THE ROLE OF EXTREME VALUE ANALYSIS TO ENHANCE DEFENDABLE SPACE FOR CONSTRUCTION PRACTICE AND PLANNING IN BUSHFIRE PRONE ENVIRONMENTS

Research proceedings from the Bushfire and Natural Hazards CRC & AFAC conference
Adelaide, 1-3 September 2015

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Version	Release history	Date
1.0	Initial release of document	03/09/2015

Australian Government
Department of Industry and Science

Business
Cooperative Research
Centres Programme

Publisher:
Bushfire and Natural Hazards CRC

September 2015

Cover: A Strathewn house that was successfully defended on Black Saturday in 2009. Photo by the Bushfire and Natural Hazards CRC.

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ABSTRACT

Preparation of defendable space for buildings of both existing and planned urban development in bushfire prone areas relies on critical assessment of potential fire conditions. This paper offers new insights into the application of three extreme value assessment methods to the input parameters of both MacArthur and Project Vesta fire behaviour models for the determination of the defendable space and other fire safety measures. Weather data for various durations from 21 New South Wales fire weather districts are processed to derive the fire behaviour model input parameters such as the forest fire danger index and the fuel moisture content. These parameters are then subjected to probabilistic and recurrence modellings using three extreme value analysis methods. The results are evaluated to determine the most appropriate approach. It is found that the recurrence trends can be modelled with log functions with good correlation coefficients. The models are used to predict 1:50 year recurrence values of forest fire danger index which are compared with the existing policy settings. The results indicate the need to revise the policy settings for some of the weather districts.

KEYWORDS: fire weather, planning, probability, recurrence, risk assessment, wildfire.

Nomenclature

A_{max}	annual maxima
a	coefficient in the regression modelling
BAL	bushfire attach level (kW/m^2)
BoM	bureau of meteorology
b	constant in in the regression modelling
DF	draught factor
FFDI	Forest fire danger index
Fm	Fuel moisture content (%)
GCM	global climatic modelling
GEV	general extreme value
GFDI	grassland fire danger index
GPD	generalised Prato distribution
KBDI	Keetch-Byram Drought Index
NSWRFS	New South Wales Rural Fire Services
H	relative humidity (%)
T	air temperature (°C)
T_{max}	maximum daily temperature (°C)
U_{10}	average wind speed (kph) at 10 m above the ground
x	Independent parameter in probability density distribution, recurrence interval (year)
y	FFDI in the recurrence regression modelling
$\alpha, \beta, \mu, \sigma, \xi$	constants in various probability density distribution functions.

INTRODUCTION

Bushfires are frequent phenomena but variable in severity and landscape. Bushfires can occur with some regularity with season, however, extreme bushfire events are less likely and hard to quantify. These events are dependent on the antecedent weather conditions which give rise to severe bushfire conditions (Sullivan, 2004).

The determination of the severity of a potential bushfire for construction practice and land-use planning purposes is crucial in any assessment process. Property protection measures are therefore related to the concept of a 'design bushfire' (Douglas et al, 2014).

Building constructions in Australia are governed by the Building Code of Australia (BCA) and the relevant standards (ABCB, 2014). BCA is a performance based code which prescribes the performance requirement as well as the deemed-to-satisfy provisions. For performance based fire safety design, design fires provide a design reference (ABCB, 2005, Ramsay et al, 2006). Building fires are predominantly influenced by the combustible materials, ventilation conditions and the fire safety measures installed within a confined area and the selection of the design fire in building fire safety engineering is principally based on the consideration of these parameters (ABCB, 2005, SFS, 2012). Bushfire intensity, on the other hand, depends on topography, fuel loads and weather conditions and the development of design bushfires must consider these parameters. The determination of weather conditions for design bushfires is the focus of the current study.

Since weather conditions are more or less random phenomena, the selection of the design condition is usually guided by risk base principles. The quantification of extreme weather events based on a risk profile and recurrence analysis has been regularly used in areas of storm, flood and wind protection. However, similar approaches have not found wide application in bushfire protection. The application of fire weather data for planning and construction practice in bushfire prone areas has been empirically inferred from past events and relied on assumed FFDI values (NSWRFS, 2006). In some cases the selection of the reference FFDI has been supported by subsequent work although only indirectly (Hennessey et al, 2005).

Based on the assumption that the forest fire danger index follows the Weibull distribution, Douglas et al (2014) presented a generalised extreme value approach to the modelling of the recurrence of forest fire danger index (FFDI). This approach sets the selection of design bushfire on a more rigorous basis than the existing method used in the existing standard (AS 3959, 2009). The application of the method to the recorded weather data from a limited number of weather districts in NSW, where complete or continuous weather data was available, has shown good correlations between the regression lines and the FFDI recurrence data. However, in view of the existence of a number of the extreme value analysis methods, there remains a question as to whether the generalised extreme value approach is the most appropriate approach available.

Further review of the weather data record revealed that not all weather districts in New South Wales state have the complete weather data due to historical development of the weather stations. It is still unknown if the available assessment methods are robust enough to deal with incomplete weather datasets.

The objective of the current study is to test multiple extreme value assessment methods and apply them to the data obtained from all NSW weather districts. The methods will be compared against the criteria of accuracy and robustness. The study will result not only the evaluation of various extreme value analysis methods, but also the recommended design bushfire parameters for all NSW weather districts.

BACKGROUND

TOWARDS A DESIGN BUSHFIRE

A major assessment parameter for bushfire protection design is the bushfire attack level (BAL) which is expressed in heat flux exposure (AS3959, 2009). This parameter can be evaluated from flame dimensions, flame temperature and flame distance (Douglas and Tan, 2005). The latter can be a design input parameter for building design or an outcome parameter for design and planning. The former two are design input parameters and depend on bushfire intensity which in turn depends on fire weather conditions. Hence, the selection of design bushfires is reduced to the selection of design weather conditions which is characterised by the forest fire danger index (FFDI) (Noble et al, 1980).

The concept of annual occurrence of exceedance (or recurrence) for FFDI is used by the New South Wales Rural Fire Service (NSWRFS) as a major input for determining the design bushfire conditions where a solution that is alternative to deemed-to-satisfy provisions of the building code and the standard is proposed (NSWRFS, 2006).

The sensitivity of FFDI used to estimate fire danger throughout Australia has been considered by Williams et al (2001) and linked to increased recurrence of fires as measured in terms of very high and extreme events and may be linked to maximum daily temperature. However, the question remains as to the process of determining suitable risk criteria for the development of defendable space, not only for property protection for new developments, but also fire fighter safety and existing developments (Douglas, 2012).

A major difficulty therefore is in defining bushfire scenarios for design and assessment purposes. The failure to obtain the appropriate design fire can result in additional costs to the environment or construction for land holders or, alternatively, the failure of the building systems to withstand the likely fire event. For example, the environmental conditions for the Victorian bushfires in 1939 were deemed to have set the 'benchmark' of worst possible conditions for bushfires and the corresponding FFDI value was set at 100 to mark the presumed upper limit of the scale (Sullivan, 2004). However these conditions and the FFDI 100 limit have been exceeded on many occasions since. Table 1 lists recent examples of such fire events and their FFDI ratings. The exceeding of the benchmark FFDI value of 100 presents challenges as to what is the appropriate benchmark for design in bushfire prone areas and whether a unified benchmark value exists.

Table 1. Recent Australian major bushfire events exceeding FFDI 100.

Event	Year	FFDI	Source
Ash Wednesday	1983	>100	Sullivan (2004)
Mt Hall fire	2001	>100	NSW Rural Fire Service (2002)
ACT (Duffy, etc.)	2003	105	McLeod (2005)
Eyre Peninsula, South Australia	2005	200	Smith (2005)
Victoria's Black Sunday	2009	188	VRCB (2010)

These challenges are further complicated by the global warming. The overall impact of climate change is undertaken using global climatic modelling (GCM) to develop 'scenarios' arising from different emission patterns into the future (Hasson et al, 2008). However such models are not suited for infrequent extreme events at the small scale due to their limited spatial and temporal resolution.

Previous climatic assessments have largely focused on historical weather records and linear regression models (e.g. Andrews et al, 2003; Bradstock et al, 1998). Recent work by Cechet et al (2013) and Sanabria et al (2014) have illustrated the role of extreme value assessment to map fire weather return periods based on forest fire danger index (FFDI) across the landscape using GCM to incorporate the potential effects of climate change. Such mapping exercises are initially attractive but rely on complex models to translate a weather and climatic scenario for events which are occurring in different time frames and conditions. Li and Heap (2011) identified the challenges of environmental mapping under such conditions, which include the needs for larger numbers of data-points (i.e. weather stations) within a landscape for model enhancement.

An alternate approach is to progressively build up weather station data within the landscape, based on BoM weather prediction districts, and increase the number of weather station data-points for comprehensive climatic model validation.

This paper provides an update of progress in the broader study of extreme value assessment techniques and their applications for land use planning and construction practice in NSW fire weather areas. The content covers weather related parameters only. Vegetation classes and fuel structure assessments are excluded, though they also form part of this broader investigation.

MCARTHUR AND PROJECT VESTA BUSHFIRE BEHAVIOUR MODELS

The determination of flame characteristics, including dimension, temperature and rate of spread, is central to consideration of land use planning and construction practice. Bushfire behaviour models therefore underpin the site assessment and construction measures used in bushfire prone areas and are sensitive to the underlying assumptions made as inputs to these models for the development of bushfire attack levels (BAL) and defendable space. In essence these assumptions relate primarily to weather and vegetation (Douglas and Tan, 2005).

The two key models for fire behaviour to be considered for forest fire in Australia are those of McArthur (Noble et al 1980) and Project Vesta (Gould et al, 2007).

In the McArthur fire behaviour model, the forest fire danger index (FFDI) has been recognized as the most indicative of forest fire behaviour. This index is mathematically formulated by Noble et al (1980) and has been applied to limited weather data as part of the National Fire Weather Data set (Lucas, 2010). FFDI is used to determine both the rate of spread and flame length (Noble et al, 1980), although the model is believed to be suited to low range of FFDI index or low intensity fires (Gould et al, 2007, McCaw et al, 2008Dowdy et al, 2009).

The more recent model developed in the Project Vesta is believed to more accurately reflect the rate of spread in higher intensity fires (Gould et al, 2007). However its fuel assessment approach differs from McArthur approach as does the use of weather parameters in deriving fire behaviour including El Nino Oscillation and Inter-decadal Pacific Ocean events (Verdon et al, 2004).

The two models require different fire weather inputs. The McArthur model relies on the forest fire danger index which incorporates a set of weather data including wind speed, relative humidity, temperature and draught factor, whereas the Project Vesta model uses primarily wind speed, fuel configuration and fuel moisture (Gould et al 2007, Cheney et al, 2012).

DATA COLLECTION AND ANALYSIS

DATA

The State of NSW has 21 Fire Weather Districts (NSWRFS, 2006) as shown in Figure 1. Each weather area has multiple weather stations. However, not all weather stations have a complete dataset to calculate FFDI. Data from at least one weather station in each NSW fire weather area were used in the present study. Some areas investigated for FFDI may be better associated with GFDI which is not included in the current study. The twenty-one (21) weather station locations in the 21 fire weather districts are listed in Table 2.

Figure 1 NSW fire weather districts (NSWRFS, 2006) and some weather station locations (Source: BoM).

For the current study, three weather datasets have been acquired from the Bureau of Meteorology (BoM) including:

- 1976/86-2009 data on FFDI/GFDI and associated data (Lucas, 2010) (16 stations);
- All 1950-2009 daily data available at 3:00pm including wind speed and direction, relative humidity (H), temperature (T), gusts and rainfall;
- 1994-2009 drought indices (DF and KBDI) with 3pm relative humidity, daily maximum temperature (T_{max}) and 24 hr rainfall (88 stations).

The datasets have been consolidated and 30 location datasets have been produced covering all 21 fire weather districts (see Figure 1). These include FFDI (and GFDI in western NSW), 3:00pm wind speed and directions, relative humidity and the daily maximum temperature. For each area, forest fuel moisture was also calculated on a daily basis using models described by Gould et al (2007). The data obtained from the Lucas (2010) datasets cover the period from 1976 to 2009 and the data derived from BoM covers the period of 1994-2009. Due to significant data gaps and geographical spread, not all weather datasets by Lucas (2010) have been used (see Sanabria et al, 2014).

Table 2. Fire Weather Areas (Districts), and associated weather stations used in the study (BoM after Lucas 2010, NSWRFS, 2006).

Fire Weather Districts No.	Fire Weather Area Name	Weather Station
1	Far North Coast	Grafton
2	North Coast	Coffs Harbour
3	Greater Hunter	Williamtown
4	Greater Sydney	Sydney
5	Illawarra/Shoalhaven	Nowra
6	Far South Coast	Batemans Bay
7	Monaro-Alpine	Cooma
8	Australian Capital Territory	Canberra
9	Southern Ranges	Goulburn
10	Central Ranges	Bathurst
11	New England	Armidale
12	Northern Ranges	Tamworth
13	North-Western	Moree
14	Upper Central West Plains	Coonamble
15	Lower Central West Plains	Dubbo
16	Southern Slopes	Young
17	Eastern Riverina	Wagga Wagga
18	Southern Riverina	Deniliquin
19	Northern Riverina	Hay
20	South Western	Mildura
21	Far Western	Cobar

METHOD OF ANALYSIS

Overview

In the past, practice has been to consider the limited data available for a site and determine whether any of the following policy decision should be based on:

a) FFDI has been exceeded on more than one recorded occasion;
b) FFDI which is a frequency percentile value of the dataset (e.g. 95% value of FFDI>12); or
c) derived FFDI from maximum values of wind speed, (lowest) relative humidity, maximum temperature and drought factor for summer data.

Each of these methods has significant shortfalls and does not necessarily represent a valid risk based approach to the assessment of fire weather. They have been used in the absence of a clear methodological and statistically appropriate approach (e.g. Douglas and Tan, 2005). In particular, they are all based on the past records which may not give true representation or prediction of the likely and the extreme scenarios. The exceedance of traditional limiting value of 100 for FFDI is a typical example of the limitation of this kind of approaches.

In the current study, a number of probability distribution functions have been hypothesised to describe various parameters namely FFDI and fuel moisture content (F_m) in the two identified bushfire behaviour models. The corresponding recurrence models are then established to predict the parameter recurrence values for a specified recurrence interval. These methods are applied to the derived fire weather index data for all 21 NSW fire weather districts. The results are compared with the current policy or standard settings in bushfire protection practice.

Derived parameters for bushfire behaviour modelling

Historically extreme value analysis has been used for directly measurable weather parameters such as rainfall, floods, temperature, relative humidity and wind, however, such analysis has not been routinely undertaken for fire weather. The reason may be attributed to fire weather being described by a composite of differing parameters as explained in Eq. (1) below (Noble et al, 1980):

$$F = 2\exp\left[-0.45 + 0.987\ln(D) - 0.0345H + 0.0338T + 0.0234U_{10}\right] \quad (1)$$

where F denotes FFDI, D is drought factor derived from Keetch-Byram Drought Index (Griffith, 1999), H is relative humidity (%), U_{10} is wind speed at 10 m above ground (kph) and T is air temperature (°C).

Similarly, the fuel moisture correlation used in the Project Vesta model is dependent on relative humidity and air temperature in the following equation:

$$F_m = 5.658 + 0.04651H + 3.151 \times 10^{-4}H^3/T - 0.1854T^{0.77} \quad (2)$$

where F_m is fuel moisture.

It is unlikely at any given time that all individual independent parameters could attain their extreme values simultaneously to yield an 'extreme' value of the derived or dependent variables such as forest fire danger index F or the fuel moisture F_m. Therefore, one cannot rely on the results of the extreme value analysis of individual weather parameters to deduce the extreme value of F or

F_m. It is nevertheless possible to extend extreme value to the dependent parameters themselves.

Probabilistic description of the derived parameters

As discussed earlier, the derived parameters F and F_m are random parameters because of the random nature of the weather parameters on which they depend on. Extreme value assessment provides a useful tool for the determination of risk associated with the occurrence of extreme events (Coles, 2004). Although some work has been undertaken using extreme value techniques on large fires, only limited work has been done in relation to assessing fire weather parameters. For example, Andrews et al (2003) and Douglas et al (2014) employed the generalised extreme value (GEV) method, whereas, the use of generalised Pareto distribution (GPD) was reported by Cechet et al (2013) and Sanabria et al (2013). There remains a question as to which method is more suitable. Furthermore, it is hypothesised that a Gumbel type distribution may be an alternative description of the random characteristics of F. Hence, this study uses the following three extreme value assessment techniques:

a) Generalised Extreme Value (Weibull) distribution (GEV);
b) Annual Maxima (Gumbel) distribution (Amax); and
c) Generalised Pareto distribution (GPD).

The Weibull probability density function is expressed by the following equation:

$$f(x) = \frac{\alpha}{\beta}\left(\frac{x}{\beta}\right)^{\alpha-1} e^{-\left(\frac{x}{\beta}\right)^{\alpha}} \tag{3}$$

where α and β are constants and the domain of x is (0, ∞).

The distribution governing the annual maxima is believed to be Gumbel distribution of the form:

$$f(x) = \frac{1}{\beta}\exp\left(-\frac{x-\mu}{\beta}\right)\exp\left[-\exp\left(-\frac{x-\mu}{\beta}\right)\right] \tag{4}$$

where β and μ are distribution parameters, and the domain for x is (0, ∞).

The probability density function for the generalised Pareto distribution (GPD) takes the form:

$$f(x) = \frac{1}{\sigma}\left[1 + \frac{\xi}{\sigma}(x-\mu)\right]^{-\left(1+\frac{1}{\xi}\right)} \tag{5}$$

For $x \geq \mu$ when $\xi \geq 0$ and $\mu \leq x \leq (\mu - \sigma/\xi)$ when $\xi < 0$. In all of the above three probability density distribution functions, variable x represent FFDI.

Recurrence modelling

The application of the GEV method to obtain the regression fit and estimate of recurrence values of FFDI is explained in Douglas et al (2014). Detailed descriptions of GEV method can be found in Makkonen (2006).

In the annual maxima approach, the annual maximum FFDI value for each calendar year is selected and ranked in a similar way as in the GEV approach.

Unlike other GEV approaches, the plot of recurrence trend based on GPD approach relies on determining the proportion of exceedance values above a threshold. This is often referred to as a peaks over threshold approach where FFDI values are ranked and the proportion of values being exceeded are then plotted in a similar way to GEV (Makkonen, 2006). To calculate average return intervals a partial duration series dataset (as opposed to annual maximum) was constructed, using:

$$ARI_y = \frac{\text{Total number of data points}}{\text{Number of data points where FFDI} > y} \quad (6)$$

where ARI_y is the average return (or recurrence) interval with the condition of FFDI>y. The advantage of the GPD approach is that it is not reliant on seasonal or calendar considerations. The disadvantage however, is that it has stringent requirement on the continuity of data string. Any gap in the data string will have a greater influence on the output than in either GEV or A_{max} approaches.

The recurrence trends based on the three methods are fitted with log functions of the form:

$$y = a \ln(x) + b \quad (7)$$

where a and b are the constants of best fit to the recurrence trends. Variable x in the above equation represents the recurrence interval and y the corresponding forest fire danger index. From the established correlations the forest fire danger index for any specified recurrence interval can be predicted. It is noted that the prediction can be extrapolated beyond the period of the data collection.

These three approaches have been used and compared to maximum recorded values in the dataset. For illustrative purposes, 1:50 year return using GEV only for fuel moisture has also been determined.

RESULTS AND DISCUSSION

RESULTS

Probability density distribution analysis

A software package EasyFit (Mathwave, 2015) was used to obtain the probability density distribution functions described earlier. An example of the histogram and the fitted distribution functions for the FFDI values obtained from the Sydney Airport weather station are shown in Figure 2. It can be seen from this figure that Weibull distribution curve produces a monotonously decreasing trend that gives the best fit to the histogram. Both the fitted GPD and Gumbel have a peak that is not observed in the histogram.

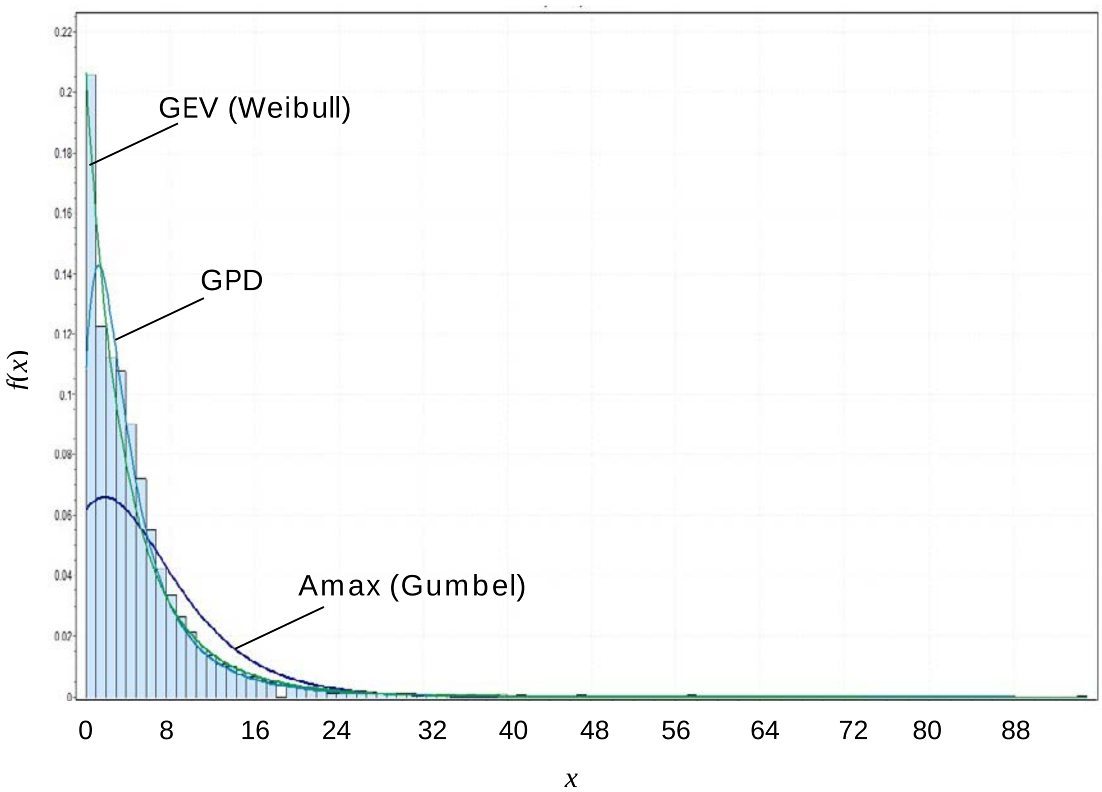


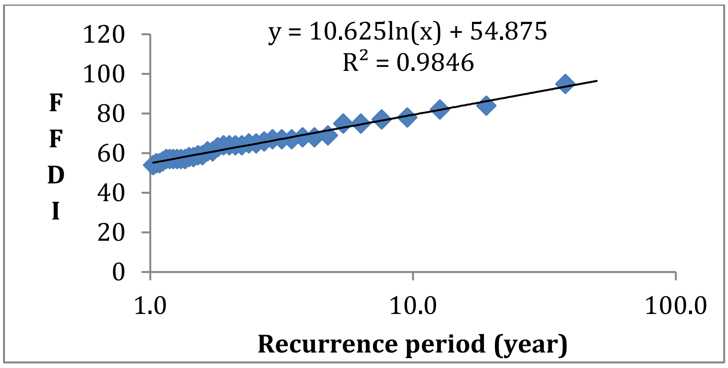
Figure 2. Histogram of FFDI and fitted probability density distribution functions.

The fitted distribution functions underwent Kolmogorov-Smirnov (K-S) test (Corder and Foreman, 2014) and, not surprisingly, the results indicated that the Gumbel distribution attains the lowest ranking among the three and the Weibull distribution the highest ranking. Therefore, the Weibull distribution is the most suitable description of the probabilistic characteristics of FFDI obtained from the Sydney Airport weather station. Similar outcomes were found for the majority of the stations listed in Table 2.

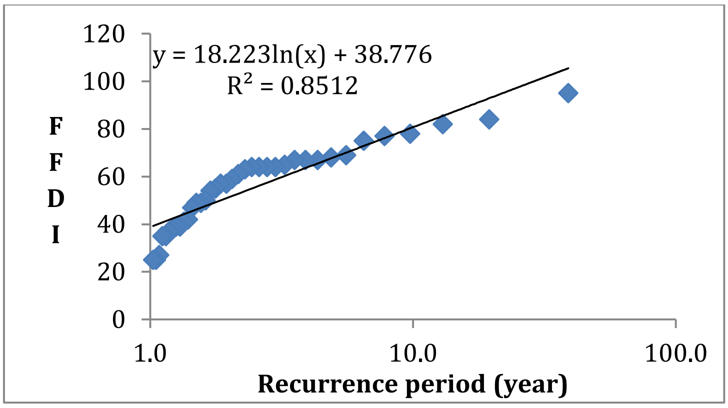
Recurrence analysis

Recurrence analyses were conducted over the FFDI values of all 21 fire weather districts using the GEV, Amax and GPD approaches. An example of the graphical representations of the recurrence plot based on three techniques is shown in

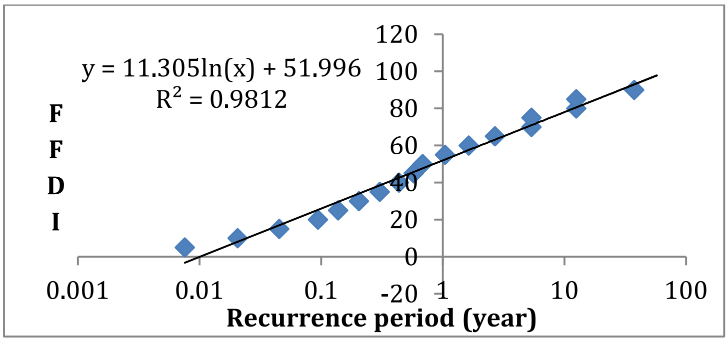
Figure 3 for the Sydney Airport district. It can be discerned that GEV [Figure 3(a)] resulted in the best log regression model over that of Amax [Figure 3(b)] (which has the lowest correlation coefficient, or the R^2 value) or GPD [Figure 3(c)].



(a) Results of GEV method.



(b) Results of Amax method.



(c) Results of GPD method.

Figure 3. Graphical representation of FFDI recurrence plots with regression models for Sydney Airport.

The three methods of recurrence analyses were applied to the FFID data of all 21 NSW fire weather districts. The GEV method, which yields the best fit among all three methods, was also applied to fuel moisture data. The predicted results of 1:50 year recurrence are presented in Table 3 and are compared to the existing policy settings that are prescribed in the New South Wales *Planning for Bush Fire Protection* (NSWRFS, 2006) and Australian Standard *Construction in bushfire prone areas* (AS3959, 2009). Also included in Table 3 are the recorded maximum FFDI at 3:00 pm for all fire weather districts.

Table 3. Evaluated recurrence, standard setting and maximum recorded FFDI, and recurrence fuel moisture content for 21 weather stations.

District No.	$FFDI_{1:50}$			FFDI		$Fm_{1:50}$ (%)
	GEV	A_{max}	GPD	AS3959	3:00pm Max	GEV
1	101	120	94	80	93	2.64
2	96	94	82	80	95	2.86
3	106	121	101	100	99	1.84*
4	98	110	96	100	95	2.47
5	112	122	104	100	120	3.55
6	97	112	90	100	74	3.07
7	83	96	84	80	68	2.28
8	100	115	96	100	99	2.48
9	105	121	104	100	91	2.00
10	83	100	82	80	91	2.93
11	46	52	46	80	46	3.07
12	100	101	100	80	105	2.44
13	115	104	103	80	125	2.41
14	123	163	121	80	121	2.29
15	107	121	101	80	99	2.60
16	79	97	89	80	71	2.35
17	122	144	121	80	138	2.26
18	131	146	125	80	121	2.42
19	108	125	106	80	125	1.55*
20	136	150	130	80	132	2.40
21	116	128	113	80	117	2.22

* The predicted value is less than the limit of 2% (McArthur, 1967) and hence practically unlikely.

DISCUSSION

The application of extreme value techniques to forest fire danger index allows the interrogation of multiple weather parameters for the determination of appropriate design bushfire conditions for bushfire protection. Table 3 shows that there can be significant variation between techniques though the GEV and GPD approaches align more closely with the processed data than Amax. The latter generally produce higher estimate of the 50 year recurrence FFDI values that the former two. Higher estimate of recurrence FFDI value for planning and design purposes will lead to conservative or safer protection outcome.

What is also apparent in Table 3 is that the current policy and standard settings of reference or design FFDI for a number of districts in the North Coast (Districts 1 and 2) and inland areas (Districts 10, 13 - 17) are lower than 1:50 year return period FFDIs. In other areas (notably District 12) policy settings are higher than the evaluated 1:50 year recurrence FFDI. Although not all stations can be said to be representative for the whole of the fire weather districts, the data from these stations and the subsequent analyses do provide references of recurrence values for those areas. It, however, should be borne in mind that because of the nature of the vegetation cover, far western NSW would be better represented with GFDI than FFDI.

It is noted that in the Project Vesta model, the fuel moisture correlation as given by Eq. (2) has a lower mathematical limit of 2.66% corresponding to the limiting case of 5% relative humidity and 41°C temperature. Anecdotally, temperatures higher than 41 °C have been observed in many parts of NSW. Therefore, it may be possible that the limit is even lower. In the literature, a limit of 3% was cited by Gould et al (2007) and Cheney et al (2012). The physical limit identified by McArthur (1967) is 2%. The predictions of the 1:50 year recurrence values for some fire weather districts (No. 3 Greater Hunter and No. 19 Northern Riverina, see Table 2 and Table 3) are found to be below this limit. Care should be taken when apply these recurrence values for design bushfire selection, bearing in mind that lower fuel moisture value would result in higher risk assessment outcome. It is recommended that the minimum threshold value of 2% be used.

This study has found that *prima facie*, the north coast and inland areas of NSW should be brought up from FFDI=80 to a more appropriate FFDI=100. The major exceptions to this are the Central West (Bathurst), Southern Slopes (Young) and Cooma-Monaro (Cooma) fire weather areas which should retain FFDI=80. In the case of New England (Armidale), the fire weather area comprises areas of higher and lower elevations which could affect the FFDI return value. While an FFDI=80 value currently exists, the reduction of the weather area to FFDI=50 may be appropriate unless fire services seek further investigation and confirmation with other weather station data. Areas of western NSW, which do not exhibit forest vegetation should also be included in FFDI=100, although there FFDI values are found to exceed 100.

CONCLUSION

Three extreme value analysis methods have been used in the current study to obtain probabilistic descriptions and recurrence modellings of forest fire danger index and fuel moisture content from the weather data records for the 21 fire weather districts in New South Wales state.

The current study illustrates that the extreme value techniques can be used when determining FFDI and fuel moisture for bushfire behaviour modelling. For planning and design purposes, GEV (Weibull) method appears more suitable than Amax (Gumbel) and GPD methods because of its generally high ranking by the Kolmogorov-Smirnov test and high correlation coefficient of the recurrence regression. Although Amax method is the least accurate approach, it may give a more conservative (safer) design reference FFDI value over the other two methods. GPD method produced reasonable description of FFDI. It is, however, sensitive to the continuity or the period length of data.

The extreme value analysis and recurrence modelling allow us to predict the recurrence values at recurrence period longer than the length of the data collection period from which the model is developed. However, care should be taken when extrapolating the recurrence values. The results should be subjected to the physical constraints based on field experiment and studies. Notably the modelled 1:50 year recurrence fuel moisture value based on GEV method was observed to fall below the 2% threshold in some weather districts of NSW.

The existing approaches to mapping of the forest fire danger index in the regulatory policy area may be problematic in that they deviated significantly from the estimates based on rigorous methods. Adjustments of the policy mapping are recommended to reflect the local weather district conditions presented in this paper.

The data processed in the current study was selected from one typical station in each of the 21 NSW fire weather districts. Multiple weather stations in different locations exist in most districts. The application of the extreme value analysis to additional weather station data within a district will assist in establishing design reference FFDI and fuel moisture with better ore more appropriate spatial resolution within the landscape.

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