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Original Articles

Fire regimes at the arid fringe: A 16-year remote sensing perspective (2000–2016) on the controls of fire activity in Namibia from spatial predictive models

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ABSTRACT

Dry-season fires affect the grassland and savanna ecosystems in Namibia and other regions around the globe. Whereas climate, especially precipitation, has been found to constrain fire activity in (semi-)arid regions through productivity, the feedbacks with human systems lack generalization. Here, we assess the biophysical and human-related controls of fire activity in Namibia based on a 16-year record (2000–2016) of the MODIS Burned Area product (MCD45A1). The two derived parameters of fire activity include burned area (positive continuous) and the number of fire occurrences (zero-inflated counts), and are individually investigated at a 0.1°-resolution by means of five common statistical and machine-learning techniques. We evaluate performance and consistency among the models using the adjusted coefficient of determination and the root mean square error, which is obtained from 5-repeated 10-fold cross-validation. A comparable measure of predictor importance among the models is assessed by means of a permutation-based approach. As spatial autocorrelation is present for both parameters of fire activity, we consider this with a spatial cross-validation setup, where *k*-Means clusters of geographic coordinates are used to derive the test partitions. We find complex machine-learning techniques generally improve the predictions of both parameters of fire activity. Our results confirm the exceptional importance of mean annual precipitation for fire activity across Namibia and highlight human impacts as an additional control of fuel availability. Apart from an increase of burned area and fire occurrences at a mean annual precipitation of approximately 400 mm, population and livestock densities strongly limit fire activity in the best-performing Random Forest models. The largest burned areas are found with moderate green-up rates of vegetation, which we attribute to the presence of open landscapes. The consideration of spatial autocorrelation generally decreases model performances but the relative decreases are higher for the models of burned area, which we attribute to the increased spatial autocorrelation present with this response variable. Resultantly, we recommend accounting for spatial autocorrelation in the evaluation of spatial ecological models and the assessment of predictor importance. Although Namibia's land use practices denote a special case, our model may be of relevance to other regions located at the arid fringe of fire-affected ecosystems and those with projected future aridification.

1. Introduction

Southern Africa is a hotspot of global fire activity (Andela et al., 2017; Giglio et al., 2013). The evolution and maintenance of these savanna and grassland ecosystems have been causally linked to recurring fire occurrence (Bond, 2008; Bond and Keeley, 2005; Cerling et al., 1997). Fires impact greenhouse gases and aerosol emissions (Bond et al., 2013; Giglio et al., 2013; Lehsten et al., 2009), vegetation succession (Heinl et al., 2007; Keeley et al., 2005), nutrient cycling (Coetsee et al., 2010; Pivello et al., 2010) and species composition/diversity (Pausas and Verdú, 2008; Uys et al., 2004). Thus, their spatio-temporal patterns are critical inputs for global climate and dynamic vegetation models (Mouillot et al., 2014; Thonicke et al., 2010). Global climate change is likely to alter these patterns (Bowman et al., 2009; Krawchuk et al., 2009), yet large uncertainties about the direction and regional influence remain (Settele et al., 2014). Hence, the assessment

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of the typical fire occurrence in a region, i.e. the fire regime, and a detailed understanding of its controls build a vital framework to address these uncertainties and to potentially adapt policies.

Operationally produced fire records from Earth observation systems, such as the National Aeronautics and Space Administration's (NASA) Moderate-resolution Imaging Spectroradiometer (MODIS) Burned Area (BA) product (Roy et al., 2005), are currently widely used in the fire research domain as they are globally available and of unique spatial and temporal consistency. With almost 20 years in orbit, the MODIS BA record also allows for the capturing of variability of lower-frequency fire recurrence, such as those found at the arid fringe of fire-affected ecosystems.

Within the (semi-)arid spectrum of fire-affected ecosystems, such as Namibia, fire activity is generally constrained by productivity (Krawchuk and Moritz, 2011; Pausas and Ribeiro, 2013). Thus, the availability of (surface) fuels, which is a function of preceding precipitation and its variability, limit the initiation and spread of fires, although atmospheric conditions during dry season would promote these. The importance of climate-fuel interactions for fire regimes has been confirmed at various scales and for different savanna regions – e.g. Northern Australia (Spessa et al., 2005), Eastern (Nelson et al., 2012) and Southern Africa (Archibald et al., 2009, 2010a; Heinl et al., 2006; O'Connor et al., 2011; van Wilgen et al., 2004). Fire activity in Namibia follows a distinct climatic gradient from the arid South and West to the more humid North-East, where approximately 30–50% of the land area burns on an annual basis (Verlinden and Laamanen, 2006).

Biophysical determination accounts for the framework of fire occurrence. However, humans strongly impact fire regimes as they accidently and deliberately ignite fires, while simultaneously directly and indirectly suppressing them (Archibald et al., 2012; Guyette et al., 2002). Indirect human suppression pathways act on fuel load via reduction as well as fragmentation, e.g. from land conversion or livestock grazing. All over Southern Africa the majority of fires are intentionally lit by humans (Archibald et al., 2010b), who use fire as a tool for land management (e.g. hunting, pest control, land clearance, nutrient recycling, green shoot initiation, among others). Accordingly, Archibald et al. (2010a) conclude that the climatic controls on fire are stronger in protected areas, which are hypothesized to be less affected by humans as compared to the whole subcontinent. However, generalizations of human impacts on the fire regime appear difficult, even at a regional scale. Increasing human densities were found to reduce BA (Archibald et al., 2009), and shift fire size distributions towards smaller, more frequent fires (Archibald et al., 2010b). Le Roux (2011) finds Namibian fire regimes to differ among land tenures which he attributed to the corresponding fire management strategies and capabilities. The importance of management is supported by a study of the Kavango-Zambezi Transfrontier Conservation Area (Pricope and Binford, 2012), that documents the marked differences in BA and fire recurrence as a function of the fire policies in the five countries involved (including Namibia).

A large set of facilitating and limiting variables of biophysical and human origin and their complex interactions may, thus, be responsible for the observed patterns of fire activity in a region. State-of-the-art predictive modeling techniques help us to quantitatively understand such patterns and to unveil the dependencies behind these. So-called machine-learning algorithms are often shown to improve complex pattern identification as compared to conventional statistical methods in the fire research domain (e.g. Amatulli et al., 2006; Bar Massada et al., 2012; Bedia et al., 2014; Cortez and Morais, 2007; Faivre et al., 2016; Rodrigues and de la Riva, 2014; de Vasconcelos et al., 2001), as well as other disciplines (e.g. Goetz et al., 2015; Singal et al., 2013 – among many others). However, no single method has been identified as the best method, rather each has different strengths and weaknesses (e.g. with the handling of factor predictors and extreme values, the treatment of interactions, and interpretability).

With regards to predictive modeling, a major limitation of the approach arises from the fact that the ignitions can only be inferred from indirect variables (Krawchuk and Moritz, 2014). The exact occurrence of an ignition, especially of unintentional origin or from lightning, carries an indeterminable uncertain degree of stochasticity. As fires originate from an ignition source and propagate under facilitating conditions, their observations are likely to be autocorrelated, i.e. their patterns show distinct spatial, but also temporal dependencies. Where the presence of Spatial Autocorrelation (SAC) violates the assumption of independence with parametric techniques, its negligence may generally result in biased models (Dormann et al., 2007; Dorner et al., 2002). Best-practice spatial modeling accounts for SAC, either by including SAC as a separate (weighing) variable in the model or removing SAC from the observations, e.g. by selection of a non-correlated subset (see Dormann et al. (2007) for an overview). Another approach is to correct for the underestimation of model errors as a result of SAC by spatially clustering the evaluation partitions in a cross-validation procedure (Ruß and Brenning, 2010). Hence, the full set of observations may be used to fit the model and the effects of SAC on model performance. In addition, predictor importance can easily be assessed by comparing 'non-spatial' vs. 'spatial' evaluations across various predictive techniques.

Here, we apply a predictive modeling approach to investigate the controls of two main fire regime parameters derived from a 16-year Earth-observation record, namely Burned Area (BA) and Fire Occurrence (FO), in Namibia. We use five common statistical and machine-learning techniques to predict BA, which is positive-continuous, and FO, which comprises zero-inflated counts. We assess the models' performance and consistency, and consider spatial dependency structures as indicated by SAC. Precipitation is hypothesized to be the primary control of overall fire activity in Namibia as it determines fuel availability. Human activities (e.g. land fragmentation or tenure) could alter and even override the climate-fire relationship. We expect that human activities may lead to diverse feedbacks on fire activity, i.e. they negatively affect the spatial extent of fires (BA) but could cause more frequent fires (FO). Both fire regime parameters should show distinct spatial structures, which would justify the consideration of SAC in the model evaluation. Furthermore, we expect complex interactions with biophysical and human-related predictors, favoring the usage of machine-learning over conventional statistical techniques.

The expected insights of our work contribute to the highly-needed quantitative understanding of the linkage between biophysical and human systems (Beringer et al., 2015). As fire management plans and policy decisions are often determined nationwide, our investigation on the national scale could deduce important implications for the management of fire and ecosystems in Namibia, as well as for countries with comparable environmental conditions and land use practices. Ultimately, our case study may prove as a reference for the understanding of fire regime responses to future aridification as proposed for many savanna regions (Kirtman et al., 2013).

2. Materials and methods

2.1. Study area

In Namibia, the most arid country of Sub-Saharan Africa, precipitation is largely restricted to the Austral summer, where the dependence on convective complexes introduces a pronounced spatial variability in intra-seasonal water availability (Blamey and Reason, 2013). Inter-annual variability of precipitation is a function of aridity due to the increasing dependence on single events for Mean Annual Precipitation (MAP). Relative variability is most pronounced in the West and South of Namibia and the North and North-East reach the highest MAP of up to approximately 600 mm (Mendelsohn et al., 2002). The gradient of MAP largely determines natural vegetation, but edaphic properties may alter this pattern of productivity. For instance, high salinity in the proximity of ephemeral water bodies facilitates the