FOREST BIOSECURITY AND PROTECTION

Use of Long-term Fire Danger Data Sets to Predict Fire Season Severity

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A final report summarising research completed by Forest Research as part of the joint NIWA-Forest Research project "Prediction of Fire Season Severity".

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Abstract/Executive Summary

- Although not having one of the worst fire climates in the world, New Zealand still experiences around 3000 vegetation fires each year that burn around 7000 ha of rural lands. Strong winds, high temperatures, low humidities and seasonal drought can combine to produce dangerous fire weather situations. To effectively manage this risk, New Zealand fire managers require indications of likely trends in fire danger and fire season severity, based on comparisons with previous seasons and long-term averages.

- The compilation of a comprehensive database of daily fire weather and fire danger information (conducted as a pre-cursor to the research described here) has provided a better description of New Zealand's fire climate. It also allows fire managers to identify similar fire seasons from the past that can be used as a reference for predicting conditions during the forthcoming season. Armed with a knowledge of the impacts of this previous season on fire activity, fire authorities are then better able to respond to the risks associated with the forthcoming season.

- The principal objective of the current research was to maximise the utility of the fire climatology database by developing an analytical methodology for comparing and predicting fire season severity. This was achieved by conducting statistical analyses on measures of fire season severity – such as Cumulative Daily Severity Ratings (CDSR), Drought Code (DC) and Buildup Index (BUI) – for a subset of 7 weather stations with long-term fire climate records (>30 years).

- Two contrasting analytical approaches were investigated:
  (1) analyses of statistical similarity between fire season trend curves, as the basis for identifying the historical season most similar to current conditions; and
  (2) fitting of parametric functions that characterise the general shape of fire season trend curves, and use of derived function descriptors to predict intermediate as well as fire season end values.

- Both approaches were found to be effective at grouping seasons with similar fire severity as determined through CDSR. The similarity approach was better for grouping seasons according to BUI and DC as neither of these two indices had temporal patterns that could be easily modelled with a parametric function. The parametric curve fitting method was successfully able to model overall fire season severity outcome as measured through CDSR but, more importantly, also proved successful in predicting seasonal severity 1-2 months ahead.

- The parametric curve fitting approach offers the most promise in terms of being able to forecast trends in fire season severity, at least up to 1-2 months in advance. As well as refining the methodology for CDSR, future work should focus on distinguishing between the effects of dryness and windiness in high CDSR seasons. This could be achieved by continuing to investigate the usefulness of other fire danger indices such as DC and BUI, or by looking directly at the relevant meteorological inputs (i.e., wind speed and direction, and rainfall) contributing to seasonal severity.

- An Excel™-based spreadsheet package encompassing the parametric curve fitting approach was developed and, while still requiring further development and testing before it can be used in an operational setting (e.g., within FWSYS), this does appear to offer promise as a means of predicting future trends in fire season severity.

Table of Contents

Introduction

Although not having one of the worst fire climates in the world, New Zealand still experiences around 3000 rural vegetation fires each year that burn some 7500 ha of rural lands[1]. Strong winds, often associated with high temperatures, low humidities and seasonal drought, can combine to produce dangerous fire weather situations. To effectively manage this risk, New Zealand fire managers require indications of likely trends in fire danger and fire season severity, and comparisons with previous seasons and long-term averages.

The production of a comprehensive climatology of daily fire weather and fire danger in prior research (Pearce *et al*. 2003) has provided a better description of New Zealand's fire climate. In itself, this enables rural fire authorities and the National Rural Fire Authority (NRFA) to increase the focus of fire prevention and mitigation activities. However, the compilation of current and historical fire climate data also allows fire managers to identify similar fire seasons from the past that can be used as a reference for predicting the potential for critical fire conditions during the forthcoming season. Armed with a knowledge of the impacts of this previous season on fire activity (e.g., number of fires or area burned, and areas most affected), fire authorities will then be able to better respond to the risks associated with the coming season.

Scope of the Study

This report summarises research completed by Forest Research as part of the joint NIWA-Forest Research project "Prediction of Fire Season Severity". The joint project aimed to extend the results of previous investigation into methods for predicting the severity of fire seasons in advance. It combined complementary research undertaken by Forest Research to develop a national fire climatology database and associated analytical tools with NIWA-led research on the prediction of fire season severity from regional and global climate factors for use in improving regional fire danger forecasts for New Zealand.

The Forest Research component of the joint project involved development of an analytical methodology for comparison and prediction of fire season severity by:

- Reviewing statistical forecasting techniques to determine appropriate methods for application to seasonal fire weather and fire danger data;
- Testing techniques for comparison of individual fire seasons and prediction of future trends using updated long-term data sets of fire weather and fire danger information;
- Applying appropriate statistical techniques identified to the station datasets of updated fire weather and climatology compiled under the previous NZFSC-funded project 'Fire Danger Climatology Analyses and Tools', and automation of the comparison and forecasting methodology; and
- Development of a graphical interface display package to enable graphical comparison of present fire season conditions and indications of future trends.

The research aimed to develop a method for determining the similarity of fire seasons, and for identifying the historical season that is most similar to current conditions as a predictor for what is to come. This was done using measures of fire season severity, such as the Cumulative Daily Severity Rating (CDSR), as well as other fire danger rating system components, such as the Drought Code (DC) and Buildup Index (BUI).

[1] From statistics for the period 1993/94-2002/03 produced by the National Rural Fire Authority, based on the Annual Return of Fires form completed by New Zealand fire authorities.

Background

Assessment of the effect of fire weather (and other fire environment factors of fuels and topography) on potential fire occurrence and fire behaviour is assisted by the use of the New Zealand Fire Danger Rating System (NZFDRS) (Fig. 1a), which is based on the Canadian Forest Fire Danger Rating System (CFFDRS). The NZFDRS is used by New Zealand fire authorities to assess the probability of a fire starting, spreading and doing damage. New Zealand's adoption and continued adaptation of the CFFDRS has been described by Fogarty *et al*. (1998).

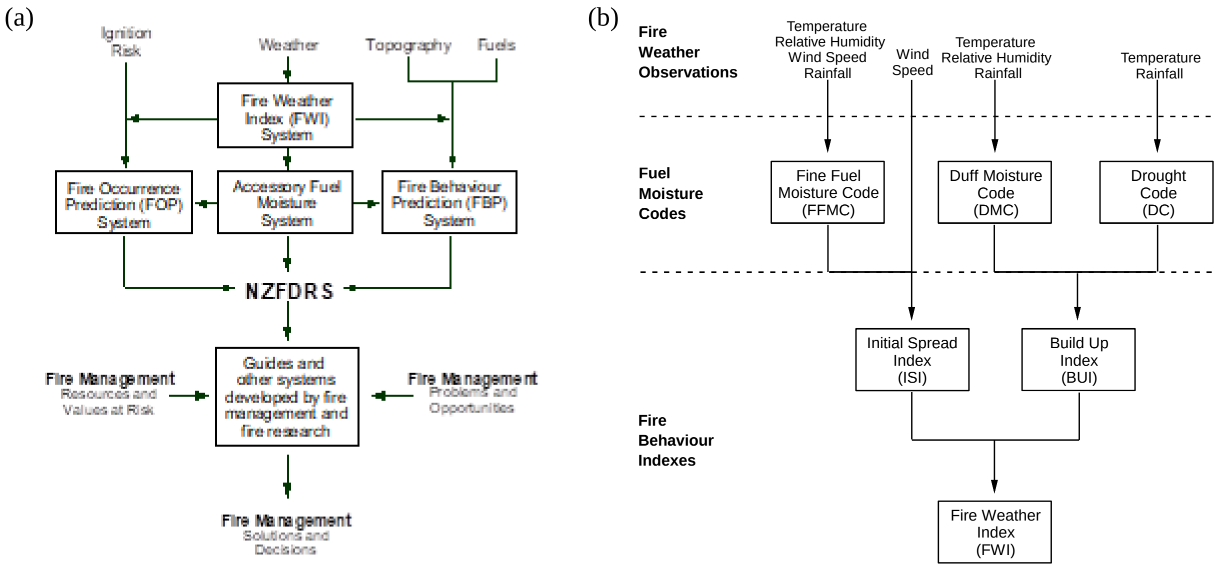

Figure 1. Simplified structure diagrams for **(a)** the New Zealand Fire Danger Rating System (NZFDRS), illustrating the linkage to fire management actions (after Fogarty *et al*. 1998); and **(b)** the Fire Weather Index (FWI) System (after Anon. 1993).

The Fire Weather Index (FWI) subsystem of the CFFDRS was adopted by the former New Zealand Forest Service in 1980. Based solely on weather observations, the FWI System (Fig. 1b) provides numerical ratings of relative ignition potential and fire behaviour which can be used as guides in a wide variety of fire management activities including (after Alexander 1992a):

- prevention planning (e.g., informing the public of pending fire danger, regulating access and risk associated with public and industrial use of forest and rural areas);
- preparedness planning (e.g., level of readiness and prepositioning of suppression resources);
- detection planning (e.g., lookout manning and aerial patrol routing);
- initial attack dispatching;
- suppression tactics and strategies on active wildfires; and
- prescribed fire planning and execution.

Daily observations made at noon local standard time of temperature, relative humidity, wind speed, and 24-hour accumulated rainfall recorded by a network of remote automatic weather stations located around the country are used to compute values of the three fuel moisture codes and three fire behaviour indexes. These may be determined from tables (e.g., Anon. 1993) or by computer calculation (Van Wagner and Pickett 1985).

While production of climatologies for the standard weather elements are commonplace (e.g., NZMS 1983), analyses of fire danger are much less routine (Nikleva 1973, Tapper *et al*. 1993). Despite a clear need being expressed for such analyses (Valentine 1978, p. 35, Alexander

1992b), few New Zealand examples of fire climate studies exist. In trialling the FWI System prior to its introduction, Valentine (1978) compared fire season climatologies for British Columbia and New Zealand, and Cooper and Ashley-Jones (1987) used fire danger class frequencies to investigate the economics of fire prevention activities. Pearce (1996) produced a fire climatology for 20 weather stations (Fig. 2) and, based on the example of Simard and Valenzuela (1972) from Canada, presented long-term average and extreme values for both weather inputs and fire danger components in a summary table for each station. This database was extended in 1998 to investigate the potential impact of the 1997/98 El Nino event on regional fire dangers (Anon. 1998, Pearce 1998), and in 2001 to further illustrate the use of severity ratings to compare and predict fire season conditions (Majorhazi and Pearce 2001).

The high value of fire climatological information for fire management is evidenced by the vast number of studies and wide variety of applications illustrated in the literature. A significant number of these studies have attempted to use fire climatologies to describe fire activity (Cheney 1976, Haines *et al*. 1980, Harrington *et al*. 1983). However, fire danger climatologies have also been used to illustrate seasonal trends in fire danger (McAlpine 1990), to determine length of fire season (Wotton and Flannigan 1993), and to delineate fire climate zones (Simard 1973, Stocks 1978). They have also been used to define impacts of El Nino-Southern Oscillation events (Williams 1998) and climate change (Wotton *et al*. 1998). Perhaps more importantly, fire climatologies have also been used to develop systems to assist with the full range of fire management activities, including prevention (OMNR 1989, Borger 1997), preparedness (Gray and Janz 1985, Fogarty and Smart 1994), fire suppression (Andrews *et al*. 1998, Fogarty and Slijepcevic 1998), and prescribed fire planning (Martell 1978, Furman 1979, Andrews and Bradshaw 1990).

To this end, a major effort was undertaken by Forest Research to develop a more comprehensive fire climatological database for New Zealand as part of the preceding NZFSC-funded project “Fire danger climatology analyses and tools”. This project resulted in the production of data sets of weather and fire danger components for 127 of the weather stations contained within the NRFA’s fire weather network (see Fig. 2). As well as the 20 stations included in the original Pearce (1996) study, the analysis included all stations that had greater than 5 years of record available. The principal output from the analysis was a summary table for each of the 127 stations containing the long-term average and extreme values of each of the weather and FWI System components and fire danger classes summarised by month, fire season and year (Pearce *et al*. 2003). Summary statistics for each station were also used to identify the individual weather stations and geographic regions with the most severe fire climates. Stations in Marlborough and Canterbury demonstrated the highest values of the three fire climate severity measures contrasted.

The compilation of a comprehensive database of daily fire weather and fire danger information for 127 of the 179 weather stations for which data were available was the other major output from the analysis. In its own right, it also provides an extremely useful tool for the NRFA and fire managers in making more informed fire management decisions on prevention, preparedness, and prescribed burning activities. However, this database is also an essential component of associated research being conducted by both NIWA and Forest Research on prediction of fire season severity, with the results from the latter being described here. Based on the results of a pilot study (Salinger *et al*. 1999), the closely aligned NZFSC-funded research undertaken by NIWA both as part of the current “Prediction of fire season severity” and previous “Climate and severe fire seasons” projects aims to identify large scale global and regional climate factors influencing fire season severity as a basis for improving fire danger forecasts (Heydenrych *et al*. 2001, Heydenrych and Salinger 2002, Gosai *et al*. 2003, Gosai *et al*. 2004, Gosai and Salinger 2004, Renwick and Salinger 2004).

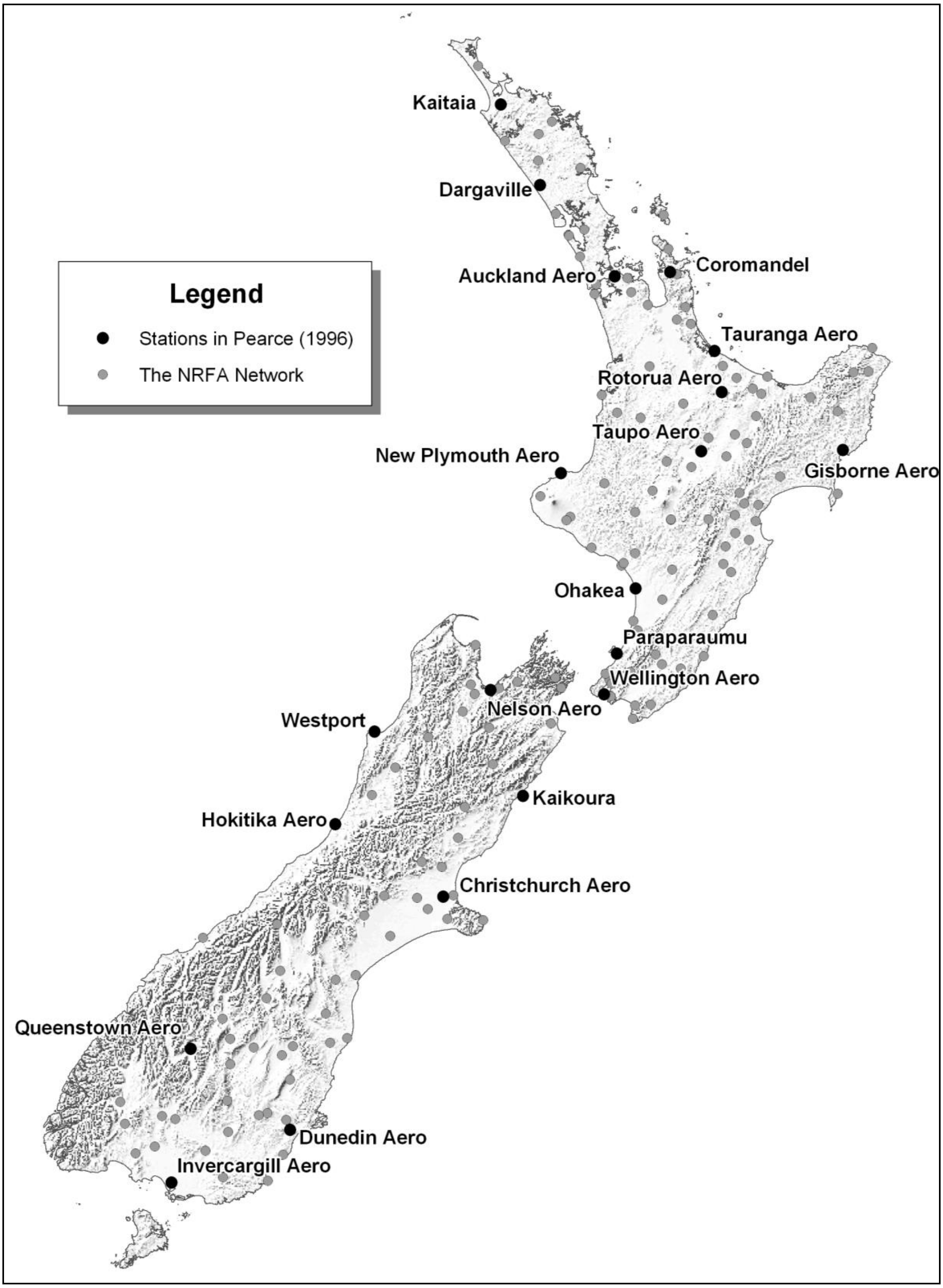

Figure 2. Weather stations (•) included in the fire danger climatology analysis of Pearce (1996), and current station coverage (•) included on the National Rural Fire Authority's (NRFA) fire weather monitoring network.

Fire Season Severity

Comparing the severity of a particular fire season[2] with previous years is notoriously difficult, and is often dependent on fire incident statistics, such as the number of fires, area burned or suppression costs (Majorhazi and Pearce 2001). However, when considered alone, fire statistics do not always indicate the severity of burning conditions as they do not capture the periods of elevated fire danger when fires do not occur. It is commonly recognised that the best means of accurately comparing the burning conditions from one year to another is to use an accumulative daily fire danger index computed from observations collected at a representative fire weather station network (Harvey *et al*. 1986).

Fire danger rating systems, such as the NZFDRS and CFFDRS from which it is derived, typically include criteria for defining a fire danger class or classes based on the underlying fire danger index(es). It has become accepted practice to compare fire season severity by summing the number of days within various classes, and comparing these with previous years (e.g., Cooper and Ashley-Jones 1987, Pearce 1996, Pearce *et al*. 2003) (see Fig. 4a). However, a limitation of this method is that two years can have the same number of days in a particular fire danger class, when one year may have far more severe conditions than the other. It is also necessary to have a direct measure of how much more severe the Extreme class is from Very High, or Moderate from Low. Then each day can be weighted according to the severity factor of the fire danger class into which it falls, and these individual daily values totalled to provide a severity figure for the fire season or any other period of interest (Alexander and Stocks 1987).

Fire danger index scales bear no numerical relationship to severity, and therefore the indices themselves should not be summed or averaged to indicate seasonal severity (Van Wagner and Pickett 1985). As an example (after Alexander and Stocks 1987), in two fire seasons of equal length, if one had all Moderate days and the other had half in Low and half in Extreme, the total and average fire danger would be the same in each case, but the second would be expected to be the more severe fire season. In spite of this, some studies (e.g., Simard 1973) have used fire danger index frequency distributions to describe fire climate severity on the basis that use of a large sample size (such as fire danger index data for a period in excess of 10 years) removes the potential for distributional variability (i.e., bimodality). Harvey *et al*. (1986) used the percentage of days with fire danger ratings above a specified critical value (i.e. FWI ≥19) to contrast fire season severity for two consecutive years (1980 and 1981) in Alberta, but acknowledged that while this did provide an indication of the amount of time a heightened state of preparedness needed to be maintained, it did not differentiate between values just above the threshold and those significantly higher (e.g., FWI 20 vs. 90).

New Zealand fire managers have long recognised that fire danger indices can be used to track trends in fire season severity, and have used seasonal graphs of various components of the FWI System, such as Drought Code (DC) and Buildup Index (BUI) (see Fig. 3), to present a visual measure of fire season conditions (Alexander 1994, p. 29-31). More recently, maps depicting the spatial variability of the individual FWI system components (such as the DC[3]) have been used to contrast seasonal severity, including long-term average fire climate (Leathwick and Briggs 2001, Majorhazi 2003)[4].

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[2] In New Zealand, the "fire season" historically refers to the seven-month period from October 1 to April 30. However, the term is not entirely appropriate as fires can potentially occur all year round due to New Zealand's temperate climate with relatively mild winters. In the future, it is proposed to identify more appropriate fire season start and end dates for individual weather station locations using the results of the fire danger climatology analysis (Pearce *et al*. 2003).

[3] See: http://nrfa.fire.org.nz/fire_weather/DC_2002-03_WEB.MPG

[4] Also see: http://nrfa.fire.org.nz/fire_weather/Index.htm#SURFACES

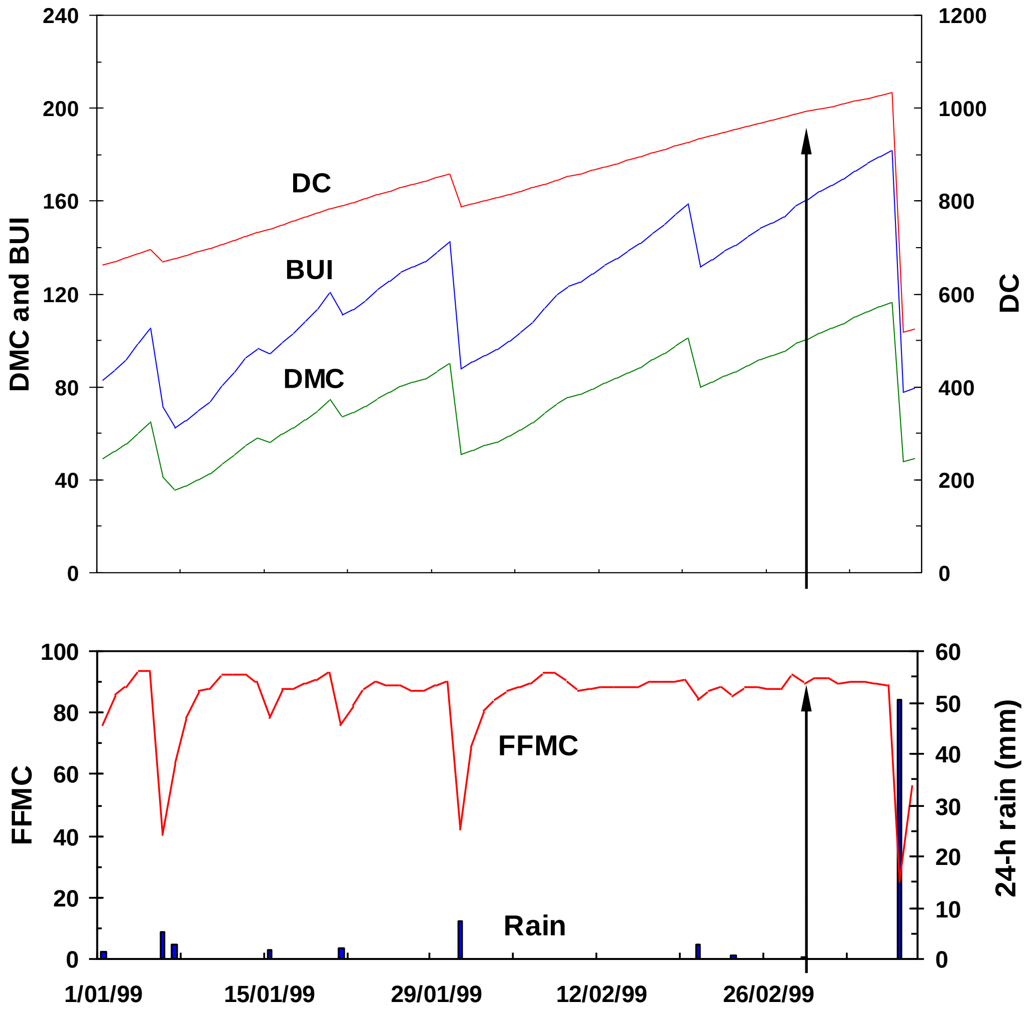

Figure 3. Use of FWI System components to track trends in fire danger during the fire season. The example illustrated shows fire danger conditions (including rainfall) in the lead-up to the Springvale Fire near Alexandra, on 28 February 1999 (indicated by the arrows), based on wind data from Lauder and other weather inputs from Clyde. Note the Drought Code (DC) component which peaked at a value over 1000, and at the time represented the highest DC value recorded in New Zealand. [This value was subsequently bettered in 2000/01, when the DC reached 1182 at Awatere Valley in Marlborough].

A method of rating fire season severity based on the fire danger index was devised by Williams (1959), and this was subsequently converted for use with the Fire Weather Index (FWI) by Van Wagner (1970). The Daily Severity Rating (DSR) is a numerical measure which rates the daily fire severity at a particular station based on the FWI value[5]:

$$DSR = 0.0272 \times (FWI)^{1.77}$$

Severity ratings can be calculated for any desired period by simply summing the individual DSRs and then dividing by the number of days in the chosen time period, e.g., Weekly (WSR), Monthly (MSR) or Seasonal Severity Ratings (SSR) (Harvey *et al.* 1986, Alexander and Stocks 1987). In addition, a Cumulative Daily Severity Rating (CDSR) value can be determined by summing the individual DSR values over a period such as a year or fire season (Harvey *et al.* 1986).

[5] Not to be confused with Days Since (significant) Rain, the Daily Severity Rating (DSR) is determined directly from FWI and therefore relates to fire intensity. It is designed so that the impact of the FWI is reduced at low values but rises sharply as FWI increases, thus better reflecting control difficulty and the amount of work required to suppress a fire as fire intensity increases (Van Wagner 1987).

The intention of FWI severity rating analyses is to allow an objective comparison to be made, strictly in terms of the influence of fire weather on potential fire behaviour, of one fire season against another or one station or area against another (Harvey *et al*. 1986). For example, Stocks (1971) determined the normal MSR pattern as it varies from month to month in Ontario, while Street and Stocks (1983) used the TSR to compare the 1980 fire season in northwestern Ontario with the average seasonal severity for similar periods over the previous decade. Stocks *et al*. (1981) further analysed the 1980 fire season in west-central Canada using the MSR and SSR components.

In New Zealand, the year-to-date SSR was compared with 30-year average and maximum SSR to indicate the severity of 2000/01 fire season (Anon. 2001), while comparisons of fire season MSR (and CDSR) with long-term averages were also used to illustrate the severity of fire seasons associated with the May 2002 Atawhai (Anderson 2002; see Pearce 2002) and February 2003 Miners Road (Anderson 2003) wildfires. Maps of MSR and SSR have also been used to illustrate the progressive build-up in seasonal severity, as well as providing comparisons with previous years (Majorhazi 2003)[6]. However, it is the CDSR that perhaps offers the simplest illustration of the progressive build-up in seasonal severity and comparison between the severity of individual fire seasons (e.g., Pearce 1998, Majorhazi and Pearce 2001). It can also be averaged over a number of years to provide another objective measure by which the severity of fire dangers at individual stations can be compared (Pearce 1996, Pearce *et al*. 2003).

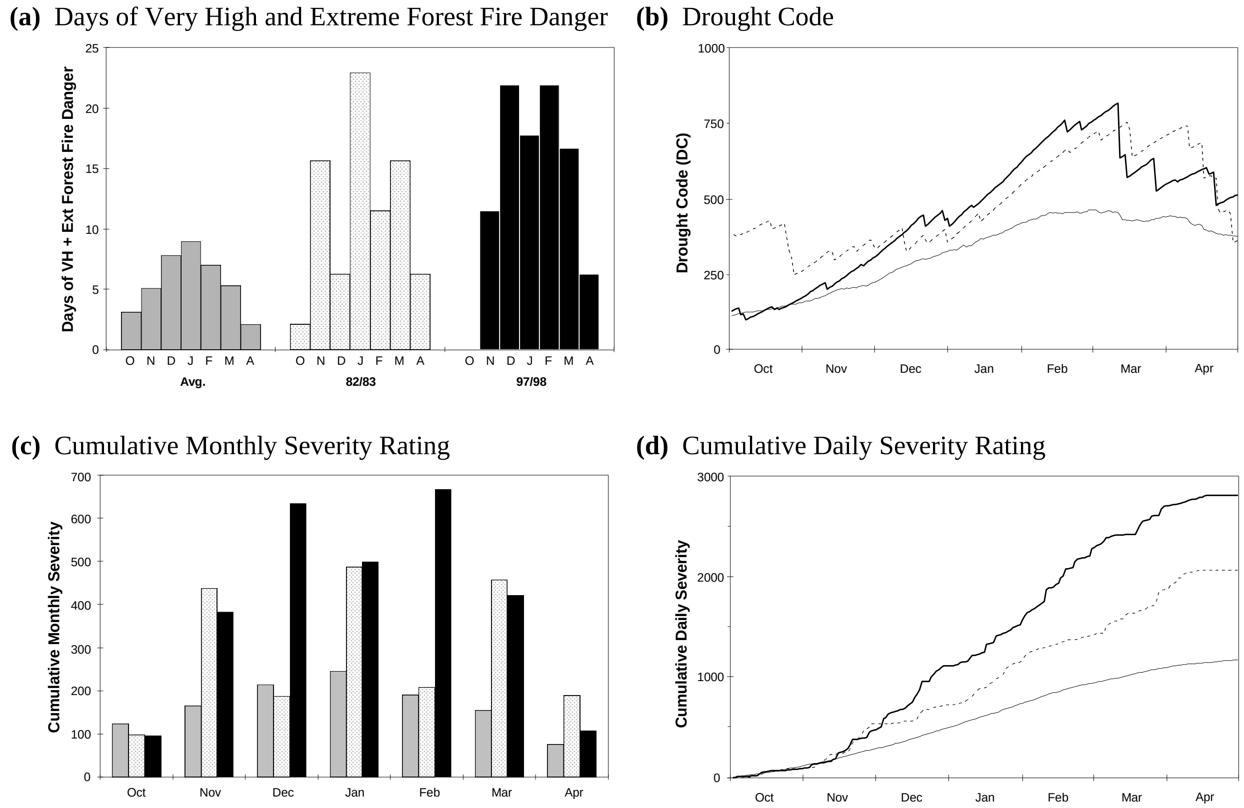

Figure 4. Comparison of fire season severity at Christchurch Aero for the 1982/83 and 1997/98 El Nino fire seasons, using: **(a)** number of days each month of Very High and Extreme Forest fire danger, **(b)** Drought Code (DC), **(c)** cumulative Monthly Severity Rating, and **(d)** Cumulative Daily Severity Rating. In (a) and (c), the long-term average is depicted by the medium grey bars, 1982/83 with the light grey bars, and the 1997/98 fire season by the solid black bars. In (b) and (d), the 1997/98 fire season is depicted by the heavy solid line (—), 1982/83 with the hashed line (----), and the long-term average by the thinner solid line (—). (Source: Pearce 1998).

[6] Also see: http://nrfa.fire.org.nz/fire_weather/monthly_severity/severity/index.

It has been suggested (Alexander and Stocks 1987) that the approach to fire season severity rating using the DSR component from the FWI System represents the best integrated measure and objective yardstick for comparing burning conditions within a fire season, or from season to season or place to place. However, even this approach fails to depict all the facets of fire danger contributing to seasonal severity. As a direct product of the FWI, which in itself integrates the combined influence of the weather on fuel moisture and potential fire behaviour, the DSR (or its subsequent averages or totals) on its own cannot distinguish between the factors contributing to daily or fire season severity, namely fuel dryness and windiness. That is to say, a high severity rating value can be the result of either drier or windier conditions than normal, or a combination of both of these factors. The contribution of seasonal dryness and increased fuel availability to higher FWI and DSR values, and therefore greater potential fire intensity (i.e., more severe fire weather), is reflected in the BUI and its contributory DMC and DC components (as well as precipitation), whereas the effect of wind is reflected in the ISI or the wind speed values themselves (Majorhazi and Pearce 2001). Thus, when analysing severity ratings, it is necessary to also consider the relative contribution of each of these factors to fully appreciate the cause of elevated values, or seasonal or location differences.

It should also be remembered that FWI-based severity ratings cannot, by their very nature, be expected to provide a complete indication of the total effort or work required to contain all fires in an area within a given time (Harvey *et al*. 1986). They are based solely on past and current weather and, while an indicator of potential fire behaviour, do not consider the effect of ignition pattern and available resources required in a more complete measure of fire activity (Van Wagner 1987). Designed to represent a numerical measure of the effort required to suppress a single forest fire, the DSR does not accurately reflect the *fire load*, which refers to "the number and magnitude of all fires requiring suppression action …" (Turner 1973). Fire load is usually a function of incidence, size and intensity. Hence, severity ratings can only be considered as qualitative indicators of fire activity based on statistics such as area burned, number of fires and suppression expenditures, since politicians and the general public will often measure the severity of a particular fire season in terms unlikely to relate directly to fire weather severity alone (e.g., pattern of fire occurrence, volume of merchantable timber lost, other damages, community evacuations) (Harvey *et al*. 1986). Severity ratings do, however, still provide a very useful tool for research and administration for objectively analysing the influence of weather conditions on potential fire behaviour.

The emphasis of previous analyses (Pearce 1996, Pearce *et al*. 2003) was on compiling climatologies for fire weather and fire danger from data collected from the NRFA's network of fire weather stations, and use of these to describe and contrast fire danger in various parts of the country. While these analyses indicate seasonal trends in fire danger values based on long-term averages, no attempt was made to define methods for prediction of fire season severity, although both studies indicated the potential to do this from the resulting data sets. In particular, the Pearce (1996) study suggested the use of frequency and/or probability distributions in predicting trends in fire season severity, while Pearce *et al*. (2003) referred to use of statistical similarity tests to identify the historic season or seasons most similar to current conditions that might be used as an indicator of the likely future conditions.

Methodology

The broad aim of the current research was to maximise the utility of the updated and extended fire climatology database (Pearce *et al*. 2003) by developing a number of analytical tools, including methods for comparing and predicting fire season severity. More specifically, the objective of this particular study was to develop a methodology for comparison and prediction of fire season severity by using long-term fire danger data sets to identify the historical season most similar to current conditions and therefore indicative of what is likely to come.

<u>Selection of fire danger variables for analysis</u>

It was proposed that this be achieved by conducting statistical analyses on measures of fire season severity, such as the Cumulative Daily Severity Rating (CDSR), as well as other fire danger rating system components, such as the Drought Code (DC) and Buildup Index (BUI).

In particular, the CDSR was considered to be the most useful variable for analysis because it provides the most direct measure of fire season severity compared with other FWI System codes or indices (Van Wagner 1970, Harvey *et al*. 1986, Alexander and Stocks 1987). It had also been used in the previous fire climatology analyses (Pearce 1996, Pearce *et al*. 2003). In addition, when plotted graphically, the CDSR displays a sigmoidal (‘S’ shaped) curve that builds slowly at first, then rises more rapidly through the middle of the fire season before flattening out again (see Fig. 4d). While there will be significant variations in the shape and maximum values reached by the curve in different seasons for the same station, or in the same season for different parts of the country, due to areas experiencing a peak in fire danger activity at different times of the year, this characteristic sigmoidal shape of the CDSR distribution makes it possible to fit parametric functions that describe the shape of the curve for individual years or locations.

Use of the Drought Code (DC) and Buildup index (BUI) was also proposed as they provide indicators of seasonal drought (Anon. 1993) and, as such, might be able to be used (potentially in conjunction with the CDSR) to distinguish between severe fire seasons resulting from seasonal dryness versus windiness. The DC is also not influenced to the same extent by day-to-day variability as are the other components of the FWI System (e.g., FFMC, ISI and FWI). The DC has previously been used to review seasonal trends (Nikleva 1973, McAlpine 1990) and to highlight potential problem fire seasons (Muraro and Lawson 1970). In a study of the seasonal trends of all the codes and indices within the FWI System, Nikleva (1973) found the DC was the only index to show a consistent seasonal trend, with a generally steady rise in values throughout the fire season interspersed by drops and rebuilding phases associated with infrequent rain events (see Fig. 3). McAlpine (1990) provided graphs of average daily values throughout the fire season for stations across Canada, together with the trend for the most severe fire season on record at each station (i.e., the fire season reaching the highest recorded value). Lines indicating the average season plus or minus one standard deviation were also used to illustrate the normal variability in DC values between seasons, so that unusually dry (or wet) years showed up clearly as being above (or below) this line. Generally, weather stations in New Zealand receive enough rainfall during winter to start the DC at or close to zero at the beginning of each fire season, and certainly below its standard spring start-up value (of 15) (Alexander 1982, Anon. 1993). However, in dry years following winter drought, the DC values at the start of the fire season can commence at already elevated values contributing to a more severe fire season.

Station selection

Data from seven stations representing the range of fire season severities identified by Pearce *et al*. (2003) were analysed to determine whether it was possible to predict fire season severity (Table 1). All were airport stations included in both the Pearce (1996) and subsequent Pearce *et al*. (2003) studies, for which data sets could be readily updated (to March 2004) using data from NIWA's National Climate Database. As a result, all 7 stations selected had long-term data sets comprising greater than 30 (and often 35-40) seasons of record available for analysis.

Table 1. Characteristics of the seven weather stations selected for analysis of fire season severity.

Station	Name	Length of Record (years)	Annual Rainfall (mm)	Average CDSR	Average VH+E FFDC (days/year)	Fire Climate Severity Rank[1]
CHA	Christchurch	41	629	1300	39	3
GSA	Gisborne	39	1012	1029	32.5	8
NSA	Nelson	39	1022	520	10.1	29
DNA	Dunedin	38	700	485	7.3	42
PPA	Paraparaumu	39	1024	307	3.6	52
WSA	Westport	31	2224	58	0	121
HKA	Hokitika	37	2852	43	0	123

[1] Fire climate severity ranks were calculated by Pearce *et al*. (2003) based on CDSR, FFDC and Scrubland Fire Danger Class (SFDC). Rankings range from 1 to 127, with 1 being the most severe.

Stations were selected on the basis of covering a range of fire climate severities as described using the average CDSR and average number of days per year of Very High and Extreme Forest fire danger (VH+E FFDC). Two stations (Christchurch and Gisborne) were in the upper range of severities (ranked in the top 10, with CDSRs higher than 1000, and greater than 30 days/year of VH+E FFDC), two (Westport and Hokitika) in the lower severity range (ranked in the bottom 10, with CDSRs less than 100, and less than 1 day/year of VH+E FFDC), and the remaining three had mid-range severities (ranked 29-52, CDSRs of 300-520, and 3-10 days/year of VH+E FFDC). Similarly, the 7 stations covered a full range of mean annual rainfall values, with two stations with an annual total less than 700 mm, two with greater than 2000 mm, and three intermediate stations with rainfall of around 1000 mm (see Table 1).

As it was desirable to have the data sets for analysis as up-to-date as possible, the long-term data sets for each of these seven stations listed in Table 1 was updated to include weather and fire danger ratings to 25 March, 2004. In almost all cases, this was achieved simply by adding 1200 noon NZST weather inputs from the appropriate stations from the National Climate Database, and calculating FWI System and fire danger class outputs using the Excel™ spreadsheet developed by Forest Research's Fire Research Programme for this purpose. However, in a few cases, periods of missing 1200 noon data were required to be substituted using the procedures outlined in Pearce *et al*. (2003), in particular using 1100 and 1300 hour data where this was available or, alternatively, 1200 noon data from the closest substitute station.

Analytical approaches

At the outset of the study, it was proposed to investigate the development of a method for comparing and predicting fire season severity using two contrasting approaches:

1. Analyses of statistical similarity between CDSR, DC and BUI curves for individual seasons, as the basis for identifying the historical season that is most similar to current conditions that can be used as an indicator of what is to come; and

2. Parametric curve fitting involving fitting of appropriate functions for characterising the general shape of the CDSR and DC curves, and use of derived function descriptors to predict intermediate as well as the end-point of the curve for the current season.

The first of these approaches has been used informally for some time (Pearce 1998, Majorhazi and Pearce 2001), with fire seasons being compared visually using graphical routines contained within commercial software packages (e.g., Remsoft's WeatherPro) or the NRFA's online fire weather monitoring system, FWSYS. However, this method is indicative only, as it does not provide any quantitative measure of the similarity of fire seasons. Opportunities to improve on this exist via use of measures of statistical similarity such as least squares regression methods. However, this approach does not provide any true forecasting capability, with estimates of future fire season severity being restricted to the trends indicated by the previous seasons identified as being the most similar to current conditions. Because of its existing usage, however, and the ability to compare indicated future fire season severity with known conditions from previous seasons (as opposed to a predicted peak severity rating without any direct comparison), it was felt that this first approach warranted further investigation.

Following a review of the most appropriate statistical forecasting techniques for application to seasonal fire weather and fire danger data, the second of the two approaches was believed to hold the most promise. A number of potential techniques were identified, including time series analysis, order statistics and parametric curve fitting. The latter appeared to hold the most promise, and appropriate functions for characterising the shape of the CDSR curve included many of the standard non-linear growth curves such as the Gompertz function and Chapman-Richards equation (Draper and Smith 1998). As well as offering a truly quantitative means of describing individual fire season trends, the curve fitting approach also had the potential to predict future conditions based on the general fitted relationship and early fire season data.

A more detailed methodology for each of these two approaches is outlined below.

Fire season start date

Analyses using both approaches first require an estimate of the true fire season start date, so the first step was to determine the most logical starting point for the fire season. Currently, the official starting date for the fire season is 1 October. However, a more logical date would coincide with the minimum values of the DC, BUI and DSR. To calculate the seasonal trend in these indices, values for each of the years were normalised so that they ranged between 0 and 1. This was achieved by subtracting the minimum value from each measurement and then dividing by the range in values; e.g., relative DC was calculated as follows:

$$\mathrm{rel(DC)}_{ij} = \frac{\mathrm{DC}_{ij} - \min(\mathrm{DC})_j}{\max(\mathrm{DC})_j - \min(\mathrm{DC})_j} \qquad [1]$$

where *i* is Julian[7] day in the year *j*. Relative BUI and DSR were calculated in the same manner. Only results from the analysis of data from the Dunedin Aero (DNA) station are presented here; results from the other stations are presented in Appendix 1.

[7] The Julian day is the number of days corresponding to the date determined from 1 January. For example: January 1st is Julian day 1; February 1st is Julian day 32; July 1st is Julian day 182 (or 183 in a leap year).

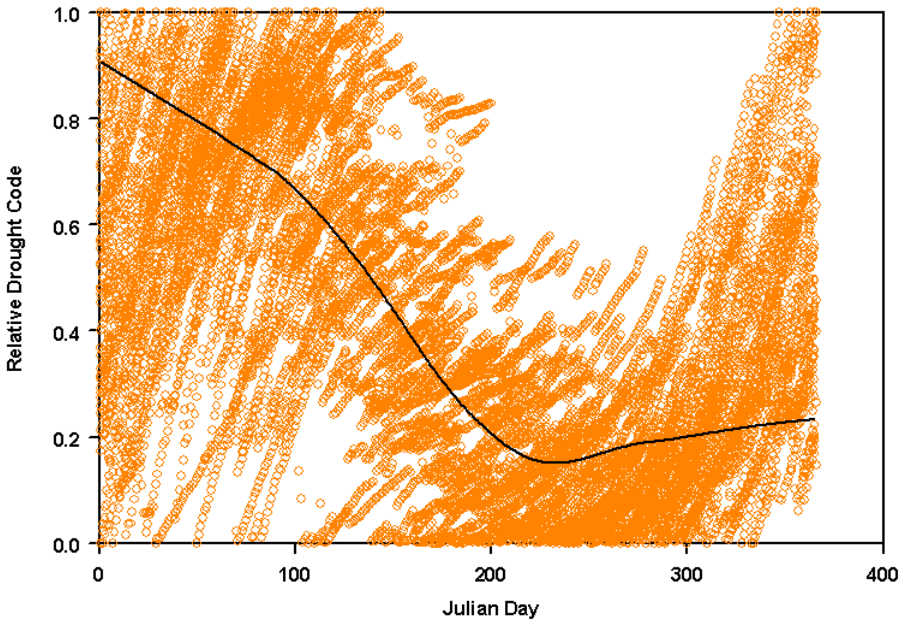

Figure 5. Seasonal trends in relative Drought Code (DC) at the Dunedin Aero weather station. The solid line corresponds to a robust local smoothing (`lowess`) function fitted to the data.

The relative DC decreased with time since January 1st, reached a minimum at Julian day 244 (approximately September 1st), and then increased slowly after this date (Fig. 5). Despite considerable variation between years, this broad trend can be seen by the robust local smoothing (`lowess`) function (Cleveland 1979) fitted to the data. Similar results were found for seasonal trends in BUI and DSR (Figs. 6 & 7). In the case of these latter two indices, the minimum value was reached at Julian day 196 and 187, respectively. This corresponds approximately to July 1st. In the analysis of seasonal and between season trends in CDSR (and DSR), DC and BUI to follow, it was therefore assumed that the fire season began on 1 July (i.e., Julian day 181).

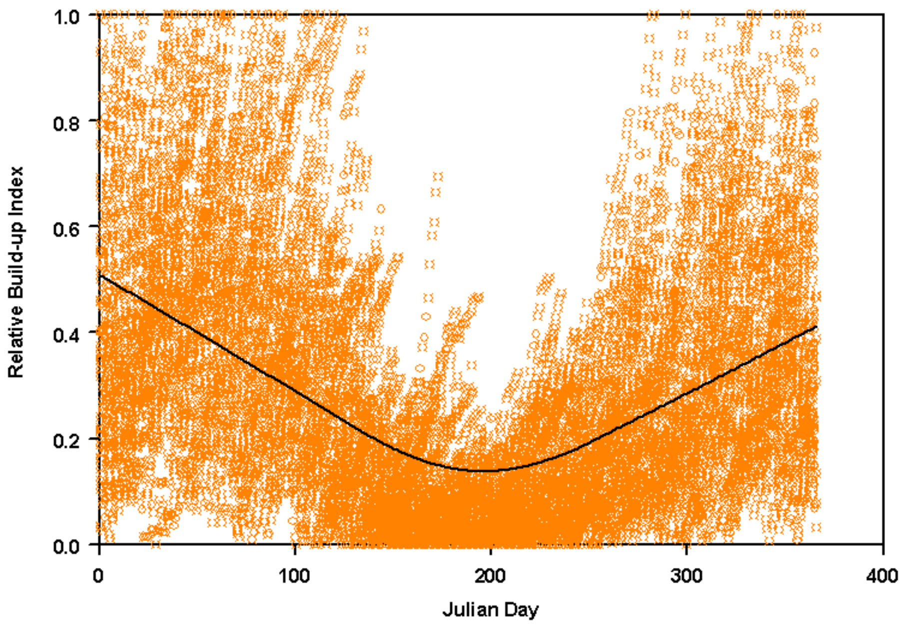

Figure 6. Seasonal trends in relative Build-up Index (BUI) at the Dunedin Aero weather station. The solid line corresponds to a robust local smoothing (`lowess`) function fitted to the data.

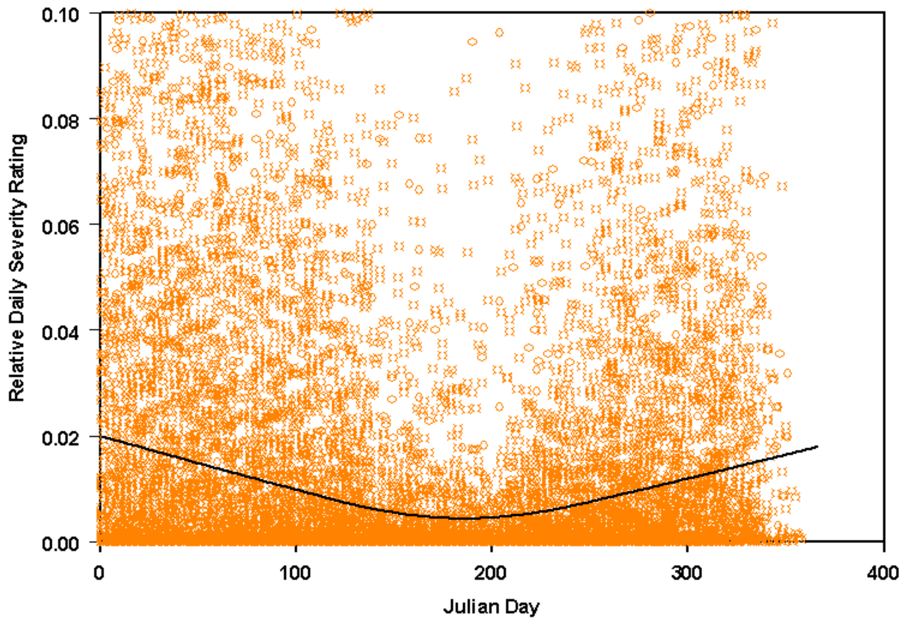

Figure 7. Seasonal trends in relative Daily Severity Rating (DSR) at the Dunedin Aero weather station. The solid line corresponds to a robust local smoothing (`lowess`) function fitted to the data.

1. Analyses of statistical similarity

A number of measures were available for comparing the statistical similarity of data sets (e.g., correlation, sums of squares). In this study, ordinary least squares regression analysis was used to compare fire seasons in terms of their similarity. Linear regression analyses were performed for each of the seven stations listed in Table 1. For each station, values of CDSR, BUI and DC for each fire seasons were regressed against corresponding values for all other fire seasons. In each case the following linear model form was used:

$$Y_{kj} = b_0 + b_1 Y_{ki} \qquad [2]$$

where: Y_{kj} = value of CDSR, BUI or DC on day k in year j;

Y_{ki} = value of CDSR, BUI or DC on day k in year i ($i \neq j$);

b_0 and b_1 are model parameters.

The similarity of these indices between fire seasons was compared through the values of b_1 and the coefficient of determination (r^2) for each of the regressions. A value of b_1 close to 1.0 indicates that the linear relationship between the two fire seasons is approximately 1:1, while the r^2 value is an indicator of the goodness of fit. The higher the r^2 value, the more variation in the value of the chosen index in fire season j is explained by the variation in the value of the corresponding index in fire season i. Both these measures of similarity are required. If fire seasons were only compared on the basis of r^2, then two seasons could be found to be similar when in fact the CDSR in one season was double the CDSR in the other season. In this case a high r^2 value could occur because the trend in CDSR during the fire season was similar in both years (e.g., CDSR at any point in one season was always approximately half the CDSR value at the same point in the other season).

The output from the regression analyses (Appendix 2) was exported to an Excel™ spreadsheet and a macro written to select pairs of fire seasons with similar seasonal trends and values of CDSR, BUI and DC. Selection was based on the users' criteria for r^2 and the upper and lower bounds of b_1. The analysis was repeated using data from the first 120 days of the fire season to determine whether pairs of seasons that were found to be most similar based on data from the whole season, were also found to be most similar after the first 120 days of the fire season. If this was found to be the case then it would offer fire managers some forecasting capabilities.

2. Parametric curve fitting

The trend in CDSR with days since July 1st follows a sigmoidal growth trajectory that can be represented using the Chapman-Richards equation (Draper and Smith 1998) which has the following form:

$$\mathrm{CDSR} = a\left(1 - e^{-b \times \mathrm{time}}\right)^{c} \qquad [3]$$

where *time* is the number of days since July 1st and *a*, *b* and *c* are model parameters. This particular equation was chosen as it is widely used to model monotonic growth and its properties are well understood. Individual Chapman-Richards models were fitted to each of the fire seasons for which data from each individual weather station were available. An example for Dunedin Aero from 1968/69 is shown in Figure 8. In all years at each station the model appeared to provide a reasonable fit to the data.

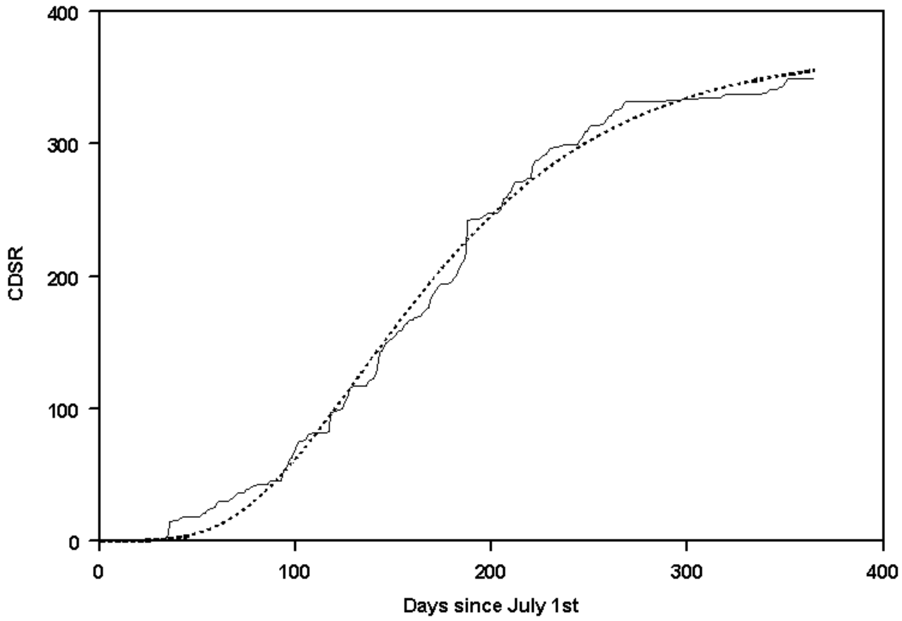

Figure 8. Growth in Cumulative Daily Severity Rating (CDSR) with time since July 1st for 1968/69 at Dunedin Aero. The raw data are represented by the solid line while the fitted Chapman-Richards equation is represented by the dashed line.

The next step was to replace these individual Chapman-Richards models with a non-linear mixed effects model (NLME; Pinhero and Bates 2000) in which *time* was treated as a fixed effect and fire season was treated as a random effect (Fig. 9). In other words, the manner in which CDSR increases with time since July 1st was assumed to be constant (i.e., fixed) between fire seasons, but the maximum value that it reaches at the end of the fire season was assumed to vary between fire seasons (i.e., it was random). The was achieved by including the *a* parameter (i.e., the asymptote or endpoint) as both a random and a fixed effect within the NLME model.

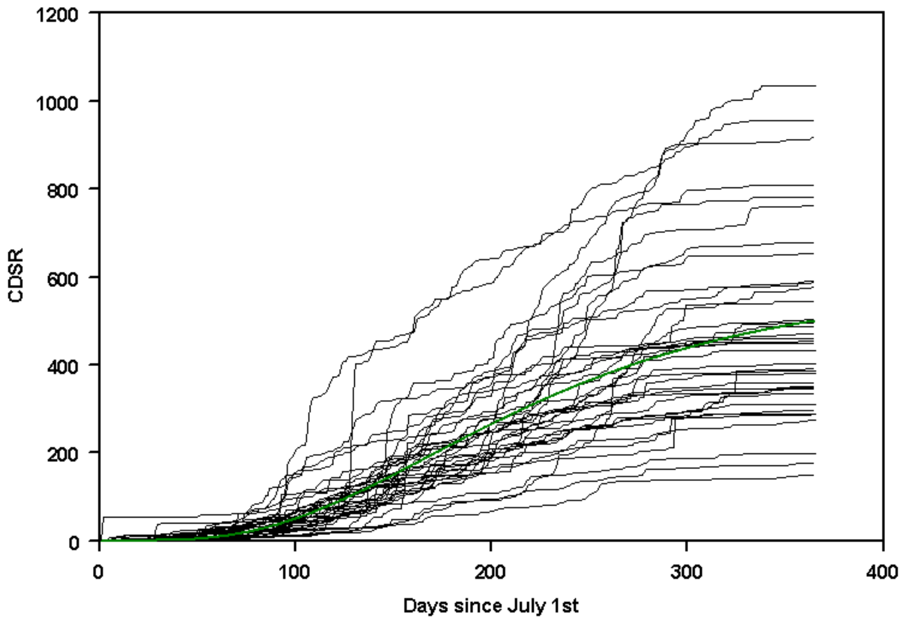

Figure 9. Growth in Cumulative Daily Severity Rating (CDSR) with days since July 1st using data from all fire seasons recorded at Dunedin Aero. The solid green line corresponds to a fixed effect of time since July 1st obtained from the non-linear mixed effects model fitted to the data.

The seasonal trends in DC were not as clear as those for CDSR and did not conform to any of the standard parametric model forms (with the exception of higher order polynomials). Therefore, it was decided not to attempt to model the seasonal trends in DC using a parametric model.

Results and Discussion

Analyses of statistical similarity

Strong linear relationships were found between CDSR values for most pairs of fire seasons at each station. For the Dunedin Aero station, 60 pairs of seasons with similar trends in CDSR were identified using the criteria that $r^2 \geq 0.95$ and $0.95 \leq b_1 \leq 1.05$ (see Appendix 2). All but seven of the 40 individual fire seasons had at least one other fire season where the relationship between CDSR values met these criteria. Four examples of these are plotted in Figure 10. The relationships between seasons for DC and BUI values were not as strong. At Dunedin Aero, no pairs of seasons were found where the relationships between BUI or DC values met the criteria that $r^2 \geq 0.95$ and $0.95 \leq b_1 \leq 1.05$. Only nine pairs of fire seasons with similar trends in BUI were identified using the criteria that $r^2 \geq 0.50$ and $0.80 \leq b_1 \leq 1.20$, while 51 pairs of seasons with similar trends in DC were identified using the criteria that $r^2 \geq 0.60$ and $0.90 \leq b_1 \leq 1.10$. Examples of each of these are plotted in Figures 11 and 12. None of these pairs of seasons corresponded to those which had similar trends in CDSR.

Slightly more relaxed criteria ($r^2 \geq 0.90$ and $0.90 \leq b_1 \leq 1.10$) were used to identify pairs of stations with similar trends in CDSR up to 120 days into the fire season. This was done so that for a particular fire season there would be several other fire seasons with similar trends to date, but with a range of future trends. Of the 93 fire season pairs identified under this criteria for Dunedin Aero, only 6 corresponded to those identified as having similar trends in CDSR for the entire fire season.

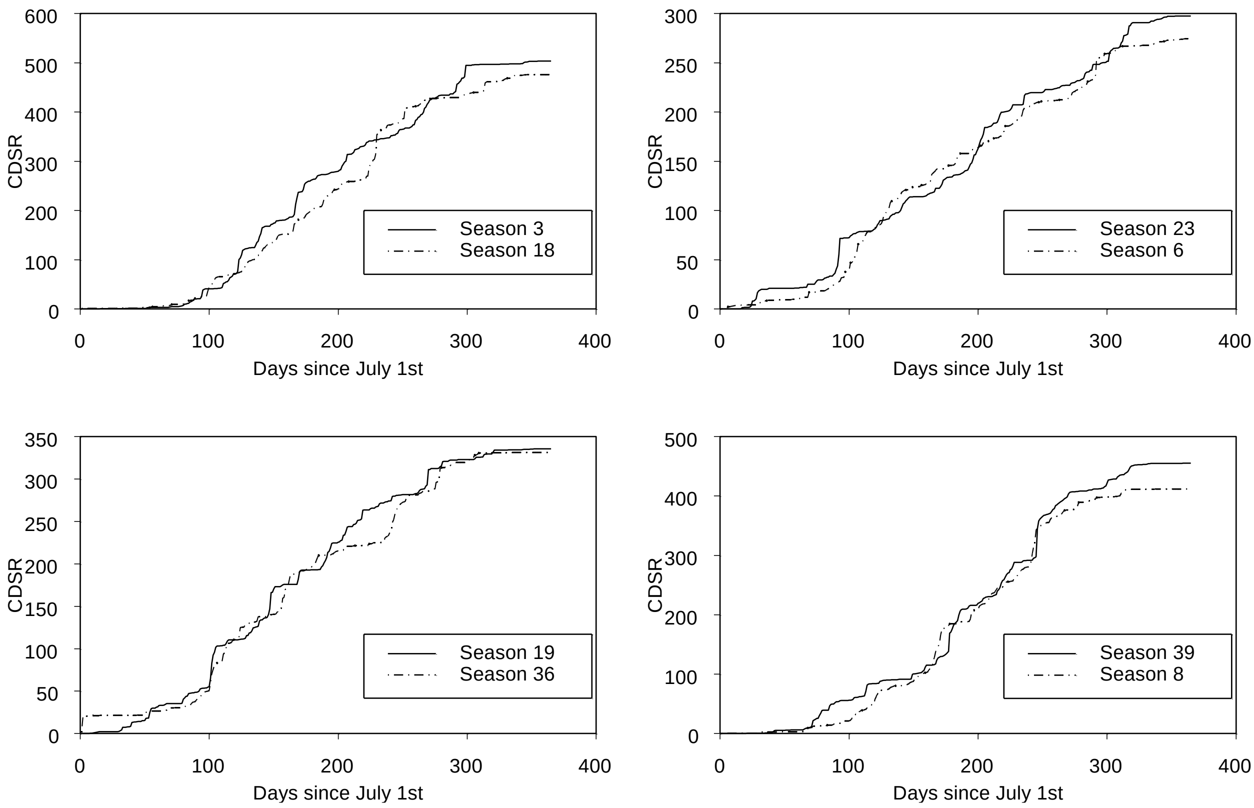

Figure 10. Comparison of four pairs of fire seasons with similar trends in CDSR. Data are from the Dunedin Aero station (DNA).

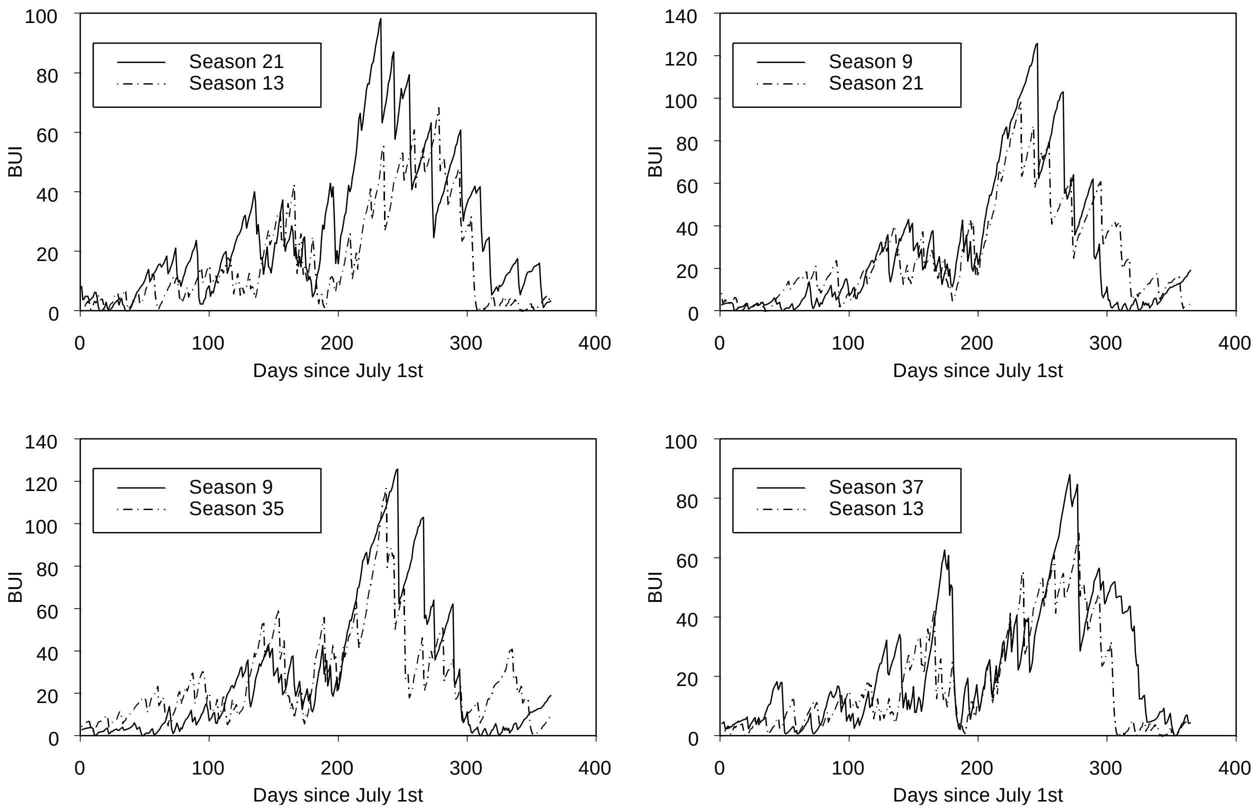

Figure 11. Comparison of four pairs of fire seasons with similar trends in BUI. Data are from the Dunedin Aero station (DNA).

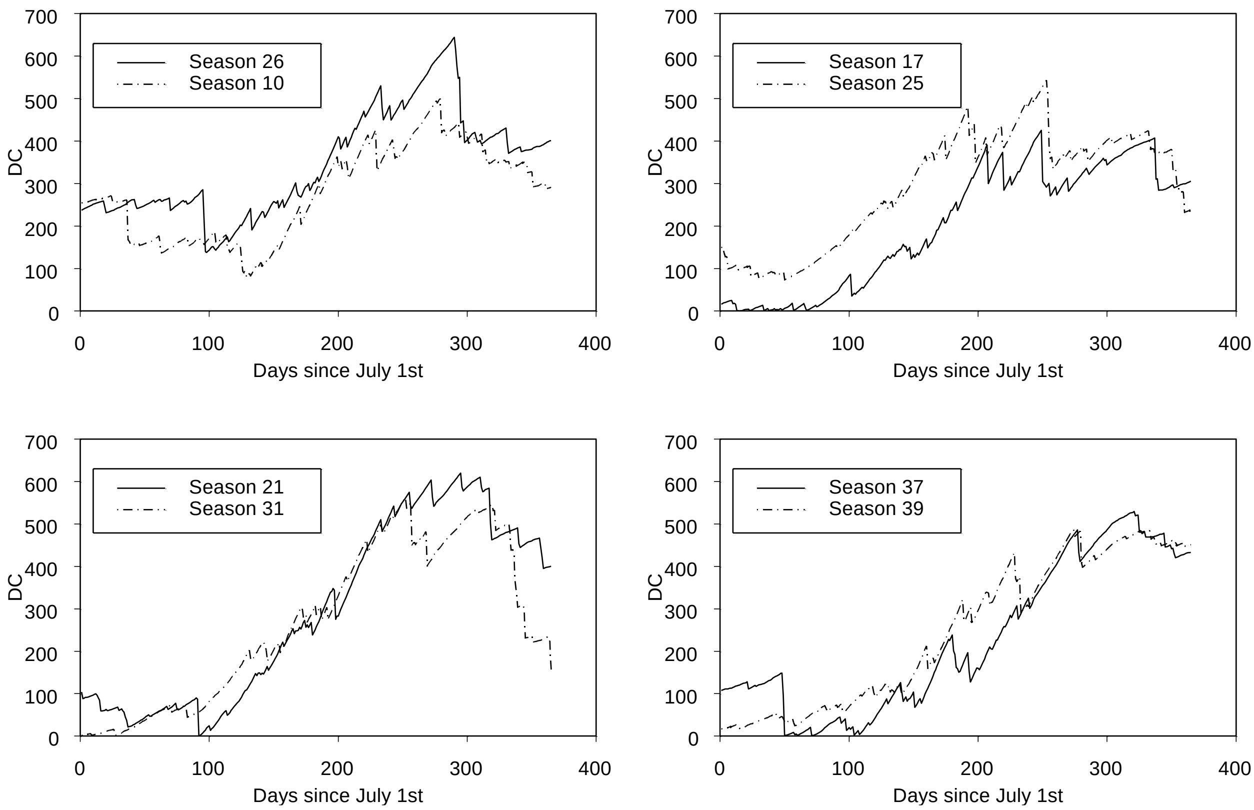

Figure 12. Comparison of four pairs of fire seasons with similar trends in DC. Data are from the Dunedin Aero station (DNA).

The use of linear least squares regression to compare fire seasons is really just an extension of sums of squares and correlation. While sums of squares (and least squares regression in particular, which minimises the sum of squares) can indicate the season most closely resembling the season in question (i.e., with the least variation from day to day), it may not indicate the most similar fire season end-point (for example, see Fig. 12, lower left). Correlation is a measure of the linear association between random variables X and Y, and it can be shown that the correlation coefficient (r_{XY}) for the linear association between the two random variables X and Y is related to b_1 for the linear relationship between X and Y. The unit-free and scale-free correlation r_{XY} measures linear association between X and Y, while b_1 measures the size of change in Y which can be predicted when a unit change is made in X (Draper and Smith 1998). Scale changes in the data will affect b_1 but not r_{XY}. Therefore, comparisons made using the b_1 parameter have the advantage over simple correlation analysis because they identify pairs of seasons that not only follow a similar trend over time but also have similar values of CDSR, BUI or DC. However, a disadvantage of the similarity approach is the lack of forecasting capability, and it was found that there was very little correspondence between pairs of seasons that met the CDSR similarity criteria after 120 days and those that met the criteria at the end of the season.

<u>Parametric curve fitting</u>

The resulting parameter estimates for the fixed effects component of the NLME model for each of the seven stations are listed in Table 2. Complete fit statistics and plots of the random effects and actual CDSR data for each station are given in Appendix 3.

These curves therefore represent the development of CDSR at these seven stations during an "average" fire season. As expected, the value for the fixed effect of the *a* parameter was very similar to the mean value of CDSR found by Pearce *et al.* (2003) given in Table 1. Typically, the value for the asymptote or fire season endpoint, *a*, is somewhat higher than the mean CDSR value calculated by Pearce *et al*. (2003); however, the fixed component of *a* is governed by the fact that the random components must sum to zero, whereas the value calculated by Pearce *et al*. (2003) is a straight arithmetic mean and is influenced by skewness in the data.

At any time during the fire season, a fire manager can calculate whether CDSR is above or below average for that time of year by substituting the relevant parameters into Equation [3] and comparing the result with the observed value of CDSR.

Table 2. Parameter estimates for the fixed effects in the Chapman-Richards equation.

Station	Name	a	b	c
CHA	Christchurch	1394.337	0.015	12.884
GSA	Gisborne	1064.559	0.017	18.013
NSA	Nelson	556.847	0.018	29.731
DNA	Dunedin	552.159	0.010	5.783
PPA	Paraparaumu	341.859	0.016	23.669
WSA	Westport	68.250	0.011	9.086
HKA	Hokitika	55.176	0.008	4.283

When the values of the random effect are plotted against fire season for a particular station, there appear to be a number of natural groupings. In the case of Dunedin Aero (Fig. 13), fire seasons 12, 31, 9 and 25 (seasons 77/78, 96/97, 74/75 and 90/91) stand out as being particularly severe, while seasons 32, 33, 38 and 29 (97/98, 98/99, 03/04 and 94/95) appear to be particularly mild. These groupings are similar to those found from the similarity analysis described above.

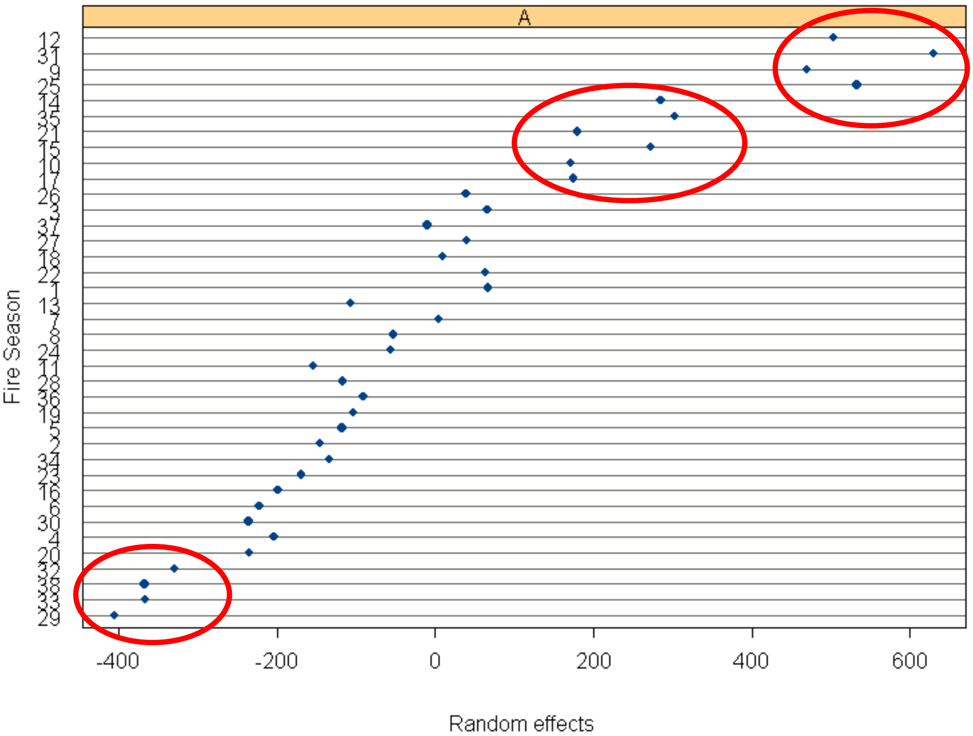

Figure 13. Value of the random component of the *a* parameter in the Chapman-Richards equation fitted to Cumulative Daily Severity Rating (CDSR) for all fire seasons at Dunedin Aero (season 1 = 66/67, season 38 = 03/04). The ellipses highlight groupings of fire seasons with (from bottom left to top right) below, above and well-above average CDSR values, respectively.

In order to predict fire season severity using this curve-fitting methodology, one approach is to attempt to predict the value of the random component of the *a* parameter using other variables measured earlier in the fire season. This has not been explored in great detail, except for some basic analysis using the value of CDSR at different times in the fire season to predict the value of the random component of the *a* parameter (i.e., the fire season severity/maximum CDSR). In this analysis, the difference between the actual value of CDSR for each fire season and the fixed component of the NLME model of CDSR was calculated at 90, 120, 180, 210, 240, 270, 300 and 330 days since July 1st. These differences were then used to attempt to predict the value of the random component of the *a* parameter.

From Figure 14 it can be seen that, as expected, the ability to predict the overall severity (i.e., final CDSR for the season) improves as the season progresses. At 150 days after July 1st (i.e., approximately December 1st), it was possible to explain 46% of the variation in the value of the *a* parameter, while at 180 days (i.e., approximately January 1st) it was possible to explain 62% of the variation. From an operational perspective, it is important to be able to predict the likely fire season severity as early as possible in order to allocate sufficient resources to prevention and preparedness. Therefore, it is desirable to be able to predict the likely fire season severity by December 1st. Of some concern at present is the fact that the model does not appear to be conservative. In other words, some fire seasons which have been predicted to be mild end up being quite severe. This could lead to a false sense of security among fire managers in some years. Further work is therefore required to develop these predictive models of fire season severity.

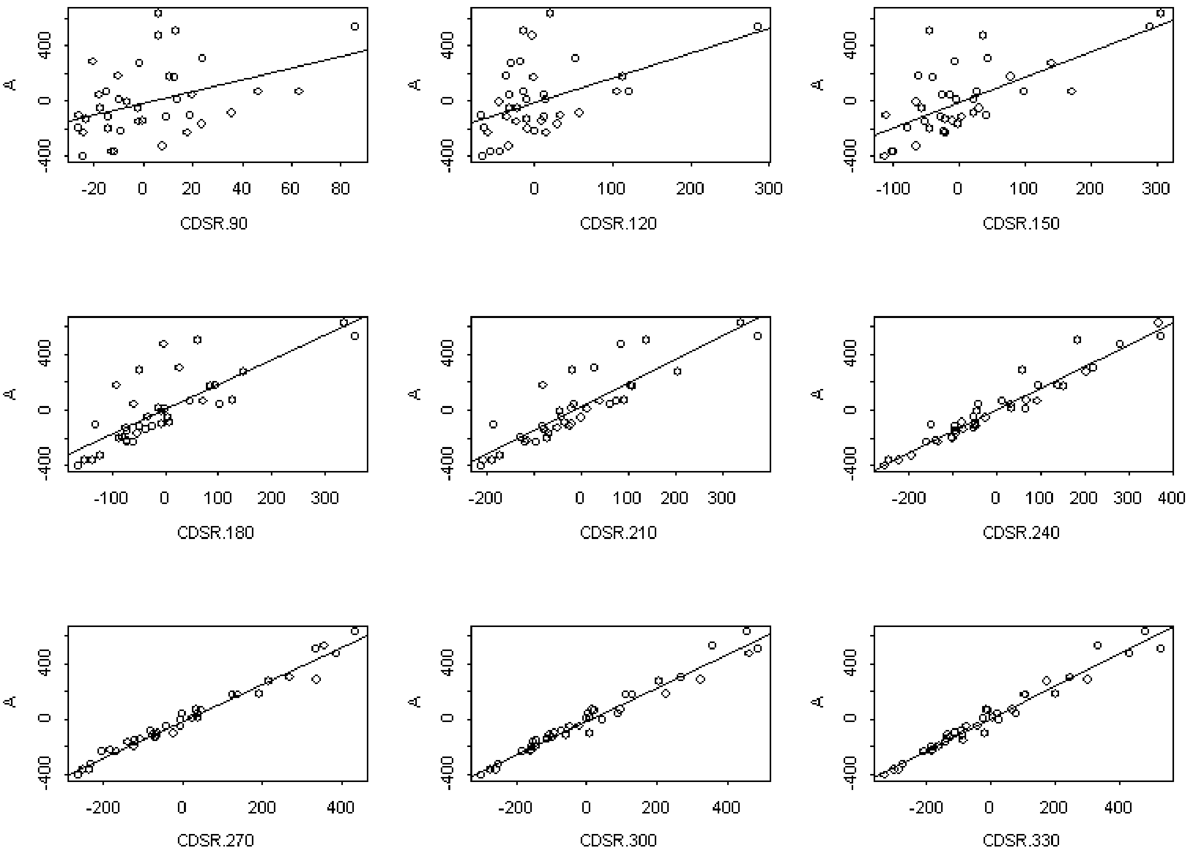

Figure 14. Relationship between the value of the random component of the *a* parameter in the non-linear mixed effects version of the Chapman-Richards model fitted to Cumulative Daily Severity Rating (CDSR) and the difference between actual CDSR and the fixed component of the non-linear mixed effects model calculated at different times since July 1st for Dunedin Aero. The graphs show that the ability to predict the overall seasonal severity improves markedly as the season progresses. (CDSR.90 = approx. Oct. 1st, CDSR.330 = approx. Jun. 1st).

As opposed to predicting the overall seasonal severity (i.e., the maximum CDSR), what is probably of more use to operational fire managers is the ability to predict mid-fire season severity one to three months ahead, particularly during the period from 1 October to 1 January. Therefore, rather than predicting the random component of the *a* parameter, an attempt was made to make the following predictions of CDSR:

CDSR at 210, 240 and 270 days from CDSR at 180 days
CDSR at 180, 210 and 240 days from CDSR at 150 days
CDSR at 150, 180 and 210 days from CDSR at 120 days
CDSR at 120, 150 and 180 days from CDSR at 90 days

This approach is essentially examining temporal autocorrelation in the data and was tested using data from the Dunedin Aero station. Results show that there is a relatively strong relationship between CDSR at day *i* and CDSR at day *i* + 30 (Table 3). Not unexpectedly, this relationship is weaker for *i* + 60 and *i* + 90. However, the relationship between CDSR at day *i* and day *i* + 30 improves with time into the fire season (cf. *i* = 90 and *i* = 180). From 1 November (approx. day 120) onwards it is possible to explain at least 55% of the variation in CDSR up to 2 months ahead of the forecast date. This figure is closer to 80% for forecasts up to 1 month ahead.

Table 3. Coefficient of determination (r^2) for linear relationships between the value of the Cumulative Daily Severity Rating (CDSR) at day *i* and CDSR value at day *j* for Dunedin Aero.

Day *i*	Days into Fire Season, Day *j*						
	90	120	150	180	210	240	270
90	1.00	0.77	0.52	0.51	-	-	-
120		1.00	0.68	0.55	0.46	-	-
150			1.00	0.78	0.72	0.53	-
180				1.00	0.90	0.65	0.43

Overall, both analytical approaches were found to be effective at grouping seasons with similar fire severity as determined through CDSR. The similarity approach was better for grouping seasons according to BUI and DC as neither of these two indices had temporal patterns that could be easily modelled with a parametric function. However, the parametric curve fitting offered the most promise in terms of being able to forecast trends in fire season severity, as measured through CDSR, at least up to 1-2 months in advance.

Method automation and interface development

By combining the results from the most promising of the above techniques, parametric analysis, it is possible to construct a crude system for predicting the future trend in CDSR during the fire season. For a particular station, the trend in CDSR for an “average” fire season can be obtained from the Chapman-Richards equation using the parameter estimates provided in Table 2 (see Figure 15). Given the value of CDSR at some time (*i*) into the fire season, a point estimate of the value (along with 95% confidence intervals) of CDSR at time *i* + *n* (*n* = 30, 60 or 90 days) can be obtained using the relationships developed above. Finally, the likely trend in CDSR through to the end of the fire season can be estimated using the relationships which are shown graphically in Figure 14. With this approach, the estimates of CDSR for 30-60 days ahead are considered more reliable than the estimate of the trend in CDSR through to the end of the fire season. An Excel™-based spreadsheet package encompassing this approach has been developed and a copy included (as an electronic appendix) with this report.

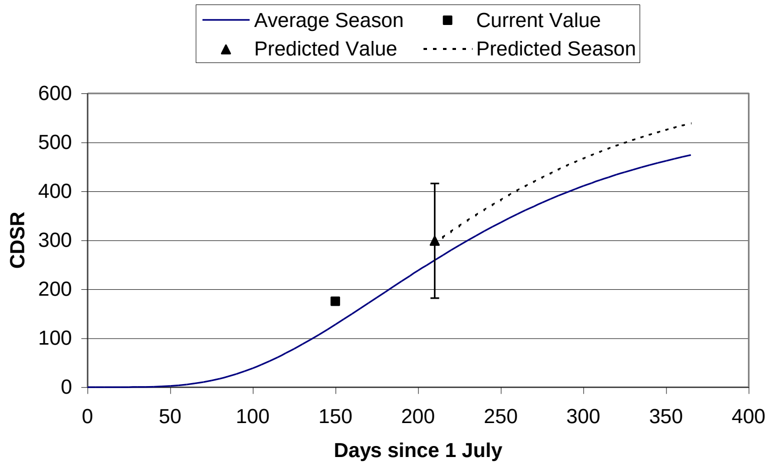

Figure 15. Graphical representation of a system for predicting CDSR at future dates into the fire season based on the current value (see text immediately above for a description of the system).

This system needs to be developed and tested further before it could be used in an operational setting (e.g., within FWSYS), but it does appear to offer promise as a means of predicting future trends in CDSR. Not surprisingly, the ability to predict future trends in CDSR improves as the fire season progresses and the challenge is to develop a robust system which can provide operational managers with a means of reliably predicting future values of CDSR (and other fire danger indices potentially) as early as possible into the fire season.

Conclusion

Two contrasting approaches to comparing and predicting fire season severity have been investigated – statistical similarity and parametric curve fitting. While both approaches were useful, the latter approach was found to hold most promise, with the Chapman-Richards equation successfully being used to model trends in Cumulative Daily Severity Rating (CDSR) through the fire season. This approach was less successful in predicting seasonal trends in Drought Code (DC) and Buildup Index (BUI), but it could still potentially offer some predictive capability for these two indices. The parametric curve fitting method was successfully able to model overall fire season severity outcome but, more importantly, also proved successful in predicting seasonal severity 1-2 months ahead. A tool has also been developed that uses this latter approach; it is currently based on an Excel spreadsheet, but could readily be coded to work in a different operating environment such as the NRFA's internet-based fire weather monitoring system, FWSYS, following further development and testing.

As well as refining the methodology for CDSR, future work should focus on distinguishing between the effects of dryness and windiness in high CDSR seasons. This could be achieved by continuing to investigate the usefulness of other fire danger indices such as DC and BUI, or by looking directly at the relevant meteorological inputs (i.e., wind speed and direction, and rainfall) contributing to seasonal severity.

The approaches investigated here for forecasting seasonal severity certainly hold promise and warrant further study. Using such tools, fire managers will be better able to predict severe fire seasons in advance so that prevention programmes and preparedness systems can be implemented in a timely and effective manner. Use of the fire danger climatology and associated analytical tools will also lead to more effective and efficient use of equipment, and ultimately a reduction in the incidence and consequences of rural fires.

Acknowledgments

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References

Alexander, M.E. 1982. Calculating spring Drought Code starting values in the prairie provinces and Northwest Territories. Environment Canada, Canadian Forestry Service, Northern Forest Research Centre, Edmonton, Alberta. Forest Management Note No. 12. 4 p.

Alexander, M.E. 1992a. Fire danger rating and fire behaviour prediction. Lecture to New Zealand Certificate in Forestry (NZCF) Stage V course 5170, Protection and Environmental Studies, September 17, 1992, Forestry Training Centre, Rotorua. 25 p.

Alexander, M.E. 1992b. Wildfires and fire danger rating. Seminar to NZ Meteorological Service Head Office staff, May 27, 1992, Wellington. (Abstract only).

Alexander, M.E. 1994. Proposed revision of fire danger class criteria for forest and rural fire areas in New Zealand. National Rural Fire Authority, Wellington. Circular 1994/2. 73 p.

Alexander, M.E.; Stocks, B.J. 1987. Severity rating. In Status of the Canadian Forest Fire Danger Rating System (CFFDRS): a progress report by the CFS Fire Danger Group. pp 34-37.

Anderson, S.A.J. 2002. The Atawhai Fire of 7 May 2002: A case study. 27 p.

Anderson, S. 2003. The Miners Road Fire of 2nd February 2003. New Zealand Forest Research, Forest and Rural Fire Research Programme, Christchurch. Fire Technology Transfer Note 28 (May 2003). 12 p.

Andrews, P.L.; Bradshaw, L.S. 1990. RXWINDOW: defining windows of acceptable burning conditions based on desired fire behaviour. USDA Forest Service, Intermountain Research Station, Ogden, Utah. General Technical Report INT-GTR-273. 54 p.

Andrews, P.L.; Bradshaw, L.S.; Bunnell, D.L.; Curcio, G.M. 1998. Fire danger rating pocket card for firefighter safety. In Proceedings of the Second Conference on Fire and Forest Meteorology, 11-16 January 1998, Pheonix, Arizona. pp 67-70.

Anon. 1993. Fire Weather Index System Tables for New Zealand. National Rural Fire Authority in association with the New Zealand Forest Research Institute. Wellington, N.Z. 48 p.

Anon. 1998. Rural alert for El-Nino. New Zealand Fire Service. Star Magazine 20 (January 1998): 16.

Anon. 2001. Keeping an eye on the climate. Star 54 (February/March 2001): 21. [Majorhazi, K.]

Borger, B.H. 1997. Closure of Conservation Lands for Public Safety Reasons: Fire Danger on Somes Island, Wellington, New Zealand. Department of Conservation, Wellington. Unpublished Report. 22 p.

Cheney, N.P. 1976. Bushfire disasters in Australia, 1945-1975. Australian Forestry 39(4): 245-268.

Cleveland, W.S. 1979. Robust locally weighted regression and smoothing scatterplots. Journal of the American Statistical Association 74: 829-836

Cooper, A.N.; Ashley-Jones, C. 1987. Economics of fire prevention in New Zealand plantations. New Zealand Forestry 31(4): 14-18.

Draper, N.R.; Smith, H. 1998. Applied Regression Analysis – Third Edition. John Wiley and Sons, New York.

Fogarty, L.G.; Pearce, H.G.; Catchpole, W.R.; Alexander, M.E. 1998. Adoption vs. adaptation: lessons from applying the Canadian Forest Fire Danger Rating System in New Zealand. In

Proceedings, 3rd International Conference on Forest Fire Research and 14th Fire and Forest Meteorology Conference, Luso, Coimbra, Portugal, 16-20 November, 1998. pp 1011-1028.

Fogarty, L.; Slijepcevic, A. 1998. The influence of wind speed on the effectiveness of aerial fire suppression. New Zealand Forest Research Institute, Forest and Rural Fire Research Programme. Fire Technology Transfer Note 17 (February 1998). 8 p.

Fogarty, L.G.; Smart, P.N.; 1994. The development of initial attack guides and incident management structures. Paper presented to the Central North Island Forest Companies Fire Cooperative, July 1994, Waiotapu.

Furman, R.W. 1979. Using fire weather data in prescribed fire planning: two computer programs. USDA Forest Service, Rocky Mountain Forest and Range Experiment Station, Fort Collins, Colorado. General Technical Report RM-63. 11 p.

Gosai, A.; Heydenrych, C.; Salinger, J. 2003. Climate and severe fire seasons: Part III - Climate patterns and high fire severity in Northland and Canterbury. Report prepared for the National Rural Fire Authority, March 2003. National Institute of Water and Atmospheric Research Ltd, Auckland. NIWA Client Report: AKL2003-024. 19 p. + Appendices.

Gosai, A.; Griffiths, G.; Salinger, J. 2004. Climate and severe fire seasons: Part IV – Daily weather sequences and high fire severity in Auckland, West/Waikato, North Canterbury, McKenzie Basin and Central Otago/Inland Southland. Report prepared for the National Rural Fire Authority. National Institute of Water and Atmospheric Research Ltd, Auckland. NIWA Client Report: AKL2003-026. (in press).

Gosai, A.; Salinger, J. 2004. Seasonal Fire Weather Climate Outlook for January-March 2004. Report prepared for the National Rural Fire Authority, January 2004. National Institute of Water and Atmospheric Research Ltd, Auckland. NIWA Client Report: AKL2004-02. (Available at: http://nrfa.fire.org.nz/fire_weather/niwa/FireJan-Mar04.pdf).

Gray, H.W.; Janz, B. 1985. Initial-attack initiatives in Alberta: a response to the 1980s. In Proceedings of the Intermountain Fire Council 1983 Fire Management Workshop, October 25-27, 1983, Banff, Alberta. Canadian Forestry Service, Northern Forestry Research Centre, Edmonton, Alberta. Information Report NOR-X-271. pp 25-36.

Haines, D.A.; Main, W.A.; Frost, J.S.; Simard, A.J. 1980. Fire danger rating and wildfire occurrence in the north-eastern United States. Forest Science 29(4): 679-696.

Harrington, J.B.; Flannigan, M.D.; Van Wagner, C.E. 1983. A study of the relation of components of the Fire Weather Index to monthly provincial area burned by wildfire in Canada 1953-80. Canadian Forest Service, Chalk River, Ontario. Information Report PI-X-25.

Harvey, D.A.; Alexander, M.E.; Janz, B. 1986. A comparison of fire-weather severity in northern Alberta during the 1980 and 1981 fire seasons. Forestry Chronicle 62(6): 507-513.

Heydenrych, C.; Salinger, J. 2002. Climate and severe fire seasons: Part II - New Zealand fire regions. Report prepared for the National Rural Fire Authority, 28 March 2002. National Institute of Water and Atmospheric Research Ltd, Auckland. NIWA Report AK02045. 46 p.

Heydenrych, C.; Salinger, J.; Renwick, J. 2001. Climate and severe fire seasons: a report on climatic factors contributing to severe fire seasons in New Zealand. National Institute of Water and Atmospheric Research Ltd, Auckland. NIWA Report AK00125. 117 p.

Leathwick, J.R.; Briggs, C.M. 2001. Spatial prediction of wildfire hazard across New Zealand. Report prepared for the National Rural Fire Authority under the New Zealand Fire Service Commission's Contestable Research Fund. Landcare Research Contract Report: LCR 0001/081.

Majorhazi, K. 2003. Mapping New Zealand's fire climate. In Conference Proceedings, 3rd International Wildland Conference, 3-6 October 2003, Sydney, Australia. CD-ROM.

Majorhazi, K.; Pearce, G. 2001. Tracking fire season severity: a convenient method of tracking the fire season severity using the Daily Severity Rating. Online. National Rural Fire Authority website, http://nrfa.fire.org.nz/ publications/ articles/fireworm/index.htm (28/2/01).

Martell, D.L. 1978. The use of historical fire weather data in prescribed burn planning. Forestry Chronicle 54: 96-98.

McAlpine, R.S. 1990. Seasonal trends in the Drought Code component of the Canadian Forest Fire Weather Index System. Forestry Canada, Petawawa National Forestry Institute, Chalk River, Ontario. Information Report PI-X-97E/F. 36 p.

Muraro, S.J.; Lawson, B.D. 1970. Prediction of duff moisture distribution for prescribed burning. Canadian Department of Fisheries and Forests, Canadaian Forestry Service, Pacific Forestry Research Centre, Victoria, British Columbia. Information Report BC-X-46. 25 p.

Nikleva, S. 1973. Fire Weather Index climatology for Prince George, B.C. Environment Canada, Atmospheric Environment Service, Pacific Region, Vancouver, B.C. 16 p.

NZMS. 1983. Summaries of climatological observations to 1980. New Zealand Meteorological Service. NZMS Miscellaneous Publication 177. 172 p.

OMNR. 1989. Guidelines for modifying forest operations in response to fire danger. Ontario Ministry of Natural Resources, Aviation Fire Management Centre, Sault Ste. Marie, Ontario. 13 p.

Pearce, G. 1996. An initial assessment of fire danger in New Zealand's climatic regions. New Zealand Forest Research Institute, Forest and Rural Fire Research Programme. Fire Technology Transfer Note 10 (October 1996). 28 p.

Pearce, G. 1998. Fire research update. In Proceedings, Forest and Rural Fire Association of New Zealand (FRFANZ) 8th Annual Conference, 5-7 August, 1998, Palmerston North.

Pearce, G.; Anderson, S.A.J. 2002. Wildfire documentation: the need for case studies illustrated using the example of "The Atawhai Fire of 7 May 2002: a case study" by S.A.J. Anderson. New Zealand Forest Research, Forest and Rural Fire Research Programme, Christchurch. Fire Technology Transfer Note 26 (November 2002). 2 p. + Attachment.

Pearce, H.G.; Douglas, K.L.; Moore, J.R. 2003. A fire danger climatology for New Zealand. Forest Research Contract Report No. 10052, prepared for the New Zealand Fire Service Commission Contestable Research Fund. 289 p. [New Zealand Fire Service Commission Research Report No. 39].

Pinheiro, J.C.; Bates, D.M. 2000. Mixed-Effects Models in S and S-Plus. Springer-Verlag, New York. 528 p.

Renwick, J.; Salinger, J. 2004. Validation of Seasonal Fire Weather Climate Outlooks. Report prepared for the National Rural Fire Authority. National Institute of Water and Atmospheric Research Ltd, Auckland. NIWA Client Report: AKL2003-034. (in press).

Salinger, J.; Zheng, X.; Thompson, C. 1999. Climate and severe fire seasons. National Institute of Water and Atmospheric Research Ltd., Auckland. Report prepared for the National Rural Fire Authority. 22 p.

Simard, A.J. 1973. Forest fire weather zones of Canada. Environment Canada, Canadian Forestry Service. (Poster with text).

Simard, A.J.; Valenzuela, J. 1972. A climatological summary of the Canadian Forest Fire Weather Index. Canadian Forestry Service, Forest Fire Research Institute, Ottawa. Information Report FF-X-34. 425 p.

Stocks, B.J. 1971. Fire severity index distribution in Ontario 1963 to 1968. Canadian Forestry Service, Great Lakes Forestry Research Centre, Sault Ste. Marie, Ontario. Information Report O-X-151. 18 p.

Stocks, B.J. 1978. Delineating fire climate zones in Ontario. 5th National Conference on Fire and Meteorology, New Jersey, March 14-16, 1978.

Stocks, B.J.; Van Wagner, C.E.; Clark, W.R.; Dube, D.R. 1981. The 1980 forest fire season in west-central Canada - social, economic, and environmental impacts. Environment Canada, Canadian Forestry Service. Task Force Report. 27 p.

Street, R.B.; Stocks, B.J. 1983. Forest fire weather and wildfire occurrence in the boreal forest of northwestern Ontario. In Resources and Dynamics of the Boreal Zone. Proceedings of a Conference, 23-26 August, 1982, Thunder Bay, Ontario. Association of the Canadian University of Northern Studies, Ottawa, Ontario. pp 249-265.

Tapper, N.J.; Garden, G.; Gill, J.; Fernon, J. 1993. The climatology and meteorology of high fire danger in the Northern Territory. Rangeland Journal 15(2): 339-351.

Turner, J.A. 1973. A fire load index for British Columbia. Environment Canada, Canadian Forestry Service, Pacific Forest Research Centre, Victoria, British Columbia. Information Report BC-X-80. 10 p.

Valentine, J.M. 1978. Fire danger rating in New Zealand: review and evaluation. New Zealand Forest Service, Forest Research Institute, Production Forestry Division, Rotorua. Forest Establishment Report No. 123. 53 p.

Van Wagner, C.E. 1970. Conversion of William’s severity rating for use with the Fire Weather Index. Canadian Forest Service, Petawawa Forest Experiment Station, Chalk River Ontario. Information Report PS-X-21. 5 p.

Van Wagner, C.E. 1987. Development and structure of the Canadian Forest Fire Weather Index System. Government of Canada, Canadian Forestry Service, Ottawa, Ontario. Forestry Technical Report 35. 37 p.

Van Wagner, C.E.; Pickett, T.L. 1985. Equations and FORTRAN program for the Canadian Forest Fire Weather Index System. Government of Canada, Canadian Forestry Service, Ottawa, Ontario. Forestry Technical Report 33. 18 p.

Williams, D.E. 1959. Fire season severity rating. Canadian Department of Northern Affairs and Natural Resources, Forest Research Division. Technical Note 73. 13 p.

Williams, A.A.J. 1998. Observed extreme fire weather in Australia and the impact of ENSO. In Proceedings, 13th Conference on Fire and Forest Meteorology, 27-31 October 1996, Lorne, Australia. International Association of Wildland Fire. pp. 279-285.

Wotton, B.M.; Flannigan, M.D. 1993. Length of fire season in a changing climate. Forestry Chronicle 69(2): 187-192.

Wotton, B.M.; Stocks, B.J.; Flannigan, M.D.; Laprise, R.; Blanchet, J-P. 1998. Estimating future 2xCO2 fire climates in the boreal forest of Canada using a regional climate model. In Proceedings, 3rd International Conference on Forest Fire Research and 14th Fire and Forest Meteorology Conference, Luso, Coimbra, Portugal, 16-20 November, 1998. pp 1207-1221.

Appendices

Appendix 1. Seasonal trends in relative Drought Code (DC), Buildup Index (BUI) and Daily Severity Rating (DSR) for each weather station.

Appendix 2. Output from the similarity analysis of Cumulative Daily Severity Rating (CDSR) data from the Dunedin Aero meteorological station.

Appendix 3. Model fit statistics, and plots of random effects and raw Cumulative Daily Severity Rating (CDSR) data for each station.

Appendix 1. Seasonal trends in relative Drought Code (DC), Buildup Index (BUI) and Daily Severity Rating (DSR) for each weather station.

CHA – Christchurch Aero

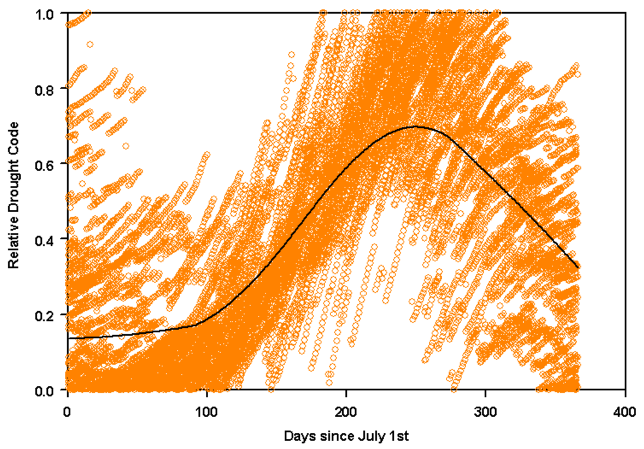

Figure A1.1. Seasonal trends in relative Drought Code (DC) at Christchurch Aero. The solid line corresponds to a robust local smoothing (`lowess`) function fitted to the data.

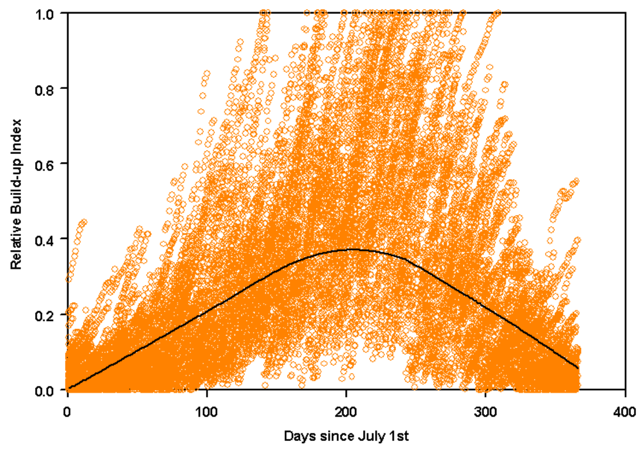

Figure A1.2. Seasonal trends in relative Build-up Index (BUI) at Christchurch Aero. The solid line corresponds to a robust local smoothing (`lowess`) function fitted to the data.

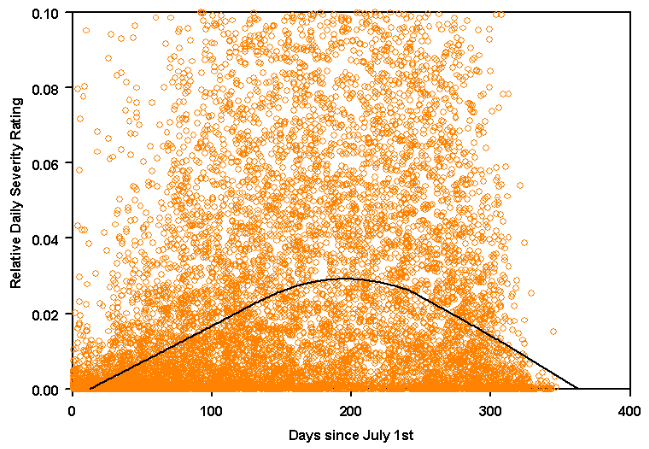

Figure A1.3. Seasonal trends in relative Daily Severity Rating (DSR) at Christchurch Aero. The solid line corresponds to a robust local smoothing (`lowess`) function fitted to the data.

Appendix 1. cont.

DNA – Dunedin Aero

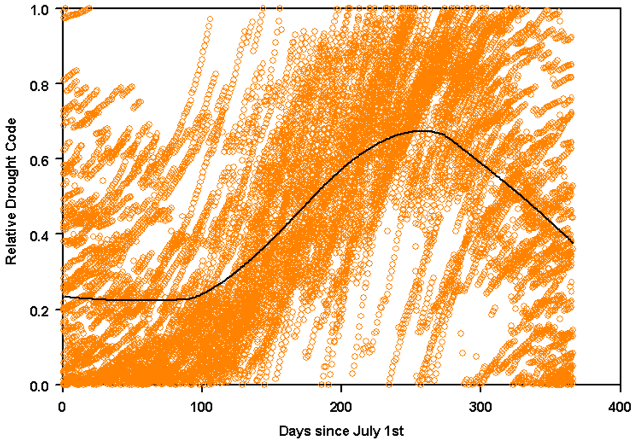

Figure A1.4. Seasonal trends in relative Drought Code (DC) at Dunedin Aero. The solid line corresponds to a robust local smoothing (`lowess`) function fitted to the data.

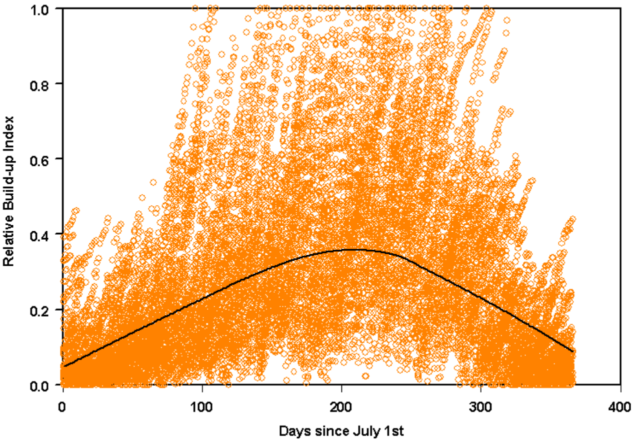

Figure A1.5. Seasonal trends in relative Build-up Index (BUI) at Dunedin Aero. The solid line corresponds to a robust local smoothing (`lowess`) function fitted to the data.

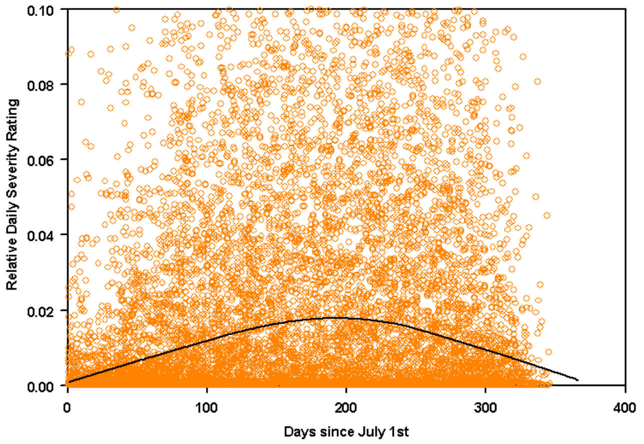

Figure A1.6. Seasonal trends in relative Daily Severity Rating (DSR) at Dunedin Aero. The solid line corresponds to a robust local smoothing (`lowess`) function fitted to the data.

Appendix 1. cont.

GSA – Gisborne Aero

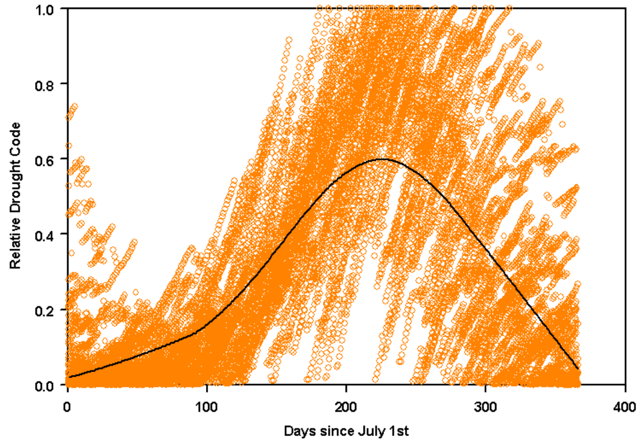

Figure A1.7. Seasonal trends in relative Drought Code (DC) at Gisborne Aero. The solid line corresponds to a robust local smoothing (`lowess`) function fitted to the data.

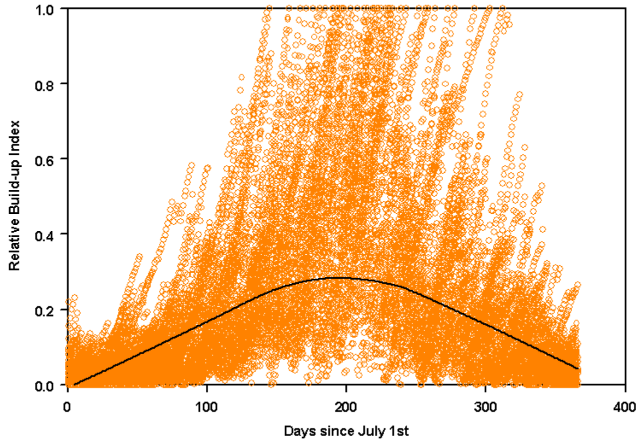

Figure A1.8. Seasonal trends in relative Build-up Index (BUI) at Gisborne Aero. The solid line corresponds to a robust local smoothing (`lowess`) function fitted to the data.

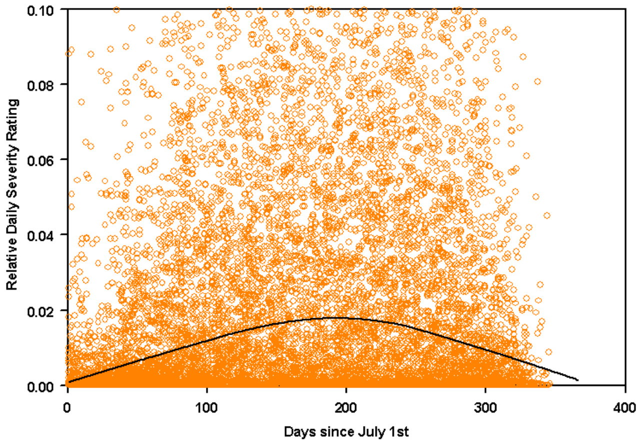

Figure A1.9. Seasonal trends in relative Daily Severity Rating (DSR) at Gisborne Aero. The solid line corresponds to a robust local smoothing (`lowess`) function fitted to the data.

Appendix 1. cont.

HKA – Hokitika Aero

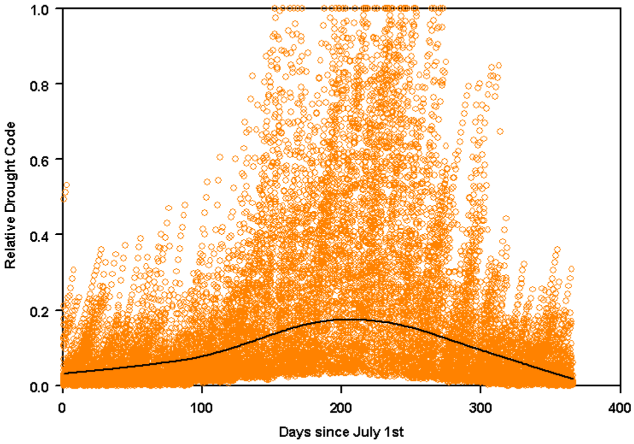

Figure A1.10. Seasonal trends in relative Drought Code (DC) at Hokitika Aero. The solid line corresponds to a robust local smoothing (`lowess`) function fitted to the data.

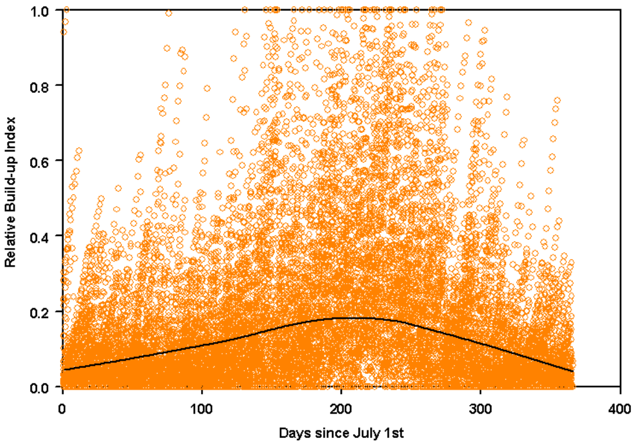

Figure A1.11. Seasonal trends in relative Build-up Index (BUI) at Hokitika Aero. The solid line corresponds to a robust local smoothing (`lowess`) function fitted to the data.

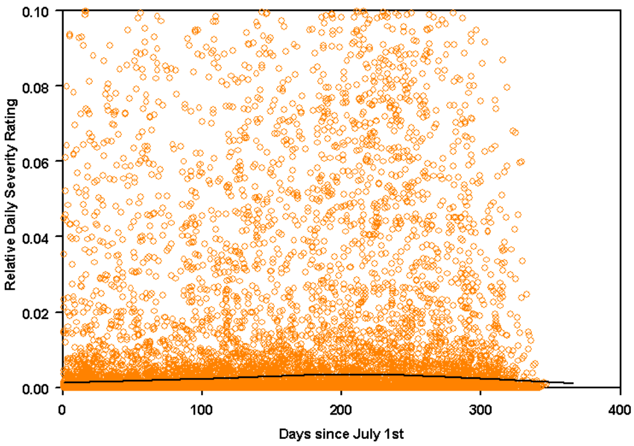

Figure A1.12. Seasonal trends in relative Daily Severity Rating (DSR) at Hokitika Aero. The solid line corresponds to a robust local smoothing (`lowess`) function fitted to the data.

Appendix 1. cont.

NSA – Nelson Aero

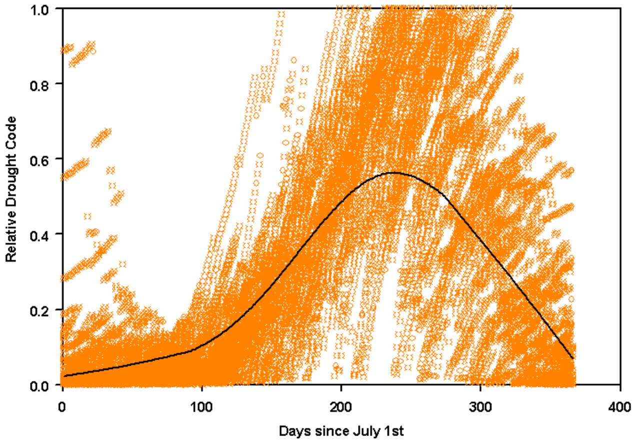

Figure A1.13. Seasonal trends in relative Drought Code (DC) at Nelson Aero. The solid line corresponds to a robust local smoothing (`lowess`) function fitted to the data.

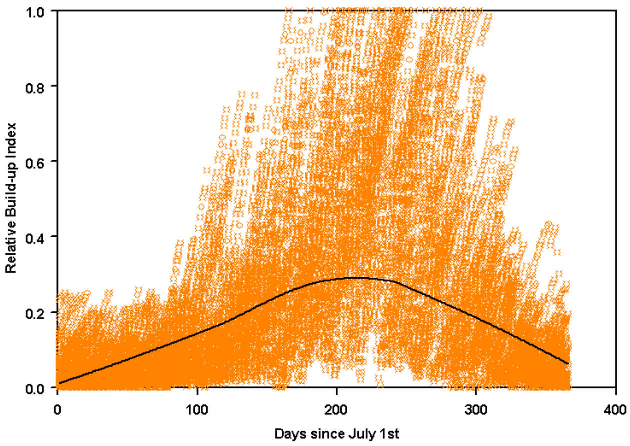

Figure A1.14. Seasonal trends in relative Build-up Index (BUI) at Nelson Aero. The solid line corresponds to a robust local smoothing (`lowess`) function fitted to the data.

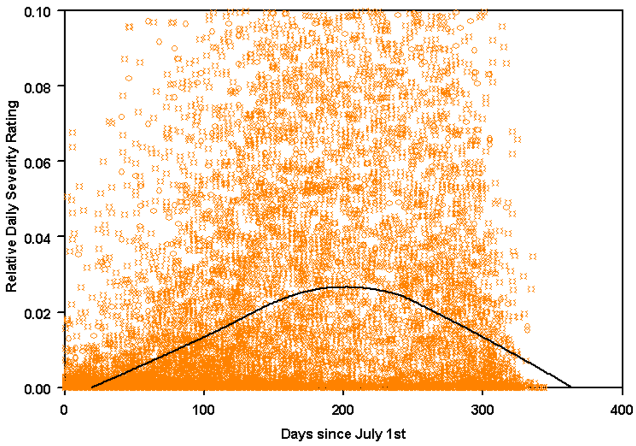

Figure A1.15. Seasonal trends in relative Daily Severity Rating (DSR) at Nelson Aero. The solid line corresponds to a robust local smoothing (`lowess`) function fitted to the data.

PPA – Paraparaumu Aero

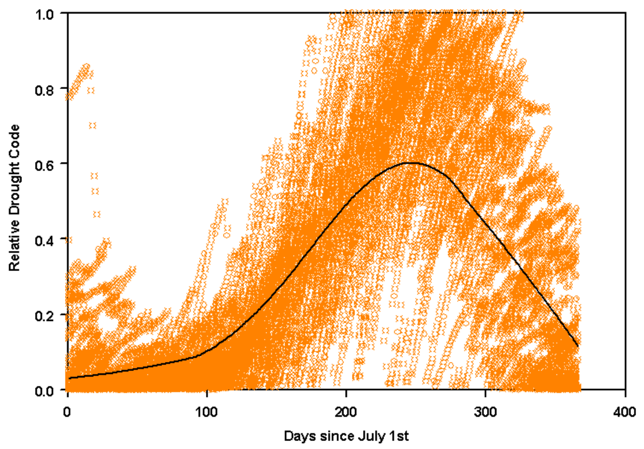

Figure A1.16. Seasonal trends in relative Drought Code (DC) at Paraparaumu Aero. The solid line corresponds to a robust local smoothing (`lowess`) function fitted to the data.

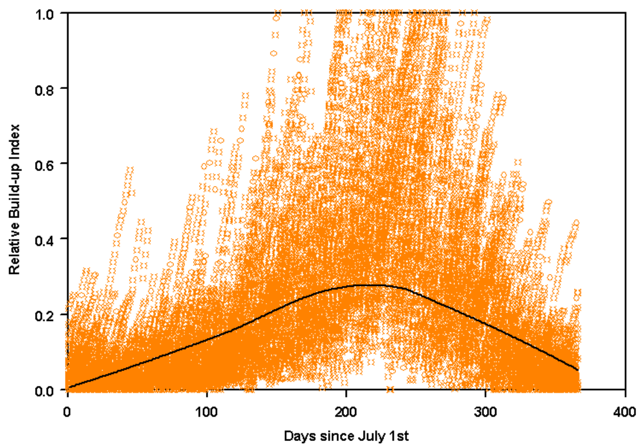

Figure A1.17. Seasonal trends in relative Build-up Index (BUI) at Paraparaumu Aero. The solid line corresponds to a robust local smoothing (`lowess`) function fitted to the data.

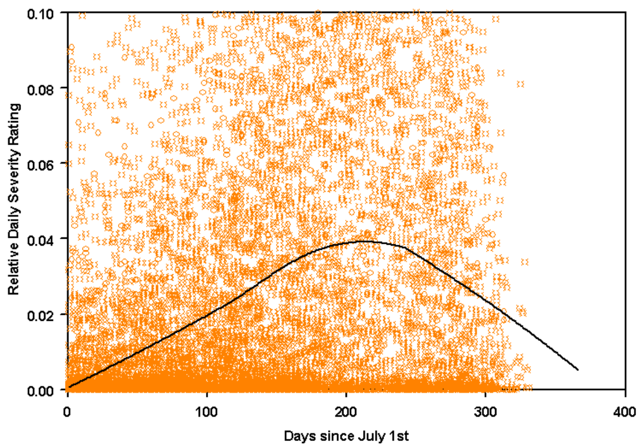

Figure A1.18. Seasonal trends in relative Daily Severity Rating (DSR) at Paraparaumu Aero. The solid line corresponds to a robust local smoothing (`lowess`) function fitted to the data.

Appendix 1. cont.

WSA – Westport Aero

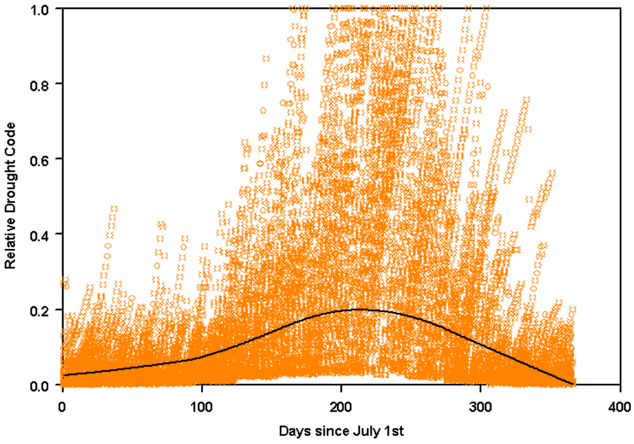

Figure A1.19. Seasonal trends in relative Drought Code (DC) at Westport Aero. The solid line corresponds to a robust local smoothing (`lowess`) function fitted to the data.

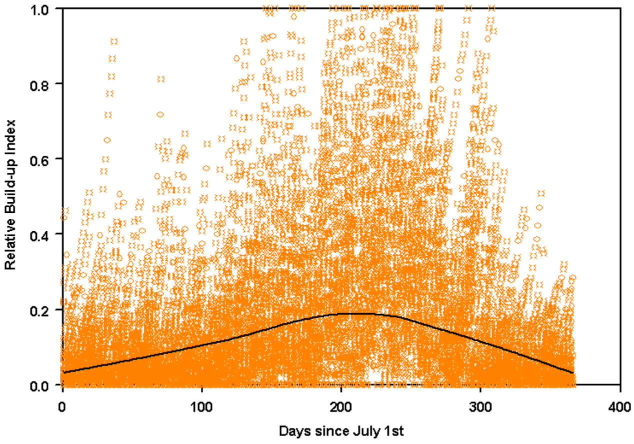

Figure A1.20. Seasonal trends in relative Build-up Index (BUI) at Westport Aero. The solid line corresponds to a robust local smoothing (`lowess`) function fitted to the data.

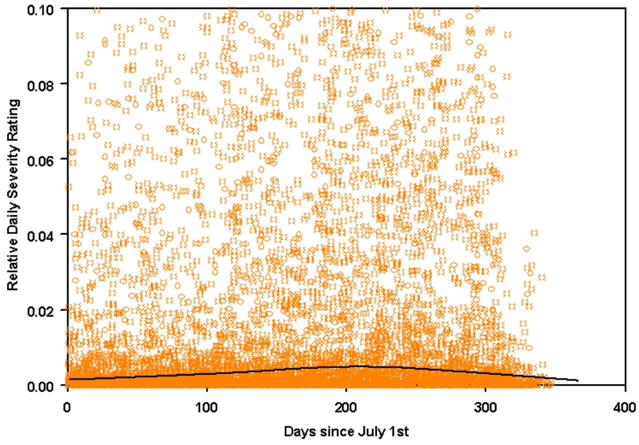

Figure A1.21. Seasonal trends in relative Daily Severity Rating (DSR) at Westport Aero. The solid line corresponds to a robust local smoothing (`lowess`) function fitted to the data.

Appendix 2. Output from the similarity analysis of Cumulative Daily Severity Rating (CDSR) data from the Dunedin Aero meteorological station.

b_1 parameter

Fire season	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40
1	1.00	1.32	0.81	1.41	1.22	1.64	0.90	0.91	0.41	0.76	1.22	0.39	0.83	0.46	0.66	1.33	0.80	0.83	1.30	1.59	0.50	0.97	1.55	1.12	0.62	0.69	0.88	1.04	2.65	1.97	0.52	2.21	2.28	1.14	0.51	1.35	0.76	2.17	0.86	0.71
2	0.69	1.00	0.62	1.06	0.90	1.21	0.68	0.71	0.33	0.58	0.94	0.32	0.69	0.37	0.51	1.04	0.60	0.64	0.96	1.18	0.41	0.70	1.17	0.84	0.44	0.56	0.66	0.82	2.08	1.41	0.39	1.68	1.77	0.86	0.40	1.00	0.61	1.72	0.68	0.47
3	1.11	1.61	1.00	1.71	1.45	1.95	1.10	1.15	0.53	0.94	1.52	0.51	1.12	0.60	0.82	1.69	0.96	1.03	1.54	1.92	0.66	1.11	1.88	1.36	0.71	0.90	1.07	1.33	3.37	2.26	0.64	2.69	2.86	1.39	0.65	1.62	0.99	2.78	1.09	0.73
4	0.64	0.93	0.57	1.00	0.85	1.12	0.64	0.67	0.30	0.55	0.87	0.29	0.63	0.35	0.47	0.97	0.56	0.60	0.89	1.10	0.38	0.65	1.08	0.78	0.41	0.51	0.62	0.76	1.94	1.30	0.36	1.55	1.65	0.81	0.38	0.93	0.56	1.58	0.63	0.47
5	0.77	1.09	0.67	1.17	1.00	1.32	0.75	0.77	0.35	0.64	1.02	0.33	0.73	0.40	0.56	1.13	0.65	0.70	1.05	1.30	0.44	0.77	1.27	0.92	0.49	0.59	0.73	0.88	2.25	1.54	0.43	1.82	1.92	0.95	0.43	1.09	0.65	1.83	0.73	0.57
6	0.58	0.82	0.50	0.86	0.74	1.00	0.55	0.58	0.26	0.47	0.76	0.26	0.56	0.30	0.41	0.84	0.49	0.52	0.79	0.97	0.33	0.57	0.96	0.69	0.36	0.45	0.54	0.66	1.69	1.17	0.32	1.37	1.44	0.70	0.33	0.82	0.49	1.40	0.55	0.38
7	1.00	1.45	0.89	1.55	1.32	1.74	1.00	1.04	0.48	0.85	1.36	0.46	1.00	0.54	0.74	1.52	0.86	0.94	1.39	1.72	0.60	1.01	1.69	1.23	0.64	0.80	0.96	1.19	3.03	2.03	0.57	2.43	2.58	1.27	0.59	1.44	0.88	2.47	0.98	0.72
8	0.92	1.37	0.85	1.47	1.24	1.65	0.94	1.00	0.46	0.81	1.30	0.44	0.98	0.53	0.70	1.46	0.81	0.89	1.30	1.62	0.58	0.94	1.60	1.16	0.59	0.78	0.91	1.14	2.93	1.89	0.54	2.30	2.47	1.20	0.57	1.37	0.85	2.39	0.95	0.63
9	1.88	2.89	1.78	3.08	2.57	3.45	1.99	2.12	1.00	1.71	2.73	0.96	2.15	1.15	1.46	3.10	1.71	1.89	2.72	3.38	1.27	1.95	3.39	2.43	1.22	1.68	1.89	2.44	6.24	3.93	1.14	4.86	5.22	2.53	1.22	2.86	1.83	5.14	2.01	1.17
10	1.13	1.67	1.03	1.80	1.52	2.01	1.15	1.21	0.56	1.00	1.58	0.53	1.17	0.63	0.86	1.77	1.00	1.08	1.60	1.99	0.70	1.16	1.95	1.42	0.73	0.94	1.13	1.38	3.53	2.31	0.66	2.80	3.01	1.46	0.68	1.67	1.03	2.87	1.15	0.83
11	0.72	1.05	0.65	1.12	0.95	1.27	0.72	0.76	0.35	0.62	1.00	0.34	0.73	0.40	0.53	1.11	0.63	0.68	1.01	1.25	0.44	0.73	1.24	0.89	0.46	0.59	0.70	0.87	2.21	1.47	0.42	1.77	1.88	0.91	0.43	1.05	0.65	1.81	0.72	0.49
12	1.86	2.91	1.81	3.07	2.56	3.49	1.98	2.13	1.01	1.72	2.78	1.00	2.21	1.17	1.47	3.12	1.71	1.90	2.73	3.40	1.28	1.93	3.44	2.44	1.22	1.73	1.91	2.49	6.31	3.96	1.16	4.91	5.29	2.52	1.22	2.90	1.88	5.29	2.04	1.01
13	0.79	1.27	0.79	1.34	1.11	1.51	0.87	0.94	0.45	0.75	1.20	0.44	1.00	0.53	0.64	1.37	0.74	0.83	1.18	1.47	0.58	0.83	1.49	1.06	0.52	0.76	0.82	1.10	2.81	1.70	0.50	2.14	2.32	1.10	0.55	1.26	0.83	2.35	0.90	0.40
14	1.55	2.43	1.51	2.58	2.15	2.90	1.67	1.80	0.85	1.44	2.30	0.83	1.88	1.00	1.23	2.62	1.43	1.60	2.28	2.83	1.09	1.61	2.85	2.04	1.02	1.44	1.59	2.09	5.35	3.28	0.97	4.10	4.42	2.13	1.04	2.42	1.57	4.44	1.72	0.86
15	1.32	1.92	1.19	2.06	1.76	2.32	1.33	1.39	0.63	1.14	1.82	0.61	1.32	0.72	1.00	2.04	1.14	1.24	1.85	2.32	0.79	1.34	2.24	1.64	0.85	1.07	1.30	1.58	4.03	2.68	0.76	3.22	3.43	1.68	0.78	1.93	1.17	3.26	1.30	0.98
16	0.62	0.94	0.58	1.00	0.84	1.12	0.64	0.68	0.32	0.56	0.89	0.30	0.67	0.36	0.48	1.00	0.55	0.61	0.89	1.11	0.40	0.64	1.09	0.79	0.40	0.53	0.62	0.78	1.99	1.28	0.37	1.57	1.68	0.82	0.39	0.93	0.58	1.62	0.64	0.43
17	1.17	1.66	1.02	1.77	1.51	2.01	1.13	1.18	0.54	0.97	1.55	0.51	1.12	0.61	0.83	1.72	1.00	1.06	1.60	1.96	0.67	1.17	1.95	1.39	0.74	0.91	1.10	1.34	3.42	2.36	0.65	2.78	2.92	1.44	0.67	1.66	1.00	2.82	1.11	0.81
18	1.04	1.54	0.95	1.64	1.39	1.85	1.06	1.11	0.51	0.91	1.45	0.49	1.09	0.59	0.78	1.63	0.92	1.00	1.47	1.82	0.65	1.06	1.80	1.30	0.67	0.87	1.02	1.27	3.26	2.13	0.61	2.58	2.75	1.34	0.63	1.54	0.95	2.66	1.05	0.71
19	0.73	1.03	0.63	1.10	0.94	1.25	0.70	0.73	0.33	0.60	0.97	0.32	0.69	0.38	0.52	1.07	0.62	0.66	1.00	1.23	0.41	0.73	1.21	0.87	0.46	0.56	0.69	0.83	2.12	1.48	0.41	1.73	1.82	0.89	0.41	1.04	0.62	1.75	0.69	0.51
20	0.58	0.82	0.51	0.88	0.75	1.00	0.56	0.59	0.27	0.48	0.77	0.26	0.55	0.30	0.42	0.86	0.49	0.53	0.79	1.00	0.33	0.58	0.96	0.70	0.37	0.45	0.55	0.67	1.71	1.16	0.33	1.38	1.45	0.71	0.33	0.83	0.50	1.39	0.55	0.42
21	1.42	2.23	1.37	2.37	1.97	2.65	1.53	1.64	0.78	1.32	2.11	0.75	1.70	0.91	1.13	2.40	1.31	1.46	2.08	2.58	1.00	1.48	2.61	1.86	0.93	1.31	1.45	1.90	4.86	2.99	0.88	3.75	4.04	1.95	0.95	2.20	1.42	4.01	1.57	0.85
22	1.01	1.39	0.85	1.49	1.28	1.69	0.95	0.98	0.44	0.81	1.29	0.42	0.90	0.49	0.70	1.42	0.84	0.88	1.35	1.65	0.55	1.00	1.63	1.17	0.63	0.74	0.92	1.11	2.83	2.01	0.54	2.33	2.43	1.20	0.55	1.40	0.82	2.31	0.92	0.74
23	0.58	0.84	0.52	0.90	0.76	1.02	0.57	0.60	0.28	0.49	0.80	0.27	0.58	0.32	0.42	0.88	0.51	0.54	0.81	0.99	0.35	0.59	1.00	0.71	0.37	0.47	0.56	0.69	1.76	1.19	0.33	1.42	1.50	0.73	0.34	0.84	0.52	1.46	0.57	0.38
24	0.82	1.17	0.73	1.25	1.07	1.42	0.80	0.84	0.38	0.69	1.10	0.37	0.80	0.44	0.60	1.23	0.70	0.75	1.13	1.41	0.48	0.82	1.37	1.00	0.52	0.65	0.78	0.96	2.45	1.65	0.46	1.96	2.08	1.02	0.47	1.18	0.71	2.00	0.79	0.57
25	1.59	2.18	1.34	2.34	2.01	2.67	1.49	1.53	0.69	1.27	2.04	0.66	1.41	0.77	1.10	2.23	1.32	1.38	2.13	2.61	0.85	1.57	2.55	1.85	1.00	1.17	1.46	1.74	4.44	3.17	0.86	3.65	3.82	1.88	0.86	2.21	1.29	3.64	1.45	1.16
26	1.10	1.70	1.06	1.79	1.50	2.04	1.15	1.24	0.58	1.00	1.61	0.57	1.27	0.68	0.86	1.81	1.00	1.10	1.60	1.99	0.74	1.13	2.00	1.43	0.72	1.00	1.12	1.44	3.66	2.32	0.67	2.85	3.07	1.47	0.71	1.69	1.08	3.05	1.18	0.62
27	1.02	1.47	0.91	1.57	1.34	1.77	1.01	1.05	0.48	0.87	1.39	0.46	1.00	0.54	0.75	1.54	0.87	0.94	1.41	1.77	0.59	1.03	1.71	1.25	0.65	0.81	1.00	1.20	3.06	2.06	0.58	2.45	2.62	1.27	0.59	1.48	0.90	2.49	0.99	0.76
28	0.79	1.18	0.73	1.26	1.06	1.42	0.81	0.86	0.40	0.70	1.12	0.39	0.87	0.46	0.60	1.26	0.70	0.77	1.12	1.40	0.51	0.80	1.38	1.00	0.51	0.68	0.78	1.00	2.54	1.63	0.47	1.99	2.13	1.03	0.49	1.19	0.75	2.10	0.82	0.48
29	0.31	0.46	0.29	0.49	0.41	0.56	0.32	0.34	0.16	0.27	0.44	0.15	0.34	0.18	0.24	0.49	0.27	0.30	0.44	0.55	0.20	0.31	0.54	0.39	0.20	0.27	0.31	0.39	1.00	0.64	0.18	0.78	0.83	0.40	0.19	0.46	0.29	0.82	0.32	0.20
30	0.50	0.68	0.42	0.72	0.62	0.84	0.46	0.48	0.22	0.39	0.64	0.21	0.45	0.24	0.34	0.69	0.41	0.43	0.66	0.81	0.27	0.49	0.80	0.58	0.31	0.37	0.45	0.55	1.39	1.00	0.27	1.15	1.19	0.59	0.27	0.69	0.40	1.15	0.45	0.33
31	1.73	2.51	1.56	2.67	2.27	3.05	1.72	1.81	0.83	1.47	2.37	0.80	1.76	0.95	1.28	2.64	1.49	1.62	2.41	3.01	1.04	1.74	2.94	2.13	1.10	1.41	1.67	2.07	5.28	3.53	1.00	4.21	4.47	2.18	1.02	2.53	1.54	4.32	1.70	1.16
32	0.41	0.59	0.36	0.63	0.53	0.72	0.40	0.42	0.20	0.35	0.56	0.19	0.41	0.22	0.30	0.62	0.35	0.38	0.57	0.70	0.24	0.41	0.70	0.50	0.26	0.33	0.39	0.49	1.24	0.84	0.23	1.00	1.05	0.51	0.24	0.59	0.36	1.02	0.40	0.27
33	0.37	0.56	0.34	0.59	0.50	0.67	0.38	0.40	0.19	0.33	0.53	0.18	0.40	0.21	0.28	0.59	0.33	0.36	0.53	0.66	0.23	0.38	0.65	0.47	0.24	0.31	0.37	0.46	1.18	0.77	0.22	0.93	1.00	0.48	0.23	0.55	0.35	0.97	0.38	0.25
34	0.78	1.14	0.70	1.23	1.04	1.37	0.79	0.82	0.38	0.67	1.07	0.36	0.79	0.43	0.58	1.20	0.68	0.74	1.09	1.35	0.48	0.79	1.33	0.96	0.50	0.63	0.76	0.94	2.39	1.59	0.45	1.91	2.03	1.00	0.47	1.14	0.70	1.95	0.78	0.56
35	1.57	2.37	1.46	2.52	2.11	2.84	1.63	1.73	0.81	1.39	2.24	0.78	1.75	0.94	1.20	2.52	1.40	1.55	2.24	2.77	1.03	1.61	2.78	1.99	1.01	1.36	1.55	1.99	5.10	3.26	0.94	3.99	4.26	2.07	1.00	2.36	1.49	4.20	1.65	0.98
36	0.69	0.98	0.61	1.05	0.89	1.20	0.67	0.70	0.32	0.57	0.92	0.31	0.68	0.37	0.50	1.02	0.59	0.63	0.95	1.17	0.40	0.69	1.15	0.83	0.44	0.55	0.66	0.81	2.05	1.40	0.39	1.65	1.74	0.85	0.40	1.00	0.60	1.69	0.66	0.46
37	1.03	1.57	0.98	1.66	1.40	1.89	1.07	1.15	0.54	0.93	1.49	0.53	1.16	0.62	0.80	1.68	0.92	1.02	1.48	1.85	0.68	1.06	1.84	1.32	0.67	0.91	1.04	1.33	3.38	2.15	0.62	2.64	2.84	1.36	0.65	1.57	1.00	2.81	1.09	0.62
38	0.36	0.55	0.34	0.58	0.49	0.66	0.37	0.40	0.19	0.32	0.52	0.18	0.41	0.22	0.27	0.58	0.33	0.36	0.52	0.64	0.24	0.37	0.65	0.46	0.24	0.32	0.36	0.47	1.18	0.76	0.22	0.93	0.99	0.47	0.23	0.55	0.35	1.00	0.38	0.20
39	0.96	1.44	0.89	1.54	1.29	1.73	0.99	1.05	0.49	0.85	1.36	0.47	1.05	0.56	0.73	1.53	0.85	0.94	1.36	1.69	0.62	0.98	1.69	1.21	0.62	0.82	0.95	1.20	3.08	1.98	0.57	2.42	2.59	1.25	0.60	1.44	0.90	2.54	1.00	0.62
40	1.10	2.02	1.29	2.06	1.67	2.35	1.33	1.55	0.79	1.20	1.99	0.97	2.12	1.03	0.98	2.25	1.12	1.35	1.79	2.22	1.02	1.20	2.43	1.65	0.76	1.57	1.28	2.02	4.81	2.45	0.81	3.42	3.89	1.72	0.92	1.95	1.58	4.67	1.54	1.00

Appendix 2. cont.

r^2 value

Fire season	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40
1	1.00	0.91	0.90	0.91	0.94	0.94	0.89	0.84	0.76	0.85	0.88	0.72	0.66	0.71	0.88	0.83	0.94	0.87	0.95	0.92	0.71	0.97	0.90	0.92	0.98	0.76	0.90	0.82	0.81	0.98	0.90	0.90	0.85	0.89	0.80	0.94	0.78	0.79	0.82	0.78
2	0.91	1.00	0.99	0.98	0.98	0.99	0.99	0.98	0.95	0.98	0.99	0.92	0.88	0.91	0.97	0.98	0.99	0.99	0.98	0.97	0.92	0.96	0.99	0.99	0.96	0.94	0.97	0.97	0.96	0.96	0.99	0.99	0.99	0.99	0.96	0.99	0.96	0.94	0.97	0.95
3	0.90	0.99	1.00	0.97	0.97	0.99	0.97	0.98	0.94	0.97	0.99	0.93	0.88	0.91	0.97	0.98	0.97	0.98	0.98	0.98	0.91	0.94	0.98	0.99	0.95	0.95	0.98	0.97	0.97	0.95	0.99	0.98	0.98	0.98	0.95	0.99	0.97	0.95	0.97	0.95
4	0.91	0.98	0.97	1.00	0.99	0.97	0.99	0.98	0.94	0.98	0.98	0.89	0.85	0.89	0.97	0.97	0.98	0.98	0.98	0.96	0.90	0.97	0.97	0.98	0.96	0.92	0.97	0.95	0.95	0.94	0.97	0.98	0.97	0.99	0.95	0.97	0.94	0.92	0.96	0.96
5	0.94	0.98	0.97	0.99	1.00	0.97	0.98	0.96	0.90	0.98	0.97	0.86	0.80	0.85	0.98	0.95	0.98	0.97	0.99	0.98	0.86	0.98	0.97	0.99	0.98	0.89	0.98	0.93	0.93	0.96	0.97	0.97	0.96	0.98	0.92	0.98	0.91	0.89	0.94	0.95
6	0.94	0.99	0.99	0.97	0.97	1.00	0.97	0.95	0.91	0.95	0.97	0.89	0.84	0.87	0.95	0.95	0.98	0.97	0.99	0.97	0.87	0.97	0.98	0.98	0.97	0.92	0.96	0.95	0.94	0.98	0.98	0.98	0.96	0.97	0.93	0.99	0.93	0.93	0.95	0.88
7	0.89	0.99	0.97	0.99	0.98	0.97	1.00	0.98	0.95	0.99	0.98	0.90	0.87	0.90	0.98	0.98	0.98	0.99	0.98	0.97	0.92	0.96	0.97	0.98	0.95	0.92	0.97	0.96	0.96	0.94	0.98	0.98	0.98	1.00	0.96	0.97	0.94	0.92	0.97	0.96
8	0.84	0.98	0.98	0.98	0.96	0.95	0.98	1.00	0.98	0.99	0.98	0.95	0.93	0.95	0.97	0.99	0.96	0.99	0.95	0.95	0.96	0.92	0.96	0.97	0.91	0.96	0.96	0.99	0.99	0.90	0.98	0.97	0.99	0.98	0.98	0.96	0.98	0.95	0.99	0.97
9	0.76	0.95	0.94	0.94	0.90	0.91	0.95	0.98	1.00	0.95	0.95	0.97	0.97	0.98	0.93	0.98	0.92	0.97	0.90	0.90	0.99	0.86	0.94	0.93	0.84	0.97	0.90	0.98	0.98	0.85	0.95	0.95	0.97	0.96	0.99	0.91	0.98	0.96	0.98	0.92
10	0.85	0.98	0.97	0.98	0.98	0.95	0.99	0.99	0.95	1.00	0.98	0.92	0.88	0.91	0.98	0.99	0.96	0.98	0.96	0.96	0.92	0.93	0.96	0.98	0.93	0.94	0.98	0.96	0.96	0.90	0.97	0.97	0.99	0.98	0.95	0.96	0.96	0.93	0.98	0.99
11	0.88	0.99	0.99	0.98	0.97	0.97	0.98	0.98	0.95	0.98	1.00	0.94	0.88	0.91	0.97	0.98	0.97	0.99	0.97	0.97	0.92	0.94	0.99	0.98	0.94	0.95	0.98	0.97	0.96	0.93	0.98	0.98	0.99	0.98	0.96	0.97	0.96	0.94	0.98	0.98
12	0.72	0.92	0.93	0.89	0.86	0.89	0.90	0.95	0.97	0.92	0.94	1.00	0.98	0.98	0.89	0.95	0.88	0.94	0.87	0.87	0.96	0.81	0.93	0.90	0.80	0.99	0.88	0.97	0.96	0.82	0.93	0.92	0.95	0.91	0.95	0.90	0.98	0.97	0.96	0.98
13	0.66	0.88	0.88	0.85	0.80	0.84	0.87	0.93	0.97	0.88	0.88	0.98	1.00	0.99	0.85	0.92	0.83	0.91	0.81	0.81	0.98	0.75	0.87	0.85	0.74	0.97	0.82	0.96	0.95	0.76	0.89	0.88	0.92	0.87	0.95	0.85	0.96	0.96	0.94	0.86
14	0.71	0.91	0.91	0.89	0.85	0.87	0.90	0.95	0.98	0.91	0.91	0.98	0.99	1.00	0.88	0.95	0.87	0.94	0.86	0.85	0.99	0.80	0.90	0.89	0.79	0.97	0.86	0.97	0.97	0.80	0.92	0.91	0.94	0.92	0.97	0.89	0.97	0.97	0.96	0.89
15	0.88	0.97	0.97	0.97	0.98	0.95	0.98	0.97	0.93	0.98	0.97	0.89	0.85	0.88	1.00	0.98	0.95	0.97	0.97	0.98	0.89	0.94	0.95	0.99	0.93	0.92	0.98	0.95	0.95	0.92	0.98	0.96	0.97	0.98	0.93	0.96	0.93	0.90	0.95	0.96
16	0.83	0.98	0.98	0.97	0.95	0.95	0.98	0.99	0.98	0.99	0.98	0.95	0.92	0.95	0.98	1.00	0.95	0.99	0.95	0.96	0.96	0.91	0.96	0.97	0.90	0.96	0.96	0.98	0.98	0.89	0.98	0.97	0.99	0.98	0.97	0.95	0.98	0.94	0.98	0.97
17	0.94	0.99	0.97	0.98	0.98	0.98	0.98	0.96	0.92	0.96	0.97	0.88	0.83	0.87	0.95	0.95	1.00	0.97	0.99	0.96	0.88	0.98	0.98	0.97	0.98	0.91	0.96	0.94	0.93	0.97	0.97	0.98	0.96	0.98	0.93	0.98	0.92	0.92	0.95	0.92
18	0.87	0.99	0.98	0.98	0.97	0.97	0.99	0.99	0.97	0.98	0.99	0.94	0.91	0.94	0.97	0.99	0.97	1.00	0.96	0.96	0.95	0.94	0.97	0.98	0.93	0.95	0.96	0.98	0.98	0.92	0.99	0.98	0.99	0.99	0.98	0.97	0.97	0.95	0.99	0.96
19	0.95	0.98	0.98	0.98	0.99	0.99	0.98	0.95	0.90	0.96	0.97	0.87	0.81	0.86	0.97	0.95	0.99	0.96	1.00	0.98	0.86	0.99	0.98	0.98	0.98	0.90	0.97	0.94	0.93	0.98	0.97	0.98	0.96	0.98	0.92	0.99	0.92	0.91	0.94	0.91
20	0.92	0.97	0.98	0.96	0.98	0.97	0.97	0.95	0.90	0.96	0.97	0.87	0.81	0.85	0.98	0.96	0.96	0.96	0.98	1.00	0.86	0.95	0.95	0.99	0.96	0.90	0.98	0.94	0.93	0.94	0.98	0.96	0.96	0.97	0.91	0.97	0.92	0.89	0.93	0.93
21	0.71	0.92	0.91	0.90	0.86	0.87	0.92	0.96	0.99	0.92	0.92	0.96	0.98	0.99	0.89	0.96	0.88	0.95	0.86	0.86	1.00	0.81	0.91	0.89	0.79	0.96	0.86	0.96	0.97	0.80	0.92	0.92	0.95	0.93	0.98	0.88	0.97	0.95	0.97	0.87
22	0.97	0.96	0.94	0.97	0.98	0.97	0.96	0.92	0.86	0.93	0.94	0.81	0.75	0.80	0.94	0.91	0.98	0.94	0.99	0.95	0.81	1.00	0.95	0.96	0.99	0.84	0.95	0.89	0.89	0.98	0.94	0.96	0.93	0.96	0.88	0.96	0.86	0.86	0.90	0.89
23	0.90	0.99	0.98	0.97	0.97	0.98	0.97	0.96	0.94	0.96	0.99	0.93	0.87	0.90	0.95	0.96	0.98	0.97	0.98	0.95	0.91	0.95	1.00	0.97	0.95	0.94	0.95	0.96	0.95	0.96	0.98	0.99	0.97	0.97	0.95	0.97	0.95	0.94	0.97	0.93
24	0.92	0.99	0.99	0.98	0.99	0.98	0.98	0.97	0.93	0.98	0.98	0.90	0.85	0.89	0.99	0.97	0.97	0.98	0.98	0.99	0.89	0.96	0.97	1.00	0.96	0.93	0.98	0.96	0.96	0.95	0.99	0.98	0.97	0.98	0.94	0.98	0.94	0.92	0.96	0.94
25	0.98	0.96	0.95	0.96	0.98	0.97	0.95	0.91	0.84	0.93	0.94	0.80	0.74	0.79	0.93	0.90	0.98	0.93	0.98	0.96	0.79	0.99	0.95	0.96	1.00	0.84	0.95	0.88	0.88	0.98	0.94	0.95	0.92	0.94	0.87	0.97	0.86	0.86	0.90	0.88
26	0.76	0.94	0.95	0.92	0.89	0.92	0.92	0.96	0.97	0.94	0.95	0.99	0.97	0.97	0.92	0.96	0.91	0.95	0.90	0.90	0.96	0.84	0.94	0.93	0.84	1.00	0.90	0.99	0.97	0.85	0.95	0.94	0.96	0.93	0.96	0.92	0.99	0.98	0.97	0.98
27	0.90	0.97	0.98	0.97	0.98	0.96	0.97	0.96	0.90	0.98	0.98	0.88	0.82	0.86	0.98	0.96	0.96	0.96	0.97	0.98	0.86	0.95	0.95	0.98	0.95	0.90	1.00	0.94	0.94	0.93	0.97	0.96	0.97	0.96	0.91	0.97	0.93	0.90	0.94	0.97
28	0.82	0.97	0.97	0.95	0.93	0.95	0.96	0.99	0.98	0.96	0.97	0.97	0.96	0.97	0.95	0.98	0.94	0.98	0.94	0.94	0.96	0.89	0.96	0.96	0.88	0.99	0.94	1.00	0.99	0.89	0.97	0.97	0.98	0.96	0.98	0.96	0.99	0.98	0.98	0.96
29	0.81	0.96	0.97	0.95	0.93	0.94	0.96	0.99	0.98	0.96	0.96	0.96	0.95	0.97	0.95	0.98	0.93	0.98	0.93	0.93	0.97	0.89	0.95	0.96	0.88	0.97	0.94	0.99	1.00	0.88	0.97	0.96	0.98	0.97	0.98	0.95	0.98	0.97	0.99	0.94
30	0.98	0.96	0.95	0.94	0.96	0.98	0.94	0.90	0.85	0.90	0.93	0.82	0.76	0.80	0.92	0.89	0.97	0.92	0.98	0.94	0.80	0.98	0.96	0.95	0.98	0.85	0.93	0.89	0.88	1.00	0.95	0.96	0.92	0.93	0.88	0.97	0.86	0.88	0.89	0.81
31	0.90	0.99	0.99	0.97	0.97	0.98	0.98	0.98	0.95	0.97	0.98	0.93	0.89	0.92	0.98	0.98	0.97	0.99	0.97	0.98	0.92	0.94	0.98	0.99	0.94	0.95	0.97	0.97	0.97	0.95	1.00	0.98	0.98	0.98	0.96	0.98	0.96	0.94	0.97	0.93
32	0.90	0.99	0.98	0.98	0.97	0.98	0.98	0.97	0.95	0.97	0.98	0.92	0.88	0.91	0.96	0.97	0.98	0.98	0.98	0.96	0.92	0.96	0.99	0.98	0.95	0.94	0.96	0.97	0.96	0.96	0.98	1.00	0.98	0.98	0.96	0.98	0.95	0.95	0.97	0.92
33	0.85	0.99	0.98	0.97	0.96	0.96	0.98	0.99	0.97	0.99	0.99	0.95	0.92	0.94	0.97	0.99	0.96	0.99	0.96	0.96	0.95	0.93	0.97	0.97	0.92	0.96	0.97	0.98	0.98	0.92	0.98	0.98	1.00	0.98	0.97	0.97	0.98	0.96	0.99	0.98
34	0.89	0.99	0.98	0.99	0.98	0.97	1.00	0.98	0.96	0.98	0.98	0.91	0.87	0.92	0.98	0.98	0.98	0.99	0.98	0.97	0.93	0.96	0.97	0.98	0.94	0.93	0.96	0.96	0.97	0.93	0.98	0.98	0.98	1.00	0.96	0.97	0.95	0.93	0.97	0.96
35	0.80	0.96	0.95	0.95	0.92	0.93	0.96	0.98	0.99	0.95	0.96	0.95	0.95	0.97	0.93	0.97	0.93	0.98	0.92	0.91	0.98	0.88	0.95	0.94	0.87	0.96	0.91	0.98	0.98	0.88	0.96	0.96	0.97	0.96	1.00	0.94	0.97	0.96	0.98	0.90
36	0.94	0.99	0.99	0.97	0.98	0.99	0.97	0.96	0.91	0.96	0.97	0.90	0.85	0.89	0.96	0.95	0.98	0.97	0.99	0.97	0.88	0.96	0.97	0.98	0.97	0.92	0.97	0.96	0.95	0.97	0.98	0.98	0.97	0.97	0.94	1.00	0.94	0.93	0.95	0.89
37	0.78	0.96	0.97	0.94	0.91	0.93	0.94	0.98	0.98	0.96	0.96	0.98	0.96	0.97	0.93	0.98	0.92	0.97	0.92	0.92	0.97	0.86	0.95	0.94	0.86	0.99	0.93	0.99	0.98	0.86	0.96	0.95	0.98	0.95	0.97	0.94	1.00	0.98	0.99	0.98
38	0.79	0.94	0.95	0.92	0.89	0.93	0.92	0.95	0.96	0.93	0.94	0.97	0.96	0.97	0.90	0.94	0.92	0.95	0.91	0.89	0.95	0.86	0.94	0.92	0.86	0.98	0.90	0.98	0.97	0.88	0.94	0.95	0.96	0.93	0.96	0.93	0.98	1.00	0.97	0.91
39	0.82	0.97	0.97	0.96	0.94	0.95	0.97	0.99	0.98	0.98	0.98	0.96	0.94	0.96	0.95	0.98	0.95	0.99	0.94	0.93	0.97	0.90	0.97	0.96	0.90	0.97	0.94	0.98	0.99	0.89	0.97	0.97	0.99	0.97	0.98	0.95	0.99	0.97	1.00	0.96
40	0.78	0.95	0.95	0.96	0.95	0.88	0.96	0.97	0.92	0.99	0.98	0.98	0.86	0.89	0.96	0.97	0.92	0.96	0.91	0.93	0.87	0.89	0.93	0.94	0.88	0.98	0.97	0.96	0.94	0.81	0.93	0.92	0.98	0.96	0.90	0.89	0.98	0.91	0.96	1.00

Appendix 2. cont.

Pairs of fire seasons where $r^2 > 0.95$ and $0.95 \leq b_1 \leq 1.05$ are shown with a Y

Fire season	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34	35	36	37	38	39	40
1	Y																					Y																		
2		Y														Y			Y																	Y				
3			Y														Y	Y																			Y			
4				Y												Y																								
5					Y						Y																													
6						Y														Y			Y																	
7							Y	Y														Y					Y												Y	
8								Y																																
9									Y			Y																												
10			Y							Y							Y																				Y			
11					Y						Y								Y																					
12									Y			Y																												Y
13													Y																											
14														Y																					Y					
15															Y																									Y
16				Y												Y																								
17			Y							Y							Y																							
18																		Y									Y										Y			
19		Y									Y								Y																	Y				
20						Y														Y			Y																	
21																					Y														Y					
22	Y						Y															Y																		
23						Y														Y			Y																	
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36		Y		Y												Y																				Y				
37			Y															Y																			Y			
38																																	Y					Y		
39							Y	Y																															Y	
40												Y			Y																									Y

Appendix 3. Model fit statistics, and plots of random effects and raw Cumulative Daily Severity Rating (CDSR) data for each station.

CHA – Christchurch Aero

```
Nonlinear mixed-effects model fit by maximum likelihood
  Model: CDSR.seas ~ A * (1 - exp( - B * jul.day.seas))^C
 Data: cha.new
       AIC    BIC    logLik
  188545.7 188584 -94267.86

Random effects:
 Formula: A ~ 1 | fire.seas
                A Residual
StdDev: 561.6584 103.7859

Fixed effects: list(A ~ 1, B ~ 1, C ~ 1)
     Value Std.Error    DF  t-value p-value
A 1394.337  85.76216 15479  16.2582  <.0001
B    0.015   0.00012 15479 127.3387  <.0001
C   12.884   0.24478 15479  52.6366  <.0001
 Correlation:
       A      B
B -0.040
C -0.036  0.981

Standardized Within-Group Residuals:
       Min         Q1         Med         Q3       Max
 -5.846264 -0.3001529 0.05235645 0.4293314 6.775258

Number of Observations: 15524
Number of Groups: 43
```

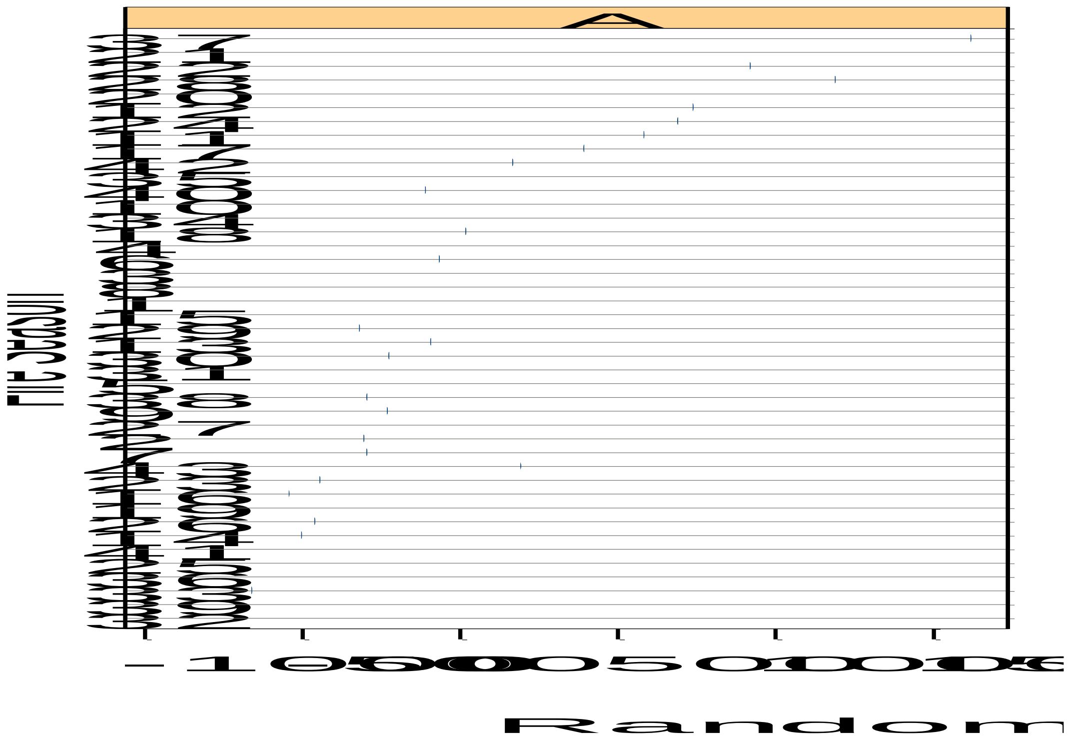

Figure A3.1. Value of the random component of the *a* parameter in the Chapman-Richards equation fitted to CDSR for Christchurch Aero.

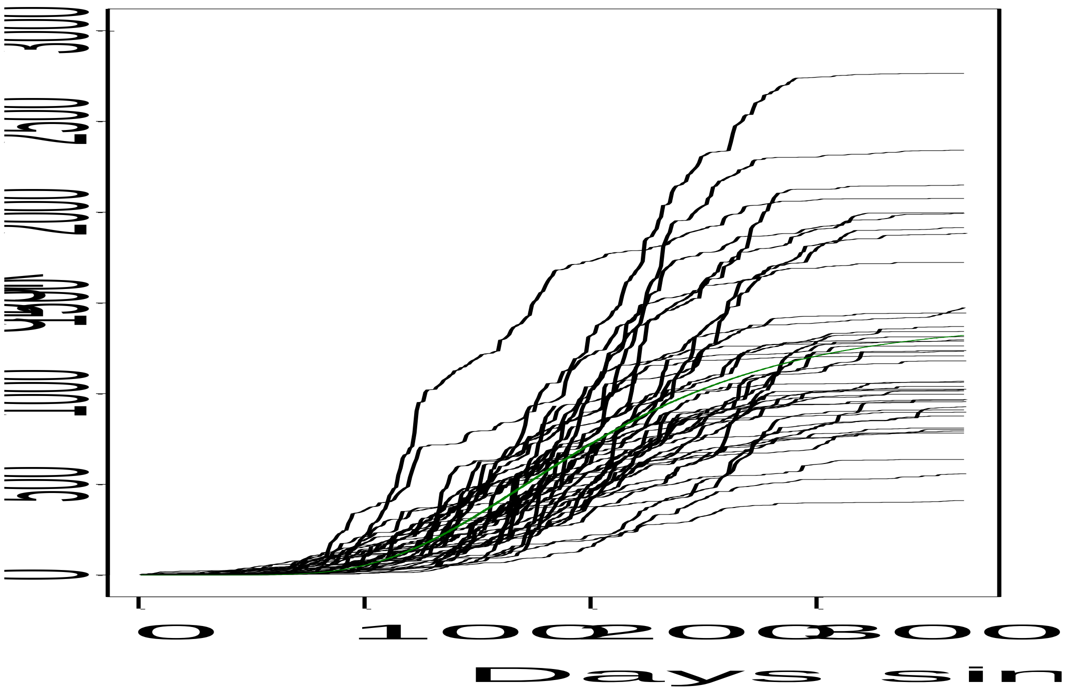

Figure A3.2. Growth in CDSR with days since July 1st using data recorded at Christchurch Aero. The solid green line corresponds to a fixed effect of time obtained from the non-linear mixed effects model fitted to the data.

Table A3.1. Coefficient of determination (r^2) for linear relationships between the value of the Cumulative Daily Severity Rating (CDSR) at day *i* and CDSR value at day *j* for Christchurch Aero.

Day *i*	Days into Fire Season, Day *j*						
	90	120	150	180	210	240	270
90	1.00	0.53	0.37	0.26 -	-	-	
120		1.00	0.77	0.59	0.44 -	-	
150			1.00	0.78	0.65	0.38 -	
180				1.00	0.83	0.55	0.51

Appendix 3. cont.

DNA – Dunedin Aero

```
Nonlinear mixed-effects model fit by maximum likelihood
  Model: CDSR.seas ~ A * (1 - exp( - B * jul.day.seas))^C
 Data: dna.new
     AIC      BIC    logLik
  148995 149032.9 -74492.51

Random effects:
 Formula: A ~ 1 | fire.seas
               A Residual
StdDev: 226.5238 40.56829

Fixed effects: list(A ~ 1, B ~ 1, C ~ 1)
     Value Std.Error    DF  t-value p-value
A 552.1585  35.95331 14471 15.35766  <.0001
B   0.0101   0.00012 14471 85.80474  <.0001
C   5.7827   0.10389 14471 55.66352  <.0001
 Correlation:
      A      B
B -0.080
C -0.073  0.977

Standardized Within-Group Residuals:
     Min          Q1         Med        Q3       Max
 -4.61266 -0.2722715 0.04858733 0.47299 4.334011

Number of Observations: 14513
Number of Groups: 40
```

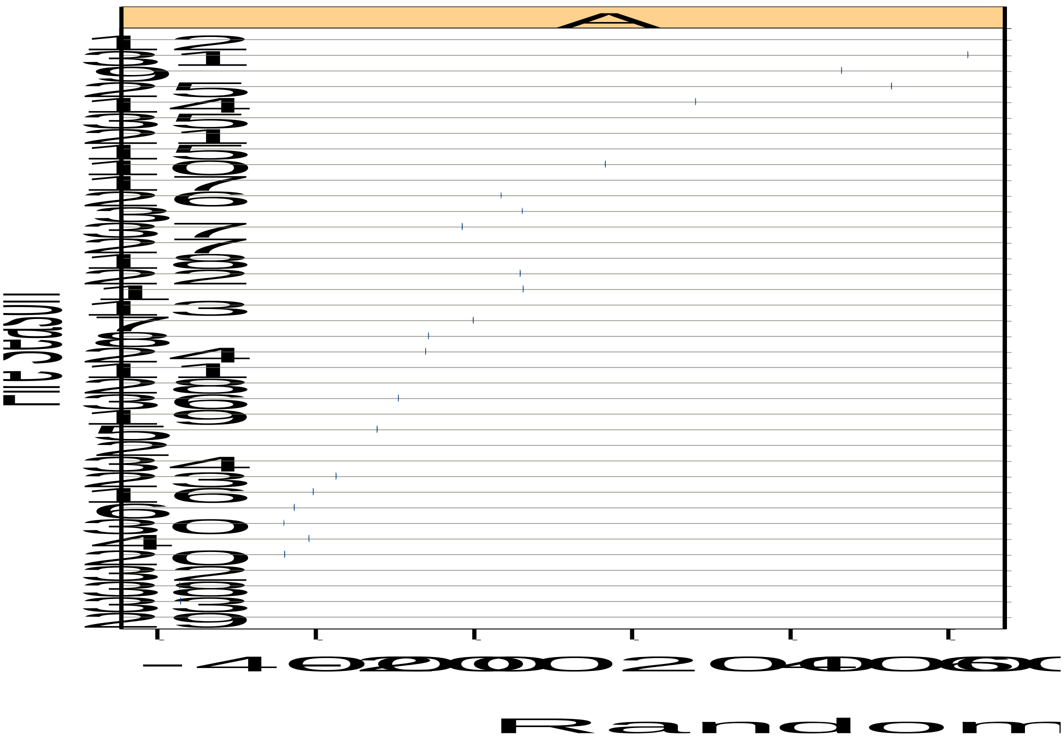

Figure A3.3. Value of the random component of the *a* parameter in the Chapman-Richards equation fitted to CDSR for Dunedin Aero.

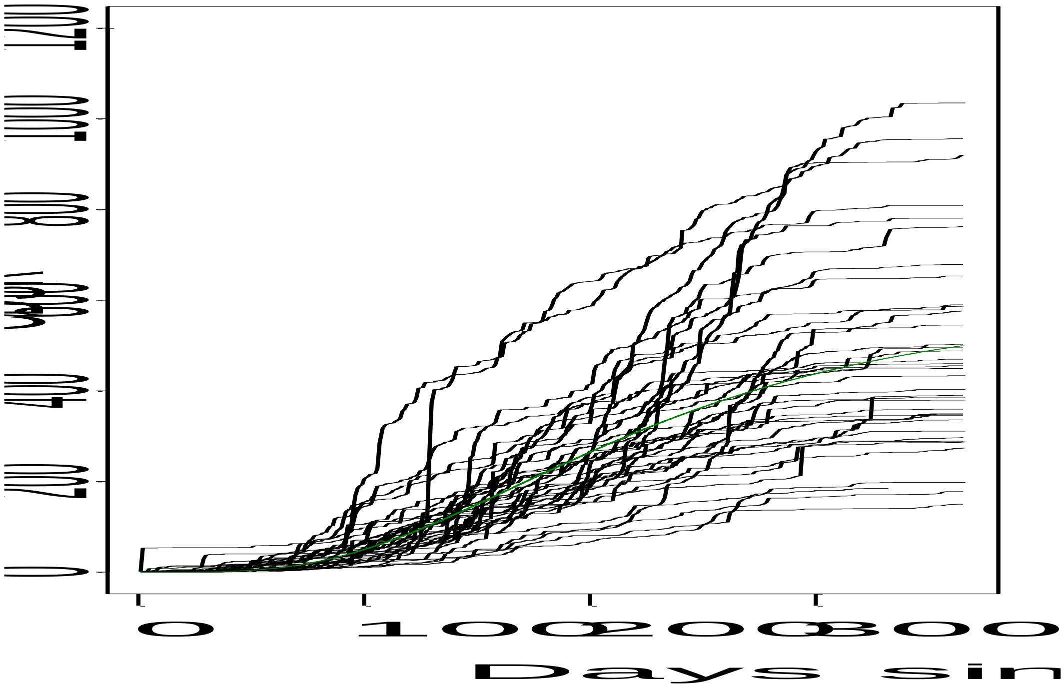

Figure A3.4. Growth in CDSR with days since July 1st using data recorded at Dunedin Aero. The solid green line corresponds to a fixed effect of time obtained from the non-linear mixed effects model fitted to the data.

Table A3.2. Coefficient of determination (r^2) for linear relationships between the value of the Cumulative Daily Severity Rating (CDSR) at day *i* and CDSR value at day *j* for Dunedin Aero.

Day *i*	Days into Fire Season, Day *j*						
	90	120	150	180	210	240	270
90	1.00	0.77	0.52	0.51	-	-	-
120		1.00	0.68	0.55	0.46	-	-
150			1.00	0.78	0.72	0.53	-
180				1.00	0.90	0.65	0.43

Appendix 3. cont.

GSA – Gisborne Aero

```
Nonlinear mixed-effects model fit by maximum likelihood
  Model: CDSR.seas ~ A * (1 - exp( - B * jul.day.seas))^C
 Data: gsa.new
     AIC      BIC    logLik
  174267 174305.1 -87128.51

Random effects:
 Formula: A ~ 1 | fire.seas
               A Residual
StdDev: 539.1957 83.52875

Fixed effects: list(A ~ 1, B ~ 1, C ~ 1)
     Value Std.Error    DF  t-value p-value
A 1064.559  84.26343 14836  12.6337  <.0001
B    0.017   0.00012 14836 132.7644  <.0001
C   18.013   0.37599 14836  47.9085  <.0001
 Correlation:
       A      B
B -0.028
C -0.025  0.983

Standardized Within-Group Residuals:
      Min         Q1         Med         Q3     Max
 -5.68781 -0.2434658 0.07910536 0.5041292 5.34727

Number of Observations: 14879
Number of Groups: 41
```

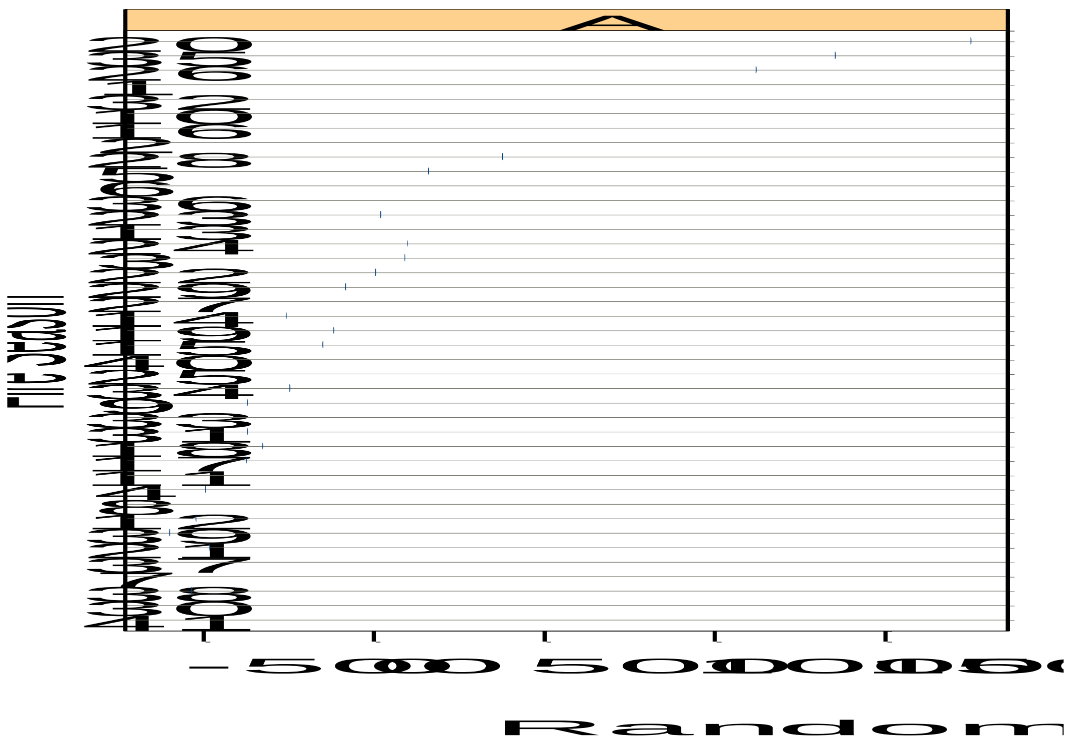

Figure A3.5. Value of the random component of the *a* parameter in the Chapman-Richards equation fitted to CDSR for Gisborne Aero.

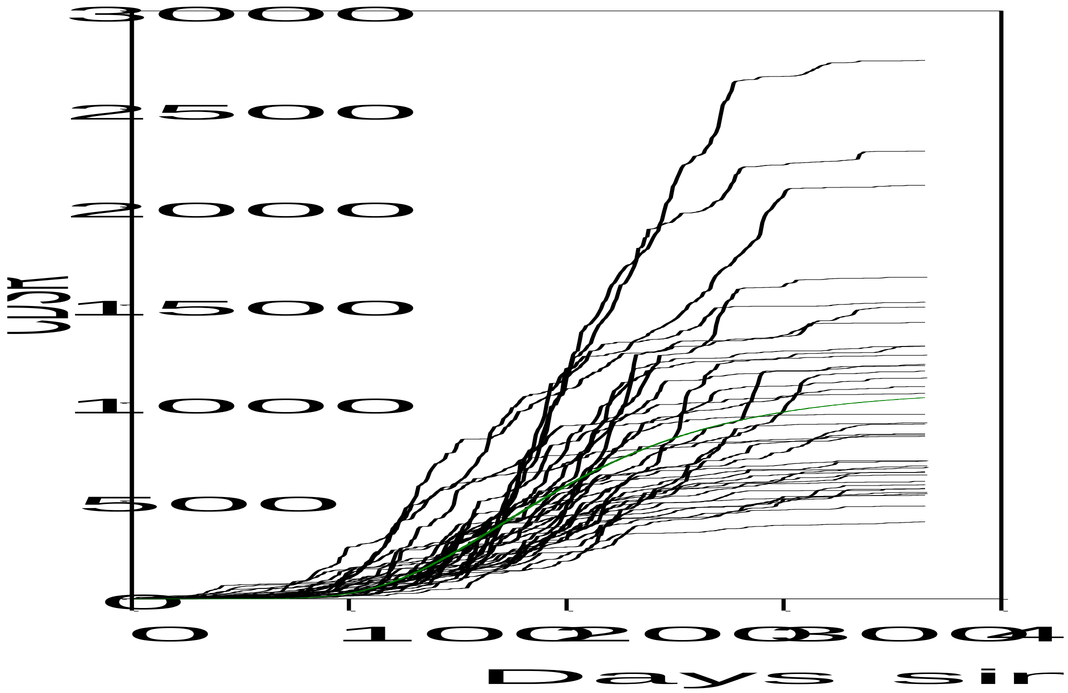

Figure A3.6. Growth in CDSR with days since July 1st using data recorded at Gisborne Aero. The solid green line corresponds to a fixed effect of time obtained from the non-linear mixed effects model fitted to the data.

Table A3.2. Coefficient of determination (r^2) for linear relationships between the value of the Cumulative Daily Severity Rating (CDSR) at day *i* and CDSR value at day *j* for Gisborne Aero.

Day *i*	Days into Fire Season, Day *j*						
	90	120	150	180	210	240	270
90	1.00	0.47	0.34	0.26	-	-	-
120		1.00	0.73	0.45	0.14	-	-
150			1.00	0.65	0.35	0.22	-
180				1.00	0.74	0.55	0.50

Appendix 3. cont.

HKA – Hokitika Aero

```
Nonlinear mixed-effects model fit by maximum likelihood
  Model: CDSR.seas ~ A * (1 - exp( - B * jul.day.seas))^C
 Data: hka.new
      AIC      BIC    logLik
  85796.1 85833.89 -42893.05

Random effects:
 Formula: A ~ 1 | fire.seas
               A Residual
StdDev: 26.69599 4.963886

Fixed effects: list(A ~ 1, B ~ 1, C ~ 1)
     Value Std.Error    DF  t-value p-value
A 55.17574  4.304264 14107 12.81886  <.0001
B  0.00843  0.000146 14107 57.73333  <.0001
C  4.28364  0.091927 14107 46.59833  <.0001
 Correlation:
      A      B
B -0.110
C -0.101  0.975

Standardized Within-Group Residuals:
      Min          Q1         Med         Q3      Max
 -3.23389 -0.4126247 0.05322187 0.5641709 4.819004

Number of Observations: 14148
Number of Groups: 39
```

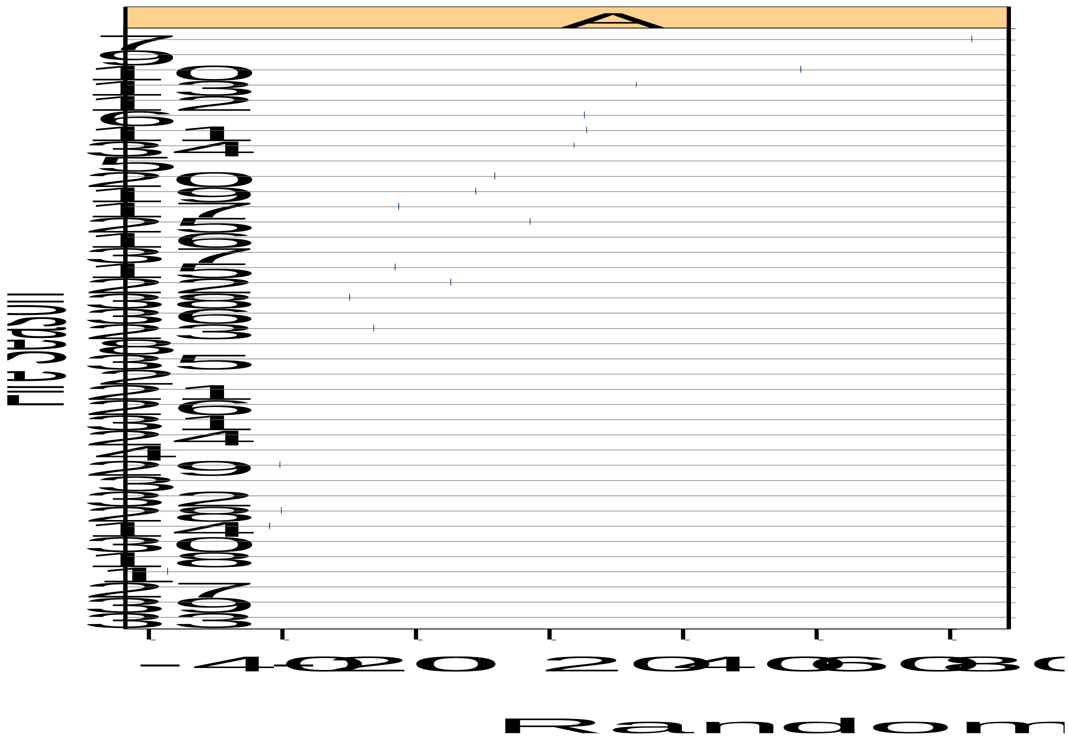

Figure A3.9. Value of the random component of the *a* parameter in the Chapman-Richards equation fitted to CDSR for Hokitika Aero.

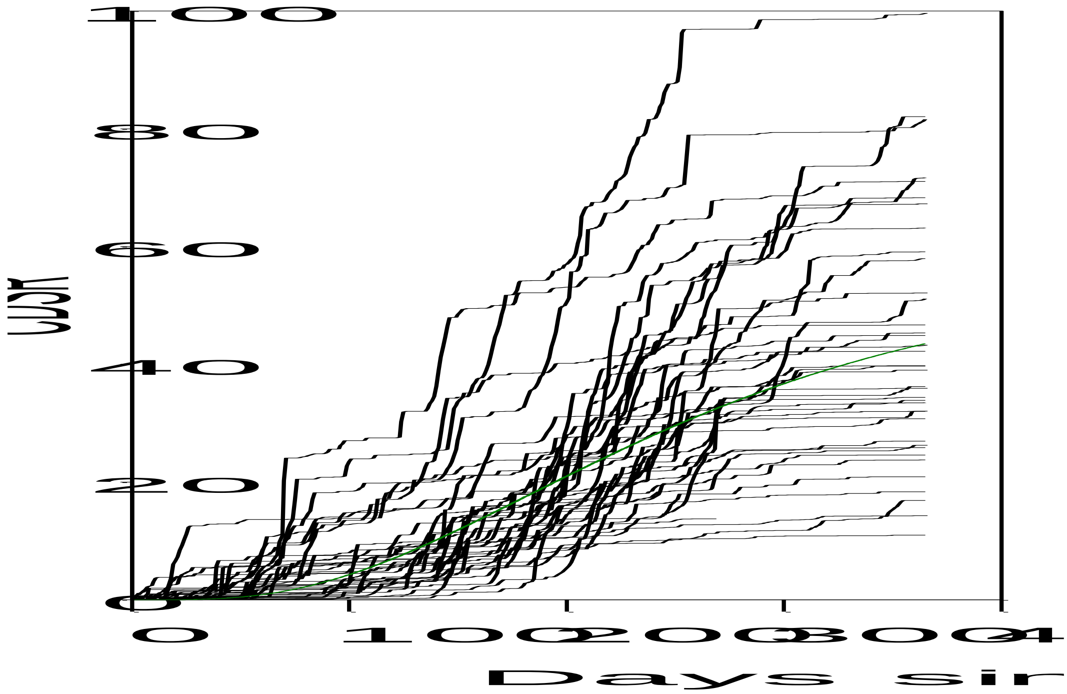

Figure A3.10. Growth in CDSR with days since July 1st using data recorded at Hokitika Aero. The solid green line corresponds to a fixed effect of time obtained from the non-linear mixed effects model fitted to the data.

Table A3.4. Coefficient of determination (r^2) for linear relationships between the value of the Cumulative Daily Severity Rating (CDSR) at day *i* and CDSR value at day *j* for Hokitika Aero.

Day *i*	Days into Fire Season, Day *j*						
	90	120	150	180	210	240	270
90	1.00	0.93	0.72	0.62 -	-	-	
120		1.00	0.81	0.70	0.41 -	-	
150			1.00	0.89	0.57	0.46 -	
180				1.00	0.76	0.59	0.54

Appendix 3. cont.

NSA – Nelson Aero

```
Nonlinear mixed-effects model fit by maximum likelihood
  Model: CDSR.seas ~ A * (1 - exp( - B * jul.day.seas))^C
 Data: nsa.new
       AIC      BIC    logLik
  150447.3 150485.3 -75218.63

Random effects:
 Formula: A ~ 1 | fire.seas
               A Residual
StdDev: 253.6565 37.51522

Fixed effects: list(A ~ 1, B ~ 1, C ~ 1)
     Value Std.Error    DF  t-value p-value
A 556.8472  39.64191 14836  14.0469  <.0001
B   0.0177   0.00012 14836 149.3264  <.0001
C  29.7310   0.63882 14836  46.5402  <.0001
 Correlation:
       A      B
B -0.029
C -0.026  0.987

Standardized Within-Group Residuals:
       Min         Q1         Med         Q3       Max
 -6.461105 -0.172914 0.09825879 0.5078845 5.866251

Number of Observations: 14879
Number of Groups: 41
```

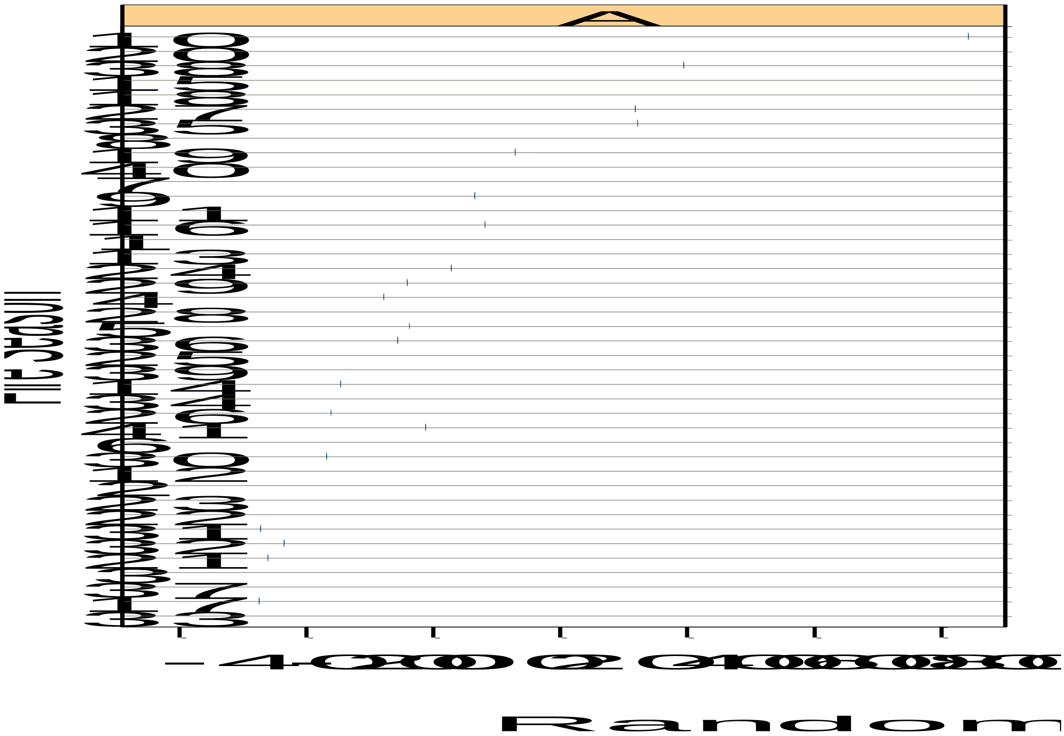

Figure A3.7. Value of the random component of the *a* parameter in the Chapman-Richards equation fitted to CDSR for Nelson Aero.

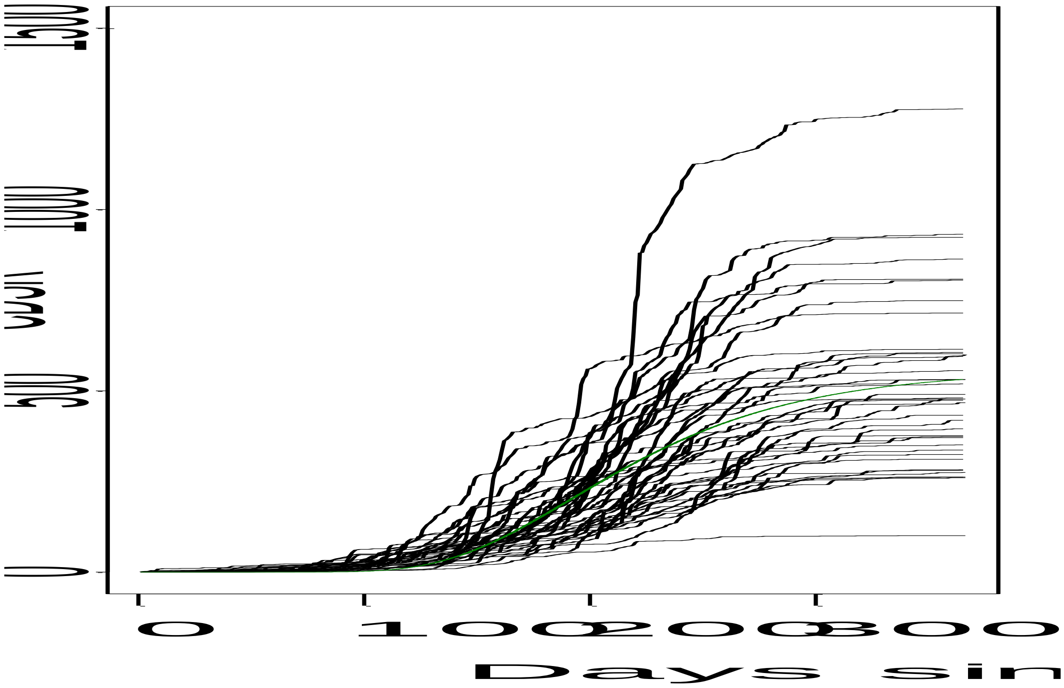

Figure A3.8. Growth in CDSR with days since July 1st using data recorded at Nelson Aero. The solid green line corresponds to a fixed effect of time obtained from the non-linear mixed effects model fitted to the data.

Table A3.5. Coefficient of determination (r^2) for linear relationships between the value of the Cumulative Daily Severity Rating (CDSR) at day *i* and CDSR value at day *j* for Nelson Aero.

Day *i*	Days into Fire Season, Day *j*						
	90	120	150	180	210	240	270
90	1.00	0.24	0.02	0.00 -	-	-	
120		1.00	0.49	0.29	0.16 -	-	
150			1.00	0.59	0.46	0.31 -	
180				1.00	0.69	0.43	0.44

Appendix 3. cont.

PPA – Paraparaumu Aero

```
Nonlinear mixed-effects model fit by maximum likelihood
  Model: CDSR.seas ~ A * (1 - exp( - B * jul.day.seas))^C
 Data: ppa.new
       AIC      BIC    logLik
  136765.9 136803.9 -68377.95

Random effects:
 Formula: A ~ 1 | fire.seas
               A Residual
StdDev: 142.5786 23.70089

Fixed effects: list(A ~ 1, B ~ 1, C ~ 1)
     Value Std.Error    DF  t-value p-value
A 341.8589  22.29746 14836  15.3317  <.0001
B   0.0158   0.00012 14836 127.5307  <.0001
C  23.6691   0.53741 14836  44.0425  <.0001
 Correlation:
       A      B
B -0.044
C -0.041  0.987

Standardized Within-Group Residuals:
       Min          Q1        Med         Q3       Max
 -8.123744 -0.1159616 0.1918375 0.6308971 4.397322

Number of Observations: 14879
Number of Groups: 41
```

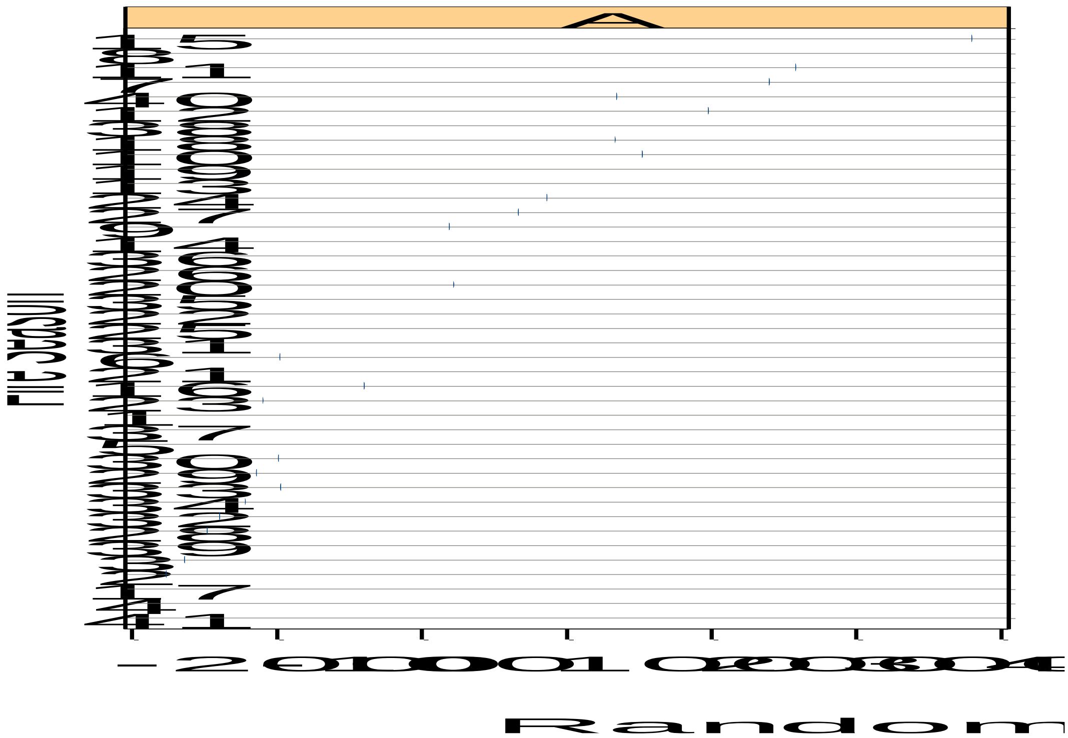

Figure A3.11. Value of the random component of the *a* parameter in the Chapman-Richards equation fitted to CDSR for Paraparaumu Aero.

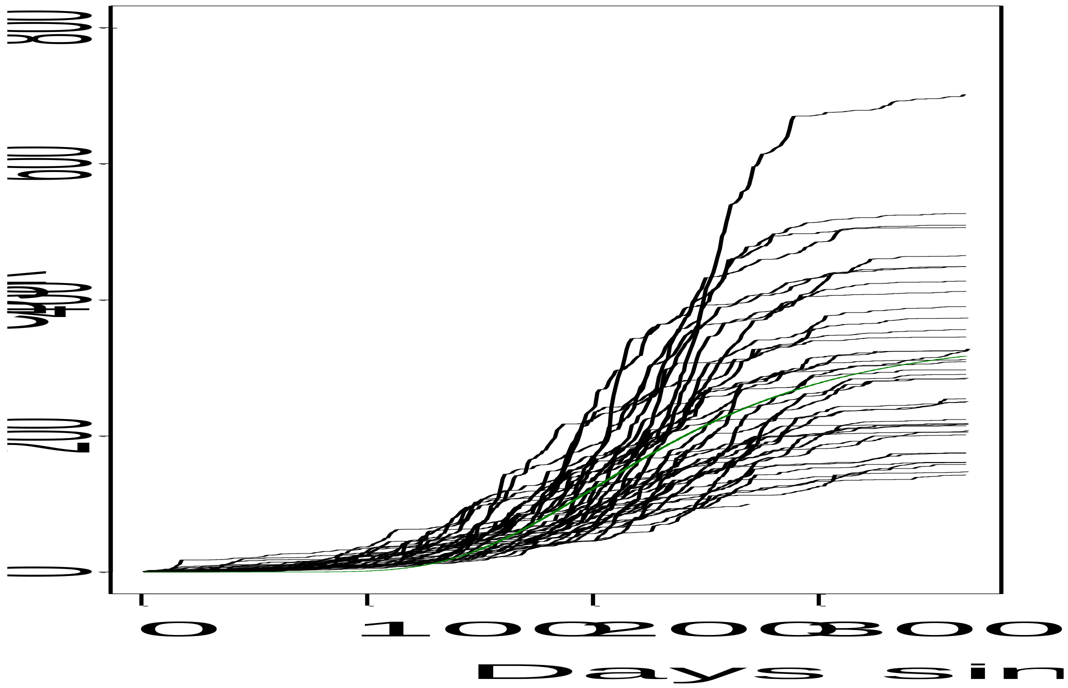

Figure A3.12. Growth in CDSR with days since July 1st using data recorded at Paraparaumu Aero. The solid green line corresponds to a fixed effect of time obtained from the non-linear mixed effects model fitted to the data.

Table A3.6. Coefficient of determination (r^2) for linear relationships between the value of the Cumulative Daily Severity Rating (CDSR) at day *i* and CDSR value at day *j* for Paraparaumu Aero.

Day *i*	Days into Fire Season, Day *j*						
	90	120	150	180	210	240	270
90	1.00	0.52	0.29	0.11 -	-	-	
120		1.00	0.41	0.13	0.02 -	-	
150			1.00	0.51	0.22	0.23 -	
180				1.00	0.62	0.46	0.31

Appendix 3. cont.

WSA – Westport Aero

```
Nonlinear mixed-effects model fit by maximum likelihood
  Model: CDSR.seas ~ A * (1 - exp( - B * jul.day.seas))^C
 Data: wsa.new
       AIC      BIC    logLik
  76062.95 76099.9 -38026.48

Random effects:
 Formula: A ~ 1 | fire.seas
              A Residual
StdDev: 35.09306 5.756312

Fixed effects: list(A ~ 1, B ~ 1, C ~ 1)
     Value Std.Error    DF  t-value p-value
A 68.24991  6.125854 11922 11.14129  <.0001
B  0.01148  0.000151 11922 75.88652  <.0001
C  9.08551  0.228416 11922 39.77620  <.0001
 Correlation:
       A      B
B -0.067
C -0.062  0.982

Standardized Within-Group Residuals:
      Min          Q1       Med         Q3      Max
 -5.60723 -0.2254966 0.1157488 0.5340132 3.886064

Number of Observations: 11957
Number of Groups: 33
```

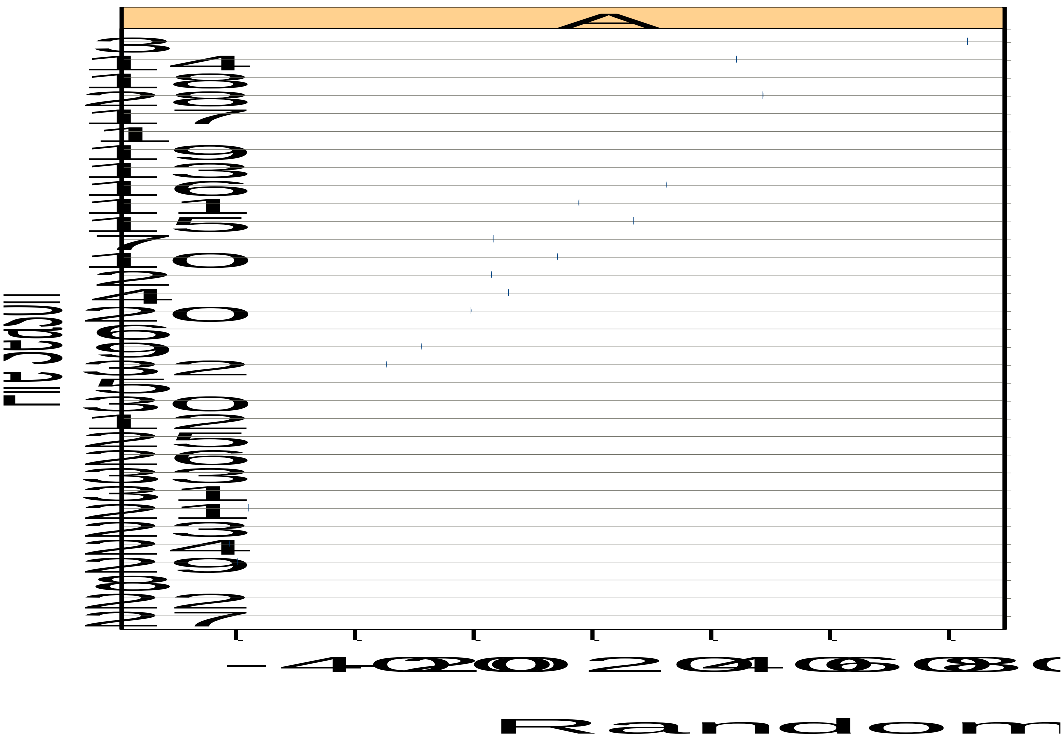

Figure A3.13. Value of the random component of the *a* parameter in the Chapman-Richards equation fitted to CDSR for Westport Aero.

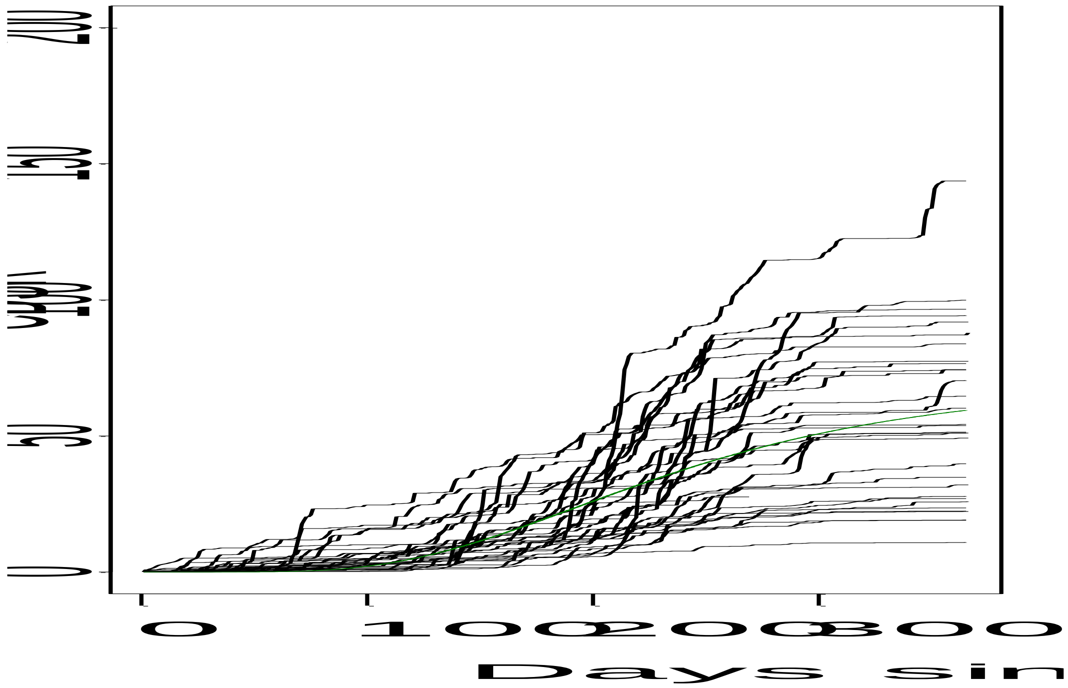

Figure A3.14. Growth in CDSR with days since July 1st using data recorded at Westport Aero. The solid green line corresponds to a fixed effect of time obtained from the non-linear mixed effects model fitted to the data.

Table A3.7. Coefficient of determination (r^2) for linear relationships between the value of the Cumulative Daily Severity Rating (CDSR) at day *i* and CDSR value at day *j* for Westport Aero.

Day *i*	Days into Fire Season, Day *j*						
	90	120	150	180	210	240	270
90	1.00	0.89	0.71	0.59	-	-	-
120		1.00	0.73	0.54	0.28	-	-
150			1.00	0.82	0.45	0.36	-
180				1.00	0.68	0.57	0.51