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Fire frequency analysis for different climatic stations in Victoria, Australia

Anirban Khastagir[1] (ORCID)

Abstract Frequent occurrence of fire events will have severe impact on Victoria's water supply catchments. Hence, it is important to perform fire frequency analysis to obtain fire frequency curves (FFC) on fire intensity using Forest Fire Danger Index (FFDI) at different parts of Victoria. FFDI is a measure of fire initiation, spreading speed and containment difficulty. FFC will guide water harvesting by providing information with regard to future fire events and the subsequent impact on catchment yield. Five probability distributions, namely normal, Log Pearson Type III (LPIII), gamma, log-normal and Weibull distributions were used for the development of FFCs at ten selected meteorological stations spread all over Victoria. LPIII distribution was identified as the best fit distribution for Victoria and subsequently applied for an additional 30 more stations to show spatial variability for the entire Victoria.

Keywords Fire frequency analysis · Bushfire · Probability distribution

1 Introduction

Bushfires are a consequence of severe weather conditions and the presence of combustible fuel. The natural ecosystem in Victoria, Australia, represented by the vegetation cover and landscape, has been shaped by both historic and recent fires. Many of Australia's native plants are fire-prone and very combustible, and they may or may not regenerate after a fire. Frequent occurrence of fire events will have severe impact on Victoria's water supply catchments. Forest Fire Danger Index (FFDI) is a measure of fire initiation, spreading speed and containment difficulty. The fire danger rating system was revised in 2009 to include a new category 'catastrophic' (code black), as shown in Fig. 1, to warn

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Fig. 1 Fire danger rating based on Forest Fire Danger Index (FFDI)

communities of the extreme risk of the spread of fires that are predictable, uncontrollable and fast moving (National Fire Warning System 2009).

Fire frequency analysis (FFA) determines the probability of exceedance of FFDI values to identify the fire intensity of a given location. FFDI values are obtained from past climatic conditions. The statistical analysis of past fire regimes is important to understand both the dynamic nature of forest ecology and the management of fire-prone ecosystems. The analysis will be primarily applicable to yearly peak FFDI values. As a result of global warming and climate change, Australia is experiencing unprecedented high temperature and changing rainfall pattern and, quite often, prolonged droughts. Karoly (2009) noted that climate change played a pivotal role in increasing the frequency of fire events. According to Karoly (2009), the FFDI for a number of sites in Victoria on 7 February 2009 (Black Saturday) reached unprecedented levels, ranging from 120 to 190, much higher than the fire weather conditions on 13 January 1939 (Black Friday) or 16 February 1983 (Ash Wednesday), and well above the "catastrophic" fire danger rating. Recently in October 2013, there were a series of bushfires in Australia across the State of New South Wales (NSW). High fuel loads, coupled with warm and windy weather, provided conditions dangerous for fires. Around 250 bushfires and more than 118,000 ha of bushland were burnt across the state, concentrated around the eastern seaboards and highlands (Khastagir 2013). Fire is an unavoidable event, particularly in the State of Victoria, because of the fire-prone vegetation types in the forests. Past bushfires in Victoria have damaged land, farm animals and property of the communities and in some instances killed people.

Cheney and Gould (1995) noted that fire and land management authorities widely used the fire danger indices to issue public warnings as well as provide appropriate levels of land management advices. There are a number of parameters, such as climatic characteristics, vegetation, fuel characteristics and topography, which combine to influence the impact of fires. Chandler et al. (1983) noted that fire danger rating is a type of fire management system that incorporates all the factors that are directly related to the risk of a fire occurring and converts them into one numerical index. Furthermore, it is important to determine the probability of the fire index values exceeding a given threshold value (probability of exceedance) within a year to determine fire season severity. Several indices have been developed both in Australia and overseas to convert qualitative fire danger into a numerical index. The fire danger indices that are in common use in different parts of the world are as follows: Fire Weather Index (FWI) in Canada (Van Wagner 1987); Nesterov Index in Russia (Nesterov 1949); WBKZ-M68 in north-eastern Germany (Alexander et al. 2010); Angström Index in Sweden (Skvarenina et al. 2003) and Forest Fire Danger Index in Australia (McArthur 1966, 1967).

In FFA, a probability distribution is fitted mathematically to the observed FFDI data, enabling the probability of a specified magnitude to be calculated. Several studies have used the different fire danger indices as a means of representing the probability of an intensity of fire occurrence in a certain period of time. Dayananda (1977) developed a model for forest fires with the given environmental conditions represented by the Keetch–Bryam drought index (Keetch and Bryam 1968). Mandallaz and Ye (1997) used a Poisson distribution model to evaluate the relationship between various European dryness indices and climatic variables. Landres et al. (1999) and Allen et al. (2002) reported that the understanding of the relationship between past fire occurrence and fire intensity should be the focus of fire-related analysis and research. Schoenberg et al. (2003) provided a non-parametric estimation of the probability of fire versus the age of fuels, in addition to estimates for other variables (i.e. temperature, fuel moisture and precipitation) at a particular location. Cox (1962) reported that the Weibull distribution also played a role in fire models based on renewal theory and survival analysis. In most of the above studies, emphasis was placed to obtain a best fit distribution of the interval of fire occurrence. Several studies (e.g. Peng and Schoenberg 2001; Grissino-Mayer 1999) have considered the frequencies of forest fire as a function of time since the last fire. Chou et al. (1993) used stepwise logistic regression with different climatic variables (precipitation, temperature) and neighbourhood effects (vegetation, human structures and transportation) to construct a probability model of wildland fire occurrence. Xiaowei et al. (2012) established fire risk probability models based on fire indices over different climatic regions in China. The above authors developed semi-parametric logistic (SPL) regression models between the indices adopted in Canada, USA and Australia, and location, time, altitude, vegetation and fire characteristics.

Johnson (1979) and Schoennagel et al. (2004) noted that the probability of burning due to extreme fire events is not primarily driven by the time since the last fire, but due to extreme weather conditions which favour fire initiation. Bessie and Johnson (1995) revealed that the age and spatial variation of vegetation are not constraints to fire ignition and its spread under certain climatic conditions. Hence, the present study focuses on FFA, taking into consideration the weather conditions (e.g. temperature, relative humidity, wind speed and drought factor) to estimate FFDI to the frequency of fire occurrences.

The main objective of the study is to carry out an FFA using the FFDI at a number of locations in Victoria with a view to select the best fit probability distribution. Five probability distributions, namely normal, Log Pearson Type III (LPIII), gamma, log-normal and Weibull distributions were selected for the analysis. A best fit probability distribution for all selected locations will be used to identify the variation of FFDI values in different parts of Victoria for different average recurrence interval (ARI).

2 Methodology

2.1 Data used in the study

The study area consists of 40 stations spread all over Victoria as shown in Fig. 2. Figure 3 depicts the frequency of the number of years of daily data available for the stations used in this study. It shows that the number of years of available daily data varied between 9 and 51 years. The climatic data that were obtained from the Bureau of Meteorology website

Fig. 2 Locations of the meteorological stations selected for the study

Fig. 3 Frequency of the number of years of data available for the stations selected for this study

(www.bom.gov.au) are temperature (*T*—9 am and 3 pm), relative humidity (RH—9 am and 3 pm) and wind speed (*U*—9 am and 3 pm).

In this study, Forest Fire Danger Index (FFDI) developed by McArthur (McArthur 1966, 1967) was used as an indicator to identify the risk of occurrence of fire in different parts of Victoria. This index has been especially designed for determining fire danger in south-east Australia. Furthermore, FFDI is widely used in Victoria to categorize the severity of bushfires. Fire danger can be determined using McArthur's forest and grassland fire danger meters. The McArthur forest fire danger meter first appeared operationally in 1967. Several researchers (e.g. Noble et al. 1980; Sneeuwjagt and Peet 1985; Catchpole et al. 1999) carried out investigations to obtain relationships with fire danger indices and climatic parameters such as: temperature, fuel moisture content, relative humidity, wind

speed and drought factor. In this study, Eq. (1) derived by Noble et al. (1980) was used to estimate daily FFDI for all 40 stations.

$$\mathrm{FFDI} = 2\exp(-0.45 + 0.987\ln\mathrm{DF} + 0.0338T - 0.0345\mathrm{RH} + 0.0234U), \qquad (1)$$

where T is the temperature (°C), RH the relative humidity (%), U the wind speed (km/h) and DF the drought factor.

FFDI was calculated using daily mean values of T, RH and U. The drought factor (DF) gives an estimate of the fuel available for combustion. McArthur (1973) developed DF to predict the amount of fine fuel available which would be consumed by fire. The DF which ranges between 1 and 10 gives an estimate of the fuel available for combustion (Eq. 2). A DF = 10 indicates a maximum fuel available for combustion. In Australia, this DF is derived from either the Keetch–Byram Drought Index (KBDI) (Keetch and Byram 1968) or Mount's Soil Dryness Index (MSDI) (Mount 1972) depending on the agreed practices in Australian states (Finkele et al. 2006). Current KBDI (mm) considers the topmost layers of soil such that their field capacity is 200 mm of available water. The index estimates how much effective rainfall is needed to saturate this depth of soil at any given time. It is assumed that the moisture is lost from the soil only by evaporation due to temperature. A DF value of 10 is taken for this study, which means a maximum fuel load was available for combustion during bushfires.

$$\mathrm{DF} = \frac{0.191(I + 104)(N + 1)^{1.5}}{3.52(N + 1)^{1.5} + P - 1} \ \ \mathrm{If} \ \ \mathrm{DF} > 10, \ \mathrm{DF} = 10, \qquad (2)$$

where I is the the Keetch–Byram drought index in millimetre equivalent, N is the time since the last rain in days and P is the the last recorded daily precipitation in millimetres.

2.2 Fire frequency analysis (FFA)

FFA illustrates the probability of the risk of fire occurrence with certain intensity (i.e. FFDI) at a given location. A probability distribution is fitted mathematically to the observed data, enabling the probability of FFDI to be calculated. Few studies have used the FFA as a means of representing a certain magnitude of fire occurring at a place for a given return period. The selection of data for frequency analysis may be based on the types of analysis identified. The types of analysis identified are: annual maximum and annual exceedance. In annual maximum analysis, only the peak FFDI values of each year are selected. In annual exceedance, the FFDI values that exceed a given threshold value are selected. In annual exceedance, the 'N' highest peaks within the "n" years of data are selected for the analysis (Gordon et al. 2004). The selection of a threshold value is based on recognition of the fact that if multiple events occur in a calendar year it would be included in the data analysis. It is important that the data (i.e. FFDI) in annual exceedance are independent of each other, and similarly the annual maximum series are also independent of each other (ARR 1987). In hydrology, the use of annual maximum is more popular compared to annual exceedance (Cunnane 1973; Takeuchi 1984; Madsen et al. 1997; Lang et al. 1999).Australian Rainfall and Runoff (ARR 1987) recommends the use of annual maximum for flood frequency analysis. As both flood and fire are considered to be extreme events, it was decided to use annual maximum series to ensure consistency with ARR study. In addition, more than 50% stations used in this study have long data series (exceeding 30 years).

2.3 Probability distributions

Extreme value probability distributions can be used effectively for any extreme events. The concept of extreme value probability distribution was invented by Fisher and Tippett (1928) and Gumbel (1958). Fisher and Tippett (1928) divided the extreme value distributions into three types: Type I, Type II and Type III. Sivandran (2002) noted that extreme values normally occur at low probabilities and hence it was necessary to separate these extreme values from the original distribution. The main goal of FFA is to determine the frequency and severity of fire danger index exceeding a certain magnitude.

Gordon et al. (2004) reported that Type I and Type III could be effectively used for flood and low flow studies, respectively. Type I distribution is widely known as the double exponential distribution and log-normal distribution is a special example of the Type I distribution (Gordon et al. 2004). Log-normal distribution is one of the frequently selected techniques for flood frequency analysis and its use is important for the analysis of multivariate flood studies (Yue 2000). Hence, in this study, log-normal distribution is also considered for FFA.

Type III distribution is used in annual minimum flow analysis and Weibull distribution is a very common Type III distribution. Van Wagner (1978), Johnson (1979) and Johnson and Wagner (1985) have carried out FFA in North American forests based on the cumulative distribution of forest age classes and found that the Weibull distribution (Weibull 1951) fitted better than the gamma distribution (Cohen and Whitten 1982). The Weibull distribution has an exponential distribution similar to the gamma distribution. The exponential distribution has a constant hazard function, which makes the risk of fire independent of the time since the last fire. As a result, it is important to check the efficacy of the Weibull distribution for FFA in Australia.

Blokhinov and Sarmanov (1968) and Moran (1970) have used gamma distribution for hydrological frequency analysis. Yue (2001) reported that flood peak and flood volume have skewed distribution. According to Stedinger et al. (1993), gamma distribution is also an appropriate distribution for flood study. Thus, a similar approach can also be adopted for FFA. The gamma distribution is frequently a probability model for the time interval study. For instance, the time interval between extreme events is a random variable that can be modelled with a gamma distribution.

The Pearson distribution is a family of continuous probability distributions developed by Pearson in (1895) and subsequently extended in 1901 and 1916 in a series of articles on biostatistics. Pearson (1895) identified four types of distributions (numbered I to IV) in addition to the normal distribution. The three-parameter gamma distribution originated from Pearson's work (Pearson 1893, 1895) and was later known as the Pearson Type III distribution. Australian Rainfall and Runoff (ARR 1987) noted that the Log Pearson Type III (LPIII) distribution fitted best with flood frequency analysis covering the whole of Australia. Hence, in this study, it was decided to test the LPIII distribution for fire frequency analysis.

Hence, the probability distributions considered for testing in this study are: normal, Log Pearson Type III (LPIII), gamma, log-normal and Weibull distributions. Two approaches can be followed for obtaining the best fit probability distribution in a region. It is possible to fit a number of probability distribution functions to the same set of data and adopt the best fit distribution for that particular location. In this approach, it can identify different best fit probability distributions for different locations of a region. In the other approach, it determines one probability distribution function that fits best all the locations in the region.

In this study, it was decided to explore the use of the latter approach for carrying out the FFA. The obtained fire frequency curve can be used to predict vulnerability to fire events and to identify the fire-prone characteristics of a specific location. These curves will help planners and designers by providing information for infrastructure with regard to future fire events.

2.4 Removal of outliers

Before carrying out any frequency analysis, it is important to identify outliers. An outlier is an observation that is numerically distant from the rest of the data series. In frequency analysis, outliers are events which are different from the overall trend of the data. Based on ARR (1987), outliers are classified as high and low outliers. The low outliers in the dataset can change the fitted probability distribution and hence affect the estimation of high fire danger event. ARR (1987) noted that high outlier could occur due to error in data, changes in catchment conditions, occurrence of an event with average recurrence interval (ARI) much lower than high ranking observed events and occurrence of extreme events due to unusual type of phenomenon.

Grubbs and Beck (1972) test is an effective test to identify outliers. ARR (1987) has modified Grubbs and Beck test for 5% significance level considering wide variation in skewness in Australian climatic parameters. Hence, high and low outliers were identified using Grubbs and Beck test for 5% significance level (Eqs. 3 and 4) as recommended by ARR (1987). These outliers were not considered for further frequency analysis.

$$FFDI_H = M + (\beta \times K_N \times S),$$ (3)

$$FFDI_L = M - (\theta \times K_N \times S),$$ (4)

where $FFDI_H$ is the high outlier threshold in log units, $FFDI_L$ the low outlier threshold in log units, K_N the value for 5% significance level from Table 10.6 of ARR (1987), β the adjustment factor for high outliers obtained from Table 10.7 of ARR (1987), θ the adjustment factor for low outliers obtained from Table 10.10 of ARR (1987) and S the standard deviation of logs of FFDI.

2.5 Selection of best fit distribution

The five probability distributions selected above were fitted separately to annual maximum data series. The Anderson–Darling (AD) test (Stephens 1986) was used to obtain the best fit distribution. The Anderson–Darling test, named after Theodore Anderson and Donald Darling, is a statistical test carried out to identify whether a data set fits into a specified distribution. The lowest AD value indicates the best fit distribution. The Anderson–Darling test is effective for relatively small sample sizes and heavy-tailed distributions, such as those often encountered in flood frequency analysis (Onoz and Bayazit 1995). Ahmed et al. (1988) modified the AD test, with an emphasis on the upper or on the lower tail. However, Arshad et al. (2002) did not find that this modification improved the efficiency of the test. The AD test result is calculated using Eq. (5). Initially, ten stations were selected to identify the best probability distribution using the AD test. Later, it was decided to use the AD test for the remaining stations with the best probability distribution identified from the preliminary analysis.

$$AD = \left(\frac{\sum \left[(2j-1)\ln\left(F_j\right) + (2n+1-2j)\ln\left(1-F_j\right) \right]}{n} - n \right) \times \left(1 + \frac{0.2}{\sqrt{n}} \right), \quad (5)$$

where AD is the AD test statistic, j the position in an ascending order of magnitudes, n the number of data points and F_j the non-exceedance probability of the jth smallest value in the data series. If the AD test result is greater than the critical value (AD_{Cr}) as shown in Eq. (6), then the distribution is rejected for the significance level of 0.05. The rejection rule is:

$$AD_{Cr} = \frac{0.752}{1 + \frac{0.75}{n} + \frac{2.25}{n^2}}. \quad (6)$$

3 Results and discussion

As mentioned earlier, the FFDI values in this study were calculated on a daily basis for all the 40 stations. The annual maximum values from calendar years were selected for calculating four primary moments of the probability distribution (e.g. mean, standard deviation, coefficient of variation and skewness). All these moments of the probability distribution are shown in Fig. 4.

It can be observed from Fig. 3a that the mean annual maximum series FFDI values of north-western Victoria were significantly higher than the rest of Victoria. Similar
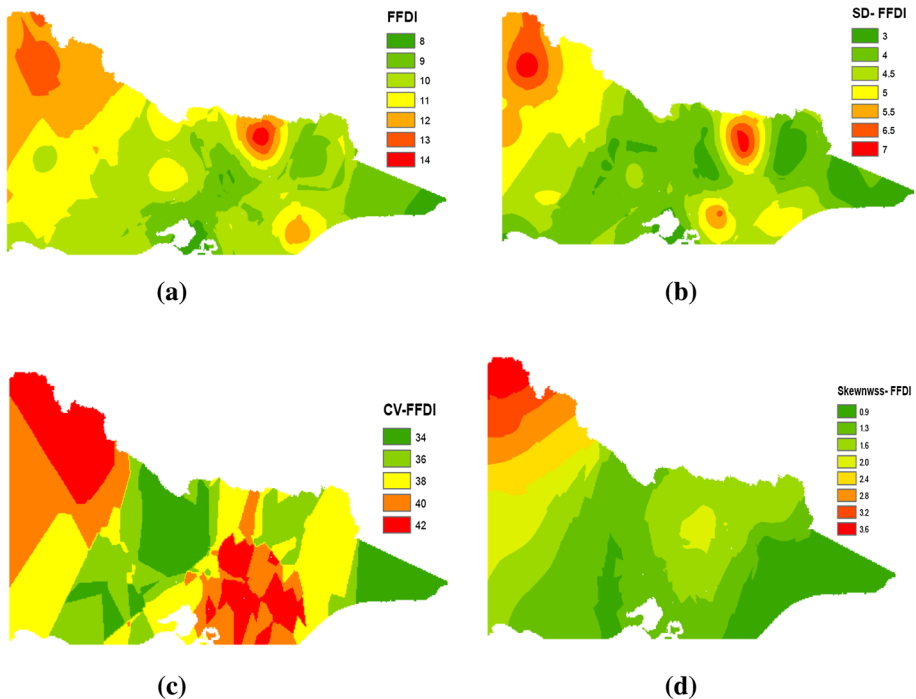
Fig. 4 Moments of probability distribution of the annual series FFDI values; **a** mean, **b** standard deviation, **c** coefficient of variation (CV) and **d** skewness

Table 1 AD values from five different probability distributions for the selected ten stations

Stations	AD$_{Cr}$ value	AD values				
		Normal	Log-normal	Gamma	Weibull	LPIII
Mildura	0.74	0.61	0.39	0.43	0.82	0.41
Mallacoota	0.71	0.21	0.20	0.63	0.29	0.19
Phillip Island	0.73	0.93	0.25	0.34	0.65	0.29
Warrnambool	0.74	1.3	0.71	0.70	1.1	0.69
Horsham	0.74	0.85	0.64	0.50	0.32	0.49
Shepparton	0.71	0.84	0.69	0.75	0.85	0.62
Castlemaine	0.73	0.87	0.38	0.43	0.84	0.39
Lakes Entrance	0.74	1.3	0.34	0.37	0.76	0.29
Mangalore	0.74	0.58	0.52	0.38	0.45	0.40
Port Fairy	0.73	0.34	0.28	0.26	0.28	0.24

variations can be observed in Fig. 3b, which illustrates the standard deviation of FFDI for different parts of Victoria. Based on Fig. 3c, the percentages of CV across Victoria are 34–42%. Figure 3d reports the spatial variation of skewness of FFDI for Victoria. All the locations of Victoria show that the positive (+ve) skewness varied between 0.9 and 3.6. It is interesting to note that all these moments of probability distribution are high in the north-western corner in general compared to others parts of Victoria.

Ten stations, namely Mildura, Mallacoota, Phillip Island, Warrnambool, Horsham, Shepparton, Castlemaine, Lakes Entrance, Mangalore and Port Fairy (Fig. 1), were selected to identify the best fit distribution. These stations were selected based on climatic variability, catchment characteristics and previous fire history. The locations of these stations are shown in Fig. 1. Table 2 shows the AD$_{Cr}$ and AD values for different distributions obtained for these ten stations. The statistical software Minitab was used to fit the probability distributions into the annual maximum series. From Table 2, it can be observed that for the normal distribution, the AD values are higher than the AD$_{Cr}$ for Philip Island, Warrnambool, Horsham, Shepparton, Castlemaine and Lakes Entrance. The AD values for Mallacoota, Mangalore and Port Fairy are consistently lower than AD$_{Cr}$ for all the probability distributions. It can be noted that the values of the AD are smallest for the LPIII distribution in all the stations, while the log-normal and gamma distributions are close to each other but higher than LPIII in general. From Fig. 3d, it can be noted that there is considerable skewness for the majority of the stations considered for this study.

It is important to choose the correct distribution if all the distributions fit all the data reasonably well. Cox (1961) reported the effect of choosing the wrong distribution. It can be observed from Table 2 that both log-normal and gamma distributions show similar results in AD values for all the stations. Johnson et al. (1995) noted that both log-normal and gamma distributions can be used efficiently for positively skewed dataset. Wiens (1999) reported that these two distributions are always interchangeable. Kundu and Manglick (2005) illustrated that even though these two models may provide similar results for moderate sample sizes, it is important to identify the more accurate model. Hence, the study suggested making the best possible decision based on the given observations from AD values.

Table 2 FFDI values using LPIII distribution for different ARI for the study area

Stations	FFDI value and category of fire danger									
	1 in 2 years		1 in 5 years		1 in 10 years		1 in 20 years		1 in 100 years	
Horsham	11.3	LM	15.3	HI	17.4	HI	19.1	HI	22.4	HI
Mildura	15	HI	18	HI	22	HI	24	HI	28	VH
Mallacoota	5.3	LM	7.5	LM	8.6	LM	9.4	LM	12.5	HI
Warrnambool	10.5	LM	15	HI	17.7	HI	20.5	HI	25.4	HI
Phillip Island	4.3	LM	6.4	LM	7.8	LM	9	LM	11.8	LM
Tatura	4.3	LM	6.1	LM	7.2	LM	8.2	LM	10.2	LM
Shepparton	11.4	LM	14.3	HI	16	HI	17.5	HI	20.6	HI
Redesdale	11.6	LM	15.1	HI	16.5	HI	17.7	HI	20.2	HI
Nhill	7.8	LM	12.4	HI	15.5	HI	18.5	HI	25	VH
Mangalore	9.3	LM	12.2	HI	14.1	HI	15.6	HI	18.8	HI
Kyabram	6.2	LM	8.7	LM	10.2	LM	11.5	LM	14.4	HI
Echuca	12.1	HI	16.1	HI	18.6	HI	20.7	HI	25.2	VH
Dookie	5.7	LM	7	LM	7.8	LM	8.4	LM	9.8	LM
Castlemaine	8.6	LM	12.9	LM	15.5	HI	18	HI	23	HI
Bendigo	7.3	LM	9.3	LM	10.5	LM	11.5	LM	13.6	HI
Walpeup	12.1	HI	17.6	HI	21.1	HI	24.2	VH	30.8	VH
Cape Nelson	6.1	LM	7.6	LM	8.5	LM	9.3	LM	11	LM
Point Hicks	5.3	LM	7.8	LM	9.3	LM	10.6	LM	13.6	HI
Eildon Fire Tower	8	LM	9.5	LM	10.3	LM	11.2	LM	15.2	HI
Gabo Island	4.3	LM	6.2	LM	7.4	LM	8.5	LM	10.8	LM
Lakes Entrance	10	LM	15.1	HI	18.4	HI	21.4	HI	27.9	VH
Ouyen	13.5	HI	18.8	HI	22.1	HI	24.2	VH	30.8	VH
Port Fairy	7.5	LM	9.2	LM	10.2	LM	11.1	LM	12.8	HI
Benalla	8.7	LM	11.8	LM	12.4	HI	15.4	HI	18.9	HI
Cerberus	4.9	LM	6.7	LM	7.8	LM	8.8	LM	12.8	HI
Dartmouth	5.9	LM	7	LM	7.6	LM	8	LM	9	LM
Dinner Plain	9.4	LM	10.5	LM	11.1	LM	11.7	LM	12.7	HI
EDI Upper	11	LM	16.9	HI	20.6	HI	24.1	VH	31.4	VH
Falls Creek	5	LM	7	LMI	8.3	LM	10	LM	12	HI
Gelantipy	8	LM	10.3	LM	11.6	LM	12.8	HI	15.3	HI
Maryborough	8.6	LM	10.5	LM	11.6	LM	12.5	HI	14.5	HI
Mount Baw Baw	5.8	LM	7.8	LM	9.3	LM	11.5	LM	14.3	HI
Mount Nowa Nowa	5.5	LM	7.6	LM	8.8	LM	10	LM	12.4	HI
Mount Buller	7.2	LM	10.8	LM	13.1	HI	15.3	HI	19.8	HI
Mount Hotham	5.1	LM	7.5	LM	9	LM	10.4	LM	13.4	HI
Noojee	10.3	LM	15	HI	17.6	HI	19.9	HI	25	VH
Omeo	6.6	LM	10.8	LM	13.5	HI	17.1	HI	21.6	HI
Sale	14	HI	16.5	HI	20.1	HI	22.3	HI	30.7	VH
Strathbogie	4.5	LM	6.3	LM	7.5	LM	8.5	LM	10.5	LM
Wangaratta	12	HI	15.1	HI	16.9	HI	18.5	HI	21.8	HI

Italics represents the presence of high fire events for 1 in 100 ARI for different locations
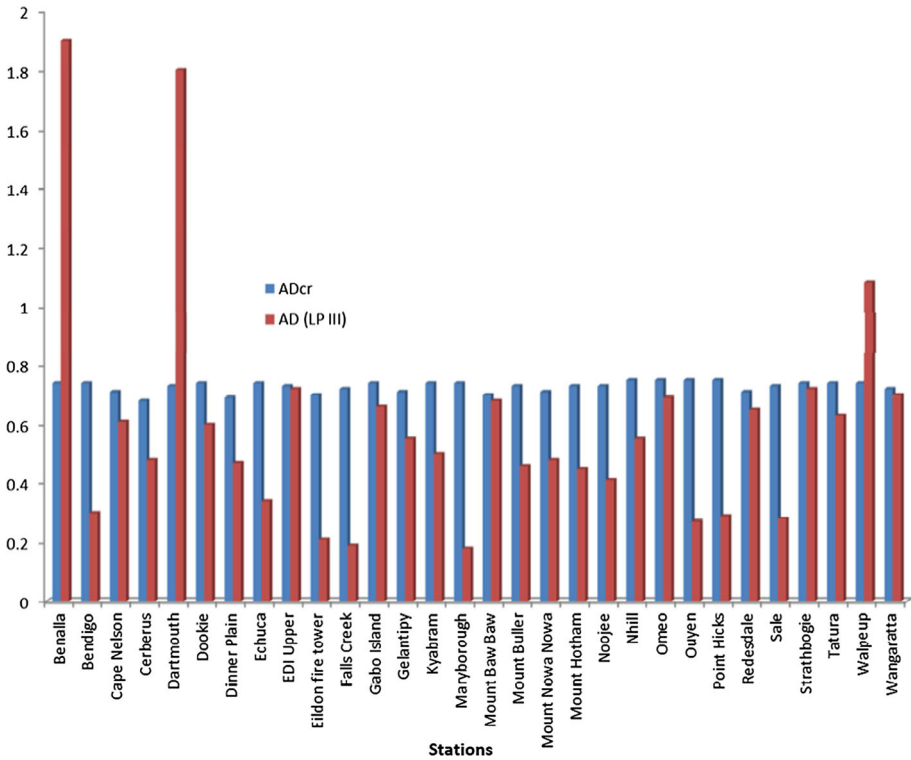
Fig. 5 AD values for the remaining 30 stations using LP III distribution

Cohen and Whitten (1988) and Abernethy (2006) illustrated that the Weibull distribution can be used effectively to describe the distribution of lifetime data. It can be observed from Table 1 that the AD values obtained using Weibull distribution is different from others, because it is considered to be a less accurate model in survival analysis among the other distributions. Nevertheless, from Table 2 it can be observed that LPIII distribution fitted better compared to other distributions. As mentioned earlier, the LPIII distribution has the advantage of accounting for the skewness of the dataset, whereas the lognormal distribution does not take skewness into consideration. It was decided to consider LPIII distribution as the best fit distribution for further FFA in Victoria. This also ensures consistency between flood as per ARR (1987) and fire frequency analyses.

Figure 5 depicts the variation of AD values for all the remaining 30 stations in the study area. It can be observed that for all the stations except three, the AD test results using LPIII distribution are smaller than the critical values (AD_{Cr}).

Figure 6 shows the fire frequency curves (FFC) developed for all the 40 stations in the study area. The relationships of FFDI values and its non-exceedance probabilities calculated by fitting LPIII distribution are shown in these FFC. To show the numerical variation of FFDI values at different ARI, Table 2 was obtained from Fig. 6. It clearly shows that a high fire danger situation (i.e. FFDI 12–24) exists for more than 80% stations every year for at least 1% probability of occurrence (i.e. 1 in 100 ARI). One-fourth of the stations have also 1% probability of occurrence of very high fire danger (FFDI 25–49) every year.
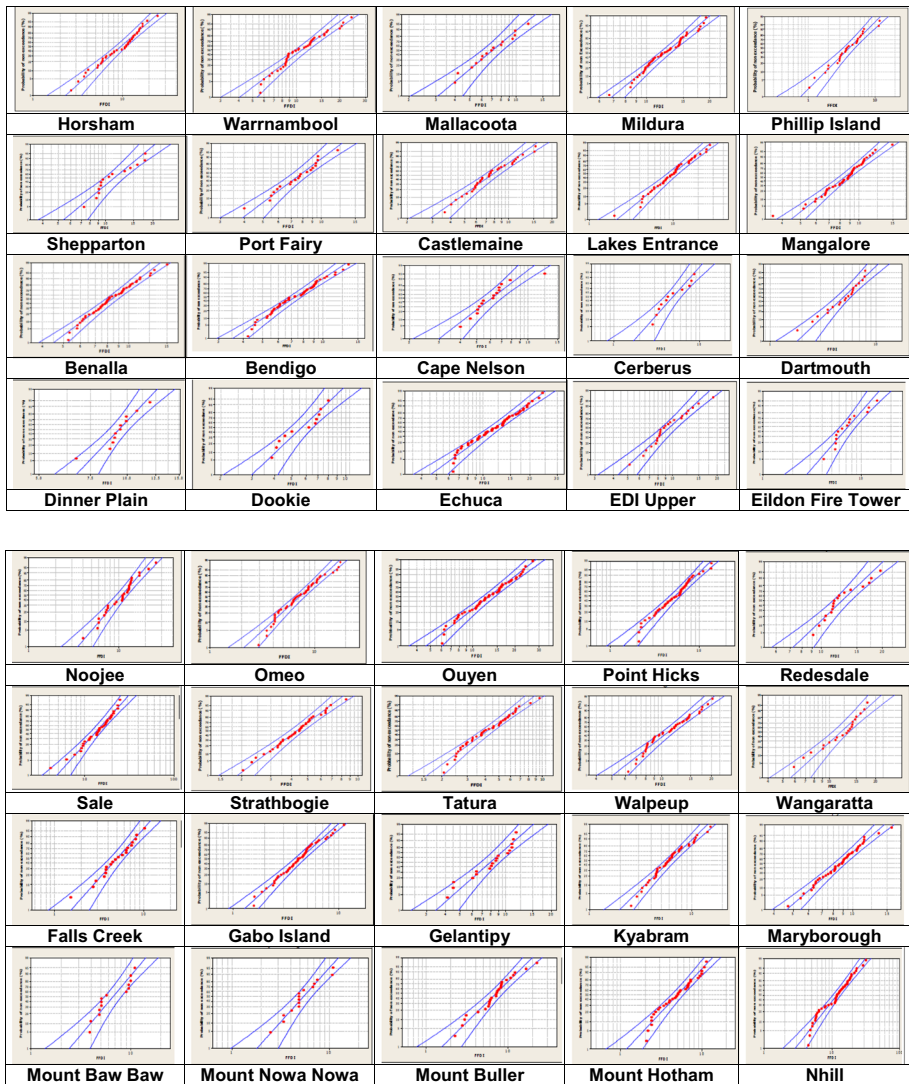
Fig. 6 Fire frequency curves (FFC) for different locations in Victoria using LPIII distribution

It is worthy to note that outliers such as Black Saturday, Ash Wednesday along with few others very high FFDI values were excluded for this FFC analysis.

Based on the FFDI values in Table 2 and comparing these with the fire danger rating (Fig. 1), it can be concluded that Nhill, Mildura, Warrnambool, Echuca, Noojee, Walpeup, Ouyen, EDI Upper, Lakes Entrance and Sale are the most fire-prone areas. On the other hand, Strathbogie, Dartmouth, Gabo Island, Tatura, Cape Nelson, Dookie and Phillip Island can be considered as low fire-prone areas.

To show the spatial variation of FFDI values in Victoria for different ARI, the FFC values from Fig. 6 were used to develop Fig. 7. For ARI 1 in 2 of all FFDI values are lower than 12, except in the north-western corner of Victoria. There is 50% probability (i.e. every
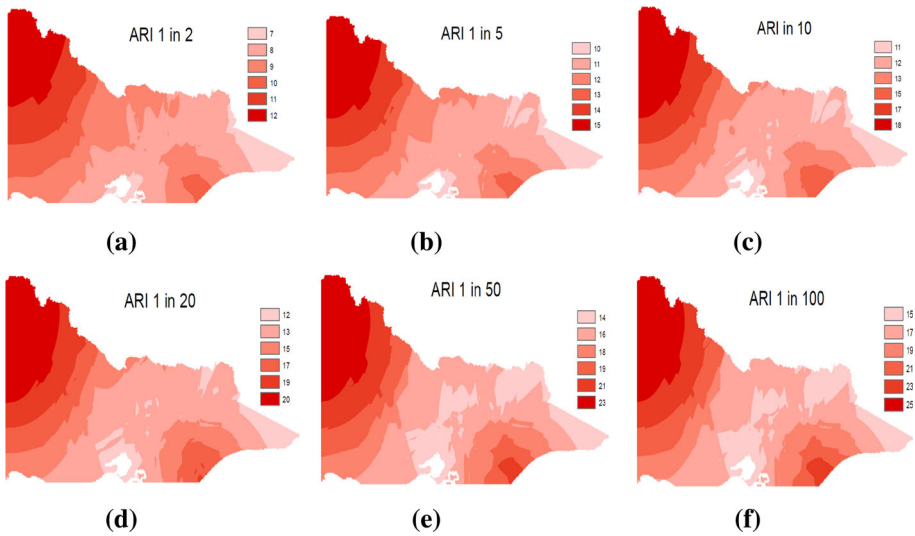
Fig. 7 Variation of FFDI values in different parts of Victoria for different ARI

alternate year) that a risk of high fire danger event could occur in that area. In another example, the FFDI values represented in Fig. 6d are 12–20, showing that there is a 5% probability of high fire danger all over Victoria. On the other hand, according to Fig. 6f, the north-western corner of Victoria would experience a very high fire danger at 1% probability of occurrence. These curves developed for Victoria will guide government and private organisations when designing and managing infrastructure by providing information with regard to future fire events.

4 Conclusion

Fire frequency analysis illustrates the probability of a fire occurring with certain intensity at a given location. Based on Anderson–Darling (AD) test results, Log Pearson Type III (LPIII) distribution fits well to all 40 stations across Victoria. LPIII fire frequency curves (FFC) that were developed for all the 40 stations can be used effectually to derive probabilistic fire events for each station. The probability of exceedance of a certain intensity of fire is important in planning and designing infrastructure to mitigate fire incidences. Furthermore, the FFC can be used to identify the fire-prone nature of an area. As for example, Nhill, Mildura, Warrnambool, Echuca, Noojee, Walpeup, Ouyen, EDI Upper, Lakes Entrance and Sale are the most fire-prone areas in Victoria, because using FFC it can be observed that there is probability of high fire events (FFDI more than 12) on those areas in the next 5 years.

Based on the results obtained from the 40 stations in the study area, it can be concluded that north-western Victoria is the most fire-prone area compared to other parts of Victoria. This result is consistent with that obtained from the Black Saturday bushfire, when Mildura (north-western Victoria) was severely affected. On the other hand, southern and eastern Victoria can be considered as low fire-prone areas because there is a low probability of occurrence of high fire events in the next 10 years due to significantly lower FFDI values

compared to north- western Victoria. The figures developed for different ARI for the whole of Victoria showed that there was 1% probability of very high fire danger (FFDI) and 50% probability of high fire danger in north-western Victoria. These probability distributions are useful to government and private organisations in assessing the fire risk when designing and managing infrastructure.

References

Abernethy R (2006) The New Weibull handbook: reliability and statistical analysis for predicting life, safety, supportability, risk, cost and warranty claims, 5th edn. Barringer & Associates, Hickory

Ahmed M, Sinclair C, Spurr B (1988) Assessment of flood frequency models using empirical distribution function statistics. Water Resour Res 24:1323–1328

Alexander A, Harald V, Herbert F, Alexander B (2010) A collection of possible fire weather indices (FWI) for alpine landscapes. www.alpffirs.eu/index.php?option=com_docman&task=doc. Accessed 5 June 2012

Allen C, Savage M, Falk D, Suckling K, Swetnam T, Schulke T, Stacey P, Morgan P, Hoffman M, Klingel J (2002) Ecological restoration of southwestern ponderosa pine ecosystems: a broad perspective. Ecol Appl 12:1418–1433

Arshad M, Rasool M, Ahmed M (2002) Power study for empirical distribution function tests for generalized Pareto distribution. Pak J Appl Sci 2:1119–1122

Australian Rainfall and Runoff (ARR) (1987) A guide to flood estimation, vol 1. Institution of Engineers, Australia, pp 195–235

Bessie WC, Johnson EA (1995) The relative importance of fuels and weather on fire behavior in subalpine forests. Ecology 76:747–762

Blokhinov YG, Sarmanov IO (1968) Gamma correlation and its use in computations of long-term streamflow regulation. Sov Hydrol Sel Pap 1:36–54

Catchpole WR, Bradstock R, Choate J, Fogarty L, Gellie N, McCarthy G, McCaw L, Marsden-Smedley J, Pearce G (1999) Cooperative development of prediction equations for fire behaviour in heathlands and shrublands. In: Proceedings of bushfire'99. Albury, New South Wales

Chandler C, Cheney P, Thomas P, Trabaud L, Williams D (1983) Fire in forestry, vol I. John Wiley and Sons, NewYork

Cheney N, Gould J (1995) Separating fire spread prediction and fire danger rating. CALM Sci Suppl 4:3–8

Chou Y, Minnich R, Chase R (1993) Mapping probability of fire occurrence in San Jacinto mountains, California, USA. Environ Manag 17(1):129–140

Cohen A, Whitten B (1982) Modified moment and maximum likelihood estimators for parameters of the three-parameter gamma distribution. Commun Stat Simul Comput 11:197–216

Cohen AC, Whitten BJ (1988) Parameter estimation in reliability and life span models. Marcel Dekker Inc, New York

Cox DR (1961) Tests of separate families of hypotheses. In: Proceedings of the fourth Berkeley symposium in mathematical statistics and probability, Berkeley, University of California Press, 105–123

Cox D (1962) Renewal theory. Wiley, London

Cunnane C (1973) A particular comparison of annual maxima and partial duration series methods of flood frequency prediction. J Hydrol 18:257–271

Dayananda A (1977) Stochastic models for forest fires. Ecol Model 3(4):309–313

Finkele K, Mills GA, Beard G, Jones DA (2006) National gridded drought factors and comparison of two soil moisture deficit formulations used in prediction of forest fire danger index in Australia. BMRC research report 119, Bureau of Meteorology, Melbourne, Australia

Fisher RA, Tippett LHC (1928) Limiting forms of the frequency distribution of the largest or smallest member of a sample. In: Proceedings of the Cambridge philosophical society, vol 24, no II, pp 180–191

Gordon N, McMahon T, Finlayson B, Gippel C, Nathan R (2004) Stream hydrology: an introduction for ecologists, 2nd edn. John Wiley and Sons Ltd, West Sussex

Grissino-Mayer HD (1999) Modeling fire interval data from the American Southwest with the Weibull distribution. Int J Wildland Fire 9:937–950

Grubbs FE, Beck G (1972) Extension of sample sizes and percentage points for significance tests of outlying observations. Technometrics 14(4):847–854

Gumbel EJ (1958) Statistics of extremes. Columbia University Press, New York

Johnson E (1979) Fire recurrence in the subarctic and its implications for vegetation composition. Can J Bot 57:1374–1379

Johnson E, Wagner C (1985) The theory and use of two fire history models. Can J For Res 15:214–219

Johnson N, Kotz S, Balakrishnan N (1995) Continuous univariate distributions, 2nd edn. Wiley, New York

Karoly DJ (2009) Bushfires and extreme heat wave in southeast Australia. www.RealClimate.org. Accessed 16 Feb 2016

Keetch J, Byram G (1968) A drought index for forest fire control. USDA forest service research paper No. SE-38, pp 1–32

Kundu D, Manglick A (2005) Discriminating between the log-normal and gamma distributions. J Appl Stat Sci 14:175–187

Landres P, Morgan P, Swanson F (1999) Overview of the use of natural variability concepts in managing ecological systems. Ecol Appl 9:1179–1188

Lang M, Ouarda T, Bobee B (1999) Towards operational guidelines for over-threshold modelling. J Hydrol 225:103–117

Madsen H, Pearson C, Rosbjerg D (1997) Comparison of annual maximum series and partial duration series methods for modeling extreme hydrologic events, 2. Regional modelling. Water Resour Res 33:759–769

Mandallaz D, Ye R (1997) Prediction of forest fires with Poisson models. Can J For Res 27:1685–1694

McArthur A (1966) Weather and grassland fire behaviour. Department of National Development, Forestry and Timber Bureau Leaflet No. 100, Canberra

McArthur A (1967) Fire behaviour in eucalypt forests. Department of National Development, Forestry and Timber Bureau Leaflet No. 107, Canberra

McArthur AG (1973) Forest fire danger meter, Mark V. Forest Research Institute, Forest and Timber Bureau of Australia, Leaflet No. 107, Canberra

Moran PAP (1970) Simulation and evaluation of complex water systems operations. Water Resour Res 6(6):1737–1742

Mount AB (1972) The derivation and testing of a soil dryness index using run-off data. Tasmanian Forestry Commission Bulletin, no 4. pp 31

National Fire Warning System (2009) New warning system explained. http://www.cfaconnect.net.au/index.php?option=com_k2&view=item&id=873. Accessed on 2 Dec 2009

Nesterov V (1949) Forest fires and methods of fire risk determination. Goslesbumizdat, Moscow

Noble I, Bary G, Gill A (1980) McArthur's fire-danger meters expressed as equations. Aust J Ecol 5:201–203

Onoz B, Bayazit M (1995) Best-fit distributions of largest available flood samples. J Hydrol 167:195–208

Pearson K (1893) Contributions to the mathematical theory of evolution. Proc R Soc Lond 54:329–333

Pearson K (1895) Contributions to the mathematical theory of evolution, II: skew variation in homogeneous material. Philos Trans R Soc Lond 186:343–414

Peng R, Schoenberg F (2001) Estimation of wildfire hazard using spatial-temporal fire history data. Technical report, Statistics Department, UCLA

Schoenberg FP, Peng R, Woods J (2003) On the distribution of wildfire sizes. Environmetrics 14:583–592

Schoennagel T, Veblen T, Romme W (2004) The interaction of fire, fuels, and climate across Rocky Mountain forests. Bioscience 54:661–676

Sivandran G (2002) Effects of rising water tables and climate change on annual and monthly flood frequencies. Department of Environmental Engineering, University of Western Australia

Skvarenina J, Mindas J, Holecy J, Tucek J (2003) Analysis of the natural and meteorological conditions during two large forest fire events in the Slovak Paradise National Park. In: International bioclimatological workshop, p 11

Sneeuwjagt J, Peet B (1985) Forest fire behaviour table for Western Australia. WA Department of Conservation and Land Management, Perth

Stedinger JR, Vogel RM, Foufoula-Georgiou E (1993) Frequency analysis of extreme events. McGraw-Hill, New York

Stephens M (1986) Tests based on EDF statistics. Goodness-of-Fit techniques, New York, pp 97–193

Takeuchi K (1984) Annual maximum series and partial duration series—evaluation of Langbein's formula and Chow's discussion. J Hydrol 68:275–284

Van Wagner C (1978) Age class distributions and forest fire cycle. Can J For Res 8:220–227

Van Wagner C (1987) Development and structure of the Canadian forest fire weather index system. Canadian forest service technology report no. 35

Weibull W (1951) A statistical distribution function of wide applicability. J Appl Mech Trans ASME 18(3):293–297

Wiens BL (1999) When log-normal and gamma models give different results: a case study". Am Stat 53(2):89–93

Xiaowei L, Guobin F, Zeppel MJB, Xiubo Y, Gang Z, Eamus D, Qiang Y (2012) Probability models of fire risk based on forest fire indices in contrasting climates over China. J Resour Ecol 3(2):105–117

Yue S (2000) The bivariate log-normal distribution to model a multivariate flood episode. Hydrol Process 14:2575–2588

Yue S (2001) A bivariate gamma distribution for use in multivariate flood frequency analysis. Hydrol Process 15:1033–1045