Prescribed burning effects on savanna fire spread, intensity, and predictability

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Abstract

Fire is an integral part of the Earth for millennia. Recent wildfires exhibited an unprecedented spatial and temporal extend and their control is beyond national firefighting capabilities. Prescribed or controlled burning treatments are debated as a potential measure for ameliorating the spread and intensity of wildfires. Machine learning analysis using random forests was performed in a spatio-temporal data set comprising a large number of savanna fires across 22 years. Results indicate that controlled fire return interval accounts of 3.5% of fire spread and 3.5% of fire intensity. Manipulating burn seasonality accounted for 5% of fire spread and 6% of fire intensity. While manipulated fire return interval and seasonality moderated both fire spread and intensity, their overall effects were low in comparison with hydrological and climatic variables. Predicting fire spread and intensity has been a poor endeavour thus far and we show that more data of the variables already monitored would not result in higher predictive accuracy. Given that the main driving factors of fire spread are related to hydrological and climatic variables, we suggest investigating further the use of climatic refugia against wildfires.

Keywords

Machine learning; data analytics; random forests; prescribed burning; savanna; fire management; environmental informatics; essential data
Introduction

Humans are the sole species that can proactively ignite or suppress fires, shaping landscapes (Brown et al. 2009). Fire is not necessarily a hazard; it is an indissoluble ecosystem component having also several positive ecosystem aspects (Lino et al. 2019). However, recent wildfires are extended to very large surface areas, and their duration is exhibiting longer temporal scales. The vast majority of fires occurs in savanna ecosystems (Randerson et al. 2018) and savannas cover about a fifth of the global land surface and about half of the area of Africa, Australia, and South America (Scholes and Archer 1997, Moustakas et al. 2010).

Despite several decades of research our understanding of factors shaping fire dynamics remains poor. The causes of increased fire risk are linked to climate change, resulting in increased prevalence of hotter and drier periods (Di Virgilio et al. 2019). However, increased fire risk can also derive by economic and social changes, and political decisions (Hesseln 2000, Tàbara et al. 2003, Poudyal et al. 2012). In some areas fires are exacerbated by rural land abandonment and increased ignition probability in the growing rural-to-urban interface (Flannigan et al. 2009). In some other areas anthropogenic fire, at a higher frequency than the natural fire return interval, has traditionally been practiced for pasture, agriculture or fire prevention (McDaniel et al. 2005). Increased fire risk merits research, regarding how fire spreads in these complex fuel loads and what is the relative contribution of each factor into fire spread or intensity (Flannigan et al. 2009).

The increased fire risk is debated whether it can be moderated by prescribed (also referred to as controlled) burning (Penman et al. 2011). By human-induced controlled burning there is a potential for reducing the fuel load for large wildfires to occur (North et al. 2012). This can modulate both fire spread and intensity (Volkova and Weston 2019). This is feasible by burning during seasons that fuel is more humid or by burning frequently so that fuel load is lower (Higgins et al. 2007). Manipulating fire frequency and seasonality has potential effects on carbon emissions (Van der Werf et al. 2003), soil (Francos et al. 2019), carbon balance (Merino et al. 2019), species composition (Fisher et al. 2009), water & air quality (Lucas-Borja et al. 2019, Ravi et al. 2019) and thus the overall trade-off between frequent controlled fire, fire suppression, or fire control after ignition need to be accounted for (Tilman et al. 2000).

There are several studies regarding the effect of prescribed burning on fire spread and intensity. Several other studies quantify fire spread and intensity using additional climatic, hydrological, or biological explanatory variables (Espinosa et al. 2019, Lucas-Borja et al. 2019). While these studies strongly facilitate our understanding on fire dynamics, common hindrances to generalizing or training predictive models include the limited sample size of fire events (Ching et al. 2018, Nikolopoulos et al. 2018). Experimental burning treatments often have limited duration due to associated costs, legal limitations, or ethics resulting in limited spatial or temporal sample size replicate. Naturally occurring fires (i.e. not controlled fire experiments) provide data for understanding how fire spread or intensity is influenced by hydrological, climatic, and biological variables but they do not provide the what-if manipulative experimental option of quantifying fire properties had controlled burning or fire suppression preceded the fire event.

In this study we quantify the independent effect of human-induced controlled burning, climatic, hydrological, and geological characteristics on savanna fire spread and intensity across a large number of fires. The prescribed burning return interval expands both below and above the long-term mean “natural” return interval in the absence of prescribed burning, thereby including both more frequent burning as well as fire suppression. We explicitly refrained from formulating any hypotheses regarding the effects of prescribed burning as often when we make a hypothesis, we may become attached to it (Platt 1964); instead we performed data-driven analysis, making the implicit hypothesis that an underlying dependence between collected data can be objectively mined (Moustakas et al. 2019). Such
approaches (van Helden 2013) are not competitive to hypothesis-led studies; instead they are complementary and iterative with them (Kell and Oliver 2004).

Methods

A 22-year spatio-temporal dataset comprised of 956 savanna fires in the Kruger National Park (KNP), South Africa was used. KNP is located on a low-lying savanna landscape covering at total area of 19,485 km², and it forms one of the best studied ecosystems in terms of fire (Higgins et al. 2007). KNP is comprised of four savanna landscapes (Govender et al. 2006). All data used here have been published elsewhere addressing different questions (Govender et al. 2006, Higgins et al. 2007). The dependent variables analyzed included fire spread and fire intensity; the analysis was repeated twice, once for each depended variable, all else been equal regarding the independent variables. Fire spread and fire intensity were quantified as a function of fire return interval, wind speed, fuel load, soil type, relative humidity, fuel moisture, air temperature, and rainfall during the last year. These are variables commonly used for monitoring fires. The study plots are generally flat and for this reason no topographical variables were used.

Explanatory variables

A detailed data description is provided in (Govender et al. 2006, Higgins et al. 2007). In brief: each experimental burning treatment (i.e. fire event) consisted of a seven hectares surface area plot. Each of the 956 fire events consists of a combination of a fire return interval and fire seasonality. A unique fire frequency and seasonality treatment is applied on each plot through years. Prescribed burning treatments included a manipulated fire return interval of 1, 2, 3, 4, and 6 years, when the natural fire return interval is 4.5 years. Fire seasonality as prescribed burning intervention included autumn, winter, spring, and summer burns. Fuel load before each fire event was estimated in the field using a disc pasture meter (Bransby and Tainton 1977) calibrated for KNP (Trollope and Potgieter 1986). The average of 100 random records of fuel load within each plot prior to each fire event in kg m⁻² was used as a fuel load value for the fire event. The predominant soil bedrock on each experimental burning plot was recorded. These included basalt or granite. Prior to each fire, the moisture content of the fuel load was estimated by sampling four 100-g swards. The samples were stored in air-proof bottles and sequentially dried moisture content was expressed as a percentage of dry mass: $M = \frac{[(W - D)/D]}{100}$, where $M$ is the fuel moisture content, $W$ the wet mass of the grass sward sample and $D$ the dry mass of the sample. Mean precipitation over the previous two years preceding the fire event was used as a proxy of rainfall. Then mean of two years instead of one was used because the effect of rainfall on perennial grasses persists for more than a year (Van Wilgen et al. 2004). Precipitation data were obtained from the nearest to the fire plot permanent rainfall recording gauges within KNP in mm year⁻¹. The mean wind speed recorded in m sec⁻¹, air temperature in °C, and the relative humidity (%) of the air during each fire event were also retrieved from the nearest weather recording KNP gauges.

Fire spread and intensity

Fire intensity was estimated as Byram’s (Byram 1959) fire-line intensity $I = H * w * r$, where $I$ is fire intensity (kW m⁻¹), $H$ is heat yield (kJ g⁻¹), $w$ is the combusted fuel mass (g m⁻²), and $r$ is the rate of spread of the heat fire front (m sec⁻¹). Heat of combustion was determined with a calorimeter, and values were corrected to heat yields to allow for incomplete combustion in vegetation fires (Byram 1959, Govender et al. 2006). All fire intensity values were ranked from lowest to highest and binned to five bin classes from bin class one representing the lowest fire spread to bin class five representing the highest fire spread. Approximately equal data representation per bin class was used.
Fire spread was estimated (Govender et al. 2006) as \( r = A/(L \times T) \), where \( r \) is the rate of spread (m sec\(^{-1}\)), \( A \) is the area burned as a head fire (m\(^2\)), \( L \) the mean fire front length (m) and \( T \) the duration of the fire (s). All fire spread values were ranked from lowest to highest and binned to five bin classes with approximately equal data representation within each bin. Bin one represents the slower spreading fires while bin five the fastest.

**Data analytics**

Random Forests (RF); (Breiman 2001) employ boosting (Schapire et al. 1998) and bagging algorithms (bootstrap aggregating; (Breiman 1996)) of the Classification And Regression Tree (CART; (Breiman 2017)) model, and use a more random but more efficient node splitting strategy than standard CARTs (Liaw and Wiener 2002). RFs have been employed in a wide variety of classification and prediction problems (Daliakopoulos et al. 2017, San-Miguel et al. 2020) as they rank among the most efficient analytic tools for extracting information in noisy, complex, and high dimensional datasets (Wager et al. 2014, Scornet et al. 2015). An extensive data-driven model inter-comparison by (Fernández-Delgado et al. 2014) showed that they may be one of the strongest data analytics tools for real-world problems.

We trained and tested a RF classifier, using 10 different random states, for each train-to-testing data split candidate. The data split partitioning explored included the following training to testing data partitions: 90-10, 80-20, 75-25, 70-30, 50-50 measuring each time the model accuracy. The optimal partitioning was chosen with respect to minimizing the out-of-bag CART error based on bagging of a selection of the input observations (James et al. 2013).

Having detecting the optimal train-to-testing data split, we quantified the partial dependence (Friedman 2001) of fire return interval and fire seasonality on fire spread. The partial effect of fire return interval was also quantified on fire intensity. Partial effects in RF quantify the independent effect of an independent variable on the dependent variable as a percentage all else been equal (Friedman 2001). For example a 5% increase in fire spread when the fire return interval increases from 2 years to 3 years, indicates that when fire return interval increases by a unit of one (year), there is a 5% chance of fire spread increasing by one bin, to the next bin that includes higher spread binned data (Zhao and Hastie 2019).

In order to quantify the relative independent contribution of each of the nine explanatory variables of fire spread or fire intensity we calculated the percentage of increase in mean square error of each variable. This analysis quantifies the relative change in the predictive accuracy of the dependent variable (fire spread or fire intensity) based on changes in the explanatory variables. A variable can be considered a strong predictor when permuting it increases the prediction error (Gregorutti et al. 2017). To that end such analysis provides a ranked explanatory analysis of the most informative variables for predicting fire spread or intensity from the ones examined. The analysis can handle partly correlated variables (Gregorutti et al. 2017).

The code used for implementing all random forests analytics and visualization in Python is provided in the supplementary material.

Linear regression between fuel load (dependent variable) and fire return interval was performed to quantify whether a linear relationship between fuel load and fire return interval exists. Analysis of variance (ANOVA) was performed between fuel load (dependent variable) and fire return interval as a continuous variable or fire seasonality as a factor. ANOVA results were plotted at each factor level mean, the overall mean, and the 95% decision limits (Schilling 1973). If a point falls outside the decision
limits, then evidence exists that the factor level mean represented by that point is significantly different (at a 5% significant level) from the overall mean (Schilling 1973).

Results

The optimal training-to-testing data split minimizing mean error included a 75-25 % partition for fire spread and 70 – 30 % for intensity.

Fire spread increased with increased values of fire return interval as indicated by a positive partial dependence increasing from 0.19 when annual burn occurred to 0.235 when the fire return interval was six years (Fig. 1a). Fire spread was minimized during winter months with a partial dependence of 0.14 on fire spread, increased with an almost identical effect of spring and autumn fires with a partial dependence close to 0.23, while it maximized during summer months with a dependence effect of 0.24 (Fig. 1b).

Fire intensity increased with increased values of fire return interval with the partial dependence increasing from 0.19 when annual burn occurred to 0.245 when the fire return interval was six years (Fig. 1c). Fire intensity was minimized during winter months with a partial dependence of 0.15 on fire intensity, increased with spring fires to a partial dependence of 0.21 and autumn to 0.22 with summer fires exhibiting the highest partial dependence on fire intensity of 0.225 (Fig. 1d).

The most informative variable for predicting fire spread was fuel moisture with a relative independent effect of 21%, followed by relative humidity with an effect of 15%, wind speed 14%, last years’ rainfall explaining 14%, fuel load 13%, and air temperature 11.5% (Fig. 2a). Fire return interval explained a 3.5% of the total (mean value) reaching a maximum explanatory power of 5% (upper level of the error bar); (Fig. 2a). Seasonality of fire had a relative independent effect of 6% reaching a maximum explanatory power of 10% (upper level of the error bar); (Fig. 2a). The least important predictor was soil type explaining 2% (Fig. 2a).

Fire intensity was best explained by fuel load with a relative independent effect of 21.5% followed by fuel moisture 16.5%, relative humidity 12.5%, air temperature 12.5%, rainfall 12.5%, and wind speed 12% (Fig. 2b). Seasonality of fire explained 5% with a maximum explanatory power of 6.5% (upper level of the error bar), while fire return interval 3.5% with a maximum explanatory power of 5% (Fig. 2b). Soil type also explained 3% (Fig. 2b).

The predictive accuracy (i.e. predicting the bin size of fire spread based on values of the independent variables using the trained RF model minimizing the out-of-bag CART error based on bagging of a selection of the input observations (James et al. 2013)) of fire spread is in general lower than or close to 50% (Fig. 3a). The predictive accuracy is not sensitive to the overall amount of available data as partitioning the dataset into a range of 50% training 50% testing or 90% learning 10% testing would yield very small differences in the predictive accuracy of fire spread (Fig. 3a).

The predictive accuracy of fire intensity is in general lower than or close to 50% (Fig. 3b). The predictive accuracy is not sensitive to the overall amount of available data as partitioning the dataset into a range of 50% training 50% testing or 90% learning 10% testing would yield very small differences in the predictive accuracy of fire spread (Fig. 3b).
Fuel load is only weakly correlated with fire return interval with an $R^2 = 1.9$%; linear regression

$$\text{Fuel load} = 3227 + 241.9 \times \text{Frequency}, SS = 44953185, F = 19.5, p << 0.001.$$ 

ANOVA between fuel load and fire return interval indicated that annual burning decreased the mean fuel load as well as burning every six years (Fig. 3c). However, burning every three years increased the mean fuel load, while burning every two or four years had an effect that could not be differentiated from random (Fig. 3c). ANOVA between fuel load and seasonality of burning indicated increased fuel loads for autumn and summer burns, decreased fuel loads for winter burns, and no significant effect of spring burns (Fig. 3d).

**Discussion**

The analysis performed here indicates that savanna fire spread is only mildly influenced by fire return interval and fire seasonality. Instead, fire spread is mainly determined by hydrological and climatic factors; the top three most important variables for fire spread include hydrology-related phenomena, while the next two more informative one include temperature and wind characteristics. To that end inclusion of hydrological ecosystem variables can enhance the understanding of fire spread (Taufik et al. 2017). Therefore, abrupt climatic changes regarding drought, heat, and intensive wind are highly likely to influence/increase fire spread. Abrupt events have also been shown to increase temporal synchrony across increasing spatial scales (i.e. generating cycles that can last longer across greater spatial extend) and to that end fires may become more temporally synchronized (Hansen et al. 2013, Sheppard et al. 2015, Moustakas et al. 2018). Based on the results derived here and despite an overall small effect, manipulating seasonality has an overall higher impact on fire spread and intensity than manipulating fire return interval. This means has implications for potential de-synchronization of available fuel loads by seasonally asynchronous burning in different locations thereby reducing the risks of climate-induced synchronized fires across landscapes or regions.

Prescribed burning will moderate fire spread and intensity but the net cumulative effect of both burning more frequently and during the winter will account for less than 10% on average of fire spread and fire intensity. The net $\approx 10$% positive effect of prescribed burning on fire spread and intensity needs to be examined in synergy with potential interaction effects. More frequent burning may increase carbon emissions (Brown and Johnstone 2011) in comparison to the ones that would have occurred in the absence of human intervention potentially feeding back the climate-fire loop. On the other hand, fire suppression can result in increased carbon uptake by land (Arora and Melton 2018, Jones et al. 2019) as well as it may play an important role in offsetting impacts of increased ignitions (Keeley et al. 1999). In addition, more frequent burning shapes the environment by potentially selecting for fire prone species, or fast growing plant species (Hengst and Dawson 1994, Schwilk and Ackerly 2001). Fire may also facilitate invasive alien species (Fisher et al. 2009).

Fire intensity was best explained by fuel load. What is the reciprocal effect of prescribed burning on fuel load? Annual burning and winter burning reduced fuel loads. However, the overall relationship between fire return interval and fuel load is not linear (six year burning reduced mean fuel loads but two, three and four-year burns did not), and fuel load is developed rapidly since last fire (Pausas and Ribeiro 2013). Thus, frequent burning reduces fuel load but the overall effect of fire frequency on fuel load remains complex indicating that there are other interacting factors shaping fuel load. It is important to note that despite fuel load ranking first in predicting fire intensity, the effect of fuel moisture and relative humidity (the 2$^{nd}$ and 3$^{rd}$ most important variables) are having cumulative a predictive accuracy of $\approx 30$%.

The predictive accuracy of fire spread and intensity was low despite using a large number of fires deriving from one of the most well-studied savanna fire ecosystem on Earth. Predicting fire intensity or fire spread has in general been a poor endeavour so far; accuracy of predictions have not yet
exceeded 50% (Cruz et al. 2018, Coffield et al. 2019). Interestingly, having additional data would not result in higher predictive accuracy as reported here. While increased sample size enhances model training, a trained model may not go beyond the information content of the variables sampled (Evans et al. 2014). Thus, there is a need for developing “essential fire variables” as suggested for biodiversity or forestry (Evans and Moustakas 2016, Jetz et al. 2019) for increasing fire spread and intensity predictive accuracy. Which interactive variables/factors could include predictive accuracy? There is species adaptation to fire (Schwil and Ackerly 2001) by partitioning underground resources and thus including species identity could increase the predictive ability. Enhanced nutrients after fire (Van de Vijver et al. 1999), or drought-related indexes such as the standardized precipitation index (Keyantash 2018) or factors influencing fuel load are likely to improve the predictive accuracy. Spatial information such as density effects, distance to the nearest neighbours, or spatial distribution of trees or fuel load may also be critical (Hochberg et al. 1994, Moustakas 2015). Additional second order (more local) hydrological and climatic variables that seem to play a major role for fire spread and intensity may also increase predictive accuracy.

Conclusions, data science, and ecosystem management implications

It is common in scientific studies to conclude with a call for more data and revisit the reported results in the light of more data. On an information-theoretic approach, ‘information’ about the system under study exists in the data and the goal is to extract knowledge from this information in a compact way (Evans et al. 2014, Lonergan 2014). More often than not, the more data available the more information exists, and thus the deviance between model fit and the reality as expressed from data will be minimized – but see also (Boivin and Ng 2006) and discussion in (Moustakas 2017). However, recent advances in data analytics and data science bring an additional element which is to quantify the predictive ability of a trained model and its transferability of predictions in a dataset different than the one used for model training (Padarian et al. 2019). If data set size is having an effect on the variance rather than the mean of predictive accuracy this can serve as an indicator of investigating the inclusion of additional phenomena using information-theoretic approaches.

While fire return interval or seasonality had a relatively small effect on ameliorating fire spread and intensity, intensity was best predicted by fuel load. Albeit fuel loads exhibit a non-linear relationship with fire return interval, annual burn and winter fires reduced fuel loads in the savanna studied. Thus, in cases where keeping open landscapes is desired, or for agricultural purposes, or for avoiding the dominance of thorny woody species, frequent burning will reduce fuel loads as traditionally practiced through centuries (Sheuyange et al. 2005). However, prescribed burning seems unlikely to be an efficient option for controlling the spread of wildfires at least in fire-prone savannas such as the one studied. Savannas have been fire-prone ecosystems for very long time scales and fires are both natural and anthropogenic to a point that is hard to distinguish between them (O’Connor et al. 2011, Bowman et al. 2016). Given that the major variables related with fire spread and cumulatively with fire intensity are related with climatic and hydrological properties, a potential option that would merit further investigation would be to create climatic refugia; climatic refugia as a term was originally introduced to refer to locations where species survived the last glacial period (Bennett and Provan 2008), and they have recently been attributed with species conservation against climate change (Graham et al. 2019, Li et al. 2019). Based on the findings reported here, climatic refugia can act as barriers against wildfires. Locations with fuel moisture and relative humidity are good candidate areas for climate refugia against fire spread and intensity. It can also be an option for future research to examine the spatial coexistence of climatic refugia with fire refugia. Fire refugia are areas minimally affected by wildfires facilitating ecosystem resilience and recovery after fire (Downing et al. 2019).
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Figure 1. Partial dependence plots of fire return interval and seasonality on fire spread and intensity. A partial dependence plot indicates the percentage of change in the dependent variable based on the values (units) of the independent variable, all else been equal. The units of the dependent variables here are bins (of fire spread or intensity) from one to five, while the dependent variable follows its reciprocal units. Results from a 75-25 % training to testing data split are shown, replicated across 10 different random states. a. Partial dependence of fire return interval in years on the rate of fire spread. b. Partial dependence of seasonality (Fall, Winter, Spring, Autumn) of fire on fire spread. c. Partial dependence of fire return interval in years on fire intensity. d. Partial dependence of fire season (Fall, Winter, Spring, Autumn) on fire intensity.
Figure 2. Percentage of increase in mean square error of each independent variable, in red solid boxes. Higher values indicate higher importance of that variable for predicting the dependent variable. Vertical black lines indicate the 95% confidence intervals of the effect of each independent variable. Values in each graph add to one. **a.** Percentage of increase in mean square error in predicting fire spread. Results from a 75-25% training-to-testing data split are shown, replicated across 10 different random states. **b.** Percentage of increase in mean square error in predicting fire intensity. Results from a 70-30% training-to-testing data split are shown, replicated across 10 different random states.
Figure 3. a. Mean predictive accuracy of fire spread based on the ratio of the training-to-testing data set size. For each dataset partitioning size, the data analysis was replicated across 10 different random states and the mean accuracy with 95% confidence intervals are plotted. b. Mean predictive accuracy of fire intensity based on the ratio of the training data set size as a percentage of the total data. For each dataset partitioning size the data were analyzed 10 times to account for stochasticity and mean accuracy with 95% confidence intervals are plotted. c. Analysis of variance (ANOVA) between fuel load (kg m⁻²) and fire return interval (years). Horizontal solid green line indicates the mean effect of fire return interval on fuel load. Horizontal dotted red lines indicate the upper and lower 95% confidence intervals. Vertical solid blue lines indicate the effect of each fire return interval value on the grand mean. Values crossing the dotted confidence interval indicate a significant effect, while the remaining may not be differentiated from a random effect. Values crossing the upper confidence interval indicate a positive effect, while values crossing the lower indicate a negative effect on the grand mean. d. ANOVA between fuel load and seasonality of burn.