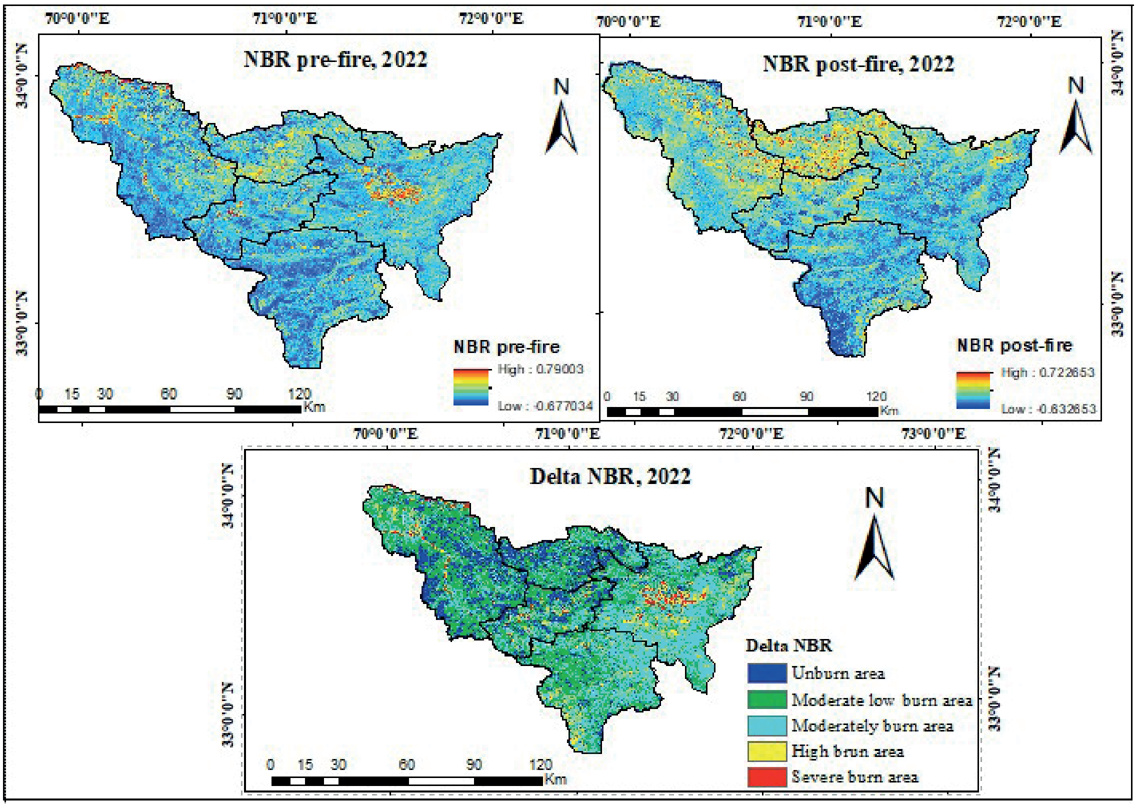

Figure 12. Wildfire assessment in Kohat Division, 2022

3.14. Burnt area polygons

The dNBR index helps to assess fire intensity; however, due to pixel mixing, this index also includes unburnt regions, which can affect the final results of the study. To resolve this issue, the raster-to-polygon tool in ArcMap is used to convert raster pixels into polygons. In order to identify burnt regions and separate burnt area polygons, a burnt area composite is created using three Landsat sensor bands: Red, NIR, and SWIR. This composite distinguishes burnt area patches from other features in the image through light to dark purple tones. Each polygon is identified using the identify feature tool in ArcMap software. After highlighting the burnt area polygons, they are separated from unburnt regions and displayed on the DEM of the study site for the decade-long study period, as presented in Figure 13.

3.15. Cumulative burnt area assessment (2013 to 2022)

The cumulative map of fire patches in the study area is derived from burnt area polygons extracted from burnt area composites spanning one decade. These patches indicate fire intensity, with deep, large patches representing higher fire intensity and small, brownish patches showing old scars with lower fire intensity. The number and size of scars represent the fire intensity in each district of the study area. In terms of spatial distribution, large fire patches are observed in lower Kurram, Orakzai, and northern areas of Kohat district. Medium-sized patches are found in the Hangu region, while small scars are located in some regions of Kohat and Karak. Regarding the frequency of fire incidents, Kurram district shows the highest number of fire patches in the study area, followed by Orakzai and Kohat districts, which also exhibit significant fire scars. Hangu district shows fewer patches, while Karak district represents a considerable number of fire incidents in the study area, as presented in Figure 14.

3.16. Pattern assessment of Wildfire

Pattern assessment is performed for a one-decade period from 2013 to 2022, during which wildfire incidents showed an increasing trend. These incidents occur approximately every year in the study site with varying intensity levels, ranging from low to high, which need to be addressed. For

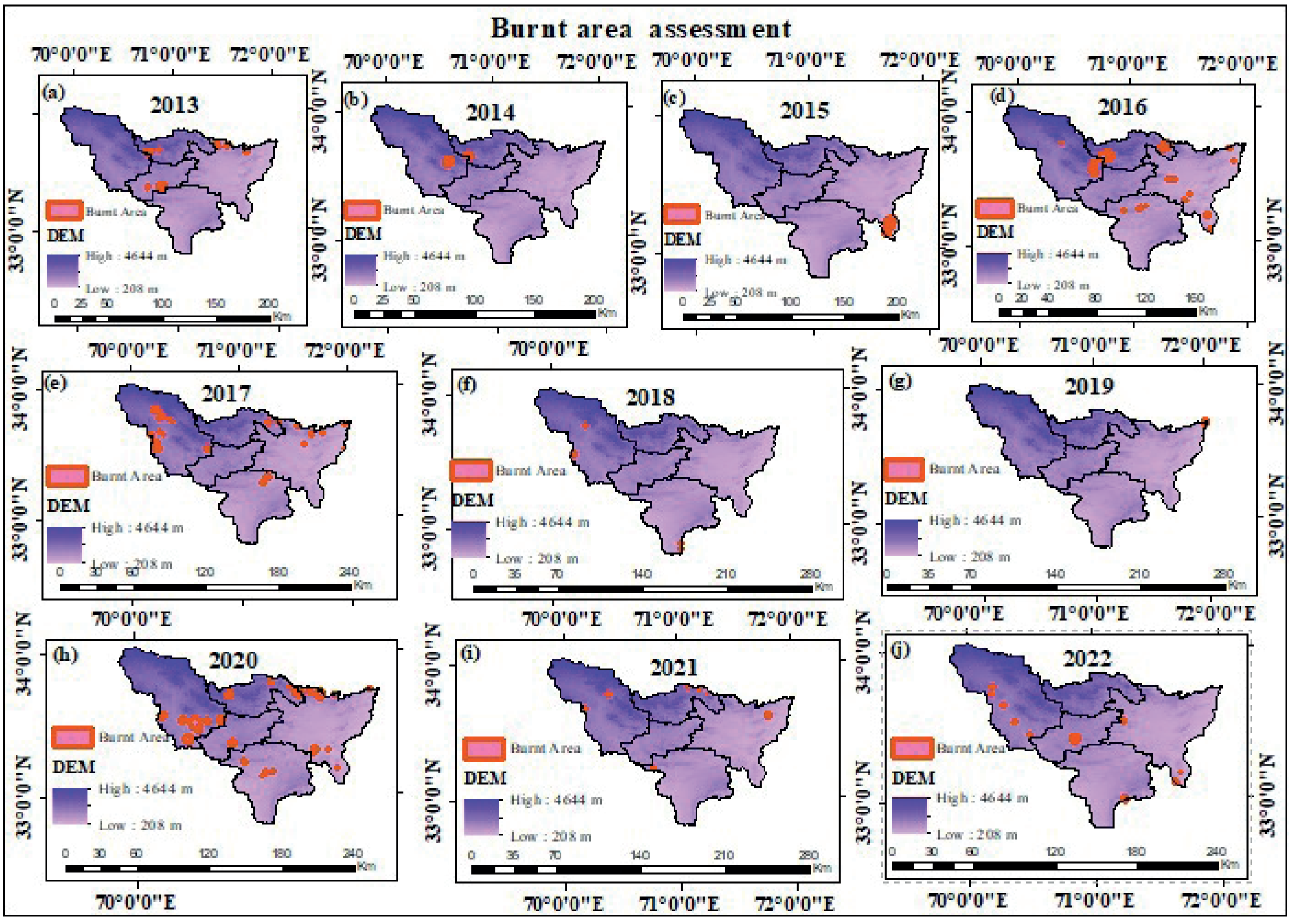

Figure 13. Burnt area assessment for the year 2013, 2014, 2015, 2016, 2017, 2018, 2019, 2020, 2021 and 2022, Kohat Division

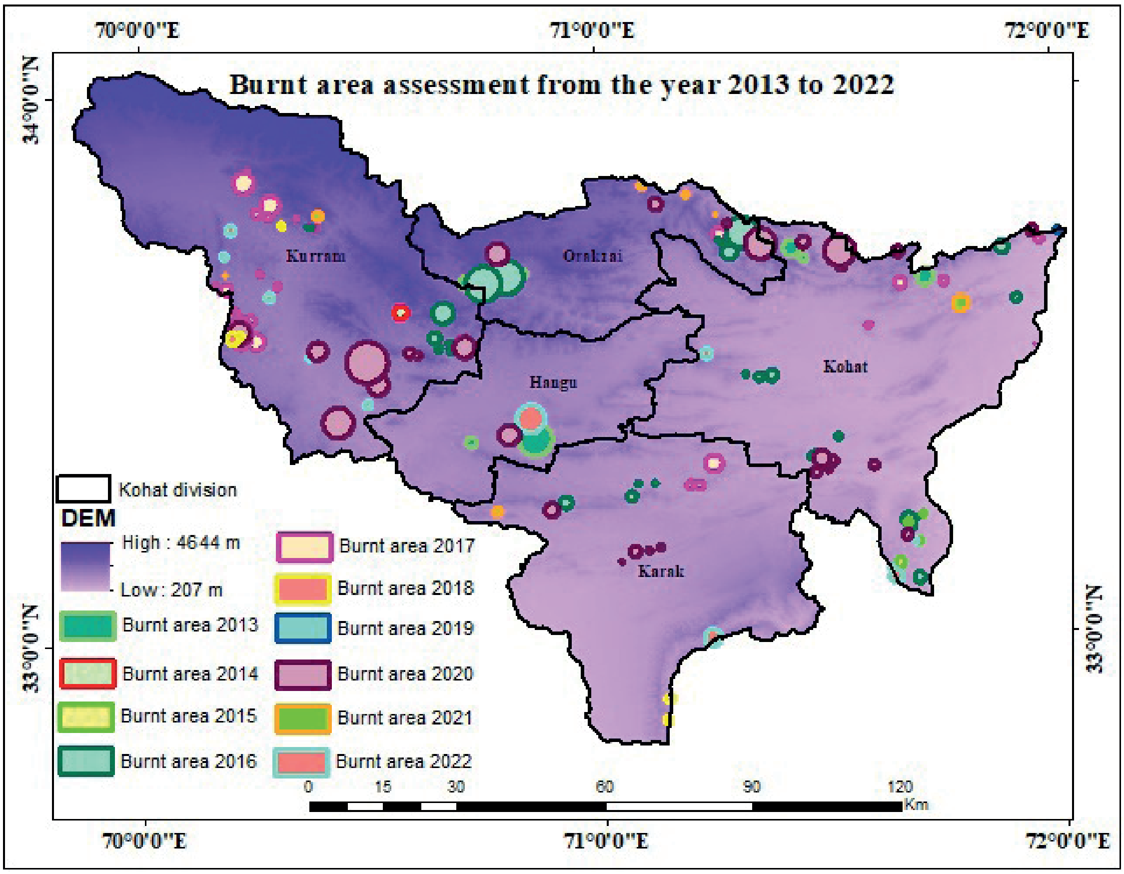

Figure 14. Burnt area assessment for the year 2013-2022, Kohat Division

this purpose, burnt ratio indices are utilized to distinguish burnt regions from unburnt regions, where higher values represent lush green vegetation and lower values are associated with burnt or barren areas. However, pixel mixing can lead to confusion between unburnt and burnt regions. Therefore, burnt area polygons are segregated from unburnt region polygons, and the size and number of polygons help assess the severity level of fire. The size of each polygon determines the fire intensity for each year (Table 1).

Table 1. Pattern assessment for the year 2013-2022, Kohat Division

Sr. No	Year	Burnt Area (ha)	Area (%)
1.	2013	1600.28	0.13
2.	2014	165.16	0.01
3.	2015	61.29	0.005
4.	2016	3159.89	0.259
5.	2017	1282.69	0.10
6.	2018	166.75	0.01
7.	2019	17.38	0.001
8.	2020	3060.99	0.25
9.	2021	194.49	0.01
10.	2022	800.92	0.06

Table 1 shows that fire intensity was at its peak in 2016, followed by 2020. These two years are considered peak fire years, covering areas of approximately 3,159.89 ha and 3,060.99 ha, respectively. The size and color of fire scars indicate both intensity and duration of fire events. Larger fire scars in different areas of the study site represent greater fire intensity, while the hue of the scar distinguishes between old and recent scars. Old scars appear in orange to brownish shades, while fresh or recently burnt areas are represented in purple shades in burnt area composite images.

3.17. Trend Pattern of Wildfire

Wildfire trends can be visually interpreted using a trendline created in Microsoft Excel based on the burnt area assessment data (Table 1). The burnt area in hectares for each year is plotted to reveal temporal patterns. The trendline equation is $y = -0.019x + 438.34$, with an R^2 value indicating the goodness of fit between the trendline and observed data values. The trendline shows peak fire years in 2016 and 2020, while fire intensity in 2013, 2014, 2017, 2018, 2021, and 2022 is also notable. Lower fire intensity is observed in 2015 and 2019. The overall trend suggests variability

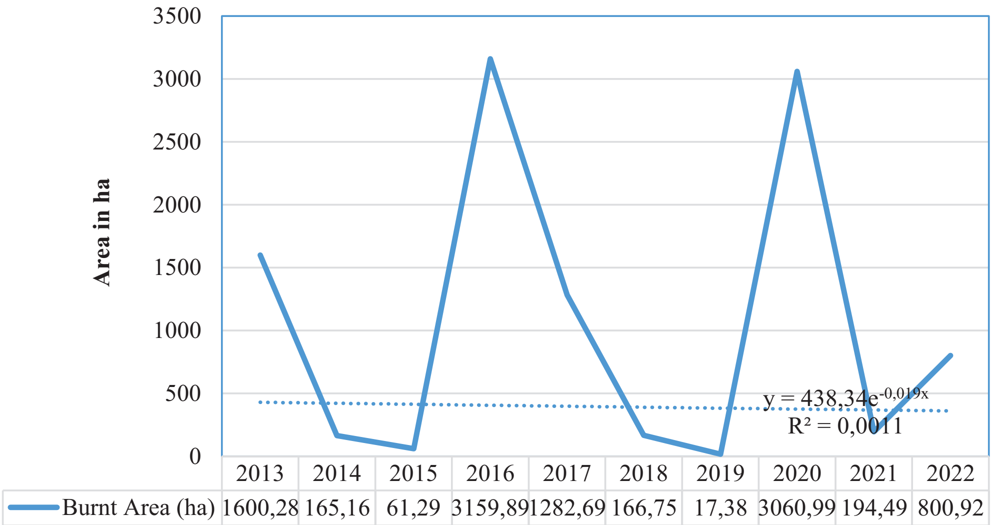

Figure 15. Trend pattern of Burnt area, 2013-2022, Kohat Division

in annual wildfire occurrence, with periodic peaks rather than a consistent increase or decrease over the decade. The trendline for wildfire assessment in the study area is presented in Figure 15.

3.18. Average Temperature variations from 2013 to 2022

Average temperature variations have been estimated for each year corresponding to the satellite image acquisition dates. Monthly average temperatures for pre-fire months (March, April, May, and June) and post-fire months (September, October, and November) are calculated to examine the relationship between temperature and fire occurrence. The images are obtained in consideration of fire incidents that occur annually in the region and the availability of cloud-free images from the United States Geological Survey (USGS) website. Temperature variations for each year are shown in Table 2.

Table 2. Average temperature variation from 2013–2022, Kohat Division

Sr. No	Year	Average temperature (Pre-fire season)	Average temperature (Post-fire season)
1.	2013	31°C	28°C
2.	2014	29°C	27°C
3.	2015	29°C	28°C
4.	2016	31°C	30°C
5.	2017	32°C	30°C
6.	2018	32°C	29°C
7.	2019	30°C	28°C
8.	2020	25°C	27°C
9.	2021	30°C	28°C
10	2022	33°C	27°C

Table 2 shows that the maximum pre-fire season temperature occurred in 2022 (33°C), while the minimum was observed in 2020 (25°C). In the post-fire season, the maximum temperatures were observed in 2016 and 2017 (30°C), while the minimum temperatures occurred in 2014, 2020, and 2022 (27°C). Overall, pre-fire season temperatures range from 25°C to 33°C, while post-fire season temperatures range from 27°C to 30°C.

4. Discussions

In this study, we analyzed and mapped the spatiotemporal dynamics of wildfires in the study area from 2013 to 2022, reveals the pattern of patterns of fire occurrence, extent and potentially driving factors. Wildfires are triggered by different factors which may include vegetation, temperature, precipitation, topographic characteristics and anthropogenic activities. It is impossible to avoid such a catastrophe but it can be monitored and controlled through different techniques. The findings demonstrate that wildfire incidents are not uniformly distributed across time with distinct peak years and seasons that warrants further research. Our analysis identified 2016 and 2020 as exceptional years, with burned areas of approximately 3159.89 ha and 3060.99 ha, respectively. These figures are substantially higher than other years in the study period, such as 2013 (1600.28 ha), 2017 (1282.69 ha), and 2022 (800.92 ha). In contrast, 2019 and 2015 observed minimal fire activity with burned areas of only 17.38 ha and 61.29 ha. This pattern of high-intensity fire years interspersed with periods of lower activity is consistent with research conducted in the Himalayan region of Pakistan, which has noted increasing variability in fire regimes (Tariq et al., 2022). However, the specific peak years we identified may differ from other studies, highlighting the localized influence of factors such as regional weather anomalies or specific anthropogenic events. However, these peak years we identified may differ from other regional studies, as wildfires are influenced by localized factors such anthropogenic activities and weather anomalies. The observation arises when comparing the 2016 and 2020 fire seasons. Our analysis, which utilized pre-fire (March-June) and post-fire (September-November) satellite imagery, shows that while 2016 had a high average pre-fire temperature of 31°C, the year 2020, which experienced an almost equally extensive burn, had a lower recorded temperature range. This divergence strongly indicates that temperature is not the sole driver of fire severity and points toward the significant role of other factors. The identification of numerous, dispersed wildfire patches in 2020, despite lower temperatures, implies a high frequency of ignition sources, likely anthropogenic in origin. This aligns with studies in other ecologically similar regions of Pakistan that have attributed the majority of wildfires to human activities like charcoal making and negligence (Tariq et al., 2021).

In 2021, the fire incidents damage area of about 194.49 ha while in 2018 and 2014, approximately 166.75 ha and 165.16 ha area is influenced by the fire. In 2015 and 2019, few of the fire incidents are observed which consume less area of about 61.29 ha and 17.38 ha approximately. It is also one of the concern that in which season wildfires are at peak either in pre-monsoon or post-monsoon season. The results indicates that wildfire events observed higher in pre-monsoon season during March to June and the same is consistent with established ecological patterns across South Asian forests where dry conditions are the cause of high fire risk (Kodandapani et al., 2004). The positive trend line observed from 2013 to 2022 shows fluctuations rather than a simple linear increase and reflects this complex interplay It is suggested that while the baseline risk of wildfires is present annually during the pre-monsoon season, the ultimate fire outcome in any given year is determined by a combination of climatic conditions and human activities (Naseer & Chaudhary, 2025). The burned area get exposed to other natural hazards and the rainfall in post-fire period increase the risk of soil erosion and landsliding, which is a common hazard in high slope region of Pakistan (Rahman et al., 2017). The occurrence of high-severity fire years (e.g., 2016 and 2020) indicates that a uniform annual policy is inadequate. Therefore, it is recommended that authorities develop scalable response plans that can be intensified during years exhibiting early signs of climate stress and increased anthropogenic pressure in forest zones. Emphasis should be placed on public awareness campaigns and the enforcement of strict regulations governing forest activities, particularly during the dry months (March to June). Furthermore, wildfire management policies should incorporate periodic satellite-based monitoring and rapid ground-level interventions to prevent fires from escalating into uncontrollable events. The lack of socio-economic and field data, coupled with an overreliance on satellite-derived information in this study, presents significant limitations in accurately detecting smaller fire patches and identifying the underlying causal drivers of wildfire events. The temporal resolution of satellite imagery affects the accuracy of detection, as short-lived fires—lasting only a few hours or one to two days—may not be captured by sensors and may extinguish before satellite overpass. Furthermore, the spectral similarity between old burn scars and barren lands may cause misclassification errors.

5. Conclusion

This study examined the spatial and temporal dynamics of wildfires in the Kohat Division, Pakistan, from 2013 to 2022, using remote sensing and GIS techniques. The findings revealed that 2016 and 2020 were the most severe wildfire years observing the largest burnt areas. However, fire events were observed throughout the decade though some years may remained undocumented due to the limited availability of wildfires records in Pakistan and low resolution of satellite data. Temperature and precipitation are the dominant climatic drivers influencing wildfire activity. High temperature reduce vegetation moisture content, while prolonged dry spells and heatwaves increase vegetation flammability and fire risk. In contrast, post-fire rainfall may exacerbate secondary hazards such as soil erosion and landslides. The analysis also observed the significant role of human activities and their negligence in wildfire occurrences. This study concludes that wildfire incidence in the Kohat Division is a result of complex interactions among climatic and human factors. The findings emphasize the need for continuous satellite-based monitoring, early warning systems and community-based fire management strategies. Strengthening institutional capacity, promoting awareness among local communities and preventive measures during the dry season can significantly reduce future wildfire risks and protecting Pakistan's vulnerable forest ecosystems.

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