

Article

Impacts and Drivers of Summer Wildfires in the Cape Peninsula: A Remote Sensing Approach

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Abstract: Over the years, the Cape Peninsula has seen a rise in the number of fires that occur seasonally. This study aimed to investigate the extent of fire spread and associated damages during the 2023/2024 Cape Peninsula fire events. Remote sensing datasets from Sentinel-5P, Sentinel-2, Moderate Resolution Imaging Spectroradiometer (MODIS), and Modern-Era Retrospective analysis for Research and Applications, Version 2 (MERRA-2) were used. Most of the fires on the northern side of the Cape Peninsula had a short burning span of between 6 and 12 h, but fires with a duration of 12–24 h were minimal. The northern area is composed of low forests and thickets as well as fynbos species, which were the primary fuel sources. Excessive amounts of carbon monoxide (CO) and black carbon (BC) emissions were observed. High speeds were observed during the period of the fires. This is one of the factors that led to the spread of the fire. Relative humidity at 60% was observed, indicating slightly dry conditions. Additionally, the Leaf Water Content Index (LWCI) indicated drier vegetation, enhancing fire susceptibility. High temperatures, low moisture and strong winds were the main drivers of the fire. The Normalized Burn Ratio (NBR) values for the targeted fires showed values close to −1, which signifies presence of a fire scar. The study can be of use to those in the fire management agencies and biodiversity conservation in the region.



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Keywords: fire scar; fire detection; biomass burning; LWCI; black carbon

1. Introduction

The rise in global temperature has led to an increase in wildfire activities [1,2]. Wildfires can be produced by natural or anthropogenic causes and are estimated to burn approximately 82 million ha per year worldwide [3]. Wildfires can have harsh environmental and societal impacts on urban settlements, agricultural lands, climate and ecosystems [4,5]. Conditions such as high temperatures and low precipitation can lead to drier-than-normal conditions which favour the start and spread of wildfires. During dry conditions, fuels for wildfire such as grasses and trees, can desiccate and thus become more susceptible to ignition and high flammability [6,7].

Although most wildfires are considered harmful, some plant communities depend both directly and indirectly on consistent fires in order to survive. Fire plays a crucial role in shaping and maintaining fynbos ecosystems, and many plant species within this habitat have evolved adaptations to survive and even thrive in fire-prone conditions. [8,9]. Fires can also kill diseases and insects that could otherwise destroy many plants [10]. On the other hand, fires can modify ecosystems by introducing invasive alien species which can colonise and drive plant diversity in that habitat [11–13].

The burning of vegetation is known to release toxic greenhouse gases into the atmosphere, thereby creating a hazardous environment [14,15]. Such gases include carbon dioxide, methane and nitrous oxide [16]. Other pollutants released into the atmosphere

include black carbon, organic carbon and smoke. Due to the dispersion and transport of these pollutants, this has an impact on the budget of organic trace gases in the tropical marine atmosphere and in the remote troposphere [17]. Moreover, vegetation burning emissions are also a source of a number of halogenated compounds such as methyl chloride and methyl bromide that are long-lived enough to destroy ozone in the stratosphere [16].

Over the years there have been several devastating wildfires globally, which resulted in large amounts of pollutants injected into the atmosphere. California, in the United States of America (USA), has experienced many extensive fires. Keeley and Syphard [18] showed that in the year 2020, the most extensive wildfires were experienced in the history of California. Eck et al. [19] also showed that the California wildfires during the August-to-October-2020 period were exceptional in terms of the fire severity and area burned. Extremely dry conditions exacerbated by high temperatures were some of the drivers for the large fires. The Australian region also experienced extensive wildfires in the period of September 2019 to February 2020 [20,21]. The fires were responsible for 33 direct deaths, over 400 smoke-related premature deaths and the loss of over 3000 houses [22]. Jalaludin et al. [23] showed that the fire burned more than 12.6 million hectares and emitted about 430 tonnes of carbon dioxide into the atmosphere.

South Africa has also witnessed extreme wildfires in the past, but not to the level of the California and Australia fires discussed earlier. As an example, approximately 35,000 fires were reported during the 2008 fire season, with a majority of fires originating from open flames during waste, grass or bush burnings [24], but none of the fires were devastating. More recently, in June 2017, a large wildfire was reported to have burned about 150 km² around the town of Knysna in the Western Cape province [25]. The fire destroyed over 800 buildings and about 50 km² of forest plantations, and was responsible for seven deaths [24]. Drought conditions experienced during the winter season of 2017 were one of the factors that contributed to the spread of the fire [25,26]. In the weeks leading to the fire, hot and dry berg wind conditions were observed, which reduced already critically low plant-moisture and soil-moisture levels [26].

Since 2019, the WC fires have been more frequent and severe, raising a concern about the water and air quality, land condition, biodiversity, vegetation structure, and greenhouse gas emissions of the affected area [27]. More recently, large wildfires were observed near Cape Town between the 24th and 26th of December 2023. The wildfires started on the mountain slopes of Simon's Town and swept across thousands of hectares in the area, resulting in a lot of residents being evacuated from their homes. Minimising the occurrence of these fires and reducing their impact on the environment requires a clear understanding of the drivers, and the potential consequences. However, obtaining such information is often challenging to acquire, especially during the fire, due to its hazardous nature.

Remote sensing (RS) technologies allow for acquisition of information even in inaccessible areas without any human contact, and are equipped with instruments that can detect burnt surface areas. When vegetation burns, it goes through physical and chemical changes. This process involves the changes in the temperature, charring of stems, and loss of chlorophyll and water, leading to alterations in the colour and texture of the burned area, and, consequently, a formation of a blackened surface and charcoal residues. These changes produce a distinct spectral reflectance of the burnt vegetation, with charcoal residues causing reduced absorption of red light and increased reflection of near-infrared (NIR) light. The thermal infrared (TIR) wavelength is sensitive to the rise in temperatures caused by a fire, enabling effective detection of emitted smoke. The loss of water from vegetation during fires induces water stress. The short-wave infrared (SWIR) region is responsive to vegetation's water content, and burnt scars cause increased reflection in this region [28]. It is these alterations in the spectral signature of vegetation that enable the detection of post-fire scars and greenhouse emissions from satellite imagery.

Currently, RS of wildfire management focuses on the use of MODIS 4- and 11-micrometre radiances fire products, which have been proven to be accurate and effective for fire management [29]. Several sensors from the ESA Sentinel missions are equipped

with the above-mentioned fire-sensitive wavelengths; for example, Sentinel-2, with an improved spatial resolution of 10 m to 20 m. The sensor is also equipped with three narrow bands in the red-edge position (REP) which is proven to be sensitive to changes in vegetation's biochemicals and biophysical composition, demonstrating a potential for detection of burn-area scars. The use of Sentinel-2 datasets for mapping wildfire scars and quantifying fire severity have rarely been investigated [30]. It is against this background that this work explores the potential of the Sentinel-2 MSI to detect the post-fire scars, quantify the severity, and also monitor the emission of greenhouse gasses from wildfires in fynbos vegetation using Sentinel-5P datasets.

The objective of this study is, therefore, to characterise the extent and drivers of the wildfires that occurred in the Cape Peninsula during the 2023/2024 summer season by analysing climatic, environmental, and meteorological data. In this work, we provide insights into the factors that contributed to the wildfires and their impacts on the environment and local communities. Studying factors such as fire sources, fuels, and the environment can enable the use of measures aimed at controlling and preventing wildfires. Moreover, leveraging advanced technologies such as remote sensing can assist in forecasting forest fire occurrences. This information facilitates timely interventions, mitigating the impact of wildfires on biodiversity and human health. Ultimately, research into forest fires plays a crucial role in safeguarding ecosystems, resources, and human well-being.

2. Study Site

The study area covers approximately 475 km² and is located in the southwestern region of South Africa [31]. It is predominantly covered by fire-prone fynbos shrubs. Figure 1 displays a land-cover map depicting part of the Cape Peninsula. The Cape Peninsula experiences a Mediterranean climate characterized by warm, dry summers and cool, rainy winters. Winter precipitation is brought by frontal cyclones originating from circumpolar westerly winds, occurring typically once a week during the mid-winter months from June to August [32]. In summer, the climate is influenced by the South Atlantic High-Pressure Cell, resulting in southeasterly winds along the west coast. Anthropogenic climate change has altered weather patterns in this area, leading to increased conditions favourable for fires [32].

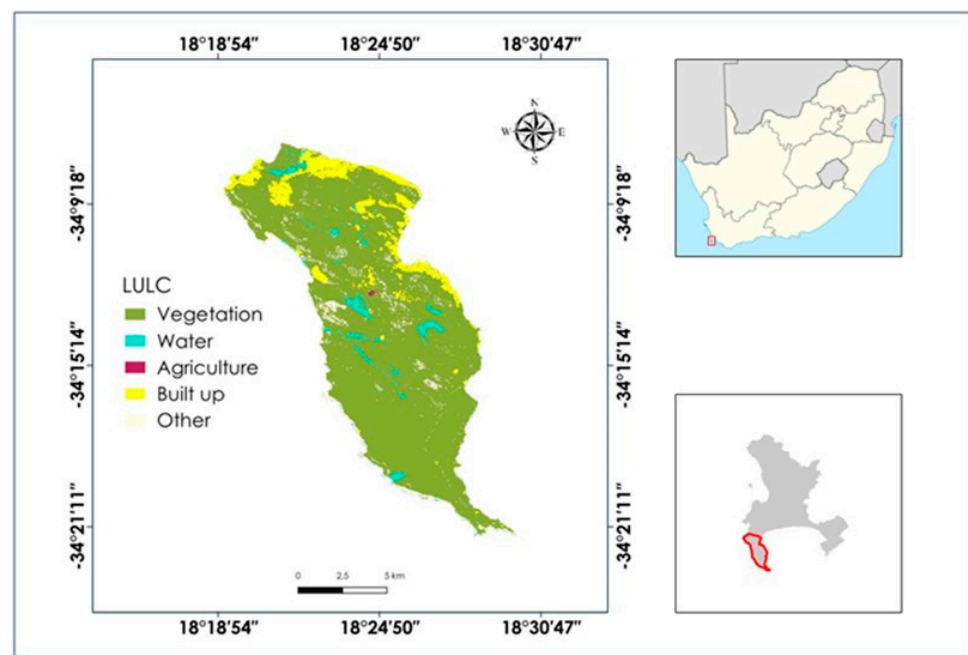


Figure 1. Land-cover map of the Cape Peninsula. The data were retrieved from the South African Department of Forestry, Fisheries and the Environment.

The topography of the Cape Peninsula features sandstone mountains, nutrient-poor soils, and diverse climatic conditions, contributing to its designation as a biodiversity hotspot. These environmental factors, coupled with the region’s infertile soils and fire intervals occurring every 4–40 years, make the Cape Peninsula highly susceptible to fires. The dominant vegetation types, such as fynbos and renosterveld, have evolved to depend on and thrive under these fire regimes, which are crucial for maintaining ecological balance and biodiversity in the area [31].

3. Data Acquisition and Methods

The description of the datasets used in this study is summarised in Table 1. A brief description of the dataset and the methods are shown in Sections 3.1 and 3.2.

Table 1. Summary of the parameters used in this study.

Data Source	Product Name	Spatial Resolution	Spectral Resolution	Date of Acquisition	Output Data
TROPOMI	CO	7.0 km × 3.5 km	267—2389 nm	12–25 December 2023	Spatial distribution map and Timeseries plot
MODIS	Burnt Area date and LST	500 m	36 bands (400–14,400 nm)	1 January 2023 to 30 April 2024	Spatial distribution map and Timeseries plot
AIRS	Relative Humidity	13.5 km	2378 channels (3.7–15.4 μm)	1 January 2023 to 30 April 2024	Timeseries plot
MERRA-2	Wind Speed	0.625° × 0.5°	N/A	1 January 2023 to 30 April 2024	Timeseries plot
OMI	UVAI	13 × 24 km ²	0.42–0.63 nm	1 January 2023 to 30 April 2024	Timeseries plot
Sentinel-2	ΔNBR	10 m, 20 m, 60 m	13 bands (443–2190 nm)	Mean for Jan 2024; October 2023	Spatial distribution map
HYSPLIT model	5-day forward air-mass trajectories	-	-	25–29 December 2023	Map showing trajectory of air masses

3.1. Data Acquisition

3.1.1. Sentinel-5P/TROPOMI

Sentinel-5P employs the TROPOspheric Monitoring Instrument (TROPOMI) to conduct global measurements of atmospheric trace gases, aerosols, and cloud distribution. TROPOMI, a hyperspectral imaging spectrometer, captures Earth’s radiance in ultraviolet–visible (UV–VIS, 267–499 nm), near-infrared (NIR, 661–786 nm), and shortwave infrared (SWIR, 2300–2389 nm) wavelengths, achieving a ground pixel resolution as fine as 7.0 km × 3.5 km. With a swath width of 2600 km, it provides nearly daily coverage of the entire globe. TROPOMI can map various trace gases such as nitrogen dioxide, ozone, formaldehyde, sulfur dioxide, methane, and carbon monoxide (CO). More details about Sentinel-5P can be found in References [33–35]. This study specifically focuses on the CO data.

3.1.2. MODIS

The Moderate Resolution Imaging Spectroradiometer (MODIS) is installed on both the Terra and Aqua satellites [36]. It features a broad swath width of 2330 km and captures images of the entire Earth’s surface every 1 to 2 days. MODIS sensors are equipped to measure 36 spectral bands ranging from 0.405 to 14.385 μm, providing data at three spatial resolutions: 250 m, 500 m, and 1000 m [36]. Justice et al. [37] provide a comprehensive discussion of various MODIS products. This study specifically focuses on two MODIS products: Land Surface Temperature (LST) and Thermal Anomalies/Fire products. LST data are derived using two algorithms: the generalized split-window algorithm and the day/night algorithm, detailed by Zhao et al. [38]. The fire detection algorithm is further elaborated in the work of Giglio et al. [39].

3.1.3. AIRS

The Atmospheric Infrared Sounder (AIRS) is a hyperspectral instrument onboard NASA’s Aqua satellite, launched in 2002 for climate research on greenhouse gases and weather forecasting. It utilizes a scanning spectrometer with 2378 infrared (IR) channels distributed across wavelengths in the ranges of 3.74–4.61 μm, 6.20–8.22 μm, and 8.8–15.5 μm,

crucial for profiling atmospheric temperature and relative humidity. Additionally, AIRS includes four visible (VIS) and near-infrared (NIR) channels spanning 0.40–0.94 μm , primarily used for cloud detection within the IR field of view. The instrument achieves an IR horizontal resolution of 13.5 km and vertical resolution of 1 km, while the spatial resolution for VIS/NIR is approximately 2.3 km. For more details on AIRS, refer to Aumann and Miller [40], Chahine et al. [41], and Menzel et al. [42]. This study specifically focuses on utilizing relative humidity data obtained from AIRS.

3.1.4. MERRA-2

The Modern-Era Retrospective analysis for Research and Applications, Version 2 (MERRA-2) integrates satellite observations of aerosols and models their interactions with other physical processes in the climate system. It replaces the original Global Modeling and Assimilation Office (GMAO) reanalysis, MERRA [43]. MERRA-2 is generated using version 5.12.4 of the Goddard Earth Observing System Data Assimilation System (GEOS DAS). Gridded data are available at a resolution of 0.625° longitude $\times$ 0.5° latitude across 72 sigma–pressure hybrid layers from the Earth’s surface up to 0.01 hPa [44]. For more information on MERRA-2, refer to Gelaro et al. [45], Buchard et al. [46], and Randles et al. [47]. This study utilizes wind speed data obtained from MERRA-2.

3.1.5. OMI

The Ozone Monitoring Instrument (OMI) was launched aboard the EOS-Aura satellite in July 2004. OMI observes backscattered solar radiance during the dayside part of each orbit and solar irradiance near the northern hemisphere terminator once daily, across three wavelength channels covering 270–500 nm (UV-1: 270–310 nm, UV-2: 310–365 nm, visible: 350–500 nm), with spectral resolutions ranging from 0.42 to 0.63 nm [48]. OMI data products are derived from the ratio of Earth radiance to solar irradiance and are provided in Level-2 orbit files containing measurements of trace gases such as O_3 , NO_2 , SO_2 , and HCHO , as well as UV-absorbing aerosol and cloud properties. For a comprehensive overview of OMI, consult Levelt et al. [49].

3.1.6. HYSPLIT Model

The Hybrid Single-Particle Lagrangian Integrated Trajectory (HYSPLIT) model is a versatile tool capable of computing simple air-parcel movements as well as conducting complex simulations of dispersion and deposition [50]. One of its primary uses involves performing back-trajectory analyses to determine the origins of air masses and establish relationships between emission sources and receptor locations [51]. The trajectory-frequency feature initiates trajectories from a specified location and altitude every 3, 6, or 12 h throughout the duration of the meteorological dataset. It then counts how often trajectories pass over each grid cell defined by the user. Trajectories are computed using vertical motion calculations, detailed at <http://ready.arl.noaa.gov/HYSPLIT.php>, accessed on 1 June 2024. The computation of trajectories introduces inherent uncertainties due to potential inaccuracies in input meteorological data and numerical methods used. To address uncertainties associated with individual trajectories, HYSPLIT can operate in ensemble mode, generating multiple trajectories from a single meteorological dataset [52].

3.2. Methods

Sentinel-2

Sentinel-2 consists of a pair of polar-orbiting satellites, Sentinel-2A and Sentinel-2B, positioned in the same sun-synchronous orbit with a 180° phase difference between them. The primary objective of Sentinel-2 is to monitor changes in land surface conditions. It features a broad swath width of 290 km and provides high revisit times: every 10 days at the equator with one satellite, and every 5 days with two satellites under cloud-free conditions, resulting in a revisit time of 2–3 days at mid-latitudes. Sentinel-2 is equipped with 13 bands covering the Visible and Near-Infrared (VNIR) region with 8 bands,

and the Shortwave Infrared (SWIR) region with 2 bands, offering spatial resolutions of 10 m, 20 m, and 60 m. For further information on Sentinel-2, consult Spoto et al. [53] and Sudmanns et al. [54].

Two Sentinel-2 images from before (December 2019) and after (December 2023) the fire were acquired from the Google Earth Engine cloud processing software. The Leaf Water Content Index (LWCI) data were calculated for both images, using the formula

$$\text{LWCI} = \frac{R_{\text{NIR}} - R_{\text{SWIR}}}{R_{\text{NIR}} + R_{\text{SWIR}}} \quad (1)$$

where R_{NIR} is the Near Infrared Band and R_{SWIR} is the Short-Wave Infrared Band. The difference in leaf water content between the two years was determined by subtracting the 2019 Leaf Water Content Index (LWCI) values from the 2023 LWCI values. The LWCI index ranges from -1 to 1 , where higher values indicate greater leaf-water content, suggesting healthier vegetation, while lower values indicate reduced water content, often due to stress or damage such as fire [55].

Mapping fire scars and assessing burn severity can be challenging, due to the absence of standardized measures [56]. Consequently, various techniques are employed to identify post-fire scars and evaluate severity, with many methods relying on vegetation response. Previous research has demonstrated that image differencing is an effective method for detecting post-fire scars [56,57]. Normalizing data improves the accuracy of fire-scar detection [58]. Although the Normalized Difference Vegetation Index (NDVI) has traditionally been used for fire-scar mapping between Near-Infrared (NIR) and visible (red) wavelengths, its accuracy can be affected by pre-fire vegetation density and greenness [27,56]. Moreover, atmospheric interference from smoke and dust during fires can diminish the accuracy of indices derived from visible wavelengths. Studies indicate that utilizing the Shortwave Infrared (SWIR) region enhances accuracy in mapping burn severity. In this study, the Normalized Burn Ratio (NBR) between NIR and SWIR regions is employed to detect recent fires in the Cape Peninsula area and assess burn severity based on NBR changes. The change in NBR (ΔNBR) is then utilized to quantify fire severity. NBR values range from -1 to 1 , with values closer to -1 indicating recently burned areas or bare ground, and values approaching 1 indicating healthy vegetation presence. Values near zero signify non-burned areas.

$$\text{NBR} = (R_{\text{NIR}} - R_{\text{SWIR}}) / (R_{\text{NIR}} + R_{\text{SWIR}}) \quad (2)$$

Then,

$$\text{dNBR} = \text{prefireNBR} - \text{postfireNBR} \quad (3)$$

where dNBR is delta NBR, R_{NIR} is the reflectance at the NIR and R_{SWIR} is the reflectance at SWIR. For this work we adopted the dNBR interpretation values proposed by the USGS to classify levels of severity of the present fire; see Table 2 for reference.

Table 2. Burn-severity levels obtained calculating dNBR, proposed by USGS.

Severity Level	dNBR Range (Scaled by 1000)
Enhanced regrowth, high (post-fire)	-500 to -250
Enhanced regrowth, low (post-fire)	-250 to -101
Unburned	-100 to 99
Low Severity	100 to 269
Moderate–low severity	270 to 439
Moderate–high severity	440 to 659
High severity	660 to 1300

4. Results and Discussion

4.1. Fire Detection and Burnt Scars

Figure 2 shows images of the burned-area dates in the Cape Peninsula (Figure 2a) and the areas where fires were detected on 22 December 2023 (Figure 2b). Most of the fires on

the northern side of the Cape Peninsula had a short burning span of between 6 and 12 h, but fires with a duration of 12–24 h were minimal. The northern area is composed of low forests and thickets, as well as fynbos species (see Appendix A). The low forests and thicket have predominantly short-lived, bird-dispersed diaspores which produce shade-tolerant seedlings that require long fire-free intervals for recruitment into fynbos [24]. This is one of the reasons for the short fire span. Fynbos species, on the other hand, depend on regular crown fires which stimulate recruitment from persistent soil- and canopy-stored seed banks of relatively short-lived species [59]. In the central part of the Cape Peninsula, several fires with a duration of 12–24 h are dominant. This area is dominated by low-shrubland fynbos species. Although fynbos requires burning every 12–15 years to survive, shorter or longer time intervals would eliminate many shrub species. A few fires with a duration of more than a day are also observed. These fires had an impact on the residential areas (built up area) (see Figure 1). Additionally, the fires are likely to have burnt the infrastructure in this area. Figure 3c shows the NBR index derived from Sentinel-2 imagery for the burnt area. This index was used to detect the presence of fire scars in the Cape Peninsula area. NBR values for the targeted fires are close to -1 , which denotes the presence of a fire scar. The largest burnt area is calculated to be 32.93 km^2 , accounting for 6.93% of the total area burnt. The fire scar can be used for (i) assessing fire hazard and risk, (ii) monitoring and reporting ecological impacts of fire, (iii) developing strategic and operational fire planning and management, and (iv) informing carbon abatement schemes and greenhouse emissions.

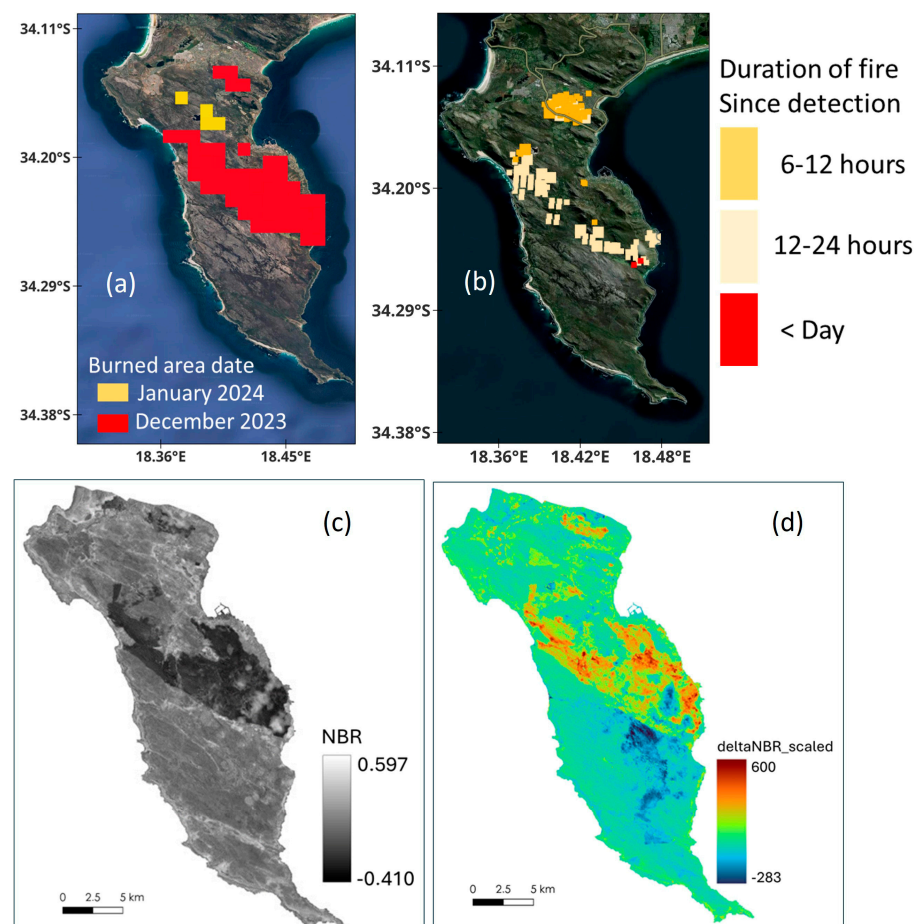


Figure 2. (a) Burned area dates for December 2023 and January 2024. (b) Fire duration on 22 December 2023. (c) NBR scar detection and (d) deltaNBR fire severity at the Cape Peninsula on 20–25 December 2023.

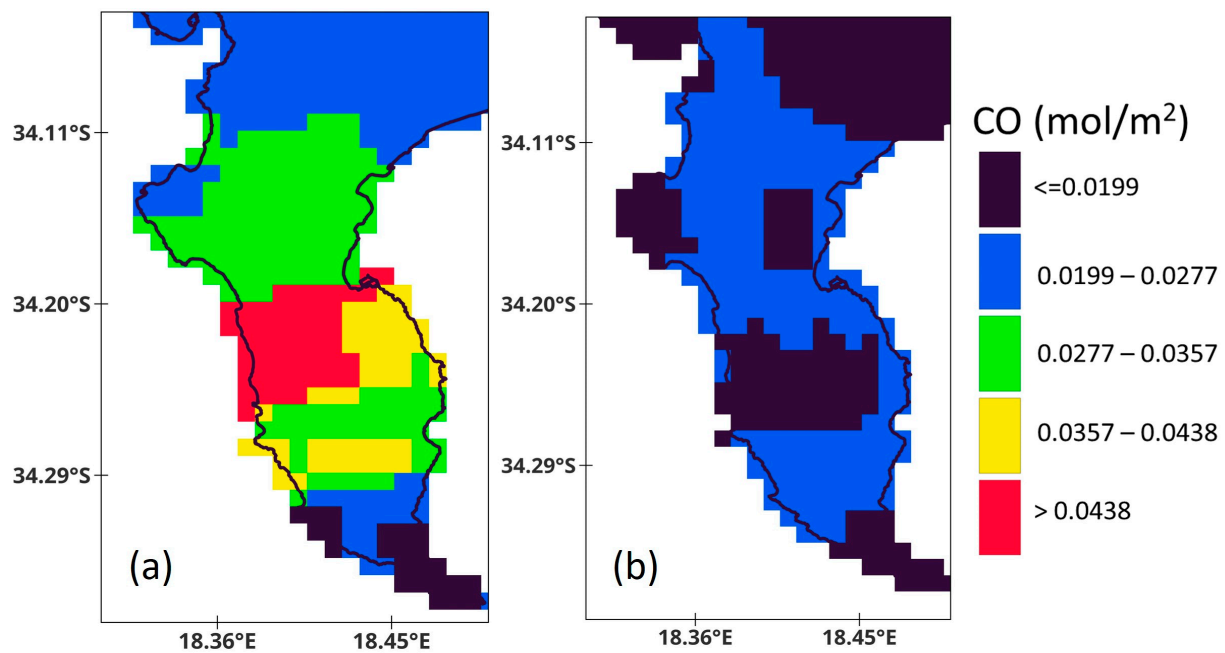


Figure 3. CO distribution over the Cape Peninsula on (a) 12–15 December 2023 and (b) 22–25 December 2023.

The severity of the fire was quantified using deltaNBR, shown in Figure 3d. The deltaNBR values observed from the detected scar range between 140 and 600. The largest portion of the fire scar had deltaNBR values ranging from 440 to 600, which, according to the burn-severity levels proposed by the USGS (see Table 2), indicate moderate to highly severe fires.

4.2. Emissions and Meteorological Drivers

Wildfires release a mix of gases and particulate matter into the atmosphere [60]. CO and BC are some of the pollutants emitted during the biomass burning processes [17]. They are by-products of incomplete combustion of carbon-containing fuels. Figure 3a,b show the spatial distribution of CO during and after the wildfire episodes in the Cape Peninsula. During the wildfire, see Figure 3a, low CO column-density values between 0.0199–0.0250 mol/m² are observed in the northern part of the Cape Peninsula. Moreover, moderate-to-high CO column-density values between 0.0277 and 0.0438 mol/m² are observed from the central to some southern parts of Cape Peninsula. Wildfires tend to increase the concentration of CO in the region. This is also an area dominated by fynbos. The results suggests that fynbos species release significant amounts of CO into the atmosphere. Figure 3b, on the other hand, shows low-to-moderate CO column-density values of 0.0199–0.0277 mol/m². This can be regarded as the background CO levels during non-fire periods. Agriculture, agro-processing, vehicle emissions, and domestic fuels for heating and cooking [16], are some of the daily activities that release CO and contribute to the background CO.

Figure 4a shows the BC concentration time-series for the January to December 2023 period. The blue rectangles represent the time when the wildfires occurred and the period with the highest BC emissions. Of interest to this study are peaks that occurred during the December 2023 and the January 2024 periods. BC concentrations of above 3.1 µg/m³ are observed during these periods. This result implies large emissions from large amounts of fuel burnt. This is contrary to the CO column density with large peaks in September 2023 and January 2024 (see Figure 4b). The results imply that the fuel burnt does not release a large amount of CO. The CO released could be mainly from the vegetation, and not from the built-up areas. The Angstrom Exponent (AE) is related to the aerosol particle size. Values less than 1.5 imply an optical dominance of coarse particles, while values greater

than 1.5 imply dominance of fine particles. Figure 4c shows the time-series of AE for the period of January 2023 to January 2024. A mixture of fine particles (due to the smoke) and coarse particles (due to black carbon) are observed during the wildfire episodes. AE values of up to 1.8 are observed during the December 2023 period. This result confirms the release of pollutants into the atmosphere from the wildfires. Similar to the AE, the ultraviolet Aerosol Index (UVAI) also determines the presence of dust and smoke. The UVAI indicates the presence of elevated absorbing aerosols in the troposphere. Figure 4d shows a time-series of the UVAI for the period January 2023 to January 2024. The negative UVAI values indicate non-absorbing aerosols such as sulfate, while positive UVAI values indicate absorbing aerosols. The positive UVAI values include biomass-burning emissions from wildfires such as smoke. During December 2023 and January 2024, positive UVAI values are observed, correlating to the wildfires.

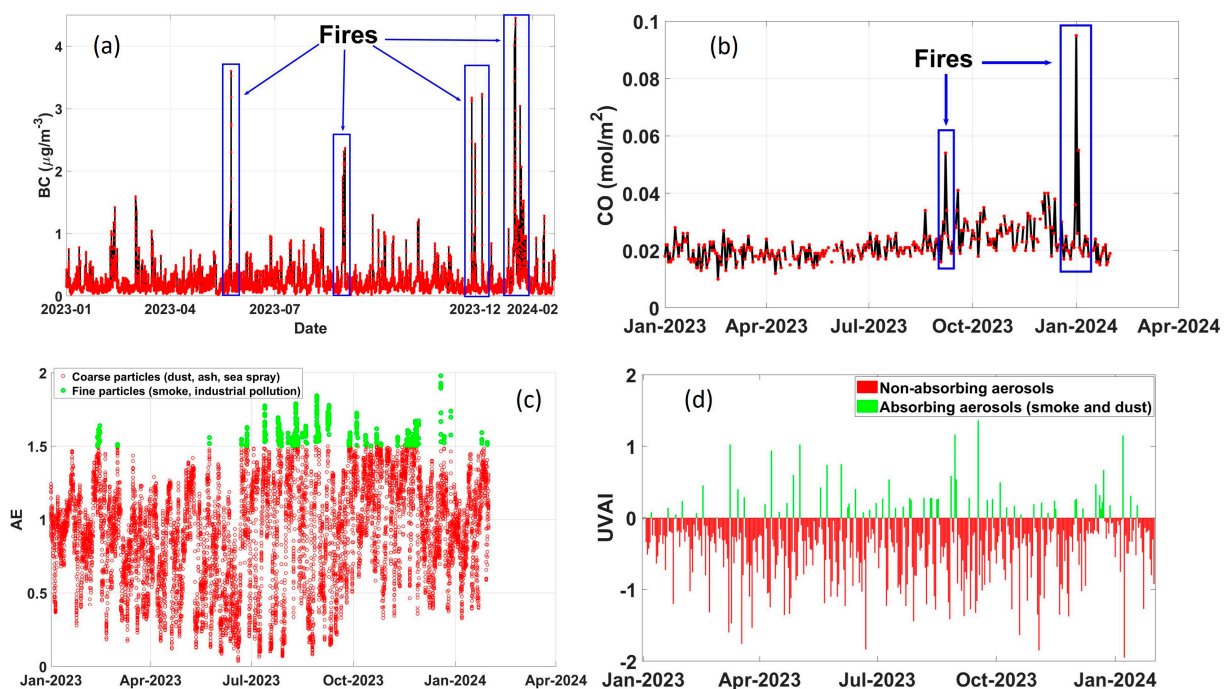


Figure 4. Time-series for the Cape peninsula region for the period of January 2023 to January 2024 for (a) BC, (b) CO, (c) AE and (d) UVAI.

The meteorological parameters such as temperature, wind speed, precipitation and relative humidity are important in generating extreme fire behaviour [61,62]. Figure 5 shows the meteorological parameters that influenced the wildfires in the Cape Peninsula region. Figure 5a shows the land-surface-temperature (LST) timeseries for the period of January 2021 to January 2024. High temperatures above 27 °C are observed during the summer season. No unusual temperatures were observed during the December 2023 and January 2024 wildfire period. However, with a lack of precipitation, these temperatures have the capacity to desiccate the vegetation, leaving it vulnerable to fires. Additionally, low relative humidity also helps in drying out vegetation. Again, moderate relative humidity of about 60% does play a role in drying out the vegetation. Higher relative humidity above 80% usually prevents fire from starting and spreading more easily. Figure 5b shows that during the wildfire episodes, the relative humidity was within the range of 60%, contributing slightly to the dry vegetation. Figure 5c shows speeds from December 2023 to January 2024. Wind speeds above 14.5 m/s imply a greater chance of a fire spreading rapidly. These higher speeds were observed during the period of the fires. This is one of the factors that led to the spread of the fire. Figure 5d further shows a 5-day air mass forward trajectory from the source point. All the air mass from 500, 1500 and 2000 m showed that

the air parcels travelled to Namibia. This is significant, because it is known that air masses transport pollutants [63,64]. The transport of these pollutants can have a negative impact on health, climate and the environment [65].

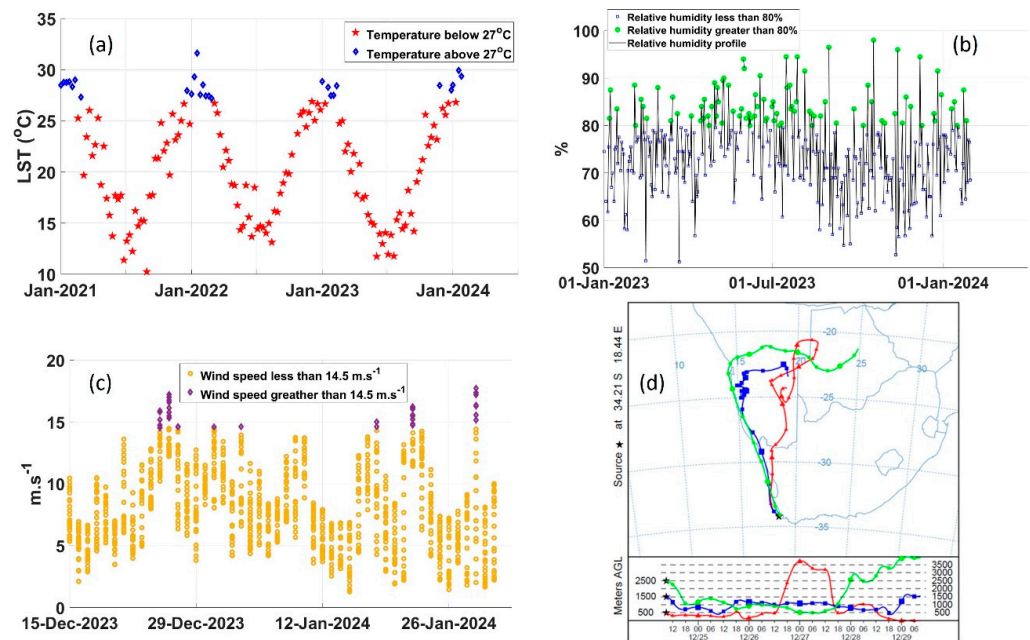


Figure 5. Time-series of (a) LST, (b) relative humidity and (c) wind speed over the Cape Peninsula. (d) 120 h-forward trajectory from 25–29 December 2023.

The Leaf Water Content Index (LWCI) is used as a representation of water content in vegetation. It is used to estimate changes in the water content in leaves [66]. Negative values of LWCI indicate dry leaves, while positive values indicate higher moisture content in the leaves. Figure 6 shows the LWCI in the Cape Peninsula for the period of 2019 and 2023 during the December periods. In the period 2019, positive values around the fire scar are observed, while negative values are observed in 2023; see Figure 6a,b, respectively. The values shown in Figure 6c clearly shows a decrease in LWCI for the year 2023. The vegetation became drier and more susceptible to the spread of wildfires.

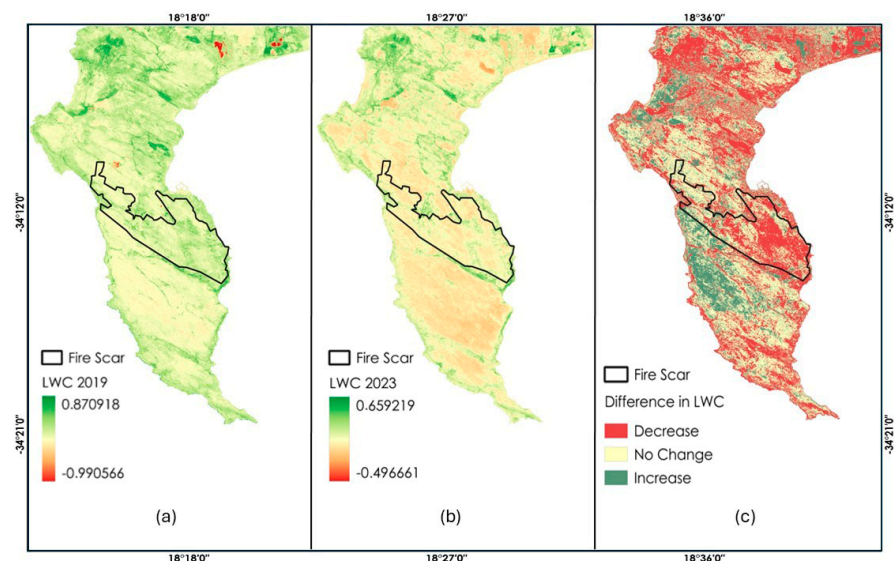


Figure 6. LWCI over Cape Peninsula for (a) December 2019, (b) December 2023 and (c) difference [2019–2023].

5. Summary and Conclusions

Over the years, the Cape Peninsula has seen a rise in the number of fires that occur seasonally. The region is known to have hot and dry summer conditions which have led to uncontrollable wildfires. Emergency services are always on the alert to intervene when the blazing fires become intense and dangerous. The current wildfire under study is one of the worst of its kind in the region. Therefore, an effort was made to understand the drivers of these fires. Meteorological conditions are definitely a significant driver in the start and spread of the fires. High temperatures, low moisture and strong winds are the main drivers for the fire. It is also clear that fires also destroyed fynbos, which need to burn every 10–15 years to reproduce properly. A four-to-five-year repeated short interval between fires can eliminate dominant reseeding shrubs, and increased fire frequency favours resprouting species. The presented results provide valuable insights into the wildfire regime at the Cape Peninsula. The study can be useful to those in fire management and biodiversity conservation in the region. It is advisable to implement proactive measures such as controlled burns and ecosystem restoration efforts to help mitigate the risk of wildfires and promote the resilience of the local ecosystems.

Monitoring of wildfires is crucial, and remote sensing plays a critical role in observing the wildfire locations and characterising its emissions. Currently low-earth-orbiting (LEO) satellites are used for this purpose. However, one of the challenge is the long revisit time, which impedes the near real-time estimation of wildfire emissions. Furthermore, the passive sensors on these satellites are limited by obstacles such as clouds and thick smoke, i.e., when the imagery of the burnt area is required. The grand challenge is that most of these satellite sensors were not specifically designed for fire monitoring, which poses some limitations on their use. Nonetheless, a multi-sensor approach does give some insight into the wildfire. On the upside, Chen et al. [67] showed that the growing number of medium- and high-resolution satellites, such as Sentinel-2a and Sentinel-2b, Landsat 8 and Landsat 9, and commercial platforms like Planet Labs PlanetScope and DigitalGlobe WorldView, provide detailed imagery for detecting and mapping burnt areas with unprecedented accuracy. Moreover, the launch and operation of Sentinel 5P has been used to assess the impact of wildfires on the air quality and to monitor toxic gases. The monitoring of toxic gases facilitates a quick response to wildfire events. One of the tasks going forward is to develop a localised fire-forecasting system that predicts emissions of wildfires in that area using past fire data and climate variables.

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Appendix A

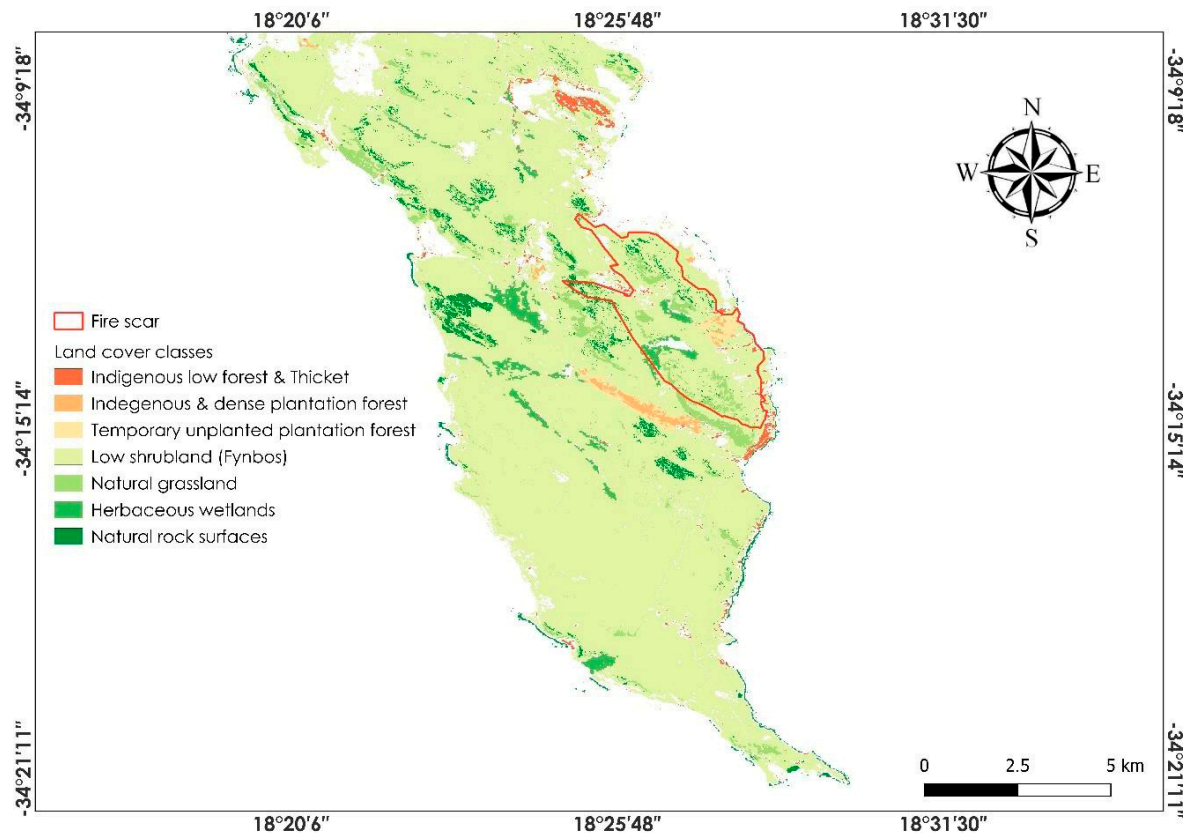


Figure A1. Land Cover map of the Cape Peninsula. The data was retrieved from the South African Department of Forestry, Fisheries and the Environment.

References

- Halofsky, J.E.; Peterson, D.L.; Harvey, B.J. Changing wildfire, changing forests: The effects of climate change on fire regimes and vegetation in the Pacific Northwest, USA. *Fire. Ecol.* **2020**, *16*, 4. [\[CrossRef\]](#)
- Swati, S. Forest fire emissions: A contribution to global climate change. *Front. For. Glob. Chang.* **2022**, *5*, 925480. [\[CrossRef\]](#)
- Zhang, Z.; Long, T.; He, G.; Wei, M.; Tang, C.; Wang, W.; Wang, G.; She, W.; Zhang, X. Study on Global Burned Forest Areas Based on Landsat Data. *Photogramm. Eng. Remote Sens.* **2020**, *86*, 503–508. [\[CrossRef\]](#)
- Gill, A.M.; Stephens, S.L.; Cary, G.J. The worldwide “wildfire” problem. *Ecol. Appl.* **2013**, *23*, 438–454. [\[CrossRef\]](#) [\[PubMed\]](#)
- Bowman, D.M.J.S.; Kolden, C.A.; Abatzoglou, J.T.; Johnston, F.H.; van der Werf, G.R.; Flannigan, M. Vegetation fires in the Anthropocene. *Nat. Rev. Earth. Environ.* **2020**, *1*, 500–515. [\[CrossRef\]](#)
- Cardil, A.; Tapia, V.M.; Monedero, S.; Quiñones, T.; Little, K.; Stoof, C.R.; Ramirez, J.; de-Miguel, S. Characterizing the rate of spread of large wildfires in emerging fire environments of northwestern Europe using Visible Infrared Imaging Radiometer Suite active fire data. *Nat. Hazards Earth Syst. Sci.* **2023**, *23*, 361–373. [\[CrossRef\]](#)
- Cruz, M.G.; Alexander, M.E.; Kilinc, M. Wildfire Rates of Spread in Grasslands under Critical Burning Conditions. *Fire* **2022**, *5*, 55. [\[CrossRef\]](#)
- Van Wilgen, B.W.; Le Maitre, D.C.; Kruger, F.J. Fire Behaviour in South African Fynbos (Macchia) Vegetation and Predictions from Rothmel’s Fire Model. *J. Appl. Ecol.* **1985**, *22*, 207–216. [\[CrossRef\]](#)
- Mucina, L.; Rutherford, M. The vegetation of South Africa, Lesotho and Swaziland. In *Strelitzia*; South African National Biodiversity Institute: Pretoria, South Africa, 2006; Volume 19.
- Dendy, S.P.; Tong, B.; Alexander, H.M.; Fay, P.A.; Murray, L.; Xing, Y.; Garrett, K.A. A long-term study of burning effects on a plant pathogen in tallgrass prairie. *Plant Pathol.* **2019**, *66*, 1308–1317. [\[CrossRef\]](#)
- Riveiro, S.F.; García-Duro, J.; Cruz, Ó.; Casal, M.; Reyes, O. Fire effects on germination response of the native species *Daucus carota* and the invasive alien species *Helichrysum foetidum* and *Oenothera glazioviana*. *Glob. Ecol. Conserv.* **2019**, *20*, e00730. [\[CrossRef\]](#)
- Riveiro, S.F.; Cruz, Ó.; Casal, M.; Reyes, O. Fire and seed maturity drive the viability, dormancy, and germination of two invasive species: *Acacia longifolia* (Andrews) Willd. and *Acacia mearnsii* De Wild. *Ann. For. Sci.* **2020**, *77*, 60. [\[CrossRef\]](#)
- He, T.; Lamont, B.B.; Pausas, J.G. Fire as a key driver of Earth’s biodiversity. *Biol. Rev.* **2019**, *94*, 1983–2010. [\[CrossRef\]](#)

14. Yao, W.; Zhao, Y.; Chen, R.; Wang, M.; Song, W.; Yu, D. Emissions of Toxic Substances from Biomass Burning: A Review of Methods and Technical Influencing Factors. *Processes* **2023**, *11*, 853. [\[CrossRef\]](#)
15. Johnston, H.J.; Mueller, W.; Steinle, S.; Steinle, S.; Vardoulakis, S.; Tantrakarnapa, K.; Loh, M.; Cherrie, J.W. How Harmful Is Particulate Matter Emitted from Biomass Burning? A Thailand Perspective. *Curr. Pollut. Rep.* **2019**, *5*, 353–377. [\[CrossRef\]](#)
16. Koppmann, R.; von Czapiewski, K.; Reid, J.S. A review of biomass burning emissions, part I: Gaseous emissions of carbon monoxide, methane, volatile organic compounds, and nitrogen containing compounds. *Atmos. Chem. Phys. Discuss.* **2005**, *5*, 10455–10516. [\[CrossRef\]](#)
17. Andreae, M.O.; Merlet, P. Emission of trace gases and aerosols from biomass burning. *Glob. Biogeochem. Cycles* **2001**, *15*, 955–966. [\[CrossRef\]](#)
18. Keeley, J.E.; Syphard, A.D. Large California wildfires: 2020 fires in historical context. *Fire Ecol.* **2021**, *17*, 22. [\[CrossRef\]](#)
19. Eck, T.F.; Holben, B.N.; Reid, J.S.; Sinyuk, A.; Giles, D.M.; Arola, A.; Slutsker, I.; Schafer, J.S.; Sorokin, M.G.; Smirnov, A.; et al. The extreme forest fires in California/Oregon in 2020: Aerosol optical and physical properties and comparisons of aged versus fresh smoke. *Atmos. Environ.* **2023**, *305*, 119798. [\[CrossRef\]](#)
20. Deb, P.; Moradkhani, H.; Abbaszadeh, P.; Kiem, A.S.; Engström, J.; Keellings, D.; Sharma, A. Causes of the widespread 2019–2020 Australian bushfire season. *Earth's Future* **2020**, *8*, e2020EF001671. [\[CrossRef\]](#)
21. Shikwambana, L.; Kganyago, M. Observations of Emissions and the Influence of Meteorological Conditions during Wildfires: A Case Study in the USA, Brazil, and Australia during the 2018/19 Period. *Atmosphere* **2021**, *12*, 11. [\[CrossRef\]](#)
22. Clarke, H.; Cirulis, B.; Penman, T. The 2019–2020 Australian forest fires are a harbinger of decreased prescribed burning effectiveness under rising extreme conditions. *Sci. Rep.* **2022**, *12*, 11871. [\[CrossRef\]](#)
23. Jalaludin, B.; Johnston, F.; Vardoulakis, S.; Morgan, G. Reflections on the Catastrophic 2019–2020 Australian Bushfires. *Innov. J.* **2020**, *1*, 100010. [\[CrossRef\]](#)
24. Strydom, S.; Savage, M. A spatio-temporal analysis of fires in South Africa. *S. Afr. J. Sci.* **2016**, *112*, 1–8. [\[CrossRef\]](#)
25. Kraaij, T.; Baard, J.A.; Arndt, J.; Vhengani, L.; van Wilgen, B.W. An assessment of climate, weather, and fuel factors influencing a large, destructive wildfire in the Knysna region, South Africa. *Fire Ecol.* **2018**, *14*, 4. [\[CrossRef\]](#)
26. Quiroz, N.F.; Gibson, L.; Conradie, W.S.; Ryan, P.; Heydenrych, R.; Moran, A.; van Straten, A.; Walls, R. Analysis of the 2017 Knysna fires disaster with emphasis on fire spread, home losses and the influence of vegetation and weather conditions: A South African case study. *Int. J. Disaster Risk Reduct.* **2023**, *88*, 103618. [\[CrossRef\]](#)
27. Fernández-Manso, A.; Fernández-Manso, O.; Quintano, C. SENTINEL-2A red-edge spectral indices suitability for discriminating burn severity. *Int. J. Appl. Earth Observ. Geoinform.* **2016**, *50*, 170–175. [\[CrossRef\]](#)
28. Suwanprasis, C.; Shah Nawaz, S. Mapping burned areas in Thailand using Sentinel-2 imagery and OBIA techniques. *Sci. Rep.* **2024**, *14*, 9609. [\[CrossRef\]](#)
29. Giglio, L.; Schroeder, W.; Justice, C.O. The collection 6 MODIS active fire detection algorithm and fire products. *Remote Sens. Environ.* **2016**, *178*, 31–41. [\[CrossRef\]](#)
30. Kim, M.; Jung, M.; Kim, Y. Histogram matching of Sentinel-2 spectral information to enhance Planetscope imagery for effective wildfire damage assessment. *Korean J. Remote Sens.* **2019**, *35*, 517–534. [\[CrossRef\]](#)
31. Cowling, R.M.; MacDonald, I.A.W.; Simmons, M.T. The Cape Peninsula, South Africa: Physiographical, biological, and historical background to an extraordinary hot spot of biodiversity. *Biodivers. Conserv.* **1996**, *5*, 527–550. [\[CrossRef\]](#)
32. Pooley, S. Fire Geography and Urbanisation on the Cape Peninsula. In *Burning Table Mountain*; Palgrave Studies in World Environmental History; Palgrave Macmillan: London, UK, 2014. [\[CrossRef\]](#)
33. Theys, N.; Hedelt, P.; De Smedt, I.; Lerot, C.; Yu, H.; Vlietinck, J.; Pedergnana, M.; Arellano, S.; Galle, B.; Fernandez, D.; et al. Global monitoring of volcanic SO₂ degassing with unprecedented resolution from TROPOMI onboard Sentinel-5 Precursor. *Sci. Rep.* **2019**, *9*, 2643. [\[CrossRef\]](#) [\[PubMed\]](#)
34. Tilstra, L.G.; de Graaf, M.; Wang, P.; Stammes, P. In-orbit Earth reflectance validation of TROPOMI on board the Sentinel-5 Precursor satellite. *Atmos. Meas. Tech.* **2020**, *13*, 4479–4497. [\[CrossRef\]](#)
35. Verhoelst, T.; Compernelle, S.; Pinardi, G.; Lambert, J.C.; Eskes, H.J.; Eichmann, K.-U.; Fjæraa, A.M.; Granville, J.; Niemeijer, S.; Cede, A.; et al. Ground-based validation of the Copernicus Sentinel-5P TROPOMI NO₂ measurements with the NDACC ZSL-DOAS, MAX-DOAS and Pandora global networks. *Atmos. Meas. Tech.* **2021**, *14*, 481–510. [\[CrossRef\]](#)
36. National Aeronautics and Space Administration. MODIS Data. Available online: <https://terra.nasa.gov/data/modis-data> (accessed on 16 November 2022).
37. Justice, C.O.; Townshend, J.R.G.; Vermote, E.F.; Masuoka, E.; Wolfe, R.E.; Saleous, N.; Roy, D.P.; Morisette, J.T. An overview of MODIS Land data processing and product status. *Remote Sens. Environ.* **2002**, *83*, 3–15. [\[CrossRef\]](#)
38. Zhao, B.; Mao, K.; Cai, Y.; Shi, J.; Li, Z.; Qin, Z.; Meng, X.; Shen, X.; Guo, Z. A combined Terra and Aqua MODIS land surface temperature and meteorological station data product for China from 2003 to 2017. *Earth Syst. Sci. Data* **2020**, *12*, 2555–2577. [\[CrossRef\]](#)
39. Giglio, L.; Descloitres, J.; Justice, C.O.; Kaufman, Y.J. An Enhanced Contextual Fire Detection Algorithm for MODIS. *Remote Sens. Environ.* **2003**, *87*, 273–282. [\[CrossRef\]](#)
40. Hartmut, H.; Aumann, H.; Miller, C.R. Atmospheric infrared sounder (AIRS) on the earth observing system. In Proceedings of the Advanced and Next-Generation Satellites, Paris, France, 25–28 September 1995; Volume 2583.

41. Chahine, M.T.; Pagano, T.; Aumann, H.; Atlas, R.; Barnett, C.; Blaisdell, J.; Chen, L.; Divakarla, M.; Fetzer, E.; Goldberg, M.; et al. AIRS: Improving weather forecasting and providing new data on greenhouse gases. *Bull. Am. Meteorol. Soc.* **2006**, *87*, 911–926.
42. Menzel, W.P.; Schmit, T.J.; Zhang, P.; Li, J. Satellite-Based Atmospheric Infrared Sounder Development and Applications. *Bull. Am. Meteorol. Soc.* **2018**, *99*, 583–603. [\[CrossRef\]](#)
43. Rienecker, M.M.; Suarez, M.J.; Gelaro, R.; Todling, R.; Bacmeister, J.; Liu, E.; Bosilovich, M.G.; Schubert, S.D.; Takacs, L.; Kim, G.; et al. MERRA: NASA's Modern-Era Retrospective Analysis for Research and Applications. *J. Clim.* **2011**, *24*, 3624–3648. [\[CrossRef\]](#)
44. Wargan, K.; Labow, G.; Frith, S.; Pawson, S.; Livesey, N.; Partyka, G. Evaluation of the Ozone Fields in NASA's MERRA-2 Reanalysis. *J. Clim.* **2017**, *30*, 2961–2988. [\[CrossRef\]](#)
45. Gelaro, R.; McCarty, W.; Suárez, M.J.; Todling, R.; Molod, A.; Takacs, L.; Randles, C.A.; Darmenov, A.; Bosilovich, M.G.; Reichle, R.; et al. The Modern-Era Retrospective Analysis for Research and Applications, Version 2 (MERRA-2). *J. Clim.* **2017**, *30*, 5419–5454. [\[CrossRef\]](#)
46. Buchard, V.; Randles, C.A.; da Silva, A.M.; Darmenov, A.; Colarco, P.R.; Govindaraju, R.; Ferrare, R.; Hair, J.; Beyersdorf, A.J.; Ziemba, L.D.; et al. The MERRA-2 Aerosol Reanalysis, 1980 Onward. Part II: Evaluation and Case Studies. *J. Clim.* **2017**, *30*, 6851–6872. [\[CrossRef\]](#)
47. Randles, C.A.; da Silva, A.M.; Buchard, V.; Colarco, P.R.; Darmenov, A.; Govindaraju, R.; Smirnov, A.; Holben, B.; Ferrare, R.; Hair, J.; et al. The MERRA-2 Aerosol Reanalysis, 1980 Onward. Part I: System Description and Data Assimilation Evaluation. *J. Clim.* **2017**, *30*, 6823–6850. [\[CrossRef\]](#)
48. Kroon, M.; de Haan, J.F.; Veeckind, J.P.; Froidevaux, L.; Wang, R.; Kivi, R.; Hakkarainen, J.J. Validation of operational ozone profiles from the Ozone Monitoring Instrument. *J. Geophys. Res.* **2011**, *116*, D18305. [\[CrossRef\]](#)
49. Levelt, P.F.; van den Oord, G.H.J.; Dobber, M.R.; Mälikki, A.; Visser, H.; de Vries, J.; Stammes, P. The ozone monitoring instrument. *IEEE Trans. Geosci. Remote Sens.* **2006**, *4*, 1093–1101. [\[CrossRef\]](#)
50. Stein, A.F.; Draxler, R.R.; Rolph, G.D.; Stunder, B.J.B.; Cohen, M.D.; Ngan, F. NOAA's HYSPLIT atmospheric transport and dispersion modeling system. *Bull. Am. Meteorol. Soc.* **2015**, *96*, 2059–2077. [\[CrossRef\]](#)
51. Fleming, Z.L.; Monks, P.S.; Manning, A.J. Review: Untangling the influence of air-mass history in interpreting observed atmospheric composition. *Atmos. Res.* **2012**, *104–105*, 1–39. [\[CrossRef\]](#)
52. Draxler, R. Evaluation of an Ensemble Dispersion Calculation. *J. Appl. Meteorol.* **2003**, *42*, 308–317. [\[CrossRef\]](#)
53. Spoto, F.; Sy, O.; Laberinti, P.; Martimort, P.; Fernandez, V.; Colin, O.; Hoersch, B.; Meygret, A. Overview of Sentinel-2. In Proceedings of the IEEE International Geoscience and Remote Sensing Symposium, Munich, Germany, 22–27 July 2012; pp. 1707–1710.
54. Sudmanns, M.; Tiede, D.; Augustin, H.; Lang, S. Assessing global Sentinel-2 coverage dynamics and data availability for operational Earth observation (EO) applications using the EO-Compass. *Int. J. Digit. Earth.* **2019**, *13*, 768–784. [\[CrossRef\]](#)
55. Hunt, R.; Barrett, N.; Park, S. Measurement of Leaf Relative Water Content by Infrared Reflectance. *Remote Sens. Environ.* **1987**, *22*, 429–435. [\[CrossRef\]](#)
56. Strydom, T.; Kraaij, T.; Difford, M.; Cowling, R.M. Fire severity effects on resprouting of subtropical dune thicket of the Cape Floristic Region. *PeerJ* **2020**, *8*, e9240. [\[CrossRef\]](#) [\[PubMed\]](#)
57. Cocke, A.E.; Fulé, P.Z.; Crouse, J.E. Comparison of burn severity assessments using Differenced Normalized Burn Ratio and ground data. *Int. J. Wildland Fire* **2005**, *14*, 189–198. [\[CrossRef\]](#)
58. Kushla, J.D.; Ripple, W.J. Assessing wildfire effects with Landsat thematic mapper data. *Int. J. Remote Sens.* **1998**, *19*, 2493–2507. [\[CrossRef\]](#)
59. Bertolette, D.; Spotskey, D. Remotely sensed burn severity mapping. In *Crossing Boundaries in Park Management, Proceedings of the 11th Conference on research and Resource Management in Parks and on Public Lands, MI, USA, 15 April 2021*; Harmon, D., Ed.; The George Wright Society: Hancock, MI, USA, 2021; pp. 44–51.
60. Pierce, S.M.; Cowling, R.M. Disturbance regimes as determinants of seed banks in coastal dune vegetation of the southeastern Cape. *J. Veg. Sci.* **1991**, *2*, 403–412. [\[CrossRef\]](#)
61. Harte, E.W.; Childs, I.R.W.; Hastings, P.A. Imizamo Yethu: A case study of community resilience to fire hazard in an informal settlement Cape Town, South Africa. *Geogr. Res.* **2009**, *47*, 142–154. [\[CrossRef\]](#)
62. Tošić, I.; Mladjan, D.; Gavrilov, M.; Živanović, S.; Radaković, M.; Putniković, S.; Petrović, P.; Mistrždelović, I.; Marković, S. Potential influence of meteorological variables on forest fire risk in Serbia during the period 2000–2017. *Open Geosci.* **2019**, *11*, 414–425. [\[CrossRef\]](#)
63. Dong, L.; Leung, L.R.; Qian, Y.; Zou, Y.; Song, F.; Chen, X. Meteorological environments associated with California wildfires and their potential roles in wildfire changes during 1984–2017. *J. Geophys. Res. Atmos.* **2021**, *126*, e2020JD033180. [\[CrossRef\]](#)
64. Kulshrestha, U.; Kumar, B. Airmass Trajectories and Long-Range Transport of Pollutants: Review of Wet Deposition Scenario in South Asia. *Adv. Meteorol.* **2014**, *14*, 596041. [\[CrossRef\]](#)
65. Febo, A.; Guglielmi, F.; Manigrasso, M.; Ciambottini, V.; Avino, P. Local air pollution and long-range mass transport of atmospheric particulate matter: A comparative study of the temporal evolution of the aerosol size fractions. *Atmos. Pollut. Res.* **2010**, *1*, 141–146. [\[CrossRef\]](#)

-
66. Canny, M.J.; Haung, C.X. Leaf water content and palisade cell size. *New Phytol.* **2006**, *170*, 75–85. [[CrossRef](#)]
 67. Chen, Y.; Morton, D.C.; Randerson, J.T. Remote sensing for wildfire monitoring: Insights into burned area, emissions, and fire dynamics. *One Earth* **2024**, *7*, 1022–1028. [[CrossRef](#)]

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