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Spatial estimates of fire risk in Victoria, Australia considering ignition likelihood and containment probability through Bayesian Network Analysis

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Abstract

Accounting for multiple changing systems in environmental decision making is challenging and requires balancing several competing priorities. In fire risk, one approach which is increasingly used to capture uncertainty within multiple systems and to prioritise management efforts is Bayesian Network (BN) analysis. Here, we have used a BN to understand the interactions between ignition likelihood, containment probability, fire behaviour, and fire weather, alongside the subsequent risks to people and property. We developed, populated and tested a BN which classifies the likelihood of outcomes for each of these systems. We then apply this BN to grid of 72,000 potential ignition locations accross Victoria to predict house and life loss values under conditions capturing the top ten worst ranked weather days in the history of each location. We use Phoenix fire behaviour simulations and landscape scale raster data to populate the parent nodes for each ignition and extract the expected values for predicted nodes under different weather scenarios and varying levels of suppression. We found values predicted by the BN broadly matched the spatial patterns of risk produced in Phoenix i.e., areas where risk was highest and lowest in terms of fire area and house loss aligned. However, the values are rescaled by the BN as it takes into account the influence of ignition likelihood and containment probability on risk estimates. The BN is also able to capture uncertainty around the values presented from across the top ten Phoenix simulations, so the recorded values represent the likely outcome for each node given the range of potential weather conditions in those scenarios. We show that BNs can be a useful management tool for estimating fire risks across a range of weather scenarios and locations while still considering ignition likelihood and suppression effectiveness.

1. Introduction

Fire is a globally significant environmental disturbance which increasingly presents risk to people, property, infrastructure, and biodiversity (Banks et al. 2011; Moritz et al. 2014; Filkov et al. 2020; Borchers Arriagada et al. 2020; Higuera and Abatzoglou 2021). Managing wildfire risks is complicated as decision makers need to account for several interacting systems which may vary spatially and temporally (Thompson and Calkin 2011; Penman et al. 2020).

Weather conditions conducive to ignition and spread, as measured by both temperature and the forest fire danger index (FFDI; Noble et al., 1980), are expected to increase under climate change (Olson et al. 2016; Clarke and Evans 2019). Therefore, improved understanding of ignition likelihood will provide managers with some of information about where and when potential wildfire risk is highest. Additionally, understanding the factors that contribute to containment probability is also essential as suppression efforts play a critical role in limiting wildfire spread and reducing risk to people and assets (Penman et al. 2015; Dunn et al. 2017). The likelihood of ignition and containment both intersect to influence how a fire spreads and the potential risk it poses to lives, infrastructure, property, and biodiversity.

Current wildfire management frameworks in Australia generally only consider containment probability and ignition likelihood in isolation and do not account for interactions between them. This makes it difficult for managers to prioritise areas of highest concern for different fire weather or environmental conditions. One tool that is increasingly being used to support environmental decision-making within multiple systems is Bayesian Network Analysis (Penman et al. 2011, 2014, 2020; Hradsky et al. 2017; Marcot and Penman 2019). Bayesian Networks (BNs) are statistical tools uniquely capable of managing the suite of uncertainties which arise in complex environmental systems, making them ideal for risk analysis research (Pollino et al. 2007; Dlamini

2010; Johnson et al. 2010; Johnson and Mengersen 2012; Kelly et al. 2013). A major advantage of using a BN in structured decision making is that it allows the use of data from multiple sources on different scales (Pollino et al. 2007; Penman et al. 2014; Marcot and Penman 2019). They can also be applied at various spatial resolutions which is an important aspect of managing risk, particularly for disturbances such as fire which impact both local and landscape scales.

Here, we aimed to understand how ignition likelihood, containment probability and subsequent fire behaviour impacts the distribution of wildfire risks across the state of Victoria, Australia. We build, parameterise, and test a Bayesian Network to answer two questions 1) how are the risks to people and property distributed across the state given a range of weather scenarios? and 2) how do ignition likelihood and containment probability influence the distribution of these risks for a range of weather scenarios? We combine our Bayesian Network with PHEONIX Rapidfire (hereafter Phoenix; Tolhurst et al. 2008) fire behaviour simulations. Phoenix is an application which simulates one or more fires using a characterisation model to capture the details of fire spread such as flame height, rate of spread and ember production etc. Here we use Phoenix simulations to generate fire impacts for ignitions across the landscape and to compare current risk estimates, which do not consider the likelihood of ignition or containment, with our estimates of risk from a Bayesian approach.

2. Model framework

Our modelling framework involved three key stages. First, we developed a conceptual model combining ignition likelihood, containment probability and fire weather to predict risk to houses and lives accross a range of scenarios and landscapes. This conceptual model (Figure 1) includes two random forest models fit to state wide datasets of historical ignition events and suppression efforts in Victoria. We took the top six most important variables from each of these models to include in our Bayesian Network. The second stage of our modelling framework expands the conceptual model into an influence diagram capturing the variables important to each of our sub-models, and from our Phoenix fire behaviour simulations, as nodes in our network. Lastly, we populated the conditional probability tables within the model using real data to learn the relationships between nodes through Bayesian inference (Korb and Nicholson 2010).

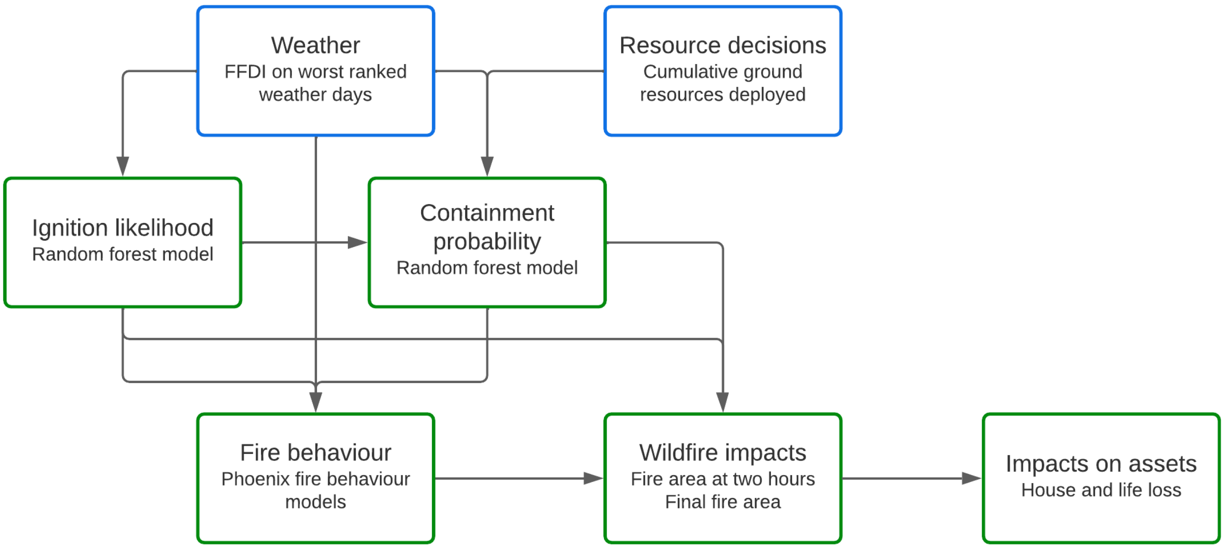

Figure 1: Conceptual model underlying the final Bayesian Network used in this study. Green boxes show sub-models and output nodes in the network. Blue boxes show decision nodes in the network.

We applied the network in R (version 3.6.2) to 71808 ignition locations across Victoria. Data on the top 50 FFDI values in history observed at each ignition location was provided by the Victorian State Government's Department of Environment, Land, Water and Planning (DELWP), who also provided us with Phoenix fire simulations under the top ten of these 50 FFDI values. To apply the BN to these locations we cycle through all locations individually. Using the FFDI values, and ten example Phoenix runs, we set the probabilities of getting each FFDI, fire area, fire area at two hours, and house loss value at that location. For each location we extract the predicted ignition likelihood, and containment probability, alongside the rescaled fire area at two hours, final fire area, house, and life loss. We compare the outputs from our BN to those produced by Pheonix runs to determine whether accounting for containment probability and ignition likelihood, as well as the range of possible phoenix outcomes, influences the predictions of risk.

3. Results and implications

The estimates of fire risk produced by Phoenix and those predicted by the BN are spatially consistent. The ignitions with the largest predicted fire area tend to occur in the same locations in both methods and therefore hotspots are easily identified using either approach. However, the BN produced rescaled values when considering the likelihood of ignition and probability of containment in its risk estimates for some areas. The fire area values, as well as the predicted house loss and life loss were far lower in the BN as compared to Phoenix. The extent to which values were rescaled also varied across the state (Figure 2). When considering ignition likelihood and containment probability the greatest reductions in fire area occurred in the north west and eastern parts of Victoria (Figure 2; A). Probably because ignition likelihood is lower in these areas as they are less populated and prone to human ignitions. Comparatively, house loss declined most in the central areas of Victoria close to the major settlements of Melbourne and Geelong (Figure 2: B). This is probably because ignition likelihood is lower than expected by Phoenix and suppression efforts are most targeted and effective in these areas. Areas with little change in house loss indicate either low predicted values using both methods or little effect of ignition likelihood or suppression on outcomes. This could provide managers with a useful tool for prioritising allocation of suppression resources to these areas.

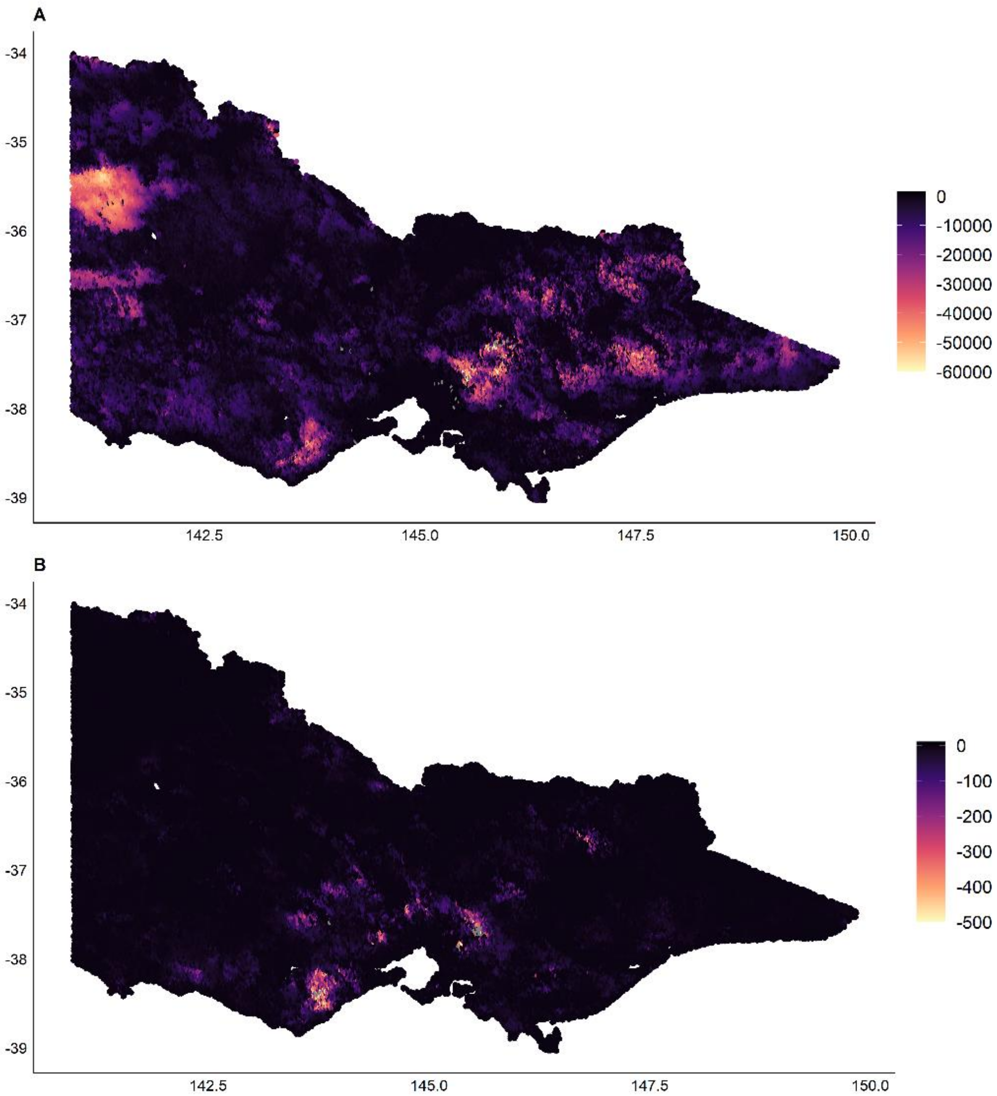

Figure2: Maps showing where the values predicted by Phoenix were different compared to those predicted by the BN for Final fire area (A) and house loss (B) nodes. Negative values indicate the Phoenix predicted values were higher than those predicted by the BN. The colours indicate the extent of these differences accross the state with dark purple indicating no or little change and light yellow showing the maximum predicted change.

4. Conclusions

Our results highlight the importance of considering multiple systems in fire risk analysis. Ignition likelihood and containment probability, as well as the environmental variables and management decisions which may influence these systems, provide essential insight into where in the landscape fires may be most impactful. While the results of our BN broadly matched the spatial patterns produce by Phoenix, the rescaled values, and the spatial differences in where rescaling was most pronounced, may offer managers nuanced insights into where resources may be most needed or most effective. This approach is also able to better account for uncertainty in multiple competing systems and can be applied to a wide range of weather scenarios and management decisions. Applying a more holistic approach to fire risk analysis will be required in the future as climate mediated shifts in ignition likelihood and fire behaviour change the patterns of fire risk to people and property. Understanding these changes will allow managers to better allocate resources to fuel management and suppression efforts.

5. References

Banks SC, Knight EJ, McBurney L, Blair D, Lindenmayer DB (2011) The effects of wildfire on mortality and resources for an arboreal marsupial: Resilience to fire events but susceptibility to fire regime change. PLoS ONE 6,. doi:10.1371/journal.pone.0022952.

Borchers Arriagada N, Palmer AJ, Bowman DMJS, Morgan GG, Jalaludin BB, Johnston FH (2020) Unprecedented smoke-related health burden associated with the 2019–20 bushfires in eastern Australia. Medical Journal of Australia 213, 282–283. doi:10.5694/mja2.50545.

Clarke H, Evans JP (2019) Exploring the future change space for fire weather in southeast Australia. Theoretical and Applied Climatology 136, 513–527. doi:10.1007/s00704-018-2507-4.

Dlamini WM (2010) A Bayesian belief network analysis of factors influencing wildfire occurrence in Swaziland. Environmental Modelling and Software 25, 199–208. doi:10.1016/j.envsoft.2009.08.002.

Dunn CJ, Thompson MP, Calkin DE (2017) A framework for developing safe and effective large-fire response in a new fire management paradigm. Forest Ecology and Management 404, 184–196. doi:10.1016/j.foreco.2017.08.039.

Filkov AI, Ngo T, Matthews S, Telfer S, Penman TD (2020) Impact of Australia's catastrophic 2019/20 bushfire season on communities and environment. Retrospective analysis and current trends. Journal of Safety Science and Resilience 1, 44–56. doi:10.1016/j.jnlssr.2020.06.009.

Higuera PE, Abatzoglou JT (2021) Record-setting climate enabled the extraordinary 2020 fire season in the western United States. Global Change Biology 27, 1–2. doi:10.1111/gcb.15388.

Hradsky BA, Penman TD, Ababei D, Hanea A, Ritchie EG, York A, di Stefano J (2017) Bayesian networks elucidate interactions between fire and other drivers of terrestrial fauna distributions. Ecosphere 8,. doi:10.1002/ecs2.1926.

Johnson S, Mengersen K (2012) Integrated Bayesian network framework for modeling complex ecological issues. Integrated Environmental Assessment and Management 8, 480–490. doi:10.1002/ieam.274.

Johnson S, Mengersen K, de Waal A, Marnewick K, Cilliers D, Houser AM, Boast L (2010) Modelling cheetah relocation success in southern Africa using an Iterative Bayesian Network Development Cycle. Ecological Modelling 221, 641–651. doi:10.1016/j.ecolmodel.2009.11.012.

Kelly RA, Jakeman AJ, Barreteau O, Borsuk ME, ElSawah S, Hamilton SH, Henriksen HJ, Kuikka S, Maier HR, Rizzoli AE, van Delden H, Voinov AA (2013) Selecting among five common modelling approaches for integrated environmental assessment and management. Environmental Modelling and Software 47, 159–181. doi:10.1016/j.envsoft.2013.05.005.

Korb KB, Nicholson AE (2010) "Bayeisan Artifical Intelligence." (CRC Press)

Marcot BG, Penman TD (2019) Advances in Bayesian network modelling: Integration of modelling technologies. Environmental Modelling and Software 111, 386–393. doi:10.1016/j.envsoft.2018.09.016.

Moritz MA, Batllori E, Bradstock RA, Gill AM, Handmer J, Hessburg PF, Leonard J, McCaffrey S, Odion DC, Schoennagel T, Syphard AD (2014) Learning to coexist with wildfire. Nature 515, 58–66. doi:10.1038/nature13946.

Noble IR, Bary GA v, Gill AM (1980) McArthur's fire-danger meters expressed as equations.

Olson R, Evans JP, di Luca A, Argüeso D (2016) The NARCliM project: Model agreement and significance of climate projections. Climate Research 69, 209–227. doi:10.3354/cr01403.

Penman TD, Bradstock RA, Price OF (2014) Reducing wildfire risk to urban developments: Simulation of cost-effective fuel treatment solutions in south eastern Australia. Environmental Modelling and Software 52, 166–175. doi:10.1016/j.envsoft.2013.09.030.

Penman TD, Cirulis B, Marcot BG (2020) Bayesian decision network modeling for environmental risk management: A wildfire case study. Journal of Environmental Management 270,. doi:10.1016/j.jenvman.2020.110735.

Penman TD, Nicholson AE, Bradstock RA, Collins L, Penman SH, Price OF (2015) Reducing the risk of house loss due to wildfires. Environmental Modelling and Software 67, 12–25. doi:10.1016/j.envsoft.2014.12.020.

Penman TD, Price O, Bradstock RA (2011) Bayes Nets as a method for analysing the influence of management actions in fire planning. International Journal of Wildland Fire 20, 909–920. doi:10.1071/WF10076.

Pollino CA, Woodberry O, Nicholson A, Korb K, Hart BT (2007) Parameterisation and evaluation of a Bayesian network for use in an ecological risk assessment. Environmental Modelling and Software 22, 1140–1152. doi:10.1016/j.envsoft.2006.03.006.

Tolhurst K, Shields B, Chong D (2008) Phoenix: Development and application of a bushfire risk management tool. The Australian Journal of Emergency Managemen 23,.

Thompson MP, Calkin DE (2011) Uncertainty and risk in wildland fire management: A review. Journal of Environmental Management 92, 1895–1909. doi:10.1016/j.jenvman.2011.03.015.