BLACK SUMMER 2019–20 RESEARCH

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FIRE RISK MODELLING FOR KANGAROO ISLAND

Black Summer 2019-20 fires

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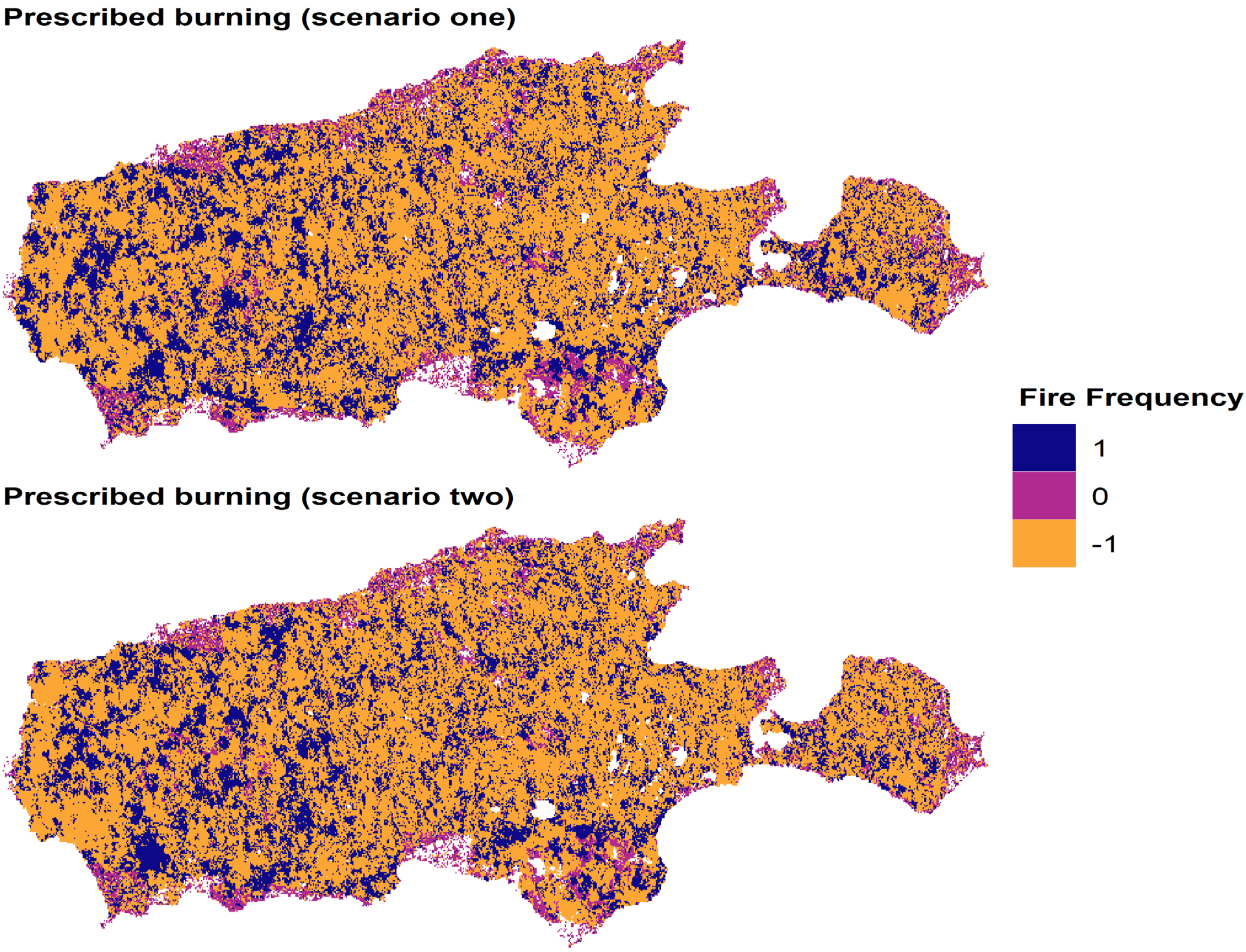

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Cover: Locations on Kangaroo Island where wildfire frequency differed between the wildfire only and the prescribed burning burning scenarios. Positive values show where the frequency of wildfires was higher in the prescribed burning scenario compared to the wildfire only scenario. Negative values show where the wildfire only scenario had a higher freuqnecy than the prescribed burning scenario and zero indicates no change in the frequency of wildfires.

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EXECUTIVE SUMMARY

Understanding changing bushfire risks to people, property and biodiversity is a key knowledge gap in many states and territories across Australia, including South Australia. In the wake of the 2019/2020 bushfires which had significant impacts on all three of these values across South Australia, understanding fire risks and potential fire impacts is crucial for making informed management decisions into the future. In our study we used a Fire Regime and Operations Simulation Tool (FROST) to model fire risk on Kangaroo Island over 50 years. We estimated the impacts of simulated fires on human life, property and biodiversity for three management scenarios (wildfires only and two prescribed burning scenarios). We found that prescribed burning resulted in a small decline in the frequency of wildfires compared to the wildfire only scenario and a lower frequency of both very high and extreme intensity fires. Despite a lower frequency of fires overall, the likelihood of very high or extreme intensity fires happening at least once over 50 years increased.

Despite reduced frequency of bushfires during wildfire seasons, exposure to people and property did not change between scenarios, probably because the extent of fires remained unchanged. Prescribed burning also resulted in a greater area burnt before minimum Tolerable Fire Interval (TFI) than wildfires alone. This is because prescribed burn efforts reduce the age classes of the remnant vegetation, resulting in the exposure of a larger proportion of vegetation below minimum TFI during the wildfire season.

These results present a preliminary understanding of fire risk on Kangaroo Island. The methods developed here could be applied to a range of case study sites in South Australia and may provide helpful estimates of future fire risk which could be incorporated into management decisions throughout the state.

INTRODUCTION

Bushfires present increasingly high risks to human life, property and biodiversity around the globe (Banks, Knight, McBurney, Blair, & Lindenmayer, 2011; Borchers Arriagada et al., 2020; R. Bradstock, Penman, Boer, Price, & Clarke, 2014; Higuera & Abatzoglou, 2021). Understanding and predicting bushfire risk to these assets is a key knowledge gap in many management jurisdictions around Australia. This gap in knowledge is only increasing under the impacts of climate change and predicting fire risk is fundamental for supporting future management decisions. The 2019/2020 bushfire season in Australia resulted in an unprecedented area of high-severity fires which impacted ecosystems across south eastern Australia and had significant impacts on people and property (Collins et al., 2021b; Filkov, Ngo, Matthews, Telfer, & Penman, 2020). Therefore, it is imperative that the risk of such megafires reoccurring is predicted into the future and where possible management actions should mitigate the potential risks to humans and biodiversity.

Understanding the risks of future fire requires some knowledge of how fire regimes are likely to shift going forward. Fire regimes are repeated patterns of burning, characterised by certain fire characteristics such as frequency, intensity, size, season, type and extent (Archibald et al., 2018; Gill, 1975; Murphy et al., 2013). Weather, fuel load, vegetation type and human activities can all influence fire behaviour and fire regimes (R. A. Bradstock, 2010). Changes to natural fire regimes can be important for influencing species richness and community composition (Andersen, Penman, Debas, & Houadria, 2009; Penman, Keith, et al., 2015; Swab, Regan, Keith, Regan, & Ooi, 2012). Inappropriate fire regimes can have significant long-term consequences for biodiversity (Banks et al., 2011; Enright, Fontaine, Lamont, Miller, & Westcott, 2014; Penman et al., 2011). Management agencies often attempt to reduce the risks caused by changing fire regimes through various management strategies, mostly focusing on fuel management i.e. thinning, clearing and prescribed burning (H. Clarke, Tran, et al., 2019; Florec, Burton, Pannell, Kelso, & Milne, 2020).

Previous work has demonstrated that management through fuel treatments can reduce risks but the placement and strategy of treatments is critical (R. A. Bradstock et al., 2012; Finney et al., 2007; Penman, Ababei, Chong, Duff, & Tolhurst, 2015; Penman, Bradstock, & Price, 2014; Plucinski, 2012). Implementing management actions, such as prescribed burns, can be difficult because they are costly, and cannot cover all affected areas (Bradshaw et al., 2013; Penman et al., 2011). Moreover, implementing optimal management strategies to reduce life and house loss is likely to require a different solution to those aimed at managing biodiversity (Bentley & Penman, 2017; Driscoll et al., 2016; Penman, Ababei, et al., 2015; Penman et al., 2011). Identifying appropriate fire management strategies which protect people and property, as well as biodiversity, is of critical importance going forward to minimise risks associated with changing fire regimes.

There are several existing fire simulators which seek to understand the effects of potential management actions on fuel and fire behaviour. One of the most commonly used tools for modelling fire behaviour is PHOENIX RapidFire (hearafter PHOENIX ; Penman et al., 2015; Tolhurst, Shields, & Chong, 2008). This tool incorporates active suppression efforts alongside various fuel management strategies (Penman et al., 2013). PHOENIX is commonly used by fire management agencies in south and eastern Australia (Penman, Ababei, et al., 2015). While this tool is very useful for modelling single fire events, it does not model fire regimes over multiple years under changing fuel and weather.

In our study, we use a recently developed fire regime simulator "Fire Regime and Operations Simulation Tool" (FROST) which incorporates the PHOENIX fire behaviour models with Bayesian Networks to predict changes in the fire regime given ignition likelihoods, fuel accumulation and management efforts (Penman, Ababei, et al., 2015). We simulate changing fire regimes over 50 years on Kangaroo Island, South Australia (SA), under a wildfire only scenario and two fuel management strategies (low and high prescribed burning) and analyse the risks to human life, property and biodiversity. This project is a first attempt to apply FROST simulations in SA and will serve as a foundation for future projects. Results of this study will provide insights to fire managers about possibilities of using FROST to predict risk across SA and to make informed decisions about future fuel management actions.

METHODS

STUDY AREA

This project focuses primarily on Kangaroo Island but collates data from across the state and creates the opportunity for future simulations. Kangaroo Island is an ~4400 km2 island located 112 km southwest of Adelaide (Figure 1) with a population of around 4259 people (www.abs.gov.au, accessed 10th May 2021). The Island is a biodiversity hotspot and approximately 65 percent of it is protected under public and private agreements, with half the remnant native vegetation intact (https://www.australianwildlife.org, accessed 10th May 2021). However, during the Black Summer bushfires, ~211,000 hectares of the 440,500-hectare island (approximately half) burnt in high severity fires resulting in devastating impacts for biodiversity and people (Filkov et al., 2020).

FIGURE 1: LOCATION OF KANGAROO ISLAND (OUTLINED IN RED) RELATIVE TO AUSTRALIA (TOP LEFT PANEL) AND THE COAST OF SOUTH AUSTRALIA (TOP RIGHT PANEL).

MODELLING APPROACH

Here we primarily use FROST, a fire regime model that builds on the strength of existing fire behaviour models and Bayesian networks, to predict wildfire risk. FROST uses a series of machines which represent an entity or model used in the fire regime program, i.e., the ignition machine is the ignition model used to predict ignition location and frequency. Data inputs for each machine must be processed in advance. A separate data preparation programme (FROMAGE) takes the raw machinery data required to run a FROST simulation, validates and modifies it for use in FROST (accessed May 31st 2021, http://frostfamily.bushfirebehaviour.net.au/fromage-documentation).

The results of each simulation are stored in SQLite databases. These FROST outputs can be utilised in multiple machines of a post-processing programme called FRAPPE which calculates impacts on a range of assets, i.e., biodiversity, people and property (accessed May 31st 2021, http://frostfamily.bushfirebehaviour.net.au/frappe-documentation/). The modelling approach employed in this research consists of three stages using the three main software applications in the FROST family (accessed May 31st 2021, http://frostfamily.bushfirebehaviour.net.au/): 1) preparation of data in FROMAGE to ensure compatibility with FROST, 2) running simulations in FROST and 3) post-processing of FROST outputs in FRAPPE to calculate impacts on people, property and biodiversity. At the first stage the data required to run FROST is collected and prepared. The most important aspect of this is ensuring that all the data is in the correct coordinate reference system and at the required resolution. The data is then processed in FROMAGE which ensures it is clipped to the extent of the study site and is compatible for use within FROST. A series of simulations are then run in parallel within FROST (stage two) and the resulting outcomes in are processed using FRAPPE (stage three).

Stage one: Data collection and preparation

Since FROST has not yet been tested in SA, this was the first use of the program within the state using SA data. The essential part of this modelling framework (FROMAGE + FROST + FRAPPE) is geographical coordinates. These coordinates use a specific coordinate reference system (CRS), depending on the location of the study region. Initial development of FROST incorporated EPSG:3111, GDA94/Vicgrid94, EPSG:3308 and GDA94/NSW Lambert coordinates as baseline CRSs. A crucial activity in this project was to adapt FROST to run simulations in SA, requiring a new CRS system to be incorporated – EPSG:3107, GDA94/SA Lambert.

Several machines are required to run a FROST simulation, but the main machines used to drive the simulations run here are the fuel, ignition, planned burn, post-processing and weather machines. We collected and processed the data required to run these machines into the correct formats and coordinate reference system (EPSG:3107). The weather machine used daily weather conditions (e.g., max forest fire danger index [FFDI]) to determine the number of ignitions and hourly weather to simulate fire behaviour and spread. We used NARCLIM weather data which provides high resolution climate change projections based on four global climate models (MIRIC, ECHAM, CCCMA and CSIRO Mk3.0). This weather data provides outputs for several variables including temperature, precipitation, windspeed, humidity etc (accessed 31 May 2021 https://climatechange.environment.nsw.gov.au/Climate-projections-for-NSW/About-NARCliM). Here we used the CSIRO Mk3.0 2020 to 2039 (near future) model using the RCP 8.5 emission pathway (NARCLIM CSIRO Mk3.0 R1; Olson, Evans, Di Luca, & Argüeso, 2016). The ignition machine used Bayesian Networks to simulate ignition probability based on empirical models built by Clarke et al. (2019). The number and time of ignitions provided by the DEWNR were used to place potential ignitions across Kangaroo Island. Ignition probability was then determined based on distance to roads, rainfall, FFDI and housing density data.

The fuel machine simulated changes in fuel hazard across the landscape for each fuel strata (surface, near-surface, elevated and bark hazard) based on the models produced by McColl-Gausden et al, (2020). Th fuel machine uses fuel hazard scores by strata collected from field assessments undertaken between 1995-2017, primarily from the study area (Victoria), but also included records from adjacent states. The fuel model uses predictor variables selected from three key drivers of vegetation distribution: climate and soil (as an indicator of vegetation productivity; Hagger, Koch, Chatzisarantis, & Orbell, 2017) and fire history (represented by time-since-last prescribed fire or wildfire; Chapin, Bret-Harte, Hobbie, & Zhong, 1996; Nano & Clarke, 2008). Soil variables are the most influential of the predictor variables for determining all fuel hazard ratings, with some exceptions for bark hazard. Relationships with fuel hazard scores of the most important climate variable (precipitation in the warmest quarter) vary by fuel strata as did relationships of time since fire with extreme fuel hazard. Probability of extreme fuel hazard in all fuel strata initially increases in this model until approximately 10-20 years. Thereafter, the probability of extreme fuel hazard plateaus for surface and bark strata but gradually decreases for near-surface and elevated fuel hazard strata to 100 years

Time since fire data were calculated from the SA fire history data provided by DEWNR up until the end of the 2021 fire season for SA. These machines provided the baseline data required to run FROST for each day in the simulation. We also used the fuel treatment manager to test different management scenarios and their impacts on fire behaviour and predicted risk. Planned burns were driven by selection algorithm (described below) inputted by the user and the fuel treatment machine simulates the burns in PHOENIX. Post-processing was conducted through a post-processing machine which uses a separate software (FRAPPE) to conduct calculations of fire impact on biodiversity, people and property (described below).

Stage two: Simulation fire regimes

We used FROST to simulate fire impacts on Kangaroo Island using current climate models. FROST uses PHOENIX models to simulate single fire events and the spread of fire from individual ignition locations (Penman, Ababei, et al., 2015; Tolhurst et al., 2008). The model uses daily weather data to predict ignition occurrence and rate. If one or more ignitions are predicting in the ignition model, the fire behaviour model is initiated with hourly weather. All ignitions are run concurrently and once the fires are complete for a day or days fuel consumption is calculated to estimate the remaining fuel at each site. At the end of the season fuels are grown based on fuel accumulation curves. Fuel treatments are implemented at the end of each wildfire season and are also run through the fire behaviour model to determine their impacts on fuel consumption. At the end of both wildfire and planned burn seasons, annual risk estimates are calculated for several asset types (Penman, Ababei, et al., 2015). We ran our simulations for 50 years in total beginning in 2020 and ending in 2070. For each scenario we repeated our simulations 50 times (replicates) to capture environmental stochasticity on our results. We ran three management scenarios; 1) wildfires only, 2) low prescribed burning efforts (~1%; hereafter scenario one) and high prescribed burning efforts (~5%; hereafter scenario two).

Stage three: Calculating fire impacts

Knowing how fires behave and their impacts on the landscape from the FROST simulations, we can calculate the fire's impacts on asset values of interest. Post-processing seeks to calculate these impacts using several post-processors accessible in the FRAPPE application. Each post-processor is a separate unit which contains an algorithm(s) to identify the impacts of a fire on a value of interest. In our study we analysed biodiversity, life and house loss.

The biodiversity post-processor calculates the total area (hectares) affected by fire before minimum Tolerable Fire Interval (TFI). Any cells which are impacted by fire, i.e., where intensity and rate of spread is greater than zero are examined and their time since fire (based on fire history) is calculated. If the time since fire is lower than the minimum TFI for that vegetation type, it is counted towards the total area burnt before TFI. This measure provides an estimate of how early age class vegetation is impacted by wildfire and an approximation of the relative risk towards biodiversity. The house loss post-processor uses a housing density layer supplied by the user to calculate the number of houses per cell exposed and lost to fire and then summing these values for each year. People exposed to fire was calculated by dividing the total population by the total number of houses on Kangaroo Island to get an average number of people per house. This value is then multiplied with the housing density layer and the number of people exposed is a sum of the values in each cell affected by fire. Estimated lives lost is determined using method of (Harris, Anderson, Kilinc, & Fogarty, 2012) from the number of people exposed.

Management scenarios

We establish three simulation scenarios;

1) wildfires only,
2) wildfire plus low prescribed burning (scenario one) and,
3) wildfires plus high prescribed burning (scenario two).

The prescribed burning machine in FROST uses burn block shapefiles with defined fuel management zones to assign prescribed burning efforts across the landscape. Burn block locations and categorisation were provided by DEWNR. Three fuel management zone (FMZ) types used on Kangaroo Island; asset protection, landscape management or bushfire moderation and unzoned. These FMZs do not cover the full extent of Kangaroo Island. Given the overall goal of the project was to test the effect of burning at a low and high percentage burn rate, prescribed burning efforts were split up for each scenario to maximise the chances of reaching these targets within the FMZs (Table 1).

Scenario	1- Asset protection	2- Landscape management	3- Unzoned
Wildfire only	0	0	0
Prescribed burning (scenario one)	20%	10%	1%
Prescribed burning (scenario two)	20%	10%	5%

TABLE 1: PERCENTAGES BURNT PER YEAR IN EACH FUEL MANAGEMENT ZONE ON KANGAROO ISLAND.

We used the minimum TFI algorithm programmed in FROST to assign prescribed burns within the ecological limitations of Kangaroo Island vegetation. Each vegetation type is assigned a minimum TFI value. During each planned burn season, the fire history and vegetation type for each burn block is analysed. Each burn-block is checked and burnt if it contains at least 80 percent of the area that is older than the minimum TFI. The algorithm continues to select and burn burn-blocks until the total target percentage for each FMZ in reached during the planned burn season.

Data analysis

Following post-processing, the results from FRAPPE and FROST were analysed in R version 3.6 (R Development Core Team, 2017). We considered three measures describing the fire regime and fire risk;

1) area burnt by wildfire (total and annual),
2) burn frequency, and
3) frequency of very high and extreme intensity fires.

Area burnt is calculated by taking the total area burnt by each fire simulated, summing the values for each fire in a year and taking an average across the 50 years and again over 50 replicates. Burn frequency is calculated for each cell in the landscape burnt with an intensity greater than zero. We summed the burn frequency for each cell over the 50 years and take an average over 50 replicates. Fires were categorised as very high intensity if they were between 5000 and 10000 kW and extreme intensity fires were any fires above 10000 kW (Bradshaw et al., 2013). We then follow the same procedure as fire frequency and count the number of times a cell is burnt. We also present three measures of risk from the post-processing results;

1) area burnt before minimum TFI,
2) house loss and houses exposed; and

3) life loss and people exposed.

Area burnt before TFI is calculated using the same method as previously. However, cells are only counted towards the total area burnt if the vegetation is below the minimum TFI when it was burnt. House and life loss metrics are averaged across the 50 replicates. We examined the area burnt for prescribed burns. However, for the remaining metrics we analysed wildfire seasons only since we are primarily concerned with how different management options impact wildfires. We took an average of all these values across the 50 replicates for each scenario.

RESULTS

FROST results

1) Area burnt

An average annual area of 34,221 and 34,142 hectares were burnt during prescribed burning in scenario one and scenario two respectively (Figure 2). This rate of burning constitutes ~7.8 percent of the total landscape burnt annually. The two prescribed burning scenarios did not significantly differ in the total or annual area burnt (Figure 2). This is likely due to the similar burn percentages in each FMZ (Table 1). Had we altered burn percentages more, we may have seen a greater difference between the two prescribed burning scenarios in the prescribed burning season. We do find the differences between scenarios are more pronounced when looking at the wildfire seasons as opposed to the prescribed burning season.

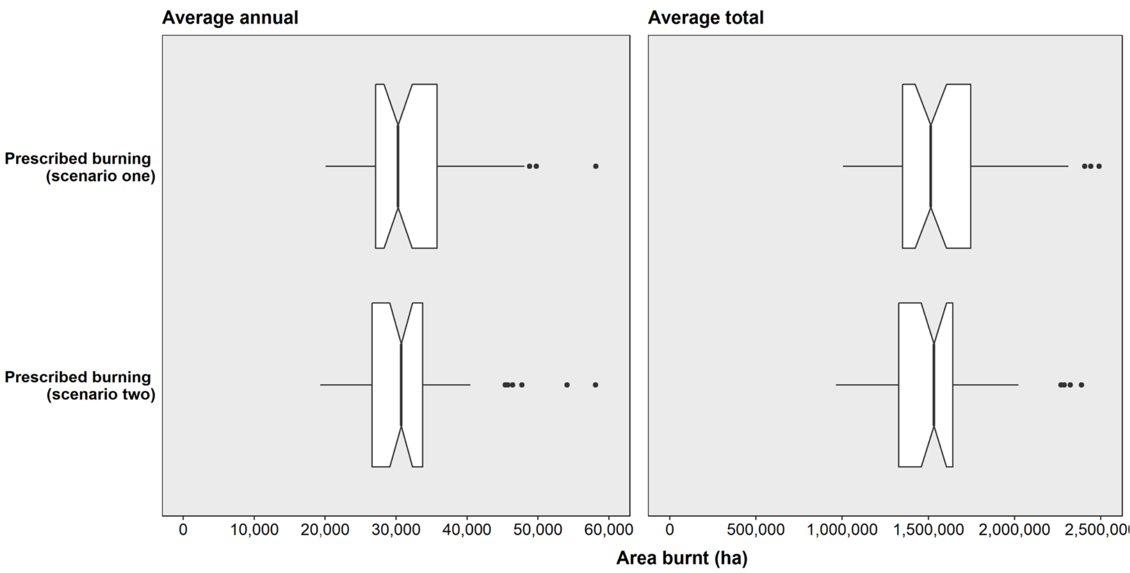

FIGURE 2: ANNUAL AND TOTAL AREA BURNT BY PRESCRIBED BURNING IN THE TWO PRESCRIBED BURNING SCENARIOS RUN.

Figure three shows a notched boxplot of annual and total area burnt during wildfire seasons in each scenario. Where the notches on these boxplots do not overlap there is a statistically significant difference between the mean values shown. Prescribed burning scenario one resulted in a statistically significant increase in the total and annual area burnt compared to the wildfire only scenario. However, prescribed burning scenario one still overlaps with the second prescribed burning scenario suggesting the observed differences between these two results were not statistically significant. Prescribed burning scenario two also did not significantly differ from the wildfire only scenario (Figure 3). These results could be explained by stochasticity in placement of prescribed burns between scenarios which is also evident in the significant variation observed around the mean area burnt for each scenario.

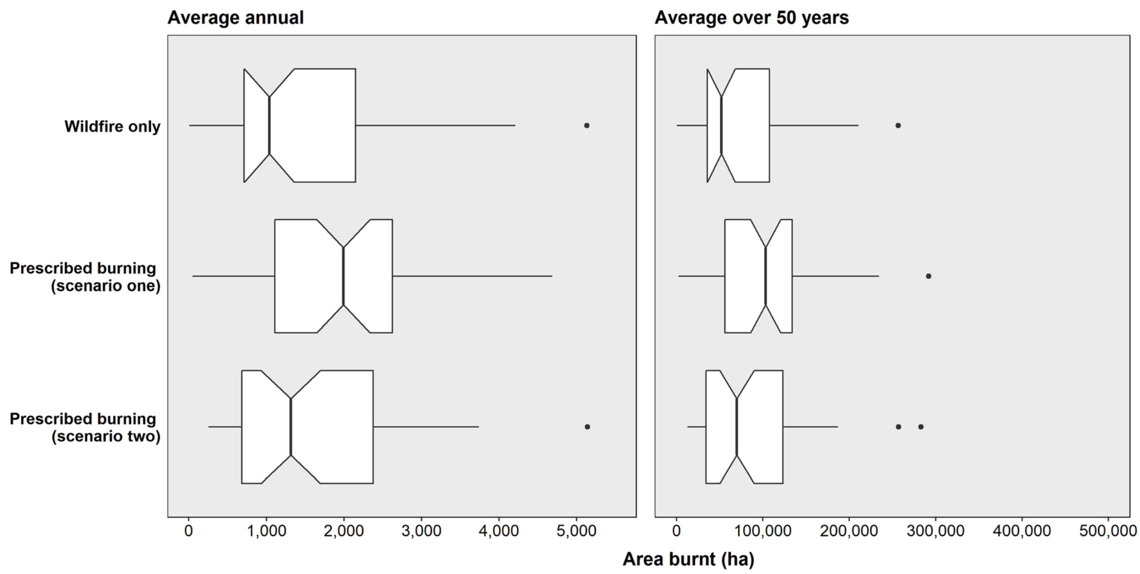

FIGURE 3: AVERAGE ANNUAL AND TOTAL AREA BURNT (HA) FOR THE THREE MANAGEMENT SCENARIOS RUN IN FROST.

2) Fire frequency

Burn frequency did not change significantly between the three management scenarios (Figure 4). All three scenarios resulted in a minimum burn frequency of one which demonstrates that each cell was burnt due to wildfire at least once on average across the 50-year simulation. Wildfire only scenarios do result in a greater maximum burn frequency of four compared to a maximum burn frequency of three in the two prescribed burning scenarios. This indicates that the prescribed burning scenarios can reduce the frequency of burns in some high-risk areas of the landscape, although this change is minimal. Despite this change in frequency, we do find that the total area burnt during the wildfire season is increased even when prescribed burning is used (Figure 3).

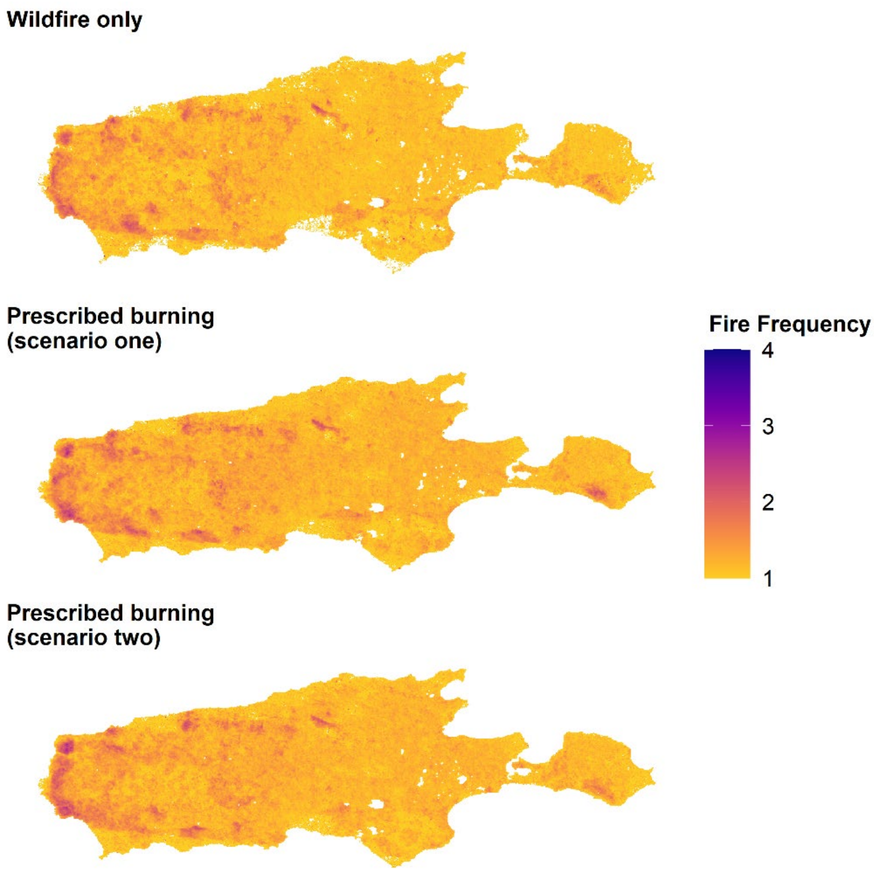

FIGURE 4: AVERAGE FREQUENCY OF WILDFIRES ON KANGAROO ISLAND ACROSS 50 YEARS OF SIMULATIONS IN FROST. RASTERS ARE SCALED BETWEEN A MINIMUM OF ONE AND A MAXIMUM OF 4. ZERO IS NOT INCLUDED AS ALL CELLS IN THE LANDSCAPE WERE IMPACTED BY WILDFIRES BY THE END OF THE 50-YEAR SIMULATION AND WHEN AVERAGED ACROSS REPLICATES.

Across all three scenarios, fire frequency was highest in western half of the Island, particularly in areas with a greater proportion of intact native vegetation such as in the Flinders Chase National Park. This was also one of the main locations impacted heavily by the 2020 bushfires. In the southern half of the Flinders Chase National Park fewer bushfires were predicted than on the rest of the Island. This is potentially due to the recent fire history we included which incorporates the 2020 bushfires. Wildfires shifted spatially under prescribed burning scenarios compared to the wildfire only scenario. Figure five shows locations where wildfires occurring in prescribed burning scenarios one and two were different to those in the wildfire only scenario. Zero values indicate frequency was unchanged between wildfire seasons in each scenario. Values below zero show locations where frequency was higher in the wildfire only scenario and above zero shows locations where frequency is higher in the prescribed burning scenarios (Figure 5).

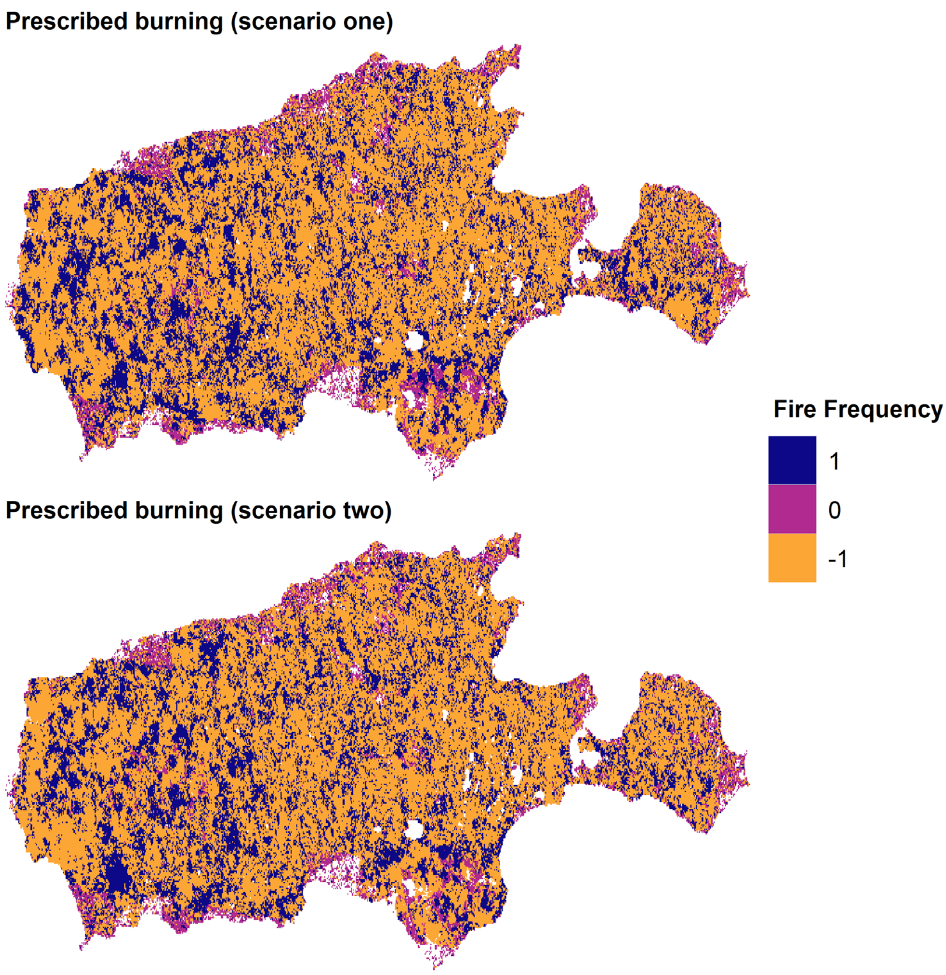

FIGURE 5: LOCATIONS ON KANGAROO ISLAND WHERE WILDFIRE FREQUENCY DIFFERED BETWEEN THE WILDFIRE ONLY AND THE PRESCRIBED BURNING BURNING SCENARIOS. POSITIVE VALUES SHOW WHERE THE FREQUENCY OF WILDFIRES WAS HIGHER IN THE PRESCRIBED BURNING SCENARIO COMPARED TO THE WILDFIRE ONLY SCENARIO. NEGATIVE VALUES SHOW WHERE THE WILDFIRE ONLY SCENARIO HAD A HIGHER FREUQNECY THAN THE PRESCRIBED BURNING SCENARIO AND ZERO INDICATES NO CHANGE IN THE FREQUENCY OF WILDFIRES.

3) Fire intensity

Frequency of very high and extreme intensity wildfires also did not change significantly between scenarios (Figure 6). However, extreme intensity fires impacted a total of 34,751 hectares across all 50 years at least once in the wildfire only scenario compared to 40,915 and 40,414 hectares in prescribed burning scenarios one and two. Therefore, while frequency tends to go down in prescribed burning scenarios, there is a slightly greater extent experiencing very high or extreme intensity fires at least once. The maximum frequency of very high intensity fires observed was four for the wildfire only scenario and three in both prescribed burning scenarios. Again, there was a greater area impacted by very high intensity wildfires in the two prescribed burning scenarios. On average across all 50 years and replicates a total of 71,316 hectares experience at least one very high intensity wildfire in the wildfire only scenario. Prescribed burning scenarios result in 81,915 and 82,025 hectares for scenarios one and two respectively.

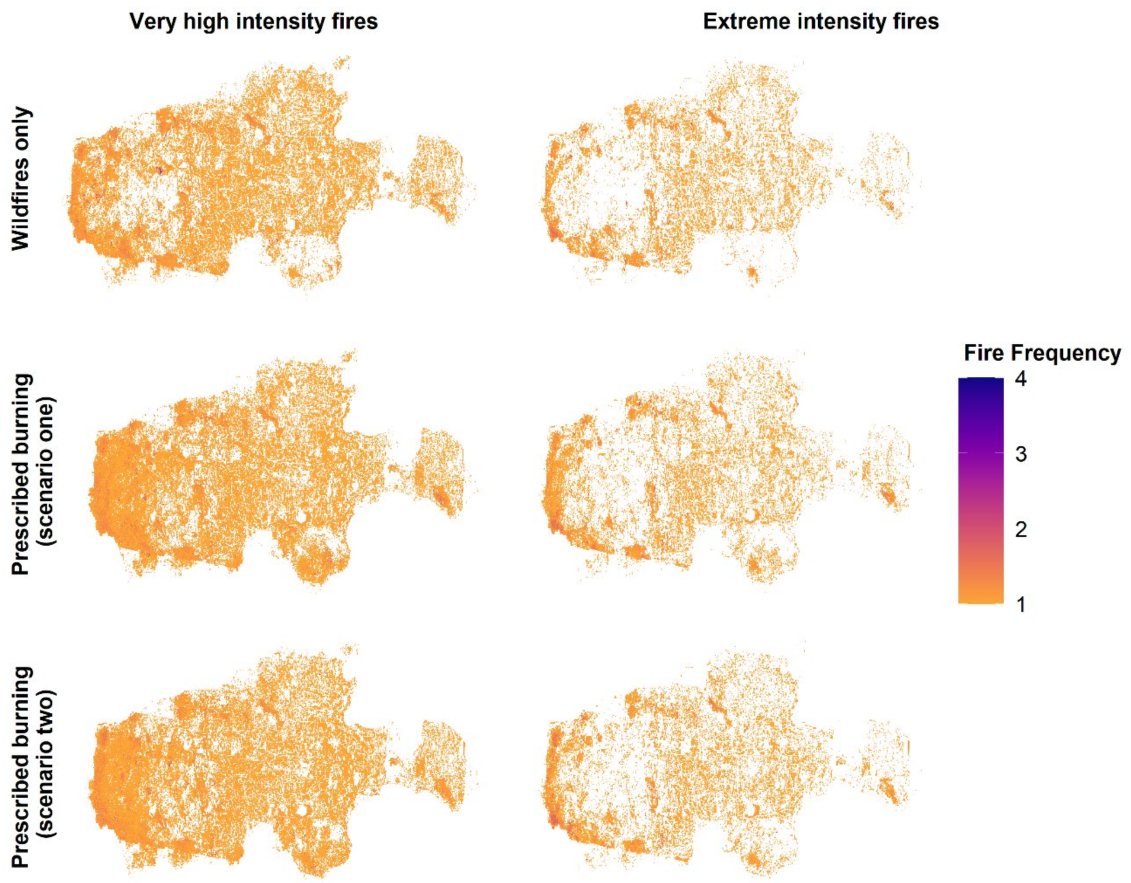

FIGURE 6: FREQUENCY OF EXTREME INTENSITY FIRES AVERAGED ACROSS REPLICATES AND YEARS FOR WILDFIRES IN THREE MANAGEMENT SCENARIOS ON KANGAROO ISLAND.

The increased extent in very high and extreme intensity fires tends to corelate with areas of the landscape where predicted fire frequency was greater for prescribed burning scenarios (Figure 5). In the wildfire only scenarios extreme and very high intensity fires were more frequency around the western coastline (Figure 7). Comparatively, prescribed burning scenarios tend to result in a higher frequency of extreme or very high intensity fires further inland in the Flinders Chase National Park than the wildfire only scenario (Figure 7).

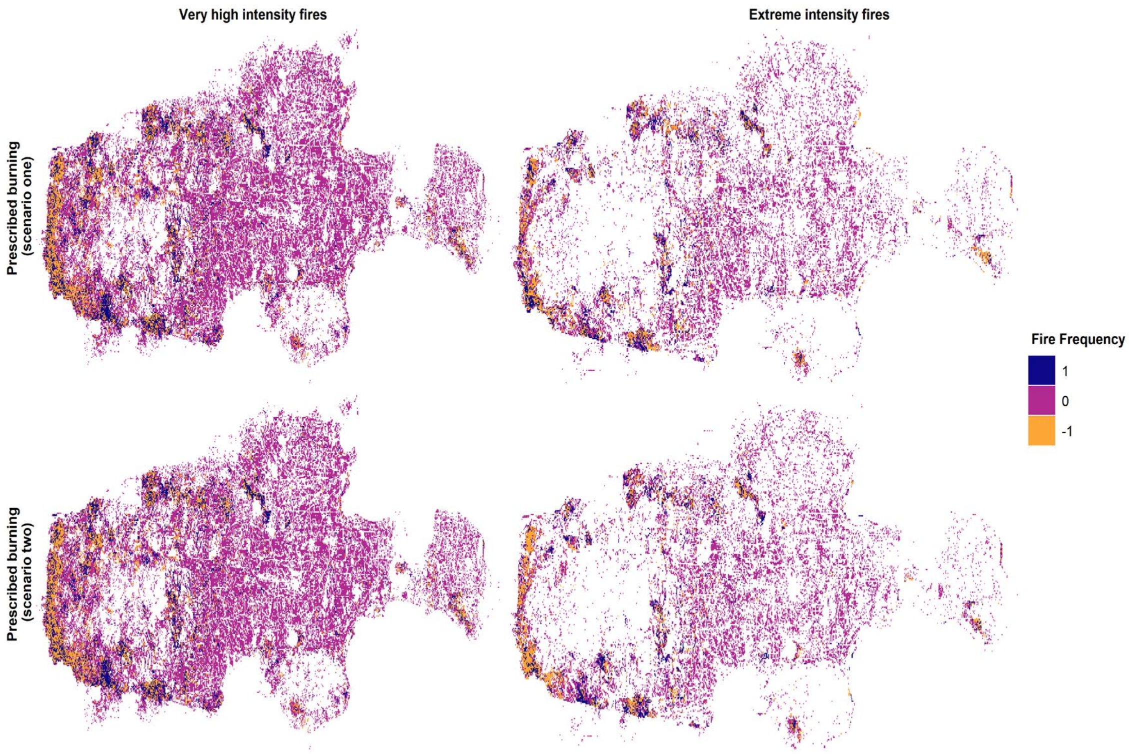

FIGURE 7: LOCATIONS ON KANGAROO ISLAND WHERE THE FREQUENCY OF VERY HIGH AND EXTREME INTENSITY WILDFIRES DIFFERED BETWEEN THE WILDFIRE ONLY AND THE PRESCRIBED BURNING BURNING SCENARIOS. POSITIVE VALUES SHOW WHERE FREQUENCY WAS HIGHER IN THE PRESCRIBED BURNING SCENARIO COMPARED TO THE WILDFIRE ONLY SCENARIO. NEGATIVE VALUES SHOW WHERE THE WILDFIRE ONLY SCENARIO HAD A HIGHER FREUQNECY THAN THE PRESCRIBED BURNING SCENARIO AND ZERO INDICATES NO CHANGE IN THE FREQUENCY OF WILDFIRES.

FRAPPE results

The total area burnt per year (averaged across replicates) before TFI was significantly higher in both prescribed burning scenarios than in the wildfire only scenarios (Figure 8). This is likely because prescribed burning results in an overall lowering of the age classes. Therefore, when wildfire season is implemented in FROST, a greater proportion of the vegetation burnt is below the minimum TFI.

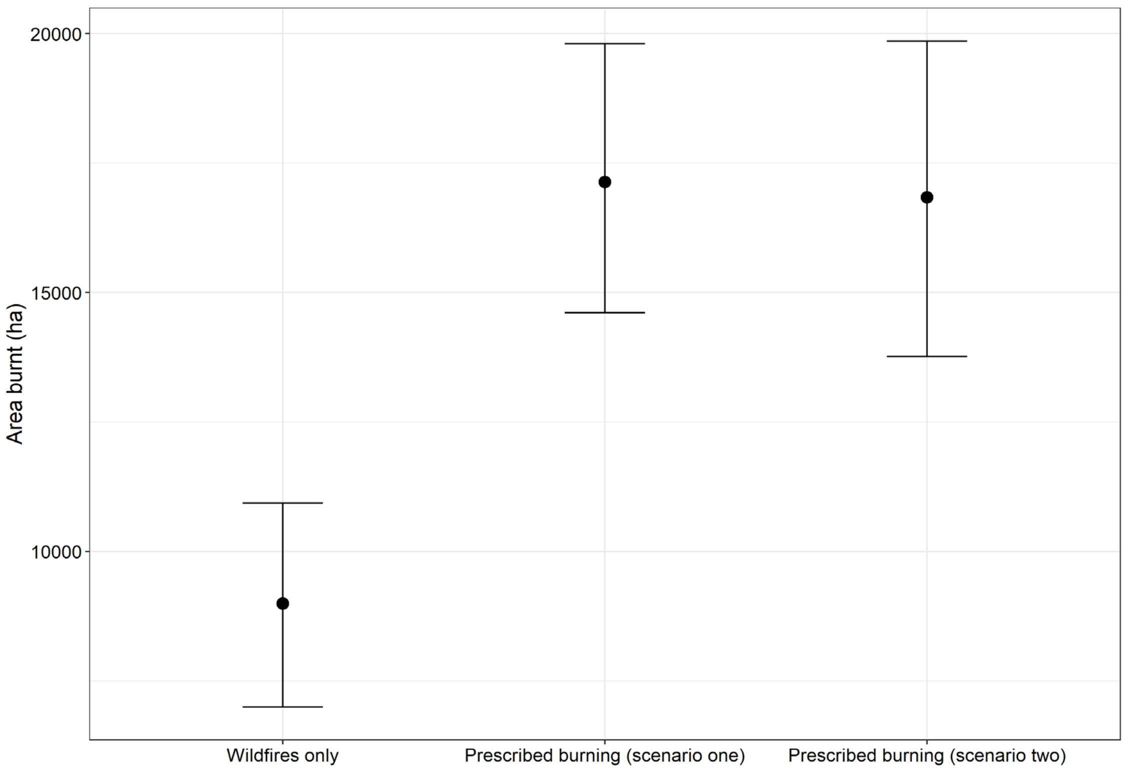

FIGURE 8: AREA BURNT (HECTARES) BEFORE MINIMUM TFI FOR ALL THREE MANAGEMENT SCENARIO.

Conversely, for both people and property, prescribed burning did not significantly impact the predicted number of these values exposed or lost (Figure 9). Slight changes between scenarios in the number of houses and people exposed to fire likely reflect the shifting of fire impacts. This is due to spatial stochasticity or cases where prescribed burning causes changes in the locations affected by wildfire compared to wildfire only scenarios, exposing more people and property (Figure 5). However, all three scenarios result in house and life loss values just above or on zero and they do not change based on the levels of prescribed burning.

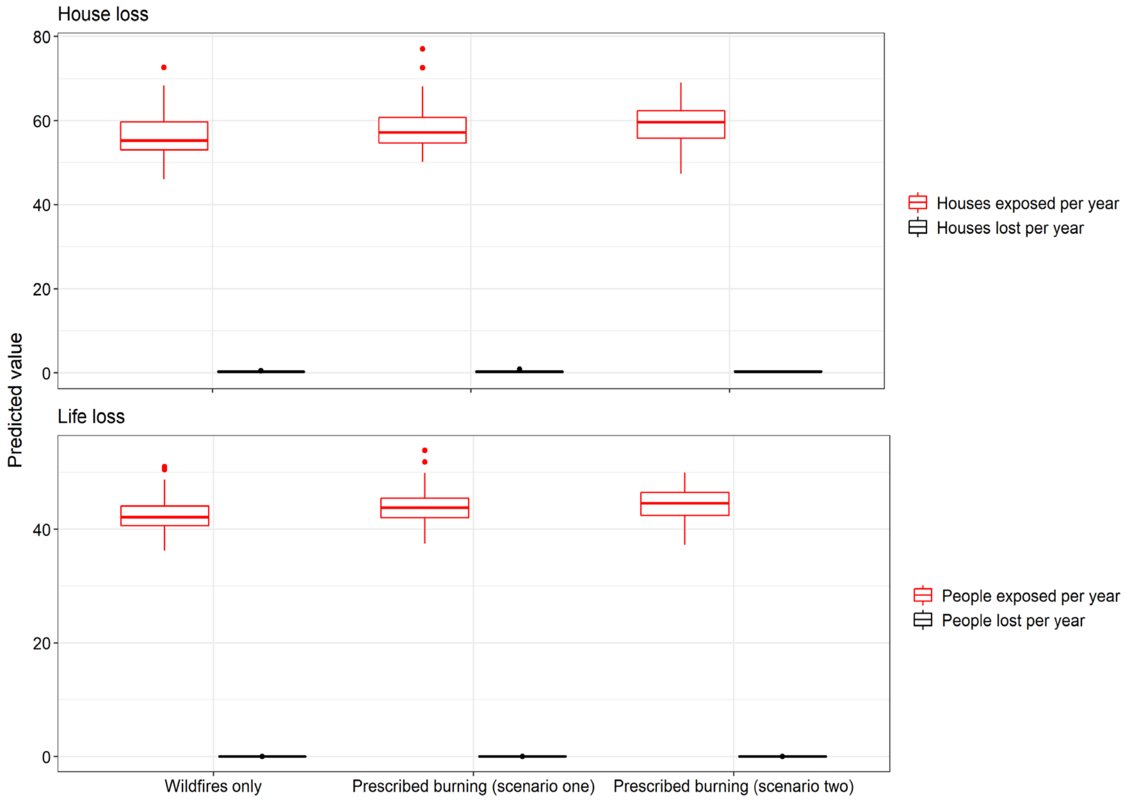

FIGURE 9: PREDICTED NUMBER OF HOUSES AND PEOPLE EXPOSED AS WELL AS THOSE LOST PER YEAR FOR THREE MANAGEMENT SCENARIOS.

DISCUSSION

Improving our understanding of bushfire risk is an essential task to inform future management practices and to protect human life, property and biodiversity (Ager, Kline, & Fischer, 2015; Banks et al., 2011; Torre & Díaz, 2004). During the 2019/2020 Black Summer fires, the extent of high severity wildfires was larger than previously recorded and the total area burnt amounted to almost 19 million hectares across South Eastern Australia (Collins et al., 2021a; Filkov et al., 2020). House losses in SA were the highest in 20 years and across the continent, impacts to people, property and biodiversity were unprecedented (Filkov et al., 2020). Predicting the likelihood and frequency of future megafires and understanding the risks to biodiversity and people is essential going forward. This study aimed to predict risks of changing fire regimes on people, property and biodiversity on Kangaroo Island and identify the impacts of three management scenarios on these risks. This is the first time FROST has been used to predict changing bushfire risks in SA and to estimate risks to assets. The results we have presented here provide the first insight into how fire regimes are likely to shift in terms of extent, frequency and intensity on Kangaroo Island. From these results we are better able to understand the benefits and limitations of different management strategies on fire risk and the likely impacts for people, property and biodiversity.

Fire frequency during wildfire seasons is reduced by prescribed burning efforts, but this reduction in frequency was not influenced by the level of prescribed burning used (Figure 4). This is probably because the two prescribed burning scenarios we tested only differed (in terms of percentage burnt) in the currently unzoned FMZs which constitutes less than one percent of the ~120,000 hectares worth of burn blocks. Asset protection and landscape management zones were both burned at the same percentage between scenarios (Table 1). Increased burning in these zones in scenario two may generate greater differences in outcomes between the two prescribed burn scenarios and improve our ability to prioritise management strategies for Kangaroo Island. Despite the slight decline in fire frequency in prescribed burning scenarios, we see only a small shift in the total and annual area burnt between the wildfire only scenario and the first prescribed burning scenario (Figure 3). However, there was no difference between the wildfire only and second prescribed burning scenario, or the latter and prescribed burning scenario one (Figure 3). While a decline in the frequency of very high and extreme intensity fires was observed, we saw an overall increase in the area of the landscape which experienced very high or extreme intensity fires at least once (Figure 6). This suggests that prescribed burning scenarios could result in a greater total area burnt over the next 50 years and a greater area burnt by very high and extreme intensity fires.

These results concur with previous research which suggests that prescribed burning can reduce the frequency and intensity of wildfires but ultimately the levels of burning required to achieve these outcomes result in a greater area of the landscape burned overall (King, Cary, Bradstock, & Marsden-Smedley, 2013; Penman et al., 2011; Price, Pausas, et al., 2015; Price, Penman, Bradstock, Boer, & Clarke, 2015). Moreover, the effectiveness of prescribed burns is dependent on the likelihood of a wildfire encountering one or more treated areas (Agee & Skinner, 2005; Finney et al., 2007; Price, Penman, et al., 2015). This was also supported in our results as we saw a spatial shift in the impacts of wildfires across

Kangaroo Island under prescribed burning scenarios (Figure 5). Wildfires in our prescribed burning scenarios do not burn as frequently in some areas as the wildfire only scenario, suggesting prescribed burning was effective in these burn blocks. However, impacts seem to shift elsewhere the landscape, resulting in a higher fire frequency in areas where the wildfire only scenario did not impact.

Our post-processing results show the impacts of frequent fuel reduction due to prescribed burning on the area burnt before TFI (Figure 8). When prescribed burns were applied, a greater proportion of the intact vegetation is below minimum TFI, resulting in a greater impact on biodiversity during wildfire seasons. Fire frequency is known to be important in Australian ecosystems (Andersen et al., 2005; R. A. Bradstock, Bedward, Scott, & Keith, 1996; Penman et al., 2011) and can drive community composition and diversity (Andersen et al., 2009; Penman, Binns, Shiels, Allen, & Kavanagh, 2008; Penman & Towerton, 2008). It is however, unclear how prescribed burning efforts may impact species and populations long-term because few ecological studies have examined biodiversity response to the impacts of varying fire regimes and prescribed burning efforts (M. F. Clarke, 2008; Penman et al., 2011). Further research is required to identify management techniques which result in appropriate fire regimes for maintaining biodiversity (R. A. Bradstock, Bedward, Kenny, & Scott, 1998; McCarthy, Possingham, & Gill, 2001). These are likely to be different to those used to manage fire frequency and intensity for the purposes of protecting people and property (Bentley & Penman, 2017; Driscoll et al., 2016; Penman, Ababei, et al., 2015).

Fire management to date has focused primarily on reducing the incidence, intensity and extent of wildfires as these are the aspects of fire regimes which present the greatest risk to properties and human lives (Boer, Sadler, Wittkuhn, McCaw, & Grierson, 2009; Russell-Smith, Mccaw, & Leavesley, 2020). Our simulations found high predicted exposure of people and houses to wildfire, but with a resulting lower loss of life and property. These results did not differ between management scenarios and prescribed burning strategies tested did not appear to directly impact these assets. Future research should explore a greater variety of management scenarios (i.e. different levels and strategic placement of prescribed burning) and examine the impacts of these management scenarios under a variety of climate scenarios. This would help improve our understanding of how fuel management influences exposure of people and property to the direct impacts of wildfires. Future research should also aim to identify how the exposure of people and property through wildfire impacts these assets long-term, particularly when considering the less immediate hazards which accompany wildfires such as smoke.

Wildfires release large amounts of smoke, which can pose a hazard to human health by impacting air quality. Global average wildfire emissions were estimated to be 2.2 billion tons per year from 1997 to 2016 (Magidimisha & Griffith, 2017). Many wildfire emissions can have acute or long-term health implications on the exposed populations (Stone et al., 2019; WHO Regional Office for Europe, 2013).Globally, average annual mortality from wildfire smoke is estimated to be 339,000 deaths, with the worst impacted areas being sub-Saharan Africa and South east Asia (Johnston et al., 2012. Studies have also found an association between daily mortality from wildfires for all-causes of death, including cardiovascular disease (Reid et al., 2016). For instance, Borchers Arriagada et al.,

(2020) estimated that bushfire smoke during the Black Summer fires was responsible for 417 excess deaths, 1124 hospitalisations for cardiovascular problems and 2027 for respiratory problems, and 1305 presentations to emergency departments with asthma. While not everyone who is exposed to thick smoke will have health problems, further research on the effects of exposure to wildfire smoke are warranted. Risks caused by wildfire smoke should be taken into consideration when estimating potential life loss from future wildfires and planning management strategies and suppression efforts. For example, due to higher exposure rates firefighters may be more at risk of long-term health issues related to smoke inhalation (Engelsman, Toms, Banks, Wang, & Mueller, 2020), therefore managing firefighters exposure and personal protective equipment during wildfire season is critical. Population exposure and respiratory health impacts of wildfire smoke is likely to grow in the future as global wildfire activity and human population growth both increase.

FUTURE RESEARCH

One key outcome of this research was the establishment of a protocol for predicting fire risk in SA. This research has established the foundations required to expand our study and examine fire risks in different parts of the state. Future research should capitalise on this capability to expand and explore bushfire risk under different climate scenarios and alternative management approaches to those presented here. For example, different levels of prescribed burning, the use of fuel breaks, or increased suppression efforts would likely change our estimates of wildfire risk on Kangaroo Island. We were only able to explore one climate scenario here but to expand on this study, we could explore a series of climate models and make predictions using far future climate change scenarios (e.g., 2060 to 2079). Future research should also conduct sensitivity analyses by varying the number of replicates used and exploring different lengths of simulations. This would improve the accuracy of our predictions of risk and establish a baseline against for the ideal simulation protocol in SA going forward.

We have shown here that a greater area of vegetation is burnt before minimum TFI in the prescribed burning scenarios compared to wildfires only. Prescribed burning efforts are known to influence richness, composition, diversity and potentially even persistence (Andersen et al., 2009; Penman et al., 2008; Penman & Towerton, 2008). However, it is still unclear what the medium to long-term implications of such actions are to biodiversity beyond immediate changes to vegetation or community composition. Future research could utilise the results of FROST simulations and population studies for key species to examine the impacts of wildfires on medium and long-term viability (Penman, Keith, et al., 2015; Swab et al., 2012). There are several approaches which can be used to model changes in persistence through time including Bayesian Networks and population viability analyses (Akçakaya & Root, 2005; Visintin et al., 2020). Providing estimates of abundance and long-term population persistence for keystone species under current and future fire regimes may provide insight for managers on how biodiversity holistically is impacted by shifting fire risks. Such analyses would inform both fire management practices and could help us better understand the effectiveness of conservation efforts under the pressure of changing fire regimes.

Lastly, current methods of estimating risks to people and property consider only the direct impacts of fire and fail to account for the less immediate hazards caused by wildfires. These include the health hazard risks which may increase life loss (through smoke inhalation or long-term health impacts), as well as the risks to people's livelihood (loss of income through tourism or agriculture, etc). Future research should examine what the long-term health implications in increase fire frequency are as well as the economic risks associated with changing fire regimes. This may give us a more accurate representation of the actual impacts of wildfires on people and help to direct management efforts to minimise the most at-risk communities.

CONCLUSIONS

Our simulations explore only a small set of the management strategies and climate scenarios available. While we do observe a decline in the frequency of wildfires in prescribed burning scenarios, these scenarios result in a greater area burnt by very high and extreme intensity fires at least once across the 50-year simulations. We also found that prescribed burning results in more area burnt before minimum TFI during wildfires and therefore prescribed burning is likely to have an impact on biodiversity on Kangaroo Island. However, we see no difference in the number of houses or people exposed to wildfire between scenarios. This research has highlighted that ideal fuel management practices on Kangaroo Island should be carefully considered and strategically planned to manage risks to different asset values. It has also demonstrated how FROST can be used to predict bushfire risks in SA and explore different management options.

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