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REVIEW ARTICLE

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Progress in the remote sensing of veld fire occurrence and detection: A review

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Abstract

Our research provides a detailed overview of the progress in remotely sensed fire monitoring techniques, which have been developed and employed for fire occurrence and detection. Our overview is provided from a literature search of English-peer reviewed articles, conference proceedings and scientific book sections published between the periods of 1980 and 2019. Literature reveals that historically, fire detection through remotely sensed techniques has mainly occurred through ground-based, airborne and satellite systems. Mathematical models, such as decision tree models, Species Distribution Models, Dynamic Global Vegetation Models and Global Climate Models, have also been employed alongside satellite systems to facilitate a greater understanding of fire dynamics and its susceptibility to changes in ecological and climatic variables. Fire frequency and severity are known to be influenced by atmospheric conditions, fuel load and ignitions. However, the literature suggests that targeting inappropriate wildfires with these techniques may still result in wildfires outside of the natural fire regime. Most studies regarding fire occurrence and/or monitoring focus on satellite-based techniques as they provide the greatest coverage of wildfires at varying spatial and temporal resolutions depending on the sensor used. Satellite systems are advantageous for fire monitoring as they provide extensive coverage inexpensively. Finally, fire occurrence is explicitly influenced by moisture-limited climatic conditions and/or fuel load in the form of leaf-litter or water-stressed plants.

Résumé

Notre recherche fournit un aperçu détaillé des progrès réalisés dans les techniques de surveillance des incendies par télédétection, qui ont été développées et utilisées pour la détection et l'apparition des incendies. Notre aperçu est fourni à partir d'une recherche documentaire d'articles, de comptes rendus de conférences et de sections de livres scientifiques en anglais, publiés entre 1980 et 2019. La littérature révèle qu'historiquement, la détection des incendies par des techniques de télédétection s'est principalement faite par des systèmes terrestres, aériens et satellitaires. Des modèles mathématiques, tels que les modèles d'arbres de décision, les Modèles de Répartition des Espèces, les Modèles Dynamiques de Végétation Globale et les Modèles Climatiques Globaux, ont également été utilisés parallèlement aux systèmes satellitaires pour faciliter une meilleure compréhension de la dynamique des incendies et de leur sensibilité aux changements des variables écologiques et climatiques. On sait que la fréquence et la gravité des incendies sont influencées par les conditions atmosphériques, la charge en combustible et les inflammations. Cependant, la littérature suggère que le fait de cibler des incendies de forêt inappropriés avec ces techniques peut toujours entraîner des incendies de forêt en dehors du régime naturel des incendies. La plupart des études portant sur l'occurrence et/ou la surveillance des incendies se concentrent sur les techniques satellitaires, car elles offrent la plus grande couverture des incendies de forêt à des résolutions spatiales et temporelles variables en fonction du capteur utilisé. Les systèmes satellitaires sont avantageux pour la surveillance des incendies, car ils offrent une couverture étendue à moindre coût. Enfin, la survenue d'un incendie est explicitement influencée par des conditions climatiques limitées par l'humidité et/ou par la charge de combustible sous forme de litière de feuilles ou de plantes stressées par l'eau.

KEYWORDS
fire monitoring framework, fire suitable conditions, fuel load, modelling and monitoring, satellite data

1 | INTRODUCTION

Fire dynamics have often been misunderstood and viewed as either a destructive force or an ecological necessity. However, it has been recognised that fires are ecosystem engineers, which is contrary to the belief that only climate and soils dictate the structure of an ecosystem (Bond & Keeley, 2005). The idea between the parallels of fire and ecosystem engineering is that, in the absence of fire, large populations of plant species will be lost while other species will proliferate. Ultimately, the absence of fire results in a transformed ecosystem similar to tropical forest environments with minimum fire as compared to savannah environments that fires have modified. Although fires are a necessity for ecological diversification and the suppression of bush encroachment especially in Savannah environments, if fires are not timely monitored and managed it can lead to the destruction of hectares of land which might be costly (Dube, 2013; Strydom & Savage, 2018). To avert these likely setbacks, there is a need to develop models that can help to predict the occurrence of wildfires, based on environmental factors that influence the dynamics of fires.

The severity and frequency of fires are a result of three factors, which include the atmospheric conditions, the fuel load and the ignition (Moritz et al., 2012). However, the environmental covariates ought to be used when predicting the probability of fires vary because of the different environmental conditions across various regions. For example, from a global perspective, Moritz et al. (2012) used net primary productivity, annual precipitation, the precipitation in the driest month, temperature seasonality, the mean temperature of the wettest month and the mean temperature of the warmest month to measure distribution. On the other hand, Liu et al. (2010) used the Keetch–Byram drought index, which is based on the soil moisture deficit and which relies on daily temperature and daily and annual precipitation data to determine the distribution of fires globally. The different parameters used by Liu et al. (2010) and Moritz et al. (2012) to measure the global fire distribution have resulted in contrary results that agree only on the fact that global fire distribution will increase in some places and decrease in others, due to climate.

From a regional perspective, Gonzalez et al. (2006) used elevation, tree size, stand structure and species composition in a statistical model to predict fire distribution in forest stands in Catalonia, Northeast Spain. Contrary, Mpakairi et al. (2018), used elevation, Normalized Difference Vegetation Index (NDVI), human population density and mean air temperature to predict the distribution of fires and possible hotspots in the Kavango Zambezi Transfrontier Conservation Area. The difference between the parameters used to determine wildfire probability and distribution differ with regard to the physical template of the environment and the model type. In addition, the heterogeneity of landscapes makes it difficult to have specific environmental covariates.

In South Africa, fires have been recognised for the role that they play in the ecological structure and function (Bond & Keeley, 2005; Van Wilgen & Richardson, 1985). Bond and Keeley (2005) suggested that, in the absence of fire, indigenous grassland and Fynbos biomes would be dominated by tree species, which would ultimately result in the loss of diversity. In contrast, fires that occur outside of the natural regime would promote the encroachment of invasive species (Van Wilgen et al., 2010). Fire management in South Africa occurs by using prescribed burning, which has proven to be inefficient and does not reduce the fuel load (Van Wilgen et al., 2010). According

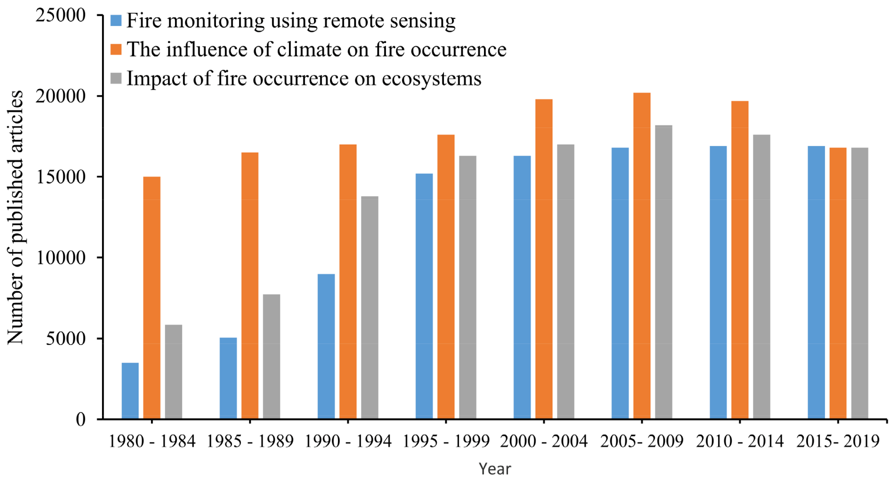

FIGURE 1 Number of articles published on fire monitoring using remote sensing, the influence of climate on fire occurrence and impact of fire occurrence on ecosystems.

to Van Wilgen et al. (2010), most fires in the Western Cape occur as wildfires, with only a small percentage actually taking place as prescribed burning. The Western Cape experiences a Mediterranean climate and the most abundant plant species is Fynbos, which creates an interesting environment where a highly flammable plant species occurs within highly flammable climatic conditions (Van Wilgen et al., 1994). From a South African perspective, it is therefore important to understand the environmental conditions that favour the occurrence of fires, in order to effectively determine where fire management efforts should be directed. Although the application of remote sensing has been widely discussed from a fire-mapping perspective (San-Miguel-Ayanz et al., 2005), knowledge gaps still exist globally and regionally, since most models disagree on the environmental covariates that must be used when mapping the incidence of fires. Furthermore, models often do not include a bi-temporal analysis to determine the predictive capability of the said model, even though this has since been proven to be valuable (Escuin et al., 2008). The main objective of this article was to develop a detailed overview on the progress in remotely sensed fire monitoring techniques and mathematical models that have long since been developed and employed for fire occurrence and its detection.

2 | MATERIALS AND METHODS

2.1 | Literature search

The literature search consisted of English-peer reviewed articles, conference proceedings and scientific book sections published between the period of 1980 and 2019, in order to ensure that the most relevant information was sourced for this study. All articles were sourced from Google Scholar through the use of a targeted search that followed certain criteria. The criteria of search were as follows: (a) the use of remote sensing techniques and systems for fire monitoring, (b) environmental conditions and climate characteristics that influence fire occurrence and (c) publication in a journal article or other sources of reputable academic literature. This review only considered articles in which remote sensing, fire monitoring and fire description were key features of assessment and/or directly influenced the determination of the results in said articles. The articles were then grouped into three categories (a) fire monitoring using remote sensing, (b) the influence of climate on fire occurrence and (c) impact of fire occurrence on ecosystems (Figure 1). For the first category, 'fire monitoring using remote sensing', the publication of articles were very limited for much of the 1980s and fire monitoring through the use of remote sensing only became popular in the late 1990s (Figure 1). This can be seen based on the number of articles published, where between 1980 and 1994 only 17,530 articles were published, whereas between 1995 and 2019, 82,100 articles were published. For the second category, 'the influence of climate on fire occurrence' the number of articles published every 4 years since 1980 remained virtually unchanged (Figure 1). This simply suggests that the influence of climate on fire occurrence has remained a popular topic but similarly could suggest that as climate is ever changing so too does the climatic thresholds that influence fire occurrence. For the third and final category, 'impact of fire occurrence on ecosystems', this topic seemingly increased in popularity in the late 1990s, possibly due to a shift in the previous theory that fire is an environmental hazard as can be seen in Bond and Keeley (2005).

Interestingly, since 1980, the number of published articles regarding the use of remote sensing in fire monitoring remains fewer than that of the amount of articles regarding the influence of climate on fire occurrence and the impact of fire occurrence on ecosystems (Figure 1). This suggests that while many try to understand the dynamics of fire occurrence and its impacts, less try to actively predict and monitor its occurrence. This leaves a gap in knowledge that needs to be filled through the advancement of remote sensing techniques to actively monitor fire occurrence. As such, there is a need for more remotely sensed frameworks that focus on the characteristics needed to model and predict fire occurrence. The key concept here being that an advancement in remotely sensed frameworks for fire monitoring would allow for more viable remote sensing techniques when monitoring and predicting fire occurrence. This improvement in remotely sensed frameworks and consequent improved fire monitoring through remote sensing will ultimately help fire management strategies make more informed decisions regarding fire suppression and human intervention.

3 | THE PHYSICAL AND CLIMATIC CONDITIONS THAT INFLUENCE THE OCCURRENCE OF WILDFIRES

Moritz et al. (2012) argued that fires were influenced (a) atmospheric conditions (b) biomass or vegetation structure and growth rate, and lastly, (c) ignitions, which refers to any activity that starts a fire. While these factors undoubtedly influence fires, they do not consider smaller scale disturbances that are climate-specific, such as precipitation pulses, where an increase in precipitation in an already moist climate will diminish fires, but a similar increase in precipitation in a drier climate will increase flammability.

In Southern Africa, most studies concur that fires are influenced by elevation, soil moisture, precipitation, vegetation characteristics, anthropogenic activities and temperature; however, very few actively apply all of these in their models (Chingono & Mbohwa, 2015; Mpakairi et al., 2018). Vegetation characteristics, such as structure, length and moisture content, all determine the flammability of a plant and its contribution to the fuel load (Van Wilgen et al., 1990). For example, the Fynbos species consists of dry shrubland plants that are naturally fire-prone, due to their dry, woody-like structure and high oil content, which makes them more flammable than other plant species found in South Africa. Likewise, plants that hold more moisture or produce less leaf litter, such as succulent plants, will naturally be less flammable. Studies in Southern Africa have also showed that wildfire probability increases with increasing NDVI, with the highest fire probability being when NDVI ranges between 0.5 and 0.9 (Chingono & Mbohwa, 2015; Mpakairi et al., 2018). In addition, warmer temperatures facilitate drier conditions through evaporation. This is indicative of fire-prone areas that have less available moisture, such as savannahs and Mediterranean climates. Various studies concur that temperatures of between 20°C and 27°C have the highest probability for wildfires (Mpakairi et al., 2018).

Similarly, precipitation determines the amount of available moisture. This, in turn, influences the dryness of any given area, where a balance between a variable precipitation and the dry season increases the plant growth rate, which facilitates the available dry biomass during the dry season (Archibald et al., 2008). Archibald et al. (2008) showed that the burned areas decrease where the tree cover is greater than 40%, and tree cover that exceeds 40% only occurs in areas that receive rainfall of more than 800 mm. Therefore, this suggests that the perfect precipitation threshold that is necessary for fire to occur ranges between 500 mm and 700 mm. Elevation influences the spread of fires in a linear fashion, where a higher frequency of fire is related to a higher elevation, which often influences the moisture conditions and the resultant varying vegetation (Kitzberger et al., 2005; Maingi & Henry, 2007). It is important to note that the aforementioned environmental factors are all independent variables that act in a flammable environment, while there are also other factors that influence fires, most of which are dependent and act to intensify a fire, rather than to initiate it.

4 | CURRENT FIRE CONTROL MECHANISMS AND THEIR EFFECTIVENESS

To date, many studies have discussed the importance of fire for biodiversity (Bond & Keeley, 2005; Van Wilgen et al., 1994, 2010; Van Wilgen & Richardson, 1985), and most of them concur that fire is necessary to promote the richness of species and to eradicate alien invasive species. Unmanaged fires can, however, have an adverse effect on the environment, economy and human lives (Dube, 2013). Thus, to prevent fires and to ensure that they promote species richness, various management techniques are used to control the fire regime.

These methods mainly include prescribed burns, firebreaks and slash-and-burn techniques. Prescribed burns are fires that are initiated in a controlled environment, usually by trained personnel, with the intention of maintaining the natural fire regime of an area and protecting the richness of the indigenous species (Mpakairi et al., 2020). Firebreaks usually consist of a physical break that acts as a boundary between the vegetation stands, with the intention of suppressing the spread of fire from one sector to the next (Mpakairi et al., 2020). The slash-and-burn technique involves the logging of trees, leaving the material to dry and then burning the said material as a means of increasing the fertility of the soil and eliminating invasive species (Ngadze et al., 2020). While these techniques are supposed to promote viable environments that are not prone to fires, they can have adverse effects on the environment. These effects include but are not limited to, soil erosion, soil contamination, air pollution, sedimentation and turbidity (Crutzen & Andreae, 1990; Rosenfeld, 1999; Swanson, 1981).

Van Wilgen et al. (2010) showed that the probability of fires in Fynbos biomes remain largely unaffected by the post-fire age. The study also showed that only a small area was burned under prescribed burns and that most fires occurred as wildfires, which suggests that prescribed burning in these environments will not reduce the risk of wildfires. Van Wilgen et al. (1994) suggested that, instead of having prescribed burning, a better option would be to allow wildfires to burn freely in delineated areas, based on an assessment of the following four characteristics: (a) where fires should not occur; (b) where fires are allowed to burn; (c) where vegetation has reached complete maturity and/or are adding detritus; and lastly, (d) where prescribed burns are essential for wildfire control. Thus, there is a continuous need for remotely sensed data and specifically for models that allow for the prediction and characterisation of fire-prone areas, based on the environmental conditions that facilitate them. Currently, a vast majority of models exist that cater for

TABLE 1 Satellite sensors and their specifications.

Sensor name (launch date)	Bands (spectral reflectance)	Spatial resolution	Temporal resolution	Examples
MODIS (MOD14A1)	16 visible near-infrared bands Three shortwave-infrared bands 17 thermal bands	250 m 500 m 1000 m	1 day	Giglio et al. (2008) Justice et al. (2002) Chand et al. (2007)
ASTER	Four visible near-infrared bands Six shortwave-infrared bands Five thermal bands	30 m	Does not collect continuous data due to hardware and data issues	Yamaguchi et al. (1998) Giglio et al. (2008)
LANDSAT-8 OLI	Five visible bands One near-infrared bands One band for Cirrus cloud detection Two shortwave infrared bands 2 thermal bands	30 m	16 days	Schroeder et al. (2016)
VIIRS	Six visible bands Three near-infrared bands Five shortwave-infrared bands Three mid-infrared bands Four longwave-infrared bands One day–night band	375 m	12 h	Schroeder et al. (2014)
DMSP-OLS	Visible near-infrared (0.58–0.91) Thermal (10.5–12.5)	0.56 km fine resolution 2.7 km-smooth resolution	12 h	Chand et al. (2007) Huang et al. (2014)

Abbreviations: ASTER, Advanced Spaceborne Thermal Emission and Reflection Radiometer; DMSP-OLS, Defense Meteorological Program Operational Linescan System; MODIS, Moderate Resolution Imaging Spectroradiometer; OLI, Operational Line Imager; VIIRS, Visible Infrared Imaging Radiometer Suite.

the spatial distribution of fires on a global scale, and there are also some that cater for hotspot analyses on a regional scale (Chingono & Mbohwa, 2015; Gonzalez et al., 2006; Liu et al., 2010; Moritz et al., 2012; Mpakairi et al., 2018).

5 | TRADITIONAL AND CONVENTIONAL FIRE MONITORING SYSTEMS

Most fire-monitoring systems have been developed to detect fires, with variable success. The most successful of these developed systems can be subdivided further into three main categories, namely, satellite-borne systems, airborne systems and fixed-ground platforms (San-Miguel-Ayanz et al., 2005). These three remote sensing systems detect fires in the following way: (a) by using the difference in temperature with respect to the normal temperature conditions; (b) by using the difference in temperature with respect to the background temperature conditions; and (c) by detecting the smoke plume. These methods commonly use the mid-infrared and thermal spectral bands to allow for the detection of fires. The mid-infrared and thermal bands are optimal for the detection of fires as they occur far from the peak of the earth's solar radiation, which is measured at 0.5 μm–9.7 μm and 8 μm–12 μm, respectively, for the aforementioned bands. Fixed-ground platforms are operated either under human surveillance, or autonomously, and they are advantageous in that they allow for the continuous surveillance of large areas with mid-infrared and thermal cameras. The validity of fixed-ground platforms can be influenced by different factors, for example, the solar effects, heated objects, artificial lights and combustion points from human activities, and these may cause the false detection of fires. A recent study by Mpakairi et al. (2020) showed that, utilising the blue spectral band which is usually available on most satellite-borne sensors (e.g. Landsat and Sentinel) can be useful in detecting fires when the atmospheric conditions do not permit.

Airborne systems, which are similar to fixed-ground systems, are also operated mainly under human surveillance. The humans base the operation of these systems on smoke plume detection and they may inherently be influenced because of this, as detection can only occur once a fire has occurred. Although airborne systems are reactive, as opposed to proactive, in their response, they are still advantageous as they can assist with the ongoing firefighting upon fire detection. Airborne systems also make use of the mid-infrared, thermal and visual portions of the electromagnetic spectrum to detect fires, by using algorithms; however, similar to fixed-ground platforms, there are different background factors that can produce a false alarm.

Satellite systems are by far the most advantageous systems, due to their low operational costs and their high spatio-temporal resolution, and they are widely used for fire monitoring (Table 1). They also provide greater information about the fires, as opposed to other systems, by including fire severity through indices such as Normalized Burned Ratio (NBR) (Escuin et al., 2008). While they can still suffer from detection errors for various reasons, such as the fire size and/or fire temperature, these can be corrected more effectively not only through algorithms, but also through the exploitation of other bands, to remove cloud masking. Thus, image processing is also cost-effective and can be time-efficient when done through geospatial data analytical platforms.

Satellite systems that are used for fire monitoring, extract information from the visual, mid-infrared, shortwave-infrared and thermal portions of the electromagnetic spectrum. Most active fire detection algorithms use brightness temperatures as a means of detecting active fires via temperature thresholds. These thresholds are divided into fire temperature and/or background temperature, and examples of these can be seen in the Moderate Resolution Imaging Spectroradiometer (MODIS) and Visible Infrared Imaging Radiometer Suite (VIIRS) systems. MODIS, for instance, determines absolute fires if the temperatures are above a given threshold, and it determines weaker fires (that are not above the absolute threshold) based on the thermal emissions of the surrounding pixels, that is, background temperatures (Justice et al., 2002). Furthermore, the red and near-infrared channels are used to remove 'false detection' if the fire pixels have a reflectance above 30% in these channels. Landsat 8 Operational Land Imager (OLI) uses an active fire detection algorithm that is split into day and night modules and that are driven by the shortwave infrared channel. Thus, during the day, the near-infrared (NIR) channel is used alongside the SWIR channel to remove the reflective solar component that may cause 'false alarms', as it is unresponsive to fire-affected pixels, but it correlates well with the shortwave infrared (SWIR) channels over fire-free surfaces (Schroeder et al., 2016). Fire detection algorithms function like algorithms that make use of thermal infrared channels, in that they use SWIR radiance to detect the fire-affected pixels, based on their background values. This section does not focus on the algorithms of the other sensors mentioned above, namely The Defense Meteorological Program Operational Linescan System (DMSP-OLS) and The Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER), due to the limitations that are associated with them. DMSP-OLS, for example, can only provide valuable night time data due to its available spectral channels in the visual and thermal portion (Chand et al., 2007). ASTER, on the other hand, is no longer fully operational and cannot provide the continuous data that is required for active fire detection (Yamaguchi et al., 1998). Therefore, DMSP-OLS and ASTER are frequently used alongside other sensors, or as validation tools.

Thus, when reflecting upon which sensors are the most efficient, it is important to consider the factors listed in Table 1. Temporal resolution refers to the frequency at which any satellite passes and collects data from a geographical location on earth during its orbit. Therefore, for successful active fire monitoring, one will require a high temporal resolution that will preferably allow for the diurnal cycles of data acquisition, which allows a more rapid response to fire detection. Spatial resolution refers to the number of pixels in a given sample and directly affects the amount of detail perceived and thus the quality of the data that can be retrieved. For example, the lower the spatial resolution, the greater the size and temperature of the fire that is needed, for detection to occur, thus excluding the occurrence of smaller fires. Spatial resolution also influences the environmental factors that can be included in a model, based on the physical size of the phenomenon, for example, the vegetation type. Spectral reflectance influences the intensity of the fire that can be captured by the sensor, or more specifically, the saturation of the band, thus error propagation is dependent on the number of channels available and the range of spectral reflectance for the said channels. For example, a false alarm may occur if the temperature of a given area is high enough to saturate the bands. However, if the temperature of the fire is too low for the active fire algorithm to detect, smaller fires may be excluded, based on the spectral threshold. In the MODIS active fire algorithm, for example, fires have to meet the following conditions for absolute fire detection: $T4 > 360\,K$ ($330\,K$ at night), $T4 > 330\,K$ ($315\,K$ at night) and $T4–T11 > 25\,K$ ($10\,K$ at night). Therefore, most studies on fire detection and fire severity exploit these bands in order to extract information from them about the said fires (Chingono & Mbohwa, 2015; Escuin et al., 2008; Gonzalez et al., 2006; Liu et al., 2010; Moritz et al., 2012; Mpakairi et al., 2018).

6 | CURRENT REMOTE SENSING APPROACHES AND FRAMEWORKS FOR FIRE MONITORING AND FIRE PREDICTION

Most studies incorporate different variables into their respective models, based on the spatial scale of their study area, the type of model used or the physical template of their study area. For example, the difference between the variables described in Liu et al. (2010) and Moritz et al. (2012) (Table 2) is rooted in the different models that they used to determine the fire trends; for example, Liu et al. (2010) used KBDI and Moritz et al. (2012) used MaxEnt modelling. Furthermore, a close look at the differences between the variables selected for the global models and the regional scale models mentioned above highlights the fact that the spatial scale influences the variables selected for each of the models. More specifically, the variables selected for the global model have a coarser spatial scale, compared to the regional model, which prefers more locally factored variables at a much finer spatial scale (Archibald et al., 2008; Gonzalez et al., 2006; Mpakairi et al., 2018). The role of the physical template in the decision of which variables to select can also be seen in the study by Gonzalez et al. (2006), which catered specifically for forest stands, as opposed to a more climate-specific model (Table 2).

There is, however, clear concurrence between the majority of the reviewed studies in Table 2, which determined that the elevation, NDVI, temperature and precipitation were among the most important, although not the only, contributors to the fire potential, whether it was on a regional or global scale. In Mpakairi et al. (2018)

TABLE 2 Current studies that try to predict fire occurrence, based on various modelling techniques.

Application	Scale of application	Data	Variables incorporated into model	Techniques	Results	Reference
Distribution of wildland fires and possible hotspots	North-Western Zimbabwe/ Kavango-Zambezi transfrontier conservation areas (~71,479 km^2)	MODIS wildland fire point data SPOT 10 day, 1 km NDVI data human population data was obtained from www.worldpop.org.uk ASTER Mean air temperature data was obtained from: http://biogeo.ucdavis.edu/data	NDVI Elevation Human population density Mean air temperature	Maximum entropy was used to model wildland fire probability Getis–ord was used for hotspot analysis AUC was used to determine accuracy of model	MaxEnt was successful in predicting potential distribution of wildland fire AUC = 0.78 MAT = 61.4%, Elevation = 26.3%, Human population density = 9.8% NDVI = 2.5% The MaxEnt model showed that fire probability increased with an increase in MAT and NDVI but population density had no effect	Mpakairi et al. (2018)
Fire probability for forest stands	Northeast Spain/ Catalonia (~0.2 km^2)	Fire reports were compared with images from (LANDSAT, SPOT, CASI and orthophotos)	Elevation (*Ele*) Basal-area-weighted mean diameter (D_g) 12 years probability of fire occurring in a given stand (P_{fire}) Total basal area (*G*) Portion of hardwood species of the number of trees (P_{hard}) Standard deviation of the breast height diameters of trees (*SD*) Relative variability of tree diameter ($SD/D_g + 0.01$)	Logistical distribution model Logistic model was fitted to modelling data using a binary logistic procedure in SPSS	Variables used in equation were found to be the best fit as they gave a NagelKerke R squared of 0.181 Furthermore, the variables included in the model were proven significant based on the Wald test ($p < 0.5$) The results showed that there was a higher probability of fires at lower *Ele*, where *G* and *SD* are higher Stands with higher values of P_{hard} and D_g have a lower probability of fire	Gonzalez et al. (2006)

(Continues)

TABLE 2 (Continued)

Application	Scale of application	Data	Variables incorporated into model	Techniques	Results	Reference
The effect of climate change on the geographical distribution of fires	The entire terrestrial surface of the world with the exception of Antarctica and small islands	MODIS collection 5 CMG European space agency's advanced and along track scanning radiometer	Mean annual precipitation Precipitation of driest month Temperature seasonality Mean temperature of the wettest month Mean annual precipitation of the warmest month	Winnowing was performed to remove variables that were highly correlated The 'climate + baseline NPP' model was used to model the global distribution of biomass The 'climate-only' model was used model future distributions of fire MaxEnt was used to model fires The fire models were evaluated respectively by 16 GCMs which was validated using the AUC technique	Both models predicted low fire potential where biomass is sparse In the 'climate + baseline NPP' model, NPP contributed 36% is as such the most important variable, whereas in the 'Climate only' model, mean temperature of warmest month and annual precipitation had the biggest contribution. The AUC values were 0.93 and 0.92 for 'Climate + baseline NPP' and 'Climate only', respectively, when adjusted for prevalence 37.8% of the world show model agreement for the 2010–2039 period, while 54.1% show low agreement. A total of 61.9% of the world show model agreement for increases in the 2077–2099 period, with 20.1% showing agreement for decreases and 17.9% showing no agreement with the model	Moritz et al. (2012)
Global trends of fires based on changing climate	The terrestrial surface of the Earth from (90 N- 90 S) and (180 E – 120 W)	Climate Research Unit (CRU) Global climate data set Four general circulation models (HadCM3, CGCM2, CSIRO and NIES)	Moisture deficiency of current and previous day KBDI increment Daily maximum temperature at 2 m above the ground Daily precipitation Mean annual rainfall A time increment set equal to 1 day	The Keetch– Byram Drought Index (KBDI) was used to model and classify fire trends A sensitivity analyses was used to examine the dependence of fire potential on changes in meteorological variables, emission scenarios, choice of GCMs and to determine the importance of precipitation and temperature GCMs simulation output was used for four emission scenarios (A1, A2, B1, B2) Present and future KBDI values were determined using the observed and simulated GCM meteorological data respectively	Regions with the most significant future increase in potential are synonymous with those with the greatest fire potential at present with the exception of Southern Europe and Northern Africa. KBDI is function of increased temperature and decreased precipitation Large KBDI increases are found in areas where temperature increases by at least 4°C and where precipitation decreases by 0.25 mm/day A1 and A2 scenarios produce the largest KBDI values globally with B1 and B2 being less pronounced NIES and HadCM3 produce the largest KBDI values out of the four GCMs used in the study	Liu et al. (2010)

TABLE 2 (Continued)

Application	Scale of application	Data	Variables incorporated into model	Techniques	Results	Reference
Examination of the drivers of burnt area in Southern Africa	100 km × 100 km sampling window for 899 sample points	MODIS burned area product Southern Africa Fire Network MODIS active fire product FAO livestock distribution data set Land tenure maps for South Africa, Namibia, Botswana and Zimbabwe were combined with the World Protected Areas map The Global Land Cover 2000 Africa product The monthly Tropical Rainfall Measuring Mission (TRMM) best-estimate precipitation rate product Shuttle Radar Topography Mission (SRTM) elevation data Global Hydrology Resource Centre	Mean annual rainfall (previous 2 years) Soil fertility Tree cover Grazing Length of dry season Topographical roughness Road density Fraction of transformed land Mean lightning strikes over the burn season Population density Percentage communal land	Statistics of each data set was defined by a fixed 100 km × 100 km sampling window Mean values were used to determine all the independent variables with an exception to grazing and human population density. Grazing and human population were determined using median A random forest regression tree was used to investigate the drivers and their relationship with burnt area and was created using the splitting procedure. The influence of a variable was tested by the difference in mean square error between a tested sample and randomly permuted test sample.	Both the predictive capability of the random forest regression tree as well as the number of nodes decreased with an increase in window size with the latter being more pronounced r^2 for the predicted values from the random forest and observed burned area was 0.62	Archibald et al. (2008)

Abbreviations: ASTER, Advanced Spaceborne Thermal Emission and Reflection Radiometer; AUC, Area Under the Curve; CASI, Compact Airborne Spectrographic Imager; CGCM2, Canadian Global Coupled Model, version 2; CSIRO, Commonwealth Scientific and Industrial Research Organisation; FAO, Food and Agriculture Organization; GCM, Global Climate Model; HadCM3, Hadley Centre Coupled Model, version 3; MAT, Mean Annual Temperature; MaxEnt, Maximum Entropy; MODIS, Moderate Resolution Imaging Spectroradiometer; NDVI, Normalized Difference Vegetation Index; NIES, National Institute for Environmental Studies; NPP, Net Primary Productivity; SPOT, Satellite pour l'Observation de la Terre; SPSS, Statistical Package for the Social Sciences.

TABLE 3 Examples of frequently used models for fire management.

Model type	Advantages	Limitations	References
Species Distribution Models (SDM)	• Certain SDM requires presence-only data along with associated features to model reality • It can utilise both continuous and categorical data and model interactions between different variables • Algorithms exist that allow for the optimal determination of maximum entropy • MaxEnt modelling is generative, rather than discriminative, which can prove advantageous when the amount of training data is limited	• Not much is known about its general use and there are limited methods for error propagation • It uses exponential modelling for probabilities which means that it can return values for environmental conditions that are larger than what actually occurs in the study area. • MaxEnt is not available in standard statistical packages and thus special software is required for its use. • Some SDM requires presence and absence data to operate • Does not predict well with smaller sample sizes	Phillips et al. (2006)
Decision Tree Models	• Allows for the use of qualitative and quantitative data • Extensive methods by which to do model evaluation • Able to explain variation within original data set • Semi-qualitative data can be used when full qualitative data set is unavailable • They include non-additive behaviour and complex interaction between variables • Can model large data sets with quick feedback	• The implication of qualitative data requires a great understanding • Greater error propagation when trying to extrapolate model • Mainly used to determine burnt areas, as opposed to being used for predictive modelling • Mainly used in forest areas and not suitable for other areas (i.e. shorter vegetation types)	McKenzie et al. (2000)
Dynamic Global Vegetation Model (DGVM) and Global Climate Model (GCM)	• Allows for the projection of potential future distributions of natural phenomena, such as fire, based on scenarios (i.e. climate changes, emissions) • Allows for the projection of continuous or very large-scale data sets	• Coarse-scale resolution can limit available data sets • Model valuation tends to be difficult at a global scale due to lack of data at certain times, long time scales required and the effects of human activities • Dependence of vegetation on bioclimatic constraints	Bond and Keeley (2005) Moritz et al. (2012) Liu et al. (2010)

and Archibald et al. (2008), population density had very little effect on the occurrence of wildfires. Archibald et al. (2008) showed that the population density had a negative effect on burnt area occurrence, and more specifically, where the population density decreased, so the size of the wildfires would also increase. Mpakairi et al. (2018) found no change in the occurrence of wildfires, based on the effect of population density.

The results in Moritz et al. (2012) and Liu et al. (2010) differed significantly, even though both studies aimed to understand the present and future distribution of fires, based on the effects of climate change. While some of the aforementioned factors could potentially drive the differences between these models, this was not actively determined and thus it remains speculation. It does, however, become clear that models that cater for 'climate-specific' functions or variables, with the exception of elevation, tend to show a significant influence on the occurrence and distribution of wildfires. Thus, the influence of climatic differences is impossible to ignore when one considers, for example, that the drying rates differ across climates, which is ultimately a function of precipitation (Liu et al., 2010). Hence, the error propagation would be greater if a model designed for a different climate is used, as the conditions are not climate-specific. Ultimately, there is a need for climate-specific models when trying to develop a remote sensing framework for fire monitoring that relies on specific climatic variable thresholds, in order to achieve greater model success.

7 | FREQUENTLY USED MATHEMATICAL MODELS FOR FIRE DESCRIPTION

Table 3 provides examples of models frequently used for fire distribution and potential modelling. Global Climate Models (GCMs) and Dynamic Global Climate Models (DGVMs) are similar in that they have advantages and disadvantages, but not similar functions. DGVMs are ecological models that simulate vegetation dynamics and predict projected changes in vegetation/potential biomass based on global climate change mathematically (Bond & Keeley, 2005). DGVMs are also used for fire monitoring due to the shared dynamics between fire and vegetation (Quillet et al., 2010). In addition, DGVMs facilitate the vegetation component of GCMs, which focus on climate behaviour based on physical laws, specifically fluid dynamics and thermodynamics (Bonan et al., 2003; Kucharik et al., 2000; Sitch et al., 2003). GCMs are used to understand climate change and for weather forecasting, as well as to determine the present and future distribution of fires based on changing climate. Both GCMs and DGVMs exist in multiple versions that serve similar functions.

In contrast, decision tree-based models were developed as an alternative to linear regression models that cannot handle complex relationships. Tree-based models are non-parametric statistical models that fit data into increasingly homogenous subsets and are used primarily as exploratory techniques to reveal differences and correlations in data (Pham et al., 2020). Regression models consist of stochastically trained data subsets that allow for more independent estimates using binary recursive partitioning (Felicísimo et al., 2013; Pashynska et al., 2016). While decision trees can be used for predictive modelling, they only work when the predictors in the new database fall within the range of the modelling framework. Therefore, decision trees do not allow for an efficient predictive fire monitoring system. Examples of tree-based models include support vector machines, multiple regression trees, random forest trees, classification and regression trees, and partial least squares regression.

Species Distribution Models (SDMs) are used to model the geographical distribution of species by combining observed species numbers with environmental estimates (Phillips et al., 2006). Most SDMs require two training samples: presence and absence data. MaxEnt is an exception that allows for predictive modelling of environment requirements and geographical distributions when only presence data are available (Liu et al., 2009). MaxEnt determines an estimate for the probability distribution of a given target by determining the probability distribution of maximum entropy based on incomplete information of absence data (Phillips et al., 2006; Phillips & Dudík, 2008). In this case, the information given by MaxEnt modelling is represented as features, where each feature should closely relate to the average of all the sample points taken for the said feature. Features refer to various factors, such as climatic variables, elevation, soil moisture, species type and other environmental variables and functions. When MaxEnt is used to model presence-only data, the pixels of the study area determine the area where the MaxEnt probability distribution is possible and the pixels with occurrence data represent the sample points.

8 | FUTURE RESEARCH DIRECTIONS AND RECOMMENDATIONS FOR FIRE MANAGEMENT

Literature reveals that many studies, both global and regional, agree on the factors that influence fire-suitable conditions, regardless of climate. These conditions include: (a) atmospheric conditions, such as precipitation, evaporation and temperature; (b) physical resources, including vegetation characteristics and available fuel load; and (c) ignitions, often in the form of lightning or anthropogenic activities. However, fewer studies delve into the small-scale disturbances that are specific to particular climates. As such, future research should focus on understanding the local fire climate by examining local climate thresholds and climate-influenced characteristics that shape the natural fire climate. Doing so will allow for more accurate determinations of fire occurrence in targeted areas where a generalised framework would lead to inaccuracies. Examples of such small-scale disturbances include precipitation pulses and vegetation characteristics such as oil content, moisture content, growth rates and plant structure.

Regarding fire management strategies, prescribed burns and fire suppression efforts should only be undertaken in areas appropriate for such interventions. Fire management agencies should first understand whether a targeted area is at risk of fire occurrence and whether such fires exist within the natural fire regime. Therefore, it is recommended that fire management agencies incorporate fire monitoring and mathematical models to gain an understanding of fire dynamics.

Current studies regarding fire monitoring, future fire distributions and fire risk analysis all use satellite systems to acquire the necessary data. The most effective satellite systems for fire monitoring are currently MODIS and VIIRS and should be recommended for future research. Lastly, it is imperative that future studies consider localised variables that influence fire occurrence. Many studies neglect the influence of local climate on fire occurrence in targeted areas. Therefore, it is recommended that future studies first aim to understand the local fire climate before including environmental variables in a framework for fire monitoring.

9 | CONCLUSION

In conclusion, ecological diversification requires fire, which occurs naturally under specific climatic conditions and available fuel load. Without proper understanding, fire management strategies will be ineffective, and wildfires will continue to be the most common form of fire occurrence. To address this issue, fire management strategies should rely on prescribed burns, firebreaks and slash-and-burn techniques, all based on localised conditions. Remote sensing is the most common form of fire monitoring, providing early detection and prediction capabilities. However, ground-based and airborne remote sensing techniques are often too expensive or inefficient, needing more spatial and temporal resolution for effective monitoring. Therefore, current studies focus on satellite-based techniques, which increase spatial and temporal resolution while reducing data acquisition costs. Models alongside satellite-based monitoring can help predict the areas needing fire management. Thus, a remote sensing framework for fire monitoring will assist with fire management strategies and improve their efficiency.

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CONFLICT OF INTEREST STATEMENT

No conflicts of interest.

DATA AVAILABILITY STATEMENT

The authors confirm that the data supporting the findings of this study are available within the article (and/or) its references.

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