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Deriving forest fire ignition risk with biogeochemical process modelling☆

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ABSTRACT

Climate impacts the growth of trees and also affects disturbance regimes such as wildfire frequency. The European Alps have warmed considerably over the past half-century, but incomplete records make it difficult to definitively link alpine wildfire to climate change. Complicating this is the influence of forest composition and fuel loading on fire ignition risk, which is not considered by purely meteorological risk indices. Biogeochemical forest growth models track several variables that may be used as proxies for fire ignition risk. This study assesses the usefulness of the ecophysiological model BIOME-BGC's 'soil water' and 'labile litter carbon' variables in predicting fire ignition. A brief application case examines historic fire occurrence trends over pre-defined regions of Austria from 1960 to 2008. Results show that summer fire ignition risk is largely a function of low soil moisture, while winter fire ignitions are linked to the mass of volatile litter and atmospheric dryness.

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1. Introduction

Climate change is expected to impact forests in a number of ways, both directly and indirectly. One of the most important indirect effects in many regions is the possibility of increasing wildfire risk (Brown et al., 2004), and the introduction of fire as an important shaper of landscapes in areas where this has not been the case for centuries or millennia (Schumacher, 2004). Fires are an integral part of many forest ecologies, and have always been fundamental in shaping forest structures and assemblages (Bond et al., 2005; Bowman, 2005; Lynch et al., 2007). Fire regimes are strongly interlinked with climate changes (Whitlock et al., 2003; Meyer and Pierce, 2003; Taylor and Beaty, 2005), and so it is not unreasonable to expect changes in the occurrence and severity of forest fires in many regions. Increased temperatures alone do not necessarily mean that more fires will occur; several other climatic and non-climatic factors are also involved such as ignition sources, fuel loads, vegetation characteristics, rainfall, humidity, wind, topography, landscape fragmentation and management policies (Flannigan et al., 2000). Taking these factors into account Flannigan et al. (2005) reviewed fire predictions for North America and suggested that overall increases in area burned may be in the order of 74–118% by the end of the 21st century. A further observed impact of recent environmental change is an increase in forest growth in many areas (i.e. Phillips et al., 1998; Hasenauer et al., 1999; Nemani et al., 2003), which may lead to increased fire hazard due to changing fuel loads (Lenihan et al., 1998) and depleted soil moisture.

Several studies have been conducted in an attempt to assess possible future fire risk under changed climatic conditions (i.e. Pitman et al., 2007; Malevskii-Malevich et al., 2007; Good et al., 2008; Krawchuk et al., 2009; Holsten et al., 2013). Well-validated predictive tools for forest fire risk would be useful for resource allocation (Cantwell, 1974; McCarthy et al., 2003; Prestemon and Donovan, 2008), emergency services budgeting (Thompson et al., 2013), infrastructure planning (Eastaugh and Molina, 2011, 2012) and warning systems (Valese et al., 2010; Arpaci et al., 2013). Such studies generally rely on defining some meteorological index of fire risk, and calculating the development of that index under future

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climate scenarios. Inherent in this approach is the assumption that the relationship between the meteorological variables and fire risk will remain constant, which may not be the case if the future climate, management activities or natural ecosystem development with aging alters forest conditions. Recent work from Pausas and Paula (2012) suggests that ecosystem productivity may be a key determinant of fire sensitivity, in which case an ideal fire risk indicator must take such non-climatic factors into account.

Numerous fire risk indices have been developed over the past seventy years, beginning with the purely empirical meteorological indices of Ångström and Nesterov in the 1940s. Käse (1969) modified the Nesterov index to account for higher probability of fire in spring, dependent on the budburst date of birch and robinia trees. Keetch and Byram (1968) developed an index of soil moisture deficit (KBDI) for use by fire agencies, on the principle that soil dryness is likely to be accompanied by fuel dryness. The more sophisticated Canadian Forest Fire Weather Index of Van Wagner (1987) expressly considers how weather conditions affect the moisture content of different fire fuel layers. The more easily ignited fine fuels lose moisture quickly under dry atmospheric conditions, while larger fuels dry only after extended periods. Tanskanen and Venäläinen (2008) have pointed out however that the accuracy of the indices can vary seasonally depending on the proportion of dead to live fine fuels on the forest floor. To some extent this suggests that fire ignition risk may potentially be reduced through appropriate management regimes, although this will require a comprehensive understanding of how ignition risk relates to forest physiological processes. It is likely that the sophisticated biogeochemical process models developed over recent years may be useful to assist this understanding. We chose here the Angström, Nesterov and KBDI indices to represent a continuum of fire index types from a simple instantaneous index, to one that includes consideration of precipitation, to a more complex accumulative index with a physical interpretation.

Many of the various parameters implicated in forest fire behaviour are also important parameters in biogeochemical forest growth models. Keane et al. (1996) took advantage of this in linking the FOREST-BGC model of Running and Coughlan (1988) with the specifically fire-optimised gap model FIRESUM (Keane et al., 1989). More recently, Keane et al. (2011) used the BIOME-BGC model (Thornton, 1998) as an input into Fire-BGCv2, a highly sophisticated research tool linking biogeochemical modelling, forest succession models and fire spread behaviour. Management-sensitive parameters such as fuel volumes clearly have an impact on fire behaviour (Finney, 2006), but the possible link between these parameters and the relative likelihood of fire ignition has not yet to our knowledge been explicitly studied with a biogeochemical model.

Biogeochemical models track the pools and fluxes of water, carbon and (often) nitrogen in an ecosystem, and allocate the carbon taken up by photosynthesis to various components of the system. With various degrees of complexity, the models include consideration of soil moisture and litter volumes and composition. Our contention is that these variables may prove to be reasonable indicators of forest fire ignition risk, at least comparable with meteorological indices over short time frames. If this is the case, then it is likely that the model-derived indices would be superior over longer timescales, due to their incorporation of how forests change over time, particularly in a changing climate or under varying forest management practices.

Although the focus of this work is on exploring the use of biogeochemical forest growth modelling in forest fire risk evaluation, we also provide a brief application case, examining the seasonal drivers and trends of fire ignition risk in Austria. Central European alpine regions are not typically considered high fire risk areas but there is mounting concern over the possibility of increased risk in the near future (Conedera et al., 2006; Gossow et al., 2009; Wastl et al., 2012). Fires are generally not large, but in rugged terrain they can be difficult to control and can have serious long term effects on the protection function of mountain forests (Brang et al., 2006; Sass et al., 2010, 2012a,b). Conedera et al. (1996) reported an increase in forest fires in Switzerland from the 1960s and 1970s, and noted that this “could not be explained simply through the analysis of particular meteorological factors or the inclusion of the major anthropogenic causes”, while Zumbrunnen et al. (2009) have pointed to the importance of both meteorological and fuel load conditions to fire occurrence in Alpine areas. We choose the Austrian situation due to the availability of a quality-checked national fire database (Müller et al., 2013; Eastaugh and Vacik, 2012), a validated climate interpolation (Thornton et al., 1997; Petritsch and Hasenauer, 2007) and a previously parameterized biogeochemical model (Pietsch et al., 2005; Eastaugh et al., 2011).

The purpose of this study is to assess whether the inclusion of forest physiological properties can potentially provide improved estimates of forest fire ignition risk, compared to simple meteorological indices. We apply the species-specific version of BIOME-BGC (Pietsch et al., 2005) to 2014 forested sites of the Austrian National Forest Inventory (NFI; Gabler and Schadauer, 2006), and record daily values of simulated soil water content (*sw*), labile litter carbon (*llc*) and vapour pressure deficit (*vpd*) at each site from 1960 to 2008. Defining two indices as BGC-SW = *sw* and BGC-LV as *llc***vpd*, we assess their precision against recorded fire occurrence data from 1995 to 2008, and compare this with the precision of the Angström, Nesterov and KBDI indices. For the application study the model outputs are geographically aggregated according to regions defined by Eastaugh et al. (2011), being those parts of Austria that have experienced climate change over the past half-century of more than one standard deviation different to the national average. The output of the application study shows trends in the BGC-LV index from 1960 to 2008, and compares the BGC-SW extremes from 1991 to 2008 against a 1960–1990 baseline. The model and the index performance comparisons allow us to suggest explanations for the seasonal variation in forest fire risk in Alpine areas. Specific outputs are:

a) A comparative evaluation of the five indices at the national scale, for both summer and winter seasons, in terms of their ability to reflect overall fire ignition risk and the occurrence of extreme risk conditions,
b) An analysis of overall trends in fire ignition risk at the regional scale using the BGC-LV index, and
c) An analysis of trends in extreme summer fire ignition risk at the regional scale using the BGC-SW index.

2. Technical background

2.1. Meteorological indices

2.1.1. Angström

Ångström (1942, cited by Ångström, 1949) developed a simple instantaneous meteorological index relating fire risk to relative humidity (*Rh*) and temperature (*T*) (Eq (1)) from field experiments in Sweden. The Angström index *AI* is calculated as:

$$AI = \frac{Rh}{20} + \frac{29 - T}{10} \tag{1}$$

The *AI* gives lower values when fire risk is higher. Fire is generally considered ‘very likely’ at values less than 2.0, and ‘unlikely’ at values over 4.0.

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