WILDFIRE FREQUENCY-AREA STATISTICS AND THEIR ECOLOGICAL AND ANTHROPOGENIC DRIVERS

James D.A. Millington

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DEPARTMENT OF GEOGRAPHY

MSc DISSERTATION

I, ……………………………………………………………

Hereby declare (a) that this Dissertation is my own original work and that all source material used is acknowledged therein; (b) that it has been specially prepared for a degree of the University of London; and (c) that it does not contain any material that has been or will be submitted to the Examiners of this or any other university, or any material that has been or will be submitted for any other examination.

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Abstract

Frequency-area statistics of wildfire regimes in USA and British Columbia, Canada, are examined and suggested to exhibit power-law behaviour across many orders of magnitude. Two parameters are used to compare regimes for anthropogenic and ecological drivers of this behaviour. The frequencies of fires (logα) and ratios of large to small fires (β) are greater for: USA National Parks (NPs) compared to their surrounding areas; Washington state NPs compared to British Columbia NPs; and human-caused fires compared to lightning-caused fires. Recent work on the self-organization and thermodynamics of open systems is presented and related to wildfire occurrence in ecosystems of the USA.

Acknowledgements

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INTRODUCTION

Wildfires are highly complex in nature, involving multiple causal variables such as climate, vegetation, and human activity (Whelan 1995). When the seasonality, intensity and frequency-area characteristics of all wildfires in a region – the wildfire 'regime' – are considered, complexity is further increased making the specific wildfire regime details difficult to predict. Therefore, wildfire regime studies often examine the broader patterns exhibited and attempt to reduce their description to a few parameters. In this dissertation, the frequency-area statistics of wildfire regimes in the USA and British Columbia, Canada, are examined with reference to the potential factors influencing them. Wildfire occurrence data for these regions are suggested to exhibit power-law behaviour, and two parameters are used to compare regimes.

While the behavioural subtleties of wildfire regimes may be difficult to anticipate, understanding the broader patterns produced is important from a management perspective. Due to the ecological feedbacks involved, the management strategies of today may have serious implications for the wildfire regimes of tomorrow. The impact of past management strategies in the USA and British Columbia on current wildfire regimes is examined here in an attempt to aid understanding of these implications. Further, the influence of humans as a cause of wildfire is examined with reference to natural causes, again to improve understanding of how 'natural' wildfire regimes may have changed recently due to anthropogenic influence.

Although anthropogenic influence on wildfire regimes is evident across much of the globe, investigation into their ecological drivers may still be possible. In this study, natural variables, such as vegetation and climate, are considered by taking an ecosystem classification approach to examine broad areas of similar ecology. Using this approach may allow some indication of the effects of these variables on wildfire regimes. Recent literature concerning wildfire regimes, and their potential frequency-area distributions, is now presented and used to formulate the aims and objectives of this study.

1.1 Wildfire Frequency-Area Distributions

One method of quantifying a wildfire regime is to examine the frequency-area statistics of the fires. Recent frequency-area studies of wildfire occurrence data for several regions of the world have suggested a power-law behaviour over many orders of magnitude, of the form:

$$f(A_F) \propto A_F{}^{-\beta} \qquad \text{(Eq.1)}$$

where $f(A_F)$ is the frequency of fires with size A_F, and β is a constant. This distribution decays with negative β and is often referred to as a heavy-tail distribution (Mitzenmacher In Press), decaying much more slowly than a normal (Gaussian) distribution.

Malamud *et al.* (1998) were the first to examine data from real wildfires for power-law frequency-area distributions. The four data sets they examined for the USA and Australia all showed good power-law behaviour, over up to six orders of magnitude with β = 1.3 – 1.5, despite complex differences in the factors influencing the individual fire regimes. Song *et al.* (2001) examined real wildfire data for regions of China and also found good power-law behaviour over 3 orders of magnitude with β = 1.25 – 1.76. Ricotta *et al.* (1999; 2001) found power-law behaviour of real wildfire data for the Mediterranean Basin, but not over the whole range of data (3.5 orders of magnitude at most, with β = 0.1 – 1.2). Most recently Ricotta (2003) again found breaks in power-law behaviour and suggested that instead of a succession of restricted power-law regions, wildfire regimes might have frequency-size statistics that is best modelled by a power-law exponent that changes continuously with scale. Other studies, not specifically studying the power-law scaling nature of wildfire, to have presented power-law frequency-area statistics for real wildfire data include Minnich (1983) for possible anthropogenic influence in Southern and Baja California, and Niklasson and Granström (2000) for a period covering nearly 1000 years until present in Sweden.

Other studies however, have suggested different frequency-area distributions apply to wildfire occurrence data. Cumming (2001) found that the best-fitting parametric distribution was a truncated power-law. Most recently Schoenberg *et al.* (2003a) found similar results, finding that a tapered power-law distribution was the most appropriate from a range tested. Baker (1989) suggested an exponential frequency-size distribution, and more recently Reed and McKelvey (2002) presented variations on Weibull distribution models. Reed and McKelvey (2002) in particular suggest that a simple power-law distribution of wildfire sizes is too simplistic, and invalid, for the description of frequency-area distributions across their full range of scales.

Of the studies above only Ricotta *et al.* (1999; 2001) and Ricotta (2003) have examined the potential ecological processes driving such statistical behaviour. Ricotta *et al.* (1999) suggest that the continuous input of solar energy has evolved the Italian landscape under examination, specifically its vegetation, to a state where the next wildfire could be any size. This suggests the natural landscape may have evolved to a state such that the incoming solar energy is dissipated through, among other channels, wildfire. Upon further study, Ricotta *et al.* (2001) found breaks and 'cut-offs' in the frequency-area distributions they examined and suggested these might be related to abrupt landscape pattern-process changes at landscape-specific scales. Finally, Ricotta (2003) continued this discussion, suggesting that breaks in power-law behaviour are in good agreement with the distinct scales of pattern and process expected by ecological hierarchy theory (O'Neill *et al.* 1996). However, Ricotta goes on to note that pattern-process changes in landscapes may not be so 'crisp' after all, and a continuously changing scaling exponent could replace cut-offs and breaks in restricted power-law behaviour. Only as the number of fires approached infinity would power-law behaviour across all orders of magnitude be realised.

1.2 Aims and Objectives

From the literature above there is some uncertainty as to whether wildfire frequency-area statistics show power-law behaviour over many orders of magnitude, restricted power-law behaviour over few orders of magnitude, or whether the power-law distribution is invalid. Further, few studies (e.g. Minnich 1983; Minnich and Chou 1997) have considered the impact of anthropogenic activity on observed frequency-area distributions, and limited work (Ricotta *et al.* 1999; 2001) has been done on understanding the physical or ecological processes driving these distributions. Therefore, this study sets out to examine the ecological and anthropogenic drivers of wildfire frequency-area statistics for data sets detailing fires in the USA and British Columbia, Canada between 1970 and 2000.

Broad questions to be addressed include:

1. Do the wildfire data show power-law behaviour over many orders of magnitude in their frequency-area statistics?
2. How do ecological and anthropogenic factors influence wildfire frequency-area statistics?

Specific ecological and anthropogenic factors to be examined are:

1. The influence of different management practices between Washington state and the lower region of British Columbia, Canada.
2. The influence of management practices within USA National Parks.
3. The impact of anthropogenic versus natural sources of ignition.
4. The influence of climate and vegetation 'ecoregions' (according to Bailey 1995).

Initially, the processes of data collection and manipulation and the theory underlying examination of frequency-area statistics are explained. Using the data sub-sets derived from this initial data manipulation, frequency-area statistics are examined and the results presented. These results are then examined in turn for evidence of the ecological and anthropogenic influences outlined above, and discussion on how any influences might be explained is undertaken. Before final conclusions and implications of the research are presented, the potential overarching processes driving observed frequency-area distributions are discussed.

2

DATA AND METHODS

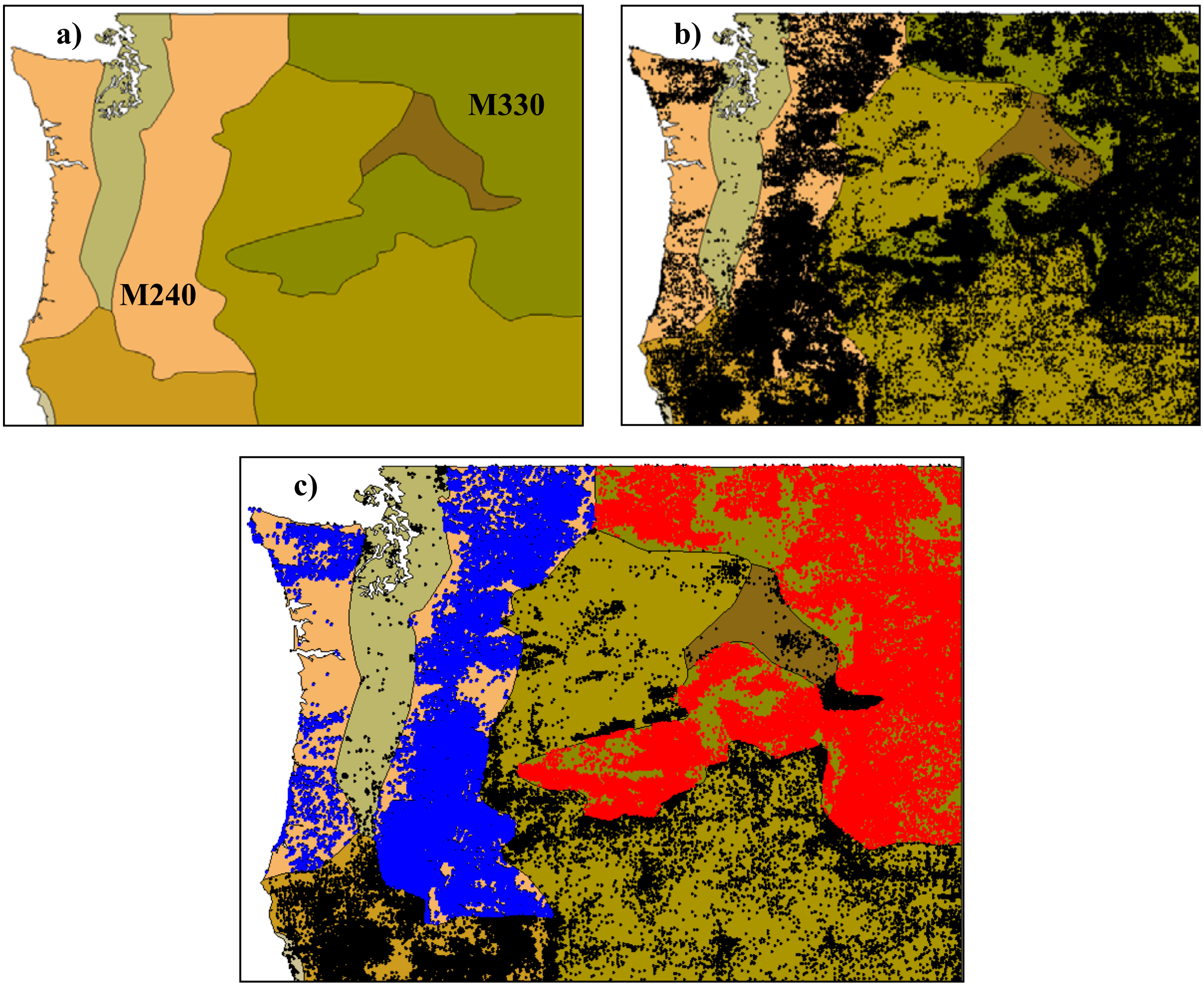
2.1 Data Used

This study examines two wildfire occurrence data sets detailing the locations, sizes and causes of 537,713 wildfires in the USA (CEFA 2003) and 78,114 wildfires in British Columbia, Canada (BCFSRB 2003), between 1970 and 2000. The USA data was complied as part of the program for Climate, Ecosystem and Fire applications and is composed of data from the USDA Forest Service (USFS) and the Department of Interior agencies, Bureau of Indian Affairs, Bureau of Land Management, U.S. Fish and Wildlife Service and National Park Service. Details concerning its compilation and an assessment of the quality of the data used can be found in Brown *et al.* (2002). The data for British Columbia was complied from British Columbia Forest Service Research Branch records (BCFSRB 2003).

2.2 Data Manipulation

Both sets of data were split into several smaller sub-sets according to the spatial location of the fires. This was done to enable examination of the potential impact of different variables upon wildfire regimes, for example the impact of differing management practices between Washington state and British Columbia. This spatial segregation was done using the GeoProcessing extension in *Arcview GIS (Version 3.3)* (ESRI 2002). Spatial data used for this purpose included: a) USA National Parks boundary, USA City and Town boundary, and USA State boundary polygon data (FGDC 2003); b) Canadian National and Provincial Parks boundary polygon data (GeoGratis 2003); and c) Bailey's Ecoregions of the USA polygon data (USFS 2003). Figure 1 illustrates this segregation process.

Figure 1. Segregation of data into sub-sets in *ArcView.* Polygon



boundary files, such as Bailey's ecoregion boundaries (a), were used to spatially 'clip' the dataset. b) shows the locations of fires which were split into sub-sets according to their ecoregion: M240 (blue) and M330 (red) in c).

At the smallest wildfire sizes incomplete data is often a problem as fires may go undetected or are binned into certain size classes (e.g. 0.5 acres) for convenience and because of the measurement accuracy used (Brown *et al.* 2002). Therefore, all fires below 0.004 km^2 (0.4 hectare = 1 acre) were ignored in this study. This reduced the total number of fires in the USA data to $N_{FT} = 179{,}192$ and in the British Columbian data to $N_{FT} = 19{,}184$.

2.3 Data Analysis Techniques

This dissertation is interested in the frequency-area statistics of burned areas, which may be examined in cumulative or non-cumulative form. In general, cumulative and non-cumulative distributions are related; the cumulative distribution is the integral (sum) of the non-cumulative, and the non-cumulative distribution the derivative (best-fit slope) of the cumulative. Assuming a power-law distribution (Eq. 1) for our non-cumulative distribution, then the cumulative distribution is given by:

$$\int A_F{}^{-\beta} dA_F \propto \begin{cases} A_F{}^{-(\beta-1)} & ,\beta \neq 1 \qquad \text{(Eq.2)} \\ \\ \ln(A_F) & ,\beta = 1 \qquad \text{(Eq.3)} \end{cases}$$

a power-law with negative exponent $(\beta - 1)$ when $\beta \neq 1$, and a natural log when $\beta = 1$. In this study the frequency-area statistics are presented in non-cumulative form. This avoids the curvature that occurs as the cumulative distribution approaches $\ln x$ when β approaches 1 (see Figure 2).

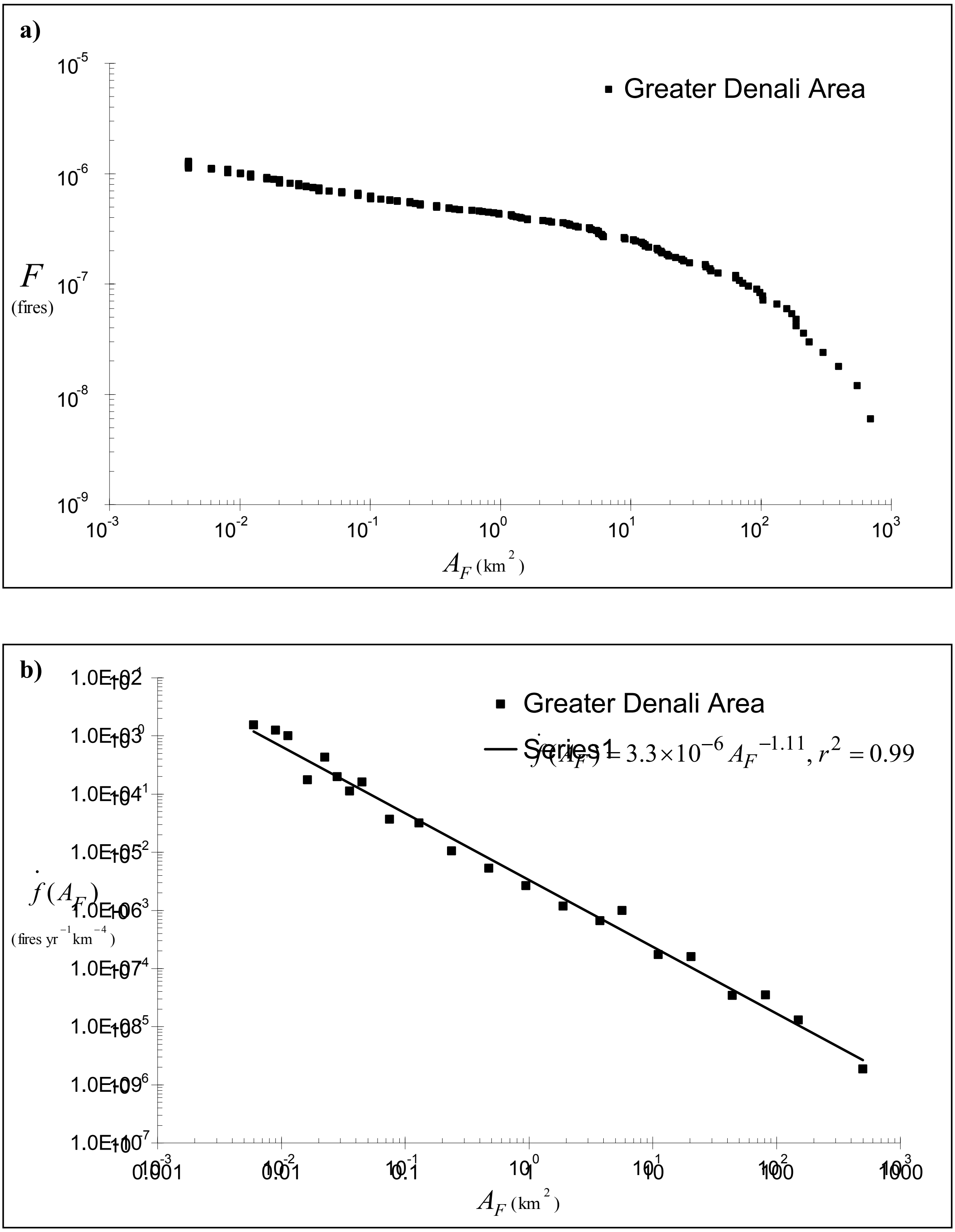


Figure 2. a) Cumulative and b) Noncumulative frequency-area distributions of Greater Denali NP area fires. a) illustrates the curvature that occurs as β approaches 1 for a cumulative distribution (Eq. 3). Using a noncumulative distribution overcomes this problem (Eq. 2).

The frequency density of fires (fires km^{-2}), in 'bins' of 'unit' size, is:

$$f(A_F) = \frac{n}{\delta}, \qquad \text{(Eq.4)}$$

where: n = number of fires between A_F and $A_F + \delta$,

A_F = area of fire (km^2),

δ = 'bin' size (km^2).

To allow comparison of data between regions and sub regions of this study, $f(A_F)$ is normalized by A_{study}, the total region area studied (km^2), and T, the period of observation (years):

$$\dot{f}(A_F) = \frac{f(A_F)}{A_{study}T} \qquad \text{(Eq.5)}$$

$$= \frac{n}{\delta A_{study}T} \qquad \text{(Eq.6)}$$

Thus, the units of $\dot{f}(A_F)$ are fires yr^{-1} km^{-4}. From Eq.1, if the non-cumulative frequency-area statistics follow an inverse power-law then:

$$\dot{f}(A_F) = \alpha A_F^{-\beta}, \qquad \text{(Eq.7)}$$

where α and β are constants.

Taking the log (base 10) of both sides of Eq.7 gives:

$$\log\left[\dot{f}(A_F)\right] = -\beta \log A_F + \log\alpha \qquad \text{(Eq.8)}$$

On logarithmic axes this gives a straight line with negative slope β and y-intercept of $\log\alpha$ when $A_F = 1\,\mathrm{km}^2$ $(\log A_F = 0)$. These parameters (α and β) will be used when analysing data; slopes (β) of best-fit lines indicate the scaling of fire sizes, and intercepts (α) indicate normalized frequency density of the 1 km^2 fire. Thus for large values of β, the ratio of large fires to small fires is greater than for smaller values of β. That is:

$$\beta \text{ large} \rightarrow \frac{\dot{f}(A_F = \text{large})}{\dot{f}(A_F = \text{small})} = \text{large} \qquad \text{(Eq.9)}$$

$$\beta \text{ small} \rightarrow \frac{\dot{f}(A_F = \text{large})}{\dot{f}(A_F = \text{small})} = \text{small} \qquad \text{(Eq.10)}$$

$$\beta = 0 \rightarrow \frac{\dot{f}(A_F = \text{large})}{\dot{f}(A_F = \text{small})} = 1 \qquad \text{(Eq.11)}$$

Equations 7 and 8, and in particular the parameters α and β, will be used in the next section for the analyses of the two data sets.

3

ANALYSIS

The specific ecological and anthropogenic factors given in section 1.2 are now examined in turn for evidence of their influence on wildfire frequency-area statistics.

3.1 Power-Law Behaviour

As noted above (section 1.2), there is uncertainty and disagreement regarding the validity of power-law distributions to describe wildfire frequency-area statistics. Therefore, the first step in the analysis of data here is to establish whether power-law behaviour is observed. Normalized frequency-density (Eq.5), as a function of area (A_F), is plotted for the USA and British Columbia (BC) data sets ($A_F \geq 0.004$ km^2) and displayed in Figure 3. On logarithmic axes both data sets show power-law behaviour (i.e. straight lines) over multiple orders of magnitude, with excellent fits (r^2 = 0.99).

As will be shown, power-law behaviour is also found in many of the data sub-sets examined (e.g. Figures 3, 4, 5, 7, 8 and 18). The poorest correlations presented below show r^2 = 0.92, though the majority of fits have $r^2 \geq 0.97$. Greatest deviations from best-fit lines are found at the upper extreme of the data (A_F very large) as has been observed in previous studies, though this is not significant enough to reject that power-law behaviour is evident. Discussion on this deviation, and the potential for alternative distributions to be fit, is given below (section 4.2). However, the above results indicate that power-law behaviour of the wildfire frequency-area statistics studied here does hold over many (greater than 5) orders of magnitude.

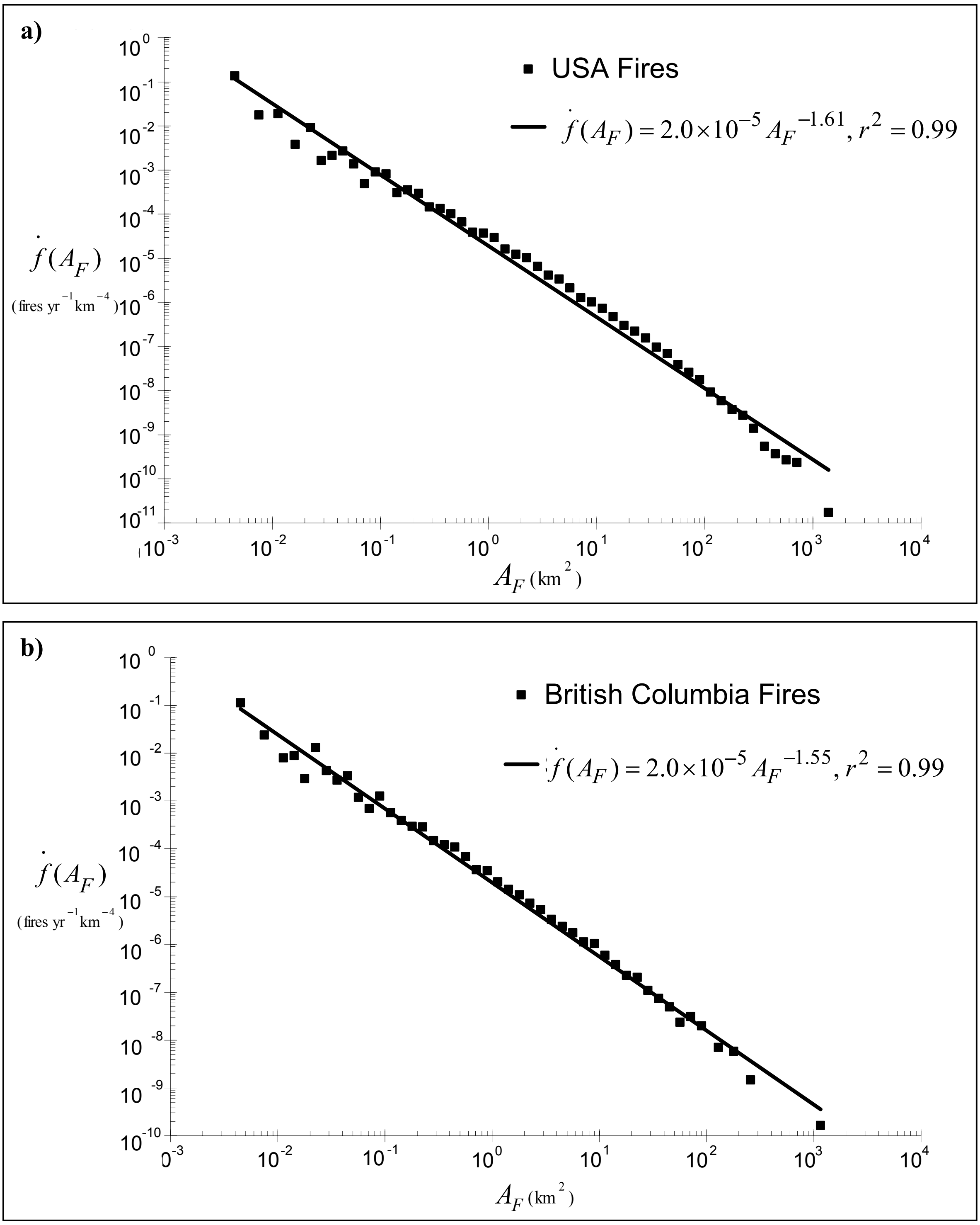


Figure 3. Noncumulative frequency-area distributions of a) USA and b) British Columbia data. Both datasets show good power-law behaviour over 5 orders of magnitude.

The USA and BC datasets have $N_{FT} = 179{,}192$ and 19,184 fires respectively with $A_F \geq 0.0004$ km^2. The contribution of the largest fires to total burned area can also be examined. Table I gives the area burned by the 1% of fires that are largest (i.e. 1,791 and 192 largest fires for USA and BC respectively). In the two cases, 95 – 96% of the total burned area was due to the largest 1% of fires.

Table I. Area burnt by the largest 1% of fires. The vast majority of area (> 95%) is burned by the largest 1% of fires.

	Total Burnt Area (km^2)	*Area Burnt by Largest 1% of Fires (km^2)*	*Total Area Burnt by Largest 1% of Fires*
USA	194,907	185,267	95.1 (%)
British Columbia	20,275	19,380	95.6 (%)

3.2 Fire Management

3.2.1 British Columbia and Washington State Fire Management

With similar climate and vegetation, differences between the wildfire regimes of Washington State, USA, and the lower 3° of British Columbia (BC) (equivalent latitudinal range of Washington) can be examined with reference to management strategies. Both regions are characterized by a cool temperate climate, coastal vegetation comprising needle-leaf forests of Douglas-fir, Western Redcedar, Western Hemlock, Sitka Spruce and Ponderosa Pine, and interior zones of steppe vegetation (Bailey 1995). Previous studies have done similar analysis for Southern and Baja California (Minnich 1983; Minnich and Chou 1997; Minnich 1998; 2001). Minnich (1983) suggested that fire suppression in Southern California had reduced the number of fires but not total burned area, and thus fires increased in size compared to Baja California, Mexico, where suppression had not been practiced. However, Keeley and Fotheringham (2001) have recently disputed this. Thus, to examine potential impacts of differing management strategies on frequency-area statistics, fire data for Washington and BC are now compared.

When all fires in BC and Washington are plotted and compared, very similar frequency-area behaviour is found (see Figure 4a). Washington has a smaller β value (1.48 versus 1.63) indicating that the ratio of large fires to smaller fires is less than for BC (Table II). This is shown quantitatively in Table II – 0.01 km^2 fires are a quarter less frequent in Washington than in BC, but 100 km^2 fires are twice as frequent. When all fires are considered, overall frequency-density is found to be 8% greater in Washington.

If fires within all parks (National Parks in Washington, National and Provincial in BC) are compared (Figure 4b, Table II), differences in behaviour are observed. β values for parks are more similar to each other (β = 1.38 and 1.41) than to the total area outside parks (β = 1.48 and 1.63), and thus it would seem that the scaling relationship across fire sizes is similar in these areas. However, Washington has normalized frequency-densities much greater (by over 400%) than BC. Thus, it would appear that the differences in management between the areas (within and outside parks) have had very large and differing impacts upon the recent fire regimes.

Further examination of the regions shows that the differences between fires regimes within parks and the overall region also vary markedly between the two countries.

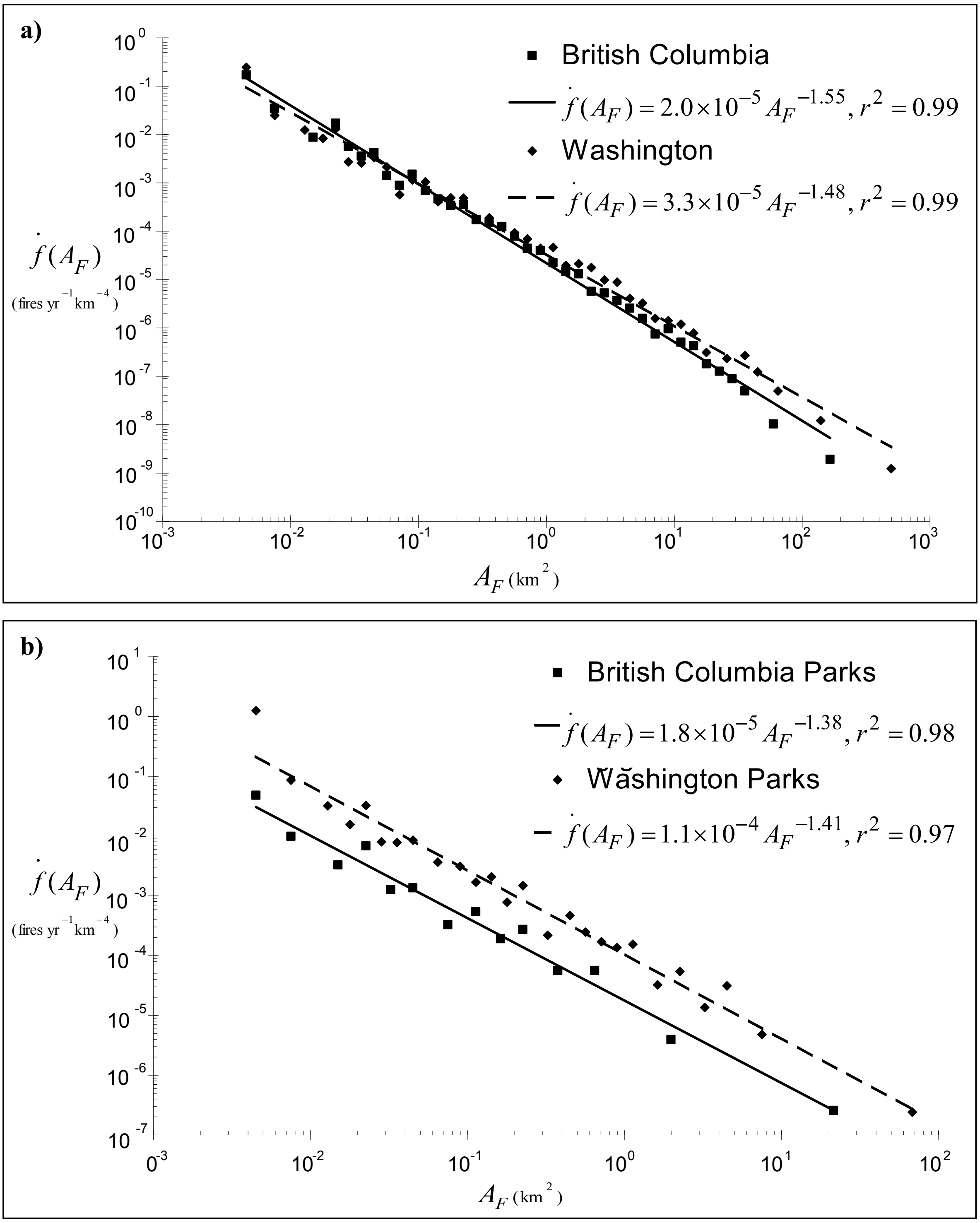


Figure 4. Noncumulative frequency-area distributions for a) British Columbia and Washington, and b) National and Provincial parks within these regions. All show good power-law behaviour. Washington's parks are shown to have greater frequency-densities than BC.

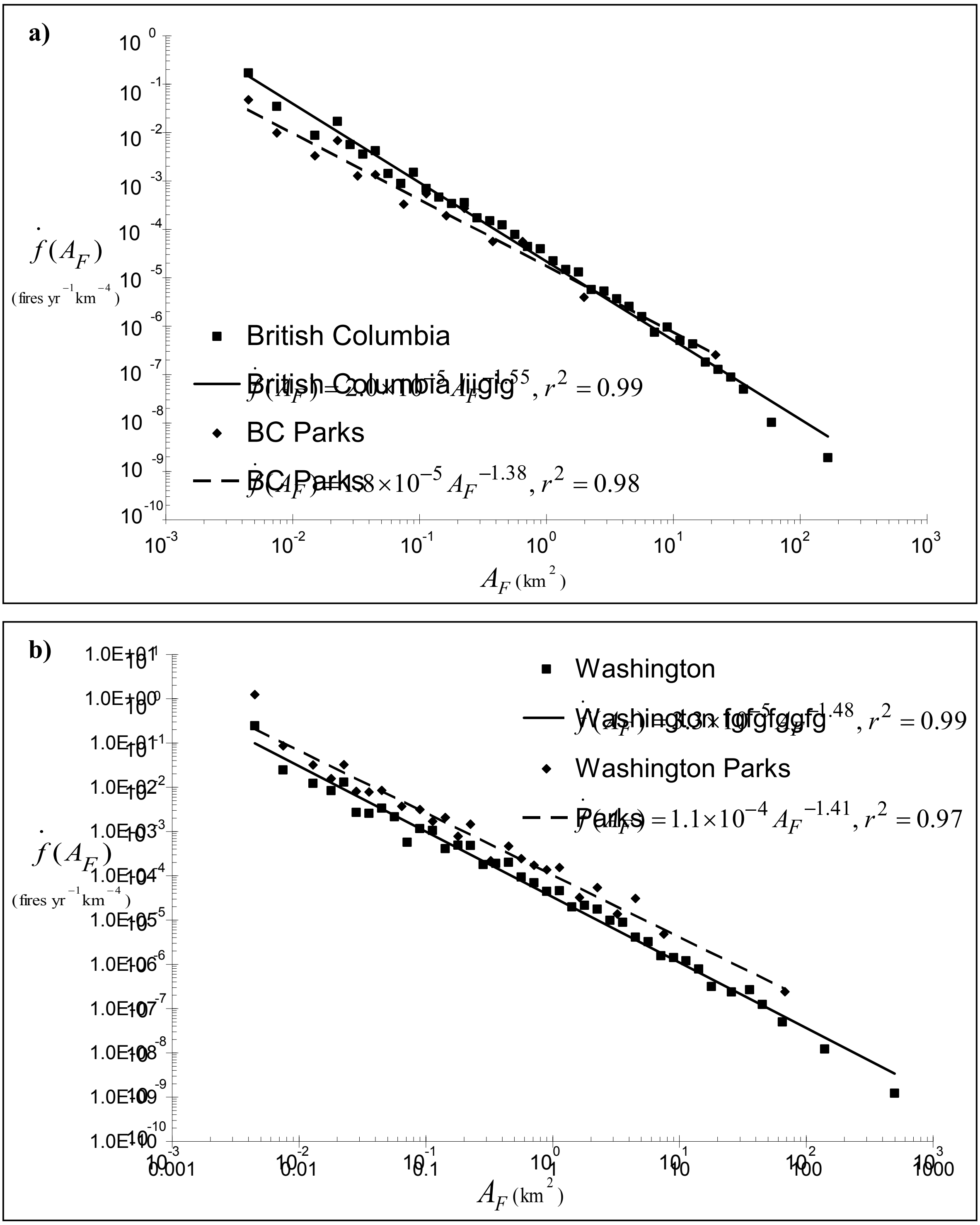


Figure 5. Noncumulative frequency-area distributions for a) British Columbia and parks, and b) Washington and parks. BC parks show decreased frequency-density when compared with the rest of the region, and Washington vice versa.

Table II. Normalized frequency-densities and β values for fires in Washington and British Columbia. Figures in *italics* are regressed values, i.e. no fires were recorded of that size in the study area.

	$\dot{f}(A_F)^{(a)}$ *for:*			$\beta^{(b)}$	$\frac{N_{FT}}{A_{study}}^{(c)}$
	$A_F = 0.01\ km^2$	$A_F = 1\ km^2$	$A_F = 100\ km^2$		
British Columbia	0.04	2.2×10^{-5}	1.2×10^{-8}	1.63	0.03
British Columbia Parks	0.01	1.8×10^{-5}	*3.1×10^{-8}*	1.38	0.01
(Change)$^{(d)}$	(-75 %)	(-19 %)	*(+156 %)*	(-15 %)	(-64 %)
Washington	0.03	3.3×10^{-5}	3.7×10^{-8}	1.48	0.03
Washington Parks	0.07	1.1×10^{-4}	*1.6×10^{-7}*	1.41	0.10
(Change)$^{(d)}$	(+133 %)	(+216 %)	*(+328 %)*	(-4 %)	(+233 %)
British Columbia	0.04	2.2×10^{-5}	1.2×10^{-8}	1.63	0.03
Washington	0.03	3.3×10^{-5}	*3.7×10^{-8}*	1.48	0.03
(Change)$^{(d)}$	(-25 %)	(+52 %)	*(+206 %)*	(-9 %)	(+8 %)
British Columbia Parks	0.01	1.8×10^{-5}	*3.1×10^{-8}*	1.38	0.01
Washington Parks	0.07	1.1×10^{-4}	*1.6×10^{-7}*	1.41	0.10
(Change)$^{(d)}$	(+592 %)	(+495 %)	*(+412%)*	(+2 %)	(+908 %)

(a) Normalized frequency-density for fires of size A_F, units are fires $yr^{-1}\ km^{-4}$
(b) β is the negative exponent of Eq. 7
(c) Frequency density (number of fires/study area), units are fires km^{-2}
(d) Changes (in %) are given for the lower area as a proportion of the upper

In Washington parks' normalized frequency-densities are consistently much *more* than the total state area (by at least 100%, see Table II). Conversely, in BC the normalized frequency-densities are generally *less* than in the total lower 3° of the province. Management in BC parks seems to have reduced the frequency of fires, while Washington parks management has increased the frequency of fires between 1970 and 2000. However, there are similarities between the two regions in that the ratio of large fires to small fires in increased in parks compared to the total regions of study. This is shown in plots as shallower slopes (lower β values) for parks compared to total regions (see Figure 5).

Comparing the fire management histories of the two areas shows that a common trajectory was followed (Parminter 1978; Pyne 1982). Evidence shows that the arrival of European settlers in the early 19th century increased the number of fires in both regions, and initially fire was seen as a problem and all efforts were taken to suppress every fire, regardless of cause (Pyne 1997). The level of fire protection and suppression would appear more rudimentary in BC compared to the US initially, however by the end of the second world war technology and resources were much more comparable. Fire was recognised much more as a tool for management in BC throughout the 20th century, where prescribed burns were used as a means to dispose of logging slash, though both regions vigorously suppressed fire. In 1968 the practice of prescribed burning was introduced in the USA and policy changed dramatically following the publication of the Leopold report (Leopold *et al.* 1963) to one of wilderness preservation (Schullery 1989). Thus, until the period considered by the data here, both regions have followed similar management practices, though BC would seem to have been less vigorous in its fire suppression through the 20th century, due to reduced resources prior to 1945 and greater recognition of fire as a management tool. This may in part be responsible for the differences observed between parks and non-parks in the two regions. However, a much more thorough analysis of management differences between the regions is needed.

3.2.2 Fire Management of USA National Parks

The vigorous fire suppression undertaken by the USA National Parks Service (NPS) during the first half and more of the 20th century has just been noted. While the management strategies of the NPS have been less aggressive during the study period examined here (1970 – 2000), the implications of the suppression strategy practiced previously may still be influencing current wildfire regimes. Analysis of USA National Park (NP) and non-park wildfire regimes is now undertaken to establish the impact of the NPS management strategies prior to 1970.

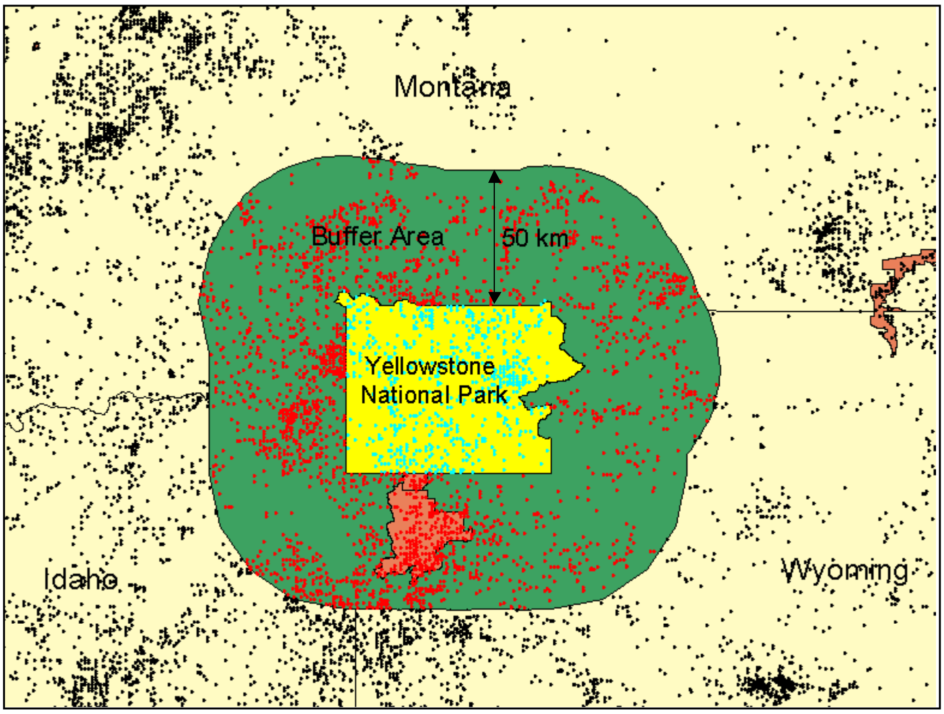


Figure 6. Creation of 50 km buffers around USA National Parks in *ArcView*. Once buffers had been created data was spatially subset as shown in Figure 1 and indicated here by red, blue and black dots.

Using *ArcView*, buffers of 50 km were produced around 10 NPs and the fires within parks and buffer areas spatially sub-set (see Figure 6). Parks are treated as named in Table III except 'Sequioa', which refers to Sequoia *and* Kings Canyon NP.

Frequency-area distributions for parks versus their buffer area were plotted (Figure 7). Details of frequencies of different fire sizes and β values are shown in Table III.

Table III. Normalized frequency-densities and β values for fires in USA National Parks and their surrounding areas. Figures in *italics* are regressed values, i.e. no fires were recorded of that size in the area.

	$\dot{f}(A_F)^{(a)}$ *for:* $A_F = 0.01\ km^2$	$A_F = 1\ km^2$	$A_F = 100\ km^2$	$\beta^{(b)}$	$\frac{N_{FT}}{A_{study}}^{(c)}$
Crater Park	0.0824	2.4×10^{-4}	$\mathit{6.9 \times 10^{-7}}$	1.27	0.0837
Crater Buffer	0.0257	3.2×10^{-5}	$\mathit{4.1 \times 10^{-8}}$	1.45	0.0370
(Change) $^{(d)}$	(-69 %)	(-86 %)	*(-94 %)*	(+14 %)	(-56 %)
Denali Park	0.0023	1.4×10^{-5}	8.3×10^{-8}	1.11	0.0044
Denali Buffer	0.0004	2.0×10^{-6}	9.9×10^{-9}	1.15	0.0007
(Change) $^{(d)}$	(-83 %)	(-86 %)	(-88 %)	(+4 %)	(-84 %)
Glacier Park	0.1050	2.9×10^{-4}	$\mathit{8.1 \times 10^{-7}}$	1.28	0.1042
Glacier Buffer	0.0433	4.1×10^{-5}	$\mathit{3.9 \times 10^{-8}}$	1.51	0.0475
(Change) $^{(d)}$	(-59 %)	(-86 %)	*(-95 %)*	(+18 %)	(-54 %)
Mt. Ranier Park	0.0431	8.6×10^{-5}	$\mathit{1.7 \times 10^{-7}}$	1.35	0.0189
Mt. Ranier Buffer	0.0087	1.0×10^{-5}	$\mathit{1.3 \times 10^{-8}}$	1.46	0.0114
(Change) $^{(d)}$	(-80 %)	(-88 %)	*(-93 %)*	(+8 %)	(-39 %)
Olympic Park	0.1190	2.5×10^{-4}	$\mathit{5.2 \times 10^{-7}}$	1.34	0.0276
Olympic Buffer	0.0096	1.0×10^{-5}	$\mathit{1.1 \times 10^{-8}}$	1.48	0.0090
(Change) $^{(d)}$	(-92 %)	(-96 %)	*(-98 %)*	(+11 %)	(-67 %)
Santa Monica Park	0.0403	2.5×10^{-4}	$\mathit{1.5 \times 10^{-6}}$	1.11	0.0659
Santa Monica Buffer	0.0633	1.1×10^{-4}	2.0×10^{-7}	1.38	0.0887
(Change) $^{(d)}$	(+57 %)	(-55 %)	*(-87 %)*	(+24 %)	(+35 %)
Sequioa Park	0.0765	2.3×10^{-4}	$\mathit{7.0 \times 10^{-7}}$	1.26	0.1026
Sequioa Buffer	0.0395	5.7×10^{-5}	$\mathit{8.3 \times 10^{-8}}$	1.42	0.0551
(Change) $^{(d)}$	(-48 %)	(-75 %)	*(-88 %)*	(+13 %)	(-46 %)
Wrangell Park	0.0010	4.3×10^{-6}	$\mathit{1.8 \times 10^{-8}}$	1.18	0.0011
Wrangell Buffer	0.0004	1.3×10^{-6}	4.9×10^{-9}	1.22	0.0005
(Change) $^{(d)}$	(-63 %)	(-69 %)	*(-73 %)*	(+3 %)	(-54 %)
Yellowstone Park	0.0072	3.5×10^{-5}	1.7×10^{-7}	1.16	0.0127
Yellowstone Buffer	0.0114	2.1×10^{-5}	3.8×10^{-8}	1.37	0.0089
(Change) $^{(d)}$	(+59 %)	(-40 %)	(-77 %)	(+18 %)	(-30 %)
Yosemite Park	0.0950	2.7×10^{-4}	$\mathit{7.5 \times 10^{-7}}$	1.28	0.1417
Yosemite Buffer	0.0346	5.5×10^{-5}	8.7×10^{-8}	1.40	0.0490
(Change) $^{(d)}$	(-64 %)	(-79 %)	*(-88 %)*	(+10 %)	(-65 %)

(a) Normalized frequency-density for fires of size A_F, units are fires $yr^{-1}\ km^{-4}$
(b) β is the negative exponent of Eq. 7
(c) Frequency density (number of fires/study area), units are fires km^{-2}
(d) Changes (in %) are given for the lower area as a proportion of the upper

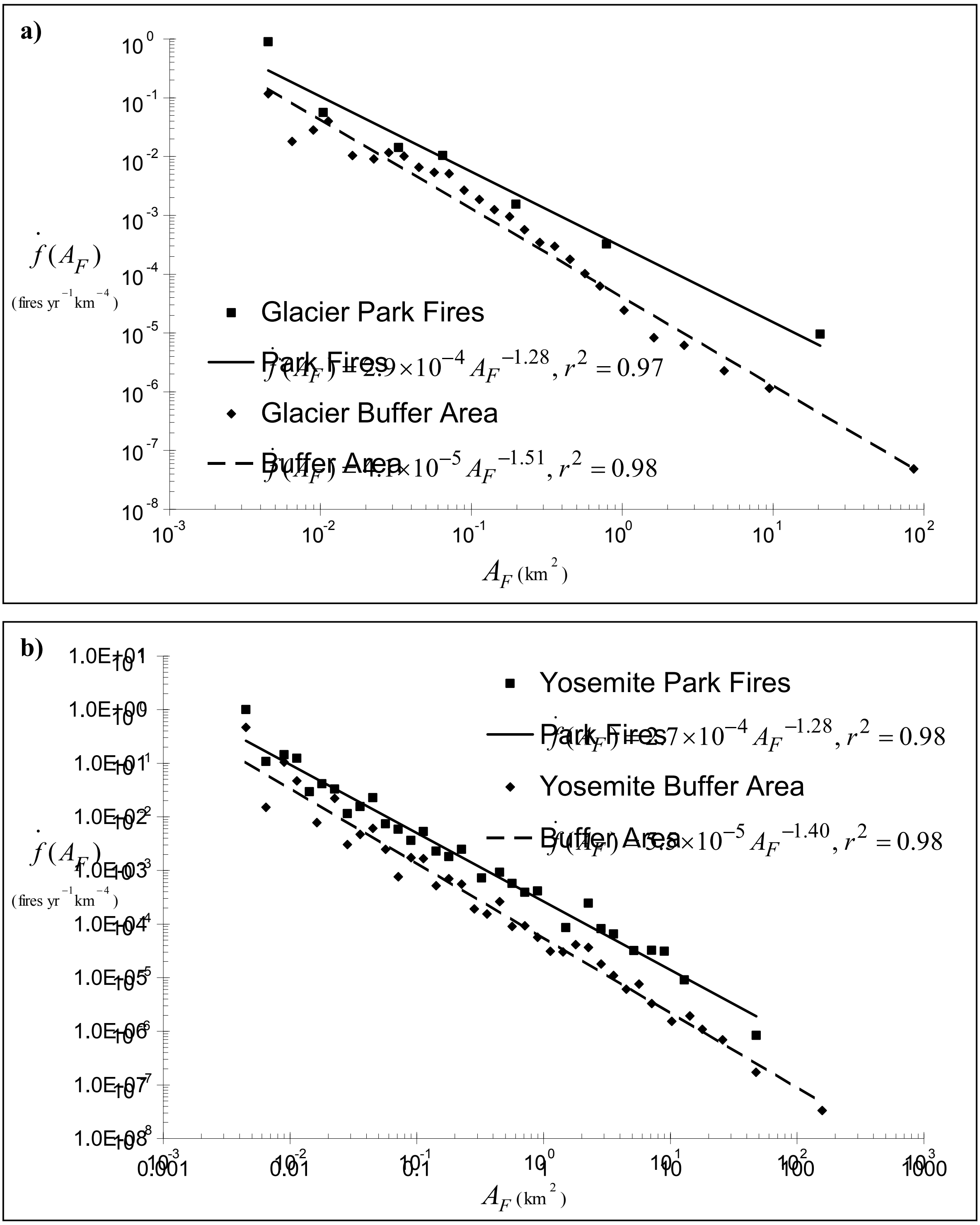


Figure 7. Noncumulative frequency-area distributions for a) Yosemite and b) Glacier parks and buffer areas. Frequency-densities are greater for parks than their surrounding buffer areas.

From analysis of Figure 7 and Table III it is observed that frequency-density is greater within national parks than in their surrounding buffers. This is true over all sizes of fire, except in Yellowstone and Santa Monica (see Table III). Secondly, all parks show reduced β values compared to the wildfire of their surrounding buffer areas. Thus, the ratio of large to small fires is less within parks compared to surrounding areas (see Table III). It would appear that these changes are as a direct response of NPS management strategies. Potential reasons for this are discussed in section 4.1.4

3.2.3 Management Summary

Analysis shows that the frequency of fires in Washington and the lower 3° of British Columbia is similar, but that the scaling of fires sizes varies. The ratio of large to small fires is greater in the former than in the latter (Figure 4 and Table II). The frequency of fires in Washington's parks is found to be vastly increased compared to BC (by over 400%) and the non-park areas of Washington (Table II). Further, this increase in fire frequency and fire size ratio is also found in other national parks in the USA (Figure 7, Table III). The impact of management appears to be great in the USA, though a very brief examination of management history could not elucidate any concrete reason for differences between Washington and British Columbia.

3.3 Wildfire Cause

3.3.1 The Human Influence

The predominant natural cause of wildfire is lightning, though other ignition sources include sparks from rock falls, volcanoes and extraterrestrial impacts (Pyne 2001). The arrival of humans as a source of ignition has changed the nature of wildfire regimes around the majority of the globe, and very few parts are now untouched by human influence. For example, in the Mediterranean Basin humans are the dominant ignition source, and probably have been for thousands of years (Naveh 1975; Vazquez and Moreno 1998). While in the Mediterranean Basin human influence changed fire regimes gradually over millennia (Naveh 1994), in the USA the change has been much more rapid since the arrival of European settlers. American Indians had been using fire for many purposes before this (for cooking, communication using smoke, felling trees and hunting), but the arrival of Europeans saw rapid and great changes to both fire regimes and the vegetation they fed off, mainly through logging and the use of fire for agricultural land clearance (Pyne 1982). Recent data analysis suggests that anthropogenic ('human') fire is now more frequent than naturally caused fire in the USA, contributing to 57% of all fire between 1970 and 2000 (Brown *et al.* 2002). As lightning attributed 99.997% of the non-human caused fire in the dataset (Brown *et al.* 2002), the term 'lightning' fire is used here and should be taken as synonymous with naturally caused fire. Assessing the differences in frequency-area behaviour between fires caused anthropogenically or naturally may help us to understand the relative impacts of these causes upon wildfire regimes. This is turn will aid management and policy decisions.

The frequency-area statistics of USA data are now analysed according to whether the general cause given for the ignition of the fire was human or lightning. The data was subset according to Bailey's (1995) ecoregion classification at the division level, and plotted for human versus lightning cause (e.g. Figure 9). Bailey's ecoregion classification takes an ecosystem approach to classify regions according to a combination of climatic, vegetation and topographic factors. These regions are shown for the USA in Figure 8, and a list of their codes in Table IV. This approach allows analysis of the wildfire data in sub-sections according to factors related to natural drivers of the wildfire regime and not arbitrary administration boundaries (such as state boundaries). The use of ecozones in this way makes the analysis similar to Vazquez and Moreno (1998) and Stocks *et al.* (2003), who used Spanish phytogeographic sectors and Canadian ecozones respectively. A more detailed discussion of ecoregions and their potential as an organising framework to understand the natural drivers of wildfire frequency-area statistics is given below (sections 3.4 and 4.1.4).

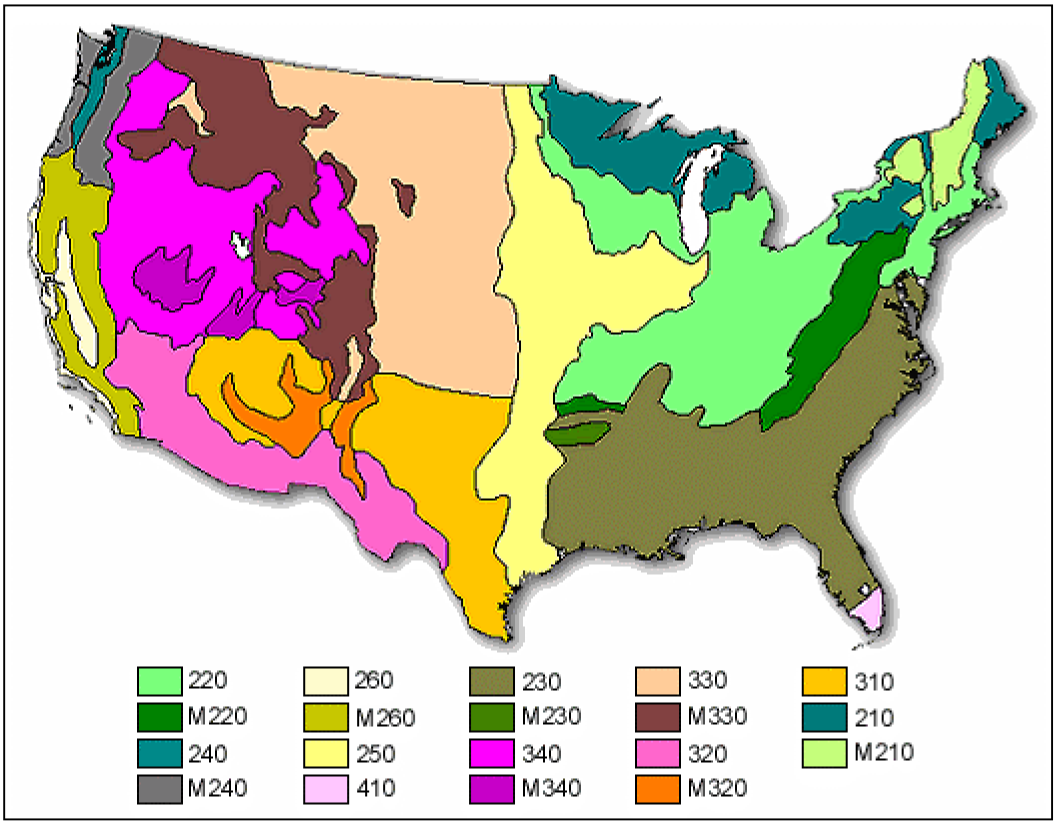


Figure 8. Bailey's ecoregion divisions of the contiguous USA. Bailey (1995) derived these ecoregion based on climate, vegetation and topography. Regions designated 'M' are mountain regions of their corresponding division. (Figure from UACE 2003)

Table IV. Ecoregion division codes and names. These names and codes will be referred to in the rest of the study.

Ecoregion Division	*Name*
120	Tundra Division
M120	Tundra Regime Mountains
130	Subarctic Division
M130	Subarctic Regime Mountains
210	Warm Continental Division
M210	Warm Continental Regime Mountains
220	Hot Continental Division
M220	Hot Continental Regime Mountains
230	Subtropical Division
M230	Subtropical Regime Mountains
240	Marine Division
M240	Marine Regime Mountains
250	Pairie Division
260	Mediterranean Division
M260	Mediterranean Regime Mountains
310	Tropical/Subtropical Steppe Division
320	Tropical Subtropical Desert Division
M320	Tropical Subtropical Desert Regime Mountains
330	Temperate Steppe Division
M330	Temperate Steppe Regime Mountains
340	Temperate Desert Division
M340	Temperate Desert Regime Mountains
410	Savanna Division

3.3.2 Analysis by Fire Cause

Table V presents the frequency-densities and β values (and percentage differences) for all human and lightning fires in each ecoregion. Figure 10 shows this data spatially for the contiguous USA.

Table V. Normalized frequency-densities and β values for fires in USA classified by cause. Figures in *italics* are regressed values, i.e. no fires were recorded of that size in the area. Continued overleaf…

	$\dot{f}(A_F)^{(a)}$ *for:*			$\beta^{(b)}$	$\frac{N_{FT}}{A_{study}}^{(c)}$
	$A_F = 0.01\ km^2$	$A_F = 1\ km^2$	$A_F = 100\ km^2$		
120 Lightning	0.0007	2.44×10^{-6}	7.93×10^{-9}	-1.24	3.11×10^{-5}
120 Human	0.0003	9.57×10^{-7}	*3.57 x* 10^{-9}	-1.21	9.87×10^{-6}
(Change) $^{(d)}$	(-66%)	(-61%)	*(-55%)*	(+2%)	(-68%)
M120 Lightning	0.0006	1.93×10^{-6}	6.61×10^{-9}	-1.23	2.50×10^{-5}
M120 Human	0.0001	5.00×10^{-7}	*3.13 x* 10^{-9}	-1.10	4.25×10^{-6}
(Change) $^{(d)}$	(-86%)	(-74%)	*(-53%)*	(+12%)	(-83%)
130 Lightning	0.0026	1.01×10^{-5}	3.91×10^{-8}	-1.21	1.42×10^{-4}
130 Human	0.0007	1.40×10^{-6}	3.00×10^{-9}	-1.33	2.48×10^{-5}
(Change) $^{(d)}$	(-75%)	(-86%)	(-92%)	(-10%)	(-82%)
M130 Lightning	0.0014	5.82×10^{-6}	2.38×10^{-8}	-1.19	8.60×10^{-5}
M130 Human	0.0004	1.07×10^{-6}	2.58×10^{-9}	-1.31	1.80×10^{-5}
(Change) $^{(d)}$	(-69%)	(-82%)	(-89%)	(-9%)	(-79%)
210 Lightning	0.0005	6.18×10^{-7}	*7.03 x* 10^{-10}	-1.47	1.67×10^{-5}
210 Human	0.0120	2.49×10^{-6}	*5.18 x* 10^{-10}	-1.84	3.24×10^{-4}
(Change) $^{(d)}$	(+2104%)	(+303%)	*(-26%)*	(-20%)	(+1834)
M210 Lightning	(e)	(e)	(e)	(e)	1.14×10^{-6}
M210 Human	0.0007	4.98×10^{-7}	*3.67 x* 10^{-10}	-1.57	1.63×10^{-5}
(Change) $^{(d)}$	(N/A)	(N/A)	(N/A)	N/A	(+1325%)
220 Lightning	0.0003	5.09×10^{-7}	*1.02 x* 10^{-9}	-1.35	8.25×10^{-6}
220 Human	0.0231	9.59×10^{-6}	3.97×10^{-9}	-1.69	4.16×10^{-4}
(Change) $^{(d)}$	(+9010%)	(+1784)	*(+290%)*	(-20%)	(+4940%)
M220 Lightning	0.0038	3.51×10^{-6}	*3.22 x* 10^{-9}	-1.52	1.01×10^{-4}
M220 Human	0.0699	2.28×10^{-5}	*7.46 x* 10^{-9}	-1.74	1.33×10^{-3}
(Change) $^{(d)}$	(+1721%)	(+550%)	*(+132%)*	(-13%)	(+1212%)
230 Lightning	0.0020	2.04×10^{-6}	2.10×10^{-9}	-1.49	5.54×10^{-5}
230 Human	0.0281	1.03×10^{-5}	*3.80 x* 10^{-9}	-1.72	5.22×10^{-4}
(Change) $^{(d)}$	(+1317%)	(+407)	*(+82%)*	(-13%)	(+842%)
M230 Lightning	0.0179	1.31×10^{-5}	*9.58 x* 10^{-9}	-1.57	4.56×10^{-4}
M230 Human	0.1361	6.20×10^{-5}	*2.82 x* 10^{-8}	-1.67	3.11×10^{-3}
(Change) $^{(d)}$	(+661%)	(+374%)	*(+195%)*	(-6%)	(+582%)
240 Lightning	0.0007	*8.76 x* 10^{-7}	*1.03 x* 10^{-9}	-1.47	1.09×10^{-5}
240 Human	0.0034	4.51×10^{-6}	*5.97 x* 10^{-9}	-1.44	9.86×10^{-5}
(Change) $^{(d)}$	(+356%)	*(+415%)*	*(+482%)*	(+2)	(+808%)
M240 Lightning	0.0049	5.80×10^{-6}	6.87×10^{-9}	-1.46	2.23×10^{-4}
M240 Human	0.0100	9.59×10^{-6}	9.17×10^{-9}	-1.51	3.26×10^{-4}
(Change) $^{(d)}$	(+105%)	(+65%)	(+34%)	(-3%)	(+46%)

Cont…

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	$\dot{f}(A_F)^{(a)}$ for:			$\beta^{(b)}$	$\frac{N_{FT}}{A_{study}}^{(c)}$
	A_F = 0.01 km^2	A_F = 1 km^2	A_F = 100 km^2		
250 Lightning	0.0001	2.86 x 10^{-7}	1.45 x 10^{-9}	-1.15	3.01 x 10^{-6}
250 Human	0.0035	3.33 x 10^{-6}	3.14 x 10^{-9}	-1.51	8.68 x 10^{-5}
(Change) $^{(d)}$	(+6157%)	(+1065%)	(+117%)	(-24%)	(+2789%)
260 Lightning	0.0004	2.05 x 10^{-6}	1.10 x 10^{-8}	-1.13	2.26 x 10^{-5}
260 Human	0.0094	2.12 x 10^{-5}	4.79 x 10^{-8}	-1.32	3.69 x 10^{-4}
(Change) $^{(d)}$	(+2356%)	(+934%)	(+335%)	(-14%)	(+1527%)
M260 Lightning	0.0138	2.22 x 10^{-5}	3.57 x 10^{-8}	-1.40	6.99 x 10^{-4}
M260 Human	0.0456	5.56 x 10^{-5}	6.77 x 10^{-8}	-1.46	1.53 x 10^{-3}
(Change) $^{(d)}$	(+231%)	(150%)	(+89%)	(-4%)	(+119%)
310 Lightning	0.0068	7.03 x 10^{-6}	7.32 x 10^{-9}	-1.49	1.99 x 10^{-4}
310 Human	0.0104	6.60 x 10^{-6}	4.20 x 10^{-9}	-1.60	2.70 x 10^{-4}
(Change) $^{(d)}$	(+53%)	(-6%)	(-43%)	(-7%)	(+36%)
320 Lightning	0.0070	1.11 x 10^{-5}	1.76 x 10^{-8}	-1.40	2.22 x 10^{-4}
320 Human	0.0244	1.89 x 10^{-5}	1.47 x 10^{-8}	-1.56	6.83 x 10^{-4}
(Change) $^{(d)}$	(+247%)	(+70%)	(-17%)	(-10%)	(+207%)
M320 Lightning	0.0429	3.61 x 10^{-5}	3.03 x 10^{-8}	-1.54	1.83 x 10^{-3}
M320 Human	0.0260	1.94 x 10^{-5}	1.44 x 10^{-8}	-1.56	1.02 x 10^{-3}
(Change) $^{(d)}$	(-39%)	(-46%)	(-52%)	(-2%)	(-44%)
330 Lightning	0.0054	5.71 x 10^{-6}	6.08 x 10^{-9}	-1.49	1.55 x 10^{-4}
330 Human	0.0163	9.23 x 10^{-6}	5.23 x 10^{-9}	-1.62	4.09 x 10^{-4}
(Change) $^{(d)}$	(+203%)	(+62%)	(-14%)	(-8%)	(+163%)
M330 Lightning	0.0178	2.06 x 10^{-5}	2.38 x 10^{-8}	-1.47	6.83 x 10^{-4}
M330 Human	0.0171	1.33 x 10^{-5}	1.04 x 10^{-8}	-1.55	4.71 x 10^{-4}
(Change) $^{(d)}$	(-4%)	(-35%)	(-56%)	(-6%)	(-31%)
340 Lightning	0.0108	2.46 x 10^{-5}	5.58 x 10^{-8}	-1.32	4.03 x 10^{-4}
340 Human	0.0147	2.20 x 10^{-5}	3.29 x 10^{-8}	-1.41	4.32 x 10^{-4}
(Change) $^{(d)}$	(+36%)	(-10%)	(-41%)	(-6%)	(+7%)
M340 Lightning	0.0160	2.41 x 10^{-5}	3.62 x 10^{-8}	-1.41	3.02 x 10^{-3}
M340 Human	0.0064	1.37 x 10^{-5}	2.93 x 10^{-8}	-1.34	2.38 x 10^{-4}
(Change) $^{(d)}$	(-60%)	(-43%)	(-19%)	(+6%)	(-92%)
410 Lightning	0.0302	6.36 x 10^{-5}	1.34 x 10^{-7}	-1.34	1.78 x 10^{-4}
410 Human	0.0817	1.98 x 10^{-4}	4.81 x 10^{-7}	-1.31	2.96 x 10^{-3}
(Change) $^{(d)}$	(+171%)	(+212%)	(+259%)	(+2%)	(+1563%)

(a) Normalized frequency-density for fires of size A_F, units are fires yr^{-1} km^{-4}
(b) β is the negative exponent of Eq. 7
(c) Frequency density (number of fires/study area), units are fires km^{-2}
(d) Changes (in %) are given for the lower area as a proportion of the upper
(e) Too few fires (N_{FT} = 4) to adequately assess distribution

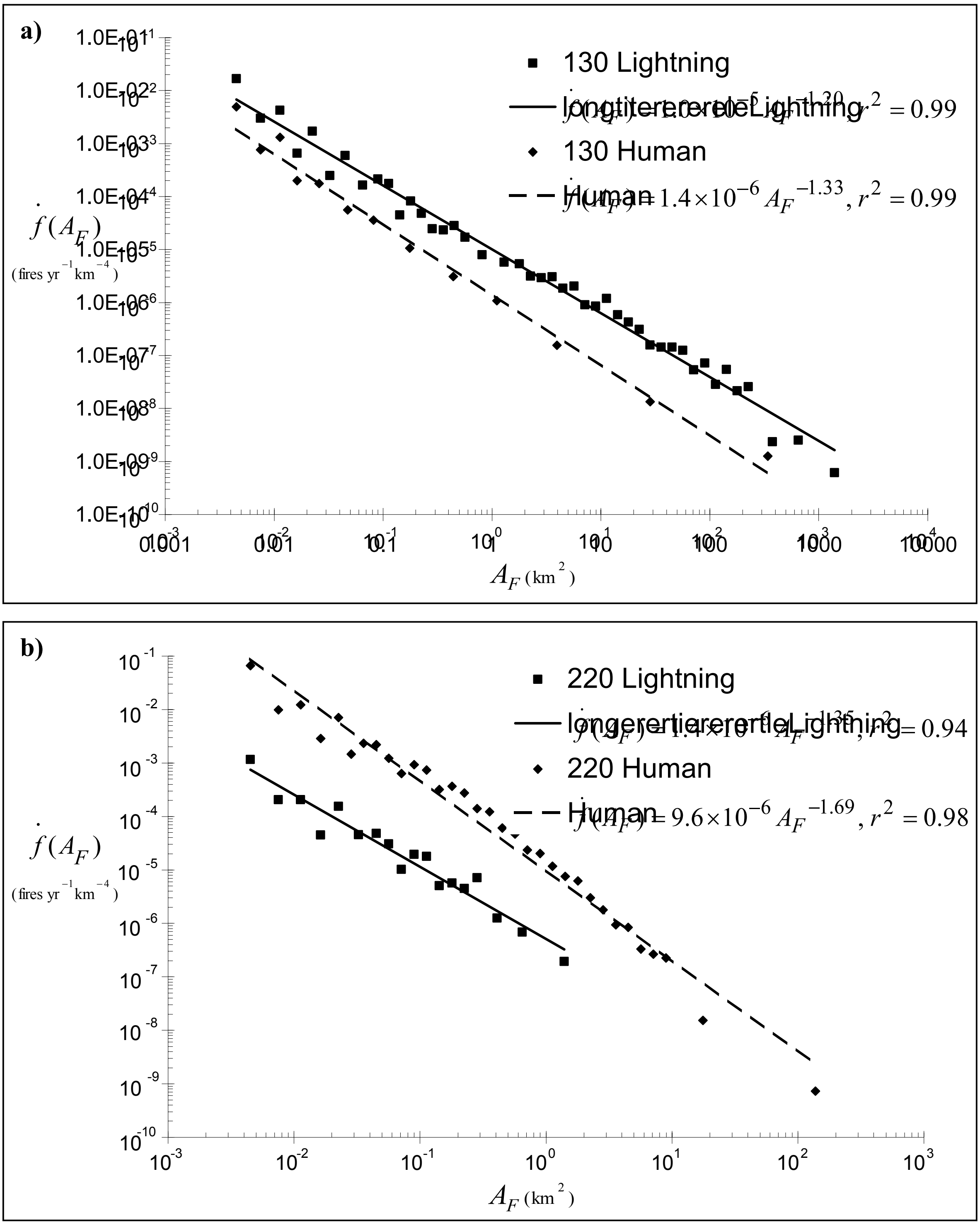

Figure 9. Noncumulative frequency-area distributions by cause for ecoregions a) 130 and b) 220. 130 shows human frequency-densities are lower than lightning, and vice versa for 220. β values are greater for human fires in both cases.

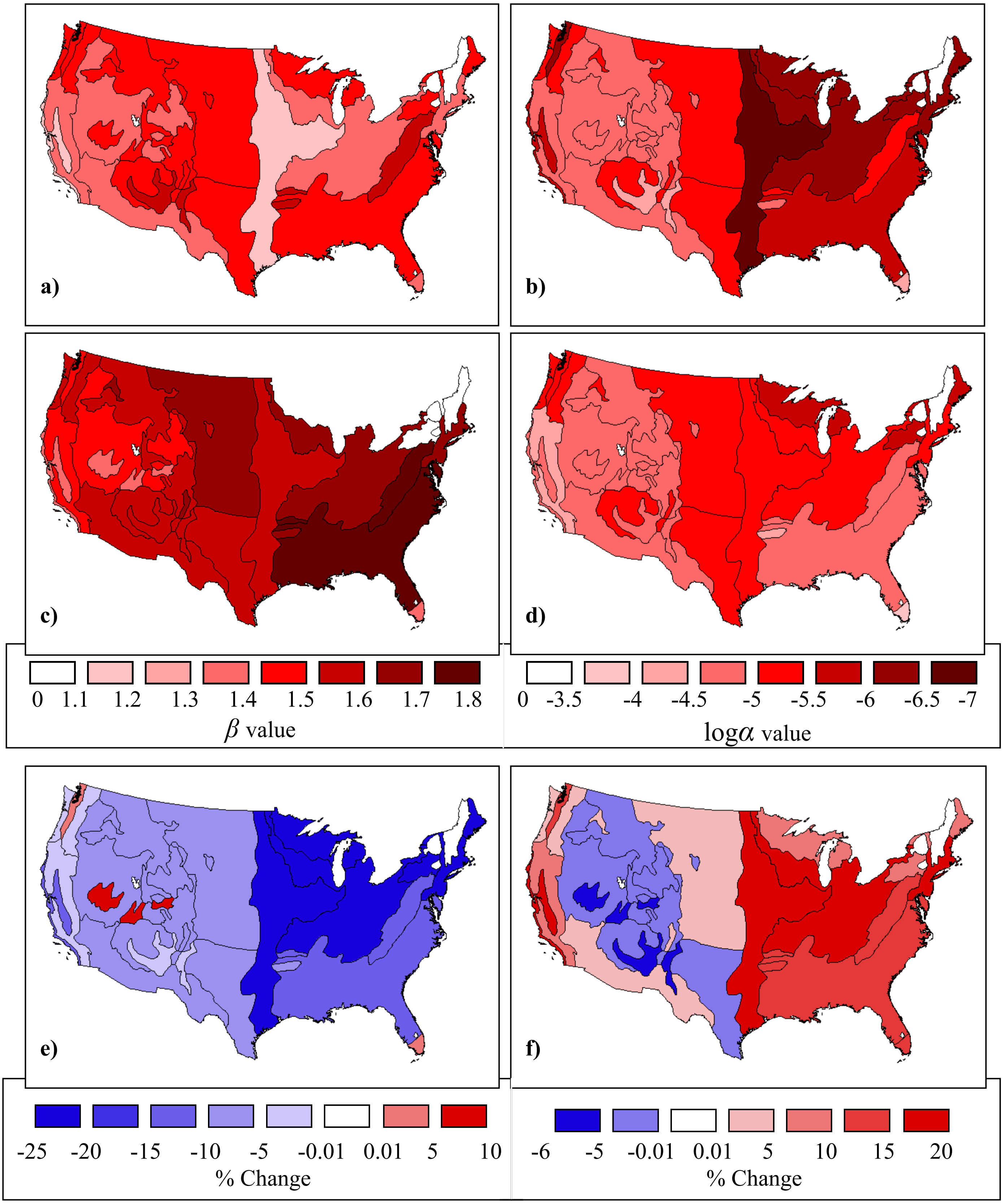

Figure 10. β and logα values and their percentage differences for human and lightning fires, mapped by ecoregion. Lightning (a) and human (c) β values and the difference between them (e), and lightning (b) and human (d) logα values and the difference between them (f).

For all regions in Alaska frequency-density of lightning fires is consistently greater than for human fires. This may be attributed to the low population density throughout much of the state. However, for the majority of the contiguous USA the reverse is true, and human fires are more frequent (e.g. Figure 9f). Many of the higher frequency-densities are found in ecoregions of the more densely populated east coast (see Figure 10). The impact of population density on these frequencies is examined more closely below (see section 3.3.5).

Secondly, in all but five ecoregions the β values of human fires is greater than the lightning fires, by up to 25% in some cases. Thus, it would appear that the scaling of fire sizes between human and lightning fires is markedly different, with the ratio of large to small fires greater for burns ignited by humans. Further, the range of β values is larger for human fires (1.10 to 1.84) than for lightning fires (1.13 to 1.57), indicating that the scaling of fires is more variable for human fires.

3.3.3 Fire Cause Data Issues

The data used for the above analysis consisted of the entire record of 179,192 USA fires in the data set greater than 0.004 km^2, minus 11,457 fires in the record with no cause given, resulting in a total of 167,735 fires. All fires with no cause given came from data from Department of the Interior (DOI) agencies – a total of 28% of all records they gave. Brown *et al.* (2002) note that it has been suggested that these fires could be classed as lightning fires as, if a human cause was not determined, it was probably lightning. If this suggestion were correct it might be a cause of the much greater human fire frequencies exhibited above, i.e. human fires appear relatively more frequent because not all the lightning fires were recorded properly. However, Brown *et al.* (2002) go on to recommend that zero causes should not be treated as lightning fires given other quality control issues in the dataset. Further, it should be noted that DOI reporting of fires was not continuous throughout the 1970s and thus is not complete. Because of these factors it was decided that the above analysis should be repeated but for USDA Forestry Service (USFS) reports only, reducing the data to N_{FT} = 87,964 fires, as this would give a better representation of the relative proportion of human versus lightning fires.

3.3.4 USFS Data Fire Causes

Table VI gives frequency-densities and β values (and percentage differences) for human and lightning fires in each ecoregion for USFS data only. Figure 12 shows the data spatially. Again, β values for plots of human caused fires are generally found to be greater than lighting fires, but the range of values is now very similar (see Table VI). Further, the spatial pattern regarding frequencies of fires would seem to be strengthened. In ecoregions on either coast of the contiguous USA, frequency-densities of human fires are found to be greater, and vice versa in the central region (see Figure 12f).

As mentioned above when the total data set was examined, and as suggested by Brown *et al.* (2002), this spatial pattern may be due to increased population densities on the coasts. However, a second factor may now also be attributed to this spatial distribution: all ecoregion divisions within the Humid Temperate Domain (see Figure 11) show human fires to have frequency-densities greater than for lightning fires, while within the Dry Domain the reverse is true (see Figure 12). Further, in all but one Humid Temperate division, human fires show greater β values than lightning fires. This behaviour is not evident in Dry divisions, where differences in frequency between the two types of fire are also generally reduced. Therefore, the differences in frequency may be driven by ecological or climatological factors rather than anthropogenic.

Table VI. Normalized frequency-densities and β values for USFS fires in USA classified by cause. Figures in *italics* are regressed values, i.e. no fires were recorded of that size in the area. Continued overleaf…

	$\dot{f}(A_F)^{(a)}$ *for:*			$\beta^{(b)}$	$\frac{N_{FT}}{A_{study}}^{(c)}$
	A_F = 0.01 km^2	A_F = 1 km^2	A_F = 100 km^2		
210 Lightning	0.0004	5.90 x 10^{-7}	8.40 x 10^{-10}	-1.42	1.31 x 10^{-5}
210 Human	0.0055	2.05 x 10^{-6}	7.60 x 10^{-10}	-1.72	1.46 x 10^{-4}
(Change) $^{(d)}$	(+1227%)	(+247%)	(-9%)	(-17%)	(+1011%)
220 Lightning	0.0002	4.32 x 10^{-6}	8.56 x 10^{-10}	-1.35	6.39 x 10^{-6}
220 Human	0.0155	4.98 x 10^{-6}	1.60 x 10^{-9}	-1.75	2.72 x 10^{-4}
(Change) $^{(d)}$	(+6999%)	(+1053%)	(+87)	(-23)	(+4163%)
M220 Lightning	0.0037	2.91 x 10^{-6}	2.31 x 10^{-9}	-1.55	9.04 x 10^{-5}
M220 Human	0.0596	1.75 x 10^{-5}	5.16 x 10^{-9}	-1.77	1.12 x 10^{-3}
(Change) $^{(d)}$	(+1531%)	(+503%)	(+123%)	(-12%)	(+1139%)
230 Lightning	0.0017	1.13 x 10^{-6}	7.35 x 10^{-10}	-1.59	4.13 x 10^{-5}
230 Human	0.0283	6.75 x 10^{-6}	1.61 x 10^{-9}	-1.81	4.49 x 10^{-4}
(Change) $^{(d)}$	(+1535%)	(+498%)	(+119%)	(-12%)	(+988%)
M230 Lightning	0.0175	1.31 x 10^{-5}	9.85 x 10^{-9}	-1.56	4.47 x 10^{-4}
M230 Human	0.0922	3.81 x 10^{-5}	1.58 x 10^{-8}	-1.69	2.08 x 10^{-3}
(Change) $^{(d)}$	(+426%)	(+190)	(+60%)	(-8%)	(+366%)
240 Lightning	0.0005	1.05 x 10^{-6}	2.32 x 10^{-9}	-1.33	1.00 x 10^{-5}
240 Human	0.0012	3.19 x 10^{-6}	8.80 x 10^{-9}	-1.28	3.76 x 10^{-5}
(Change) $^{(d)}$	(+145%)	(+205)	(+279%)	(+4%)	(+275%)
M240 Lightning	0.0038	4.21 x 10^{-6}	4.65 x 10^{-9}	-1.48	1.76 x 10^{-4}
M240 Human	0.0068	6.28 x 10^{-6}	5.80 x 10^{-9}	-1.52	2.30 x 10^{-4}
(Change) $^{(d)}$	(+79)	(+49%)	(+25%)	(-3%)	(+31%)
250 Lightning	0.0000	1.23 x 10^{-7}	8.35 x 10^{-10}	-1.08	6.26 x 10^{-7}
250 Human	0.0005	4.78 x 10^{-7}	4.72 x 10^{-10}	-1.50	1.25 x 10^{-5}
(Change) $^{(d)}$	(+2565%)	(+288%)	(-43%)	(-28%)	(+1900%)
260 Lightning	0.0003	1.42 x 10^{-6}	7.87 x 10^{-9}	-1.13	1.31 x 10^{-5}
260 Human	0.0040	9.69 x 10^{-6}	2.36 x 10^{-8}	-1.31	1.59 x 10^{-4}
(Change) $^{(d)}$	(+1461%)	(+584%)	(+199%)	(-14%)	(+1111%)

Cont…

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	$f(A_F)^{(a)}$ for:			$\beta^{(b)}$	$\frac{N_{FT}}{A_{study}}^{(c)}$
	$A_F = 0.01\ km^2$	$A_F = 1\ km^2$	$A_F = 100\ km^2$		
M260 Lightning	0.0096	1.41×10^{-5}	2.08×10^{-8}	-1.42	5.37×10^{-4}
M260 Human	0.0296	3.39×10^{-5}	3.88×10^{-8}	-1.47	1.05×10^{-3}
(Change) $^{(d)}$	(+209%)	(+140%)	(+87%)	(-4%)	(+95%)
310 Lightning	0.0039	3.21×10^{-6}	2.63×10^{-9}	-1.54	1.15×10^{-4}
310 Human	0.0028	1.93×10^{-6}	1.34×10^{-9}	-1.58	8.49×10^{-5}
(Change) $^{(d)}$	(-29%)	(-40%)	(-49%)	(-2%)	(-26%)
320 Lightning	0.0031	3.72×10^{-6}	4.52×10^{-9}	-1.46	9.83×10^{-5}
320 Human	0.0023	2.72×10^{-6}	3.26×10^{-9}	-1.46	7.16×10^{-5}
(Change) $^{(d)}$	(-26%)	(-27%)	(-28%)	(0%)	(-27%)
M320 Lightning	0.0323	2.76×10^{-5}	2.35×10^{-8}	-1.53	1.47×10^{-3}
M320 Human	0.0137	1.17×10^{-5}	1.01×10^{-8}	-1.53	6.42×10^{-4}
(Change) $^{(d)}$	(-58%)	(-57%)	(-57%)	(0%)	(-56%)
330 Lightning	0.0016	1.68×10^{-6}	1.72×10^{-9}	-1.49	5.64×10^{-5}
330 Human	0.0003	8.49×10^{-7}	2.12×10^{-9}	-1.30	1.37×10^{-5}
(Change) $^{(d)}$	(-79%)	(-49%)	(+23%)	(+15%)	(-76%)
M330 Lightning	0.0129	1.56×10^{-5}	1.89×10^{-8}	-1.46	5.40×10^{-4}
M330 Human	0.0101	8.41×10^{-6}	6.97×10^{-9}	-1.54	3.14×10^{-4}
(Change) $^{(d)}$	(-21%)	(-46%)	(-63%)	(-5%)	(-42%)
340 Lightning	0.0013	2.28×10^{-6}	3.89×10^{-9}	-1.38	5.89×10^{-5}
340 Human	0.0012	2.32×10^{-6}	4.69×10^{-9}	-1.35	4.95×10^{-5}
(Change) $^{(d)}$	(-14%)	(+2%)	(+20%)	(+3%)	(-16%)
M340 Lightning	0.0043	6.50×10^{-6}	9.87×10^{-9}	-1.41	1.69×10^{-4}
M340 Human	0.0020	3.73×10^{-6}	7.11×10^{-9}	-1.36	7.66×10^{-5}
(Change) $^{(d)}$	(-54%)	(-43%)	(-28%)	(+4%)	(-55%)

(a) Normalized frequency-density for fires of size A_F, units are fires yr^{-1} km^{-4}
(b) β is the negative exponent of Eq. 7
(c) Frequency density (number of fires/study area), units are fires km^{-2}
(d) Changes (in %) are given for the lower area as a proportion of the upper

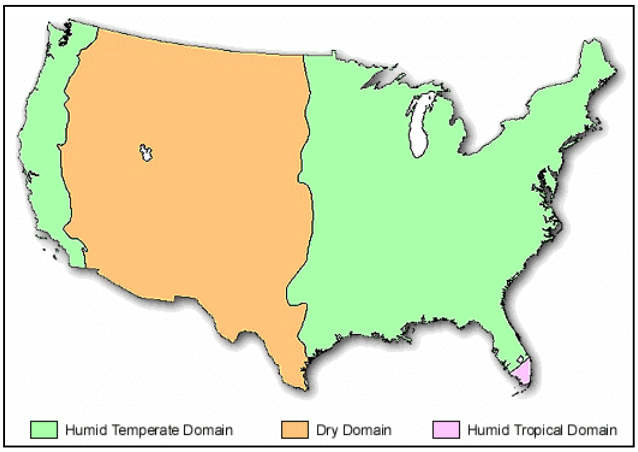

Figure 11. Bailey's ecoregion domains of the contiguous USA. A similar pattern is observed between this ecoregion domain map and Figures 9f and 11f. (Figure from USACE 2003)

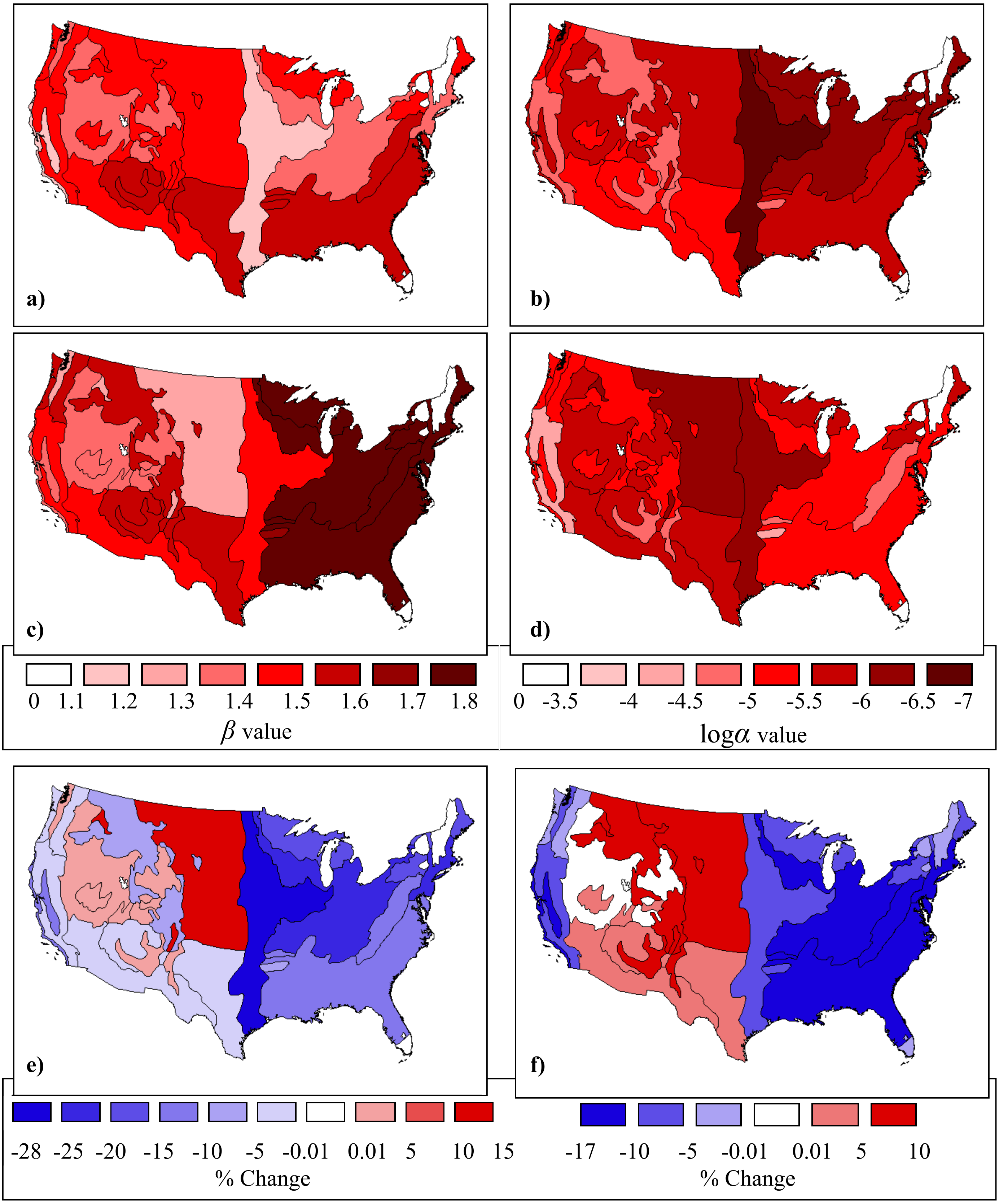

Figure 12. β and logα values and their percentage differences for USFS human and lightning fires, mapped by ecoregion. Lightning (a) and human (c) β values and the difference between them (e) and lightning (b) and human (d) logα values and the difference between them (f).

3.3.5 Spatial Analysis of Fire Causes

To examine whether population density is significantly related to ignition cause, a correlation analysis was run on the geographic distribution of population and fire frequency for the two causes, and for both the complete dataset and USFS data alone. USA county population density data supplied with *Arcview GIS (Version 3.3)* (ESRI 2002) was converted to raster format (Figure 13), and fire location data was used to create maps of fire frequency at 0.2 degree (≈22 by 8 km) resolution (see Figure 14).

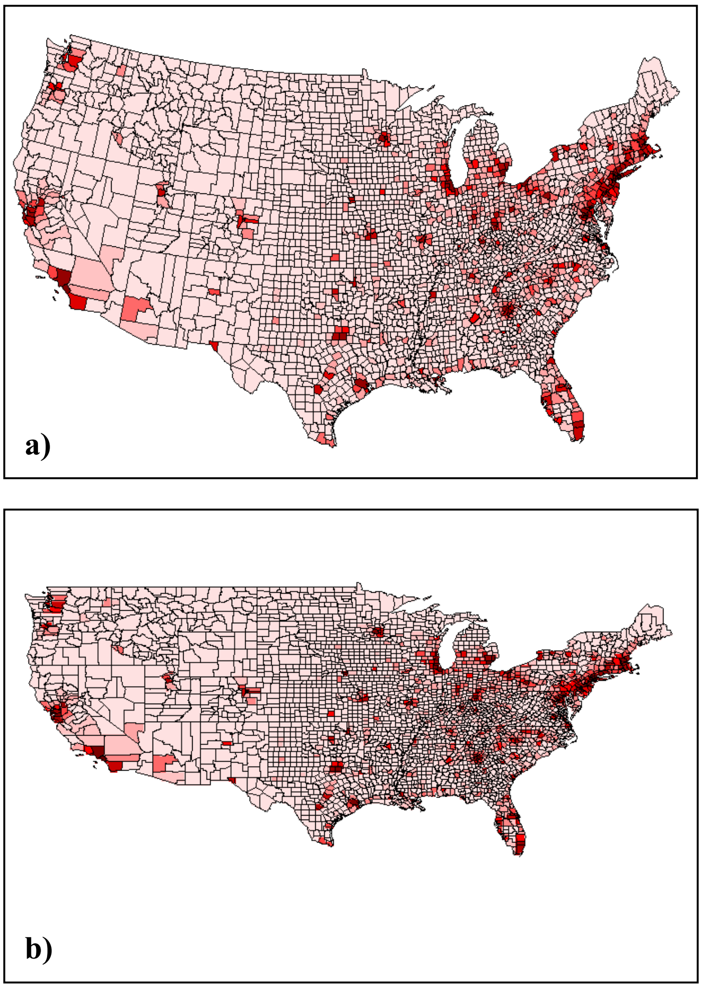

Figure 13. Conversion of USA counties population density vector map (a) to raster grid (b). Greater population densities are darker red. Note the change in projection from Lambert Equal Area to Geographic Lat-Long due to the conversion to a grid format.

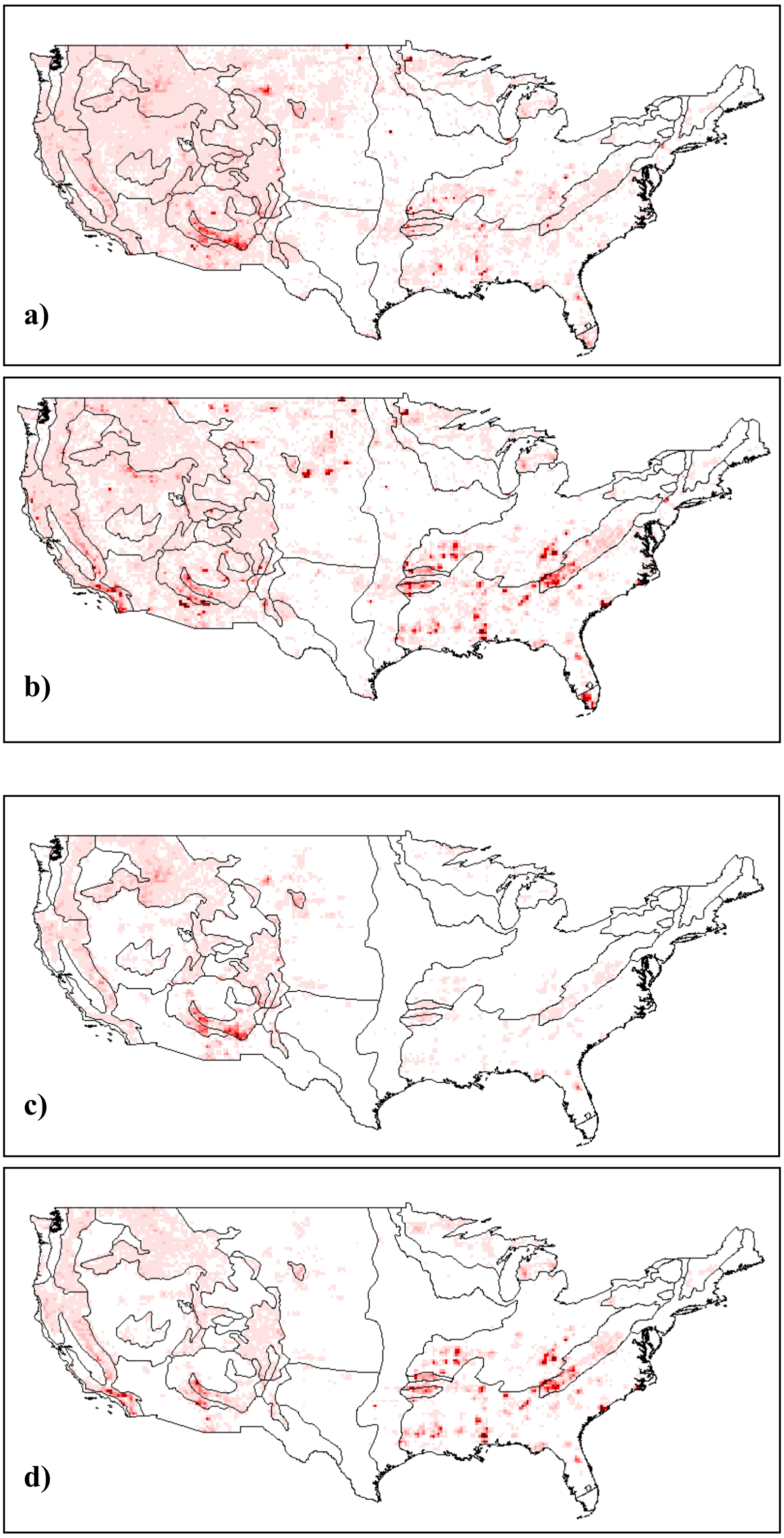

Figure 14. Fire frequency grids produced at 0.2 degree resolution. a) lightning and b) human fire frequency for the whole dataset, and c) lightning and d) human fire frequency for USFS data only.

From the resulting grids, 100 pixels were selected randomly from pixels that had non-zero values for fire frequency, and a spearman rank correlation run. Pixels were selected only from areas where fires had occurred to avoid correlation of points where it would be impossible for a wildfire to occur, e.g. the centre of an urban area. This analysis showed no statistical correlation between population density and both human and lightning fires for the total data set. However, when only the USFS data is considered, a positive correlation between population density and human fire frequency is observed at the 0.95 significance level. No significant correlation was observed between population density and lightning fires for the USFS data. This indicates that population density might be related to the frequency of human fires, though a more detailed analysis is needed.

Previous studies have examined the relationship between lightning occurrence and lightning fires. Fowler and Aleson (1984) examined factors influencing lightning fire distribution for a region in Idaho, and Podur *et al.* (2003) examined spatial patterns of lightning fires in Ontario. Pyne (2001) presents maps of number of thunderstorms and number of lightning fires per year for the USA (see Figure 15). The greatest number of days with thunderstorms occurs in Florida, but lightning fires occur most in the southwest of the country. A similar lightning fire distribution was found here, as shown by Figures 14a and c. When the southwest USA is examined in more detail, and human and lightning fire densities contrasted, there would appear to be a difference in spatial distribution (see Figure 16). Human fires are denser nearer to the coast, while lightning fires cluster at greater elevations inland (as found by Brown *et al.* 2002). The human distribution might be explained by proximity to the urban areas of San Diego, Los Angeles and Phoenix. Differences in spatial distribution between the causes would also appear apparent in the southern Appalachians (see Figure 16). Here, lightning frequency-densities are low but human frequency densities show several 'hotspots' of clustered wildfire ignition. This apparent increase in human-caused fires might be due to high recreation use of the forested lands in this area.

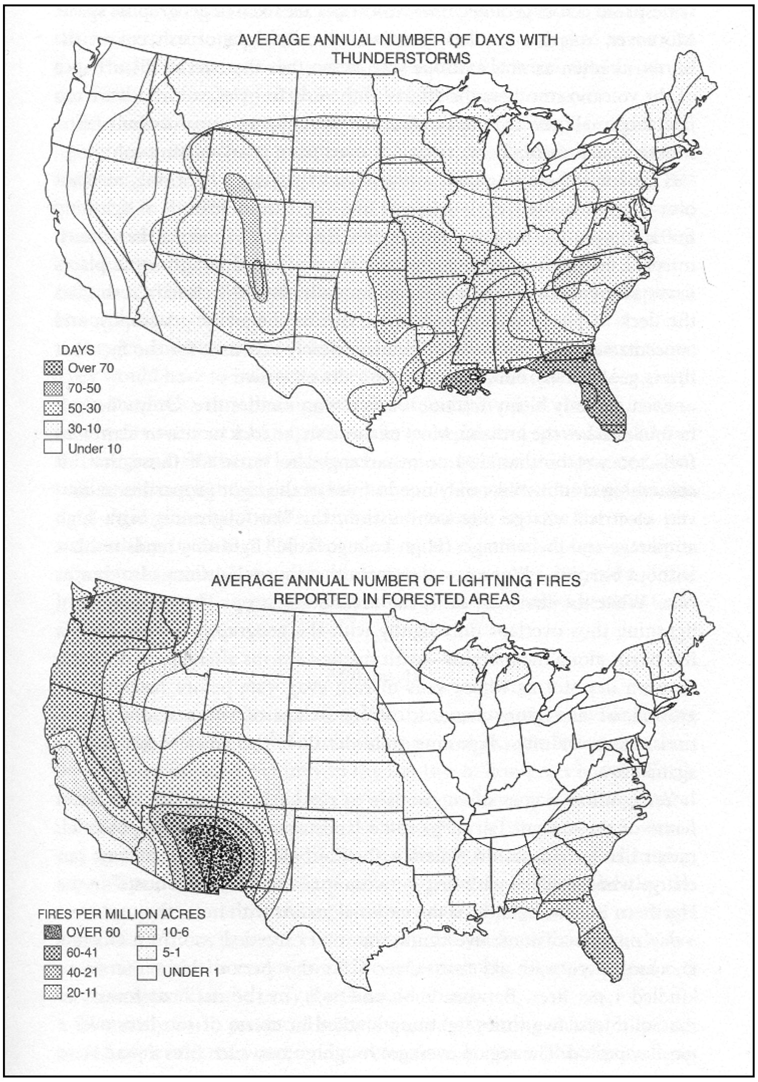

Figure 15. Spatial distribution of thunderstorms and lighting fires across the contiguous USA. Lightning is most frequent in the southwest of the USA, but lightning fires area most frequent in the southeast. A similar lightning fire distribution was found in the data here (see Figure 14). (Figure from Pyne 2001)

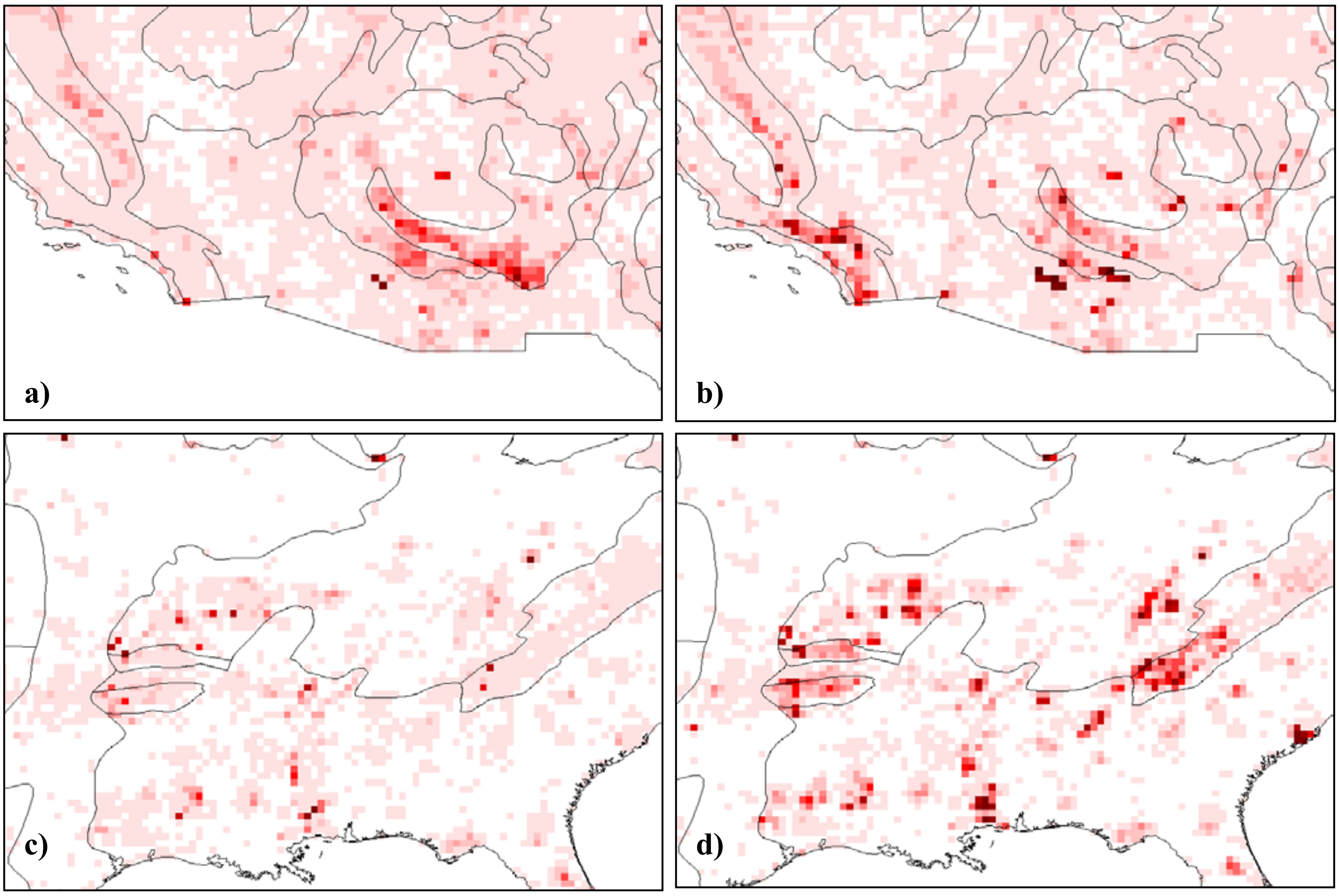

Figure 16. Spatial distribution of lightning and human fire in the southwest USA and the southern Appalachians. a) lightning and b) human fires in the southwest, and c) lightning and d) human fire in the southern Appalachians. Human fire densities are found to be much more 'patchy', clustering in certain areas.

3.3.6 Wildfire Cause Further Study

Restricted functionality of *ArcView* prevented a mapping of total burnt area per pixel (as done by Vazquez and Moreno 1998), and a correlation analysis of this (by cause) against population density. This, along with a more rigorous statistical analysis of spatial distribution differences between causes, such as the use of the test developed by Syrjala (1996), is analysis that would be interesting to pursue in the future.

3.3.7 Wildfire Cause Summary

Results for both the whole dataset and USFS records only, show human fire to have been much more frequent than lightning fire during the period of study (Figure 9a, Tables V and VI). This increased frequency of human fires, rather than the influence of vegetation and climatic factors, is likely to be driving observed differences in spatial distribution between the causes (section 3.3.5). This is suggested by the fact that human fire densities have been found to be related to population density, and by the apparent difference in spatial distribution between causes. Generally, human fires exhibited greater β values (Figure 9, Tables V and VI), meaning a greater ratio of large to small fires, compared to lightning.

3.4 Ecoregions

3.4.1 Potential Ecological Drivers of Wildfire Regimes

There have been very few studies that have attempted to explain observed wildfire frequency-size power-law behaviour from an ecological perspective (i.e. only Ricotta *et al.* 1999; 2001; Ricotta 2003). Here, a broad analysis of the frequency-size statistics behaviour of USA ecoregions (Bailey 1995) is made, and reasons for their differences are suggested with reference to climate, vegetation and energy flows. This will lead on to a more detailed discussion below exploring the potential use of ecological energetics and thermodynamics as a framework to examine potential processes during power-law frequency-area statistics.

The basic theory that this analysis is based upon is that energy input, via solar energy, allows vegetation to grow and produce biomass to store this energy. Growth is restricted by the availability of other resources, particularly precipitation. Energy stored as vegetation biomass is released, or dissipated, as it is consumed by herbivores, detritivores (decomposers) and fire. However, for fires to start ignition is needed. Frequency and timing of ignition is restricted by the presence of lightning naturally, and by humans otherwise. Here, only lightning is considered as a source of ignition in an attempt to explain the natural ecological drivers of the regimes.

3.4.2 Ecoregion Wildffire Regimes

Figure 17 and Table VII present the β and logα values for all ecoregion divisions in the USA. Major differences can be observed between ecoregions in terms of both β values (scaling of sizes) and logα values (frequency-density of the 1 km^2 fire), as highlighted by Figure 18. Using the basic theory outlined above, these differences between ecoregions can be explained. For example, the large difference in frequency between the Savanna (410) and Tundra (120) divisions can be explained by the large differences in solar and precipitation energy input throughout the year. Lying in the Humid Tropical Domain, 410 receives large amounts of rainfall and maintains year-round high temperatures allowing great vegetation growth. Combined with a large number of ignition sources (thunderstorms), and a short dry season, this makes wildfire a very frequent occurrence (logα = -3.61). The Tundra (120) division meanwhile has very short, cool summers and long severe winters meaning vegetation growth is restricted to grasses, sedges and lichen. Combined with infrequent ignition opportunities (lighting) this makes wildfire infrequent (logα = -5.53).

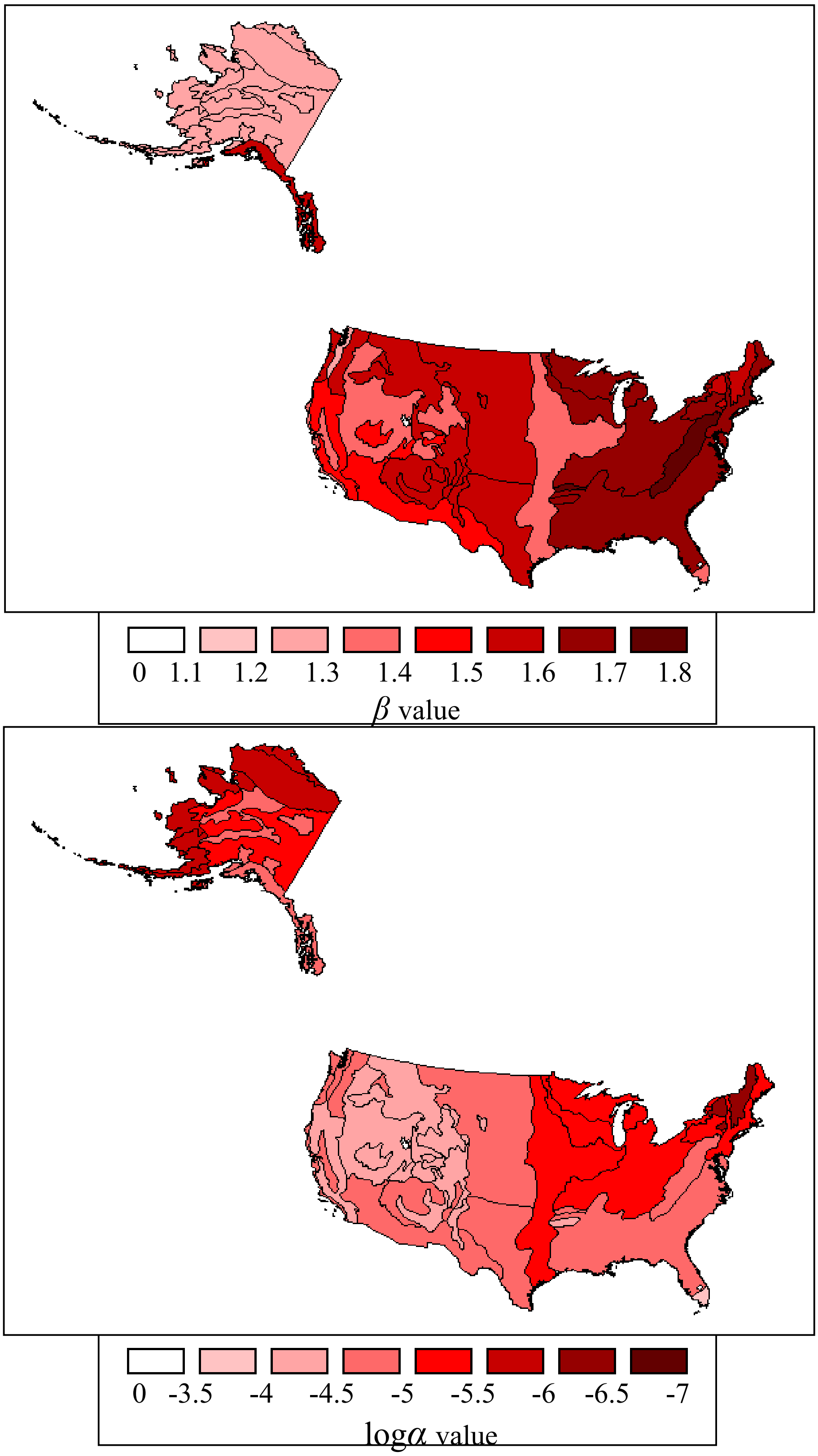

Figure 17. Map of β and logα values for ecoregions of the USA. Variation in β and logα values is explained by climatic, vegetation and topographic factors.

Table VII. Normalized frequency density of fire occurrence for fires of varying size in USA ecoregions. Figures in *italics* are regressed values, i.e. no fires were recorded of that size in the area.

Ecoregion	$\dot{f}(A_F)^{(a)}$ *for:* A_F = *0.01 km²*	A_F = *0.01 km²*	A_F = *0.01 km²*	$\beta^{(b)}$	*log*$\alpha^{(c)}$	$\frac{N_{FT}}{A_{study}}^{(d)}$
120	0.0011	2.9×10^{-6}	8.1×10^{-9}	1.28	-5.53	0.0013
M120	0.0007	2.2×10^{-6}	7.3×10^{-9}	1.24	-5.65	0.0009
130	0.0033	1.1×10^{-5}	3.8×10^{-8}	1.23	-4.95	0.0053
M130	0.0020	7.2×10^{-6}	2.6×10^{-8}	1.22	-5.14	0.0033
210	0.0094	5.6×10^{-6}	3.3×10^{-9}	1.61	-5.26	0.0112
M210	0.0007	*5.0×10^{-7}*	*3.7×10^{-10}*	1.57	-6.30	0.0005
220	0.0238	9.6×10^{-6}	3.9×10^{-9}	1.70	-5.02	0.0129
M220	0.0766	2.4×10^{-5}	*7.7×10^{-9}*	1.75	-4.61	0.0445
230	0.0370	1.9×10^{-5}	9.9×10^{-9}	1.64	-4.72	0.0208
M230	0.1577	6.7×10^{-5}	*2.8×10^{-8}*	1.69	-4.18	0.1105
240	0.0055	1.7×10^{-5}	*5.2×10^{-8}*	1.26	-4.77	0.0060
M240	0.0189	1.7×10^{-5}	1.5×10^{-8}	1.52	-4.77	0.0184
250	0.0046	8.2×10^{-6}	*1.4×10^{-8}*	1.38	-5.09	0.0050
260	0.0113	2.6×10^{-5}	5.9×10^{-8}	1.32	-4.59	0.0137
M260	0.0608	7.8×10^{-5}	9.9×10^{-8}	1.45	-4.11	0.0738
310	0.0162	1.4×10^{-5}	1.2×10^{-8}	1.53	-4.85	0.0149
320	0.0301	3.0×10^{-5}	2.9×10^{-8}	1.50	-4.53	0.0286
M320	0.0684	6.1×10^{-5}	5.4×10^{-8}	1.52	-4.21	0.0898
330	0.0202	1.6×10^{-5}	1.2×10^{-8}	1.55	-4.80	0.0186
M330	0.0388	3.7×10^{-5}	3.4×10^{-8}	1.51	-4.44	0.0370
340	0.0277	4.7×10^{-5}	7.9×10^{-8}	1.39	-4.33	0.0272
M340	0.0246	3.7×10^{-5}	5.4×10^{-8}	1.41	-4.44	0.0252
410	0.1228	2.5×10^{-4}	5.0×10^{-8}	1.35	-3.61	0.1271

(a) Normalized frequency-density for fires of size A_F, units are fires yr^{-1} km^{-4}
(b) β is the negative exponent of Eq. 7
(c) logα is the log of the normalized frequency y-intercept at A_F = 1 km^2
(d) Frequency density (number of fires/study area), units are fires km^{-2}

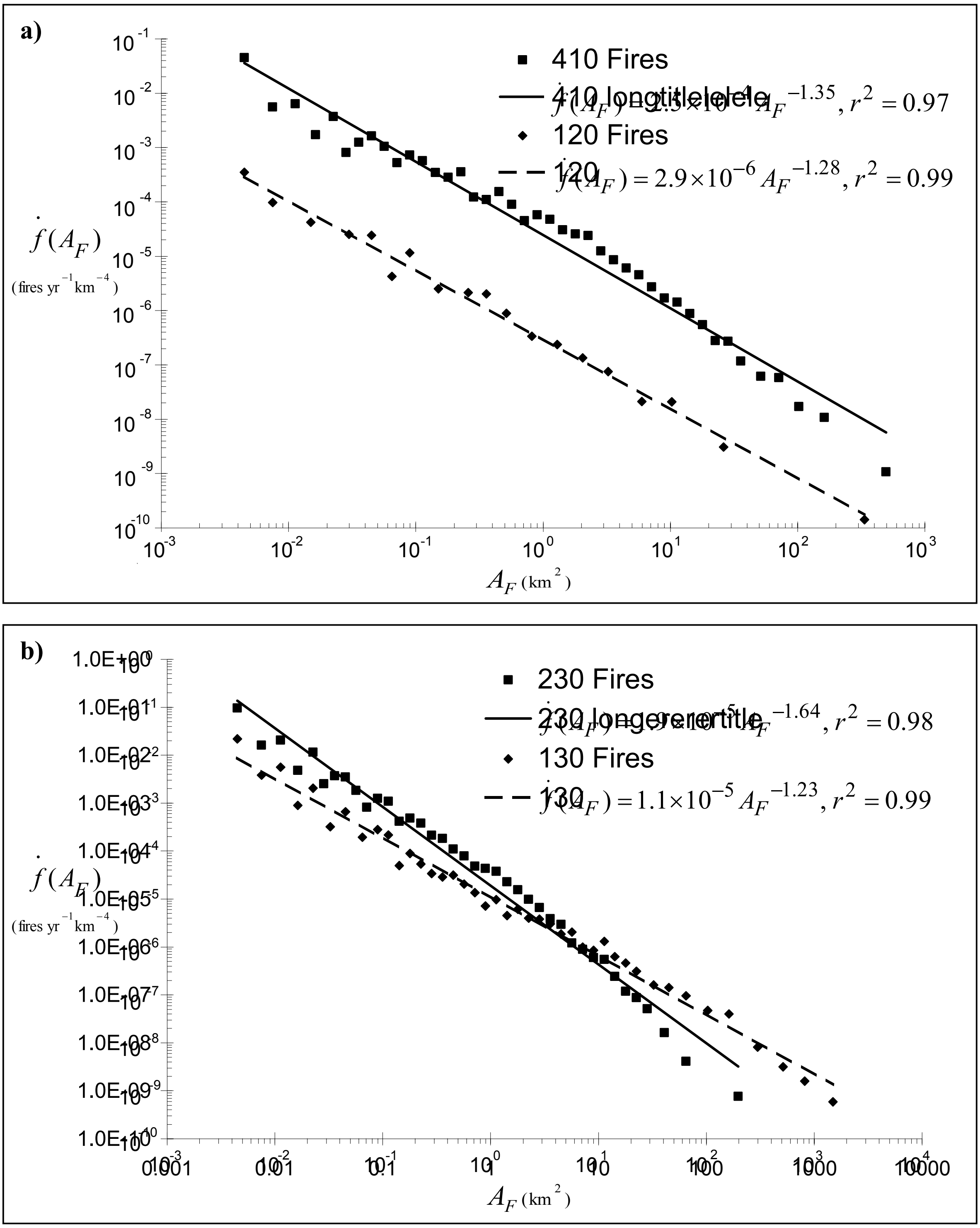

Figure 18. Noncumulative frequency-area distributions for all fire in ecoregions a) 120 and 410 and b) 130 and 230. Figures demonstrate large differences in a) logα, and b) β values.

The great difference in β between the Subarctic (130) and Subtropical (230) is explained through a combination of their climate-induced vegetation mass and structure and the potential number of ignitions (lightning strikes). The Subarctic division is very similar in nature to the Tundra division, though with greater vegetation biomass (boreal forest), and a similar lack of ignition sources. Thus, when fires do (infrequently) start, they are large in nature because of the need to dissipate energy stored (as vegetation biomass) since the last burn. This produces a low β value (β = 1.23). The natural vegetation of the Subtropical division is deciduous forest and today is covered by second growth loblolly and slash pine (Bailey 1995). Thus, while much energy is stored throughout the year the high frequency of thunderstorms and associated lightning provides frequent opportunities to burn. This allows energy to be dissipated more frequently in smaller events, producing a high β value (β = 1.64). Further, reduced rates of decomposition and herbivory due to the climate in the Subarctic division emphasises the accumulation of energy build-up, in contrast to the Subtropical division where detritivores and herbivores are more active.

3.4.3 Classification of Wildfire Regime Frequency-Area Parameters

From Table XII, scales to classify β values and logα values according to their relative sizes were derived empirically (Table VIII). These can be used to give an idea of the relative scaling of fires sizes and frequency-density between regions and may be used to compare regimes from other data. Using these scales the characteristics of wildfire regimes in the four ecoregion domains of the USA have been described in Table IX.

Table VIII. Classification of wildfire frequency-area β and logα values. These values give an idea of scaling of fires sizes and frequency-densities and can be compared with other data.

β	*Classification*	*logα* *(Fires yr^{-1} km^{-4})*
Greater than 1.6	*Very High*	Greater than -4.0
1.5 to 1.6	*High*	-4.0 to -4.5
1.4 to 1.5	*Average*	-4.5 to -5
1.3 to 1.4	*Low*	-5 to -5.5
Less than 1.3	*Very Low*	Less than -5.5

Table IX. Classification of USA ecoregion (domain) β and logα values. Using the classification presented in Table VIII.

Ecoregion (Domain)	*Mean β value*	*β Classification*	*Mean logα value*	*logα Classification*
100	1.25	Very High	-5.32	Low
200	1.53	Low	-4.86	Average
300	1.49	Average	-4.51	Average
400	1.35	High	-3.61	Very High

4

DISCUSSION

A discussion on the potential processes causing the observed frequency-area power-law distribution behaviour is now presented. The potential of other distributions to fit the data is also addressed.

4.1 What Drives Wildfire Power-Law Behaviour?

4.1.1 Ecosystems as Dissipative Structures

Recent work on the self-organization and thermodynamics of open systems, such as ecosystems and human systems, has led to the development of the idea that these open systems are dissipative structures that maintain themselves in a stable state far from (thermodynamic) equilibrium (e.g. Nicolis and Prigogine 1977; Prigogine and Stengers 1984). As open systems, ecosystems experience energy and material fluxes across their boundaries, the most important here being the continual high quality energy received from the sun. In this sense, high quality energy is that which has a large potential to drive the system away from thermodynamic equilibrium, or set up energy gradients, compared to lower quality energy. 'E**x**ergy' is a measure of this potential and hence reflects the quality of the energy (Schneider and Kay 1994). Thus, high quality solar energy drives ecosystems away from thermodynamic equilibrium. The second law of thermodynamics states that if there are any processes occurring in a system then the quality of energy will be degraded (Toussaint and Schneider 1998), or in terms of exergy, destroyed. It has been suggested therefore that self-organizing, dissipative processes spontaneously emerge in ecosystems, manifested as structures that utilize material resources to degrade energy (or, dissipate exergy), in an attempt to resist movement away from equilibrium (Schneider and Kay 1994; Zhou *et al.* 1996; Jorgensen *et al.* 1998; Kay *et al.* 1999). “As more high quality energy is pumped into a system, more organization emerges, in a step-wise way, to dissipate the exergy” (Kay *et al.* 1999 p.723).

The autotrophs in an ecosystem (e.g. plants) use incoming solar energy (alongside other raw materials) to both maintain their metabolic activities and create new biomass. This biomass is a store of potential energy that can then be transferred through a food chain to various consumers, accompanied by a loss of energy as heat (Zhou *et al.* 1996). Thus, while increasing organization (decreasing entropy) within the ecosystem (the dissipative structure), heat loss to the surrounding environment increases the entropy (disorganization) globally, ensuring that, as the second law of thermodynamics states, the entropy of the universe never decreases (Toussaint and Schneider 1998). The study of energy flows in ecosystems – ecological energetics – was initiated by R.L. Lindenman’s (1942) study on trophic dynamics, and continued more recently by H.T. Odum (e.g. Odum 1983). Odum (1988) demonstrated the use of the concepts of e<u>**m**</u>ergy and transformity to examine ecosystems, which, while not dealing with energy quality in the thermodynamic sense (Zhou *et al.* 1996), have been reconciled with the idea of exergy in ecosystem organization (e.g. Patten 1995; Bastianoni and Marchettini 1997). Odum (1988) states that observed ecosystem designs are the result of self-maximising energy flows. At each step up the food chain (trophic level) the majority of the energy available (i.e. exergy stored as biomass) is degraded as smaller amounts of higher quality energy are created at the next (Odum 1988). That is, organisms higher up the trophic hierarchy dissipate more exergy when creating biomass and maintaining their metabolic activities. This continues to the highest trophic level where the energy stored is insufficient to support another higher trophic level (i.e. larger organism), leading to 'pyramid of numbers' in terms of biomass, energy and organisms (e.g. Lindenman 1942). Further, it has been suggested that the relationship between species density in an ecosystem and that species' average body weight presents power-law behaviour (Holling 1992; Jorgensen *et al.* 1998; Allen and Holling 2002). "Thus, an ecosystem continually uses high quality energy and gradually degrades it to heat at ambient temperature, at which point it is no longer available to carry out the processes necessary to maintain life in the ecosystem in its highly organized state" (Zhou *et al.* 1996 p.292).

4.1.2 Wildfire as a Dissipative Process

To show how this theory relates to wildfire occurrence in ecosystems we need to consider the work of Holling (1986; 1992) and Naveh (1987; 1994). Figure 19 shows Holling's four-box model of ecosystem function. Starting at exploitation, dissipative processes will emerge to utilize the exergy content of incoming solar energy, increasing biomass. As Kay *et al.* (1999) note, as structures grow (i.e. biomass increases as stored exergy increases) their ability to obtain and utilize resources and exergy increases, enabling further growth and exergy utilization in a positive feedback. The conservation 'box' therefore represents the point at which thermodynamic organization is maximum (i.e. exergy is utilized as much as possible), but also the point furthest away from thermodynamic equilibrium (as this distance is measured by exergy content) (Kay *et al.* 1999). According to the second law of thermodynamics, restated for non-equilibrium systems (Prigogine and

Stengers 1984), the more exergy in a system, the more likely that a dissipative process will arise to take advantage of it. In ecosystems this process may be in the form of pests, storms or fire (Holling 1986). The exergy stored as biomass is released (or rather, degraded to a lower quality), in the case of fire mainly as heat to the atmosphere. Following release (or 'creative destruction'), renewal or reorganization occurs, as the resources are once again available to utilise incoming solar energy. Thus, the first thermodynamic branch followed (from exploitation to conservation, away from thermodynamic equilibrium) is that of increasing biomass and stored exergy (succession), and the second (from release to reorganization, toward

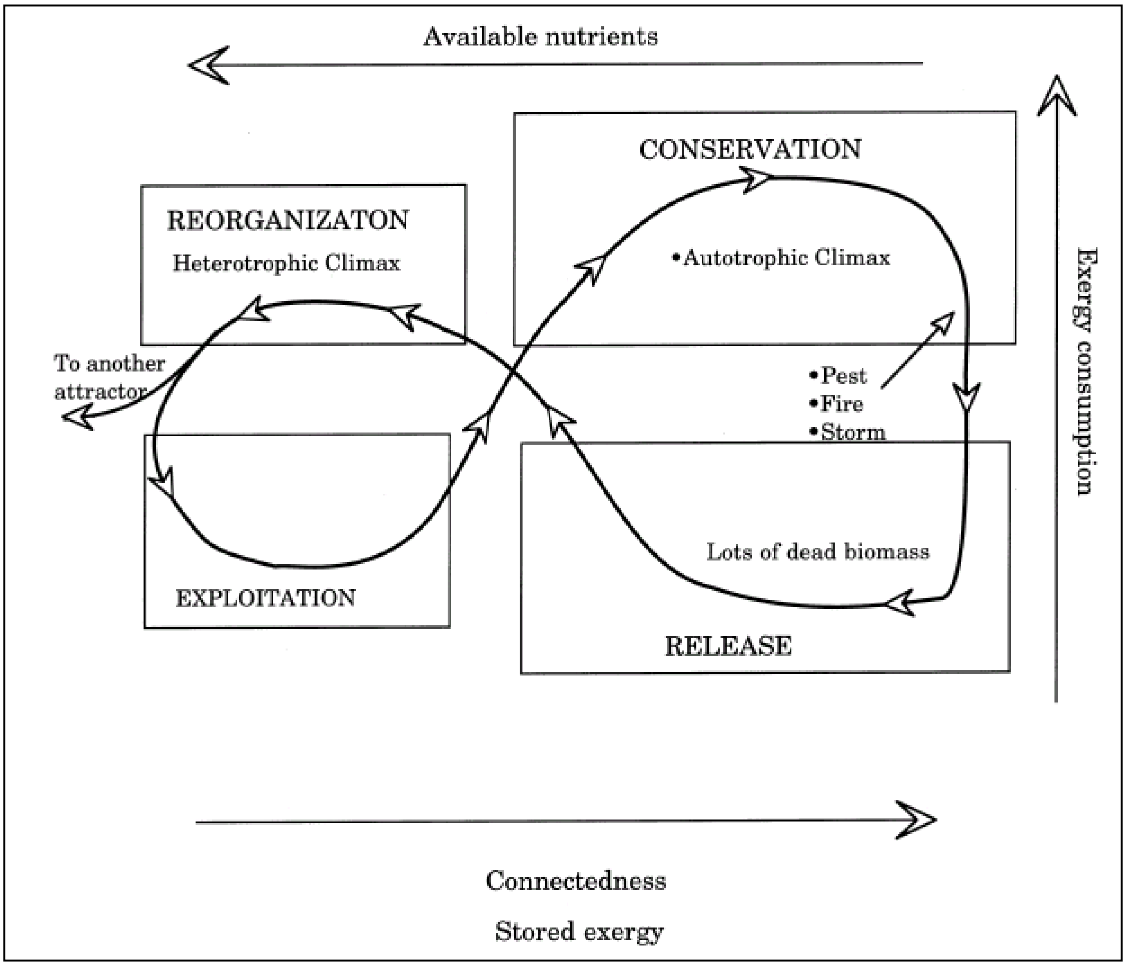

Figure 19. Holling's four-box model of ecosystem function. Energy is dissipated in this cycle of 'creative destruction' and renewal (Figure from Kay *et al.* 1999).

thermodynamic equilibrium) involves the release of exergy and biomass (decomposition). Naveh (1987; 1994) presents similar ideas but using rates of entropy consumption by the ecosystem to explain the cyclical behaviour of peturbation and renewal (see Figure 20). Thus, through the processes described above, cycles of order and disorder occurring in ecosystems are re-set by perturbations such as fire. But, rather than returning to a constant equilibrium, ecosystems return to a 'perturbation trajectory' driven by rates of entropy destruction and production (Naveh 1994). This suggests that there may be 'optimum' perturbation regimes that humans should attempt to emulate.

4.1.3 Dissipative Structures in Ecology

This theory of dissipative structures highlights the dynamic nature of ecosystems. Although the theory described above considers ecosystems as dissipative structures maintaining themselves in a *stable* state far from (thermodynamic) equilibrium, this should not be taken to mean ecosystems are 'fixed' or 'not fluctuating' (Capra 1997). Rather, the overall structure is maintained to ensure the continual flow of energy and material as exergy is dissipated maximally. Thus, 'matter circulates, energy dissipates' (Odum, E. 1953, c.f. Capra 1996). Naveh and Lieberman (1994 p.63) note that this dynamic behaviour produces "order through fluctuation", and the behaviour also suggests disturbance may maintain floral composition and structure in a dynamic equilibrium (White 1979). This highlights the 'structural determinism' of dissipative processes and the structures they manifest (i.e. their behaviour is dictated by their structure), and highlights the importance of considering the feedbacks between pattern and process (Turner 1989). Studies of both model and real world

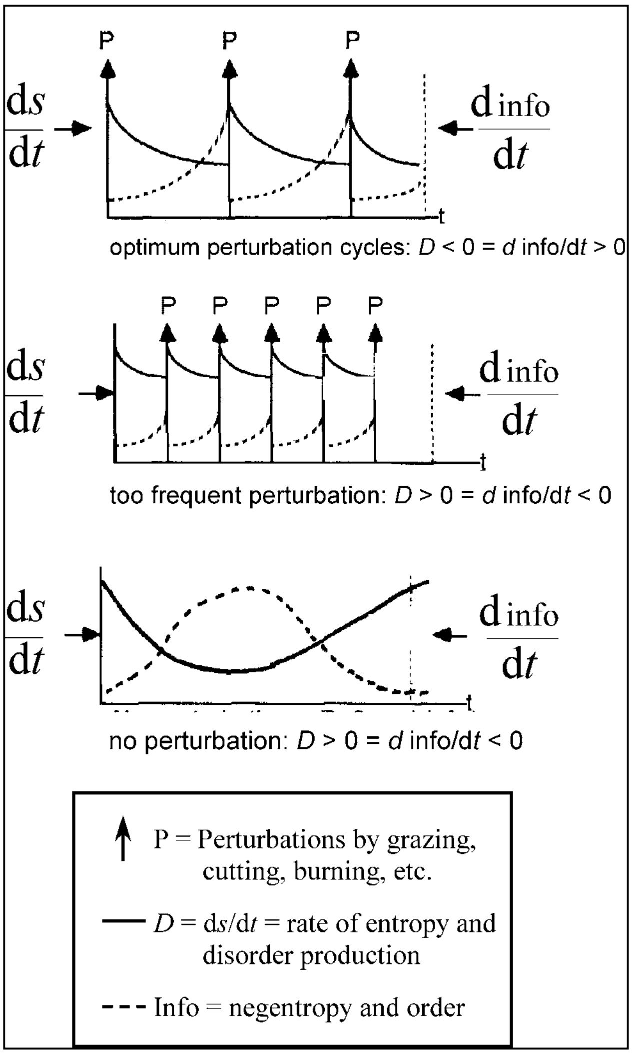

Figure 20. Naveh's ecosystem theory of thermodynamic reaction to perturbation regimes. Following a disturbance entropy decreases in the landscape until a new disturbance 're-sets' the level of order. Naveh (1994) notes there may be 'optimum' disturbance frequencies to maintain this balance of order. (Figure from Naveh 1994)

landscapes have shown evidence of changes in spatial pattern produced due to changes in system structure (Minnich and Chou 1997; Cochrane *et al.* 1999), and self-organization producing landscape structure through system memory (Holling *et al.* 1996; Peterson 2002). It would seem that the theory of ecosystems as dissipative structures certainly fits with the non-equilibrium, disturbance oriented view that has become increasingly adopted by ecologists and biogeographers over the last 30 years (e.g. Perry 2002).

4.1.4 Evidence for Wildfire as a Dissipative Process

If this theory of ecosystems as dissipative structures, and its implications for wildfire, were to be used, what patterns would be expected the data examined in section 3? Before this can be addressed an important point needs to be made. The recent studies of power-law behaviour in wildfire regimes (i.e. Malamud *et al.* 1998; Ricotta *et al.* 1999; 2001 etc.) examined wildfire frequency-area statistics, and this was also undertaken here. The discussion above however, has concerned itself with energy flows and storage within ecosystems, and therefore any examination of wildfire in the real world to test this theory should also consider energy. Study of earthquakes and their behaviour has shown that the energy released in such an event can be precisely related to the rupture area (e.g. Lay and Wallace 1995). However, the nature of fire means it is not possible to directly and accurately relate burn area to energy released, as combustion efficiency (the proportion of initial biomass actually volatised) varies by fire intensity (McNaughton *et al.* 1998), uniformity of burn area (Lambin *et al.* 2003), and seasonality of burn (due to variation in fuel moisture, Hoffa *et al.* 1999). Thus, the examination of results here uses area only as a rough proxy for energy. The future development of remote sensing products to measure active fire radiative energy (e.g. Wooster *et al.* 2003) may provide data for a more rigorous, quantitative analysis than is presented here.

Using area as a proxy for energy to examine the frequency-area data here, integrating under the frequency-area curve will give total energy dissipated by fire. Assuming solar input for a set region is constant, any changes in fire frequency will produce changes in the scaling of fires as the system ensures energy is dissipated maximally, that is, the area under the curve will remain constant. It was found above that the largest 1% of fires burned >95% of the total area (Table I). Thus, as $\log\alpha$ increases (fire frequency increases) a corresponding decrease in β would also be expected (reducing the ratio of large to small fires) to ensure energy dissipation is maximal. The reverse would also be expected. The results of Minnich (1983) and Minnch and Chou (1997) suggest this behaviour. They found that reduced fire frequencies for Southern California versus Baja California decreased the slope of Southern California frequency-area curves, between 1920 and 1971. Thus, for the data examined in section 3.2 (management) we will look for these changes in $\log\alpha$ and β.

Fires in British Columbian parks increase in frequency ($\log\alpha$) and also show an increase in their β values (see Figure 5a, Table II), as expected. However, when parks in Washington are compared with non-park areas, and when national parks are compared with their surrounding non-park areas, increased frequencies ($\log\alpha$) are consistently accompanied by *decreases* in β (see Figures 5b and 7, Table III). This suggests that the energy dissipated by park ecosystems is greater than the surrounding areas. From this brief analysis, it would seem that the theory of ecosystems as dissipative structures is not manifested in the wildfire data examined in this study. However, the potential reasons for deviation from the expected behaviour in USA parks should be considered. As the major differences between the areas studied (parks and non-parks) are that of vigorous management versus non-management it is possible that this may have impacted wildfire regimes. The vigorous suppression strategies of management in USA parks in the century previous to the start of the study period (see section 3.2.1) may have produced an increased energy store (exergy as biomass) that is only now being released. However, this is merely conjecture and cannot be established either way here.

Secondly, the dissipative theory of ecosystems suggests that regions of the globe that receive different amounts of solar energy (due the tilt of the earth axis) will dissipate different amounts of energy (exergy), and will therefore produce different structure to do so. Hence, differences in wildfire regime will occur, observed here as variation in logα and β values. This idea is implicit in the derivation of Bailey's ecoregions (1995), and it was shown in section 3.4 that the basic theory of ecosystems as dissipative structures works well to describe observed variation in wildfire regimes across ecoregions. It is likely that using frequency-energy plots would improve this description. Further, the use of vegetation classifications according to the laws of thermodynamics, such as Zhang and Wu's (2002) thermodynamic model of the organizational order of vegetation (OOV), alongside accurate frequency-energy data derived from remote sensing, holds the potential for a much more rigorous, quantitative analysis of the implications of the ecosystems as dissipative structures theory outlined above.

4.1.5 Evidence for Wildfire as Self-Organized Critical Systems

Self-Organized Criticality (SOC) was first presented by Bak *et al.* (1987) as the theory that dynamical systems order themselves naturally to a critical state regardless of initial conditions and independent of any outside driving force. Bak (1996) suggests that at the critical state, small inputs to the system can cause events of any magnitude in intermittent periods of activity and prediction of the size of future events is impossible as the system is contingent upon all that has gone before. Events will exhibit power-law behaviour in their frequency-size distribution (Bak and Tang 1989). This behaviour has been noted in many natural systems including frequency and magnitude of earthquakes (Bak and Tang 1989), frequency and drainage area in river networks (Rodriguez-Iturbe and Rinaldo 1997), and frequency and size of biologic extinctions (Bak and Paczuski 1995). It has also been observed in anthropogenically-driven systems such as the Internet (Faloutsos *et al.* 1999) and economics (Bouchaud and Mezard 2000). In these systems the largest events can only be understood by holistic consideration of the properties of the entire system (Bak 1996) rather than reductionist consideration of individual constituent elements.

Bak *et al.* (1987) first presented the concept of SOC through using models of coupled-pendulums and, more famously, sandpiles. Later, Bak *et al.* (1990) took a cellular automaton approach to model forest fires. Their model (the Forest Fire Cellular Automaton, FFCA) assumed a grid whose cells may be empty, a live tree, or a burning tree. Trees grow in empty cells with probability p, one at each time step. A burning tree becomes an empty cell at the next time step, whilst green trees may become burning trees if at least one of its neighbours is burning. Using these simple rules Bak *et al.* (1990) found that uniformly injected energy (trees) is dissipated (burning trees) in a spatial manner that may be termed 'fractal', or self-similar in shape. Drossel and Schwabl (1992) used a similar FFCA, adding a rule to the above that trees are struck by lightning and start to burn with probability f. They showed that the FFCA organized itself to a SOC state where fire sizes (patches of contiguous cells that burn due to one lightning strike) exhibited power-law frequency-area statistics. Further, they showed that the SOC state is organized such that the number of growing and burned trees (i.e. the energy dissipation) is maximal, i.e. all trees (energy) will be burned (dissipated) as quickly as possible (maximally).

If we now compare the theory that ecosystems are dissipative structures maintaining themselves in a stable state far from (thermodynamic) equilibrium with the FFCA of Drossel and Schwabl (1992) we can note some similarities. First, both consider a constant input of energy; above this is as solar energy and in the FFCA as trees growing in the grid. Further, they show that in the SOC state there is a double separation of time scales: the length of time taken for a fire to burn is much shorter than the time for a tree to grow, which in turn is much shorter than the time for lighting to strike twice at the same site. The power-law distribution of fire sizes is thus due to the potential for a large amount of energy to be deposited in the system between burns (Drossel and Schwabl 1992). Though it is hard to quantify the time between lightning strikes at a single point in the real world (e.g. Podur *et al.* 2003), the length of time it takes for a fire to burn is much shorter than landscape-scale fire return periods in many ecosystems (e.g. ≈70 years in Mediterranean environments, Minnich and Chou 1997; 100's of years in both lowland tropical rainforest, Cochrane *et al.* 1999, and boreal forest Lesieur *et al.* 2002). Thirdly, the theory above shows that the self-organization of the system will produce maximal energy flows through the system (Odum 1988). When thermodynamic organization is at a maximum, stored exergy is at a maximum and is released (from Holling's four-box model, Kay *et al.* 1999). This is manifested in the FFCA: Drossel and Schwabl (1992) show the model self-organizes itself to ensure that energy dissipation is maximal in the SOC state. Finally, Bak (1996) notes that the critical state is one in which a small disturbance can lead to an event of any size. A recent study by Schoenberg *et al.* (2003b) suggests that there is little difference in wildfire ignition risk for conditions that are *sufficient* for wildfire against those that could produce *extreme* events. These similarities suggest that the ecosystems as dissipative structures theory outlined above may be useful to examine whether real wildfire data, such as presented here, exhibits SOC behaviour.

4.2 Tapered Power-Law Behaviour?

The basic premise that the analysis in this study has followed is that the data exhibits power-law behaviour over many orders of magnitudes. However, several studies have questioned whether wildfire data exhibit this behaviour (Ricotta *et al.* 1999; 2001; Cumming 2001; Schoenberg *et al.* 2003a). Both Cumming (2001) and Schoenberg *et al.* (2003a) suggest that at upper extreme of the distribution is tapered (or truncated). That is, at the largest fire sizes the distribution falls away from a straight line in log-log space. This has also been seen in cellular automata models of forest fire, which first suggested the presence of power-law behaviour in wildfire data (Bak *et al.* 1990; Drossel and Schwabl 1992). This behaviour in the cellular automata models was due to the restriction of the maximum size of fire by the size of the grid on which the model was run. Similar restrictions are probably present in real landscapes due to variables such as topography, vegetation distribution, and most recently, urban areas. Thus, a true power-law distribution in nature is not possible. The use of tapered or truncated power-law distributions will likely be more useful for wildfire models that require accurate wildfire size distributions for the regime they are modelling (e.g. DISPATCH, Baker *et al.* 1991). The simplicity of using two parameters (α and β) to describe a wildfire regime that accepting the power-law distribution enables however, makes it much more useful when studying the broader scale differences in wildfire regime such as was attempted here.

5

CONCLUSIONS

This dissertation examined the frequency-area statistics of wildfire regimes in the USA and British Columbia, Canada, with reference to the potential ecological and anthropogenic factors influencing them. Wildfire occurrence data for these regions was suggested to exhibit power-law behaviour across many (five) orders of magnitude (section 3.1), and two parameters (α and β) were used to compare the regimes. β values (best-fit slopes) were found to lie between 1.8 and 1.1. Frequency-densities were normalized to allow comparison with other data from different regions and time spans.

The influence of different management practices between Washington state and the lower region of British Columbia, Canada (section 3.2.1); the influence of management practices within USA National Parks (section 3.2.2); the impact of anthropogenic versus natural sources of ignition (section 3.3); and the influence of climate and vegetation 'ecoregions' (section 3.4) were all examined.

The frequency of fires ($\log\alpha$) and ratio of large to small fires (β) in Washington's parks was found to be vastly increased compared to British Colombia and the non-park areas of Washington. Further, this increase in fire frequency and fire size ratio was also found in other national parks in the USA when they were compared to their surrounding, non-park areas. The impact of management appears to be great in the

USA, though a very brief examination of management history could not elucidate any concrete reason for differences between Washington and British Columbia.

Analysis also showed human fire to have been much more frequent than lightning fire during the period of study. Spatial differences in distribution between natural and human-caused fires were found and it was suggested that the increase in frequency of human fires, rather than the influence of vegetation and climatic factors, is likely to be driving this. Generally, human fires exhibited greater β values, meaning a greater ratio of large to small fires, compared to lightning. A classification of logα and β values was derived empirically and presented in section 3.4.

Recent work on the self-organization and thermodynamics of open systems was presented and related to wildfire occurrence in the ecosystems (ecoregions) of the USA. The data presented in section 3 was examined for evidence of this theory of ecosystems as dissipative structures, and it was suggested that the ecoregion data (section 3.4) did correspond with the theory presented. Analysis was far from rigorous however, and future methods to study this further were suggested. Finally, it was suggested that the theory of ecosystems as dissipative structures showed parallels with the theory of self-organized criticality.

6

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