UNIVERSIDADE DE LISBOA

INSTITUTO DE GEOGRAFIA E ORDENAMENTO DO TERRITÓRIO

WILDFIRE SUSCEPTIBILITY MODELLING IN MAINLAND PORTUGAL

JOÃO CARLOS RODRIGUES MOREIRA VERDE

ORIENTADOR: PROF. DOUTOR JOSÉ LUÍS ZÊZERE

TESE ESPECIALMENTE ELABORADA PARA OBTENÇÃO DO GRAU DE DOUTOR EM GEOGRAFIA
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2015

If you discussed this thesis with me, if you talked to me about this, if you gave me ideas and pointers, if you read this, if you helped me in any way, then you should know that I am forever grateful, and that this thesis is also yours.

Thank you all*, so very much*

« If there is certainty, there is no risk. »

Omar Cardona

« (...) Then I saw that wisdom is better than foolish ways,
as the light is better than the dark. »

Ecclesiastes 2:13

« (...) "Geographies," said the geographer, "are the books which, of all books, are most concerned with matters of consequence. They never become old-fashioned. It is very rarely that a mountain changes its position. It is very rarely that an ocean empties itself of its waters. We write of eternal things."»

Antoine de Saint-Éxupèry, in "The Little Prince"

Preamble

Becoming a physical geographer is like learning to read. From the moment we are taught how to group syllables, and with those, words, it becomes impossible, in full faculty, to stare at a word and not decipher it, translating its graphical shapes into an idea. The same happens with geography. When one becomes a geographer, one loses the ability of looking around and not giving meaning to what is seen. Mountains are no longer just mountains. Rivers are no more just water running into the ocean. Landscapes morph from scattered things into something a geographer decodes. For everything there is a process. In all things you find evolution, and the physical geographer reads it, even if he doesn't want to or actively thinks about it.

Learning to read is not an end. Learning to read is just the beginning, part of the process that makes us read better and faster, and then, writing. In a person's academic run, a Ph.D cannot be an end in itself. A Ph.D is just part of evolution. It is not a moment when all is done, but a moment where reading and writing is perfected, and questions multiply themselves. Beyond a Ph.D lies practice. The practical application of what has been studied and defended. To give back to others, for a common benefit and knowledge, the time they've given us to reach this far. I understand, now, that a Ph.D is, far from an ending, a start.

Risk is everywhere, but that's not something we think about every day when we wake up, even though we spend our time assessing risk in our brains, even if not consciously. We might not perceive it, but every action we take, from the minor to the most significant, bears a risk. When we move forward, when a concrete action is taken, it's because our brains, in a split second, evaluated the risk of taking it and decided it was acceptable: the benefit outweighed the risk. From the many risks we're presented within our lives, my course has led to wildfires. Hazard and risk are human properties I consider fit for a physical geographer to study, but their application on the subject of wildfires only appealed to me after cooperating with the team that devised the technical proposal for the National Wildfire Prevention Plan, in 2005. Up until then, as to most Portuguese, wildfires were just a thing on the news, on prime time television, during the summer silly season. I looked at it as a national inevitability, inextricably linked with summer temperatures and, who knows, other questionable or obscure reasoning, summer after summer. I came to learn that was not the case. At all.

I worked for the National Forest Authority (AFN) between 2006 and 2009, and witnessed how selflessly, in those gloomy offices, some of their younger workers strove to develop public service, something often made extremely hard by contingencies I can't easily frame in the spirit of science or gently adjective. It was in that context that, from 2005 to 2008, I developed my personal investigation and MSc thesis on the subject of Wildfire Hazard assessment, which I defended before a jury, at the University of Lisbon, on January 7th 2009.

Like my experience before that, with the National Wildfire Prevention Plan, working for the National Forest Authority gave me a better understanding of Portuguese wildfires, if only partially, because at the time I was only working with half of it – the prevention side. For a fuller, more global understanding of the problem at hand, I needed the experience that came after that when, in 2009, I became a National Operations Assistant of the National Command for Relief Operations, of the National Authority for Civil Protection (ANPC). Prevention met fire suppression efforts. The picture was, if not complete, brighter. Or, should I say, grimmer?

I found it extremely hard to evaluate wildfire risk and had, at the time, to stop at hazard. While I worked for AFN, not even foresters dared to put a value on things. While there, I invested most of my efforts on harmonizing the conceptual risk framework, bringing it closer to the concepts internationally used and accepted with other phenomena. It wasn't easy as I suppose, for many, the notion of value was not convenient. At AFN I was given the notion that most investments were made on the side of fire suppression, making it harder for prevention to show results, as it takes several years for it to show. Putting that in perspective, later on, at ANPC, I understood that regardless of how numerous or equipped your fire suppression teams are, there are moments when nothing seems to stop fire, in particular in a country where people seem to live happily with fire on their backyards and use it frequently for landscape management. They just don't like it when fire shows up at the door. Their door. Fire suppression investments were a painkiller. A much needed painkiller, in fact, as prevention takes decades. But the Portuguese must behave differently. The number of daily ignitions, during summertime, is extremely high and must be reduced. How can anyone accept a toll of 400 (even 500) daily ignitions? Hardly.

Civil Protection, in Portugal, seems easily mistaken for wildfire suppression during summer and severe weather conditions during the winter. Far from the truth. Civil Protection is much more than that, and for sure, many of those working in civil protection would rather not have to deal with such an effort during summer. It must be understood that each and every wildfire summer campaign takes a lot of time to plan and prepare during the rest of the year. It's hardly conceivable to spend so much time preparing for something that has no justification, when there are so many other risks to think, plan and prepare for. If we cannot move Portugal from its place, all we have left is to move the Portuguese. Their minds, that is.

As I investigated for my MSc thesis, I concluded that meteorological parameters had little relevance for wildfire hazard modelling. As a matter of fact, high air temperatures, rainfall and other parameters do have influence when an ignition has already taken place, both slowing fire and making for an easier suppression, or allowing fire to grow and spread faster. But their influence on a structural approach, though, is near naught. My personal experience has shown me that weather conditions carry a blame they don't always have. It is not rare to experience days with very high severity rating (from the Canadian Fire Weather Index system) and still there are no significant ignitions, in number or affected areas. On the other hand, I have worked on days when the severity rating is reasonably low and yet the number of ignitions skyrocketed. Wildfires in Portugal, as per official reports, are mostly linked to human motivations. Thus, wildfire hazard assessment is possible using few variables, because as hard as it is to model human behavior, historical patterns do help. As a physical geographer, my concern is to perfect as much as possible my work on wildfire risk assessment, creating a tool to reduce uncertainty. We know there is a problem. We know the problem. Everything has been identified. The causes and the most wildfire prone territories are clearly known. It's necessary, now, to address those questions that, in the field of science, still persist. Wildfires in Portugal will only continue to be a problem for as long as nobody really cares about solving it. The solutions are all at hand.

Abstract

Wildfires are a recurrent phenomenon in mainland Portugal, mainly of a seasonal nature, during summer, even though, depending on favourable conditions for ignition and fire spreading, wildfires can occur at any time of the year. Wildfires represent a problem for mainland Portugal because they destroy significant areas of which some populations are dependent on, but also because wildfires lead to significant expenditures in suppression efforts. In this thesis, a low complexity model, integrating high spatial correlation layers has been tested with an updated land cover coverage, showing a good predictive capacity with only land cover, slope and historical data as layers. However, this model benefits from a double integration of historical data in that past wildfires not only enter the model as an independent layer but are also the basis for computing favourability scores for any other layer. For that reason, another method has been explored: Weights of Evidence. This second method is statistically robust and unbiased, and when put to the test with several evidence layers, such as land cover, slope, elevation, aspect, population density, population growth ratio and distance to roads, has shown that it has comparable results to those of the simpler, lower complexity model. It has also shown that adding more evidence layers does not necessarily lead to improved predictive performance.

Wildfire susceptibility assessment at a regional level (NUTSII) has also been studied, showing that with the exception of the smaller NUTSII region (Lisboa), all other regions show worse predictive performance than the model run for the entire mainland, and frequency-area statistics show that while large wildfires are responsible for most of the total burnt area in mainland Portugal, they are generally smaller than what would be expected from a power-law of good fitting. On the other side of the spectrum, smaller wildfires are found to be larger in area than what they should be in regards to statistics.

Keywords

Mainland Portugal, Susceptibility, Wildfire, Risk, Spatial Modelling

Resumo

Os incêndios rurais em Portugal continental são um fenómeno recorrente, de natureza essencialmente sazonal, com um pico de ocorrências durante o Verão, pese embora possam ocorrer em qualquer momento do ano desde que existam condições favoráveis à ignição e propagação. Os incêndios rurais representam um problema para Portugal na medida em que não só destroem vastas áreas florestais das quais as populações dependem, colocando em perigo a segurança e sobrevivência das populações, como também implicam um investimento avultado, anualmente renovado, em meios de supressão.

A floresta nacional é uma paisagem razoavelmente recente, que ao longo dos séculos foi muitas vezes depredada a favor da construção naval ou criação de áreas agrícolas, e que hoje se divide entre povoamentos e áreas incultas com grandes continuidades que promovem a propagação do fogo, após um século XX com algum investimento no sector florestal, quer para efeitos de defesa nacional, quer para captação de fundos comunitários.

Verificou-se, observando algumas das mais relevantes publicações sobre esta matéria, que as abordagens científicas à modelação de risco – nas suas várias componentes – estão muito orientadas ou para os aspectos dinâmicos, por via da exploração de índices numéricos que traduzam a probabilidade de ocorrência do fogo, ou para componentes intrínsecas ao território, que são utilizadas para a sua divisão em várias classes de susceptibilidade.

Nesta tese, a noção de risco que conduz o raciocínio implica o conhecimento de valor, na medida em que se entende um risco como algo que está a jusante da perigosidade: um efeito sobre algo, uma vez concretizado um fenómeno potencialmente danoso, o que pressupõe a identificação da susceptibilidade do território, aliada à probabilidade de ocorrência de um incêndio e, sobre isso, a valoração de elementos em risco com uma determinada vulnerabilidade, algo a que a literatura consultada por diversas vezes alude, embora pareçam existir dificuldades em efectivamente produzir mapas de risco, pela provável complexidade de valoração dos elementos em risco, pese embora se reconheça que o valor directo da floresta Portuguesa se mantenha em torno de mil milhões de euros, não contando assim com valores indirectos que elevam este valor, numa última estimativa conhecida, para um total de mais de 7 mil milhões de euros.

Aplicou-se, inicialmente, um modelo de complexidade reduzida já objecto de publicação em momento anterior, e uma actualização da cobertura do solo, obtendo-se resultados muito positivos em matéria de capacidade preditiva do modelo. Trata-se de um modelo que recorre a temas de forte correlação espacial: a cobertura do solo, os declives e o histórico de incêndios, tendo uma característica que o diferencia face a outros métodos: a informação histórica tem um duplo-uso, constituindo não apenas uma variável independente mas servindo, também, como base para a computação dos *scores* de favorabilidade de quaisquer outras variáveis nele integradas, o que se entendeu poder servir como um indicador indirecto do comportamento humano, destacando áreas de recorrência das de acidente isolado.

Ainda assim, obviando a dupla entrada em modelação da informação histórica, investigou-se a aplicabilidade de um outro método, criando modelos com recurso ao método *Weights of Evidence*, estatisticamente robusto e isento, que com a integração de diversos temas como a

ocupação do solo, declive, altitude, orientação de vertentes, densidade populacional, taxa de variação da população e distância à rede viária, demonstrou atingir bons resultados preditivos, comparáveis com o modelo de menor complexidade previamente explorado, demonstrando, ainda, que a integração de variáveis adicionais não resulta necessariamente numa melhoria do comportamento do modelo.

A susceptibilidade regional aos incêndios rurais (no caso, NUTSII) também foi estudada, tendo sido observado que, com excepção para a menor região (Lisboa), todas as regiões têm um comportamento preditivo inferior ao modelo para a totalidade de Portugal continental, e as estatísticas de frequência-área demonstram que os grandes incêndios são responsáveis pela maior parte da área ardida ainda que, de um ponto de vista estatístico se apresentem globalmente inferiores ao potencial de acordo com uma regra potencial com a qual exibem uma forte correlação. Inversamente, os pequenos incêndios tendem a ser mais extensos do que a estatística faria crer.

Verificou-se, também que não existe um número definitivo de anos a incluir numa série de modelação, embora os modelos estudados apresentem valores elevados de predição com séries curtas de apenas 10 anos de modelação. É possível modelar com séries mais curtas, tanto quanto se pode optar por modelar com toda a série disponível, deixando, porém, um ano para validação independente que permita verificar se o modelo ainda revela ajuste face à realidade, desde que mantendo presente a noção de que os modelos abordados nesta tese não se destinam a prever o comportamento de nenhum ano isolado, mas sim a uma utilização num cenário futuro não limitado, para efeitos de planeamento.

Na observação do comportamento dos modelos com o crescimento das séries anuais de modelação, verificou-se como um ano muito destacado face aos demais pode introduzir perturbações muito visíveis na capacidade preditiva dos modelos. Efectivamente, tomando o ano 2003 como exemplo, observa-se que foi de tal modo pouco selectivo no tipo de ocupação do solo que afectou, que perturbou a capacidade preditiva dos modelos, algo que se estima poder ocorrer de novo, assim exista outro ano com tamanho desvio. Constitui um aspecto relevante o facto de um ano muito distinto ter mais influência na validação do modelo do que na própria modelação, i.e., o ganho que um modelo possa ter por passar a integrar um ano com muita área ardida não é de todo comparável, em magnitude, à perturbação que esse mesmo ano induz na capacidade preditiva dos modelos.

Concluída esta dissertação, demonstrou-se que a susceptibilidade a incêndio rural pode ser avaliada com recurso a um número limitado de temas ou camadas de informação, tais como informação histórica, declive e ocupação do solo, a que podem juntar-se outras conforme o método escolhido. O método base apresentado em primeiro lugar é de muito fácil aplicação e produz resultados que podem replicar-se, de modo aproximado, com o método *Weights of Evidence*. Tal facto comprova que é possível realizar avaliações de susceptibilidade com qualidade, servindo de base a uma correcta gestão de risco que ajude a definir, entre outras estratégias, onde criar quebras de combustível, onde fazer uso prioritário de fogo controlado, onde ter especial atenção na restrição à edificação, por forma a evitar criar novos elementos em risco ou até, numa nota mais operacional, onde incrementar a vigilância e onde privilegiar o pré-posicionamento de meios técnicos e humanos de supressão de incêndios.

Não se apresenta, porém, uma solução à prova de toda e qualquer fragilidade. Enquanto abstracção da realidade, um modelo terá sempre margem para erro. Deve existir particular atenção na escala a que se aplica o modelo, que pode tornar necessária a utilização de outras camadas de informação, e, de grande relevância, a adequação da classificação à realidade. Nesta dissertação, a classificação com base em quintis foi adequada para o nível nacional e aplicou-se, também, ao nível regional (NUTSII), mas este tipo de classificação, na tentativa de alocação de 20% das unidades matriciais a cada classe, pode sobrevalorizar as classes, e.g., atribuindo áreas mais extensas às classes de maior susceptibilidade do que verdadeiramente se justifica no território estudado. Dessa forma, a observação cuidada das curvas de predição e o seu uso para uma classificação mais objectiva – quando as curvas não se prestem à classificação baseada em quintis – deve ser acautelada a todo o instante.

Palavras-chave

Portugal Continental, Susceptibilidade, Incêndio, Risco, Modelação Espacial

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Chapter 1. Introduction

Fire does not need to be a problem. Facing fire as anything else other than a problem is when it becomes useful to part fire from wildfire. Fire has been useful for populations since mankind learnt to tame it, around 400 thousand years ago (Bowman et al., 2009). The opportunity to get warm, to cook food and get protection from wild animals might have given man such a satisfaction that he nearly forgot how controlling fire is so many times more apparent than real. When that control gets lost, fires turn into wildfires, with all their consequences: the irreparable loss of lives, and several other values, both tangible and intangible. A wildfire is an unplanned or uncontrolled fire affecting a forested area, even if in a smaller area compared to an agricultural space affected by the same occurrence.

Wildfires have destroyed, in recent years, thousands of hectares in mainland Portugal. Not being a new phenomenon, it has seen increased media coverage in the early years of this century: burnt areas were significant, and fire came too close to cities and their people and the media can quickly get to the places where fire suppression is ongoing. This is also an era of social networks, and wildfires also spread online, contributing for increased attention.

Wildfires can be studied in regard to the number of occurrences or the extent of burnt areas. Treating occurrences, depending on the purpose of a study, might be less interesting: they should not cause a problem if they are quickly suppressed. It should be noted that the greatest number of occurrences in mainland Portugal is recorded in densely populated areas, and particularly along the north coastal zone. While numerous, they do not create special damage as they are usually small fires due to quick intervention and suppression. It is true, though, that being numerous, they present a burden to the fire suppression effort, and if firefighting is dispersed in numerous, yet small, wildfires, equipment and men will not be available to suppress large wildfires, or to prevent some smaller wildfires to grow into big and seemingly uncontrollable ones. Whereas the northern coastal areas are known for numerous ignitions, it is in the countryside that the number of ignitions is smaller, but wildfires tend to burn the most area.

1.1 Identifying the problem

Man, under normal living conditions, no longer needs fire in the open to get warm, cook or protect himself, except if an adventurous tourist, but fire is still very useful to take on tasks that would, otherwise, be expensive and time consuming. In the Mediterranean, fire has been used as a tool for fuel management, reducing forest and agricultural waste that would, otherwise, be available to burn in an uncontrolled manner. Pasture renewal is also a frequent purpose for the use of fire. Taming fire can be far more complex than what many would think at first, and when control over some parameters affecting combustion and fire progression is lost, fires evolve into wildfires that transform landscapes in a fashion Portugal very well knows, for as Atlantic as we might be, our traditions have a lot of the Mediterranean.

Notwithstanding some moments of exceeded optimism, the last of which after the wildfire campaigns of 2007 and 2008, what continues to be observed in mainland Portugal, for at least the past 30 years, is a significant burnt area due to wildfires (Fig. 1.1). The cooler 2014 summer of lesser burnt area and ignitions seems to have helped in decreasing the impact of wildfires, but the future, by definition, is uncertain.

After the highly discussed years of 2003 and 2005, which until now retain the record for burnt areas, it appeared as if something had changed because the following years were of a decrease in yearly burnt areas and somewhat discreet numbers in comparison to previous years. The same was observed for the number of ignitions which also dropped. It was considered, until 2009, that the changes in the fire campaigns and, possibly, a change in negligent behaviors, had allowed for a better control of wildfires and that this problem was, finally, in train to be solved. Unfortunately, the 2009 and 2010 campaigns came as proof that the problem persists, and that those optimistic speeches made in 2007 and 2008 did not have a solid ground.

Given that we cannot change our geography and climate, even though they are not, by themselves, to blame, it becomes necessary to change how the Portuguese relate themselves with fire. It cannot be accepted as a given or natural fact that the number of daily ignitions, for a continued time, reaches above three or four hundred wildfires.

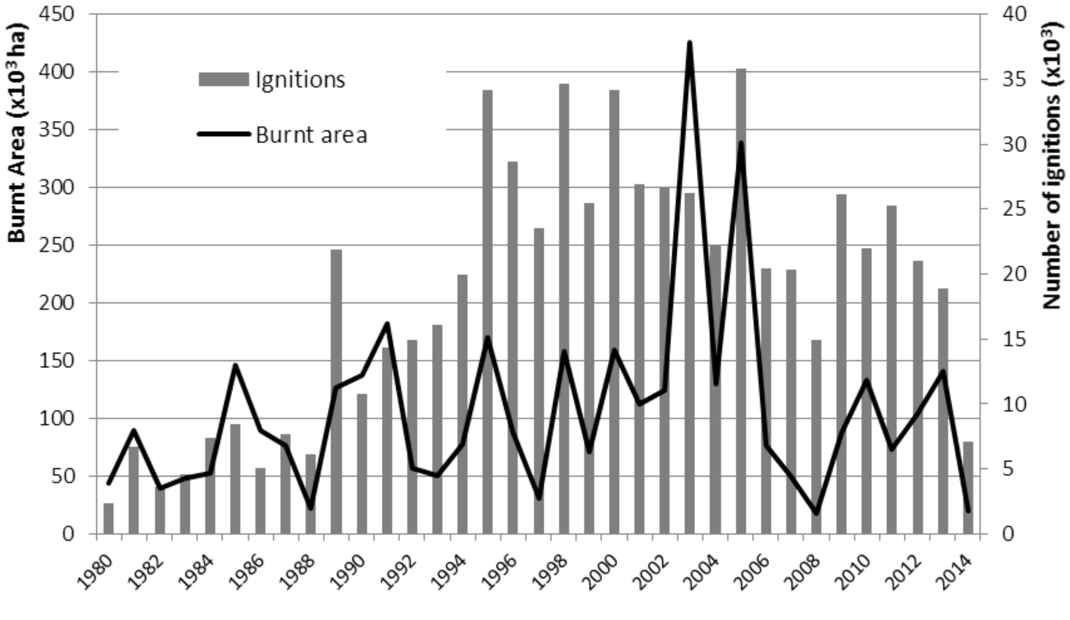


Figure 1.1 – Burnt area and ignitions, between 1980 and 2014, according to official reports. Source: National forest authority (website browsed on June 8th 2015)

In 2009, for the period of August 1st to September 30th, the daily number of wildfires was almost always above 100, peaking close to 500 ignitions (Fig. 1.2). These numbers were, however, far more expressive in 2010 (Fig. 1.3). From July 1st and up until the 23rd, the number of ignitions was manageable. After that, and until August 30th, there were 24 consecutive days above 300 daily ignitions. On two occasions, the symbolic mark of 500 ignitions was surpassed. These ignitions are those on forests (forest stands and shrubs) but also on agricultural land, in the sense that the means and operatives employed on these two scenarios are, essentially, the same. It should be noted, though, that agricultural fires are not accounted for on Portuguese statistical reports. The year 2011 deserves to be mentioned as well. Usually, the higher number of ignitions is registered from July to September, a period known as the "Charlie Phase" of the wildfire suppression campaign, which typically coincides with the most meteorologically favourable conditions for ignition and spreading of fire. In 2011, however, wildfires went well over that period, and October, usually a quiet month as to wildfires are concerned, in particular after the first autumn showers, was dry and hot, keeping wildfires on the agenda. After a peak of 435 ignitions, on October 15th, wildfires began a downwards tendency, which would be kept until Wednesday, the 19th (Fig. 1.4). On that day, the media started to report that rain was expected for the weekend. Without any significant change on daily severity (in regard to the Canadian Fire Weather Index), the next day saw a rise from 268 to 365 ignitions, and the yearly maximum was reached on Saturday, October 22nd, with 459 ignitions. Even on the day after that, 262 ignitions were recorded, until rainfall hit land and aided firefighters. At 14:20 (UTC+1, Local time), when rainfall was hitting the coastal areas (Fig. 1.5), there were still 33 simultaneous active wildfires inland. As rain progressed inwards, wildfires came to the end, and after several days with hundreds of ignitions, the season was finally over.

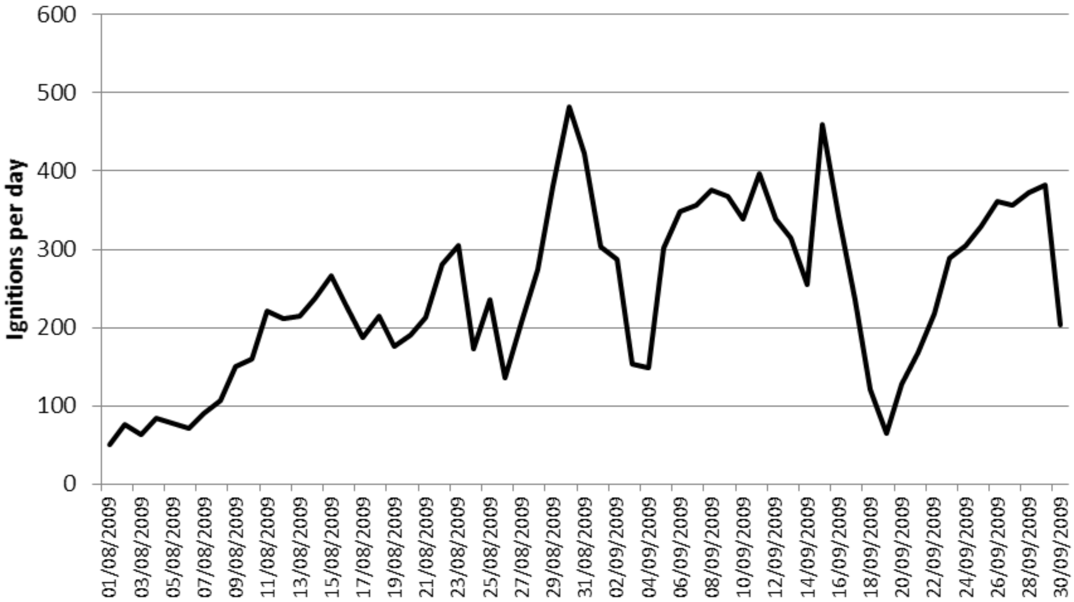


Figure 1.2 – Ignitions, between August 1st and September 30th 2009. Source: National Authority for Civil Protection.

This country remains, thus, exposed to loss in value, due to a very high number of daily ignitions, which, in turn, creates good conditions for the loss of control over some of those. As those lost ignitions gain extension, losses will be far higher and hinder local sustenance for those populations exploring the land. This does not come without a sense of irony, in that those same populations are, sometimes, the originators of the wildfires that will put them in a precarious condition.

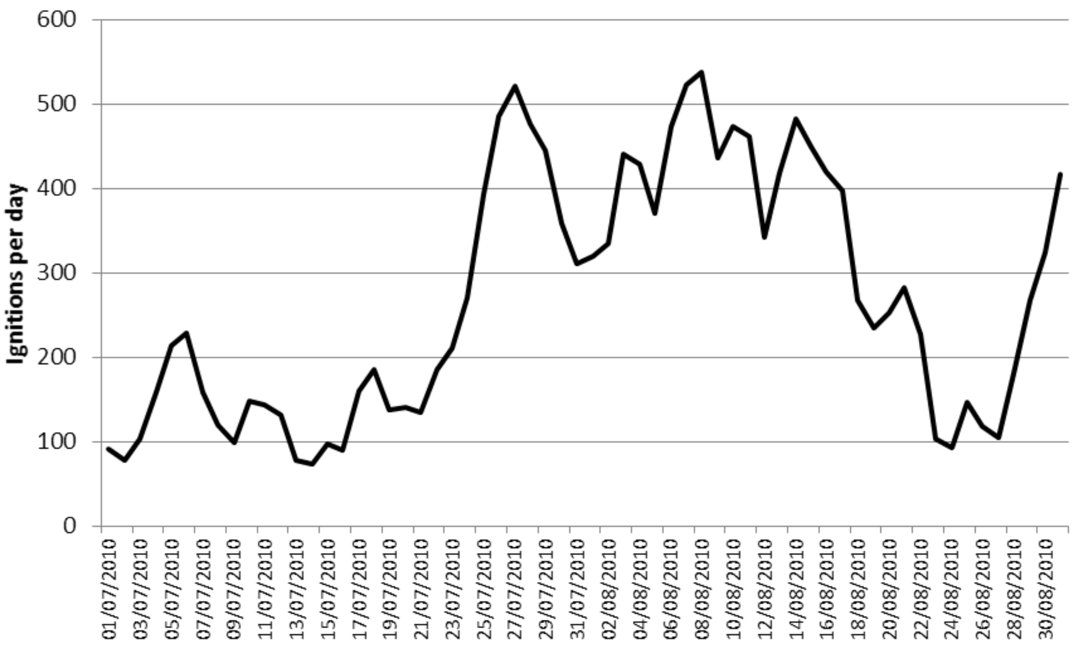


Figure 1.3 – Ignitions, between July 1st and August 30th 2010. Source: National Authority for Civil Protection.

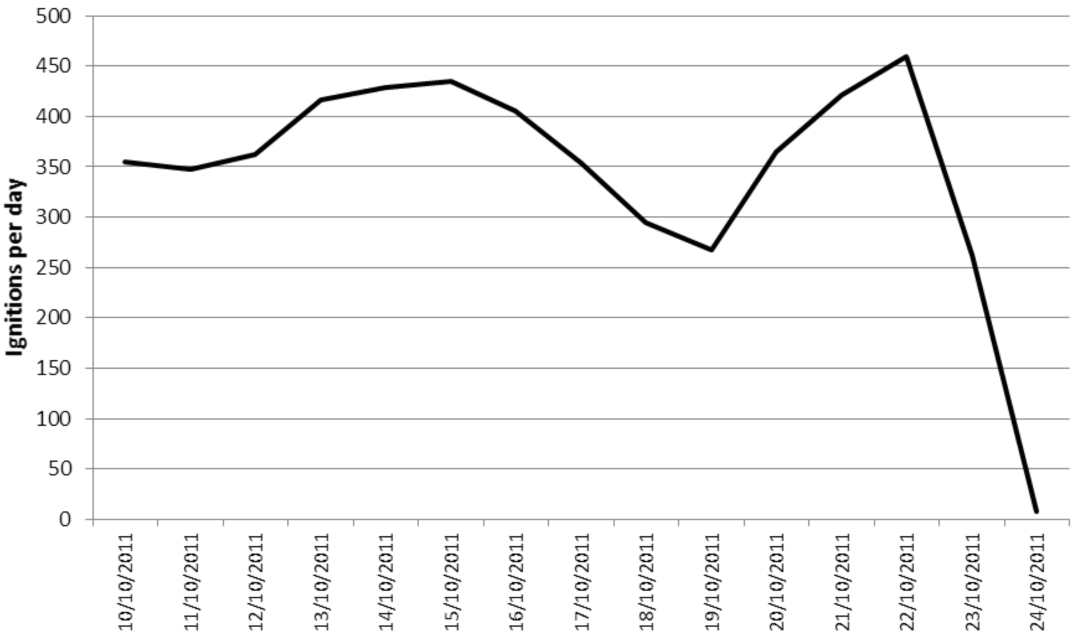


Figure 1.4 – Ignitions, between October 10th and 24th, 2011. Source: National Authority for Civil Protection.

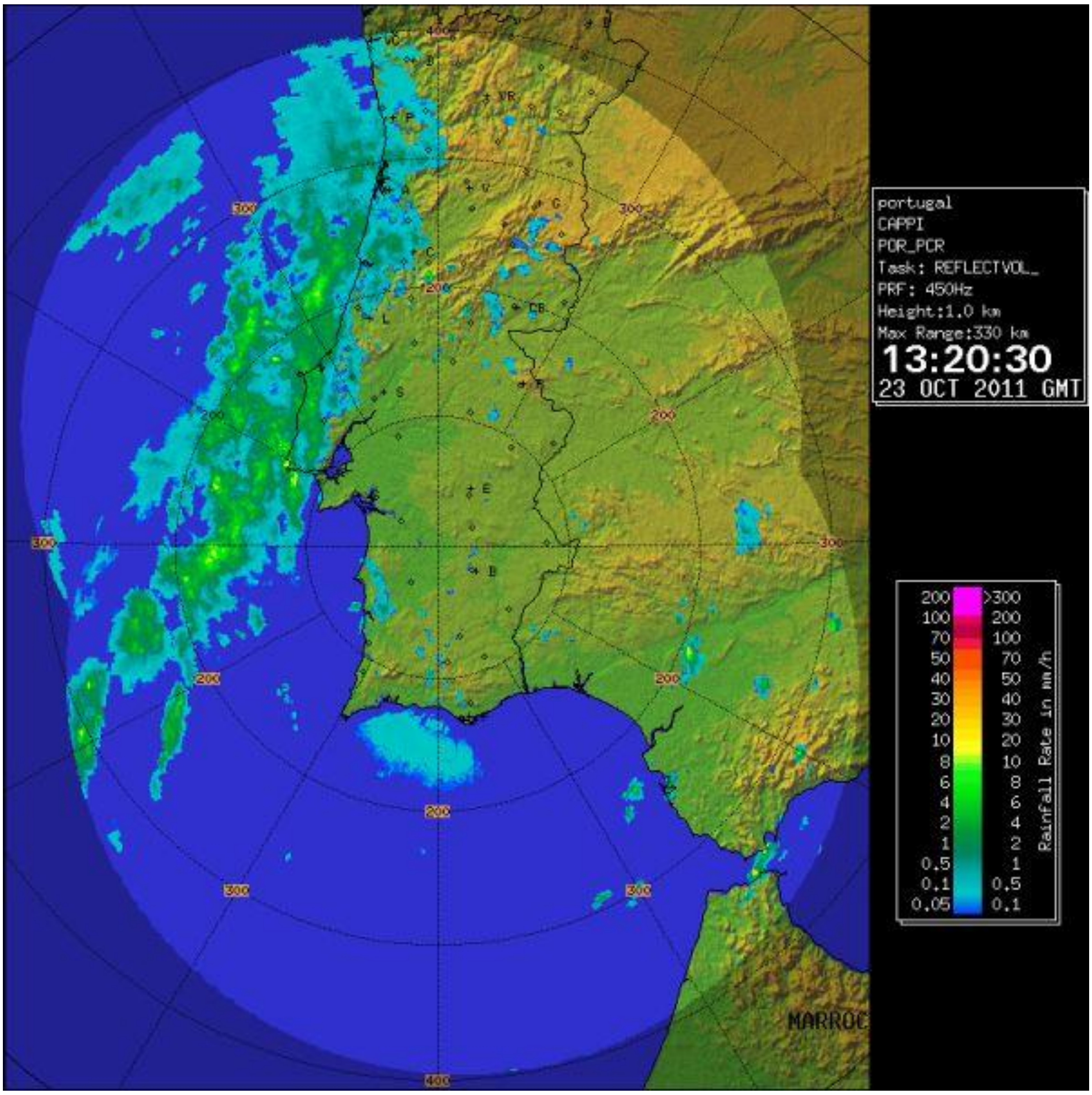


Figure 1.5 – Doppler composite (Rainfall Rate) for October 23rd 2011 at 13:20 UTC. Source: National meteorological authority.

This reality presents itself as an opportunity to address wildfires in mainland Portugal under a different perspective, given what has been done up until now. As investigations reveal that a large percentage of wildfires are due to human causes, including pasture renewal (GNR, 2013), it might prove useful – if not efficient – to closely follow, during wet seasons, the need to burn shrubs with prescribed fire, in an orderly and planned fashion to avoid further losses but, still, meeting the needs of those living in rural areas on a daily basis. For that matter, decision makers and operatives need to know exactly where it is desirable and possible, to carry out that kind of pasture land management.

Wildfires, in Portugal, happen mainly North of the Tagus River, and follow a clearly identifiable pattern, as shown in figure 1.6. Dividing the cartographic series of 1975-2013 in 10 year intervals, the affected areas show some recurrence.

From the diversity of tools available to plan those interventions, like land cover maps and others, risk mapping is extremely relevant because susceptibility maps clearly point out where are the most favourable conditions for wildfire ignition and spreading (also, they give a clear view of how hard it would be to suppress fire on those places, because slope is one of the entry parameters used for modelling), and risk maps identify where the potential for loss of value is higher.

Making use of risk mapping requires that models used for production are perfected and validated, having as good susceptibility maps as possible. For that reason, there are some questions that should be answered for as solid a mapping as possible, and these questions are considered drivers for better susceptibility mapping and objectives in this thesis:

1. What kind of forest does mainland Portugal have and why are wildfires a problem?
2. How does the changing in land cover affect a low complexity wildfire susceptibility model of good predictive capability?
3. How can the Weights of Evidence method help with wildfire susceptibility assessment in mainland Portugal?
4. How many layers should be considered in wildfire susceptibility assessment?
5. How does model behaviour change with yearly dataset intervals?
6. How does wildfire susceptibility change with Portuguese NUTSII regions and what do they show about wildfire magnitude?

Figure 1.6 – Burnt areas on 10 year intervals. Clockwise (starting from top left), 1975 - 1984; 1985 – 1994; 1995 – 2004 and 2005 – 2013 (2013 is the last year in the series, hence a 9 year interval).

1.2 The context

The problem has been identified in the previous section and a context description is in order. Not being an expert in Portuguese forest history, the author does not intend to do an extensive research in this area. Thus, only a very brief presentation of Portuguese forests is made, which can be complemented by other works, which portray a fairly complete picture of how the forest areas have evolved over the years in Portugal (see, for example, the National Wildfire Prevention Plan, ISA (2005), or Vieira (2006)).

Portugal has about two thirds of its territory occupied by forested areas, mostly private. The National Forest Inventory published in 2013 identified as forest areas (forest stands and shrubs and pastures) about 6 million hectares in 2010, slightly more than the 5.9 million hectares in 2005 or 5.8 million hectares 10 years earlier in 1995 (Table 1.1) (ICNF, 2013). In 15 years there has been a decrease in the area occupied by forest stands (from 3,305.4 to 3,154.8 million hectares) and an increase in the area taken by shrubs and pastures (2,539.3 to 2,853.2 million hectares).

The Portuguese forests are dominated by maritime pine, eucalyptus and cork oak, which together represented more than 71% of forested areas in 2010. Among these species only the area of eucalyptus has steadily increased in the last three inventories (+94.6 thousand hectares), while the maritime pine suffers the biggest drop in 15 years, losing 263.4 thousand hectares. The decrease in the area of cork oak is comparatively more discreet, with just 10 thousand hectares as compared to 1995, in spite of a higher loss until 2005 (table 1.2).

Table 1.1 – Areas by land cover, in thousands of hectares, in the national forest inventories of 1995, 2005 and 2010. Percentual differences given for the previous inventory. Source: ICNF

Land cover	1995	2005	2010
Forest stands	3,305.4	(-2.8%) 3,211.8	(-1,8%) 3,154.8
Shrubs and pastures	2,539.3	(+7.1%) 2,720.3	(+4.9%) 2,853.2
Total	5,844.7	(+1.5%) 5,932.1	(+1.3%) 6,008.0

Table 1.2 – Areas by species, in thousands of hectares, for the three most significant species, in the national forest inventories of 1995, 2005 and 2010. Percentual differences given for the previous inventory. Source: ICNF

Species	1995	2005	2010
Maritime pine	977.9	(-18,7%) 795.5	(-10,2%) 714.5
Eucalyptus	717.3	(+9,5%) 785.8	(+3,3%) 811.9
Cork oak	746.8	(-2,1%) 731.1	(+0,8%) 736.8

CORINE Land Cover 2000, according to what the Portuguese forest authority considers forested areas, accounts for a total of about 4.8 million hectares, a value that stays relatively unchanged in the CORINE Land Cover 2006 even though the latter nears 4.9 million hectares with a difference, between land coverages, below 40 thousand hectares (fig. 1.7), 4,843,200 hectares in 2000 versus 4,882,396 in 2006. In this coverage, cork oak forests have been included in the agricultural class (as agro-forestry areas) which contributes to the difference when compared to the national forest inventories. CORINE Land Cover will be used in this work as the reference land cover layer given its scale and nature (CORINE Land Cover is a polygon coverage whereas the national inventory is a point coverage, requiring interpolation and, therefore, higher commission and omission errors).

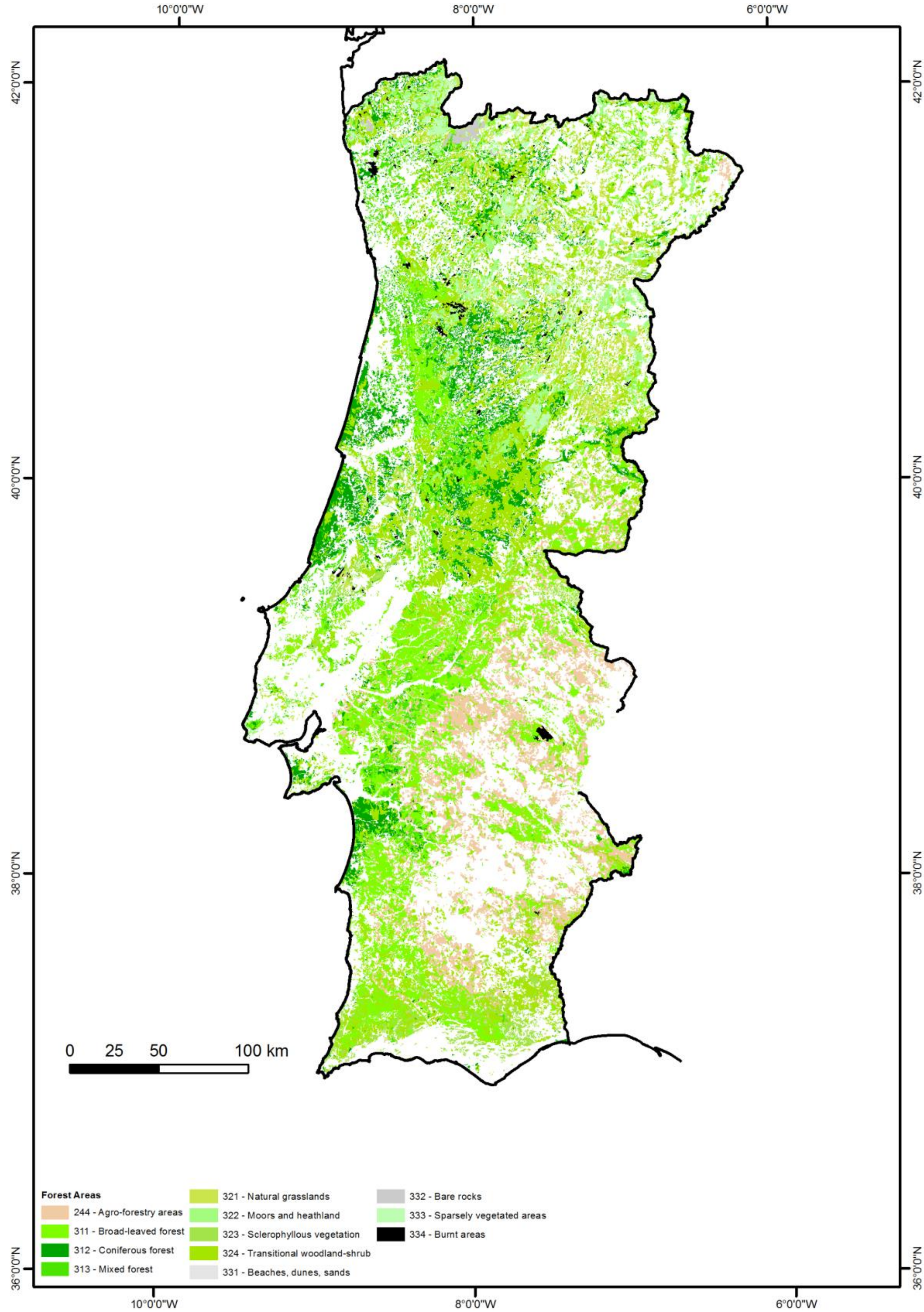


Figure 1.7 – Forest areas in 2006 in mainland Portugal. Source: CORINE Land Cover 2006

In spite of the fluctuations between the three most recent inventories, the final balance remains similar: about two thirds of the territory correspond to forest areas that, in addition to the notion often conveyed that the country has this capability and vocation, makes people believe that Portugal is in fact a forest country. The seasonal attention given to wildfires drives the public to the idea that wildfires are leading to the destruction of forest spots that have always existed and had resisted until now, more or less unharmed, by human activity. That is not entirely accurate.

The Portuguese forest has not always been extensive, and the forest that existed was often decreased in area, as a response to needs for wood or for pasture and agriculture. Vieira (2006) states that "the depletion of the forest is quite old, intensified especially in the time of the Romans who, drawing on its extensive and dense road network, were supplied of resin and wood by the Iberian Peninsula" (op.cit., p.22). The same author references the logging to meet the needs of an emerging empire: "from 1377, even the free log of royal forests was promoted to build ships (...) the time of the discoveries ended up as responsible for deforestation of important patches of cork oak, holm oak and other oaks, as well as pine" (op.cit., p. 23). The need for raw materials, as well as space for an agriculture that supported the evolution and livelihood of populations, is, indeed, something common to the whole Mediterranean. The interaction between man and natural areas transformed them in a way that, as pointed out by Ribeiro (1963, p.7), "it is not always easy to sort out what comes from his action from what preceded it or escaped it".

An historical perspective, in the National Wildfire Prevention Plan (PNDFCI), points out the "need for arable land (...), the urgency of vast treeless areas for grazing, deforestation of woods and forests for shipbuilding and the recovery effort developed after the 1755 earthquake" (APIF, 2005, p.23) as factors that led to the destruction of national forests by the end of the eighteenth century. As a result, the importance of forests in Portugal was reduced in the nineteenth century. According to Vieira (2006), "an estimate made in 1868 (...) pointed to only 112,436 hectares of forest throughout the country, representing a mere 1.3% of the territory" (op.cit. p.28). However, important steps for afforestation have been taken starting in the nineteenth century. A diagnosis of the Portuguese forest dated 1868 and titled *General Report on the afforestation of the country* (Ribeiro and Delgado, 1868), reports a bleak picture, but it represents a turning point for the development of afforestation. Later, in the twentieth century, the publication of the forest regime (in 1901), allowed for the advance of pine tree with concerns for sandy coastline fixation, regularization of river beds, protection of agricultural areas and even slope stabilization.

The twentieth century and the *Estado Novo*[1] gave the Portuguese forest a new momentum. After the wheat campaign (started in 1929, lasted until 1934), during which all the attention had focused on agriculture at the expense of afforestation, the afforestation plan of 1939 and the Forest Development Fund in 1965 sought to develop and conserve forests: "The Fund afforested, in the period 1965-1974, 77 thousand hectares, mainly in large estates of the south, that found in afforestation (...) an alternative to the decrease of cereals since the sixties" (Radich and Baptista, 2005, p.148). Even though there was also investment in cork oak, it was especially in the maritime pine that afforestation sat. Fast-growing and adaptable even to skeletal soils, this species allowed a profit on several fronts such as resin, wood and paper production. It should be noted that, during the *Estado Novo*, the eucalyptus, which later came

[1] Estado Novo (*New State*) was an authoritarian, conservative political regime, which lasted from 1933 to 1974, led by António de Oliveira Salazar until 1968 and afterwards by Marcello Caetano.

to increase its expression was very little used, occupying only 76 hectares in 1956 (Vieira 2006, p.43).

During the *Estado Novo*, afforestation served not only interests linked to hydrological correction or timber production, but also military interests. According to Rego (2001, p.56), in reference to the afforestation plan of 1939, "a key objective of the afforestation of border areas has to do with issues of national defense". In 1936, Salazar had coordinated with its Minister of Interior, Mário Pais de Sousa, an intensification of border controls (Nogueira Pinto, 2007, p.111), making it, therefore, not surprising that the afforestation of areas near the border had also the purpose of actively marking the boundaries of the country in face of a Spain where there were "two traditions, both annexationist and Iberist: Castilian rightist imperialism and militarist and (...) Iberian leftist and progressive federalism" (op.cit. , p.119).

The revolutionary period after April 1974 would modify the Portuguese forest: Forestry Services, which had up until then maintained management and an active presence in the territory, had undergone changes that had weakened its action. On the other hand, although most of the traditional owners chose to keep the management of communal lands in charge of the Forestry Services, the legal provision to return them to the communities that once had managed them, would weaken the ability to effectively do so. In the transition from a regime of authoritarian character to one marked by a revolutionary context, natural resources were allowed to be used without special care. Moreover, the action of the Forestry Services had previously been interpreted as an extension of the *Estado Novo* regime over the territory, due to its presence, hence, not always popular. Such was the case of the afforestation plan of 1939, which collided with people's interests, including afforestation of uncultivated land that served as pastures, creating local conflicts. The revolutionary context thus determined the loss of influence of the Forestry Services, in addition to the management of public forest areas also took on the policing of privately owned areas.

In the years following the political revolution of 1974, the depopulation of the interior and the decline in investment in pine was accentuated (there was not, for example, people to collect resin and keep forest stands in good order), giving way to stands of eucalyptus, a rapid growing species allowing earnings in a shorter time interval. To this end have contributed the funds that still existed from the "Fundo de Fomento Florestal" (Forest Development Fund, a legacy of the *Estado Novo*, of 1965) and from the World Bank, via the "Projecto Florestal Português" (Portuguese Forestry Project of 1981), which were directed to the planting of eucalyptus, attractive to landowners for translating into faster earnings, taking advantage of the State's interest in that industrial sector (Pinho, 2000; APIF, 2005).

After 1975, wildfires became one of the major concerns for the Portuguese forest. The increase in burnt area was expressive, and even quadrupled by 1980 (APIF, 2005), the year that saw the creation of the National Fire Service (SNB), under the Ministry of Internal Affairs, and, shortly thereafter, the National Service for Civil Protection (SNPC). With these two new services, and the publication of the Regulatory Decree No. 55/1981, which established the responsibilities of all parties involved (SNB, SNPC, Forestry Services, and Local Authorities), the approach to wildfires began to be made within the framework of civil protection, giving priority to people and their assets. Forest Services retained the responsibility for prevention and detection, but fire suppression had ceased to rely on the experience of this traditional institution.

The funds coming from the Community Support Frameworks allowed for greater investment in afforestation since 1986. The profits from stands of eucalyptus has made this a long coveted species, which would only change in the late '90s, when the economy made this species of less interest (DGRF, 2007). The most recent years, in the transition from the twentieth to the twenty-first century, have been characterized by a forest subjected to a number of challenges, such as proper management, and concerns about the sustainability of forests and with plagues (such as the nematode - *Bursaphelenchus xylophilus* - which kills pines, or platypus - *Platypus cylindricus* - which affects the cork). However, wildfires are by far the phenomenon which destroys most forested areas, in a period in which the latest National Forest Inventory seems to point towards a slight increase of these areas, accompanied by changes in its structure.

In the interval 1980-2014, according to official data (ICNF), wildfires have consumed over 3.7 million hectares: more than The Netherlands! This also goes to say that in the aforementioned period, an area larger than currently taken by forest stands has been subjected to wildfires. The two thirds the country has in forested areas provided, in 2005, many essential products for industrial activities, such as pulp and paper, cork and furniture. In addition, they contributed “to generate 3.2% of GDP, 15 000 direct jobs, [...] 12% of industrial GDP and 11% of exports" (APIF, 2005, p13).

By itself, what is reproduced above, adds to the problem. Particularly as the global value of the Portuguese forest was “around 7,750 million euros" and the problem of wildfires endangered "the sustainability of 64% of the territory, covered by forests and wastelands" (APIF, 2005). The aforementioned value is a global one, considering tangible and intangible values, given that in accordance with the authors, a direct revenue value was close to 1,1 billion euros, quite in line with what Lopes and Cunha-e-Sá (2014) found out to be the direct value of Portuguese forests, at about 1 billion euros (10^9€). The Portuguese forest is mostly privately owned, and a lot of this sector depends on private development. A recent legal document, the Decree-Law n. 96/2013 of July 19th, has raised discussion as it has been understood by nature conservancy organizations as giving way to freely plant rapid growth species (as Eucalyptus), renewing worries about major wildfires.

The loss of value of forest areas is a phenomenon that needs to be countered. These spaces, as we have seen, contribute to the creation of wealth for the country. Wildfire suppression has been done since 1980, within the civil protection, whose actions are primarily directed towards the protection of people and their homes. It can be argued if suppressing all wildfires is, indeed, a civil protection responsibility, and ensuring the livelihood of citizens cannot be limited to keeping wildfires away from their homes. The livelihood of citizens should include the protection of those areas from which they get sustenance. Apart from any political or emotional factors, making choices based on economics, to counter the loss of value of forest areas, can and should be a concern.

One cannot properly manage what one does not know, and to make a proper risk management it is necessary to know what elements are at risk and the characteristics of the territories that contribute to the presence of a risk.

Chapter 2. The conceptual framework

Achieving the earlier set goals, demands a very clear definition of what is understood as risk and all the other concepts behind it. Dealing with a risk model, even though in this thesis not all of it is developed, it is most useful to present a clear conceptual framework.

It is difficult to achieve a consensus on the terminology of risk models. In this regard, Bachmann and Allgower have already pointed out the need to define a consistent conceptual framework. In a 1999 article, they refer that "the somewhat inconsiderate use of the various terms 'danger', 'hazard', and 'risk' may result in misunderstandings that can have fatal consequences" (Bachmann and Allgower, 1999, p.1). Indeed, if there is not a common understanding of terminology, mapping products can be used whose contents do not match what is expected by the reader; e.g., a risk map that provides information on financial loss will not allow a correct reading if someone is looking to interpret it as a map that informs about the susceptibility of the territory to be affected by a dangerous phenomenon. Should this error occur in an operational situation and the map used as basis for decisions related to pre-positioning of men or equipment, or choice of fire suppression methods, consequences may prove disastrous.

Still from the same authors above, " the phenomenon fire has many aspects as people who are dealing with it (…) based on their primary interests, each of these 'communities' has different notions of the term 'wildfire risk'" (op.cit. p.1). This remark is as true as there are several schools producing *risk* maps, including forestry, environmental engineering, geography and others. The conceptual framework we intend to apply is the same guiding other studies, internationally, in the fields of risk assessment for mass movements (Guzzetti et al., 2003; van Westen, 2006; Zêzere et al., 2008; van Den Eeckhaut and Hervás, 2012; Fabbri et al., 2015), floods (Hall et al., 2003; Büchele et al., 2006; Messner and Meyer, 2006; Jonkman, 2007; Apel et al., 2009) or earthquakes (Barbat et al., 1996; Ellingwood, 2001; Pitilakis, 2006; Carreño et al., 2007; Cardona et al., 2008; Tesfamariam et al., 2010).

In common language, the word "risk" is used in an indiscriminate manner to refer to situations of potential harm and likelihood of occurrence. Just as quickly as people use the term "risk" to convey the notion of imminent occurrence of some phenomenon, people also use the same word to refer to loss, whether financial, material or personal. If, in common language, a consistent terminology is only desirable, in scientific and technical documents it is mandatory. In a simplified form, in the conceptual model we apply in this document, risk means money and security. The probability of occurrence associated with the conditioning factors of the territory is something different: *it is hazard*.

According to Bachmann and Allgower (1999, p.5), wildfire risk is defined as "the probability of a wildfire to occur at a specified location and under given circumstances and its expected outcome as defined by the impacts on the affected objects". This definition of Bachmann and Allgower meets the objective of covering all components of the risk model, and it is the definition adopted in this thesis to characterize wildfire risk. Figure 2.1, presents the risk model used in throughout this work.

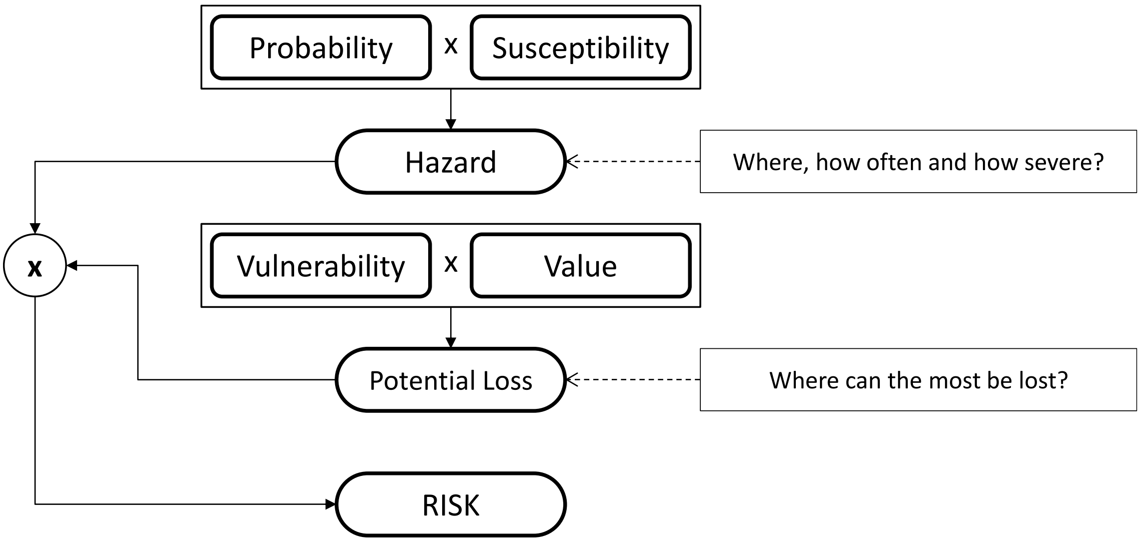


Figure 2.1 – Risk model components

Having presented the risk model in a schematic way, we know present its components and concepts behind them.

Probability

Probability expresses the likelihood of a certain event occurring, which can also be understood as an indicator for uncertainty. In a classical approach, if an event is not conditioned by a previous event, all events have the same possibility of occurrence and, hence, the same probability. If an event relies on a previous event for its occurrence, then its probability is also conditioned by the probability of occurrence of the first event (Reis et al., 2003).

Susceptibility

The susceptibility expresses the propensity of a given area or territorial unit to be affected by the studied phenomenon, evaluated from the properties that are intrinsic to that area or territory. A territorial unit will be more or less susceptible in relation to its ability to be more or less affected, or able to potentiate the occurrence and development of the phenomenon. In the case of wildfires, a particular area will be as susceptible as it allows for the generation and/or progression of fire (Verde and Zêzere, 2010).

Hazard

Hazard, as defined by Varnes (1984, p.10), is «the probability of occurrence within a specific period of time and within a given area of a potentially damaging phenomenon». This notion encompasses the notion of space and time, as well that of magnitude, for which calculations can take into consideration susceptibility, addressing those aspects related to the territory, and probability, given by historical data. A hazard, under the notion given by ISO GUIDE 73:2009 (ISO, 2009), is a source of a potential harm, either tangible or intangible.

Vulnerability

Vulnerability translates into the degree of loss that a given element is subjected to in the presence of a given phenomenon. Vulnerability can be expressed in a range of zero to one, whereas zero means there is no loss, and one means that the element is totally lost (Varnes, 1984; Cardona, 2004).

Potential Loss

In the literature, risk is many times referred to as the mathematical expression R = H x V (UNDP-BCPR, 2004) according to which risk is the product of hazard and vulnerability. This definition poses a challenge which is not being able to adequately differentiate the real loss of different elements with a different vulnerability. Looking at wildfires, and as an example, a small building might have a higher vulnerability than that of a forest stand where fire works as part of its reproductive strategy, which will make the small building subjected to a higher risk. However, if based on that information and taking R = H x V as verbatim, assuming risk to be higher on the small building, people will most likely try and defend it from fire, leaving the forest stand to burn even if the forest stand has a much higher economic value than the small building people have chosen to defend.

Risk

In this work, risk is understood in the same manner as per Bachmann and Allgöwer (1999, p.5), that is, «the probability of a wildland fire occurring at a specified location and under specific circumstances, together with its expected outcome as defined by its impacts on the objects it affects». As such, risk can also be understood as the product of hazard and potential loss (fig. 2.2), which is compatible with the notion of an effect of uncertainty on objectives or a deviation from expected, via a combination of events and consequences, as per the International Organization for Standardization in its Guide 73 (ISO, 2009).

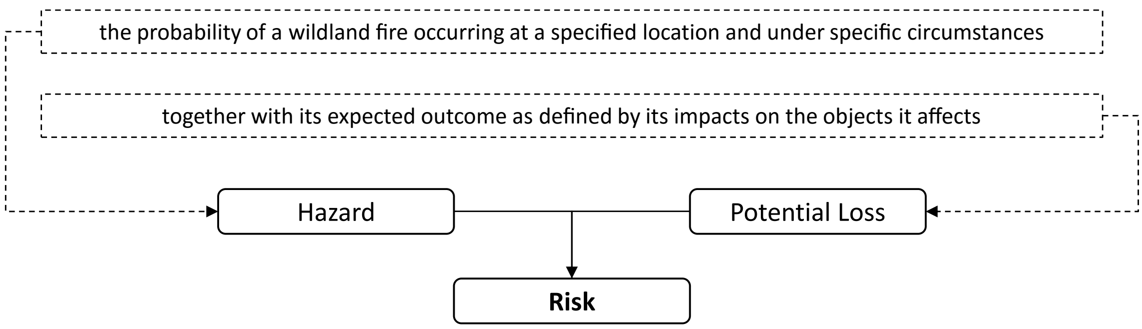


Figure 2.2 – Risk definition of Bachmann and Allgöwer (1999), adapted to the conceptual model herein adopted

Chapter 3. The state of knowledge on the field of wildfire hazard and risk assessment and mapping

Studying wildfire risk components is not a new concern, as many authors have devoted their time investigating new ways of approaching wildfire hazard and risk assessment, not only in Portugal but certainly worldwide. Those approaches are usually directed towards hazard and do not always have mapping as a purpose. In some cases, as it will be demonstrated, the goal is to produce a numeric index that can be used to help predict fire behavior, warn the population, apply restrictions defined by law or even to maintain public information devices or websites.

The terms used are varied and in some cases do not fit the conceptual model adopted in this thesis. When making reference to any work, the work title is the original, even though the analysis of the content is, in the context of this document, made in regard to the conceptual framework adopted and presented in the previous chapter.

The methods and parameters used are also different. Some authors choose additive formulations, others more complex probabilistic calculations, depending on their purpose.

Wildfire hazard assessment is usually two-fold: a dynamic analysis, which focuses primarily on meteorological aspects that allow assessing the fire behavior under parameters such as wind and temperature, and a structural analysis, which evaluates the favorability of the territory for the occurrence of the phenomenon.

The way wildfires impact economy and the environment, social and cultural habits, but also the development of new methodologies, have been motivating authors to invest in this subject. In this chapter it will not be possible to reference all wildfire hazard assessment studies, but key authors, whose work has been the basis for further development or used for planning will be referenced. Since the area of interest of this thesis is mainland Portugal, a significant part of this chapter will address Portuguese studies, but other authors and studies will be referenced.

3.1. Meteorological-based wildfire studies

One of the Portuguese authors studying this subject for the longest is Luciano Lourenço, whose work presents indexes derived from, in accordance to the author, the two most fire related meteorological parameters, temperature and relative humidity [3.1] (Lourenço, 1991).

$$IR_{LL} = T / U + V \qquad [3.1]$$

For a given hour of the day, this index uses temperature (T) and relative humidity (U), adding a correction value (V) according to wind speed and direction at that same given hour. According to Lourenço (1991), the most extreme «risk» conditions are met with the maximum daily values for each variable (for relative humidity, the minimum), even though those extremes (maximum and/or minimum for T and U) do not usually occur at the same time [3.2].

$$IRMAX_{LL} = T_{max} / U_{min} + V_{max} \quad [3.2]$$

Initially, the author found some difficulties in integrating wind in his proposed formulae because determining exactly how the wind influenced fire behavior was still ongoing, but later on, as a development of his method, Lourenço (1996a) perfected wind integration for achieving the desired index and differentiate the calculation: not using wind, if the purpose is to only calculate the odds of ignition, or using wind as in [3.3] if wanting to know how fire would behave.

$$IRPIF_{LL} = (T / U) + (V / 100) \quad [3.3]$$

With this method iteration, winds would be considered in a more precise way, including two wind types that are most relevant to wildfires: East winds, helping ignition as they are dry and North winds which make fire progression faster and sometimes uncontrollable. It has also been considered useful to know the odds for days ahead, as a way of helping firefighters, for which the author proposed the formula [3.4] (Lourenço, 1996b).

$$TIRIFF_{LL} = \left[\left(\frac{Tdc}{Udc} + \frac{Vdc}{100} \right) + \frac{2(Tds - Tdc) + (Udc - Uds) + (Vds - Vdc)}{100} \right] R \quad [3.4]$$

In this last proposition by Lourenço (op.cit.), a wildfire «risk» tendency would be calculated just as before, given that temperature (T), relative humidity (U) and wind speed (U) would be those of the day in question (when suffixed with “dc”) and for the day after, with the suffix “ds”. Variable R is a regional correction constant based on wildfire history for any given municipality.

The work by Luciano Lourenço uses a different conceptual framework as that proposed in this document, which can clearly be illustrated as the author says that «This was one more attempt for knowing risk, in a timely fashion, to, through prevention, reduce danger and avoid crisis (…)», in regards to a paper named *Risco de Incêndio* (Wildfire Risk) where he presents the conceptual framework and proposes a method for calculating a meteorological index for risk class definition (Lourenço, 2004, p.173). His conceptual framework is, therefore, the reverse of what is proposed here.

Ramos and Ventura (1992) also proposed a meteorological based index to classify wildfire hazard. Having studied meteorological conditions present at the time of big wildfires (those with 100 hectares or more of burnt area), they came to the conclusion that «the days with more big wildfires are those after long periods without rainfall when high temperatures come together with dryness and wind favourable to propagation» (Ramos and Ventura, 1992, p.84).

Notwithstanding such observation, due to difficulty in defining rainfall boundaries considered enough to put an end to a series of dry days and other difficulties in integrating parameters that would have to be included, the authors chose to correlate daily temperature with atmospheric moisture. As such, in the formula of Ramos and Ventura [3.5], the daily wildfire hazard index would comprise five classes (Very Low, Low, Medium, High, Very High) and consider air temperature at 18:00 local time (T), dew point temperature at the same hour (Td) and daily maximum temperature (TM).

$$I = i \times i' \qquad [3.5]$$

With

$i = T - Td$

and

$i = 1; (T\text{-}Td) < 5$
$i = 2; 5 \leq (T\text{-}Td) < 10$
$i = 3; 10 \leq (T\text{-}Td) < 15$
$i = 4; 15 \leq (T\text{-}Td) < 20$
$i = 5; (T\text{-}Td) \geq 20$

$i' = 1; TM < 20$
$i' = 2; 20 \leq TM < 25$
$i' = 3; 25 \leq TM < 30$
$i' = 4; 30 \leq TM < 35$
$i' = 5; TM \geq 35$

Meteorological parameters such as rainfall, relative humidity or temperature have been frequently used in studies and models relating to wildfires. Rebelo (1980, p.653) stresses the pervasive role of weather declaring that «summer dryness, [...], is the first explanation; man, however, through carelessness or deliberate actions, works, almost always as a detonator», and Pereira M.G. et al. (2005, p.12) also claim that «weather influences fire indirectly, through its effect on fuel moisture, and directly, through the role of wind on promoting convective heat transfer, and affecting the formation of convection columns on large fires». Ventura and Vasconcelos (2006, p.94) also stated that «while vegetation and meteorology are mainly conditioned by soil, climatic and topographic characteristics of each region, in many areas the ignition of fires is mainly dependent on human activity», hence, the conditioning role of the weather is clear: impeding progression (or even ignition) when relative humidity or rainfall prevents so, or favoring the phenomenon when the relative humidity is low, temperatures are high, or winds are strong. More so, as Pereira M.G. et al. (2005) concluded, spring weather conditions are strongly correlated to large wildfire occurrence in Summer months.

Lourenço (2006) revisited wildfires with a paper called *Geografia dos Incêndios Florestais em Portugal Continental,* meaning Geography of Wildfires in Mainland Portugal in which he sets to analyze burnt area distribution, focusing on 2003 thru 2005, correlating the number of ignitions and burnt areas with the observed meteorological parameters. In that analysis, the author concludes that even though meteorological parameters from 2003 to 2005 were highly favourable to fire ignition and spreading, those are not the only or even main reasons for the number of ignitions and extension of burnt area in those years. As the author clearly states, should that be the case «wherever those meteorological conditions were met, there would have been fires and those areas would therefore be incinerated which, happily, did not happen» (Lourenço, 2006, p.60).

Still on the connection of climate and weather with wildfires, Trigo et al. (2006; 2013) explored the different types of atmospheric circulation in the Iberian Peninsula, coming to the conclusion that climatic conditions observed in northwestern Iberia would be highly influential on Summer wildfires and their size, later confirmed by the conclusions by Amraoui et al. (2015) who also found the largest Summer wildfires to occur in northwestern Iberia although two peaks for wildfire occurrence are identified, in August and in March, the first mostly related with an amplification of an anticyclone centered near the Azores and extending to Central Europe, bringing into Portugal easterly winds of a very dry and low humidity levels, and the second also related to winds from the East, of low humidity, that in conjunction with landuse practices and negligence result in a different but still noticeable peak in wildfire occurrences.

The conditioning role of weather makes it useful if not a requirement to use these parameters in calculations that can be integrated into dynamic risk models or for establishment of hazard indices for preparation of suppression efforts and alerts to the population. One such product is in use in Portugal, the Fire Weather Index (FWI), a subsystem of the Canadian Forest Fire Danger Rating System , which is an indicator of the risk of fire expressing “fire behavior on a level terrain and for a reference type of fuel (adult pine Pinus banksiana)» (Fernandes, 2005). This index, computed by the Institute of Meteorology, according to Fernandes (op.cit.), has been interpreted improperly as a risk index. In fact, this interpretation is somewhat transverse to the currently produced papers in Portugal on this subject, so that climatic elements have hence contributed for hazard products and not risk. The calculations for the FWI only include temperature, relative humidity, accumulated rainfall in the previous 24 hours, the wind speed at 10m height in open terrain and, strictly speaking, constitute an index that informs the user about the severity a fire may have under the observed conditions. First presented in Canada, in 1970, and after several years of development, this indexing system comprises six main components (Van Wagner, 1987), three of which are moisture indices that follow the changes in moisture of different reaction time fuels (fine, loosely compacted, and deep compacted organic fuel), and the other three are indices for fire behavior as in speed of progression, fuel consumption and intensity (Figure 3.1).

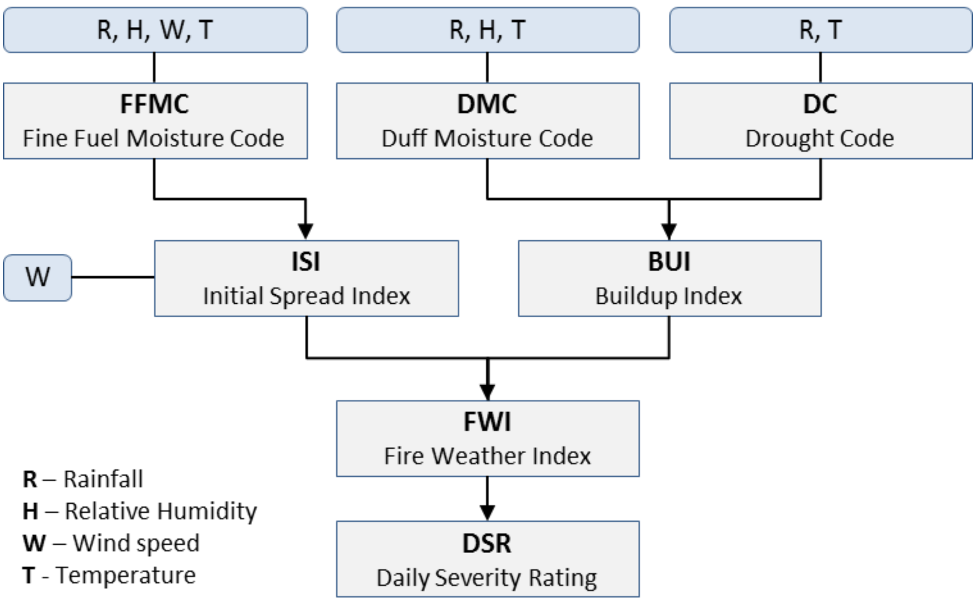


Figure 3.1 – FWI structure, adapted from Van Wagner (1987)

To the six main components of the Canadian model, a seventh can be added, derived from the FWI index, the DSR or Daily Severity Rating, introduced by Williams (1959) and adapted by Van Wagner (1987) to facilitate defining hazard classes after observing that the correlation between the FWI index and fire suppression efforts was not linear. With the DSR index, a logarithmic relation is assumed, accentuating FWI as it grows, better representing suppression efforts.

Individually, the Canadian Fire Weather Index components offer useful information to fire suppression operatives. The Fine Fuel Moisture Code varies quickly over the days and gives a good idea of how dry and flammable the fine fuels are. The Duff Moisture Code is very useful for planning prescribed fire actions, thus diminishing available fuel, and the Drought Code is particularly relevant in orienting mop up operations (that is, preventing rekindles) so that ground fires are not a menace in days with an elevated DC index. Presently, the Canadian FWI system is used in Portugal by three organizations: the Portuguese forest authority (the Institute for Forest and Nature Conservation), the meteorological authority (Institute for Sea and Atmosphere) and the civil protection authority (National Authority for Civil Protection).

Using the Canadian FWI does make sense in that it has been useful in predicting wildfire occurrence in countries such as Greece (Karali et al., 2014), and, as Venäläinen et al. (2014) express, “weather conditions make the occurrence of fires possible and humans in most cases ignite de fire”. The approach by Venäläinen et al. (op. cit.) is an interesting one in that the authors sought to “investigate whether the recent changes in climate have had a discernible impact on weather-related fire danger in Europe”, in the period 1960-2012, and they used the Canadian FWI for that intent, coming to the conclusion that the occurrence of wildfires does not always follow an increase in the FWI. Still, as an indicator of fire spread intensity, the Canadian FWI continues to be used and generally accepted because weather, as important as it is as a conditioning factor, is recognized as not being the sole responsible factor in wildfire occurrence. Other than that, the Canadian FWI is the standard in Europe, following an EU recommendation in 1997 (Fujioka et al., 2008).

3.2. Terrain-based wildfire studies

In 2003, the Portuguese forest authority (which, as an organization, has had several names over the past few years) published a study by Cardoso Pereira and Nobre dos Santos (Pereira and Santos, 2003) called “Fire Risk and Burned Area Mapping in Portugal”, which presented cartography that would replace the one published with the Regulatory Decree n. 55/81 of December 18th (op.cit., p.5)

The aforementioned study benefited from the first set of ten years of burnt scar mapping through remote sensing, starting in 1990 and made possible via a protocol between the forest authority and the Forestry Engineering Department at the *Instituto Superior de Agronomia* – ISA (agronomy institute). The burnt areas of 1990 thru 1999, used by Cardoso Pereira and Nobre dos Santos, have minimum mapped areas that became finer over the years: 25 hectares between 1990 and 1992, 15 hectares in 1993 and 1994, and 5 hectares from 1995 onwards.

The conceptual framework they used in their work is the same used here, as they also use the Bachmann and Allgöwer (1999) wildfire risk definition presented in the previous chapter. However, these authors do not integrate in their model all the components needed for risk mapping, choosing to represent what they consider to be elements at risk by drawing a layer on top of the models result, a hazard map – even though the burnt area scenario is not clear.

The layers considered by Pereira and Santos (op.cit.) are land cover, from the Portuguese project COS90 (northern Portugal) and CORINE Land Cover (southern Portugal) (op.cit., p.34), elevation and slope, resident population from the 1991 Census, and two climatic layers from the 1961-90 period: the number of days with temperature above 25ºC and the number of days with rainfall between May and September.

Burnt areas are not directly considered in this model. As described by the authors, burnt areas were interpolated to the purpose of filtering local anomalies without any expression on the scale the map is intended for (the pixel is 1 km^2), Therefore, «it is important to emphasize that this was the spatial pattern of incidence of fire that was modeled to assess the risk of forest fire, and not the original spatial pattern of occurrence of fires» (Pereira and Santos, 2003, p.32). The authors computed the probability for each pixel to be subjected to ignition in a period of 30 years. That probability was correlated with the other layers through a regression tree, «using the Classification and Regression Trees (CART) algorithm (Breiman et al (1984))» (op.cit., p.45).

As a result, Pereira and Santos present a map with five classes of probability, 0-10%, 10-20%, 20-30%, 30-40% and higher than 40%. Overlapped to this map, a layer of large contiguous forested areas and forested areas considered critical is shown, giving origin to the title *Carta de Risco de Incêndio*, or Wildfire Risk Map.

For validation purposes, using burnt areas of the year 2000, they verified that 85.4% of that year's burnt areas were contained in the two topmost probability classes, with 57.3% of the total burnt area in the topmost class alone. Those were results that motivated the authors, in that it constituted an independent test because it was information that was not used to model, confirming the assumption that the methodology could be applied to identify the areas with the highest propensity to burn.

Because vulnerability and value were not considered, that was a map we can refer to as a hazard map, in that it combines layers of susceptibility with probabilistic information for a given timeframe and affected area (which anyhow is not clear in the document). As a hazard map it was the national reference for several years, adopted by the Portuguese forest authority and published in the Decree-Law nr. 156/2004 of June 30th, later revoked by Decree-Law nr. 124/2006 of June 28th whose regulation in this matter was never revised.

Cardoso Pereira and Nobre dos Santos alerted for the caveats of their method suggesting that it should be improved in the future. Considering the method empirical and inductive (op.cit., p.52), they reference how this map must be carefully read, pointing that, for instance, southern Portugal is mainly in the lowest hazard classes, which might change as new forest stands are grown or as meteorological conditions worsen.

As for improving the methodology, Pereira and Santos suggest refining interaction between climatic themes and elevation, or decomposing susceptibility according to land cover classes, which this thesis addresses on the next chapter.

After this publication of 2003, the map produced by these authors became two-fold. A structural approach and a cyclical one, being that the cyclical approach, as it rolls over areas recently burnt, lowers their probability of burning again in the following years. On a structural approach, the map would support decision makers in regards to infrastructure or planning, whereas the cyclical approach could support fire suppression assets and operatives' deployment or defining surveillance paths (Pereira, Carreiras and Santos, 2004). The cyclical approach has been used by the meteorological authority to cross with the Canadian FWI in order to achieve what they consider to be a combined risk map (weather plus landscape, after a fashion) (fig. 3.2).

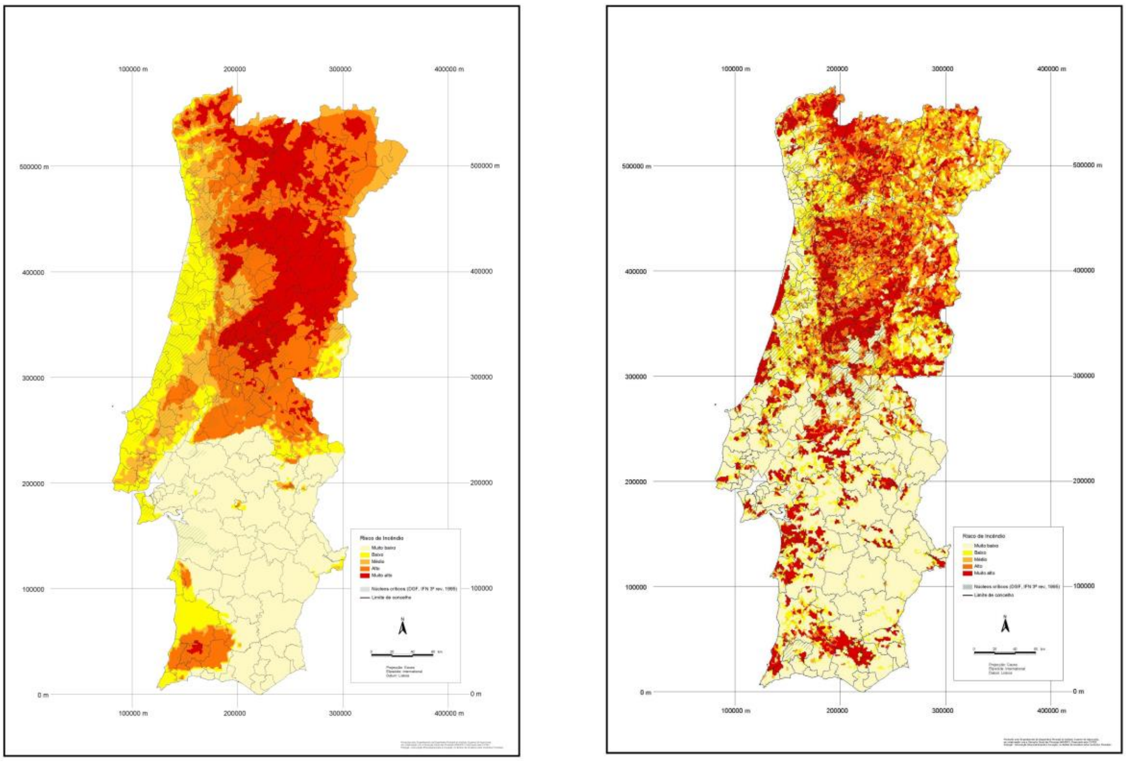


Figure 3.2 – Structural hazard map (left) and Cyclical hazard map (right) in 2004 (Pereira, Carreiras and Santos, 2004)

In parallel to Pereira, Carreiras and Santos, the *Instituto Geográfico Português – IGP*, the Portuguese geographical institute (currently Direcção Geral do Território) implemented a different methodology for mapping what they called wildfire risk, in reality wildfire susceptibility maps, with a spatial resolution of 25 meters, built at the district level – even though the maps can be merged together to form a single, national, map. Being a three year project, between 2006 and 2008, this mapping methodology was carried out north to south, with four districts mapped in 2006, six districts in 2007 and the remaining in 2008 (the national map has since been completed and made publicly available).

IGP's approach began in 2004 with the district of Viseu with a methodology originally based on seven layers of information: land cover, slope, aspect, transportation (distance to roads, and road density), demographic density and surveillance post visibility. In a 2007 revision the surveillance post visibility layer was dropped resulting in the dispersal of the weigh it had to the transportation layer, to which IGP added railways and also electricity networks) (IGP, 2007). On table 3.1 the layers and their weights are presented, in the 2007 iteration of the methodology.

According to the report written in 2004 for the district of Viseu (IGP, 2004), the weighing of the layers was made by a group of experts, in a subjective way. The final weighs were obtained by crossing all expert evaluations even though the specifics are not clear. Afterwards, it is considered that a given maximum value is to be divided by the layers according to their weighs, being the final result a weighed sum. As this equates to a previously known universe of pixel values, the different district maps can be directly compared and joined to form bigger, merged, maps.

In figure 3.3 the wildfire susceptibility map for the district of Viana do Castelo (northern Portugal) is presented, after IGP's methodology, in 2007. In light of the conceptual framework presented in the previous chapter, and since IGP does not present one, it can be inferred that IGP's methodology results in susceptibility maps. Further hazard and risk parameters are absent.

Susceptibility or hazard's classification, depending on the product, is traditionally divided into five classes with diverse formulation, given that, generally speaking, classes range from "Very Low" to "Very High" or "Minimum" to "Extreme". Those class names have a strong anchor point in what has been the law.

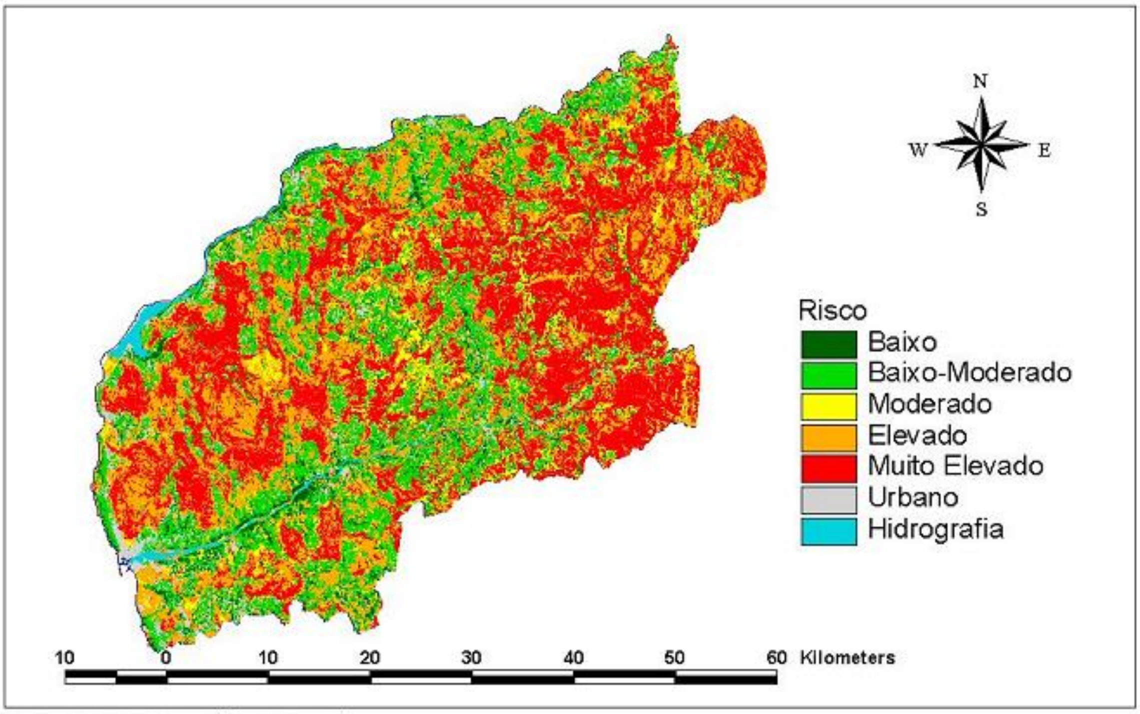
The Decree-Law n. 327/80 of August 26th, written after considerable losses and changes in the coordination of various agents for prevention and detection of wildfires, as can be read in the preamble of the law, has laid the foundation for risk mapping. Indeed, as in subparagraphs b) and g) of paragraph 1 of Art. 2. of this Decree-Law, it was necessary to "declare the areas and seasons of danger 'and' prepare and publish a map of the region in which the danger zones were highlighted".

This urge was to be addressed later on, under Regulatory Decree n. 55/88 of December 18th, which would, for several years, contain the reference map in regards to wildfire susceptibility. In its Art. 2, under the title "Mainland zoning according to wildfire risk", this Regulatory Decree would present a map with only four classes, I – Extremely sensitive, II – Very sensitive, III – Sensitive, IV – Minor sensitivity, whose classification was based in factors like distribution and nature of forest species, their vulnerability to fire, flammability, average temperatures from May to September, average air humidity in the same period, topography, aspect and finally demographic indices. In addition, wherever classes I and II existed, as long as there were large forested areas requiring special protection measures, "critical zones" could be designated. Those critical zones are still referred to on the current legislation. Figure 3.4 presents the map published with this Regulatory Decree, which was only revoked in 2004.

Table 3.1 – Themes, classes and their weighs according to IGP's methodology

Layers	Variables		Class weigh inside each layer		Layer weigh	
			%	Value	%	Maximum criteria value
Land cover	Class 1		100 %	590	59 %	590
	Class 2		80 %	472		
	Class 3		70 %	413		
	Class 4		40 %	236		
	Class 5		30 %	177		
	Class 6		10 %	59		
	Class 7		1,5 %	9		
Slope	Above 40%		100 %	210	21 %	210
	30 – 40 %		66.67 %	140		
	20 – 30 %		22.38 %	47		
	10 – 20 %		11.43 %	24		
	0 – 10 %		3.81 %	8		
Roads	Proximity to roads	Up to 25m	100 %	90	9 %	90
		25 – 50 m	46.32 %	42		
		50 – 100 m	20.58 %	19		
		100 – 150 m	9.55 %	9		
	Density of agricultural and forest roads and trails	< 5 m/ha	50 %	45		
		5 – 12.5 m/ha	23.52 %	21		
		12.5 – 20 m/ha	10.29 %	9		
		20 – 30 m/ha	5.14 %	5		
		30 – 40 m/ha	5.14 %	5		
		40 – 65 m/ha	10.29 %	9		
		65 – 80 m/ha	23.52 %	21		
		> 80 m/ha	50 %	45		
Aspect	135º - 225º		100 %	60	6 %	60
	225º - 315º		57.45 %	34		
	45º - 135º		21.28 %	13		
	315º - 45º		6.38 %	4		
	-1 Level		0%	0		
Demographic Density	Up to 250 pop./km2		100 %	50	5 %	50
	250 to 1500 pop./km2		21.05 %	11		
	Above 1500 pop./km2		100 %	50		

Carta de Risco de Incêndio do Distrito de Viana do Castelo



Fonte: Instituto Geográfico Português

Figure 3.3 – IGP's susceptibility map for the district of Viana do Castelo, Portugal, 2007

The publishing of Decree-Law n. 156/2004, of June 30th, which revoked the Regulatory Decree n. 55/81 of December 18th, gives origin to two new Ordinances that would present the national wildfire probability map, and a new set of "critical zones". In this new Decree-Law, due to Art. 6., five wildfire probability classes are defined (I – Very Low, II – Low, III – Medium, IV – High, V – Very High) using, as described on paragraph 2 of that same article, history of burnt areas, land cover, topography, climate and demographics. The definition of "critical zones", much like what had been done in 1981, attends to those areas where the most extensive measures for protection against wildfires is deemed as a priority, not only as to economic value but also social and ecological. The Ordinance n. 1056/2004 of August 19th details these "critical zones" stating that, among other factors, they should lie in the intersection of wildfire probability classes "Very High" and "High", but the map would only be published later with Ordinance n. 1060/2004 of August 21st (figure 3.5).

Just two years had passed and 2006 would see the publishing of Decree-Law n. 124/2006 of June 28th, revoking the previous Decree-Law but not having novelties in regards to risk mapping. The classes are still five, with the same names but under a different map title. Whereas the 2004 law referred to a map called "Wildfire Probability", the 2006 law referred to "Spatial Wildfire Risk" to part it from another map produced with weather conditions, roughly translatable to "Weather Wildfire Risk". This *weather risk map*, which was to give a picture of how favorable the conditions for ignition where, and how hard it could be suppress fire, was under the responsibility of the Portuguese forest authority but was, in fact, produced and publicized, daily, by the meteorological authority (figure 3.6) crossing weather data with the map from Pereira and Santos (2003).

The sometimes confusing use of terminology and elusiveness of clear conceptual frameworks has created a crossing between different maps and indices, resulting in a multitude of designations, to which the successive laws have not contributed in stabilizing the concepts, possibly due to technical inputs from professionals of different areas of knowledge.

Having the same references as in the Decree-Law of 2004, there is nothing in this new text of 2006 that allows map outputs to be considered as risk products, in light of the conceptual framework herein. New Ordinances are still to be published, and the new Decree-Law n. 17/2009, of January 14th made slight revisions to Decree-Law n. 124/2006 of June 28th, which got republished, hence having nothing new regarding risk mapping.

The year 2014 brings yet another update of Decree-Law nr. 124/2006 of June 28th, via Decree-Law nr. 83/2014 of May 23rd, but still the relevant ordinances are missing, and the changes in the law are focused on suppression fire and totally void on matters of susceptibility, hazard or risk assessment notions and methodologies.

Internationally, and beyond the Canadian Fire Weather Index previously mentioned, several authors have proposed solutions for assessing one or more components of the risk framework.

Chuvieco and Congalton (1989) are authors whose work on the field of wildfire susceptibility mapping is widely known having served as reference for many other studies, both national and international. The approach they followed, for a test area on the Spanish Mediterranean coast, was based on a set of themes they believed to be conditioning factors for wildfire occurrence, as vegetation type, elevation, slope, aspect, presence of buildings or proximity to roads. The authors consider vegetation (fuel) to be the most relevant factor, followed by slope in a two-fold manner, given that «(...) steep slopes increase the rate of spread because of a more efficient convective preheating and ignition by point contact. Slope also has a major effect in the suppression of the fire, because it affects crew fatigue, rolling material, and safety» (op.cit. p.150). Aspect and elevation have been considered in the model assuming that the most solar radiation exposed slopes will favor dryness and combustion, and that as elevation rises, humidity also rises resulting in less fire-prone fuels. Regarding the existence of buildings and road proximity, Chuvieco and Congalton (1989) deemed those themes as relevant, as roads can function as fire breaks or, on the other hand, as fire enhancer due to human presence. This ambivalence is clearly stated: « (...) Trail and road locations are also an important factor in fire hazard mapping. Two major effects can be considered. First, they can serve as fire breaks or pathways for suppression of the fire (…) second, they are potential routes for hiking or camping areas (…) they increase forest fire hazard because of the more intense human activity» (op.cit., p.152).

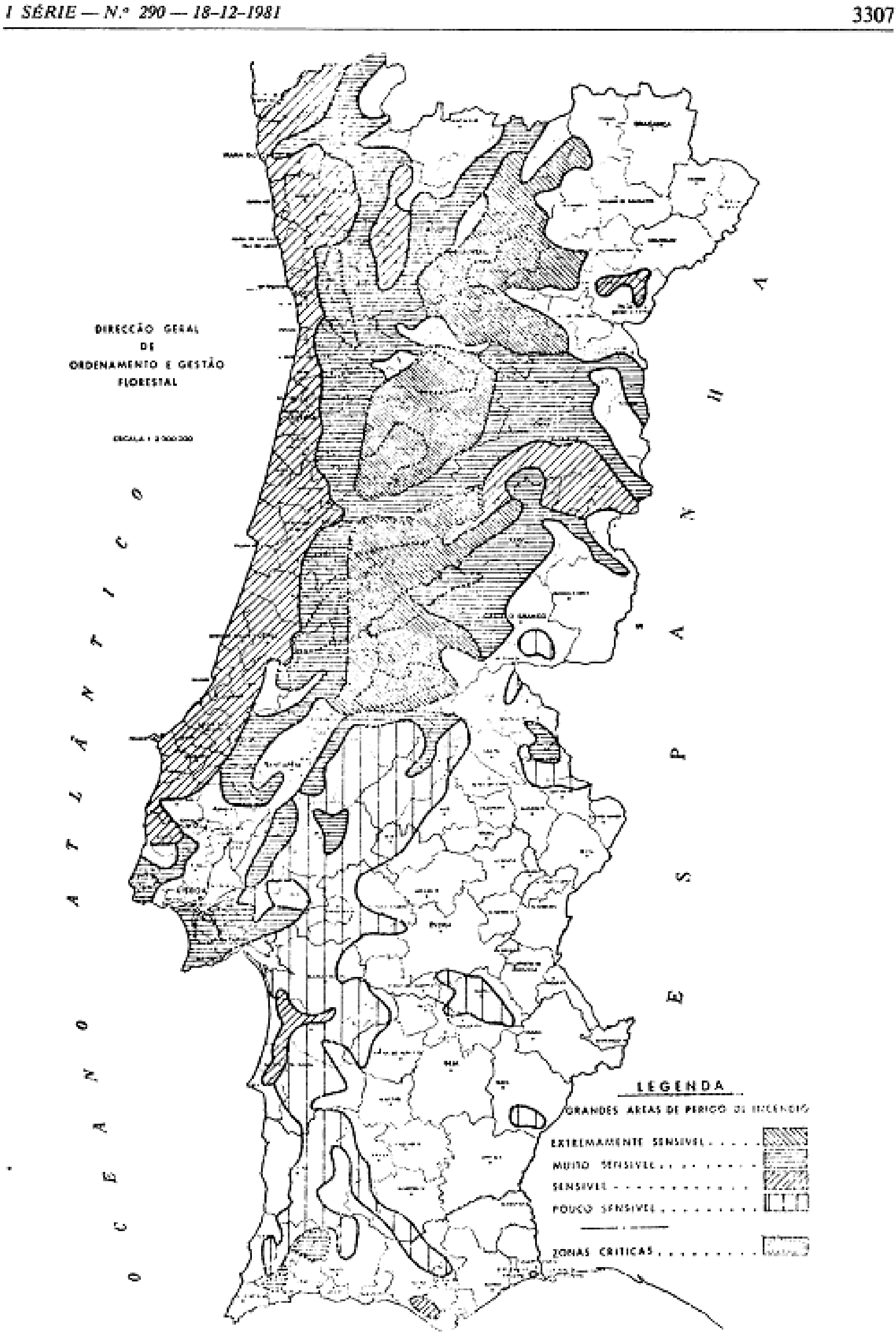


Figure 3.4 – Annex to Regulatory Decree n. 55/81, of December 18th, defining wildfire susceptibility classes and «critical zone» location in mainland Portugal.

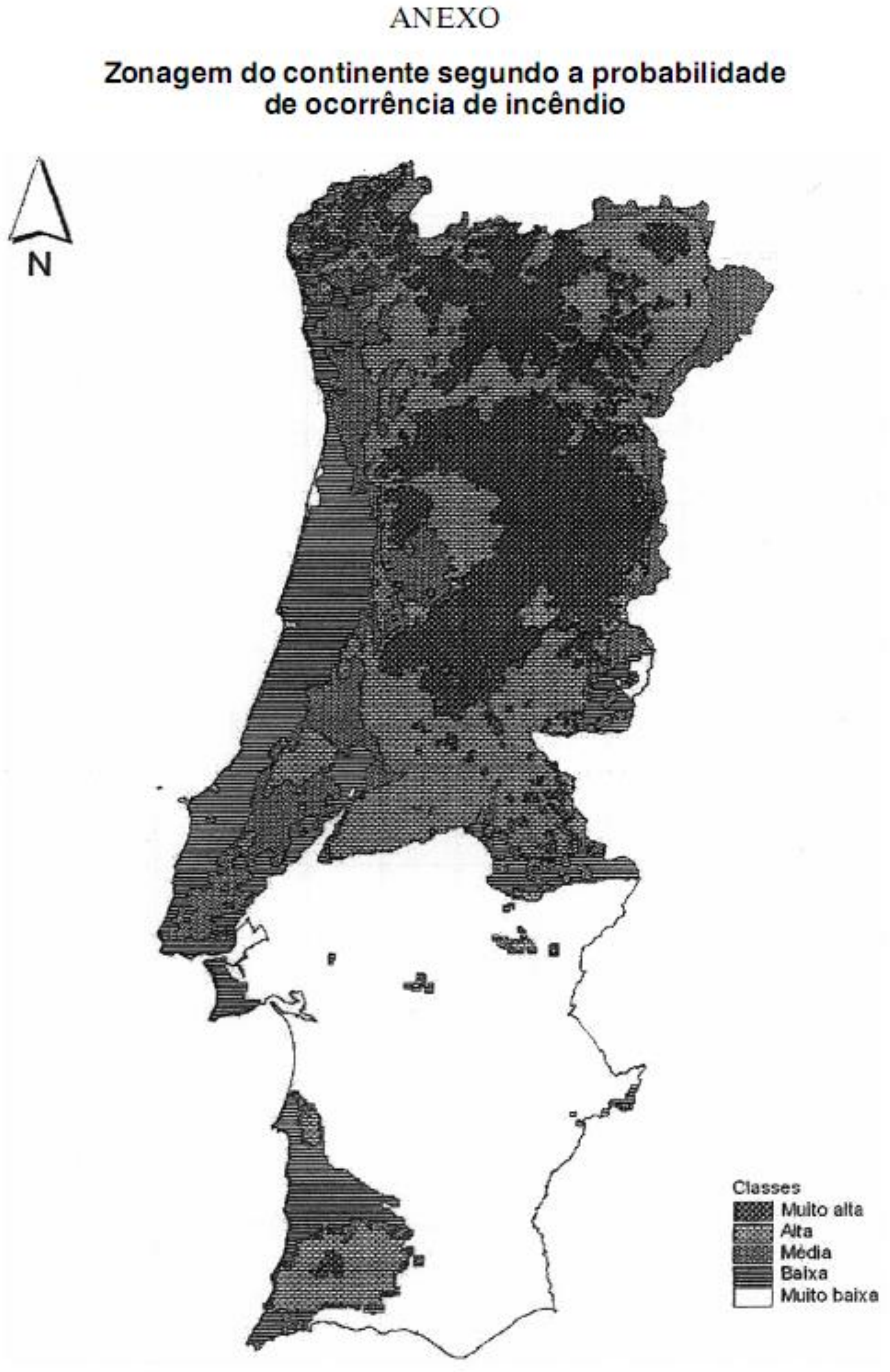


Figure 3.5 – Annex to Ordinance n. 1060/2004, of August 21st (mainland Portugal).

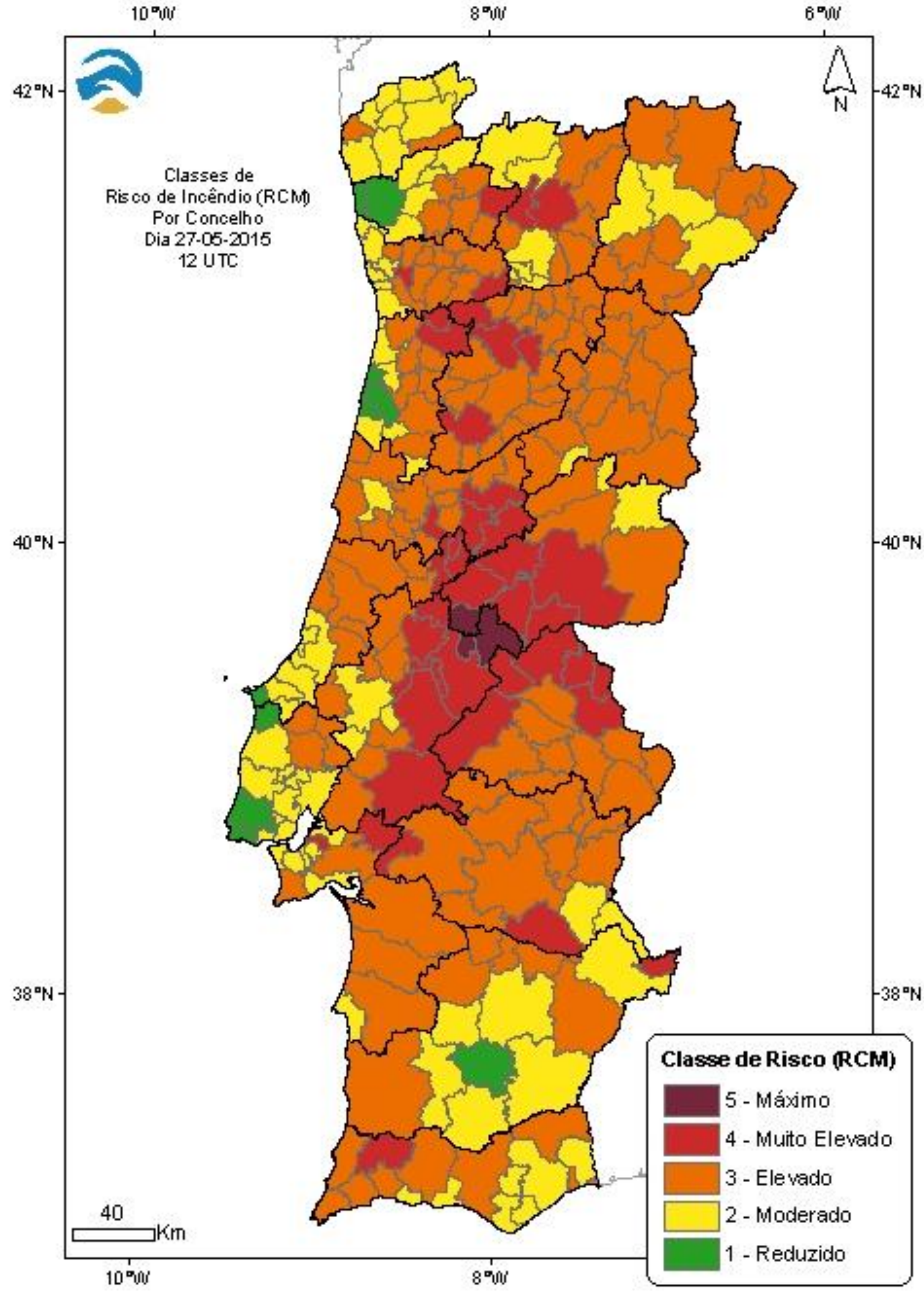


Figure 3.6 – Predicted risk classes by municipality in mainland Portugal. Source: Portuguese meteorological authority.

Model integration for these themes is achieved by adding weighed factors, as in [3.6].

$$H = 1 + 100v + 30s + 10a + 5r + 2e \quad [3.6]$$

In the previous equation, H represents the susceptibility index (in the original, designated as hazard, however the authors did not compute probabilities), ‘v’ is the vegetation coefficient, ‘s’ is the slope, ‘a’ is the aspect, ‘r’ is the road proximity and buildings and, finally, ‘e’ is the coefficient for elevation. These coefficients are arbitrary, like the authors declare, after the classification given in figure 3.7.

In this model, the lower values have the highest susceptibility, on a range 0 to 255. Values of zero are reserved for urban and wet areas, and any value that goes beyond 255 is reclassified to the upper limit so that a 8 bit pixel representation is always possible. This caveat does not greatly affect the results in that susceptibility lowers as the pixel value increases, from the coefficient weighing previously shown. When applied to the area of interest, the model revealed a poor predictive capacity: « (...) our model performed poorly in predicting the burned area (...) », something that Chuvieco and Congalton (op.cit., p.157) attribute to the fact that their model is not intended for fire behavior assessment, but for susceptibility mapping (not considering parameters as wind or air humidity).

Interestingly, notwithstanding the poor results in predictive capacity by the model from Chuvieco and Congalton (1989), their work influenced many other authors that ended up basing their own work on this one, as was the case with Freire, Carrão and Caetano (2002), IGP (2007), or Ferraz and Vettorazzi (1998). In Portugal, many municipalities have adopted the methodology of Chuvieco and Congalton (op.cit.) for producing their own risk mapping for the municipal planning against wildfires.

On influencing the work of many other authors, in very distinct areas, take for instance the work of Jung et al. (2012) applying a similar approach to the Tamil Nadu district in India or even that of Adab et al. (2013) whose work also considers the approach of Chuvieco and Congalton (1989), trying to address what the authors consider to be one of the higher risk areas in the Middle East (the Alborz Mountains in eastern Iran).

Original Classes	*Fire Hazard Groups*	*Coefficient*
	1.1. Vegetation Layer (Weight 100)	
Dense pine tree	high	0
Medium pine tree	high	0
Sparse pine tree + shrub	medium	1
Dense shrub	medium	1
Medium shrub	medium	1
Sparse shrub	low	2
Almond trees	low	2
Vineyards	low	2
Orange trees	low	2
	2.1. Slope Layer (Weight 30)	
0–4%	low	2
5–8%	low	2
9–12%	low	2
13–16%	medium	1
17–20%	medium	1
21–36%	medium	1
27–40%	medium	1
41–44%	high	0
> 44%	high	0
	2.3. Aspect Layer (Weight 10)	
Southeast	high	0
Southwest	medium	1
North	low	2
	2.4. Proximity to Roads Layer (Weight 5)	
Inside buffered area (< 150 m from any trail or < 50 m from any road)	high	0
Outside buffered area	low	1
	2.5. Elevation Layer (Weight 2)	
0–3 m	low	1
3–6 m	low	1
398–400 m	high	0
401–404 m	high	0
405–407 m	high	0

Figure 3.7 – Coefficients in the Chuvieco and Congalton (1989) model

A common feature in these studies is the reliance on expert evaluations which are, by nature, subjective. As such, one of the problems that must be considered is, as stated by Jung et al. (2012), that "it was found that pre-knowledge of the study site affected the opinions of the groups; hence, the final mapping results" (op. cit., p.2144). The bias introduced by subjective evaluations and the differences in the knowledge of the territories are caveats that cannot be ignored when using such methods.

Trying to work on a complete risk framework, Bachmann (2001) has disserted, based on the conceptualization of risk by Bachmann and Allgöwer (1999), presented in chapter 2, about a model of reference for computing and managing wildfire risk. In this conception, risk analysis is to be done over a risk matrix for specific situations, integrating scenarios and objects: « (...) the key elements of the risk matrix are scenarios (risk donors), objects (risk acceptors) and situations. (…) » (Bachmann, op.cit., p.74). A given scenario, or risk enhancer under this conception, can materialize as an ignition point, described by location and probability. Objects are elements at risk, any entities of any kind considered by risk managers as relevant, just as buildings, forest stands or linear elements like electricity networks. Situations are the context in which fire occurs, determined by the type of fuel, topography, wind and moisture, among other conditioning factors. The risk matrix (figure 3.8) under this approach allows for individual risk computation, on a per-object basis, as well as risk computation for a given scenario or, globally, the sum of all present risks.

In a more recent paper by Chuvieco et al. (2012), efforts to map wildfire risk are revisited, and a framework far more compatible with that herein considered, somewhat divergent with what is many times used only among fire researchers, is described. Chuvieco's paper (2012) actually integrates the notion of loss and as such is capable of mapping not only components that could be fitted under the concept of susceptibility and hazard, but also components of vulnerability and, finally, risk (figure 3.9). Chuvieco et al. (2012) moves away from the expert opinion methodology and resorts to probabilistic methods to integrate variables into the model, resulting in what could be considered a far more solid, unbiased approach.

		Scenarios							Individual Risk of an Object
		S_1 p_1	S_2 p_2	…	S_i p_i	…	S_{n-1} p_{n-1}	S_n p_n	
Objects	O_1								
	O_2								
	…								
	O_j				e_{ij} $k_{ij} = p_i \cdot e_{ij}$ d_{ij}				$k_j = \sum_{i=1}^{n} k_{ij}$ $d_j = \sum_{i=1}^{n} k_{ij} \cdot d_{ij}$
	…								
	O_{m-1}								
	O_m								
Collective Risk of a Scenario					$k_i = p_i \cdot \sum_{j=1}^{m} e_{ij}$ $d_i = \sum_{j=1}^{m} e_{ij} \cdot d_{ij}$				$k = \sum_{i=1}^{n} k_i$ $d = \sum_{i=1}^{n} p_i \cdot d_i$

Figure 3.8 – Risk matrix (Bachmann, 2001, p.75)

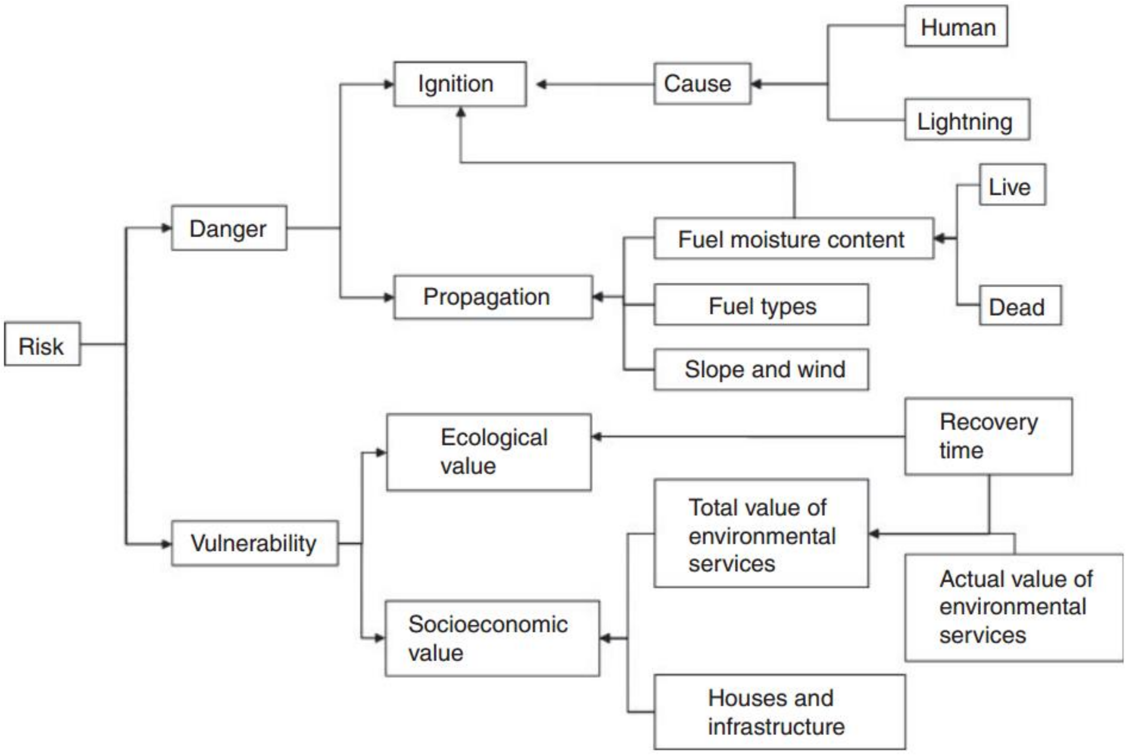


Figure 3.9 – Wildfire risk assessment framework, as per Chuvieco et al. (2012), adapted from Chuvieco et al. (2010)

When moving away from qualitative, expert based, methodologies, the most common statistical approach is logistic regression, as used in many works such as those by Chou (1992), Cardille et al. (2001), Pew and Larsen (2001), de Vasconcelos et al. (2001), Krawchuk et al. (2006), Kalabokidis et al. (2007), Prasad et al. (2008), Syphard et al. (2008), Martínez et al. (2009) or Catry et al. (2010), just to name a few. The methods might differ, but the predisposing factors are common across methodologies. Some factors are very common and appear in almost every study, like vegetation (which is adamant), proximity to buildings and or roads, temperature and rainfall, but also population density. Historical data, topography, road density and aspect are seldom used in the above mentioned studies. One interesting predisposing factor, even if used in only one of those studies is the density of livestock (Kalabokidis et. al. 2007), which can be explained due to the potential conflicts in land use or the pressure livestock creates on the landscape, but, as the authors discovered, there is little effect of livestock density on wildfire occurrence in their area of interest.

Romero-Calcerrada et al. (2008) took this subject under a different approach, that of subjecting wildfires in a region of Madrid aplying a methodology first used in the medical field (Spiegelhalter and Knill-Jones, 1984), the Weights of Evidence. Romero-Calcerrada et al. (op.cit.) focused on human related factors, choosing not to incorporate physical factors like land cover or topography. Instead, the authors used population density, secondary housing density, cattle, sheep and goat density, distance to urban and industrial areas, distance to roads and tracks and distance to camping and recreational areas, for a total of eleven independent variables, for which positive and negative weights were calculated as in [3.7] and [3.8]. In Romero-Calcerrada's approach (op.cit.), and hence in the weights of evidence method, the positive weight for a class i of a predictor variable B denotes how the predictor's presence (B_i) is relevant for the occurrence of wildfires (D), while the negative weight for the same class i of predictor B shows how the presence of predictor B is relevant in the non occurrence of wildfires ($\overline{D}$). This method will be addressed in detail in chapter 5 of this thesis.

$$W_i^+ = \log_e \frac{P\{B_i|D\}}{P\{B_i|\overline{D}\}} \quad [3.7]$$

$$W_i^- = \log_e \frac{P\{\overline{B}_i|D\}}{P\{\overline{B}_i|\overline{D}\}} \quad [3.8]$$

In Romero-Calcerrada et al. (2008) it is interesting to note how the density of livestock helps avoiding wildfire ignitions, while secondary housing density promotes them.

In regards to wildfires, understanding susceptibility (or any other component of a risk framework) is not the only vector of research. Researchers are also interested in understanding what drives wildfire frequency and size.

Malamud et al. (2005) explored power-law wildfire adherence to understand wildfire regime in the United States. These authors were closely followed by Moreno et al. (2011) for Spain and Hantson et. al (2015) on a global scale. Their work heavily relies on the fact that wildfires tend to follow a power-law on the form of [3.9], which, on a log-log space, allows for interpretation on frequency versus size, and as such, a better comprehension on how to tackle each type of wildfire regarding its size.

$$f(A_F) = \alpha {A_F}^{-\beta} \quad [3.9]$$

On [3.9] above, as per Malamud et al. (op.cit.), Moreno et al. (op.cit.) and Hantson et al. (op.cit.), $f(A_F)$ is the frequency density of fires with a size given by A_F, with α and β being power-law function constants. Wildfires are distributed per logarithmic sized bins with counts normalized by bin size.

On this specific matter, Malamud et al. (2005) has concluded that power-law distributions are adequate to describe how large wildfires contribute to the overall wildfire regime, and that normalized values of β and α allow for comparison of wildfire dynamics between different regions. Moreno et al. (2011) also found that a strong fit between a power-law and frequency-area statistics exists for Spain, exploring some reasons for different wildfire distribution, such as agricultural practices or suppression tactics, and Hantson et al. (2015), again confirming a good power-law fit for wildfires, concluded that wildfires are globally driven not only by climate but also strongly influenced by human practices.

From what has been laid out along this chapter, there are two main vectors of research, one that primarily studies the relationship of wildfires with the atmosphere, and another that correlates wildfires with physical, unchanging or slowly changing (at a human scale) terrain-based factors. From those vectors, predictors are sought regarding specific weather conditions and the creation or perfection of indices, and spatial modelling is carried out either through empirical knowledge or various statistic methods, often relying on variables that are considered as of strong correlation with wildfires such as human presence, land cover, terrain characteristics or even some climatic variables. There does not seem to be a lack of research on this subject; quite the opposite. There are so many studies being published on the matter of wildfires that it is certainly not by absence of knowledge that they continue to present a risk, causing losses on safety and livelihood.

Chapter 4. The definition of a base model

In previous studies (Verde, 2008; Verde and Zêzere, 2010), one of the quests was finding out if a susceptibility model of low complexity could yield good results in regards to predictive capacity of wildfire distribution. With that purpose in mind, the authors have run a series of models integrating predisposing themes such as land cover (CORINE Land Cover 2000), slope, elevation, rainfall and temperature, which were combined with the simple probability based on past occurrences. For a modelling interval of 1975-1994 and an independent validation interval of 1995-2004, the authors have concluded that adding more variables did not directly translate into a better predictive capacity, and that meteorological or climatological themes were of no added value to wildfire susceptibility maps. As such, a base model, composed of only land cover (C), slope (S) and simple probability (P) was then proposed and designated as the CDP model, due to the Portuguese original theme designations. As that model is brought again to this study, it shall be referred to as the CSP model.

Since the original studies, the burnt areas cartography has increased, and the CSP model is now brought back to this chapter in order to update it with a uniform data series – which now models with 1975-1994 and validates with 1995-2013 – and, simultaneously, to study how a new land cover coverage (the CORINE Land Cover 2006, released after the original studies) affects the base model.

4.1 Methodology

The methodological procedures leading to wildfire susceptibility assessment in mainland Portugal took place in a Geographic Information System, raster based, after preparation and transformation of the available information in vector format. The option for raster processing has to do fundamentally with the ease of calculation and lower processing power requirements, given that a relatively small logical area has been chosen, of only 0.64 hectares per pixel.

The assumptions that guide this work are the same as in Verde (2008) and Verde and Zêzere (2010), the latter presented as annex to this thesis, according to which:

- The probability or likelihood of burned areas can be assessed quantitatively using statistical relationships between the areas burned in the past and a set of spatial databases;
- It is assumed that wildfires, assessed by their burned areas, occur under conditions that can be characterized by the layers included in the aforementioned database, which will then be considered as conditioning factors (or predisposition factors), integrated into the susceptibility model.

The adopted pixel size was 80 meters (0.64 hectares), a limitation imposed not only by the digital elevation model from which slopes were derived, NASA's Shuttle Radar Topology Mission, but also due to the scale of the CORINE Land cover, which, at 1:100.000, makes 80 meters an adequate pixel size. The base model uses historical data transformed into a simple probability, derived from annual mapping of burnt areas, for the period of 1975 to 1994. The period 1995 to 2013 is used to perform independent validation, resulting in an almost equal split in the 39 total years (20 to model, 19 to validate). Favourability scores for the various classes within each variable or theme (land cover and slope) can be computed as in Chung and Fabbri (1993) and Fabbri et al. (2002). Simple probability enters the model as percentages.

Favourability scores were computed dividing the number of burnt pixels by the number of available pixels in each class. For convenience, due to software issues, the result of that division was multiplied by 100 and rounded, avoiding GIS operations with decimal values [4.1].

$$Sfx = \frac{umAx}{\Omega x} \times 100 \qquad [4.1]$$

Where *Sfx* represents the favourability score for variable *x, umAx* is the number of burnt pixels in that same variable and Ω *x* stands for the total number of pixels in variable *x*.

Historical data enters the model after being transformed into a simple probability which can be read as a percentage that informs the reader of what the probability is, each year, of any single pixel being affected by a wildfire, undergoing combustion, taking into account past occurrences. This approach results from applying the equation [4.2]. This allows taking advantage of a long data series, differentiating patterns of combustion from those places where wildfires are less frequent.

$$P = \frac{f}{N} \times 100 \qquad [4.2]$$

Where *f* is the number of times each pixel has been burnt, and *N* is the number of years in the data series. It is inferred that a pixel that burned every year has 100% probability, while a pixel that has never burned has zero probability. The reason for a given pixel not having been burnt before is unknown and, given the existence of fuel, it cannot be guaranteed that the likelihood that this pixel will be affected is effectively zero, only that the probability is reduced. On the other hand, because this is a multiplicative model, and the number zero is an absorber element of multiplication, the pixels with this probability should not be evaluated as such. Thus, it was decided to reclassify all pixels of value zero (absorbent) to one (neutral). Hence, pixels that have had no combustion in the data series will be considered neutral, not affecting the final result. The remaining pixels are classified according to the likelihood that results from applying the equation previously expressed in [4.2]. A pixel that has burned 10 times in 20 years will have an annual probability of having combustion of 50%.

In the data capture process, the susceptibility score for any given pixel is obtained by multiplying favourability scores for all variables and simple probability in each pixel, giving origin to unique conditions, as in [4.3] and [4.4]:

Unique Condition = $P \cap Sf1 \cap Sf2 \cap \ldots \cap Sfn$ [4.3]

Unique Condition Favourability = F(*P*) x F(*Sf1*) x F*(Sf2)* x F(…) x F*(Sfn)* [4.4]

Where F() is the favourability function (previously described in [4.1]), *P* is the simple probability and *Sf* is the favourability score for each model variable.

For data analysis and supporting of some options made in this work, success and prediction curves and rates were plotted and computed (Chung and Fabbri, 2005), as well as areas under the curve (Bi and Bennett, 2003; Liu et al., 2005).

Success and prediction curves not only help in determining the susceptibility model's accuracy, but they also serve the purpose of data classification when preparing a final map. The success curve is calculated from cross tabulation of unique conditions and those burnt areas that have been integrated into the model. In this regard, the success rate (visually represented by a curve) shows how the model fits the data that was used to run it, but it does not allow the reader to make any consideration on the adequacy of the susceptibility map that the model creates, in regards to the future. Prediction curves, on the other hand, allow for an independent validation and determination of model accuracy. The process is exactly the same as with success curves, but the cross tabulation for prediction curves is made with a reserved dataset of burnt areas that was not used in the model runs, therefore having no direct relation with the model results.

Areas under the curve (AUC) are a useful indicator of which curve behaves the best. Since success and prediction curves have been represented as percentages, AUCs can also be read as percentages. For computing AUCs, the success and prediction curves where decomposed into smaller polygons whose areas where subsequently summed.

4.2 Updating the original CSP model

Wildfire hazard requires susceptible areas for ignition and fire propagation, making no sense to assess hazard where these areas do not exist. For this reason, all land cover classes of levels 1, 4 and 5, which correspond to artificial surfaces, wetlands and water bodies, have been deliberately left off the analysis. The CORINE Land cover classes that have been used on the model are those listed ahead, on table 4.1. It is noticeable how the land cover classes differ from those presented in chapter 1 (fig. 1.7) in that we consider not only forested areas but all those land cover classes that, not being artificial, can be affected, contribute, or be the source of, wildfires. In figure 4.1, CORINE Land cover classes for the 2006 coverage are presented (cross with table 4.1 for class Ids).

There are burnt areas contained in what CORINE Land Cover considers to be artificial or even inland water bodies (whose land cover changed seasonally, drying during summer), however, to maintain the criteria, those burnt areas were discarded from this analysis where only CORINE Land Cover levels 2 and 3 are considered.

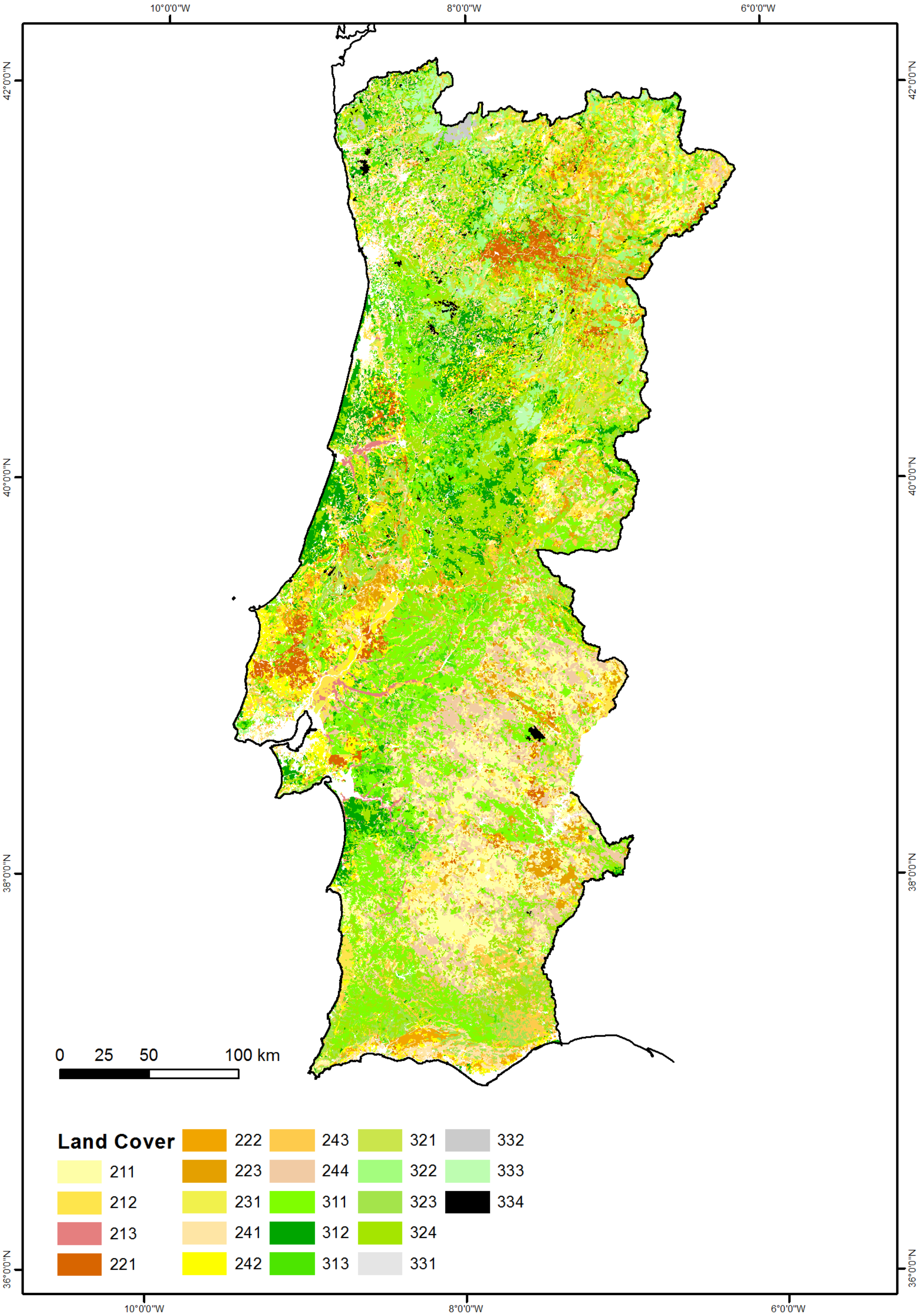


Figure 4.1 – CORINE Land Cover 2006 in mainland Portugal (for Class Ids see table 4.1)

Table 4.1 – Corine Land cover classes considered to model wildfire susceptibility

2. Agricultural areas	21. Arable land	211. Non-irrigated arable land 212. Permanently irrigated land 213. Rice fields
	22. Permanent crops	221. Vineyards 222. Fruit trees and berry plantations 223. Olive groves
	23. Pastures	231. Pastures
	24. Heterogeneous agricultural areas	241. Annual crops associated with permanent crops 242. Complex cultivation patterns 243. Land mainly occupied by agriculture, with significant areas of natural vegetation 244. Agro-forestry areas
3. Forest and semi natural areas	31. Forests	311. Broad-leaved forest 312. Coniferous forest 313. Mixed forest
	32. Scrub and/or herbaceous vegetation associations	321. Natural grasslands 322. Moors and heathland 323. Sclerophyllous vegetation 324. Transitional woodland-shrub
	33. Open spaces with little or no vegetation	331. Beaches, dunes, sands 332. Bare rocks 333. Sparsely vegetated areas 334. Burnt areas

Other than CORINE Land Cover, slope and simple probability are also addressed in this chapter, following what has been proposed in Verde (2008) and Verde and Zêzere (2010). These two themes are revisited in the following section.

4.2.1. Slope and simple probability

This basic wildfire susceptibility model, other than land cover, integrates slope and simple probability. Slope is considered because where the slope is steeper, convective heating of fuels uphill will contribute for wildfire propagation, whereas on flat surfaces wildfires should progress slower, except if in the presence of strong winds or any other external factors not directly connected to any predisposing factor or physical characteristic, such as incorrect suppression actions or tactics. As in table 4.2 and figure 4.2, it can be observed that mainland Portugal is not a mainly mountainous territory, with the most area in the less steep classes, up to 10 degress in slope. The flatter the land, the less favourable are those areas to wildfires, and steeper classes become more favourable, showing added relevance of that evidence layer, as slope increases, which is due to the fuel pre-heating uphill during a wildfire (Rothermel, 1983; Mermoz et al., 2005; Verde, 2008). The spatial distribution of slope in mainland Portugal is presented in figure 4.3 where it can be seen how the major slopes exist in the north and central parts of the country.

Simple probability enters the model as it allows to define patterns, differentiating where fire is an accident or a rare event, from those other places where wildfire is recurrent. In that regard, given that a very high percentage of Portuguese wildfires are of human causality, with official numbers on know causes nearing 99% due to human behavior, a simple probability can also be interpreted as a proxy because even if recurrence does not inform us about the specific reason for the ignition, it does inform us about the presence of a pattern. It has been publicized, following official investigations after wildfires, how many events are due to negligence but also to other random motivations like romantic or professional issues, drinking problems and even varying degrees of dementia. On the other hand, pasture renewal and other agricultural and forestry practices are also accounted for, but it is extremely hard to integrate in a model how humans will behave at any given point. From a model standpoint, it is impossible to know when someone will ignite a fire because he or she is heartbroken, drunk or unemployed. It is impossible to know exactly where, or when, someone will see fit to ignite a fire for pasture renewal, therefore a simple probability will help differentiate areas where some behaviors are more prominent.

Table 4.2 – Favourability scores for land cover classes in mainland Portugal

Slope	Pixels		Favourability Score
Degrees	Available	Burnt	
0 - 2	3,769,671	176,063	47
2 - 5	4,620,398	410,381	89
5 - 10	3,113,286	603,791	194
10 - 15	1,363,989	424,216	311
15 - 20	659,408	253,866	385
> 20	392,260	168,735	430
Total	**13,919,012**	**2,037,052**	

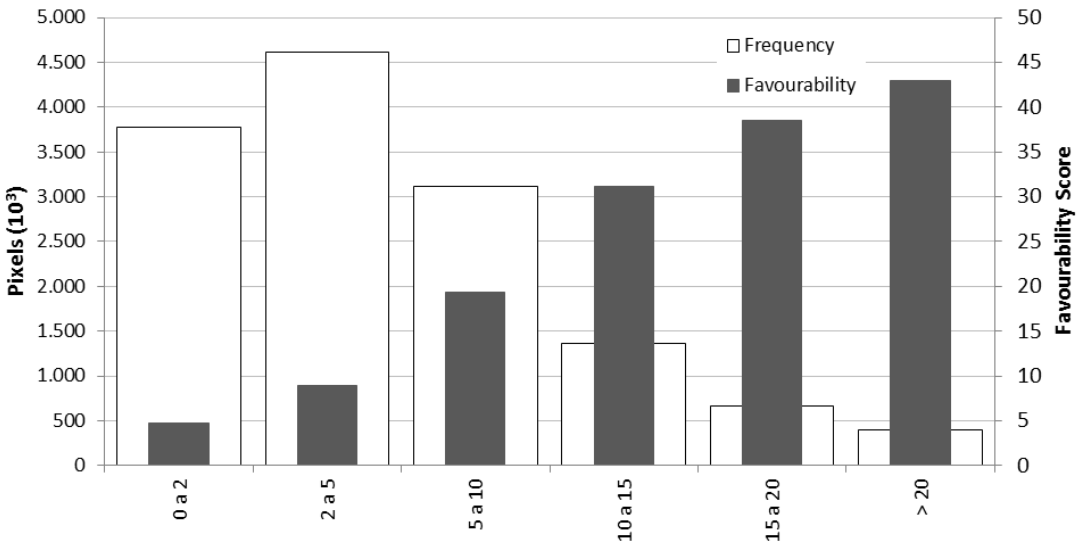


Figure 4.2 – Favourability and Frequency for slope classes in mainland Portugal

Simple probability does not have favourability scores, the pixel is attributed itself a value representing the annual probability, as a percentage, of being affected by fire. As such, what has been presented for the slope theme is not applicable, but figure 4.4 shows what that theme looks like before integration in the model.

Although it is not easy to discern on the map exactly where each simple probability value falls, it can nonetheless be observed that the most fire prone areas are in the north and central zones of the country, and that there are areas with a 45% annual chance of being affected by fire, which in a 20 year modelling period is almost as saying that some areas burn almost each other year. As previously mentioned, the information given by this theme, independently, helps dividing areas of occasional fire from those of recurrent fire.

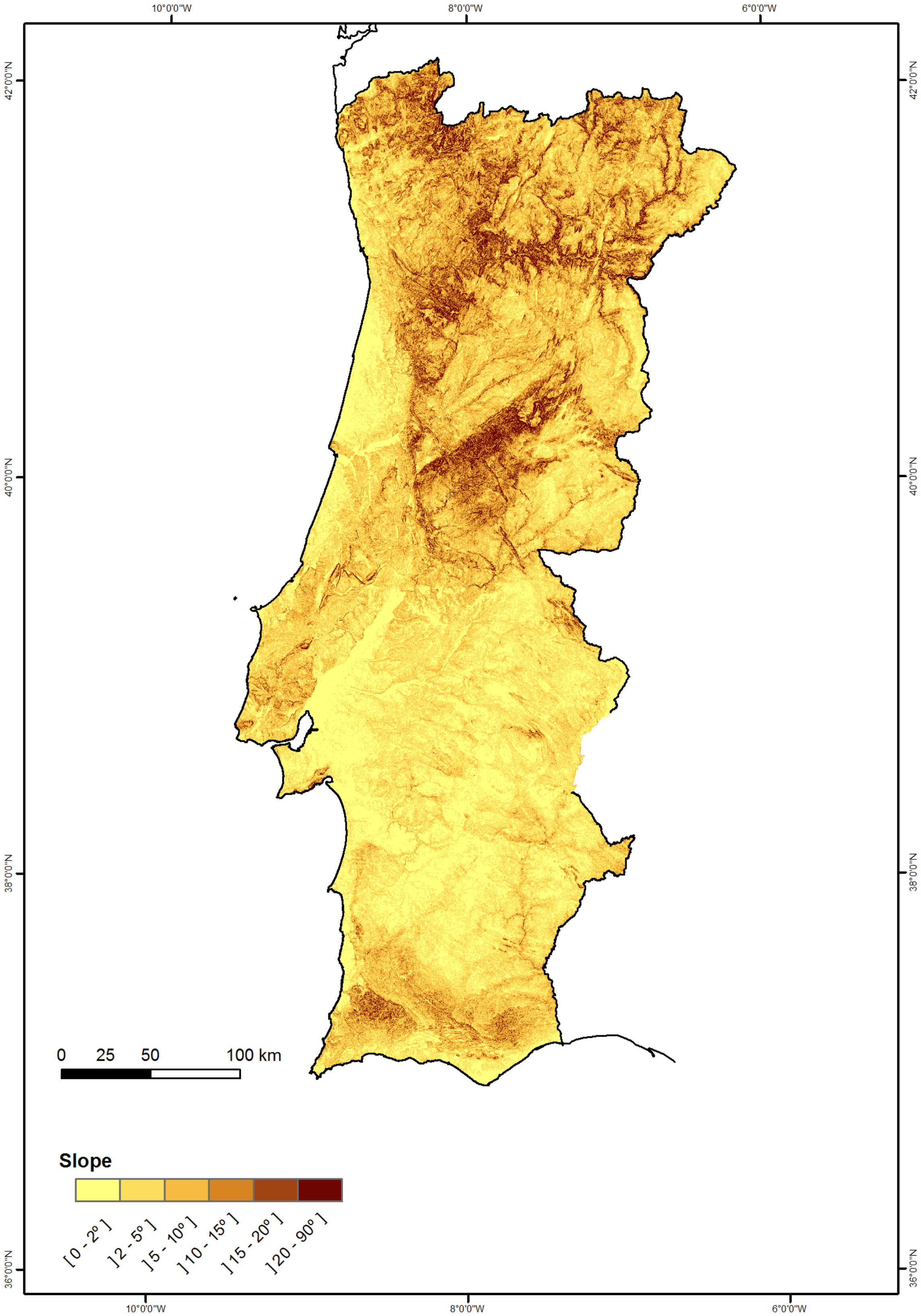


Figure 4.3 – Slope in mainland Portugal

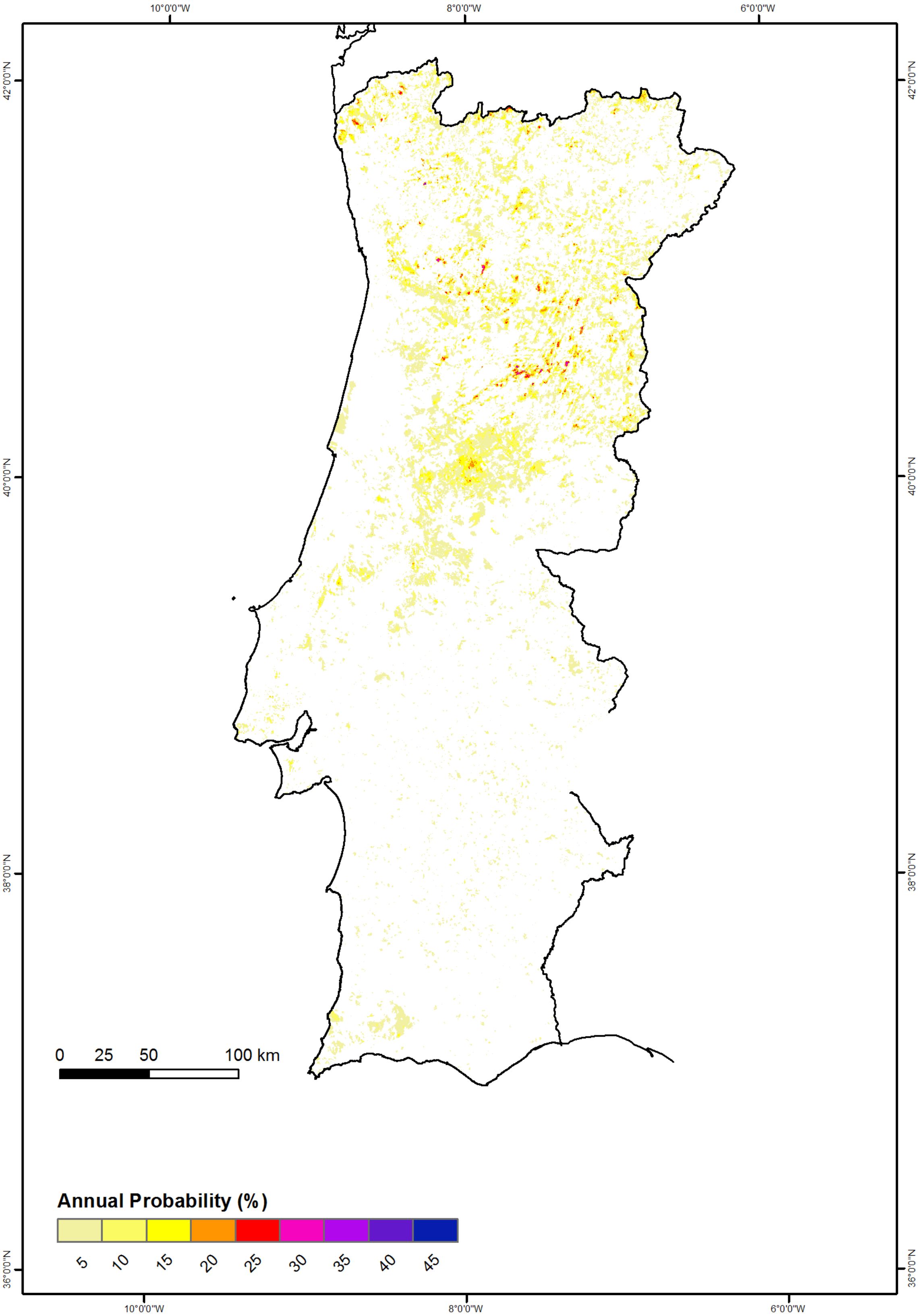


Figure 4.4 – Simple probability of wildfire (from the interval 1975-1994) in mainland Portugal

4.2.2. Land cover

CORINE Land Cover coverages are available for 1990, 2000 and 2006, and it is reasonable to argue how to cross land cover coverages with the available burnt scar data series. Since the series of burnt scar data ranges 1975-2013 and the modelling block in Verde (2008) and Verde and Zêzere (2010) is 1975-1994, is it reasonable to model with a dataset that does not encompass the year to which land cover pertains? The model should be as faithful as possible to what is the ground truth, and since land cover is a paramount layer, changes in that layer have a very strong impact on what is being modelled. In Verde (2008) it has been demonstrated how it was safe to model with a dataset of 1975-1994 and a land cover layer of 2000, given that prediction was not hindered by the fact that there was no correspondence between the modelling block and the land cover edition. In fact, the best results were not those of overlap, the best results were achieved when crossing different time periods. However, in Verde (2008) only CORINE Land Cover 2000 was tested against different modelling intervals, and even though the results were satisfactory, it is needed to make similar tests to CORINE Land Cover 1990 and 2006.

For that purpose, in trying to keep a modelling block of around 10 years – which at this time is not possible due to CORINE Land Cover 2006 –, three modelling blocks have been constructed around each CORINE Land Cover edition, with corresponding validation blocks.

For CORINE Land Cover 1990, a modelling block of 1986-1994 was created, with 1990 in the middle of the series (4 years before, 1990, and 4 years after, for a total of 9 years in the modelling block) and an independent validation block of 1995-1997. Independent validation blocks only have three years due to the modelling block for CORINE Land Cover 2006 which only leaves 2011-2013 available for independent validation.

CORINE Land Cover 2000's modelling block has the interval 1996-2004 with an independent validation block 2005-2007 and, finally, CORINE Land Cover 2006 models with 2002-2010 and independently validates with 2011-2013 (table 4.3).

Table 4.3 – Modelling and independent validation blocks for CORINE Land Cover 1990, 2000 and 2006 in mainland Portugal

Modelling block	Independent validation block
CORINE Land Cover 1990	
1986, 1987, 1988, 1989, $\boxed{1990}$, 1991, 1992, 1993, 1994	1995, 1996, 1997
CORINE Land Cover 2000	
1996, 1997, 1998, 1999, $\boxed{2000}$, 2001, 2002, 2003, 2004	2005, 2006, 2007
CORINE Land Cover 2006	
2002, 2003, 2004, 2005, $\boxed{2006}$, 2007, 2008, 2009, 2010	2011, 2012, 2013

Having defined modelling and independent validation blocks for the three available CORINE Land Cover coverages, a series of model runs were conducted with each CORINE Land Cover, Slope and simple probability, as described in section 4.1, in order to compute areas under the curve (AUC) for each model run prediction curve. Each modelling block was not only independently validated against its own validation block, but also against validation blocks for the other modelling blocks, this way crossing time intervals and determining how the model behave with temporal differences between datasets. This allowed for the construction of the matrix in table 4.4.

Table 4.4 – Areas under the curve for prediction curves for the available editions of CORINE Land Cover (%) in mainland Portugal

Modelling blocks	Independent validation blocks		
	1995-1997	2005-2007	2011-2013
1986-1994 (CLC1990)	82.76	80.13	80.10
1996-2004 (CLC2000)	87.40	76.56	79.92
2002-2010 (CLC2006)	83.19	93.24	78.53

When considering the expected independent validation blocks, e.g. those immediately after the modelling intervals, CORINE Land Cover 1990 has the best prediction, with the higher AUC at 82.76%. CORINE Land Cover 2006 is the second best model in this exercise. The predictive AUC for the CORINE Land Cover 2006 validated with 2005-2007 does stand apart at 93.24%, but that is not a surprise: actually, as the interval 2005-2007 is contained in the modelling block for CORINE Land Cover 2006, this AUC, even if computed for a prediction curve like all others in table 4.4, is not a true predictive AUC. The fact that the validation block is a subset of the modelling block turns it into a *partial* success rather than prediction, therefore it is only natural that the AUC is very high. Not accounting for that AUC or any other with partial overlapping between modelling and validation blocks, the best result is that of CORINE Land Cover 2006 validated against 1995-1997, with an AUC of 83.19%, that is, a modelling block of the *future* being validated with an interval in the *past*. The proximity in AUCs for the three CORINE Land Cover editions in all situations where modelling and independent validation blocks do not overlap, allows for the assumption that for as long as discrepancies are low, it is safe to use this methodology with a land cover layer whose year of data capture is not contained in the burnt scar data. Under that assumption, it makes sense to model with the latest CORINE Land Cover, even if the modelling block starts earlier in 1975, as explored next, in section 4.2.3. As the burnt scar dataset grows, a point comes when options have to be made concerning how to cross that data with land cover. As land cover data pertains to a given year, if land cover changes are substantial, the modelling block cannot go far beyond the land cover data capture year, leading to leaving unused a growing number of burnt scar years. However, if the land cover does not change significantly and if changes are mainly between susceptible classes, more burnt scar years can be used.

By now, it becomes relevant to explore what has changed between 1990 and 2000 in regards to land cover. In section 4.2.3. changes between 2000 and 2006 are studied because the aim is to update the CSP model that has been introduced in Verde (2008) and later in Verde and Zêzere (2010), which used, originally, CORINE Land Cover 2000. Still, having determined predictive AUCs for the three land cover coverages, it remains to confirm or refute the idea that land cover changes have not been sufficiently drastic to affect wildfire predictive quality. With that intent, changes affecting susceptible areas (those classes in table 4.1) have been identified, given that susceptible areas can change among themselves, concede areas to non-susceptible areas like artificial areas or water bodies, or receive areas from those non-susceptible ones. Table 4.5 summarizes what has changed from CORINE Land Cover 1990 to 2000, in hectares.

Table 4.5 – Land cover changes, in hectares, from CORINE Land Cover 1990 to 2000 in mainland Portugal

Land cover changes	Hectares	%
Among susceptible classes	895,307	92.17
From susceptible to artificial classes	67,128	6.91
From susceptible to water body classes	6,945	0.72
From artificial to susceptible classes	566	0.06
From water bodies to susceptible classes	1,381	0.14
Total	971,327	100.00

Changes in land cover, affecting susceptible areas, are under one million hectares between 1990 and 2000, which could be significant should those changes disperse susceptible classes into non-susceptible ones. That has not been the case. Over 92% of the land cover changes have occurred among susceptible classes, while the transaction between susceptible and non-susceptible areas have been residual. Joining these results with those of table 4.4, it does seem reasonable not to raise an issue due to disparities in land cover and modelling blocks, for as long as these tests are conducted and they show that land cover changes are not significantly reducing susceptible areas.

As per table 4.6, it can be confirmed that most of the changes in susceptible areas have involved forested areas. Table 4.6 only shows changes above 10,000 hectares, for convenience, and yet it accounts for 76% of what has changed among susceptible land cover classes, or 70.1% of all changes (susceptible and non-susceptible).

Table 4.6 – Land cover changes, in hectares, from CORINE Land Cover 1990 to 2000, above 10,000 hectares in mainland Portugal

Rank	Change (class Id)	(% of total) Hectares	Rank	Change (class Id)	(% of total) Hectares
1	312 to 324	(15.2%) 147,595	9	334 to 324	(2.2%) 21,448
2	324 to 311	(10.8%) 104,708	10	322 to 324	(2.1%) 20,602
3	324 to 312	(7.8%) 75,749	11	243 to 324	(1.6%) 16,022
4	311 to 324	(6.9%) 67,190	12	231 to 212	(1.6%) 15,368
5	313 to 324	(6.0%) 57,934	13	211 to 324	(1.4%) 13,377
6	324 to 313	(4.2%) 40,714	14	241 to 242	(1.4%) 13,168
7	211 to 212	(4.1%) 40,007	15	324 to 334	(1.3%) 12,442
8	323 to 324	(2.4%) 23,646	16	334 to 322	(1.1%) 11,123

The most significant change between 1990 and 2000 was from coniferous forests to transitional woodland-shrubs, which goes on par with the data from the national inventories presented on chapter 1. That effect is somehow attenuated by the change from other woodland-shrubs to coniferous forests and to broad-leaved forests (ranks 2 and 3), but as table 4.6 shows, transitional woodland-shrubs (class Id 324) are mostly on the receiving end of land cover changes in that period. It seems reasonable to assume that even though there are changes in land cover, at a national level the fundamental pattern is maintained for what ignitions are mainly occurring in the same areas, or areas of similar favourability.

It is believed that in this section it has been shown it is safe to model with burnt scar data that does not fit the year of land cover data capture given that in mainland Portugal, for the past three CORINE Land Cover coverages predictive rates are high and land cover changes from 1990 to 2000 occur mainly among susceptible land cover classes. Under that assumption, in section 4.2.3 the original CSP model as in Verde (2008) and Verde and Zêzere (2010) will be updated, replacing the original CORINE Land Cover 2000 with its 2006 edition, after comparing how CORINE Land Cover 2000 and 2006 compare in regards to predictive capacity.

4.2.3. Computing new favourability scores for the updated land cover layer

Just as in Verde (2008) and Verde and Zêzere (2010), and as summarily explained in section 4.1, favourability scores were computed for levels 2 and 3 of CORINE Land Cover (table 4.7). Burnt pixels in table 4.7 refer to the modelling interval of 1975-1994. When CLC2006 was introduced, not only a new 2006 coverage was made available, but also a revised version of CORINE Land Cover 2000 (CLC2000). It was considered that even though the previous studies were done with the original CLC2000, for the purpose of comparing how CLC2006 diverges (should it be the case) from CLC2000, the revised CLC2000 should be used instead, keeping up with the new developments on land cover coverages. For convenience, table 4.7 presents, side by side, the revised values for CLC2000 and CLC2006, along with their favourability scores.

When plotting frequency and favourability scores for the revised version of CLC2000 (figure 4.5), the most abundant land cover does not have the highest favourability. What has been observed for the original CLC2000 (Verde, 2008) still holds on the revised version and the data is almost identical.

There are differences when considering the updated CLC2006, in that pixel availability per class changes, being the most obvious exchange between classes 311 (broad-leaved forests) and 324 (transitional woodland-shrub). Changes in the other classes are not as significant and the relative differences in favourability are maintained (figure 4.6).

Table 4.7 – Favourability scores for land cover classes in mainland Portugal

Land cover	CLC2000 Pixels		CLC2006 Pixels		Favourability Scores	
Class ID	Available	Burnt	Available	Burnt	CLC 2000	CLC 2006
211	1,592,821	78,282	1,533,952	76,355	49	50
212	318,661	8,661	329,142	9,194	27	28
213	85,011	678	82,539	634	8	8
221	347,995	7,920	357,728	9,485	23	27
222	157,187	5,401	157,859	5,502	34	35
223	410,828	7,044	410,985	7,873	17	19
231	65,768	3,621	65,410	3,712	55	57
241	633,987	10,862	631,195	10,980	17	17
242	952,871	17,896	948,495	18,073	19	19
243	1,093,836	78,883	1,073,231	78,235	72	73
244	982,445	22,832	971,197	23,038	23	24
311	1,758,157	210,449	1,573,550	167,975	120	107
312	1,107,274	219,866	834,578	147,555	199	177
313	852,094	149,980	743,142	119,105	176	160
321	275,271	151,744	268,595	149,647	551	557
322	452,408	263,955	444,758	258,744	583	582
323	351,866	69,951	323,117	68,626	199	212
324	1,592,661	577,745	2,205,531	727,871	363	330
331	18,499	450	18,494	450	24	24
332	37,272	19,134	37,314	19,176	513	514
333	157,136	92,583	157,610	92,372	589	586
334	46,414	24,676	51,324	22,015	532	429
Total	**13,290,462**	**2,022,613**	**13,219,746**	**2,016,617**		

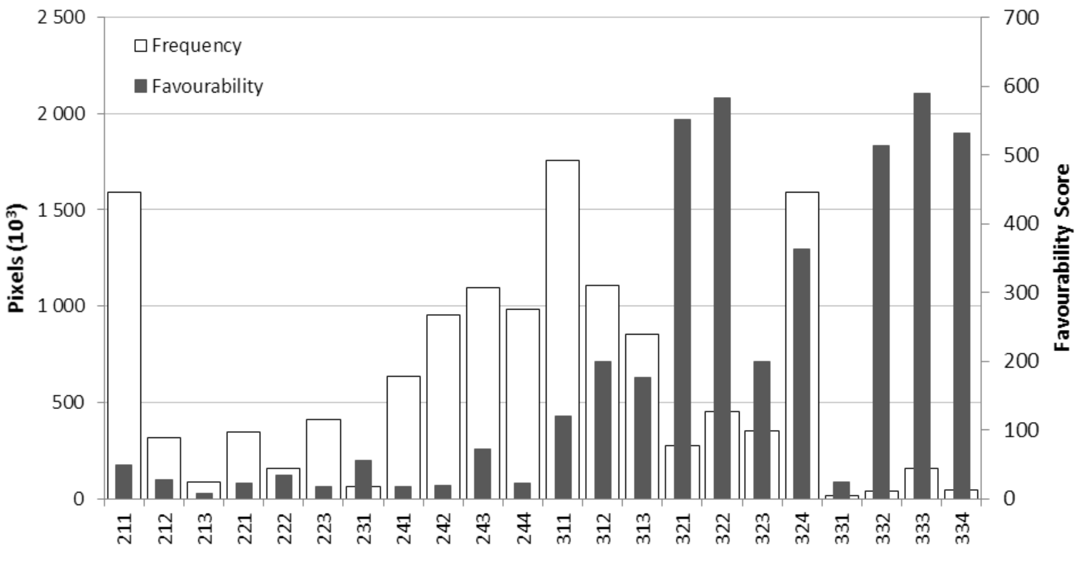


Figure 4.5 – Favourability and Frequency for land cover classes on the revised CLC2000 in mainland Portugal

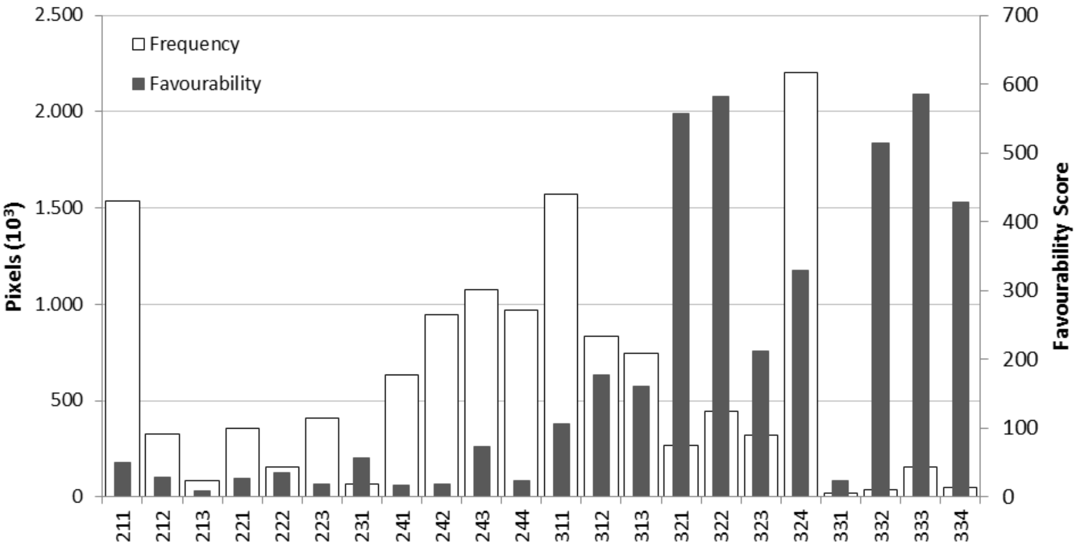


Figure 4.6 – Favourability and Frequency for land cover classes on the CLC2006 in mainland Portugal

When comparing frequencies among the three available CORINE Land Cover coverages, side by side on a column chart, what has been observed before gains expression. Overall, differences are not very significant, but broad-leaved forest areas have indeed lost area to transitional woodland-shrubs (figure 4.7).

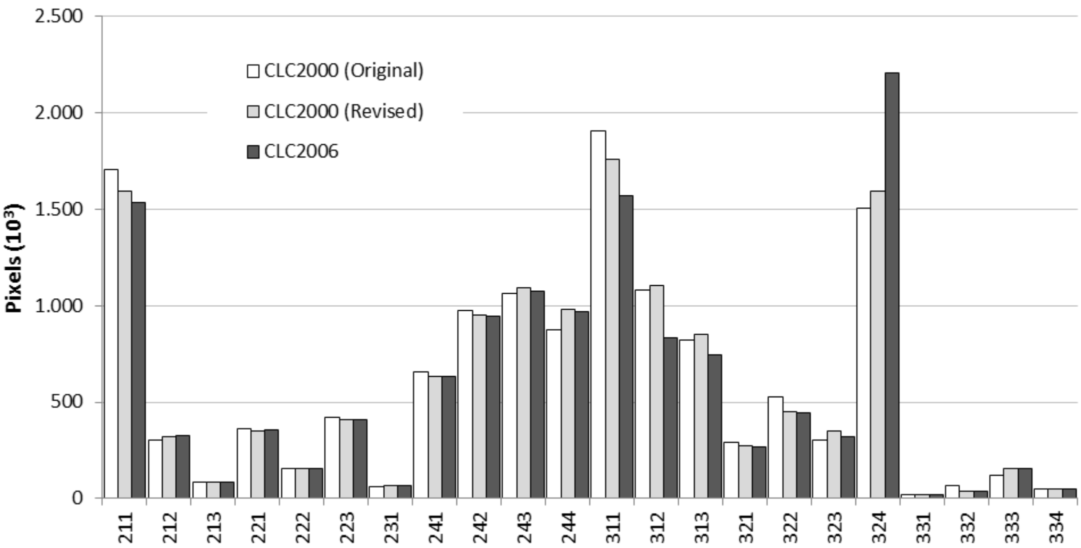


Figure 4.7 –Frequency for land cover classes in mainland Portugal

As to favourability, figure 4.8 shows that favourability scores hold considerably solid on the three CORINE Land Cover coverages, showing no major differences with the exception of class 333 (sparsely vegetated areas) which has seen its favourability score notably decreased with the CLC2000 revision, but not as much with the 2006 version, and class 334 (burnt areas) which also reduced score on the CLC2006.

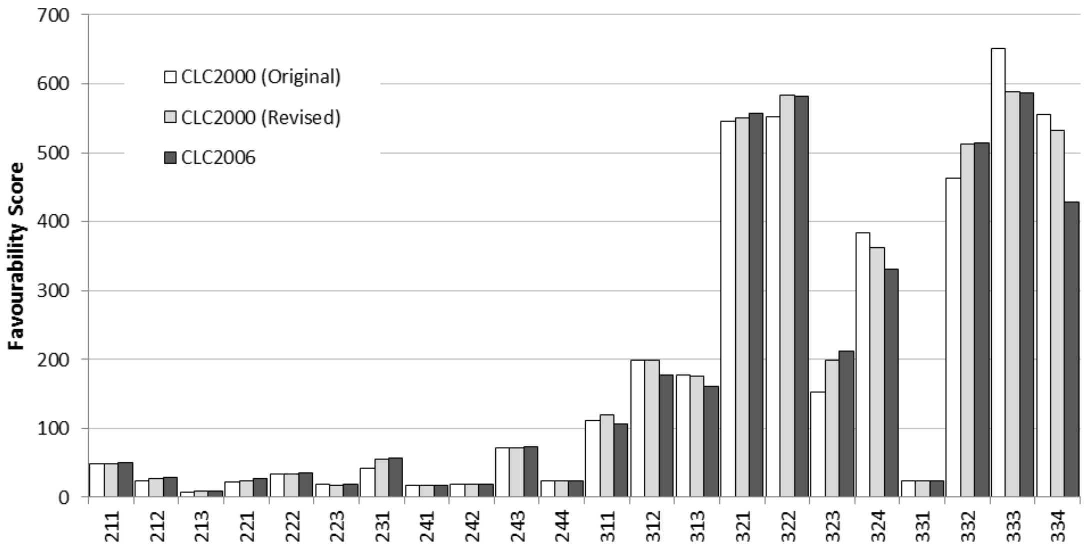


Figure 4.8 –Favourability scores for land cover classes in mainland Portugal

Considering the premise on using land cover data from CORINE Land Cover, of having levels 2 and 3 as susceptible to wildfires and discarding levels 1 (artificial) and 4 and 5 (water bodies) even though they can, at times, be affected by wildfires, the changes in land cover between CLC2000 (revised) and CLC2006 were computed and mapped (table 4.8, figure 4.9). As it came out, the most changes between 2000 and 2006 were between susceptible classes, with over 93% of total changed (a bit over 750 thousand hectares in total). Changes between susceptible areas and non-susceptible areas are negligible.

Table 4.8 – Land cover changes, in hectares, from CORINE Land Cover 2000 to 2006 in mainland Portugal

Land cover changes	Hectares	%
Among susceptible classes	708,736	93.88
From susceptible to artificial classes	27,969	3.70
From susceptible to water body classes	17,950	2.38
From artificial to susceptible classes	252	0.03
From water bodies to susceptible classes	57	0.01
Total	754,964	100.00

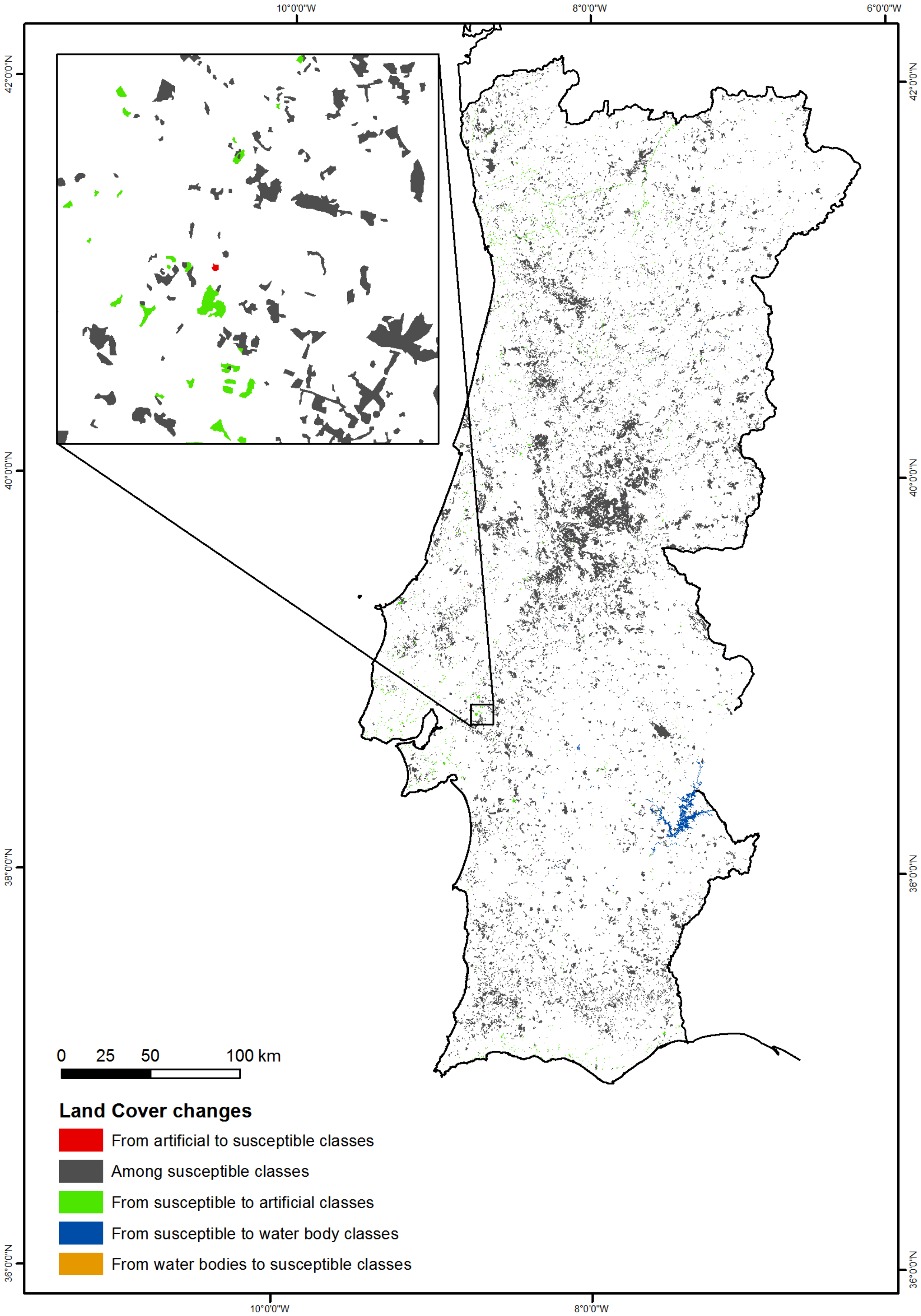


Figure 4.9 – Changes between CLC2000 (revised) and CLC2006 in mainland Portugal

4.2.3. Discussion on land cover changes' impact on model results

Having the **CSP** model as reference, two additional model runs had to be completed in order to assess how changing land cover would impact the model ability to predict future burnt areas: rerun the model with the 2006 coverage and new favourability scores, and considering the updated 2006 coverage using the old favourability scores of the 2000 coverage. This last approach allows to evaluate the dynamic change on wildfire susceptibility as a consequence of landcover change.

In figure 4.10, the reference model **CSP**, with the revised CORINE Land Cover 2000 data, is plotted along with the same model with the updated CORINE Land Cover 2006 data, using 1975-1994 for modelling and 1995-2013 for independent validation. Differences in success rates are very difficult to spot, but the prediction curve for the 2006's CORINE Land Cover is discernibly better, as table 4.9 confirms.

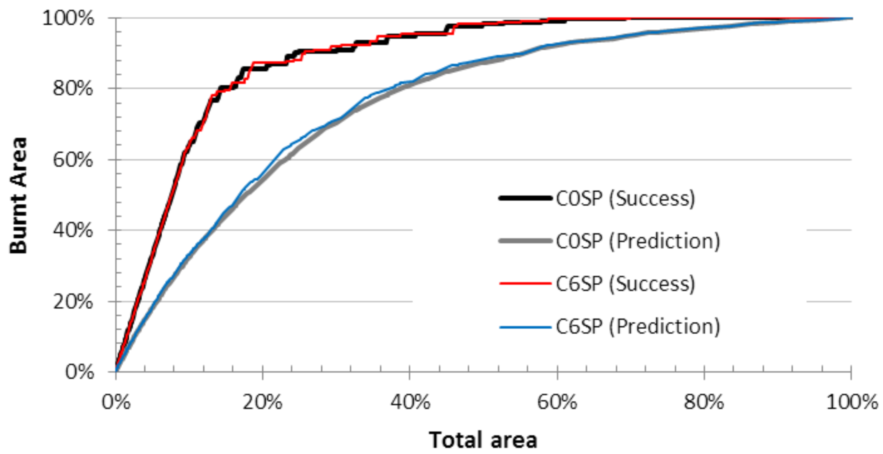


Figure 4.10 – Success and Prediction curves for the reference model CSP with CORINE Land Cover 2000 (C0SP) and CORINE Land Cover 2006 (C6SP) in mainland Portugal

Table 4.9 – Burnt area by total area marks, for success and prediction curves, in mainland Portugal. Higher values in bold. Key: S-C0SP / S-C6SP: Success rates for CORINE Land Cover 2000 and 2006 respectively; P-C0SP / P-C6SP: Prediction rates for CORINE Land Cover 2000 and 2006 respectively (%).

Total Area	10%	20%	30%	40%	50%	60%	70%	80%	90%
S-C0SP	63.94	**85.79**	**90.94**	94.98	**98.36**	**99.22**	**99.97**	**99.97**	**100**
S-C6SP	**64.12**	85.46	90.87	**95.77**	97.83	99.00	**99.97**	**100**	**100**
P-C0SP	32.46	54.36	70.55	81.08	87.56	92.42	95.13	97.13	98.87
P-C6SP	**33.21**	**56.29**	**71.23**	**82.06**	**88.24**	**92.60**	**95.14**	**97.16**	**98.91**

The difference, for the modelling set of 1975-1994, between the coverage of 2000 and 2006 is not very significant. Even though the more recent coverage is generally better in predicting future wildfires – and it should be noted that Corine Land Cover 2006 is on the uppermost part of the prediction block of 1995 to 2013 –, the results are very similar, usually around 1% in difference, which could lead to the conclusion that changing land cover layers would not be important for the overall predictive capacity of the model. In fact, one could easily wonder if the gain in prediction would balance the time investment in preparing new data and running a new model for such a low increase in the results. Still, if the difference between 2000 and 2006 is small, it could be that the territory has not changed that much in the 6-year period. It could also happen that the most changing territories are not those where wildfires usually occur, and, as such, the land cover classes that best support wildfires in the model are those that will probably take the most time to change, and let us not forget what has been determined in section 4.2.2 where it was shown that most of the land cover changes were between land cover classes considered susceptible to wildfires.

It could also be argued that using either CORINE Land Cover 2000 or 2006 to model burnt areas of years other than those immediately before and after data capture would not be adequate, as there could not be a correspondence between the actual land cover of any given year with that of the year from which burnt areas were taken. However, in Verde (2008) it has been shown that the effectiveness of the model was not affected when combining land cover of the year 2000 with burnt areas of the period 1975-1994, which has been tested, and it is considered that the same applies to the land cover of 2006. In fact, it has been demonstrated that, using land cover of the year 2000, the same model had an overall better behaviour with older burnt areas (e.g. 1975-1984) than with a block comprising the year the land cover was created with (1995-2004). In section 4.2.2 (table 4.4) it has also been demonstrated how non-coherent time intervals are capable of good predictive results. It is to be expected that this will not be the case on rapidly changing land covers, and only on somewhat stable landscapes can this be considered valid.

Given what has been presented so far, another test on the available data can be performed. How would the model behave if the scores that have been computed for the CORINE Land Cover 2000 coverage would be used with the CORINE Land Cover 2006, assuming that any given variable within that theme retained its favourability, despite potential land cover changes? For that purpose, a new theme was created, picking the 2006 land cover and reclassifying the raster to the 2000 land cover scores. After running the model, with the same dataset (e.g., 1975-1994 as modelled burnt areas and 1995-2013 as independent validation set), success and prediction curves were, again, plotted. The result is show on figure 4.11, where the new curves are compared with the ones shown earlier, on figure 4.10.

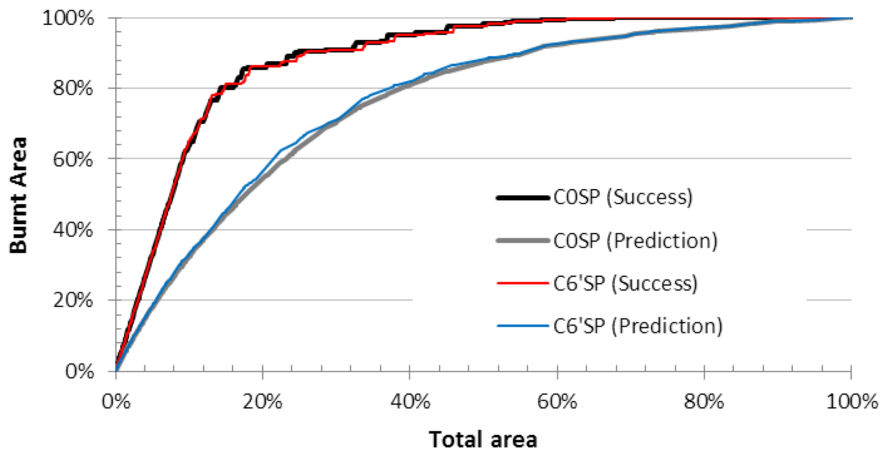


Figure 4.11 – Success and Prediction curves for the reference model CSP with CORINE Land Cover 2000 (C0SP) and CORINE Land Cover 2006 (C6'SP) using CORINE Land Cover 2000's favourability scores, in mainland Portugal

Applying CORINE Land Cover 2000's favourability scores to CORINE Land Cover 2006 results in the same difficulty in discerning significant differences in the success curves. It is easier to spot differences on the prediction curve, which appears to have some gain over the original CSP curve, but still not as good as with the previous model run of CORINE Land Cover 2006 with its own scores. Table 4.10 summarizes all curve behaviors, for convenience, and table 4.11 displays areas under the curve for the three prediction curves (C0SP, C6SP and C6'SP).

Table 4.10 – Burnt area by total area marks, for success and prediction curves in mainland Portugal. Higher values in bold. Key: S-C0SP / S-C6SP / S-C6'SP: Success rates for CORINE Land Cover 2000, 2006 and 2006 with 2000's favourability scores respectively; P-C0SP / P-C6SP / P-C6'SP: Prediction rates for CORINE Land Cover 2000, 2006 and 2006 with 2000's favourability scores respectively (%)

Total Area	10%	20%	30%	40%	50%	60%	70%	80%	90%
S-C0SP	63.94	85.79	**90.94**	94.98	**98.36**	**99.22**	**99.97**	99.97	**100**
S-C6SP	64.12	85.46	90.87	**95.77**	97.83	99.00	**99.97**	**100**	**100**
S-C6'SP	**64.88**	**86.23**	90.76	94.92	97.65	99.19	**99.97**	99.97	**100**
P-C0SP	32.46	54.36	70.55	81.08	87.56	92.42	95.13	97.13	98.87
P-C6SP	**33.21**	56.29	**71.23**	**82.06**	88.24	**92.60**	95.14	97.16	**98.91**
P-C6'SP	33.14	**56.50**	71.02	81.91	**88.29**	92.54	**95.15**	**97.18**	**98.91**

Table 4.11 – Areas under the curve for the CORINE Land Cover prediction curves (%) in mainland Portugal

	CLC2000 (C0SP)	CLC2006 (C6SP)	CLC2006 with CLC2000 scores (C6'SP)
AUC	76.27	76.94	76.93

4.2.4. Conclusions on the impact of land cover changes

Following what has been tested and verified thus far, burnt areas have been tested against two versions of CORINE Land Cover: the 2000 and 2006 coverage. It has been shown that differences are very small in the prediction capacity of the model, when tested with a modelling block comprising the period 1975-1994 and an independent block, for validation purposes, comprising the period 1995-2013.

Even though differences were small in this exercise, land cover layers should be made available as soon as they are revised and updated. Not doing so would leave users unaware of potentially hazardous changes in the territory. When revising the model, and even with very small changes in predictive capacity, researchers have an opportunity to become aware of how land cover is changing, sensing if the model retains its capacity. Any significant change detected in the success and prediction curves might show that the assumptions supporting the model are no longer valid, and that different or additional layers, or a different method, has to be applied so that the results continue to serve the purpose of providing users with a useful susceptibility map.

As per presented results, and following what has been tested in regard to the behaviour of older scores, it can be concluded that CORINE Land Cover 2000 scores are robust and could be maintained in the future, even with more recent land cover coverages, but it is useful if not mandatory to upgrade themes as they become available and rerun the model, as the results are closer to the ever changing land cover reality. The favourability for each unique condition might be considered solid, but the location of the terrain units that have each unique condition will most likely change. That, alone, is a reason for updating land cover (and any other changing theme) information. Updating the reference model **CSP** with the newest CORINE Land Cover in this case also improves prediction rates, if only by 0.01% of the area under the curve.

4.3. Discussion on the base susceptibility model

In Verde (2008) and Verde and Zêzere (2010), it was possible to conclude that using the methodology applied in this chapter, adding complexity to the susceptibility model by adding more themes did not guarantee better predictive results. It has also been verified that a low complexity model, with fewer themes – but of high correlation with wildfires – have a strong cost/benefit advantage. In the previous section, it has been shown how relevant it is to maintain updated land cover coverages.

It should be noted that the double influence of historical data (in computing the favourability scores and entering itself as a theme – simple probability) does help defining a pattern of burnt areas, and for that reason it has been reckoned as useful to maintain it that way, even though that is a point for further debate, that some might consider a pitfall of the model.

Based on the results presented in this chapter, the base **CSP** model, comprising land cover, slope and single probability is a solid model. In adopting this model as a reference, it is assumed that, for the mainland Portuguese reality, wildfire susceptibility is, in essence, determined by the type of fuel, the slope the fuel exists on, and the historical pattern of occurrence (which can be seen as a proxy for human behavior as addressed in section 4.2.1). This assumption is very much related to the Portuguese wildfire characteristics and causality, and cannot be simply extrapolated to other territories where fire might have a different causality or behavior. Actually, even in Portugal and in all likelihood, as time goes by, the model might require some refinement, should it start to show significant worsening in success and prediction rates. Figure 4.12 presents success and prediction curves overlaid on the susceptibility classes.

The success curve for the reference model shows that, for the themes that were used, with just 10% of the most susceptible area (x-axis), over 64% of burnt areas (y-axis) can be explained. To get to 90% of all burnt areas in the interval 1975-1994, only 25% of susceptible area is needed. The prediction curve, as expected, does not yield as good results as the success curve. Still, 50% of the “new” burnt areas are contained in just under 17% of the susceptible area, and, additionally, if we consider the 30% most susceptible areas, the future burnt areas predicted by the model increase to 71%. A possible interpretation for these curves is that taking for reference the interval of 1975-1994, in any given future timeframe, 71% of burnt areas in that future timeframe will be contained in the topmost 30% of the susceptible areas.

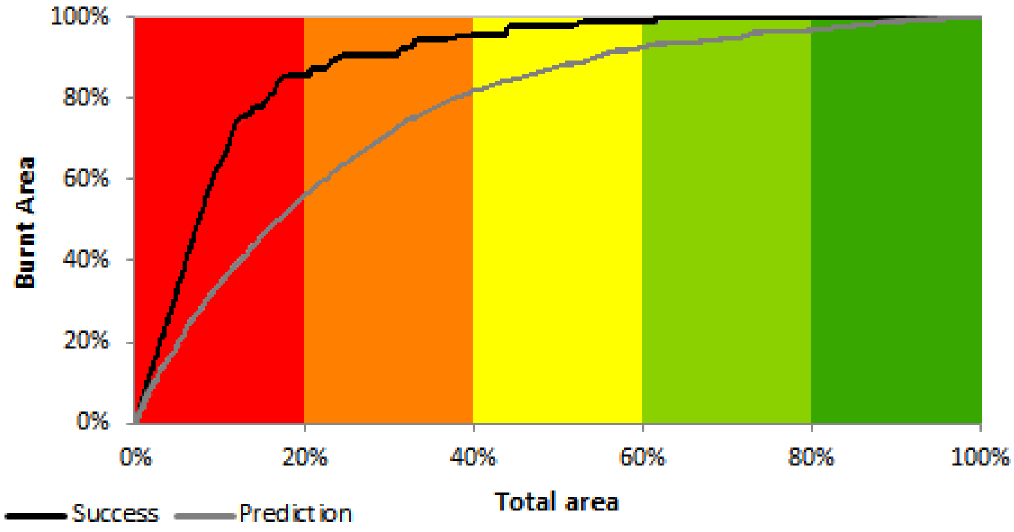


Figure 4.12 – Success and Prediction curves for the modelling series 1975-1994 and independent validation series 1995-2013, in mainland Portugal. The background colours represent the susceptibility classes according to a quintile classification, whose cartographic representation is in figure 4.13.

The prediction curve for the series 1995-2013, over the susceptibility mapping of 1975-1994 is very regular, without any major breaks that could help classifying the series. An objective and purely mathematical classification was deemed as the best solution, given that the prediction curve failed to provide significant help in classifying the values. Therefore, a quintile classification was applied, allotting almost the same number of pixels to each susceptibility class, around 20% of all pixels per class. It is a known fact that there is not the same number of pixels in the five classes, because the classification algorithm cannot divide same value pixels among different classes and, therefore, 20% is an approximate percentage (table 4.12).

Choosing quintiles as a classification method, resulting in five classes, has to do with tradition and what the law defines (Decree-Law n. 124/2006 of June 28th), under which there are five wildfire susceptibility classes named “very low”, “low”, “medium”, “high” and “very high”.

Table 4.12 shows predictive capacities for each susceptibility class. The most susceptible class, named “very high”, has a predictive value of 55%, e.g., the 20% of the territory under that class can hold 55% of future burnt areas. Going further, to 40% of the susceptible territory (the two topmost classes), 82% of the future burnt areas can be integrated. Under this model and its predictive value, 82% of future burnt areas should occur within areas of “high” and “very high” susceptibility.

Table 4.12 – Area and predictive value of wildfire susceptibility classes in mainland Portugal for the modelling block 1975-1994 and validation block 1995-2013

Susceptibility Class	Area (n. of pixels, pixel=80m)	Predictive value
Very Low	2,655,151	0.03
Low	2,642,953	0.05
Medium	2,791,731	0.11
High	2,592,262	0.27
Very High	2,535,362	0.55

Updating the CSP base model with a new land cover coverage and extending independent validation has improved the model's predictive value, as in Verde (2008) and Verde and Zêzere (2010) the combined predictive value of the two topmost susceptibility classes was 80%, whereas it is now 82%. Figure 4.13 presents the updated susceptibility map in regards to what was produced before in Verde (2008).

The methodology described and used throughout this chapter presents some strong points but also some weaknesses that must be fully understood in order to avoid using it beyond its purpose but also as an opportunity for improvement. When applied as proposed, it is a simple methodology, using themes that are easily gathered for free on the internet. Slope (derived from a digital terrain model), land cover and historical data are themes that are available in Portugal from credible sources. The calculations this methodology uses are relatively straightforward and of low complexity, therefore easily used by many professionals, regardless of their specific scientific education or field of work.

However, one must be clear on what conditions must be met in order to successfully apply this method with the themes described herein. One of the limitations to consider is scale. Scale should correspond to the themes, particularly slope and land cover. With a 80 meter pixel (6400 square meters or 0.64 hectares), and a land cover produced for the scale of 1:100,000, it is not adequate to conduct analysis for the local administrative level, like it would happen should the information be produced for a scale of 1:10,000 or even 1:25,000. This methodology and scale are useful for analysis on a broader administrative scale, either national or regional, like NUTSII or NUTSIII. Also, it should be noted that any conclusion derived from the work done up until this chapter must be considered valid only for the time series that has been used. As more years are added it shall be seen if results continue to satisfy, and everyone using this methodology should be aware that results will most likely be different if the time series does not span the same interval as the one herein.

Land cover is the most changing prone theme. Major changes in slope are not expected, but land cover can change quite drastically in a short period. The speed at which land cover coverages are released does not meet the potential for those changes to occur and for that reason, and for what has been seen so far, while wildfire favourabilities, as computed for the model, should remain stable, the changing location of those favourable areas might make a map become obsolete quite fast. Checking the model's response against land cover changes is, therefore, recommended if not mandatory.

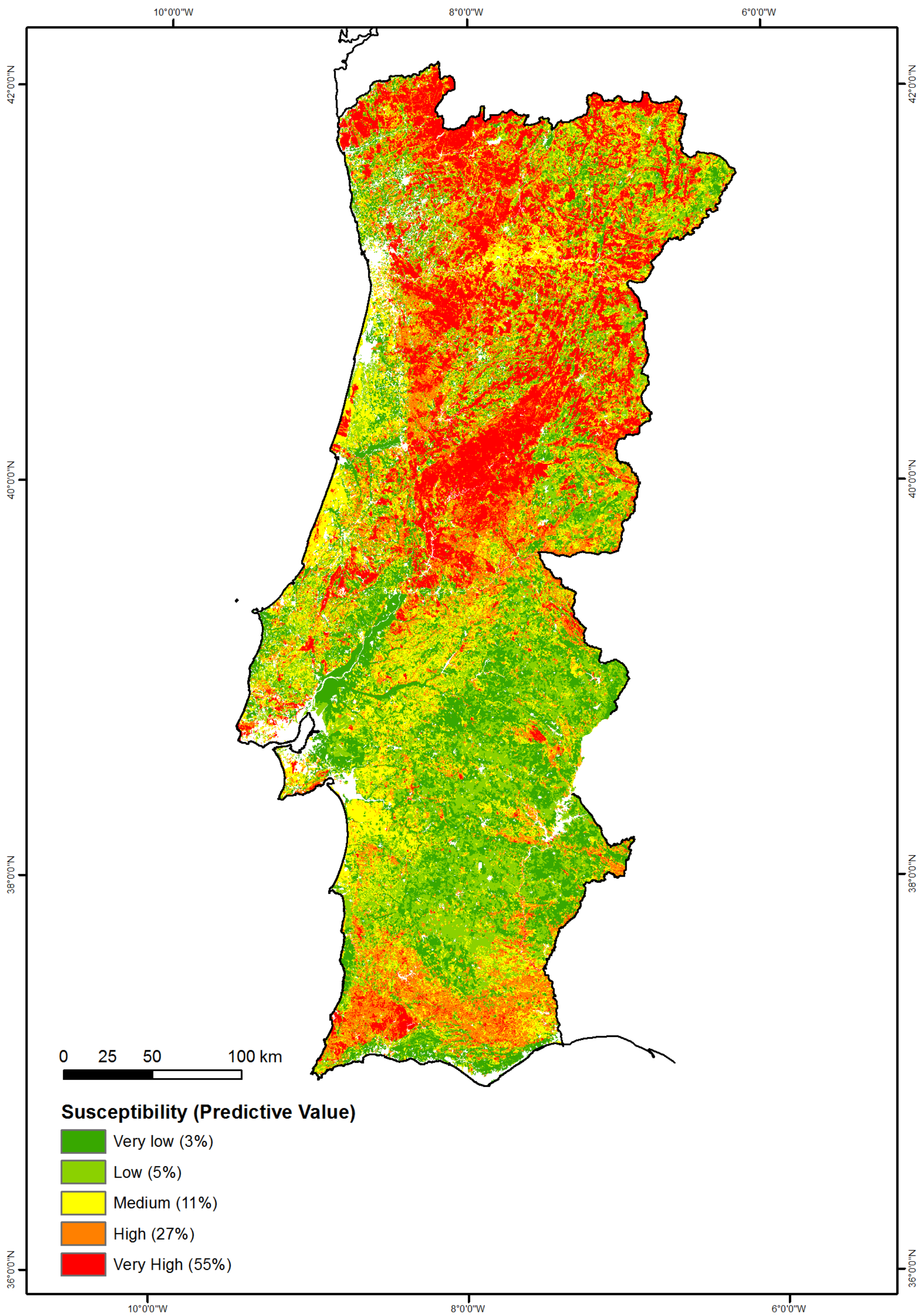


Figure 4.13 – Wildfire susceptibility in mainland Portugal (modelling block 1975-1994)

Limitations should also be reckoned as to burnt scar mapping that, in this model, is used to derive historical data and, hence, favourability scores and probabilities. Being remotely sensed, for the most part, it is likely that there will be both commission and omission errors, and even if we consider that those errors might balance each other, one must understand that not all burnt areas will be considered, and that some of those considered as burnt, might not have been affected by fire at all.

The double entry of historical data, both as an independent theme and as the source for favourability score computation, might be considered a bias in the model and a matter for discussion. If this duplicity is regarded as a serious weak point by anyone interested in modelling wildfire risk, this methodology should not be considered as-is, but there is no intention on hiding this double consideration of historical data and the reasons for that are clearly assumed in section 4.2.1: historical data is also a key to human behavior, otherwise difficult if not impossible to model.

Lastly, it must be kept in mind, at all times, that a model is merely an abstraction of reality, for reducing uncertainty. It cannot and will not represent the whole ground truth. Uncertainty will always be present, errors will always be possible.

Chapter 5. A solid approach: Weights of Evidence

In chapter 4, a methodology of low complexity was presented, yielding quite satisfactory results. Few themes were considered for a minimum reference model, the **CSP** model, since it has been shown that under that methodology, adding more themes does not translate into significantly better results. However, as pointed out in the previous chapter and stressed in section 4.3, even though efficient, that model does have – at least – one caveat that should be addressed further: the double entry of historical data.

As seen before, historical data not only enters the model as an independent layer, a single probability for any given pixel, on any given year, being affected by fire, it also enters the model in every single theme because it is used for computing every variable's favourability score inside each and every theme, according to what was laid out in section 4.1.

While being fully aware of that double role in the model, that duplicity has been reckoned as acceptable, since historical data was also a proxy for human behavior, the single major cause for wildfires in mainland Portugal. The weight historical data has in the model used in chapter 4 helps establishing patterns and introducing behaviors that would, otherwise, be hard or impossible to model. But, still, it is recommendable to study and propose an alternative model where historical data does not have such a role. Thus, under the same assumptions as in chapter 4, in this chapter a model based on the method Weights of Evidence (WofE) is used and results compared. It should be possible, at the chapter's end, to conclude what is different between the two models, and if the less complex reference model does indeed present a strong bias due to the way historical data was used. In that regard, WofE should be considered a fit methodology as Coolbaugh and Bedell (2006) state that «a major benefit of WofE is the unbiased, statistically derived weight it provides for individual layers of data» (op.cit., p.116). WofE was originally used in medicine (Spiegelhalter and Knill-Jones, 1984; Spiegelhalter, 1986) but has since been used on other real world applications such as mining (Bonham-Carter et al., 1988, 1989), landslide prediction (Regmi et al., 2010; Armas¸ 2012; Kouli et al., 2014) but also wilfires (Romero-Calcerrada et al., 2008). Logistic Regression is far easier to find when modelling wildfire susceptibility (see chapter 3), but on the subject of wildfires, WofE should be just as adequate, and remembering the original principles, applied to medicine, the *symptoms* WofE has to deal with are those factors considered as favourable to wildfires.

5.1. Methodology

As in chapter 4, the historical data interval was that of 1975-1994 for modelling, and 1995-2013 for independent validation. As for the CORINE Land Cover, the updated 2006 coverage is used.

A prior probability can be expressed as in [5.1], considering what is available to burn in a wildfire and what has indeed been burnt in a given interval, with *P{W}* the prior probability of Wildfire, *Bp* the Burnt pixels and *Ap* the Available pixels. This is perfectly fine if there is no other information and every pixel for which this is computed will only take into account what is known about past wildfires, in that the prior probability is equal to every single pixel and would in fact be the same as the final probability should wildfire distribution be totally random lacking any type of spatially conditioning factor.

$$P\{W\} = \frac{Bp}{Ap} \qquad [5.1]$$

It is understood that wildfires will behave differently, and have different likelihood of happening, depending on some predisposing factors, like those observed before (e.g. slope, land cover, elevation), so that the probability of occurrence is actually conditioned by the presence of those factors. Taking that into account, the probability of wildfires can be modified by another given factor, *F*, as in [5.2]:

$$P\{W|F\} = \frac{P\{W \cap F\}}{P\{F\}} \qquad [5.2]$$

P{W|F} will therefore represent the conditional probability of wildfire, given the presence of factor *F*. By the relation expressed above, in [5.1], it becomes clear that the conditional probability of wildfire given the presence of a predisposing factor F can also be expressed as the division of the number of burnt pixels inside areas of factor F by the total number of pixels of that factor F.

Given what has been laid out so far, there are four possible combinations of wildfire occurrence and predisposing factors, where P1-P4 represent a given number of pixels (figure 5.1)

		Predisposing Factor	
		Present	Absent
Wildfire historical data	Did burn	P1	P2
	Did not burn	P3	P4

Figure 5.1 – Possible combinations between presence and absence of predisposing factors and wildfire past occurrences.

Under the Weights of Evidence method, there are two Weights, a positive, and a negative. A positive weight (W+) is an indication that the predisposing factor is present at wildfire affected locations, whereas a negative weight (W-) is an indication that the predisposing factor is absent of the location affected by wildfires. The magnitude of these values, or how much they differ from zero, provides an indication of how strong that correlation is (Agterberg et al., 1990; Neuhäuser and Terhorst, 2007; Deng, 2009). The difference between positive and negative weights provides what is called the Contrast (C), allowing for knowing how strong is the correlation between the studied phenomenon and the predisposing factor (which is considered as a prediction variable). In this study those correlations are not being studied, and in this particular chapter it is being assumed that all considered predisposing factors correlate to wildfires. The degree of correlation is being analyzed elsewhere, namely through the success and prediction rate curves and their areas under the curve, therefore the contrast is not being used, and only positive weights are summed together. The weights follow equations [5.3] and [5.4].

$$W^{+} = ln\frac{P\{F|W\}}{P\{F|\sim W\}} \quad [5.3]$$

$$W^{-} = ln\frac{P\{\sim F|W\}}{P\{\sim F|\sim W\}} \quad [5.4]$$

Where *F* is the presence of a predisposing factor and *~F* its absence, and *W* is the presence of wildfire affected pixels and *~W* their absence.

Recalling the four possible combinations between presence and absence of predisposing factors and wildfire affected pixels (Fig 5.1), equations [5.3] and [5.4] are operated as in [5.5] and [5.6].

$$W^{+} = ln\frac{\frac{P1}{P1 + P2}}{\frac{P3}{P3 + P4}} \quad [5.5]$$

$$W^{-} = ln\frac{\frac{P2}{P1 + P2}}{\frac{P4}{P3 + P4}} \quad [5.6]$$

In the above two equations, P1 through P4 represent the number of pixels as described earlier for the four possible combinations of presence and absence of factors and affected pixels.

After computing the weights for all considered factors, their positive weights were summed together (not multiplied as in the previous chapter), creating a final *weight* or score for each single pixel, which would be the equivalent of the favourability scores computed in chapter 4. From thereafter, the methodology is identical, leading to the graphing of success and prediction curves, area under the curve computation and comparing results, therefore conducting a sensitivity analysis. As previously mentioned, and even though other authors explore the Constrast, the correlation between predisposing factors and wildfire occurrence was not studied through this method. It was left for the sensitivity analysis to show if a predisposing factor was or was not contributing to the overall model prediction capability, rather than using the Contrast for that purpose.

The Weights of Evidence modelling did not use any existing computer programme, all calculations were partially performed in Python and PHP, specially programmed for this particular purpose.

5.2 Testing Weights of Evidence against the reference model CSP

A major reason for using Weights of Evidence (WofE) is to remove bias from the double entry of historical data in the previous methodology, doing so in a tested, statistical and objective method. Therefore, running WofE models means removing historical data (which has, so far, been integrated as a single probability) from the model as an independent layer. In this section, the reference model **CSP** is compared with a WofE run of only land cover and slope (**WofE-CS**). For comparison sake, the same data interval shall be used, that of 1975-1994 for modelling and 1995-2013 for independent validation. Following the conclusions in chapter 4, all models hereafter shall use CORINE Land Cover 2006. Table 5.1 presents positive weights for land cover classes, with the CSP favourability scores also presented for comparison.

Table 5.1 – Positive Weights of Evidence (W^+) score for Land Cover layer, with burnt pixel set of 1975 to 1994, in mainland Portugal

Land cover	Pixels		W+ Score	Favourability Score
Class Id	Available	Burnt		
211	1,533,952	76,355	-1234	50
212	329,142	9,194	-1835	28
213	82,539	634	-3146	8
221	357,728	9,485	-1888	27
222	157,859	5,502	-1606	35
223	410,985	7,873	-2221	19
231	65,410	3,712	-1096	57
241	631,195	10,980	-2319	17
242	948,495	18,073	-2226	19
243	1,073,231	78,235	-828	73
244	971,197	23,038	-2003	24
311	1,573,550	167,975	-410	107
312	834,578	147,555	177	177
313	743,142	119,105	59	160
321	268,595	149,647	1944	557
322	444,758	258,744	2045	582
323	323,117	68,626	404	212
324	2,205,531	727,871	1007	330
331	18,494	450	-1976	24
332	37,314	19,176	1770	514
333	157,610	92,372	2063	586
334	51,324	22,015	1429	429
Total	**13,219,746**	**2,016,617**		

On figure 5.2, frequency and positive weights are compared, and it is possible to see that all of agricultural classes are not favourable to wildfires, just as broad-leaved forests are not, even if not as much unfavourable, being the second most frequent land cover class among those considered in this study. Beaches, dunes and sands (class Id 331) are very unfavourable to the occurrence of wildfires, which is not much of a surprise given the nature of that land cover, but apart from that class and broad-leaved forests, all other classes within forested and semi-natural areas are favourable to wildfires. The spatial representation for CORINE Land Cover 2006 has been presented in section 4.2.1 as figure 4.1.

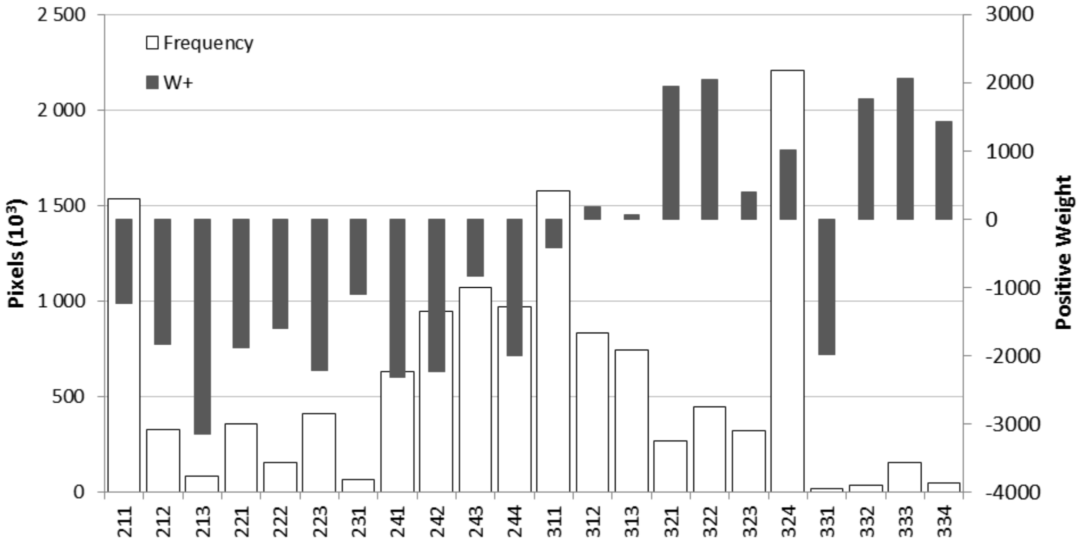


Figure 5.2 –Frequency and W+ for Land Cover layer with burnt pixel set of 1975 to 1994 in mainland Portugal

Table 5.2 presents positive weights of evidence and favourability scores (for comparison) for the slope evidence layer, and figure 5.3 shows how frequency compares to positive weights.

Table 5.2 – Positive Weights of Evidence (W^+) score for Slope layer, with burnt pixel set of 1975 to 1994, in mainland Portugal

Slope	Pixels		W+ Score	Favourability Score
Degrees	Available	Burnt		
0 - 2	3,769,671	176,063	-1253	47
2 - 5	4,620,398	410,381	-565	89
5 - 10	3,113,286	603,791	339	194
10 - 15	1,363,989	424,216	968	311
15 - 20	659,408	253,866	1295	385
> 20	392;260	168,735	1482	430
Total	**13,919,012**	**2,037,052**		

It can be observed as mainland Portugal is not a mainly mountainous territory (see fig. 4.7), with the most area in the less steep classes, up to 10 degress in slope. The flatter the land, the less favourable are those areas to wildfires, and positive weights become more favourable, showing added relevance of that evidence layer, as slope increases, which is due to the fuel pre-heating uphill during a wildfire (Rothermel, 1983; Mermoz et al., 2005; Verde, 2008).

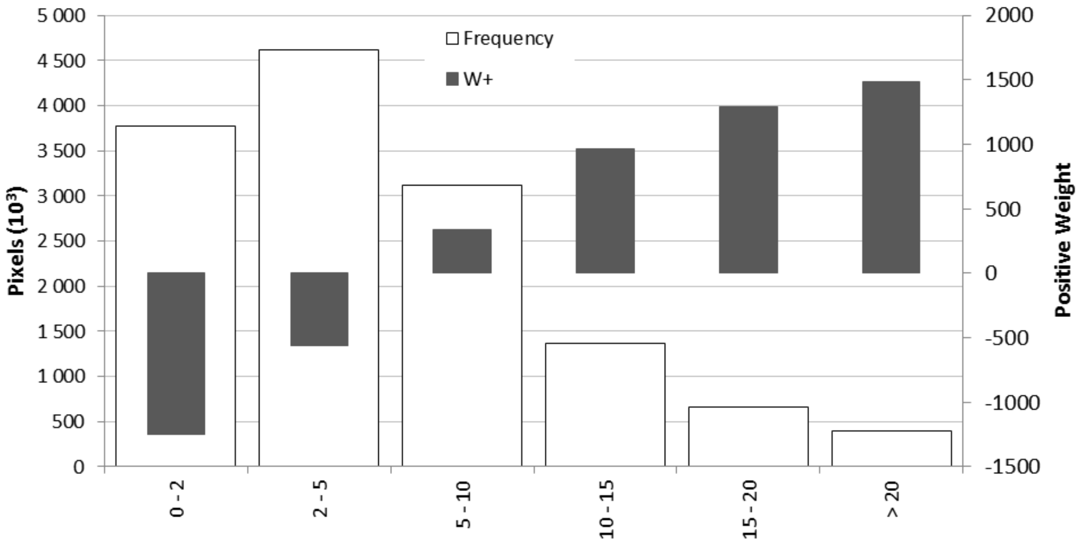


Figure 5.3 –Frequency and W+ for Slope layer with burnt pixel set of 1975 to 1994 in mainland Portugal

Figure 5.4 shows success and prediction curves comparing the two models after running both the base CSP model and the WofE-CS model.

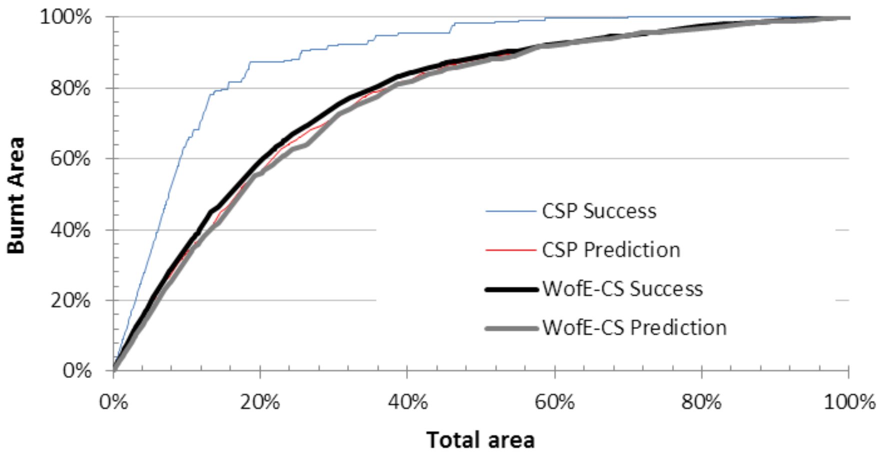


Figure 5.4 – Success and Prediction curves for the reference model CSP and Weights of Evidence WofE-CS with burnt pixel set of 1975 to 1994 in mainland Portugal

The WofE-CS model has, as notable features, a success curve which is very close to the prediction curve and, in fact, both curves almost mimic the behavior of the CSP prediction curve. When comparing the WofE-CS with the CSP model, the differences are easy to spot (tables 5.3 and 5.4), since WofE-CS has significantly worse success rates, but not so distant prediction rates. WofE-CS's prediction is, by comparison, quite capable and even when worse than the CSP model, only by a slim margin.

Table 5.3 – Compared Success rates for models "CSP" and "WofE-CS" with burnt pixel set of 1975 to 1994 in mainland Portugal. Higher values in bold. (%)

	10%	20%	30%	40%	50%	60%	70%	80%	90%
CSP	**64.12**	**85.46**	**90.87**	**95.77**	**97.83**	**99.00**	**99.97**	**100**	**100**
WofE-CS	35.24	59.29	74.53	84.15	89.00	92.40	94.90	97.71	98.94

Table 5.4 – Compared Prediction rates for models "CSP" and "WofE-CS" with burnt pixel set of 1975 to 1994 in mainland Portugal. Higher values in bold. (%)

	10%	20%	30%	40%	50%	60%	70%	80%	90%
CSP	**33.21**	**56.29**	71.23	**82.06**	**88.24**	**92.60**	**95.14**	**97.16**	**98.91**
WofE-CS	32.04	55.90	**71.33**	81.61	87.51	92.15	94.86	97.02	98.87

5.3 Strengthening Weights of Evidence with further evidence layers

The results from section 5.2 show that a model employing the Weights of Evidence method using only land cover and slope achieved interesting results, but not on par with those of the reference model **CSP** in what concerns success rate. Thus, it is of interest to repeat the process in Verde (2008), adding evidence layers, not entirely to study if more layers mean more predictive power, but to study if adding new evidence layers helps in getting closer to the reference model. Differently said, is it possible to achieve similar results with the WofE model as with the CSP model, if the historical data is absent as an evidence layer itself? To that intent, the WofE model was run using additional evidence layers, going back to what is commonly used in the literature as evidence layers on the subject of wildfires. The studies by IGP (2004; 2007) were relevant in choosing which evidence layers to address: Elevation, Aspect, Population Density, Population Growth Rate, and Distance to Roads, but that choice does bring a possible problem, mainly in regards to population and distance to roads: in creating classes similar to those of IGP (op.cit.), very large and unbalanced areas are created, having a possibly negative impact on WofE's capability to adequately differentiate what favors or hinders fire occurrence.

5.3.1. Elevation

Elevation in mainland Portugal is presented in figure 5.5. Elevation can be considered a conditioning factor given that it influences temperature and rainfall (Ventura and Vasconcelos, 2006) and therefore fuel type and density. Table 5.5 presents positive weights for this layer, as well as how they compare to the original favourability scores. Please bare in mind that those favourability scores are unused in this chapter's and are only presented for giving the reader a sense of how positive weights compare to the previously used scores under a different methodology.

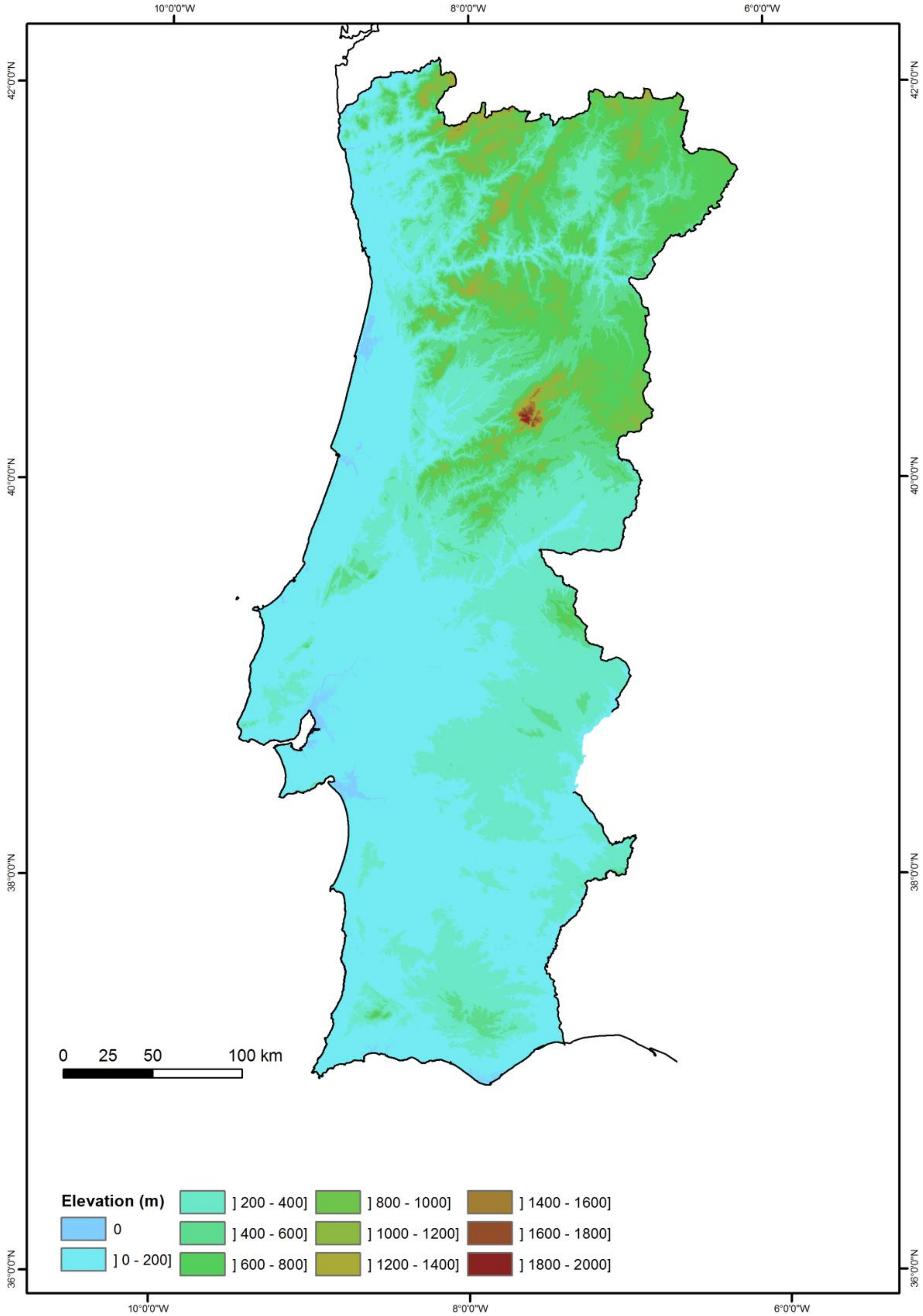


Figure 5.5 – Elevation in mainland Portugal

Table 5.5 – Positive Weights of Evidence (W⁺) score for Elevation layer, with burnt pixel set of 1975 to 1994 in mainland Portugal.

Elevation	Pixels		W+ Score	Favourability Score
Meters	Available	Burnt		
0	114,515	240	-4,402	1
1 - 100	2,769,360	103,914	-1,481	4
101 - 200	3,102,003	216,481	-826	7
201 - 300	2,490,516	237,136	-488	10
301 - 400	1,384,088	217,162	82	16
401 - 500	951,387	217,120	545	23
501 - 600	774,191	223,624	863	29
601 - 700	732,445	222,151	932	30
701 - 800	702,783	214,079	938	30
801 - 900	436,979	160,150	1,216	37
901 - 1000	221,888	100,843	1,581	45
1001 - 1100	112,622	58,780	1,851	52
1101 - 1200	59,698	34,392	2,070	58
1201 - 1300	31,791	19,637	2,243	62
1301 - 1400	14,420	7,160	1,750	50
1401 - 1500	7,932	2,240	831	28
1501 - 1600	4,695	1,110	591	24
1601 - 1700	3,961	547	-68	14
1701 - 1800	1,744	258	13	15
1801 - 1900	1,574	28	-2,248	2
1901 - 2000	420	0	0	1
Total	**13,919,012**	**2,037,052**		

Frequency and Favourability are presented on figure 5.6 and figure 5.7 shows frequency and positive weights for Elevation.

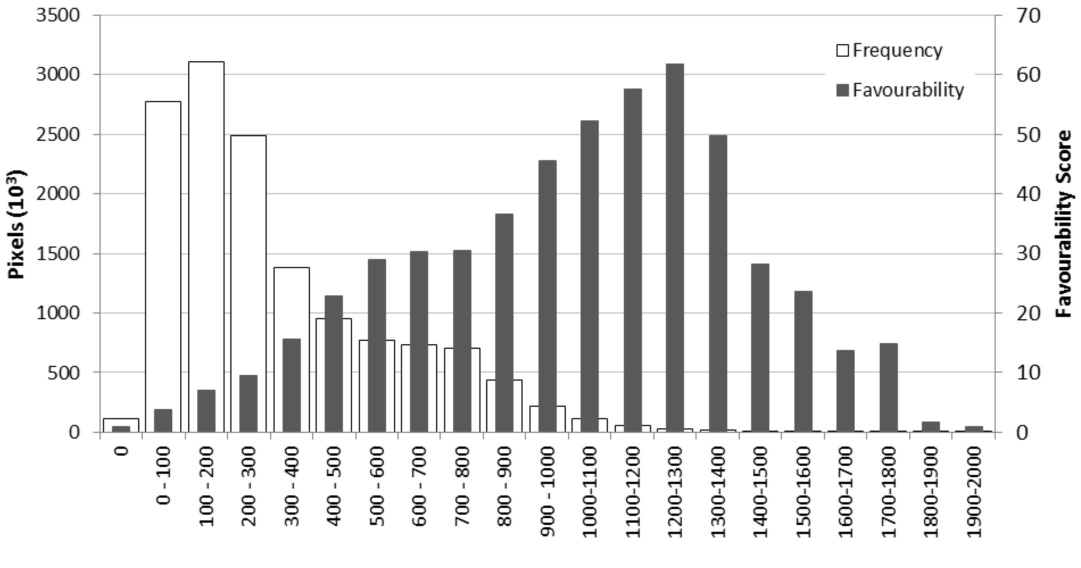


Figure 5.6 – Favourability and Frequency for Elevation layer with burnt pixel set of 1975 to 1994 in mainland Portugal

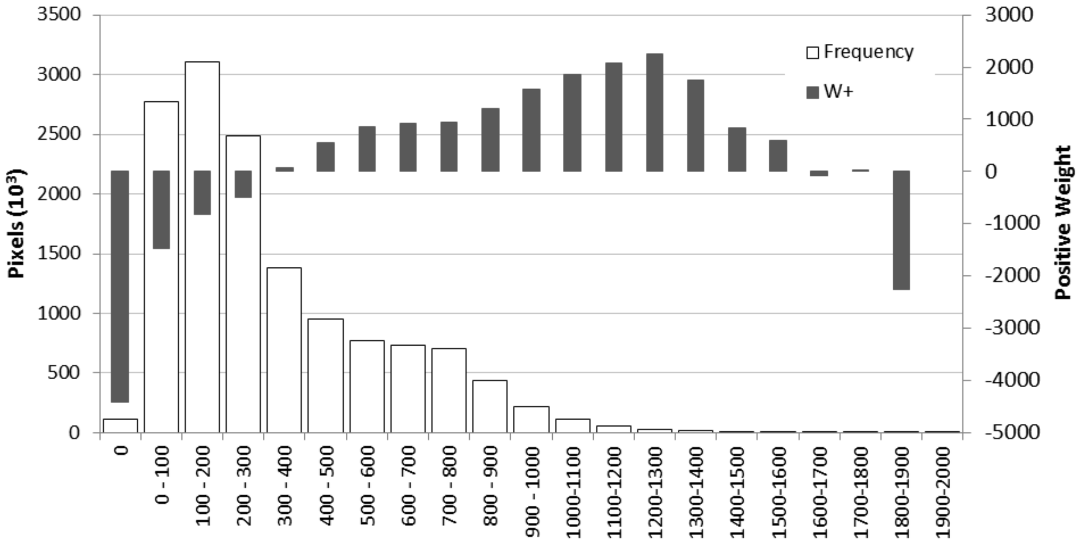


Figure 5.7 –Frequency and W+ for Elevation layer with burnt pixel set of 1975 to 1994 in mainland Portugal

Both favourability and positive weights peak at elevations of 1200 to 1300 meters. An increase in W+ is noted until elevations of 1200 to 1300 meters, after which these weights drop, probably as fuel above those heights is scarcer. Figure 5.8 presents how WofE-CSE's success and prediction curves compare to CSP's.

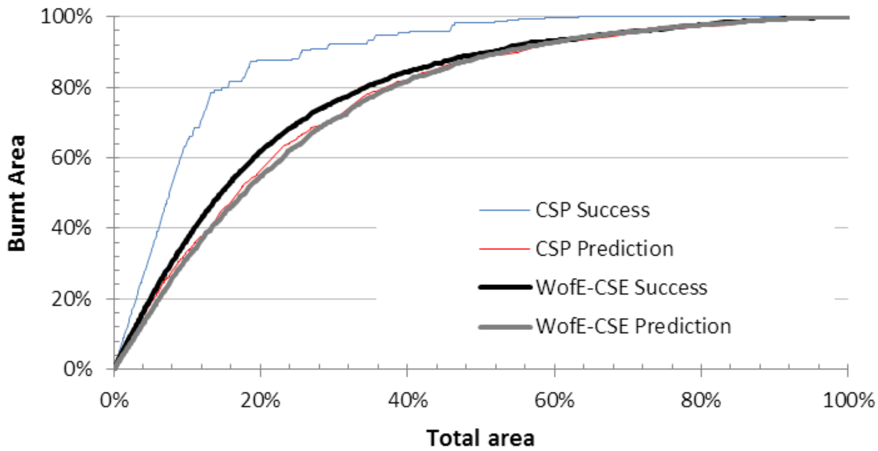


Figure 5.8 – Success and Prediction curves for the reference model CSP and Weights of Evidence WofE-CSE with burnt pixel set of 1975 to 1994 in mainland Portugal

Again, success and prediction curves are very close together, with the success curve far below that of the CSP model. Tables 5.6 and 5.7 compare the rates of the two models.

Table 5.6 – Compared Success rates for models "CSP" and "WofE-CSE" with burnt pixel set of 1975 to 1994 in mainland Portugal. Higher values in bold. (%)

	10%	20%	30%	40%	50%	60%	70%	80%	90%
CSP	**64.12**	**85.46**	**90.87**	**95.77**	**97.83**	**99.00**	**99.97**	**100**	**100**
WofE-CSE	36.86	61.78	75.81	84.37	89.50	93.19	95.67	97.62	99.19

Table 5.7 – Compared Prediction rates for models "CSP" and "WofE-CSE" with burnt pixel set of 1975 to 1994 in mainland Portugal. Higher values in bold. (%)

	10%	20%	30%	40%	50%	60%	70%	80%	90%
CSP	**33.21**	**56.29**	**71.23**	**82.06**	88.24	92.60	95.14	97.16	98.91
WofE-CSE	31.68	54.67	70.79	81.70	**88.50**	**92.73**	**95.55**	**97.65**	**99.21**

Success rates for WofE-CSE are always worse than those of CSP. Prediction rates for CSP are not always the best, but they perform better using less susceptible area, and only from mid-area upwards does WofE-CSE begin to take on the lead.

5.3.2. Aspect

Aspect is sometimes considered as a possible conditioning factor of wildfire, in that slopes facing North would have more fine fuel moisture, whereas South facing slopes would be dry, receiving more hours of direct sunlight. Therefore, South facing slopes would accelerate fire, and North facing slopes would slow its progression or make ignitions far more difficult. Hence, aspect could be an evidence layer, and one would suppose statistics would somehow favor South facing slopes in regards to susceptibility. Table 5.8 presents positive weight and favourability scores (for comparison) for each aspect class.

Table 5.8 – Positive Weights of Evidence (W^+) score for Aspect layer, with burnt pixel set of 1975 to 1994 in mainland Portugal

Orientation (Aspect)	Pixels		W+ Score	Favourability Score
	Available	Burnt		
Flat	78,167	573	-3,145	1
N	1,502,105	202,517	-95	13
NE	1,547,807	206,466	-108	13
E	1,697,259	254,176	27	15
SE	1,771,404	273,069	61	15
S	1,740,266	249,282	-25	14
SW	1,877,385	273,303	-6	15
W	1,945,038	306,108	86	16
NW	1,759,581	271,558	62	15
Total	**13,919,012**	**2,037,052**		

Figures 5.9 and 5.10 show how aspect classes relate to their favourability and positive weights (W+). Favourability plotting is presented for comparison with the methodology in chapter 4, since these scores are not used in this chapter. Overall, mainland Portugal is mainly west oriented, from the Northwest to Southwest, which makes many of these slopes facing the strong North winds very well-known and feared during the summer, the "Nortada", responsible for some of the most aggressive wildfires due to the speed of progression. It should, then, be noticed on the favourability scores, but these scores do not change all that much among the eight non-flat aspect classes.

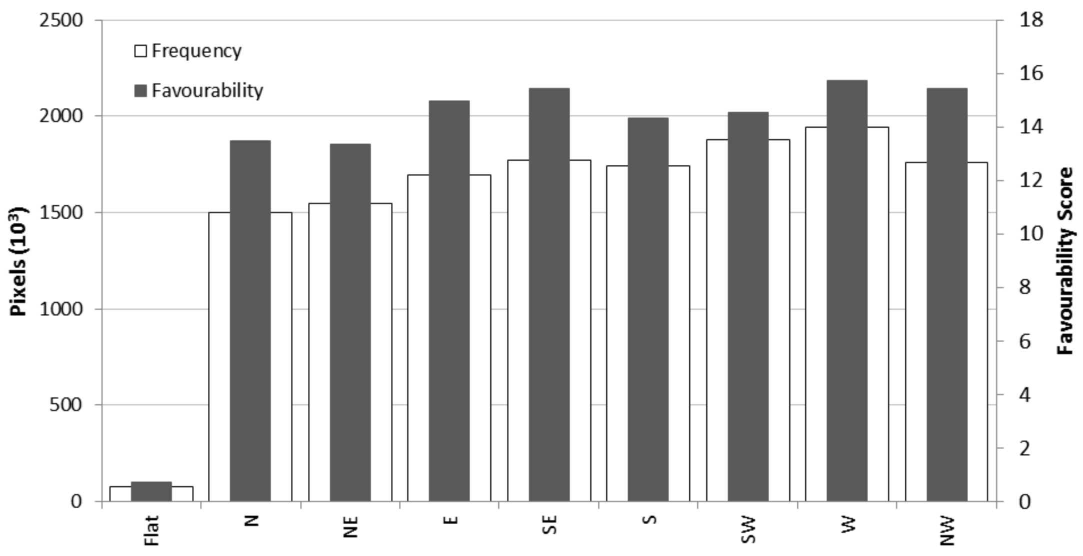


Figure 5.9 – Favourability and Frequency for Aspect layer with burnt pixel set of 1975 to 1994 in mainland Portugal

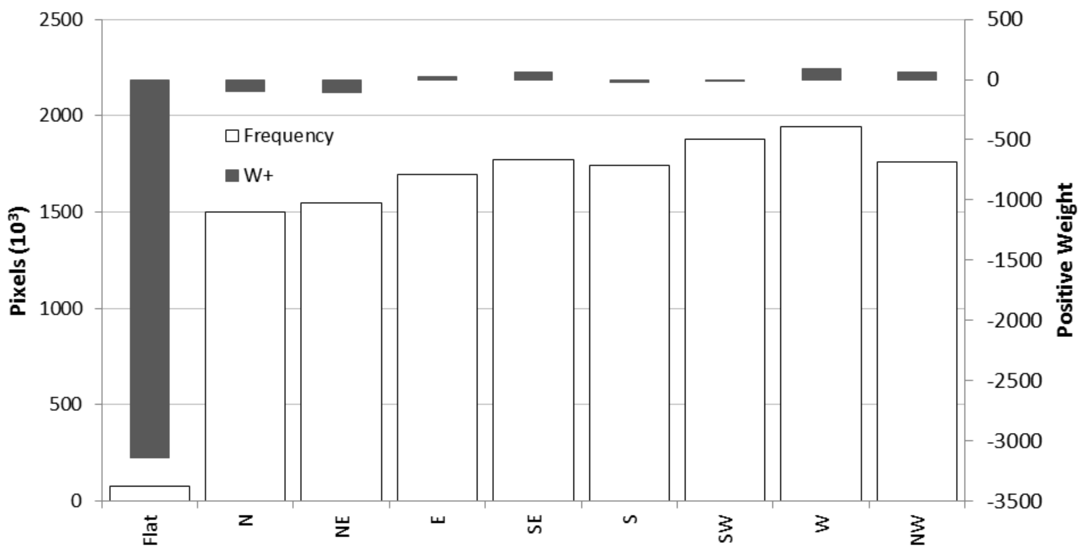


Figure 5.10 –Frequency and W+ for Aspect layer with burnt pixel set of 1975 to 1994 in mainland Portugal

If we observe the positive weights for this evidence layer, the presence of flat areas is not significant for wildfire occurrence, and they do not vary much on the other classes, always with very low absolute scores, which indicates a general weak discriminant power of the theme. Carmo et al. (2011) had also pointed out the weak selectivity of aspect in northern Portugal and in this work that conclusion appears to be also valid.

After running the WofE-CSEA model, figure 5.11 shows success and prediction curves for both models. Tables 5.9 and 5.10 compare rates of CSP and WofE-CSEA at 10% susceptible area marks. It should be noted that new evidence layers are being merged in the model with the previous ones, resulting in cumulative models. Figure 5.12 maps aspect in mainland Portugal.

Table 5.9 – Compared Success rates for models "CSP" and "WofE-CSEA" with burnt pixel set of 1975 to 1994 in mainland Portugal. Higher values in bold. (%)

	10%	20%	30%	40%	50%	60%	70%	80%	90%
CSP	**64.12**	**85.46**	**90.87**	**95.77**	**97.83**	**99.00**	**99.97**	**100**	**100**
WofE-CSEA	36.85	61.77	75.83	84.42	89.50	93.20	95.66	97.65	99.22

Table 5.10 – Compared Prediction rates for models "CSP" and "WofE-CSEA" with burnt pixel set of 1975 to 1994 in mainland Portugal. Higher values in bold. (%)

	10%	20%	30%	40%	50%	60%	70%	80%	90%
CSP	**33.21**	**56.29**	**71.23**	**82.06**	88.24	92.60	95.14	97.16	98.91
WofE-CSEA	31.53	54.58	70.82	81.84	**88.53**	**92.75**	**95.53**	**97.61**	**99.17**

The WofE-CSEA model shows a similar behavior as the WofE-CSE, and when comparing areas under the curve, their success curve AUC is exactly the same, at 78.77%, but the prediction curve AUC for WofE-CSEA is five milesimal points below that of WofE-CSE with 76.5111% (versus 76.5161%). The aspect, as an evidence layer, brings no added value, for which it has been dropped from future model runs.

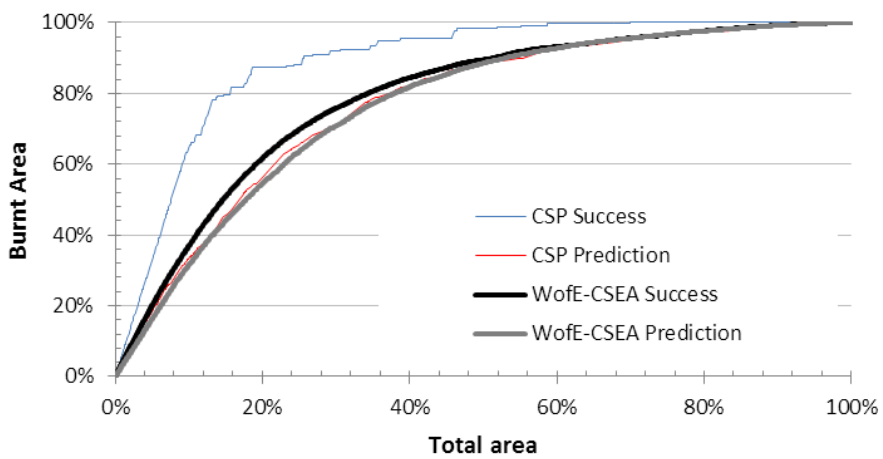


Figure 5.11 – Success and Prediction curves for the reference model CSP and Weights of Evidence WofE-CSEA with burnt pixel set of 1975 to 1994 in mainland Portugal

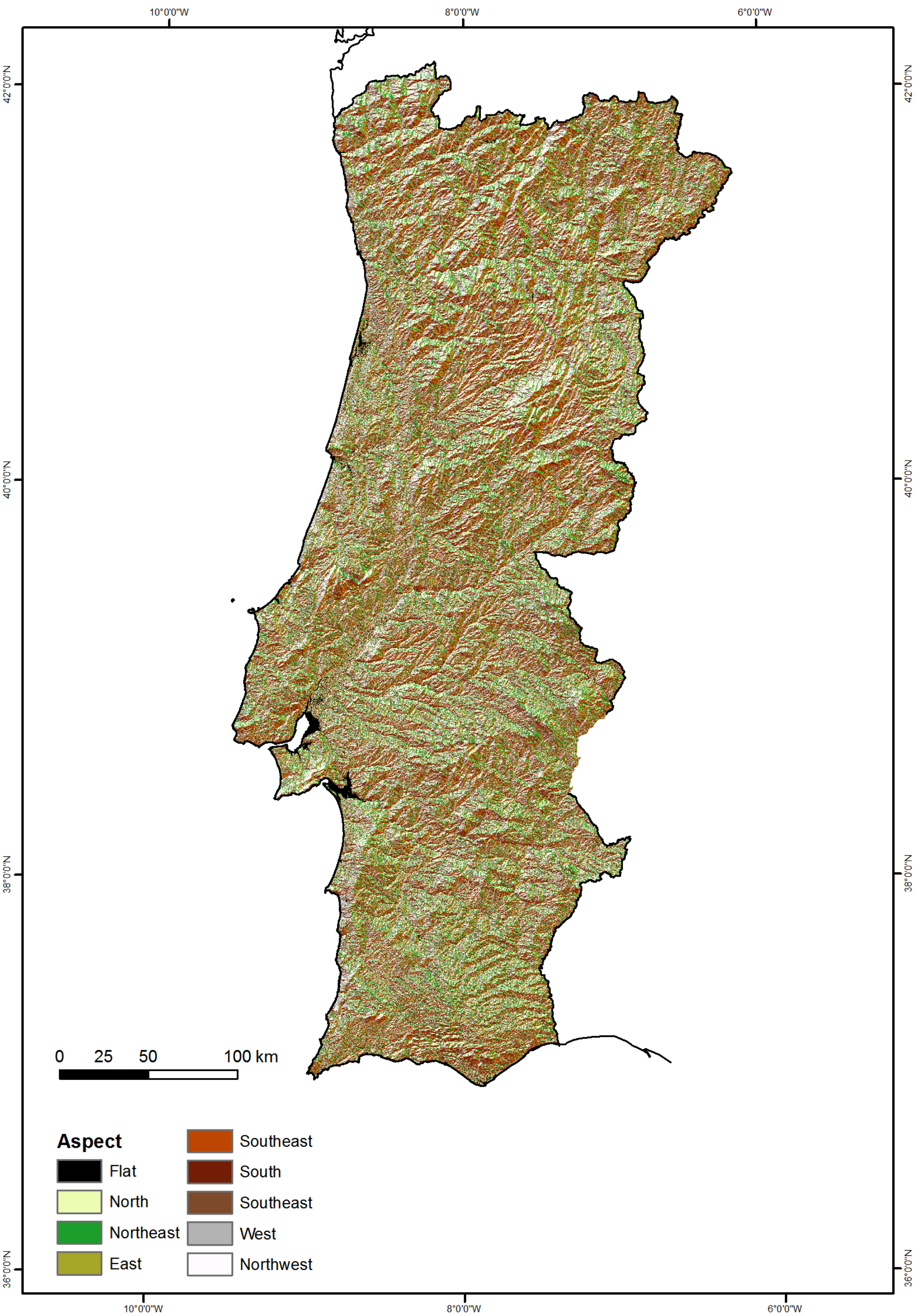


Figure 5.12 – Aspect in mainland Portugal

5.3.3. Population Density

In chapter 3, it has been shown how some existing works consider population density as a relevant factor. Chuvieco and Congalton (1989) and IGP (2004; 2007) are examples of how this evidence layer can be used, given that for those authors « (...) Trail and road locations are also an important factor in fire hazard mapping. Two major effects can be considered. First, they can serve as fire breaks or pathways for suppression of the fire (…) second, they are potential routes for hiking or camping areas (…) they increase forest fire hazard because of the more intense human activity» (Chuvieco and Congalton, 1989, p.152). In trying to catch up with the CSP model, population density will be integrated using information from the Census of 2001 and 2011, resorting to the BGRI level. The thresholds, for comparison, are the same as in IGP (2004; 2007), with three classes of population density (tables 5.11 and 5.12). With an upper limit, for the first class, of 250 residents per square kilometer, it is quite possible that this class is more useful around urban/rural interfaces than in rural areas. As in previous evidence layers, a column for the favourability score is included for comparison with what would be used in the original methodology, but it is not used in the Weights of Evidence modelling.

Table 5.11 – Positive Weights of Evidence (W^+) score for Population Density (2001 Census) layer, with burnt pixel set of 1975 to 1994 in mainland Portugal.

Density	Pixels		W+ Score	Favourability Score
(Residents/Km^2)	Available	Burnt		
Up to 250	12,785,298	2,008,027	83	16
251 to 1500	963,031	27,084	-1,779	3
More than 1501	170,201	1,941	-2,699	1
Total	**13,918,530**	**2,037,052**		

Table 5.12 – Positive Weights of Evidence (W^+) score for Population Density (2011 Census) layer, with burnt pixel set of 1975 to 1994 in mainland Portugal.

Density	Pixels		W+ Score	Favourability Score
(Residents/Km^2)	Available	Burnt		
Up to 250	12,821,138	2,009,546	81	16
251 to 1500	909,057	25,148	-1,796	3
More than 1501	188,534	2,358	-2,605	1
Total	**13,918,729**	**2,037,052**		

In the next figures (5.13 to 5.16), positive weights and favourability scores are presented.

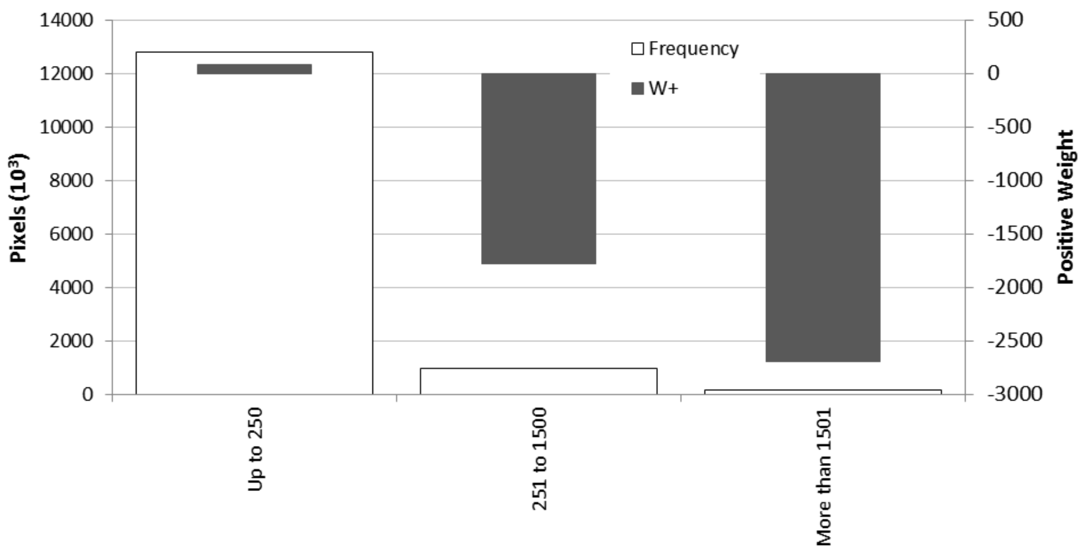


Figure 5.13 –Frequency and W+ for Population Density (2001) layer with burnt pixel set of 1975 to 1994 in mainland Portugal

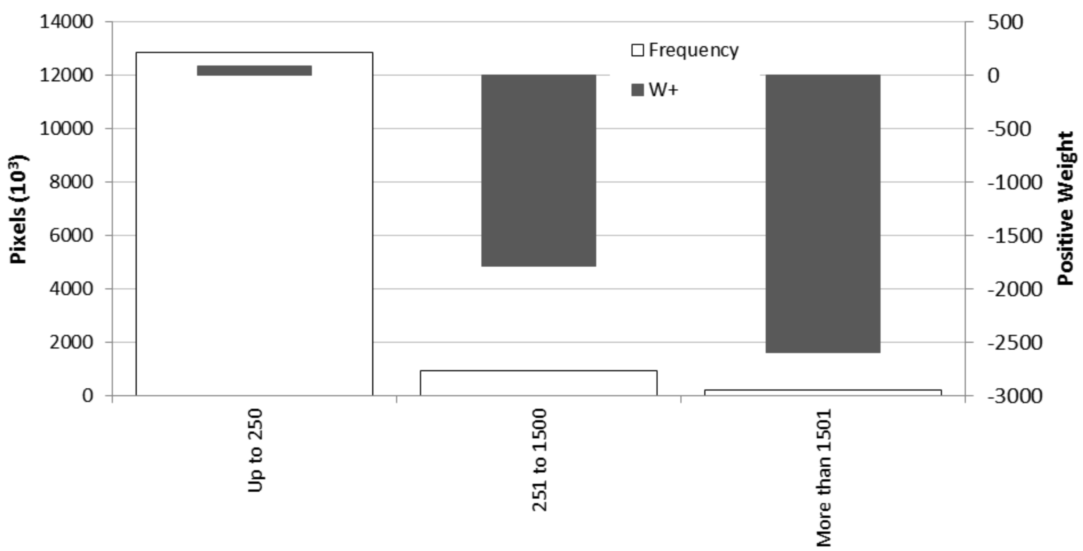


Figure 5.14 –Frequency and W+ for Population Density (2011) layer with burnt pixel set of 1975 to 1994 in mainland Portugal

With only three classes, there is not much variability. As most of the population, either in 2001 or 2011, is concentrated around urban nucleae (figures 5.17 and 5.18), most of the territory falls into the lowest density class, of up to 250 residents per square kilometer. Inside that class is also where it burns more, which seems fairly easy to understand: the most populated areas do not have as many wildfire susceptible land cover classes as the others and, on the other hand, where there is less population, fire is also detected later and can therefore progress more until it is suppressed. Not surprisingly, from the previous tables and figures, the most representative class in number of pixels has the best favourability score and the only positive weight. Regarding positive weights, the presence of more dense population impacts very negatively the occurrence of wildfires.

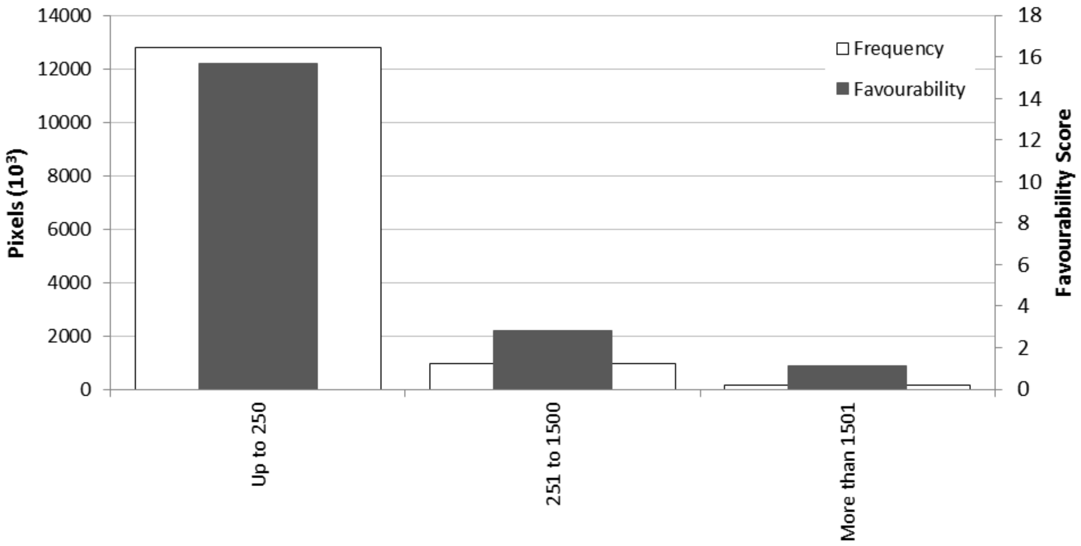


Figure 5.15 –Frequency and Favourability for Population Density (2001) layer with burnt pixel set of 1975 to 1994 in mainland Portugal

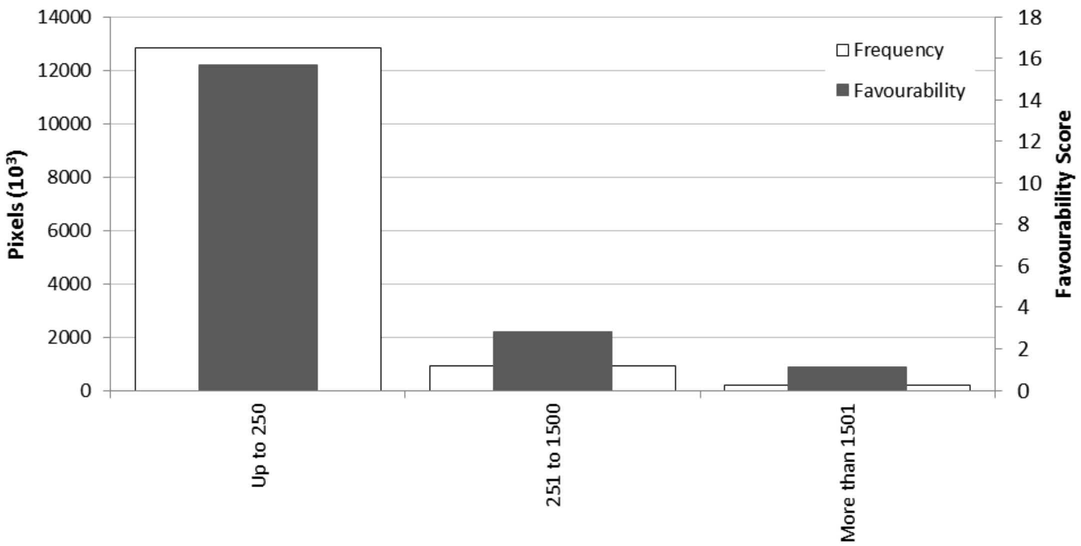


Figure 5.16 –Frequency and Favourability for Population Density (2011) layer with burnt pixel set of 1975 to 1994 in mainland Portugal

In figures 5.19 and 5.20, just as in tables 5.13 to 5.16, success and prediction rates of WofE-CSEP01 and WofE-CSEP11 are compared to the base CSP model. Whereas CSP's success is unbeatable by either WofE-CSEP01 or WofE-CSEP11, prediction rates are far closer and the WofE models even surpass the CSP model after 50% of the most susceptible areas. Still, the topmost susceptible territory has CSP as the best model.

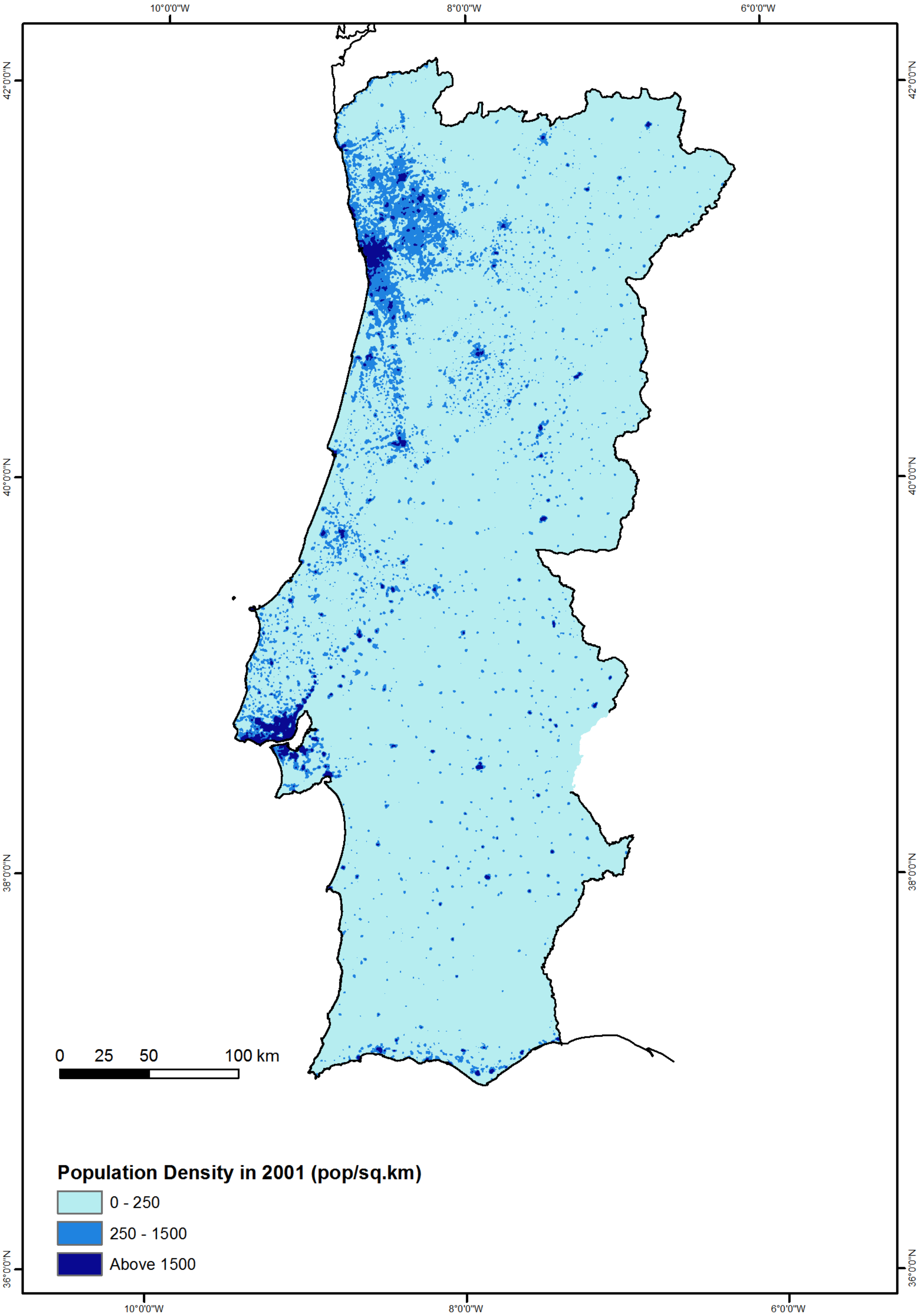


Figure 5.17 –Population Density (2001) in mainland Portugal

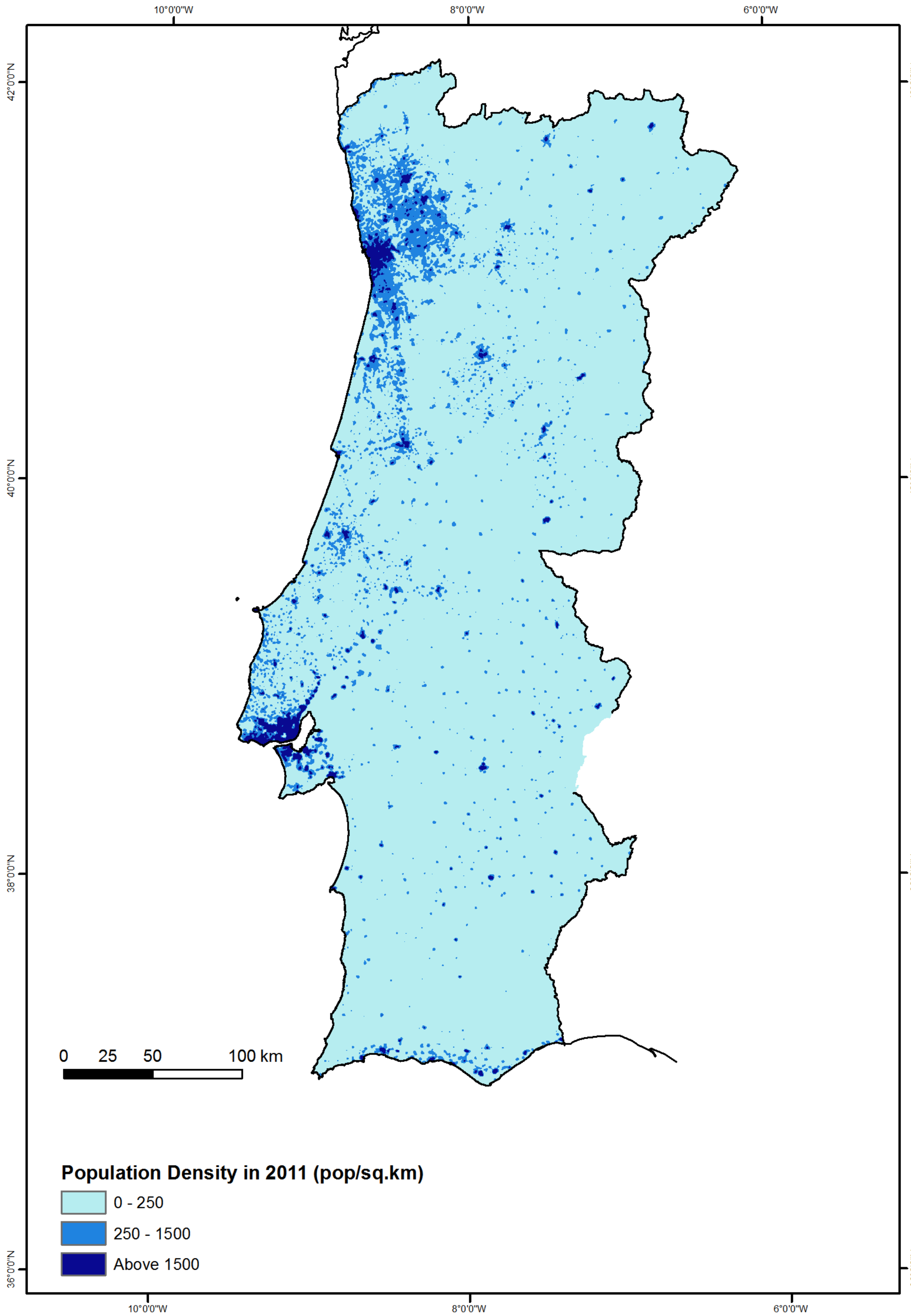


Figure 5.18 –Population Density (2011) in mainland Portugal

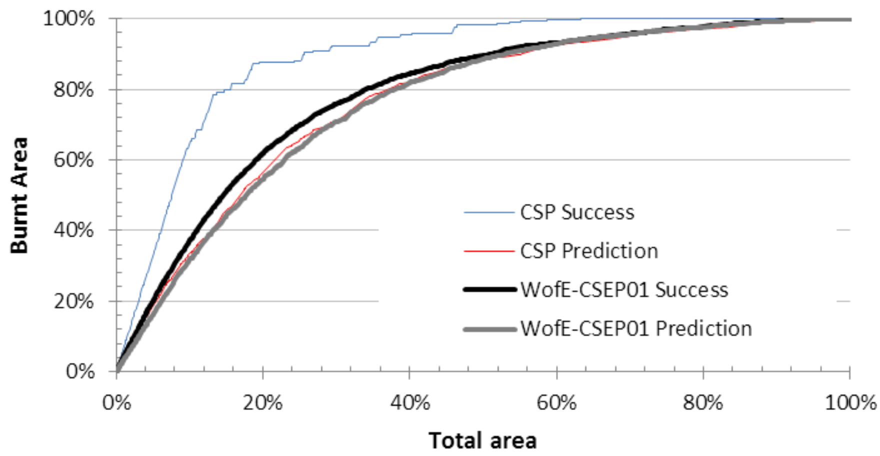


Figure 5.19 – Success and Prediction curves for the reference model CSP and Weights of Evidence WofE-CSEP01 (Census 2001) with burnt pixel set of 1975 to 1994 in mainland Portugal

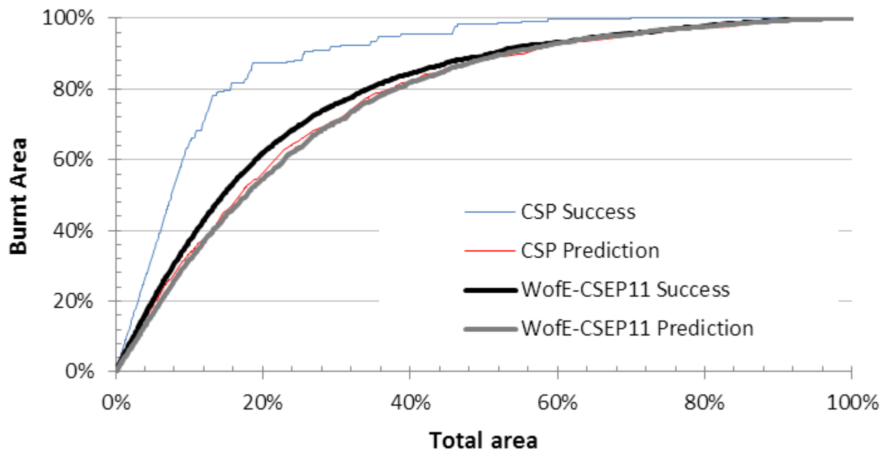


Figure 5.20 – Success and Prediction curves for the reference model CSP and Weights of Evidence WofE-CSEP11 (Census 2011) with burnt pixel set of 1975 to 1994 in mainland Portugal

Table 5.13 – Compared Success rates for models “CSP” and “WofE-CSEP01” with burnt pixel set of 1975 to 1994 in mainland Portugal. Higher values in bold. (%)

	10%	20%	30%	40%	50%	60%	70%	80%	90%
CSP	**64.12**	**85.46**	**90.87**	**95.77**	**97.83**	**99.00**	**99.97**	**100**	**100**
WofE-CSEP01	36.93	61.90	75.88	84.43	89.49	93.19	95.78	97.92	99.41

Table 5.14 – Compared Prediction rates for models “CSP” and “WofE-CSEP01” with burnt pixel set of 1975 to 1994 in mainland Portugal. Higher values in bold. (%)

	10%	20%	30%	40%	50%	60%	70%	80%	90%
CSP	**33.21**	**56.29**	**71.23**	**82.06**	88.24	92.60	95.14	97.16	98.91
WofE-CSEP01	31.68	54.54	70.69	81.95	**88.63**	**92.89**	**95.47**	**97.73**	**99.25**

Table 5.15 – Compared Success rates for models “CSP” and “WofE-CSEP11” with burnt pixel set of 1975 to 1994 in mainland Portugal. Higher values in bold. (%)

	10%	20%	30%	40%	50%	60%	70%	80%	90%
CSP	**64.12**	**85.46**	**90.87**	**95.77**	**97.83**	**99.00**	**99.97**	**100**	**100**
WofE-CSEP11	36.92	61.89	75.89	84.42	89.48	93.18	95.76	97.89	99.40

Table 5.16 – Compared Prediction rates for models "CSP" and "WofE-CSEP11" with burnt pixel set of 1975 to 1994 in mainland Portugal. Higher values in bold. (%)

	10%	20%	30%	40%	50%	60%	70%	80%	90%
CSP	**33.21**	**56.29**	**71.23**	**82.06**	88.24	92.60	95.14	97.16	98.91
WofE-CSEP11	31.69	54.57	70.75	81.97	**88.63**	**92.86**	**95.46**	**97.72**	**99.25**

5.3.4. Population Growth Rate

Population, as previously discussed, is regarded as a factor in the occurrence of wildfires, but their influence is not always clear. The presence of population can function as a trigger to wildfires, either by neglective behavior, or with criminal intent, but at the same time, having population near or at susceptible areas can also help deterring wildfires, either by early detection and suppression, by working the land and thus making it less wildfire prone, or by stopping criminal behavior. It is not always clear how the presence of population influences a model output, and in all fairness, population, as an evidence layer, has been regarded with a certain negative bias in this thesis, effectively wondering whether it should be considered at all. Integrating it in the model should, therefore, help finding out, objectively, if it is relevant.

Population density has been previously tested, with the Census of 2001 and 2011, because it was considered safe to model with these Census, crossing that data with the land cover evidence layer which is CORINE Land Cover 2006. It has been seen that population density shows interesting results, but the Census data of 1991 is also available, and using either one of these layers alone could raise some questions as to whether that is the most correct decision, or gives the most interesting results. In this section it has been decided to use the Census of 1991, just not as population density but for computing the population growth rate between 1991 and 2011. As such, the evidence layer in the model will be representing territories that lost or gained population, and the results shall show how that helps in predicting wildfires. The population growth rate follows equation [5.7] where PGR is the population growth rate, and $Pop(n)$ is the population in the year specified.

$$PGR = \left(\frac{Pop(2011) - Pop(1991)}{Pop(1991)}\right) \times 100 \qquad [5.7]$$

All calculations around population (either density or growth ratio) were based on Census data, collected at a sub-parish level named *BGRI – Base Geográfica de Referenciação da Informação*, which had to be rasterized. This BGRI level of information is very fine grained and constitutes the finer degree of data disaggregation available.

In table 5.17, positive weights and favourability scores are presented for the four defined classes. This model run joins CORINE Land Cover 2006, Slope, Elevation and Population Growth Rate.

Table 5.17 – Positive Weights of Evidence (W^+) score for Population Growth Rate (1991-2011) layer, with burnt pixel set of 1975 to 1994 in mainland Portugal.

Growth Rate	Pixels		W+ Score	Favourability Score
	Available	Burnt		
-100 - -50%	8,941,808	1,113,732	-188	12
-49 - 0%	3,886,881	804,139	419	21
1 - 50%	381,566	45,202	-245	12
> 50%	689,498	72,985	-371	11
Total	**13,899,753**	**2,037,052**		

Figures 5.21 and 5.22 present positive weights and favourability scores plotted against each class' frequency.

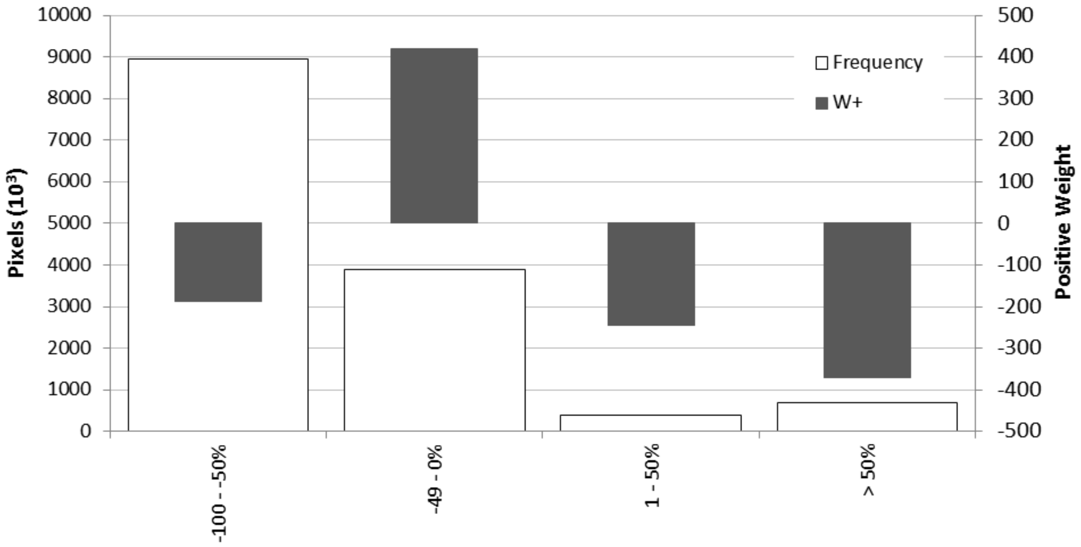


Figure 5.21 –Frequency and W+ for Population Growth Ratio (1991-2011) layer with burnt pixel set of 1975 to 1994 in mainland Portugal

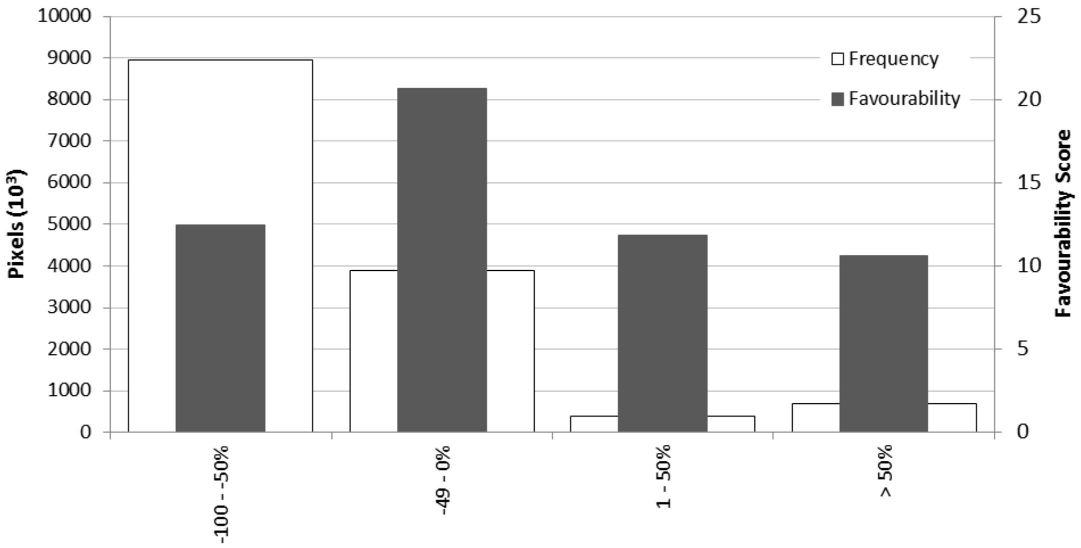


Figure 5.22 –Frequency and Favourability score for Population Growth Ratio (1991-2011) layer with burnt pixel set of 1975 to 1994 in mainland Portugal

Differences in the first method's favourability scores is a bit less expressive than with Weights of Evidence's positive weights. Whereas with favourability scores there is little difference in all classes except the class of -49% to 0%, with positive weights the difference among classes is wider. Most of the country has lost more than half of its population between 1991 and 2011, but those areas are not the most wildfire prone. Possibly because there is no one there to start a fire. The best conditions for an ignition, considering positive weights and the favourability scores, are found in areas that either stayed unchanged or lost up to half of their population, which does not help in clarifying exactly how population plays a role, if starting more fires or helping suppressing them.

Success and prediction curves can be observed on figure 5.23. There is no noticeable difference when considering the curves for other evidence layers, and, as usual, the reference CSP curves are better. Tables 5.18 and 5.19 present success and prediction rates.

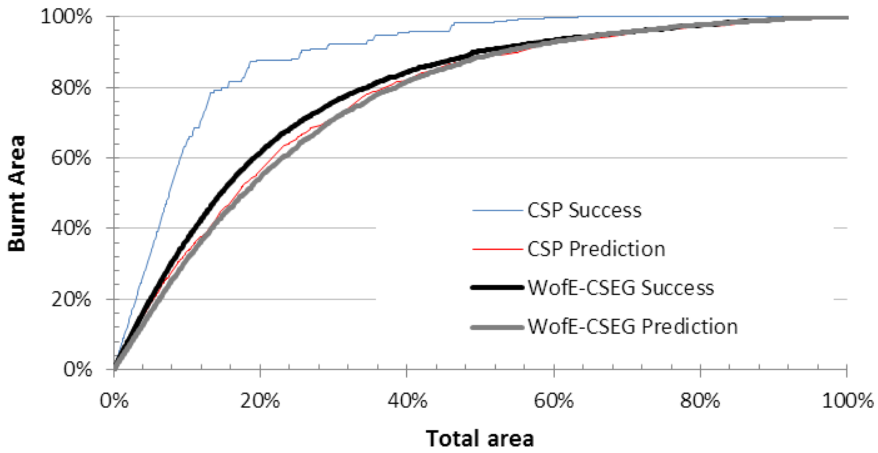


Figure 5.23 – Success and Prediction curves for the reference model CSP and Weights of Evidence WofE-CSEG with burnt pixel set of 1975 to 1994 in mainland Portugal

Table 5.18 – Compared Success rates for models "CSP" and "WofE-CSEG" with burnt pixel set of 1975 to 1994 in mainland Portugal. Higher values in bold. (%)

	10%	20%	30%	40%	50%	60%	70%	80%	90%
CSP	**64.12**	**85.46**	**90.87**	**95.77**	**97.83**	**99.00**	**99.97**	**100**	**100**
WofE-CSEG	35.51	60.55	76.14	84.25	88.96	92.79	95.23	97.18	98.52

Table 5.19 – Compared Prediction rates for models "CSP" and "WofE-CSEG" with burnt pixel set of 1975 to 1994 in mainland Portugal. Higher values in bold. (%)

	10%	20%	30%	40%	50%	60%	70%	80%	90%
CSP	**33.21**	**56.29**	**71.23**	**82.06**	88.24	92.60	95.14	97.16	98.91
WofE-CSEG	31.42	54.42	70.95	81.54	**88.58**	**92.86**	**95.64**	**97.67**	**99.19**

The WofE-CSEG model has an overall worse success rate than the CSP curve, and only after 50% of the total susceptible area does it catch up with the CSP model and presents slightly better prediction rates.

The spatial representation for this evidence layer is presented on figure 5.24.

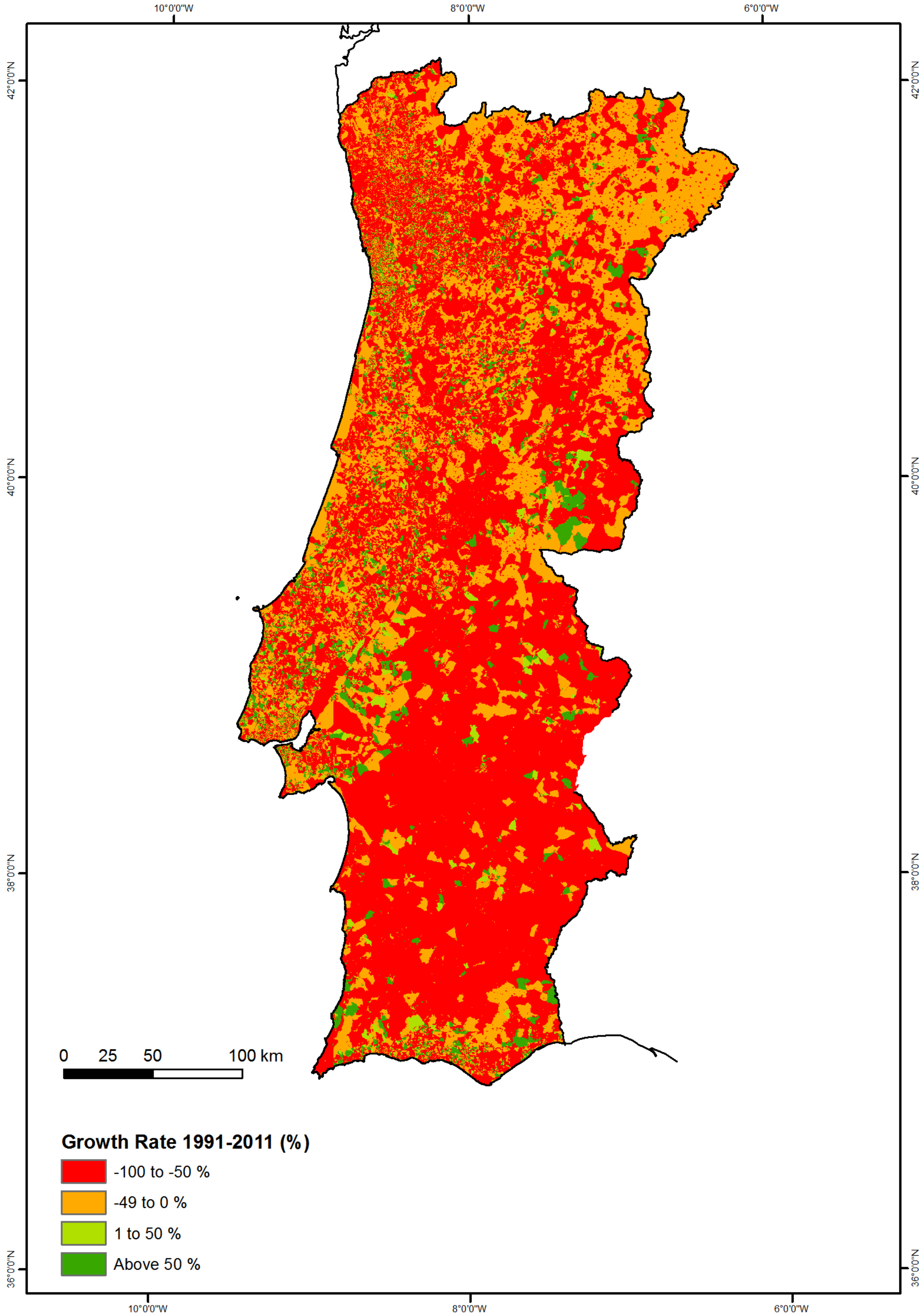


Figure 5.24 – Population Growth Rate 1991-2011 in mainland Portugal

5.3.5. Distance to Roads

Just as with population density, distance to roads is also a factor considered in studies following Chuvieco and Congalton (1989), given that distance to roads might play a role on wildfire ignition, as it provides access to fueled areas. Just as it provides access to fueled areas, it also provides access to suppression means and operatives, which makes this evidence layer somewhat ambivalent. Nonetheless, and given the pixel size used in this work, distance to roads has been integrated into the WofE models using three classes, as in table 5.20. The source for the road network was the national road plan of 2000, considering only major roads (highways, main itineraries and national roads, leaving out municipal and local roads which are extremely dense for this scale).

Table 5.20 – Positive Weights of Evidence (W^+) score for Distance to Roads layer, with burnt pixel set of 1975 to 1994 in mainland Portugal.

Distance	Pixels		W+ Score	Favourability Score
(meters)	Available	Burnt		
Up to 80	607,754	46,475	-728	8
81 to 160	566,324	48,103	-614	8
More than 160	12,744,934	1,942,474	48	15
Total	**13,919,012**	**2,037,052**		

It should not be a surprise that the higher pixel frequency belongs to those areas farther than 160 meters to roads, otherwise there would be an extremely dense network of those roads considered in this evidence layer. As figures 5.25 and 5.26 illustrate, those are the areas with the better positive weight and favourability, which is also easy to understand and allows to think that the presence of roads help more in the spotting and suppression of wildfires than with their ignition. There is little difference in the class of 0-80 meters and 81-160 meters, most likely as it is well within viewing and walking range, and in most situations there should not be a significant difference in what can happen inside these two buffer zones. While it is true that more classes could be defined, to further differentiate among classes, it was considered that the ambivalence of this evidence layer would not make it worthwile to invest in it. When wildfires occur, the most usual (if not always) complaint firefighters have is the lack of roads, therefore, the class of 160 meters and more should be adequate to test the model.

In figure 5.27 success and prediction curves are presented, not only for the reference CSP model but also for the new WofE-CSER model which integrates the distance to roads as shown on figure 5.28. Success and prediction rates are shown on tables 5.21 and 5.22.

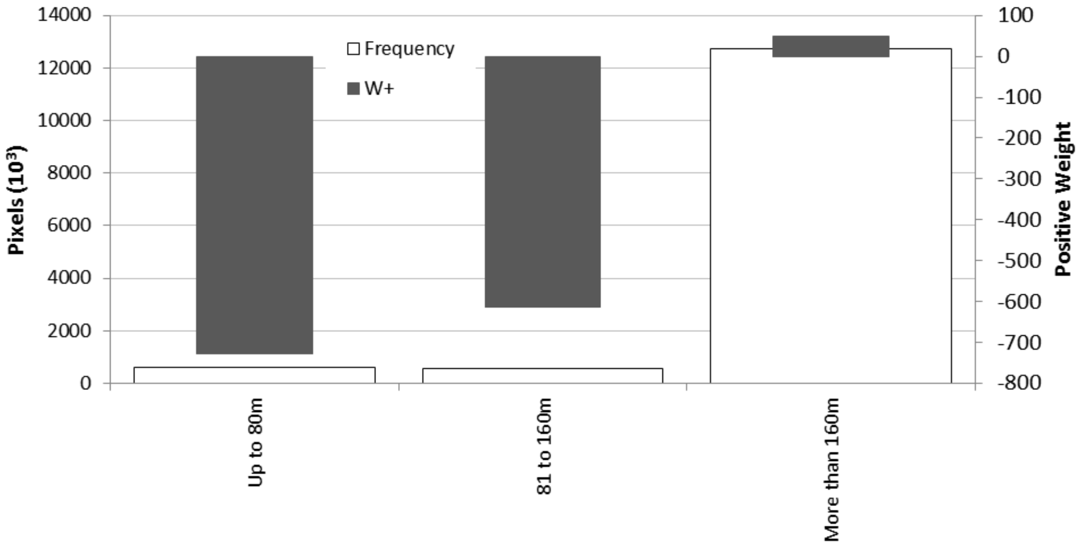


Figure 5.25 –Frequency and W+ for Distance to Roads layer with burnt pixel set of 1975 to 1994 in mainland Portugal

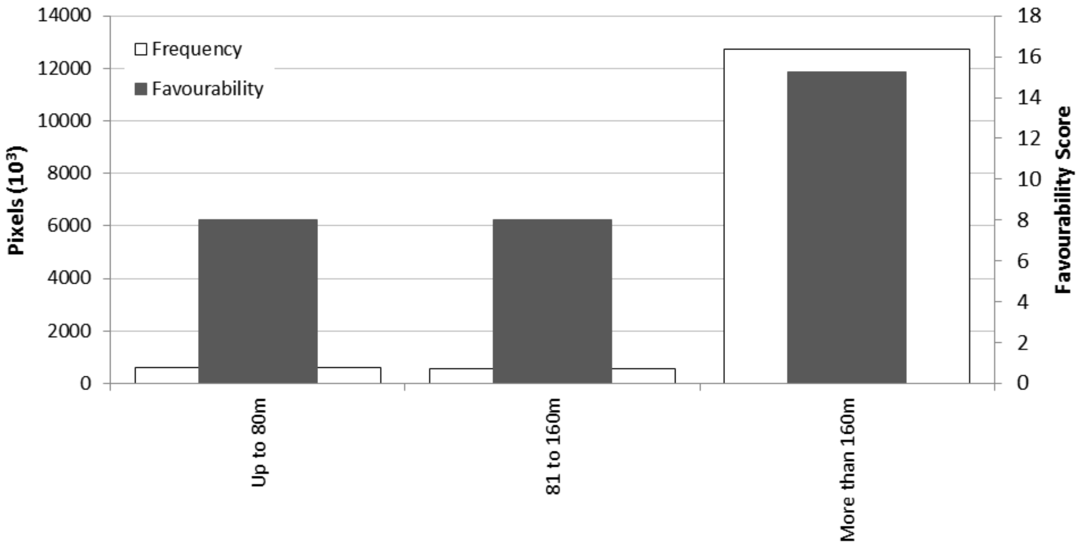


Figure 5.26 –Frequency and Favourability Score for Distance to Roads layer with burnt pixel set of 1975 to 1994 in mainland Portugal

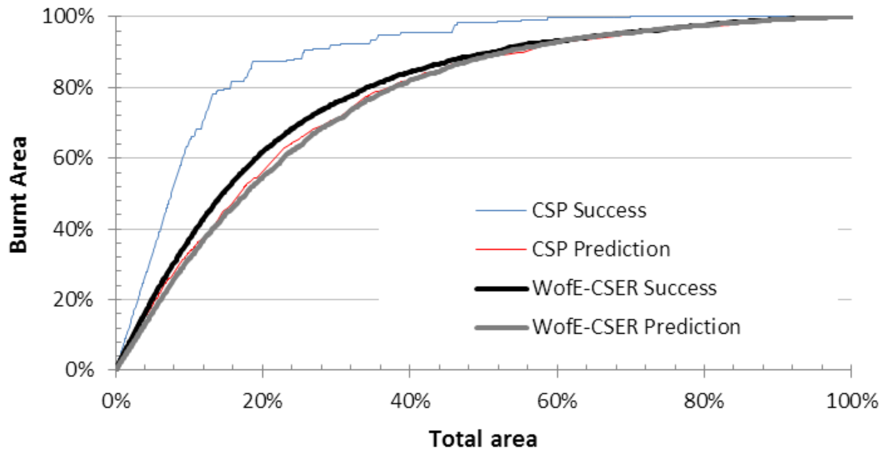


Figure 5.27 – Success and Prediction curves for the reference model CSP and Weights of Evidence WofE-CSER with burnt pixel set of 1975 to 1994 in mainland Portugal

Table 5.21 – Compared Success rates for models "CSP" and "WofE-CSER" with burnt pixel set of 1975 to 1994 in mainland Portugal. Higher values in bold. (%)

	10%	20%	30%	40%	50%	60%	70%	80%	90%
CSP	**64.12**	**85.46**	**90.87**	**95.77**	**97.83**	**99.00**	**99.97**	**100**	**100**
WofE-CSER	35.82	60.73	75.78	83.98	88.91	92.66	95.17	97.10	98.54

Table 5.22 – Compared Prediction rates for models "CSP" and "WofE-CSER" with burnt pixel set of 1975 to 1994 in mainland Portugal. Higher values in bold. (%)

	10%	20%	30%	40%	50%	60%	70%	80%	90%
CSP	**33.21**	**56.29**	**71.23**	**82.06**	88.24	92.60	95.14	97.16	98.91
WofE-CSER	31.63	54.63	70.91	82.01	**88.63**	**92.86**	**95.48**	**97.66**	**99.18**

As it has been the case in earlier model runs, adding the distance to roads evidence layer does not surpass the original CSP model in regards to success rates, which is to be expected given the nature of the CSP model with the double integration of historical data. As far as predicition goes, results for the WofE-CSER model are not very satisfactory, as only at 50% of total susceptible area does it go over the CSP model. Therefore, adding the distance to roads is not enough to reach the predictive capacity of CSP, but so it has been the case, so far, with all other WofE models whose predictive capacity only surpasses that of CSP around half the topmost susceptible area.

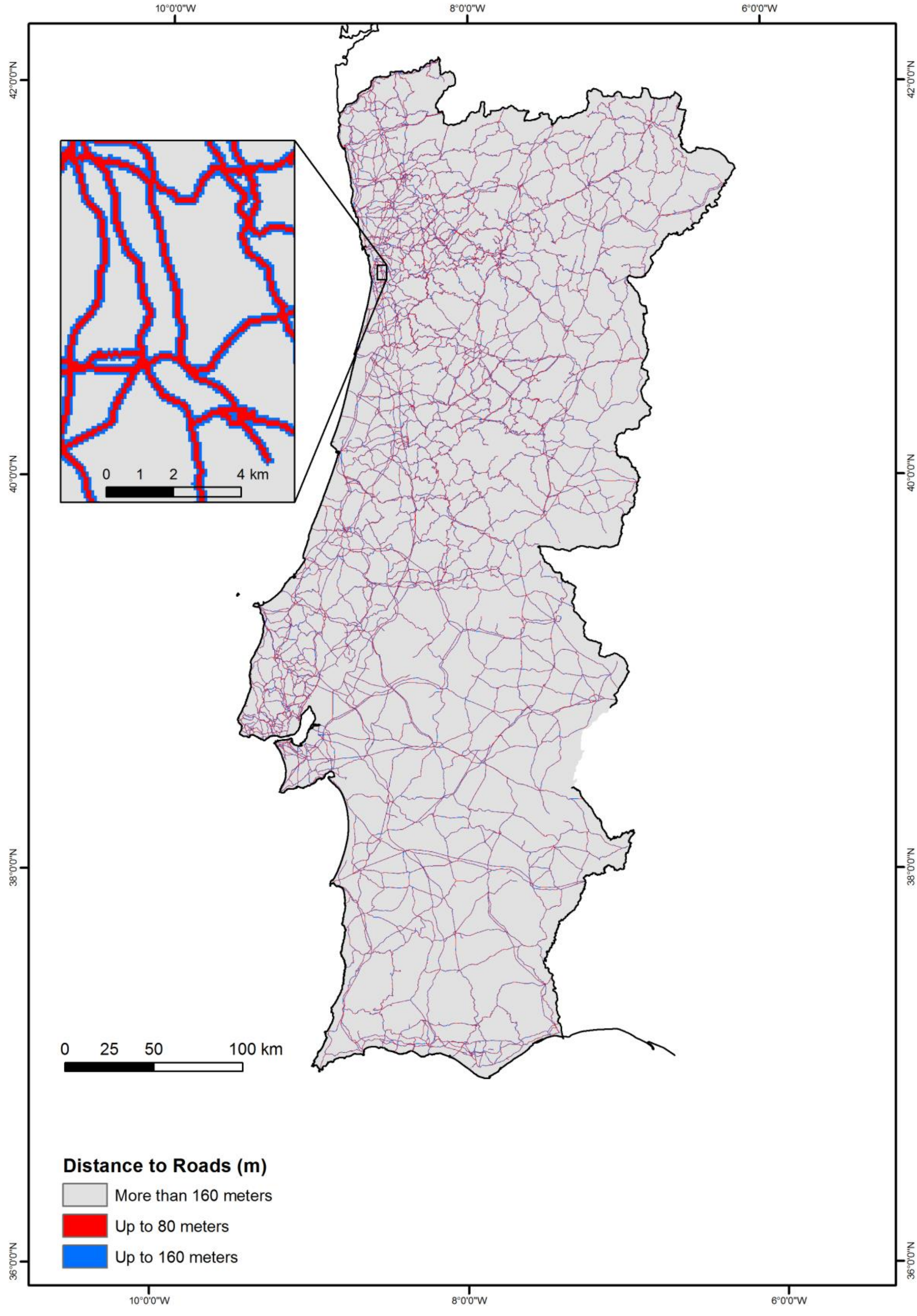


Figure 5.28 – Distance to Roads in mainland Portugal

5.3.6. Combining selected evidence layers

When the studies for this chapter began, there were several evidence layers to work with, namely, land cover, slope, elevation, aspect, population density (1991, 2001 and 2011, of which 1991 was not used due to the land cover being of 2006), distance to roads and, finally, the population growth ratio 1991-2011. The idea was to stack evidence layers, in a similar fashion as that of Verde (2008) and Verde and Zêzere (2010). Aspect was dropped since it seemed of little interest once results could be observed. Because population could be used in different manners, it was studied alone on top of land cover, slope and elevation, and to wrap the Weights of Evidence model runs with the available data, a final run was made with land cover, slope, elevation, distance to roads and population growth rate, designated as WofE-CSERG. There are other possible evidence layer combinations, e.g., aspect could be integrated, Census data could used differently, other data classification could be employed, but as it will be clear before this chapter closes, these efforts are resulting in gains under 1% in prediction, and it is therefore believed that model performance, with the most usual and available data, has hit a solid benchmark. In figure 5.29 the success and predicton curves for this last iteration are presented, along with the CSP curves.

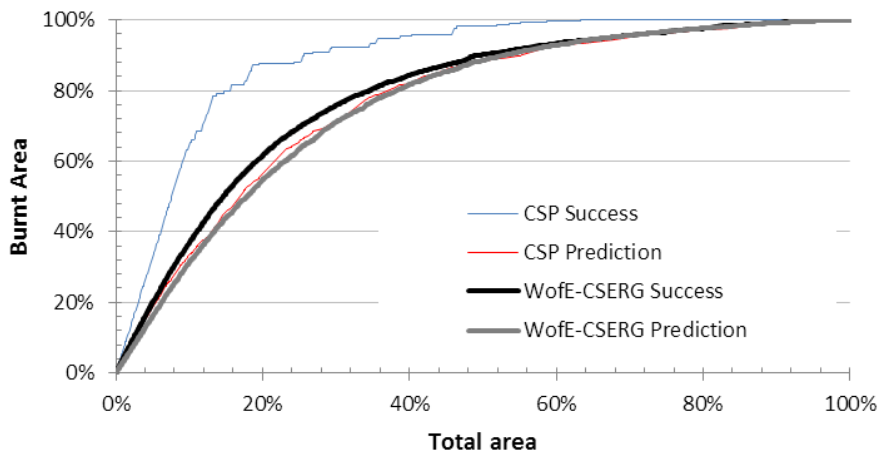


Figure 5.29 – Success and Prediction curves for the reference model CSP and Weights of Evidence WofE-CSERG with burnt pixel set of 1975 to 1994 in mainland Portugal

Tables 5.23 and 5.24 confirm what figure 5.29 shows. Success rates are always below CSP, and, as before, it takes about half the susceptible area to achieve higher prediction rates with this WofE iteration.

Table 5.23 – Compared Success rates for models “CSP” and “WofE-CSERG” with burnt pixel set of 1975 to 1994 in mainland Portugal. Higher values in bold. (%)

	10%	20%	30%	40%	50%	60%	70%	80%	90%
CSP	**64.12**	**85.46**	**90.87**	**95.77**	**97.83**	**99.00**	**99.97**	**100**	**100**
WofE-CSERG	36.83	61.56	75.88	84.38	90.19	93.39	95.65	97.60	99.22

Table 5.24 – Compared Prediction rates for models “CSP” and “WofE-CSERG” with burnt pixel set of 1975 to 1994 in mainland Portugal. Higher values in bold. (%)

	10%	20%	30%	40%	50%	60%	70%	80%	90%
CSP	**33.21**	**56.29**	**71.23**	**82.06**	88.24	92.60	95.14	97.16	98.91
WofE-CSERG	31.41	54.70	71.12	81.71	**88.53**	**92.79**	**95.66**	**97.67**	**99.17**

5.4 Closing thoughts on Weights of Evidence for Wildfire susceptibility assessment

The Weights of Evidence methodology is a solid approach to wildfire susceptibility assessment, allowing for an objective, statistically and bias free computation of further risk components as hazard and risk itself, but apart from a conceptual standpoint, numbers alone do not allow to recommend Weights of Evidence over a simpler methodology. As can be read on tables 5.25 and 5.26, WofE models usually behave worse than the simpler CSP model. That is always the case regarding success rates, which is to be expected since WofE models are lacking the double integration of historical data CSP has. Hence, CSP would always have a better degree of fit between the model results and the burnt areas that were put into it. Still, success rates are not as relevant as prediction rates. In developing such models, the goal is to predict as best as possible future burnt areas, and for that matter, WofE models do surpass CSP, just not where it is more important: in the most susceptible areas. CSP always predicts better in the first 20% of the most susceptible areas, and the first WofE model to catch up is the simpler WofE-CS model, at the 30% area mark.

Table 5.25 – Compared Success rates for models “CSP” and iterations of Weights of Evidence models, with burnt pixel set of 1975 to 1994 in mainland Portugal. Higher values in bold. When compared to the model immediately above: ▲ – higher rate, ▼ – lower rate, ▬ - no change. (%)

	10%	20%	30%	40%	50%	60%	70%	80%	90%
CSP	**64.12**	**85.46**	**90.87**	**95.77**	**97.83**	**99.00**	**99.97**	**100**	**100**
WofE-CS	35.24 ▼	59.29 ▼	74.53 ▼	84.15 ▼	89.00 ▼	92.40 ▼	94.90 ▼	97.71 ▼	98.94 ▼
WofE-CSE	36.86 ▲	61.78 ▲	75.81 ▲	84.37 ▲	89.50 ▲	93.19 ▲	95.67 ▲	97.62 ▼	99.19 ▲
WofE-CSEA	36.85 ▼	61.77 ▼	75.83 ▲	84.42 ▲	89.50 ▬	93.20 ▲	95.66 ▼	97.65 ▲	99.22 ▲
WofE-CSEP01	36.93 ▲	61.90 ▲	75.88 ▲	84.43 ▲	89.49 ▼	93.19 ▼	95.78 ▲	97.92 ▲	99.41 ▲
WofE-CSEP11	36.92 ▼	61.89 ▼	75.89 ▲	84.42 ▼	89.48 ▼	93.18 ▼	95.76 ▼	97.89 ▼	99.40 ▲
WofE-CSEG	35.51 ▼	60.55 ▼	76.14 ▲	84.25 ▼	88.96 ▼	92.79 ▼	95.23 ▼	97.18 ▼	98.52 ▼
WofE-CSER	35.82 ▲	60.73 ▲	75.78 ▼	83.98 ▼	88.91 ▼	92.66 ▼	95.17 ▼	97.10 ▼	98.54 ▲
WofE-CSERG	36.83 ▲	61.56 ▲	75.88 ▲	84.38 ▲	90.19 ▲	93.39 ▲	95.65 ▲	97.60 ▲	99.22 ▲

Table 5.26 – Compared Prediction rates for models “CSP” and iterations of Weights of Evidence models, with burnt pixel set of 1975 to 1994 in mainland Portugal. Higher values in bold. When compared to the model immediately above: ▲ – higher rate, ▼ – lower rate, ▬ - no change. (%)

	10%	20%	30%	40%	50%	60%	70%	80%	90%
CSP	**33.21**	**56.29**	71.23	**82.06**	88.24	92.60	95.14	97.16	98.91
WofE-CS	32.06 ▼	55.90 ▼	**71.34** ▲	81.62 ▼	87.52 ▼	92.16 ▼	94.86 ▼	97.02 ▼	98.87 ▼
WofE-CSE	31.68 ▼	54.67 ▼	70.79 ▼	81.70 ▲	88.50 ▲	92.73 ▲	95.55 ▲	97.65 ▲	99.21 ▲
WofE-CSEA	31.53 ▼	54.58 ▼	70.82 ▲	81.84 ▲	88.53 ▲	92.75 ▲	95.53 ▼	97.61 ▼	99.17 ▼
WofE-CSEP01	31.68 ▲	54.54 ▼	70.69 ▼	81.95 ▲	**88.63** ▲	**92.89** ▲	95.47 ▼	**97.73** ▲	**99.25** ▲
WofE-CSEP11	31.69 ▲	54.57 ▲	70.75 ▲	81.97 ▲	**88.63** ▬	92.86 ▼	95.46 ▼	97.72 ▼	**99.25** ▬
WofE-CSEG	31.42 ▼	54.42 ▼	70.95 ▲	81.54 ▼	88.58 ▼	92.86 ▬	95.64 ▲	97.67 ▼	99.19 ▼
WofE-CSER	31.63 ▲	54.63 ▲	70.91 ▼	82.01 ▲	**88.63** ▲	92.86 ▬	95.48 ▼	97.66 ▼	99.18 ▼
WofE-CSERG	31.41 ▼	54.70 ▲	71.12 ▲	81.71 ▼	88.53 ▼	92.79 ▼	**95.66** ▲	97.67 ▲	99.17 ▼

Looking at success and prediction rates over the susceptible areas is not the most accurate method of determining the best model. Areas under the curve (AUC) provide a much more precise measure of how models behave. Table 5.27 shows AUCs for success and prediction curves of all models run in this chapter. It can be seen that CSP is the best model of all nine, either success or prediction-wise. The reason is easily understood: the most probable reason for WofE models not achieving as high a result as CSP is because WofE lacks the double historical data entry. Figure 5.30 presents wildfire susceptibility for the best WofE model in regards to prediction, the WofE-CSER.

Table 5.27 – Areas under the curve for models "CSP" and iterations of Weights of Evidence models with burnt pixel set of 1975 to 1994 in mainland Portugal. Higher values in bold. When compared to the model immediately above: ▲ – higher rate, ▼ – lower rate, ▬ - no change. (%)

	Success	Prediction
CSP	**88.93**	**76.94**
WofE-CS	▼ 77.91 ▼	▼ 76.21 ▼
WofE-CSE	▲ 78.77 ▲	▲ 76.52 ▲
WofE-CSEA	▬ 78.77 ▬	▼ 76.51 ▼
WofE-CSEP01	▲ 78.88 ▲	▲ 76.54 ▲
WofE-CSEP11	▼ 78.86 ▼	▼ 76.53 ▼
WofE-CSEG	▼ 78.77 ▼	▼ 76.42 ▼
WofE-CSER	▲ 78.80 ▲	▲ 76.56 ▲
WofE-CSERG	▬ 78.80 ▬	▼ 76.46 ▼

Just as in Verde (2008) and Verde and Zêzere (2010), it became apparent that adding more information to a model does not necessarily mean that it will be better in comparison with other models of scarcer data. Adding elevation (E) to WofE models does increase success and prediction, but Aspect (A) does nothing for success and decreases prediction, for which it was abandoned. The distance to roads (R) does not help with success but offers an increase in prediction, which was considered relevant. Population data (P01, P11) gave somewhat mixed and inconsistent results, and it was considered safer to integrate population data in the model as a growth ratio (G) between two Census, rather than using a "snapshot". Finally, combining the most relevant evidence layers (last row in table 5.27, model WofE-CSERG) did not provide a model with the highest results when compared to some previous runs with less evidence layers, e.g. WofE-CSEP01 which has, among WofE models, an overall better behavior.

Choosing between WofE models and non-WofE models, in the context of this thesis, could be, therefore, a conceptual or philosophical issue, depending on wether the end-user or researcher considers acceptable to use historical data twice in a model. If that does not raise any issues, the CSP model is simpler to compute and does provide very interesting results. If using historical data twice is absolutely rejected or if a researcher looks for the comfort of a very solid, studied and unbiased methodology, then the WofE models also give very good results. All in all, it should be noted that these models differ in around one percent, as to prediction rates: most likely not a difference diserving that much of a practical discussion.

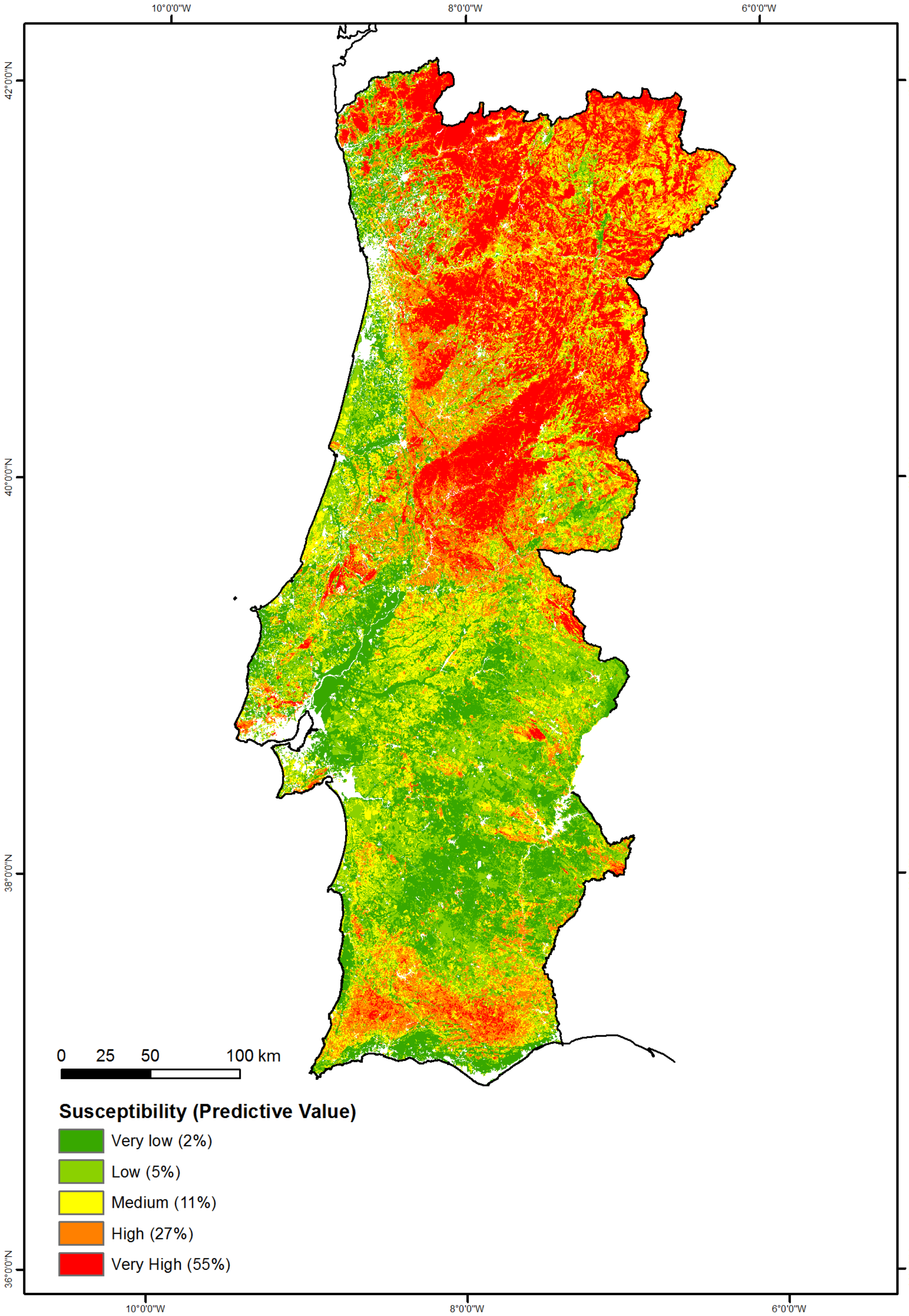


Figure 5.30 – Wildfire Susceptibility map for the WofE-CSER model in mainland Portugal

Chapter 6. On the subject of model stability

When our studies on widfires in Portugal began, the historical data interval available to the general public was that of 1990 to 2004. Burnt areas prior to 1990 (starting in 1975) were kindly made available for this study by “Instituto de Investigação Científica Tropical”. Since then, as each year passes, new burnt areas have been added to the official catalog of burnt areas, currently maintained by the Institute for Conservation of Nature and Forests (ICNF). In this thesis, burnt areas of 1975 to 1994 have been used to model, and as the series grew and a limit had to be set, the interval 1995 to 2013 has been used for independent validation and all models were revisited and updated for direct comparison. Each year the dataset grows, and regardless of the methodology one chooses, one question does rise: when is enough, enough? Is there a point in modelling with all available data or is it sufficient to work with twenty or thirty-year moving blocks? In this chapter, an attempt is made at understanding what could be considered a minimum interval for achieving satisfactory results in regards to predictive capacity. Through an iteration of model runs, successively adding modelling years and subtracting independent validation years (figure 6.1), model’s behavior will be studied. In this chapter, the historical data interval is 1975-2013, but iterations stop at 2012, so that burnt areas of 2013, alone, can be used for a minimum independent validation. It is a 39 year interval of burnt area mapping, which should allow for drawing some conclusions.

Figure 6.1 – Modelling and Validation set illustration. As the modelling set increases yearly, the validation set is equally subtracted

In the previous chapter, a series of Weights of Evidence models were run to verify if they could match the results from the reference CSP model, and how adding more evidence layers would impact model results, just as it was done in Verde (2008) and Verde and Zêzere (2010). In this chapter, when iterating model runs, the CSP model is run alongside WofE models. Models are run according to the methods described earlier, hence, for the sake of brevity, they shall not be described again in this chapter. It should be noted, however, that in this chapter success curves and rates will not be a matter of discussion. Analysis will focus on prediction curves and rates, as having already established that success rates demonstrate a good degree of fit on these models, attention lies on how models are able to predict future wildfires.

One additional change is made on this chapter. Whereas in previous chapters the curves were of burnt areas versus total susceptible area, which indeed allows the reader to say that “up to *a*% of the territory, *b*% of the burnt area has already been fitted”, the curves presented hereafter are *receiver (or relative) operating characteristics* curves, or ROC for short, which cannot be read like before, but, instead, in separating positives and negatives, provide, themselves, a reading of probability via their areas under the curve, making it a much more direct visualization of the models predictive capacity. When using ROC graphics, instance results are being plotted against a set of outcomes. As Fawcett (2006, p.862) states, «given a classifier and an instance, there are four possible outcomes. If the instance is positive and it is classified as positive, it is counted as a true positive; if it is classified as negative, it is counted as a false negative. If the instance is negative and it is classified as negative, it is counted as a true negative; if it is classified as positive, it is counted as a false positive». Transposing this rationale to wildfires, the positives and negatives are burnt and not burnt, as in the figure below (figure 6.2). In this particular case, an *instance* as per Fawcett's citation above, is a unique condition and the outcome is if it has burnt pixels or not.

		What happened?	
		Burnt	Not Burnt
What is predicted?	Will Burn	True Positives	False Positives
	Will Not Burn	False Negatives	True Negatives

Figure 6.2 – Confusion matrix for ROC applied to wildfires

Using curves as in chapters 4 and 5 was needed for knowing how much susceptible territory would be needed to achieve good results in predicting future wildfires. In fact, should one paint a map fully in red, the map will always be right, and wildfires will always intersect a class of maximum susceptibility, but those earlier curves allowed the reader to understand at what point, or how much territory was needed for, e.g., be able to predict 50% of the future burnt areas. The less area is needed for predicting a higher number of affected future pixels, the better the map is. But that is not the focus in this chapter. The focus is now on understanding how predictive capacity is affected when the number of modelled years of historical data is increased, how it fluctuates, if there is an optimum point or if there are disturbances or noise that could affect model's predictive behavior. ROC curves are extremely convenient for that purpose and more adequate than the curves used before, and transforming ROC curves into single scalar values, such as an area under the curve (AUC) allows for comparison of model performance.

6.1 Prediction from 1975 to 2012

In figure 6.3, areas under the curve for the prediction ROC curves are presented, and even though the figure is not easy to read, it can nonetheless be easily seen that the CSP model has, for a major part, the best ROC AUC of all models. The WofE models are very close together. Figure 6.3 is a far more comprehensive way of plotting ROC data, given that the alternative would be to reproduce 342 individual ROC graphics. Table 6.1 clarifies the data from the figure and allows for a better discussion.

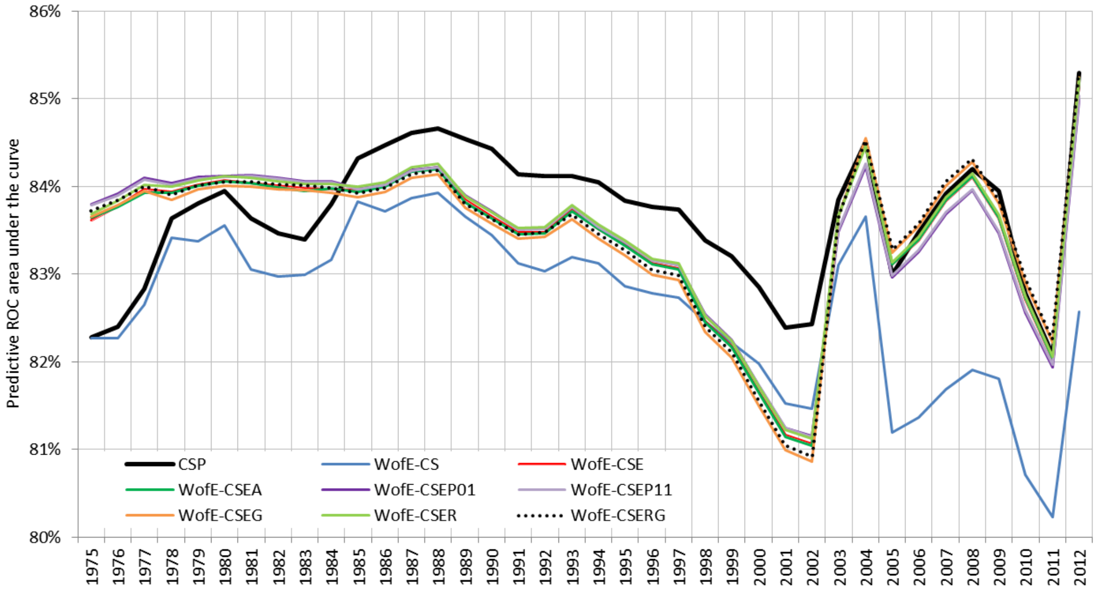


Figure 6.3 – Predictive ROC Areas Under the Curve for models run for mainland Portugal

The WofE models take the lead on the first iterations, when historical data is scarcer. It is possible that due to the nature of the models, the WofE models behave better than CSP when there is little historical data. CSP, on the other hand, takes full advantage of historical data, just as it uses it in two ways, and therefore shows better results as the modelling set gets larger. Actually, CSP is always the best model for prediction from 1975-1986 through 1975-2003. The WofE model WofE-CSEP01 has the best results until the modelling interval of 1975 to 1985, which is interesting as the population data is of the 2001 Census. Looking at WofE models alone, disregarding the CSP model, the WofE-CSEP01 is, most times, the best model, but it shares first place with, mostly, WofE-CSER and WofE-CSERG, being that the later takes the lead as the validation series shortens, as table 6.1 shows. In spite of some oscillations, ROC AUCs are somewhat stable, for most WofE models until 1988 (exceptions are the WofE-CS and the non-WofE CSP), after which the models start to degrade their predictive performance until 2002. In 2003 the burnt area is so significant (over 400 thousand hectares) that it impacts models in a significant way (WofE-CS is far less capable although it follows the trend).

Table 6.1 – Areas under the curve for receiver operating characteristic curves for prediction on the CSP and WofE models, for modelling sets from 1975-1975 to 1975-2012 in mainland Portugal. Higher values in bold. When compared with the best rate for the previous year, ▲ – the current year rises rate, ▼ - the current year lowers rate, = no change (%)

Model of 1975 to:	CSP	WofE							
		CS	CSE	CSEA	CSEP01	CSEP11	CSEG	CSER	CSERG
1975	82.28	82.26	83.62	83.64	**83.80**	83.78	83.66	83.68	83.72
1976 ▲	82.40	82.27	83.77	83.76	**83.92**	83.90	83.79	83.83	83.84
1977 ▲	82.84	82.65	83.96	83.93	**84.10**	84.08	83.95	84.01	84.00
1978 ▼	83.64	83.42	83.94	83.93	**84.03**	84.02	83.85	83.99	83.90
1979 ▲	83.80	83.37	84.02	84.00	**84.11**	84.09	83.96	84.07	84.02
1980 ▲	83.94	83.56	84.06	84.06	**84.12**	84.10	84.00	**84.12**	84.05
1981 ▲	83.63	83.06	84.04	84.04	**84.13**	84.11	84.00	84.09	84.05
1982 ▼	83.47	82.97	84.01	83.99	**84.10**	84.08	83.97	84.06	84.02
1983 ▼	83.39	82.99	83.97	83.95	**84.06**	84.05	83.95	84.03	84.01
1984 =	83.79	83.16	83.97	83.97	**84.06**	84.05	83.93	84.03	83.98
1985 ▼	84.31	83.83	83.96	83.94	**83.97**	**83.97**	83.88	84.00	83.92
1986 ▲	**84.47**	83.72	84.00	84.00	84.02	84.01	83.94	84.05	83.98
1987 ▲	**84.61**	83.86	84.17	84.16	84.19	84.18	84.10	84.22	84.14
1988 ▲	**84.66**	83.92	84.22	84.20	84.22	84.21	84.14	84.26	84.18
1989 ▼	**84.54**	83.66	83.84	83.82	83.90	83.88	83.75	83.89	83.80
1990 ▼	**84.43**	83.45	83.65	83.63	83.72	83.71	83.58	83.70	83.63
1991 ▼	**84.13**	83.12	83.47	83.46	83.52	83.51	83.40	83.52	83.45
1992 ▼	**84.11**	83.03	83.47	83.47	83.53	83.52	83.42	83.53	83.48
1993 ▲	**84.12**	83.20	83.73	83.71	83.77	83.76	83.63	83.79	83.68
1994 ▼	**84.05**	83.12	83.52	83.51	83.54	83.54	83.40	83.57	83.46
1995 ▼	**83.84**	82.87	83.33	83.32	83.37	83.36	83.22	83.39	83.27
1996 ▼	**83.77**	82.78	83.12	83.11	83.16	83.15	82.99	83.18	83.05
1997 ▼	**83.73**	82.73	83.06	83.05	83.10	83.10	82.93	83.12	82.99
1998 ▼	**83.39**	82.46	82.46	82.45	82.54	82.53	82.34	82.52	82.40
1999 ▼	**83.20**	82.22	82.17	82.17	82.25	82.24	82.04	82.23	82.10
2000 ▼	**82.85**	81.98	81.65	81.65	81.73	81.72	81.50	81.71	81.55
2001 ▼	**82.39**	81.52	81.16	81.15	81.25	81.24	80.99	81.22	81.05
2002 ▲	**82.43**	81.46	81.06	81.04	81.15	81.15	80.86	81.12	80.92
2003 ▲	**83.85**	83.10	83.66	83.66	83.48	83.50	83.65	83.67	83.66
2004 ▲	84.51	83.66	84.49	84.48	84.23	84.26	**84.55**	84.46	84.52
2005 ▼	82.99	81.20	83.11	83.11	82.96	82.98	83.25	83.14	**83.27**
2006 ▲	83.48	81.36	83.39	83.39	83.25	83.27	83.55	83.43	**83.58**
2007 ▲	83.92	81.69	83.83	83.85	83.69	83.70	84.01	83.88	**84.05**
2008 ▲	84.20	81.91	84.10	84.12	83.95	83.97	84.28	84.15	**84.32**
2009 ▼	**83.95**	81.80	83.64	83.65	83.46	83.49	83.80	83.67	83.84
2010 ▼	82.79	80.71	82.71	82.73	82.56	82.59	82.90	82.75	**82.93**
2011 ▼	82.08	80.23	82.03	82.04	81.94	81.97	82.22	82.06	**82.25**
2012 ▲	**85.29**	82.57	85.18	85.20	84.99	85.03	85.24	85.23	**85.29**

6.2 Looking at model variability

In the previous section, figure 6.3 has shown how different models compare among themselves, but they all share a common feature: prediction plunges after 1997, has a spike in 2004, and only after 2005 starts to rise again only to fluctuate and close the series on a rise. Some sort of disturbance seems to have affected models' behavior in those years.

Susceptible area has been divided into *partitions*. Each partition has 10% of susceptible area, and *future* burnt pixels will be distributed among those 10 partitions (PRT), according to their *value* or *susceptibility score*, given that, by definition, the higher the value for a given unique condition, the higher the susceptibility and, hence, the higher number of burnt pixels it should contain. The partitions are as follows: PRT 1: [0%-10.00%[, PRT 2: [10.00-20.00%[, PRT 3: [20.00%-30.00%[, PRT 4: [30.00%-40.00%[; PRT 5: [40.00%-50.00%[, PRT 6: [50.00%-60.00%[, PRT 7: [60.00%-70.00%[, PRT 8: [70.00%-80.00%], PRT 9: [80.00%-90.00%[and PRT 10: [90.00%-100%] of susceptible area.

Table 6.2 and figure 6.4 pertain to the CSP model, and show that it is a fairly consistent model when it comes to allocate burnt pixels to what is considered to be the most susceptible partition. It does miss the objective in the three first iterations, as partition 3 gets more burnt pixels in iteration 1 and the same happens for partition 2 in iterations 2 and 3. That is most likely related to the scarcity and low representativeness in historical data, and from 1975-1978 up to 1975-2012, the first partition always fits more burnt pixels, which is the expected and intended model behavior. Given that the partitions are equally sized, it is interesting to see how many burnt pixels they hold as the iterations progress. Even with some fluctuations, the first partition holds more pixels as the years go by and the second partition loses pixels. There are two major breaks in the series, one break at 1985 and another in 2003, albeit opposite. When 1985 is added to the modelling block, the two first partitions combined lose burnt pixels, meaning that burnt areas spread into less susceptible areas and, hence, less susceptible partitions. On the contrary, when 2003 entered into the model, burnt pixels were pushed into the first two partitions, reaching almost 65% of all burnt pixels in the validation set and afterwards the tendency to enlarge the number of burnt pixels in partitions 1 and 2 is maintained.

Table 6.2 – Validation burnt pixels per 10% Partition, in percent of total, for the CSP model in mainland Portugal. Higher values in bold. (%)

Model 1975 to:	Partitions									
	PRT 1	PRT 2	PRT 3	PRT 4	PRT 5	PRT 6	PRT 7	PRT 8	PRT 9	PRT 10
1975	24.30	14.93	**24.87**	13.26	5.18	6.23	3.41	3.75	0.66	3.41
1976	23.41	**26.03**	12.17	14.64	7.81	4.91	2.25	4.19	2.04	2.54
1977	24.13	**28.04**	9.55	15.84	6.44	5.00	0.76	5.67	2.76	1.81
1978	**27.36**	25.32	11.66	12.54	8.77	4.58	1.99	3.36	2.69	1.73
1979	**28.47**	23.91	10.45	14.05	8.81	4.50	2.04	3.36	2.69	1.72
1980	**29.33**	23.56	10.04	15.07	7.83	4.66	1.96	3.19	2.67	1.69
1981	**29.55**	22.07	13.28	12.34	8.54	4.67	2.40	2.74	2.69	1.71
1982	**27.72**	24.23	13.08	13.00	7.75	2.81	3.76	3.23	2.99	1.43
1983	**28.82**	24.46	12.00	12.80	7.74	2.80	3.75	3.49	2.47	1.67
1984	**27.13**	26.46	12.29	12.63	7.55	4.39	2.16	2.35	3.64	1.41
1985	**29.29**	17.09	21.90	10.97	6.39	5.69	3.06	2.12	1.92	1.58
1986	**30.51**	17.10	19.69	12.32	6.24	5.44	3.18	2.08	1.90	1.54
1987	**30.25**	19.05	19.19	11.73	6.11	5.24	3.15	2.33	1.66	1.29
1988	**30.61**	18.96	19.12	11.72	6.06	5.32	2.44	2.84	1.65	1.28
1989	**31.10**	19.61	18.36	11.58	5.96	5.64	2.76	2.05	1.77	1.16
1990	**32.12**	20.11	18.02	10.46	5.93	5.76	2.62	2.06	1.77	1.17
1991	**32.73**	21.24	15.88	11.13	5.85	5.53	2.68	2.06	1.76	1.14
1992	**32.90**	21.50	15.32	11.46	5.76	5.63	2.52	2.06	1.74	1.13
1993	**33.10**	21.64	15.37	11.41	5.35	5.54	2.10	2.63	1.75	1.12
1994	**33.01**	22.21	15.53	10.94	5.59	5.29	2.54	2.04	1.74	1.12
1995	**33.74**	21.47	15.46	10.85	5.27	5.67	2.55	2.09	1.76	1.13
1996	**33.82**	21.80	15.33	10.66	5.08	5.85	2.48	2.07	1.76	1.14
1997	**33.56**	21.52	15.82	10.72	5.08	5.85	2.50	2.06	1.76	1.14
1998	**34.12**	21.47	15.57	10.50	5.31	5.55	2.26	2.29	1.78	1.16
1999	**34.38**	21.27	15.60	10.42	4.96	5.83	2.28	2.30	1.79	1.17
2000	**33.22**	21.68	16.31	10.21	5.50	5.55	2.25	2.28	1.81	1.19
2001	**33.18**	21.78	16.04	10.26	5.28	5.77	2.34	2.32	1.83	1.19
2002	**33.62**	21.97	14.19	11.86	5.27	5.60	2.50	1.37	2.42	1.19
2003	**39.75**	22.33	14.20	9.51	4.53	4.35	1.56	1.52	1.54	0.72
2004	**41.51**	23.45	13.77	8.45	4.17	3.68	1.48	1.32	1.52	0.64
2005	**41.44**	21.09	16.40	7.41	4.32	3.73	1.96	1.47	1.43	0.75
2006	**41.77**	22.29	15.57	7.53	4.13	3.66	1.93	1.32	1.11	0.68
2007	**42.78**	22.28	15.06	7.77	4.09	3.46	1.83	1.17	0.98	0.58
2008	**45.34**	21.51	13.39	7.66	3.95	4.04	1.57	1.13	0.88	0.55
2009	**45.11**	21.88	13.37	7.72	4.11	3.90	1.53	1.06	0.79	0.52
2010	**43.26**	21.88	13.99	8.47	4.37	3.84	1.68	1.14	0.83	0.54
2011	**41.11**	22.42	15.10	8.68	4.94	3.79	1.66	1.06	0.75	0.48
2012	**50.95**	22.31	11.51	6.00	3.56	2.50	1.51	0.93	0.53	0.19

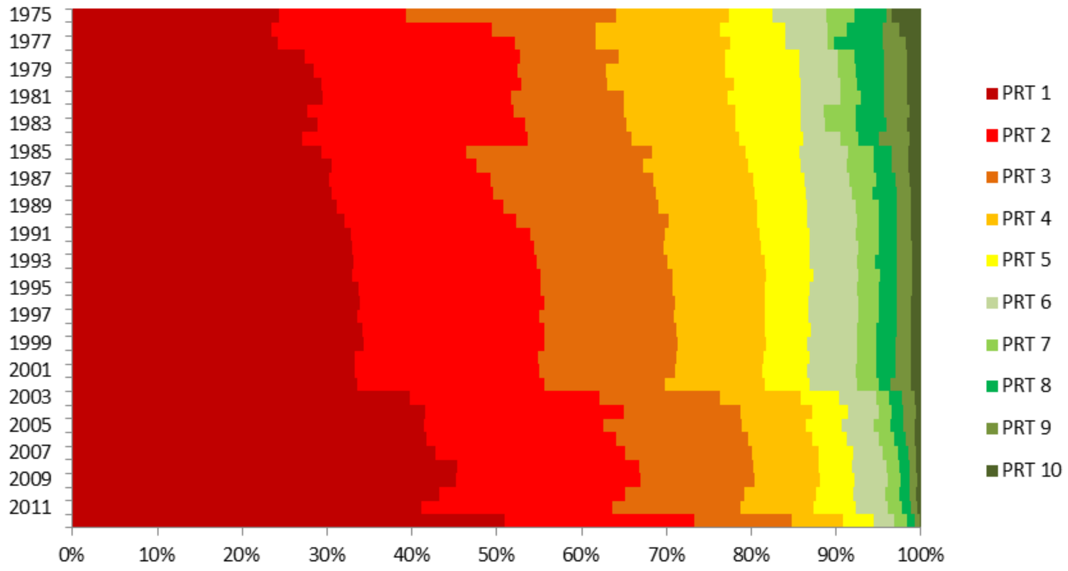


Figure 6.4 – Validation burnt pixels per 10% partition, in percent of total, for the CSP model in mainland Portugal

It has been seen how the CSP model is consistent in burnt pixel attribution to susceptible area partitions, and in table 6.3 and figure 6.5, the first Weights of Evidence model is put to the test. WofE-CS, the simpler WofE model in the series, struggles to keep the most burnt pixels in the most susceptible partition, and over the 38 years modelling set it rarely succeeds at doing so. For such a simple WofE model, of only two evidence layers, most of the burnt pixels land on the second most susceptible partition for most of the series, and only for a brief moment, 1981-1983 does it keep up. After 2003 the first partition takes the lead.

Comparing the partition from CSP with WofE-CS, partition 2 on WofE-CS is more consistent, and overall, adding partitions 1 and 2 are always around 50% of burnt pixels. Variations occur mostly on partition 3, but at that point more than half of the affected area has already been put on the 20% most susceptible territories. Just as with the previous model, after 2003 the first partition takes the lead and an increase in the first two partitions is noticeable. Again, the cumulative effect seems to play an important role in model behavior as to partition attribution of pixels, even if the mathematics behind the two models is different.

Table 6.3 – Validation burnt pixels per 10% Partition, in percent of total, for the WofE-CS model in mainland Portugal. Higher values in bold. (%)

Model 1975 to:	Partitions									
	PRT 1	PRT 2	PRT 3	PRT 4	PRT 5	PRT 6	PRT 7	PRT 8	PRT 9	PRT 10
1975	22.52	**27.78**	13.26	13.17	7.64	4.18	3.94	2.96	2.71	1.84
1976	21.30	**29.30**	10.73	14.91	7.82	4.73	1.73	4.66	2.33	2.49
1977	21.41	**28.88**	11.14	14.82	7.88	4.77	4.14	2.38	2.77	1.80
1978	22.80	**29.09**	16.15	8.25	9.13	4.78	1.95	3.42	2.71	1.72
1979	22.84	**29.07**	15.60	11.24	6.78	4.67	1.95	3.70	2.44	1.72
1980	22.90	**29.12**	9.22	17.61	6.72	4.60	3.21	2.20	2.70	1.71
1981	**29.34**	21.99	11.16	15.60	7.39	3.01	3.75	3.29	2.78	1.67
1982	**29.44**	22.01	11.07	15.55	7.41	2.98	3.76	3.59	2.51	1.68
1983	**29.53**	22.09	10.90	15.53	7.40	2.86	3.90	3.58	2.51	1.69
1984	23.09	**29.40**	10.29	15.46	7.41	4.47	2.27	3.52	2.67	1.43
1985	23.61	**29.70**	15.73	11.07	4.39	6.71	2.91	2.53	1.74	1.62
1986	23.81	**29.81**	9.20	17.31	4.52	6.68	2.83	2.51	1.74	1.59
1987	24.05	**29.98**	16.01	10.42	4.52	6.28	3.35	2.30	1.75	1.34
1988	24.29	**29.84**	16.04	10.53	4.67	6.11	3.20	2.25	1.74	1.33
1989	24.03	**30.18**	16.07	10.49	4.50	6.48	2.96	2.22	1.88	1.21
1990	24.15	**30.22**	16.00	10.30	4.58	6.62	2.75	2.29	1.88	1.21
1991	24.60	**29.96**	9.14	17.13	4.69	6.40	2.68	2.32	1.88	1.19
1992	24.75	**30.05**	10.42	15.70	4.65	6.38	2.68	2.32	1.87	1.19
1993	24.98	**30.23**	8.66	17.17	4.65	6.03	2.91	2.32	1.88	1.17
1994	24.97	**30.25**	9.07	16.84	4.75	5.96	2.81	2.30	1.87	1.17
1995	25.29	**30.25**	8.44	17.06	4.72	5.90	2.90	2.34	1.90	1.19
1996	25.23	**30.27**	8.83	16.72	4.70	5.92	2.90	2.33	1.91	1.20
1997	25.21	**30.26**	8.83	16.76	4.66	5.92	2.90	2.34	1.92	1.20
1998	25.23	**29.97**	16.05	9.65	4.77	6.14	2.75	2.27	1.94	1.22
1999	25.17	**29.92**	15.99	9.69	4.79	6.17	2.72	2.34	1.97	1.24
2000	24.95	**30.33**	15.81	9.60	4.84	6.17	2.10	2.92	2.00	1.26
2001	24.51	**30.14**	16.21	9.66	4.87	6.23	2.14	2.96	2.03	1.26
2002	24.79	**30.85**	15.46	9.67	4.93	6.14	2.01	2.89	2.00	1.26
2003	**30.71**	30.64	15.48	7.15	5.63	4.29	2.05	2.01	1.25	0.79
2004	**39.66**	24.08	14.75	6.62	5.17	3.92	2.02	1.85	1.22	0.71
2005	**37.38**	24.52	14.05	7.20	5.34	5.20	1.89	2.20	1.40	0.82
2006	**33.42**	28.59	14.29	7.27	5.38	5.24	1.90	1.98	1.17	0.76
2007	**33.77**	28.97	14.29	7.20	5.33	5.10	1.81	1.81	1.06	0.66
2008	**34.06**	29.11	14.28	7.15	5.30	5.04	1.78	1.73	0.94	0.62
2009	**34.14**	28.96	14.33	7.49	5.34	4.92	1.80	1.58	0.86	0.59
2010	**32.28**	29.05	14.87	7.92	5.76	5.10	1.78	1.73	0.90	0.61
2011	**31.18**	28.71	15.95	8.59	5.79	5.02	1.79	1.59	0.84	0.53
2012	**37.91**	29.68	13.61	6.28	4.70	3.85	1.53	1.46	0.74	0.24

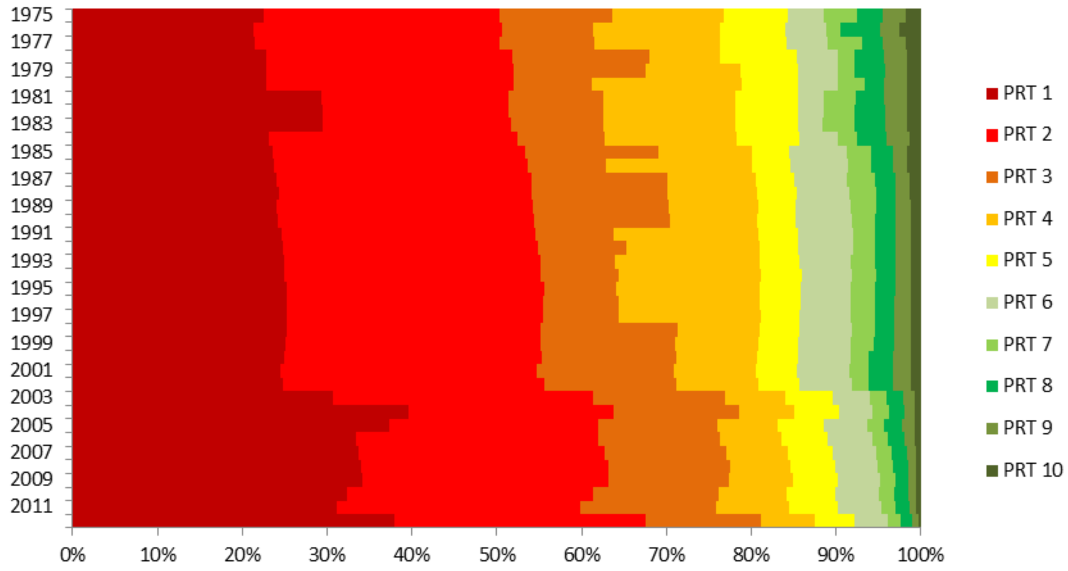


Figure 6.5 – Validation burnt pixels per 10% partition, in percent of total, for the WofE-CS model in mainland Portugal

WofE model behavior does change when an additional evidence layer (elevation) is added. Whereas in the previous model, WofE-CS, there was no consistency in getting the most burnt pixels inside partition 1, with WofE-CSE, partition 1 is always the most populated partition (Table 6.4, Figure 6.6).

WofE-CSE is very consistent along the series, and figure 6.5 shows how there is little variation in the stack of partition 1 from 1975 to 2002, even though in the later years of this interval a decrease is noticeable, probably hinting the role of the year 2003 as previously observed.

The year 2003, once more, marks a turn in the model's behavior, and partition 1 vastly, and consistently, increases in the number of *future* burnt pixels it holds. The year 2012 also changes model behavior, as the first two partitions, combined, leap over 70% of all burnt pixels.

The next models in the WofE series do not justify an independent analysis, even though they show slight differences and variations. The models WofE-CSEA (table 6.5, figure 6.7), WofE-CSER (table 6.6, figure 6.8), WofE-CSEP01 (table 6.7, figure 6.9), WofE-CSEP11 (table 6.8, figure 6.10), WofE-CSEG (table 6.9, figure 6.11) and WofE-CSERG (table 6.10, figure 6.12) all have some common features: (i) partition 1 is always the partition with the most burnt pixels, and (ii) they all show how 2003 impacts the models. As evidence layers are added, consistency improves, and there is little variation along the data series up until 2003. With the maximum number of years considered in this exercise (38 years for modelling), the WofE models (exception made to the WofE-CS) are able to fit around half of the burnt pixels in just 10% of the territory classified as most susceptible. These models, apart from what has been observed regarding 2003, also show that something happens to predictive power when 2012 is added to the modelling set, but since, at that point, only one year is left to perform an independent validation, it remains to be seen if the effect of 2012 on model's behavior is the same as for 2003; waiting for more years is a requirement for validating.

Table 6.4 – Validation burnt pixels per 10% partition, in percent of total, for the WofE-CSE model in mainland Portugal. Higher values in bold. (%)

Model 1975 to:	Partitions PRT 1	PRT 2	PRT 3	PRT 4	PRT 5	PRT 6	PRT 7	PRT 8	PRT 9	PRT 10
1975	**27.95**	23.47	16.53	10.36	7.23	4.38	4.04	2.50	1.78	1.76
1976	**28.32**	23.32	16.80	10.48	6.66	4.89	3.24	2.54	2.66	1.10
1977	**28.68**	22.93	16.82	10.50	6.60	5.14	3.04	2.72	2.49	1.09
1978	**29.03**	22.71	16.24	11.24	6.87	4.95	3.24	2.20	2.27	1.27
1979	**28.08**	24.08	15.89	10.89	7.29	4.93	3.13	2.24	2.27	1.21
1980	**29.02**	23.15	16.25	10.84	7.32	4.71	3.14	1.94	2.52	1.10
1981	**29.04**	22.81	16.86	10.82	6.56	5.02	3.22	2.28	2.32	1.08
1982	**29.16**	23.52	16.10	10.70	6.96	4.64	3.18	2.26	2.40	1.07
1983	**29.08**	23.65	16.02	10.70	6.91	4.71	3.21	2.23	2.43	1.05
1984	**29.47**	23.13	16.32	10.87	6.86	4.63	3.08	2.23	2.42	1.00
1985	**29.88**	23.16	16.19	10.92	6.82	4.57	3.41	2.24	1.78	1.04
1986	**30.39**	22.72	16.34	11.00	7.11	3.93	3.59	2.23	1.67	1.01
1987	**30.61**	23.40	16.03	10.71	6.82	4.62	3.10	2.11	1.63	0.97
1988	**30.82**	23.36	15.99	10.72	6.82	4.89	2.77	2.09	1.59	0.96
1989	**30.73**	22.93	16.19	10.99	6.78	4.96	2.78	1.89	1.77	0.97
1990	**30.72**	22.98	16.18	10.97	7.01	4.60	2.88	1.95	1.78	0.93
1991	**31.17**	22.92	15.94	11.01	6.88	4.62	2.84	2.11	1.67	0.83
1992	**31.38**	23.00	15.80	11.06	6.75	4.46	2.97	2.10	1.66	0.82
1993	**31.58**	23.11	16.05	10.86	6.87	4.25	2.75	2.10	1.54	0.89
1994	**31.63**	22.95	16.11	10.92	6.87	4.21	2.80	2.14	1.58	0.80
1995	**31.76**	23.08	15.83	10.93	6.76	4.20	2.80	2.19	1.61	0.82
1996	**31.59**	23.01	15.97	10.96	6.83	4.22	2.79	2.16	1.65	0.81
1997	**31.64**	22.91	15.99	10.96	6.84	4.23	2.79	2.06	1.76	0.81
1998	**31.27**	22.80	16.11	10.88	6.97	4.24	3.14	2.09	1.61	0.90
1999	**31.86**	21.98	16.13	10.90	7.02	4.31	3.14	2.17	1.67	0.83
2000	**31.18**	21.91	16.39	11.10	7.19	4.34	3.32	2.15	1.59	0.83
2001	**30.59**	22.05	16.47	11.28	7.27	4.51	3.23	2.16	1.61	0.82
2002	**31.15**	21.83	16.41	10.66	7.75	4.66	2.92	2.30	1.53	0.79
2003	**37.57**	23.14	16.40	9.19	5.40	3.34	1.76	1.65	1.02	0.54
2004	**39.56**	23.72	16.01	8.26	5.04	2.79	1.78	1.51	0.86	0.46
2005	**40.98**	23.77	14.20	8.40	4.48	2.97	1.99	1.76	0.96	0.49
2006	**41.10**	24.58	13.95	8.08	4.73	2.91	1.84	1.50	0.86	0.46
2007	**41.86**	24.81	13.51	8.39	4.55	2.71	1.68	1.41	0.67	0.41
2008	**42.25**	24.88	13.82	8.10	4.58	2.52	1.59	1.29	0.60	0.37
2009	**41.71**	24.64	14.34	8.35	4.58	2.59	1.64	1.25	0.56	0.35
2010	**40.12**	24.60	15.40	8.63	4.87	2.79	1.69	0.98	0.54	0.40
2011	**37.65**	25.47	16.78	8.99	4.92	2.81	1.62	0.90	0.50	0.36
2012	**45.88**	26.54	13.58	6.85	3.64	1.60	1.06	0.61	0.18	0.06

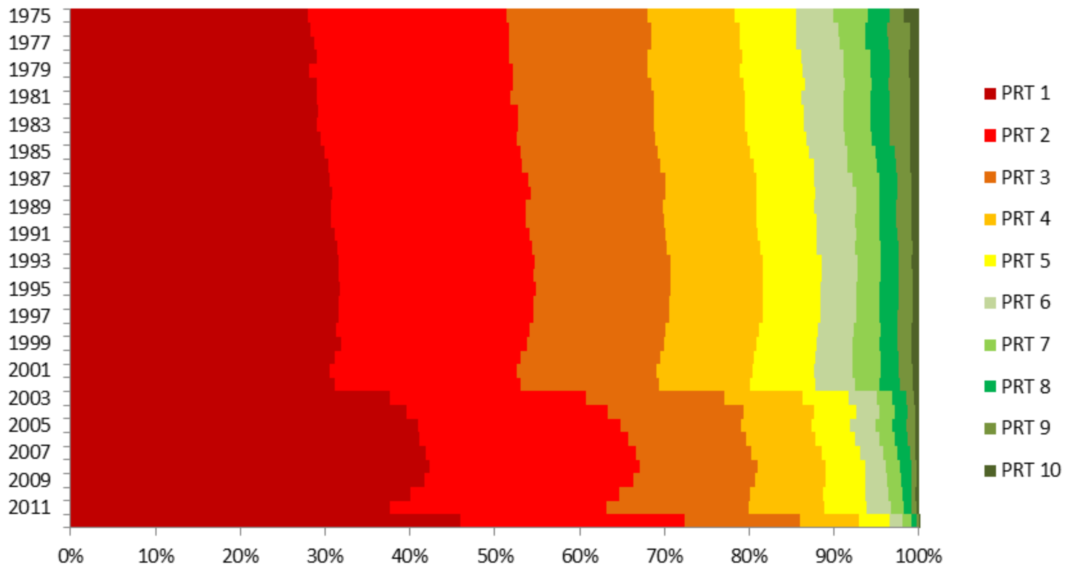


Figure 6.6 – Validation burnt pixels per 10% partition, in percent of total, for the WofE-CSE model in mainland Portugal

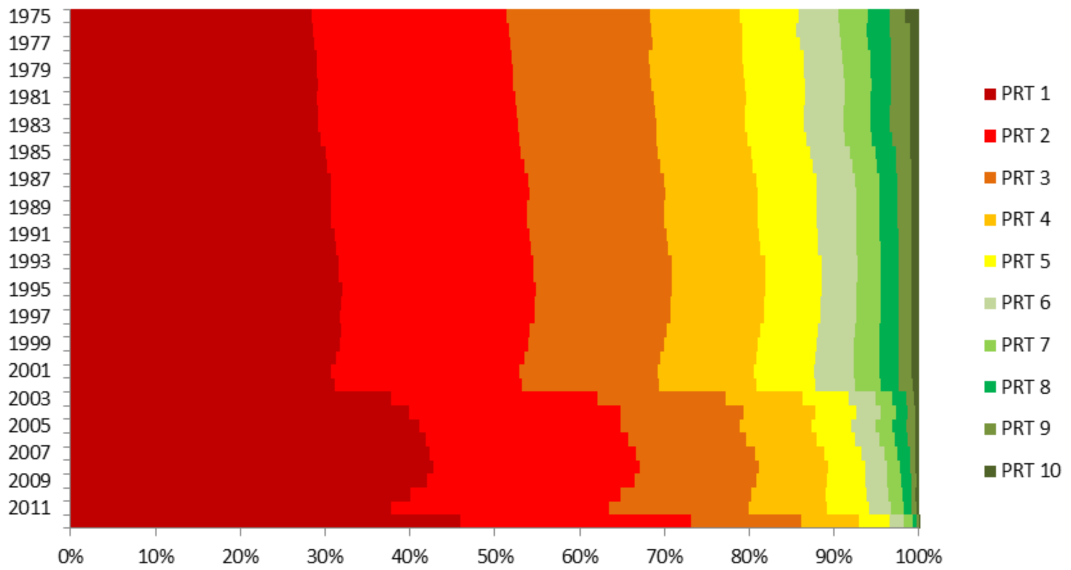


Figure 6.7 – Validation burnt pixels per 10% partition, in percent of total, for the WofE-CSEA model in mainland Portugal

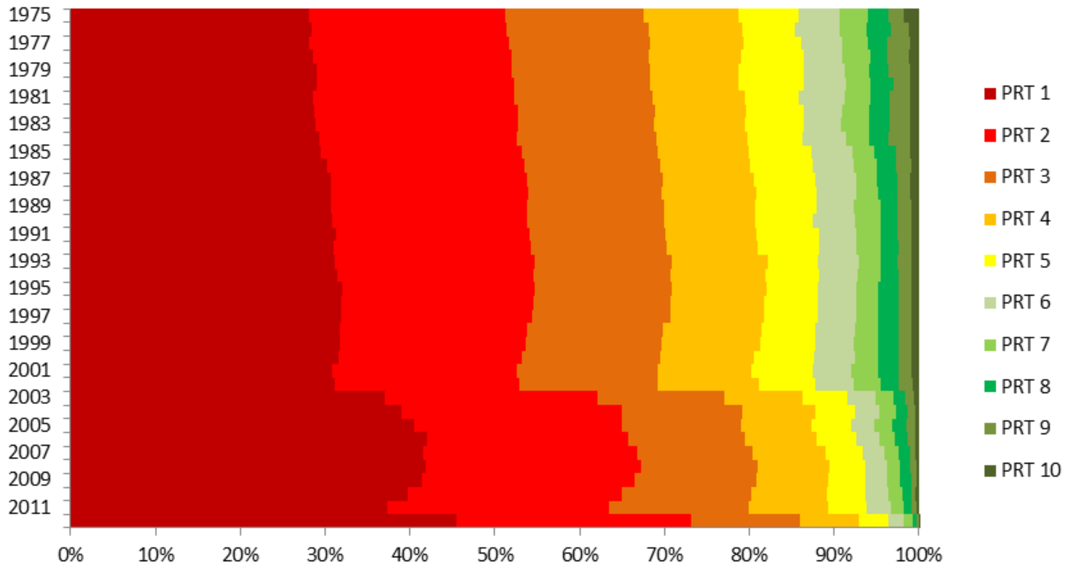


Figure 6.8 – Validation burnt pixels per 10% partition, in percent of total, for the WofE-CSER model in mainland Portugal

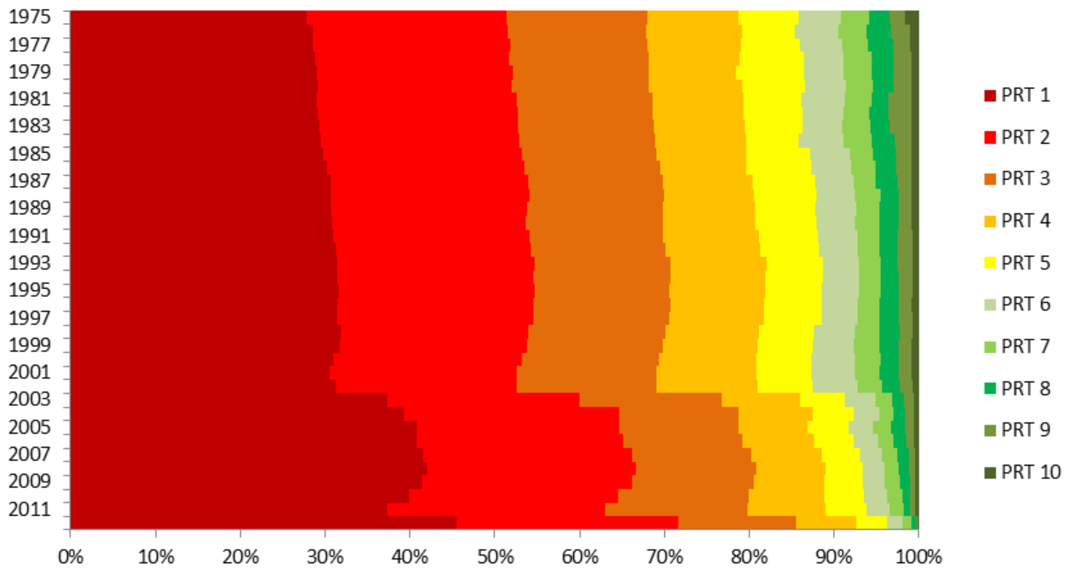


Figure 6.9 – Validation burnt pixels per 10% partition, in percent of total, for the WofE-CSEP01 model in mainland Portugal

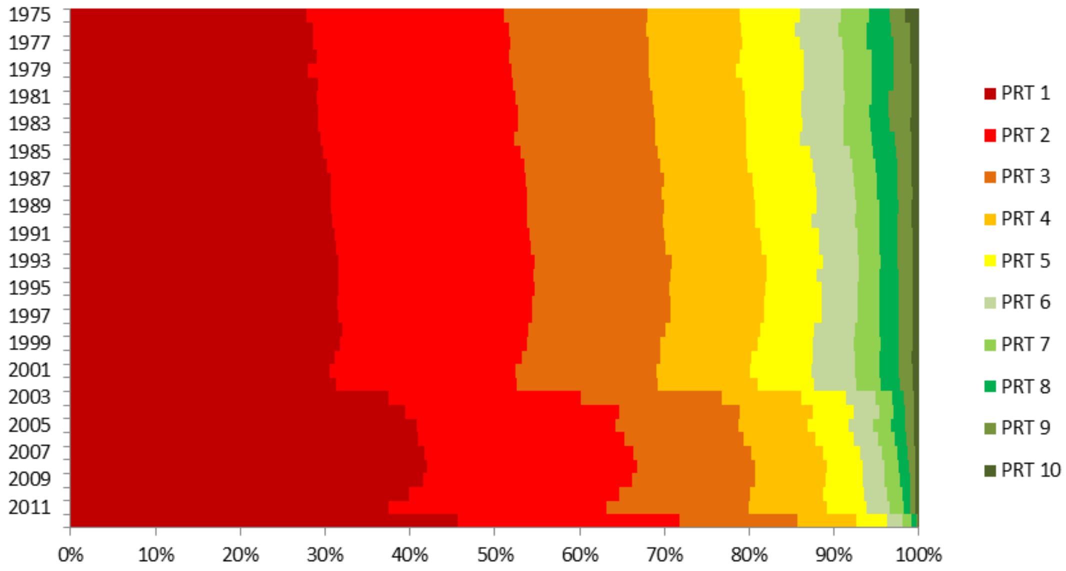


Figure 6.10 – Validation burnt pixels per 10% partition, in percent of total, for the WofE-CSEP11 model in mainland Portugal

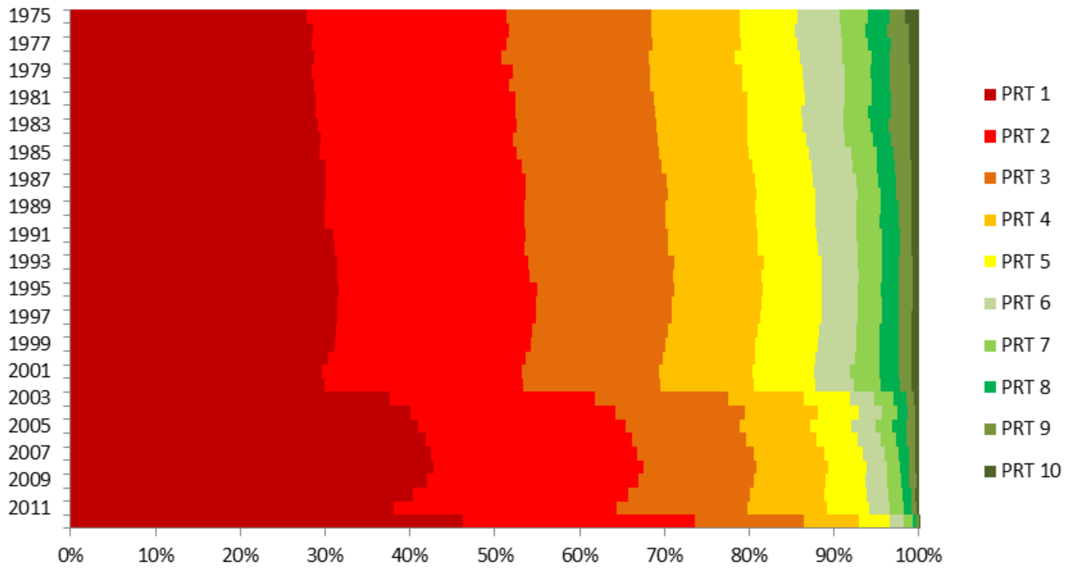


Figure 6.11 – Validation burnt pixels per 10% partition, in percent of total, for the WofE-CSEG model in mainland Portugal

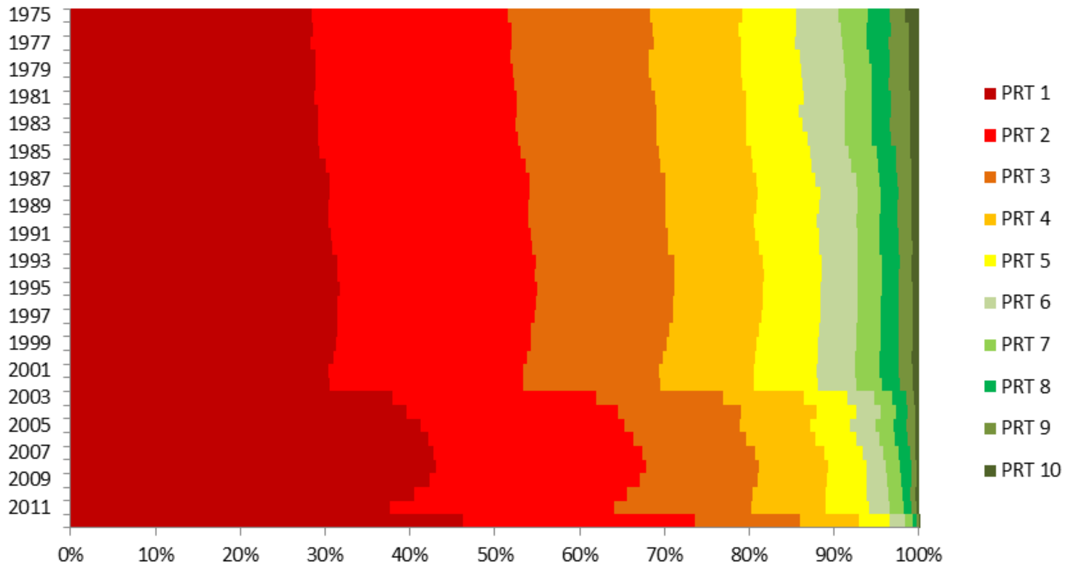


Figure 6.12 – Validation burnt pixels per 10% partition, in percent of total, for the WofE-CSERG model in mainland Portugal

Table 6.5 – Validation burnt pixels per 10% partition, in percent of total, for the WofE-CSEA model in mainland Portugal. Higher values in bold. (%)

Model 1975 to:	Partitions									
	PRT 1	PRT 2	PRT 3	PRT 4	PRT 5	PRT 6	PRT 7	PRT 8	PRT 9	PRT 10
1975	**28.37**	22.94	16.92	10.68	6.96	4.56	3.51	2.59	1.77	1.70
1976	**28.56**	23.04	16.87	10.63	6.41	5.06	3.20	2.81	2.28	1.13
1977	**28.78**	23.03	16.75	10.55	6.85	4.85	3.11	2.72	2.29	1.09
1978	**29.08**	22.84	16.26	11.05	7.12	4.59	3.35	2.37	2.22	1.13
1979	**29.07**	22.99	16.16	11.08	7.15	4.63	3.21	2.34	2.27	1.10
1980	**29.12**	23.06	16.21	11.03	7.17	4.68	3.11	2.34	2.21	1.07
1981	**29.07**	23.40	16.25	10.86	6.93	4.69	3.09	2.33	2.31	1.07
1982	**29.16**	23.47	16.24	10.62	6.95	4.64	3.19	2.29	2.38	1.06
1983	**29.25**	23.43	16.29	10.56	6.86	4.66	3.23	2.24	2.41	1.07
1984	**29.41**	23.48	16.23	10.65	6.91	4.61	3.10	2.40	2.22	1.01
1985	**30.04**	23.06	16.16	10.92	7.00	4.72	3.05	2.30	1.75	1.02
1986	**30.24**	23.24	16.03	10.89	7.04	4.64	2.97	2.24	1.75	0.96
1987	**30.66**	23.33	16.00	10.86	7.02	4.64	2.77	2.19	1.60	0.92
1988	**30.72**	23.41	15.95	10.85	7.01	4.69	2.70	2.16	1.58	0.92
1989	**30.65**	23.15	16.16	10.96	7.02	4.65	2.75	2.15	1.59	0.92
1990	**30.74**	23.04	16.15	10.98	6.98	4.65	2.80	2.12	1.62	0.92
1991	**31.13**	22.92	16.13	11.00	6.87	4.58	2.73	2.24	1.55	0.85
1992	**31.29**	22.96	16.17	10.87	6.84	4.51	2.83	2.15	1.55	0.83
1993	**31.56**	23.06	16.31	11.04	6.54	4.29	2.75	2.02	1.60	0.85
1994	**31.53**	23.05	16.23	11.03	6.67	4.24	2.78	2.08	1.55	0.84
1995	**31.97**	22.89	16.00	10.96	6.64	4.16	2.84	2.10	1.59	0.84
1996	**31.84**	22.87	16.05	10.94	6.71	4.21	2.82	2.15	1.58	0.85
1997	**31.70**	22.97	16.01	10.98	6.73	4.21	2.84	2.13	1.58	0.85
1998	**31.84**	22.29	16.07	11.02	6.85	4.41	2.91	2.14	1.63	0.84
1999	**31.73**	22.26	15.95	11.04	6.96	4.44	2.98	2.18	1.62	0.85
2000	**31.31**	22.16	16.08	11.24	6.96	4.60	3.01	2.17	1.61	0.85
2001	**30.73**	22.12	16.32	11.39	7.07	4.67	3.04	2.20	1.63	0.83
2002	**31.12**	22.00	16.29	11.35	7.07	4.66	3.01	2.15	1.58	0.78
2003	**37.78**	24.25	15.15	9.12	5.36	3.18	2.01	1.57	1.02	0.56
2004	**39.83**	24.97	14.50	8.48	4.80	2.83	1.82	1.38	0.90	0.48
2005	**41.13**	23.74	14.03	8.39	4.65	2.86	1.97	1.75	0.98	0.50
2006	**41.87**	23.89	13.84	8.38	4.53	2.84	1.81	1.49	0.88	0.48
2007	**42.34**	24.31	13.98	8.21	4.38	2.62	1.66	1.37	0.70	0.42
2008	**42.73**	24.37	14.03	8.18	4.31	2.53	1.57	1.25	0.64	0.38
2009	**42.03**	24.42	14.38	8.36	4.51	2.50	1.63	1.21	0.61	0.36
2010	**40.12**	24.76	15.35	8.83	4.72	2.62	1.68	1.00	0.52	0.41
2011	**37.73**	25.67	16.56	9.19	4.91	2.55	1.61	0.91	0.48	0.37
2012	**45.87**	27.31	12.93	6.75	3.66	1.59	1.07	0.54	0.22	0.05

Table 6.6 – Validation burnt pixels per 10% partition, in percent of total, for the WofE-CSER model in mainland Portugal. Higher values in bold. (%)

Model 1975 to:	Partitions PRT 1	PRT 2	PRT 3	PRT 4	PRT 5	PRT 6	PRT 7	PRT 8	PRT 9	PRT 10
1975	**28.12**	23.10	16.32	11.12	7.08	4.90	3.29	2.51	1.78	1.77
1976	**28.41**	23.03	16.65	11.05	6.27	5.19	3.16	2.98	2.07	1.19
1977	**28.18**	23.46	16.65	10.96	6.79	4.96	2.95	2.30	2.66	1.09
1978	**28.56**	23.41	16.24	10.86	7.38	4.46	3.37	2.01	2.57	1.16
1979	**29.06**	22.89	16.35	10.45	7.69	4.78	2.84	2.29	2.56	1.09
1980	**29.07**	23.16	16.07	10.38	7.75	4.90	2.88	2.70	2.02	1.07
1981	**28.61**	23.72	16.29	10.89	6.22	5.54	2.95	2.32	2.35	1.10
1982	**28.78**	23.93	16.16	10.71	6.80	4.64	3.15	2.40	2.36	1.08
1983	**28.92**	23.82	16.07	10.71	6.89	4.44	3.27	2.42	2.39	1.07
1984	**29.37**	23.28	16.44	10.63	6.57	5.09	2.82	2.25	2.55	1.02
1985	**29.44**	23.76	15.97	10.77	7.40	4.74	2.70	2.45	1.76	1.01
1986	**30.21**	23.29	15.98	10.54	7.48	4.78	2.75	2.27	1.75	0.95
1987	**30.67**	23.18	16.03	10.71	7.21	4.74	2.54	2.29	1.63	1.01
1988	**30.76**	23.17	15.70	11.14	7.17	4.67	2.53	2.27	1.58	1.01
1989	**30.67**	23.15	16.12	10.74	7.27	4.37	3.12	1.99	1.59	0.97
1990	**30.77**	23.09	16.04	10.71	6.88	4.99	2.94	2.03	1.60	0.94
1991	**31.30**	22.74	16.07	10.74	7.31	4.44	2.87	1.97	1.67	0.89
1992	**30.93**	23.30	16.08	10.63	7.28	4.43	2.86	2.06	1.56	0.87
1993	**31.17**	23.46	16.18	11.31	5.99	4.81	2.58	1.95	1.62	0.93
1994	**31.47**	23.02	16.22	11.19	6.26	4.58	2.73	2.14	1.51	0.87
1995	**32.05**	22.62	16.13	11.23	5.98	4.62	2.58	2.38	1.55	0.86
1996	**31.95**	22.56	16.23	11.02	6.25	4.61	2.60	2.36	1.56	0.87
1997	**31.91**	22.55	16.23	11.04	6.26	4.60	2.60	2.36	1.57	0.87
1998	**31.70**	22.16	16.00	11.55	6.43	4.63	2.76	2.35	1.57	0.86
1999	**31.79**	21.90	16.02	11.54	6.47	4.61	2.81	2.38	1.60	0.87
2000	**31.54**	21.64	16.34	10.96	7.13	4.89	2.72	2.33	1.57	0.87
2001	**30.82**	21.81	16.52	11.11	7.23	4.54	3.20	2.32	1.60	0.86
2002	**31.21**	21.62	16.42	11.83	6.65	4.54	3.25	2.03	1.65	0.81
2003	**37.09**	25.00	15.03	9.19	5.30	3.31	2.01	1.45	1.02	0.61
2004	**39.05**	25.90	14.17	8.61	4.76	2.88	1.87	1.38	0.86	0.52
2005	**40.55**	24.34	14.06	8.35	4.69	2.71	2.09	1.74	0.97	0.49
2006	**42.07**	23.62	13.83	8.42	4.63	2.76	1.84	1.50	0.87	0.46
2007	**41.49**	25.34	13.60	8.51	4.35	2.57	1.65	1.37	0.72	0.39
2008	**41.87**	25.42	13.63	8.47	4.29	2.48	1.55	1.26	0.65	0.37
2009	**41.35**	25.17	14.32	8.45	4.40	2.56	1.58	1.24	0.60	0.35
2010	**39.76**	25.14	15.32	8.84	4.55	2.82	1.64	0.96	0.57	0.39
2011	**37.30**	26.12	16.53	9.30	4.60	2.78	1.55	0.91	0.55	0.35
2012	**45.50**	27.61	12.86	6.98	3.46	1.78	0.99	0.55	0.21	0.05

Table 6.7 – Validation burnt pixels per 10% partition, in percent of total, for the WofE-CSEP01 model in mainland Portugal. Higher values in bold. (%)

Model 1975 to:	Partitions									
	PRT 1	PRT 2	PRT 3	PRT 4	PRT 5	PRT 6	PRT 7	PRT 8	PRT 9	PRT 10
1975	**27.85**	23.53	16.60	10.76	7.09	4.98	3.30	2.45	1.80	1.64
1976	**28.54**	23.03	16.25	11.26	6.26	5.17	3.26	2.97	2.15	1.10
1977	**28.56**	23.22	16.23	11.05	6.88	5.04	3.04	2.92	2.06	1.00
1978	**28.93**	22.70	16.49	10.69	7.62	4.69	3.34	2.55	2.03	0.96
1979	**29.06**	23.12	15.96	10.29	8.01	4.73	3.29	2.57	2.02	0.96
1980	**29.14**	22.90	16.13	10.96	7.36	4.86	3.20	2.48	2.01	0.95
1981	**28.96**	23.55	16.07	10.80	6.71	5.18	3.17	2.01	2.61	0.94
1982	**29.12**	23.55	15.96	10.72	6.96	4.74	3.08	2.31	2.66	0.90
1983	**29.26**	23.48	15.97	10.79	6.79	4.68	3.32	2.17	2.62	0.91
1984	**29.55**	23.32	15.98	10.70	6.32	5.23	3.29	2.72	2.00	0.89
1985	**29.78**	23.44	15.84	10.50	7.63	4.62	2.82	2.68	1.80	0.90
1986	**30.27**	23.27	15.91	10.24	7.66	4.71	2.83	2.47	1.78	0.87
1987	**30.72**	23.21	15.85	10.54	7.49	4.55	2.58	2.57	1.63	0.87
1988	**30.72**	23.30	15.92	10.56	7.40	4.54	2.97	2.11	1.65	0.83
1989	**30.71**	23.06	16.02	10.84	7.20	4.71	2.77	2.27	1.54	0.87
1990	**30.79**	22.91	16.07	10.85	7.35	4.48	2.88	2.25	1.56	0.85
1991	**31.04**	23.03	15.78	11.35	6.93	4.58	2.63	2.03	1.82	0.81
1992	**31.25**	23.05	15.75	11.29	6.90	4.58	2.56	2.13	1.73	0.77
1993	**31.51**	23.15	16.09	11.24	6.68	4.30	2.55	1.85	1.82	0.82
1994	**31.49**	23.04	16.12	11.29	6.67	4.22	2.61	2.09	1.65	0.81
1995	**31.63**	23.11	15.81	11.35	6.65	4.30	2.55	2.17	1.61	0.82
1996	**31.45**	23.08	16.12	11.14	6.69	4.28	2.59	2.25	1.57	0.83
1997	**31.50**	22.98	16.12	11.14	6.70	4.30	2.59	2.25	1.58	0.82
1998	**31.97**	22.03	16.09	11.10	6.41	4.81	2.92	2.34	1.51	0.82
1999	**31.76**	21.96	16.15	11.12	6.49	4.82	3.09	2.25	1.53	0.83
2000	**31.05**	22.11	16.18	11.54	6.48	5.13	3.04	2.10	1.52	0.84
2001	**30.46**	22.05	16.49	11.75	6.52	5.20	2.85	2.30	1.54	0.83
2002	**31.26**	21.31	16.47	11.93	6.54	5.16	2.97	2.04	1.55	0.76
2003	**37.37**	22.67	16.70	9.23	5.31	3.59	1.89	1.45	1.16	0.62
2004	**39.35**	25.25	14.08	8.72	4.82	3.03	1.74	1.39	1.01	0.60
2005	**40.76**	23.93	13.98	8.17	4.91	2.89	2.03	1.72	1.03	0.58
2006	**40.87**	24.22	14.11	8.45	4.69	2.81	1.91	1.47	0.92	0.56
2007	**41.62**	24.52	14.16	8.29	4.43	2.65	1.74	1.35	0.77	0.48
2008	**42.00**	24.59	14.19	8.25	4.38	2.55	1.64	1.26	0.71	0.44
2009	**41.47**	24.75	14.26	8.40	4.49	2.64	1.68	1.23	0.68	0.41
2010	**39.86**	24.60	15.46	8.82	4.72	2.75	1.78	0.89	0.65	0.45
2011	**37.39**	25.62	16.73	9.30	4.78	2.69	1.73	0.77	0.60	0.39
2012	**45.54**	26.09	13.84	7.13	3.58	1.85	1.12	0.52	0.26	0.08

Table 6.8 – Validation burnt pixels per 10% partition, in percent of total, for the WofE-CSEP11 model in mainland Portugal. Higher values in bold. (%)

Model 1975 to:	Partitions									
	PRT 1	PRT 2	PRT 3	PRT 4	PRT 5	PRT 6	PRT 7	PRT 8	PRT 9	PRT 10
1975	**27.88**	23.25	16.89	10.75	7.11	4.89	3.28	2.51	1.79	1.63
1976	**28.57**	23.07	16.25	11.19	6.29	5.16	3.26	2.97	2.15	1.10
1977	**28.59**	23.26	16.23	11.02	6.86	5.02	2.85	3.10	2.02	1.04
1978	**28.96**	22.74	16.46	10.73	7.56	4.64	3.33	2.55	2.03	1.01
1979	**28.02**	23.97	16.22	10.24	8.00	4.68	3.30	2.54	2.07	0.96
1980	**29.17**	22.95	16.15	10.95	7.18	4.63	3.44	2.57	2.02	0.94
1981	**28.99**	23.48	16.16	10.78	6.72	5.07	3.17	2.07	2.62	0.93
1982	**29.15**	23.52	16.05	10.67	6.65	5.04	3.06	2.30	2.63	0.93
1983	**29.22**	23.51	16.11	10.74	6.70	4.74	3.31	2.15	2.44	1.08
1984	**29.48**	22.75	16.71	10.68	6.32	5.20	3.27	2.70	2.01	0.89
1985	**29.81**	23.25	16.09	10.49	7.59	4.63	2.78	2.67	1.81	0.88
1986	**30.30**	23.22	15.97	10.29	7.62	4.68	2.81	2.46	1.78	0.86
1987	**30.69**	22.94	16.24	10.52	7.43	4.49	2.63	2.51	1.68	0.86
1988	**30.76**	23.04	15.83	10.95	7.29	4.62	2.51	2.49	1.69	0.82
1989	**30.74**	23.08	16.07	10.81	7.18	4.69	2.76	2.23	1.57	0.87
1990	**30.82**	22.95	16.08	10.81	6.70	5.11	2.87	2.07	1.74	0.85
1991	**31.07**	22.95	15.90	11.34	6.90	4.51	2.67	2.02	1.82	0.81
1992	**31.29**	22.95	15.90	11.23	6.83	4.54	2.65	2.12	1.73	0.77
1993	**31.55**	23.18	16.05	11.23	6.60	4.28	2.58	1.89	1.83	0.80
1994	**31.53**	23.03	16.18	11.22	6.02	4.88	2.48	2.21	1.64	0.81
1995	**31.66**	23.05	15.90	11.30	6.63	4.23	2.60	2.20	1.61	0.81
1996	**31.49**	22.96	16.23	11.11	6.68	4.26	2.64	2.24	1.57	0.82
1997	**31.54**	22.89	16.21	11.11	6.71	4.26	2.64	2.25	1.58	0.82
1998	**31.98**	21.98	16.13	11.16	6.39	4.78	2.92	2.31	1.54	0.82
1999	**31.80**	21.99	15.77	11.49	6.47	4.76	3.12	2.22	1.56	0.82
2000	**31.08**	22.14	16.21	10.83	7.16	5.07	2.88	2.25	1.55	0.83
2001	**30.49**	21.98	16.60	10.98	7.26	5.10	2.91	2.23	1.61	0.82
2002	**31.27**	21.36	16.49	11.87	6.56	5.07	2.82	2.24	1.56	0.75
2003	**37.42**	22.72	16.67	9.26	5.27	3.52	1.92	1.45	1.15	0.62
2004	**39.40**	25.33	14.07	8.68	4.79	2.97	1.77	1.39	1.01	0.58
2005	**40.81**	23.41	14.50	8.21	4.84	2.82	2.09	1.67	1.04	0.61
2006	**40.93**	24.27	14.13	8.42	4.59	2.78	1.94	1.42	0.93	0.58
2007	**41.68**	24.58	13.95	8.46	4.35	2.60	1.79	1.30	0.78	0.51
2008	**42.06**	24.65	13.98	8.43	4.29	2.52	1.68	1.20	0.72	0.47
2009	**41.51**	24.71	14.39	8.32	4.45	2.60	1.72	1.17	0.71	0.41
2010	**39.93**	24.67	15.46	8.62	4.82	2.71	1.82	0.89	0.63	0.45
2011	**37.45**	25.69	16.73	9.21	4.77	2.69	1.72	0.76	0.59	0.39
2012	**45.61**	26.22	13.83	6.91	3.64	1.82	1.11	0.51	0.27	0.08

Table 6.9 – Validation Burnt pixels per 10% partition, in percent of total, for the WofE-CSEG model in mainland Portugal. Higher values in bold. (%)

Model 1975 to:	Partitions									
	PRT 1	PRT 2	PRT 3	PRT 4	PRT 5	PRT 6	PRT 7	PRT 8	PRT 9	PRT 10
1975	**27.88**	23.50	17.03	10.47	6.78	4.95	3.37	2.53	1.78	1.71
1976	**28.57**	23.18	16.73	10.39	6.49	5.44	2.85	2.66	2.49	1.21
1977	**28.49**	22.87	17.21	10.45	6.67	5.20	3.14	2.58	2.21	1.18
1978	**28.68**	22.12	17.39	10.02	7.80	4.88	3.44	2.21	2.25	1.20
1979	**28.44**	23.64	16.27	10.87	6.99	4.96	3.14	2.25	2.33	1.11
1980	**28.79**	22.96	16.57	10.83	7.29	4.85	3.07	2.24	2.28	1.12
1981	**28.86**	23.58	16.33	10.93	6.84	4.69	3.14	2.25	2.29	1.09
1982	**28.89**	23.55	16.43	10.96	6.33	4.97	2.88	2.61	2.31	1.07
1983	**29.25**	23.37	16.45	10.72	6.55	4.79	3.21	2.11	2.50	1.06
1984	**29.46**	22.66	17.07	10.56	6.90	4.60	3.26	2.12	2.35	1.01
1985	**29.38**	23.18	16.84	10.51	7.16	4.87	3.07	1.99	1.99	1.01
1986	**30.15**	23.09	16.49	10.63	6.93	4.86	2.92	2.13	1.85	0.96
1987	**30.02**	23.63	16.63	10.44	6.76	5.08	2.69	2.09	1.79	0.88
1988	**30.05**	23.62	16.70	10.49	6.88	4.94	2.72	1.89	1.82	0.89
1989	**29.98**	23.50	16.63	10.54	7.17	4.82	2.77	2.12	1.60	0.86
1990	**29.95**	23.54	16.61	10.68	7.04	4.72	2.76	2.31	1.53	0.86
1991	**31.04**	22.58	16.75	10.62	6.96	4.69	2.92	2.11	1.50	0.83
1992	**31.19**	22.26	16.96	10.61	7.04	4.70	2.85	2.10	1.48	0.83
1993	**31.49**	22.46	17.15	10.60	6.87	4.25	2.82	2.02	1.53	0.82
1994	**31.41**	22.62	16.92	10.42	7.21	4.28	2.76	2.01	1.56	0.81
1995	**31.64**	23.43	16.03	10.50	6.96	4.22	2.76	2.02	1.62	0.82
1996	**31.46**	23.47	15.98	10.54	7.05	4.25	2.83	2.00	1.61	0.82
1997	**31.43**	23.43	16.01	10.37	7.22	4.26	2.84	2.00	1.61	0.83
1998	**31.34**	23.06	15.97	10.67	7.15	4.40	2.76	2.28	1.54	0.84
1999	**31.16**	23.03	15.98	10.58	7.31	4.49	2.79	2.25	1.57	0.85
2000	**30.40**	23.29	16.14	10.79	7.18	4.63	2.93	2.26	1.51	0.87
2001	**29.67**	23.51	16.12	11.06	7.32	4.20	3.47	2.26	1.52	0.87
2002	**29.93**	23.48	16.09	10.99	7.31	4.45	3.26	2.22	1.32	0.95
2003	**37.62**	24.15	15.65	9.01	5.37	2.96	2.15	1.54	0.95	0.59
2004	**40.08**	24.20	15.25	8.50	4.81	2.72	1.80	1.23	0.94	0.47
2005	**40.92**	24.45	13.48	8.33	4.85	2.90	1.89	1.61	1.05	0.51
2006	**41.80**	24.37	13.39	8.33	4.80	2.71	1.81	1.32	0.98	0.49
2007	**42.41**	24.35	13.82	8.26	4.55	2.48	1.67	1.19	0.83	0.43
2008	**42.80**	24.72	13.36	8.40	4.47	2.41	1.63	1.05	0.77	0.39
2009	**42.06**	24.88	13.61	8.45	4.72	2.46	1.70	0.96	0.79	0.36
2010	**40.42**	25.28	14.32	8.86	4.88	2.60	1.74	0.93	0.56	0.41
2011	**38.07**	26.29	15.45	9.25	4.99	2.50	1.71	0.83	0.54	0.37
2012	**46.18**	27.36	12.86	6.57	3.58	1.65	1.03	0.47	0.24	0.06

Table 6.10 – Validation burnt pixels per 10% partition, in percent of total, for the WofE-CSERG model in mainland Portugal. Higher values in bold. (%)

Model 1975 to:	Partitions									
	PRT 1	PRT 2	PRT 3	PRT 4	PRT 5	PRT 6	PRT 7	PRT 8	PRT 9	PRT 10
1975	**28.47**	23.09	16.66	10.87	6.43	5.00	3.47	2.53	1.77	1.70
1976	**28.56**	23.39	16.66	10.14	6.82	5.26	2.91	2.98	2.09	1.18
1977	**28.34**	23.71	16.62	10.37	6.30	5.58	2.91	2.62	2.40	1.15
1978	**28.84**	22.96	16.29	10.93	6.99	5.13	2.96	2.40	2.34	1.16
1979	**28.95**	23.19	16.03	10.93	7.09	5.07	3.12	2.18	2.20	1.26
1980	**28.84**	23.44	16.21	10.71	7.10	5.07	3.10	1.96	2.41	1.15
1981	**28.71**	23.87	16.34	10.72	6.78	4.81	3.22	2.18	2.29	1.07
1982	**29.17**	23.35	16.53	10.56	6.24	5.31	3.24	2.23	2.28	1.08
1983	**29.24**	23.26	16.48	10.65	6.69	4.87	3.17	2.22	2.32	1.09
1984	**29.16**	23.57	16.27	10.58	7.23	4.50	3.04	2.34	2.30	1.02
1985	**29.39**	23.62	16.39	10.79	6.99	4.46	3.37	2.21	1.79	0.99
1986	**30.06**	23.51	15.99	10.85	6.94	4.65	3.10	2.24	1.71	0.95
1987	**30.49**	23.58	16.07	10.77	6.88	4.84	2.74	2.12	1.62	0.91
1988	**30.54**	23.62	16.01	10.82	7.32	4.40	2.74	2.08	1.58	0.89
1989	**30.36**	23.58	16.22	10.60	7.51	4.42	2.71	1.97	1.74	0.89
1990	**30.44**	23.52	16.17	10.43	7.36	4.75	2.66	2.12	1.65	0.90
1991	**30.67**	23.52	16.19	10.29	7.49	4.52	2.64	2.27	1.56	0.83
1992	**30.80**	23.61	16.05	10.63	7.16	4.50	2.64	2.25	1.55	0.81
1993	**31.43**	23.41	16.31	10.39	7.01	4.20	2.93	2.00	1.48	0.85
1994	**31.41**	23.25	16.46	10.58	6.82	4.23	2.91	1.99	1.48	0.86
1995	**31.69**	23.23	16.17	10.53	6.79	4.40	2.76	2.03	1.57	0.82
1996	**31.47**	23.32	16.20	10.55	6.90	4.37	2.67	2.14	1.55	0.82
1997	**31.50**	23.25	16.25	10.49	6.94	4.36	2.68	2.08	1.62	0.82
1998	**31.40**	22.91	16.20	10.60	7.14	4.40	2.86	2.07	1.61	0.81
1999	**31.24**	23.03	16.01	10.49	7.36	4.44	2.90	2.11	1.60	0.81
2000	**30.96**	22.83	15.95	11.00	7.28	4.47	2.80	2.35	1.54	0.83
2001	**30.31**	22.95	16.09	11.14	7.37	4.52	2.89	2.34	1.55	0.82
2002	**30.59**	22.83	16.06	11.06	7.50	4.60	2.93	2.14	1.53	0.78
2003	**37.91**	24.06	14.97	9.45	5.19	3.18	2.13	1.56	1.01	0.56
2004	**39.54**	25.01	14.40	9.01	4.62	2.89	1.83	1.39	0.83	0.48
2005	**41.31**	23.99	13.61	8.20	4.79	2.96	2.04	1.65	0.94	0.50
2006	**42.11**	24.19	13.38	8.17	4.79	2.72	1.84	1.50	0.84	0.47
2007	**42.71**	24.64	13.36	8.10	4.57	2.47	1.70	1.38	0.67	0.41
2008	**43.10**	24.73	13.37	8.05	4.49	2.38	1.63	1.28	0.60	0.37
2009	**42.25**	24.87	13.79	8.19	4.65	2.42	1.69	1.21	0.59	0.35
2010	**40.44**	25.20	14.78	8.50	4.91	2.50	1.71	0.96	0.60	0.40
2011	**37.64**	26.49	16.07	8.82	5.08	2.49	1.59	0.91	0.55	0.36
2012	**46.32**	27.25	12.45	6.83	3.74	1.70	1.01	0.48	0.17	0.06

6.3 The impact of widespread affected areas

In this chapter it has already been briefly mentioned how wildfire selectiveness, or inversely, very widespread wildfires, could impact model behavior, and the previous figures and tables leave no doubt as to the changes that occurred after 2003, or how before that year models progressively degraded performance. It is, then, useful to explore a little further into what 2003's wildfires have affected, in particular accounting for land cover given that among all possible evidence layers, land cover is paramount as there will be no wildfires at all in the absence of adequate fuel.

Table 6.11 ranks, from higher to lower, land cover Class Id's for CORINE Land Cover 2006, comparing the modelling set of 1975-1994 with 2003 alone, to determine if the widespread affected areas of 2003 could have, by way of burning less susceptible areas neighbouring high susceptible ones, had a considerable diverse behavior.

Table 6.11 – Land cover ranking changes, comparing burnt areas of 1975-1994 to those of 2003 alone, in mainland Portugal. Both W+ columns are for the interval 1975-1994.

	1975-1994			2003		
Class Id	Burnt Pixels	W+	Class Id	Burnt Pixels	W+	Change in Rank relative to 1975-1994
324	727,871	1007	324	315,587	1007	0
322	258,744	2045	311	106,405	-410	+1
311	167,975	-410	323	45,013	404	+7
321	149,647	1944	243	43,902	-828	+4
312	147,555	177	322	33,181	2045	-3
313	119,105	59	321	23,363	1944	-2
333	92,372	2063	211	20,546	-1234	+2
243	78,235	-828	244	17,967	-2003	+3
211	76,355	-1234	313	17,050	59	-3
323	68,626	404	242	15,468	-2226	+4
244	23,038	-2003	223	13,388	-2221	+7
334	22,015	1429	312	13,228	177	-7
332	19,176	1770	333	8,540	2063	-6
242	18,073	-2226	241	4,757	-2319	+1
241	10,980	-2319	221	1,656	-1888	+1
221	9,485	-1888	222	1,539	-1606	+3
212	9,194	-1835	334	1,296	1429	-5
223	7,873	-2221	212	1,104	-1835	-1
222	5,502	-1606	231	935	-1096	+1
231	3,712	-1096	213	715	-3146	+1
213	634	-3146	332	465	1770	-8
331	450	-1976	331	1	-1976	0

Comparing 1975-1994 to 2003, the highest and lowest class Id remains unchanged. Transitional woodland-shrub (324) is the most affected class Id on both sets, just as beaches, dunes and sands (331) are the least affected areas. In between these extremes, though, there are noticeable changes. Splitting the table in half, the topmost 11 class Ids for 1975-1994 have an overall positive weight (W+, from chapter 5) of 3,222 whereas the topmost 11 class Ids for 2003 alone have a W+ of -3,463. Observing the bottom 11 class Ids for 1975-1994, the summed W+ is -15,114 whereas the same number of classes for 2003 has a total W+ of -8,427. Table 6.12 summarizes these findings.

Table 6.12 – Summed positive weights (W+ from the Weights of Evidence method discussed in chapter 5) for land cover class Id's in mainland Portugal

Summed W+	1975-1994	2003
Top 11 class Id's	3,224	-3,463
Bottom 11 class Id's	-15,114	-8,427

As discussed on chapter 5, and by means of simplification, a positive weight of evidence translates into a class being relevant to the occurrence of a phenomenon, while a negative positive weight is an indicator that the presence of a given class Id is a deterrent of that phenomenon's occurrence. Therefore, the year 2003 alone, as widespread as it was (burning over 425 thousand hectares) impacted land cover classes that could otherwise not have been affected. The modelling block 1975-1994 groups in the highest ranked class Id's those that contribute to the occurrence of wildfires, but 2003 does not, burning land cover classes that typically do not have a favourable positive weight for wildfire occurrence. Looking at table 6.11 and to the column at the far right, it can be seen how several class Id's have been pulled in 2003; more than 4 positions upwards from what they had in the modelling block of 20 years, such is the case of sclerophyllous vegetation and olive groves (+7 in rank), agricultural areas with natural vegetation (+4) and agro-forestry areas (also +4 in rank). It seems fair to conclude that such disturbances have affected model behavior and will do so in the future any time a year comparable to 2003 will occur.

Having observed what happened to land cover, does the same rationale hold regarding other evidence layers? Table 6.13 shows a comparison for slope, and again there are changes, just not as significant as with land cover. The top and bottom classes are unchanged, and if the same exercise of splitting the classes in half (as in table 6.12) is made, positive weights are unchanged because class swaping or change in rank occurred inside those two halves. From 1975-1994 to 2003 alone, slope does not appear to be a significant modifier on model behavior.

Table 6.13 – Slope ranking changes, comparing burnt areas of 1975-1994 to those of 2003 alone in mainland Portugal. Both W+ columns are for the interval 1975-1994.

1975-1994			2003			
Slope (degrees)	Burnt Pixels	W+	Slope (degrees)	Burnt Pixels	W+	Change in Rank relative to 1975-1994
5 - 10	603,791	339	5 - 10	205,267	339	0
10 - 15	424,216	968	2 - 5	191,047	-565	1
2 - 5	410,381	-565	10 - 15	117,050	968	-1
15 - 20	253,866	1295	0 - 2	87,151	-1253	1
0 - 2	176,063	-1253	15 - 20	60,329	1295	-1
> 20	168,735	1482	> 20	26,907	1482	0

Since other evidence layers or themes have been used to model wildfire susceptibility, could there be significant changes concerning layers other than land cover and slope? Tables 6.14 to 6.19 explore those changes for elevation, aspect, population density (2001 and 2011 Census), population growth ratio and distance to roads.

Table 6.14 – Elevation ranking changes, comparing burnt areas of 1975-1994 to those of 2003 alone in mainland Portugal. Both W+ columns are for the interval 1975-1994.

	1975-1994			2003		
Elevation (m)	Burnt Pixels	W+	Elevation (m)	Burnt Pixels	W+	Change in Rank relative to 1975-1994
201 - 300	237,136	-488	201 - 300	167,265	-488	0
501 - 600	223,624	863	101 - 200	134,686	-826	+4
601 - 700	222,151	932	301 - 400	93,444	82	+1
301 - 400	217,162	82	401 - 500	62,229	545	+1
401 - 500	217,120	545	501 - 600	51,927	863	-3
101 - 200	216,481	-826	701 - 800	47,498	938	+1
701 - 800	214,079	938	601 - 700	46,013	932	-4
801 - 900	160,150	1216	1 - 100	43,762	-1481	+1
1 - 100	103,914	-1481	801 - 900	21,651	1216	-1
901 - 1000	100,843	1581	901 - 1000	8,083	1581	0
1001 - 1100	58,780	1851	1001 - 1100	4,300	1851	0
1101 - 1200	34,392	2070	1101 - 1200	1,508	2070	0
1201 - 1300	19,637	2243	1201 - 1300	1,315	2243	0
1301 - 1400	7,160	1750	1301 - 1400	1,083	1750	0
1401 - 1500	2,240	831	1401 - 1500	949	831	0
1501 - 1600	1,110	591	1501 - 1600	949	591	0
1601 - 1700	547	-68	1601 - 1700	825	-68	0
1701 - 1800	258	13	1701 - 1800	172	13	0
0	240	-4402	1801 - 1900	79	-2248	+1
1801 - 1900	28	-2248	0	13	-4402	-1
1901 - 2000	0	0	1901 - 2000	0	0	0

Table 6.15 – Aspect ranking changes, comparing burnt areas of 1975-1994 to those of 2003 alone, in mainland Portugal. Both W+ columns are for the interval 1975-1994.

	1975-1994			2003		
Aspect (Orientation)	Burnt Pixels	W+	Aspect (Orientation)	Burnt Pixels	W+	Change in Rank relative to 1975-1994
W	306,108	86	W	95,892	86	0
SW	273,303	-6	SW	94,651	-6	0
SE	273,069	61	NW	91,272	62	+1
NW	271,558	62	S	84,982	-25	+2
E	254,176	27	SE	81,831	61	-2
S	249,282	-25	NE	80,763	-108	+1
NE	206,466	-108	E	79,918	27	-2
N	202,517	-95	N	78,243	-95	0
Flat	573	-3145	Flat	199	-3145	0

Table 6.16 – Population Density (2001 Census) ranking changes, comparing burnt areas of 1975-1994 to those of 2003 alone, in mainland Portugal. Both W+ columns are for the interval 1975-1994.

1975-1994			2003			
Pop. Dens. (per sq.km)	Burnt Pixels	W+	Pop. Dens. (per sq. km)	Burnt Pixels	W+	Change in Rank relative to 1975-1994
Up to 250	2,008,020	83	Up to 250	683,782	83	0
251 to 1500	27,084	-1779	251 to 1500	3,907	-1779	0
>= 1501	1,941	-2699	>= 1501	62	-2699	0

Table 6.17 – Population Density (2011 Census) ranking changes, comparing burnt areas of 1975-1994 to those of 2003 alone, in mainland Portugal. Both W+ columns are for the interval 1975-1994.

1975-1994			2003			
Pop. Dens. (per sq.km)	Burnt Pixels	W+	Pop. Dens. (per sq. km)	Burnt Pixels	W+	Change in Rank relative to 1975-1994
Up to 250	2,009,540	81	Up to 250	684,189	81	0
251 to 1500	25,148	-1796	251 to 1500	3,503	-1796	0
>= 1501	2,358	-2605	>= 1501	59	-2605	0

Table 6.18 – Population Growth Ratio (1991-2011 Census) ranking changes, comparing burnt areas of 1975-1994 to those of 2003 alone, in mainland Portugal. Both W+ columns are for the interval 1975-1994.

1975-1994			2003			
Growth (%)	Burnt Pixels	W+	Growth (%)	Burnt Pixels	W+	Change in Rank relative to 1975-1994
-100 – -50%	1,113,730	-188	-100 – -50%	463,993	-188	0
-49 – 0%	804,139	419	-49 – 0%	183,477	419	0
> 50%	72,985	-371	> 50%	21,204	-371	0
1 – 50%	45,202	-245	1 – 50%	18,846	-245	0

Table 6.19 – Distance to Roads ranking changes, comparing burnt areas of 1975-1994 to those of 2003 alone, in mainland Portugal. Both W+ columns are for the interval 1975-1994.

1975-1994			2003			
Distance (m)	Burnt Pixels	W+	Distance (m)	Burnt Pixels	W+	Change in Rank relative to 1975-1994
> 160	1,942,470	48	> 160	655,394	48	0
Up to 80	48,103	-728	Up to 80	16,313	-728	0
81 to 160	46,475	-614	81 to 160	16,044	-614	0

As can be seen on the previous tables, one thing remains unchanged even with an outlier like the year 2003: the topmost and lower classes, for all layers. Other than land cover and slope, elevation also shows an interesting change as 2003 happens, in that in 2003 wildfires appear do require less elevation (and thus not as steep ground) to develop, affecting more areas of lower altitude, such as the elevation class of 101-200 meters that rose 4 positions in the rank, becoming second only to the 201-300m class, which leads in both 1975-1994 and 2003. The remainder layers are of no significance in this matter, and apart from Aspect which has mixed and inconclusive results, other layers do not react to 2003 alone. As per the data shown above, land cover, slope and to some extent, elevation, are the layers that are most affected by non-selective years like 2003.

Having made the prior discussion, and recalling figure 6.3, it would be expected that as the number of years in a modelling series gets larger, prediction capacity would follow and get better, in that the model would have far more information to identify more and less susceptible areas. Still, what can be observed and has been referenced before is that as the series progresses, predictive capacity, even if above 80% of ROC AUC, does degrade until 2002, only to rise sharply when the year 2003 leaves the validation block and goes into the modelling block. In table 6.1 it can be seen that when modelling with the interval 1975-2002, the CSP model – the best model for that yearly interval – reaches 82.43% of ROC AUC for prediction, and increases to 83.85% when 2003 is added to the modelling block. However, if the year 2003 is removed from the modelling block as if it never happened, the same modelling block of 1975-2002, independently validated with a block of 2004-2013, results in a ROC AUC of 84.50% (table 6.20). In summary, 2003 is a year of major burnt area, over 425 thousand hectares, where many areas were burnt, including some that usually do not burn as largely as in that year, as seen in this section, and if 2003 is inserted in the modelling block, prediction rises by 1.42%, but if 2003 is removed from modelling and not even considered in validation, prediction rises by 2.07%. A possible interpretation, though somewhat counter-intuitive, is that 2003 is far more relevant in the validation block than in the modelling block. It could be argued that 2003 would improve models because having burnt so much, it would bring added value to the models, but then (i) areas burnt in 2003 are not readily available to burn again in the following years and (ii) the rise in prediction is higher without 2003 than with it, therefore it does make more sense to conclude that 2003 is more relevant in regards to the independent validation block.

Table 6.20 – Areas under the curve (%) for receiver operating characteristic curves for prediction on the CSP and WofE models, for modelling set from 1975-2012, with and without 2003 in the independent validation block, for mainland Portugal.

Model of 1975 to 2002:	CSP	WofE							
		CS	CSE	CSEA	CSEP01	CSEP11	CSEG	CSER	CSERG
Validated 2003-2013	82.43	81.46	81.06	81.04	81.15	81.15	80.86	81.12	80.92
Validated 2004-2013	84.50	83.11	83.50	83.50	83.37	83.38	83.47	83.51	83.48

It is also an hypothesis that the inclusion of 2003 in the independent validation block causes the models to lose predictive performance over time until 2003 itself is removed from the validation block. When the models start, information builds up and they improve their predictive capacity. Simultaneously, burnt areas for 2003 are well diluted in the information of over 30 years, but as the modelling block progresses and the validation block shortens, the weight of 2003 becomes more and more present, hindering prediction. When 2003 is finally removed from the validation block, the models regain predictive capacity. As such, years like 2003 – which was an outlier – are very difficult to predict and disturb the wildfire model's prediction capacity over time.

6.4 Closing thoughts on model stability

Having a predetermined set of data to work on a model, when that data evolves each year, does pose a question on how to use that data in the future, if all the data or just a subset. On the case at hand, there is variability. Burnt areas change over the years, even though there is a good amount or recurrence. Variability will make a model's response change, as has been seen on this chapter. Receiver operating characteristic curves have been computed and their respective areas under the curve have been plotted in such a way that variability and its effect on predictive capacity was all too clear and depending on the data interval, models can predict better or worse future events. That is one *feature* to be clearly stated and understood. It should not be seen as a *limitation* in that models cannot fully translate reality. Fluctuations in prediction, for events that also change – and many times in a not fully understood manner –, is far more than a limitation, a feature.

This chapter gave an opportunity to compare how different models behave with different sets of yearly modelling data. The reference model CSP is, for the most part, the best model in regards to prediction rate, only seldom surpassed by Weights of Evidence (WofE) models, even if differences between these two methods are, indeed, small. Still, comparing areas under the curve is only part of the picture. Allocating future burnt pixels – that is, those burnt pixels that were not included in the models – into partitions of a predefined susceptible area (10%) allowed to understand how different models, either CSP or iterations of WofE, were actually *guessing* where it would burn, given the expected susceptibility of each partition. Lack of data, in all model iterations, results in more fragile results, which is only natural, and for that reason, when the modelling block is small, the number of pixels in the most susceptible partitions is also smaller than when the modelling block is larger. As the modelling set progresses, the models get stronger in prediction as they incorporate more historical data and therefore patterns of recurrence play a role in the ability to predict what will happen in the future.

Having a good prediction rate is one of the goals of any predictive model, but doing so in the least possible area is also a goal, and in that sense, most WofE models have shown to be superior to the reference CSP model from the very first modelling block, and very solid, in that all over the data series the first partition, representing those areas of higher susceptibility, is indeed the most populated, meaning that over the years, more and more of the burnt pixels are allocated to just 10% of the total susceptible area, and as all the data is used, half of the burnt pixels are contained in those 10% of the territory. Thus, even though the CSP model shows a better result for the total modelling block and cannot be discarded, the WofE models are serious contenders, and much smoother when allocating burnt pixels to the first partitions.

Outliers will influence model results. Years of more selective wildfires, meaning wildfires following a pattern and affecting areas routinely burnt, will have a good fit in the model. Inversely, years of widespread wildfires will probably fail to be adequately predicted. It is a product of event variability, that cannot be circumvented, only understood and carefully analyzed as the model is run, checking for severe fluctuations in predictive capacity. As it has been shown, as tested for the year 2003, land cover, slope and elevation (closely related themes) are the main drivers for model performance hits and misses in the case of such an outlier.

Data shows that modelling with as many years as possible improves predictive capacity. Opting for round modelling blocks, such as 10 year or 15 year blocks, at a point in time when that represents about a third or a quarter of the available information, would always raise questions like why 10 or 15, and when to start, when to stop? Models exhibit good predictive capacities with only 10 years of data, but it could seem tempting or more adequate to use all the available data, leaving the last year for independent validation, and going through the process of repeating model runs, just as in this chapter, to study predictive behavior, should one be interested in having an always up-to-date susceptibility map. In all likelihood, partition 1 will never have 100% of burnt pixels, and one challenge for the future could be to check if and when it stabilizes, never losing thought of how variability affects these models, or if these models are indeed already stable and only reacting to uncertainty in smaller validation sets as the end of the available series nears. But in doing so, in using all years to model but the latest, the temptation of trying to predict any single year after the modelling blocks should be avoided. The models herein studied are not intended for prediction of any single year.

As validation sets decrease, variability impacts models the most, therefore it is not correct to assume that such models can be used for short term prediction. Mid and long term predictions are the most adequate uses, well suited for planning purposes.

Chapter 7. Regional susceptibility assessment

In the previous chapters, namely chapters 4 through 6, the analysis was made for mainland Portugal as a whole. The results are solid and encouraging, showing that either with a simpler CSP model or a more complex WofE model, good results can be achieved and, as such, a good basis for further risk assessment is entirely possible.

It has been written before, nonetheless, that these models are not scale agnostic, and that just as they can be used for the country, the pixel size also allows for regional application. That issue does raise a question of how the models behave when the area of interest changes. Mainland Portugal, albeit a small country, is very diverse. The northern part of the country have more wildfires than in the southern part, which does not necessarily translate into there existing more fuel on the north than in the south. Agricultural and pasture practices are different, the way people interact with fire is also different, and the northern Portugal does have more fire ignition prone conditions than the south (APIF, 2005; Pereira M.G. et al., 2011; Collins et al., 2013). Moreover, the coastal pressure on urban/rural interfaces also plays a role on wildfires, and even though wildfires near urban areas are not as extreme as to their extent, their frequency is very significant (APIF, 2005; Verde, 2008; Pereira M.G. et al., 2011). Generally, nearer the coast and to the north, wildfires are more frequent albeit smaller in burnt area, whereas to the south and farther away from the coast, they are less frequent but easily larger in burnt area (APIF, 2005; Verde, 2008).

Consequently, it becomes of interest to study how the proposed models behave when run for smaller regions. The adopted regions for this chapter are NUTSII, which are considered to fall well within the allowable scale of work (pixel size of 80m with a land cover coverage of 1:100,000) and, since adopted throughout Europe, can be compared with other studies conducted for the same statistical regions should there be such a study in the future.

The modelling intervals are those of chapters 4 and 5, e.g., 1975-1994 for modelling and 1995-2013 for independent validation, nearly splitting the available burnt scar data in half. The predisposing themes remain the same and all of them were clipped according to the mainland NUTSII for Portugal, which are named, from North to South, “Norte”, “Centro”, “Lisboa”, “Alentejo” and “Algarve” (fig. 7.1). The methodology is exactly the same as in previous chapters; the only thing changing is the extent of spatial analysis.

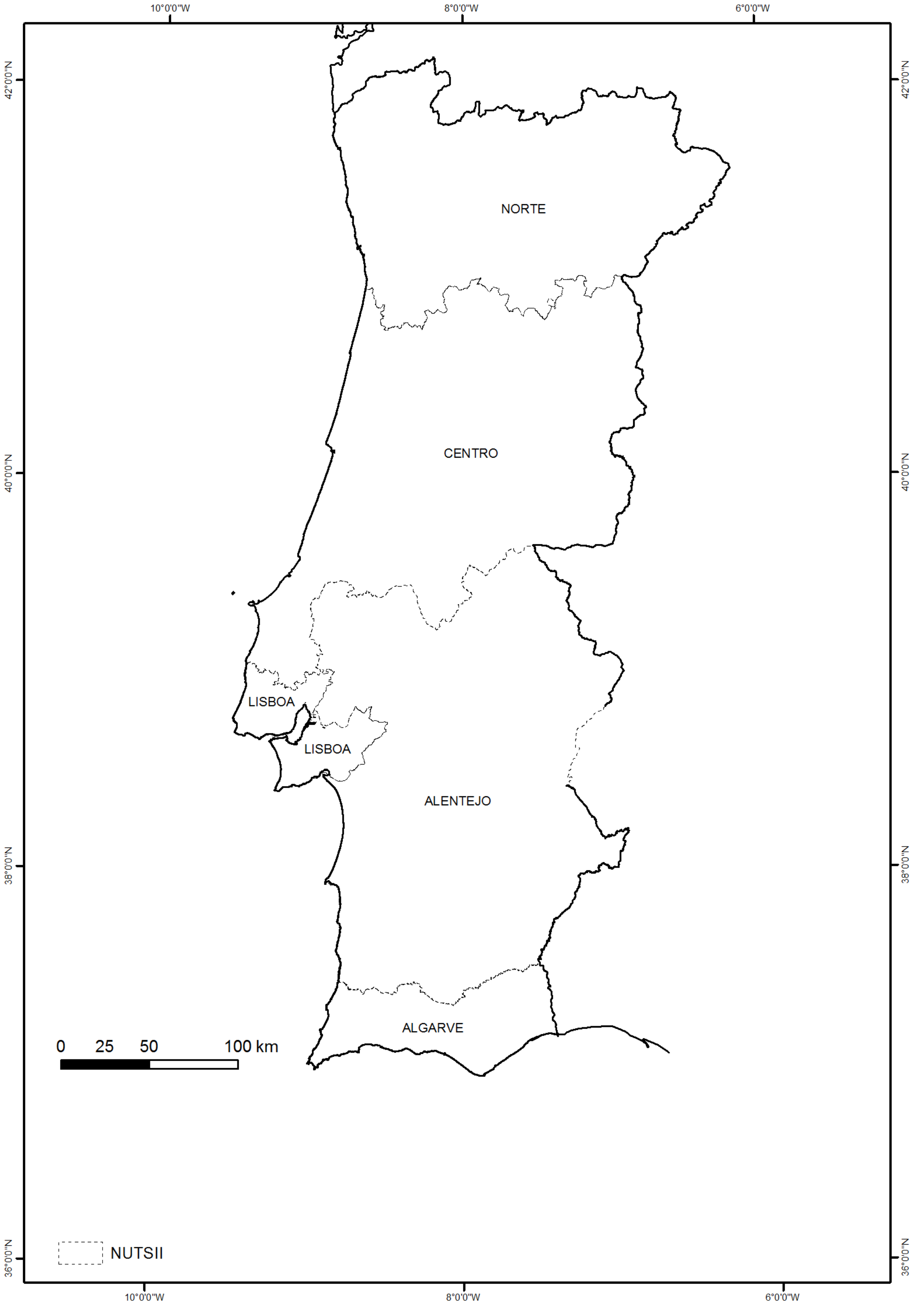


Figure 7.1 – NUTSII regions in mainland Portugal

7.1 Regional success rates

Following the same order as in chapter 5, success rates for all models in the interval 1975-1994 (independently validated with interval 1995-2013) are presented herein, so that model fit can be assessed on a regional basis. Figures 7.2 and 7.3 present success curves and areas under the curve for the base CSP model, comparing NUTSII results with that of the national (mainland) model run.

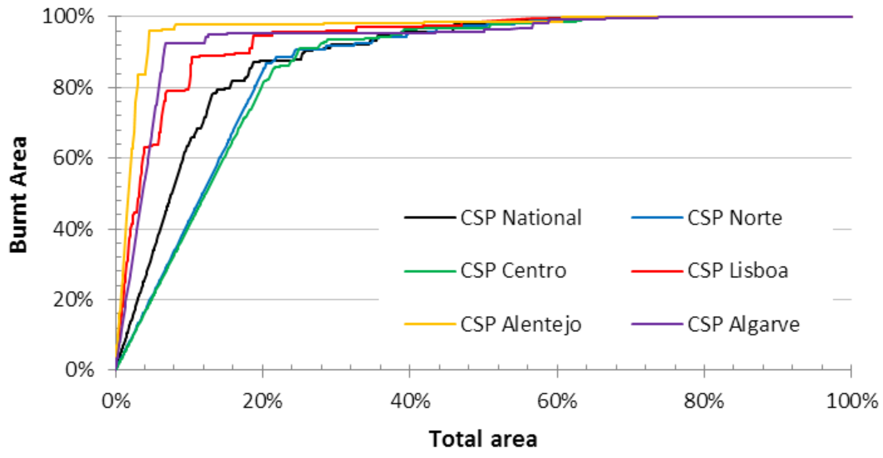


Figure 7.2 – NUTSII CSP success curves, compared with the national CSP for the modelling block 1975-1994

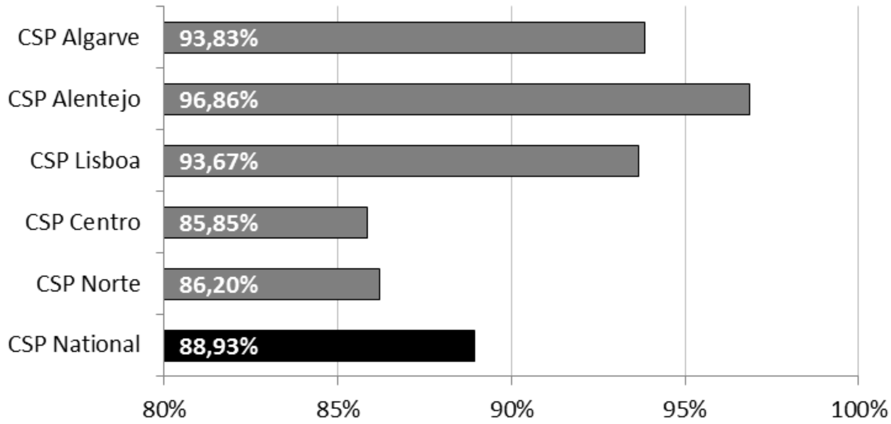


Figure 7.3 – NUTSII CSP success areas under the curve, compared with the national CSP for the modelling block 1975-1994

On the base CSP model, those NUTSII less relevant to wildfires present the best results in regards to success, surpassing the national model. Since it burns less, in comparison with NUTSII Norte and Centro, whatever has been burnt in the modelling set, given that the CSP model has a double integration of historical data (as detailed in previous chapters), has a strong influence on susceptibility and therefore on model fit.

Far different results are those of the WofE-CS model (fig. 7.4; 7.5) whose curves resemble more those of prediction rather than success, as seen on the base CSP model. In fact, as in chapter 5, the success curve for the national WofE-CS model is rather smooth and very similar to other observed prediction curves, albeit being a success curve. The NUTSII Lisboa presents a better success curve, always above the national curve, and the NUTSII Alentejo has the worse result. With the notable exception of NUTSII Lisboa, the NUTSII with less relevance to wildfires (Algarve and Alentejo, not entirely in terms of affected area but mostly of recurrence) show worse results under the Weights of Evidence methodology.

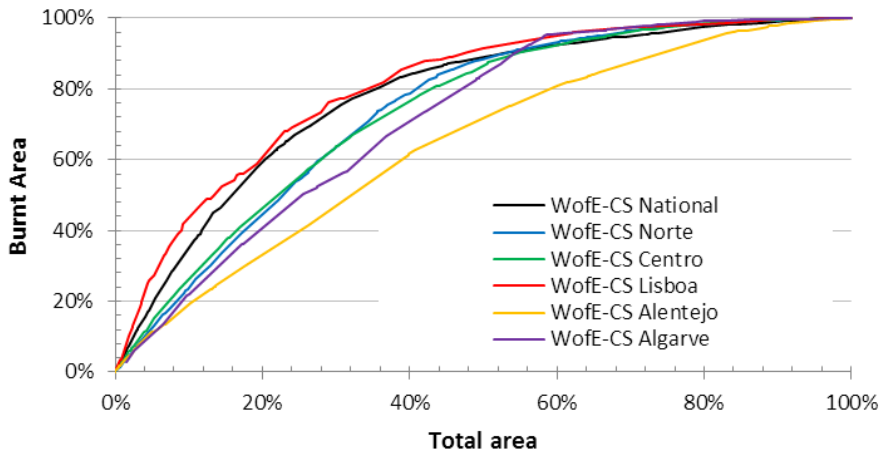


Figure 7.4 – NUTSII WofE-CS success curves, compared with the national WofE-CS for the modelling block 1975-1994

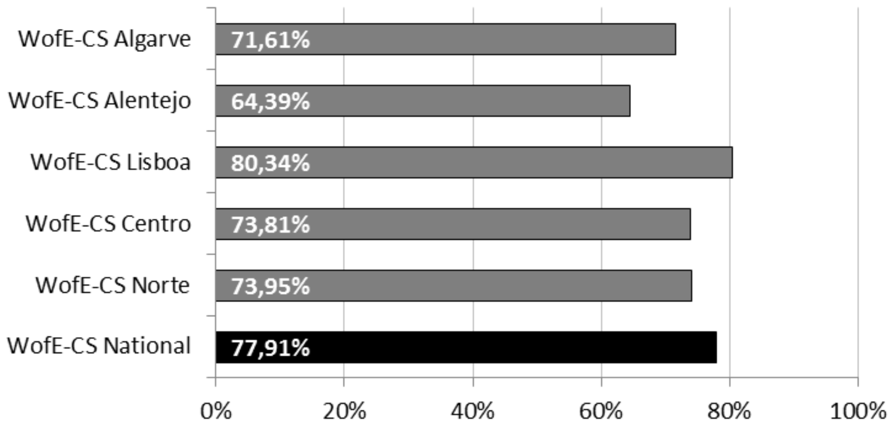


Figure 7.5 – NUTSII WofE-CS success areas under the curve, compared with the national WofE-CS for the modelling block 1975-1994

When adding elevation (E) to the previous model with landcover (C) and slope (S), some previous observations remain true. The NUTSII results for WofE-CSE model runs (fig. 7.6; 7.7) show that NUTSII Lisbon keeps a better area under the curve and that NUTSII Alentejo, one of the NUTSII with a lesser incidence of wildfire occurrences, remains on the lowest end of success rates. It would seem that elevation, as an evidence layer, helps NUTSII Lisbon in model fit, while being somewhat irrelevant in NUTSII Alentejo which is, for the most part, a low elevation area with little diversity when compared to NUTSII Norte or NUTSII Centro.

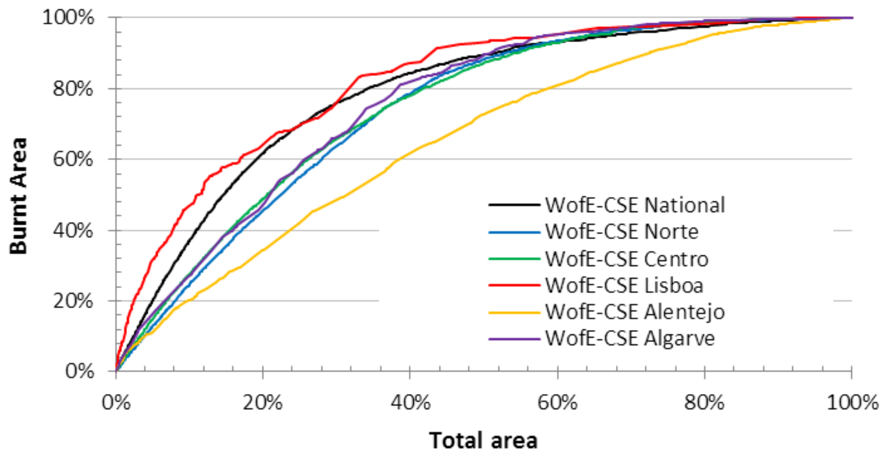


Figure 7.6 – NUTSII WofE-CSE success curves, compared with the national WofE-CSE for the modelling block 1975-1994

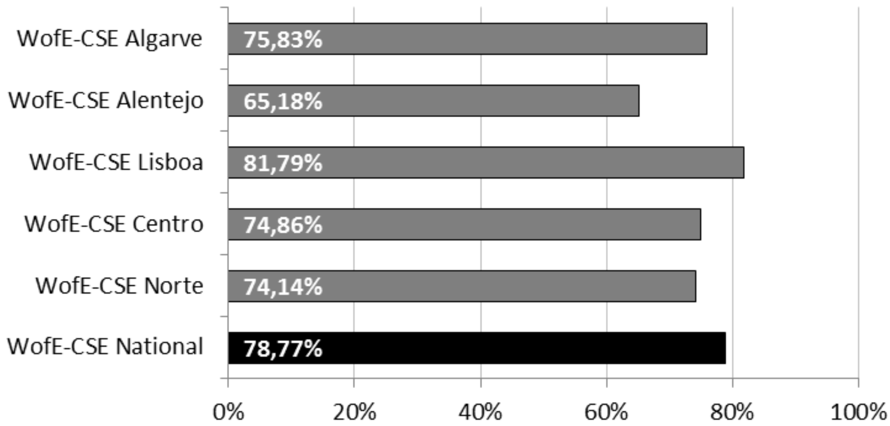


Figure 7.7 – NUTSII WofE-CSE success areas under the curve, compared with the national WofE-CSE for the modelling block 1975-1994

Just as before, in chapter 5, adding Aspect (A) to the model translates into little added value (figs. 7.8; 7.9). The relative ranking between NUTSII and mainland are the same, and even though the absolute values are different (for NUTSII Algarve and Alentejo), the difference is negligible, under 1%. Therefore, we can conclude that Aspect, as an evidence layer, does not prove to be effective in regards to model fit or differentiating success rates between NUTSII.

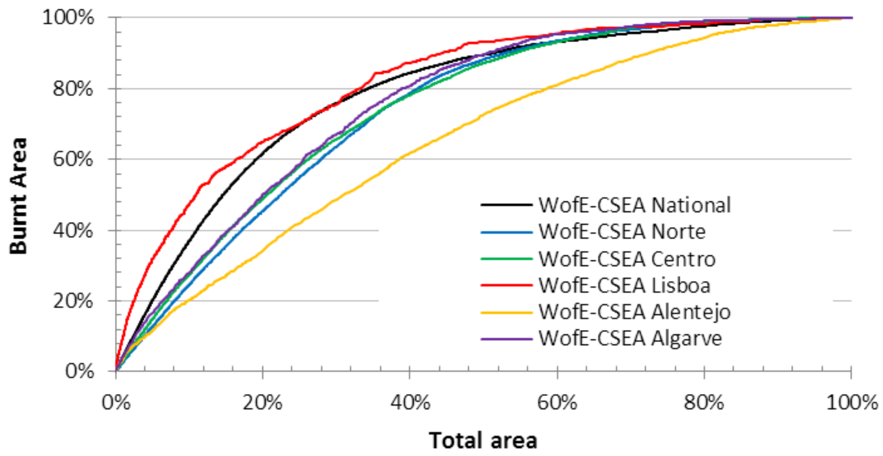


Figure 7.8 – NUTSII WofE-CSEA success curves, compared with the national WofE-CSEA for the modelling block 1975-1994

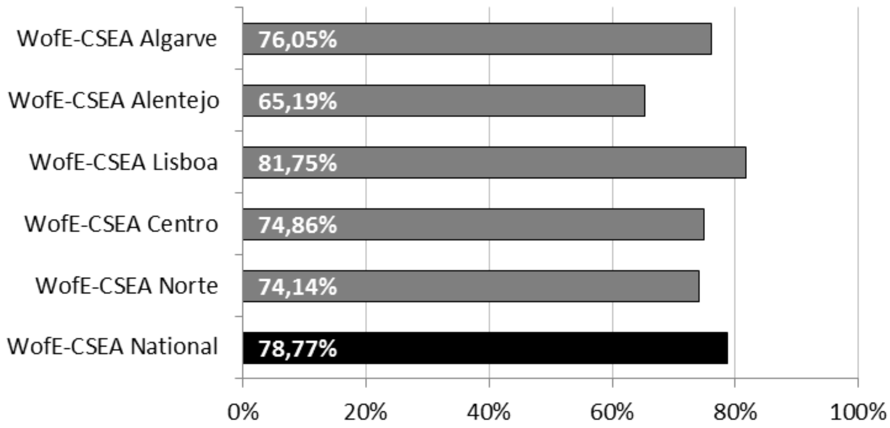


Figure 7.9 – NUTSII WofE-CSEA success areas under the curve, compared with the national WofE-CSEA for the modelling block 1975-1994

Adding Population Density in 2001 (P01) as an evidence layer positively impacts NUTSII Lisboa results, having an opposite effect on NUTSII Norte and Algarve (figs. 7.10; 7.11). NUTSII Alentejo, where population density is lower, is still the NUTSII with the worst success rate. Compared to previous models, WofE-CSEP01 does not change relative rankings between NUTSII and mainland Portugal.

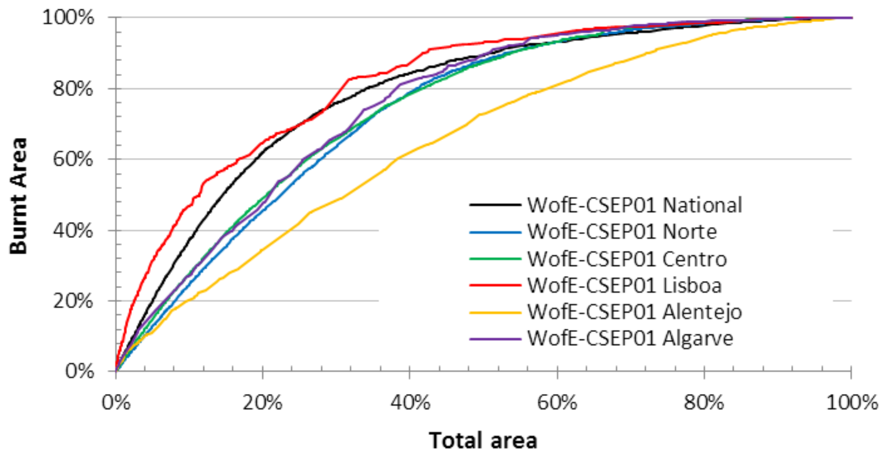


Figure 7.10 – NUTSII WofE-CSEP01 success curves, compared with the national WofE-CSEP01 for the modelling block 1975-1994

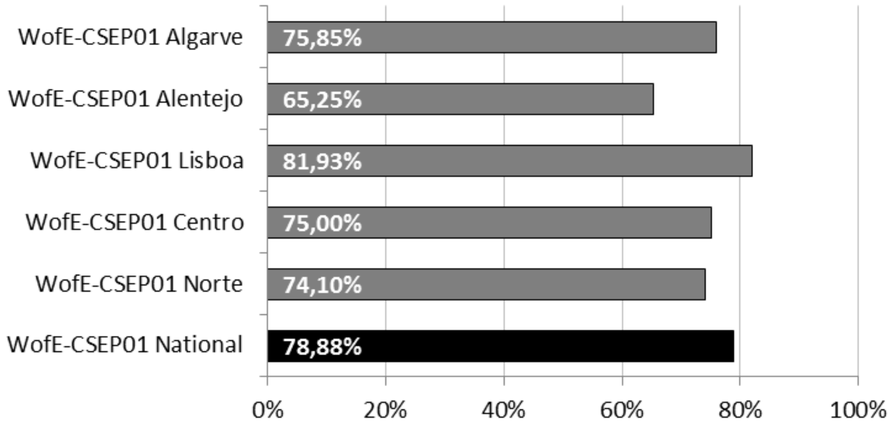


Figure 7.11 – NUTSII WofE-CSEP01 success areas under the curve, compared with the national WofE-CSEP01 for the modelling block 1975-1994

Replacing population density of 2001 with that of 2011 Census (P11) does not have a significant impact on results, and even though areas under the curve show different values, the differences are of little significance and relative rankings remain unaltered, with NUTSII Lisboa showing the best success, followed by the National model and then closely by NUTSII Algarve, NUTSII Centro, NUTSII Norte and, lastly, NUTSII Alentejo (figs. 7.12; 7.13).

In summary, we can state that Population density as an evidence layer, either that of 2001 or 2011, does not show a significant improvement in either NUTSII.

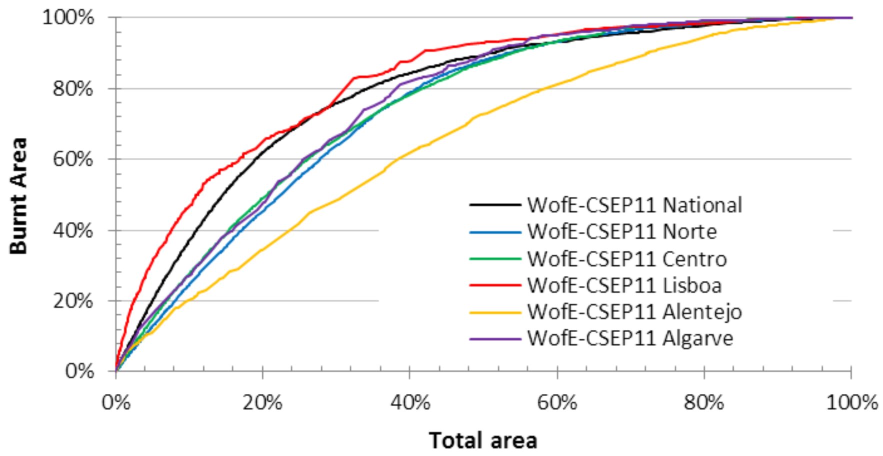


Figure 7.12 – NUTSII WofE-CSEP11 success curves, compared with the national WofE-CSEP11 for the modelling block 1975-1994

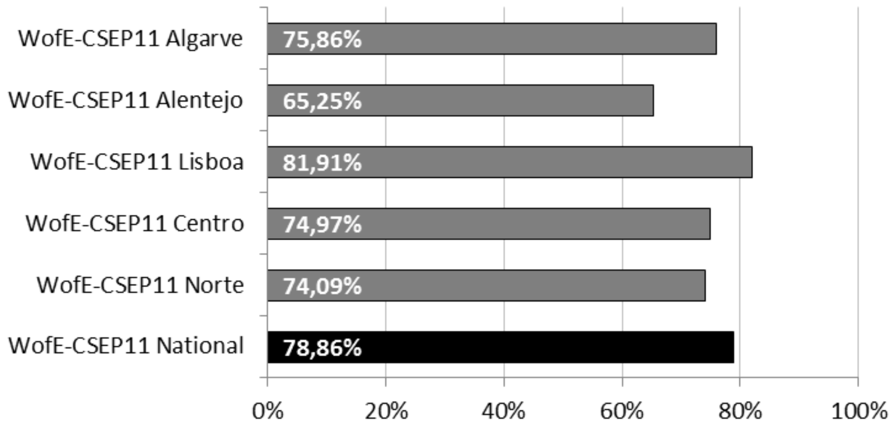


Figure 7.13 – NUTSII WofE-CSEP11 success areas under the curve, compared with the national WofE-CSEP11 for the modelling block 1975-1994

Given that population density data was also available for 1991, population growth ratio (G) was added as an evidence layer, as reasoned in chapter 5. WofE-CSEG model runs for mainland Portugal and each mainland NUTSII shows that this evidence layer maintains previous results in regards to relative rankings, showing small variations in absolute values for areas under the curve (figs. 7.14; 7.15).

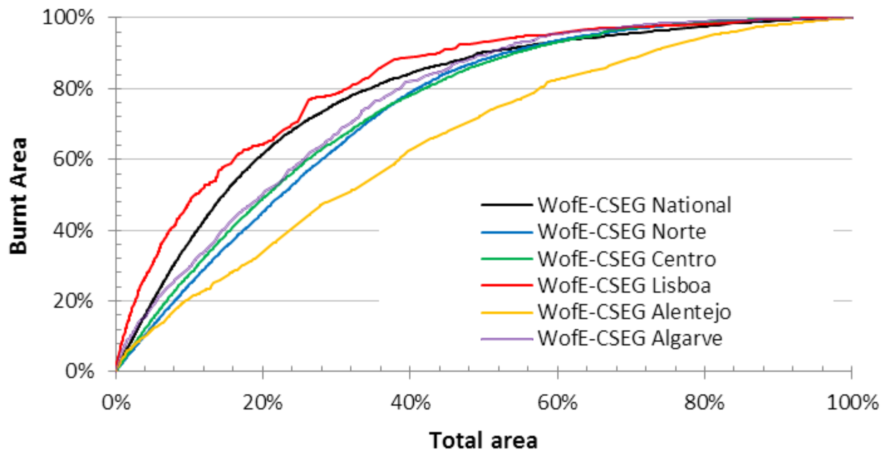


Figure 7.14 – NUTSII WofE-CSEG success curves, compared with the national WofE-CSEG for the modelling block 1975-1994

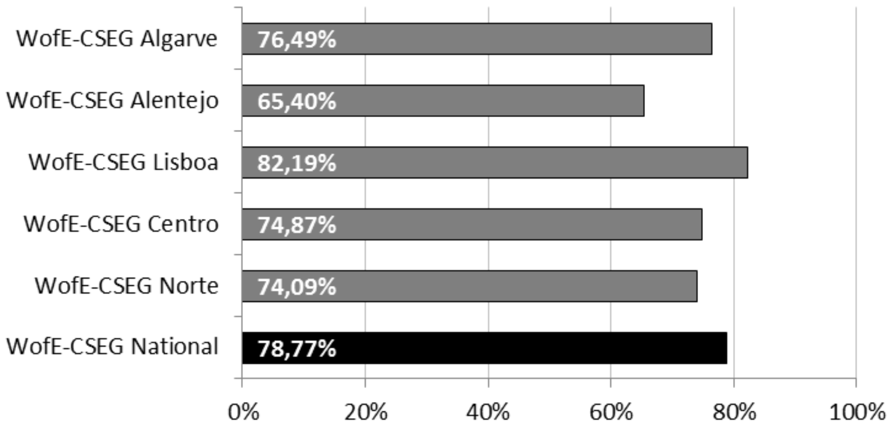


Figure 7.15 – NUTSII WofE-CSEG success areas under the curve, compared with the national WofE-CSEG for the modelling block 1975-1994

Exploring distance to roads (R) as possible evidence layer, enhancing model success rates, does not prove to actually have a positive effect. Looking at results, most areas under the curve lower their values even if under 1% in difference (figs. 7.16; 7.17). Relative positions are kept and NUTSII Lisbon still shows the better success rates.

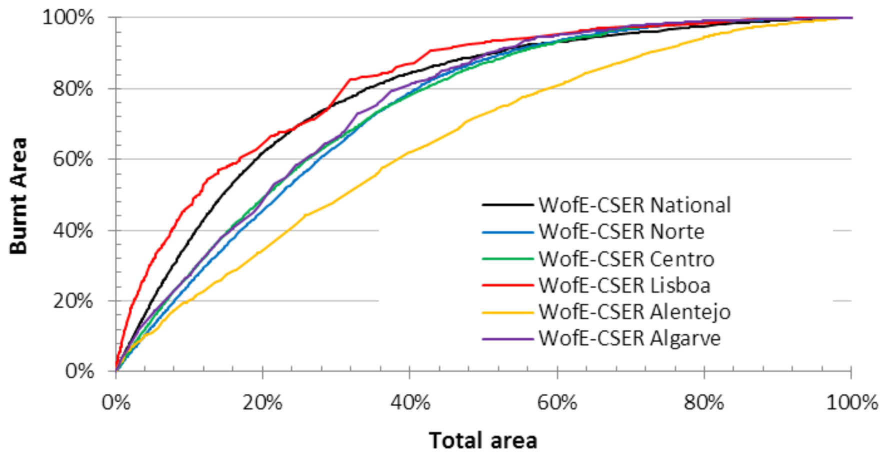


Figure 7.16 – NUTSII WofE-CSER success curves, compared with the national WofE-CSER for the modelling block 1975-1994

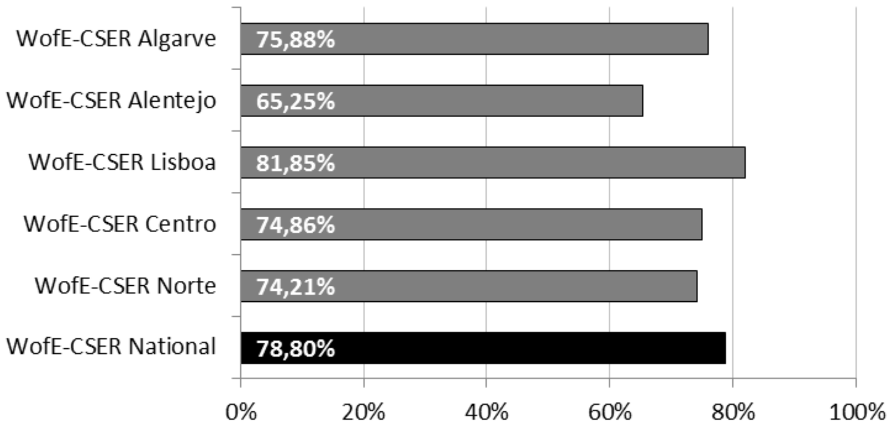


Figure 7.17 – NUTSII WofE-CSER success areas under the curve, compared with the national WofE-CSER for the modelling block 1975-1994

Finally, combining all evidence layers (with the exception of Aspect which was dropped from the model as referenced on section 5.3.2) into the WofE-CSERG model shows that in regards to success rates and NUTSII, results remain on par with the previous Weights of Evidence model runs (figs. 7.18;7.19).

In summary, Weights of Evidence models have a better model fit in NUTSII Lisboa, NUTSII Norte, Centro and Algarve have similar AUCs throughout model runs, and NUTSII Alentejo always has the worst success rate. The CSP model does not follow the same behavior, having NUTSII Alentejo as the best region, in regards to model fit.

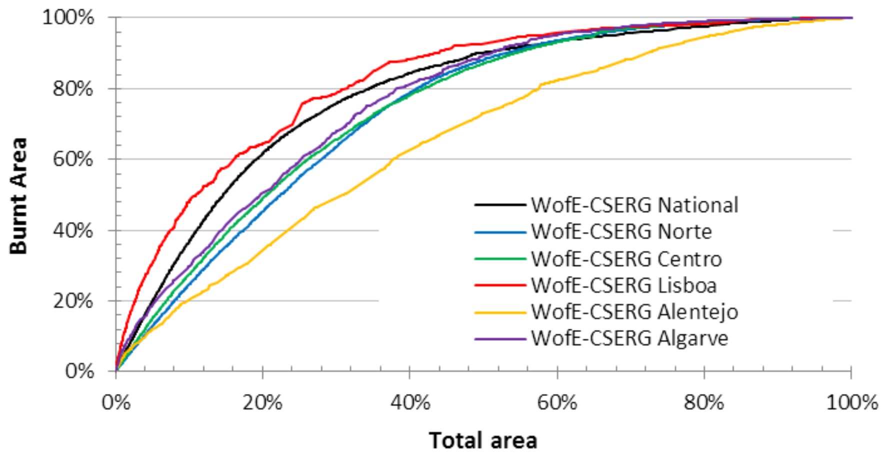


Figure 7.18 – NUTSII WofE-CSERG success curves, compared with the national WofE-CSERG for the modelling block 1975-1994

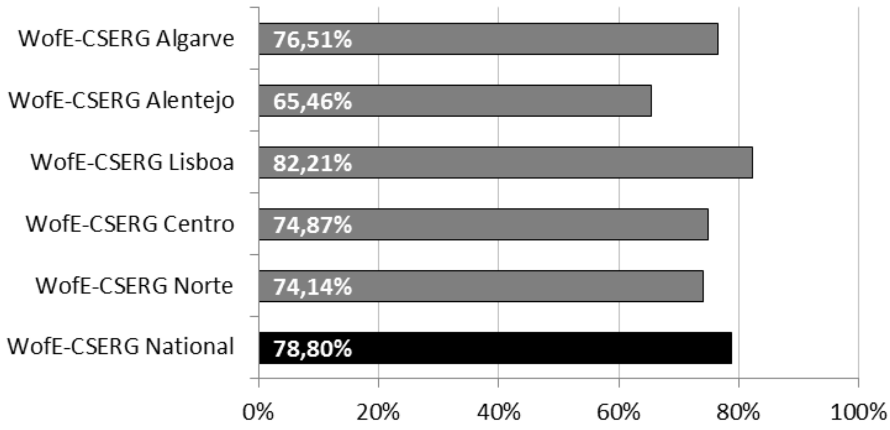


Figure 7.19 – NUTSII WofE-CSERG success areas under the curve, compared with the national WofE-CSERG for the modelling block 1975-1994

7.2 Regional prediction rates

Having presented model success rates on section 7.1, in this section, and by the same order, model prediction rates shall be presented. For the validation interval of 1995 to 2013, it will be shown if there are any differences on how the models predict future wildfires for the five NUTSII regions when compared with mainland Portugal. Figures 7.20 and 7.21 present prediction curves and areas under the curve for the base CSP model, comparing NUTSII results with that of the national (mainland) model run.

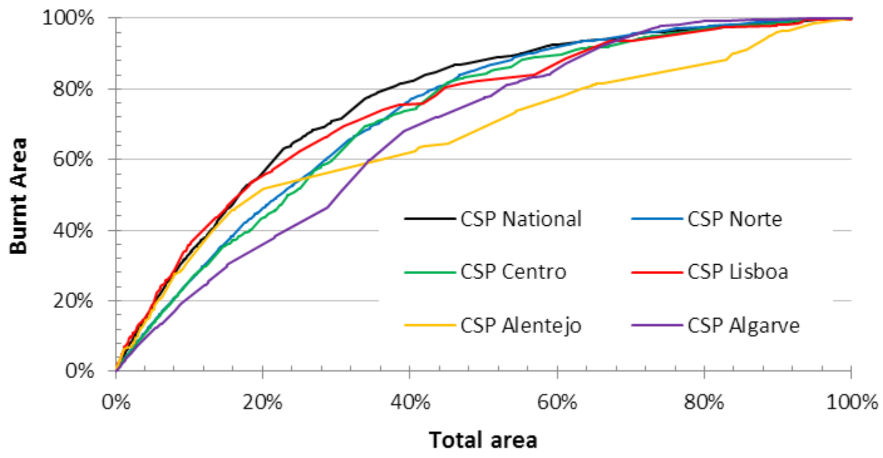


Figure 7.20 – NUTSII CSP prediction curves, compared with the national CSP for the modelling block 1975-1994 and validation block 1995-2013

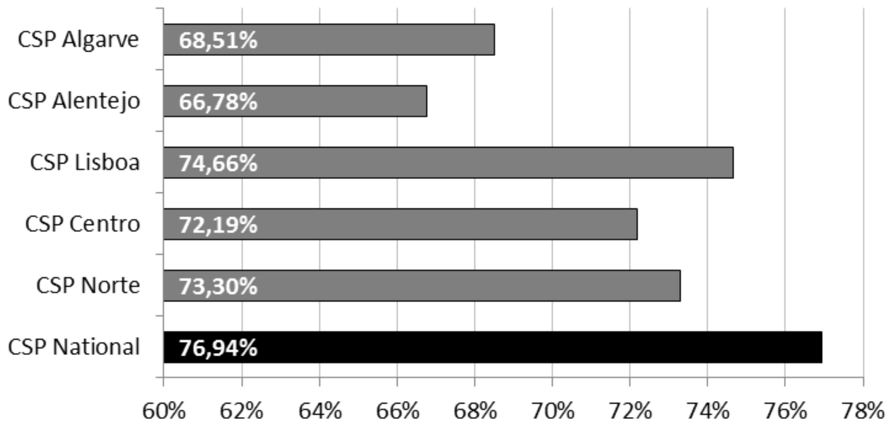


Figure 7.21 – NUTSII CSP prediction areas under the curve, compared with the national CSP for the modelling block 1975-1994 and validation block 1995-2013

The national CSP model is clearly the one with the best prediction rate, which is only to be expected as the better performing areas compensate for those where model performance is worse. It should be noted how NUTSII Lisboa, which is a small NUTSII compared to the others and therefore with a smaller susceptible territory shows the best predictive capacity of all

NUTSII. One possible reason is that having a smaller susceptible territory, when wildfires happen, they happen in, mostly, the same areas as in the past, therefore contributing for such a good predictive capacity when compared to NUTSII larger in area. Inversely, NUTSII Alentejo, which is the largest NUTSII, does not show as good a predictive capacity as the other NUTSII. This NUTSII does not have the same recurrence of wildfires and therefore it is harder for the model to achieve as good a result. Interestingly, though, up until about the 20% most susceptible area, the predictive capacity for NUTSII Alentejo is on par with either the national CSP or the NUTSII Lisboa CSP models, and only after the 20% mark does it lose performance. In NUTSII Alentejo, where there are very susceptible areas, the model is more accurate. Getting away from those more susceptible areas, the model is more of a hit and miss nature.

Making the transition to Weights of Evidence, the WofE-CS model with just landcover (C) and slope (S) show mixed results but not distant from the base CSP model (figures. 7.22; 7.23).

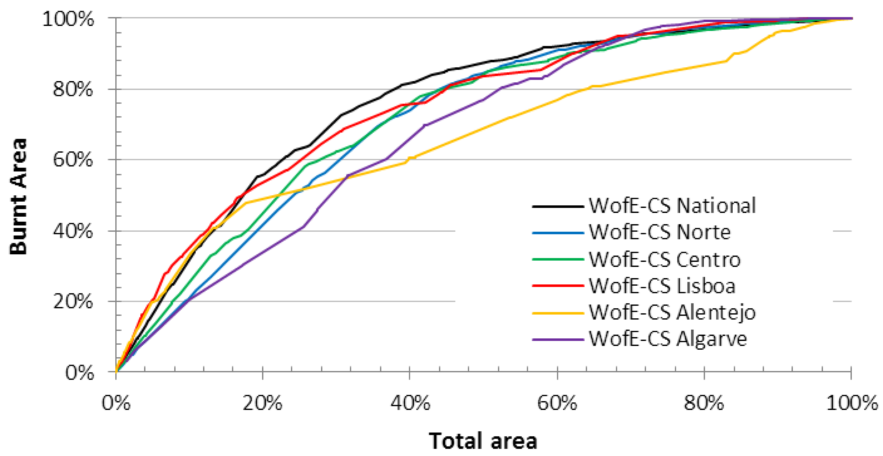


Figure 7.22 – NUTSII WofE-CS prediction curves, compared with the national WofE-CS for the modelling block 1975-1994 and validation block 1995-2013

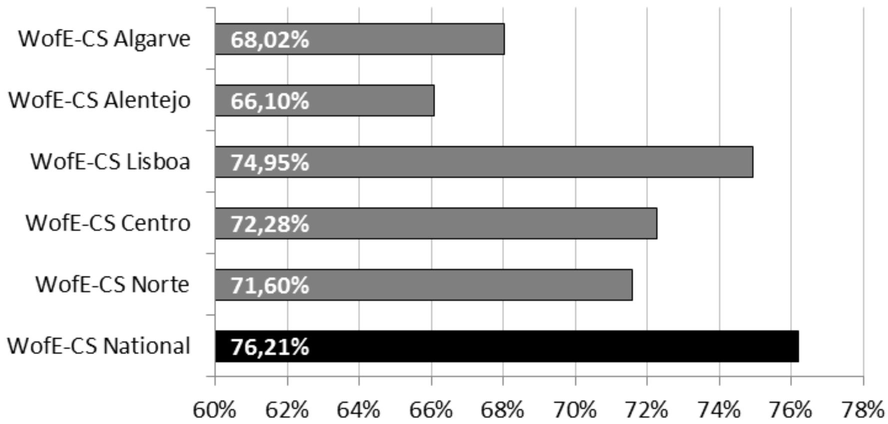


Figure 7.23 – NUTSII WofE-CS prediction areas under the curve, compared with the national WofE-CS for the modelling block 1975-1994 and validation block 1995-2013

NUTSII Lisboa shows a very good predictive result, better than with the base CSP model and the same tendency occurs with the NUTSII Centro, which is the second NUTSII regarding prediction capacity. The least predictive capacity remains in NUTSII Alentejo, which on this model lowers predictive capacity.

Adding elevation (E) to the previous model results in an overall increase in predictive capacity, and with WofE-CSE almost all results are better than with WofE-CS, with the exception of NUTSII Norte, even though the difference is only 0.18% (figures 7.24; 7.25). The NUTSII Lisboa maintains the best predictive rate and the Algarve replace the Alentejo in the last position concerning predictive capacity.

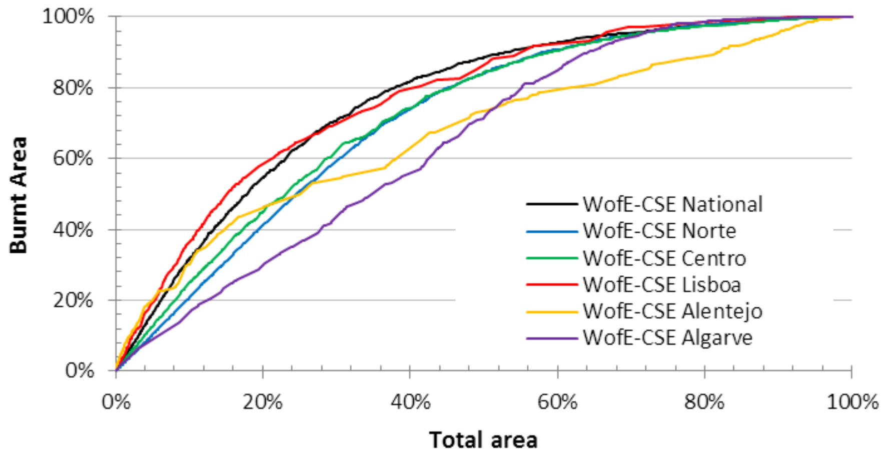


Figure 7.24 – NUTSII WofE-CSE prediction curves, compared with the national WofE-CSE for the modelling block 1975-1994 and validation block 1995-2013

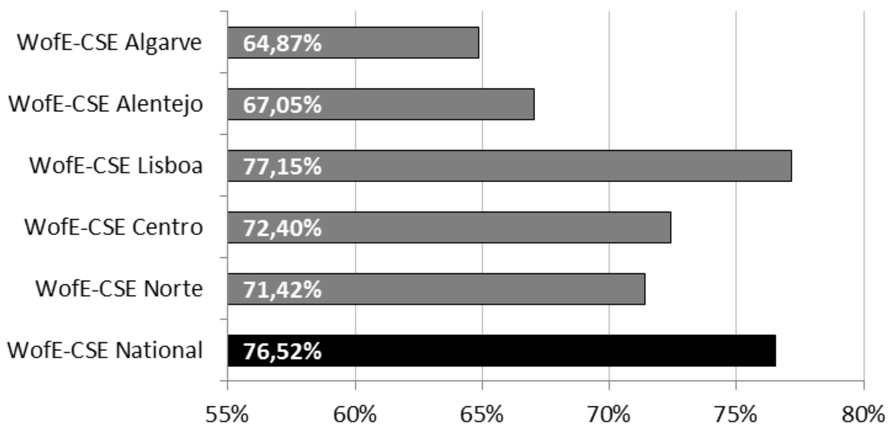


Figure 7.25 – NUTSII WofE-CSE prediction areas under the curve, compared with the national WofE-CSE for the modelling block 1975-1994 and validation block 1995-2013

It has been observed before how aspect (A) does not seem to improve the models. WofE-CSEA, which incorporates aspect as an evidence layer, either maintains predictive capacity, or decreases it, as in NUTSII Algarve, NUTSII Lisboa, NUTSII Centro and even the national WofE-CSEA. Therefore, as previously discussed, aspect, also in regards to predictive capacity, does not bring added value as an evidence layer (figures. 7.26; 7.27).

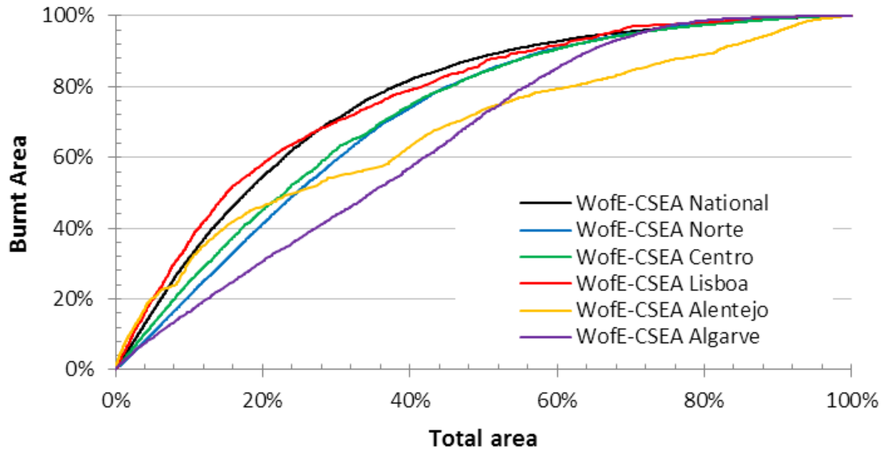


Figure 7.26 – NUTSII WofE-CSEA prediction curves, compared with the national WofE-CSEA for the modelling block 1975-1994 and validation block 1995-2013

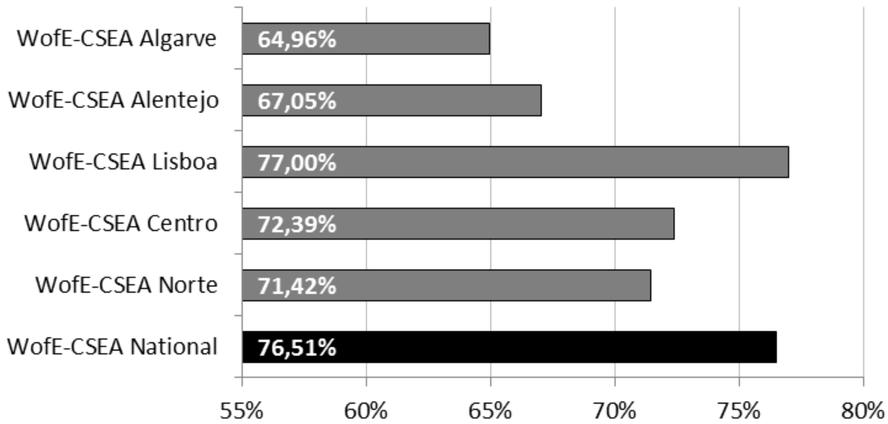


Figure 7.27 – NUTSII WofE-CSEA prediction areas under the curve, compared with the national WofE-CSEA for the modelling block 1975-1994 and validation block 1995-2013

Adding population density of the year 2001 (P01) as an evidence layer, in WofE-CSEP01 (figures. 7.28;7.30) globally increases predictive capacity, except in NUTSII Norte. Relative rankings are unchanged and it is noticeable how NUTSII Lisboa has better results than the national run for the same model, even if by a small margin.

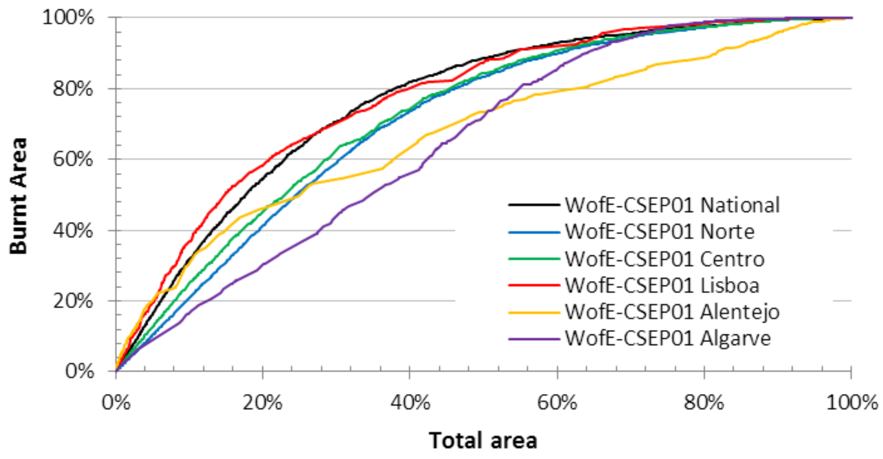


Figure 7.28 – NUTSII WofE-CSEP01 prediction curves, compared with the national WofE-CSEP01 for the modelling block 1975-1994 and validation block 1995-2013

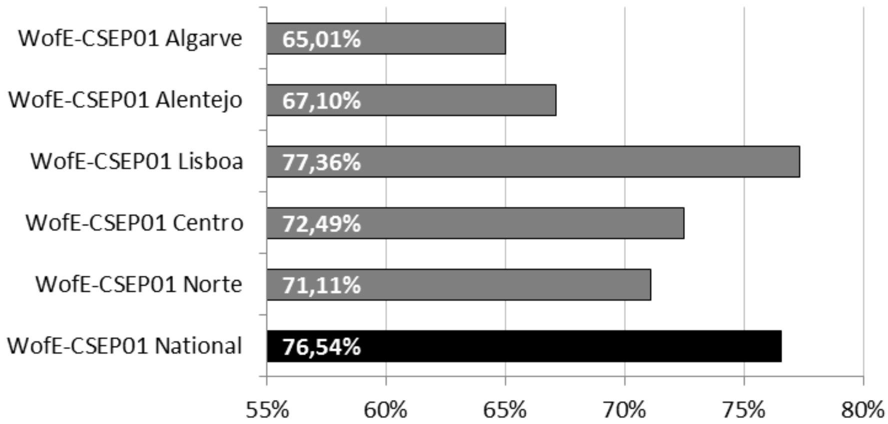


Figure 7.29 – NUTSII WofE-CSEP01 prediction areas under the curve, compared with the national WofE-CSEP01 for the modelling block 1975-1994 and validation block 1995-2013

Updating the information with the Census 2011 and introducing population density for 2011 (P11) as an evidence layer has mixed results, slightly increasing or decreasing predictive capacity, while maintaining relative rankings, and NUTSII Lisboa is now almost 1% ahead of the national WofE-CSEP11 run (figures. 7.30; 7.31)

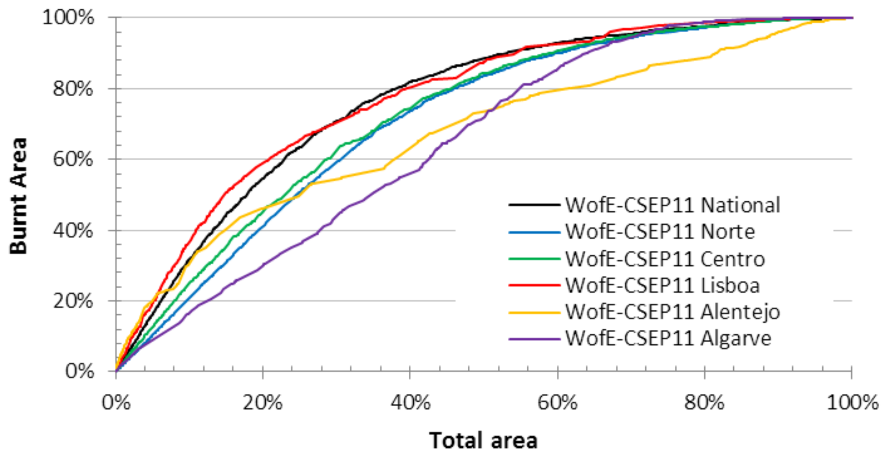


Figure 7.30 – NUTSII WofE-CSEP11 prediction curves, compared with the national WofE-CSEP11 for the modelling block 1975-1994 and validation block 1995-2013

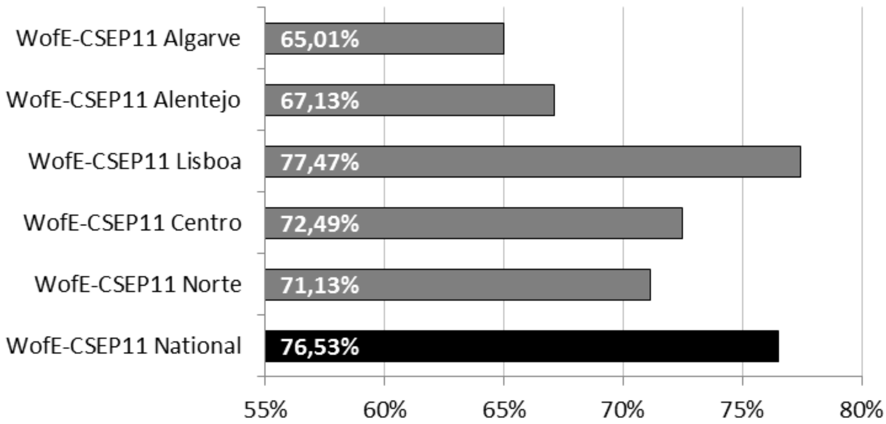


Figure 7.31 – NUTSII WofE-CSEP11 prediction areas under the curve, compared with the national WofE-CSEP11 for the modelling block 1975-1994 and validation block 1995-2013

Using data from the 1991 Census to calculate the population growth ratio between 1991 and 2011 (G), giving origin to the WofE-CSEG model, which has mixed results but it does not change the order in which each NUTSII (or the national model run) ranks (figures. 7.32; 7.33).

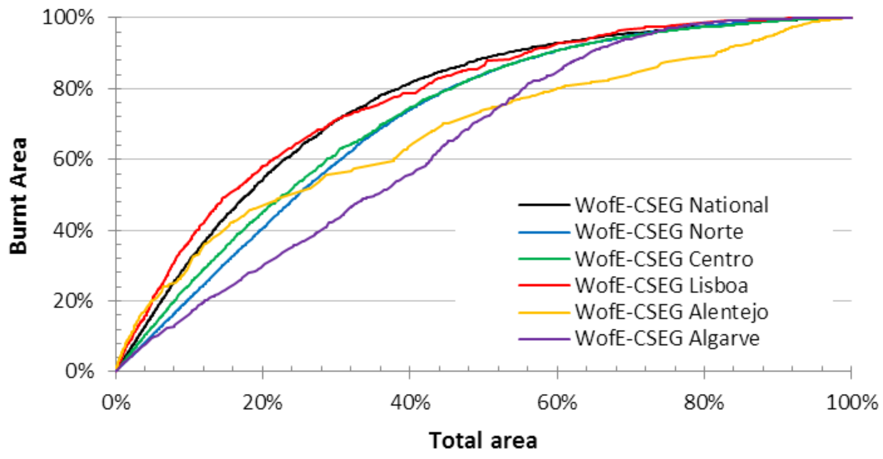


Figure 7.32 – NUTSII WofE-CSEG prediction curves, compared with the national WofE-CSEG for the modelling block 1975-1994 and validation block 1995-2013

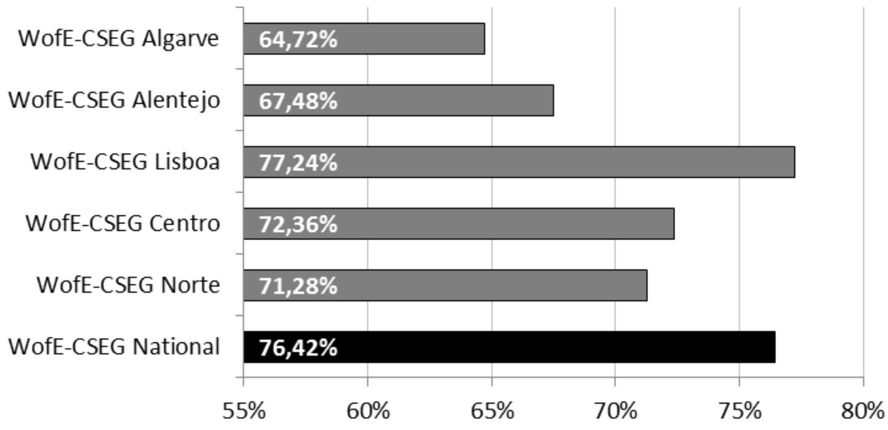


Figure 7.33 – NUTSII WofE-CSEG prediction areas under the curve, compared with the national WofE-CSEG for the modelling block 1975-1994 and validation block 1995-2013

Keeping up with what have been previous results, distance to roads in WofE-CSER maintains very similar results as to predictive capacity. NUTSII Lisboa continues to show the best results while NUTSII Algarve does not benefit that much from this evidence layer in comparison with other NUTSII (figures. 7.34; 7.35).

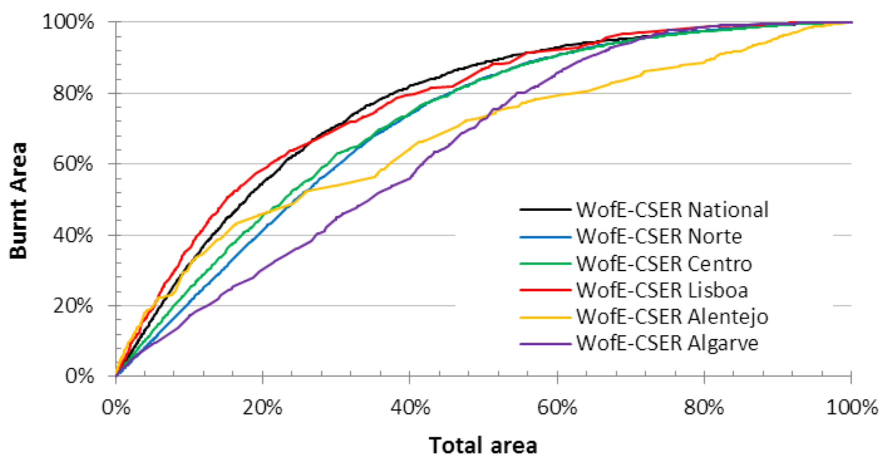


Figure 7.34 – NUTSII WofE-CSER prediction curves, compared with the national WofE-CSER for the modelling block 1975-1994 and validation block 1995-2013

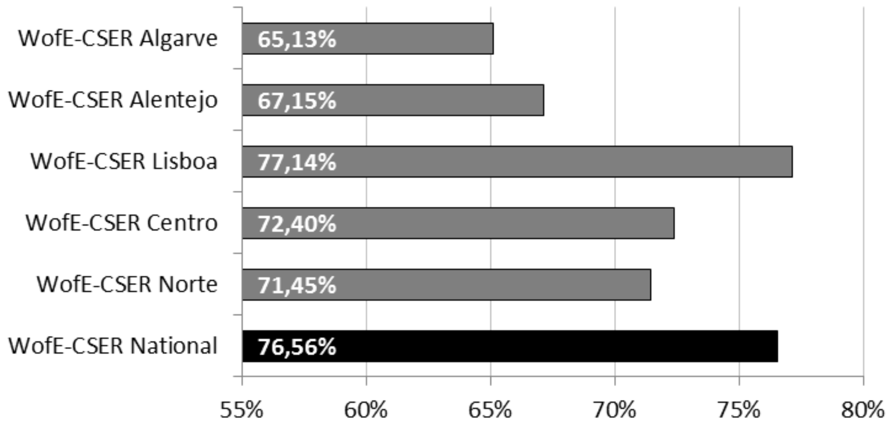


Figure 7.35 – NUTSII WofE-CSER prediction areas under the curve, compared with the national WofE-CSER for the modelling block 1975-1994 and validation block 1995-2013

This has been an exercise of mixed results, where adding evidence layers does not significantly change predictive capacity among NUTSII, which maintain their relative positions as to prediction. Putting all evidence layers together on WofE-CSERG (all as in those chosen in chapter 5) shows, again, results that somewhat increase or decrease depending on the NUTSII (figs. 7.36; 7.37), as table 7.1 shows: NUTSII Norte and NUTSII Algarve decrease prediction with all the layers, whereas NUTSII Centro, Lisboa and Alentejo gain prediction capacity.

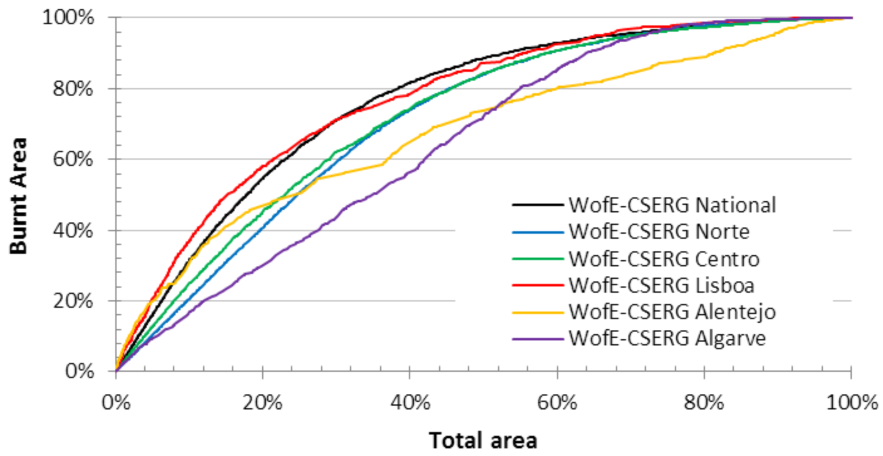


Figure 7.36 – NUTSII WofE-CSERG prediction curves, compared with the national WofE-CSERG for the modelling block 1975-1994 and validation block 1995-2013

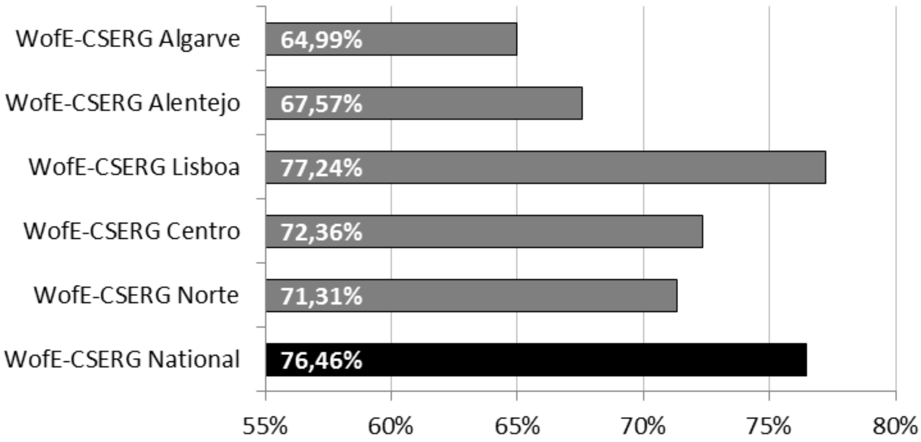


Figure 7.37 – NUTSII WofE-CSERG prediction areas under the curve, compared with the national WofE-CSERG for the modelling block 1975-1994 and validation block 1995-2013

After having presented all models for each NUTSII region, table 7.1 summarizes Areas Under the Prediction Curve, showing that while the CSP model is the best for NUTSII Norte and Algarve, in NUTSII Centro, Lisboa and Alentejo, a Weights of Evidence model produces better results, which is noticeable because such result was never achieved concerning success rates. The best models have driven the choice of susceptibility maps presented ahead.

Table 7.1 – Prediction areas under the curve per NUTSII and model,for the modelling block 1975-1994 and validation block 1995-2013. Higher results in bold. Mainland Portugal presented for reference on row labeled PT. The best models are highlighted in bold. (%)

NUTSII	CSP	WofE							
		CS	CSE	CSEA	CSEP01	CSEP11	CSEG	CSER	CSERG
Norte	**73.30**	71.60	71.42	71.42	71.11	71.13	71.28	71.45	71.31
Centro	72.19	72.28	72.40	72.39	**72.49**	**72.49**	72.36	72.40	72.36
Lisboa	74.66	74.95	77.15	77.00	77.36	**77.47**	77.24	77.14	77.24
Alentejo	66.78	66.10	67.05	67.05	67.10	67.13	67.48	67.15	**67.57**
Algarve	**68.51**	68.02	64.87	64.96	65.01	65.01	64.72	65.13	64.99
PT	**76.94**	76.21	76.52	76.51	76.54	76.53	76.42	76.56	76.46

7.3 Wildfire susceptibility mapping

Since all models were run for isolated NUTSII regions, with their own favourability scores and Weights of Evidence positive weights (W+), it is useful to render the corresponding wildfire susceptibility maps and visually perceive how different they can be. The regional maps were also classified with five quantile classes, so that they can be compared with the national map. Figure 7.38 presents the CSP model for NUTSII Norte and figure 7.39 presents the mainland Portugal CSP map clipped to the same extent.

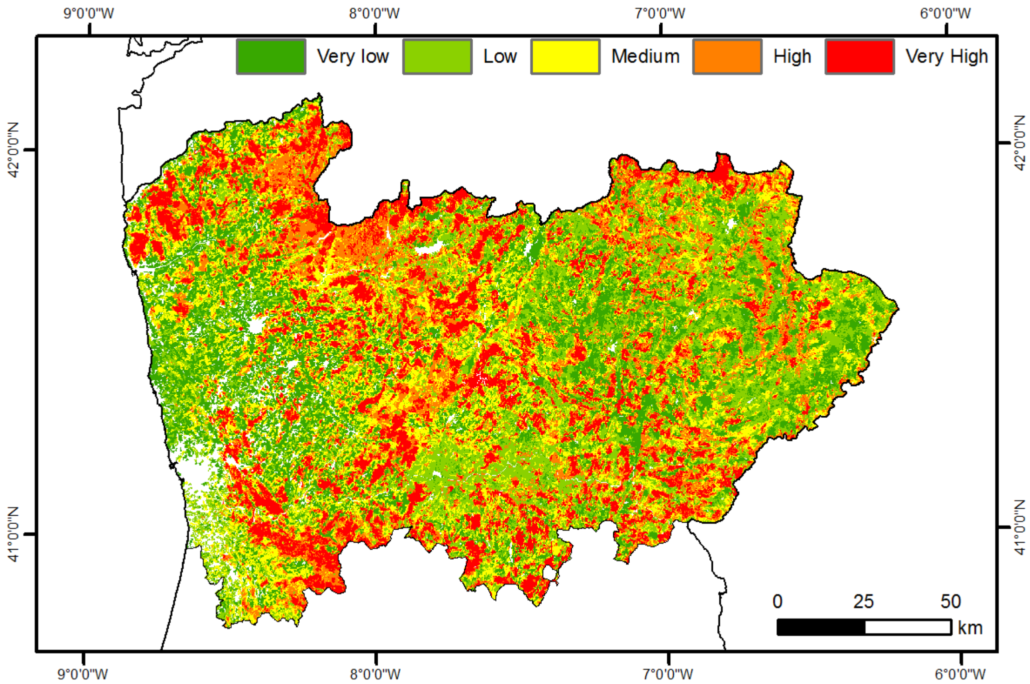


Figure 7.38 – NUTSII Norte Wildfire Susceptibility (CSP Model) for the modelling block 1975-1994 and validation block 1995-2013

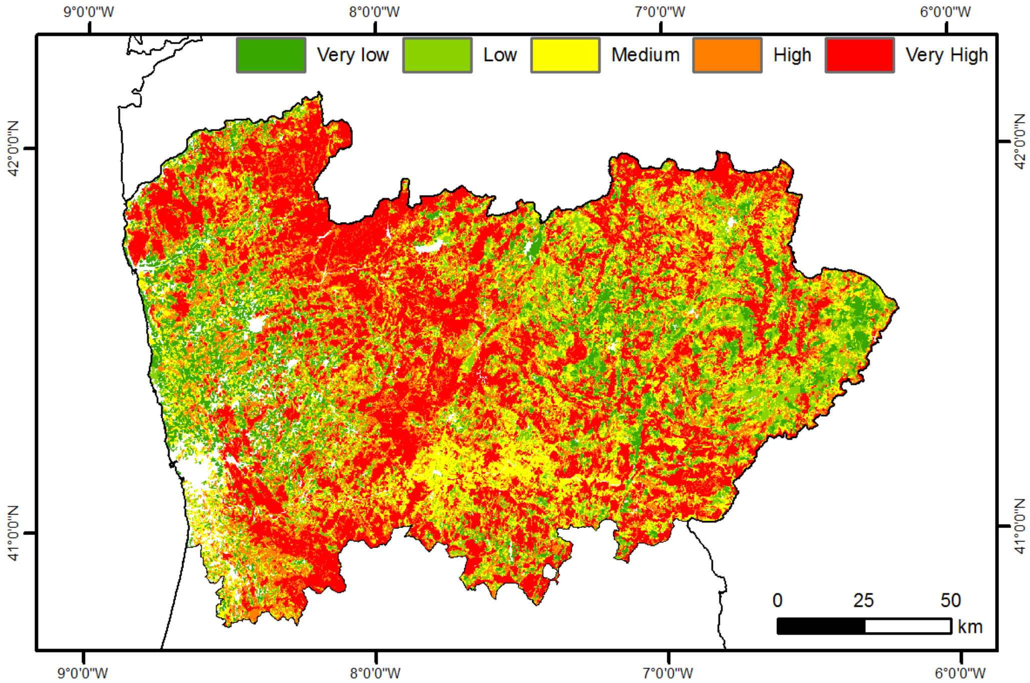


Figure 7.39 – NUTSII Norte Wildfire Susceptibility clipped from the mainland Portugal CSP Model for the modelling block 1975-1994 and validation block 1995-2013

It becomes clear, looking at those figures, that the national CSP map allocates more pixels into the higher wildfire susceptibility classes than the native regional CSP map. Clearly, while the national map highlights the northern mainland Portugal as a very susceptible area in comparison with the rest of the territory, the regional map is highlighting more susceptible areas within the region, being more selective in what it attributes to higher susceptibility classes in comparison to the mainland CSP map. That is a behavior to be expected, an effect of a different scale of analysis and should be noted just as well on the other regions.

One factor does come into play though, which should be addressed with no subterfuge: the classification method. It has been previously mentioned that for comparison all maps are classified with recourse to quintiles. That has been done for comparison sake between all maps, but quintile classification is not necessarily the best suited classification for all wildfire susceptibility maps. When classifying a susceptibility map that has an underlying parabola as a prediction curve, allocating roughly the same number of pixels to each class is adequate. The prediction curve does not have clear breaks that show there is an abrupt increase of decrease in prediction that could otherwise be used as a classification break. More so, in the context of a country, pushing 20% of all pixels into a class might be though of as a conservative and objective classification, but as the scale changes, so might the classification change.

Observing the prediction curves in this section, only the national models have smooth parabolas, as the other prediction curves are not as smooth but rather bumpy with NUTSII Alentejo and Algarve being the better examples of not as suitable prediction curves for quintile classifications.

When using quintiles regardless of how the prediction curve behaves, it is possible that wildfire susceptibility classes receive more pixels than needed, or fewer pixels than in reality are the most susceptible areas. Classifications is, therefore, a factor that cannot be lightly addressed.

Figures 7.40 and 7.41 present the same comparison as before, this time for NUTSII Centro. The same selectivity can be observed in that the mainland WofE-CSEP11 has a more susceptible area inside the extent of NUTSII Centro than the native regional map. Because the prediction curve for NUTSII Centro is also a parabola of discreet breaks, it is possible that the quintile classification does not incur in notable commission or omission errors on the native regional map, but pixel distribution is clearly different and, overall, NUTSII Centro is far more susceptible to wildfires on the mainland map than in the native WofE-CSEP11 susceptibility map, where lower susceptility classes “Very Low” and “Low” have more area allocated to them.

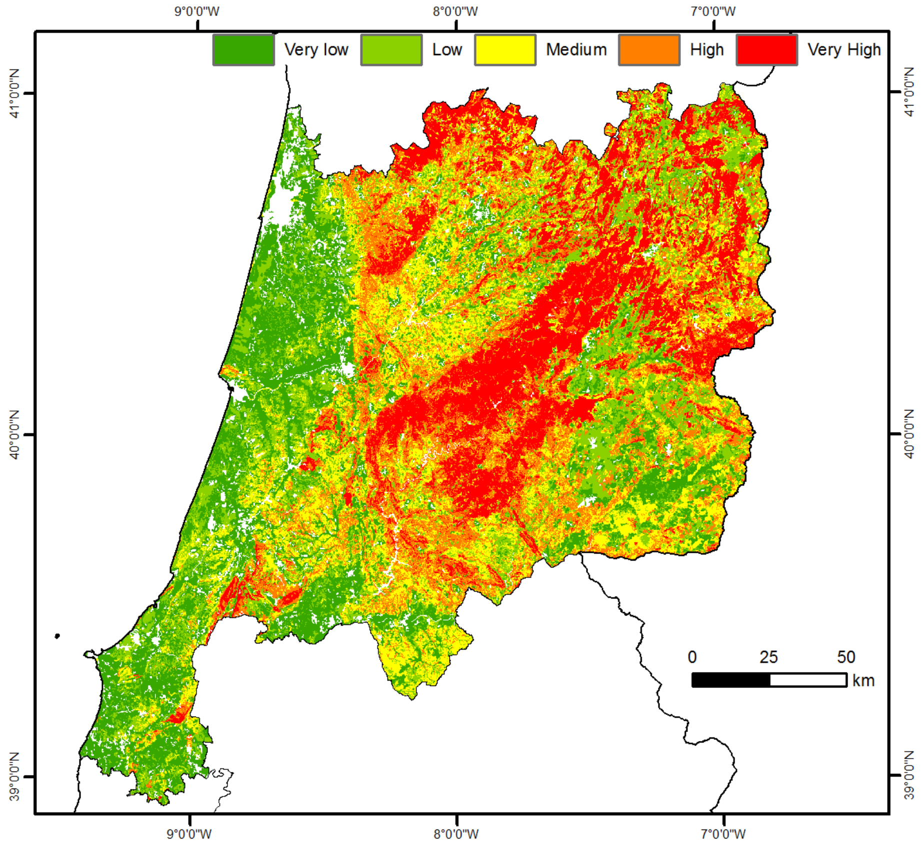


Figure 7.40 – NUTSII Centro Wildfire Susceptibility (WofE-CSEP11 Model) for the modelling block 1975-1994 and validation block 1995-2013

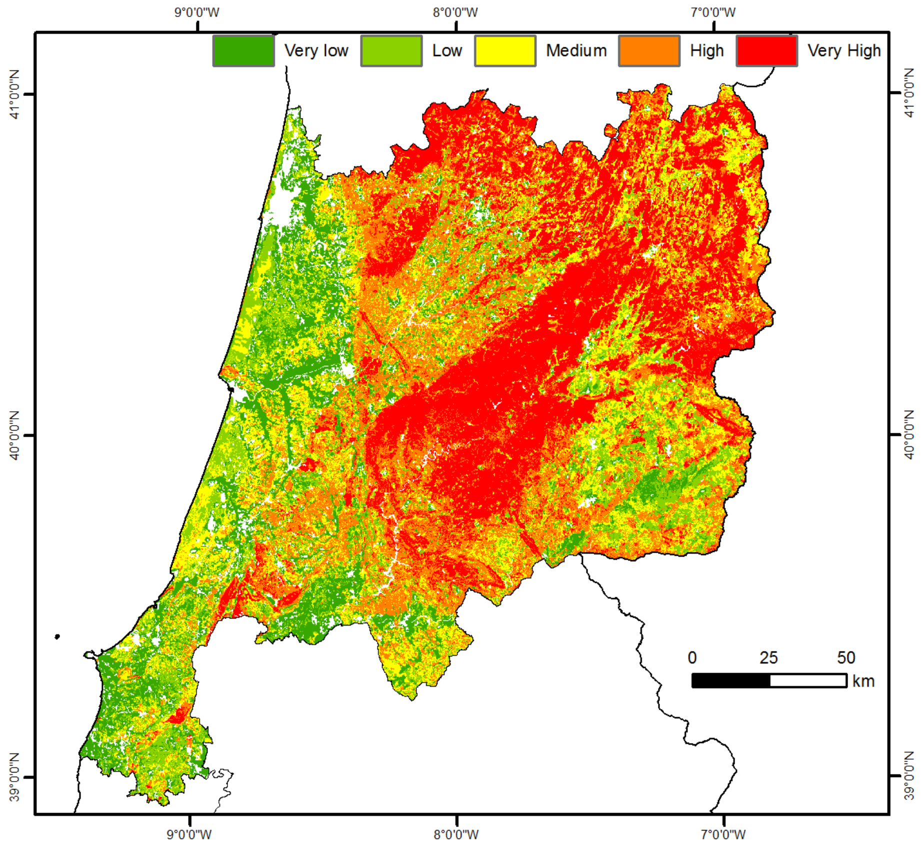


Figure 7.41 – NUTSII Centro Wildfire Susceptibility clipped from the mainland Portugal WofE-CSEP11 Model for the modelling block 1975-1994 and validation block 1995-2013

The differences between the mainland wildfire susceptibility map and the native regional wildfire susceptibility maps (using the best models as already presented on table 7.11) are very clear when looking at the NUTSII region of Lisboa (figs. 7.42; 7.43). In the mainland map, NUTSII Lisboa has few areas classified as very susceptible to wildfires, which means that in the national context, what Lisbon has of susceptible areas is comparatively less susceptible than other areas on mainland, but when susceptibility is mapped only for the extent of NUTSII Lisboa, far more areas are considered very susceptible to wildfires. The effect of scale, certainly combined with the quintile classification, changes perception of what is more or less susceptible.

NUTSII Alentejo is a very different region in regards to wildfire susceptibility wether it is looked upon its own, native, WofE-CSERG model run or the national WofE-CSERG, whereas in the national run, NUTSII Alentejo is a region of less interest and might not raise as much attention as other regions, but when observed within its own confines it does show there are some very susceptible areas (figs. 7.44; 7.45). Wildfire history in mainland Portugal does show that most wildfires happen, indeed, in the northern regions, which, on a whole country extent, does push Alentejo into the lower susceptibility classes, but mapping Alentejo alone shows that should wildfires occur in the region, the potential for wildfires does exist, with long extents of high and very high susceptibility areas.

Interestingly, NUTSII Algarve does not have as many changes in its native CSP susceptibility map as other regions (figs. 7.46; 7.47). Differences can be perceived but they are nowhere near as NUTSII Alentejo, for example, when using the quintile classification. This could imply that the regional distribution of wildfire susceptible areas in the confines of NUTSII Algarve is somewhat similar to that of the whole mainland Portugal, that is, NUTSII Algarve might have a relative distribution of susceptible classes similar to that of all mainland.

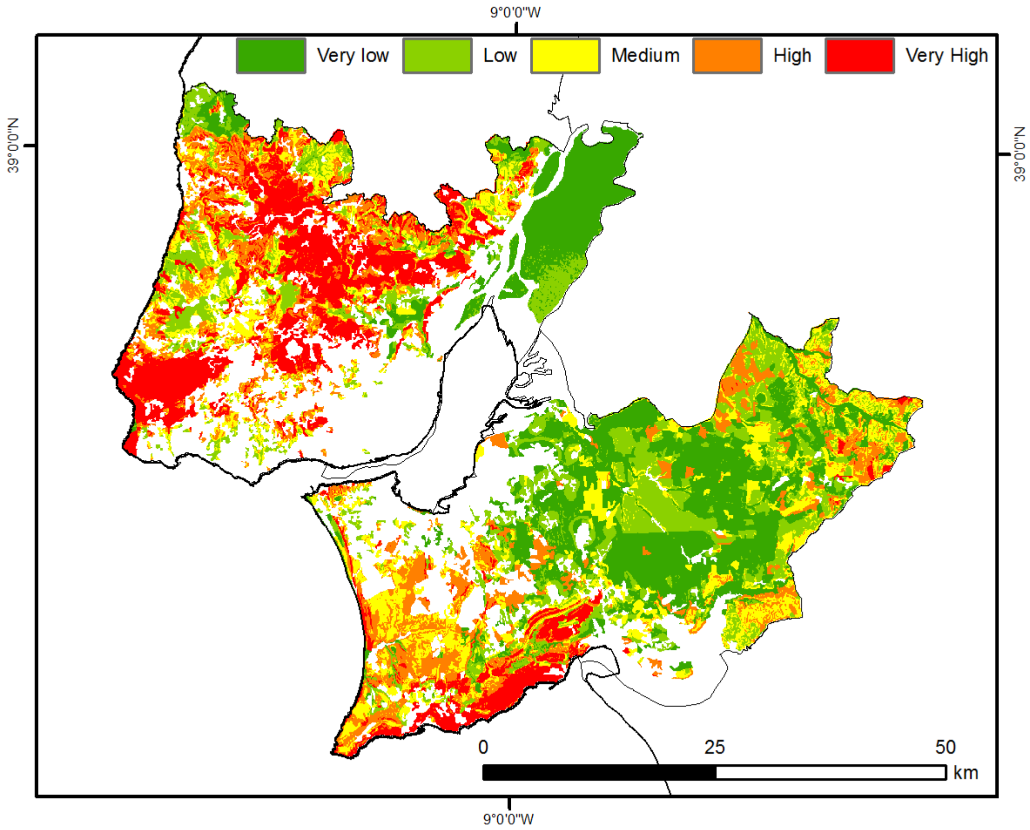


Figure 7.42 – NUTSII Lisboa Wildfire Susceptibility (WofE-CSEP11 Model) for the modelling block 1975-1994 and validation block 1995-2013

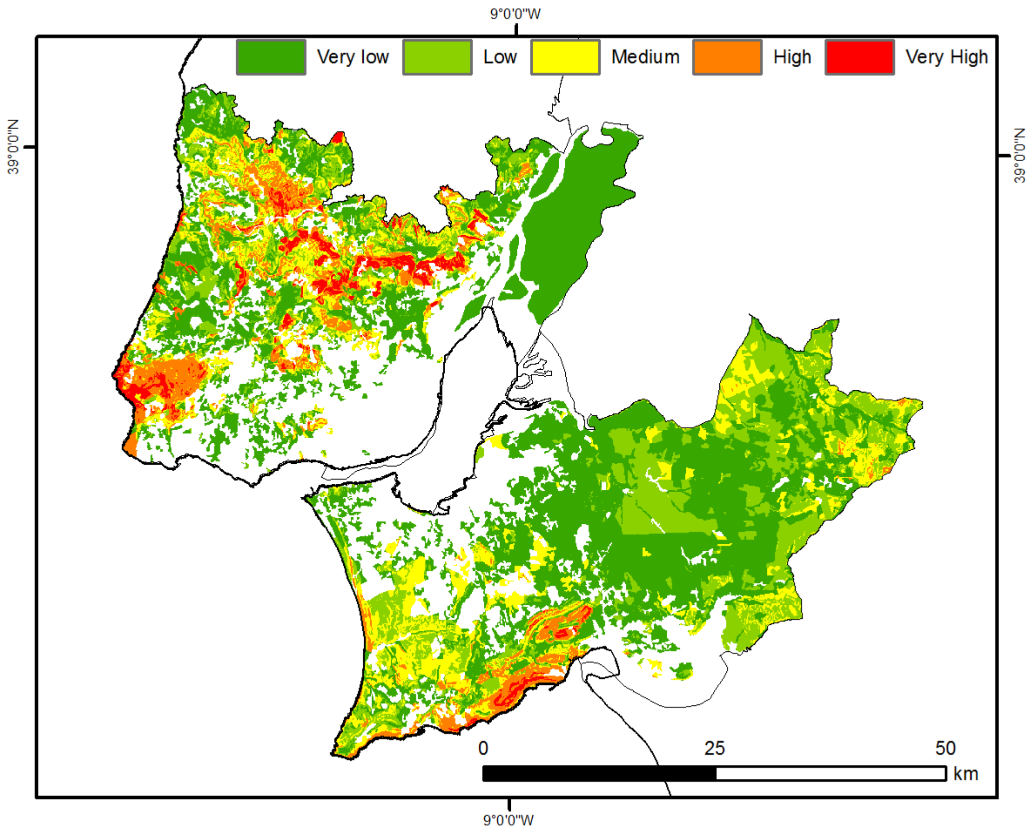


Figure 7.43 – NUTSII Lisboa Wildfire Susceptibility clipped from the mainland Portugal WofE-CSEP11 Model for the modelling block 1975-1994 and validation block 1995-2013

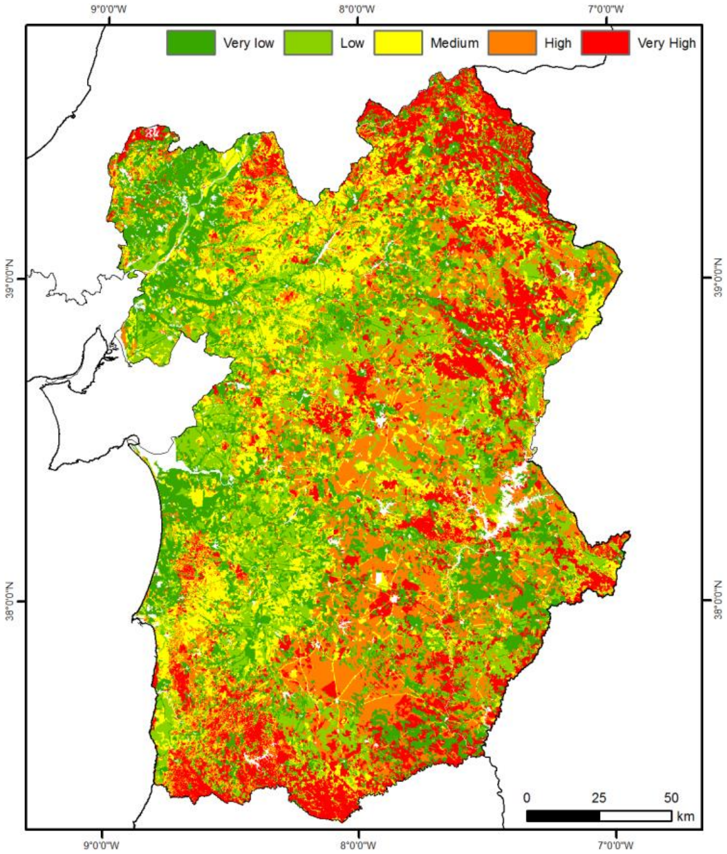


Figure 7.44 – NUTSII Alentejo Wildfire Susceptibility (WofE-CSERG Model) for the modelling block 1975-1994 and validation block 1995-2013

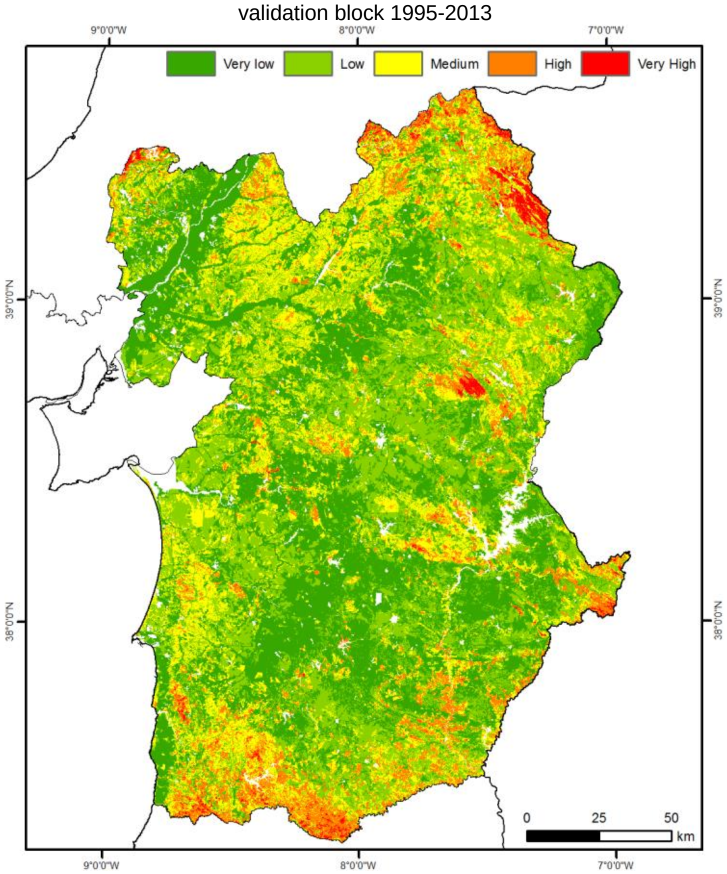


Figure 7.45 – NUTSII Alentejo Wildfire Susceptibility clipped from the mainland Portugal WofE-CSERG Model for the modelling block 1975-1994 and validation block 1995-2013

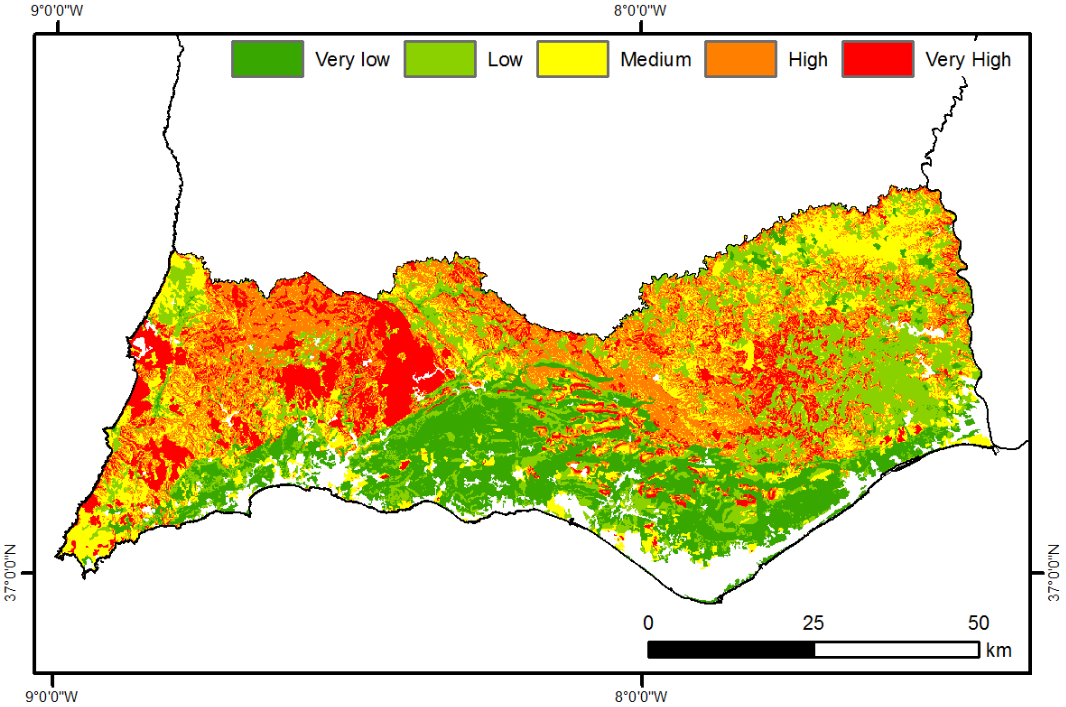


Figure 7.46 – NUTSII Algarve Wildfire Susceptibility (CSP Model) for the modelling block 1975-1994 and validation block 1995-2013

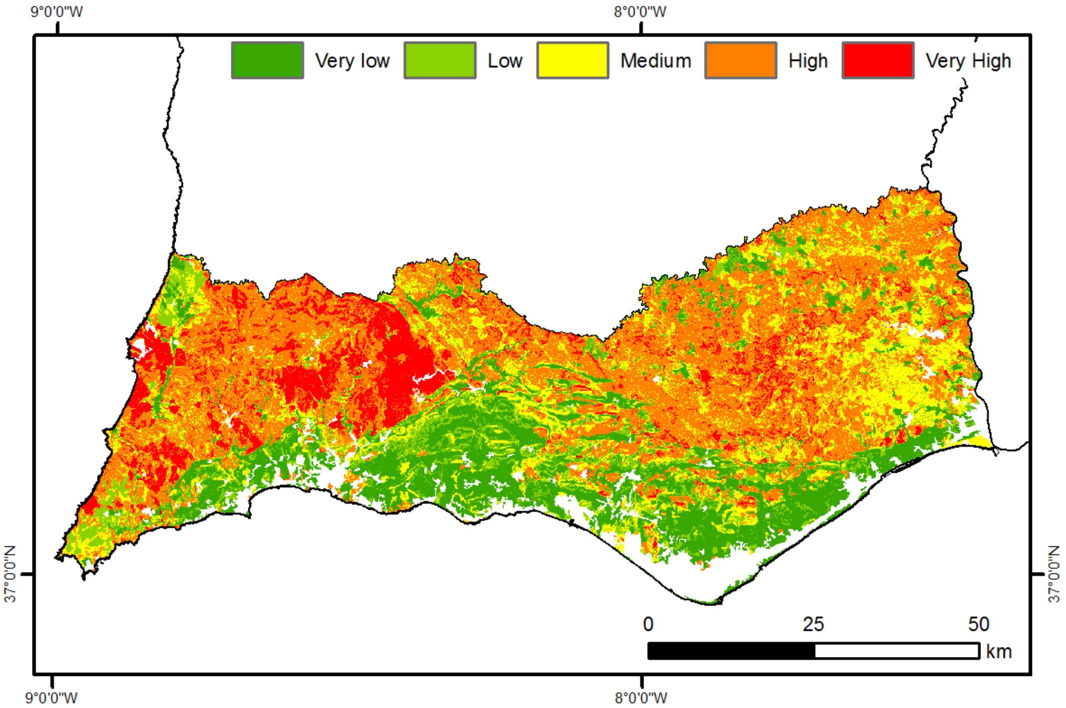


Figure 7.47 – NUTSII Algarve Wildfire Susceptibility clipped from the mainland Portugal CSP Model for the modelling block 1975-1994 and validation block 1995-2013

7.4 Regional differences regarding evidence layers

In the previous sections, model success and prediction was presented, and it became clear that different regions have different responses to the same models. It is quite possible that the predisposing factors integrated into the models do not influence all regions in the same fashion. To determine how different themes or evidence layers might be influencing different regions, this section addresses how each evidence layer behaves among NUTSII.

In tables 7.2 and 7.3, favourability scores for land cover and slope, respectively, are presented. These are favourability scores used only on the CSP model, as WofE models have their own positive weights (W+), shown on tables 7.4 and 7.5.

Table 7.2 – Favourability scores for the CORINE Land Cover 2006 layer on the CSP model, per NUTSII, for the modelling block 1975-1994 and validation block 1995-2013. Mainland Portugal presented for reference on column labeled PT.

ClassID	NUTSII					PT
	Norte	Centro	Lisboa	Alentejo	Algarve	
211	50	52	46	49	95	50
212	6	7	8	39	95	28
213	0	11	2	7	0	8
221	44	14	2	24	2	27
222	78	34	0	18	4	35
223	47	26	0	7	0	19
231	51	109	15	57	17	57
241	16	33	0	8	3	17
242	26	24	9	7	8	19
243	94	100	44	15	14	73
244	216	26	4	22	14	24
311	317	268	40	37	90	107
312	195	200	89	17	84	177
313	152	237	71	33	65	160
321	590	611	160	98	129	557
322	527	699	313	39	0	582
323	633	416	111	89	140	212
324	416	429	161	60	127	330
331	0	65	3	0	8	24
332	507	623	0	0	0	514
333	602	555	0	996	0	586
334	481	522	0	66	0	429

Looking at the table above, it can be seen how natural grasslands are always among the three topmost favourable land cover classes, which comes in line with one of the most determined causes for Portuguese wildfires: pasture renewal. Schlerophyllous vegetation is a very favourable land cover class in NUTSII Algarve and Alentejo, as these are dry regions, but it could come as a surprise that this is also a very favourable class in NUTSII Norte. In reality, this class is present mainly in the northeast of the NUTSII Norte region, and due to the nature of these favourability scores, if in the region these units have been burnt a lot, a high favourability score is to be expected. In NUTSII Norte, the three most favourable land cover classes are those of schlerophyllous vegetation, sparsely vegetated areas and natural grasslands. Following south, in NUTSII Centro, moors and heathland, bare rocks and natural grasslands account for the most favorable scores. NUTSII Lisbon is nearly identical, but bare rocks are replaced by transitional woodland-shrubs. In NUTSII Alentejo, sparsely vegetated areas, natural grasslands and scherophyllous vegetation take the lead, almost like NUTSII Algarve, where sparsely vegetated areas give way to transitional woodland-shrubs.

Table 7.3 – Favourability scores for the Slope layer on the CSP model, per NUTSII, for the modelling block 1975-1994 and validation block 1995-2013. Mainland Portugal presented for reference on column labeled PT.

Class	NUTSII					PT
	Norte	Centro	Lisboa	Alentejo	Algarve	
0 - 2	79	86	21	32	31	47
2 - 5	126	154	43	33	56	89
5 - 10	217	272	77	46	89	194
10 - 15	309	413	121	55	107	311
15 - 20	354	509	141	83	119	385
> 20	366	573	114	113	101	430

When considering slope, three out of five regions favour higher slopes as predisposing factor that promote wildfire. NUTSII Norte, Centro and Alentejo have their most wildfire favourable terrain units in slopes of 20 or more degrees, whereas NUTSII Lisboa and Algarve have the class of 15-20 degrees as more favourable. Nevertheless, the top three classes are always those above 10 degrees, showing that, generally, the steeper the slope, the more fire prone the terrain is.

The tables for positive weights (W+) are more informative than those of the CSP model in that they not only inform about how the presence of a variable favours the phenomenon, but also how that same presence hinders the occurrence.

Positive weights confirm the findings of the CSP model in that the land cover classes whose presence better serves ignition are exactly those with CSP's better favourability scores, but there is added information, showing that some land cover classes do not favour fire ignition and spreading. In NUTSII Norte, beaches, dunes and sands, as well as permanently irrigated land and annual crops associated with permanent crops are land cover classes that hinder wildfire occurrence. NUTSII Centro, apart from permanently irrigated land, introduces the novelty of rice fields and vineyards as land cover classes that in that region do not favour wildfires where present. In the region of Lisbon, vineyards, rice fields, beaches, dunes and sands are also classes whose presence hinders fire. NUTSII Alentejo has a tradition of olive groves, possibily the reason for that land cover class, along with rice fields and complex cultivation patterns having such a negative impact on the occurrence of wildfires. Lastly, NUTSII Algarve joins areas occupied by fruit trees and berry plantations to vineyards and annual and permanent crops to those that prevent wildfires from easily igniting (table 7.4).

Table 7.4 – Weights of Evidence positive weights (W+) for the CORINE Land Cover 2006 evidence layer, per NUTSII, for the modelling block 1975-1994 and validation block 1995-2013. Mainland Portugal presented for reference on column labeled PT.

ClassID	NUTSII					PT
	Norte	Centro	Lisboa	Alentejo	Algarve	
211	-1781	-1781	-140	339	278	-1234
212	-3943	-3892	-1906	100	279	-1835
213	0	-3350	-3346	-1615	0	-3146
221	-1913	-3159	-3468	-410	-3489	-1888
222	-1296	-2223	0	-688	-2970	-1606
223	-1828	-2509	0	-1614	0	-2221
231	-1760	-980	-1314	496	-1550	-1096
241	-2958	-2261	0	-1477	-3308	-2319
242	-2458	-2593	-1813	-1629	-2294	-2226
243	-1090	-1071	-172	-873	-1712	-828
244	-114	-2505	-2726	-480	-1714	-2003
311	405	122	-268	49	217	-410
312	-248	-259	575	-748	134	177
313	-547	-42	335	-72	-134	59
321	1536	1578	1245	1082	615	1944
322	1282	1965	2117	108	0	2045
323	1719	787	821	974	711	404
324	834	841	1251	554	598	1007
331	-6429	-1539	-2849	0	-2347	-1976
332	1202	1627	0	0	0	1770
333	1585	1345	0	8803	0	2063
334	1097	1212	0	648	0	1429

Positive weights (W+) for Slope are also in accordance with favourability scores of the CSP model, and looking at the classes that do not favour wildfire ignition and spreading, the preference for steeper areas is very clear in that less steep classes such as almost flat areas or of decreased slope present themselves as areas where wildfires do not have good conditions for occurring (table 7.5).

Table 7.5 – Weights of Evidence positive weights (W+) for the Slope evidence layer, per NUTSII, for the modelling block 1975-1994 and validation block 1995-2013. Mainland Portugal presented for reference on column labeled PT.

Class	NUTSII					PT
	Norte	Centro	Lisboa	Alentejo	Algarve	
0 - 2	-1224	-1187	-751	-95	-865	-1253
2 - 5	-704	-532	0	-44	-233	-565
5 - 10	-53	187	621	279	257	339
10 - 15	426	822	1121	483	467	968
15 - 20	628	1209	1292	915	587	1295
> 20	682	1466	1053	1265	395	1482

Since not all regions reach the same altitudes, the most wildfire prone elevation classes are not the same among regions, and if in NUTSII Norte there are good conditions for wildfires in elevations from 1201 to 1600 meters, NUTSII Centro has better conditions in lower elevations, from 901 to 1200 meters, even though elevation goes higher in NUTSII Centro than in NUTSII Norte. However, land cover at high elevations is not as fire prone as in intermediate elevations. Looking at table 7.6 it can be said that as far as regions go in their maximum elevation, a sweet spot for wildfires exists above 600 meters and below 1600 meters, and also that lower elevations correspond to areas that hinder wildfire occurrence.

Table 7.6 – Weights of Evidence positive weights (W+) for the Elevation evidence layer, per NUTSII, for the modelling block 1975-1994 and validation block 1995-2013. Mainland Portugal presented for reference on column labeled PT.

Class (m)	NUTSII					PT
	Norte	Centro	Lisboa	Alentejo	Algarve	
0	-4715	-4147	-4680	-4925	-3186	-4402
1 - 100	-1806	-1761	-625	-368	-124	-1481
101 - 200	-761	-643	203	-32	529	-826
201 - 300	-280	-269	1448	84	-189	-488
301 - 400	-42	-170	2368	475	-1127	82
401 - 500	145	115	2687	396	-679	545
501 - 600	22	650	0	-39	-465	863
601 - 700	72	788	0	1027	238	932
701 - 800	22	825	0	1652	1607	938
801 - 900	376	980	0	1004	3024	1216
901 - 1000	661	1744	0	0	0	1581
1001 - 1100	1101	1778	0	0	0	1851
1101 - 1200	1480	1620	0	0	0	2070
1201 - 1300	1824	1427	0	0	0	2243
1301 - 1400	1766	674	0	0	0	1750
1401 - 1500	1484	-4	0	0	0	831
1501 - 1600	2180	-24	0	0	0	591
1601 - 1700	0	-658	0	0	0	-68
1701 - 1800	0	-577	0	0	0	13
1801 - 1900	0	-2838	0	0	0	-2248
1901 - 2000	0	0	0	0	0	0

What was written before, regarding slope, finds confirmation in table 7.7, where it can be seen that the presence of flat areas in the Aspect evidence layers does not promote wildfire occurrence. There is a fair amount of variability among regions without a clear preference of any given orientation from region to region, and the very negative W+ for this evidence layer is perhaps the most notable thing to retain from this table, which confirms the very low relevance of this theme in what concerns wildfire occurrence in mainland Portugal.

Table 7.7 – Weights of Evidence positive weights (W+) for the Aspect evidence layer, per NUTSII, for the modelling block 1975-1994 and validation block 1995-2013. Mainland Portugal presented for reference on column labeled PT.

Class (Orientation)	NUTSII					PT
	Norte	Centro	Lisboa	Alentejo	Algarve	
Flat	-3525	-2876	-4202	-1535	-2494	-3145
N	-28	-85	-154	12	-290	-95
NE	10	-107	-155	46	-144	-108
E	4	-8	31	34	82	27
SE	-41	38	240	28	19	61
S	-46	6	299	-32	-152	-25
SW	33	30	214	-14	105	-6
W	65	65	-29	-12	310	86
NW	2	43	-123	-21	33	62

Tables 7.8 and 7.9 allow to verify how population density affects wildfire occurrence. Even though 10 years have passed between the two Census these tables relate to, the findings are mostly the same. In all regions, where there are more people per area unit, wildfires have less favourable conditions to spread, most likely because of a better detection or swift suppression. Inversely, the existence of less populated areas favours wildfire occurrence.

Table 7.8 – Weights of Evidence positive weights (W+) for the Population Density (2001 Census) evidence layer, per NUTSII, for the modelling block 1975-1994 and validation block 1995-2013. Mainland Portugal presented for reference on column labeled PT.

Class (Residents/ Km^2)	NUTSII					PT
	Norte	Centro	Lisboa	Alentejo	Algarve	
Up to 250	185	99	100	18	57	83
251 to 1500	-1867	-2980	63	-1804	-2804	-1779
>= 1501	-3412	-3197	-912	-2914	0	-2699

Table 7.9 – Weights of Evidence positive weights (W+) for the Population Density (2011 Census) evidence layer, per NUTSII, for the modelling block 1975-1994 and validation block 1995-2013. Mainland Portugal presented for reference on column labeled PT.

Class (Residents/ Km^2)	NUTSII					PT
	Norte	Centro	Lisboa	Alentejo	Algarve	
Up to 250	176	94	64	17	64	81
251 to 1500	-1918	-3016	228	-1892	-2990	-1796
>= 1501	-3190	-3273	-862	-2918	0	-2605

Since data from the 1991 Census is also available, computing population growth ratio from 1991 through 2011 complements the information given before, as table 7.10 shows that gaining population hinders wildfire occurrence, but not in all regions. In NUTSII Norte and Centro, as population grows, wildfire favourable conditions diminish, which does not find a comparable situation in NUTSII Alentejo and mainly NUTSII Algarve where growth ratio does not seem to impact wildfire occurrence in the same way. In fact, in Alentejo and Algarve, having more population seems to increase wildfire occurrence.

Table 7.10 – Weights of Evidence positive weights (W+) for the Population Growth Ratio (1991-2011) evidence layer, per NUTSII, for the modelling block 1975-1994 and validation block 1995-2013. Mainland Portugal presented for reference on column labeled PT.

Class (Growth Rate)	NUTSII					PT
	Norte	Centro	Lisboa	Alentejo	Algarve	
-100 - -50%	-147	-2	-299	-34	-119	-188
-49 - 0%	197	146	413	155	-61	419
1 - 50%	-535	-413	-428	164	953	-245
> 50%	-251	-773	-189	59	79	-371

As stated in chapter 5, roads offer two distinct impacts on the occurrence of wildfires. While they can be a deterrent to wildfire spreading in that they allow suppression resources to get closer to fire and also allow for fuel discontinuities or faster detection, they also allow ill intended people to reach combustible areas. In any case, what table 7.11 shows is that the presence of areas near roads are not favorable to wildfire occurrence, whereas more distant areas show some favourability towards wildfires, this being true for all regions.

Table 7.11 – Weights of Evidence positive weights (W+) for the Distance to Roads evidence layer, per NUTSII, for the modelling block 1975-1994 and validation block 1995-2013. Mainland Portugal presented for reference on column labeled PT.

Class (Distance (m))	NUTSII					PT
	Norte	Centro	Lisboa	Alentejo	Algarve	
Up to 80	-1220	-758	-365	-406	-981	-728
81 to 160	-1049	-664	-142	-293	-795	-614
More than 160	91	58	38	19	48	48

Having run a series of models on Portuguese mainland NUTSII regions, it becomes clear that some NUTSII have better results than others, and even, on occasion, better than the national model run. Running a model for the entire mainland dilutes regional differences, either by commission or omission, hiding regional peculiarities, that table 7.12 summarizes below.

To assess regional differences among NUTSII, positive weights (W+) from the Weights of Evidence method higher than zero were summed together, for each evidence layer, and then divided by the number of classes inside that evidence layer that has higher than zero W+. This goes to demonstrate how far an evidence layer can actually be relevant to the occurrence of wildfires in a NUTSII. The reason for conducting this exercise with only W+ and not with the scores from the base CSP model is simple: the original data from the C and S evidence layers, the only common layers between the CSP model and the Weights of Evidence (WofE) models, is the same. Since it was important to run through all evidence layers, it was deemed unuseful to mix values for C and S evidence layers from different methods. Since WofE has the most evidence layers, only W+ were used. In addition, even though the base CSP model has good results, WofE has been proven as a very robust method and as such, using W+ to differentiate evidence layers can be considered adequate.

Table 7.12 – Summed Weights of Evidence positive Weights (W+) per evidence layer and NUTSII, for the modelling block 1975-1994 and validation block 1995-2013

Evidence Layers	NUTSII Norte	Centro	Lisboa	Alentejo	Algarve	Drives	Baseline (mainland Portugal)
C	1208	1185	1057	1315	405	– Algarve; + Alentejo	1211
S	577	921	1022	736	427	– Algarve; + Lisboa	1021
E	928	1060	1677	773	1350	– Alentejo; + Lisboa	1108
A	23	36	196	30	110	– Norte; + Lisboa	59
P01	185	99	82	18	57	– Alentejo; + Norte	83
P11	176	94	146	17	64	– Alentejo; + Norte	81
G	197	146	413	126	516	– Alentejo; + Algarve	419
R	91	58	38	19	48	– Alentejo; + Norte	48
Driven by	+ C; – A	+ C; – A	+ E; – R	+C; – P11	+ E; – R		

Using positive weights, from the Weights of Evidence method, demonstrates how different evidence layers drive model results. Summing positive, positive weights (W+), for all variables and normalizing by the number or classes inside an evidence layer in any given region with a positive value, allows to, by comparison, determine for one what evidence layer drives results the most in that region and, secondly, for a given evidence layer, which region is most and least driven by that evidence layer. Land cover (C) is undoubtedly an important evidence layer, as there cannot be wildfires where there is no fuel, and it shows in NUTSII Norte, Centro and Alentejo. In NUTSII Lisboa and Algarve, Elevation (E) takes the lead maybe because of different reasons. The NUTSII Lisbon has a very high number of firefighters and the easier way for wildfires to get larger and progress is for them to ignite on higher ground where firefighters usually have more difficulties in suppressing fire. In the Algarve there is a noticeable difference between the flatter landscape near the coastline and the inland hills where elevation is higher and wildfires usually ignite inland, farther away from the densely populated areas of the coastline where most of firefighters are based.

Layer differences, however, do not necessarily mean that evidence layers exhibit very noticeable comparable disparities. In table 7.13, evidence layers are ordered from higher to lower W+, taking into account what was presented earlier in table 7.1. It can be observed that as true as it is that evidence layers affect regions differently, their order remains reasonably unchanged. The four topmost evidence layers are always C, E, S and G, and what changes is the order in which they come when ranked. Regional peculiarities do not change the fact that wildfires need fuel to ignite and progress (C) and that after an ignition has taken place, elevation (E) and slope (S) have an important role in progression. The relevance of population growth ratio (G) is not as direct and an explanation might be found in that gaining or losing population might affect not only detection time but also suppression efforts due to firefighters availability.

Table 7.13 – Compared rankings (higher to lower) of evidence layer relevance, per NUTSII region, for the modelling block 1975-1994 and validation block 1995-2013. Mainland Portugal presented for reference.

NUTS II Regions	1st	2nd	3rd	4th	5th	6th	7th	8th
Mainland Portugal	*C*	*E*	*S*	*G*	*P01*	*P11*	*A*	*R*
Norte	C	E	S	G	P01	P11	R	A
Centro	C	E	S	G	P01	P11	R	A
Lisboa	E	C	S	G	A	P11	P01	R
Alentejo	C	E	S	G	A	R	P01	P11
Algarve	E	G	S	C	A	P11	P01	R

The point in this section is that different regions, NUTSII in this study, do not respond in the same way to the same evidence layers. Their physical characteristics and societal aspects will condition how evidence layers discriminate, either positively or negatively, their relevance on the occurrence of a given phenomenon. Therefore, as the scale grows and analysis get local, care must be taken to properly account for the right evidence layers, even though certain evidence layers will always be relevant as they favour ignition and fire spreading.

7.5 Closing thoughts on regional susceptibility assessment

In regards to success rates, no Weights of Evidence model exceeds the base CSP model, which is of no surprise given that the base CSP incorporates burnt areas twice, therefore Weights of Evidence models are expected to present a worse model fit. As to regional success, Weights of Evidence always presents the best success rate in NUTSII Lisboa, even surpassing that of the national run. The evidence layers for NUTSII Lisboa, given the size of the region, are very effective at fitting what has been burnt in the past, as well as in the future, as shall be referred to later in this section.

Inversely, NUTSII Alentejo does not show an impressive result as to success rates. This NUTSII is the larger region but not the most affected by wildfires, meaning that in the modelling series it probably does not provide the model with enough data to accurately cross burnt areas with evidence layers, presenting a good degree of model fit.

Prediction rates are expected to be worse than success rates, given that success rates take into account burnt areas that are known and have been integrated into the model, whereas prediction is computed against unknown burnt areas that the model did not integrate. In the base CSP model, the difference between success and prediction is significant due to the model's nature. Double integration of historical data does amplify differences in success and prediction since success rates benefit from that double entry. Weights of Evidence models behave differently, though, having closer success and prediction rates, even if success, as expected, remains better than prediction.

With the exception of NUTSII Lisboa, which predicts better than mainland Portugal, the remainder NUTSII regions lose predictive capacity in comparison to the mainland, national model runs. In NUTSII Alentejo and Algarve results can actually be considered quite poor with differences of around 10% to the national model or even the NUTSII Lisboa model runs.

The consistency in successive model runs show that there does not appear to exist, among the evidence layers herein tested, a preferable evidence layer stack for any given NUTSII. As models progress, relative rankings are maintained. NUTSII with less relevance to the national problem wildfires present, are less likely to show good results, and predictive rates of about 65% are not that far of the randomness of a 50% predictive capacity. This leads to the conclusion that these evidence layers with Weights of Evidence – and to a lesser extent even the base CSP model – are not the best solution across all NUTSII regions, and that further evidence layers should be tested for better results, particularly in the two southern NUTSII regions of Alentejo and Algarve. The probable need for further evidence layers, depending on which region is studied, is confirmed as evidence layers are compared among NUTSII. As it was demonstrated earlier in this chapter, different evidence layers show different relevance from region to region and the best evidence layers are not always the same, even though there is a clear *preference* for land cover.

Chapter 8. Frequency and Magnitude of Wildfires in Mainland Portugal

In previous chapters, burnt areas have been used as derived from existing cartography, either from Landsat and MODIS captures, or from ground data, since it is a suitable source of information for spatial modelling where an areal representation is needed for the goals initially defined. Still, Portugal has a wealth of tabular data for wildfires, probably one of the best datasets in the world, from 2001 until present day in database format, with some older records still available on spreadsheet format, even if not entirely in standard collection. The Portuguese national forest authority has a database (called *Sistema de Gestão de informação de Incêndios Florestais* - SGIF) comprising 281,617 records for the interval 2001-2014, making it possible to compute frequency versus magnitude with quite a large sample. In Portugal, wildfires are considered as such in a strict sense when their area is of one hectare or more. Smaller fires are also recorded, but data quality for very small fires may differ since affected areas might not be loaded in the database even if their location and other characterization data exists. For that reason, in this chapter only wildfires (fires of 1 hectare or more of affected area) have been used, totaling 62,444 events out of the 281,617 previously mentioned.

8.1 Regional frequency densities

In sequence with the previous chapter, apart from the national perspective, regional data partitioning has also been conducted, following the NUTSII regions, to assess potential differences between regions, which is as relevant as different regions might require different approaches depending on the size and frequency of the wildfires they have. Looking at figure 8.1 it becomes clear that an inverse power-law does apply to wildfires in mainland Portugal, in that there are many small wildfires, and fewer larger ones. As the burnt area interval increases, the number of wildfires decreases.

The study of power-laws on wildfires has been made by Malamud et al. (1998), Díaz-Delgado et al. (2004), Malamud et al. (2005), Cui and Perera (2008), and Moreno et al. (2011), among others.

Following Malamud et al. (2005) and Moreno el at. (2011), the frequency-area statistic can be calculated as in [8.1]:

$$f(A_F) = \alpha {A_F}^{-\beta} \qquad [8.1]$$

having $f(A_F)$ as the frequency density, A_F the burnt area, and α and β as constants, considering that β represents the slope of a power trendline in a log-log space. When $\beta > 1$, most of the burnt area is caused by small wildfires, whereas a $\beta < 1$ denounces that large wildfires are responsible for most of the burnt area (Cui and Perera, 2008).

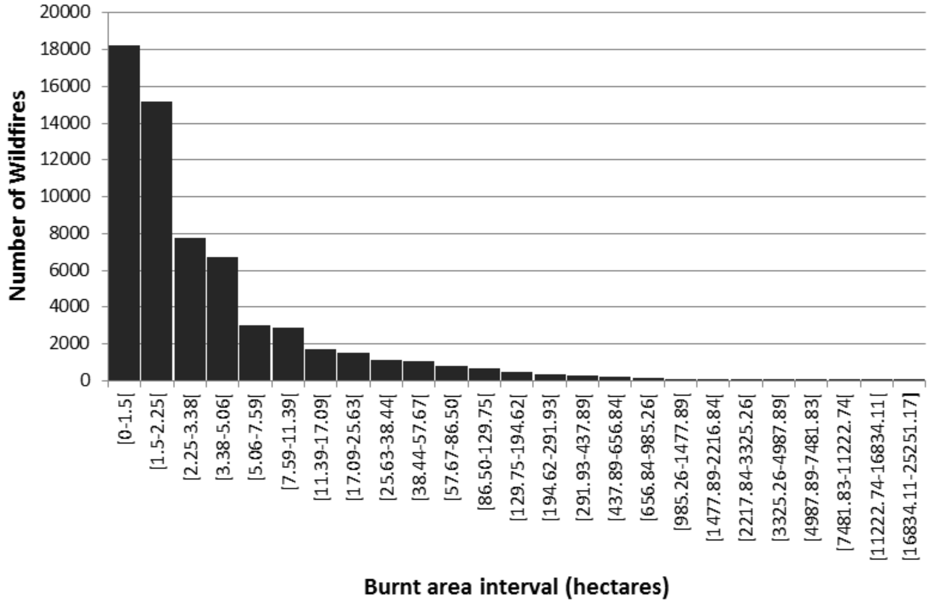


Figure 8.1 – Wildfires (events of 1 hectare or more) per burnt area class, in hectares, in mainland Portugal between 2001 and 2014.

Frequency densities, ƒ(A_F) are defined as the number of wildfires per bin, as [8.2] shows, according to Malamud et al. (1998, 2005) and Moreno et al. (2011):

$$ƒ(A_F) = \frac{\delta N_F}{\delta A_F} \qquad [8.2]$$

where A_F is the burnt area and δN_F is the number of wildfires contained in a bin with an amplitude of δA_F. The power-law distribution is not symmetrical as there are many small wildfires and fewer larger ones, therefore the bins are not of equal amplitude. Starting with a burnt area of 1 hectare, bin size was adjusted using a logarithmic rule so that the number of wildfires in any given class was never higher than the wildfires in the previous class. The coeficient for the class amplitude is not the same in all regions, hence, bins vary in size. Also, because NUTSII are different in size, for the sake of comparison, frequency densities were normalized by region susceptible area (corresponding, as in previous chapters, to each NUTSII's level 2 and 3 of CORINE Land Cover). Table 8.1 summarizes the obtained results for each NUTII and the Mainland Portugal, using equations [8.1] and [8.2].

Table 8.1 – Frequency-area statistics by NUTSII for wildfires (burnt area >= 1 hectare) from the SGIF database for the period 2001-2014. .

NUTSII	Region Area (ha)	A_F	N_F	Bin Coefficient	β	r^2
Norte	2,014,774	685,754	40,673	1.5	-1.957	0.9907
Centro	2,698,390	723,350	15,033	1.7	-1.646	0.9960
Lisboa	210,964	9,904	1,745	1.9	-1.988	0.9924
Alentejo	3,071,753	236,553	4,294	2.1	-1.680	0.9983
Algarve	463,508	132,923	699	3.0	-1.516	0.9833
Portugal	8,459,389	1,788,484	62,444	1.5	-1.794	0.9968

The next figures show how frequency-area statistics for NUTSII regions behave in a log-log space. The slope of the power low trendline ranges from -1.516 to -1.988, for the Algarve and the Lisbon region, respectively. The good adjustement of the power trendlines is comproved by the r^2 ranging between 0.983 and 0.998. It should be clearly stated that comments on the power law adjustments for each Portuguese region do include interpretations deeply rooted in the personal experience of the author, having worked on national command functions for almost 4 years. It is not possible to document or, in the scope of this study, clearly substantiate what can only be understood as an interpretation.

In figures 8.2 through 8.6, frequency-area statistics for all NUTSII regions are shown, and it is noticeable how in NUTSII Norte and Centro, the largest wildfires present an area smaller than expected. When wildfires grow bigger, reinforcements are brought in from other regions, increasing in vast numbers the number of firefighters, vehicles and aerial assets. As such, as the burnt area increases, it could be thought that it does not reach as higher an area as (statistically) expected because, by then, all attentions and efforts are into that one big wildfire. When observing middle range wildfires, they present burnt areas above the expected, from areas around 100 to 1000 hectares, areas that would reasonably belong to wildfires that are locally addressed. It is possible that in NUTSII Norte and Centro, wildfires up to 100 hectares are well dealt with by local strategies, from 100 to 1000 hectares problems start to show as deficiencies arise, and after 1000 hectares we are in the presence of major wildfires whose control has been lost and has required outside reinforcements.

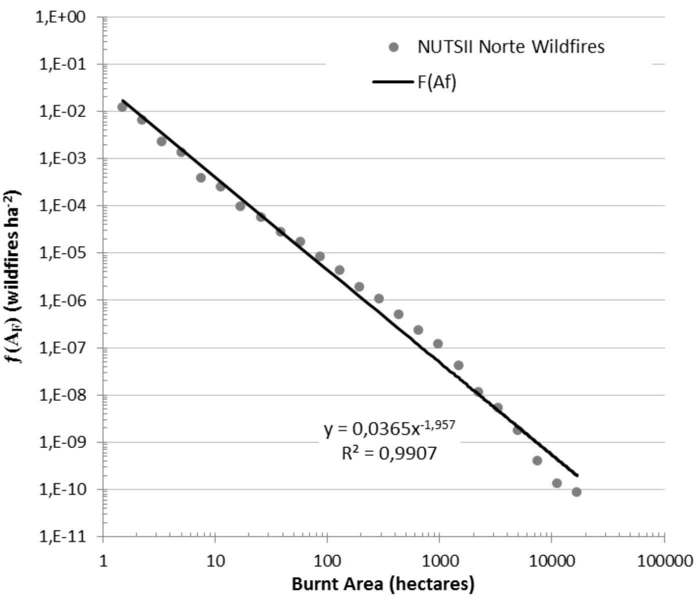


Figure 8.2 – NUTSII Norte normalized frequency-area statistics.

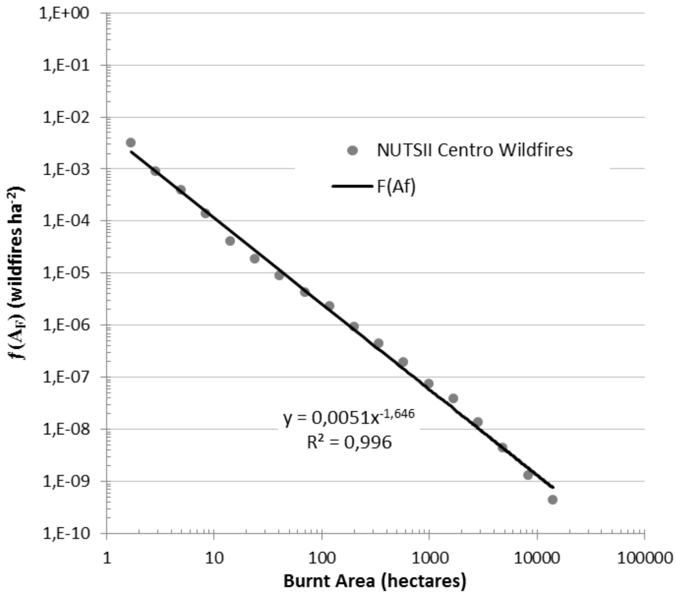


Figure 8.3 – NUTSII Centro normalized frequency-area statistics.

NUTSII Lisboa, whose frequency-area statistics are shown on figure 8.4, calls for a different interpretation than that of Norte and Centro. This region is comparably smaller and contains smaller wildfires than those in Norte and Centro. NUTSII Lisboa is also a region with a high firefighter availability, and when wildfires occur, they are quickly addressed with a large number of firefighters. It does take some external factor for wildfires to get out of control, such as severe wind or extremely high air temperature. That might be the reason for the larger wildfires to be slightly above the expected. Nonetheless, almost all wildfire dimensions are very near of what is expected.

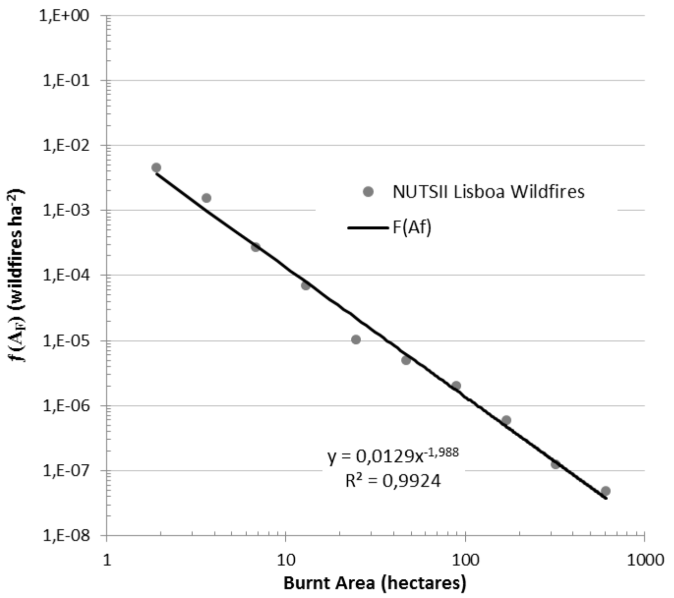


Figure 8.4 – NUTSII Lisboa normalized frequency-area statistics.

If in NUTSII Lisboa it is said that most wildfires are very near of what expected, more so happens in NUTSII Alentejo (fig. 8.5), and the r^2 confirms that with a high value of 0.9983. The largest wildfires are slightly above the frequency-area function, just as the smaller ones. NUTSII Alentejo does not have as much wildfires as the northern regions, and it also has fewer firefighters in a territory where fire spreading is helped by large extents of dry fuels. It is possible that very small wildfires are bigger than they could be because firefighters have longer distances to cover to get to them. In addition, the largest wildfires also surpass what could be expected because fewer wildfires lead to less routine and also because distances in this region are harder to cover as wildfires quickly progress through large extents of dry agricultural land.

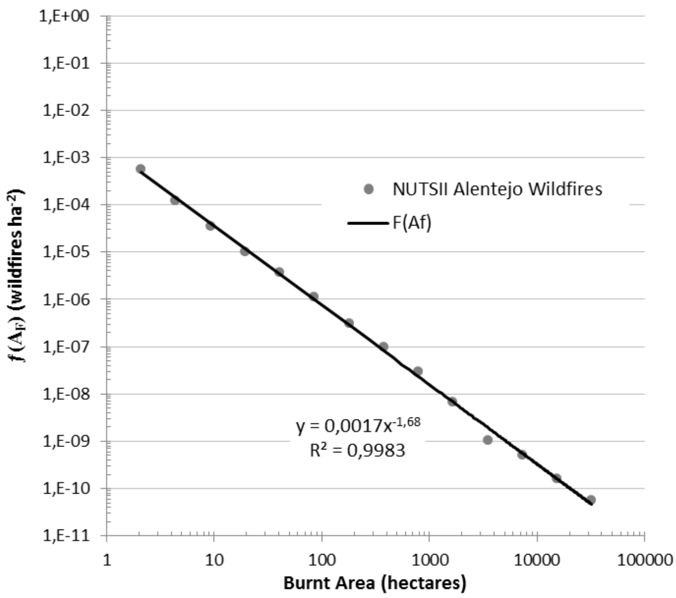


Figure 8.5 – NUTSII Alentejo normalized frequency-area statistics.

Even though wildfires can occur at any given time of the year, granted that favorable conditions are met, they are highly seasonal in mainland Portugal. Algarve is very oriented to tourism because of its climate, good beaches and warm waters, and an industry has developed around tourism putting added pressure on suppression efforts. It is possible that one for the reasons for NUTSII Algarve having small wildfires of an area higher than expected according to its frequency-density function, is the difficulty of travelling with heavy water loaded trucks from headquarters to wildfire locations, given that Algarve is notorious for traffic jammed roads, mainly during summer. One other reason could be that the coastline is densely built upon and populated, and most wildfires occur inland, bordering NUTSII Alentejo, on the higher rural areas that divide these two adjacent regions. Those are areas lacking good infrastructures and roads, where people have to travel at low speeds in very sinuous roads, wasting a long time to cover a relatively low straight line distance. Perhaps these two factors are to be considered when interpreting the frequency-density function for NUTSII Algarve in figure 8.6. Medium sized wildfires are however below the expected and larger wildfires are above. Wildfires are initially addressed by deploying a small suppression team, many times on board an helicopter, and if those initially small wildfires become larger or not vastly depends on the location and meteorological conditions at the time, as well on the assessment made by commanding staff on site. If the potential for larger wildfires is recognized, firefighters on site will request additional teams and that might contribute to a lesser affected area, but NUTSII Algarve does have limitations on what it can provide in regards to human and technical assets, and if wildfires do get out of control, being on an extreme of mainland Portugal, provided there are favorable conditions for fire progression, it will be easy for an ignition to extend well beyond average, as Tavira in July 2012 with 24,843 hectares, Monchique in September 2013 with 17,213 hectares or Loulé in July 2004 with 14,508 hectares. The average of all recorded wildfires for NUTSII Algarve is only 26 hectares.

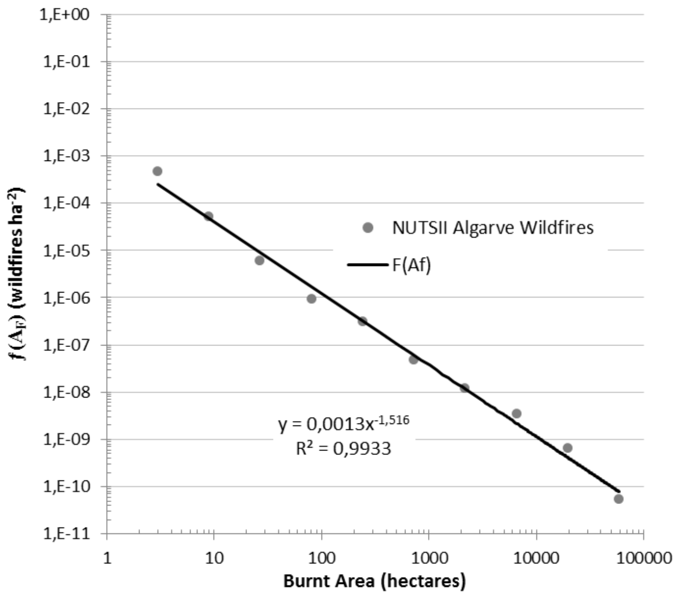


Figure 8.6 – NUTSII Algarve normalized frequency-area statistics.

Having considered regions, individually, how does mainland Portugal behave as to frequency-density function? Figure 8.7 illustrates the mainland Portugal frequency-density function showing that wildfires, when globally analysed, are very near what expected, with smaller wildfires close to or a little below the expected, medium wildfires somewhat above the function, and larger wildfires below. When the regions are merged into one single unit, what shows is that smaller wildfires are generally dealt with promptly and swiftly, but medium wildfires present a bigger challenge. It does seem adequate to think that if there is a problem with suppression – linking suppression efforts with wildfire size –, that problem exists when going from smaller to medium wildfires on the spectrum of recorded wildfires. As wildfires grow larger, doctrine mandates that they receive many combat groups and aerial assets, making those big wildfires a smorgasbord of suppression assets (either technical or human), and with more or less difficulty, no wildfire escapes extinction. But in the transition of a small to a medium wildfire, when there is an uncertainty, or over confidence, about what the outcome of that wildfire will be, conditions are met to let it escape and gain some proportion.

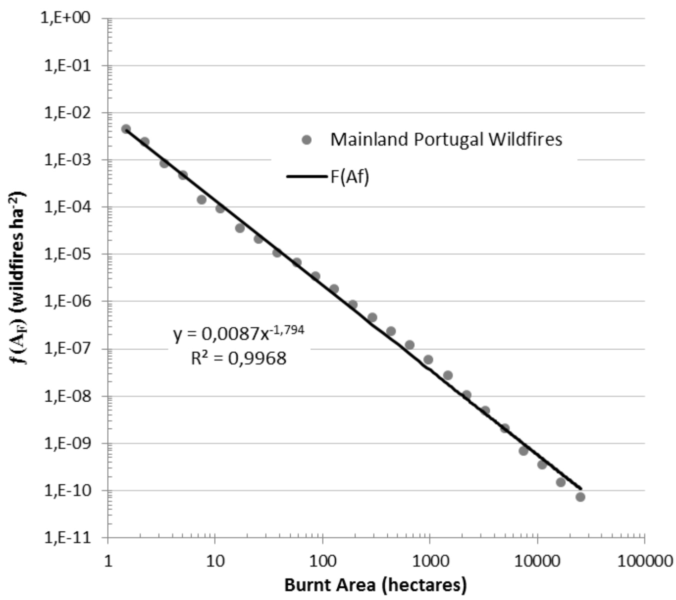


Figure 8.7 – Mainland Portugal normalized frequency-area statistics.

While it is true that this interpretation is highly argumentative, it is nonetheless the type of useage these frequency-area statistics are good for, for decision makers to look at the data and try to understand how and why wildfires have the number and area they have. Raising these hypothesis can lead to better decisions.

8.2 Closing thoughts on frequency density

Mainland Portugal, on the subject of wildfires, can be divided into two major groups: areas with many small wildfires, and areas with few major wildfires. This categorization can be made more complex if needed, but in general it is known that the northern coastline and more densely populated areas have a problem with numerous small wildfires, in most cases not even reaching 1 hectare, while inland, on less populated areas, wildfires are fewer – which does not go to say they are few, only fewer by comparison – but with potentially larger burnt areas, and it is with no surprise that the largest single wildfires are found inland, away from the most populated areas: 24,843 hectares in the district of Faro (NUTSII Algarve) in 2012; 22,190 hectares in the district of Santarém (NUTSII Alentejo) in 2003 or 20,088 hectares in the district of Portalegre (also NUTSII Alentejo) in 2003 just to pick the top three wildfires on the SGIF database.

Interpretations have been made on how to explain frequency densities on the five Portuguese NUTSII and mainland Portugal, and plotting the six frequency density functions (figure 8.8) together allows for some interesting conclusions.

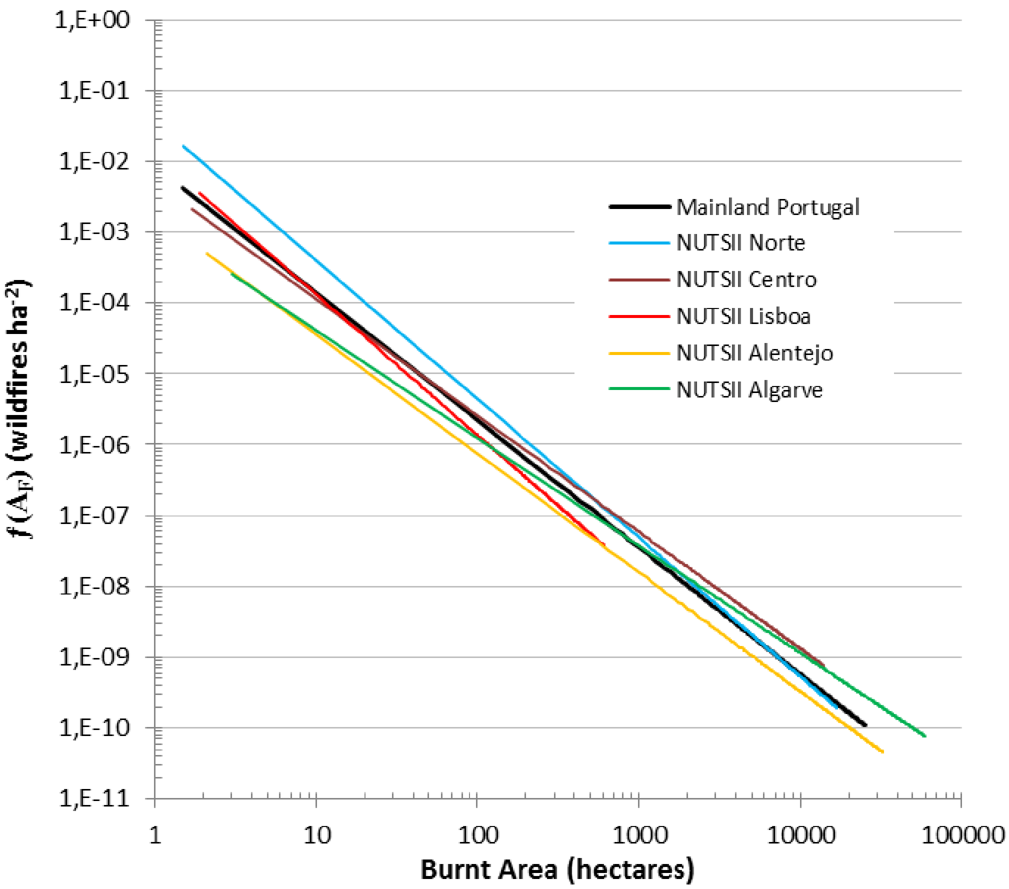


Figure 8.8 – Frequency Density functions for all regions and Mainland Portugal.

All slopes (β) are less than -1, meaning that large wildfires are responsible for the most burnt area, even if less numerous than the many small wildfires occurring on mainland Portugal, quite in line with conclusions from Strauss et al. (1989) and Bento-Gonçalves et al. (2012). From region to region the large wildfires are almost always below what their frequency density function would dictate if the power-law was entirely followed, while, inversely, the small wildfires are usually above that same function. Deviations are minor, and wildfires are close to the frequency density function. The smaller wildfires in the north are bound to get bigger than average (compared to mainland Portugal as a whole), and those smaller ones tend to be smaller in NUTSII Centro, Alentejo and Algarve, but what can most definitely be seen is that small wildfires are predominant in NUTSII Norte, followed by NUTSII Lisboa. NUTSII Alentejo will allways stay behind the national average in regards to frequency and area, and NUTSII Algarve will also lag behind for most of its wildfires, but the bigger. Clearly, what the national frequency density function masks is that, comparatively, the northern region will most likely have more of the small wildfires than the other regions, but the southernmost region, Algarve, which has less of the small wildfires, has the potential for greater affected areas.

Chapter 9. Final thoughts

The results attained in this work demonstrate that wildfire susceptibility can be assessed using a limited number of themes or evidence layers, such as historical data, slope and land cover. The relation wildfires have with land cover and slope allow for knowing the areas of higher susceptibility, and adding historical data to the models helps shaping patterns and better differentiating those places where wildfires are recurrent and therefore a problem to solve. That is as relevant as Portuguese wildfires have a causality related to negligence and criminal intent. Under equivalent conditions, areas with the same land cover and slope would have the same susceptibility, but the recurrence pattern, hugely associated with human behavior and causality, differentiates susceptible areas, indirectly introducing factors that would otherwise be extremely hard or even impossible to model with. Bachmann (2001, p.1) is very clear in stating: «(...) to predict where the next spark will ignite a fire is very difficult because in many cases this involves the consideration of hardly quantifiable socio-economic factors such as land use code, arson, and so on».

The advantages in implementing a simplified model of only three themes or layers are those of speed and process simplicity in maintaining an up-to-date mapping. Only historical data has frequent updates, usually yearly, and land cover is a periodically updated coverage. Slopes in susceptible (rural) areas are reasonably unchanged.

It has been seen how a simplified model can achieve very satisfactory results, but even if its simplicity is deemed as a caveat, Weights of Evidence can also be used as an alternative, still using a very limited number of evidence layers and with similar results. Prediction wise, either a simpler model or a WofE model are very robust options for mainland Portugal. WofE computation is somewhat more complex than the simplified model this work has presented, but it is still simple enough to consider in regular risk mapping updates. For either methodology, running the model and updating the maps is a task that relies on data that is easily acquired. The national forest authority provides historical data free of charge, land cover can also be used for free in some cases – such as CORINE Land Cover – and there are some freely available digital terrain models from which other layers can be derived, such as slope and elevation.

Having reliable solutions for risk mapping (on any component of risk), there are less and less reasons to avoid assessing hazard and risk, precious instruments for risk prevention and mitigation. These are solutions that could very well help in defining where to create fuel breaks, where to make use of prescribed fire, to avoid or forbid placing new elements at risk, or even, on a more operative note, where to increase vigilance or pre-deploy suppression assets.

Even though the results are good, with a good compromise between the number and type of data, and the predictive capacity, there is always room for improvement and no methodology should be considered as final. Nevertheless, it could be argued if there is still the need to improve, given that even in the exercises conducted in this work, improvements in a already high predicitive capacity where, quite often, only around 1% in gain. Susceptibility and/or Hazard have been such a focus of research that the next efforts should, most likely, be applied in mapping actual risk, taking into account the potential damage. It is not an easy task as finding the value of many elements at risk in a wildfire prone environment is extremely difficult. Even so, mapping wildfire risk can be extremely useful for reasons not usually taken into consideration: many people often think of risk as always negative, as a consequence of a hazardous occurrence, but as Purdy (2010, p.882) puts it, «risk (…) is neither positive nor negative but the consequences the organization experiences may vary from loss and detriment to gain and benefit». Purdy (op. cit.) goes further stating that «it has been common for risk to be regarded solely as a negative concept that organizations should try to avoid or transfer to others. However, it is now widely understood that risk is simply a fact of life and is neither inherently good nor inherently bad». What this could mean to wildfire risk managers is that assessing risk and knowing exactly where susceptible areas are and what elements at risk exist and what value they have, allows for some anticipatory measures that could very well transform a negative impact into a positive one, for instance, using prescribed burning to safeguard elements at risk and allow those same elements to keep or, desirably, add to their economic value.

As with all models, there are weaknesses that must be properly acknowledged so that future uses of these methodologies do not incur in error. A model is not an exact copy of reality. A model is an abstraction, a simplification. Models have errors, either commission or omission errors, and that must be clear. There are events that models cannot predict, a perfect hit of 100% in predicitive capacity is an illusion as much as probabilities of 100% or 0%. Scale must also be cared for. The models run in this work show very good results for scales near 1:100.000 (the scale for CORINE Land Cover, and a pixel size of 80m), but those results might not be achievable on different scales. On smaller scales they will most likely be reliable, but caution must be had if working with larger scales. Larger scales force the abstraction and challenge the simplification, and different or added evidence layers, or a different methodology altogether might be needed. The same caveat should be observed as to the territory the model is run against. For mainland Portugal, results are good, but can they be equally good on other countries? Possibly not. It has to be tested. These models do take advantage of a very complete historical data, and if other countries do not have as good a data series, models may take a plunge in predictive capacity.

Additionally, it must be noted that the classification in this study might not be adequate for other uses other than in the *academia*. The prediction curves for the data set and territory herein studied are very *smooth*, allowing for a quintile classification, but if the prediction curves show very noticeable breaks, they should be considered for data classification. Moreover, if these methods are used for planning, a quintile classification will push around 20% of the territory into the highest susceptibility class, no matter what. Special care must be taken in those cases as it might be inaccurate to proceed in such a way. Classification should always be done according to the prediction curves, and quintiles are only used in this work because quintiles are unbiased and the curves allow to do so. Data classification is always open for debate, and if there is not a right or wrong answer, researchers creating susceptibility maps should feel free to choose how to classify data as long as they are also ready to defend their choices, preferably in an unbiased way.

Having made these final thoughts, it is time to recover the initially laid out questions stated in the initial chapter, and provide them with answers.

9.1 What kind of forest does mainland Portugal have and why are wildfires a problem?

The Portuguese forest is reasonably recent, with many stands of Pine, Eucalyptus and Oak. It is a forest where forest stands have gained some expression over shrubs, and where shrubs burn more than stands. The expansion of forest stands over shrubs results in a forest of added value, where the potential loss is higher. It is also a forest mainly of private ownership (84,2%) (DGRF, 2007), for which development of the portuguese forest sector, precisely by the hands of private owners, needs a better perception of risk and, consequently, of risk reduction (op.cit.).

The loss of value, not only economic value but also that of conservation, is, perhaps, the biggest problem wildfires create in Portugal (as described in chapter one). To monetary losses, other problems are added, such as erosion (Bento-Gonçalves et al., 2013) and threats to safety thereafter. From summer wildfires, major debris flows and rock falls can happen, not only causing material losses but also jeopardizing personal safety and eventually causing deaths (Cannon and Reneau, 2000; Conedera et al., 2003). Slope erosion has multiple impacts: on water quality, on geodiversity, on slope stability. Other problems can be considered as atmospheric pollution from wildfires, health issues concerning smoke and the added difficulty in complying with international environmental protocols of which Portugal is a subscriber (DGRF, 2007; Pereira da Silva et al., 2006). These problems are not Portuguese exclusives, but, notwithstanding the comparatively good results of 2006 to 2008, and 2014, they are still pretty relevant issues for a country the size of Portugal.

9.2 How does the changing in land cover affect a low complexity wildfire susceptibility model of good predictive capability?

In chapter 4, two land cover datasets were tested in a low complexity model, the CSP model which only integrates land cover, slope and historical data. It has been shown that there are differences in model predictive capacity, as expected, but that those differences are quite small. When comparing CORINE Land Cover 2000 with CORINE Land Cover 2006, it became clear that land cover changes happened mostly within susceptible areas, therefore having different consequences from what could be expected should those changes occur in a way that susceptible and non susceptible areas would exchange between themselves most of the changes. Using the interval 1975-1994 to model and the interval 1995-2013 for independent validation, it has also been demonstrated how CORINE Land Cover 2006 inheriting CORINE Land Cover 2000's favourability scores did not result in a very poor predictive capacity. This shows that the scores computed for CORINE Land Cover 2000 are robust and even with most recent land cover coverages could still result in good predictive maps.

However, in spite of good results, and having observed that a low complexity model can retain a good predictive capability when land cover changes, it is well advised to promptly revise the model and integrate updated layers because even though favourability scores have been found to be robust, they are a property of a terrain unit whose location might change and even if, overall, the model behaves well, it should always be assured that favourability scores are being assigned to a land cover that is faithfull to ground truth. In this matter, land cover changing requires attention regardless of model complexity.

9.3 How can the Weights of Evidence method help with wildfire susceptibility assessment in mainland Portugal?

In this thesis, a methodology of low complexity was presented, named as the CSP model and yielding quite satisfactory results. However, as pointed out in section 4.3, as efficient as this model is, it does have one characteristic that might be considered a fragility or bias: the double entry of historical data. Historical data enters the CSP model not only as an indepent layer, but also as the basis for computing every variable's favourability score across all additional layers.

Using historical data as a proxy for human behavior, otherwise hard or impossible to integrate in the model, does not remove the utility of exploring a different method where historical data does not have such a bias. The Weights of Evidence method has been tested for several years in different fields of science. It is an unbiased method based on statistically derived weights for evidence layers. It should, therefore, be a solid approach to wildfire susceptibility assessment and a good alternative to the low complexity CSP model.

It has been found that the CSP model is globally better. It is always better in regards to susceptibility and better in predicting *future* wildfires in the 20% most susceptible areas, which does not add much to the Weights of Evidence method looking only at the numbers. The help Weights of Evidence brings to wildfire susceptibility assessment in mainland Portugal is actually two-fold. For one, it brings conceptual acceptance and statistical robustness to the model, should any researcher feel uncomfortable with the double role of historical data in the CSP model, and, secondly, the Weights of Evidence does help in showing that if a very robust and unbiased method lags behind the CSP model, then, that low complexity model even with a bias could be considered safe to use. Differences between the two models are small, usually around one percent, probably not enough to fuel a major discussion around which method to use, but the numbers seem to show that if nothing else, Weights of Evidence help in proving that a good wildfire susceptibility assessment is possible, in more than one way.

9.4 How many layers should be considered in wildfire susceptibility assessment?

The integration of many variables in a model of wildfire susceptibility is an attempt to consider as many conditioning factors as possible, knowing that in addition to the more direct influencing themes, such as land cover or slope, others may also have some influence. Although in chapter 5 not all imaginable themes have been used, it was nevertheless demonstrated that the addition of evidence layers to the models does not translate into a remarkable gain of their success or predictive capacity. The gains, when they exist, are discreet. Adding more or less variables is also dependant on the method used. The Weights of Evidence method is more dependant on evidence layers than the low complexity model shown on chapter 4. If the historical data is removed as an independent layer, the Weights of Evidence model of only two layers (land cover and slope) does not have as good a result. With Weights of Evidence it takes more evidence layers to keep up with the CSP model. There is not a definitive answer on how many layers to use in wildfire susceptibility models, but using high spatial correlation themes, directly connected to wildfires, should be sufficient. Land cover is mandatory as it translates into fuel to be burnt, slope has direct influence in fire progression, and historical data separates areas where wildfires are rare from those where it is a recurrent event. If the CSP model is to be considered as a benchmark, other methods will need as many layers as possible to reach CSP's predictive cabability, but even so, possibly only by a few evidence themes like elevation or population growth rate.

9.5 How does model behaviour change with yearly dataset intervals?

In chapters 4 and 5, modelling was conducted with two major data sets. A modelling block comprising burnt areas from 1975 to 1994, and an independent validation data set with burnt areas of 1995 to 2013. Splitting available data roughly in half and using twenty years to model and leaving nineteen years to independently validate results seemed a solid approach. Results shown that it was indeed a valid solution, but this is an ever growing data series, every year the national forest authority compiles and publishes an update burnt scar catalog, and the data set that is now available is different – larger – than the data set that was available when this study began. As data sets expand, when given the opportunity, or the task, for susceptibility, hazard or even risk mapping, a legitimate question is how to use data, how many years to model with? It seems clear that at its maximum, it should be *n*-1, given that at the very least, one year of data should be left out from the model to perform independent validation and sense if the assumptions behind the model are still fit.

In chapter 6 this particular question was addressed in that the model iterations repeated from just one year of historical data up until *n-1*, checking how predictive capacity behave as additional years were integrated. From the results expressed in that chapter it seems fair to say that the larger the data set, the better the results. Therefore, if no other reason or limitation exists, with the exception of the most recent year, all other years behind it in the data set could be used in the model but it is not mandatory to do so. Observing the data shows that it is possible to achieve very good results with smaller subsets with the 10% most susceptible areas fitting most burnt pixels in intervals of 10 years. Whatever the case may be, these models are not designed for any single year prediction, and should only be used for mid to long term susceptibility assessment.

It should also be noted that outliers – in this thesis the year 2003 was studied but the conclusions might apply to other years – have an impact in model performance and when wildfires affect very widespread areas, model performance might take a negative hit because as usual and unusual areas are burnt, models have difficulty in fitting all affected areas.

9.6 How does wildfire susceptibility change with Portuguese NUTSII regions and what do they show about wildfire magnitude?

Susceptibility assessment, regarding wildfires, does change, regionally, with the method employed. The simpler CSP model is more effective on a regional approach than the Weights of Evidence, but that can be attributed to the fact that, as already mentioned, the CSP model integrates historical data twice, whereas Weights of Evidence does not, hence giving CSP an advantage.

Regardless of the method, and with the exception of NUTSII Lisboa, which does have a better prediction rate than that of mainland Portugal, all other regions have worse prediction rates, with NUTSII Alentejo and Algarve having around less 10% of predictive capacity when compared to the mainland model runs. It could be thought that differences in individual evidence layers could explain the loss in model performance, but it has been demonstrated on chapter 7 that evidence layers mostly retain their relative positions in regards to positive weights, meaning that their presence contributes roughly in the same manner to wildfire occurrence from north to south.

Portuguese wildfires do not occur at random or equally distributed across all mainland. There are regions where wildfires are numerous and others where they occur less frequently, and the model predictive behavior seems to be affected by that. It is possible that a regional approach requires a different set of evidence layers to better capture the pattern and causality of wildfires.

Even at a regional scale it has been observed that larger wildfires, even if lesser numberous than the smaller ones, contribute for the most burnt area, and from region to region the story that frequency and magnitude tells is that those large wildfires are usually below what could be expected from a statistical standpoint, and if in the northern regions smaller wildfires will most likely get bigger than expected, the large wildfires find most potential to expand in the southernmost region of Algarve.

Having provided an answer for all the questions raised on chapter one, it becomes clear that no such work as this one is an end in itself if nobody gives it a practical use. Wildfires in Portugal, as individual, isolated events, are not easy to predict. But the areas they will most likely affect are indeed easy to predict, and everything is known and mapped. The one final step that still eludes the researcher community and institutions having to deal with wildfires is actual risk mapping. Nobody will protect what does not have a recognizable or known value, and that value is still missing. That is probably why, these so many years, wildfires still heat our summer, destroy property and kill people on disastrous fire suppression campaigns.

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List of Acronyms

AFN	*Autoridade Florestal Nacional*, National Forest Authority
ANPC	*Autoridade Nacional de Protecção Civil*, National Authority for Civil Protection
AUC	Area Under the Curve
BGRI	*Base Geográfica de Referenciação da Informação*, minimum territorial unit for statistical purposes
CLC	CORINE Land Cover
CORINE	Coordination of information on the environment
COS90	*Carta de Uso e Ocupação do Solo de Portugal Continental para 1990*, Land Cover por mainland Portugal, 1990
DC	Drought Code
DSR	Daily Severity Rating
EU	European Union
FWI	Fire Weather Index
GDP	Gross Domestic Product
ICNF	*Instituto da Conservação da Natureza e das Florestas*, the current designation (as of 2015) of the National Forest Authority
IGP	*Instituto Geográfico Português*, Portuguese geographical institute, currently designated *Direcção-Geral do Território*.
ISA	*Instituto Superior de Agronomia*, Agronomy Institute
ISO	International Organization for Standardization
MODIS	Moderate Resolution Imaging Spectroradiometer
NASA	United States' National Aeronautics and Space Administration
NUTS	Nomenclature of Units for Territorial Statistics
PHP	Hypertext Preprocessor
PNDFCI	*Plano Nacional de Defesa da Floresta Contra Incêndios*, National Wildfire Prevention Plan
PRT	Partition

ROC	Receiver Operating Characteristics, also known as Relative Operating Characteristics
SGIF	*Sistema de Informação de Incêndios Florestais*, Portuguese national forest authority database on wildfires
SNB	*Serviço Nacional de Bombeiros*, National Fire Service
SNPC	*Serviço Nacional de Protecção Civil*, National Service for Civil Protection
UTC	Coordinated Universal Time
WofE	Weights of Evidence

Annex

The next pages reproduce the paper by Verde and Zêzere (2010), which constitutes de basis for much of what has been discussed from chapter 4 onwards.

Verde, J.C., Zêzere, J.L. (2010). Assessment and validation of wildfire susceptibility and hazard in Portugal, Nat. Hazards Earth Syst. Sci., 10, 485-497.

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Natural Hazards and Earth System Sciences

Assessment and validation of wildfire susceptibility and hazard in Portugal

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Abstract. A comprehensive methodology to assess forest fire susceptibility, that uses variables of strong spatial correlation, is presented and applied for the Portuguese mainland. Our study is based on a thirty-year chronological series of burnt areas. The first twenty years (1975–1994) are used for statistical modelling, and the last ten (1995–2004) are used for the independent validation of results. The wildfire affected areas are crossed with a set of independent layers that are assumed to be relevant wildfire conditioning factors: elevation, slope, land cover, rainfall and temperature. Moreover, the wildfire recurring pattern is also considered, as a proxy variable expressing the influence of human action in wildfire occurrence. A sensitivity analysis is performed to evaluate the weight of each individual theme within the susceptibility model. Validation of the wildfire susceptibility models is made through the computation of success rate and prediction rate curves. The results show that it is possible to have a good compromise between the number of variables within the model and the model predictive power. Additionally, it is shown that integration of climatic variables does not produce any relevant increase in the prediction capacity of wildfire susceptibility models. Finally, the prediction rate curves produced by the independent cross validation are used to assess the probabilistic wildfire hazard at a scenario basis, for the complete mainland Portuguese territory.

1 Introduction

Wildfires have destroyed, in the past few years, thousands of hectares in Portugal (e.g. over 425 thousand ha burnt in 2003 and over 300 thousand ha in 2005) stepping up as a major environmental problem in the country. Numbers have been far more positive since 2006, but how they will evolve in the future is highly uncertain (Fig. 1). Between 1980 and 2007, wildfires have affected over 3 million ha in Portugal: that is equivalent to almost all of Belgium, one and half of Israel or twelve times the Luxembourg territory. Summed up, what was burnt in those 28 years is almost equivalent to the present day Portuguese forested areas.

Two thirds of Portugal is forested spaces, providing for paper, cork, furniture and many more products accounting for 3.2% of the Gross National Product (GNP), and 15 thousand jobs, in 2005. This data points to wildfires as a problem, not even accounting other environmental issues. Furthermore, the Portuguese forest was last evaluated at around 7750 million€. To sum it up, the problem is how to sustain 64%, roughly two thirds, of the Portuguese territory.

Wildfires are not a Portuguese exclusive and several authors have dedicated their time investigating how to best model and achieve cartographic tools for wildfire susceptibility and hazard assessment, such as the work of Chuvieco and Congalton (1989), Viegas et al. (1999), Vasilakos et al. (2007), and Verde (2008) among others. Some attempts have been made to model susceptibility by means of different methods, like nearest-neighbourhood. Such is the case of Amatulli et al. (2007) who applied interpolation techniques to map lightning/human-caused wildfires, or Durão et al. (2010) whose work, dealing with the Canadian FWI system, tried to assess the probability of fire in a given region by running simulations. Apart from the somewhat static approach of susceptibility assessments, other authors have explored the correlations of wildfires and weather conditions, such as in Pereira et al. (2005), Trigo et al. (2006) and Le Page et al. (2008). Wildfire prevention is a vector for model development, driving efforts for a better prediction of those conditions that favour fire spread, or to allow for a quicker wildfire detection. The United States National Weather Service is running an experimental interface which divulges fire weather warnings, outlooks and danger

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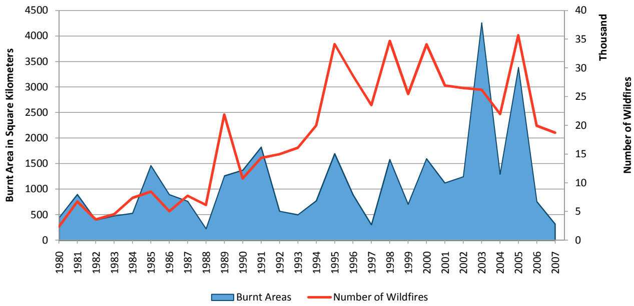

Fig. 1. Evolution of burnt area and number of wildfires in Portugal from 1980 to 2007.

ratings (NOAA, 2010), and while that information is for North America, a similar service, under the United Nations International Strategy for Disaster Reduction (UN-ISDR), provides a global early warning system for wildfires, whose objective is to "(…) provide a scientifically supported, systematic procedure for assessing current and future fire danger that can be applied from local to global scales. (…)" (GWFEWS, 2010). Other global modules have been developed under the UN-ISDR, such as the Lund-Potsdam-Jena Dynamic Global vegetation model, looking for interactions between vegetation and fire (GFMC, 2010). All these studies and approaches share a common goal, explicit or implicit: through a better knowledge of wildfire susceptibility, on land or atmospheric conditioning factors, reducing exposure and minimizing losses. The aforementioned studies have varying degrees of complexity, and many more authors have studied this subject, making it very difficult to refer them all. This paper focuses more on susceptibility as a property of the territory and less on wildfire dynamic patterns due to weather conditions, although correlations with rainfall and temperature are explored, to investigate model behaviour with similar variables as those used by other authors.

2 The conceptual framework

In Sect. 1, we have shown that the problem is how to sustain a large portion of the Portuguese territory. To do so, concepts must be clearly defined and understood, because actions might be taken to deal with the problem on the hazard level – through hazard reduction – or by risk mitigation on a broader sense.

A consensus regarding the concept of wildfire risk does not exist. Bachmann and Allgöwer (1999) have already addressed that issue, pointing out that "the somewhat inconsiderate use of the various terms "danger", "hazard", and "risk" may result in misunderstandings that can have fatal consequences" (op.cit., p. 1). Indeed, if a common understanding of what is hazard and what is risk does not exist, we might end up using products in an erroneous way: wildfire risk maps, containing financial data, cannot be read as direct

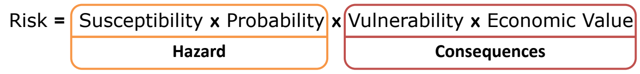

Fig. 2. Conceptual framework, based on Varnes (1984) and Bachmann and Allgöwer (1999).

indications of where a wildfire can grow faster and harder to extinguish due to increased susceptibility or recurrence patterns. If such a mistake happens at an operational level, where decisions must be made fast and accurately, consequences may be dire.

As the aforementioned authors pointed out, "the phenomenon fire has so many aspects as do people who are dealing with it (…) based on their primary interests, each of these "communities" has different notions of the term "wildfire risk" (Bachmann and Allgöwer, 1999, p. 1). The conceptual framework we adopt in this paper is the same framework widely applied to study other hazardous phenomena, like mass movements, floods or earthquakes, following the UNDRO (1979) and Varnes (1984) proposal and the risk definition given by Bachmann and Allgöwer (1999, p. 5): "the probability of a wildfire occuring at a specified location and under given circumstances and its expected outcome as defined by the impacts on the affected objects". We consider wildfire susceptibility the terrain propensity to suffer a wildfire or to support its spreading, given by the terrain's intrinsic characteristics (e.g., elevation, slope, vegetation cover). In addition, we consider wildfire hazard as the probability of a wildfire occurance associated with terrain susceptibility.

In this paper, we do not get into risk. Our study stops at hazard assessment. Figure 2 shows the adopted conceptual framework.

3 Susceptibility assessment

For susceptibility assessment, our model integrates some widely used variables in wildfire hazard modelling. The following variables were considered: elevation, slope, land cover, average annual rainfall, average number of days with minimum temperature ≥20 °C, and past burn scar mapping (which we transformed into simple probability). We have chosen to include those variables that relate to the fire triangle, air, heat and fuel, but also to the most prominent fire agent in Portugal: man. We did not consider variables that could be best used in dynamic mapping (e.g., wind speed and direction), mostly when fire is already progressing, as our purpose was to map susceptibility in the long term, as a property of the territory, as mentioned in Sect. 1. A sensitivity analysis was performed in order to assess the variable combination with the best prediction capacity. Figure 3 summarizes the adopted methodology from data capture to wildfire susceptibility and hazard evaluation.

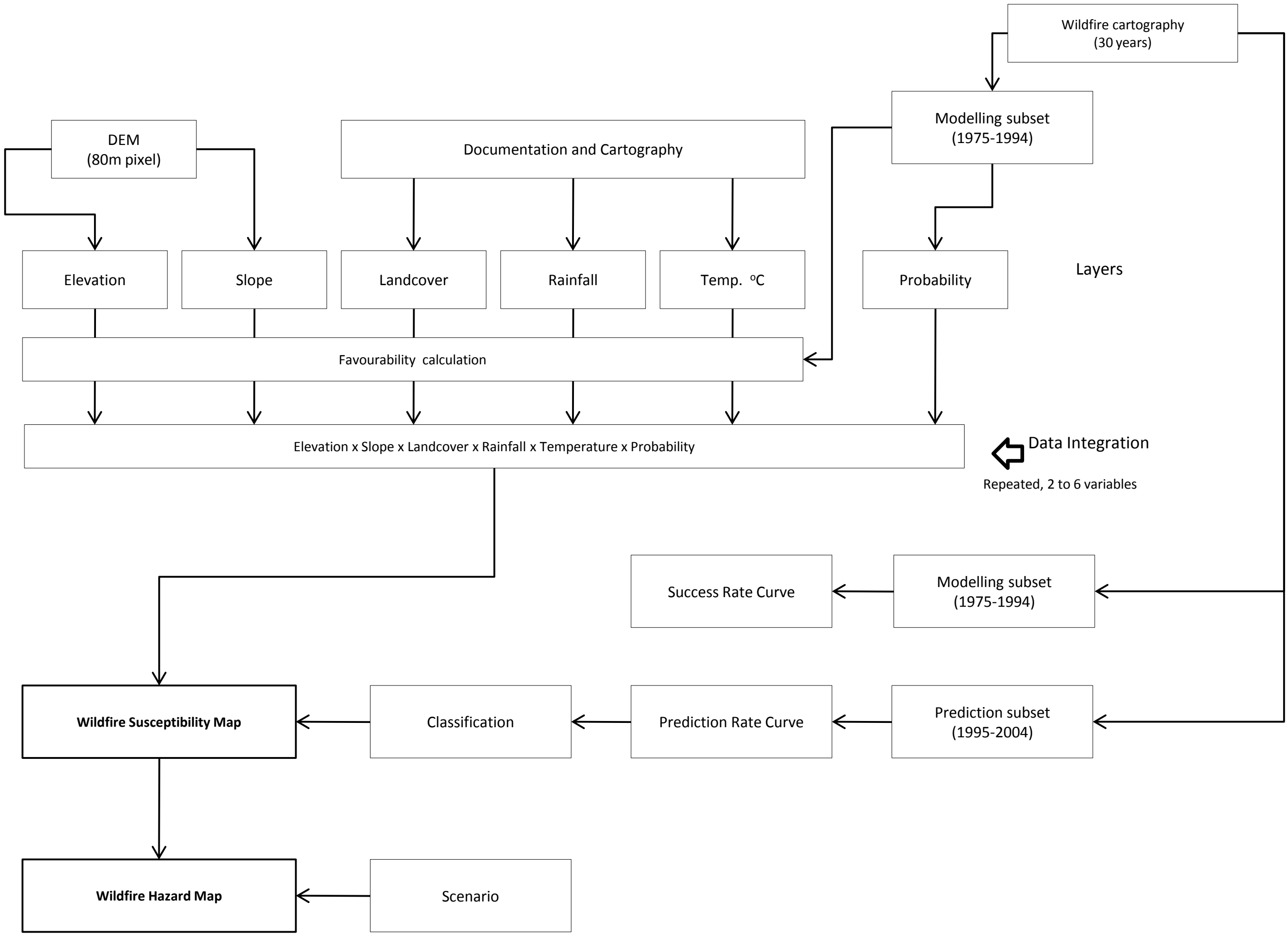

Fig. 3. General methodology from data sources and data integration, to susceptibility and hazard mapping.

3.1 Data capture

Elevation is one of the wildfire conditioning factors. Elevation "controls temperature and rainfall" (Ventura and Vasconcelos, 2006, p. 101–102), which will, in turn, influence the type and availability of fuel, as well as its humidity. Elevation is not homogeneous in Portugal, and the higher values are found in the central and northern part of the country (Fig. 4).

Influence of slope on fire progression is well known. The higher the slope, the faster fire progresses by heating of fuels uphill. Slope is also a factor that controls the wind speed (Macedo and Sardinha, 1993; Ferreira de Castro et al., 2003; Viegas, 2006). The spatial pattern of slope distribution in Portugal is similar to that of elevation (Fig. 5). The slope gradient is usually higher in the north and central part of the country.

The existence of wildfire susceptibility depends on susceptible territories, and it does not make any sense to assess wildfire susceptibility where wildfires cannot occur. Therefore, we have excluded from the land cover thematic layer (CORINE Land Cover 2000), all artificial areas, inland water bodies and ocean, corresponding to levels 1, 4 and 5 (Fig. 6).

The selection of the appropriate meteorological parameters to integrate wildfire susceptibility models is a significant issue. In Portugal, according to Pereira et al. (2006), "rainfall between January and April shows a slight positive correlation with burnt areas, possibly because it favours the growth of fine fuels (…) to burn during the summer". On the other hand, "there is a negative correlation (…) between the burnt area and rainfall during the month of May" (op.cit, p. 149) which results in higher humidity levels on those fine fuels, that become less available for ignition. In our work, rainfall influence is integrated into the model by using the mean annual precipitation from the period 1931–1960 (Fig. 7).

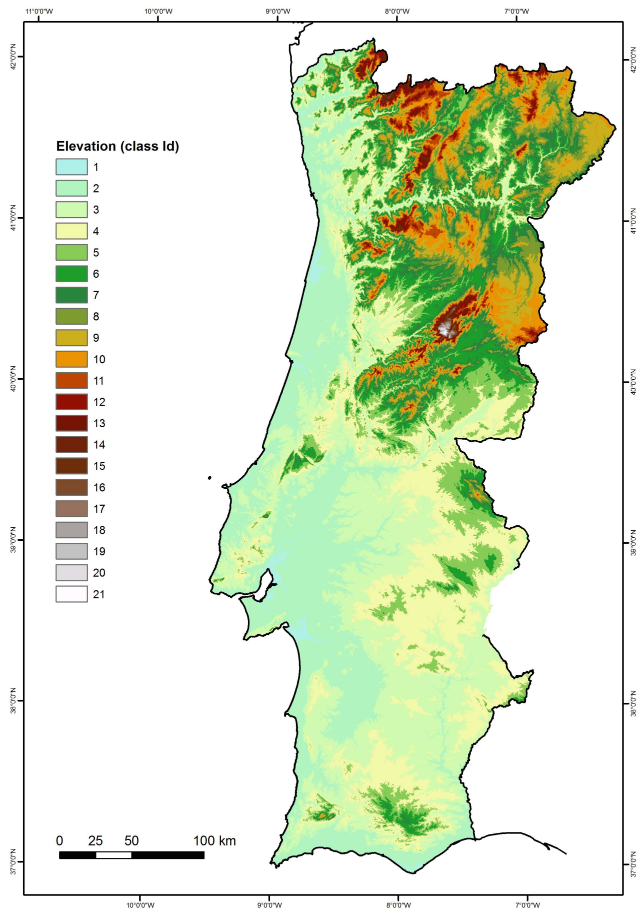

Fig. 4. Elevation map. Legend: class Id (see Table 1).

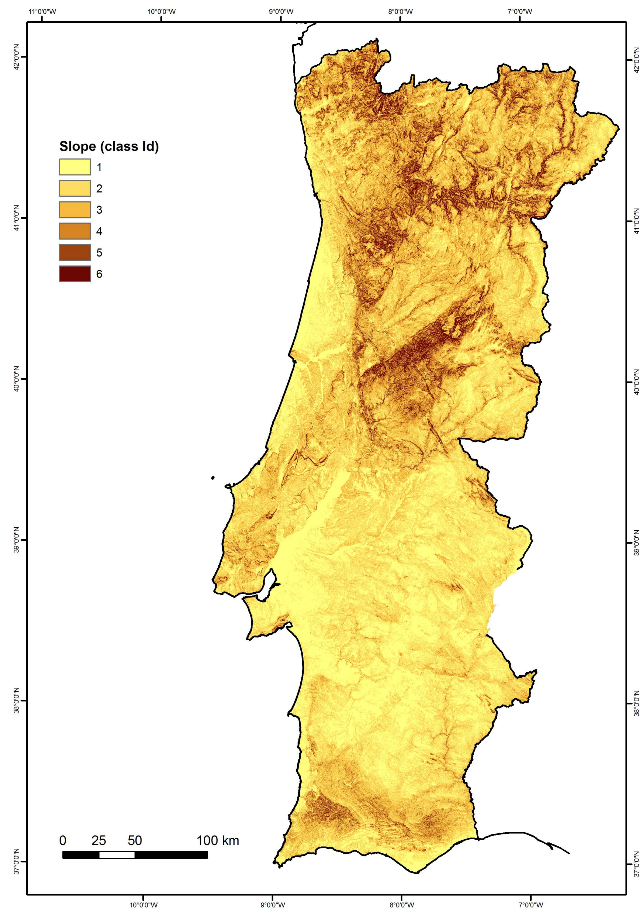

Fig. 5. Slope map. Legend: class Id (see Table 1).

The rainfall annual average does not allow for a total assessment of the above-mentioned rationale, however, knowing how rainfall is distributed in Portugal, one can assume the spatial coincidence between the higher annual rainfall and the winter rainfall maxima, hence, confirming what Pereira et al. (2006) have pointed out.

In previous studies (Pereira and Santos, 2003), air temperature has been used as a variable for wildfire susceptibility assessment, assuming that regions with higher air temperatures are those of higher wildfire susceptibility. Ventura and Vasconcelos (2006) state that high temperatures and low humidity levels favour the drying of fuels. Having this assumption in mind, we chose to integrate air temperature in a different way. Whereas in previous studies, like Pereira and Santos (2003), it was integrated as the number of days with temperatures equal or above 25 °C, between May and September, we used the average number of days with minimum temperatures equal to, or above, 20 °C (Fig. 8), for the period 1990–2007. Considering that it is during night time that wildfire suppression efforts are more likely to succeed, taking advantage of lower temperatures and higher air humidity, we assume that where there are more nights with temperatures equal or above 20 °C, wildfire susceptibility should be higher.

Past history of burnt areas enters into the model as a simple probability (Fig. 9), that allows us to read "every year, what is the probability of each ground unit to be affected by combustion?". This approach allows for discriminating, where fire is a recurring phenomenon rather than an unusual event. These wildfire records are also used to determine wildfire favourability for all other variables, as the past – from a mapped history of more than 30 years of wildfires – shows us how different classes of those variables behave under fire. Historical data is also a proxy for a factor that would, otherwise, be extremely difficult to integrate in the model: human behaviour. In fact, this factor is extremely important to understand wildfires in Portugal, because over 97% of wildfires are linked with human causality (Beighley, 2009). In Table 1, we present the legend and favourability scores for all variables, except for probability, for which no favourability score was computed. It should be noted that not all thematic layers have the same total number of pixels as a consequence of different criteria for definition of coastlines and inland water bodies. In the case of land cover, not considering levels 1,

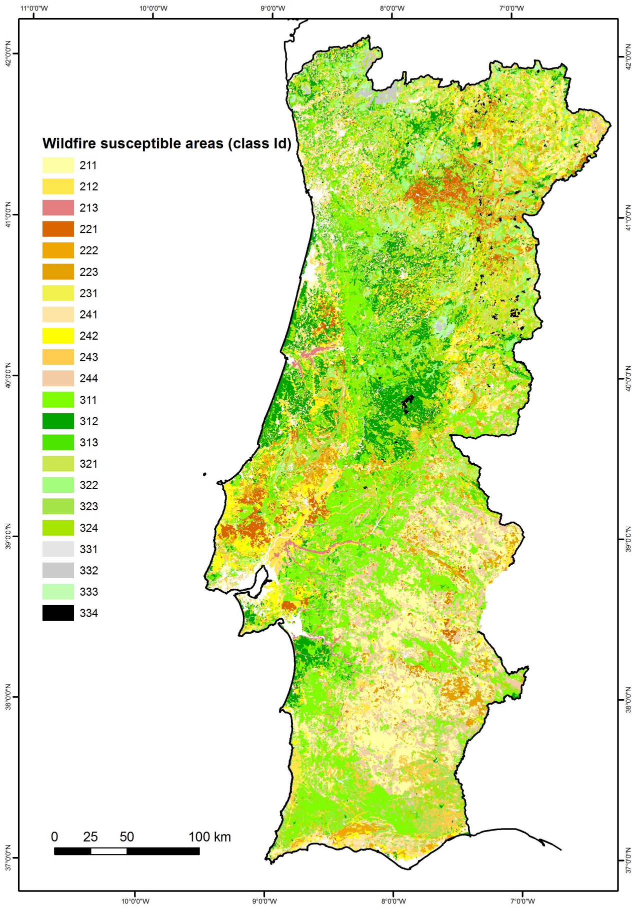

Fig. 6. Landcover map. Legend: class Id (see Table 1).

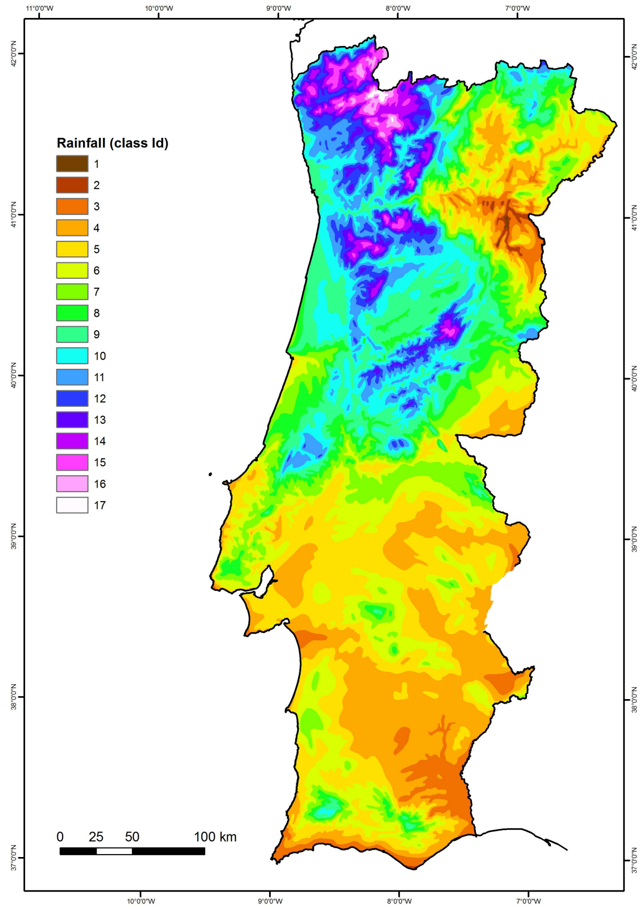

Fig. 7. Annual Rainfall map (based on Daveau et al., 1977). Legend: class Id (see Table 1).

4 and 5 as previously stated, adds to this difference. We have chosen not to force all thematic layers to the same extent because the difference was small and in doing so we could bring erroneous data into the model. In all models, we used a subset of 20 years of burnt scars (1975–1994) to compute favourability scores, and the remaining set of 10 years (1995–2004) for the independent validation of susceptibility results (Fig. 10). It becomes clear that these thematic layers do not entirely share the same timeframe and this may be considered a drawback of our model. However, in a previous work, Verde (2008) had shown that the effectiveness of the model was not affected by combining land cover of the year 2000 with burnt scars of the period 1975–1994. In fact, that author has shown that, using land cover of the year 2000, the model has an overall better behaviour with older burnt scars (e.g. 1975–1984) than with a block comprising the year the land cover was created (1995–2004). In addition, climatologic data is assumed stable regarding their spatial distribution, and we expect annual rainfall and temperature patterns to remain reasonably unchanged in the medium-long term, taking into account the Portuguese climate, where the most annual rainfall occurs during winter time and the higher temperatures during the summer.

3.2 Integrating the variables

We perform the wildfire susceptibility assessment based on the following assumptions: 1) the probability of occurrence of burnt areas can be quantitatively assessed by statistical relationships between past burnt areas and a spatial dataset; and 2) wildfires, assessed by their respective burnt areas, occur under conditions that can be characterised by the layers in the aforementioned spatial dataset, thus, considered as conditioning (or predisposal) variables, to be integrated in the prediction model.

Our work has been done in a GIS, with raster processing, after preparing and transforming vector data we had available. We used a 80-m pixel size digital elevation model (source: http://www.fc.up.pt/pessoas/jagoncal/srtm/srtm.htm) from which we derived the elevation and slope themes.

The rationale behind the use of the method used to weigh variable cases is beyond the scope of this paper, but it follows the work of Chung and Fabbri (1993) and Fabbri et al. (2002) regarding favourability scores. The basic equation

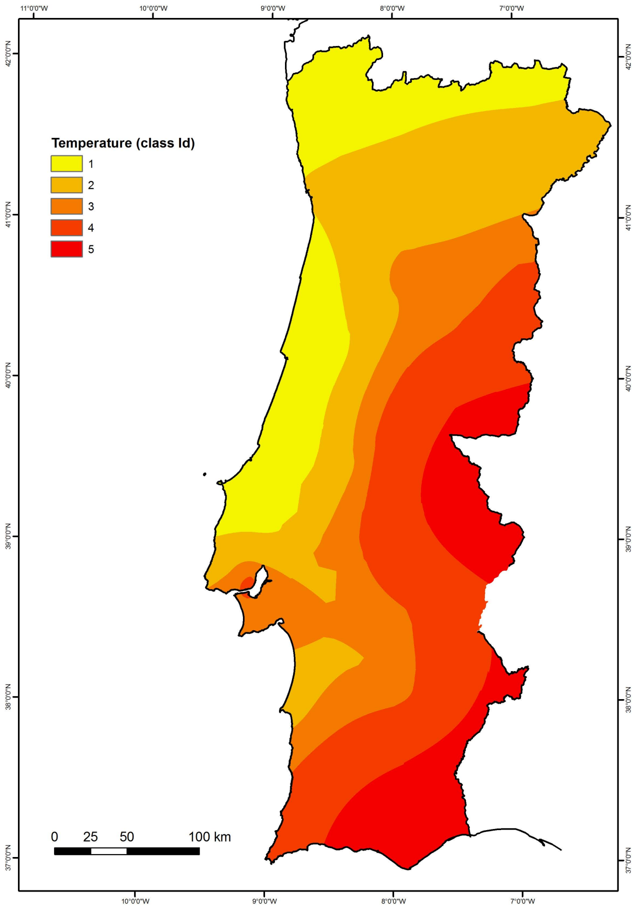

Fig. 8. Temperature map. Legend: class Id (see Table 1).

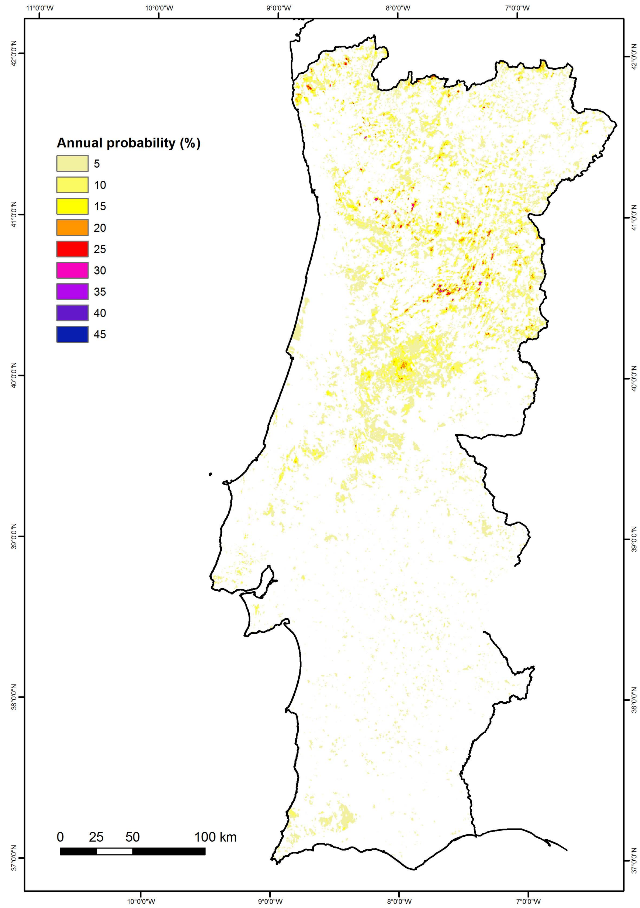

Fig. 9. Annual Probability of wildfire occurrence.

for favourability score calculation, for all variables, except probability, is:

$$\mathrm{Sfx} = \frac{\mathrm{umAx}}{\Omega x} \cdot 100 \tag{1}$$

Where Sfx is the favourability score for class x, umAx is the total number of burnt units (or pixels) in class x, and Ωx is the total number of units of class x.

In addition, the transformation of historical data into a simple probability was made using Eq. (2):

$$\mathrm{pa} = \frac{f}{N} \cdot 100 \tag{2}$$

Where pa is the probability (simple, not conditioned), f is the number of times the pixel has been burnt, and N the number of years. Due to the nature of our dataset, it is not possible for any pixel to have f higher than 1, therefore, pa can never exceed 1 (or, as per Eq. 2, 100). After all favourability scores and probability values have been calculated, we integrate the total set of variables using Eq. (3):

$$\begin{aligned} &\mathrm{UC} = \mathrm{pa} \cap \mathrm{Sf1} \cap \mathrm{Sf2} \cap \ldots \cap \mathrm{Sfn} \Leftrightarrow \\ &\Leftrightarrow \mathrm{UCF} = F(\mathrm{pa}) \cdot F(\mathrm{Sf1}) \cdot F(\mathrm{Sf2}) \cdot F(\ldots) \cdot F(\mathrm{Sfn}) \end{aligned} \tag{3}$$

Where UC is a unique condition, UCF is the unique condition favourability value and F is the favourability value of each class within each thematic layer.

The Unique Condition (UC) expresses all existing thematic layer combinations translated by the favourability value of each class in each thematic layer (pa, Sf1, Sf2,..., Sfn) as expressed in Eq. (3). The UC favourability value is calculated for each pixel and is given by the multiplication of the favourability score of each class variable present in the pixel (Eq. 3). It should be noted that wherever a favourability score computed zero, it was reclassified as the value one, thus, becoming neutral in the multiplication.

To identify each model, resulting from the integration of different variables, each layer is represented by a code, as follows: A – Elevation, D – Slope, C – Land cover, R – Rainfall, T – Temperature, P – Probability. Combining these codes identifies which variables have been used, for example, a model identified by "ACD" is a model whose calculation took into account elevation, land cover and slope.

Unique condition favourabilities (UCF in Eq. 3) for each model, when ordered in descending order and crossed with burnt areas, allow computing two types of curve: success and

Table 1. Thematic layers and favourability values of variables. The most significant results are highlighted in bold.

Thematic layer class	Class ID	Number of pixels in the class	Number of burnt pixels within the class	Favourability value	Data capture
		Elevation (m)			
0	1	114 515	240	0.0021	
0–100	2	2 769 360	103 914	0.0375	
100–200	3	3 102 003	216 481	0.0698	
200–300	4	2 490 516	237 136	0.0952	
300–400	5	1 384 088	217 162	0.1569	
400–500	6	951 387	217 120	0.2282	
500–600	7	774 191	223 624	0.2888	
600–700	8	732 445	222 151	0.3033	
700–800	9	702 783	214 079	0.3046	
800–900	10	436 979	160 150	0.3665	Derived
900–1000	11	221 888	100 843	0.4545	from DEM
1000–1100	12	112 622	58 780	0.5219	(80-m pixel)
1100–1200	13	59 698	34 392	0.5761	
1200–1300	14	31 791	19 637	**0.6177**	
1300–1400	15	14 420	7160	0.4965	
1400–1500	16	7932	2240	0.2824	
1500–1600	17	4695	1110	0.2364	
1600–1700	18	3961	547	0.1381	
1700–1800	19	1744	258	0.1479	
1800–1900	20	1574	28	0.0178	
1900–2000	21	420	0	0.0000	
Total		13 919 012	2 037 052		
		Slope angle			
0–2°	1	3 769 671	270 168	0.0717	
2–5°	2	4 620 398	647 943	0.1402	Derived
5–10°	3	3 113 286	856 590	0.2751	from DEM
10–15°	4	1 363 989	553 316	0.4057	(80-m pixel)
15–20°	5	659 408	315 286	0.4781	
$> 20°$	6	392 260	196 724	**0.5015**	
Total		13 919 012	2 840 027		
		Land cover (wildfire susceptible areas)			
Non-irrigated arable land	211	1 708 124	82 209	0.0481	
Permanently irrigated land	212	304 212	7269	0.0239	
Rice fields	213	83 543	662	0.0079	
Vineyards	221	363 891	8010	0.0220	
Fruit trees and berry plantations	222	156 557	5298	0.0338	
Olive groves	223	422 767	7772	0.0184	
Pastures	231	58 999	2444	0.0414	
Annual crops associated with permanent crops	241	656 927	10 909	0.0166	
Complex cultivation patterns	242	972 839	17 430	0.0179	
Land principally occupied by agriculture, with significant areas of natural vegetation	243	1 063 543	75 674	0.0712	Corine Land Cover 2000
Agro-forestry areas	244	874 533	20 794	0.0238	
Broad-leaved forest	311	1 908 393	212 452	0.1113	
Coniferous forest	312	1 079 951	214 363	0.1985	
Mixed forest	313	820 553	145 770	0.1776	
Natural grasslands	321	289 554	157 757	0.5448	
Moors and heathland	322	526 757	290 650	0.5518	
Schlerophyllous vegetation	323	303 814	46 371	0.1526	

Table 1. Continued.

Thematic layer class	Class ID	Number of pixels in the class	Number of burnt pixels within the class	Favourability value	Data capture
Land cover (wildfire susceptible areas)					
Transitional woodland-shrub	324	1 505 318	578 481	0.3843	
Beaches, dunes, sands	331	18 868	456	0.0242	
Bare rocks	332	69 070	32 018	0.4636	
Sparsely vegetated areas	333	121 568	79 077	**0.6505**	
Burnt areas	334	49 378	27 389	0.5547	
Total		13 359 159	2 828 548		
Yearly average rainfall (mm)					
200–300	1	3353	1488	**0.4438**	
300–400	2	37 445	16 903	0.4514	
400–500	3	530 578	52 359	0.0987	
500–600	4	2 274 773	123 320	0.0542	
600–700	5	2 653 299	163 279	0.0615	
700–800	6	1 893 065	146 436	0.0774	
800–900	7	1 247 532	143 681	0.1152	
900–1000	8	841 013	154 706	0.1840	From Daveau et al. (1977)
1000–1200	9	1 329 184	258 192	0.1942	
1200–1400	10	1 117 460	288 552	0.2582	
1400–1600	11	790 464	267 946	0.3390	
1600–1800	12	449 731	148 567	0.3303	
1800–2000	13	301 067	100 095	0.3325	
2000–2500	14	267 007	88 570	0.3317	
2500–3000	15	145 103	53 847	0.3711	
3000–3500	16	52 601	21 649	0.4116	
3500–4000	17	9002	3918	0.4352	
Total		13 942 677	2 033 508		
Average number of days, per year, of minimum air temperature above 20 °C					
0–3 d	1	2 517 498	395 707	0.1572	
3–6 d	2	3 665 182	720 590	**0.1966**	
6–9 d	3	2 561 075	466 648	0.1822	Meteorological Institute
9–18 d	4	3 358 875	383 563	0.1142	
18–36 d	5	1 816 251	70 544	0.0388	
Total		13 918 881	2 037 052		

prediction rate curves. The success rate curve results from the cross tabulation between the model results and the burnt areas used to build the model. Therefore, this curve is able to evaluate the degree of model fit. The prediction rate curve results from the cross tabulation between the model results and an independent set of burnt areas that was not used in the model, as referenced in Sect. 3.1. Hence, prediction rate curve can be used to predict the future behaviour of wildfires.

3.3 Model results and validation

The first susceptibility model run was the CDP, assuming wildfire susceptibility can be assessed through integration of fuel (land cover), slope and the historical pattern (derived from past burnt areas). This is a model of high success and prediction rates (Fig. 11; Tables 2 and 3): the 30% most susceptible territory accounts for over 90% of burnt areas contained in the model. As for the prediction, the same 30% of the territory only predicts correctly 71% of those "new" burnt areas, not considered in the model (1995–2004 sub-set).

On a second model run, another variable was added to the model: elevation. The ACDP model maintains high rates (Tables 2 and 3); however, keeping 30% of the most susceptible territory as reference, the success rate is slightly lower, but the prediction rate is somewhat better than before. In Fig. 12, we plot those curves, keeping CDP curves for comparison.

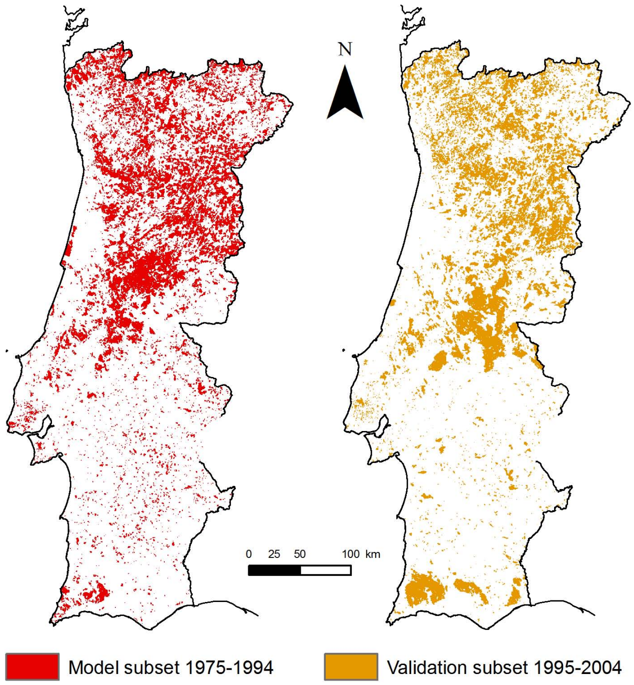

Fig. 10. Modelling and Validation wildfire data subsets.

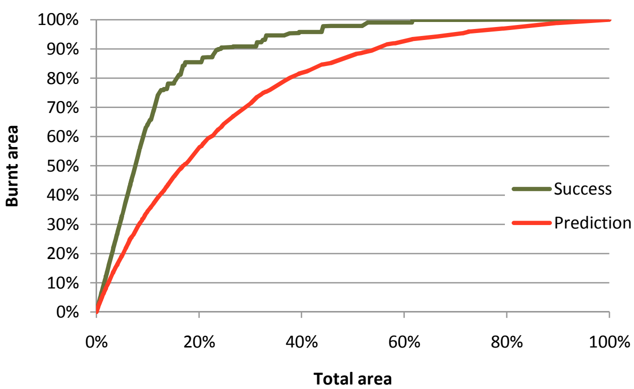

Fig. 11. Success rate and Prediction rate curves for the CDP model.

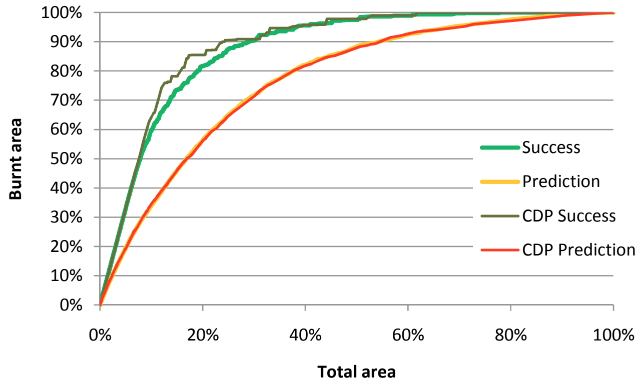

Fig. 12. Success rate and Prediction rate curves for the ACDP model.

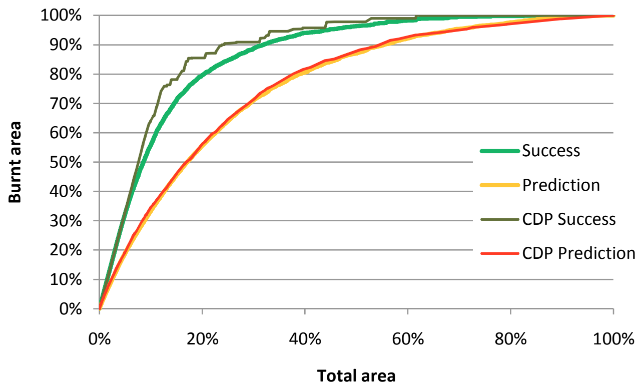

Fig. 13. Success and prediction curves for the ACDPR model.

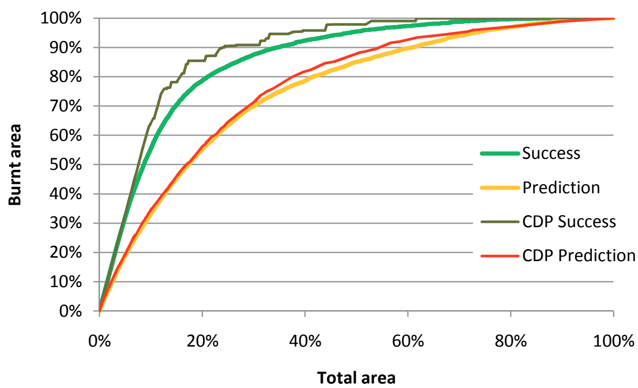

Fig. 14. Success rate and prediction rate curves for the ACDPRT model.

Next, to evaluate the impact of rainfall on susceptibility assessment, the rainfall layer was added to the model. The five variable model, ACDPR, shows the worse behaviour (Fig. 13). The prediction rate is similar to the previous model (ACDP), but the success rate is worse.

To complete this series of model runs, temperature was added to the model (Fig. 14). The six variable model, ACDPRT, has less satisfactory results, as both success and prediction rates are worse than any other previous model, as can be visually perceived in Fig. 14.

Although the general good quality of the wildfire susceptibility assessment, we wanted to evaluate the models response if burnt areas in the past (as mentioned earlier, transformed

Table 2. Success rates of susceptibility models. The most significant results are highlighted in bold.

Area	10%	20%	30%	40%	50%	60%	70%	80%	90%
CDP	**64.12%**	**85.46%**	**90.87%**	**95.77%**	**97.83%**	**99.00%**	**99.97%**	**100%**	**100%**
ACDP	59.47%	81.72%	90.42%	95.57%	97.42%	98.88%	99.73%	99.97%	99.99%
ACDPR	55.76%	79.66%	88.84%	94.06%	96.35%	98.26%	99.52%	99.82%	99.98%
ACDPRT	55.59%	79.12%	88.60%	93.55%	95.73%	97.44%	98.99%	99.77%	99.97%
CD	36.39%	60.07%	75.92%	84.83%	89.21%	92.62%	94.96%	97.84%	99.00%
ACD	37.51%	62.38%	76.24%	84.78%	89.59%	93.36%	95.77%	97.69%	99.27%
ACDR	36.90%	62.25%	77.50%	85.22%	90.00%	93.25%	95.50%	97.36%	99.00%
ACDRT	36.78%	62.47%	78.36%	85.75%	90.19%	93.25%	95.09%	97.01%	98.82%

Table 3. Prediction rates of susceptibility models. The most significant results are highlighted in bold.

Area	10%	20%	30%	40%	50%	60%	70%	80%	90%
CDP	**34.52%**	**56.36%**	71.31%	81.77%	87.87%	**92.68%**	95.02%	97.11%	**99.79%**
ACDP	33.91%	56.31%	**71.65%**	**82.08%**	**88.41%**	92.53%	95.40%	97.55%	99.23%
ACDPR	33.37%	55.65%	71.14%	80.63%	87.06%	92.21%	**95.42%**	**97.61%**	99.32%
ACDPRT	33.08%	54.13%	69.11%	79.06%	85.55%	90.51%	94.22%	97.00%	99.06%
CD	30.48%	53.29%	70.12%	80.15%	87.04%	92.39%	94.74%	96.96%	98.81%
ACD	31.04%	53.99%	70.36%	81.01%	87.81%	92.25%	95.24%	97.50%	99.22%
ACDR	30.05%	53.10%	69.35%	79.53%	86.35%	92.02%	95.28%	97.57%	99.30%
ACDRT	29.25%	51.68%	67.61%	77.83%	84.56%	90.23%	94.02%	96.89%	99.02%

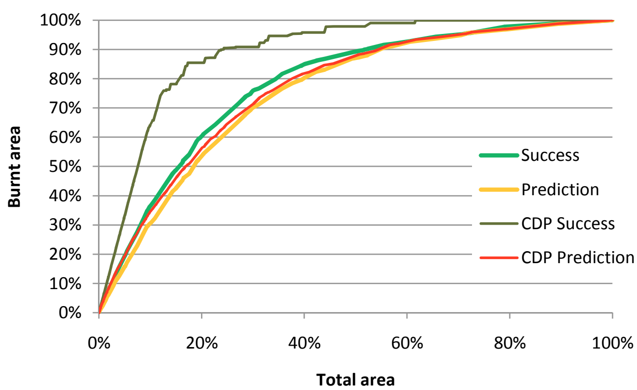

Fig. 15. Success rate and prediction rate curves for the CD model.

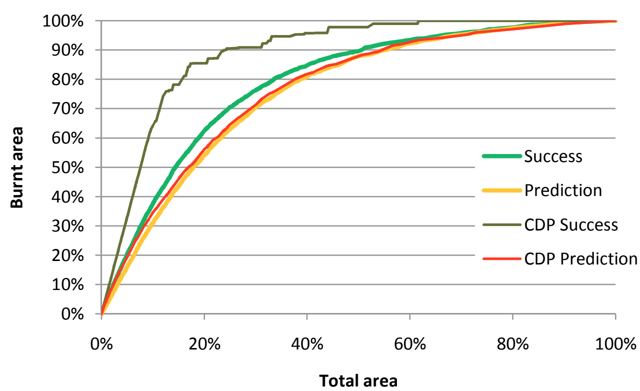

Fig. 16. Success rate and prediction rate curves for the ACD model.

into a simple probability) were to be removed. Therefore, a second set of susceptibility models was performed without the P layer.

The first model run, in this series, was the CD model (Fig. 15). By comparison with the CDP model, when using only land cover and slopes, both success and prediction rates decrease in quality. Nevertheless, the similarity between the prediction rate curves of both models, CD and CDP (difference around just 1%) is remarkable.

Figure 16 shows the differences between ACDP and ACD models. As in the previous case, the success rate is worse, but the prediction rate follows closely. In comparison to the previous model (CD), adding elevation resulted in a subtle gain, usually below 1%, on both success and prediction rates.

Adding rainfall to this series of models (ACDR) generates similar results (Fig. 17). The success rate does increase slightly, but not always, and the prediction rate is below the previous ACD model up until 70% of the territory.

Last is the ACDRT model (Fig. 18), which adds temperature, allowing for a better success rate, but overall worse prediction rate than any other variable combination.

Table 4. Areas under the curve for success and prediction rates, for the total set of susceptibility models.

	CDP	ACDP	ACDPR	ACDPRT	CD	ACD	ACDR	ACDRT
Success	89.04%	87.87%	86.79%	86.47%	78.29%	79.08%	79.07%	79.15%
Prediction	76.87%	77.06%	76.60%	75.50%	75.61%	76.05%	75.57%	74.39%

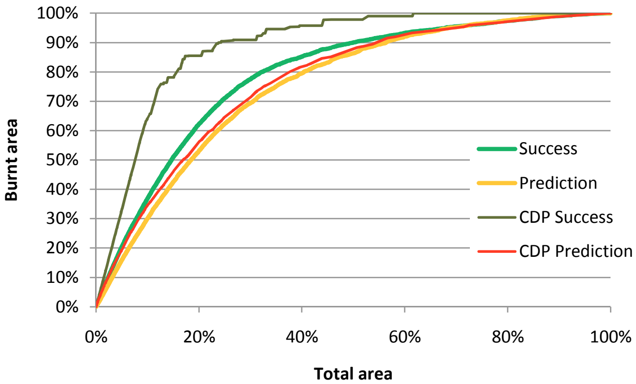

Fig. 17. Success rate and prediction rate curves for the ACDR model.

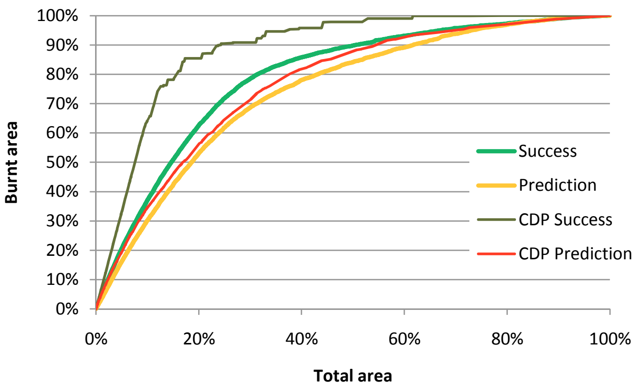

Fig. 18. Success rate and prediction rate curves for the ACDRT model.

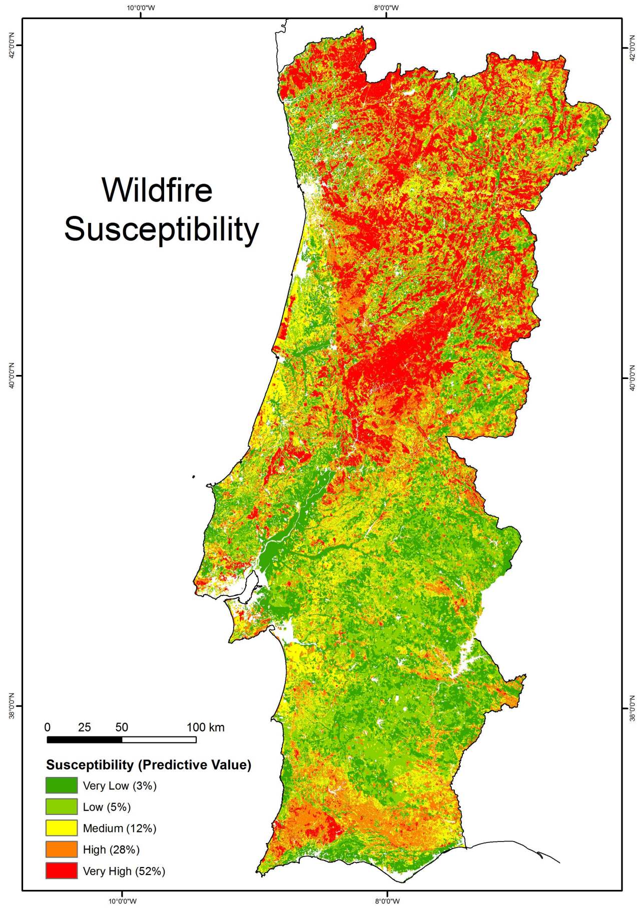

Fig. 19. Wildfire susceptibility in Portugal.

For a better perception of the susceptibility models behaviour, we computed the area under the curve (AUC) for all models (Table 4). The CDP model is not the best one for prediction at all area marks. However, it addresses more of future burnt areas requiring less territory. Overall, the CDP model has the best predictive behaviour. Also, the AUCs clearly show that the CDP model has the best success rate.

As for prediction, CDP is only the second best susceptibility model, but it uses less variables, has the best success rate and, up to 20% of the territory (the highest susceptibility class), it predicts more burnt area than any other. Therefore, the CDP model was chosen as our reference wildfire susceptibility model. Because the prediction curve is so smooth, without any clear breaks that could guide classification, a quintile classification was chosen, with each class having around 20% of susceptible territory. Figure 19 illustrates wildfire susceptibility in mainland Portugal. The prediction capacity ascribed to each susceptibility class was taken directly from the prediction rate curve of the CDP model. The meaning of the prediction values can be described as follows: 52% of the total area that will be burnt in the next future will be located in the susceptibility class "very high". On the contrary, the susceptibility class "very low" will include only 3% of the area to be affected by wildfires in the future. We have not yet explored the specific reasons behind model behaviour when adding or removing layers. It is possible

Table 5. Hazard evaluation for wildfire susceptibility classes, for a scenario of 500 000 ha burnt in a year.

Susceptibility class	Area (nr. of pixels, pixel=80 m)	Predictive value	Probability per pixel
Very low	2 783 096	0.03	0.85%
Low	2 780 358	0.05	1.40%
Medium	2 758 308	0.12	3.38%
High	2 634 032	0.28	8.42%
Very high	2 401 267	0.52	16.81%

that, due mainly to the human nature of Portuguese wildfires, variables not entirely related to the cause, but to the spread of fire, when stacked in the model, add noise that reduces its ability to accurately predict wildfire susceptibility. Many of the Portuguese wildfires are related to fuel management and landscape renewal or arsoning (AFN, 2009). Wildfires start and/or spread mainly where people want them to. It is, therefore, quite possible that the worst behaviour we get from the model, when adding more variables, simply demonstrates that their relevance, in this context, is not as high as it would be should the fire mainly be of natural origin.

4 Hazard assessment

The hazard map has the same appearance as the susceptibility map, but its classes are not subjective, they are probabilistic values, given by an underlying scenario of future burnt area.

For hazard assessment of a single pixel within a wildfire susceptibility class, we use the following equation (Zêzere et al., 2004):

$$P = 1 - \left(1 - \frac{\mathrm{aaf}}{\mathrm{at}_x} \cdot \mathrm{vpred}_x\right) \quad (4)$$

Where P is the probability; aaf is the total area to be burnt in the considered scenario; at is the total area within the susceptibility class x; vpred is the predictive value for the susceptibility class x. Table 5 shows an example of a hazard calculation for each susceptibility class in a scenario of a total of 500 000 ha burnt in a single year. It should be noted that the probabilities expressed in Table 5, are for each and every pixel within a class, that is, every pixel on the highest susceptibility class has a probability of ignition of 16.81%.

5 Conclusions

The existing large number of studies on the subject of wildfires is an indicator of how important wildfires are and how they have motivated many investigators, due to the many aspects related to fire: social, economic, environmental and cultural. This has led to the development of many methods for assessing wildfire susceptibility, not only under static approaches, for medium- and long-term analysis, but also for decision critical applications: when wildfires are already spreading, taking into account current and local weather conditions.

We have shown that wildfire susceptibility and hazard can be assessed at a national scale using few variables, like past wildfire history, slope and land use. The relationships between fire, land use and slope allow us to identify those areas of higher susceptibility. Adding historical data provides a better understanding of where wildfires have a pattern and where recurrence places a problem. That is as relevant as wildfires in Portugal are mostly of human origin.

Using only three variables makes the model quick to implement and easy to process, while having a good compromise between simplicity and predictive capacity. We have demonstrated that adding more variables does not increase the model prediction capacity substantially.

We have also demonstrated that meteorological variables do not bring enough value to prediction rates, hence not offering a good justification for including them in the wildfire susceptibility model. Meteorological data is relevant on a daily basis, for wildfire forecast mostly when wildfires are already happening. However, it does not play a significant role on long-term susceptibility assessment and mapping.

Finally, hazard evaluation is very useful in preparation for worst case scenarios, and can be used as a method for determining the number of hectares for fuel management using techniques such as landscape mosaics and prescribed burning, determining optimal size for fuel management breaks, optimal size for forest roads, the location and density of water points for vehicles and airplanes, and for dimensioning of fuel management around buildings on urban/forest interfaces.

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