# GIS investigation of the fire history of Jonkershoek Nature Reserve

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### Abstract

Fire regimes have the potential to disturb ecological aspects of a landscape and/or contribute to the maintenance of the biological diversity. Thus, a gauge of the impact of planned and unplanned fire regimes is vital to South Africa's national reserves. The Jonkershoek Nature Reserve in the Western Cape is characterized by the occurrence of indigenous Fynbos and Afromontane Forest vegetation. Geographical Information Systems (GIS) and Remote Sensing (RS) can aid the management and preservation of indigenous vegetational species. This study used knowledge of the ecological conditions of the Reserve, historical fire data, Landsat TM and Landsat OLI imagery, and geospatial analysis to investigate the impact of the fire regimes in the Reserve. Image classification was carried out from 2005 to 2015 to determine the burn patterns, with the process being aided by the fire regime history from 1970 to 2015. Ordinary Least Squares (OLS) analysis was carried out to determine how abiotic factors, such as elevation, slope and aspect, impact fires in the Reserve. The assessment of fires included the ascertainment of their location, coverage, and frequency, the Normalised Burn Ratio (NBR), the differenced Normalised Burn Ratio (dNBR) and the Normalised Difference Vegetation Index (NDVI). There were 39 fires recorded in the Jonkershoek Nature Reserve from 1970 to 2015. The largest fire events were recorded in 1999 (26503.6 ha.) and 2015 (8363.0 ha.). The lowest area of fire impact recorded occurred in the years 2010 (0.15ha.), 1973 (1.1 ha.) and 1987 (3.1 ha.). With an overall classification accuracy of 94.17%, the Landsat OLI imagery performed better with an overall classification accuracy of 94.17% than the Landsat TM at 75.83%. The OLS regression showed that fire severity was positively correlated to NDVI and elevation. This may suggest that regions of healthy vegetation at any altitude may be susceptible to burnings if there is sufficient vegetation to fuel a fire. The OLS was negatively correlated to slope and aspect. This may impact fire risk as steeper slopes may have vegetation growing in their fire shadow.

## 1. Introduction

The Jonkershoek Nature Reserve is situated in the Cape Floristic region which is one of the global biodiversity hotspots. Owing to the occurrence of endemic Fynbos species that are fire-prone, this

region is unique. Globally, fire is a form of disturbance that can lead to shifts in the ecological processes and the modification of the landscape (Leon et al., 2012; Bond & Archibald, 2003). The time taken for an ecosystem to return to a pre-fire state is referred to as recovery time. A short recovery time is a sign of resilience. On the other hand, an increasingly longer recovery time after subsequent disturbances may be a sign of a change to an alternate state or lesser function (Wilson et al, 2015).

Management of fire is crucial to the conservation of biodiversity and the preservation of indigenous vegetation. Fire is a recurrent phenomenon in the Reserve and is important for maintaining the indigenous biodiversity cover. Continual monitoring and documenting of fires, and elements such as frequency, severity, season, and spatial pattern are necessary (Mota et al., 2019; Poulos et al., 2018). Historical fire data is vital for documenting fires and is unique in that it contains both descriptive and spatial characteristics (Hamilton et al., 2005).

A fire regime is characterised by the frequency, intensity, and severity of a fire, and is used to understand the dynamics of fire on a landscape (Cissel et al, 1999). Frequency of fires is usually described as the assessment of the fire interval, which is the period that it takes for fire to again be experienced in an area. It is important for the ecological stability of vegetation (Bond & Archibald, 2003). Geospatial Science can aid the acquisition and analysis of fire, and develop a historical fire spatial database (Eugenio, 2019; Butt, 2015).

Geographic Information Systems (GIS) contribute to the development of spatial databases that allow for the compilation of historical fire data into a single, easily accessible, and manageable dataset. These datasets collate the fire data for use in land use management practices. They can assist managers in collecting information about the species that are sensitive to certain fire intervals, indicate the influence of fire on the abundance of a particular species, and explain the survival strategies of plants, with the focus on endangered species. There is a need for a greater understanding of fire regimes for effective ecosystem management (Thuiller, 2007).

Recent uncontrolled fires in and around the vicinity of the Jonkershoek Nature Reserve have raised concerns about the impact of burnings. The Reserve has a documented history of fires; however, it does not include records of the change in vegetational cover caused by fires over time. This paper aims to provide additional insights into the temporal, spatial, topographic, and the factors influencing fire severity and burn patterns in the Reserve from a Geospatial Science perspective.

### 2. Study area

Jonkershoek Nature Reserve spans an area of 11 000ha. within the Jonkershoek Valley. It forms part of the Hottentots Holland Nature Reserve. Fynbos has adapted to revegetate itself after a fire, as well as to revive the growth of the vegetation not prone to fire. Afromontane vegetation is unique (van Wilgen, 2013) in that it grows at higher altitudes. The altitude of the mountains of Jonkershoek

ranges from around 792 to 1525 m. Owing to the different fire tolerances for revegetation, this is a challenge for conservation initiatives.

The fynbos region is in the Mediterranean region of South Africa and is characterised by cold, wet winters and cool, dry summers. The Jonkershoek area is a humid mountainous area (Kruger, 1984; Kruger, 1987). The mean annual rainfall varies between 1000 mm and 3000 mm (Edwards,1984). The raining season usually occurs from April to September (van Wyk, 1987). The combination of humid conditions and high rainfall creates a unique vegetation complex in the area. Periods of dryness and high summer temperatures are usually accompanied by frequent south-easterly winds in summer and autumn, as well as hot, dry Berg Winds in spring. Such conditions usually create suitable conditions for the occurrence of fires (Edwards, 1984). Fifty-eight percent (58%) of the fire occurrences in the Western Cape region are in the summer and autumn months (December to May).

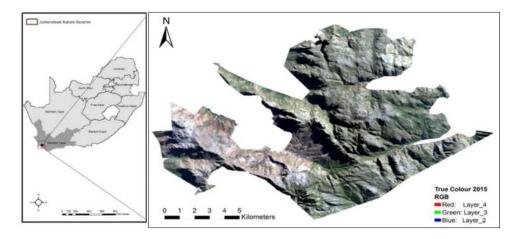


Figure 1. Jonkershoek Nature Reserve in the Western Cape, South Africa

### 3. Method and materials

The methodological framework adopted is shown in Figure 2. This study used satellite image classification to identify burn patterns in the landscape. The Normalized Burn Ratios (NBRs), Difference Normalized Burn Ratio (dNBR), and Normalized Difference Vegetation Index (NDVI) indices are used to assess vegetational change and fire severity. Owing to their ability to penetrate smoke and assess the fire scars, the near-infrared bands (NIR) of the Landsat data are recommended for fire mapping. The Ordinary Least Squares method was applied to determine how abiotic factors impact on burn patterns.

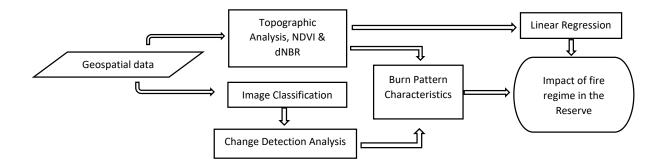


Figure 2. Methodology flowchart

Table	<ol> <li>Research</li> </ol>	1 datasets
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Data set	Specifications	Source
Landsat 5 Thematic Mapper (TM)	30 m (From 2005-2017)	EarthExplorer in USGS
Landsat 8 Operational Land Imager (OLI)	30m (From 2005-2017)	EarthExplorer in USGS
Thermal Infrared Sensor (TIRS)	30m (From 2005-2017)	EarthExplorer in USGS
Digital elevation model (DEM)	25m Resolution	Chief Directorate: National Geo- spatial Information
Fire events	1970-2015	Cape Nature BGI website

#### 3.1. Normalised ratios and indices

Post-fire vegetation succession analysis is crucial for sustainability. NBR uses the near infrared and shortwave infrared in a calculation to show the extent of a fire and the associated severity of burn on a map (Walz et al, 2007; Verbyla et al, 2008; Harris et al, 2011). Pre- and post- fire NBRs are called the differenced normal burn ratios (dNBRs), which is a measure showing the temporal differences (Harris et al, 2011; Verbyla et al, 2008). It is a measure showing how much change is caused by a fire. NDVI is also a recognized and widely accepted technique to evaluate the post fire regrowth of vegetation (Lentile et al, 2006).

The NBR was calculated (Equation 1) based on the Band 5 (near infrared) and Band 7 (shortwave infrared) of Landsat OLI images. The dNBR calculation (Equation 2) was applied before the fire occurrence and one year and two years after the initial fire occurrence. The calculation was applied to the 2 February 2015 image before the fire and to the 4 February 2015, 1January 2016, and 11 January 2017 images, after the fires.

$$NBR = (Band 5 - Band 7)/(Band 5 + Band 7)$$
[1]

[2]

### dNBR = NBR before fire - NBR after fire

The NDVI calculation is based on the near-infrared and red bands (Equation 3). The output is a raster image that has values within the range of 1 and -1 and is a measure of plant greenness.

NDVI = (NIR - Red) / (NIR + Red) = (Band 5 - Band 4) / (Band 5 + Band 4)[3]

#### 3.2. Image classification

For simplicity, a binary classification outcome was preferred with possible class outcomes of burnt and unburnt areas. A minimum of 60 training samples per class were identified for each class for better accuracy of classification. According to Ahmad & Quegan (2012) the confusion matrix is used to estimate the level-of-accuracy results of a classified imagery. The overall accuracy (Equation 4), and the nonparametric Kappa test (equation 5) were applied to check the reliability of the image classification (Butt, 2015).

$$Overall\ accurracy = \sum (correctly\ classified\ classes\ along\ diagonal) / \sum (row\ tatal)$$

120 random (60 for each class) points were stratified random sampled to evaluate the accuracy of the 2005 and 2015 image classification.

$$k = \frac{N\sum_{i=1}^{r} x_{ii} - \sum_{i=1}^{r} x_{i+} + x_{i+}}{N^2 - \sum_{i=1}^{r} x_{i+} + x_{i+}}$$
[5]

where K – Kappa coefficient, r – number of rows in the error matrix,  $X_{ii}$  – number of observations in row I and column I in the major diagonal,  $X_{i+}$  - total number of observations in row I,  $X_{+I}$  – total number of observations in column I, N – total number of observations included in the matrix.

### 3.3. Ordinary Least Squares (OLS)

Strydom & Savage (2016) used the ordinary least squares (OLS) method to assess the topographic and vegetational constraints on spatial patterns of fire severity (Equation 6). It is a generalized linear modelling technique that provides a model to predict a Y variable (Sharma et al, 2013). The regression analysis is required for the analysis of relationships and high order interactions, and it also provides for the easy interpretation of results (Collins et al, 2007).

$$Y = \beta 0 + \beta 1 x 1 + \beta 2 x 2 \dots + \beta n x n + \varepsilon$$
[6]

Y is the dependent variable or the process that is being predicted, x (x1, x2 ... xn) is the independent variable used to predict the dependent variable,  $\beta 0$  is the intercept, and  $\beta 1$ ,  $\beta 2$ ....  $\beta n$  depict the coefficients that represent the relationship strength and the type of relationship of the x variables on the Y axis (Sharma et al, 2013). The  $\varepsilon$  is the random error term (residual) which has a zero-mean value, and autocorrelation is associated with this term (Jager & King, 2004). This formula was used to assess the influence of elevation, slope, aspect, and NDVI on the fire regime.

### 4. Results and discussion

The outputs of the fire occurrence, location, extent, severity, dNBR and NDVI, image classification, change detection, and ordinary linear regression analysis are shown below.

#### 4.1. Analysis of fire occurrences

There were 39 fires recorded in the Reserve from 1970-2015. The spatial coverage is shown in Figure 4. The area of burn was also higher in the early summer/to late autumn seasons. No fires were recorded in the month of November. While December, January, March, and October showed the highest fire frequencies, with five fires, the highest overlaps occurred in the region close to the margins of the reserve. This may suggest that the fires started outside the Reserve (Figure 4). The extent of the fires is shown in red, with the overlapping fires shown in a darker shade.

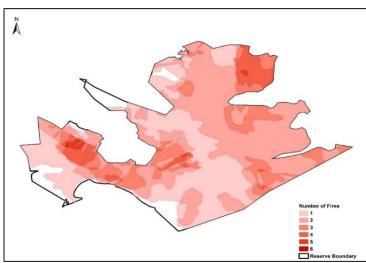


Figure 4. Overlapping fire areas and areas of occurrence of 39 single fire incidents.

In the NDVI (Figure 5) below, brown indicates areas with little vegetation, while dark green indicates areas that have are more densely vegetated. The NDVI before the fire (2 February 2015) was higher as compared to the NDVI after the fire (3 March 2015).

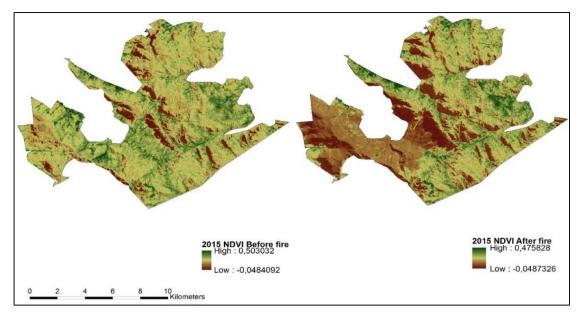


Figure 5. NDVI before the fire (2 February 2015) and after the fire (3 March 2015).

The analysis of the NBR and the change in the dNBR display the evidence of burn scar and severity of burn in the Reserve in 2015 and 2016. The NBR individual outputs before and after the fire showed the differences in the landscape before and after the fire event (Figure 6). Six classes were identified in the dNBR image, with high post-fire regrowth, low post-fire regrowth, unburnt, low severity, moderate- to-low severity, and moderate-to-high severity. The dNBR shows the severity of the burn two months after the fire (12/04/2015) and the next year (09/01/2016) following the fire. The minimum dNBR for the 2015 fire is -0,28 and the maximum value is 0,59. The mean value of the 2015 dNBR is 0,07 with a standard deviation of 0,11, while the dNBR after 2016 had a minimum value of -0.37, a maximum value of 0,51, a mean of 0,01 and a standard deviation of 0,05.

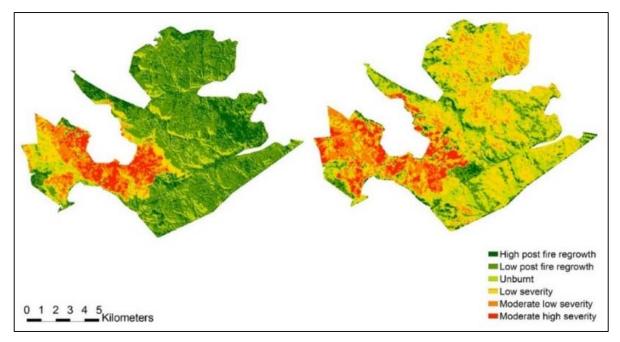


Figure 6. The dNBR recently after the fire (2 February 2015 and 12 April 2015) on the left and the following year after the fire (2 February 2015 and 9 January 2016) on the right.

The fire map (Figure 4) and the NDVI (Figure 5) suggest that vegetation growing to the east of the Reserve recovers more rapidly than vegetation growing to the west of the Reserve. Also, the fire map and the dNBR (Figure 6) suggest that vegetation growing in the western region of the Reserve experiences less severe burns than vegetation growing in the eastern region of the Reserve. Less severe fires may aid the recovery of the vegetation.

The classification of the images performed in 2005 and 2015 (Figure 7 and 8) considered only burnt and unburnt areas. A fire was recorded on 29 December 2005 and was extinguished on 3 January 2006. The area of burn in the area was considerable in the central and eastern regions. The classified image in Figure 7 shows patches of burn in isolated areas. The other fire started on the 9March 2015 and was put out on 13 March 2015. The burnt area was concentrated in the western region of the reserve (Figure 8). The overall classification accuracies for the 2005 and 2015 images are 75.83 % and 94.17% with Kappa statistics of 0,52 and 0,88 respectively (Tables 2 and 3).

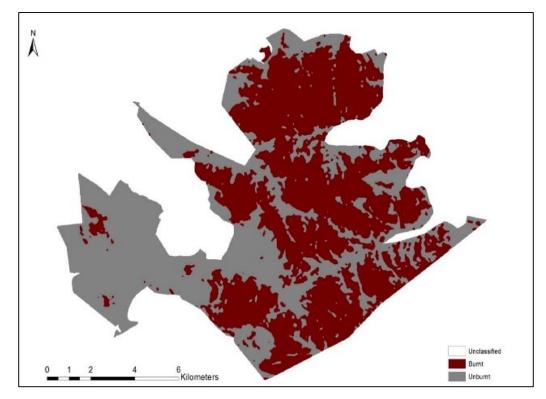


Figure 7. 2005 supervised classification of burnt area.

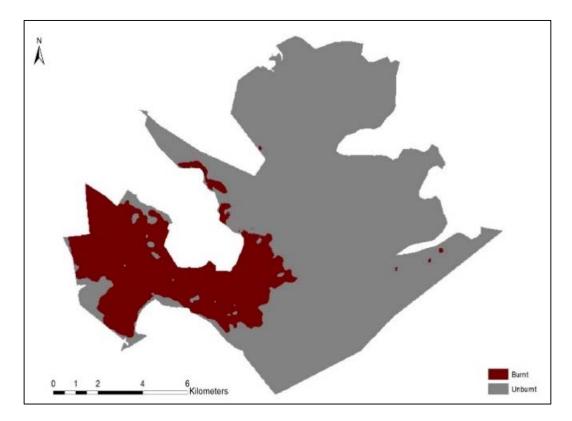


Figure 8. 2015 supervised classification of burnt area.

Land cover	Burnt	Unburnt	Total	Land	Burnt	Unburnt	Total
				cover			
Burnt	57	4	61	Burnt	46	14	60
Unburnt	3	56	59	Unburnt	15	45	60
Total	60	60	20	Total	61	59	120

Tables 2 and 3. Confusion matrix of the 2015 and 2006 classifications respectively

The map depicting the detection of vegetational change (Figure 9) showed significant land use change in the areas where the fire had occurred and limited change to land use areas outside the region where the fire had occurred. In 2005, the burnt and unburnt areas represented 6955.2ha. and 6186.2 ha., respectively. In 2015, the burnt and unburnt areas represented 10343.9 ha. and 913.8 ha., respectively.

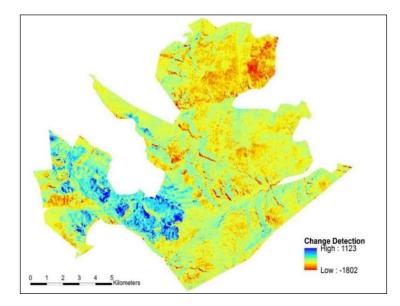


Figure 9. Change detection based on the Landsat 8 images before (2 February 2015) and after the fire (3 March 2015).

The spatial component of the results showed location, topographic factors, and the extent of the fires. The tools used, namely Landsat 5 TM, Landsat 8 OLI, and the TIRS imagery, facilitated the assessment process of describing and quantifying the fire on a landscape level. The spectral resolution of the imagery was important in investigating the severity of the fire and the burn patterns. Furthermore, the calculation of the NDVI and dNBR (Figures 5 and 6) prior to the fire (pre-fire) and post-fire also played an important role in investigating the effect of the severity of the fire on the recovery of the vegetation. It showed that areas with high NDVI values (Figures 5 and 6) prior to a fire were more seriously affected by a burn as compared to other areas with a lower NDVI. This suggests that greater quantities of vegetational fuel allow for more intense fires. Higher intensity fires

may lower the prospects for and rate of vegetational recovery. This means that vegetation in the region in question may develop a lower resilience because of high severity burns over the long term. This is especially true in cases where regions also experience high fire frequencies.

The temporal resolution of the Landsat imagery facilitated image classification of the burnt areas in 2005 and 2015 (Figures 7 and 8; Tables 2 and 3). This allowed change detection analysis to delineate the burn footprint of fire regimes over subsequent epochs. The analysis showed that more land cover change had occurred in the region that had experienced a recent fire disturbance in 2015 as compared to the land cover change in a region that had experienced a fire disturbance in 2006. This observation can be backed up by the vegetational recovery shown in the NDVI analysis. The fact that more fires occur in the summer than in any other season (Figure 3) suggests that the impact of plant phenology on burn patterns may be significant and should be assessed over the long term.

The regression analysis of the fire was based on the 2015 fire intensity variation (Table 4). A digital elevation model produced the elevation, aspect, and slope of the Reserve.

Table 4. Ordinary least squares analysis of fire severity as the dependent variable (y) and a digital
elevation model, aspect, NDVI, and slope as the explanatory/independent variables (x).

Variable	Coefficient	Std	t-Statistic	Probability	Robust_SE	Robust_t	Robust_Pr(b)	VIF
		Error						
Intercept	-0.037218	0.008646	-4.304706	0.000021*	0.008152	-4.565800	0.000007*	
DEMPOINT	0.000020	0.00001	26.855889	0.000000*	0.000001	25.599419	0.000000*	1.000625
ASPECTPOINT	-0.000011	0.000002	-5.722078	0.000000*	0.000002	-5.840184	0.000000*	1.000071
NDVIPOINT	0.798199	0.002363	337.733820	0.000000*	0.002298	347.286343	0.000000*	1.000675
SLOPEPOINT	-0.000299	0.000097	-3.071450	0.002144*	0.000092	-3.264919	0.001112*	1.000077

The signs of the coefficients suggest positive relationships between the burnings with elevation [DEM] and NDVI, along with negative relationships with slope and aspect. There is a stronger positive relationship with NDVI as compared to elevation. Also, there is a weaker relationship with slope as compared to aspect. The t-test shows that all explanatory variables were statistically significant, with the elevation and NDVI being most significant to the model. VIF suggests that none of the explanatory variables was redundant.

The OLS analysis showed negative correlations between fire severity, slope (-0.000299) and aspect (-0.000011). This may impact fire risk as steeper slopes may have vegetation growing in their fire shadow. This could allow the fire to jump across a steeply incised ravine. While elevation (0.000020) and NDVI (0.798199) were positively correlated with fire severity, this may suggest that areas of healthy vegetation at any altitude may be susceptible to burning if there is sufficient vegetation to fuel a fire. This may be linked to the composition of the vegetation and the resilience of

the ecosystem. Should this impede the maintenance of the vegetational cover and the vegetational structure necessary to ensure biodiversity and minimise invasive growth, this could be cause for concern. The monitoring of vegetational recovery in the Reserve could be vital to conservation initiatives that place particular emphasis on regions with a track record of having been subjected to high fire severity and high fire frequency.

### 5. Conclusion

This study has shown that a geospatial data-driven analytical approach can provide insights into the temporal, spatial, and factors influencing fire severity and burn patterns in the Jonkershoek Nature Reserve. A geo-database with information such as the spatial distribution of the fire (Figures 4, 7 and 8) and the frequency (Figure 5) of fire burns, along with climate, topographic, fire severity (Figure 6), and fire intensity factors could contextualise fire regimes and burn patterns. The inclusion of climate, wind direction, geology, and other relevant abiotic information would allow an OLS linear regression to identify relationships with other environmental factors. This could be used to develop a model of the fire regimes and the burn patterns observed in the Reserve.

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