Analyzing Fire Hazard Risk:

A Case Study in Table Mountain National Park, Cape Town, South Africa

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Abstract

Fieldwork is the traditional basis for creating fuel hazard maps, but it is not always cost or time effective. This study utilizes remote sensing and GIS technologies to analyze Landsat 8 and other geographic layers, exploring the use of the Normalized Difference Vegetation Index (NDVI) and the Normalized Difference Moisture Index (NDMI) as surrogates for fieldwork data to provide an inexpensive alternative for deriving a wildfire hazard map. The study focuses on the fire that occurred March 1, 2015, on Table Mountain National Park in Cape Town, South Africa, where the primary vegetation is the fire-adapted Fynbos shrubland. Calculation of NDMI values was coupled with a traditional NDVI analysis to provide additional information about plant moisture. A pre-burn Landsat 8 image was analyzed for fire hazard using five variables: vegetation moisture, slope, aspect, elevation and distance from roads and then compared to post-burn imagery to test the method's accuracy. The results indicate that NDMI may be a stronger indicator of fire hazard than the more popular NDVI.

Keywords: Landsat, remote sensing, NDVI, NDMI, wildfire, South Africa, Fynbos

Introduction

Wildfires are complex events that occur as a result of natural and human factors and are hazardous to people and the natural environment (Merlo and Rojas Briales 2000; Wenliang et al. 2010). Recent changes in both climate and anthropogenic factors related to fire hazard could transform traditional fire regimes and exacerbate the risk of fire and its negative impacts. Among these factors, the influence of climate warming on increased fire frequency and intensity has been documented in several ecosystems (Kasischke and Turetsky, 2006; Westerling et al., 2006). The encroachment of the built environment into areas of high fire risk is another important factor. This situation provides urgency for understanding the risk that wildfire hazards pose.

Evaluating the risk of fire hazard is a critical part of preventing fires and reducing fire's negative impacts. The fire hazard risk is defined as a combination of the hazard and potential damage. By determining areas of high fire risk it is possible to minimize threats to life, property, natural and economic resources (Adab et al., 2013). Pre-fire planning resources require objective tools to monitor when and where a fire is more prone to occur, or when it will have more negative effects (Martinez et al., 2009). To understand fire hazard, fieldwork is traditionally used to collect vegetation information via sample plots. This usually requires sending researchers to sample vegetation over large areas. This research is often time consuming and expensive because it requires multiple skilled workers. The use of satellite imagery with a GIS offers a cheaper alternative that could potentially save time and money.

The wildfires of Cape Town, South Africa were used as a case study for the potential application of remote sensing and GIS technologies for wildfire hazard analysis. This study sought to determine whether vegetation information derived from remote sensing data could serve as a sufficient surrogate for collecting field data when mapping fire hazards. It investigated the potential of using the Normalized Difference Vegetation Index (NDVI) and the Normalized Difference Moisture Index (NDMI). However, the fuels are difficult to discriminate between using only these indices, and therefore the Structural Fire Index (SFI) was used to incorporate other influential factors.

Study Area

The study region is Table Mountain National Park. The park extends across the Cape Peninsula to include Table Mountain and the Silvermine Nature Reserve and is adjacent to the city of Cape Town (Figure 1). The wildfire studied here occurred within the Silvermine area of the park.

The area surrounding Cape Town, South Africa, is prone to burning because of the natural fire cycle in the Fynbos biome, a fire-adapted shrubland and heath environment located only on the Cape Peninsula. This study looks at the fire that began March 1, 2015, and burned intensely across the landscape. Such fire events are natural in Fynbos, which on average burns every 10-15 years (Cowling 1992), but the fire's close proximity to this highly urbanized area presents a danger to humans. There has been limited research conducted on Fynbos fires. Historically, fires were ignited at high elevations from lighting strikes (Cowling 1992) and then burned downslope into the valleys. However, urbanization has fragmented the landscape and slowly encroached up the mountainside. This landscape change has altered the fire cycle by preventing the natural spread of the fires from mountains into the valleys.

The climate is generally categorized as Mediterranean, and although lightning strikes occur infrequently in Mediterranean climates, they are a higher risk than human-caused fires. Fires ignited by lightning tend to burn larger areas because they occur in more isolated and steeper areas and frequently have various simultaneous ignited spots. The resultant fires are more difficult to control (Wotton and Martell, 2005). Many developed countries, such as the United States and Canada, have meteorological stations available to monitor lighting strikes and relate them to wildfires (Wontton and Martell, 2005; Martinez et al., 2009). In contrast, despite its proximity to an urban area, South Africa does not have meteorological stations capable of monitoring lightning strikes close to the site of the fire studied in this paper.

Remote Sensing of Surface Fuel

Remote sensing offers a wide range of sensors that can assist in fire fuel mapping. There are many limitations to this application, such as the complexity of fuel types and high spatial and temporal variability (Keane et al., 2001). The most important limitation of these sensors is their inability to penetrate forest canopies and detect surface fuels (Keane et al., 2001), especially where two or more canopies are present. The application of this technique to shrubland areas such as the Fynbos biome, which have no overstory, is potentially more viable.

The earliest applications of remote sensing used medium to low-resolution multispectral approaches to identify fire fuels, classifying an image into vegetation categories and then assigning fuel characteristics to each category. Kourtz (1977) introduced several digital techniques for Landsat fuel-type classification including supervised classification (maximum likelihood), unsupervised classification, and principal components analysis. These methods require an input of spectral signatures from specific fuel classes that are usually obtained from fieldwork.

In research that applied remote sensing without fieldwork, several researchers attempted to map fuel types using multispectral sensors such as Landsat Multispectral Scanner (Landsat MSS) or Thematic Mapper (TM) (Salas and Chuvieco, 1995; Castro and Chuvieco, 1998; van Wagtendonk and Root, 2003). Fuel types have also been mapped by applying maximum likelihood decision rules to Landsat MSS and SPOT data (Chuvieco and Congalton, 1989; Chuvieco and Salas, 1996; Castro and Chuvieco, 1998) with accuracies ranging from 65% to 80% (Chuvieco et al., 1999). Studies have explored the use of tasseled cap transformation of Landsat TM multispectral data. These studies include Van Wagtendonk and Root's (2003) use of an unsupervised classification of NDVI, combined with graphical, visual and statistical techniques to identify 30 fuel classes. The accuracy reported by these authors was 65% and with the combined use of ancillary data (NDVI, slope, texture, illumination) accuracy improved up to 85.9% (Riano et al., 2002; Francesetti et al., 2006). Other studies utilized National Oceanographic and Atmospheric Administration-Advanced Very High Resolution Radiometer (NOAA-AVHRR) images (McGinnis and Tarpley, 1985). AVHRR imagery is popular for fire monitoring; however, its coarse resolution limits the use to regional and global scales (Dennison et al., 2005; Chuvieco and Congalton 1989; Chuvieco et al., 2004).

Methods

This study employed a minor modification to the fire hazard mapping method introduced by Chuvieco and Congalton (1989). In contrast to the original method, this study uses NDVI and NDMI values calculated from Landsat 8 imagery collected before the fire events. The fire occurred on March 1 and cloud-free images collected closest to that date occurred on February 23, 2015 (pre-burn) and March 11, 2015 (post-burn). The two images were clipped to the area extent (Figure 1, below).

Vegetation Mapping

The pre-burn imagery was analyzed using the Normalized Difference Vegetation Index (NDVI) and Normalized Difference Moisture Index (NDMI). For Landsat 8, the equations are as follows:

$$\text{Equation 1} \qquad NDVI = \frac{(NIR-R)}{(NIR+R)}$$

where NIR and R are the Landsat 8 Near-Infrared (5) and Red (4) bands, respectively; and

$$\text{Equation 2} \qquad NDMI = \frac{(NIR-SWIR)}{(NIR+SWIR)}$$

where NIR and IR are the Landsat 8 Near-Infrared (5) and Shortwave Infrared (6) bands, respectively.

NDVI values vary according to radiation absorption by the chlorophyll in the red spectral area and its reflectance in the near infrared spectrum (Dragomir and Petrosani 2012). The index values correspond to the consistency of the green vegetation and are useful for mapping vegetation health. This study assumed low NDVI values are usually associated with unhealthy and drier plants, while high values indicate good health.

NDMI values vary according to radiation absorption of the short-wave infrared band and reflectance of the near infrared. The index evaluates the different content of humidity from the landscape (soils, rocks and vegetation) and is an excellent indicator of dryness (Dragomir and Petrosani 2012). Vegetation moisture condition is important because it influence the flammability of the fuel.

Topographic Data

DEM. Elevation influences vegetation structure, fuel moisture, and air humidity (Castro and Chuvieco 1998). Two digital elevation model (DEM) files were obtained from the Shuttle Radar Topography Mission (SRTM) and mosaicked to form a single DEM of the Cape Town area. The resulting DEM was reclassified into three classes and assigned a hazard level of low, medium or high. Elevations between -17m and 100m were assigned a low hazard value. These areas are dominantly composed of highly urban flatland. The urban areas have limited Fynbos vegetation and therefore were considered a lower risk. Elevations between 100m - 200m were considered a medium hazard. The elevation of 200m is roughly the average elevation of the street that demarcates the bottom of the mountain in the Silvermine Nature Reserve and serves as a boundary between the natural area and the city of Cape Town below. This boundary serves as a firebreak between the reserve and the city below. The Fynbos vegetation primarily occurs at elevations above 200m and constituted the high hazard zone. Lightning is the natural ignition source of the fires and strikes at high elevations.

Aspect. Aspect is correlated with the amount of insolation an area receives. Aspects that experience higher insolation are assumed to have drier vegetation than aspects that are usually shaded. In the Southern hemisphere, northern facing aspects experience more insolation and are therefore more likely to have higher temperatures and drier vegetation. Western facing slopes also receive more insolation than eastern facing slopes because the sun's rays are strongest during the afternoon. Because of that relationship, fuels on north-facing and west-facing slopes present a higher fire hazard. An aspect map was derived from the DEM and then reclassified based on approximate insolation and then hazard risk. The classes included three sectors: west - north (high), northeast - southeast (medium) and south - southwest (low).

Slope. Slope is a variable that influences the spread rate of the fire: fire moves more quickly upslope and less quickly downslope. Steep slopes over 40% are reported as a crucial threshold for fire operations and increase the rate of fire spread (Brass et al., 1983). The classes for slope values were created based on natural breaks in the histogram to reflect the topography. The classes included 0 - 13% (low), 13 - 38% (medium) and 38 - 65% (high).

Fire Hazard Modeling - Structural Fire Index (SFI)

The Structural Fire Index (SFI) was used to delineate fire risk. The SFI is an empirical weighted index based on the combination of five variables influencing fire risk in Mediterranean and semi-arid climates: vegetation moisture, slope, aspect, elevation, and distance from roads (Chuvieco and Congalton 1989). The variables in the index are the basic factors that affect forest fires in Mediterranean areas (Chuvieco and Congalton 1989). Vegetation is the most influential factor, with a weight of 100, whereas elevation is the least influential with a weight of 2. This index has previously been employed in Spain (Chuvieco and Congalton 1989), Portugal (Pelizzari et al., 2008) and Iran (Adab et al., 2013) to map forest fire risk.

All topographic files were converted to raster and reclassified with integer values corresponding to fire hazard rank. NDMI and NDVI values were multiplied by 1000 to reflect the decimal values. Variables are ranked from highest to lowest influence on fire hazard, respectively: vegetation, slope, aspect, and elevation. The following formulas respectively represent the original SFI of Chuvieco and Congalton (1989) and the modified SFI used here:

$$Equation\ 3 \qquad SFI = 1 + 100v + 30s + 10a + 5r + 2e$$

Where *v*, *s*, *a*, *r*, *c* = vegetation, slope, aspect, distance from roads, and elevation, respectively.

$$Equation\ 4 \qquad Modified\ SFI = 1000v + 30s + 10a + 2e$$

Where *v*, *s*, *a*, *e* = vegetation index (NDVI or NDMI), slope, aspect, and elevation, respectively. Distance to roads was dropped because there were no road data available in the study area.

The resulting index was used to provide a visual depiction of areas with predicted high fire hazard. The final values were displayed as a continuous raster rather than divided into hazard classes to allow better visual emphasis on the differences.

Results

The following figures present the processed data layers that were combined to form the hazard model; i.e., the modified SFI. Figure 1 shows Landsat 8 images of Table Mountain National Park and adjacent Cape Town, South Africa.

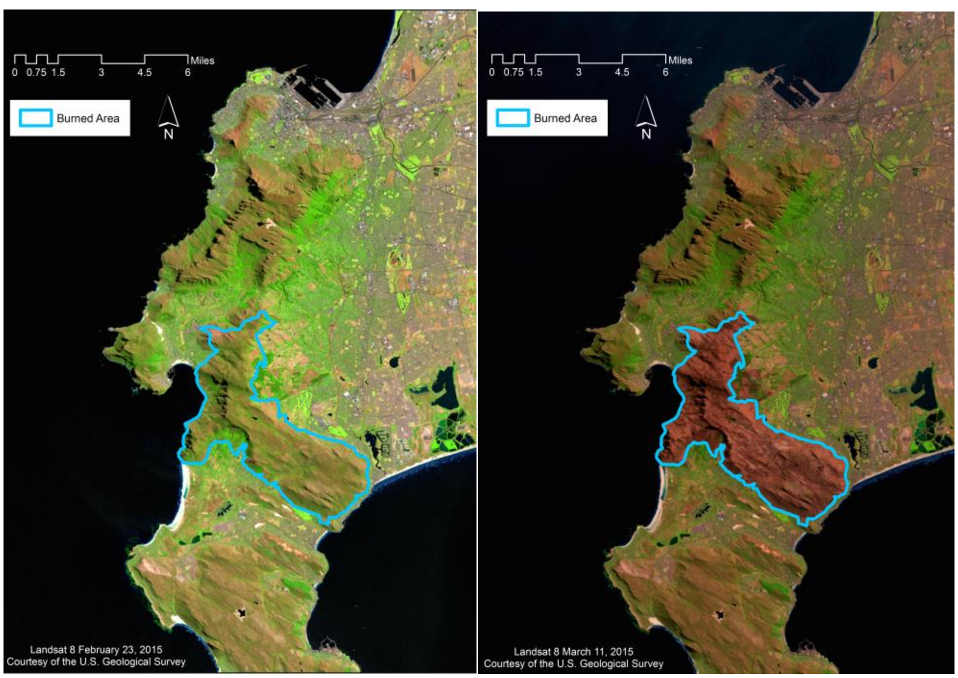

Figure 1: Landsat 8 pre-burn imagery (February 23 2015) and post-burn imagery (March 11 2015). Courtesy of the U.S. Geological Survey.

The mountainous area outlined in blue is Silvermine Nature Reserve, an area within the larger Table Mountain National Park. The images highlight the difference between vegetation in Silvermine before (left image) and after the fire (right image), with the brown area in the post-burn image showing the extent of the burnt area. The fire burned approximately 17,000 acres of the reserve.

Slope (Figure 2) was not found to be a strong indicator of fire hazard. The total burned area of high-risk slopes was minimal. Although there was correspondence between medium to high-risk slopes and burned areas, there was also a large portion of low-risk slope that burned. However, it should be considered that slope is an indicator of high risk for fire spread and not necessarily an indicator of highly burnable material.

The elevation layer (Figure 2) was divided to discriminate between the city of Cape Town and the mountains in Table Mountain National Park, with a major road (around 200m) serving as the break point. In the natural state, Fynbos would burn at lower elevations as well as higher elevations, but the city has been built over the natural vegetation. The higher elevations were all predicted to be high-risk areas as this is where lightning, a primary source of Fynbos fires, is most likely to strike.

The aspect layer introduced the most noise into the equation. Although there was correspondence between the predicted medium-risk to high-risk areas (Figure 2), there was also a large portion of the city predicted to burn due to the aspect layer being weighed so significantly in the SFI formula. While aspect does provide insight into which areas may have drier vegetation, it does not seem to be extremely important in this analysis.

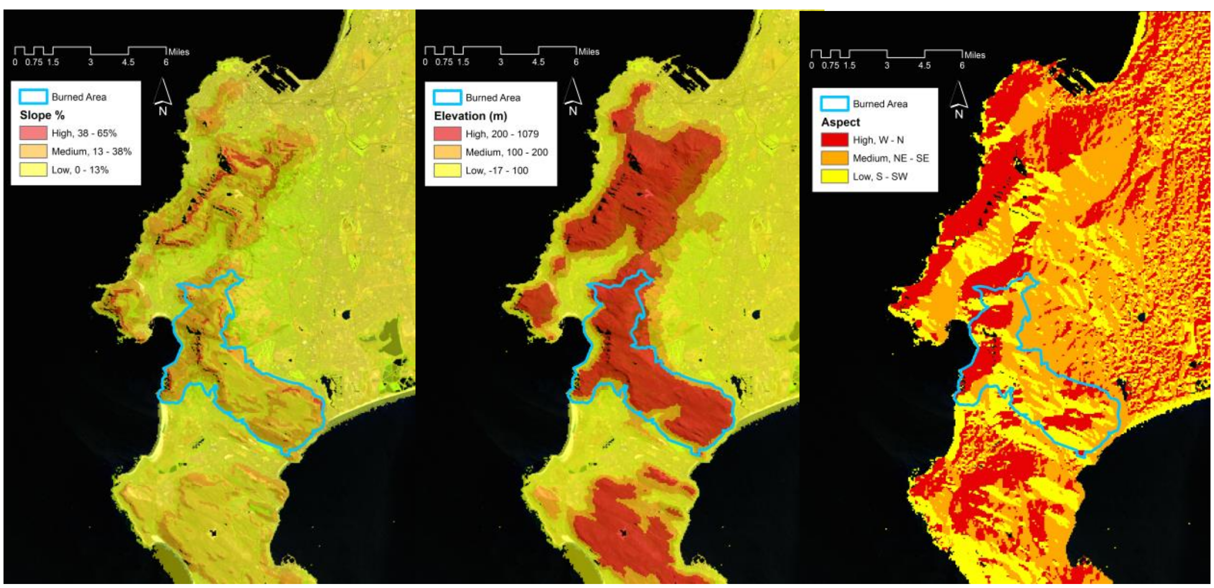

Figure 2: Slope elevation and aspect classes for fire hazard model, respectively

The first model was run with NDVI values substituting for discrete vegetation classes. By itself, the NDVI layer was a good visual indicator of greenness. However, when used in the formula, the results were too broad (Figure 3). By not presenting multiple vegetation layers, the low Fynbos shrubland allows NDVI to represent the entire range of vegetation. Nonetheless, the highly flammable shrubs do not produce high positive NDVI values and, when combined with other landscape attributes, do not appear to be clearly at risk. Ironically, many agricultural areas are identified as high risk.

The second model was run with NDMI values as a substitute for discrete vegetation classes. When compared to the NDVI model, this model displays better correspondence with the burned areas (Figure 4).

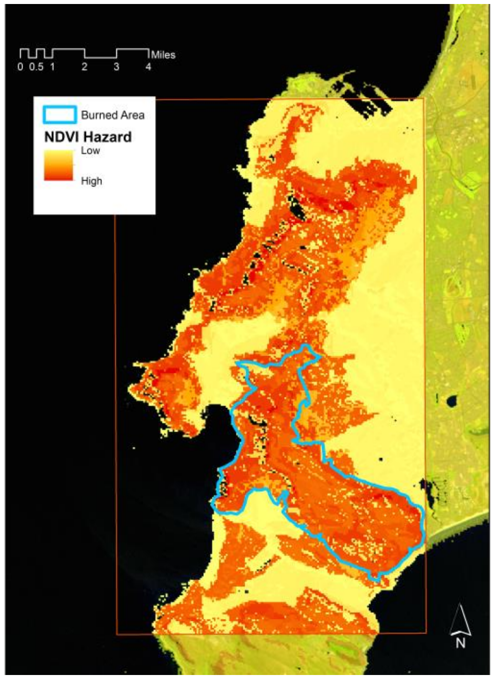

Figure 3: Fire hazard model with NDVI substitute for vegetation

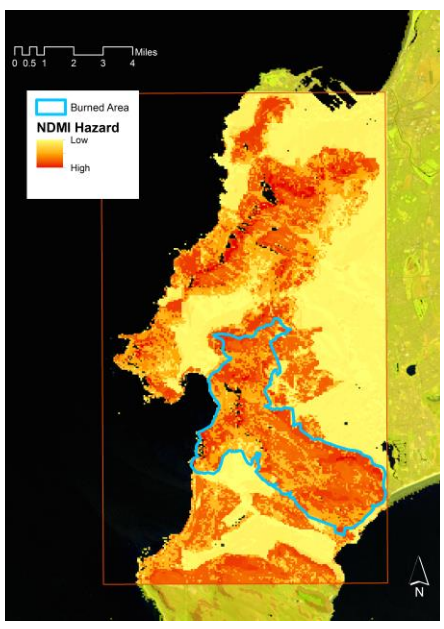

Figure 4: Fire hazard model with NDMI substitute for vegetation

Conclusions

The knowledge of fuel characteristics is essential to fire management because it can be used to estimate fire hazard, risk, and impacts. Although fire fuel mapping has traditionally been performed through fieldwork, this is a time-consuming and expensive method. Remote sensing and GIS systems potentially offer a cost-effective alternative to fieldwork. This study investigates that possibility of combining topographic information with NDVI and NDMI to produce a structural fire index in order to identify areas most likely to burn.

The results suggest that the highest elevation areas are at greatest risk. This is most likely because higher elevations are where the Fynbos vegetation is present and is also most exposed to lightning strikes. Steep-sloped areas are also high-risk areas because of chimney effects. Low-slope areas can be at high risk, too, but only if they occur at high elevation where they are exposed to lightning strikes. Aspect does not appear to contribute to hazard risk, and NDVI does not by itself discriminate fuels adequately to be a valuable tool in this application. NDMI shows promise for future applications because it does a better job discriminating fuel loads; higher resolution imagery or better ancillary information could improve future results using NDMI. In the end, however, the results are too indefinite to be valuable for fire forecasting.

Although the findings are inconclusive, they do offer the potential for better results with improved analytical techniques and data. While the hazard index was incapable of adequately predicting risk, the coupled NDMI and NDVI did provide information on the range of Fynbos. The indices also showed where the vegetation was driest and therefore at a risk of burning. By combining that information with different topographic variables, the analysis demonstrated that areas of lesser and great risk could be mapped.

The analysis was limited by the short period analyzed, the subjective weighting system used in the formula, and the lack of a comprehensive fire database for the area. The study only compared pre- and post-burn imagery, but a long-term analysis would allow for more insight into average NDVI and NDMI values for the vegetation. Comparing long-term average NDVI and NDMI values coincident with fire events could lead to a better understanding between these indices and wildfire. The subjective weightings of the formula were also a limitation because they only reflected general values of how different factors influence fire hazard; a formula specifically developed for the Fynbos vegetation and the Cape Town context would allow a better analysis. For example, the findings reported here suggested that elevation should be weighed more heavily because those values determine occurrence of the vegetation. The final limitation was the lack of a comprehensive fire database. Detailed records including date, weather, and vegetation type and area burned would help establish a better understanding of the fire cycle in the area and relationships to the variables tested here.

It is important to note that the model only aims to identify risk of fire hazard affecting an area and not actual fire behavior, which could be affected by other real-time factors such as weather and human factors (e.g., arson or fire fighters). Ultimately, improvements of the model could allow forest fire managers and emergency responders to initiate preventative policies and actions that could limit future fire damages to humans and nature.

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