Detecting Causes of Forest Loss in a Moroccan Protected Area:

A 16-year analysis of forest changes in Talassemtane National Park, North Africa

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Preface

This Practicum consists of one manuscript chapter prepared for submission to the journal *Fire*. This journal was selected for contributing to the special issue “Multi-Source and Multi-System Fire Monitoring Relying on EO Data in Mediterranean Ecosystems", which will focus on using GIS geospatial technologies and Earth Observation data for fire monitoring and management.

Abstract

Remotely sensed data gives us the ability to peer into the past and piece together the history of an area. In this study, I used data derived from Landsat and MODIS sensors to assess forest changes in the Talassemtane National Park (TNP) in North Africa from 2003-2018. The Talassemtane National Park is a protected area in northern Morocco. It is a mountainous region which is very biodiverse, with endemic species of concern such as *Abies marocana* and *Macaca sylvanus.* To help the managers of the TNP better understand how the forest has been impacted by fire and other disturbances, I combined information from remotely derived datasets, including the Hansen Global Forest Change data, Andela’s Global Fire Atlas (GFA), and surface reflectance corrected Landsat data to calculate fire severity and vegetation death. The Hansen data were used to understand where and when forest loss occurred. Hansen data are a valuable metric of forest change, but no specific causes are provided. Fire is a major agent of forest change worldwide and the GFA is a new global tool to identify fire locations and progression. Hansen data showed a net loss of 1995 ha over 16 years. The GFA identified nine large fires that resulted in 705 ha of forest loss in the same period. Within these fires, detailed image analysis showed that GFA fire boundaries were approximately correct and high-severity fire, as determined by Relativized differenced Normal Burn Ratio (RdNBR) analysis, made up about

15% of burned area. In sum, fires were linked to approximately 35% of the forest loss and the GFA was validated as a management tool. This information helps managers develop conservation strategies based on concrete data about forest threats.

Keywords

RdNBR, NDVI, Landsat, Global Fire Atlas, Hansen et al. Global Forest Change, Forest loss, *Abies marocana*

1. Introduction

Climate change poses challenges for forest sustainability across the globe by altering precipitation rates and average temperatures (Valdes et al., 2017), which will affect forest types differently and have distinct management implications. Altered disturbances such as wildfire, insect and disease outbreaks, and drought are leading indicators of changing climate's impacts on forests globally (Nagel et al., 2017, Seidel et al. 2017). Fire-dependent ecosystems such as those throughout much of western North America, Australia, and the Mediterranean Basin have experienced more frequent and severe fires in the last century (Liu et al., 2010, Chergui et al. 2018). Rising temperatures in many areas are already showing increased drought-induced forest change, which is affecting the productivity of vegetation (Thrippleton et al., 2018). Interactions of disturbance and climate change can increase the rate of tree mortality, damage to soil, and changes to overall forest structure (O'Connor et al., 2020). Forest loss is of critical concern because people all over the world rely on forest ecosystems for resources such as timber, wild harvest, spiritual and religious needs, and many other ecosystem services (Sodhi et al., 2010, Cordova et al., 2013). Human pressures such as grazing, logging, urban expansion, altered fire regimes, and agriculture have disturbed forest ecosystems, which have often degraded forests.

Remotely sensed data is a valuable resource for better understanding the dynamics of forests to develop improved strategies for reducing loss. Hansen et al. (2013) created a dataset to map all forest change beginning in 2000 using Landsat 7 Enhanced Thematic Mapper Plus (ETM+) data at a spatial resolution of 30 m; the map currently has coverage through 2019. The Hansen maps have been widely used to measure deforestation, contributing to national and global forest resource inventories and carbon accounting (Allen et al., 2015). However, forest change can occur from many different factors, including land clearing, wildfires, insect or disease outbreaks, or drought stress. Understanding the specific roles of different factors is valuable information that managers and governments can use to develop targeted science-based strategies for forest protection.

Wildfire activity can be directly monitored in real-time through MODIS (Moderate Resolution Imaging Spectoradiometer) satellite imagery. MODIS is an instrument on the Terra and Aqua satellites which gathers data on the entire Earth's surface every 1-2 days. The Global Fire Atlas (GFA) is a recently published database that integrates MODIS data over time to map fires, creating ongoing measurements of the duration and progress of individual events and base information for calculating the contemporary fire regime (Andela et al., 2019). The GFA provides data on fires globally from 2003-2018 (through July of 2018 at this writing), created using the Collection 6 MCD64A1 MODIS burned area data product at a lower spatial resolution of 500 m (Andela et al., 2019).

Wildfire effects, such as spatial patterns of fire severity, can be derived from other sensors that detect reflectance changes due to vegetation mortality. Imagery from Landsat sensors is widely used to derive burn severity metrics such as the delta normalized burn ratio (dNBR) and its relativized form (RdNBR) (Miller & Thode, 2007). Both the dNBR and RdNBR are based on the normalized burn ratio (NBR), which is an index derived by calculating the ratio between the near infrared (NIR) and shortwave infrared (SWIR) portions of the electromagnetic spectrum (Key and Benson ,2006). The RdNBR, developed by Miller and Thode (2007), with a recent update by Parks et al. (2014), has two advantages over an absolute index: (1) relative indices provide a more consistent definition of severity which allows better comparison of fires across space and time, and (2) classifying from a relative index should result in higher accuracy in heterogeneous landscapes.

The Mediterranean region is a culturally rich and diverse area that has been heavily shaped by human influences (Thirgood, 1981) and is characterized by a prominent role of fire (Keeley et al., 2012). Fires in North Africa are particularly prevalent close to the Mediterranean Sea, where the climate is sufficient in humid to semi-humid regions for abundant fuel production (Curt et al., 2020). Intensive land use by rural residents affects forest resources through land-clearing, grazing, and fire (Chergui et al., 2018, Camarero et al., 2021).

The Talassemtane National Park (TNP) located in the Rif Mountains of Morocco in northwestern Africa, a critical habitat for several endangered species, is subject to wildfires and land clearing for agricultural purposes. The national park is a mountainous area with small communities located in the valleys. The large changes in elevation allow for many different vegetation types to be present within the boundary of the park, making this a highly biodiverse area (Figure 1). Endangered or rare species in the park include the endemic Moroccan fir (*Abies marocana* Trab.), black pine of the Atlas Mountains (*Pinus nigra* subsp. *mauretanica* Maire & Peyerimoff) and the Barbary macaque (*Macaca sylvanus*). Cannabis is a traditional crop, but its cultivation has been transformed by high-yield varieties and intensive agriculture since the mid-2000s (Chouvy, 2018). Forest clearing and fires associated with cannabis cultivation (Figure 1) are considered the "main driver" of forest loss in the park (Ben-Said et al., 2020).

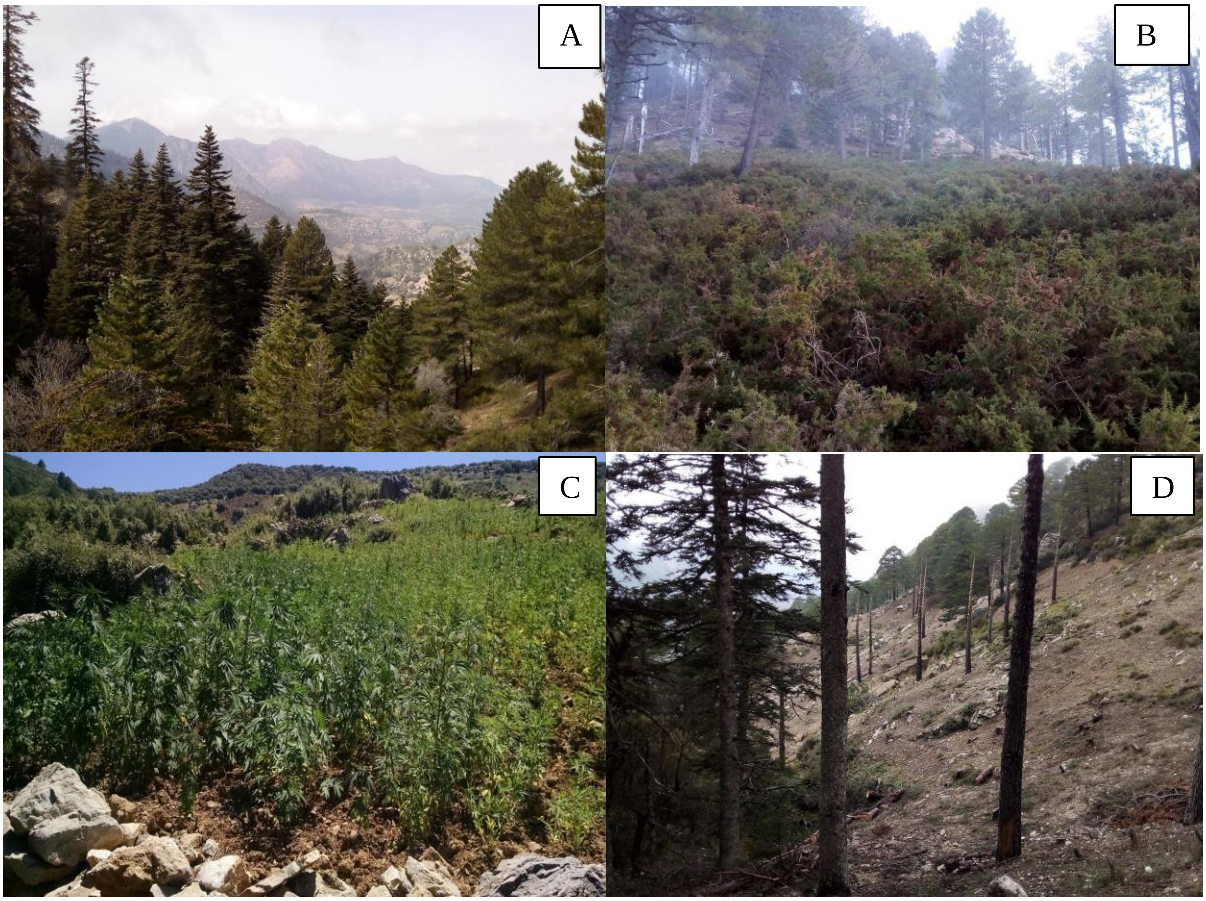


Figure 1. *A) Abies marocana forest B) Abies and chaparral intermix C) cannabis cultivation D) Recent cultivation burn*

I used multiple sources of remotely sensed data to quantify the role of wildfires as a factor of forest loss over a 15-year period. I combined the Hansen Global Forest Change data, the Global Fire Atlas data, vegetation coverages provided by Moroccan forester managers from field and aerial reconnaissance pre-2000, and processed Landsat satellite data, to determine the role of fire in overall forest change from 2003-2018. These data can help forest managers better understand the current forest impacts in the park and highlight areas that are of high concern. Our objectives were:

1. Determine overall forest change (gain/loss) annually from 2003-2018.
2. Use GFA data for a rapid estimate of large wildfires and fire regime.
3. Apply RdNBR to develop fire severity maps and test the accuracy of the GFA.
4. Determine the overall contribution of wildfire to forest loss at TNP, providing actionable information to park managers.

2. Materials and Methods

2.1 Study Area

The study area is Talassemtane National Park (TNP) in northwestern Morocco near the city of Chefchaouen (Figure 2). The area of the park is ~ 65,000 ha, with 43,616 ha defined as forested or forest plus chaparral by vegetation coverages provided by park managers. The climate in the TNP is warm and temperate. The winters are rainy while summers are hot and dry. The average rainfall is 880 mm per year and the average temperature is 15.3° C at the weather station in Chefchaouen, which is at an elevation of 600 m (ECMWF, 2021). However, the park has elevations exceeding 2000 m, which results in cooler weather and varying forest types in the higher areas. There are an estimated 1380 plant species, 314 of which are endemic to Morocco, and 86 are endemic to the park (Benabid, 2000). The dominant forest types are Moroccan fir and black pine (*Abies marocana* and *Pinus nigra*) and maritime pine (*P. pinaster*) forest intermixed with many different oak species (e.g., *Quercus rotundifolia* Lam., *Q. faginea* Lam., *Q. suber* L.), while the lower elevation of the park is composed mostly of shrubs (Benabid, 2000). The lower slopes of the mountains have been heavily cultivated for agricultural purposes, especially for high yields of cannabis production since the mid-2000s (Chouvy, 2018). Agriculture is encroaching into higher reaches of the mountains, deforesting pine and threatening fir forests. The use of fire is a common practice for clearing land for agricultural purposes but can be used improperly and start forest fires.

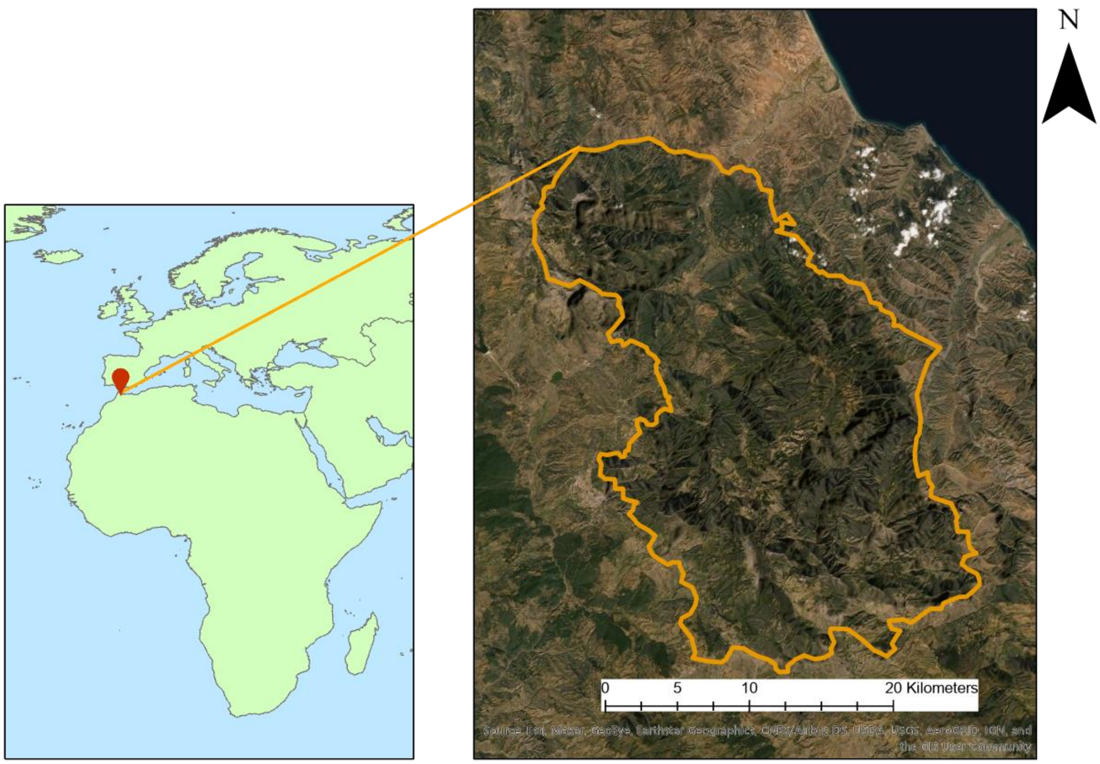


Figure 2: *The red pin shows the general location of the TNP. The map below shows the boundary of the park in orange. The coast bordering the Alboran Sea, part of the Mediterranean Sea, can be seen in the northeast corner of the map.*

2.2 Hansen et al. Global Forest Change

Disturbance-induced change in forest composition occurs regularly, whether it be a stand-replacing forest fire or a harvest from a timber company. Forest disturbances are picked up indiscriminately by the algorithm used by Hansen et al., (2013) to estimate global-scale forest change. This data product maps forest cover extent, loss, and gain between 2000 through the present using Landsat data at a spatial resolution of 30 m. The forest loss and gain in this dataset are not attributed to any specific causes. Loss is defined as a stand-replacing disturbance or complete removal of tree canopy cover more than 5m in height with a minimum 25% coverage at the Landsat pixel level (Hansen et al., 2013). Loss is updated annually. In the present study, I used the Hansen map as the basis for measuring annual forest loss in Talassemtane National Park (Figure 3). The Hansen loss includes fires, clearing being done for agriculture or construction, and tree cutting. Comparing the Hansen data to the Global Fire Atlas will help quantify the role of fire as an agent of forest loss in the park.

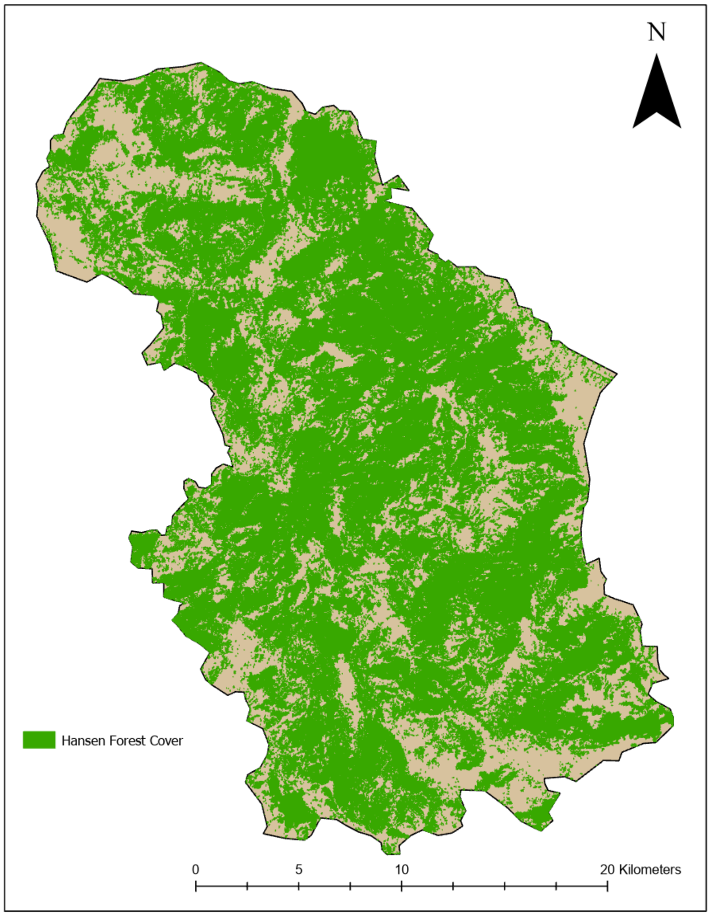
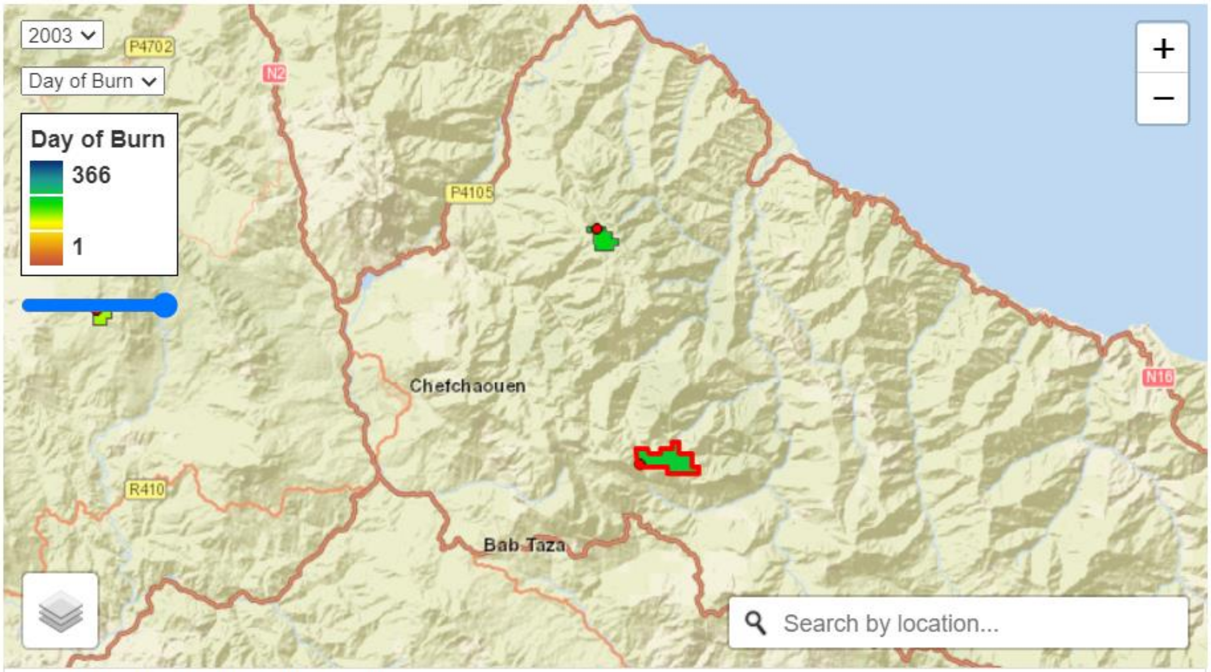


Figure 3. *Forest cover in the park as defined by the Hansen et al. data. Area in brown represents areas not defined as forest by Hansen.*

2.3 Global fire Atlas (GFA)

The Global Fire Atlas provides data on fires worldwide from 2003-2018 using the MODIS collection 6 burned-area dataset (Giglio et al. 2018). The near daily availability of MODIS data allows for quick updates on fires and detection of daily ignitions. The GFA dataset is what allows me to have definite cause for forest loss and is a cornerstone to being able to do this research. The algorithm used in the GFA tracks daily progress of individual fires at 500 m resolution to create fire behavior metrics in raster and vector formats (Andela et al. 2019). In the original publication, Andela et al. (2019) reported that the algorithm detected 13.3 million individual fires over the study period, and they showed that specific individual test case fires had good agreement with other sources of fire information in the United States (Andela et al., 2019). While the GFA is potentially a useful tool worldwide, to our knowledge the present study is the first test case from outside North America. The data can be accessed freely at https://www.globalfiredata.org/fireatlas.html. Data can be downloaded by year for the entire globe. The attributes of the data include ignition dates and locations, size of the fire, perimeter, speed, direction of spread, and duration. However, fire severities are not defined in the data.

Fire boundaries for the GFA fires that occurred in the park were obtained using the data explorer tool on the GFA website (Figure 4). Data can be found by locating the area of interest and then specifying the year. For every year that had a confirmed fire in or overlapping the park boundary, I downloaded data from the website for that year. The data downloaded are in GIS ready file formats (GeoTIFF and shapefiles) that show individual fire perimeters and ignition locations.



Current Selection: Fire_ID #226686					
Lat, Lon	35.118801, -5.0681	**Start Date**	2003-08-18	**Daily Fire Line**	0.96 km
Perimeter	14.82 km	**Duration**	13 days	**Speed**	1.17 km/day
Size	6.22 km^2	**Daily Fire Expansion**	0.48 km^2/day	**Direction of Spread**	east

Figure 4: *The data explorer tool on the Global Fire Atlas website. Fires can be searched by location. The green shapes pictured on the map are fires that happened in 2003.*

2.4 NBR and RdNBR

I calculated fire severity and vegetation change using the Normalized Burn Ratio (NBR) and Relativized delta normalized burn ratio (RdNBR) using Landsat 5 Thematic Mapper (TM), Landsat 7 ETM+ and Landsat 8 Operational Land Imager (OLI) Tier 2 surface reflectance products. Surface reflectance data has been adjusted for atmospheric effects using atmospheric correction algorithms to have a Bottom of Atmosphere view (BOA), which can improve results in change detection (Song, 2001). Multiple satellites were used because of the changes in satellite technology over the study period. I acquired Landsat imagery from the USGS

EarthExplorer (https://earthexplorer.usgs.gov/) website. The dates for the Landsat scenes were picked from the dates provided by the Global Fire Atlas for each individual fire that happened within the park. A scene was selected pre- and post-fire with the lowest cloud cover available. Post-fire images were within one year of the end date of the fire. Scenes were picked during the same seasons to avoid any effects from seasonal change in foliage. Summer (June-August) was when all but one fire took place, which is the most cloud-free time of the year in the region. The scenes were clipped to fit the boundary of the park to reduce file sizes and speed up processing times. The area of the park falls within one Landsat scene, so only one scene was needed for pre- and post-fire for every fire detected.

I calculated NBR using the near infrared (NIR) and shortwave infrared (SWIR) wavelengths. The bands for NIR are different for Landsat 5, 7, and 8 as follows:

For Landsat 4-7 TM and ETM+, NBR = (Band 4 – Band 7) / (Band 4 + Band 7).

For Landsat 8 OLI, NBR = (Band 5 – Band 7) / (Band 5 + Band 7).

I calculated dNBR as the difference between the NBR from pre-fire and post-fire images. dNBR values were multiplied by 1000 and converted to integer format. I calculated RdNBR using the formula of Miller and Thode (2007):

$$\mathrm{RdNBR} = \frac{\mathrm{dNBR}}{|(\mathrm{NBR}_{\mathrm{prefire}})|^{0.5}}$$

Fire severity is defined by Key and Benson (2006) as, “the quality or state of distress inflicted by a force. The magnitude of environmental change caused by a fire, or the resulting cost in socioeconomic terms.” Severity is often difficult to quantify. For the present study, I focused on the environmental impacts of the fire which included physical and chemical changes to the soil, loss of vegetation, and changes to forest structure or composition. The USGS Landscape Assessment (LA) Sampling and Analysis Methods (Key and Benson, 2006) recommends the use of ground measurements called the Composite Burn Index (CBI) to assess burn severity to validate the satellite data. However, CBI is not widely used in Africa and no field CBI values exist for the fires that took place within the boundary of the TNP. The lack of ground data is a common situation affecting most satellite-based fire severity assessments, even in nations with more resources available (Singleton et al., 2019). Following standard practice, we used the predicted RdNBR regression modeled thresholds developed by Miller and Thode (2007) (Table 1). Their thresholds were developed based on CBI field data in Mediterranean-climate coniferous forests with shrub understories, relatively similar to those of the Moroccan study site.

Table 1. *Regression model thresholds from Miller and Thode (2007). The final column contains the values used for the severity thresholds.*

Severity category	Field measured CBI severity value	Predicted dNBR	Predicted RdNBR
Unchanged	0-0.1	<41	<69
Low	0.1-1.24	41-176	69-315
Moderate	1.25-2.24	177-366	316-640
High	2.25-3.0	>=367	>=641

After the data were classified, I manually created fire perimeter polygons digitized at a scale between 1:24000-1:50000 to include any detectable fire impacts derived from the RdNBR calculations (MTBS, 2021, Figure 5).

Areas of high severity in gaps in Landsat 7 data were estimated by using the existing RdNBR severities for 2012 to see where there were areas where high severity was stopped abruptly along a scan line. I paired the RdNBR data with the NBR values calculated from a 2013 Landsat 8 image to fill in the missing data. I estimated there to be 116 ha of high severity area that was missing in the scan line gaps.

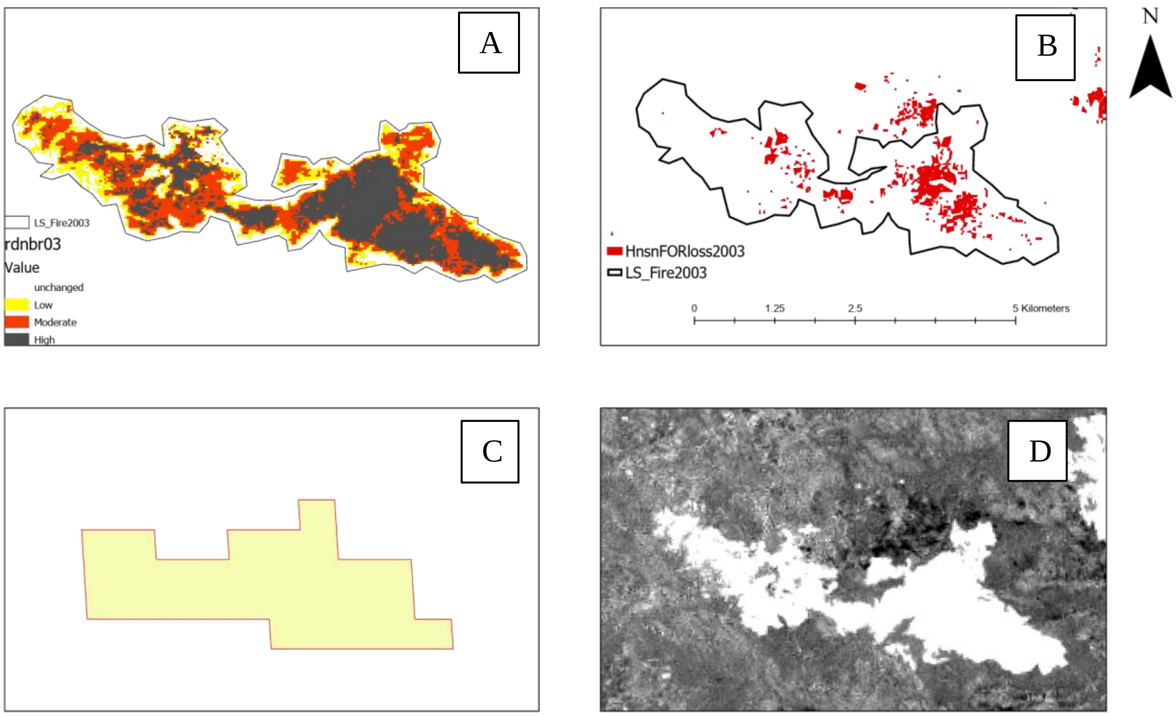


Figure 5. *2003 fire A) RdNBR showing areas of high severity in grey B) The areas of loss defined by Hansen for 2003. C) The Global fire atlas polygon for the 2003 fire. D) NBR image for the 2003 fire. Burn area can be seen in white.*

3. Results

Our initial comparison was between the Hansen forest cover data for the TNP and the vegetation type coverage for the park provided by Moroccan forest managers from field and aerial reconnaissance pre-2000. The forest coverages provided by the Moroccan foresters (Figure 6) showed 43,507 ha of forest cover while Hansen data showed 38,331 ha, a difference of 5,285 ha between the base years of both datasets. From the year 2003 to 2018, Hansen estimated 1,995 ha of forest loss in the TNP, which equals 5% loss of forest cover, defined by the 2000 Hansen forest cover base year, in the park over 16 years (Table 2). The average annual loss of forests according to the Hansen data was 125 ha per year. Of the overall Hansen loss in the park, 705 ha (35%) were within the Landsat fire polygons, accounting for a 1.8% loss of total forest cover from 2003 values.

The area of *Abies marocana* forest cover in the TNP, the rarest endemic forest in the region and one of only two *Abies* forests in Africa, was 4,441 ha at the start of the study period in 2003, including *Abies*/chaparral mix. Of this area, 113 ha (<3%) was lost to fire during the study period (Table 2). The total loss of *Abies* was 344 ha, about 8%. The greatest year for *Abies* loss was 2014, when a fire occurred entirely in what was defined as *Abies* forest cover and accounted for 83% of the total *Abies* loss from 2003-2018.

In all instances of comparing the nine fires in the study area, the Global Fire Atlas fire polygons extracted from 500 m resolution MODIS imagery had a lower area than the fire polygons I manually digitized from 30 m resolution Landsat imagery (Table 3). However, the areas of GFA polygons were highly correlated with the areas of Landsat fire polygons (r = 0.99) and Landsat forest loss (r = 0.92). The year with the lowest percent difference was 2007 (27%) and the greatest percent difference was in 2017 (80%). The average difference between the GFA and Landsat polygons was 201 ha with a total difference of 1,413 ha between the sums of the GFA and Landsat areas. In all cases, the GFA data in some way correlated with forest loss and showed evidence of fire activity.

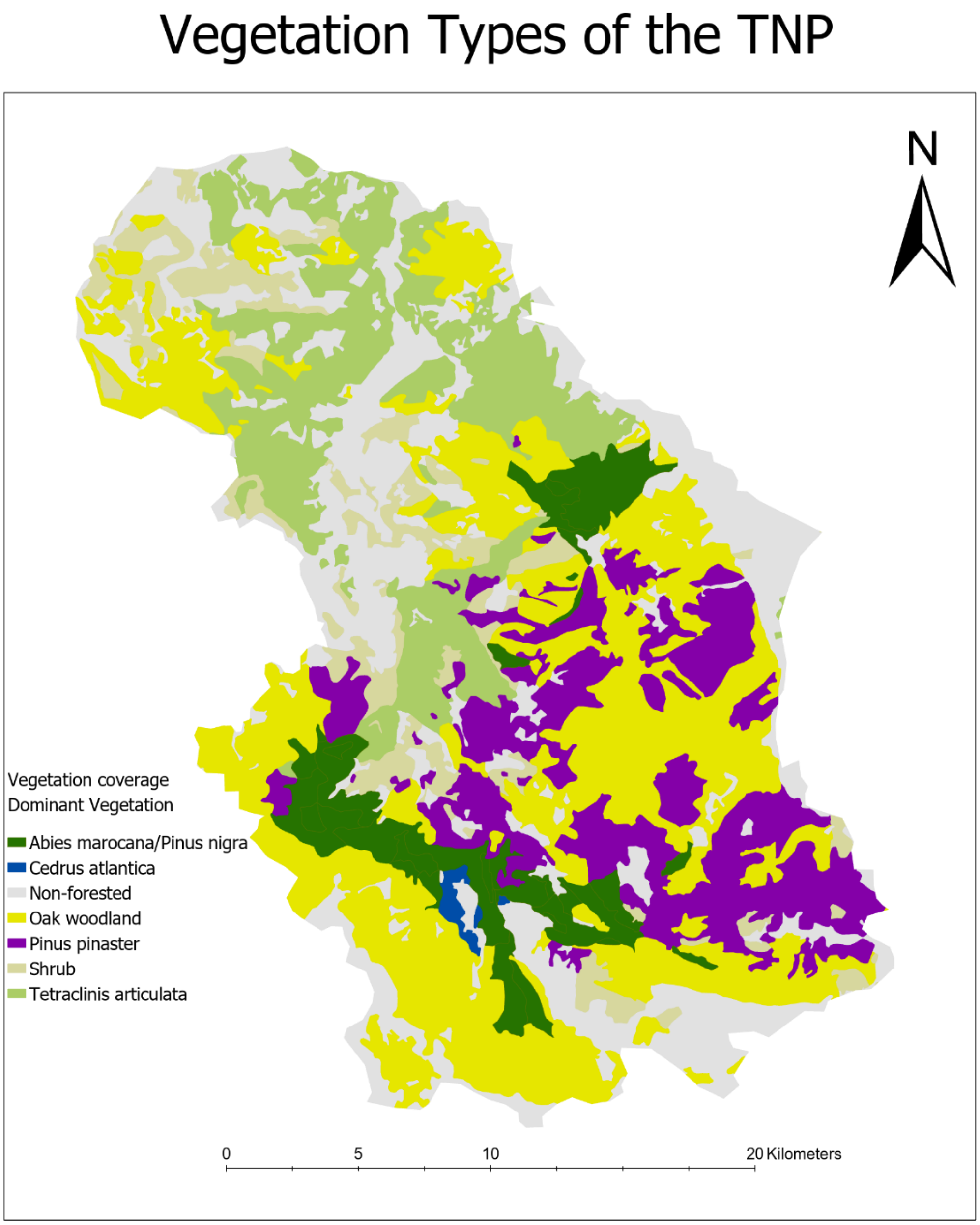


Figure 6. *Vegetation coverages provided by the Moroccan Forest Service. The vegetation types of interest for this study are Abies marocana, Cedrus atlantica, Pinus nigra, Pinus pinaster, and oak forests.*

Table 2. *Comparison of forest change and fires that happened from 2003-2018 in the park. Forest area (Hansen) tracks forest loss from year to year from the Hansen loss. This is not attributed to fire specifically, rather any loss that has happened in the park from the previous year. GFA fires is the number of fires that occurred in the year. Fire Area (GFA) is the area within the GFA polygons. Fire area (LS) is the area of the polygons created from the RdNBR data classified by Landsat imagery. Forested fire area, areas of high severity, and area of Abies forest loss were all calculated using the Landsat polygons.*

Year	Forest Area (Hansen), ha	Annual forest loss from year prior, ha	GFA Fires	GFA Fire Area, ha	LS Fire Area, ha	Forested fire area LS, ha[+]	Area considered “loss” by Hansen within LS fire perimeters—lost by the next year, ha	Area of forested high severity RdNBR, ha	Area of pine/Abies forest loss to fire, ha
2003	38,222	*109*[!]	2	901	1405	1,139	79	274	11
2004	38,079	143	none	0	0	0	0	0	0
2005	37,983	96	None	0	0	0	0	0	0
2006	37,983	21	None	0	0	0	0	0	0
2007	37,957	5	2	1051	1343	599	39	147	0
2008	37,943	123	None	0	0	0	0	0	0
2009	37,643	200	None	0	0	0	0	0	0
2010	37,622	12	None	0	0	0	0	0	0
2011	37,591	31	None	0	0	0	0	0	0
2012[*]	37,521	70	1	1953	2865	1475	317	461	8
2013	37,124	397	None	0	0	0	0	0	0
2014	36,919	205	1	193	214	296	97	80	94
2015	36,759	160	1	86	176	120	37	62	0
2016	36,710	49	None	0	0	0	0	0	0
2017	36,628	82	1	129	301	289	12	5	0
2018	36,336	401	1	129	238	217	124	3	0
Totals	36,336	1995	9	4442	6542	4,135	705	1005	113

[*]The only available imagery for the 2012 fire were Landsat 7 without the scan line corrector so there are some gaps in the data which were filled with a best estimate. [+]Area within the Landsat (LS) fire area that is defined as forested by the Hansen data. [!]Annual forest loss in 2003 is all the loss that had happened 2000-2003 and is not included in the total.

Table 3. *Difference in area (hectares) between the GFA polygons and the manually digitized Landsat fire polygons for all years that had fires. Percent difference between the original GFA polygons and the polygons manually digitized from the Landsat data. Negative numbers in the final column show that the Hansen loss value was greater than the area defined as high severity.*

Year (# of fires)	Landsat vs GFA area Difference, ha	LS vs GFA area Percent Difference	RdNBR High Severity vs Hansen Difference, ha
2003 (2)	504	43%	168
2007 (2)	292	24%	108
2012 (1)	912	37%	144
2014 (1)	105	42%	-17
2015 (1)	90	68%	25
2017 (1)	172	80%	-7
2018 (1)	109	59%	-121

The RdNBR classification of high severity fire within the manually digitized Landsat fire polygons in previously forested areas and Hansen loss within those same polygons differed in all years (Table 3). The high severity areas within the Landsat polygons had a greater sum loss than the Hansen loss areas but the Hansen loss was greater for three years of the study (Table 3). The total loss to fire defined by the Hansen data was 705 ha while the RdNBR classification showed 1,005 ha of loss due to high-severity fire. The previously forested high severity areas defined by RdNBR and the Hansen loss had a positive correlation (r =0.79).

4. Discussion

4.1 Management Implications

Our first objective was to determine overall forest change (gain/loss) annually in the park from 2003-2018. I found a net loss averaging 124 ha/yr, ranging from 0 to 317 ha/yr. While relatively small compared to the current estimate of 36,336 ha of forest in the park (0.3% per year), evidence of a lack of stability is of concern in any protected area because the forests of the TNF are incredibly unique to the region. They provide critical habitat for many species, ecotourism to stimulate the local economy, and provide traditional medicine to many locals (Redouan et al., 2020, Rhattas et al., 2015). Knowing where forest loss is happening, and better understanding fire frequencies and severities is valuable information when deciding how to manage a protected area. Identifying areas with high impact can bring attention to areas in need of post-fire rehabilitation.

Our second objective, to use GFA data for a rapid estimate of large wildfires and fire regime, proved to be a fast and straightforward technique. I found that the Global Fire Atlas was a reliable and simple tool for mapping fires. Advantages of GFA include a lower resolution that allows the sensor to pick up fires every other day, giving the GFA a robust amount of fire data that is openly available to the public. Even with just using the data explorer tool on the GFA website, managers can surmise fire frequency and peak fire season. Overall, the GFA polygons provide a quick way to highlight fire areas and better understand the environmental changes that are happening in the area in the last 16 years in relation to changing climates.

The third objective, apply RdNBR to develop fire severity maps and test the accuracy of the GFA, was successful. Andela et al. (2019) had previously shown that a test set of GFA fires was consistent with burned area analysis using detailed Landsat data in the US from the Monitoring Trends in Burn Severity (MTBS) program. Our results confirm a strong relationship between easily accessed GFA data and detailed Landsat fire severity analysis in our North African study area. Landsat imagery is quite versatile to better understand the impacts of fires. The fire severity metrics can help identify the general area where action is most needed. Areas classified as high severity can be potential areas for high erosion, low soil productivity, and a potential shift in species composition.

Finally, our last objective was to determine the overall contribution of wildfire to forest loss at TNP, providing actionable information to park managers. Fire was a sizable contributor to the overall forest loss in the park, accounting for about 5% loss of overall forest cover and 35% of the Hansen defined forest loss over the 16-year period. In a study done on the role of fire in global forest loss dynamics during the period from 2003 - 2018 on average 38± 9% of global forest loss was associated with fire (Van Wees et al., 2021) . Fire was a particular threat to the rarest forest type, the endemic *Abies marocana*, killing trees on 94 ha in a 2014 fire. While Abies forests in general are characterized by infrequent but severe stand-replacing fire regimes (CITE), special attention is warranted in the case of a highly restricted, rare species such as *A. marocana*. Mapping of the severe fire area could be applied to post-fire surveys of regeneration, for example, to assess the recovery trajectory of the burned area.

By separating out which areas were *not* affected by fire, the non-burned Hansen Global Forest Change data can indicate areas that are potentially being targeted for agricultural expansion. Areas outside of the fire polygons that show loss could identify areas being encroached upon by agriculture. Paired with the vegetation coverages, the Hansen and GFA data can highlight areas where important forest types are being lost to help conserve biodiversity in the park. The Hansen data also shows reforestation but does not indicate what type of forest is being regenerated in the place of the former vegetation type. It will be up to management to follow up on what is regenerating in the areas of loss.

4.2 Limitations

Burn severity classification is limited in many ways due to inherent differences between vegetation types, lack of field data, and differing spectral characteristics of different sensors used over time. Lacking ground data from the post fire areas, I chose to use the regression model thresholds developed by Miller and Thode (2007). These thresholds were created for ecosystems found in California. Areas in both this and the Miller & Thode (2007) studies contained conifer and oak species with shrubby understories growing in a Mediterranean climate. However, these similarities cannot make the thresholds match perfectly. There is expected to be about 60% user accuracy overall using this method (Miller & Thode, 2007). I found in most cases greater areas for the high severity than for the Hansen loss. I speculate that this may be attributed in some part to the intermix of forest cover and chaparral which by the Hansen dataset is not defined as forest but still had great change from pre- to post-fire. It may also indicate that our threshold for "high severity" is set too low to create the forest mortality detected by the Hansen analysis.

The fire that burned in the park in 2012 occurred when the Landsat 5 satellite was non-functional and before Landsat 8 had been launched. Therefore, Landsat 7 had to be used for analysis. The Landsat 7 data has blank scan lines of missing data which for this analysis resulted in 33% of the area inside of the Landsat fire polygon to be missing for the severity calculations.

One region in the southeastern area of the park had four fires which overlapped during the study period. Overlapping fires may have resulted in some inaccuracies in total forest cover/forest loss from the Hansen data. In 2017 and 2018, the high severity area was lower than the forest loss area. This was most likely due to the overlap in the fire areas. These were the only two years where the forest loss area was greater than the fire severity area.

Because of the coarse resolution of MODIS data there are some fires that were too small to be picked up by the sensor. Some fire loss will not be accounted for because of this and will be considered general loss for this study. The Hansen data can give us a relatively good guess as to how accurate the fire severity metrics are but without ground data there is no way for sure to say how accurate the RdNBR values are.

There was a 5,285-ha difference between the forest coverages provided by the Moroccan foresters and the Hansen 2000 forest cover base year. This large gap was mainly because of the forest plus chaparral intermix classes in the forest coverage layer. Much the intermix did not meet the minimum tree coverage defined by Hansen. Of the total 43,616 ha, 23,776 ha was defined as chaparral intermix and 18,730 defined as forest. The Hansen data overlapped with 17,601 ha, which is a 6,165 ha difference. The Hansen 2000 base year was 880 ha greater than the area that was defined as forest (without chaparral intermix). Some areas defined as pure chaparral by the vegetation coverages overlapped with the Hansen forest cover. The difference between the chaparral intermix was much greater than the “pure” forest types.

5. Conclusion

Baseline data on how the forest is changing can help managers understand the possible new trends in forest change brought on by human activities and warming climate. Using multiple remote sensing data sets, I was able to quantify the forest change history over16 years in the TNP and identify severe wildfires as the cause for about a third of the forest loss. These data will help identify highly impacted areas, better understand fire return intervals, and identify potential areas of encroachment. Landsat data can give a good overview of fire history, severity, and size with relatively accurate results. The Global Fire atlas is a simple tool to identify fires. The frequency of the MODIS scans allows it to almost never miss a large fire. Individually each dataset that I used for this project has great utility but combined they create a robust history of forest change.

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Appendix A:

GIS Steps and Tools Used

This project was completed using ArcGIS Pro version 2.4.

- NBR
  - Landsat scenes for NIR and SWIR were sized down to the park boundary using *Clip Raster.*
  - The resized raster data was then used to calculate NBR using the *Raster Calculator (spatial analyst tool)* done for pre- and post-fire
    - For Landsat 4-7 TM and ETM+, NBR = (Band 4 – Band 7) / (Band 4 + Band 7).
    - For Landsat 8 OLI, NBR = (Band 5 – Band 7) / (Band 5 + Band 7).
- dNBR
  - The pre- and post- fire image for each year there was a fire were then used to calculate dNBR. In this step dNBR was multiplied by 1000 to convert to integer format. Done using *Raster Calculator (spatial analyst tool)*
    - $dNBR = \left(\frac{pre-post}{pre+post}\right) * 1000$
- RdNBR
  - Done using *Raster Calculator (spatial analyst tool)*
    - $$\mathrm{RdNBR} = \frac{\mathrm{dNBR}}{|(\mathrm{NBR}_{\mathrm{prefire}})|^{0.5}}$$
- Severity Classification
  - Thresholds were defined by Miller and Thode, 2007 (Table 1)
    - *Image Classification* was used to create classes for low, moderate, high, and unburned areas.
    - *Classification Wizard* was used to define severity using values that fell within the class values.

- A new polygon *Feature Class* was created for each fire year. Using *Create Features* in the edit tab, I manually digitized a new polygon around the perimeter of the classified RdNBR using the MTBS guidelines Mapping Methods | MTBS .
- The classified RdNBR values were then clipped to new fire polygon feature class.
- The RdNBR layer was then converted by using *Raster to Polygon* conversion tool. The high severity class was then selected by attribute and the selected layer was then a new feature class was the created from the selection.
- A new attribute was then created in the attribute table to calculate area in hectares using the *Calculate Geometry Attributes* data management tool.

Appendix B:

NDVI

The Normalized Difference Vegetation Index (NDVI) was initially intended to be a part of the project but decided against in this practicum project. The same Landsat scenes were used for calculating NDVI that were used for calculating RdNBR. NDVI is calculated using the red band and NIR band.

$$NDVI = (NIR - red)/(NIR + red)$$

$$Landsat\ 4-7, NDVI = \frac{(Band\ 4 - Band\ 3)}{(Band\ 4 + Band\ 3)}$$

$$Landsat\ 8, NDVI = \frac{(Band\ 5 - Band\ 4)}{(Band\ 5 + Band\ 4)}$$

Every scene was sized down to the boundary of the park using the Clip Raster Tool. This was done for every scene. NDVI was calculated using the respective bands in the Raster Calculator tool. Once NDVI was calculated I used a test threshold of 0.2-0.25 which was an average value for bare soil defined by the USGS and a rough estimate from a few other studies (Malak and Pausas 2006, Ryu et al. 2018). Severity classification was done using the same tools and approaches as the RdNBR classification (Appendix A) but with different threshold values. Although the total loss of area is closer between NDVI and Hansen loss than the RdNBR high severity and Hansen loss the correlation between NDVI and Hansen was negative (r= -0.35). The year 2014 showed no values from 0-.02.

Table B1. Area of NDVI with a value between 0- 0.2 that fall within the manually created Landsat polygons.

Year	NDVI area (ha)	Hansen Loss (ha)
2003	109	79
2007	130	39
2012*	96	317
2014	0	97
2015	153	37
2017	217	12
2018	165	124
Totals	716	705

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