Extreme Value Analysis for Bushfire House Losses in Australia

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handed in by

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ABSTRACT

In the light of the catastrophic bushfire season 2019-20 in Australia, which claimed more than 3000 homes, the aim of this study is to estimate return periods of extreme bushfire house losses. A data set of 66 events with a total of 13,730 house losses was compiled for the time period from 1939 to 2020. The data set is characterized by an increasing trend and a few major events dominating the house loss record. Extreme value theory (EVT) was applied to calculate bushfire house loss return periods under current and future conditions. The effect of climate, exposure, and efforts in risk reduction are discussed in order to account for non-stationarity. Integrated covariates are temperature and precipitation, which allowed to model the aggregated house loss time series under RCP4.5 and RCP8.5 conditions for the year 2030 and 2090. The analysis highlights the fire season 2019-20 as extraordinary in terms of house losses and has expected return periods of more than 100 years. Nevertheless, historical records show a clear property loss increase for the most damaging events. Harsher fire weather is projected under climate change scenarios and therefore fire intensity and frequency is likely to increase. House loss return periods are expected to shorten drastically towards the end of the century. Return periods of extreme house loss events like during the fire season 2019-20 decrease from 100 years to 50 years by 2090 under RCP4.5. For RCP8.5 the expected return period is equivalent to 25 years and emphasizes the role of climate change in the increased frequency and severity of house loss events.

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1. INTRODUCTION

"Australia is on fire" was headline news in the 2019-20 fire season, which continued for months and demonstrated the immense potential of this natural hazard to cause enormous damage. Major bushfires had started already in the beginning of the fire season in June, and rapidly developed into many out-of-control fires by September. While hundreds of new fires ignited, the peak was reached during December 2019 to January 2020. Various regions were heavily impacted, especially in the east and south east. In the states of New South Wales and Victoria, large areas were affected. After more than half a year, the last devasting fires burned out in March. An estimated 18 million hectares were destroyed, which is more than four times the size of Switzerland or half the area of Germany. Almost 10,000 buildings were burned down, 3,000 homes were destroyed, and 34 people died. It is assumed that one billion animals have fallen victim to the fire and that some endangered species are now on the verge of total extinction (UN Environment, 2020). Unsurprisingly, the 2019-20 fire season was claimed several times to be an extraordinary event which even exceeded historical records. (Wahlquist, 2020; Cave, 2020 & BBC, 2020)

In general, bushfires in Australia are a regularly occurring phenomenon, which has played a significant role in shaping the landscape and the development of vegetation in the past (Steffensen, 2020). Fire events are not unusual for Australia; nevertheless, they have the potential to cause considerable damage to humankind and the environment (GOA, 2014). Numerous research projects were conducted to learn more about bushfire behavior and its determining factors. Considerable research has been conducted to analyzed fire weather conditions and their changes over time (Sharples et al., 2016). Fire weather in Australia is usually described by the forest fire danger index (FFDI) from McArthur which measures *H* relative humidity (%), *V* wind speed (km/h), *T* surface temperature (‘C) and *D* drought factor derived from KBDI (Williams, Karoly, & Tapper, 2001).

$$\mathrm{FFDI} = 2 \times \exp(0.987 \times \ln(\mathrm{DF}) - 0.0345 \times \mathrm{H} + 0.0338 \times \mathrm{T} + 0.0234 \times \mathrm{V} - 0.45)$$

Forest fire danger index	Fire danger rating
0–5	Low
5–12	Moderate
12–24	High
24–50	Very high
50–100	Extreme

TABLE 1: MCARTHUR FOREST FIRE DANGER INDEX FFDI RATING SCALE

Despite weak evidence, due to a lack of historical data, an increasing trend in FFDI, and extreme bushfire frequency has been observed over the last few decades. Under the inclusion of climate change scenarios this trend is projected to be even more pronounced in the coming years. These findings are confirmed and reinforced by Clarke, Lucas, and Smith (2013) and the Australian Bureau of Meteorology.

Blanchi, Lucas, Leonard, and Finkele (2010) analyzed statistical relationships between meteorological fire weather conditions in the FFDI, and house losses for the time period 1939-2009. Their study points out that most building damage is due to a few extreme events, which occurred above the 99.5 percentile level of the daily FFDI distribution. This is represented by three major events (Black Tuesday 1967, Ash Wednesday 1983, and Black Saturday bushfires in Victoria 2009) which account roughly for 64% of total house losses. A higher FFDI increases the probability of fire occurrence, but also its intensity, which makes surroundings and infrastructure more vulnerable to being damaged or burned down.

Nevertheless, severe fire weather does not directedly lead to bushfires and building losses. A complex set of factors such as fuel load, local topography, vulnerability, exposure, preparedness and others are determinants (Blanchi et al., 2010). Most bushfires occur in rural regions and cause little property damage, whereas few events cause the majority of losses. By approaching a populated area, a fire's probability to cause large losses rapidly increases. FFDI is therefore more of a prerequisite and McAneney (2005) claims the house loss potential to depend on the disposition to the bushland boundary. Crompton et al. (2010) adjusted historical dwelling damages to current societal conditions for the time period from 1925 to 2009. No upward trend could be observed for dwelling damages after the normalization despite an increased FFDI. The absence of a trend suggests that bushfires did not change in intensity and frequency, but rather more houses seem to have been exposed to bushfire prone areas.

Bushfires are a classic example of extreme events. While ordinary fires occur often and have little or no impact, few extreme events pose a considerable hazard to the environment and human property. Understanding the connections between unusual natural events and economic consequences is of fundamental importance to design risk management strategies. Of interests are return periods of theses catastrophic events. Based on a robust evaluation, fire authorities can predetermine the size of fire crews and supporting forces. Furthermore, it becomes possible to evaluate costs of past and future fires, which is especially important for governmental agencies and reinsurance companies to allocate resources efficiently (Evin, Curt, & Eckert, 2018).

Since the house loss distribution is dominated by a few extremes, it cannot be sufficiently described by only considering the mean and variance. It is much more appropriate to focus on the upper tail of the distribution. Extreme value theory (EVT) is a field of statistics which deals with the tails of distributions. It allows to estimate the probability of rare events or even the probability of events which are more extreme than any other that has been observed yet. The underlying idea is to separate frequent events with high probability from the rare and extreme ones (Coles, S., Bawa, J., Trenner, L., & Dorazio, 2001).
EVT is widely used to analyze natural catastrophes as avalanches, landslides, or earthquake (Holmes, Huggett, & Westerling, 2008). Previous studies conducted EVT to analyze wildfire behavior. E.g. Jiang and Zhuang (2011) applied EVT to characterize extreme large fires in Canada. Under consideration of spatial and temporal covariables such as climate and fuel load, fire behavior was analyzed to predict future fire size and frequency. In order to support fire suppression policy, Evin et al. (2018) used a similar approach, focusing on return periods of very large burned areas in southern France. Holmes et al. (2008) published a general paper on statistical analysis of wildfires and the research field of EVT. Discussed is the inclusion of explanatory variables such as climate factors and fire management, which are demonstrated on an example of fires in the Sierra Nevada Mountains, California. However, extreme fires are rare in contrast to ordinary fires and thus the tail distribution is often not well characterized (Malamud, Millington, & Perry, 2005). Therefore it was mentioned that limitations to statistic-based approaches occurred due to a limited time depth of the available data.

Overall, heavy tailed distributions are suggested to be suitable to characterize large fires, but only few studies have focused on the socioeconomic impacts such as house losses. A range of studies investigated fire weather, fire behavior and the extent of burned area. However, in order to estimate bushfire house loss return periods, it is more meaningful to address bushfire property losses directly. On the occasion of the destructive fire season 2019-20 which claimed more than 3000 homes, the aim of my master’s thesis is to calculate return periods for socioeconomic bushfire damage in terms of house losses. Thereby the role of climate conditions and societal development will be considered and future risk under climate change scenarios estimated. The following two questions will be addressed:

1. Is Australia likely to face a fire season as bad as 2019-20 again any time soon?
2. Should we expect even more damaging fire seasons due to climate change?

To answer these questions, historical bushfire house loss data will be collected up until the most recent fire season 2019-20. EVT is applied to fit the Australian house loss time series from 1939-2020 to the generalized extreme values (GEV) distribution. With a Poisson point process (PP) approach extreme statistic models are used to calculate return periods and return levels. In this context, return levels are defined as the number of houses expected to exceed a certain threshold once during a y-year return period. Since the house loss time series shows an increasing trend for the most damaging events, it is assumed to be non-stationary. Changes in property impact over time are usually driven by changes in climate and weather conditions, exposure of infrastructure and efforts in risk management (Bouwer 2019). Consequently, these factors with high explanatory power are integrated into the model as covariates to account for non-stationarity. In a further step, the effect of climate change on house loss probability is assessed. Climate covariables are adjusted for risk specific characterizations. RCP4.5 and RCP8.5 are investigated for the year 2030 and 2090 and associated return levels calculated. In a final step the model results, its limitations, and uncertainties will be discussed.

2. DATA

This chapter provides insight into the development of the house loss data set, which is subsequently used for the EVA. Inconsistencies between different sources of historical records are shown and potential reasons are discussed. The final data set is statistically described and illustrated with a time series and probability density function.

2.1 HOUSE LOSS DATA

Despite the frequency and severity of bushfire and bushfire damage, there is no central record for house losses. Different records show considerable variation and inconsistencies with regard to the number of historical house losses. E.g. the data set from Blanchi et al. (2010) reports 454 house losses in Victoria for the year 1962, whereas Harris et al. (2011) only reports 376 houses for the same year and state. Even larger record differences are found for the fire season 1943-44 where Harris et al. (2011) list 92 destroyed houses, while the Forest Fire Management Victoria (2019) lists 500 house losses . To some extent, differences can be explained by the fact that there is no uniform record systematic for the broad range of sources. Some disaster records are very detailed and describe individual location specific bushfire events, whereas others summarize damage for whole states and years. Generally, the further back in time an event occurred, the less detailed and reliable the sources are. Another reason for these inconsistences is the underling definition of building damage. It becomes apparent that some refer to all buildings as residential, public, commercial, industrial, etc., while others only include homes or insured losses. In this study the term "house losses" is used and defined as bushfire related residential house losses, homes or dwellings, and excludes other infrastructure damage.

Unfortunately, house loss data is often not publicly available due to commercial use. Access to comprehensive data bases as PerilAUS which was the basis for a range of studies (e.g. Crompton, McAneney, Chen, Pielke, & Haynes, 2010; McAneney, 2005) was denied. However, Blanchi et al. (2010) compiled an accessible house loss data set for the time period 1957-2009 in their research paper appendix. The data was collected from various sources such as journals, governmental and historic reports. The set contains 54 bushfire events causing a total of 8,256 residential house losses. This basis is supplemented with additional house loss events, which are referenced with historical reports, newspapers and fire authority publications and used for the following analysis. Events during the initial period were added and the time period extended. The new data set consists of 66 events with a total of 13,730 house losses and covers the time period 1939-2020.

(A)

Date	House Losses	State	Name
31.01.2020	3094	NSW	Black Summer
11.02.2017	35	NSW	NA
19.12.2015	116	VIC	NA
25.11.2015	91	SA	NA
02.01.2015	38	SA	NA
15.01.2014	45	VIC	NA
...	...	...	...

(B)

NSW	VIC	TAS	ACT	SA	Total
4,402	7,074	1,551	523	309	13,730

TABLE 2: (A) BUSHFIRE HOUSE LOSS RECORDS & (B) SUMMARY OF HOUSE LOSSES PER STATE FOR THE TIME PERIOD 1939-2020.

Regarding the chronological records of bushfire house losses, changes in frequency for bushfire house loss events can be observed. As mentioned above, the further back in time, the less detailed records are and house loss events are often aggregated for fire seasons. On the other hand, recent events are mostly recorded in detail and separated into individual events. This leads to changes in frequency which can be explained to a large extent by irregular recording systematics.

In order to homogenize the data set, all bushfire house loss events are summarized for annual fire seasons. The typical bushfire season in southern and eastern Australia starts on the 1st of June in year y and ends the next year $y+1$ on the 31st May. To give an example, three damaging events are recorded for the year 2015. House losses from 2.1.2015 are counted to the fire season 2014, while 25.11.2015 and 19.12.2015 are part of the fire season 2015.

Due to this aggregation of data for fire season, location, time and corresponding meteorological information are lost for individual events. Since the aim of this study is to estimate the probability of reoccurrence of extreme fire seasons, individual events are neglected in favor of larger time depth. Nevertheless, the data basis is not suitable for downscaling. In other words, findings based on the aggregated fires season data are not appropriate for specific regional predictions.

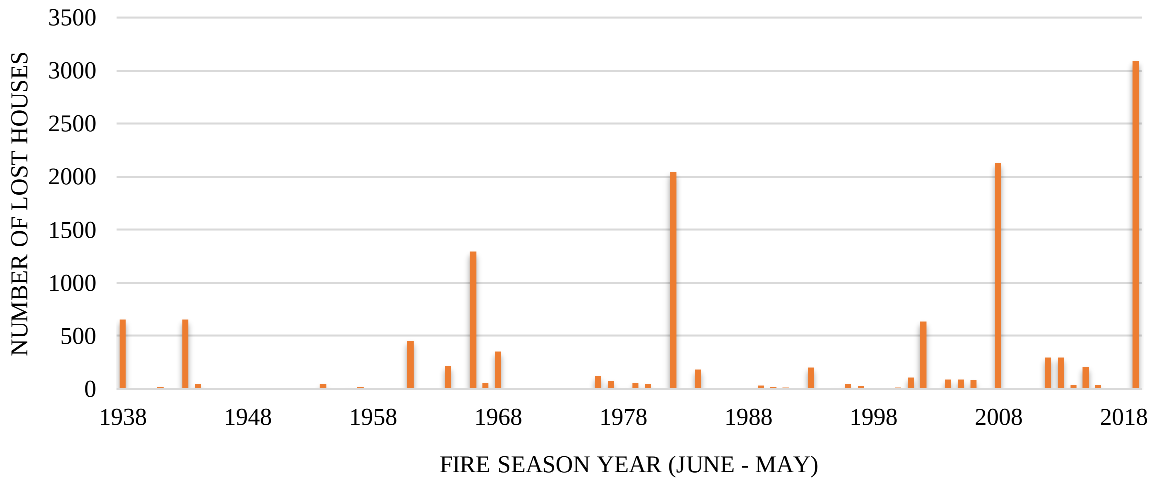

FIGURE 1: ANNUAL AGGREGATED BUSHFIRE HOUSE LOSS RECORDS FOR FIRE SEASONS YEARS 1938 TO 2019.

The annual aggregated bushfire house loss data set covers the time period 1938-39 to 2019-20 and includes 82 fire seasons. Residential property losses are recorded for 41 fire seasons. 50% of the years caused zero house losses. The range of damage varies tremendously from zero up to a maximum of 3094 during the fire season 2019-20. On average 167.4 houses are lost per year. However, the mean tends to be misleading, since it differs substantially from the median of 0.5. This indicates that few events are responsible for the majority of the damage. This is

also indicated by the probability density function for bushfire house losses (Figure 2). The histogram shows clearly that the distribution is not normal. It is highly positively skewed and thus might be Pareto distributed (heavy-tailed).
While most observations caused little or no damage, few outliers resulted in extreme losses. It is noticeable that the time series is dominated by four major fire seasons which substantially exceed the mean and account for 60% of all recorded house losses. These are: Black Tuesday 1966, Ash Wednesday 1982, Black Saturday 2009 and the fire season 2019-20.

Despite the aggregation of events to fire seasons, a change in frequency can be observed. For recent years, records are more frequent. This may be attributed to changes in climatic and socio-economic conditions, however, it might also be due to the reliability of the records. While it is likely that large events were recorded in the past, smaller events may have been lost.
Furthermore a linear upward trend for the number of house losses is observed (Figure 1). This is especially true for the most extreme fires over the last century. While extreme events in 1938 destroyed 700 houses, recent years recorded more than three times higher losses. As a consequence the assumption of stationarity is violated and the trend has to be incorporated into the analysis.

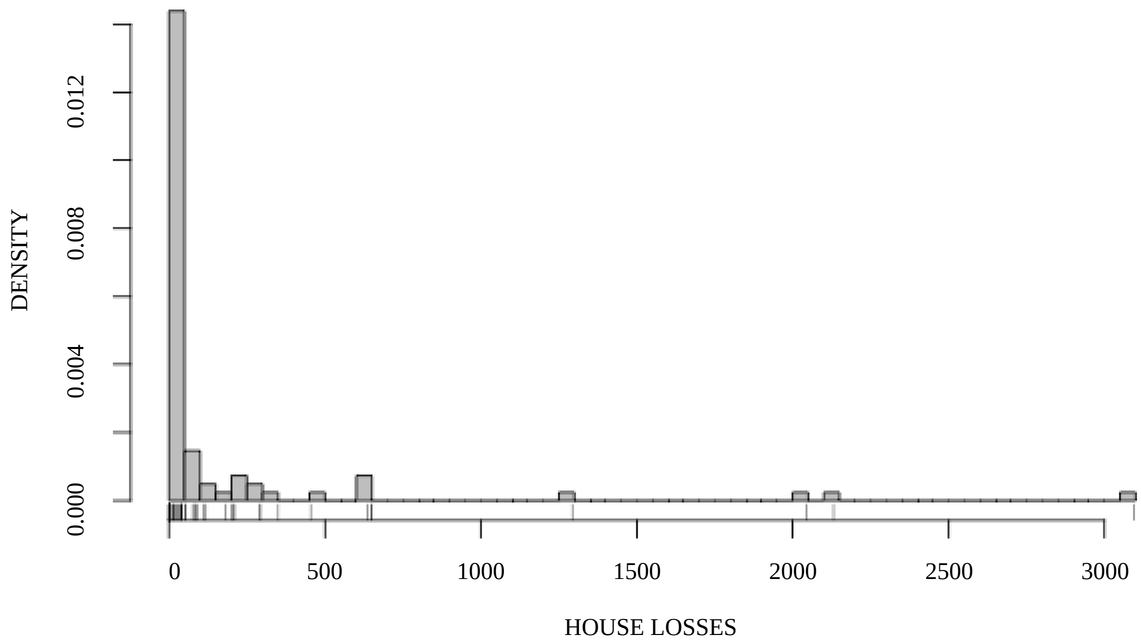

FIGURE 2: PROBABILITY DENSITY FUNCTION FOR BUSHFIRE HOUSE LOSSES FOR FIRE SEASONS YEARS 1938-2019

3. METHOD

The following section deals with the successive steps of EVT and describes the methodological procedure of fitting a non-stationary model to extreme bushfire house loss data. All steps are executed in R (Team R. Core., 2019) and performed with the package extRemes and its guidelines, published by Eric Gilleland and Richard Katz (2016). The basic structure of the analysis is developed according to the generalized workflow from Towler, Llewellyn, Prein, and Gilleland (2020).

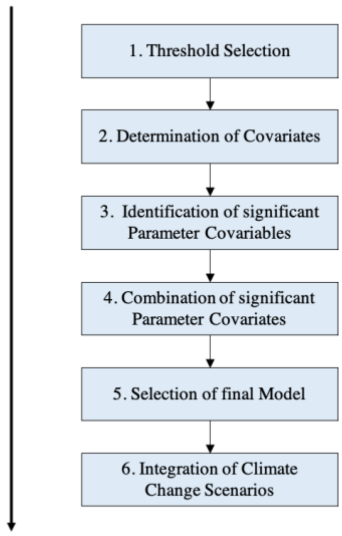

FIGURE 3: FLOWCHART FOR FITTING A NON-STATIONARY PP MODEL; OWN ILLUSTRATION

3.1 THRESHOLD SELECTION

For the development of a statistical EVT model it is necessary to separate the normal values from the extreme ones. There are two main approaches to extract these extreme values. The first approach is called block maxima where the dataset is separated into equally sized subsets. The maxima of every block is determined and used to describe the probability distribution. The disadvantage of this method is that only the most extreme observation within one block is used and therefore valuable data might be lost. The second approach is based on the concept of threshold excess and includes the peak over threshold (POT) and point process (PP) approach (Coles, Bawa, Trenner & Dorazio, 2001).

For this analysis the threshold excess approach is chosen. This is argued with the fact that the data set is already summarized for fire season house losses and therefore in yearly units. With only few observations and the intention to incorporate all extreme fire seasons, BM is not appropriate.

The challenge to select a threshold lies in the tradeoff between a minimized bias and variance. If the threshold is too low, normal events are not divided from the extreme ones and therefore the statistical assumptions are violated which leads to high bias. On the other hand, if the threshold is too high, the number of exceedances is too small, leading to high variance (Coles, 2001). Several diagnostic tools, e.g. the mean residual life plot (MRL), are available to facilitate the threshold selection. However, the choice of a threshold is to some extent subjective and therefore it is reasonable to try a range of values (Towler et al., 2020). In this case, two thresholds are selected and tested within the POT and PP approach. Based on the Akaike's information criterion (AIC) the best model is then chosen for the subsequent analysis.
In addition, the extreme dataset is tested for independence. While independence is often unrealistic for weather extremes, Jiang et al. (2011) argues that it is rarely a problem for extreme fires. The auto-trail dependence function (atdf), as well as the extremal index aid to diagnose if the observations depend on each other. In case of dependence, Gilleland and Katz (2016) provide implemented methods for declustering time series in the extRemes package.

3.2 Determination of Covariates

The stationarity assumption is a central requirement for EVT. Stationarity implies constant distribution of observations and no changes over time. Since the extremes of fire losses are likely to vary over the long term, this assumption might not hold and is therefore assumed to be non-stationary. If the processes leading to non-stationarity are known, measurable, and data is available for the entire time period of interest, the information can be incorporated with covariates to model the parameters (location, scale & shape). In addition covariates can be used to modify the likelihood of extremes. This allows to characterize risk specific profiles. For instance, a variety of climate change scenarios such as the RCPs can be incorporated.

It is important to mention that the selection of covariates is to some extent subjective and also dependent on the availability of data. It is clear that the selection also determines the results to a certain degree. The key criteria of covariate identification are a high prediction and explanatory power (Towler et al., 2020). While a complex set of interactive factors such as human activity, exposure, vulnerability, preparedness, house density, topography, forest fuels and others are determinants for bushfire house losses (Dunlop, McLennan, Peters, Kelly, & Riseborough, 2011), Bouwer (2019) refers to three major attributes for changes over time: (i) natural climate variability, including anthropogenic climate change and large scale weather conditions as the El Nino-Southern Oscillation (ENSO) and Indian Ocean Dipole (IOD); (ii) exposure and vulnerability of infrastructure, and (iii) efforts in risk reduction and management.

3.3 Identification of significant Parameter Covariates

In the next step it is tested if and which of the determined covariates improve the model fit. Every covariable is separately included in the model for the location, scale and shape parameter in a linear and quadratic form. The non-stationary models with covariates and the nested model without covariates are then compared to each other. Based on a likelihood-ratio test, significant covariate parameters are identified and determined if they are reasonable to include in the final model.

With the POT approach only the scale and shape parameter can be modeled. The PP approach allows to model all three parameters. In this case, the PP approach is preferred over the POT due to the greater flexibility of covariate modeling.

3.4 Combination of significant Parameter Covariates

To begin, single significant covariates are tested for the location parameter. In a next step combinations of multiple significant covariates are created for the location parameter. The same procedure is done for the scale and shape parameter. Afterwards, combinations of the location and scale parameter are tested and in a final step combinations of the location, scale and shape parameter are created. To determine significant model improvements, a likelihood-ratio test is employed for every combination.

3.5 Final Model Selection

The aim of this step is to select the model which is the most appropriate representation of the house loss extreme data and allows to model climate scenarios. As before, based on a likelihood-ratio test, only significantly better models than the restricted one (without covariates) are considered. For the models that meet these requirements the Akaike (AIC) and Bayesian information criterion (BIC) are calculated to compare different models and evaluate which one is the best fit. The AIC considers the number of independent variables used (model complexity) as well as the goodness-of-fit. A lower AIC or BIC value indicate a better fit (Akaike, 1974). In addition to the AIC, it is considered if the model makes intuitive sense, which is to some extent subjective. In this regard it is of interest if the model allows to model climate conditions which are associated with fire weather.

The final model is then used to calculate return levels under the inclusion of covariables to account for non-stationarity. Return levels consider values, which are exceeded at least once in a y year event (Coles et al., 2001). In this context, return levels represent the number of bushfire house losses which are exceeded in a y year fire season.
Further are individual parameter covariates modified separately, in order to determine the relationship between individual covariates and return levels. Of interest is whether the effect on return levels is positive or negative.

3.6 Integration of Climate Change Scenarios

In order to assess the effect of climate change on bushfires house losses, a covariance matrix is created for the final non-stationary model and characterized by specific risk scenarios. The included climate parameter covariables are adjusted according to RCP4.5 and RCP8.5 for the years 2030 and 2090. Associated return levels are calculated and the effect of climate change on house losses is determined.

4. RESULTS

The result section is structured identically to the methods part. Thus, intermediate results towards the final PP model are subsequently presented. Significant covariate parameters are identified and integrated into the non-stationary EVT model. The final PP model is selected and house loss return levels are calculated for both current conditions and climate change scenarios.

4.1 THRESHOLD SELECTION

To begin, independent peaks over a certain threshold are extracted from the annual aggregated house loss data set. The number of house losses ranges from zero to 3094. While the threshold should not be too low in order to separate extremes from normal events, it should neither be too high due to the number of available observations and associated variance (Coles, 2001).

With the facilitation of the MRL (Mean Residual Life) plot two thresholds are selected. Since a good fit is indicated by an approximately straight line within the uncertainty bounds, 40 and 125 seem to be a reasonable threshold choice. It is noted that during the time period 1938-2019 only 24 fire seasons exceed 40 house losses and for the same period only 15 seasons exceeded 125. In order to ensure to have enough data, higher thresholds are not incorporated.

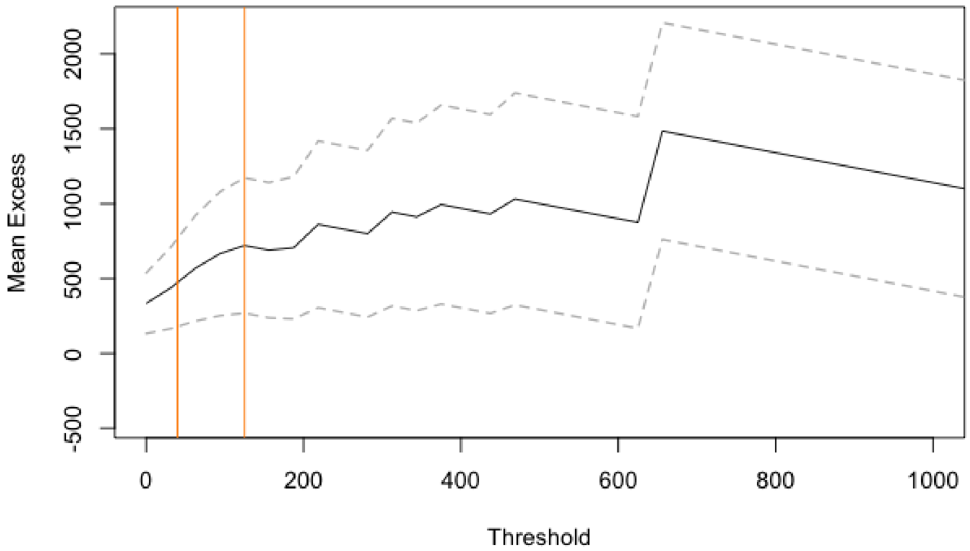

FIGURE 4: MEAN RESIDUAL LIFE PLOT WITH THE THRESHOLD OF 40 AND 125 HOUSE LOSSES, INDICATED BY ORANGE LINES. THE 95% CONFIDENCE INTERVALS FOR THE MEAN EXCESS IS REPRESENTED BY THE DASHED GREY LINES.

Subsequently, POT and PP models are fit to the data under the inclusion of the selected thresholds and compared with each other. The Akaike's information criterion (AIC) is clearly lower for both approaches for the threshold of 125. This suggest a better model fit and is therefore chosen.
The inspection for dependence is examined with the auto-trail dependence function (atdf) and extremal index. As expected and supported by Jiang et al. (2011), the data is independent and therefore declustering is not necessary. As a result, all subsequent results use independent observations, exceeding the threshold of 125.

4.2 Determination of Covariates

To account for the effect of non-stationarity the following three covariate categories are defined. The underlying explanatory power of each category is discussed in detail and the covariables used for the EVT described:

i. Weather and Climate Conditions
ii. Exposure - Number of Total Houses
iii. Efforts in Risk Reduction – Fire Suppression with Aircrafts

4.2.1 Weather and Climate Conditions (I)

Due to the large geographical size of the country, a wide range of climate classifications can be allocated to Australia. In the north, an equatorial and tropical climate with rainforest prevails. Further south, along the east coast, the climate is subtropical and even temperate in the states of Victoria, Tasmania and parts of South Australia. The countryside is dominated by grassland and desert. Australia is characterized by extensive droughts and wet periods which are affected by various weather systems. Perhaps the strongest influence is the El Niño-Southern Oscillation (ENSO), whereby the El Niño phase is associated with reduced rainfall, warmer temperatures, later monsoon onset and an increase in fire danger in southern Australia. Future climate drivers are the Indian Ocean Dipole (IOD), monsoons, Southern Annual Mood (SAM), and Madden-Julian Oscillation (MJO). Those are crucial for the climate variability and especially the variation in yearly precipitation in Australia (CSIRO and Bureau of Meteorology, 2016; Australian Bureau of Meteorology, 2014).

While studies have already investigated the relationship between extreme weather conditions and individual house losses events (Clarke et al., 2013), the FFDI is not meaningful for aggregated fire seasons, since the index is extremely time and location specific. Nevertheless the associated variables are of interest to incorporate long term effects on bushfire house losses.

Climate change is a potential factor for non-stationarity. Changing conditions over time are likely to affect the frequency and intensity of fire occurrence which increases the probability of bushfire house losses. The prevailing climate along the East Coast, where most of the historically recorded house losses are located, is most adequately represented by the climate super-cluster Eastern Australia, which is composed of the East Coast and Central Slopes climate clusters. Of interest are variables which have a significant impact on fire weather. Regarding the FFDI, temperature, wind, precipitation and relative humidity are key drivers (Clarke et al., 2013). An underlying assumption for the variables is the availability for the entire time period from 1938-2019. The Bureau of Meteorology [http://www.bom.gov.au/] provides a broad range of historical weather records, where variables can be selected by region and period of interest. Temperature and precipitation are available for the whole time period, as well as the Southern Oscillation Index (SOI) which is an indicator for the intensity and development of an El Niño (La Niña) year.

Metrological variables are available for financial years (July to June), which is almost congruent to fire seasons and thus to the aggregated annual house loss data set. Therefore, temperature mean and maximum are used in financial year periods, and likewise total precipitation and precipitation anomaly. In addition, since most of the house losses occur during the summer months (DJF), the summer season is investigated separately. The BoM allows to extract specific seasons for the same variables and time period. Therefore, mean and maximum temperature, as well as precipitation anomalies are selected separately for the summer season. An overview of the tested metrological variables is provided in Table 3.

El Nino	Temperature	Precipitation
Southern Oscillation Index (SOI)	Temp. Max. Anomaly (°C) Eastern Australia, Financial Year (July - June) Average (1961-90) 27.0 °C	Prec. Total (mm) Eastern Australia, Financial year (July to June)
	Temp. Mean Anomaly (°C) Eastern Australia, Financial Year (July - June) Average (1961-90) 20.5 °C	Prec. Anomaly (mm) Eastern Australia, Financial year (July to June) Average (1961-90) 629.7 mm
	Temp. Max Anomaly DJF (°C) Eastern Australia, DJF Average (1961-90) 32.7 °C	Prec. Anomaly DJF (mm) Eastern Australia, DJF Average (1961-90) 267.6 mm
	Temp. Mean Anomaly DJF (°C) Eastern Australia, DJF Average (1961-90) 26.2 °C	

TABLE 3: OVERVIEW OF CLIMATE VARIABLES:

4.2.2 EXPOSURE – NUMBER OF TOTAL HOUSES (II)

While some studies found anthropogenic climate change as major driver for changes in residential property losses, Pielke et al., (2008) and Bouwer (2011) suggest increasing exposure as much more significant. In case of a fire, it is predominantly the distance to the heat flux from flames that determines whether the fire spreads to urban interface and causes damage (Mell et al. 2010). However, to assess the likelihood of bushfire house losses, the total number of houses exposed is as crucial.

A growth in population and wealth leads to higher average living space per person and increasing number of residential houses. The Australian population has more than doubled in only 50 years. Since the 1966 Census, the population grew from 11.6 to 23 millions in 2016. The same trend is observable for residential houses which grew from 3.4 millions in 1966 to 9.9 millions in 2016. All reported house losses occurred in the states of New South Wales, Victoria, Tasmania, Queensland, Australia Capital Territory or South Australia. These areas are located in the east or south-east of the country (Australian Bureau of Statistics, 2017). Roughly 80% of all residents live along the east coast, thus a correlation between total houses and house losses seems to be intuitive. Under the assumption that the number of houses exposed to fire developed at the same rate as the number of total residential houses, it is chosen as indicator for exposure. In other words, the more houses, the higher the number of exposed houses to bushfire prone area.

The general approach to compare disaster losses over time is to normalize impacts for socioeconomic conditions by correcting impacts for population growth, wealth and inflation (Pielke & Landsea, 1998). As a result, historical events can be compared to recent events as if they occurred under the same socioeconomic conditions. Since this study is interested in the evaluation of return levels, rather than comparing historical events, the normalization approach is rejected and the number of houses are integrated as covariables for the period of interest.

The number of residential houses are available at the Australian Bureau of Statistics and is reported in the census of population and housing [http://www.abs.gov.au]. Reports are provided within the time period 1921-2016 and since 1961 data is collected in a cyclical process of 5 years. The missing number of houses between census years were calculated through linear interpolation and estimated by extrapolation from 2016 to 2020.

4.2.3 Efforts in Risk Reduction – Fire Suppression with Aircrafts (III)

Major bushfire seasons like in 2002-2003 or events such as 2009 Black Saturday Bushfires caused substantial damages to urban and rural property, infrastructure, primary production systems, environment and even lives were lost. Due to the extent of the fire impacts, the Council of Australian Government (COAG) commissioned inquiries to continuously improve bushfire mitigation and management (Kanowski, Whelan, & Ellis, 2005). The vision for fire policy is:

> *"Fire regimes are effectively managed to maintain and enhance the protection of human life and property, and the health, biodiversity, tourism, recreation and production benefits derived from Australia's forests and rangelands."* (GOA, 2014, p. 9)

The majority of historical house losses occurred in a few extreme fires. A fully developed fire has a massive destruction potential and is likely to overwhelm firefighting authorities and gets out of control (McAneney, Chen, & Pitman, 2009). In order to prevent extreme fires, it is crucial to contain fires at an early stage. Plucinski et al. (2007) identified four main characteristics that determine the success of fire suppression: (i) time to arrival of initial attack response; (ii) prevailing weather; (iii) level of fuel hazard, and (iv) size of the fire at arrival of initial attack response. Except for the prevailing weather, all determinants can be improved by efficient fire management.

In general, ground crews are the primary suppression force. If fire escapes the initial combatting attempts, neighbor districts will form the supporting force and are coordinated at state level (CISRO, 2009). The use of aircraft for fire suppression has received increased attention in recent years due to three major advantages over conventional ground forces. These are speed, access, and observation, allowing aircrafts to reach fires at an early stage (Plucinski et al., 2007). The spread of fire can thus be contained or slowed down to limit the extent until the arrival of ground crews.

If fires are suppressed in an initial phase, less fires have the potential to get out of control and therefore the probability of extreme fires decreases, as well as associated house losses. In 2003 the National Aerial Firefighting Centre (NAFC) was founded to improve bushfire suppression on a national level. Highly specialized aircrafts were introduced and are available to support firefighting authorities.

Under the condition that efforts in risk management must be numerically expressible in order to be integrated as covariates, a dummy variable is created . Adopted by the study from Holmes et al. (2008) the variable *Aircraft* is used to approximate the effect of aircrafts for fire suppression. For the years prior to the intensified use of aircraft since 2003, the dummy variable is set to zero and consequently one for subsequent years.

4.3 Identification of significant Parameter Covariates

The significance of covariates is tested with a likelihood-ratio test for every parameter in a linear and quadratic form for the POT and PP models. Models with no significant improvements in comparison to the restricted model are excluded from the analysis. The same is done for those where no covariance-matrix could be calculated, since this is a necessary assumption for the calculation of non-stationary return levels. In other words, only significant covariate parameters with a covariance matrix are further considered.

None of the covariate parameters is significant for the POT approach which is therefore excluded from further analysis. For the PP approach eight covariate parameters are significant for the linear functional form and none for the quadratic. However, only six meet the assumption of significance and a covariance-matrix. These are *Temp.max.DJF, Prec.anom* and *Prec.anom.DJF* for the location, *Temp.mean.DJF* for the scale and *Temp.max.DJF* and *Temp.mean.DJF* for the shape parameter. These are highlighted in green in Table 4.

Covariable		**Location**		**Scale**		**Shape**	
	Functional Form	Covar. Matrix	Lr.test	Covar. Matrix	Lr.test	Covar. Matrix	Lr.test
El Nino (SOI)							
SOI	linear	✓	0.8546	✓	0.6835	✓	0.5848
	quadratic	✓	0.8552	✓	0.6024	✓	0.2589
Temperature							
Temp.max	linear	✓	0.0785	✓	0.6024	✓	0.2589
	quadratic	✓	0.1307	✓	0.1885	✓	0.2515
Temp.mean	linear	✓	0.1135	✓	0.0594	✓	0.0925
	quadratic	✓	0.1097	✓	0.2266	✓	0.3060
Temp.max.DJF	linear	✓	**0.0262**	x	**0.0022**	✓	**0.0046**
	quadratic	✓	0.7069	✓	0.1796	✓	0.1265
Temp.mean.DJF	linear	✓	0.0923	✓	**0.0042**	✓	**0.0030**
	quadratic	✓	0.7317	✓	0.1656	✓	0.1108
Precipitation							
Prec	linear	✓	0.0698	✓	0.1796	x	0.1265
	quadratic	✓	0.0678	x	**0.0260**	x	0.1228
Prec.anom	linear	✓	**0.0161**	x	0.0824	x	0.0629
	quadratic	✓	0.4324	x	0.1086	x	0.0863
Prec.anom.DJF	linear	✓	**0.0023**	x	**0.0260**	x	0.1228
	quadratic	✓	0.7600	x	0.8320	x	0.8000
Number of Houses							
H_Number2	linear	✓	0.4280	✓	0.3034	✓	0.2304
	quadratic	✓	0.3257	✓	0.2321	✓	0.1843
Fire Suppression							
Aircraft	linear	✓	0.3997	✓	0.2321	✓	0.1843
	quadratic	✓	0.3997	✓	0.2163	✓	0.3997

TABLE 4: SUMMARY OF LOCATION, SHAPE AND SCALE PARAMETER COVARIATES, TESTED FOR SIGNIFICANCE AND COVARIANCE-MATRIX. IF A COVARIANCE MATRIX COULD BE CALCULATED THE SYMBOL (✓) IS USED, OTHERWISE (X). FOR THE LIKELIHOOD-RATIO TEST A P-VALUE < 0. 05 INDCATES SIGNIFICANT IMPROVEMENTS OVER THE NESTED MODEL. SIGNIFICANT COVARIATES WITH A COVARIANCE-MATRIX ARE HIGHLIGHTED GREEN.

4.4 Combination of significant Parameter Covariates

The same selection procedure as for the prior determination of covariables is applied for the combinations of covariates. For the exclusion process single covariables are tested, as well as combinations for the location, scale and shape parameter. Models without a covariance matrix or no significant improvements are not further considered. From 19 tested PP models, no covariance-matrix could be calculated for the models: *fit.PP.combined_1.9, 1.10, 1.12, 1.13, 1.15* and *1.16.* For the three models *fit.PP.combined_1.14, 1.17* and *1.18* the likelihood-ratio test suggests no significant improvements over the initial PP model and are therefore not used for the subsequent analysis. The rest of the models are investigated in the next section.

4.5 Final Model Selection

In order to compare models to each other and determine the most appropriate, the AIC and BIC are calculated. Table 5 provides an overview of the tested models and shows the corresponding covariate parameter as well as the estimated ACI and BIC values. It is noticeable that the AIC and BIC values differ only slightly between models. With 326.73 *fit.PP.combined_1.2* has the lowest AIC value, which indicates the best fit. However, *fit.PP.combined_1.11* allows to model multiple parameters (location + scale) and has an only slightly higher AIC (329.46). It contains the covariables temperature (location: *Temp.max.DJF*; shape: *Prec.anom*) and precipitation (location: *Temp.mean.DJF*) and thus enables to incorporate fire weather relevant climate factors. Consequently *fit.PP.combined_1.11* is chosen as final model.

Model	Parameter	Covariable	AIC	BIC
fit.PP	none	none	333.99	336.12
fit.PP.combined_1.0	location	Temp.max.DJF	331.05	333.88
fit.PP.combined_1.1	location	Prec.anom	330.20	333.04
fit.PP.combined_1.2	location	Prec.anom.DJF	326.73	329.56
fit.PP.combined_1.3	location	Temp.max.DJF	328.75	332.29
		Prec.anom.DJF		
fit.PP.combined_1.4	location	Temp.max.DJF	329.75	334.00
		Prec.anom		
		Prec.anom.DJF		
fit.PP.combined_1.5	scale	Temp.mean.DJF	327.81	330.64
fit.PP.combined_1.6	shape	Temp.max.DJF	327.97	330.80
fit.PP.combined_1.7	shape	Temp.mean.DJF	327.16	329.99
fit.PP.combined_1.8	shape	Temp.mean.DJF	329.48	333.02
		Temp.max.DJF		
fit.PP.combined_1.11	location	Temp.max.DJF	329.46	333.71
		Prec.anom		
	scale	Temp.mean.DJF		

TABLE 5: COMBINATION OF SIGNIFICANT COVARIATES FOR PP MODELS

Subsequently is the final non-stationary PP model compared to the initial model. It is tested if the models show major differences and if improvements could be achieved. Regarding the Q-Q plots at the top in Figure 5, it is noticeable that under the inclusion of covariables (top right) the points are closer to the line and consequently predictions more accurate. However, not all points are falling perfectly on the standard normal variate. Thus, it can be concluded that the data is not normally distributed. Both plots indicate a positively skewed distribution with an estimated shape parameter of 0.434 for the initial and 0.427 for the final model. This positive estimate suggest that the distribution is Fréchet. Unfortunately, the density plot is not provided for non-stationary models in the extRemes package (Gilleland & Katz, 2016).
Comparing the Z plots (bottom), improvements for smaller values could be achieved. However, for the highest quantiles, the fit seems to be rather poor. Further can be observed that the confidence bounds are very wide, especially for rare events.

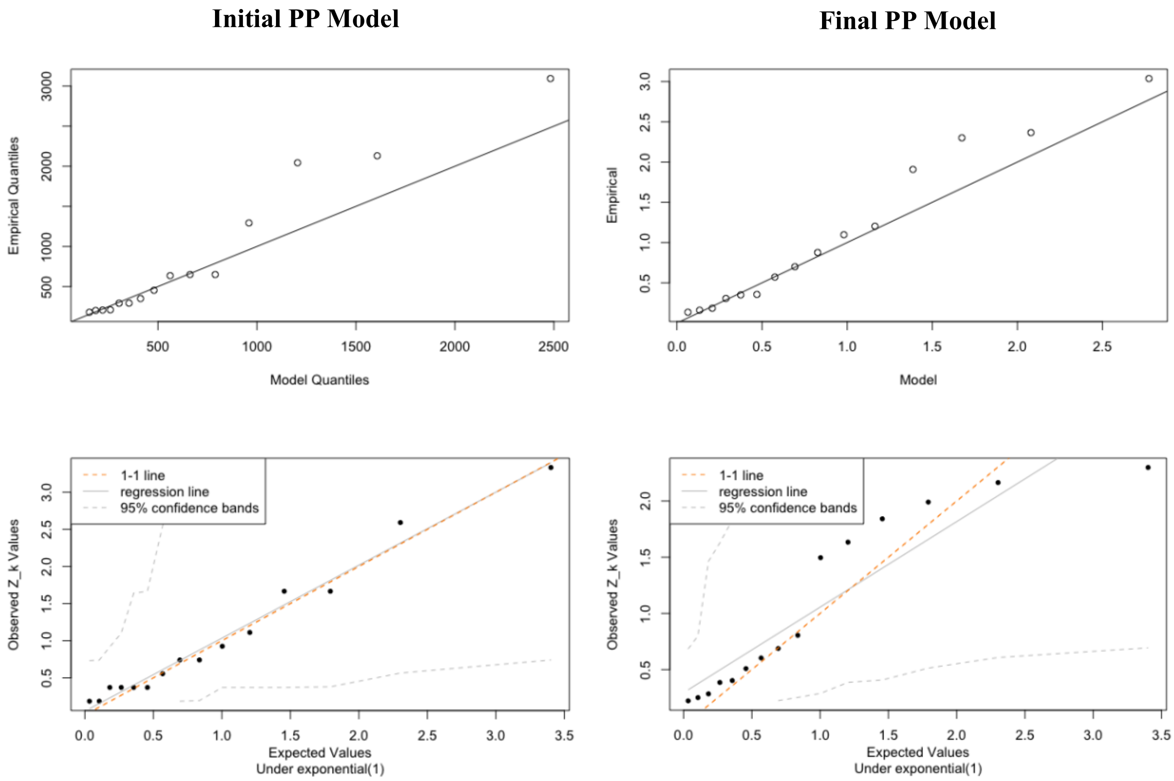

FIGURE 5: Q-Q PLOT (TOP) AND Z PLOT (BOTTOM) FOR THE INITIAL (LEFT) AND FINAL PP MODEL (RIGHT).

Return levels and associated confidence intervals are calculated for 10, 25, 50 and 100 year return periods. The results are summarized in Table 6. Regarding a 10-year event for the final model (bottom), approximately 220 houses losses are expected. For a 25-year return period 860 destroyed houses, 1,530 houses for a 50-year period and 2,430 houses for a 100-year return period are estimated to be lost. It is remarkable that the initial model (top) has considerably lower estimates for all return levels. The 100-year return level from the initial model with an estimate of 1,765 house losses is approximately equivalent to the 50-year return level from the final model with 1,532 house losses.

Due to the few extreme observations the range of damages is extremely high for rare events with long return periods. Despite the lower AIC for the final model, the CI become larger under the inclusion of covariates. The 95% confidence intervals for a 50-year event reach from 116 to 2,948 house losses. For a 100-year period the range is even higher and shows values from -328 to 5,194.

During the fire season 2019-20 a new record of 3094 house losses was reported. Regarding the final model, such a destructive fire season is extremely rare and is estimated to have return periods of more than 100 years.

Initial Model	95% lower CI	Estimate	95% upper CI
10-year return level	-144.89	69.70	284.28
25-year return level	96.67	556.61	1016.55
50-year return level	285.61	1071.76	1857.92
100-year return level	301.10	1764.70	3228.30

Final Model	95% lower CI	Estimate	95% upper CI
10-year return level	-205.88	219.72	645.32
25-year return level	80.78	859.33	1637.88
50-year return level	116.20	1532.21	2948.22
100-year return level	-328.02	2432.88	5193.77

TABLE 6: RETURN LEVEL ESTIMATES AND 95% CONFIDENCE INTERVALS FOR 10, 25, 50 AND 100 YEARS FOR THE INITIAL (TOP) AND FINAL PP MODEL (BOTTOM).

4.6 Integration of Climate Change Scenarios

CISRO and the Bureau of Meteorology provide comprehensive climate predictions for Australia’s NRM (Natural Resource Management) regions [https://www.climatechangeinaustralia.gov.au]. As for the determined climate conditions covariables in 4.2.1 the east coast climate cluster is again investigated, since most of the recorded bushfire house losses are located along the east coast. The East Coast Cluster Report deals in dept with climate projections for this region. A range of simulated climate variables from the CIMP5 model archive are available for different RCPs for the time period 2020-2039 (2030) and 2080-2099 (2090).

Table 7 provides a summary of the East Coast Cluster Report projections for the climate variables included in the final PP model. Of interest are maximum and mean temperature for the summer months DJF, as well as the annual precipitation. Under both RCP scenarios a very high model agreement on substantial temperature increase is projected. This trend is found for the mean and maximum temperature. It is conspicuous that both develop at the same rate. For the year 2030, RCP4.5 and RCP8.5 show only little or no differences. Towards the end of the century differences become increasingly evident and relative to 1986-2005, temperature increases 4°C for RCP8.5 and only 2.2°C for RCP4.5.

In contrast to temperature, precipitation is likely to decrease over the next years. However, only small changes are projected for rainfall with high model agreement for the time period 2030 and medium agreement for 2090. In conclusion, the east coast is projected to see a continuous increase of mean and maximum temperature and a light decrease in rainfall. This combination results in more droughts and is therefore likely to cause harsher fire weather climate (Dowdy et al. 2015).

Covariable	Unit	2030 RCP4.5	2030 RCP8.5	2090 RCP4.5	2090 RCP8.5
Temp.max.DJF	°C	0.9 (0.5 to 1.7)	1.1 (0.4 to 1.8)	2.3 (1.5 to 3.2)	4.1 (2.8 to 5.3)
Temp.mean.DJF	°C	1 (0.5 to 1.5)	1 (0.4 to 1.7)	2.2 (1.3 to 3.1)	4 (2.7 to 5.4)
Prec.anom	%	-2 (-11 to 7)	-1 (-13 to 8)	-4 (-16 to 6)	-6 (-23 to 18)

Very high model agreement on substantial increase | High model agreement on substantial increase | High model agreement on little change | Medium model agreement on little change

TABLE 7: CLIMATE PROJECTIONS FROM THE EAST COAST CLUSTER REPORT FOR TEMPERATURE AND RAINFALL VARIABLES UNDER THE CIMP5 MODEL. THE TABLE SHOWS THE MEDIAN (50TH PERCENTILE) CHANGE, WITH 10TH TO 90TH PERCENTILE RANGE WITHIN BRACKETS. VALUES ARE RELATIVE TO THE 1986-2005 PERIOD AND PROVIDED FOR RCP4.5 AND RCP8.5 FOR THE TIME PERIOD 2030 (2020-2039) AND 2090 (2080-2099) (DOWDY ET AL., 2015, P.41).

In a next step the effect of individual climate variables on return levels is investigated. Each covariate parameter is modified separately while the others are hold constant and tested for the sensitivity for the final PP model. Against the expectations, an increase of the location parameter for average summer temperature (*Temp.mean.DJF*) leads to lower return levels. However, the effect seems to be rather small. The adjustment of the location parameter for annual precipitation (*Prec.anom*) results in increased return levels, as projected by the East Coast Cluster Report. As for *Temp.mean.DJF*, the effect of the modified location parament is small. On the contrary to the two location parameter, the adjustment of the scale parameter (*Temp.max.DJF*) has a substantial effect on return levels. An increase of maximum summer temperature results in considerably higher house loss estimates for all return periods and is thus the most determinant covariable for the final PP model.

Following, climate projections according to RCP4.5 and RCP8.5 are used to characterize future house loss risk profiles for the years 2030 and 2090. All covariate parameters from the final PP model are adjusted to the RCP reference period 1986-2005 and then simultaneously modified with the values provided in Table 7. Thus, return levels are estimated (Table 8).

		2030			**2090**		
	Return Level	**95% lower CI**	**Estimate**	**95% upper CI**	**95% lower CI**	**Estimate**	**95% upper CI**
RCP 4.5	10-Year	-144.38	360.86	866.09	-190.16	670.84	1531.83
	25-Year	127.01	1088.97	2050.93	108.68	1659.24	3209.80
	50-Year	120.55	1854.95	3589.35	-34.70	2699.05	5432.80
	100-Year	-459.80	2880.24	6220.27	-1038.27	4090.87	9220.00
RCP 8.5	10-Year	-139.31	362.58	864.48	-321.66	1252.26	2826.18
	25-Year	125.05	1090.69	2056.33	28.03	2735.22	5442.40
	50-Year	115.02	1856.67	3598.33	-400.32	4295.31	8990.93
	100-Year	-466.70	2881.96	6230.62	-2231.98	6383.53	14999.05

TABLE 8: RETURN LEVEL ESTIMATES AND 95% CONFIDENCE INTERVALS FOR THE FINAL NON-STATIONAR PP MODEL, ADJUSTED ACCORDING TO RCP4.5 AND RCP8.5 FOR THE YEARS 2030 AND 2090.

For the next decade a clear increase of house losses is estimated for all return levels. In comparison to the final model (Table 6) with 2,430 house losses for the 100-year return level, model projections for 2030 result in 2,880 house losses for the same return level. It is emphasized that for the year 2030 RCP4.5 and RCP8.5 show nearly identical values for all return levels. The estimated 10-year return level causes 360 losses. 1,090 are projected for the 25-year level, 1,850 for the 50-year level and 2,880 for the 100-year return level.
By the end of the century, the number of estimated house losses return levels increases dramatically. Under the risk characteristics of RCP4.5 a 50-year event is estimated to cause 2,700 house losses. Once every 100 years, at least 4,090 houses are expected to be lost in a single fire season. In contrast to 2030, RCP4.5 and RCP8.5 show considerable large differences for the year 2090, whereby RCP8.5 exceeds the RCP4.5 return levels by far. The 50-year return level for RCP8.5 (4,295) is even higher than the 100-year return level for RCP4.5 (4,090).

Under the final PP model house losses of 3,094 as during the fire season 2019-20 are considered extremely rare and estimated to occur once in 100 years. With the risk scenario adjustments for RCP4.5 2090 the same losses are expected every 50 years and under RCP8.5 even every 25 years. Nevertheless, it must be noted that the confidence intervals for estimates are wide for all return levels.

5. DISCUSSION

The bushfire season 2019-20 broke the residential house loss record for Australian bushfires with 3094 destroyed homes. The massive impact drew attention to the underlying factors and the role of climate change and socioeconomic development. The probability of such extreme disasters occurring and how bushfire behavior will change in the future is of great interest. While diverse studies have analyzed climatic and weather trends for bushfire conditions over the last century, the aim of this paper is to address return periods for extreme house loss events. Regarding the aggregated bushfire house loss time series from 1938-2020 in Figure 1, the record is dominated by four major fire seasons. For the most extreme bushfires a significant upward trend could be detected. Due to the underlying EVT assumption of stationarity, the increasing trend was taken into account by integrating a range of driving factors as covariates. Tested covariate categories are (i) weather and climate conditions, (ii) exposure – number of total houses and (iii) efforts in risk reduction – fire suppression with aircrafts.

Based on a likelihood-ratio test only covariates from the category (i) weather and climate conditions could be identified as significant. Unfortunately the covariance-matrix could not be calculated for all significant variables. This is most likely due to the small house loss sample size. From a total of 82 observations only 15 exceed the threshold value of 125. Thus, no convergence can be found for the estimated covariate models. *Temp.mean.DJF* (location), *Prec.anom* (location), *Temp.max.DJF* (scale) improve the model fit significantly and meet the condition of a covariance-matrix. Therefore they are integrated into the final non-stationary PP model. Return levels as high as during 2019-20 (3,094 house losses) are estimated to be extraordinary and occur less than once every 100 years. If conditions are kept constant, 2,430 house losses are calculated for a 100-year return level. However, the 95% confidence intervals are wide, ranging from -328 to 5,194. The negative values indicate a problem with the model, since it is physically unrealistic to have negative damages from a bushfire event. Consequently the lower bound should be restricted to zero.

Under RCP4.5 and RCP8.5 the final PP model projects little changes for the year 2030. This finding is likewise supported by McAneney et al., (2009) that house losses are unlikely to alter in the near future despite intensified bushfire weather. Nevertheless, towards the end of the century the final PP model suggests for both scenarios a clear trend of increasing house loss probability. By 2090 projected RCP8.5 return levels exceeds RCP4.5 return levels by far. In comparison to today, the number of lost houses during the fire season 2019-20 decreases from a 100-year return period to a 50-year return period for RCP4.5. The same losses even correspond to a 25-year return period under RCP8.5.

Since Australia has a wide range of climate zones and influences, impacts of climate change differ between regions. For example, while precipitation is likely to increase in some regions, it will decrease in others. The same is true for temperature (IPCC, 2013). The model neglects these regional differences and is therefore not appropriate for downscaling. However, since the majority of house losses is recorded along the east coast, it seems reasonable to focus on the east coast climate cluster to estimate national house loss return levels.

With very high confidence climate projections predict more hot days and warm spells which points to a harsher fire weather in the future (CSIRO and Bureau of Meteorology, 2016). Clarke et al., (2013) investigated fire weather in Australia between 1973 and 2010 using the Forest Fire Danger Index (FFDI). Annual FFDI increased significant for most stations and none was decreasing. This trend is attributed to an increase in magnitude and lengthening in fire season. In addition does an increased FFDI value indicate higher probability for fire occurrence, but also increase the fire intensity (Luke and McArthur, 1978). Blanchi et al., (2010) points out the house loss record domination of few major events occurring under catastrophic fire weather above the 99.5th percentile of daily FFDI. In summary, it appears that these findings are in line with the final PP model in terms of climate change and the effect on bushfire weather and associated house losses. Nonetheless, it is noted that the model is simplified and does not take into account all FFDI variables.

Fortunately, not all severe fire weather results in bushfire. It is emphasized that even under extreme conditions bushfires do not directly lead to high numbers of lost houses. Complementary to fire weather, vegetation and terrain would be deceive factors for fire behavior (Sharples et al., 2016). Unfortunately this would go beyond the scope of the paper. A set of interactive factors as human activity, location and house development are important to consider, too. While the Northern Territory regularly faces widespread fires in rural areas that cause nearly zero damage, fires close to populated areas massively increase the potential for damage (Blanchi et al., 2010; Dunlop et al., 2011).

Crompton et al. (2010) argue that despite an increasing FFDI, no upward trend for house losses can be detected for the period 1925-2009 once they are normalized for current social conditions. This hypothesis emphasizes that bushfires did not change in intensity or frequency, but rather more houses are exposed to bushfire prone areas. This is consistent with similar research papers

summarized by Bouwer (2019), that found that anthropogenic greenhouse-gas climate change signals cannot be detected in Australian property losses, once it has been adjusted for current societal conditions. In this way, the role of socioeconomic factors is highlighted for the increasing house loss trend.
Demographic development is the main driver of growth in house numbers, and thus of how many houses are exposed and might be lost to fire. In Australia, the population is likely to keep increasing linearly, and therefore the number of houses as well. This trend has been observed in the last few years [http://www.abs.gov.au]. Concluding those statements, house losses due to bushfire might increase linearly in future years.

Despite the strong explanatory power and findings of other studies, the covariable (ii) exposure – number of total houses, it is not significant. Unfortunately, the final PP model is therefore not able to account for these effects. Reasons why the number of total houses is not significant could either be due to a wrong intuition, wrong functional form or the quality of the data. Regarding the intuition, McAneney et al., (2009) argues that the potential for damage depend on the disposition of houses to the bushland boundary, rather than on the number of total houses. The risk of losses is particularly high where people live immediate next to bushland and where there is risk of destroying a large number of houses. In this case, the damage depends on the extent of the fire front and whether and how it intersects populated area and if it is defended or not.
As all other covariables, the number of total houses was tested for the location, scale and shape parameter for a linear and quadratic form. Nevertheless, none was significant for the PP model. Most likely this is due to the limited data of only 15 observations exceeding the threshold of 125, as described above.

The covariable (iii) efforts in risk reduction is based on the likelihood-ratio test not significant either. This is assumed for the same reasons. On the one hand, the covariable is extremely simplified and only contains a dummy variable for the intensified use of fire suppression aircrafts from 2003 onwards. Besides these measures there are numerous other firefighting efforts which are continuously improved. E.g. important aspects are more reliable weather forecasts, communication between the fire organizations and information of the population. On the prevention side, planned and protective burnings are crucial to avoid large fires (Kanowski et al., 2005). A further interpretation is that a significant decrease in losses could not be achieved despite improved firefighting techniques and warning systems. This might be due to the few most extreme fires overwhelming firefighting authorities and account for most of the damage. By the time a fire exceeds a certain level, it is extremely hard to intervene until either weather conditions change or the fire runs out of fuel. Therefore a simplified conclusion could be, that major house loss events can only be avoided if all fires occurring close to populated are extinguished in an early stage. However, firefighting resources are limited to a certain extent (Crompton et al., 2010).

6. CONCLUSION

Bushfires in Australia are a major natural hazard and affect the ecosystem and human property. It remains a challenge to predict the frequency and intensity of the most damaging fires. In this paper extreme value statistics is used to analyze the heavy tailed bushfire house loss distribution.

Overall, the fire season 2019-20 could be identified as extraordinary and represents the highest bushfire house loss number ever recorded. Based on limited data, the EVT approach allowed to calculate return periods for bushfire house losses under current and future conditions. The analysis suggests that property losses as during 2019-20 are very rare and have a return period of over 100 years. Nevertheless, it is observed that the most damaging events, which account for the majority of all losses, have a clear increasing trend.

While the final PP model allowed to model the aggregated house loss time series for 2030 and 2090 under RCP4.5 and RCP8.5 conditions, socioeconomic aspects could not be included for future house loss projections. Integrated climate variables are precipitation and temperature. In accordance with previous studies, the model corresponds to the hypothesis that the effect of climate change will not be observed on a large scale in the next few years. However, under the inclusion of very high confidence projections of increasing temperature and high confidence for decreasing precipitation, harsher fire weather is very likely by the end of the century (IPCC, 2013; CSIRO and Bureau of Meteorology, 2016). Under this assumption the final PP model predicts considerably higher house loss probability for RCP4.5 and RCP8.5. By the year 2090 return levels adjusted for RCP4.5 are roughly 30% higher than under current conditions and RCP8.5 return levels are doubled.

This finding is supported by climate change favoring bushfire weather which increases the probability of occurrence and the intensity of the fire. Therefore is it more likely that firefighting authorities are overwhelmed and fires get out of control. This increases the potential of house losses, especially if fires are close to populated area.

In conclusion, the final PP model is simplified and future scenarios are only modeled under temperature and precipitation projections. Bushfire house losses are driven by a variety of factors and complex interactions. Factors as exposure, vulnerability, or the development of risk management are completely neglected. Complementary to the effect of climate change on bushfire weather and associated house losses, all these variables would be crucial for a comprehensive risk assessment. The model is therefore limited in its explanatory power and resulting return levels must be considered with caution.

To better understand the risk of future bushfire house losses, it would be essential to disentangle different house loss driving factors. Future work is needed to analyze to what extent (i) weather and climate conditions, (ii) exposure and (iii) efforts in risk reduction determine the development of property losses. As a result, the role of climate change and fire weather would become clearer. On the other hand, regulations and fire mitigations strategies could be introduced to restrict bushfire effects. It remains a key challenge for future studies to incorporate socioeconomic aspects and to determine to what extent they account for the house loss development and associated return levels.

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8. APPENDIX

fevd(x = H_Loss_FS, data = dat_fs, threshold = 125, location.fun = ~Temp.max.DJF + Prec.anom, scale.fun = ~Temp.mean.DJF, type = "PP", time.units = "0.5/year")

Final PP Model	**95% lower CI**	**Estimate**	**95% upper CI**	**Standard Error**
10-year return level	-205.88	219.72	645.32	217.14
25-year return level	80.78	859.33	1637.88	397.23
50-year return level	116.20	1532.21	2948.22	722.47
100-year return level	-328.02	2432.88	5193.77	1408.65

Final PP Model under RCP reference period (1986-2005)	**95% lower CI**	**Estimate**	**95% upper CI**	**Standard Error**
10-year return level	224.66	83.77	392.21	157.3683
25-year return level	81.77	577.62	1073.47	252.99
50-year return level	183.45	1097.15	2010.86	466.18
100-year return level	-36.87	1792.56	3622.00	933.40

Final PP Model 2030 RCP4.5	**95% lower CI**	**Estimate**	**95% upper CI**	**Standard Error**
10-year return level	-144.38	360.86	866.09	257.78
25-year return level	127.01	1088.97	2050.93	490.81
50-year return level	120.55	1854.95	3589.35	884.92
100-year return level	-459.80	2880.24	6220.27	1704.13

Final PP Model 2030 RCP8.5	**95% lower CI**	**Estimate**	**95% upper CI**	**Standard Error**
10-year return level	-139.31	362.58	864.48	256.08
25-year return level	125.05	1090.69	2056.33	492.68
50-year return level	115.02	1856.67	3598.33	888.62
100-year return level	-466.70	2881.96	6230.62	1708.53

Final PP Model 2090 RCP4.5	**95% lower CI**	**Estimate**	**95% upper CI**	**Standard Error**
10-year return level	-190.16	670.84	1531.83	439.29
25-year return level	108.68	1659.24	3209.80	791.12
50-year return level	-34.70	2699.05	5432.80	1394.80
100-year return level	-1038.27	4090.87	9220.00	2616.95

Final PP Model 2090 RCP8.5	95% lower CI	Estimate	95% upper CI	Standard Error
10-year return level	-321.66	1252.26	2826.18	803.04
25-year return level	28.03	2735.22	5442.40	1381.24
50-year return level	-400.32	4295.31	8990.93	2395.77
100-year return level	-2231.98	6383.53	14999.05	4395.75

TABLE A 1 RETURN LEVELS FOR THE FINAL PP MODEL, THE REFERENCE PERIOD 1986-2005, AND 2030 AND 2090 UNDER RCP4.5, RCP8.5.