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A lightning-caused wildfire ignition forecasting model for operational use

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ABSTRACT

Lightning-caused wildfires are responsible for substantial losses of lives and property worldwide. Convective storms can create large numbers of ignitions that can overwhelm suppression efforts. Both long- and short-term risk planning could benefit from daily, spatially-explicit forecasts of lightning ignitions. We fitted a logistic regression generalised additive model to lightning-caused ignitions in the state of Victoria, Australia. We proposed a new method for model selection that complemented existing methods and further reduced the number of variables in the model with minimal change to predictive power. We introduced an approach for deconstructing ignition forecasts into contributions from the individual covariates, which could allow model output to be more readily integrated with existing intuitive understandings of ignition likelihood. Our method of model selection reduced the number of variables in the model by 37.5% with little change to the predictive power. The final model showed good predictive ability (AUC 0.859) and we demonstrated the utility of the model for short term forecasting by comparing model predictions with observed lightning-caused fires over three time periods, two of which had extreme fire conditions, while the third was randomly chosen from our validation dataset. The model presented in this paper shows good predictive power and advancements in model output could allow fire managers to more easily interpret model forecasts.

1. Introduction

1.1. Lightning-caused wildfire

Lightning caused wildfire, which we will here on call lightning fire, is a significant concern for fire management agencies worldwide. Lightning fires are an important source of wildfire ignitions, with some studies attributing upwards of 40% of recorded ignitions to lightning (Anderson, 2002; Hall and Brown, 2006). Unlike other ignition sources, lightning fires often occur in remote and inaccessible locations making detection and suppression particularly challenging (Flannigan and Wotton, 1991; Kourtz and Todd, 1992). Furthermore, individual lightning storms can result in larger numbers of fires clustered in space which can easily overwhelm suppression efforts (Podur et al., 2003). Due to these factors, lightning fires burn disproportionate amounts of land. For example, in Ontario, Canada, roughly 40% of wildfires are lightning-caused yet they go on to burn 70% (Flannigan and Wotton, 1991) to 81% of the total area (Wotton and Martell, 2005).

In Victoria, Australia, lightning fire was responsible for 70% of land burnt in the period of 1973–2014, despite constituting only 11% of ignitions. The 2003 Alpine Fires saw a cold front creating lightning storms that started 87 lightning fires in Victoria, which went on to burn approximately 1.1 million ha (Stephenson, 2010). The thunderstorms caused further fires in NSW and the ACT, which burnt a further 760,000 ha. Similarly, the 2006-07 Great Divide Fires saw 70 fires caused by a single thunderstorm, burning a cumulative 1.1 million ha. These large-scale landscape fires pose serious risks to life, property and agriculture and can cause disruptions to infrastructure. Large-scale landscape fires also disrupt ecosystem services (Gill et al., 2013), and, in water catchments, water supply and water quality (Feikema et al., 2013).

Lightning ignition can be understood as the product of three processes: lightning strike occurrence, fire ignition given a lightning strike and the ignition surviving until detection (Anderson, 2002). These processes are complex, involving vegetation, fuel moisture and weather conditions conducive to both fire growth and the occurrence of lightning. While there are strong correlations between ‘fire weather’ and lightning-caused wildfire ignition there is still much unknown about the likelihood of ignition on a given day. Dry lightning, a strike with less than 2.5 mm of accompanying precipitation, is of particular interest to land managers. Early work (Rorig and Ferguson, 1999), which has since been built upon (Dowdy, 2015; Dowdy and Mills, 2009), showed that the 850-500 hPa temperature lapse and 850 hPa dewpoint depression are influential in predicting dry lightning. There is also a link to the

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Convective Available Potential Energy (CAPE) index, which is related to lightning occurrence more generally. Work has looked at the relationship between elevation, vegetation and lightning strike density (Dissing and Verbyla, 2003; Kilinc and Beringer, 2007). Elevation can cause forced convection, resulting in lightning strikes, and topographic effects play an important role in defining vegetation type.

Given the occurrence of a lightning strike, fuel characteristics and fuel moisture determine if an ignition will occur and survive until detection. For this, there must be fuel present, it must be in a condition where it can ignite and burn (i.e. fine enough to be ignited when exposed to heat and be in a state where it can effectively release heat on combustion) and there must be a suitable degree of connectivity between flammable fuel elements to allow the fire to sustain (Duff et al., 2017). Of these, the ability of the fuel to combust is the most dynamic; as it is strongly defined by the amount of moisture in the fuel, which is a function of the moisture in the environment (Matthews, 2014). Of most interest are the dead fine fuels – particularly on the surface, as these show the greatest response to changing moisture levels, both in the air and in the soil (Matthews, 2014). The Keetch-Byram Drought Index (KBDI) represents the moisture deficit in the top 200 mm soil layer and is calculated using the maximum air temperature, total rainfall for the past 24 h and yesterday's KBDI (Keetch and Byram, 1968). As such, it reflects both daily and long-term conditions. The drought factor (DF), which represents the proportion of fine fuel available to burn in the event of a fire, uses the KBDI in its calculation (Dowdy and Mills, 2009). Both the KBDI and the DF play an important role in calculating the McArthur Forest Fire Danger Index (FFDI), which is the primary numerical tool used to communicate bushfire risk to the Australian public. It was originally developed to describe fire behaviour such as rate of forward spread, flame height and spotting distance (McArthur, 1967), but it has been shown to be related to wildfire ignition (Bradstock et al., 2009).

Finally, weather properties such as temperature, relative humidity, wind speed and precipitation can affect all parts of the lightning ignitions process. Beyond their direct involvement in calculating fuel moisture indices, they are related to lightning formation and ignition survival. There is also some suggestion that wind speed is negatively related to ignition detection since it can disperse smoke plumes (Wotton and Martell, 2005).

1.2. Modelling lightning-caused wildfire

Modelling lightning fire occurrence poses significant challenges due to the large number of environmental factors involved in the process and the inherent stochasticity caused by the "highly variable numbers of cloud-to-ground lightning strikes accompanied by very spotty rainfall" which in turn results in a highly variable number of ignitions (Wotton and Martell, 2005).

Work on lightning ignition models has been motivated by the need to produce forecasts to assist fire managers in resource allocation and suppression efforts (Martell et al., 1989, 1987; Plucinski et al., 2014; Preisler et al., 2004, 2008; Preisler and Westerling, 2007; Wotton and Martell, 2005) as well as to understand how the length of time between burning can affect ignition likelihood (Penman et al., 2013), or the effects of climate change on ignition likelihood (Liu et al., 2012; Woolford et al., 2014, 2010; Wotton et al., 2003).

Models have often focused on either human- or lightning-caused ignition but in general the approaches are the same. Early work looked at the probability of a day with one or more fires (Haines et al., 1983; Martell et al., 1987; Plucinski et al., 2014). Others divided a large study region into smaller subregions and modelled the number of fires per day in each of the subregions, which added some spatial discrimination to the model (Plucinski et al., 2014). This has been further extended, with models estimating gridded maps of daily ignition likelihood (Guo et al., 2016; Magnussen and Taylor, 2012; Preisler et al., 2004; Woolford et al., 2011). Alternatively, some have modelled the probability of fire given a lightning strike has occurred which isolates the conditions suitable for initial fire survival and growth and ignores those conducive to lightning occurrence (Wotton and Martell, 2005).

As discussed in the previous section, wildfire ignition is a complex physical process and there are a large number of covariates that could be influential in forecasting. For example, in the wildfire ignition literature, Guo et al., 2016 considered 33 covariates and selected 11 for inclusion in the final model based on the significance of coefficients in intermediate models. In Woolford et al., 2011 the authors considered 16 covariates, choosing a model with 8 covariates based on an AIC and likelihood ratio test procedure. Magnussen and Taylor, 2012 considered 70 covariates and settled on a two models containing between 15 and 19 covariates using stepwise regression (Hosmer et al., 2013), however stepwise variable selection can result in biased parameter estimation (Whittingham et al., 2006). This makes model selection, and in particular, the problem of which covariates to include in a model, an important component of modeling wildfire ignition location.

Along with issues of parsimony, the need to obtain data for a large number of covariates before making predictions can make models unwieldy for operational use. The ease of application of models is not a consideration of information theoretic model fitting approaches; however for models to be adopted for using in non-scientific fields – i.e. decision making – ideally they need to be robust, have a degree of transparency in how they reach outcomes and be no more complex than absolutely necessary. During personal communications with firefighting authorities, they expressed the need to be able to explain and communicate model output in terms of the environmental conditions driving it. This was seen as important because it would allow authorities to integrate the model output with their intuitive understanding of lightning ignition likelihood, and would give them the ability to 'sanity check' the model forecasts. In the case of linear regression models, deconstructing the forecasted likelihood into the effects of the individual covariates is simple since an increase (or decrease) in a covariate will result in an increase (or decrease) in the ignition likelihood. However, in the case of more sophisticated, non-linear models, it is not immediately clear how to do this.

1.3. Aims

We aim to produce a model that is suitable for operational use and for improving long-term risk forecasts. At a minimum, this requires the model to produce daily, spatially explicit forecasts. Furthermore, we introduce new methods that advance the model in two ways.

1 A new model selection approach allows for statistically significant, but relatively uninfluential covariates to be identified and removed from the model. The process produces a compact model without compromising on predictive accuracy.
2 A method of deconstructing a model forecasts into contributions from each of the environmental factors. This allows the model forecast to be easily integrated with intuitive understandings of lightning ignition likelihood within the firefighting community.

2. Data & methods

We used historical ignitions data and data on various covariates to produce a logistic regression model for forecasting lightning ignition. Daily forecasts are produced with a spatial resolution of 20 km.

2.1. Data

We used the combined Victorian Department of Environment, Land, Water and Planning (DELWP) / Country Fire Authority (CFA) Bushfire Ignitions dataset for ignition points and ignition causes. The word 'bushfire' is a synonym for wildfire in the study area. This dataset is the combination of the fire records kept by the two firefighting agencies in Victoria. The oldest of these records includes fires from 1903 onwards and the youngest includes fires from 1997 onwards. The copy of the