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FACULDADE DE CIÊNCIAS
DEPARTAMENTO DE ENGENHARIA GEOGRÁFICA, GEOFÍSICA E ENERGIA

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Statistical models to forecast summer burned area in Portugal based on meteorological indices of fire danger

Sílvia Almeida Nunes

Dissertação

Mestrado Integrado em Engenharia da Energia e do Ambiente

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Orientadores:

Professor Doutor Carlos da Camara (Professor Associado FCUL)

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“O passado está na tua cabeça, o futuro nas tuas mãos”

Abstract

Like in other Mediterranean regions, climate and weather are the major drivers of fire activity in Portugal. The aim of the present study is to assess the role of meteorological factors on the inter-annual variability of burned area over a region of Central Portugal. The study covers a 32-year period that extends from 1980 to 2011. The study region is dominated by forest and the high percentages of maritime pine, eucalyptus and oak, that are extremely flammable in summer, explain the fact that, although occupying only 18% of the territory of Portugal, the chosen study area is responsible for 43% of the burned area in August during the study period.

A normal distribution model is fitted to the 32-year sample of decimal logarithms of monthly burned area during August over the study area. This model is then improved by introducing as covariates two different measures of prevailing meteorological conditions as derived from Daily Severity Rate (DSR), an indicator of meteorological fire danger; DSR_{cum} which consists of cumulated values of monthly means of DSR from April to June and DSR_{+} which consists of the square root of the mean of the squared daily deviations of DSR in August from the climatology, the average being performed only over days of positive deviation. Three models were accordingly derived; the "climate anomaly" model that uses DSR_{cum} as a covariate; the "weather anomaly" model that uses DSR_{+} as a covariate; and the "combined" model that uses both DSR_{cum} and DSR_{+} as covariates. The three models were used to define background fire danger, D_{BG}, fire weather danger, D_{FW}, and combined fire danger, D_{COMB}, respectively. These three types of danger respectively quantify the increase or decrease in probability of having a large fire in August that is attributed to pre-fire season conditions, to fire season conditions and to both conditions.

Results from the "climate anomaly" model put into evidence the role of long-term pre-fire season conditions on the inter-annual variability of burned area. All but one of the 11 cases modeled as of low (high) level of background fire danger belong to the severe (mild) category. However short-term meteorological conditions during August have a key role on inter-annual variability as illustrated by the relatively better performance of the "weather anomaly" model. The two meteorological factors, *i.e.* the "climate anomaly" and the "weather anomaly" have nevertheless to be taken together into account in order to improve modeling of the moderate years. This is demonstrated by the increase in performance of the "combined" model that was mainly due to an increase in the number of moderate years that were modeled as of medium danger.

Keywords:

Fire activity, extreme events, climate and meteorological conditions, statistical models, fire prevention

Resumo

Nos últimos anos, os incêndios florestais têm vindo a cativar a atenção da comunidade científica, procurando os investigadores identificar os principais fatores que controlam estes eventos, que têm vindo a tornar-se cada vez mais extremos. No contexto europeu a zona Mediterrânica assume especial relevância na medida em que representa cerca de 85% de toda a área ardida na Europa. Só em Portugal Continental, segundo estatísticas oficiais, arderam cerca de 3 468 986 ha no período de1980 a 2011, uma área que é equivalente a 3/5 de toda a floresta portuguesa, sendo que no final deste período foi quando se registou um maior aumento destes valores, que teme-se que continuem a aumentar.

Os incêndios em Portugal, tal como em toda a Europa mediterrânica, são um fenómeno natural relacionado com mecanismos meteorológicos, atividade antropogénica e condições da vegetação que se traduzem na quantidade de combustível disponível. Mesmo que as ações do homem, como a migração do interior para o litoral com o consequente abandono das terras, numa escala global, sejam responsáveis por grande parte da ignição dos fogos, diferentes estudos apontam as condições meteorológicas e climáticas como grandes responsáveis pelo aumento das áreas ardidas, na medida em que o clima em Portugal é caracterizado por invernos chuvosos e fracos seguidos de verões muito quentes e secos que induzem um stress elevado na vegetação quando chega o verão, época de ocorrência da maioria dos fogos. Tem-se assim que, caso não estejam reunidas as condições necessárias para todas as diferentes etapas presentes num incêndio, rápida e facilmente este será apagado. Assim, por exemplo, a precipitação e a temperatura são dois fatores importantes na primavera na medida em que condicionam a quantidade de combustível existente para arder, o vento e a precipitação são de extrema importância para o desenvolvimento e extinção do fogo e a temperatura é crucial para a ignição deste. Diversos estudos apontam, ainda, que, para Portugal, os dois fatores que controlam a variabilidade interanual da área ardida são os relacionados com a ocorrência de longos períodos de seca sem precipitação na pré-época de incêndios e de dias de elevada temperatura, associados a ondas de calor no verão, durante o período mais favorável à ocorrência de incêndios florestais.

Com o presente trabalho pretende-se ter uma melhor compreensão da contribuição dos diversos fatores meteorológicos para a inter-variabilidade anual de área ardida em Agosto numa região central de Portugal. Os fatores meteorológicos são, normalmente, caracterizados a partir de sistemas de avaliação do risco de incêndio, os quais normalmente dependem de índices provenientes de parâmetros meteorológicos. No presente estudo recorre-se ao denominado *Daily Severety Rating* (DSR), uma componente do *Canadian Forest Fire Danger Rating System* (CFFDRS). Este índice será utilizado para caracterizar a pré-época de incêndio, respetivamente em termos de stress térmico e stress hídrico da vegetação, bem como constituirá um indicador de condições meteorológicas extremas que ocorrem nos meses de verão.

O presente estudo foi motivado pelo projeto de licenciatura da autora, subordinado título “Vegetation stress and summer fire activity in Portugal’. Este trabalho teve como objetivo principal o de avaliar a importância da informação proveniente de meios de deteção remota para a monitorização do *stress* da vegetação durante a pré-época de incêndios, tendo-se demonstrado que esta informação específica pode contribuir para a construção de cenários de severidade para as épocas de incêndio que imediatamente se seguem (Nunes, 2012). Procedeu-se a uma análise dos ciclos de temperatura, ao nível da superfície do solo bem como condições fenológicas da vegetação para determinados anos separados em classes caracterizadas por valores muito elevados ou muito baixos de área ardida. O *stress* térmico da vegetação foi analisado usando uma série temporal de compósitos de 10 dias de temperatura de brilho a 10,8 µm, enquanto que o *stress* hídrico foi caracterizado por uma série temporal de compósitos de 10 dias de dois índices vegetativos, os denominados *normalized difference vegetation index* (NDVI) e *leaf area index* (LAI). Os resultados obtidos põem em evidência o papel do *stress* térmico nos meses de Verão (Julho e Agosto), enquanto o *stress* hídrico toma um papel mais importante para os meses de Primavera (Abril até Junho). Anos com valores elevados de área ardida mostram-se associados a anomalias positivas de LAI na Primavera e temperatura no Verão, ou seja, mais biomassa na Primavera e mais *stress* no Verão. Anos com valores mais baixos apresentam um comportamento completamente oposto, mostrando-se associados a anomalias negativas de LAI na Primavera e de temperatura no Verão, ou seja, défice de biomassa e condições desfavoráveis para ignição no Verão. Com base nesta informação, construiu-se um modelo de lógica vaga (modelo verbal) para a severidade dos incêndios no Verão. Devido à relação entre o *stress* da vegetação com as condições meteorológicas de longo prazo durante Primavera, expressas em termos de temperatura e precipitação, e dada a relação estreita do *stress* térmico da vegetação com as condições meteorológicas extremas que favorecem a ignição e propagação do fogo, este estudo também colocou em perspetiva a importância de fatores climáticos e meteorológicos quando se pretende avaliar a severidade da época de incêndios (Nunes, et al., 2013).

O objetivo do presente estudo é o de proporcionar uma melhor compreensão do papel desempenhado pelas condições meteorológicas durante a pré-época e a época de incêndios, bem como analisar a importância relativa dos seus impactos na inter-variabilidade anual de área ardida. Começa por mostrar-se-se que os valores logarítmicos decimais de área ardida em Agosto na área em estudo para o período de 1980 a 2011 seguem uma distribuição normal. Seguidamente mostra-se que essa distribuição normal pode ser melhorada incorporando no modelo covariáveis baseadas em dois tipos de valores acumulados de DSR: DSR_{cum} que consiste em valores mensais médios acumulados de DSR de April a Julho e DSR_{+} que consiste na raiz quadrada da média diária dos quadrados dos desvios climatológicos dos valores diários DSR em Agosto, operando a média apenas sobre os dias com desvio positivo. Derivaram-se assim três diferentes modelos, nomeadamente o modelo de “anomalia climática” que utiliza o DSR_{cum} como co variável, o modelo de “anomalia meteorológica” que utiliza o DSR_{s} como covariável e o modelo “combinado” que utiliza ambos os DSR_{cum} e DSR_{+} como covariáveis. Mostra-se, em seguida, que o desempenho do modelo de “anomalia meteorológica” apresenta melhores resultados que o modelo de “anomalia climática” e que o desempenho do modelo “combinado” é significativamente melhor do que o dos modelos anteriores. Esta informação é especialmente interessante na medida em que aponta para o facto das condições de pré-época de incêndios não poderem ser ignoradas quando se analisa a variabilidade interanal de área ardida. Os resultados obtidos proporcionam ainda uma perspetiva interessante em relação ao desenvolvimento de modelos estatísticos que antecipem a severidade da época de incêndios, uma ferramenta que poderá ser de importante uso na prevenção e gestão de incèndios.

Os três modelos desenvolvidos foram ainda utilizados para definir “perigo de background”, D_{BG}, “perigo meteorológico”, D_{FW} e “perigo combinado”, D_{COMB}. Os três tipo de perigo de incêndios quantificam respetivamente o acréscimo ou decréscimo da probabilidade de ocorrência de grandes incêndios em Agosto que se pode atribuir a condições meteorológicas na pré-época de incêndios, na época de incêndios ou ambas. Finalmente mostr$_a$-se que anos como 1991, 2003 e 2005, caracterizados por atividade muito elevada de incêndios, se encontram associados a níveis elevados de D_{BG}, D_{FW} and D_{COMB}, enquanto anos como 1988, 1997 e 2008, caracterizados por atividade muito baixa de incêndios, se encontram associados a níveis baixos de D_{BG}, D_{FW} and D_{COMB}, ficando assim evdenciado os papéis desempenhado pelas condições meteorológicas de pré-época de incêndio, que atuam à escala mensal a sazonal, e pelas condições meteorológicas durante a época de incêndios, que atuam à escala de um a 10 dias.

Palavras-chave:

Fogos florestais, eventos extremos, condições meteorológicas e climatéricas, modelos estatísticos, modelo de prevenção de fogos florestais.

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Acronyms and Abbreviations

AD: Anderson-Darling

BA: Burned Area

BUI: Buildup Index

cdf: Cumulative Difference Function

CFFBPS: Canadian Forest Fire Behavior Prediction System

CFFDRS: Canadian Forest Fire Danger Rating

CFFWIS: Canadian Forest Fire Weather Index System

DC: Drought Code

DMC: Duff Moisture Code

DSR: Daily Severity Rating

FFMC: Fine Fuel Moisture Code

FWI: Fire Weather Index

GoF: Goodness of Fit

IPMA: Instituto Português do Mar e da Atmosfera (National Weather Service)

ICNF: Instituto da Conservação da Natureza e das Florestas

ISI: Initial Spread Index

ha: hectares

LAI: Leaf Area Index

NDVI: Normalized Difference Vegetation Index

pdf: Probability Density Distribution Function

PRFD: Portuguese Rural Fire Database

PROF: Planos Regionais de Ordenamento Floresta (Regional Plans for Forest Management)

SSR: Seasonal Severity Rating

Symbols

μ *: mean*

σ*: standard deviation*

$\mathcal{P}$*: probability*

n*: data length*

N_x*: normal cumulative distribution function*

Λ*: likelihood function*

L*: log-likelihood function*

N*: assumed normal distribution*

a,b,c: parameters of linear relationships

D_{b0}*: baseline danger*

x_0*: threshold*

DSR_{cum}*: cumulate DSR from April up to July*

DSR_{+}*: square root of the mean of squared deviations from the climatological mean*

D_{ca}*: climate anomaly danger*

D_{BG}*: background fire danger*

A_d*: daily weather anomaly*

D_{wa}*: weather anomaly danger*

D_{FW}*: fire weather danger*

D_{c+w}*: climate and weather anomaly*

D_{COMB}*: combined fire danger*

Chapter 1

Introduction

Fire events have been gradually acquiring increasing importance in the last few decades not only because of the dramatic destruction of vegetation at the global scale and associated changes at the landscape level, but also because of the related emissions in greenhouse gases, namely in CO_2. The impact of emissions resulting from fire activity on the radiative balance of the planet cannot be disregarded and the assessment of the role of global fires on climate change is a major topic of current research at the international level. The expected warmer climate that is associated to future climate scenarios is also likely to lead to more frequent and long-lasting extreme events of fire activity and to larger values of total burned area with increased variability.

At the European level, these problems are especially relevant in Mediterranean Europe, one of the most wildfire-affected regions, being responsible for 85 % of all European burned area and related economic and ecologic losses and damage (Pausas, et al., 1999; San-Miguel-Ayanaz, et al., 2013). When looking to the case of Portugal, one finds the highest scores of fire occurrences and affected area in all Mediterranean (Pereira, et al., 2005). According to the official records, during the period between 1980 and 2011, 3 468 986 hectares have burned in Mainland Portugal, which is equivalent to around 3/5 of the total forested surface (Direção de Unidade de Defesa da Floresta, 1980 to 2012). In fact, in the last few years, the amount of burned area, number of large fires and fire severity had a very significant increase in Portugal (Pereira, et al., 2011).

Fire activity in Portugal, as in Mediterranean Europe, is a natural phenomenon linked to meteorological mechanisms, anthropogenic activity and vegetation conditions or fuel availability (San-Miguel-Ayanz, et al., 2003). Fire activity in Mediterranean Europe is also closely related to the climatological background and associated weather conditions: rainy and mild winters, followed by warm and dry summers, may induce high levels of vegetation stress leading to a likely occurrence of major fire events in case of suitable weather conditions promoting the fire ignition and spread (Pereira, et al., 2005). Even though, at the global scale, the majority of fires are caused by human activity (like depopulation of rural areas and abandonment of agricultural lands), several studies have pointed out that the major drivers of fire activity (in fires with the largest burned area) are weather and climate. If the right conditions to all stages of the fire (*i.e.* ignition, development and extinction) do not exist, then the fire will easily be extinguished. For instance, precipitation and temperature in the pre-fire season will influence the fuel availability; wind and precipitation are crucial elements when in the development and extinction stages; temperature is one of the most factors responsible for fire ignition (Aldersley, et al., 2011).

Meteorological factors are therefore a crucial part when studying the different perspectives of fire activity, like intensity, frequency and total burned area. For instance, (Pereira, et al., 2005) have shown that the inter-annual variability of burned area in Portugal during the summer season is conditioned by two main meteorological factors working at different temporal and spatial scales, namely the long dry periods without precipitation in the pre-fire season and the intense dry spells during days of extreme synoptic situations that favor fire ignition and spreading.

The aim of the present study is to contribute to a better understanding of the meteorological factors that affect inter-annual variability of burned area in August over a region in Central Portugal characterized by large fire activity. Meteorological factors are usually characterized by means of fire danger rating systems that rely on sets of indices that are based on meteorological parameters. The present study will make use of the so-called Daily Severity Rate (DSR) that is part of the Canadian Forest Fire Danger Rating System (CFFDRS). This index will be used to characterize the pre-fire season in terms of levels of heat and water stress of vegetation as well as an indicator of extreme meteorological conditions taking place in summer.

This present study was motivated by the author's bachelor degree project entitled "Vegetation stress and summer fire activity in Portugal'. The main goal of that study was to assess the added-value of remote sensed information to monitor vegetation stress during the pre-fire season and demonstrate that this specific information could contribute to building up scenarios of the severity of the following summer fire season (Nunes, 2012). For this purpose, an analysis was performed of the cycles of land surface temperature and phonological activity of vegetation for classes of years characterized by very high or very low levels of fire activity. Thermal stress of vegetation was analyzed based on long time series of 10-day composites of brightness temperature at 10.8 µm whereas water stress was characterized by means of 10-day composites of the normalized difference vegetation index (NDVI) and of the leaf area index (LAI). Results obtained put into evidence the role of thermal stress in summer (July and August) and the water stress in spring (April to June). Years of high fire activity showed to be associated to positive anomalies of LAI in spring and temperature in summer, which means more biomass in spring and more stress in the summer. An opposed behavior characterized years of low fire activity, which were associated with negative anomalies of LAI in spring and of temperature in summer, which means lack of biomass and unfavorable conditions to ignitions. Based on this information a fuzzy model (verbal model) was built that was able to model fire activity in summer. Because of the relationship of vegetation stress with the long-term meteorological conditions in spring in terms of temperature and precipitation and given the close relationship of thermal stress of vegetation with extreme meteorological conditions favoring fire ignition and spread, performed research also brought into perspective the importance of climate and meteorological factors when assessing the severity of the fire season (Nunes, et al., 2013).

The aim of the present study is to better understand the role played by meteorological conditions during the pre-fire and during the fire seasons and to analyze the relative importance of their impact on inter-annual variability of burned area. First it will be demonstrated that the decimal logarithms of burned area in August over the study area for the period 1980-2011 are normally distributed. It will then be shown that such normal model may be improved by incorporating covariates consisting of DSR-based quantities of two kinds; DSR_{cum} consisting of cumulated values of monthly means of DSR from April to July and DSR_{+} consisting of the square root of the mean of the squared daily deviations of DSR in August from the climatology, the average being performed only over days of positive deviation. The following three models will then be derived: the "climate anomaly" model that uses DSR_{cum} as a covariate; the "weather anomaly" model that uses DSR_{+} as a covariate; and the "combined" model that uses both DSR_{cum} and DSR_{+} as covariates. It will be shown that the performance of the "weather anomaly" model is better than the one of the "climate anomaly" model and that the performance of the "combined" model is significantly better than the weather model. This is especially interesting because it shows that pre-fire season conditions cannot be disregarded when analyzing burned area amounts at the monthly level. Results obtained also open an interesting perspective towards the development of statistical models to anticipate the severity of the fire season, a tool that could be of great use in fire prevention and management.

The three models are then used to define background fire danger, D_{BG}, fire weather danger, D_{FW}, and combined fire danger D_{COMB}, respectively. These three types of danger respectively quantify the increase or decrease in probability of having a large fire in August that is attributed to pre-fire season conditions, to fire season conditions and to both conditions. Finally it is shown that years like 1991, 2003 and 2005, characterized very high fire activity, are associated to high levels of D_{BG}, D_{FW} and D_{COMB}, whereas years like 1988, 1997 and 2008, characterized by very low fire activity, are associated to low levels of D_{BG}, D_{FW} and D_{COMB}. In turn, years of moderate activity are usually characterized by different levels of D_{BG}, D_{FW} and D_{COMB}, stressing the importance of the roles played by the pre-fire season meteorological conditions, working at the monthly to the seasonal scales, and the ones played by fire season weather conditions working at the daily to 10-day scales.

Chapter 2

Data and methods

2.1 Fire Database

Information about burned area in Portugal was derived from the official Portuguese Rural Fire Database (PRFD) as supplied by the Portuguese authority for forests (*Instituto de Conservação da Natureza e das Florestas*, ICNF) which was screened for inconsistencies and corrected by (Pereira, et al., 2011). Data inconsistencies included records with null burned area, repeated records with the same date, time and spatial location, time error or negative durations, missing information (*e.g.* data, time, location), multiple records with similar location, date and time and suspicious information about area and duration.

The PRFD database includes more than half a million records of fire events over forest, shrub land, natural grassland and agricultural lands, covering the 32-year period 1980-2011. Relying on information provided by firefighters, the PRFD database includes a variety of information, which includes date and time of ignition and extinction, total burned area, cause of fire, land cover type and location of ignition as expressed in terms of the administrative division in Portugal, *i.e.*, in 2008, 18 districts (*distritos*), 278 municipalities (*concelhos*) and 4 050 parishes (f*reguesias*). A full description of the corrected PRFD database is provided in (Pereira, et al., 2011).

2.2 Fire Danger Rating

Fire danger is characterized by means of the so-called Daily Severity Rating (DSR), which is based on the Fire Weather Index (FWI) that is part the Canadian Forest Fire Danger Rating System (CFFDRS). Since 1970 CFFDRS is a major component of forest protection in Canada and since 2002 FWI is operationally used in Portugal by the National Weather Service (*Instituto Português do Mar e da Atmosfera*, IPMA).

CFFDRS currently consists in two large subsystems: the Canadian Forest Fire Weather Index System (CFFWIS) and the Canadian Forest Fire Behavior Prediction System (CFFBPS). As shown in Figure 1, CFFWIS consists of six different components based on fuel moisture and wind, which may be grouped in three fuel based mechanisms and in three fire behavior indices (Anderson, et al., 2007; Van Wagner, 1987).

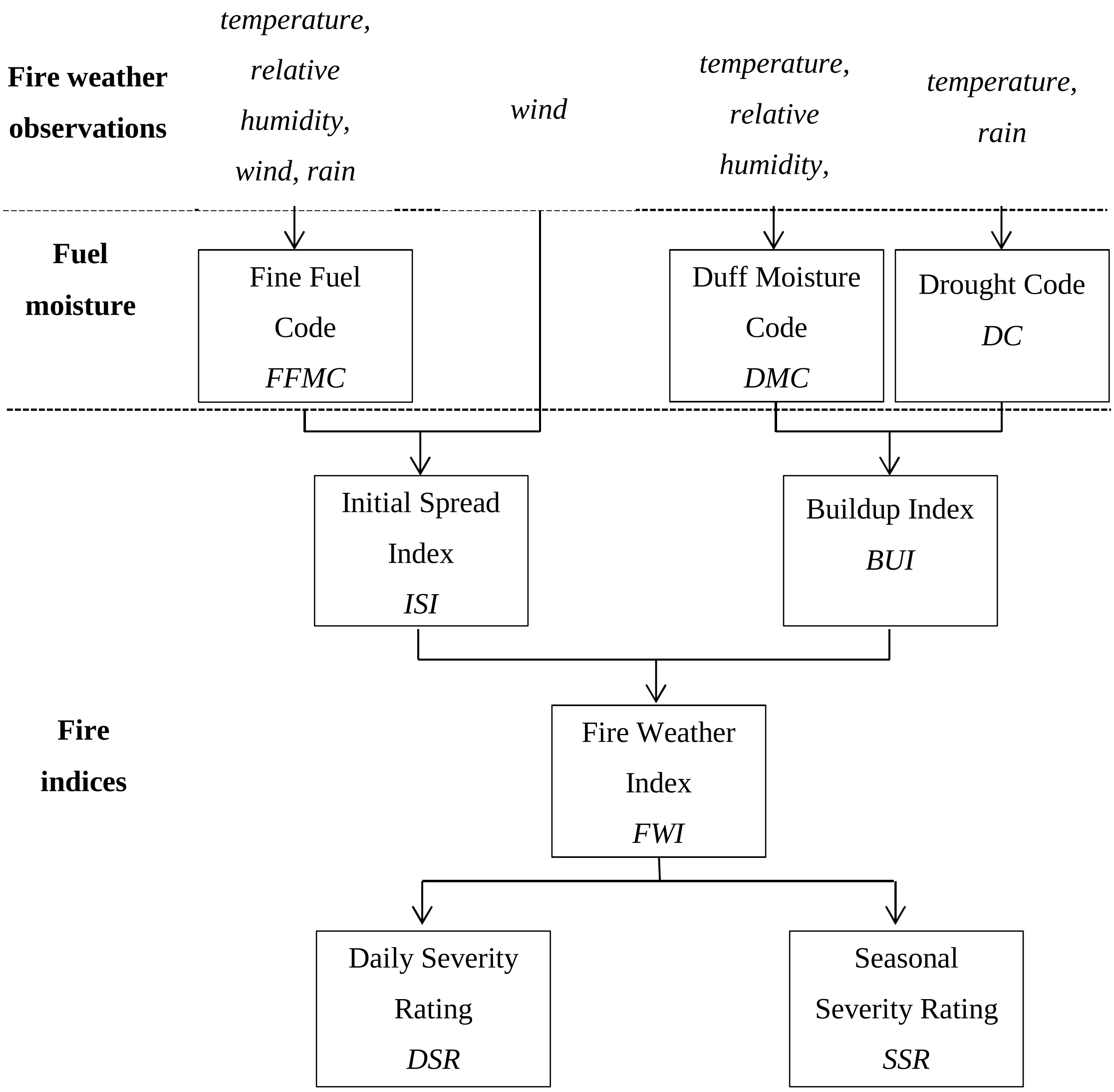

Figure 1 - The structure of CFFWIS (based on Anderson, et al (2007))

The three fuel based mechanisms, *i.e.* the Fine Fuel Moisture Code (FFMC), the Duff Moisture Code (DMC) and the Drought Code (DC), are numeric ratings of the moisture content of litter and other fine fuels, the average moisture content of loosely compacted organic layers of moderate depth, and the average moisture content of deep, compact organic layers. These codes are based on daily observations of temperature, relative humidity, wind speed, and 24-hour rainfall.

The three behavior fire indices, *i.e.* the Initial Spread Index (ISI), the Buildup Index (BUI) and the Fire Weather Index (FWI) represent the rate of fire spread, the fuel available for combustion, and the frontal fire intensity. The first one, ISI, is a combination of the FFMC with wind effects whereas the second one, BUI, is a blend of the last two fuel moisture codes, DMC and DC. The last code, FWI, results from the combination of ISI and BUI.

Daily values of FWI may be transformed into the so-called Daily Severity Rating (DSR), according to the following relationship:

$$DSR = 0{,}0272\ FWI^{1{,}77} \qquad (1)$$

DSR is a numeric rating of the difficulty of controlling fires and is considered as an extension of CFFWIS. DSR was specifically designed for averaging (or cumulating) either in time or in space. An example is the Seasonal Severity Rating (SSR), defined as:

$$SSR = \sum_{i=1}^{n} \frac{DSR_i}{n} \quad (2)$$

where DSRi is the DSR value for day i, and n is the total number of considered days. SSR is routinely used in the official annual reports of fire activity in Portugal (Direção de Unidade de Defesa da Floresta, 1980 to 2012).

2.3 Study Area

The study area consists of five contiguous regions as defined by the so-called Regional Plans for Forest Management (*Planos Regionais de Ordenamento Florestal*, PROFs). PROfs are sectorial tools for land management that support establishing intervention rules about the use and occupation of forest areas (ICNF, 2013). The aim is to provide each PROF with an appropriate technical and institutional background in order to make the most appropriate choice of soil and silviculture models since, at the regional scale, several of them may be used.

The territory of Portugal is subdivided in 21 PROFs [Figure 2, left panel] and the study area consists of the following five: *Dão e Lafões, Beira Interior Norte, Beira Interior Sul, Pinhal Interior Norte* and *Pinhal Interior Sul* [Figure 2, right panel]. Choice of the study region was done using *AreaStat*, a simple software that allows retrieving for each PROF information about the types of land use, the dominant species and the area covered by them (ICNF, 2013). The main characteristics of the five chosen PROFS are given in Table 1.

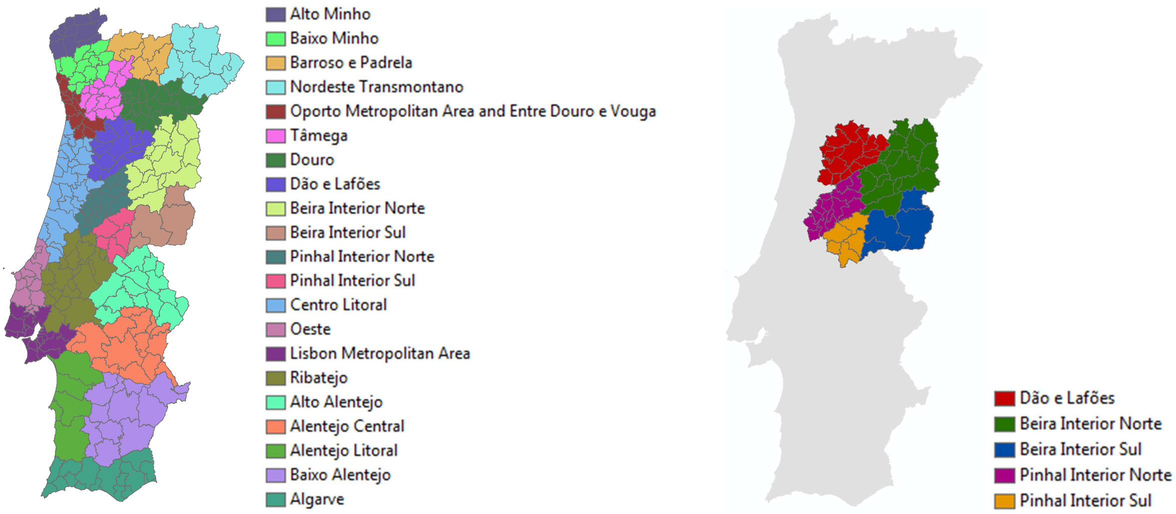

Figure 2 – The 21 Regional Plans for Forest Management (left panel) and the five PROFS that constitute the study region (right panel).

The *Dão e Lafões* PROF includes the 15 municipalities (*concelhos*) of Aguiar da Beira, Carregal do Sal, Castro Daire, Mangualde, Mortágua, Nelas, Oliveira de Frades, Penalva do Castelo, Santa Comba Dão, São Pedro do Sul, Sátão, Tondela, Vila Nova de Paiva,Viseu and Vouzela. The PROF covers a total area of 348 862 ha with 42% of the area being covered by forest. The two predominant species are maritime pine (*Pinus Pinaster*) and oak, covering 68% and 22% of the forested area, respectively.

The *Beira Interior Norte* PROF includes the 15 municipalities of Meda, Figueira de Castelo Rodrigo, Pinhel, Trancoso, Almeida, Fornos de Algodres, Celorico da Beira, Guarda, Gouveia, Sabugal, Seia, Manteigas, Belmonte, Covilhã and Fundão, spreading over a total area of 630 582 ha, 22% of which is forest .The predominant specie is *Pinus Pinaster* covering 63% of the forested area, followed by oak that covers 23%.

The *Beira Interior Sul* PROF includes the four municipalities of Castelo Branco, Idanha-a-Nova, Penamacor and Vila Velha de Ródão, covering a total area of 373 827 ha. Forests cover 43% of the area and the predominant species are eucalyptus and *Pinus Pinaster* which correspond to 32% and 31% of the forested area, respectively.

The *Pinhal Interior Norte* PROF includes the 14 municipalities of Oliveira do Hospital, Tábua, Arganil, Vila Nova de Poiares, Góies, Lousã, Miranda do Corvo, Penela, Castanheira de Pêra, Pampilhosa da Serra, Pedrógão Grande, Ansião, Figueiró dos Vinhos and Alvaiázere. The PROF spreads over an area of 261 663 ha, 43% corresponding to forest. The predominant species is *Pinus Pinaster* occupying 53% of the forested area, followed by oak occupying 35%.

The *Beira Interior Sul* PROF includes the five municipalities of Oleiros, Proença-à-Nova, Sertã, Vila de Rei and Mação, occupying a total area of 190 292 ha, 61% of the area corresponding to forests. The predominant species are eucalyptus and *Pinus Pinaster* that cover 61% and 24% of the forested area, respectively.

The five contiguous PROFs that form the study area present similar amount of the total forested area, with values ranging from about 116 up to 148 thousand ha. *Pinus Pinaster* , eucalyptus and oak are the predominant species in all five PROFS, the first two species representing a large majority in all cases, ranging from 63% in Beira Interior do Sul up to 98% in Pinhal Interior Sul. Eucaliptus is the second predominant species in four out of the five considered PROFs, oak placing second in Beira Interior do Norte, where it occupies 23%. The large fractions of the forested area with high percentages of Pinus Pinaster and eucalyptus, that are extremely flammable in summer (Regueira, et al., 1996), explain the fact that, although occupying only 18% of the territory of Portugal, the chosen study area is responsible for 43% of the burned area in August during the period 1980-2011 (Figure 3).

Table 1- General characteristics of the study area

	Dão e Lafões	***Beira Interior Norte***	***Beira Interior Sul***	***Pinhal Interior Norte***	***Pinhal Interior Sul***
Total Area (ha)	348 862	630 582	373 827	261 663	190 292
Forest (%)	42	22	43	51	61
Total Forest Area (ha)	148 247	135 957	160 534	133 030	115 571
Pinus Pinaster (%)	68	63	31	52	84
Eucalyptus (%)	22	5	32	35	14
Oak (%)	7	23	2	5	0
Other Hardwoods (%)	2	2	1	4	1
Other Coniferous (%)	0	1	1	1	0
Chestnut (%)	0	2	0	2	0
Stone Pine (Pinus Pinea) (%)	0	0	0	0	0
Quercus Ilex (%)	0	2	18	0	0
Quercus Suber (%)	0	2	16	0	0

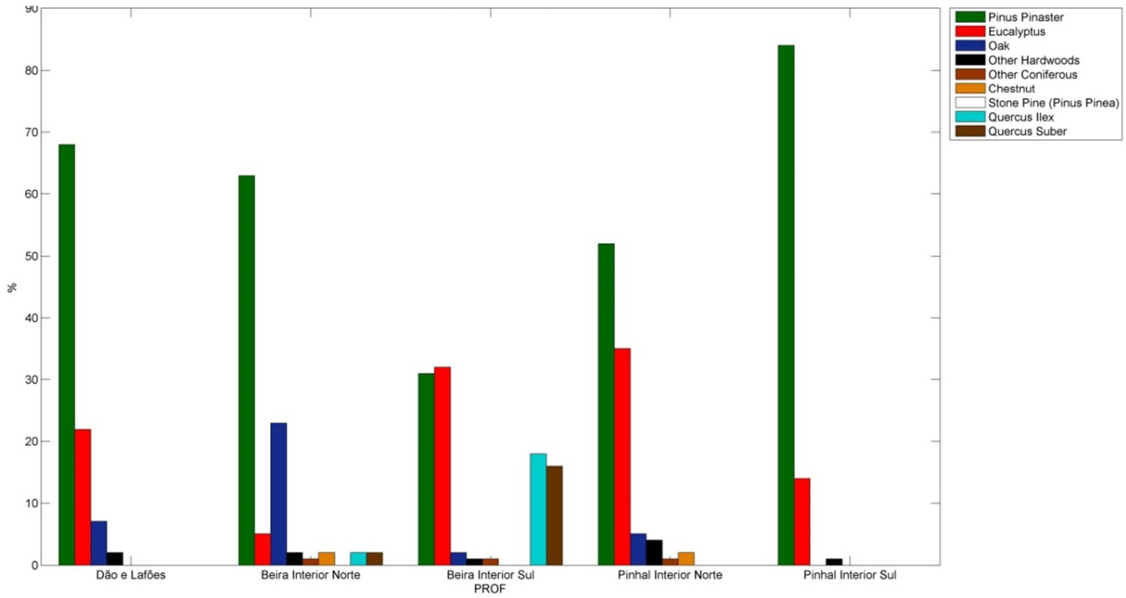

Figure 3 - Percentage of the different species in the forested area of the five PROFs that constitute the study area.

2.4 Study Period

The study focuses on yearly amounts of cumulated burned area in August over the study area, during the 32-year period from 1980 to 2011, hereafter referred to as $BA_{study\ area}$ or simply BA. As shown in Figure 4 (upper panel), the time series of BA presents a very large inter-annual variability, with pronounced peeks in 1991, 2003 and 2005 and very low values in 1988, 1997 and 2008. The time series of $BA_{study\ area}$ presents a very good agreement (correlation coefficient of 0.93) with the one over mainland Portugal, hereafter referred to as $BA_{Portugal}$ and the ratio $BA_{study\ area}$ / $BA_{Portugal}$ varies between about 20 and 80% (Figure 4, bottom panel), with an average of 43%. As already pointed out this figure is to be compared with the area of the study area that only represents 18% of the country.

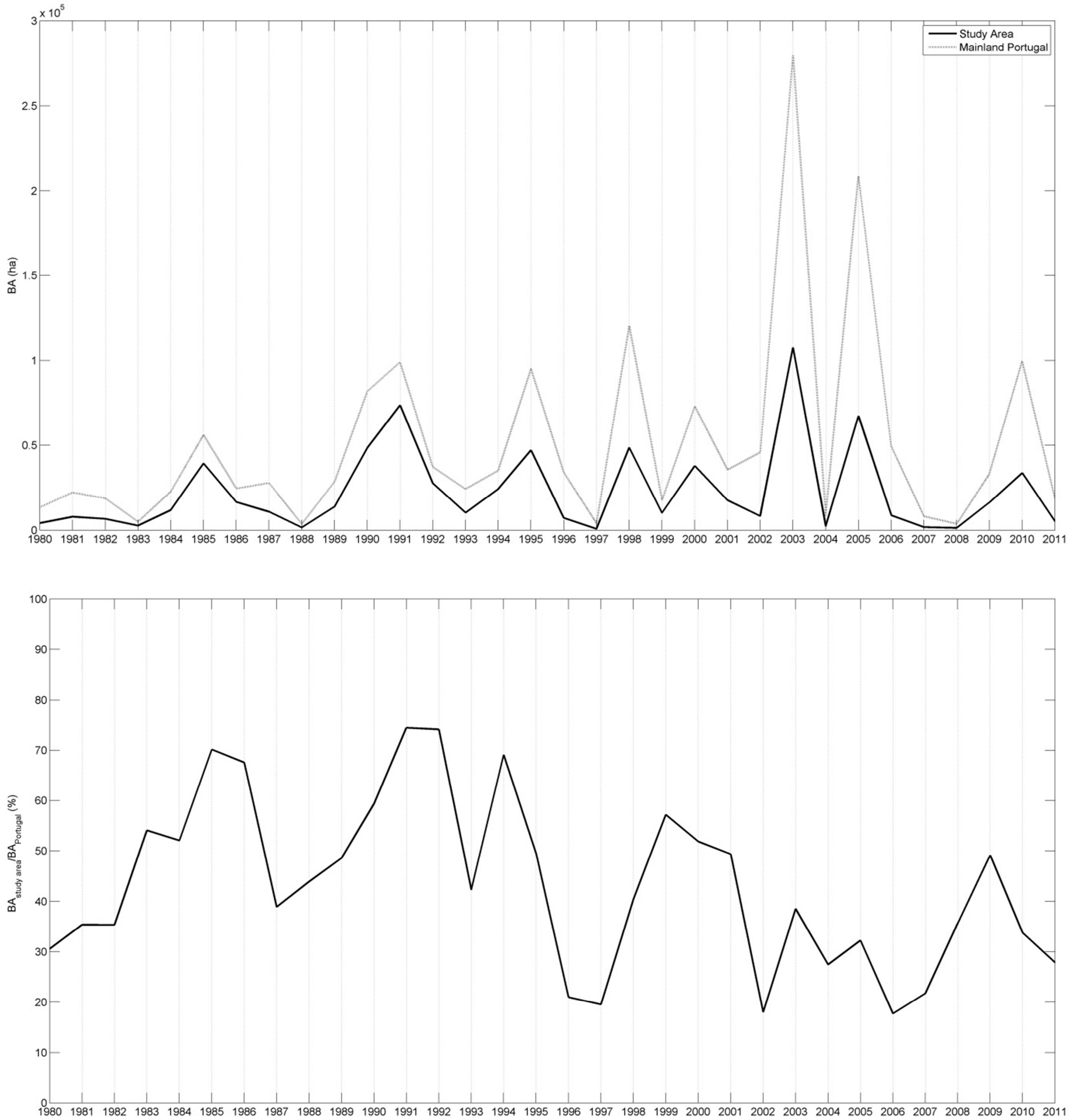

Figure 4 – Time series of cumulated burned area in August over the study area ($BA_{study\ area}$) and over Continental Portugal ($BA_{Portugal}$) (upper panel) and time series of the ratio $BA_{study\ area}$ / $BA_{Portugal}$ (bottom panel).

The distribution of $BA_{study\ area}$ is highly skewed (Figure 5, left panel), the first quartile, the median and the third quartile present 5 908, 11 315 and 35 759 ha. As shown in Figure 5 (right panel), the skewness of the distribution may be considerably reduced by using decimal logarithms of burned area, hereafter referred to as $\log_{10}(BA_{study\ area})$ or simply $\log_{10}(BA)$.

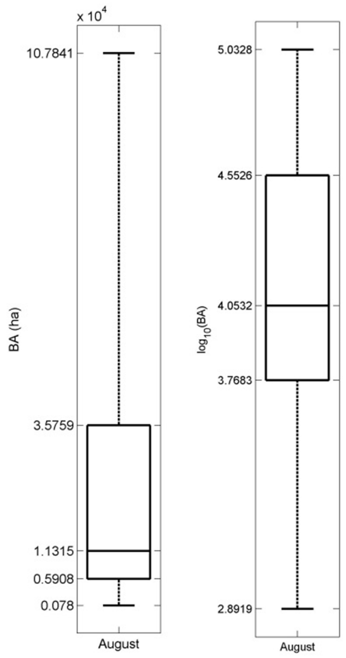

Figure 5 – Box-and-whisker plots of BA (left panel) and of $\log_{10}$(BA) (right panel) during the study period (1980-2011). The bottom and top of each box are the first and third quartiles, the line inside the box is the median and the whiskers extend down to the minimum value and up to the maximum.

Each year was classified into one of three categories, namely severe, moderate and mild. As shown in Figure 6, severe years are those with amounts of BA above 45 000 ha, whereas mild years are those with amounts below 3 000 ha. The list of years sorted in descending order and the respective classification may be found in Table 2.

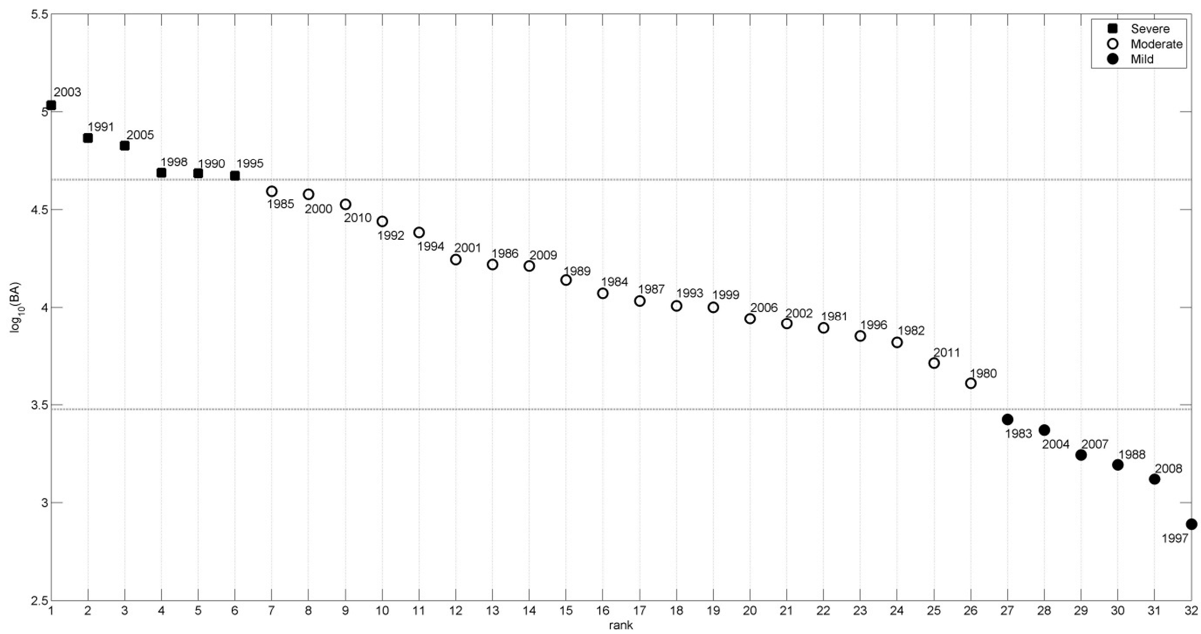

Figure 6 – Schematic representation of years sorted in descending order of $\log_{10}$(BA). The two horizontal lines represent the two thresholds corresponding to 45 000 and 3 000 ha. Severe years, moderate years and mild years are represented by black squares, open circles and black circles, respectively.

Table 2- List of years by descending order of burned area.

Rank	*Year*	*BA (ha)*	*Log_{10} (BA)*	*Classification*
1	2003	107841	5.03	Severe
2	1991	73647	4.87	
3	2005	67334	4.83	
4	1998	48651	4.69	
5	1990	48471	4.69	
6	1995	47058	4.67	
7	1985	39283	4.59	Moderate
8	2000	37860	4.58	
9	2010	33657	4.53	
10	1992	27574	4.44	
11	1994	24217	4.38	
12	2001	17554	4.24	
13	1986	16567	4.22	
14	2009	16300	4.21	
15	1989	13816	4.14	
16	1984	11820	4.07	
17	1987	10811	4.03	
18	1993	10209	4.01	
19	1999	10024	4.00	
20	2006	8751	3.94	
21	2002	8263	3.92	
22	1981	7848	3.89	
23	1996	7138	3.85	
24	1982	6619	3.82	
25	2011	5198	3.72	
26	1980	4104	3.61	
27	1983	2668	3.43	Mild
28	2004	2354	3.37	
29	2007	1763	3.25	
30	1988	1568	3.20	
31	2008	1323	3.12	
32	1997	780	2.89	

2.5 Models of burned area

Following Pereira, et al (2013) who have shown that the decimal logarithm of burned areas recorded in July and August over Continental Portugal during the 32-year period 1980-2011 is normally distributed, the normal distribution was also used here as a model to assign probabilities to $\log_{10}$(BA).

The probability density distribution function (pdf) of the normal distribution of $\log_{10}$(BA) is given by (Caswell, 1995):

$$f(x \mid \mu, \sigma) = \frac{1}{\sigma\sqrt{2\pi}} \exp\left(-\frac{(x-\mu)^2}{2\sigma^2}\right) \qquad (3)$$

where x=$\log_{10}$(BA) is the random variable, μ the mean and σ is the standard deviation of the distribution.

The probability $\mathcal{P}(x < X)$ that the random variable x takes on a value less than or equal to X is given by the cumulative difference function (cdf), $N_x(X)$:

$$\mathcal{P}(x < X) = N_x(X \mid \mu, \sigma) = \int_{-\infty}^{X} f(x \mid \mu, \sigma)\, dx \qquad (4)$$

Estimates of the two parameters μ and σ of the normal distribution may be obtained from a given sample by maximum likelihood, i.e. by maximizing the so-called likelihood function:

$$\Lambda(\mu, \sigma) = \sigma^{-n}\left(\sqrt{2\pi}\right)^{-n} \prod_{i=1}^{n} \exp\left[-\frac{(x_i-\mu)^2}{2\sigma^2}\right] \qquad (5)$$

the same is to say by maximizing the log-likelihood function:

$$\mathrm{L}(\mu, \sigma) = \ln[\Lambda(\mu, \sigma)] = -n\ln(\sigma) - n\ln\left(\sqrt{2\pi}\right) - \frac{1}{2\sigma^2}\sum_{i=1}^{n}(x_i-\mu)^2 \qquad (6)$$

Estimates of μ and σ are therefore obtained by solving the following pair of equations:

$$\frac{\partial L(\mu, \sigma)}{\partial \mu} = \frac{1}{\sigma^2}\left[\sum_{i=1}^{n} x_i - n\mu\right] \qquad (7)$$

$$\frac{\partial L(\mu, \sigma)}{\partial \sigma} = -\frac{n}{\sigma} + \frac{1}{\sigma^3}\sum_{i=1}^{n}(x_i-\mu)^2 \qquad (8)$$

leading to:

$$\bar{\mu} = \frac{1}{n}\sum_{i=1}^{n} x_i \qquad (9)$$

$$\bar{\sigma} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(x_i - \bar{\mu})^2} \quad (10)$$

Quality of fitting of obtained normal distributions to the respective samples may be visually checked by means of quantile-quantile (q-q). Q-q plots, also called probability plots, are obtained by representing the sorted sample data versus the corresponding theoretical normal scores. Theoretical normal scores are obtained by inverting the normal cumulated distribution function (with the estimated mean and standard deviation from the sample) using the following empirical quantiles:

$$P(X_i) = \frac{l_i}{n+1} \quad (11)$$

where l_i is the rank of the i^{th} sorted value of the sample and n is the size if the sample. When the plotted values closely follow a straight line, it is plausible that the data follows a normal distribution (Romeu, 2002).

A more formal statistical procedure of assessing whether a given normal model adequately fits a given sample is by means of Goodness of Fit (GoF) tests. The so-called Anderson-Darling (AD) test is one of these GoF tests which are often used to test the null hypothesis whether a given sample follows a normal distribution. The AD test belongs to the so-called “distance tests” class as it uses the cumulative distribution function approach. For this kind of tests some steps are taken, starting with assuming a pre-specified distribution and estimating the distribution parameters and ending with an assessment whether the evaluated and theoretical values agree. If they do then the distribution is accepted.

In the case of the AD test, the following statistics is evaluated:

$$A^2 = \sum_{i=1}^{n}\frac{1-2i}{n}\{\ln(N[Z_i]) + \ln(1 - N[Z_{n+1-i}])\} - n \quad (12)$$

where n is the sample size, N is the assumed normal distribution and Z_i is the i^{th} sorted sample normalized value. If A^2 exceeds a given critical value, then the hypothesis of normality is rejected at some significance level (Romeu, 2003).

Normal models for $\log_{10}$(BA) may be improved by incorporating one or more covariates based on monthly values of indices of fire danger. Such covariates, e.g. π, χ, are incorporated in the normal models by assuming linear dependence of the mean μ of the distribution on one or more covariates, i.e. by considering relationships of the type:

$$\mu = a \times \pi + c, \qquad \mu = b \times \chi + c, \qquad \mu = a \times \pi + b \times \chi + c \quad (13)$$

Estimates of coefficients a and/or b and c of the linear relationships and of the standard deviation σ are again obtained by maximum likelihood. Performance of the new alternative models is compared against the null model (i.e. the normal model without covariates) by using the so-called standard likelihood ratio test (Neyman and Pearson 1933). The test is based on the following statistics:

$$\Lambda = 2(\ln L' - \ln L) \quad (14)$$

that compares the maximum likelihood L’ of the alternative model with the maximum likelihood L of the null model (Wilks, 2006).

Chapter 3

Results

3.1 The baseline model

A normal distribution model was fitted to the 32-year sample of $\log_{10}(BA)$ (Table 2). Obtained maximum likelihood estimates of the mean and standard deviations are $\mu = 4.07$ and $\sigma = 0.31$, respectively. The probability associated to the Anderson-Darling statistic is 0.66, meaning that the null hypothesis that the sample is normally distributed is accepted at the level of 5%. The goodness of fit of the distribution may be visually confirmed by inspecting the obtained probability plot (Figure 7).

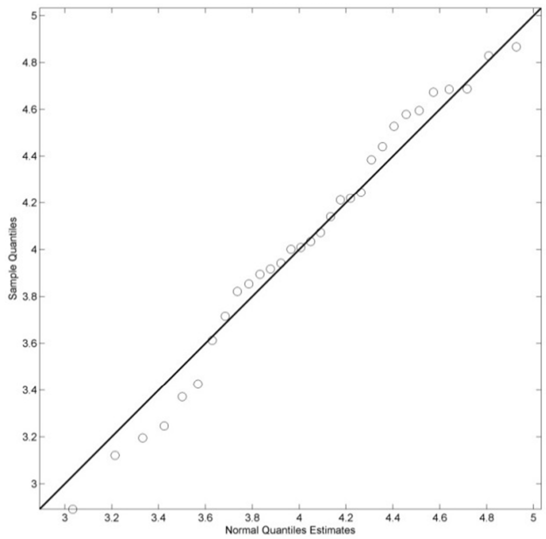

Figure 7 - Probability plot for the fitted normal model of $\log_{10}(BA)$. The plot represents fitted model quantiles (x-axis) versus sample data quantiles (y-axis).

The fitted model, hereafter referred to as the baseline model, may be used to estimate baseline danger which is defined as the probability D_{b0} that a certain threshold, x_0, of $\log_{10}(BA)$ is exceeded, *i.e.*:

$$\mathrm{D_{b0}} = D_b(x_0) = 1 - N_x(x_0 | \mu = 4.07, \sigma = 0.31) \qquad (15)$$

where N_x is the cumulative distribution function of the normal distribution, as given by equation (4). The excess threshold, x_0, associated to a prescribed level of baseline danger D_{b0} may be obtained by inverting equation (15)

$$\mathrm{x_0} = x(D_{b0}) = N^{-1}(1 - D_{b0}) \qquad (16)$$

As shown in Figure 8, the excess threshold associated to a baseline risk $D_{b0} = 33\%$ is $x_0 = \log_{10}(BA) = 4.31$, corresponding to a cumulated burned area BA = 20 600 ha.

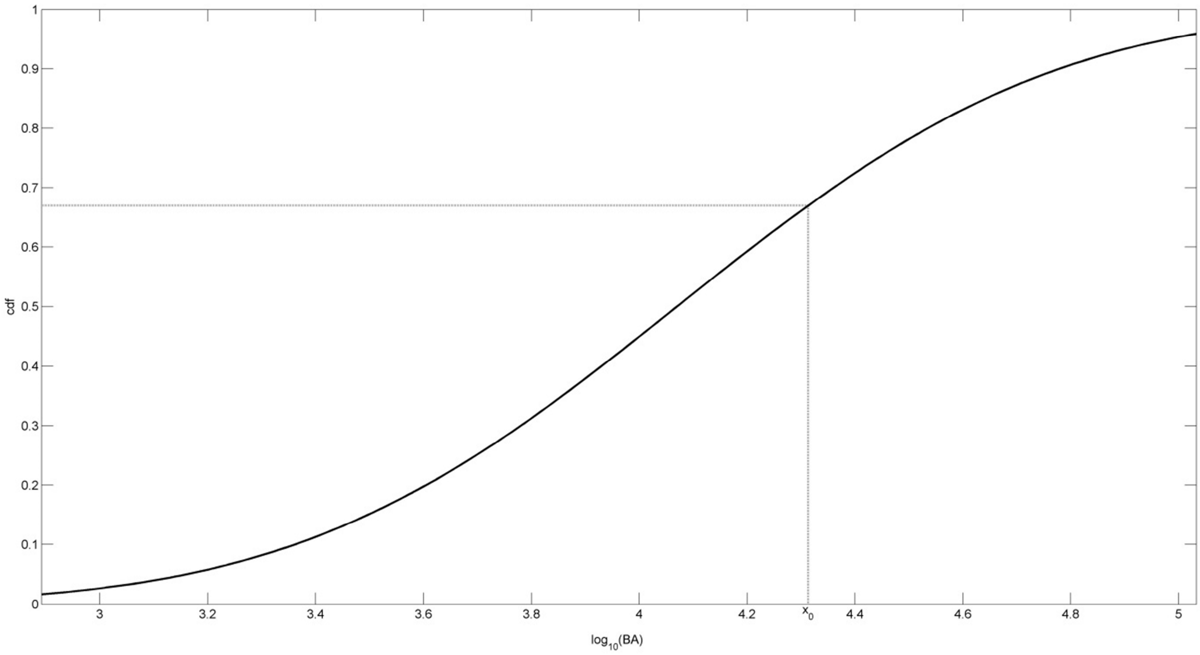

Figure 8 – Cumulative distribution function of the baseline model. The dashed lines graphically illustrate the inversion process to determine the excess threshold x_0 associated to the prescribed value of 33% for baseline danger D_{b0}.

3.2 Meteorological factors

As shown by Pereira, et al (2005) the extent of burned area in Portugal is controlled by two kinds of meteorological factors associated to different temporal scales. The first kind, referred to by the authors as the "climate anomaly", is linked to long dry periods with absence of precipitation in late spring and early summer, whereas the second kind, referred to as the "weather anomaly" is related to the occurrence of very intense dry spells in days of extreme synoptic situations. (Pereira, et al., 2013) have recently shown that the "climate anomaly" and the "weather anomaly" may be respectively quantified by means of monthly values of DSR in the pre-fire season (May, June) and in the fire season (July, August).

The role played by the "climate anomaly" is depicted in Figure 9 that presents composites of cumulated monthly mean values of DSR over the study region (starting on April). The black line is the median of cumulated DSR for all 32 years of the study period, whereas the red and the green lines are the medians respectively of the subsets of severe and mild years as defined in Table 2. Whiskers in the curves for the two subsets delimit the respective first and third quartiles. Results suggest that cumulated values of DSR for severe (mild) years tend to deviate towards larger (lower) values than the overall median; they also suggest that differences between the statistical distributions of the two subsets systematically increase from May to July. As discussed in Pereira, et al (2013) the increasing tendency for severe years to present larger values of cumulated DSR than the overall median is associated to systematic increases in temperature and to systematic decreases in precipitation that take place in the pre-fire season and drive biomass to high levels of heat and water stress, making it prone to trigger large wildfires in case of favorable meteorological conditions in the fire season, which are very likely to occur in hot and dry summers. The opposite situation is observed in the case of mild years, where the tendency in mild years towards lower values of DSR than the overall median is associated to decreases in temperature and to increases in precipitation that make vegetation much less prone to trigger large wildfires, even in case of favorable meteorological conditions.

Results obtained suggest assessing the role played by the "climate anomaly" by looking at the impact on the distribution of $\log_{10}(BA)$ of cumulated DSR up to July, hereafter referred to as DSR_{cum} and defined as:

$$\mathrm{DSR_{cum}} = \overline{\mathrm{DSR_{April}}} + \overline{\mathrm{DSR_{May}}} + \overline{\mathrm{DSR_{Jun}}} + \overline{\mathrm{DSR_{Jul}}} \qquad (17)$$

where $\overline{(\ )}$ the monthly mean operator.

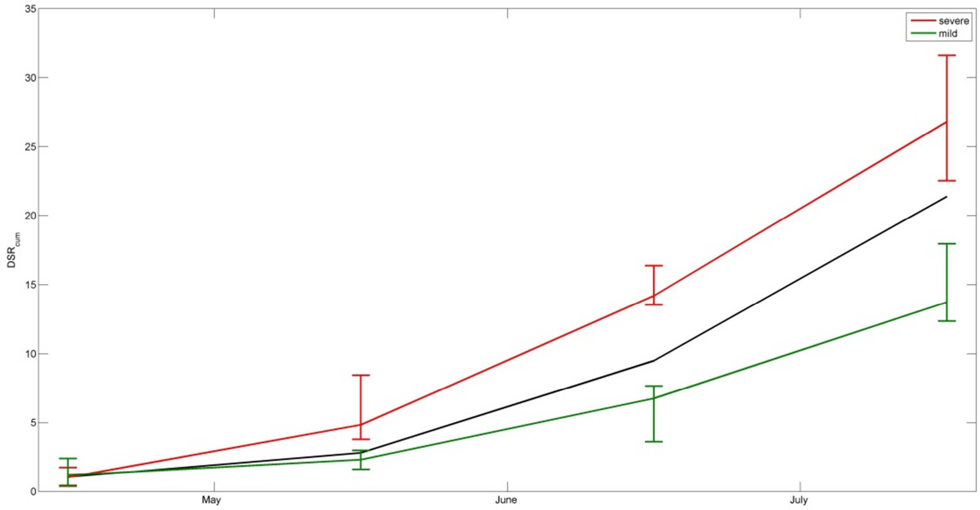

Figure 9 – Median values of cumulated monthly means of DSR for the entire study period (black curve) and for the two sub-periods of severe years (red curve) and mild years (green curve). Red and green whiskers delimit the first and third quartiles of the subsamples of severe and mild years respectively.

As opposed to the "climate anomaly" that is associated to the monthly or seasonal scale, the "weather anomaly" is of a totally different temporal nature since it is associated to extreme synoptic situations that favor the advection of very hot and dry air throughout central Iberia (Pereira, et al., 2005). An illustrative example is the extreme case of August 2003 (Figure 10) where the majority of burned area in the entire year occurred during a short period of 15 days (between 1st and 15th of August) associated to daily values of DSR well above the climatological average, when the country was affected by a severe heat wave.

Four typical situations of variability of daily DSR during August are shown in Figure 11, two of them corresponding to mild years (2004 and 2008) and the other two to severe years (2003 and 2005). 2004 is characterized by the virtual absence of days with values of DSR larger than the respective climatological mean whereas 2008 presents two periods, at the beginning and at the end of August, with values of DSR moderately above the climatological means. As already mentioned, 2003 presents a period of two weeks, at the beginning of the month, with values of DSR much higher than the climatological means whereas August 2005 is dominated by very high values of DSR (much larger than the climatological means), the exception being one with of daily values of DSR below the climatological means.

Results obtained suggest characterizing the "weather anomaly" during August by means of a parameter that is especially sensitive to the occurrence of days within the month associated to large positive departures of DSR from the respective daily climatology, *i.e.* days characterized by large values of anomaly A_d defined as:

$$\mathrm{A_d} = DSR_d - \overline{DSR_d} \qquad (18)$$

where DSR_d and $\overline{DSR_d}$ denote the daily value of DSR on day d of a given year and the respective daily climatological mean performed over the 32-year period 1980-2011. The chosen parameter, hereafter referred to as DSR_+ is the square root of the mean of squared anomalies performed over the days where $DSR > \overline{DSR_d}$, i.e.:

$$\mathrm{DSR}_+ = \sqrt{\frac{\sum_{d=1}^{31} H[A_d]\,(A_d)^2}{\sum_{d=1}^{31} H[A_d]}} \qquad (19)$$

where H[x] is the Heaviside step function whose value is zero for negative argument and one for positive argument.

Obtained values of DSR_+ for the already four typical cases are also shown in Figure 11. The two considered mild years are associated to low values of DSR_+ (1.0 for 2004 and 12.0 for 2008) whereas the two severe years present much larger values (31.4 for 2003 and 35.4 for 2005). This suggest using DSR_+ to assess the role played by the "weather anomaly" on the distribution of $\log_{10}$(BA). This is further confirmed in Figure 12 that presents composites of DSR_+ for all 32 years and for mild and severe years. The black open circle is the median of DSR_+ for the entire period of study, whereas the red and the green open circles are the medians respectively of the subsets of severe and mild years as defined in Table 2. Whiskers extending from the red and green open circles delimit the first and third quartiles of the severe and mild subsets. Results suggest that distributions of DSR_+ for severe (mild) years tend to deviate towards larger (lower) values than the overall median.

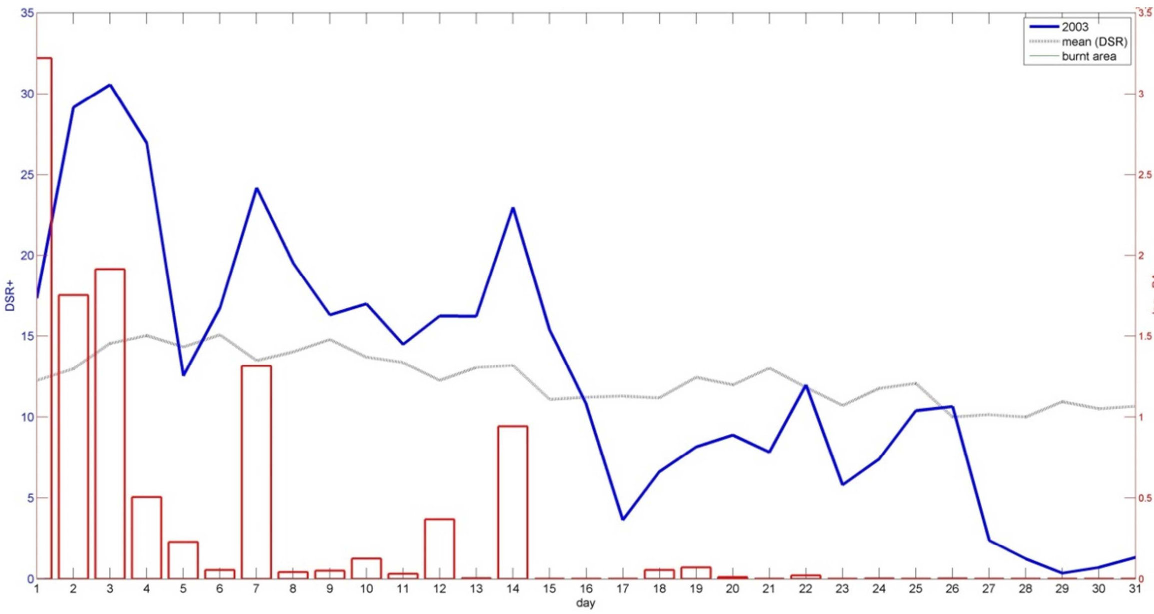

Figure 10 – Daily values of DSR during August 2003 (blue curve), corresponding daily climatological means (grey curve) for the period of study (1980-2011) and associated daily values of $\log_{10}$(BA) (brown bars).

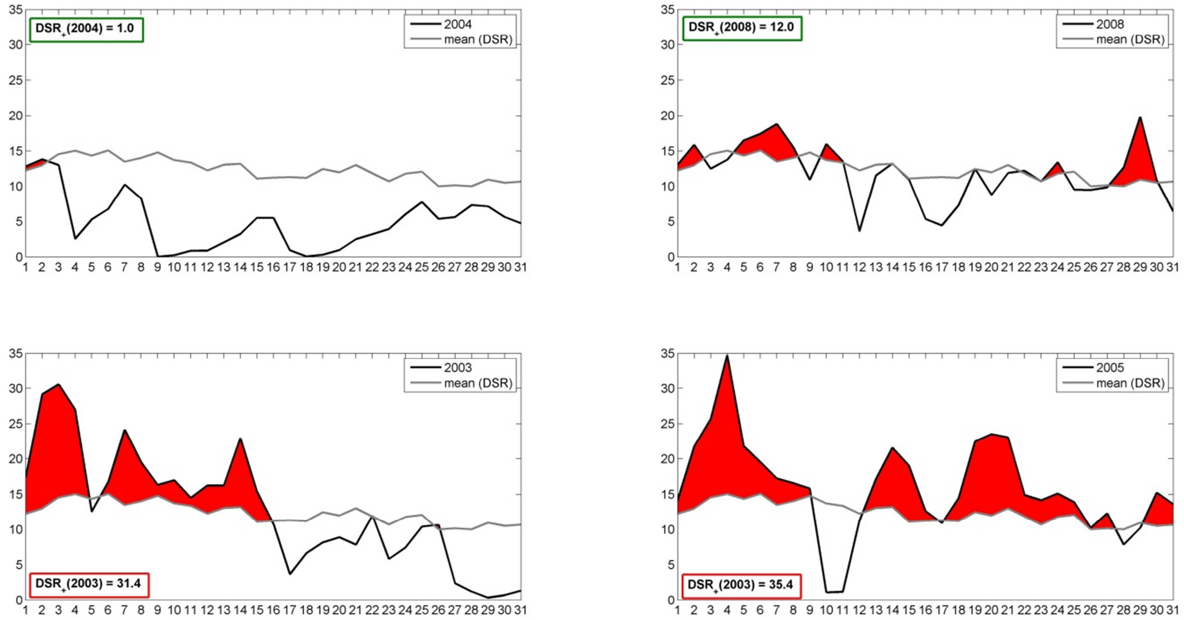

Figure 11 - Daily values of DSR during August (black curves) for two mild years (upper panels), namely 2004 (left) and 2008 (right) and for two severe years, namely 2003 (left) and 2005 (right). Red area indicate sequences of days with values of DSR larger than the corresponding daily climatological means (grey curves) for the period of study (1980-2011).

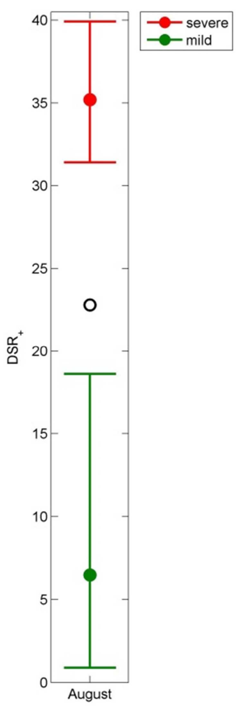

Figure 12 - Median values of DSR_{+} for the entire study period (open black circle) and for the two sub-periods of severe years (open red circle) and mild years (open green circle). Red and green whiskers delimit the first and third quartiles of the subsamples of severe and mild years respectively.

3.3 Background fire danger

The role played by the "climate anomaly" was assessed by analyzing the impact of DSR_{cum} on the distribution of $\log_{10}$(BA). For this purpose, the dataset of $\log_{10}$(BA) was subdivided into subgroups associated with different ranges of DSR_{cum}. Accordingly, values of DSR_{cum} were sorted in ascending order and 12 subgroups of years were defined as respectively associated with values of DSR_{cum} between ranks 1 and 21, between ranks 2 and 22, and so on up to between ranks 12 and 32. Normal distributions were then fitted to each subset and plots were made of estimated values of mean μ versus the mean values of cumulated values of DSR_{cum} in the considered range.

Results are shown in Figure 13 and it may be noted that the mean (μ) tends to linearly increase with DSR_{cum}. Impact of the "climate anomaly" was modeled by introducing DSR_{cum} as a covariate of the mean (μ) of the normal model of $\log_{10}$(BA) by means of a linear relationship of the type:

$$\mu = a \times DSR_{cum} + b \tag{20}$$

Obtained maximum likelihood estimates of model parameters are a = 0.04, b = 3.27 and σ= 0.55, respectively. Performance of the new model, hereafter referred to as the "climate anomaly" model is compared against the null model (i.e. the baseline model, as derived in section 3.1) by means of the likelihood ratio test. The p-value obtained is 0.0045 meaning that adding DSR_{cum} as a covariate leads to an improvement in the model that is statistically significant at the 0.5% level. Sensitivity of the "climate anomaly" model to DSR_{cum} is illustrated in Figure 14 that shows a systematic displacement of both pdf and cdf curves towards higher values of the logarithm of burned area with increasing values of DSR_{cum}.

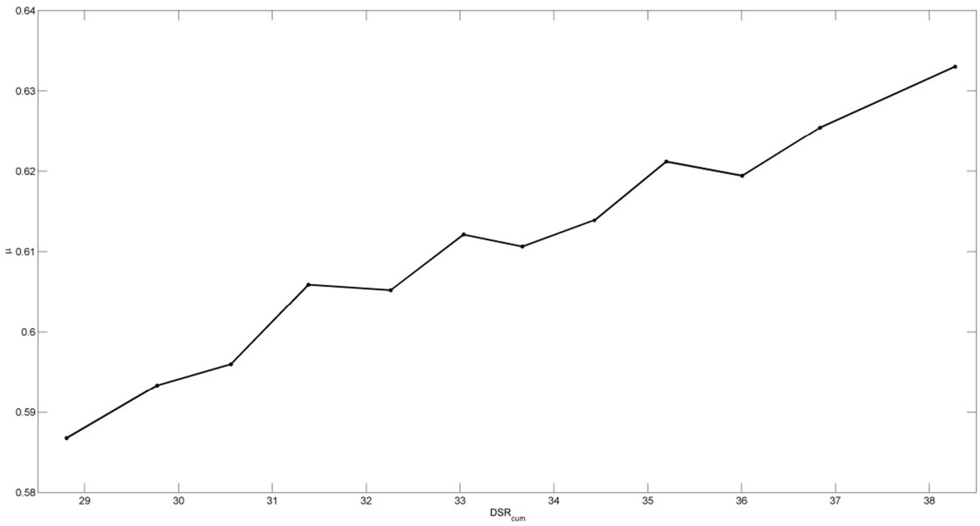

Figure 13 – Dependence on DSR_{cum} of mean (μ) of normal distribution model of $\log_{10}$(BA).

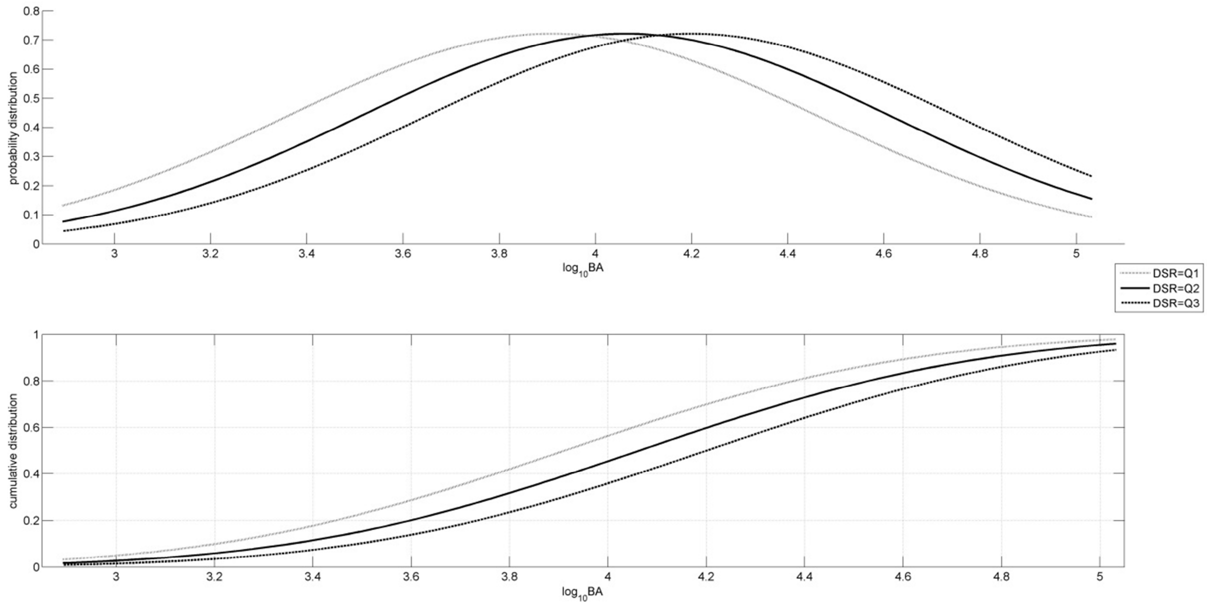

Figure 14 - Pdf (upper panel) and cdf (lower panel) curves for three fixed values of DSR_{cum}, respectively the first quarter, the median and the third quarter.

The “climate anomaly” model may be used to estimate the “climate anomaly” danger which is defined as the probability D_{ca} that a certain threshold, x0, of $\log_{10}$(BA) is exceeded given a value of DSR_{cum}:

$$\mathrm{D_{ca}}(x_0 \mid DSR_{cum}, a, c) = 1 - N(x_0, a \times DSR_{cum} + c) \qquad (21)$$

Following DaCamara, et al (2013), the impact of the “climate anomaly” on burned area was statistically characterized by defining the background danger D_{BG}, which combines information about climate anomaly danger (D_{ca}) and baseline danger (D_{b0}) according to the following procedure:

1. A given threshold of baseline danger, D_{b0}, is fixed over the entire study area;
2. The corresponding threshold of logarithm of burned area x_0 is computed using the baseline model, as given by (16);
3. For each year, the “climate anomaly” model is used to estimate the “climate anomaly” danger, D_{ca}, based on the corresponding baseline threshold and the observed daily value of DSR_{cum} as given by (21);
4. Background danger, D_{BG}, is finally defined as the ratio of “climate anomaly” danger D_{ca} to prescribed baseline danger D_{b0}:

$$\mathrm{D_{BG}} = \frac{D_{ca}}{D_{b0}} \qquad (22)$$

As shown in Figure 15, values of D_{BG} were computed over the 32-year study period for a fixed value of baseline danger $D_{b0} = 0.33$. Two thresholds for D_{BG} were then empirically defined with values respectively of 0.75 and 1.00. These values were used to stratify modeled values of D_{BG} into three levels of danger: high, when $D_{BG} > 1$, medium when $0.75 \leq D_{BG} \leq 1$ and low when $D_{BG} < 0.75$.

As shown in Table 3, performance of the "climate anomaly" model was evaluated by comparing the three observed categories of years (as defined in Table 2) with the three modeled layers of D_{BG}. The overall performance of the climate anomaly" model is quite poor, taking into account that there is an agreement between observed categories (mild, moderate and severe) and modeled levels (low, medium and high) in only 16 out of the 32 cases, i.e. in 50% of the cases, evenly distributed among the three categories; 5 in the severe class, 6 in the moderate class and 5 in the mild class. The performance of the model is particularly poor in the moderate category where 14 out of the 20 observed cases are modeled as belonging to the extreme levels, 9 in the high class and 5 in the low class. However the model performs surprisingly well in the case of the two extreme categories, both severe and mild years being correctly classified in 5 out of 6 cases. It may be however noted that the two erroneously classified extreme categories correspond to extreme levels of the opposite type: 1998 is a severe year but is modeled as of low danger whereas 2004 is a mild year but is modeled as of high danger.

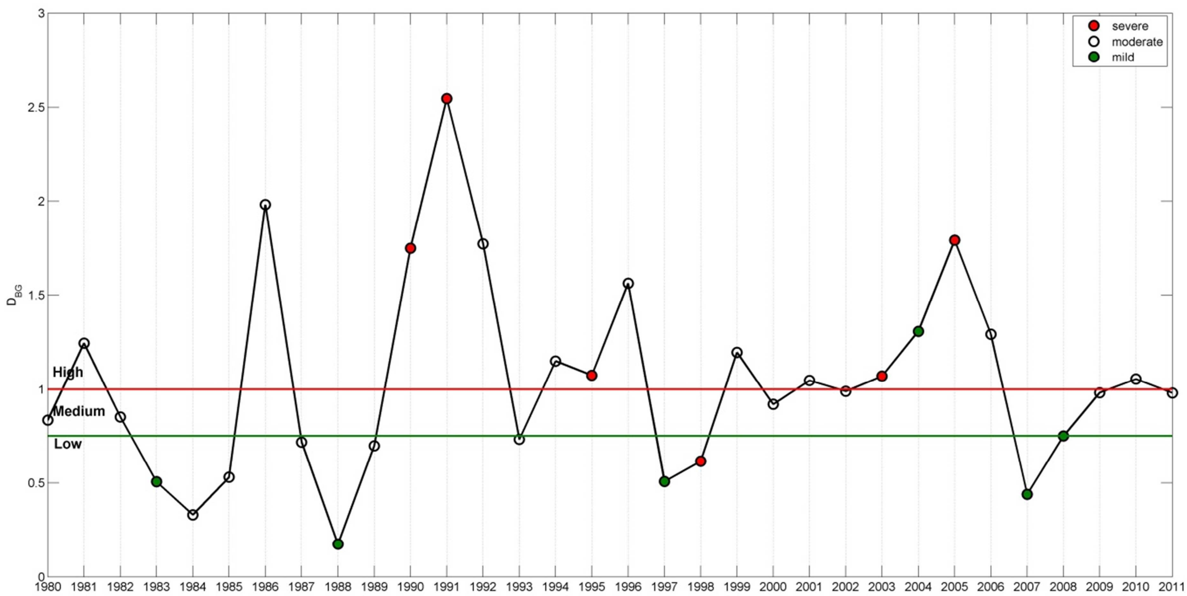

Figure 15 – Background fire danger D_{BG} for the period of study as estimated using the "climate anomaly" and the baseline models. Values of D_{BG} located above the red horizontal line (D_{BG}=1) are modeled as of high danger whereas those located below the green horizontal line (D_{BG}=0.75) are modeled as of mild danger. Observed severe and mild years are identified by red and green circles, respectively.

Table 3- Quality assessment of the "climate anomaly" model based on contingency tables of observed categories of burned severity versus modeled levels of background danger.

		Modeled levels of background danger		
		High	*Medium*	*Low*
Observed categories	*Severe*	5	0	1
	Moderate	9	6	5
	Mild	1	0	5

		Modeled levels of background danger		
		High	*Medium*	*Low*
Observed Categories	*Severe*	1990 1991 1995 2003 2005	-	1998
	Moderate	1981 1986 1992 1994 1996 1999 2001 2006 2010	1980 1982 2000 2002 2009 2011	1984 1985 1987 1989 1993
	Mild	2004	-	1983 1988 1997 2007 2008

3.4 Fire weather danger

The same rationale that was followed in the previous section to assess the role played by the "climate anomaly" was adapted to analyze the impact of DSR_+ on the distribution of $\log_{10}(BA)$. The dataset of $\log_{10}(BA)$ was accordingly subdivided into 12 subgroups of 11 years associated with different ranges of sorted DSR_+ in ascending order. Normal distributions were fitted to each subset and plots were made of estimated values of mean μ versus the mean values of cumulated values of DSR_+ in the considered range.

As shown in Figure 16 the mean (μ) tends to linearly increase with DSR_+, suggesting to model the impact of the "weather anomaly" by introducing DSR_+ as a covariate of the mean (μ) of the normal model of $\log_{10}(BA)$ by means of the following linear relationship:

$$\mu = b \times DSR_+ + c \tag{23}$$

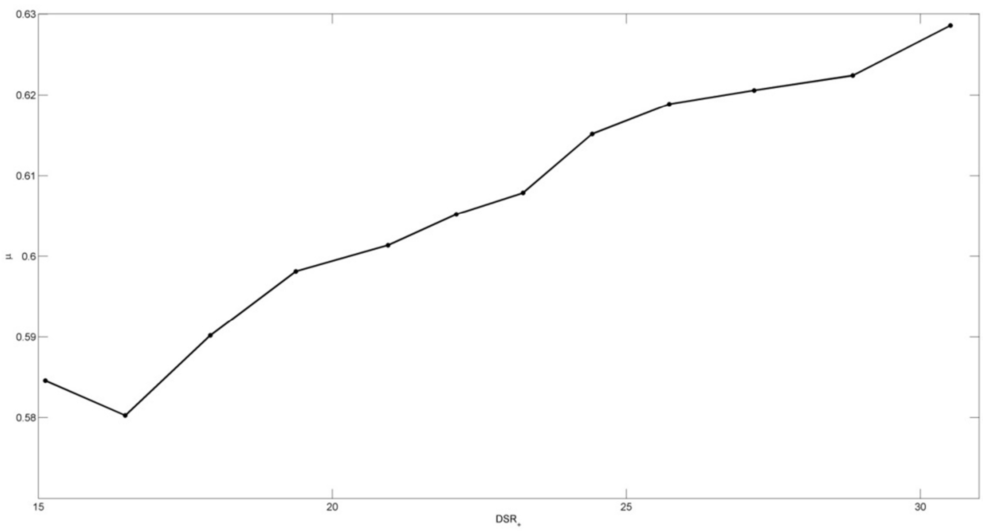

Figure 16 – Dependence on DSR_+ of mean (μ) of normal distribution model of $\log_{10}(BA)$.

Obtained maximum likelihood estimates of model parameters are b = 0.03, c = 3.46 and σ= 0.55, respectively. The likelihood ratio test was again used to compare the improvement obtained when introducing covariate DSR_+ with respect to the baseline model. The p-value obtained is 0.0002 meaning that adding DSR_+ as a covariate results in an improvement in the model that is statistically significant at the 0.02% level. Figure 17 presents the sensitivity of the "weather anomaly" model to DSR_+ and it is worth noting the systematic displacement of both pdf and cdf curves towards higher values of the logarithm of burned area with increasing values of DSR_+.

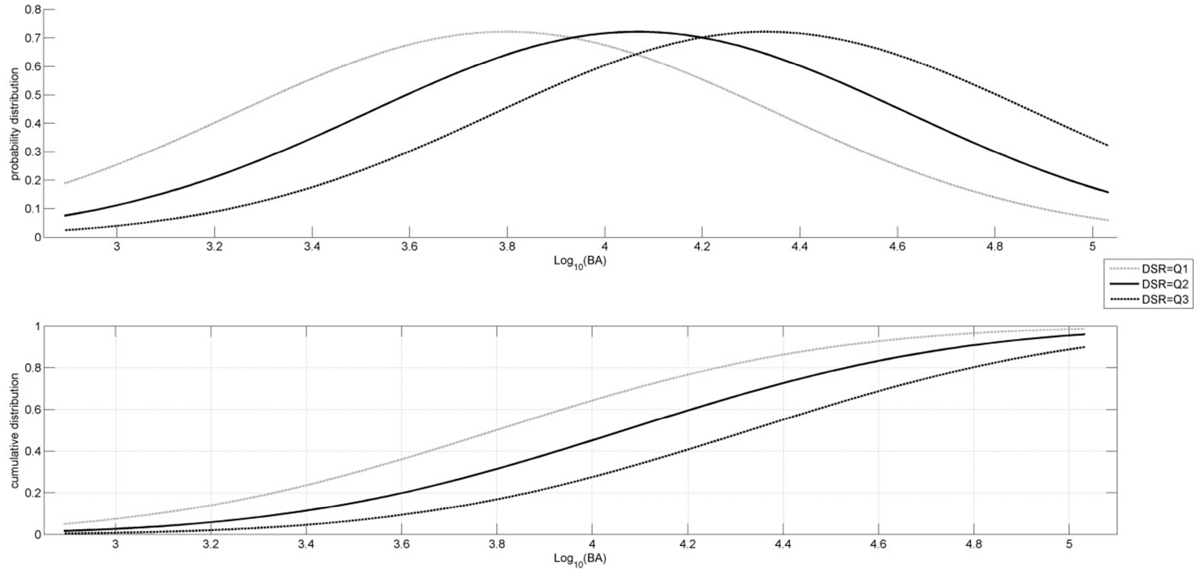

Figure 17 - Pdf (upper panel) and cdf (lower panel) curves for three fixed values of DSR_+ , respectively the first quarter, the median and the third quarter.

As in the previous case of the "climate anomaly" model, the "weather anomaly" model was used to estimate the "weather anomaly" danger which is defined as the probability D_{wa} that a certain threshold, x0, of $\log_{10}$(BA) is exceeded given a value of DSR_+:

$$\mathrm{D_{wa}}(x_0 \mid DSR_+, b, c) = 1 - N(x_0, b \times DSR_+ + c) \qquad (24)$$

The "weather anomaly" danger (D_{wa}) may in turn be combined with baseline danger (D_b) to define fire weather danger (D_{FW}), according to the relationship:

$$\mathrm{D_{FW}} = \frac{D_{wa}}{D_{b0}} \qquad (25)$$

where D_{b0} is the baseline danger associated to a fixed threshold x_0. As shown in Figure 18, values of D_{FW} were computed over the 32-year study period for a fixed value of baseline danger $D_{b0} = 0.33$. Two thresholds for D_{FW} were then empirically defined with values respectively of 0.80 and 1.40. These values were used to stratify modeled values of D_{FW} into three levels of danger, respectively severe, when $D_{FW} > 1.40$, moderate when $0.80 \le D_{FW} \le 1.40$ and mild when $D_{FW} < 0.80$.

As in the case of the "climate anomaly" model, performance of the "weather anomaly" model was evaluated by comparing the observed three observed categories of years (as defined in Table 2) with the three modeled levels of D_{FW}. As shown in Table 4, the overall performance of the "weather anomaly" model is better than the one of the "climate anomaly" model, an agreement between observed categories and modeled levels being observed in 19 out of the 32 cases, (to be compared with 16 out of 32 in the case of the "climate anomaly" model), i.e. in 59% of the cases. The "weather anomaly" model also performs very well in the extreme categories, with all 6 of the severe cases and 5 out of 6 of the mild cases being correctly classified as of high and low levels respectively, the missed mild case being nevertheless classified as of moderate danger. It is again in the moderate class that the model shows the poorest performance, with 12 out of the 20 observed cases being classified as belonging to the extreme categories, 4 in the high level and 8 in the low level. Finally it may be noted that when comparing the 8 correctly classified moderate years by the "weather anomaly" model (1982, 1984, 1985, 1986, 1993, 1996, 2000 and 2009) with the 6 correctly classified cases (1980, 1982, 2000, 2002, 2009, 2011) by the "climate anomaly" model, there are only 3 years in common (1982, 2000 and 2009) which suggests that a better performance is to be expected from a model that uses both DSR_{cum} and DSR_{+} as covariates.

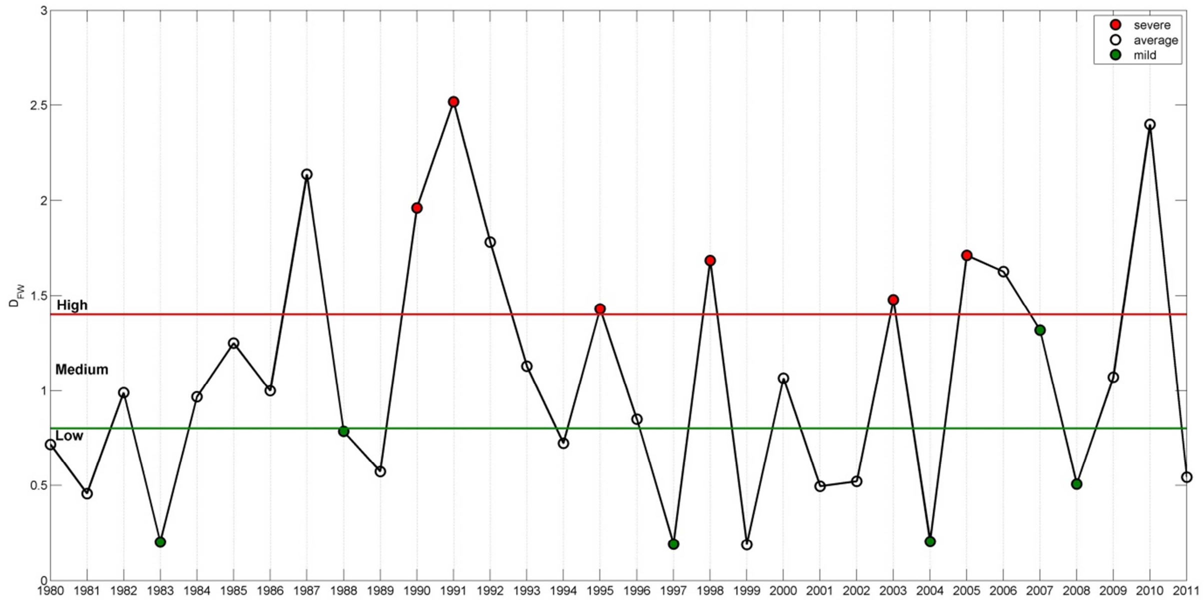

Figure 18 – Fire weather danger D_{FW} for the period of study as estimated using the "weather anomaly" and the baseline models. Values of D_{FW} located above the red horizontal line (D_{FW}=1.40) are modeled as of high danger whereas those located below the green horizontal line (D_{FW}=0.80) are modeled as of mild danger. Observed severe and mild years are identified by red and green circles, respectively.

Table 4- Quality assessment of the "weather anomaly" model based on contingency tables of observed categories of burned severity versus modeled levels of background danger.

		Modeled levels of fire weather danger		
		High	*Medium*	*Low*
Observed categories	*Severe*	6	0	0
	Moderate	4	8	8
	Mild	0	1	5

		Modeled levels of fire weather danger		
		High	*Medium*	*Low*
Observed categories	*Severe*	1990 1991 1995 1998 2003 2005	-	-
	Moderate	1987 1992 2006 2010	1982 1984 1985 1986 1993 1996 2000 2009	1980 1981 1989 1994 1999 2001 2002 2011
	Mild		2007	1983 1988 1997 2004 2008

3.5 Combined fire danger

A model combining the "climate anomaly" with the "weather anomaly" was therefore defined where DSR_{cum} and DSR_{+} are introduced as covariates of the normal model of $\log_{10}(BA)$ by the following linear relationship:

$$\mu = a \times DSR_{cum} + b \times DSR_{+} + c \qquad (26)$$

Obtained maximum likelihood estimates of model parameters are a = 0.02, b = 0.02, c = 3.08 and σ= 0.55, respectively and the p-value obtained for the likelihood ratio test is 0.0001, indicating that adding both DSR_{cum} and DSR_{+} as covariates results in an improvement in the model that is statistically significant at the 0.01% level.

The obtained model, hereafter referred to as the "combined" model allows estimating the "climate + weather" anomaly which is defined as the probability D_{c+w} that a certain threshold, x0, of $\log_{10}(BA)$ is exceeded given two values of DSR_{cum} and DSR_{+}:

$$\mathrm{D_{c+w}}(x_0 \mid DSR_{cum}, DSR_{+}, a, b, c) = 1 - N(x_0, a \times DSR_{cum} + b \times DSR_{+} + c) \qquad (27)$$

Following the same procedure as in the "climate anomaly" and "weather anomaly" models, D_{c+w} was combined with baseline danger D_b to define the "combined" fire danger D_{COMB}:

$$\mathrm{D_{COMB}} = \frac{D_{c+w}}{D_{b0}} \qquad (28)$$

where D_{b0} is the baseline danger associated to a fixed threshold x_0. As shown in Figure 19 values of D_{COMB} were computed over the 32-year study period for a fixed value of baseline danger D_{b0} = 0.33. Two thresholds for D_{COMB} were empirically defined with values respectively of 0.50 and 1.25 which were used to stratify modeled values of D_{COMB} into three levels of danger, respectively severe, when D_{COMB} > 1.25, moderate when 0.50 ≤ D_{COMB} ≤ 1.25 and mild when D_{COMB} < 0.50.

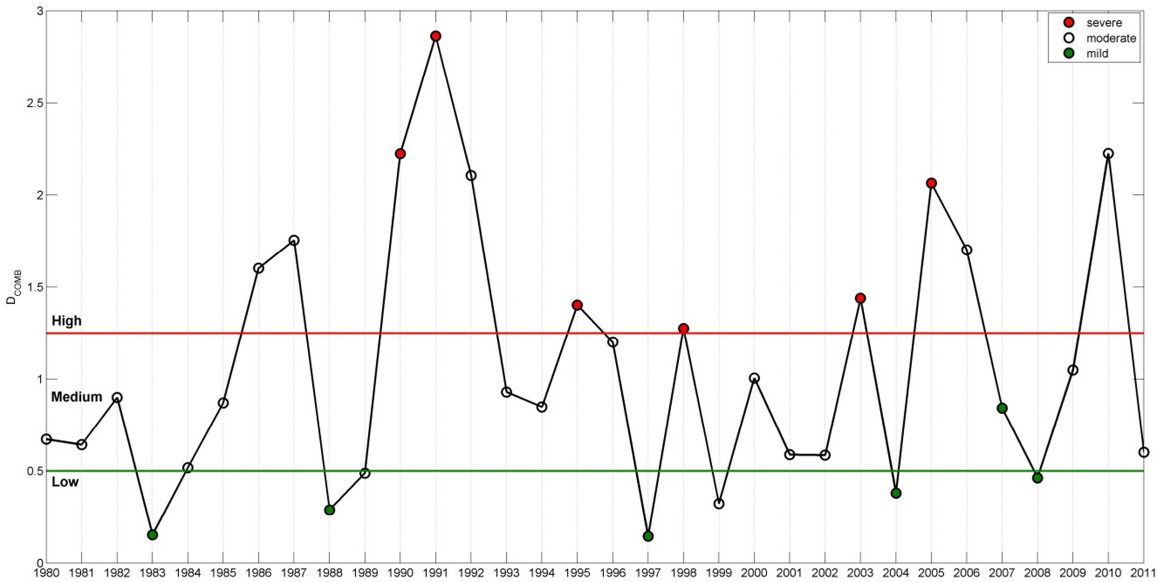

Figure 19 – Combined fire danger D_{COMB} for the period of study as estimated using the "combined" and the baseline models. Values of D_{COMB} located above the red horizontal line (D_{FW}=1.25) are modeled as of high danger whereas those located below the green horizontal line (D_{FW}=0.50) are modeled as of mild danger. Observed severe and mild years are identified by red and green circles, respectively.

As shown in Table 5, performance of the "combined" model was evaluated by comparing the observed three observed categories of years (as defined in Table 2) with the three modeled levels of D_{COMB}. The overall performance of the "combined" model is considerably better than the ones of the "climate anomaly" and "weather anomaly" models, an agreement between observed categories and modeled levels being observed in 24 out of the 32 cases, i.e. in 75% of the cases. As observed with the "weather anomaly" model, the "combined" model also correctly attributes all 6 severe cases to the high level of danger and 5 out of 6 the mild cases to the low level of danger. A significant improved is observed in the moderate category, the model attributing 13 out of the 20 cases to the medium level of danger, a score that is worth comparing with the score of 8 out of 20 and of 6 out of 20 that were obtained with the "weather anomaly" model and with "climate anomaly" model, respectively. Finally it is worth noting that the "combined model" is able to model as of medium danger all but one of the moderate years that were also correctly classified as of medium danger by the "climate anomaly" and the "weather anomaly" models, the exception being the moderate year of 1986 that is classified as of high danger by the "combined" model and as of medium danger by the "weather anomaly" model.

Table 5 - Quality assessment of the "combined" model based on contingency tables of observed categories of burned severity versus modeled levels of background danger.

		Modeled levels of combined fire danger		
		High	*Average*	*Mild*
Observed Categories	*Severe*	6	0	0
	Moderate	5	13	2
	Mild	0	1	5

		Modeled levels of combined fire danger		
		High	*Average*	*Mild*
Observed categories	*Severe*	1990 1991 1995 1998 2003 2005	-	-
	Moderate	1986 1987 1992 2006 2010	1980 1981 1982 1984 1985 1993 1994 1996 2000 2001 2002 2009 2011	1989 1999
	Mild	-	2007	1983 1988 1997 2008 2004

3.6 Concluding remark

The different performances of the "climate anomaly" and of the "weather anomaly" models and the complementary character they present which translates into the much better performance of the "combined" model suggests performing a systematic comparison of results obtained from the three model in order to understand the role played by the long-term pre-fire season "climate anomaly" and by the short-term fire-season "weather anomaly".

An overview of results obtained is provided in Table 6 and it is worth noting that in the case of the 6 cases of severe years (1990, 1991, 1995, 2003 and 2005) all but one case are modeled with a high level of background fire danger (D_{BG}), fire weather danger (D_{FW}) and combined fire danger (D_{COMB}). The exception is 1998 where D_{BG} is low and both D_{FW} and D_{COMB} are high.

In the case of years classified as mild (1983, 1988, 1997, 2004, 2007 and 2008) 4 out of 6 are modeled with a low level of D_{BG}, D_{FW} and D_{COMB}. The exceptions are 2004 where D_{BG} is high and both D_{FW} and D_{COMB} are low and 2007 where D_{BG} is low and both D_{FW} and D_{COMB} are moderate.

These results put into evidence the importance of the role played by both "climate" and "weather" anomalies in the two extreme cases of severe and mild anomalies.

Table 6- Comparison of results from the "climate anomaly", "weather anomaly" and combined models. The observed category of each year is identified by the color of the "Year" column (green, white and red identifying mild, moderate and severe years). The modeled level of fire danger is identified by the color of the respective column (green, white and red identifying low, medium and high levels of risk).

Year	D_{BG}	D_{FW}	D_{COMB}
1980	**0.83**	**0.71**	**0.67**
1981	**1.24**	**0.46**	**0.64**
1982	**0.85**	**0.99**	**0.90**
1983	**0.51**	**0.20**	**0.15**
1984	**0.33**	**0.97**	**0.51**
1985	**0.53**	**1.25**	**0.87**
1986	**1.98**	**1.00**	**1.60**
1987	**0.72**	**2.14**	**1.76**
1988	**0.18**	**0.78**	**0.29**
1989	**0.70**	**0.57**	**0.50**
1990	**1.75**	**1.96**	**2.23**
1991	**2.55**	**2.52**	**2.86**
1992	**1.77**	**1.78**	**2.10**
1993	**0.73**	**1.13**	**0.93**
1994	**1.15**	**0.72**	**0.85**
1995	**1.07**	**1.43**	**1.40**
1996	**1.56**	**0.85**	**1.20**
1997	**0.51**	**0.19**	**0.15**
1998	**0.62**	**1.68**	**1.28**
1999	**1.20**	**0.19**	**0.32**
2000	**0.92**	**1.07**	**1.00**
2001	**1.05**	**0.49**	**0.59**
2002	**0.99**	**0.52**	**0.59**
2003	**1.07**	**1,48**	**1.44**
2004	**1.31**	**0.20**	**0.38**
2005	**1.79**	**1.71**	**2.06**
2006	**1.29**	**1.63**	**1.70**
2007	**0.44**	**1.32**	**0.84**
2008	**0.75**	**0.51**	**0.46**
2009	**0.98**	**1.07**	**1.05**
2010	**1.05**	**2.40**	**2.23**
2011	**0.98**	**0.54**	**0.60**

Chapter 4

Conclusions

A study was performed aiming to assess the role of meteorological factors on the inter-annual variability of burned area over a region of Central Portugal. The study covers a 32-year period that extends from 1980 to 2011. The study region is dominated by forest, maritime pine, eucalyptus and oak being the predominant species. The large fractions of the forested area and the high percentages of three species that are extremely flammable in summer explain the fact that, although occupying only 18% of the territory of Portugal, the chosen study area is responsible for 43% of the burned area in August during the study period 1980-2011.

The distribution of monthly burned area during August over the study region is highly skewed and decimal logarithms of burned area were used in order to reduce skewness. A normal distribution model was fitted to the 32-year sample of decimal logarithms of monthly burned area. This model was then improved by introducing as covariates two different measures of prevailing meteorological conditions as derived from Daily Severity Rate (DSR), an indicator of meteorological fire danger; DSR_{cum} which consists of cumulated values of monthly means of DSR from April to June and DSR_{+} which consists of the square root of the mean of the squared daily deviations of DSR in August from the climatology, the average being performed only over days of positive deviation.

DSR_{cum} was shown to be a good indicator of the so-called “climate anomaly” that is linked to long dry periods with absence of precipitation in late spring and early summer leading to high levels of vegetation stress in the pre-fire season. DSR+ was shown to be instead an indicator of the “weather anomaly” which is related to the occurrence of very intense dry spells in days of extreme synoptic situations which may trigger the onset and spreading of large wildfires.

Three models were derived by introducing DSR_{cum} and DSR_{+} as covariates of the normal model of decimal logarithms of burned area; the “climate anomaly” model that uses DSR_{cum} as a covariate; the “weather anomaly” model that uses DSR_{+} as a covariate; and the “combined” model that uses both DSR_{cum} and DSR_{+} as covariates.

The three models were used to define background fire danger, D_{BG}, fire weather danger, D_{FW}, and combined fire danger, D_{COMB}, respectively. These three types of danger respectively quantify the increase or decrease in probability of having a large fire in August that is attributed to pre-fire season conditions, to fire season conditions and to both conditions.

The overall performance of the “climate anomaly” model is quite poor, the model assigning only 50% of the observed categories of severe, moderate and mild years to the modeled levels of low, medium and high danger. However the model performs well in the case of the two extreme categories, both severe and mild years being classified as respectively of high and low risk in 5 out of 6 cases.

The overall performance of the “weather anomaly” model is better than the one of the “climate anomaly” model, but even so only 59% of severe, moderate and mil years are modeled as of low, medium and high danger. The “weather anomaly” model also performs very well in the extreme categories, with all 6 of the severe cases and 5 out of 6 of the mild cases being modeled as of high and low levels respectively.

The overall performance of the “combined” model is considerably better than the ones of the “climate anomaly” and “weather anomaly” models, an agreement between observed categories and modeled levels being observed in 75% of the cases. As observed with the “weather anomaly” model, the “combined” model also correctly attributes all 6 severe cases to the high level of danger and 5 out of 6 the mild cases to the low level of danger.

Results from the “climate anomaly” model put into evidence the role of long-term pre-fire season conditions on the inter-annual variability of burned area. All but one of the 11 cases modeled as of low (high) level of background fire danger belong to the severe (mild) category. However short-term meteorological conditions during August have a key role on inter-annual variability as illustrated by the relatively better performance of the “weather anomaly” model.

The two meteorological factors, *i.e.* the “climate anomaly” and the “weather anomaly” have nevertheless to be taken together into account in order to improve modeling of the moderate years. This is demonstrated by the increase in performance of the “combined” model that was mainly due to an increase in the number of moderate years that were modeled as of medium danger.

Results from the present study put into perspective the key roles played by the “climate anomaly” and the “weather anomaly” factors on the occurrence of fire seasons characterizes by very high or very low fire activity. This information may be of use to forest managers when organizing fire preventing measures and firefighting capacity and when allocating resources for both. It may be also useful when developing an on-line alarm system to predict the event of extreme fires since such a system depends on constructing a sound model that links the fire size process to the multivariate exploratory variables.

Bibliography

Aldersley A., Murray S. J. and Cornell S. E. Global and regional analysis of climate and human drivers of wildfire [Article] // Science of The Total Environment. - 2011. - 18 : Vol. 409.

Anderson K., Englefield P. and Carr R. Predicting fire-weather severity using seasonal forecasts [Conference] // 7th Symposium on Fire and Forest Meteorology. - [s.l.] : American Meteorological Society, 2007. - Vols. 23-25.

Caswell F. Success in statistics [Book]. - London : John Murray, 1995. - Vol. 3rd edition.

DaCamara C. C., Calado T. J, Ermida S L., Trigo I. F., Amraoui M., Turkman K. F. Calibration of the Fire Weather Index over Mediterranean Europe based on fire activity retrieved from MGC satellite imagery [Article]. - [s.l.] : subbmited, 2013.

Direção de Unidade de Defesa da Floresta Relatório Anual de Áreas Ardidas e Incêndios Florestais [Report]. - [s.l.] : Autoridade Florestal Nacional, 1980 to 2012.

ICNF Instituto da Conservação da Natureza e das Florestas [Online] // http://www.icnf.pt/. - 2013.

Nunes S. A. Incêndios Florestais de Verão em Portugal Continental - severidade da época de fogos e sua relação com ciclos anuais de vegetação e temperatura. - 2012.

Nunes S. A., Camara C C and Calado T J Vegetation stress and summer fire activity in Portugal [Conference] // Associação Portuguesa de Meteorologia e Geofísica. - 2013.

Pausas J. G. and Vallejo V. R. The role of fire in European Mediterranean Ecosystems [Article]. - [s.l.] : Remote sensing of large wildfires in the European Mediterranean basin, 1999. - pp. 3-16 : Vols. E. Chuvieco (Ed.), Springer-Verlag, Berlin.

Pereira M. G., Pereira M. G., Calado T. J., DaCamara, C. C., Calheiros T. Potential effects of regional climate change on rural fires in Portugal [Article] // submitted to Climate Research. - 2013.

Pereira M. G., Trigo R. M., DaCamara C. C., Pereira J. M.C., Leite S. M. Synoptic patterns associated with large summer forest fires in Portugal [Article]. - [s.l.] : Agricultural and Forest Meteorology, 2005. - 11-25 : Vol. 129.

Pereira M. G., Malamud B. D., Trigo R. M., Alves P. I. The history and characteristics of the 1980-2005 Portuguese rural fire database [Article]. - [s.l.] : Natural Hazards and Earth System Sciences, 2011. - 3343-3358 : Vol. 11.

Plano Regional de Ordenamento Florestal de Dão Lafões Instituto da Conservação da Natureza e das Florestas [Online]. - 2013. - http://www.icnf.pt/portal/florestas/profs/dao-laf.

Regueira L N, Anon J R and Castineiras J P Calorific values and flammability of forest species in Galicia. Coastal and hillside zones [Article]. - [s.l.] : Technology, 1996. - 283-289 : Vol. 57(3).

Romeu J. L. Anderson-Darling: A Goodness of Fit Test for Small Samples Assumptions [Article] // Selected Topics in Assurance Related Technologies. - [s.l.] : Reability Analysis Center, 2003. - 5 : Vol. 10.

Romeu J. L. Empirical Assessment of Normal and Lognormal Distribution Assumptions [Article] // START - Selected Topics in Assurance Related Technologies. - [s.l.] : ReliabilityAnalysis Center, 2002. - 6 : Vol. 9.

San-Miguel-Ayanaz J., Moreno J. M. and Camia A. Analysis of large fires in European Mediterranean landscapes: Lessons learned and perspectives [Article]. - [s.l.] : Forest Ecology and Management, 2013. - 11-22 : Vol. 294.

San-Miguel-Ayanz J., San-Miguel-Ayanz J., Carlson J. D., Alexander M., Tolhurst K., Morgan G., Sneeuwjagt R., Dudley M. Current Methods to Assess Fire Danger Potencial [Book Section] // Wildland Fire Danger Estimation and Mapping. - [s.l.] : Ed Chuvieco, 2003. - Vols. 20-61.

Van Wagner C. E. Development and structure of the Canadian Forest Fire Weather Index System [Book]. - Ottawa : Canadian Forestry Service, 1987. - Vol. Forestry Technical Report 35.

Wilks D. S. Statistical methods in the atmospheric sciences [Book]. - [s.l.] : Academic Press, 2006. - Vol. 91.