MODELLING OF NATURAL FIRE OCCURRENCES: A CASE OF SOUTH AFRICA

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ABSTRACT:

In contemporary literature there have been growing concerns regarding preservations of natural ecosystems. Given the global growth in awareness of global warming, the need for natural fire prediction models has grown rapidly. Using South Africa as a case study, we evaluate the potential of integrating several natural fire prediction models and geographical information system (GIS) platforms. Initially, natural fire prone regions in South Africa were spatially demarcated basing on municipal historical data records. Thereafter, the natural fire prediction models were applied/tested in parallel to identify the best prediction models that give optimum results in predicting natural fires. The models were assessed for accuracy using historical data. Preliminary results reveal locations in the North West, Mpumalanga and Limpopo province had the highest recorded potential for natural fires. In conclusion, the work demonstrates huge potential of prediction models in informing the likelihood of natural fire outbreaks. Lastly, the work recommends the adoption of natural fire prediction models and the subsequent formulation and use of relevant future natural fire mitigation policies and techniques to avert disasters in time.

1 INTRODUCTION

In contemporary literature, there have been growing concerns regarding preservations of natural ecosystems. Given the global growth in awareness of global warming, the need for natural fire prediction models has grown rapidly. The global choice of increasing capital expenditure to enhance global fire prevention suppression is part of the sustainable development goals (SDGs) that explicitly encourage the environmental conservation. Within the developing world context, this has been boosted by policy changes such as the fire exclusion policy (Stephens et al., 2014).

Looking at Sub-Saharan Africa which is prone to natural fires, the fire management decision-making processes is guided by research which seeks to unpack temporal and spatial fire ignition distribution whilst also identifying the key drivers which are attributed to environmental and human influences (Schneider et al., 2008; Elia et al., 2019). The era of remote sensing and big data has allowed for the monitoring, prevention and prediction of wildfire over vast spatial locations (Arroyo et al., 2008; Liu et al., 2012; Zhang et al., 2016). The monitoring and management of vegetation fire in the developing world is vital for developing polices practices that safeguard community livelihoods. This paper therefore aims to find effective predictive model measures based on remote sensing in the case of South Africa to monitor, manage and predict wildfires.

2 RELATED WORK

Recent literature has extensively addressed future fire projections for countries in both the developed and developing worlds. Liang et al., (2008) have articulated how predictive models generally have biases towards current climate conditions as this is used systematically into the projections for future climate at regional scales. There is a need for adaptive models that measure the change and diversity of temperature and precipitation between the current and future climate. Additional to regional variations, the spatial characterization of distribution of wildfires is dependent on the spatial scale, which are influenced by top-down control interactions and these among others include climatic gradients and bottom-up controls such as weather, local fuel conditions and topography (Falk et al., 2011; Parisien et al., 2011; Liu et al., 2012). Several literature sources have also shown that the majority of studies on prediction of spatial fire occurrences have focused on a single scale which ranges from local (Guo et al., 2017; Syphard et al., 2008;), regional (Syphard et al., 2007; Su et al., 2019;) to national and global scales (Chuvieco and Justice, 2010; Botequim et al., 2013).

Various models have been utilized for the prediction of fire occurrences at regional and global scales (Johnson et al., 2004; Molthan et al., 2015; Mandel et al., 2016; Ahmadov et al., 2018). To model global fires, Bowman et al., (2009) articulated the underlying requirement for long term predictions over timescales of decades to centuries to consider several dynamic factors such as vegetation typology, human activity and climate changes. Such long-term fire prediction models are

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linked to sources of ignitions and vegetation biomass flammability (Arroyo et al., 2008). In cases involving large geographical areas, research has shown that it is more reasonable to find varied relationships rather than ones that are constant (Martínez-Fernández et al., 2013; Rodrígues et al.,2014; Nunes et al., 2016). Such relationships can be described with models that allow for local spatial variation of model coefficients which include Geographically Weighted Regression (GWR). The GWR is a spatial analysis technique that has encountered escalating attention in recent literature. A number of studies which use the GWR model mainly focus on the fire occurrence prediction, despite presence or absence of fire ignition points (e.g. Zhang et al., 2016; Rodrígues et al.,2014, Rodrígues et al.,2018, Guo et al., 2017;) or on fire density prediction (Koutsias et al., 2010; Nunes et al., 2016; Su et al., 2019). Point data on the other hand is used to represent locations of wildland fire ignition whilst surface data is generally used in representing environmental and human variables (sources). Additionally, the Auto-Regressive Integrated Moving Average (ARIMA) model has also been used for simulating wildfires in North America. (Preisler & Westerling (2007) used ARIMA for temperature forecasting fire risks over a monthly timeseries analysis, whilst (Safford & Miller 2012) conducted trend exploration in large high severity fires.

The variations in spatial and temporal characteristics of fire in South Africa, according to various studies (Kruger et al., 2006; Strydom & Savage, 2016) indicate that the most frequent fires occur within the north-eastern regions of the country and mountainous areas such as Mpumalanga and Kwazulu-Natal as well as the Western Cape. A study by Strydon & Savage (2016) focused on an 11-year dataset where active fire hot spots were analysed using an open geographical information systems (GIS) source and the study culminated to the mapping of the national fire frequency. In a study by Goslar (2006) in Limpopo, South Africa, ground vegetation biomass detection and remote sensing imagery (ASTER and MAS - MODIS Airborne Simulator) were used for fire prediction taking into consideration the various seasons and NDVI into context which proved effective as a prediction model for wildfires in South Africa. In 1998, South Africa adopted the National Veld and Forest Fire Act (No. 101 of 1998) as a tool for the management and monitoring of wildfires (Kruger et al., 2006). The Working on Fire Organization in Cape Town discovered that 70% of the ecosystems covered in South Africa are on the risk of encountering a wildfire (www.workingonfire.org). In 2004, the Electricity Supply Commission (Eskom) which embodies South Africa's largest power company, executed South Africa’s first satellite-based fire information to help combat and monitor fires in South Africa (Özelkan, 2011). However, since then not much has been done to extend and provide new prediction strategies for wildfires that cover the entire country. Consequently, this paper seeks to add to existing literature by exploring the potential of modelling fire occurrences in South Africa using remote sensing data.

3 METHODOLOGY

The study relied on shapefile active fire data of Visible Infrared Imaging Radiometer Suite (VIIRS) and Moderate Resolution Imaging Spectroradiometer (MODIS) datasets for the study area, South Africa for the period 2012-01-01 to 2019-12-31. The data is available open source from the NASA archives. Although the data is already reprocessed to ensure calibration and algorithm refinements; the authors further cleaned the data to ensure only high confidence fire pixels with positive observations of natural fires were accessed in the analysis. The first process of data cleaning was removing all the fire mask pixel classes with a detention confidence level less than 80%. This was done to reduce redundant data and false recordings in the analysis. Consistently, only ‘presumed vegetation fire’ type classes were considered during the analysis. Table 1 outlines the dataset for MODIS and VIIRS datasets after preliminary data cleaning.

Table 1: Dataset

Column ID	Column Name	Unit	Interpretation
1	YYYYMMDD	-	Detection date in year (YYYY), month (MM), and day (DD)
2	HHMM	-	Detection time hour (HH) and minute (MM)
3	SAT	A or NPP or T	Satellite type: Aqua (A) or Suomi (NPP) or Terra (T)
4	LAT	Degrees	Latitude at centre of fire pixel
5	LON	Degrees	Longitude at centre of fire pixel
6	T3 (MODIS) or T_14 (VIIRS)	Degrees Celsius	Band 31 (MODIS) or Band 14 (VIIRS) brightness temperature of fire pixel
7	FRP	MW	Fire radiative power
8	CONF	%	High Detection confidence class (80 -100%)
9	TYPE	-	Inferred hot spot type: 0=presumed vegetation fire
10	DN	-	Day/night algorithm flag: day (D) or night (N)

Authors’ Compilation (2020)

After data cleaning 92701 fire pixel points were retained for the VIIRS and 162221 fire pixel points were retained for MODIS. In addition to the dataset having a high-temporal-spatial-resolution, this also enhances the dataset capability to numerous applications for varying timeframes. For the paper’s analysis the time-series analysis was conducted over yearly intervals, for other analysis this can also be carried out over months to assess seasonal trends.

3.1 Statistical analysis

GeoDa (version 1.14.1) was used to calculate Global Moran I and Local Indicators (LI) for auto correlation Local Moran I to show the distribution of fire incidences in South Africa. GeoDa was chosen as it provides a myriad of sophisticated functions for example spatial weights construction, sensitivity analysis and visualisation for spatial autocorrelation. Local Moran I using empirical Bayesian statistical function with 9999 permutations where utilised to calculate the global and local Moran because Empirical Bayesian statistics reduces biases. A significant level of 0.05 was used to calculate the indices.

When calculating the Local Moran, I, we used the queen contiguity weights option to ensure that each fire incident has a neighbour and ensure a uniform distribution. The queen's weight offers a histogram that is much more symmetric and has compact distribution of the neighbour cardinalities (Figure 1).

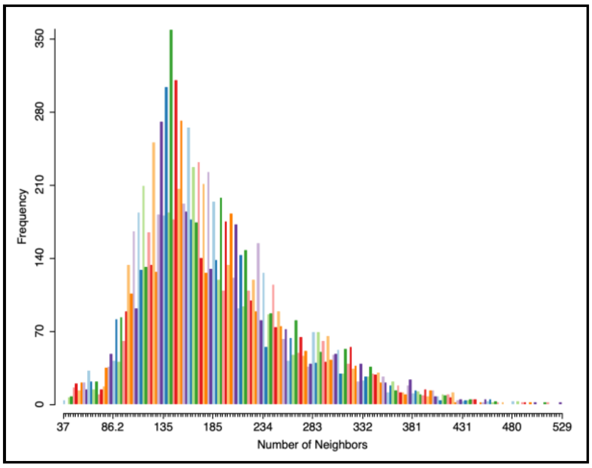

Figure 1: Histogram of sample VIR data

For the weights, each fire incident had a minimum ten neighbours and for each year we had histogram, connectivity map and graph (Figure 2).


Figure 2: Sample connectivity map and graph for queen continuity weights on VIR data

After running we would convert the points into theisen polygons for better visualisation of the clusters and label them High-High (HH, clusters of high fire incidences next to each other, High to low (HL, high incidences next to low incidences), Low-Low (LL, low incidences of fire next to each other) and , Low-High, (LH, low incidences next to high incidence areas.

4 RESULTS AND CONCLUSION

The capabilities of exploring remote sensing data have greatly enhanced fire occurrence analysis. The results reveal variations of fire incidents. 2012 to 2014 VIIRS data shows variations of fire occurrences. Overall the local Moran I classification results show that using VIIRS data, in 2012, most fire clusters with a a with a high-high significance level occurs in the Western Cape (WC) (see figure 3).

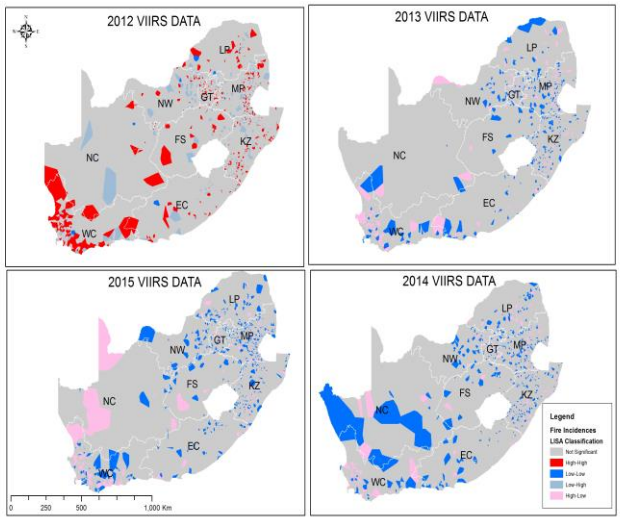

Figure 3: 2012 to 2014 VIIRS

In 2013, most fires occurred in WC and Limpopo (LP) with high-low significance levels. In 2014, most of the fires recorded were in Northern Cape (NC) and WC with high-low significance levels. 2014 saw WC, NC and Free State (FS) with most fire occurrences, the significant levels ranged from high-low to low-low (see figure 4).

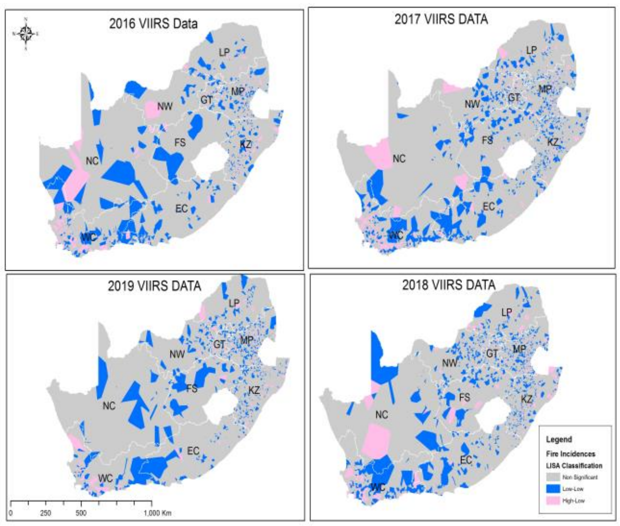

Figure 4: 2016 to 2019 VIIRS

2016 VIIRS data shows that NC, WC, FS and North West (NW) has the most fire occurrences with high-high and low-low significance levels. 2017 data shows NC, EC and WC recording the most fires. The significance levels still ranged from high-high to low-low. 2018 and 2019 data showed an increase in fires in NC and NW with Eastern Cape (EC) and Mpumalanga (MP) recording high-high significant levels for the LISA classification.

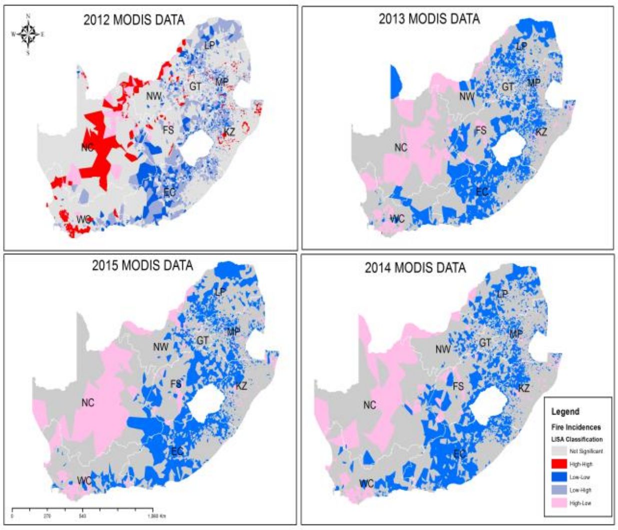

Figure 5: 2012 to 2014 MODIS

Figure 5 shows the MODIS data for the local Moran I from 2012 to 2019. There is evidence that shows a prevalence of fires with a high significance levels of high-high in WC, NC, NW and some parts of FS for the year 2012. High-high significant levels were also appearing in some parts of the country like KwaZulu Natal (KZ) and Gauteng (GT) as well as MP. EC has significant levels of low-high. 2013 had low-low significant levels throughout the country and a high-low significance level in NC and WC. Furthermore, the same pattern was observed for 2014 and 2015 for the MODIS data where NC, WC and FS recorded high-low and the rest of the provinces ranged from low-low to not significant.

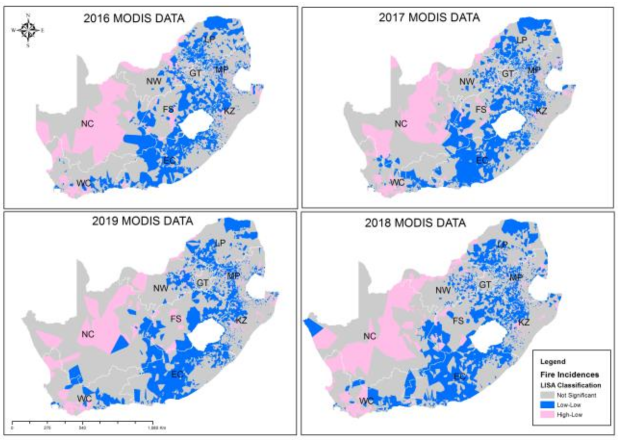

Figure 6: 2016 to 2019 MODIS

When comparing both MODIS and VIIRS data it shows that 2012 was the deadliest year of fire incidents with significant occurrences of high-high fire clusters.

Figure 6 visualizes the 2016 to 2019 fire occurrences for both MODIS and VIIRS, shows that the western cape and northern cape are fire hotspots. This even more pronounced with MODIS data compared to VIIRS within the country owing to the very arid nature of these areas. The other localized fire hot spots are found in the other provinces, but the spatial spread is not as big as in the western cape and northern cape. The fires often destroy landscapes, infrastructure and livelihoods.

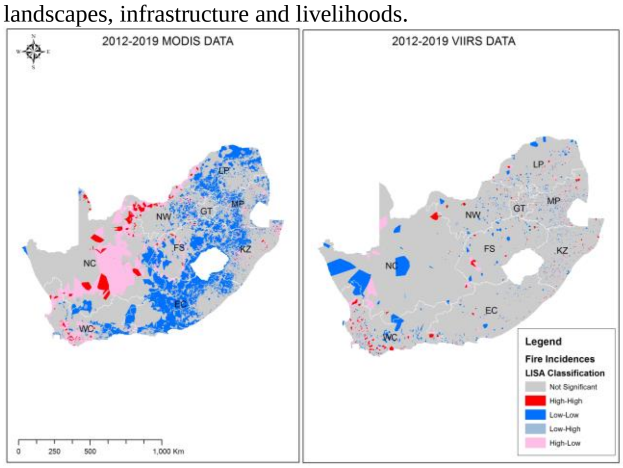

Figure 7: 2012 to 2019 VIIRS and MODIS

An analysis of trends from 2012 to 2019 for the VIIRS dataset reveals a dominant belt crossing from the LP, MP, EC and parts of WC and the NW which falls under the Low-low LISA classification. Whilst for the MODIS dataset most of the country falls under the Not Significant LISA classification with some parts in the NC and WC having portions of Low-low LISA classification.

5 CONCLUSION

The monitoring and management of fire occurrence is novel approach to meeting the SDGs whilst also ensuring the preservation of the natural environment. In the paper the authors have explored the potential of using VIIRS and MODIS datasets to visualise natural fire occurrences in South Africa. The results reveal locations in the Western cape, North West, Mpumalanga and Kwa-Zulu Natal provinces had the highest recorded potential for natural fires. It is crucial to monitor the fire occurrences and also comprehend the drivers of fire occurrences. Fire also shapes the landscapes and also affect livelihoods, hence mapping map will assist in developing response mechanisms and sustainable land use planning. Lastly, the work recommends the adoption of natural fire prediction models and the subsequent formulation and use of relevant future natural fire mitigation policies and techniques to avert disasters in time.

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