PRACTICES AND APPLICATIONS

USING FIRE HISTORY DATA TO MAP TEMPORAL SEQUENCES OF FIRE RETURN INTERVALS AND SEASONS

Roy S. Wittkuhn[1,2,*] and Tom Hamilton[1]

[1]Science Division, Department of Environment and Conservation,
Locked Bag 104, Bentley Delivery Centre, Western Australia, 6258, Australia

[2]Bushfire Cooperative Research Centre, Level 5,
340 Albert Street, East Melbourne, Victoria, 3002, Australia

[*]Corresponding author: Tel.: 061-8-9334-0520; e-mail: roy.wittkuhn@dec.wa.gov.au

ABSTRACT

Analysis of complex spatio-temporal fire data is an important tool to assist the management and study of fire regimes. For fire ecologists, a useful visual aid to identify contrasting fire regimes is to map temporal sequences of data such as fire return intervals, seasons, and types (planned versus unplanned fire) across the landscape. However, most of the programs that map this information are costly and complex, requiring specialist training. We present a simple yet novel method for creating sequences of temporal data for mapping fire regimes using basic geographic information system (GIS) techniques and logical test functions in Microsoft® Excel 2003 (Microsoft, Bellevue, Washington, USA). Using fire history data (1972 to 2005) for southwestern Australia, we assigned integer classifications to fire return intervals (short, moderate, and long) and fire types and seasons (wildfires and prescribed burns in different seasons) and joined the integer classifications together to form a sequence of numbers representing the order of either fire return intervals or fire seasons in reverse time sequence. This sequence can be mapped in a GIS environment so that spatial dimensions formed by overlapping polygons are readily observed, and the temporal sequence of fire data within each polygon can be interpreted across the landscape. We applied the technique to examine experimental design options for investigating the effects of contrasting fire regimes on biota at the landscape scale. This investigation identified several important factors: 1) patterns were evident in fire types and seasons, 2) patterns were evident for fire return interval sequences, and 3) combining fire types and seasons with fire return intervals significantly constrained options for the study design. A visual analysis of this type highlights fire regime patterns in the landscape and permits a feasibility study for the development of study design options and the spatial arrangement of potential study sites.

Keywords: fire history data, fire management, fire regimes, fire return interval sequences, fire season sequences, Geographic Information Systems, prescribed burning, southwest Western Australia, spatio-temporal analysis, wildfires

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INTRODUCTION

Questions of patterning in space and time are fundamental to ecology and the management of natural resources (Levin 1992, Cadenasso *et al.* 2006) and find particular application in fire management (Fulé *et al.* 1997, Brockett *et al.* 2001, Bradstock *et al.* 2005, Burrows 2008). Although the spatial patterning of individual fires and their attributes (intensity, season, size, etc.) can be easily ascertained, the complexity of patterns increases with multiple fires overlapping through time. The collection and archival of fire history information into spatio-temporal databases provides the opportunity to evaluate spatial and temporal patterning of fire regimes in the context of landscape ecology and management (Morgan *et al.* 2001, McCaw *et al.* 2005, Boer *et al.* 2009, Hamilton *et al.* 2009). Advances in geographic information systems (GIS) have formalised the accurate capture of spatial data such as perimeter and area of fires, temporal data such as year and season-of-burn, and attribute data such as fire type (wildfire or prescribed burn) and measures of intensity and severity. Such data are important for understanding interactions between fire regimes and a range of values including biodiversity, water, and carbon fluxes (Burrows and Abbott 2003, Wittkuhn *et al.* 2009). Additionally, historical fire datasets become important for land and risk management in the face of climate change (Cary 2002).

To maintain best-practice in land management and conservation, science plays an important role in assessing the impact of fire on ecological processes (Andersen 2003, Burrows 2008). Although the most valuable knowledge is obtained through the design of long-term studies that address specific research questions in relation to fire and biota, these experiments take a long time to yield results and even longer to be transferred to practical applications. In contrast, retrospective studies that utilize historical data provide the opportunity to rapidly assess fire's effects on ecosystems. To assess these effects, the first step is to obtain a basic understanding of historical fire patterns across the landscape. Spatial databases that maintain fire perimeter data as vector files can be used for mapping the occurrence of past fires, and it is usual to create a data layer at any point in time showing overlapping fire events (Hamilton *et al.* 2009). The challenge for fire ecologists with a limited knowledge of GIS is to create a visual representation of the temporal attributes for these overlapping fires, such as fire return intervals, seasons, and order of fire types. In other words, how can we show the sequence of past fire attributes on a spatial representation (map) of fire occurrences? Unfortunately, the utility of GIS databases for displaying temporal sequences in a spatial scale is limited (Wittkuhn *et al.* 2009).

We describe a method that combines simple GIS techniques with logical test functions in the Microsoft® (MS) program Excel (Microsoft, Bellevue, Washington, USA) to produce maps of spatial fire perimeters, labelled with temporal fire attributes within each polygon formed by overlapping fires. We chose to use Excel because of its common use across a range of scientific disciplines for data storage and manipulation. Specifically, we mapped sequences of fire return intervals and a combined classification of fire types (prescribed burns or wildfires) and seasons-of-burn to provide a broad overview of patterns in fire history across the landscape. We demonstrate the effectiveness of this technique by presenting results from a case study that used these temporal sequences to investigate contrasting fire regimes as a basis for an ecological study at a landscape scale (Wittkuhn *et al.* 2008, Wittkuhn *et al.* 2009).

METHODS

Fire History Dataset and Study Area

We used ArcView (Environmental Systems Research Institute, Redlands, California, USA) to create the sequences of fire return intervals and fire type and seasons from a fire history dataset (FHD) for the Warren Region of southwestern Australia (Figure 1), an administrative region of the Western Australian Department of Environment and Conservation (DEC). The FHD that we used was constructed by digitising fires between 1972 and 2005 from maps or by importing information directly from previous GIS datasets (Hamilton *et al.* 2009). Attributes for each fire polygon include: year of burn, fire type (wildfire or prescribed burn), season-of-burn, district, cause, perimeter, and area. A separate vector file was created for each fire-year, where a fire-year is recorded as 1 July to 30 June because the fire season in southwestern Australia occurs between ~October and March (the dry season of the prevailing Mediterranean climate). These separate vector files are a snapshot model because they represent the spatial distribution of fires at a given point in time (Pelekis *et al.* 2005). Shapefiles for each fire-year were then merged into one fire history dataset, resulting in overlapping polygons from different years whilst maintaining the spatial integrity and attributes of all original polygons (Hamilton *et al.* 2009). This dataset is an example of a space-time composite data model in which polygons for every year are intersected with one another to form a polygon mesh (Pelekis *et al.* 2005). An overview of the data sources and steps described in this paper is presented in Figure 2.

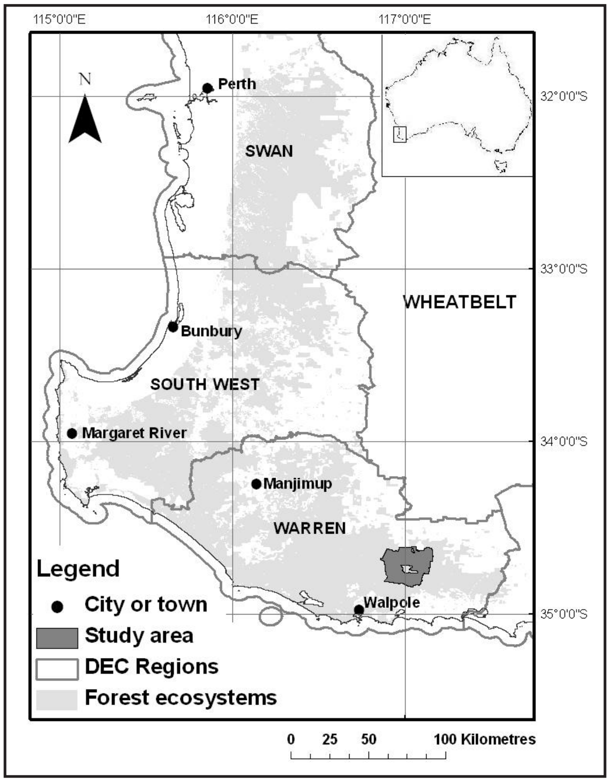


Figure 1. Map showing the Warren Region of southern Western Australia in relation to the Australian coastline (inset). The study area used for an investigation of the temporal sequence data is shown and was burnt in either a wildfire or prescribed burn in 2002/03, representing the same time-since-fire at the time of undertaking this study.

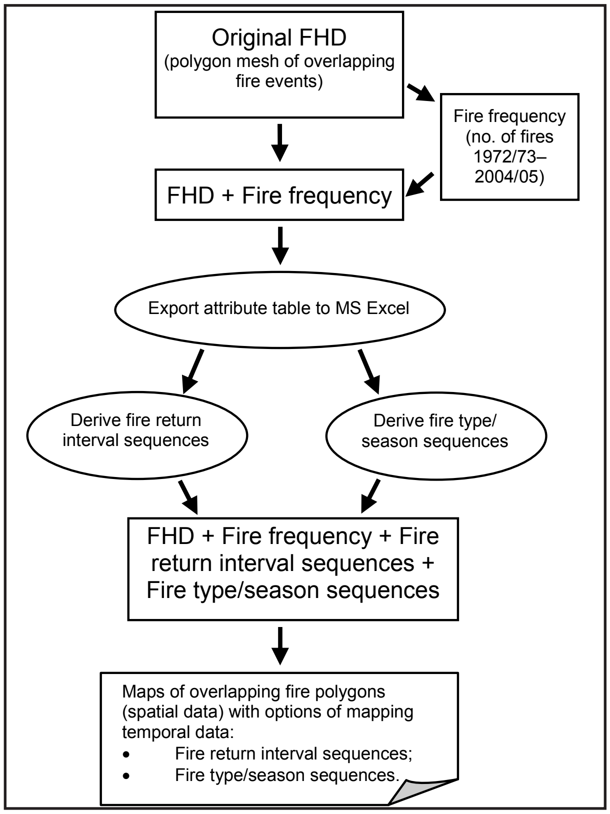


Figure 2. Overview of the data sources and steps used to produce spatial maps of temporal fire data.

Fire Frequency

Fire frequency was calculated for every polygon in the FHD between 1972/73 and 2004/05 (Figure 2). We started with the original vector files that contained data for fire occurrence in a single fire-year only (e.g., 1992/93). A column was created in each vector file (called, for example, 92_93) and a number one (1) was entered for every record (row) in that vector file to indicate the presence of a fire event. All vector files from 1972/73 through 2004/05 were then joined together using the 'Union' command, which has the effect of combining overlapping polygons into singular polygons that contain the attributes of all source polygons. All columns were deleted except those showing the presence or absence of fires in each fire-year (e.g., only the columns 72_73, 73_74, … , 04_05 were retained). Every row in the vector file represented a spatial group, which is defined here as a polygon created by overlapping fires that has a unique fire history in space and time. Each row was identified as such by being assigned a unique identifier (a column we named RECNO1). This identifier becomes important in later steps that combine datasets.

In ArcView, a column was created (FIREFREQ72) within which the occurrences of fire were summed for each row to determine the number of fires that had occurred in that polygon between 1972/73 and 2004/05. This frequency column was retained, along with RECNO1, while all the individual year columns were deleted. Using the 'Union' command, this file was joined with the 1972/73 to 2004/05 merged FHD, with the effect of adding the FIREFREQ72 and RECNO1 columns to the shapefile.

A second unique identifier (RECNO2) was created for every overlapping polygon (i.e., every record in the attribute table). This associated table from the shapefile was used as the basis for calculating the temporal fire sequences. This table was converted to a MS Excel 2003 format (extension .xls) from a database file (extension .dbf) to write the functions described below.

Calculating Fire Return Intervals

In MS Excel, all columns were deleted except those needed for subsequent calculations and to rejoin the Excel table to the Fire Frequency shapefile, these being RECNO1, RECNO2, YEAR, and SEASON. The column YEAR had been created from FIRE_YEAR within ArcGIS 9.0. This converted fire-years (e.g., of the form 1988/89) to single years (e. g., of the form 1988), by dropping the second part of the fire-year, which enabled simple arithmetic to calculate fire return intervals in the next stage of the process.

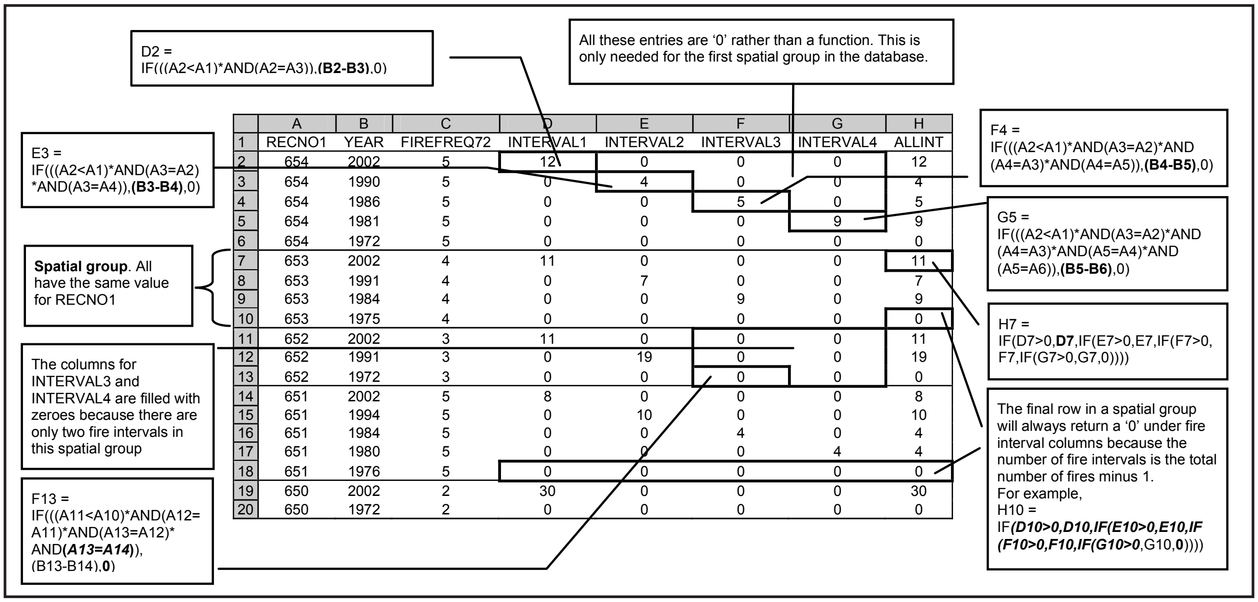
Using Excel, all records were sorted firstly by the unique identifier (RECNO1), and then by YEAR in a descending order. This organised the data into spatial groups that represented the overlapped fire history contained within one polygon (Figure 3).

New columns were created: INTERVAL1, INTERVAL2, INTERVAL3, and INTERVAL4, which were filled with actual fire return intervals (in years). For our data, the highest fire frequency was five; hence, we needed to calculate a maximum of four intervals. Any number of fire return intervals could be calculated, such that the number of INTERVAL columns equals the highest fire frequency minus one.

Each INTERVALx column was filled with either a value showing the fire return interval in years, or a zero if not relevant for that column and row combination. This was performed using a logical test function in MS Excel, which checks whether a condition is met (the logical test) and returns one value if true, and another value if false. The general form of this function is as follows:

$$\text{Cell value} = \text{IF}\ (\text{[logical test]}, \text{[value if true]}, \text{[value if false]}). \tag{1}$$

Figure 3 presents an excerpt from the Excel file, and shows how the logical test functions were written to calculate the INTERVALx values.



D2 =
IF(((A2<A1)*AND(A2=A3)),**(B2-B3)**,0)

All these entries are ‘0’ rather than a function. This is only needed for the first spatial group in the database.

E3 =
IF(((A2<A1)*AND(A3=A2)
*AND(A3=A4)),**(B3-B4)**,0)

F4 =
IF(((A2<A1)*AND(A3=A2)*AND
(A4=A3)*AND(A4=A5)),**(B4-B5)**,0)

Spatial group. All have the same value for RECNO1

G5 =
IF(((A2<A1)*AND(A3=A2)*AND
(A4=A3)*AND(A5=A4)*AND
(A5=A6)),**(B5-B6)**,0)

H7 =
IF(D7>0,**D7**,IF(E7>0,E7,IF(F7>0,
F7,IF(G7>0,G7,0))))

The columns for INTERVAL3 and INTERVAL4 are filled with zeroes because there are only two fire intervals in this spatial group

The final row in a spatial group will always return a ‘0’ under fire interval columns because the number of fire intervals is the total number of fires minus 1.
For example,
H10 =
IF***(D10>0,D10,IF(E10>0,E10,IF(F10>0,F10,IF(G10>0***,G10,**0**))))

F13 =
IF(((A11<A10)*AND(A12=
A11)*AND(A13=A12)*
AND***(A13=A14)***),
(B13-B14),**0**)

	A	B	C	D	E	F	G	H
1	RECNO1	YEAR	FIREFREQ72	INTERVAL1	INTERVAL2	INTERVAL3	INTERVAL4	ALLINT
2	654	2002	5	12	0	0	0	12
3	654	1990	5	0	4	0	0	4
4	654	1986	5	0	0	5	0	5
5	654	1981	5	0	0	0	9	9
6	654	1972	5	0	0	0	0	0
7	653	2002	4	11	0	0	0	11
8	653	1991	4	0	7	0	0	7
9	653	1984	4	0	0	9	0	9
10	653	1975	4	0	0	0	0	0
11	652	2002	3	11	0	0	0	11
12	652	1991	3	0	19	0	0	19
13	652	1972	3	0	0	0	0	0
14	651	2002	5	8	0	0	0	8
15	651	1994	5	0	10	0	0	10
16	651	1984	5	0	0	4	0	4
17	651	1980	5	0	0	0	4	4
18	651	1976	5	0	0	0	0	0
19	650	2002	2	30	0	0	0	30
20	650	1972	2	0	0	0	0	0

Figure 3. Excerpt from the MS Excel file used for calculating actual fire return intervals for five polygons (spatial groups) in the dataset. We have omitted columns that are irrelevant to the computation of the fire return intervals. Boxes represent the logical test functions that have been written to compute the values for the highlighted cell. For the logical test functions in each box, the value returned in the cell is highlighted in bold (either ‘value if true’ or ‘value if false’). Where it is ‘value if false,’ the section of the logical test that is not upheld is highlighted in bold italic.

A new column, ALLINT, was created to bring values from INTERVAL1 to INTERVAL4 into one column. In this case, a nested logical test function was used to fill each cell. A nested function incorporates further test functions as the ‘value if false’ argument. This function was designed to systematically check each INTERVALx column for an entry that is not zero, and fill the ALLINT cell with that entry (Figure 3). The function was of the form:

Cell value (ALLINT) =
IF(INTERVAL1>0,INTERVAL1,
IF(INTERVAL2>0,INTERVAL2, (2)
IF(INTERVAL3>0,INTERVAL3,
IF(INTERVAL4>0,INTERVAL4,0)))).

Notice that the second IF statement is also the ‘value if false’ argument to the first IF statement. Similarly, the third IF statement is the ‘value if false’ argument to the second IF statement, and so on. Note also that if > 4 fire return intervals are contained in the FHD, more IF statements would be required.

Classifying Fire Return Intervals

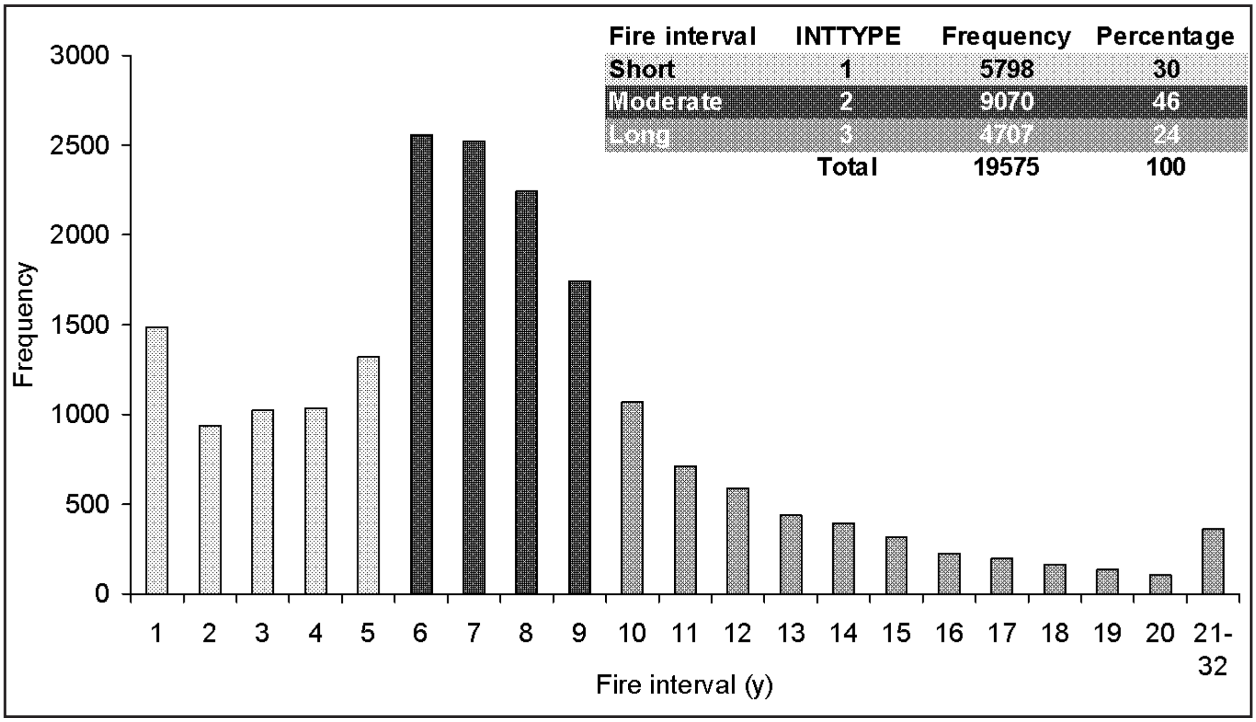
Remembering that each row in Figure 3 corresponds to a single fire event within a spatial group, values under the ALLINT column now represent the time-since-fire preceding that fire event. This information can be displayed in the GIS environment, but only one fire return interval can be mapped at a time.

The first step was to simplify the ALLINT column to three classifications: short (≤5 yr), moderate (6 yr to 9 yr), and long (≥10 yr) fire return intervals. The number of classifications and the range they encompass can all be dictated by the user, though our method allows for a maximum of ten as we use single numbers (0 to 9) for the classifications. For example, very short and very long intervals could be included. To define our short fire return intervals, we investigated juvenile periods of floristic taxa (Burrows *et al.* 2008), and to define our long return intervals, we investigated the time-since-fire at which fuels will carry an intense fire under normal (not extreme) weather conditions (Gould *et al.* 2007).

Juvenile period is defined as the time taken for a floristic species to reproduce following fire (Gill 1975), and the occurrence of lethal fire during the juvenile period can lead to localised extinction of the species (Gill and Nicholls 1989, Burrows and Friend 1998). Therefore, Gill and Nicholls (1989) suggest that to maintain community composition, the minimum fire return interval should be based around the conservative approach of doubling the juvenile period of the slowest maturing and fire sensitive species. Based on this recommendation, Burrows and co-workers defined a high fire frequency (synonymous with a regime of short fire return intervals) as one fire at fewer than six-year intervals for the environment in which our study occurred (Burrows and Friend 1998, Burrows *et al.* 2008). Hence, we defined our short fire return interval as being five years or less.

To define long fire return intervals, we took a risk management approach. We defined long intervals as those of ten years or more, based on fire hazard and fuel age. In particular, surface fuel hazard scores, defined by Gould *et al.* (2007), begin to plateau at ten years after fire in southern jarrah forest. It is the surface fuel layer that constitutes the bulk of fuel consumed and contributes most of the energy released by fire (Gould *et al.* 2007). Therefore, we considered ten years to be a reasonable starting point for a long interval in relation to fire hazard. In addition, our data analysis was constrained by the retrospective nature of the study. In this highly managed landscape, less than one quarter of the total number of fire return intervals across space and time were ten years or greater (Figure 4).

The column INTTYPE was created to convert the real fire return intervals under ALLINT into the following integer classifications: 1 = short (≤5 yr), 2 = moderate (6 yr to 9 yr), and 3 = long (≥10 yr), using a nested logical test function of the form:



Fire interval	INTTYPE	Frequency	Percentage
Short	1	5798	30
Moderate	2	9070	46
Long	3	4707	24
	Total	19575	100

Figure 4. Frequency distribution of fire return intervals for the period 1972/73 to 2004/05 for the Warren Region dataset (polygons >1 ha). Intervals of 21 yr to 30 yr have been summed together on the right hand side of the x-axis. Inset shows the breakdown of intervals into short, moderate, and long classifications (INTTYPEs 1, 2, and 3, respectively). Colour shading of the bars corresponds to the INTTYPE classifications.

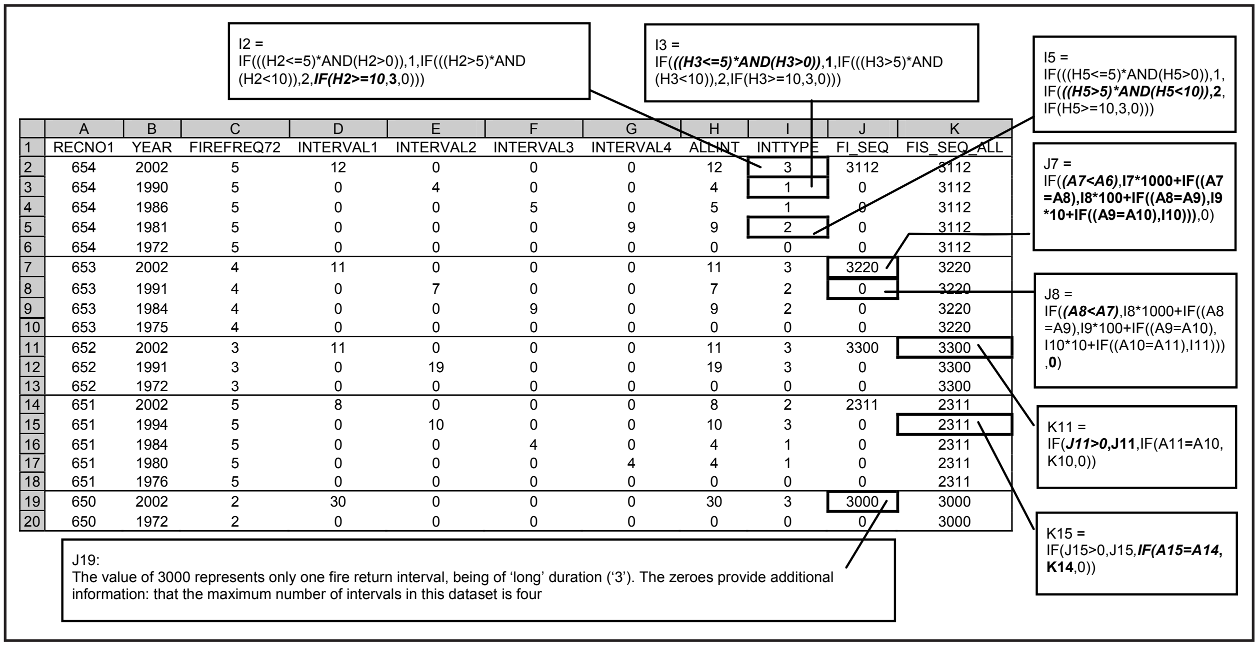
$$\begin{aligned}&\text{Cell value }(\text{INTTYPE}_q) =\\ &\text{IF}(((\text{ALLINT}_q{<=}5)*\text{AND}(\text{ALLINT}_q{>}0)),1,\\ &\text{IF}(((\text{ALLINT}_q{>}5)*\text{AND}(\text{ALLINT}_q{<}10)),2,\\ &\text{IF}(\text{ALLINT}_q{>=}10,3,0))),\end{aligned} \tag{3}$$

where subscript q refers to row q in the Excel spreadsheet, and the * symbol is syntax required by MS Excel to perform the function (i.e., it is not a multiplication symbol). Figure 5 shows the outcome in the Excel file, including examples of functions used to generate the integer classifications from fire return intervals.

Creating Fire Return Interval Sequences

Two columns were added to the Excel file: FI_SEQ and FI_SEQ_ALL (Figure 5). The completed fire return interval sequences were calculated in these columns from classifications in the INTTYPE column using a nested logical test function. The aim of this function was to transpose the vertical classifications that appear under INTTYPE to a horizontal sequence of the classifications, which is a whole number made up of 1s, 2s, and 3s. This whole number indicates the temporal sequence of fire return interval classifications and is contained within a single cell and therefore available for mapping and labelling in GIS. A key part of calculating the four-digit whole number that represents the fire return interval sequence is a simple step of multiplying each value under INTTYPE by decreasing factors of 10, and adding them together. In this case, the sequence is a four-digit number because we have a maximum of four fire return intervals in our dataset. Adjustments can be made to the calculations to allow for less or more intervals by decreasing or increasing the multiplication factors respectively.

To calculate the fire return interval sequence in the qth row of the FI_SEQ column, the following logical test function applies:



I2 =
IF(((H2<=5)*AND(H2>0)),1,IF(((H2>5)*AND (H2<10)),2,***IF(H2>=10***,**3**,0)))

I3 =
IF(***((H3<=5)*AND(H3>0))***,**1**,IF(((H3>5)*AND (H3<10)),2,IF(H3>=10,3,0)))

I5 =
IF(((H5<=5)*AND(H5>0)),1,
IF(***((H5>5)*AND(H5<10))***,**2**,
IF(H5>=10,3,0)))

	A	B	C	D	E	F	G	H	I	J	K
1	RECNO1	YEAR	FIREFREQ72	INTERVAL1	INTERVAL2	INTERVAL3	INTERVAL4	ALLINT	INTTYPE	FI_SEQ	FIS_SEQ_ALL
2	654	2002	5	12	0	0	0	12	3	3112	3112
3	654	1990	5	0	4	0	0	4	1	0	3112
4	654	1986	5	0	0	5	0	5	1	0	3112
5	654	1981	5	0	0	0	9	9	2	0	3112
6	654	1972	5	0	0	0	0	0	0	0	3112
7	653	2002	4	11	0	0	0	11	3	3220	3220
8	653	1991	4	0	7	0	0	7	2	0	3220
9	653	1984	4	0	0	9	0	9	2	0	3220
10	653	1975	4	0	0	0	0	0	0	0	3220
11	652	2002	3	11	0	0	0	11	3	3300	3300
12	652	1991	3	0	19	0	0	19	3	0	3300
13	652	1972	3	0	0	0	0	0	0	0	3300
14	651	2002	5	8	0	0	0	8	2	2311	2311
15	651	1994	5	0	10	0	0	10	3	0	2311
16	651	1984	5	0	0	4	0	4	1	0	2311
17	651	1980	5	0	0	0	4	4	1	0	2311
18	651	1976	5	0	0	0	0	0	0	0	2311
19	650	2002	2	30	0	0	0	30	3	3000	3000
20	650	1972	2	0	0	0	0	0	0	0	3000

J7 =
IF(***(A7<A6)***,**I7*1000+IF((A7 =A8),I8*100+IF((A8=A9),I9 *10+IF((A9=A10),I10)))**,0)

J8 =
IF(***(A8<A7)***,I8*1000+IF((A8 =A9),I9*100+IF((A9=A10), I10*10+IF((A10=A11),I11))) ,**0**)

K11 =
IF(***J11>0***,**J11**,IF(A11=A10, K10,0))

K15 =
IF(J15>0,J15,***IF(A15=A14,*** **K14**,0))

J19:
The value of 3000 represents only one fire return interval, being of ‘long’ duration (‘3’). The zeroes provide additional information: that the maximum number of intervals in this dataset is four

Figure 5. Excerpt from the MS Excel file used for calculating fire return interval sequences for five polygons (spatial groups) in the dataset. This spreadsheet is an extension of that shown in Figure 3. Boxes represent the logical test functions that have been written to compute the values for the highlighted cell. For the logical test functions in each box, the value returned in the cell is highlighted in bold (either ‘value if true’ or ‘value if false’). Where it is ‘value if true,’ the section of the logical test that directly produces the result is highlighted in bold italic. Where it is ‘value if false’ (cell J8 only in this example), the section of the logical test that is not upheld is highlighted in bold italic.

$$\begin{gathered}\text{Cell value }(\text{FI\_SEQ}_q) = \\ \text{IF}((\text{RECNO1}_q<\text{RECNO1}_p), \\ \text{INTTYPE}_q*1000+\text{IF}((\text{RECNO1}_q=\text{RECNO1}_r), \\ \text{INTTYPE}_r*100+\text{IF}((\text{RECNO1}_r=\text{RECNO1}_s), \\ \text{INTTYPE}_s*10+\text{IF}((\text{RECNO1}_s=\text{RECNO1}_t), \\ \text{INTTYPE}_t))),0)\end{gathered} \tag{4}$$

where subscripts p, q, r, s, and t represent ordered rows in the Excel spreadsheet, and * represents the multiplication function.

FI_SEQ shows the sequence of fire return interval classifications in reverse time series (i. e., most recent back to the oldest fire return interval; see column J in Figure 5). FI_SEQ only shows the fire return interval sequence in the first row of each spatial group (Figure 5). This is because the logical test will be false for subsequent cells until it reaches the first row of a new spatial group (for example, see the syntax of equation 4 and the calculations for cell J8 in Figure 5). To assign the fire return interval sequence to all fires in a spatial group (i.e., each row), another column, FI_SEQ_ALL, was created. The reason for wanting the fire return interval sequence assigned to all fires in a spatial group is so that the user can obtain the fire return interval sequence by selecting any of the overlapping fires within the spatial group, rather than only the most recent. To automate the filling of cells under FI_SEQ_ALL, another nested logical test function was written that related to the values in FI_SEQ (Figure 5):

$$\begin{gathered}\text{Cell value }(\text{FI\_SEQ\_ALL}_q) = \\ \text{IF}(\text{FI\_SEQ}_q>0,\text{FI\_SEQ}_q, \\ \text{IF}(\text{RECNO1}_q=\text{RECNO1}_p,\text{FI\_SEQ\_ALL}_p, 0))\end{gathered} \tag{5}$$

where subscripts p and q refer to subsequent rows in the Excel spreadsheet. Values in FI_SEQ_ALL represent the sequences of fire return intervals for each polygon in the dataset, and are the data used for mapping of temporal data.

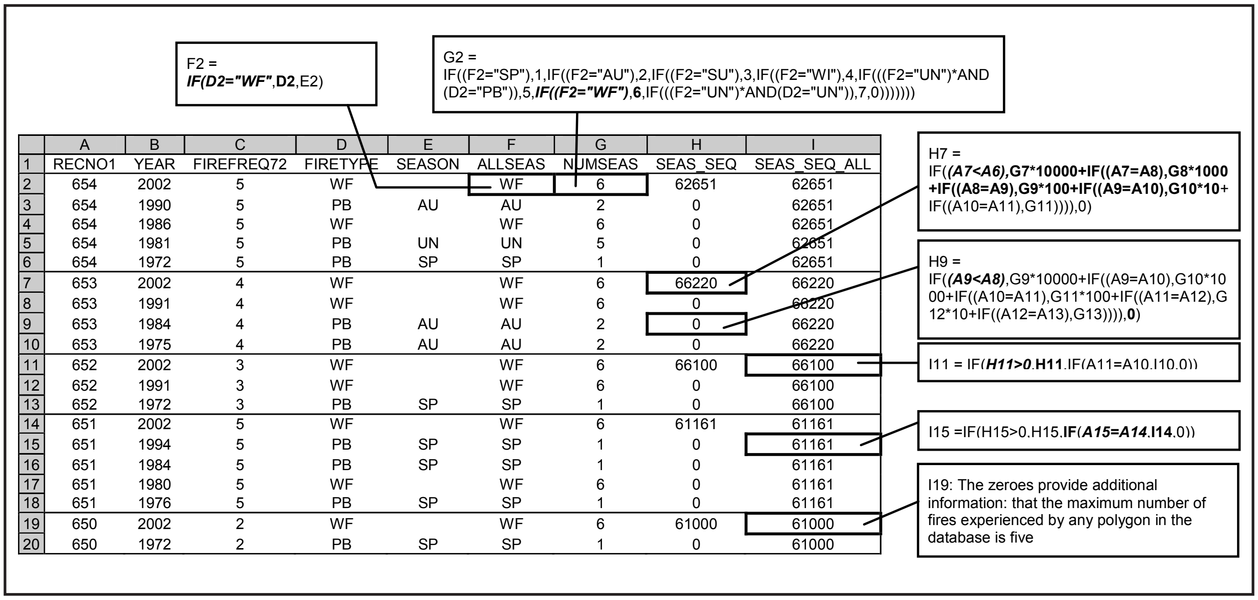
Creating Fire Season Sequences

Creating fire season sequences followed a similar process as used for deriving fire return interval sequences, though we supplemented the information by producing a combined classification for fire type (wildfire or prescribed burn) and fire season (Figure 2). The data for deriving fire season and type sequences were derived from two columns containing text. These columns were: 1) FIRETYPE, with values of WF (indicating wildfire), PB (prescribed burn), or UN (unknown); and 2) SEASON, with values of SP (spring), AU (autumn), SU (summer), WI (winter), or UN (unknown). The wildfire entries contained information only for FIRETYPE (WF), whereas the PBs also contained information for SEASON. Thus, we made a single column called ALLSEAS, which dropped the PB notation and contained only the following entries: WF, SP, AU, SU, WI, and UN. To populate the ALLSEAS column, we used a logical test function of the form:

$$\begin{gathered}\text{Cell value }(\text{ALLSEAS}_q)=\text{IF}(\text{FIRETYPE}_q = \\ \text{“WF”},\text{FIRETYPE}_q,\text{SEASON}_q)\end{gathered} \tag{6}$$

where subscript q refers to row q in the Excel spreadsheet (Figure 6). Thus, for a given row, if FIRETYPE is wildfire (WF), a WF is returned in the cell under ALLSEAS (the ‘value if true’). However, if that row represents a PB, then the season of that burn (given in column SEASON) is returned into the ALLSEAS column (the ‘value if false’).

We then substituted a numerical classification for each of the fire types by creating the column NUMSEAS and writing a nested logical test function that related back to ALLSEAS and FIRETYPE. The form of the function for NUMSEAS is shown in Figure 6 (column G), and substitutes integers for the FIRETYPE/SEASON combinations (the classifications are shown in Table 1).



F2 =
IF(D2="WF",**D2**,E2)

G2 =
IF((F2="SP"),1,IF((F2="AU"),2,IF((F2="SU"),3,IF((F2="WI"),4,IF(((F2="UN")*AND(D2="PB")),5,***IF((F2="WF")***,**6**,IF(((F2="UN")*AND(D2="UN")),7,0)))))))

	A	B	C	D	E	F	G	H	I
1	RECNO1	YEAR	FIREFREQ72	FIRETYPE	SEASON	ALLSEAS	NUMSEAS	SEAS_SEQ	SEAS_SEQ_ALL
2	654	2002	5	WF		WF	6	62651	62651
3	654	1990	5	PB	AU	AU	2	0	62651
4	654	1986	5	WF		WF	6	0	62651
5	654	1981	5	PB	UN	UN	5	0	62651
6	654	1972	5	PB	SP	SP	1	0	62651
7	653	2002	4	WF		WF	6	66220	66220
8	653	1991	4	WF		WF	6	0	66220
9	653	1984	4	PB	AU	AU	2	0	66220
10	653	1975	4	PB	AU	AU	2	0	66220
11	652	2002	3	WF		WF	6	66100	66100
12	652	1991	3	WF		WF	6	0	66100
13	652	1972	3	PB	SP	SP	1	0	66100
14	651	2002	5	WF		WF	6	61161	61161
15	651	1994	5	PB	SP	SP	1	0	61161
16	651	1984	5	PB	SP	SP	1	0	61161
17	651	1980	5	WF		WF	6	0	61161
18	651	1976	5	PB	SP	SP	1	0	61161
19	650	2002	2	WF		WF	6	61000	61000
20	650	1972	2	PB	SP	SP	1	0	61000

H7 =
IF((A7<A6),G7*10000+IF((A7=A8),G8*1000+IF((A8=A9),G9*100+IF((A9=A10),G10*10+IF((A10=A11),G11)))),0)

H9 =
IF(***(A9<A8)***,G9*10000+IF((A9=A10),G10*1000+IF((A10=A11),G11*100+IF((A11=A12),G12*10+IF((A12=A13),G13)))),**0**)

I11 = IF(***H11>0***,**H11**,IF(A11=A10,I10,0))

I15 =IF(H15>0,H15,**IF(*A15=A14*,I14**,0))

I19: The zeroes provide additional information: that the maximum number of fires experienced by any polygon in the database is five

Figure 6. Excerpt from the MS Excel file used for calculating fire season sequences for five polygons (spatial groups) in the dataset. We have omitted columns that are irrelevant to the computation of the fire season sequences. Boxes represent the logical test functions that have been written to compute the values for the highlighted cell. For the logical test functions in each box, the value returned in the cell is highlighted in bold (either 'value if true' or 'value if false'). Where it is value if true, the section of the logical test that directly produces the result is highlighted in bold italic. Where it is value if false, the section of the logical test that is not upheld is highlighted in bold italic, or where it is a nested logical test function, the part of the nested function that is upheld is highlighted in bold italic.

Table 1. Classifications given to combinations of fire type and season of burn to derive sequences of fire seasons. NUMSEAS are the integer classifications used in the final fire season sequences, and are derived from the FIRETYPE and ALLSEAS columns. Notation: PB = prescribed burn; WF = wildfire; SP = spring; AU = autumn; SU = summer; WI = winter; UN = unknown.

FIRETYPE	SEASON	ALLSEAS	NUMSEAS
PB	SP	SP	1
PB	AU	AU	2
PB	SU	SU	3
PB	WI	WI	4
PB	UN	UN	5
WF		WF	6
UN	UN	UN	7

Constructing sequences of fire season data followed the same procedure used for fire return intervals. However, unlike fire return intervals, which require two fires to calculate, we were looking at data associated with every fire in the dataset. Hence, we needed to add an extra order of magnitude to the calculations to derive the sequences (see cell H7 in Figure 6). Sequences of fire season data were constructed in a column named SEAS_SEQ, and these sequences were assigned to every fire in a spatial group under the column SEAS_SEQ_ALL (examples of logical test functions are shown in Figure 6).

Rejoining Temporal Fire Sequences with the Fire History Dataset

Using the unique identifier (RECNO2) for each record, we rejoined the calculated fire return interval data (consisting of actual fire return intervals in years, and the fire return interval sequences) and the calculated fire season sequences to the FHD containing information on fires for all years (Figure 2).

Censored Data

By limiting our data analysis to 1972/73 onwards, there existed some fire return intervals that represented the time from the oldest fire back to 1972 (when a fire may or may not have occurred). Where a fire did not occur, these censored data (Polakow and Dunne 1999, Moritz *et al*. 2009) represent non-real fire return intervals and were therefore ignored.

The dataset also contained a recent, incomplete fire return interval (equivalent to time since the most recent fire). We have not allowed for this incomplete interval as the experimental design for our case study described below stipulated a consistent time-since-fire for all sites. Hence, although there was a recent, incomplete fire return interval within each polygon, it was equal for all.

CASE STUDY: DESIGNING A RETROSPECTIVE STUDY TO INVESTIGATE EFFECTS OF FIRE REGIME ON BIOTA

We used the temporal sequences to investigate experimental design options for a study investigating contrasting fire regimes and their effects on components of the biota (Wittkuhn *et al.* 2009). Our study maintained a constant time-since-fire by restricting the study area to ~50 000 ha that burnt in either prescribed burns of November 2002, or a wildfire of March 2003 (the 2002/03 fire-year; Figure 1). We did this to remove the time-since-fire effect on the results of the study, which can be significant for all components of the biota in southwestern Australia (Bell and Koch 1980, Burrows and Wardell-Johnson 2003, van Heurck and Abbott 2003, Robinson *et al.* 2008).

Using ArcGIS 9.0, we first investigated the sequences of fire seasons by labelling all polygons using values in SEAS_SEQ and visually inspecting the results (Figure 7). Using this technique, we readily identified those areas burnt most recently by wildfires and those burnt most recently by PBs. We then used the 'Select polygons by attributes' command in ArcGIS 9.0 to further refine historical patterns in burning histories into the following groups:

(1) wildfire most recent fire; previous fires prescribed in spring, some also experiencing other wildfires;
(2) wildfire most recent fire; previous fires prescribed in autumn, some also experiencing other wildfires;
(3) wildfire most recent fire; previous fires both spring and autumn PBs, some also experiencing other wildfires and PBs of unknown seasons;
(4) PB spring most recent fire; previous fires PB spring and wildfires;
(5) PB spring the only fire type;
(6) PB spring most recent fire; previous fires a mix of seasons and wildfires; and
(7) PB spring most recent fire; previous fires include PB in autumn, no wildfires (Figure 7).

To investigate fire return interval sequences, we were interested in the occurrence of successive short or long fire return intervals given their potential to influence species composition (Cary and Morrison 1995). We investigated the mapped fire return interval sequences to identify polygons with the following patterns (Figure 8):

(1) consecutive short intervals (short-short = those with 11 in the sequence);
(2) consecutive long intervals (long-long = those with 33 in the sequence);
(3) mixed intervals (any combination of 1s, 2s, or 3s, but not with 11 or 33 in the sequence), or moderate intervals (made up predominantly of 2s in the sequence).

While we used ten years as the definition of a long fire return interval, we expected to find intervals much longer (Figure 4). Hence, we also investigated in more detail polygons that contained a single long interval (sequence 3000). Three polygons were identified, though only one was of a size worthy of consideration

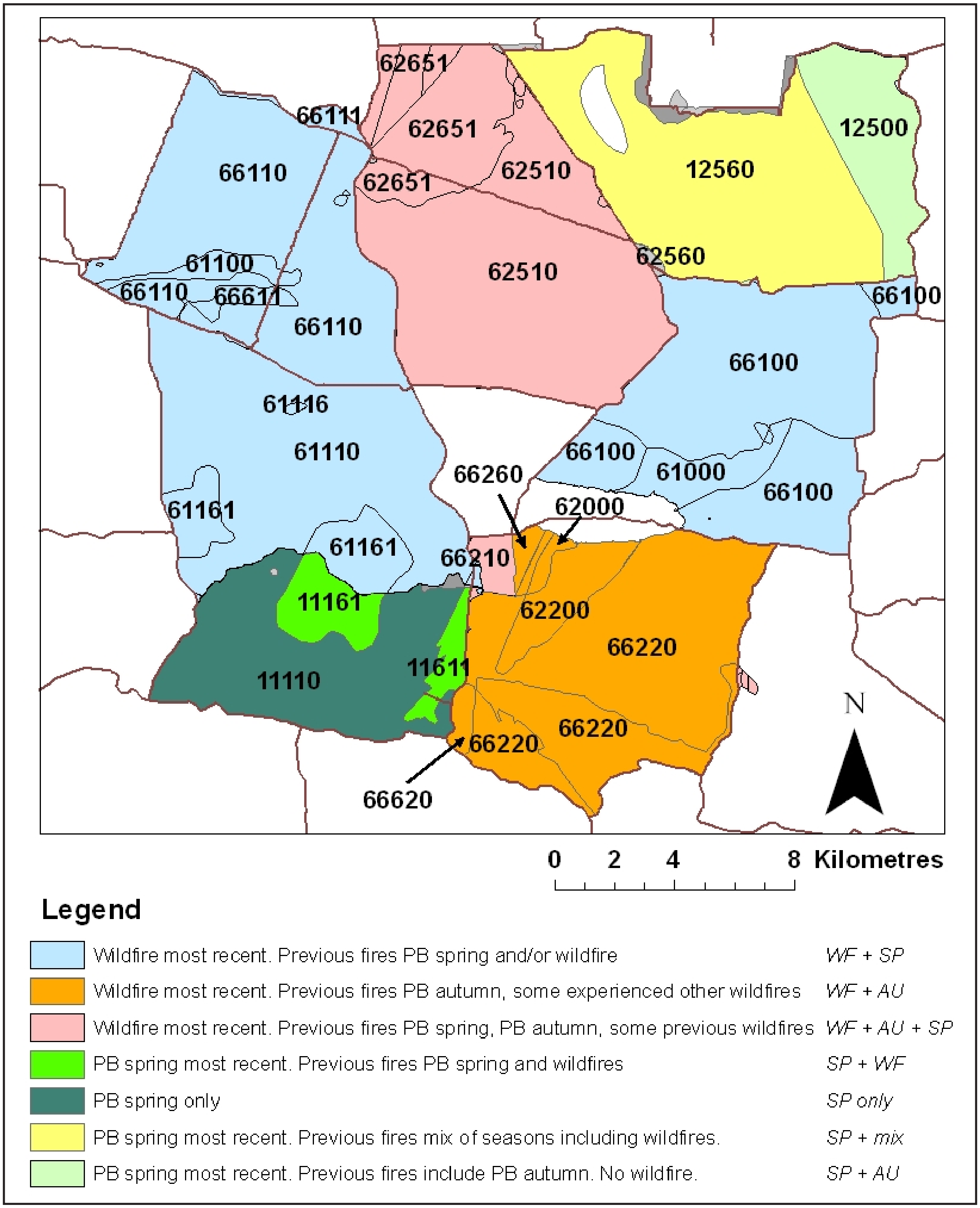


Figure 7. Polygons in the study area labelled with the five-digit fire season sequences (from column SEAS_SEQ in GIS). Numbers in the sequence correspond with classifications given in Table 1. Sequences of fires (reading left to right) are from most-recent to least-recent. The shading corresponds to patterns identified through a visual inspection of the fire season sequences as shown in the legend and discussed in the text. Brown lines are unsealed roads and grey lines are fire history polygons formed by overlapping fires.

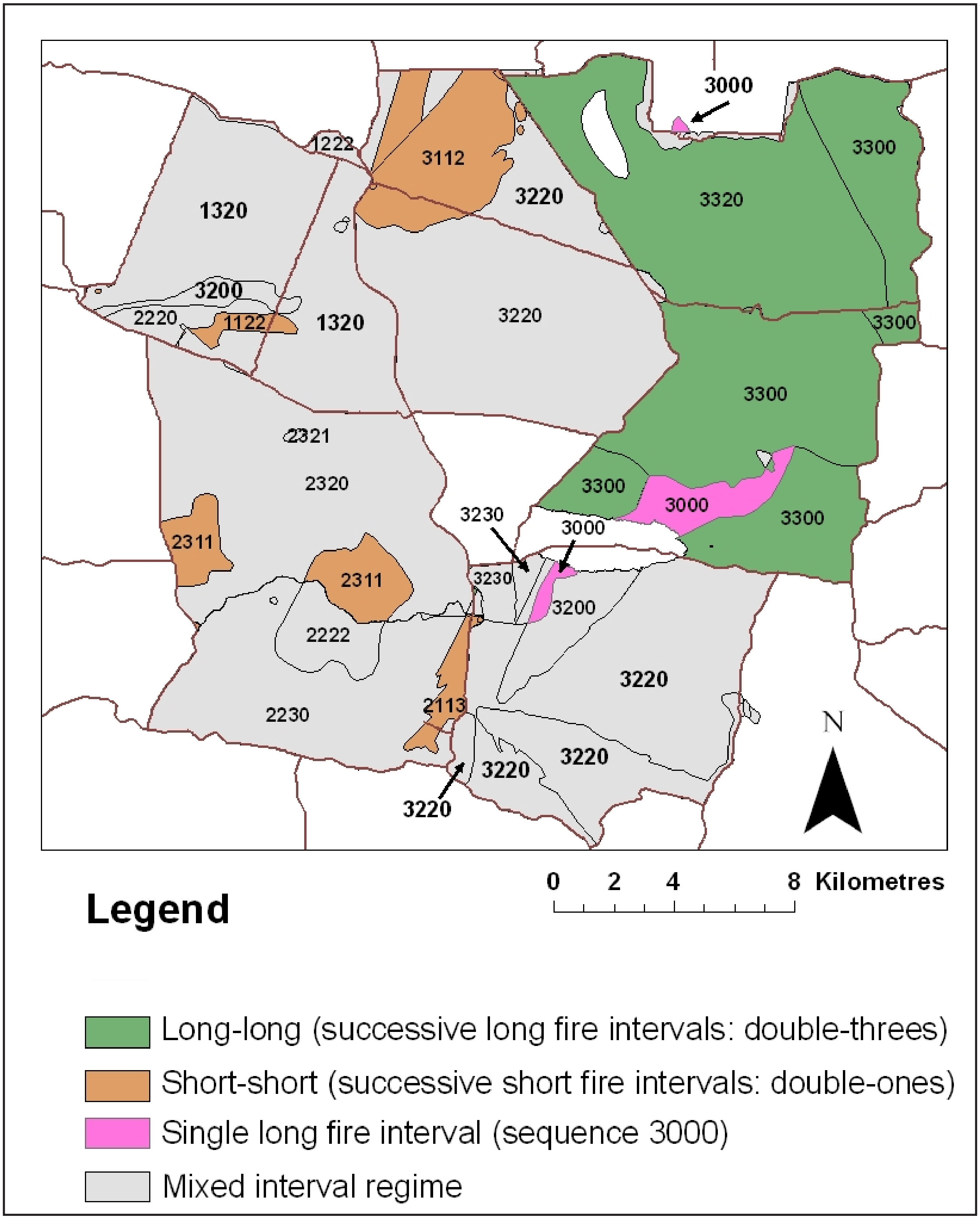


Figure 8. Polygons in the study area labelled with the four-digit fire return interval sequences showing short, moderate, and long intervals (mapped from column FI_SEQ in GIS). 1 = short (≤5 yr), 2 = moderate (6 yr to 9 yr), and 3 = long (≥10 yr). Sequences of fires (reading left to right) are from most recent to least recent. The shading corresponds to patterns identified through a visual inspection of the fire return interval sequences into the four groups shown in the legend and discussed in the text. Brown lines are unsealed roads and grey lines are fire history polygons formed by overlapping fires.

for biological surveying (Figure 8). This area had a 30-year fire return interval prior to the most recent fire, which is significant for the region (Figure 4) and would be an important inclusion in a survey investigating the influence of long fire return intervals on the biological community.

We combined the investigation of fire season sequences and fire return interval sequences by creating individual shapefiles for the short-short, long-long, mixed-moderate and 30-year interval fire interval sequences, retaining all the attribute information, including SEAS_SEQ. Each fire return interval group was then divided into fire season patterns by selecting polygons in ArcGIS 9.0 that related to the seven groups described above and shown in Figure 7.

Twelve contrasting fire regimes were identified by combining the visual analyses of fire season and fire return interval sequences (Figure 9). These regimes were based primarily on four patterns of fire return interval sequence: short-short, long-long, mixed-moderate and 30-year interval; and secondarily on seven patterns of fire season sequences (Table 2 and Figure 9). These factors did not occur universally in combination, which would restrict the experimental design of a study investigating the complete range of fire regimes in the area.

To determine the experimental design of our case study, we gave higher priority to the fire return interval pattern over season pattern because previous work has demonstrated the importance of fire return interval sequences on biota (Cary and Morrison 1995, Watson and Wardell-Johnson 2004), and because of the fact that there were no homogenous sequences of a fire season due to the dominance of wildfires throughout the fire history (Figure 7). Patterns in fire season sequences were more strongly aligned to the absence of a certain season rather than the predominance of a particular one. The most obvious initial pattern was the type of fire experienced most recently: either wildfire or a PB in spring. For those areas burnt most recently in wildfires, we noticed further temporal patterns, particularly the occurrence of spring or autumn PBs in the absence of other seasons (Figure 7).

One drawback to undertaking a retrospective study such as this is the difficulty of finding replicate sites that combine all the factors identified in the historical dataset. The mixed-frequency fire regime contained the widest spread of fire season patterns, though the number of polygons available for site selection was few (Table 2). Both the spread of fire season patterns and number of polygons available for site selection reduced for the short-short and long-long fire return interval patterns, commensurate with their reduced area in relation to the mixed-frequency regime. The results suggest that it will be difficult to develop a study with suitable replicates based on past fire season sequences, but a study investigating the contrasting fire return interval sequences would provide an adequate number of replicate sites (Table 2).

DISCUSSION

We have described a technique for creating sequences of fire return interval and fire season classifications from complex spatio-temporal data to display it in a GIS. We have provided an Excel file for creating the sequences with logical test functions pre-written as supplementary material available from the primary author. The Excel format is useful as it is familiar to many users, rather than software for spatio-temporal databases that is either still in development (Abraham and Roddick 1999), expensive to obtain, or designed for the GIS specialist. While we acknowledge the future for fire history data is in highly functional spatio-temporal databases (see Yuan 1997), our work fills a current gap in computational requirements for recognising broad patterns in spatio-temporal fire data that may be useful to fire ecologists with limited GIS knowledge.

Fire return interval sequences and fire season sequences can be set subjectively to correspond to the appropriate environment to which

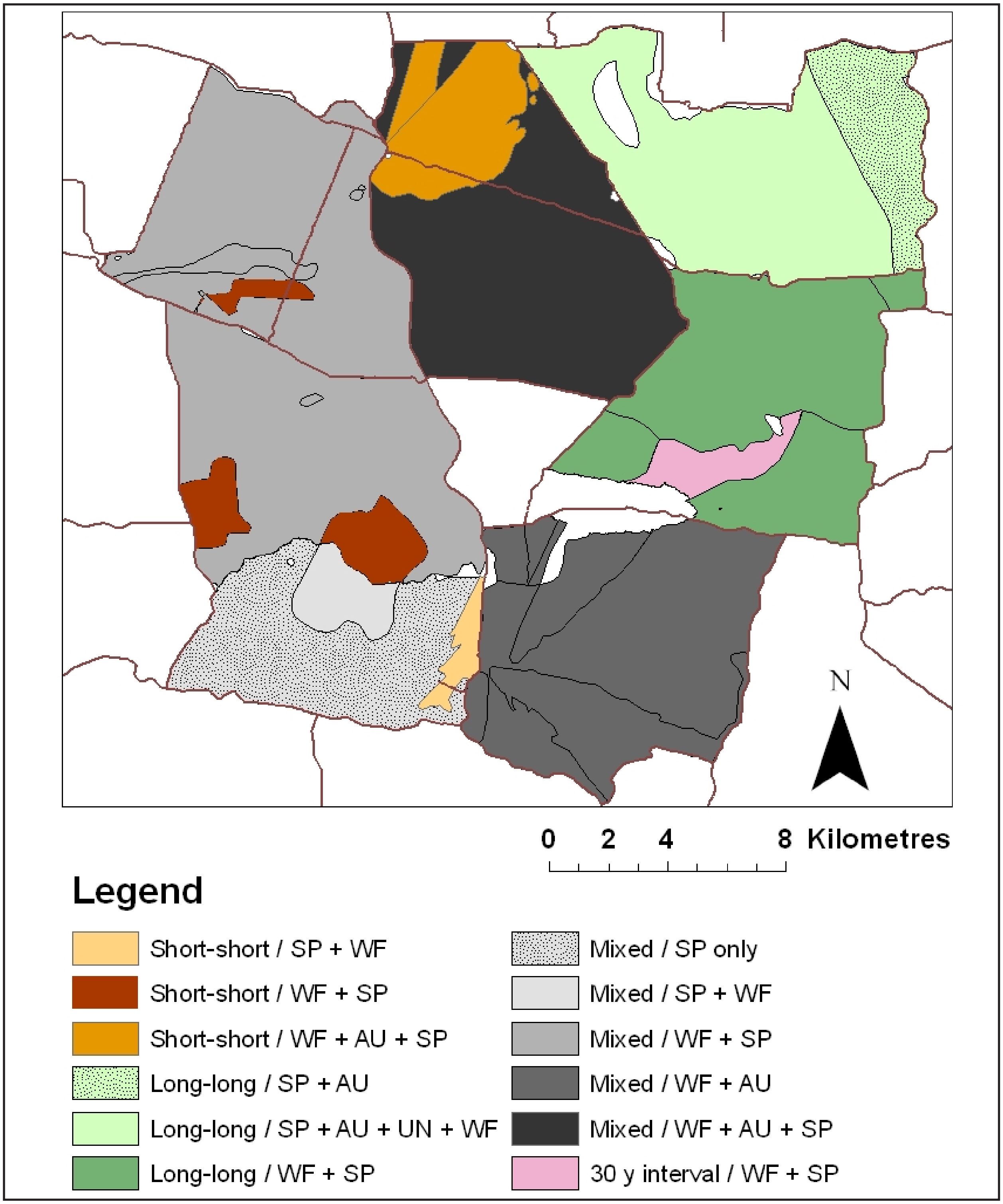


Figure 9. Map of the study area showing the 12 contemporary fire regimes identified through mapping fire season and fire return interval sequences. Short-short indicates two fire intervals of ≤5 years in succession at some time in the past, long-long indicates two fire intervals of ≥10 years in succession at some time in the past, and mixed indicates either a mixed frequency regime or predominantly moderate (6 yr to 9 yr intervals) regime. The pattern of fire season is indicated by first showing the most recent fire type/season, followed by a + and the historical pattern of fire types/seasons. SP = spring prescribed burn, WF = wildfire, AU = autumn prescribed burn, UN = prescribed burn in unknown season. Brown lines are unsealed roads and grey lines are fire history polygons formed by overlapping fires.

Table 2. Number of spatially explicit polygons for each combination of fire return interval and fire season sequence for the case study investigating contemporary fire regimes in southwestern Australia. Polygons <100 ha have been omitted. For fire season sequences: where a pattern begins with WF, this indicates the most recent fire was a wildfire; where a pattern begins with SP, this indicates the most recent fire was a prescribed burn in spring. Types/seasons written after the + sign indicate the other types of fires experienced historically. WF = wildfire, SP = spring prescribed burn, AU = autumn prescribed burn.

	Pattern of fire interval sequence				
Pattern of fire season sequence	**Short-short**	**Mixed-moderate**	**Long-long**	**30-year interval**	**Total**
WF+SP	3	4	3	1	11
WF+AU	-	6	-	-	6
WF+AU+SP	2	1	-	-	3
SP+WF	1	1	-	-	2
SP only	-	1	-	-	1
SP + mix*	-	-	1	-	1
SP+AU	-	-	1	-	1
Total	6	13	5	1	25

* SP + mix has a mix of many fire types/seasons with no discernible pattern, including prescribed burn(s) in unknown season(s).

the data applies because they represent categorical data. We highlighted the utility of developing fire return interval and season sequences through the investigation of experimental design options for a retrospective study of the effects of contrasting fire regimes on biota of southwestern Australia. We see this type of data presentation as having wide application to land management authorities, as well as research personnel who are trying to identify patterns in their spatio-temporal data. The technique described in this paper is useful for investigating a snapshot of any form of spatio-temporal data. While we have used it for fire data, similar versions could be used for other forms of spatio-temporal data for which sequences of events are of interest. The technique could also be used to demonstrate changes to individual-based or point-based data. Examples of this may be bird or animal surveys or water quality data where counts or measures are classified and mapped in time sequences to demonstrate changes through time across the landscape. The main benefit of this technique, and the reason we investigated it in our study, was to provide a broad overview of the temporal patterns in data, and how they were arranged across the landscape. The advantage of doing this in a GIS is that additional themes can be added such as vegetation types, geology, hydrology, or rainfall that may correlate with spatial differences between temporal patterns.

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