Effects of fire frequency and seasonality on the population dynamics of the critically endangered Clanwilliam cedar

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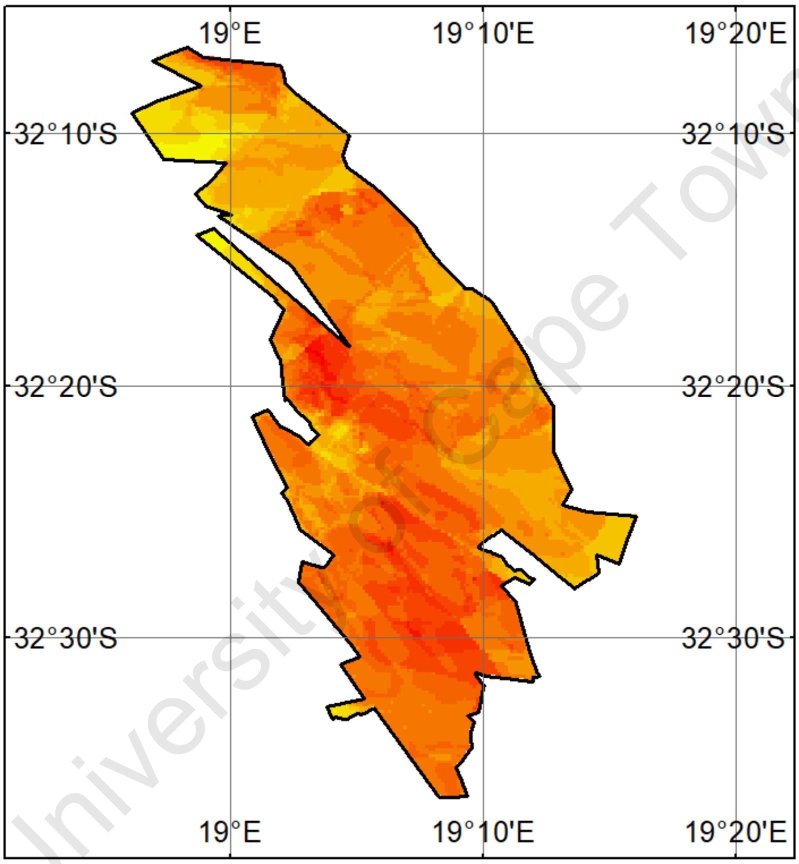

University of Cape Town

Minor dissertation presented in partial fulfilment of the requirements for the degree

Master of Science in Conservation Biology

FitzPatrick Institute of African Ornithology

University of Cape Town

Rondebosch, 7701

South Africa

February 2019

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Acknowledgements

As a physical geographer I had never imagined that I would ever acquire the skill set that this project allowed. For this reason, I would like to start by immensely and humbly acknowledging and thanking my supervisor Dr. Vernon Visser, for imparting his expertise and knowledge in this study. Thank you so much for your patience, enthusiasm, and motivation. There are not enough words to express my genuine and deepest appreciation for your supervision, how lucky was I? You went above and beyond to make me understand fire ecology, learn to code and eventually love R and its complexities, your patience and Afrikaans lessons and prompt responses did not go unnoticed!

I would also like to acknowledge Prof. Jeremy Midgley and Joseph White, for the meetings and invaluable insight on the Clanwilliam cedar and the Cederberg at large. Prof. Edmund February generously provided a report containing missing parameter data and for that I would like to acknowledge him as well. I would also like to extend my sincerest gratitude to Dr. Jasper Slingsby for kindly providing the Clanwilliam cedar localities data, Prof. Timm Hoffman for his kind words and time and lastly Prof. Claire Spottiswoode for introducing me to the Clanwilliam cedar.

Most importantly thank you Jesus!

Abstract

The Clanwilliam cedar, (*Widdringtonia wallichii*, formerly *W. cedarbergensis*) is a threatened conifer endemic to the fire-adapted fynbos vegetation of the Cederberg mountains, South Africa. Here its population size has drastically declined, and its conservation status subsequently escalated to critically endangered in 2013 by IUCN Red List of Plants. Studies have hypothesised that excessive exploitation for timber products, climate change and unfavourable fire regimes (frequency, intensity and season) have contributed to this species' decline. This decline led to the overarching aim of the study to gain a better understanding of the effects of fire frequency and seasonality on the life history of Clanwilliam cedar. To characterise fire patterns in the Cederberg Wilderness Area, I used a latent class analysis on fire indices calculated from a fire history database. To explore the effects of fire seasonality on the cedar count numbers I used a negative binomial hurdle model using seasonal fire indices and environmental data. To examine the impact of fire frequency and seasonality on the life-history of the Clanwilliam cedar, I used a stochastic demographic model based on parameter values obtained from the literature. Findings from the latent class model indicated that the main axes of variation in fire frequency were the fire indices representing total fire frequency, summer fires, autumn fires in the last 30 years and fires in the last 30 years. Although these fire indices were able to distinguish relatively well between the three latent classes, it however was difficult to disentangle the relative importance of each fire index due to their strong covariation. This points to a more general pattern, suggesting that it is necessary to examine the entire fire frequency history and the seasonality pattern in order to understand the current state of the population of the Clanwilliam cedar. The linear count model revealed autumn fires as being positively associated, whereas mean annual precipitation and mean annual temperature and precipitation seasonality were negatively associated with the cedar numbers. The stochastic demographic model showed both summer and winter fires induce positive growth rates at fire-return intervals greater than 10 years, but winter fires always permitted a higher population growth rate. The sensitivity analysis of the stochastic population growth rate (log λs) to changes in the life-history parameters at fire-return intervals of 10 and 20 years showed that fire mortality was most important for a summer fire regime, and growth rates of adult trees were most important for a winter fire regime. The different methods used in this study provided different but complementary results, and thus insights from these various models could potentially contribute to the development of fire management strategies that reflect the complexities of fire frequency and seasonality on the population dynamics and thus persistence of the Clanwilliam cedar.

1 Introduction

1.1 *Widdringtonia* genus

Widdringtonia is a genus in the cypress family (*Cupressaceae*) and is named after Edward Widdrington, a well-known conifer botanist (Kamatou et al, 2010). *Widdringtonia* is often referred to as the African cypress is represented by evergreen tree as well as some shrubs species'(Pauw and Linder, 1997).It is closely related to *Tetraclinis* — a monotypic genus of North Africa and Malta and *Callitris* genus native to Australia (Thomas, 1995).

Widdringtonia is geographically restricted to southern Africa (Kamatou et al., 2010), and is represented by four species', the Willowmore cedar (*W. schwarzii*) endemic to South Africa's Kouga and the Baviaanskloof mountains in the Eastern Cape. The mountain cypress (*W. nodiflora*) which is the only shrub-like species within the genus and the only species in the genus to coppice after fire. It can be found in mountainous areas distributed from the Cape Peninsula of South Africa to Malawi. The Mulanje cedar (*W. whytei*) is native to the Mulanje and Zomba regions of Malawiand, together with the mountain cypress, has the northern-most occurrence of the genus (Thomas, 1995; Pauw and Linder, 1997). The fourth species of the *Widdringtonia* genus is the Clanwilliam cedar, now W. *wallichii* (formerly *W. cedarbergensis*) (Govaerts, 2018). It is arguably a well-known and well-studied plant species in the Fynbos biome (Privett, 1994).The Clanwilliam cedar is an important conifer with both economic and aesthetic value (Mustart et al, 1995). It is considered a paleoendemic to an area that is approximately 250 km^2 in the Cederberg Mountains within the fynbos vegetation of the Western Cape, South Africa. Most of these mountain ranges are formally protected in the Cederberg Wilderness Area (CWA) (White et al, 2016).

1.2 Conservation status of the Clanwilliam cedar

The conservation status of the Clanwilliam cedar was elevated in 2013 by IUCN Red List of Plants to Critically Endangered (CR) under the criterionA2 (e.g. a decline of ≥ 80% of numbers over the last 10 years) indicating the degree and magnitude to which its population has declined (Farjon et al, 2013). Several reasons for this decline have been proposed. Firstly, there was extensive historical exploitation for timber by Cape colonists, with some researchers suggesting the Clanwilliam cedar population has declined to the point at which it cannot recover (Andrag, 1977; Manders, 1986; Thomas,1995). Secondly, climate change has shifted the species range into marginal habitats as a result of a changing and intensified fire regime (Higgins, Manders and Lamb, 1989). This altered fire regime, together with land-use change, has led to further declines (Higgins, Manders and Lamb, 1989). These hypotheses have not yet been quantified and are therefore not well supported. The Clanwilliam cedar continues to decline in the CWA and is faced with possible extinction (White et al, 2016).

1.3 Fynbos biome ecology and fire

The fynbos biome is characterised by three different vegetation types, namely renosterveld, strandveld and fynbos, with the latter being the most widespread in the Cape Floristic Region (CFR) (Rebelo et al, 2008). Fynbos, like other heathlands globally is associated with low nutrients (e.g. phosphorus and nitrogen) and sandy soils (acidic sands or leached coastal sands). Fynbos vegetation is well-adapted to fire, with exposure to fire dating back millions of years. It has been a driving force in the evolutionary diversification of the CFR (Bytebier et al, 2011; Kraaij et al, 2013). Since the evolution of terrestrial plants approximately 420 Mya, fire has been a key component in the evolution and ecology of the earth's biodiversity (He and Lamont, 2018). Fire is an important natural disturbance agent which influences the composition, function and structure of plant communities (Van Coller et al, 2018).

Fire regimes are characterised by the intensity, size, frequency and seasonality of fires, and these define the function and composition of fire-prone ecosystems (Bowman et al., 2009). Plants and animals in fire-prone ecosystems are generally adapted to the fire regime in which they occur, and the dominant plant species often influence the character of the local fire regime (Archibald et al., 2018; Pausas and Parr, 2018). Plant communities in fire-prone ecosystems have adapted to fire through two post-fire regeneration strategies, namely sprouting or reseeding (Altwegg, De Klerk and Midgley, 2015). Sprouters (also referred to as resprouters) are multi-stemmed in nature, with sprouting taking place from buds after the destruction of aboveground biomass (Kruger, Midgley and Cowling, 1997). Reseeders in contrast cannot sprout following a disturbance (e.g. a crown fire). Plant species adapted to this strategy can only re-establish through the process of regeneration of seeds (Manders and Botha, 1989). These fire-adapted strategies are evident in major families of woody plant species, such as the Proteaceae, and can be observed in Mediterranean-type climate ecosystems including the Fynbos biome in South Africa (Altwegg, De Klerk and Midgley, 2015; Rundel et al, 2018).

Fire in the fynbos is an important feature and dominant natural disturbance, and fire is critical for management of fynbos, in that different fire regimes (e.g. fire seasonality, frequency and intensity) can have both deleterious or beneficial effects (Andrag, 1977; Thuiller et al, 2007; Van Wilgen, 2008). Fire not only determines the distribution of fynbos vegetation, but it also maintains species richness (Van Wilgen, Higgins and Bellstedt, 1990; Thuiller et al, 2007).

Fire seasonality in the fynbos varies, from occurring predominantly in the dry summer months in the western winter-rainfall areas (Van Wilgen, 2009; Van Wilgen,2013; Kraaij et al, 2017), to any time of the year in eastern areas, with winter fires characterised by hot berg wind conditions (Kraaij et al, 2013). In the absence of anthropogenic influences, fire in the fynbos occurs at intervals of 10-50 years across (Van Wilgen, 2009). However, due to increasing ignitions by humans, Fire-return intervals have decreased (Van Wilgen et al, 2010).

1.4 Effects of fire frequency and seasonality on life history of the clanwilliam cedar

The Clanwilliam cedar is a slow-growing conifer (Privett, 1994; White et al, 2016), and appears to be fire sensitive, but confined to a fire-prone environment. Fire is important for the life cycle of the cedar trees, although it may kill the trees, it is an integral process for regeneration (Manders and Botha, 1989). Juvenile and adult Clanwilliam cedar trees alike are vulnerable to fires with increased mortality observed in hot summer fires (Andrag, 1977; Manders, 1986; Privett,1994). This may help to explain the distribution of this species at high altitudes between 800-1900m where populations are sporadically distributed, either as individuals or clusters, on rocky outcrops and mountaintops or even in deep, narrow kloofs (Thomas, 1995; Mitrani, 2017). Here populations receive protection from the effects of fire. Notably, a recent study drawing from repeat photography revealed increased mortality at lower altitudes, emphasising the importance of altitude and the rocky nature of the environment associated with the occurrence of the Clanwilliam cedar (White et al, 2016). It is important to emphasise that fire seasonality is important for the Clanwilliam cedar, as it can influence re-establishment of the population, late summer and early autumn fires have been documented as the optimal seasons for regeneration with fires boosting germination. Winter and spring fires may contribute to the decline in that seeds released from these fires if they germinate, they may not have enough time to developed in such a way that they can survive the following summer (Manders and Botha, 1989).

1.5 Aim and objectives

The overall aim of this study is to gain a better understanding of the effects of fire frequency and seasonality on the life history of the Clanwilliam cedar. To achieve this I (1) investigated the use of aerial and satellite imagery for monitoring fire mortality of Clanwilliam cedar trees; (2) characterised and described fire patterns in the CWA using a latent class analysis (LCA); (3) used count models to explore the relationships between seasonality of fire in CWA and Clanwilliam cedar numbers; and (4) examined the impact of fire frequency and seasonality on the life-history of the Clanwilliam cedar using a stochastic demographic model.

The different methods used in this study provided different but complementary results. The LCA identified the major axes of variation in fire regimes in the CWA. The linear count models assessed the drivers of cedar densities, particularly fire, using a large database of cedar occurrences. The stochastic demographic model, unlike previous studies that modelled the population dynamics of the Clanwilliam, incorporated seasonality to model the probability of a fire occurring and its effect on the life-history of the species. Insights from these various models could potentially contribute to the development of fire management strategies that reflect the complexities of fire frequency and seasonality on the population dynamics and thus persistence of the Clanwilliam cedar.

2 Methods

2.1 Aerial and satellite imagery for monitoring cedar fire mortality

Google Earth (GE), which is a good source of aerial imagery, was first used to identify the Clanwilliam cedar trees using the available historical imagery. However, the low spatial resolution of this imagery made this impractical. An alternative was to use high spatial resolution Landsat 8 and Sentinel-2 satellite imagery (<3 m spatial resolution, which is probably the minimum required to detect individual trees). However, these also proved impractical due to these satellites only having been launched in 2013 2015, respectively and the cost associated with purchasing the satellite imagery (Li and Roy, 2017). As a third alternative, imagery of the same time period as that of the fire history database was requested from South Africa's Department of Rural Development and Land Reform (DRDLR)—Chief Directorate: National Geo-spatial Information (NGI). However, it should be noted that aerial imagery for the CWA from 1920 to 2016 is limited, with imagery and flight plans for the CWA and neighbouring areas such as Citrusdal and Clanwilliam only available for 1948, 1959, 1960, 1971, 1978, 1980, 1986, 1994, 1998 and 2003. To monitor cedar fire mortality, the imagery and associated flight plans were assessed. The ArcGIS georeferencing tool was used to allocate coordinates for the imagery and align it using the ArcGIS imagery basemap.

2.2 CapeNature fires database

Data on the history of fires in the CWA were obtained from SANBI BGIS (http://bgis.sanbi.org/):the CapeNature fire database contains a fire history record of the Western Cape from 1927 to 2016 (CapeNature,2016).This database was compiled by reserve managers by digitising fires using on-screen digitising of aerial and satellite imagery and GPS (either by walking or flying the fire line) and entering the attributes of the fire report directly into CapeNature's fire database. These were validated by the GIS fire technician at the scientific services. The dataset also went through a rigorous data cleaning process, which involved overlaying fire scars per fire season and clearing out duplicates, slivers and overlaps that lead to unrealistically short fire intervals. Furthermore, fire records from 2005 onwards were further verified using the annual SPOT5 satellite mosaic images that were available on an annual basis (CapeNature, 2016).

2.3 Point occurrence data

The point occurrence data of adult Clanwiliam cedar trees within the CWA were provided by Dr Jasper Slingsy in a shapefile format containing over 13 000 points (Fig. 1). These occurrences were manually mapped by Jasper and Peter Slingsby using 2013 high-resolution CNES/Airbus satellite imagery available from Google Earth (Slingsby and Slingsby, 2019). Each individual tree was identified based on its canopy colour, shape, size as well as shadow. These trees were validated through ground-truthing by recording the GPS location and size class (adult = canopy >4 m^2, sub-adult = canopy >1 and <4 m^2 and seedlings = canopy <1 m^2) of all trees. This field-based observational survey was thereafter compared with population estimates using satellite images (Slingsby and Slingsby, 2019).

2.4 CWA boundary

The CWA boundary which was crucial for masking the fire dataset to the study area was also obtained from the SANBI Biodiversity GIS portal (http://bgis.sanbi.org/) in shapefile format.

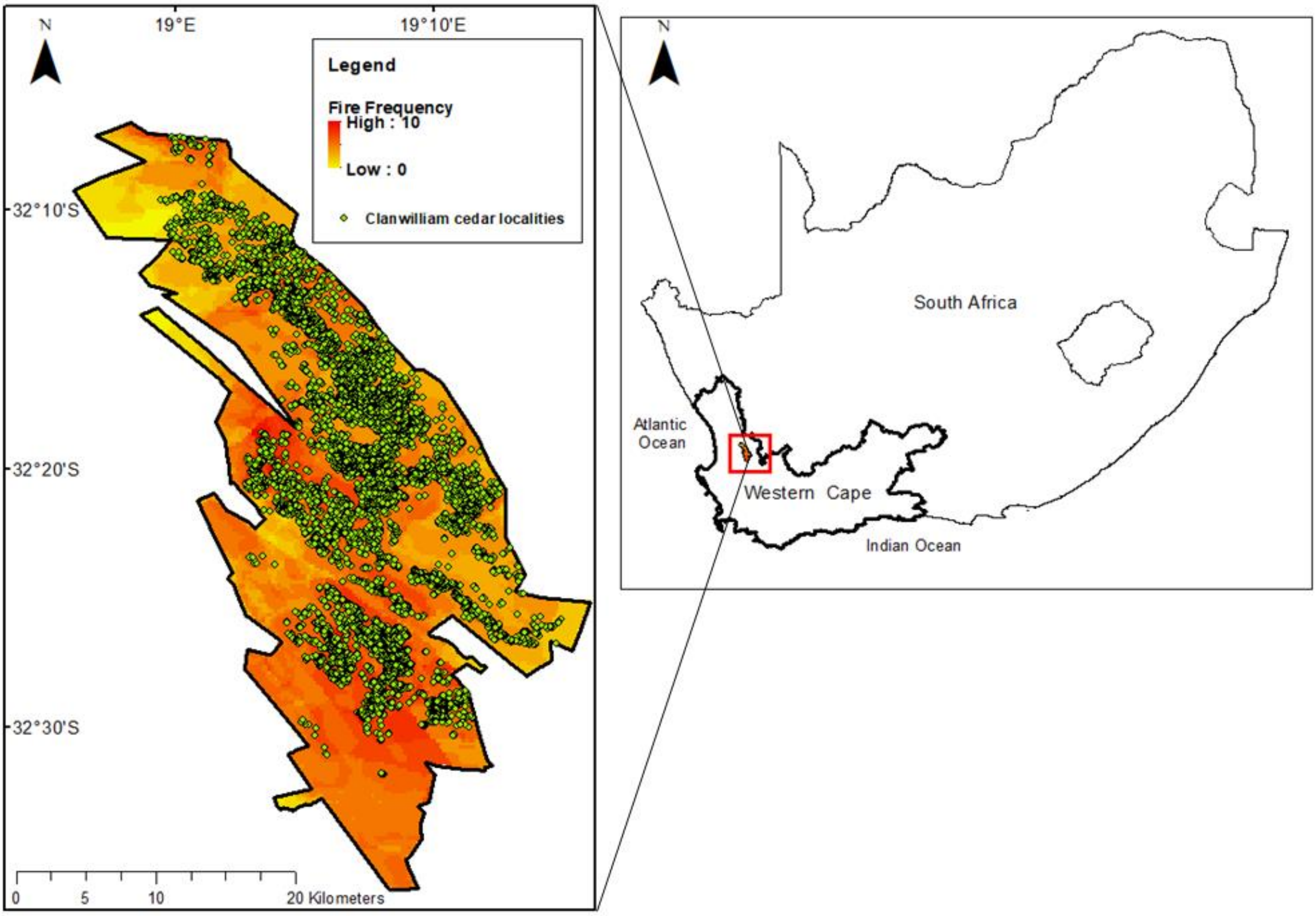

Figure 1. Map of the CWA located in the Western Cape province of South Africa, showing the tree localities (>13 000) observable as green points in concert with the fire frequency record.

2.5 Characterising fire patterns using select fire indices

The CapeNature fire history database (Fig. 1) was used to calculate several fire indices potentially important to the Clanwilliam cedar. As a basis for characterising fire patterns in the CWA, I derived in R version 3.5.1 (R Core Team, 2018) several fire indices from the CapeNature fire history data. These indices included: all fires since records began in 1945, number of fires in the last 30 years, number of fires in each decade since 1945, it should be noted that the first decade 1945-1955 was excluded as it had a low frequency, number of fires in each season for the entire time period (e.g. # fires in summer: Dec, Jan, Feb; # fires in autumn: Mar, Apr, May; # fires in winter: Jun, Jul, Aug; # fires in spring: Sep, Oct, Nov), and the number of fires in each season in the last 30 years (e.g. since 1987). The frequency of winter fires in the last 30 years was considerable small and thus excluded.

To calculate the sum of fires for each index, each fire polygon was rasterised (using the *rasterize* function in the *raster* package) and the resulting and relevant raster layers summed to produce each index. Polygons were rasterised to a raster layer of the same extent as the CWA fire layer, and with a spatial resolution of 0.125 degrees (~230 m^2). This resolution was chosen because fire polygons smaller than this produced errors in the rasterisation process, but the smallest possible resolution was chosen to minimise the potential for missing smaller fires in the calculations. Rasterisation of the fire polygons resulted in some NA pixel values for very small fires, which were excluded from further analysis.

2.6 Using latent class analysis to characterise fire patterns in the CWA

First introduced in 1950, latent class modelling is a methodology which was developed to analyse relationships of categorical data. In other words, relationships between variables scored at either a nominal or ordinal level of measurement (McCutcheon, 1987, p.11). A latent class model's key function is to estimate and remove measurement errors from the vector of latent class membership probabilities (Lanza et al, 2007). It is important to note that latent class models are applied as clustering and scaling tools for indicators dichotomous in nature (Vermunt, 2010). These models are directly analogous to factor analysis models (Ruscio et al, 2011). However, the distribution as well as the nature of a latent variable makes them distinguishable. The latent variable is said to be multinomial in distribution (Collins and Lanza, 2009, p. 6). It is also based on the premise that covariation seen between variables is a direct result of the observed variable's relationship to that of the latent variable. Essentially, the latent variable can be used to interpret the relationships among the observed variables (McCutcheon, 1987, p. 5). This is often referred to as a latent class analysis (LCA) (Kamata et al, 2018). Latent class models have the advantage of not making any assumptions relating to the distribution of the variables, other than that of local independence (Lanza et al, 2007), meaning that latent class variables or indicators are independent.

In recent years latent class analysis has received much momentum as a multivariate approach to behavioural research (Chung et al, 2006). Latent class models have been applied in various fields, including social and health sciences, as well as resource economics pertaining to market research (Wedel and Kamukura, 2000, p. 58). More recently these models have been applied in studies pertaining to recreational demand, to understand people's willingness to pay for environmental services in terms of stated preference and public preference (Glenk, 2011). A recent study by Brouwer et al (2010) made use of LCA to infer spatial preference heterogeneity pertaining to the spatial distribution of water quality improvements in the Guadalquivir River basin. The study results revealed that people's value of the water improvements was significantly dependent on their proximity to the basin. Nguyen et al (2013) made use of the latent class approach to assess the behavioural patterns of fishermen who fish sockeye salmon (*Oncorhynchus nerka*) on a recreational level, in the lower Fraser River of British Columbia. They developed three latent class models based on the anglers, fishing behaviours and preferences, perceived risks to salmon survival and level of support for education programmes (Nguyen et al, 2013). The models suggested that the anglers had a strong awareness of the best fishing practices pertaining to catch and release, with lake-species specialists exhibiting a greater awareness.

To spatially characterise patterns of fire history and seasonality in the CWA, I used LCA. This was done in R using the mix function of the depmixS4 package. The LCA was used to identify three states (latent classes) that represent major axes of variation in fire frequency and seasonality as derived from the fire indices. A Pearson's chi-squared test was then used to compute the correlation between these states and cedar densities.

2.7 Linear modelling of the Clanwilliam cedar densities as a response to fire and climate

LCA provides a useful approach for mapping spatial patterns of fire frequency and seasonality, and to provide an indication of how these factors relate to the distribution and density of Clanwilliam cedar trees. However, an alternative approach is to use linear modelling, which can provide direct estimates of effect sizes of each of the fire indices and their associated statistical significances but is limited in the predictor variables that can be used depending on their covariation, e.g. the problem of collinearity. Therefore, the two methods, LCA and linear count modelling, provide complimentary methods for the analysis of the Clanwilliam cedar count data. Count data are typically modelled using a Poisson error distribution. However, count data may exhibit zero inflation—a large proportion of observations with a value of zero. Certain linear modelling approaches allow one to account for an excess of zeros (as with the cedar count numbers). These include zero-inflated Poisson (ZIP) models and hurdle models with a Poisson or negative binomial error distribution. I therefore tested these various modelling approaches to investigate Clanwilliam cedar counts as a response to some of the fire indices and the following environmental predictors were selected for the analysis and obtained from various sources. Data on the mean annual temperature (MAT) and mean annual precipitation (MAP) available as 1 arc minute gridded data were obtained from the SA Risk and Vulnerability Atlas (http://sarva2.dirisa.org/atlas/weather-and-climate/weather-and-climate/). The minimum temperature of coldest month (Bio6) and precipitation seasonality (Coefficient of Variation) (Bio15) were obtained from (http://worldclim.org/bioclim) with a spatial resolution of 10 arc minutes. The digital elevation model (DEM) with a 30 seconds spatial resolution was obtained from (https://www.diva-gis.org/). These were selected in part, based on their statistical significance in previous studies relating to the Clanwilliam cedar. These layers were cropped to the same extent as that of the cedar count raster. The DEM was used to derive the Aspect layer. These layers were cropped to the same extent as CWA and resampled using the bilinear remote sensing technique. Prior to model fitting, predictors were checked for collinearity using Pearson's correlation coefficients. The effect of fire seasonality on the cedar count was then explored through fitting 5 competing models. I first performed a Poisson regression model in which the count data was modelled, that is regressing the cedar count densities on all predictor variables; fire season indices (FiresAut, FiresWin, FiresSpr and FiresSum) and environmental predictors. I tested how well the model fits the data using the *rootogram* function in the *countreg* package. In doing so discovered that the count data had an access of zeros that is a large proportion of observations with a value of zero. To account for this, I then generated hurdle negative binomial models, again regressing fire season indices (FiresAut, FiresWin, FiresSpr and FiresSum) and environmental predictors. For model selection, I used the *LRstats* function in the *vcdExtra* package to infer the best model denoted by their AIC values.

2.8 Using a stochastic demographic model to investigate the Clanwilliam cedar population responses to fire frequency and seasonality

Understanding what drives and affects reproduction and survival of populations is fundamental in ecology and allied fields (Salguero-Gómez et al, 2016). Population models, initially developed by animal ecologists, are mathematical models that can be applied to interpret population dynamics (Worster, 1994, p. 409). The individual is the basic unit in such models (Metz and Diekmann, 1986, p3). These models can also be applied to plant species as refinements have been made to accommodate the nature of plant species (Tuljapurkar and Caswell, 1997). It is important to bear in mind that developing models for population dynamics can come with uncertainties in terms of formulation and parameterisation of the model (Freckleton et al, 2008)

Population models specify changes over time through a distribution function which considers the number of individuals in each life stage. This is communicated in a mathematical form extracted from an understanding of the transition of an individual through its life cycle (Tuljapurkar and Caswell, 1997). They can be referred to as individual-based models, which as indicated by Tuljapurkar and Caswell (1997) in a sense are structured population models. Modelling single species as one population is challenging, and for that same reason, populations are often modelled as a structured population whereby individuals within a given population are partitioned into different categories, including size, age, developmental stage and sex (Briggs et al, 2010). These categories can be referred to as *i*-state variables and are assigned in accordance with important individual differences (Tuljapurkar and Caswell, 1997). These can be determined by the modeller, whereby they explicitly define a modelling methodology that incorporates all the necessary biological details on an individual level in a mathematical form (Metz and Diekmann, 1986, p3). For example, size can play a key role in the mortality risk of plants. Large adults and seedlings react differently to a disturbance and age affects the rate of reproduction differently. If size was more important than age, it would be better to use size to describe the distribution of a population (Caswell et al, 1997, p.4).

Matrices were first introduced into population mathematics by Lewis in 1942 then Leslie in 1945 (Doubleday, 1975). Although simplistic in mathematical approaches, computational power is essential for matrix models. These models can be useful in studying and identifying demographic responses, which are fundamental in evolutionary dynamics (Metcalf and Pavard, 2007). Matrix models received little attention by ecologists until the late 1960s when they remerged, uncovered by human demographers and ecologists (Lefkovitch, 1965). By the 1970s they were put into practice by plant ecologists (Caswell, 1977, p.19).

2.8.1 Deriving parameters for the stochastic demographic model

To explore the effect of fire frequency and fire seasonality on the life history of the Clanwilliam cedar, a stochastic demographic model was created. It is based on the modification an Altwegg et al (2014) demography model of reseeding and resprouting proteas species in the Mediterranean-type ecosystems.14 size classes were defined to reflect the different life stages of the Clanwilliam cedar (Table 1), with an expansion on the juvenile stage with 12 classes aligning with the time it generally takes the Clanwilliam cedar to reach maturity and produce cones (Privett, 1994). The description of the size classes was informed by Manders (1985) size classes (Table 2). To run the model for the Clanwilliam cedar, demographic data were obtained firstly through deriving life stages or commonly termed size classes. The size classes used in this model (Table 1) were informed, matched and compared to existing size classes derived in previous studies, for instance (Table 3). Model demographic data was sourced following the derived size classes, parameter values such as germination and mortality are literature values (e.g. fire mortality obtained from Privett,1994 and germination from Manders, 1987a).

Table 1. Size classes selected for the model used in this study.

Size classes used in this study	**Description**
1	Seedling
2 to 11	Vegetative
12	Small adult
13	Medium adult
14	Large adult

Table 2. Size classes derived by Manders (1985) matched to the size classes used in this study. This matching was necessary to determine parameter values for the stochastic demographic model.

Manders (1985) classes	**Size classes used in this study**	**Description**
1		Seed
2	1	<= 25cm high
3	2 to 11	>25cm and <=50cm high
4	2 to 11	50cm and <=75cm high
5	2 to 11	75cm and <=100 cm high
6	2 to 11	100cm and <= 125cm high
7	12	125cm and <=150cm high
8	12	125cm and <=150cm high
9	13	5cm diameter and <= 10cm diameter
10	13	10cm diameter and <=20cm diameter
11	14	>20cm diameter and <= 40cm diameter
12	14	40cm diameter and <=60cm diameter
13	14	>60 cm diameter

Table 3. Size classes derived by Privett (1994) matched to the size classes used in this study. This matching was necessary to determine the parameter values.

Privett (1994) Classes	**Size classes used in this study**
1	1 to 11
2	12 to 13
3	14

Germination estimates are literature values. Growth rate was estimated from (Higgins, February and Skowno, 2001) figure 4A then calculated as a function of diameter increment of stem over diameter of stem. Fecundity (seed production) was estimated from (Higgins, February and Skowno, 2001) figure 3. Fire mortality was calculated using the equation Mx = (1- Sx) in which survival values were obtained from Privett (1994). Survival was calculated as the inverse of mortality— mortality values were obtained from (Higgins, February and Skowno, 2001) figure 5A. The parameter values (Table 4) were used in the simulation of the stochastic demographic model. A 10 and 20 *FRI* relating to the fire interval at which fynbos vegetation typically burns (Brown et al, 1991; Van Wilgen, 2013), was used to model the stochastic population growth rate log λs and its sensitivity to changes in life history parameters parameterised for either summer or winter fires.

Table 4. Life-history parameters of the Clanwilliam cedar for the stochastic demographic summer and winter model.

Parameter	**Summer value**	**Winter value**
Seedling survival	0.90	0.90
Survival vegetatives	0.90	0.90
Survival small adults	0.99	0.99
Survival medium adults	0.95	0.95
Survival large adults	0.97	0.97
Growth from vegetative to small adults	0.20	0.20
Growth from small to medium adults	0.08	0.08
Growth from medium to large adults	0.01	0.01
Fecundity small adults	70	70
Fecundity medium adults	250	250
Fecundity large adult	2300	2300
Germination rate after fire	0.08	0.15
Germination rate no fire	0.06	0.06
Fire mortality vegetatives	0.99	0.89
Fire mortality small adults	0.93	0.78
Fire mortality medium adults	0.93	0.78
Fire mortality large adults	0.40	0.00

3 Results

3.1 Aerial and satellite imagery for monitoring cedar fire mortality

Almost all the NGI aerial imagery was of areas outside the CWA extent, such as Citrusdal and Clanwilliam. Consequently, the use of aerial imagery to determine historical fire mortality of the Clanwilliam cedar trees was not possible.

3.2 Latent class analysis (LCA)

The LCA investigated spatial patterns of fire frequency and seasonality using fire indices (Fig. 2). The index, the sum of fires for the entire 60 period ("FiresAll"), was found to exhibit the greatest variation and differentiability of the three latent classes (Fig. 3). Other indices that were able to distinguish relatively well between the three latent classes were in the sum of summer fires for the entire period ("FiresSum"), the sum of autumn fires in the last 30 years ("FiresAut30") and the sum of fires for the last 30 years ("Fires30") (Fig. 3). All other indices were largely invariant across the three latent classes (Fig. 3). Latent class 1 was associated with an intermediate frequency of fires, latent class 2 with low fire frequencies, and latent class 3 with the highest fire frequencies across the four aforementioned most important indices (Fig. 3).

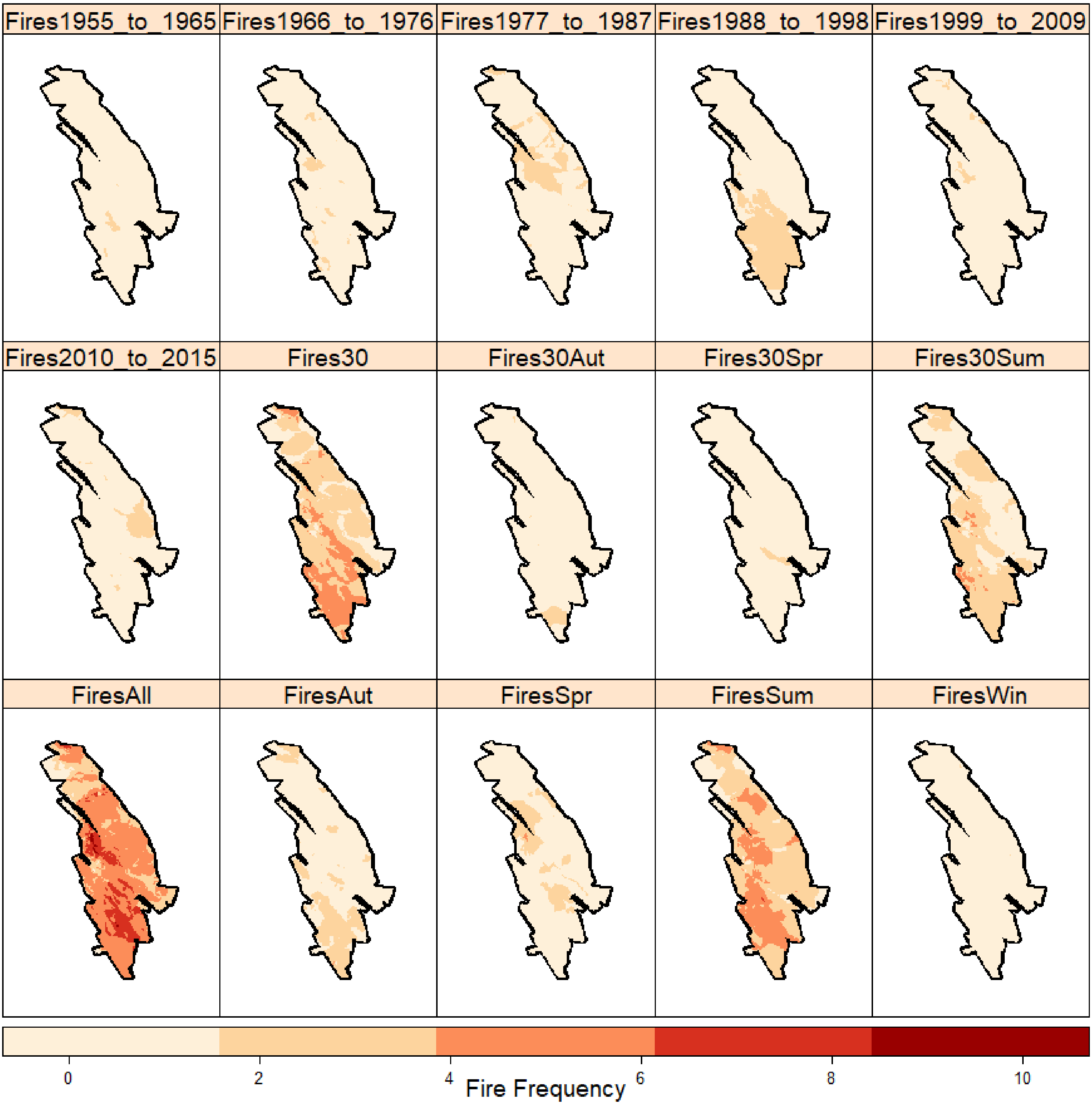

Figure 2. Spatial fire patterns of the Cederberg Wilderness Area (CWA) for a 60-year period (1955-2015).15 fire indices are shown depicting decadal fires from (~1955), fires in the last 30 years (>1987) partitioned into seasons, all fires—these were also portioned into seasons. Frequencies range between 2 and 7, with a mean of 4 fires.

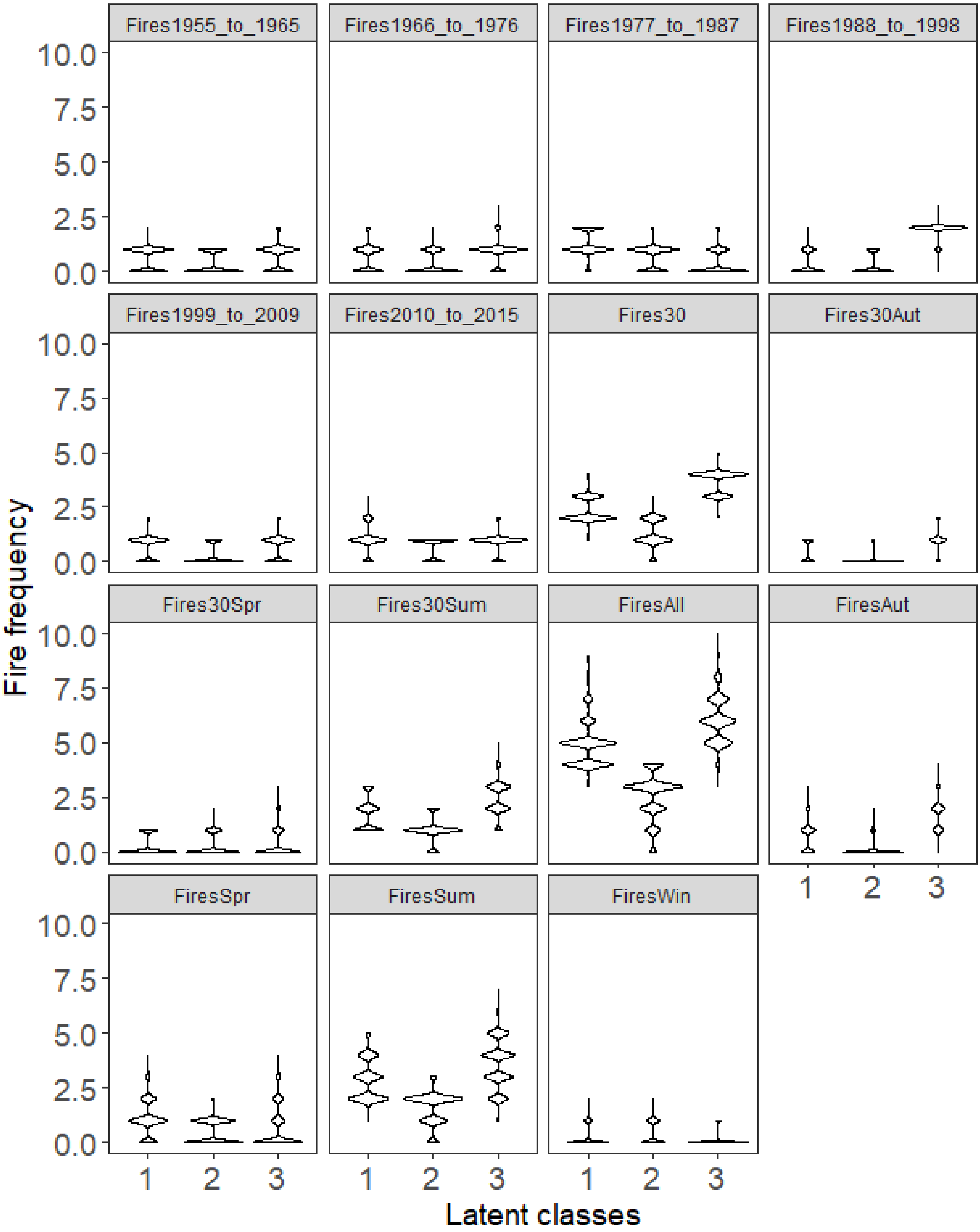

Figure 3. Violin plots depicting the relationship between the 15 fire indices calculated for the Cederberg Wilderness Area (CWA) and the three latent classes

3.3 Linear count models

Several hurdle negative binomial models in which the effects of fire seasonality on the cedar count densities were evaluated. First, correlations between all predictors was examined (Fig. 4). Although the correlation between the variables is low for the most part (Fig. 4), it still shows however that there is a strong positive correlation with a strong correlation between the Bio6 and Bio15 predictors, with the former excluded as a result. Model fitting the data with a Poisson regression revealed an over-dispersion in the data, with a zero-inflation spike (Fig. 5).

Hurdle models can account for an access of zeros in data, five hurdle negative binomial hurdle models were fitted, in part to address this and examine the relationship between the fire season indices with the cedar count. Five hurdle models were then tested where the cedar count densities were first regressed with each fire season index and environmental predictors. These models were all significant (Table 5). The cedar count was regressed again with all predictors combined. Since the models were significant on their own, it was expected that the best model with lowest AIC value would be the model that combined all predictors (Table 5). Model evaluation was performed again, this time with mod.hnb.seas.evn, (Fig. 6) shows that the model fitted the data well. The hurdle model was further evaluated to make inferences on the effect of fire seasonality on the cedar count (Table 6). The results of this analysis shows that FiresAut is positively associated with the cedar count whereas MAP and Bio15 are negatively associated. Note however that the model did not accuralely predict the cedar count numbers (Fig.7).

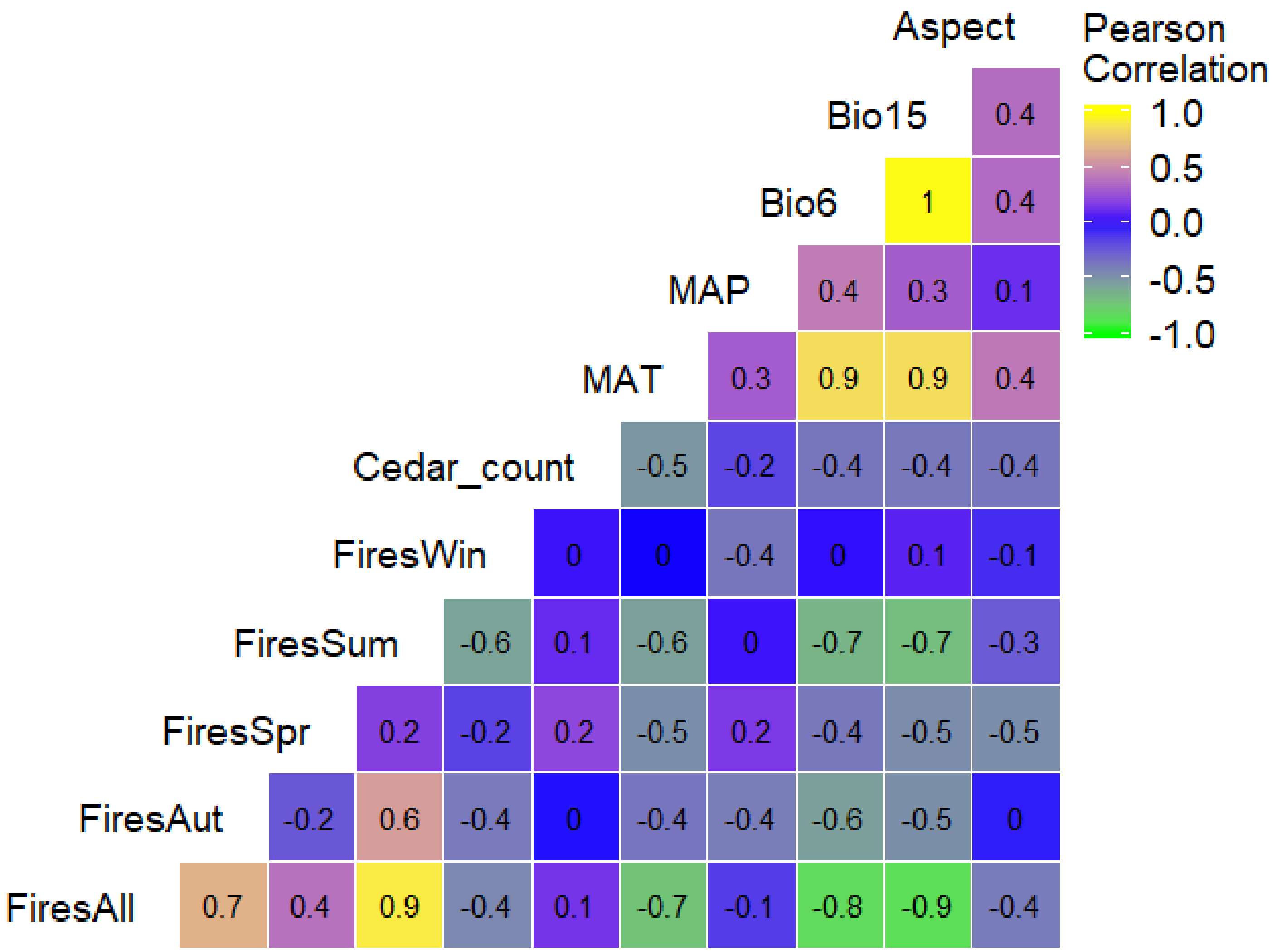

Figure 4. Pearson's correlation coefficients between the response, cedar count, and potential predictor variables. Predictor names as described in sections 2.7. The correlation coefficient is between -1 and 1, where positive correlations are displayed in light yellow and negative correlations in light green colour**.**

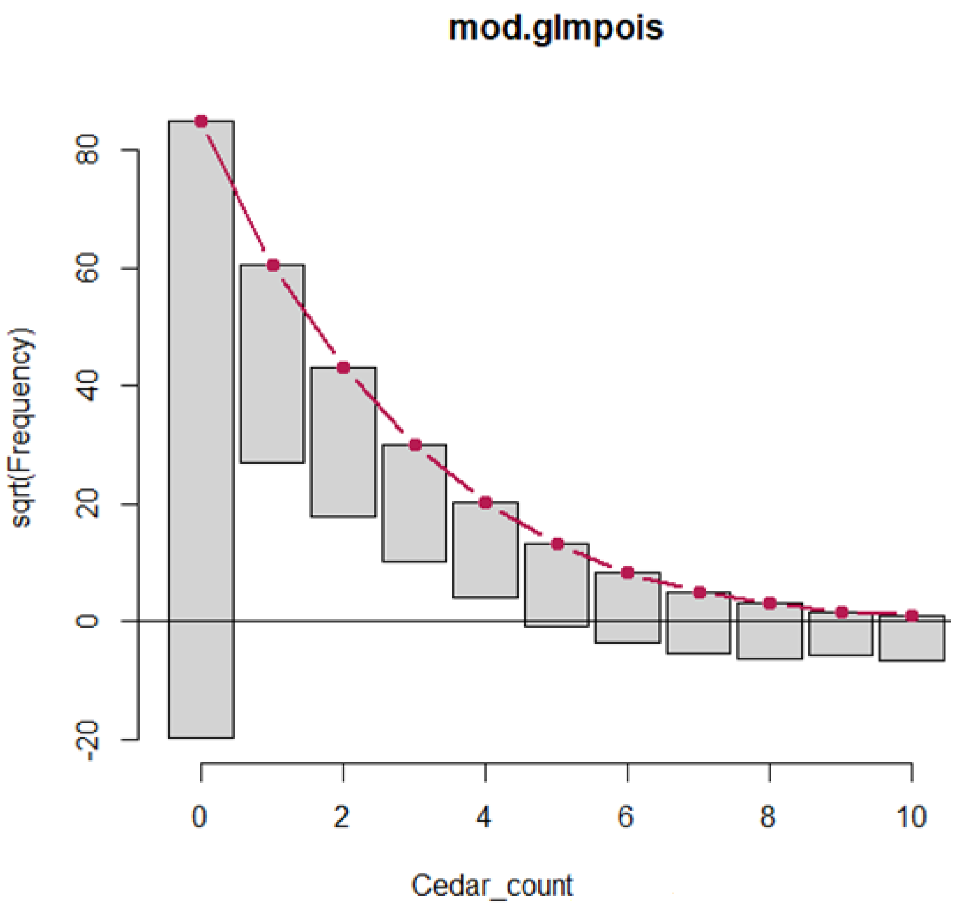

Figure 5. Rootogram depicting the Poisson regression model with an observed zero inflation.

Table 5. Results of the 5 competing linear count models, where a low AIC represents the best model.

Model	**Variables**	**Akaike information criterion (AIC) values**
mod.hnb.seas.evn	Cedar_count ~ FiresAut + FiresSpr + FiresSum + FiresWin + MAT + MAP + Aspect + Bio15	27752
mod.hnb.FiresWin.evn	Cedar_count~ FiresWin + MAT + MAP + Aspect + Bio15	27814
mod.hnb.FiresAut.evn	Cedar_count~ FiresAut + MAT + MAP + Aspect + Bio15	27858
mod.hnb.FiresSpr.evn	Cedar_count~ FiresSpr + MAT + MAP + Aspect + Bio15	27882
mod.hnb.FiresSum.evn	Cedar_count~ FiresSum + MAT + MAP + Aspect + Bio15	27883

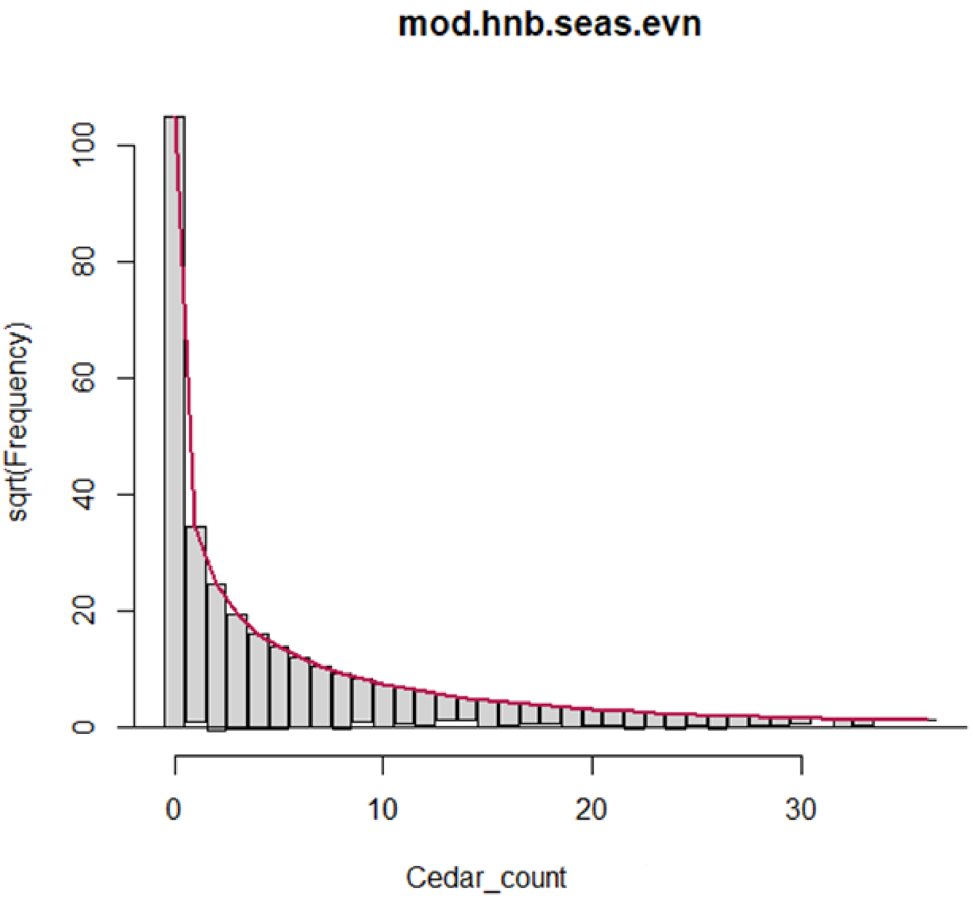

Figure 6. Rootogram depicting model fit of the best hurdle negative binomial (HNB) model (mod.hnb.seas.evn) relative to simulated negative binomial distributed data.

Table 6. Results of the fitteed HNB model showing the relationship of fire indices and environmental predictors to cedar count.

Predictor	**Coefficients**	**Std. Error**	***p*-value**	
FiresAut	0.23	0.04	0.00	***
FiresSpr	-0.007	0.05	0.9	
FiresSum	0.02	0.03	0.5	
FiresWin	0.07	0.08	0.4	
MAT	-0.26	0.03	0.00	***
MAP	0.003	0.00	0.00	***
Aspect	-0.00	0.00	0.6	
Bio15	-0.12	0.02	0.00	***

Signif. Codes: *** $p < .001$ **$p < .01$ *$p < .05$

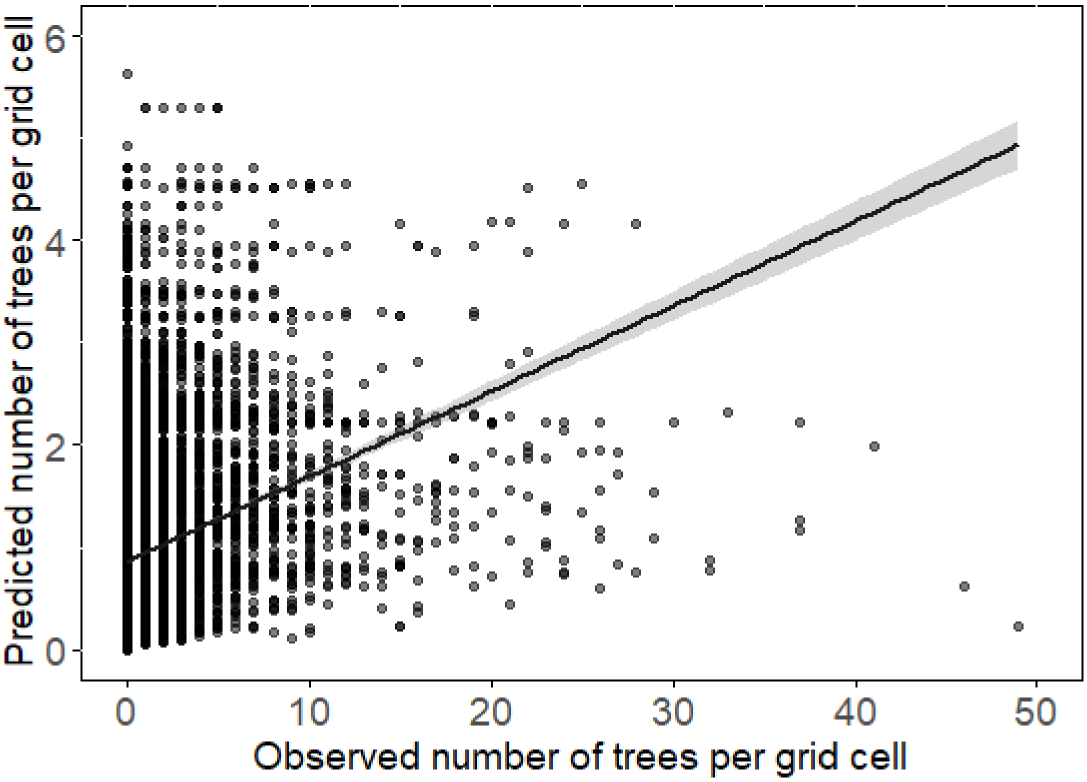

Figure 7. Assessment of the accuracy of the hurdle negative binomial model to predict cedar count numbers.

3.4 Stochastic demographic model

The Clanwilliam cedar population increased at short and long fire-return interval (Fig. 8). At fire intervals of 10 and 20 years—which are realistic intervals between fires for the fynbos fire-adapted vegetation, both summer and winter fires resulted in positive growth rates. Winter fires performed better than summer fires revealing maximum population growth for the Clanwilliam cedar population (Fig. 8).

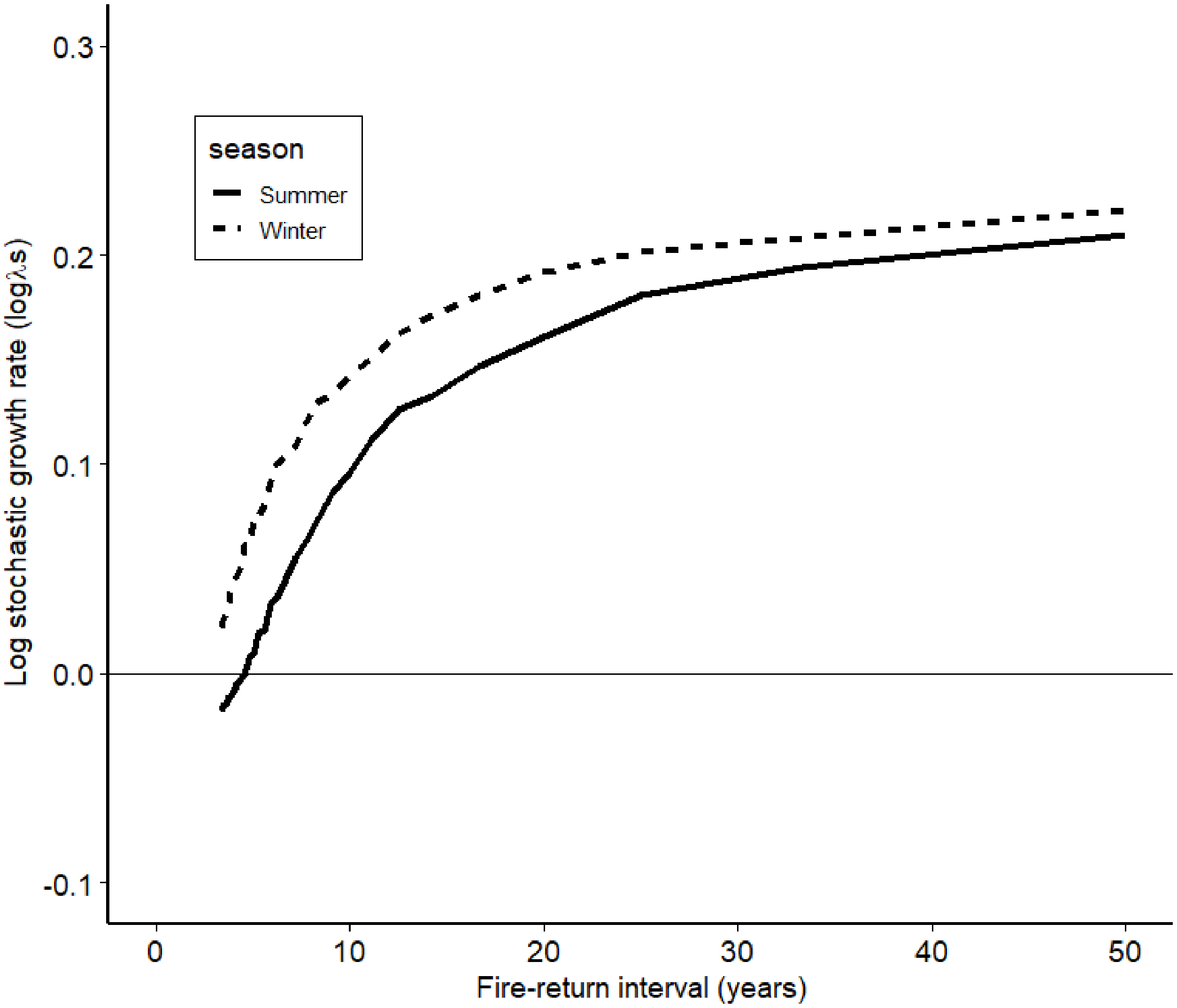

Figure 8. Projected stochastic population growth rate [log(λs)] of the Clanwilliam cedar relative to fire-return intervals *(FRI)* for two models parameterised for either summer or winter fires.

The results for the sensitivity analysis of the stochastic population growth rate (log λs) to changes in the life-history parameters at fire-return intervals (*FRI*) of 10 and 20 years are shown in Table 7, with the important life-history parameters highlighted in bold. At an interval of 10 years the Clanwilliam cedar stochastic population growth rate was most sensitive to changes in small adults survival and generally to fire mortality at early life stages in summer fires and adult growth rate in winter fires. A similar pattern was revealed at an interval of 20 years, in which the stochastic population growth rate was most sensitive to fire mortality at early life stages in summer fires and adult growth rate in winter fires.

Table 7. Sensitivity of the stochastic population growth rate (log λs) to changes in the life-history parameters at fire-return intervals (*FRI*) of 10 and 20 years.

	Summer		**Winter**	
	***FRI*= 10**	***FRI*= 20**	***FRI*= 10**	***FRI*= 20**
Seedling survival	-0.54	-1.40	0.05	0.04
Survival vegetatives (s1)	-0.54	-1.40	0.05	0.04
Survival vegetatives (s2)	-0.54	-1.40	0.05	0.04
Survival vegetatives (s3)	-0.54	-1.40	0.05	0.04
Survival vegetatives (s4)	-0.54	-1.40	0.05	0.04
Survival vegetatives (s5)	-0.54	-1.40	0.05	0.04
Survival vegetatives (s6)	-0.54	-1.40	0.05	0.04
Survival vegetatives (s7)	-0.54	-1.40	0.05	0.04
Survival vegetatives (s8)	-0.54	-1.40	0.05	0.04
Survival vegetatives (s9)	-0.54	-1.40	0.05	0.04
Survival vegetatives (s10)	-0.54	-1.40	0.05	0.04
Survival vegetatives (s11)	-0.54	-1.40	0.05	0.04
Survival small adults (s12)	**-0.68**	-1.18	0.12	0.12
Survival medium adults (s13)	-0.42	-1.24	0.27	0.29
Survival large adults (s14)	-0.53	-1.34	0.17	0.19
Growth from vegetative to small adult (g12)	-0.58	-1.43	0.02	0.02
Growth from vegetative to small adult (g23)	-0.58	-1.43	0.02	0.02
Growth from vegetative to small adult (g34)	-0.58	-1.43	0.02	0.02

Table 7. (Continued)

	Summer		**Winter**	
	***FRI*= 10**	***FRI*= 20**	***FRI*= 10**	***FRI*= 20**
Growth from vegetative to small adult (g56)	-0.58	-1.43	0.02	0.02
Growth from vegetative to small adult (g67)	-0.58	-1.43	0.02	0.02
Growth from vegetative to small adult (g78)	-0.58	-1.43	0.02	0.02
Growth from vegetative to small adult (g89)	-0.58	-1.43	0.02	0.02
Growth from vegetative to small adult (g910)	-0.58	-1.43	0.02	0.02
Growth from vegetative to small adult (g1011)	-0.58	-1.43	0.02	0.02
Growth from vegetative to small adult (g1112)	-0.58	-1.43	0.02	0.02
Growth from medium to large adult (g1213)	-0.42	-1.34	0.28	0.28
Growth from medium to large adult (g1314)	0.21	-0.61	**1.00**	**1.01**
Fecundity small adults (f12)	-0.60	-1.45	0.00	0.00
Fecundity medium adults (f13)	-0.60	-1.45	0.00	0.00
Fecundity large adults (f14)	-0.60	-1.45	0.00	0.00
Germination rate after fire	-0.43	-1.24	0.14	0.14
Germination rate no fire	-0.03	-1.08	0.33	0.30
Fire mortality vegetatives (m1)	**-0.62**	-1.47	-0.01	-0.01
Fire mortality vegetatives (m2)	**-0.63**	-1.49	-0.02	-0.03
Fire mortality vegetatives (m3)	**-0.64**	-1.51	-0.02	-0.03
Fire mortality vegetatives (m4)	**-0.64**	**-1.53**	-0.03	-0.03
Fire mortality vegetatives (m5)	**-0.65**	**-1.54**	-0.03	-0.03
Fire mortality vegetatives (m6)	**-0.65**	**-1.55**	-0.03	-0.03
Fire mortality vegetatives (m7)	**-0.65**	**-1.54**	-0.03	-0.03
Fire mortality vegetatives (m8)	**-0.65**	**-1.53**	-0.03	-0.03
Fire mortality vegetatives (m9)	**-0.64**	-1.52	-0.03	-0.03
Fire mortality vegetatives (m10)	**-0.64**	-1.50	-0.03	-0.03
Fire mortality vegetatives (m11)	**-0.62**	-1.48	-0.02	-0.03
Fire mortality small adults (m12)	**-0.65**	-1.51	-0.05	-0.05
Fire mortality medium adults (m13)	**-0.63**	-1.50	-0.05	-0.06
Fire mortality large adults (m14)	**-0.61**	-1.47	-0.03	-0.04

4 Discussion

The analyses presented in this thesis were focused on investigating the use of remote sensing imagery as a tool for monitoring fire mortality, characterising and describing fire patterns within the CWA extent using a latent class model. Count models were used to explore the relationships between seasonality of fire in CWA and Clanwilliam cedar numbers as well as examine the impact of fire frequency and seasonality on the life-history of the Clanwilliam cedar using a stochastic demographic model. The purpose of this study was to gain a better understanding of the effects of fire frequency and seasonality on the life history of the Clanwilliam cedar. In this chapter the main findings as related to the literature on the population dynamics of the Clanwilliam cedar are summarised.

4.1 Remote sensing imagery analysis

The objective of this analysis was to assess fire mortality of the Clanwilliam cedar using aerial imagery. It was found that although Google Earth is typically a good source of aerial imagery, providing free imagery for more recent years at a high resolution, it does not have high resolution imagery for periods more than even a decade ago. High spatial resolution imagery, including IKONOS, WorldView 3 satellite imagery, with < 3 m spatial resolution, which is probably the minimum required to detect individual trees (Hartling et al, 2019), are typically expensive, being commercial satellite imagery products, and are only available for the last few years (Anderson, 2018). Aerial imagery from South Africa's Department of Rural Development and Land Reform (DRDLR)—Chief Directorate: National Geo-spatial Information (NGI) was then explored as the final alternative but was also unsuccessful due to a lack of imagery for the study area. The result from this analysis showed that assessing fire mortality of the Clanwilliam cedar using the historical imagery may not be well suited for the CWA. Technological advancements, such as unmanned aerial vehicles, and increasing availability of high spatial resolution satellite imagery can potentially support studies of this nature in the future (Yao, Qin and Chen, 2019).

Although I was unable to generate any results from this analysis, this section is included partly because of the considerable effort and time that was invested in this objective, as well as to make other researchers aware of the unsuitability of the imagery that was investigated for assessing long-term mortality patterns of the Clanwilliam cedar.

4.2 Latent class analysis (LCA)

LC model was used to identify spatial patterns of fire frequency in the number of cedar count densities. The main conclusion from the findings of this analysis revealed the main axes of variation in fire frequency as being biased towards the following fire indices; FiresAll, FiresSum, FiresAut30 and Fires30. Although these fire indices were able to distinguish relatively well between the three latent classes, it was difficult to disentangle the relative importance of each fire index due to their strong covariation. This points to a more general pattern, suggesting that it is necessary to examine the entire fire frequency history and the seasonality pattern in order to understand the current state of the population of the Clanwilliam cedar.

It is important to emphasise the role of fire for many species in the fynbos: it is an important disturbance mechanism shaping the structural composition of the fynbos vegetation in doing so maintaining species richness (van Wilgen et al, 1990; Thuiller et al, 2007). It may have exhibit deleterious or beneficial effects on such species depending on the frequency and seasonality of fires (Andrag, 1977; Thuiller et al, 2007; van Wilgen, 2008). The findings from this analysis highlight the importance of understanding and characterising the fire regime as it can improve our knowledge on the population dynamics of the Clanwilliam cedar. This is particularly critical for the Clanwilliam cedar like many slow growing species that solely rely on the reseeding strategy for regeneration (van Wilgen, 2008).

4.3 Linear count models

To better understand the effects of fire seasonality on Clanwilliam cedar number, I used a count model approach, specifically negative binomial hurdle models. The best performing model included fire frequency for all seasons, aspect, mean annual temperature, mean annual precipitation, minimum temperature and precipitation seasonality as predictors (Table 6). Autumn fires were positively associated with the cedar count numbers while mean annual temperature and precipitation seasonality were negatively associated. The positive association of autumn fires with cedar numbers may influence the Clanwilliam cedar, while the climatic factors may limit its persistence. Generally, the best time to burn fynbos vegetation is during the late summer/early autumn period when seedling regeneration is optimal for the Clanwilliam cedar and many other species, including Proteaceae species and the Cape bulge-lily (*Watsonia borbonica*) (Le Maitre, 1984; Le Maitre, 1988). To minimise the effects of summer wildfires inducing increased mortality rates of the Clanwilliam cedar, prescribed burns during this period have previously been recommended (Manders, 1986). Findings from this analysis relate to studies in the past that hypothesised temperature and precipitation as factors contributing to the drastic population decline. Increasing temperatures and declining precipitation are contributing to the decline of the Clanwilliam cedar as a result of these factors contributing to changes in fire regimes, and that in the future fire may become more frequent (Meadows, 1991). It has been pointed out that populations at high elevations and rocky sites where temperatures are much cooler with water accessibility show higher persistence of adult trees (White et al, 2016).

We can learn much about the factors influencing the population persistence of the Clanwilliam cedar, which will likely be more important in future environments.

4.4 Stochastic demographic model

The stochastic demographic model showed that winter fires are more important than summer fires for the population persistence of the Clanwilliam cedar, in that winter fires may positively influence the population growth rate increasing survival of the earlier life-stages of the Clanwilliam cedar. This agrees with another study using a demographic model for the Clanwilliam cedar (Privett, 1994), which showed that survival was higher in winter fires than summer fires.

In addition to deriving the optimal population growth rate, the stochastic model also measured sensitivities of the population growth rate to changes in life history parameter values. A sensitivity analysis can be useful in making inferences about the life history parameters that can influence the population growth, survival and fecundity (Miller et al, 2011). Sensitivities for the Clanwilliam cedar were estimated using two different fire-return intervals (10 and 20 years) for both summer and winter fires. The general conclusion from the findings showed that in summer fires, seedling survival and fire mortality at earlier stages are the most important life-history parameters with adult growth rate important in winter fires. These findings suggest that the population persistence of the Clanwilliam cedar may be influenced by seedling survival and the transitioning of trees from medium to large adult — a life-stage in which mature seeds may be produced. Fire mortality at earlier stages of the Clanwilliam cedar lifecycle may in contrast limit its persistence. These findings differ with some previous demographic transition matrices models, that have highlighted important life-history parameters for the Clanwilliam cedar. Manders (1987b) studied the population dynamics of the Clanwilliam cedar in the absence of fire using data from permanent plots initially established in 1970—which had experienced two wildfires and prescribed burns. The study suggested that the transition from seed to seedling was the most important life-history stage of the Clanwilliam cedar. However, Higgins, February and Skowno, (2001) using demographic parameters including recruitment, seed production, and population growth rate and covariates including completeness of burn showed life-history parameters related to recruitment, survival and growth as the most important. These relate to the findings of this analysis with survival and growth a the most important life-history parameters.

5 Conclusion

This thesis had the aim of studying the effects of fire frequency and seasonality on the life history of the Clanwilliam cedar. Fire in the fynbos ecosystem is an important disturbance for many species like the Clanwilliam cedar that are slow growing and depend on a reseeding strategy for re-establishment. To better manage and conserve the Clanwilliam cedar, findings from this study highlight the importance of understanding the CWA fire history to be able to infer effective fire management strategies particularly with regards to fire seasonality. Moreover, this study identified environmental factors (temperature and precipitation) that may be influencing the population persistence of the Clanwilliam cedar. Understanding the impact of these factors will become increasingly important in the future with an anticipated temperature increase and decline in precipitation.

As with any study there are potential limitations. The major limitation of this study was the possibility that factors other than fire is driving the observed patterns in cedar densities. This is a limitation with a correlative analyses, that is although it may be good at evaluating the strength of a relationship between variables (e.g. fire indices and environmental predictors), it does not assume causation that is, factors (e.g. fire indices and/or the environmental variable) that influence cedar numbers. The study showed that temperature and precipitation covary with fire, changing climatic conditions have been observed as the main drivers of tree mortality (Neumann et al, 2017). Increased temperature resulting in drier conditions, altering the fire regime by increasing fire frequency may increase the Clanwilliam cedar mortality (White et al,2016).

An additional limitation was data accessibility relating to life history parameter estimates. I should stress that although some data were available in unpublished reports, these were difficult, if not impossible, to acquire. Some parameter values were also outdated, highlighting the need for updated field studies on the Clanwilliam cedar. The lack of up-to-date or accurate life history parameter estimates may explain some of the discrepancies between the results of the count models and the stochastic demographic models.

I also found not being familiar with the CWA made it challenging to identify tree localities in Google Earth, regardless of the spatial resolution. For this reason, fieldwork should accompany secondary data-based studies. Another possible issue was that the accuracy of the mapped fires and tree localities could not be efficiently assessed. However, given that the fire data were often checked in the field (e.g. “by walking or flying the fire line” by reserve managers; CapeNature, 2016), we can be fairly confident that areas recorded as unburnt were indeed unburnt, but we have no quantitative measure of the accuracy of the fire data.

Research on fire and population dynamics would benefit from field-based observations to discern many important life-history and demographic characteristics of the Clanwilliam cedar, such as fecundity, growth and survival. Furthermore, future studies should take advantage of the available NGI aerial imagery of more recent years and high-spatial resolution satellite imagery, as well as satellite imagery (e.g. Sentinel-2a and 2b, IKONOS, WorldView 3 and LandSat 8) to assess fire mortality and potentially explore factors that can boost seedling recruitment and better conserve the adult trees in future climates. It should be noted that the count model showed autumn fires to favour the Clanwilliam cedar adults whereas the stochastic demographic model showed winter fires are beneficial for the population growth. However Slingsby and Slingsby (2019) found more adults trees than juveniles whereas the stochastic demographic model revealed winter fires to influence population growth rate and thus more juveniles, this mismatch may in part be a result of discrepancies in the parameter estimates or maybe means that there is a mismatch between which fire seasons favour adults and juveniles. Future research can thus investigate the seedling to adult ratio to better understand the population dynamics of the Clanwilliam cedar.

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Appendices

FIRE INDICES

```
#Load library
library(raster)
fires = shapefile('DATA/SANBI_BGIS/1927-2017_FIRE_DATA/All_fires_16_17_gw.shp')
#Get Cederberg layer
cberg = shapefile('DATA/Boundaries/Cederberg/C.shp')
# ************************************************
#FIRE ENTIRE PERIOD
# ************************************************
#Select only fire polygons within Cederberg
firesInCberg = over(fires, cberg)
fires = fires[!is.na(firesInCberg$Type),]
#Create an ID variable
fires$FID = 1:nrow(fires)
#Create a dummy variable for calculating sum of fires over time
fires$dummy = 1
#Write new layer to a shapefile
library(rgdal)
writeOGR(fires, dsn='DATA/GIS Layers/Fire_layers (indices)/FiresInCederberg.shp', layer='FiresInCederberg', driver='ESRI Shapefile', overwrite_layer=T)
#Create a raster for rasterizing the fire shapefiles to. It should be about the same extent as the fire polygons
extent(fires) #Check extent
xmin = extent(fires)[1] #Get min x (lon)
xmax = extent(fires)[2] #Get max x (lon)
ymin = extent(fires)[3] #Get min y (lat)
ymax = extent(fires)[4] #Get max y (lat)
res = 0.002083332 #Set spatial resolution of new raster = 1/0.002083332 = 480; 60/480 = 0.125 degrees; which is ~ 230 m
(numCols = round(c(xmax-xmin)/res,0)) #Calculate number of columns of new raster
(numRows = round(c(ymax-ymin)/res,0)) #Calculate number of rows of new raster
emptyRast = raster(xmn=xmin, ymn=ymin, xmx=c(xmin+res*numCols), ymx=c(ymin+res*numRows),
nrows=numRows, ncols=numCols, crs=projection(fires)) #Create new raster
emptyRast[] = 0 #Assign a value of 0 to all cells

#Create empty raster stack for storing all rasterized fire polygons
firesStack = stack()

#Loop through all fire polygons, rasterize them, and add them to raster stack
for(f in 1:nrow(fires)){
fireSub = fires[fires$FID==f,] #Select fire polyogon based on FID
fireSubRast = rasterize(fireSub, emptyRast, field='dummy', fun=max) #Rasterize the polygon based on the "dummy" value = 1
  names(fireSubRast) = paste0('FID',f) #Change the name of the rasterized polygon
```

```
firesStack = stack(firesStack,fireSubRast) #Add rasterized polygon to raster stack
 print(round(f/nrow(fires)*100,1)) #Print progress (in %)
}

#Remove rasterized polygons with NA values (these are too small to rasterize and can be ignored)
naRasts = which(is.na(maxValue(firesStack)))
firesStack = dropLayer(firesStack, i=naRasts)

#Calculate sum of fires for entire period
firesSum = calc(firesStack, fun=sum, na.rm=T)

#Mask to Cederberg extent
firesSum = mask(firesSum, cberg)

#Plot sum of fires for entire period
plot(firesSum)

#Write sum of fires for entire period to file
dir.output = 'OUTPUT/Fire_indices' ## laptop directory where rasters are saved
if(!file.exists(dir.output)) {dir.create(dir.output)}
writeRaster(firesSum, filename='OUTPUT/Fire_indices/Sum_fires_entire_period.tif', format='GTiff', overwrite=T)
# *************************************************
TOTAL FIRES IN THE LAST 30 YEARS
# *************************************************
fires = shapefile('DATA/SANBI_BGIS/1927-2017_FIRE_DATA/All_fires_16_17_gw.shp')

#Get Cederberg layer
cberg = shapefile('DATA/Boundaries/Cederberg/C.shp')

fires30 = fires[fires$Year>=1987,]

#Select only fire polygons within Cederberg
firesInCberg = over(fires30, cberg)
fires30 = fires30[!is.na(firesInCberg$Type),]

#Create an ID variable
fires30$FID = 1:nrow(fires30)

#Create a dummy variable for calculating sum of fires over last 30 years
fires30$dummy = 1
```

```
#Create empty raster stack for storing all rasterized fire polygons
fires30Stack = stack()

#Loop through all fire polygons, rasterize them, and add them to raster stack
for(f in 1:nrow(fires30)){
fireSub = fires30[fires30$FID==f,] #Select fire polyogon based on FID
fireSubRast = rasterize(fireSub, emptyRast, field='dummy', fun=max) #Rasterize the polygon based on the "dummy" value = 1
  names(fireSubRast) = paste0('FID',f) #Change the name of the rasterized polygon
  fires30Stack = stack(fires30Stack,fireSubRast) #Add rasterized polygon to raster stack
  print(round(f/nrow(fires30)*100,1)) #Print progress (in %)
}

#Remove rasterized polygons with NA values (these are too small to rasterize and can be ignored)
naRasts = which(is.na(maxValue(fires30Stack)))
fires30Stack = dropLayer(fires30Stack, i= naRasts)

#Calculate sum of fires for last 30 years
fires30Sum = calc(fires30Stack, fun=sum, na.rm=T)

#Mask to Cederberg extent
fires30Sum = mask(fires30Sum, cberg)

#Plot sum of fires for the last 30 years
plot(fires30Sum)

#Write sum of fires for the last 30 years
writeRaster(fires30Sum, filename='OUTPUT/Fire_indices/Sum_fires30.tif', format='GTiff', overwrite=T)
# ************************************************
# FIRES IN EACH DECADE FROM ENTIRE PERIOD
# ************************************************
#DECADE 1 1944- 1954 omitted, fires too minuscule

#1955-1965 (DECADE 2)
firdec2 = fires[fires$Year %in% c(1955:1965),]

#Select only fire polygons within Cederberg
firesInCberg = over(firdec2, cberg)
firdec2 = firdec2[!is.na(firesInCberg$Type),]
```

```
#Create an ID variable
firdec2$FID = 1:nrow(firdec2)

#Create a dummy variable for calculating sum of fires over decade 2
firdec2$dummy = 1

#Create empty raster stack for storing all rasterized fire polygons
firdec2Stack = stack()

#Loop through all fire polygons, rasterize them, and add them to raster stack
for(f in 1:nrow(firdec2)){
fireSub = firdec2[firdec2$FID==f,] #Select fire polyogon based on FID
fireSubRast = rasterize(fireSub, emptyRast, field='dummy', fun=max) #Rasterize the polygon based on the "dummy" value = 1
  names(fireSubRast) = paste0('FID',f) #Change the name of the rasterized polygon
  firdec2Stack = stack(firdec2Stack,fireSubRast) #Add rasterized polygon to raster stack
  print(round(f/nrow(firdec2)*100,1)) #Print progress (in %)
}
#Remove rasterized polygons with NA values (these are too small to rasterize and can be ignored)
naRasts = which(is.na(maxValue(firdec2Stack)))
firdec2Stack = dropLayer(firdec2Stack, i= naRasts)

#Calculate sum of fires for decade 2
firdec2Sum = calc(firdec2Stack, fun=sum, na.rm=T)

#Mask to Cederberg extent
firdec2Sum = mask(firdec2Sum, cberg)

#Plot sum of fires for decade 2
plot(firdec2Sum)

#Write sum of fires for decade 2
writeRaster(firdec2Sum, filename='OUTPUT/Fire_indices/Sum_fires_dec2.tif', format='GTiff', overwrite=T)


#1966-1976 (DECADE 3)
firdec3 = fires[fires$Year %in% c(1966:1976),]

#Select only fire polygons within Cederberg
firesInCberg = over(firdec3, cberg)
firdec3 = firdec3[!is.na(firesInCberg$Type),]
```

```
#Create an ID variable
firdec3$FID = 1:nrow(firdec3)

#Create a dummy variable for calculating sum of decade 3
firdec3$dummy = 1

#Create empty raster stack for storing all rasterized fire polygons
firdec3Stack = stack()

#Loop through all fire polygons, rasterize them, and add them to raster stack
for(f in 1:nrow(firdec3)){
fireSub = firdec3[firdec3$FID==f,] #Select fire polyogon based on FID
fireSubRast = rasterize(fireSub, emptyRast, field='dummy', fun=max) #Rasterize the polygon based on the "dummy" value = 1
  names(fireSubRast) = paste0('FID',f) #Change the name of the rasterized polygon
  firdec3Stack = stack(firdec3Stack,fireSubRast) #Add rasterized polygon to raster stack
  print(round(f/nrow(firdec3)*100,1)) #Print progress (in %)
}

#Remove rasterized polygons with NA values (these are too small to rasterize and can be ignored)
naRasts = which(is.na(maxValue(firdec3Stack)))
firdec3Stack = dropLayer(firdec3Stack, i= naRasts)

#Calculate sum of fires for decade 3
firdec3Sum = calc(firdec3Stack, fun=sum, na.rm=T)

#Mask to Cederberg extent
firdec3Sum = mask(firdec3Sum, cberg)

#Plot sum of fires for decade 3
plot(firdec3Sum)

#Write sum of fires for decade
writeRaster(firdec3Sum, filename='OUTPUT/Fire_indices/Sum_fires_dec3.tif', format='GTiff', overwrite=T)

#1977-1987 (DECADE 4)
firdec4 = fires[fires$Year %in% c(1977:1987),]

#Select only fire polygons within Cederberg
firesInCberg = over(firdec4, cberg)
```

```
firdec4 = firdec4[!is.na(firesInCberg$Type),]

#Create an ID variable
firdec4$FID = 1:nrow(firdec4)

#Create a dummy variable for calculating sum of fires over decade 4
firdec4$dummy = 1

#Create empty raster stack for storing all rasterized fire polygons
firdec4Stack = stack()

#Loop through all fire polygons, rasterize them, and add them to raster stack
for(f in 1:nrow(firdec4)){
fireSub = firdec4[firdec4$FID==f,] #Select fire polyogon based on FID
fireSubRast = rasterize(fireSub, emptyRast, field='dummy', fun=max) #Rasterize the polygon based on the "dummy" value = 1
  names(fireSubRast) = paste0('FID',f) #Change the name of the rasterized polygon
  firdec4Stack = stack(firdec4Stack,fireSubRast) #Add rasterized polygon to raster stack
  print(round(f/nrow(firdec4)*100,1)) #Print progress (in %)
}

#Remove rasterized polygons with NA values (these are too small to rasterize and can be ignored)
naRasts = which(is.na(maxValue(firdec4Stack)))
firdec4Stack = dropLayer(firdec4Stack, i= naRasts)

#Calculate sum of fires for decade 4
firdec4Sum = calc(firdec4Stack, fun=sum, na.rm=T)

#Mask to Cederberg extent
firdec4Sum = mask(firdec4Sum,cberg)

#Plot sum of fires for decade 4
plot(firdec4Sum)

#Write sum of fires for decade 4
writeRaster(firdec4Sum, filename='OUTPUT/Fire_indices/Sum_fires_dec4.tif', format='GTiff', overwrite=T)

#1988-1998 (DECADE 5)
firdec5 = fires[fires$Year %in% c(1988:1998),]

#Select only fire polygons within Cederberg
```

```
firesInCberg = over(firdec5, cberg)
firdec5 = firdec5[!is.na(firesInCberg$Type),]

#Create an ID variable
firdec5$FID = 1:nrow(firdec5)

#Create a dummy variable for calculating sum of fires decade 5
firdec5$dummy = 1

#Create empty raster stack for storing all rasterized fire polygons
firdec5Stack = stack()

#Loop through all fire polygons, rasterize them, and add them to raster stack
for(f in 1:nrow(firdec5)){
fireSub = firdec5[firdec5$FID==f,] #Select fire polyogon based on FID
fireSubRast = rasterize(fireSub, emptyRast, field='dummy', fun=max) #Rasterize the polygon based on the "dummy" value = 1
  names(fireSubRast) = paste0('FID',f) #Change the name of the rasterized polygon
  firdec5Stack = stack(firdec5Stack,fireSubRast) #Add rasterized polygon to raster stack
  print(round(f/nrow(firdec5)*100,1)) #Print progress (in %)
}

#Remove rasterized polygons with NA values (these are too small to rasterize and can be ignored)
naRasts = which(is.na(maxValue(firdec5Stack)))
firdec5Stack = dropLayer(firdec5Stack, i= naRasts)

#Calculate sum of fires for decade 5
firdec5Sum = calc(firdec5Stack, fun=sum, na.rm=T)

#Mask to Cederberg extent
firdec5Sum = mask(firdec5Sum, cberg)

#Plot sum of fires for decade 5
plot(firdec5Sum)

#Write sum of fires for the decade 5 to file
writeRaster(firdec5Sum, filename='OUTPUT/Fire_indices/Sum_fires_dec5.tif', format='GTiff', overwrite=T)
```

```
#1999-2009 (DECADE 6)

firdec6 = fires[fires$Year%in%c(1999:2009),]


#Select only fire polygons within Cederberg

firesInCberg = over(firdec5, cberg)

firdec6 = firdec6[!is.na(firesInCberg$Type),]


#Create an ID variable

firdec6$FID = 1:nrow(firdec6)


#Create a dummy variable for calculating sum of fires over time

firdec6$dummy = 1


#Create empty raster stack for storing all rasterized fire polygons

firdec6Stack = stack()


#Loop through all fire polygons, rasterize them, and add them to raster stack

for(f in 1:nrow(firdec6)){

fireSub = firdec6[firdec6$FID==f,] #Select fire polyogon based on FID

fireSubRast = rasterize(fireSub, emptyRast, field='dummy', fun=max) #Rasterize the polygon based on the "dummy" value = 1

  names(fireSubRast) = paste0('FID',f) #Change the name of the rasterized polygon

  firdec6Stack = stack(firdec6Stack,fireSubRast) #Add rasterized polygon to raster stack

  print(round(f/nrow(firdec6)*100,1)) #Print progress (in %)

}


#Remove rasterized polygons with NA values (these are too small to rasterize and can be ignored)

naRasts = which(is.na(maxValue(firdec6Stack)))

firdec6Stack = dropLayer(firdec6Stack, i= naRasts)


#Calculate sum of fires for decade 6

firdec6Sum = calc(firdec6Stack, fun=sum, na.rm=T)


#Mask to Cederberg extent

firdec6Sum = mask(firdec6Sum, cberg)


#Plot sum of fires for decade 6

plot(firdec6Sum)


#Write sum of fires for decade 6 to file

writeRaster(firdec6Sum, filename='OUTPUT/Fire_indices/Sum_fires_dec6.tif', format='GTiff', overwrite=T)
```

```
#2010-2020 DECADE 7
firdec7 = fires[fires$Year %in% c(2010:2020),]

#Select only fire polygons within Cederberg
firesInCberg = over(firdec7, cberg)
firdec7 = firdec7[!is.na(firesInCberg$Type),]

#Create an ID variable
firdec7$FID = 1:nrow(firdec7)

#Create a dummy variable for calculating sum of fires over time
firdec7$dummy = 1

#Create empty raster stack for storing all rasterized fire polygons
firdec7Stack = stack()

#Loop through all fire polygons, rasterize them, and add them to raster stack
for(f in 1:nrow(firdec7)){
fireSub = firdec7[firdec7$FID==f,] #Select fire polyogon based on FID
fireSubRast = rasterize(fireSub, emptyRast, field='dummy', fun=max) #Rasterize the polygon based on the "dummy" value = 1
  names(fireSubRast) = paste0('FID',f) #Change the name of the rasterized polygon
  firdec7Stack = stack(firdec7Stack,fireSubRast) #Add rasterized polygon to raster stack
  print(round(f/nrow(firdec7)*100,1)) #Print progress (in %)
}

#Remove rasterized polygons with NA values (these are too small to rasterize and can be ignored)
naRasts = which(is.na(maxValue(firdec7Stack)))
firdec7Stack = dropLayer(firdec7Stack, i= naRasts)

#Calculate sum of fires for decade 7
firdec7Sum = calc(firdec7Stack, fun=sum, na.rm=T)

#Mask to Cederberg extent
firdec7Sum = mask(firdec7Sum, cberg)

#Plot sum of fires for decade 7
plot(firdec7Sum)

#Write sum of fires for decade 7
```

```
writeRaster(firdec7Sum, filename='OUTPUT/Fire_indices/Sum_fires_dec7.tif', format='GTiff', overwrite=T)

#### code to plot multiple plots on one sheet ########

par(mfrow=c(3,3))

# ************************************************
# ALL DATA (SEASONS)
# ************************************************
#Summer (1,2,12)
names (fires)

unique(fires$"Month") # Check seasons

firSummALL = fires[fires$Month %in% c(1,2,12),]

#Select only fire polygons within Cederberg
firesInCberg = over(firSummALL, cberg)
firSummALL = firSummALL[!is.na(firesInCberg$Type),]

#Create an ID variable
firSummALL$FID = 1:nrow(firSummALL)

#Create a dummy variable for calculating sum of fires in Summer all data
firSummALL$dummy = 1

#Create empty raster stack for storing all rasterized fire polygons
firSummALLStack = stack()

#Loop through all fire polygons, rasterize them, and add them to raster stack
for(f in 1:nrow(firSummALL)){
fireSub = firSummALL[firSummALL$FID==f,] #Select fire polyogon based on FID
fireSubRast = rasterize(fireSub, emptyRast, field='dummy', fun=max) #Rasterize the polygon based on the "dummy" value = 1
  names(fireSubRast) = paste0('FID',f) #Change the name of the rasterized polygon
firSummALLStack = stack(firSummALLStack,fireSubRast) #Add rasterized polygon to raster stack
  print(round(f/nrow(firSummALL)*100,1)) #Print progress (in %)
}

#Remove rasterized polygons with NA values (these are too small to rasterize and can be ignored)
naRasts = which(is.na(maxValue(firSummALLStack)))
```

```
firSummALLStack = dropLayer(firSummALLStack, i= naRasts)

#Calculate sum of fires for Summer all data
firSummALLSum = calc(firSummALLStack, fun=sum, na.rm=T)

#Mask to Cederberg extent
firSummALLSum = mask(firSummALLSum, cberg)

#Plot sum of fires for Summer all data
plot(firSummALLSum)

#Write sum of fires for Summer all data to file
writeRaster(firSummALLSum, filename='OUTPUT/Fire_indices/Sum_firSummALL.tif', format='GTiff', overwrite=T)

#Autumn (3,4,5)
firAutALL = fires[fires$Month %in% c(3,4,5),]

#Select only fire polygons within Cederberg
firesInCberg = over(firAutALL, cberg)
firAutALL = firAutALL[!is.na(firesInCberg$Type),]

#Create an ID variable
firAutALL$FID = 1:nrow(firAutALL)

#Create a dummy variable for calculating sum of fires for Autumn all data
firAutALL$dummy = 1

#Create empty raster stack for storing all rasterized fire polygons
firAutALLStack = stack()

#Loop through all fire polygons, rasterize them, and add them to raster stack
for(f in 1:nrow(firAutALL)){
fireSub = firAutALL[firAutALL$FID==f,] #Select fire polyogon based on FID
fireSubRast = rasterize(fireSub, emptyRast, field='dummy', fun=max) #Rasterize the polygon based on the "dummy" value = 1
  names(fireSubRast) = paste0('FID',f) #Change the name of the rasterized polygon
firAutALLStack = stack(firAutALLStack,fireSubRast) #Add rasterized polygon to raster stack
  print(round(f/nrow(firAutALL)*100,1)) #Print progress (in %)
}

#Remove rasterized polygons with NA values (these are too small to rasterize and can be ignored)
```

```
naRasts = which(is.na(maxValue(firAutALLStack)))
firAutALLStack = dropLayer(firAutALLStack, i= naRasts)

#Calculate sum of fires for Autumn all data
firAutALLSum = calc(firAutALLStack, fun=sum, na.rm=T)

#Mask to Cederberg extent
firAutALLSum = mask(firAutALLSum, cberg)

#Plot sum of fires for Autumn all data
plot(firAutALLSum)

#Write sum of fires for Autumn all data to file
writeRaster(firAutALLSum, filename='OUTPUT/Fire_indices/Sum_firAutALL.tif', format='GTiff', overwrite=T)

#Winter (3,4,5)
firWinALL = fires[fires$Month %in% c(6,7,8),]

#Select only fire polygons within Cederberg
firesInCberg = over(firWinALL, cberg)
firWinALL = firWinALL[!is.na(firesInCberg$Type),]

#Create an ID variable
firWinALL$FID = 1:nrow(firWinALL)

#Create a dummy variable for calculating sum of fires for Winter all data
firWinALL$dummy = 1

#Create empty raster stack for storing all rasterized fire polygons
firWinALLStack = stack()

#Loop through all fire polygons, rasterize them, and add them to raster stack
for(f in 1:nrow(firWinALL)){
fireSub = firWinALL[firWinALL$FID==f,] #Select fire polyogon based on FID
fireSubRast = rasterize(fireSub, emptyRast, field='dummy', fun=max) #Rasterize the polygon based on the "dummy" value = 1
  names(fireSubRast) = paste0('FID',f) #Change the name of the rasterized polygon
firWinALLStack = stack(firWinALLStack,fireSubRast) #Add rasterized polygon to raster stack
  print(round(f/nrow(firWinALL)*100,1)) #Print progress (in %)
}
```

```
#Remove rasterized polygons with NA values (these are too small to rasterize and can be ignored)
naRasts = which(is.na(maxValue(firWinALLStack)))
firWinALLStack = dropLayer(firWinALLStack, i= naRasts)

#Calculate sum of fires for Winter all data
firWinALLSum = calc(firWinALLStack, fun=sum, na.rm=T)

#Mask to Cederberg extent
firWinALLSum = mask(firWinALLSum, cberg)

#Plot sum of fires for Winter all data
plot(firWinALLSum)

#Write sum of fires for Winter all data to file
writeRaster(firWinALLSum, filename='OUTPUT/Fire_indices/Sum_firWinALL.tif', format='GTiff', overwrite=T)

#Spring
firSprALL = fires[fires$Month %in% c(9,10,11),]

#Select only fire polygons within Cederberg
firesInCberg = over(firSprALL, cberg)
firSprALL = firSprALL[!is.na(firesInCberg$Type),]

#Create an ID variable
firSprALL$FID = 1:nrow(firSprALL)

#Create a dummy variable for calculating sum of fireS for Spring all data
firSprALL$dummy = 1

#Create empty raster stack for storing all rasterized fire polygons
firSprALLStack = stack()

#Loop through all fire polygons, rasterize them, and add them to raster stack
for(f in 1:nrow(firSprALL)){
fireSub = firSprALL[firSprALL$FID==f,] #Select fire polyogon based on FID
fireSubRast = rasterize(fireSub, emptyRast, field='dummy', fun=max) #Rasterize the polygon based on the "dummy" value = 1
  names(fireSubRast) = paste0('FID',f) #Change the name of the rasterized polygon
firSprALLStack = stack(firSprALLStack,fireSubRast) #Add rasterized polygon to raster stack
  print(round(f/nrow(firSprALL)*100,1)) #Print progress (in %)
}
```

```
#Remove rasterized polygons with NA values (these are too small to rasterize and can be ignored)
naRasts = which(is.na(maxValue(firSprALLStack)))
firSprALLStack = dropLayer(firSprALLStack, i= naRasts)

#Calculate sum of fires for Spring all data
firSprALLSum = calc(firSprALLStack, fun=sum, na.rm=T)

#Mask to Cederberg extent
firSprALLSum = mask(firSprALLSum, cberg)

#Plot sum of fires for Spring all data
plot(firSprALLSum)

#Write sum of fires for Spring all data to file
writeRaster(firSprALLSum, filename='OUTPUT/Fire_indices/Sum_firSprALL.tif', format='GTiff', overwrite=T)

# ************************************************
#FIRES IN EACH SEASON OVER THE LAST 3O YEARS
# ************************************************
#Summer last 30 years
firSum30 = fires[fires$Month %in% c(1,2,12) &fires$Year>= 1987,]

#Select only fire polygons within Cederberg
firesInCberg = over(firSum30, cberg)
firSum30 = firSum30[!is.na(firesInCberg$Type),]

#Create an ID variable
firSum30$FID = 1:nrow(firSum30)

#Create a dummy variable for calculating sum of fires over last 30 years
firSum30$dummy = 1

#Create empty raster stack for storing all rasterized fire polygons
firSum30Stack = stack()

#Loop through all fire polygons, rasterize them, and add them to raster stack
for(f in 1:nrow(firSum30)){
fireSub = firSum30[firSum30$FID==f,] #Select fire polyogon based on FID
fireSubRast = rasterize(fireSub, emptyRast, field='dummy', fun=max) #Rasterize the polygon based on the "dummy" value = 1
```

```
  names(fireSubRast) = paste0('FID',f) #Change the name of the rasterized polygon
  firSum30Stack = stack(firSum30Stack,fireSubRast) #Add rasterized polygon to raster stack
  print(round(f/nrow(firSum30)*100,1)) #Print progress (in %)
}

#Remove rasterized polygons with NA values (these are too small to rasterize and can be ignored)
naRasts = which(is.na(maxValue(firSum30Stack)))
firSum30Stack = dropLayer(firSum30Stack, i= naRasts)

#Calculate sum of fires for last 30 years
firSum30Sum = calc(firSum30Stack, fun=sum, na.rm=T)

#Mask to Cederberg extent
firSum30Sum = mask(firSum30Sum, cberg)

#Plot sum of fires for last 30 years
plot(firSum30Sum)

#Write sum of fires for the last 30 years to file
writeRaster(firSum30Sum, filename='OUTPUT/Fire_indices/Sum_firSum30.tif', format='GTiff', overwrite=T)

#Autumn last 30 years
firAut30 = fires[fires$Month %in% c(3,4,5) &fires$Year>= 1987,]

#Select only fire polygons within Cederberg
firesInCberg = over(firAut30, cberg)
firAut30 = firAut30[!is.na(firesInCberg$Type),]

#Create an ID variable
firAut30$FID = 1:nrow(firAut30)

#Create a dummy variable for calculating sum of fires last 30 years
firAut30$dummy = 1

#Create empty raster stack for storing all rasterized fire polygons
firAut30Stack = stack()

#Loop through all fire polygons, rasterize them, and add them to raster stack
for(f in 1:nrow(firAut30)){
fireSub = firAut30[firAut30$FID==f,] #Select fire polyogon based on FID
```

```
fireSubRast = rasterize(fireSub, emptyRast, field='dummy', fun=max) #Rasterize the polygon based on the "dummy" value = 1
  names(fireSubRast) = paste0('FID',f) #Change the name of the rasterized polygon
  firAut30Stack = stack(firAut30Stack,fireSubRast) #Add rasterized polygon to raster stack
  print(round(f/nrow(firAut30)*100,1)) #Print progress (in %)
}

#Remove rasterized polygons with NA values (these are too small to rasterize and can be ignored)
naRasts = which(is.na(maxValue(firAut30Stack)))
firAut30Stack = dropLayer(firAut30Stack, i= naRasts)

#Calculate sum of fires for last 30 years
firAut30Sum = calc(firAut30Stack, fun=sum, na.rm=T)

#Mask to Cederberg extent
firAut30Sum = mask(firAut30Sum, cberg)

#Plot sum of fires for last 30 years
plot(firAut30Sum)

#Write sum of fires for the last 30 years to file
writeRaster(firAut30Sum, filename='OUTPUT/Fire_indices/Sum_firAut30.tif', format='GTiff', overwrite=T)

# Spring
firSpr30 = fires[fires$Month %in% c(9,10,11) &fires$Year>= 1987,]

#Select only fire polygons within Cederberg
firesInCberg = over(firSpr30, cberg)
firSpr30 = firSpr30[!is.na(firesInCberg$Type),]

#Create an ID variable
firSpr30$FID = 1:nrow(firSpr30)

#Create a dummy variable for calculating sum of fires last 30 years
firSpr30$dummy = 1

#Create empty raster stack for storing all rasterized fire polygons
firSpr30Stack = stack()

#Loop through all fire polygons, rasterize them, and add them to raster stack
for(f in 1:nrow(firSpr30)){
```

```
fireSub = firSpr30[firSpr30$FID==f,] #Select fire polyogon based on FID
fireSubRast = rasterize(fireSub, emptyRast, field='dummy', fun=max) #Rasterize the polygon based on the "dummy" value = 1
  names(fireSubRast) = paste0('FID',f) #Change the name of the rasterized polygon
  firSpr30Stack = stack(firSpr30Stack,fireSubRast) #Add rasterized polygon to raster stack
  print(round(f/nrow(firSpr30)*100,1)) #Print progress (in %)
}
#Remove rasterized polygons with NA values (these are too small to rasterize and can be ignored)
naRasts = which(is.na(maxValue(firSpr30Stack)))
firSpr30Stack = dropLayer(firSpr30Stack, i= naRasts)

#Calculate sum of fires for last 30 years
firSpr30Sum = calc(firSpr30Stack, fun=sum, na.rm=T)

#Mask to Cederberg extent
firSpr30Sum = mask(firSpr30Sum, cberg)
#Plot sum of fires for last 30 years
plot(firSpr30Sum)
#Write sum of fires for the last 30 years to file
writeRaster(firSpr30Sum, filename='OUTPUT/Fire_indices/Sum_firSpr30.tif', format='GTiff', overwrite=T)
```

LATENT CLASS ANALYSIS (LCA)

```
#Load library

library(raster)

#Load Fire layers

files = list.files(path = './Hurdle_Model/Fire_indices/', pattern = ".tif", all.files =  FALSE, full.names =  TRUE, recursive = F )

#Load Cedar occurrence

countRast = raster('./Hurdle_Model/Cedar_count_densities.tif')

plot(countRast)

names(countRast)

names(countRast) = 'cedarCount'

#Raster stack

st = stack(files,countRast)

# Create a dataframe to be used in the latent classes

df = data.frame(getValues(st))

summary(df)

#Create a row ID variable

df$rowID = 1:nrow(df)

#Remove NA values

df = na.omit(df)


#************************************************

# LATENT CLASSES

#************************************************

set.seed(100)

#Load library

library(depmixS4)

mod1 = mix(list(Fires30Aut~1,FiresAut~1,Sum_fires_dec2~1,Sum_fires_dec3~1,Sum_fires_dec4~1, Sum_fires_dec5~1,Sum_fires_dec6~1,

              Sum_fires_dec7~1, FiresTotal~1, Fires30~1,Fires30Spr~1, FiresSpr~1,Fires30Sum~1,FiresSum~1,

              FiresWin~1), #Specify your indicators

        data= df[,1:c(ncol(df)-1)], #The dataset to use

nstates=3, #The number of latent classes


family=list(multinomial("identity"),multinomial("identity"),multinomial("identity"),multinomial("identity"),multinomial("identity"),multinomial("identity"),multinomial("identity"),multinomial("identity"),multinomial("identity"),multinomial("identity"),
multinomial("identity"),multinomial("identity"),multinomial("identity"),multinomial("identity"),multinomial("identity"))) # family

#of each indicator -gaussian for continuous variables, but multinomial("identity") for categorical indicators

fmod1 = fit(mod1) #Fit the model

#Get the posterior probabilities - these are the probabilities of each sample belonging to each latent class

posterior.states = depmixS4::posterior(fmod1)

posterior.states$state = as.factor(posterior.states$state)

#Load libraries
```

```
library(tidyr)
library(dplyr)
pStatesPlot = posterior.states %>% gather(LC, prob, c(S1,S2,S3))
head(pStatesPlot)
#Visual :
library(ggplot2)
#jpeg('LC_probability_assignment.jpg', width=16, height=12, res=300, units='cm')
ggplot(pStatesPlot, aes(LC, prob)) +
geom_boxplot() +
scale_x_discrete(labels = c('LC1','LC2','LC3')) +
facet_wrap(~state, labeller=labeller(state = labels)) +
labs(title='Latent class assignment',
     x='Latent class probabilities',
     y='Probability') +
theme_bw() +
theme(plot.title = element_text(hjust=0.5))

#Plot to see how the latent classes relate to each variable (indicator)
#Reformat data for plotting
plot.data<- cbind(df, posterior.states) %>% #Join df and posterior.states
gather(key="measure",value="value",Fires30:  Sum_fires_dec7) #Reformat data into long format, collapsing all indicators into "measure" and their associated values into "value"
#Boxplots for each indicator
ggplot(plot.data, aes(y=value, x=state)) +
geom_boxplot(varwidth = T) +
facet_wrap(~ measure, scales='free_y')
#Same as above, but violin plots - gives a better idea of the frequency across each indicator
ggplot(plot.data, aes(y=value, x=state)) +
geom_violin(color ="black") +
facet_wrap(~measure)+theme_bw()+labs(x='Latent classes', y = 'Fire frequency')+theme(panel.grid = element_blank(),axis.text.y = element_text(size=14), axis.text.x = element_text(size=14),axis.title.x = element_text(color="black", size=14),axis.title.y = element_text(color="black", size=14))

#************************************************
Get a typical LCA plot
#************************************************
#First we must get the standardised score (z) for each latent class across all indicators. The standardisation is calculated by getting the mean value divided by its standard deviation
summary.plot.data<- plot.data %>%
group_by(state, measure) %>%
summarize(z=mean(value, na.rm=T)/sd(value, na.rm=T))
#Plot:
```

```
ggplot(summary.plot.data, aes(y=z, x=measure, group=state, color=state)) +

geom_line(size = 2) + theme_bw() +

theme(axis.text.x = element_text(angle = 45, hjust = 1),axis.line = element_line(colour = "black"),panel.grid = element_blank(),panel.border = element_blank())

#Compare the assigned latent classes to cedar densities (counts).

df$class<- as.factor(posterior(fmod1)$state) #Add latent class assignment

ggplot(df, aes(class, cedarCount)) +

geom_violin(color ="black") +theme_bw() +

theme(panel.grid = element_blank(),axis.line = element_line(colour = "black"),panel.border = element_blank())

ggplot(df, aes(cedarCount)) +

geom_histogram() + theme_bw() +

theme(panel.grid = element_blank(),axis.line = element_line(colour = "black"),panel.border = element_blank())

#Most cells have fewer than about 10 trees, see what it looks like when we lump these into one category of "many" trees (>10)

df$cedarCountMany = df$cedarCount

df$cedarCountMany[df$cedarCountMany>10] = 15

ggplot(df, aes(class, cedarCountMany)) +

geom_violin(color ="black") +theme_bw() +

theme(panel.grid = element_blank(),axis.line = element_line(colour = "black"),panel.border = element_blank())

ggplot(df, aes(cedarCountMany)) +

geom_histogram() + theme_bw() +

theme(panel.grid = element_blank(),axis.line = element_line(colour = "black"),panel.border = element_blank())


#And if we look at only cells that contain trees (remove zeroes)

dfno0 = df[df$cedarCount>0,]

ggplot(dfno0, aes(class, cedarCountMany)) +

geom_violin(color = "black") +theme_bw() +

theme(panel.grid = element_blank(),axis.line = element_line(colour = "black"),panel.border = element_blank())


ggplot(dfno0, aes(cedarCountMany)) +

geom_histogram() + theme_bw() +

theme(panel.grid = element_blank(),axis.line = element_line(colour = "black"),panel.border = element_blank())

#Seem to be more trees in cells classified as classes 1 and 3, Cut the number of trees into categories 0, 1-5, 10-15,>15

cuts = c(0,1,5,10,15,max(df$cedarCount))

df$cedarCountCut = cut(df$cedarCount, breaks=cuts, include.lowest=T, labels=F)

cuts20 = cuts[-2]

cuts20[cuts20==max(cuts20)] = 20

df$cedarCountCut = cuts20[df$cedarCountCut]

#Calculate the "correlation" between latent class assignment and number of cedars using a Chi-square test

outxtabs<- xtabs(~ class + cedarCountCut, data=df)

summary(outxtabs)

round(prop.table(outxtabs),2)
```

```
#Visualise chi-sq expected values

chisq<- chisq.test(outxtabs)

#Load library

library(corrplot)

cc=corrplot(chisq$residuals, is.cor = FALSE) #Blues indicate greater than expected numbers of cedars, reds fewer than expected.

M <- cor(chisq$residuals)

rownames(chisq$residuals) <- c("Latent class 1", "Latent class 2", "Latent class 3")

colnames(ccc) <- c("Cedar count: 0 ", "Cedar count: 5", "Cedar count: 10", "Cedar count: 15",

          "Cedar count: 20")

corrplot(ccc)
```

LINEAR COUNT MODEL

```
#Load libraries

library(raster)

library(rgdal)

#Load Fire layers

files = list.files(path = './Hurdle_Model/Fire_indices/', pattern = ".tif", all.files =  FALSE, full.names =  TRUE, recursive = F )

#Load Cedar occurrence

countRast = raster('./Hurdle_Model/Cedar_count_densities.tif')

names(countRast) = 'Cedar_count_densities'

plot(countRast)

#************************************************

#Load Environmental variables

#************************************************

#MAT

MAT = raster('./Hurdle_Model/MAT/MAT.asc')

MAT = crop(MAT, extent(countRast))

MAT = resample(MAT, countRast, method='ngb')

plot(MAT)

#MAP

MAP = raster('./Hurdle_Model/MAP/MAP.asc')

MAP = crop(MAP, extent(countRast))

MAP = resample(MAP,  countRast, method='ngb')

plot(MAP)

#Aspect

Aspect = raster('./Hurdle_Model/Elevation/Aspect.tif')

Aspect = crop(Aspect, extent(countRast))

Aspect = resample(Aspect,  countRast, method='ngb')

plot(Aspect)

#Min Temperature of Coldest Month

Bio6 = raster('./Hurdle_Model/bio/Bio6.tif')

Bio6 = crop(Bio6, extent(countRast))

Bio6 = resample(Bio6,  countRast, method='ngb')

plot(Bio6)

#Precipitation Seasonality

Bio15 = raster('./Hurdle_Model/bio/Bio15.tif')

Bio15 = crop(Bio15, extent(countRast))

Bio15 = resample(Bio15,  countRast, method='ngb')

plot(Bio15)
```

```
#Raster stack
st = stack(files,countRast, MAT, MAP,Aspect)
df = data.frame(getValues(st))
df = na.omit(df)


library(dplyr)
library(corrplot)
#***********************************************
#Get correlation matrix
#***********************************************
M = cor(df, use='complete.obs')
#Plot collinearities
corrplot.mixed(M)
#Plot collinearities
ggcorr(M,method = c("pairwise", "pearson"),hjust = 1,size = 5, color = "black",layout.exp = 2,
legend.size = 14) +(scale_fill_gradient2(low = "green", high = "yellow", mid = "blue",midpoint = 0, limit = c(-1,1), space = "Lab",
                                                  name="Pearson\nCorrelation")) +
  ggplot2::theme(legend.justification = c(0, 1),
legend.position = c(1,0.98))
#----------------------------------------------------------------------------------------------------------------------------------
library(vcd)
library(gpairs)
library(countreg)
#install.packages("countreg", repos="http://R-Forge.R-project.org")
#______________________________________________________
#Hurdle negative bionomial model
mod.hnb.FiresAut.evn = hurdle(formula = Cedar_count_densities ~ FiresAut + MAT + MAP + Aspect + Bio6 + Bio15, data = df, dist = "negbin")
mod.hnb.FiresSpr.evn = hurdle(formula = Cedar_count_densities ~ FiresSpr + MAT + MAP + Aspect + Bio6 + Bio15, data = df, dist = "negbin")
mod.hnb.FiresSum.evn = hurdle(formula = Cedar_count_densities ~ FiresSum + MAT + MAP + Aspect + Bio6 + Bio15, data = df, dist = "negbin")
mod.hnb.FiresWin.evn = hurdle(formula = Cedar_count_densities ~ FiresWin + MAT + MAP + Aspect + Bio6 + Bio15, data = df, dist = "negbin")
mod.hnb.seas.evn = hurdle(formula = Cedar_count_densities ~ FiresAut + FiresSpr + FiresSum + FiresWin + MAT + MAP + Aspect + Bio6 + Bio15, data = df, dist = "negbin")


#***********************************************
#Check which model works best
#***********************************************
library(vcdExtra)
LRstats(mod.hnb.tot, mod.hnb.dec, mod.hnb.seas, mod.hnb.tot.evn, mod.hnb.dec.evn, mod.hnb.seas.evn, mod.hnb.tot.evn.int, mod.hnb.seas.int, mod.hnb.seas.int.evn,
```

```
        mod30.hnb.tot, mod30.hnb.dec, mod30.hnb.seas, mod30.hnb.tot.evn, mod30.hnb.dec.evn, mod30.hnb.seas.evn, mod30.hnb.tot.evn.int,
mod30.hnb.seas.int, mod30.hnb.seas.int.evn, sortby = "AIC")

# Best model: mod.hnb.seas.int.clim

summary(mod.hnb.seas.int.evn)

#******************************************************

Model accuracy/evaluation

#******************************************************

sp=  ggplot(accdat, aes(obs, pred)) +geom_point(alpha = 0.5)  + stat_smooth(aes(x = obs, y = pred), method = "lm", colour='gray10') +

labs(

     x = 'Observed number of trees per grid cell',

     y = 'Predicted number of trees per grid cell'

   ) +

theme(panel.background = element_rect(fill='white', colour='black'),axis.text.y = element_text(size=14), axis.text.x = element_text(size=14,

axis.ticks = element_line(colour = "black") )+theme(axis.title.x = element_text(color="black", size=14),axis.title.y =
element_text(color="black", size=14)) #face="bold" ))


sp + scale_x_continuous(trans='log10') +

scale_y_continuous(trans='log10')+xlim(0, 50)+ylim(0, 6)
```

STOCHASTIC POPULATION MODEL

```
#

#Code for summer and winter models#

#Change parameter values according to fire season

#************************************************

#set parameters and define matrices

#************************************************

Ssbk<-0.1 #seed survival in seed bank # estimate

Sseed<-0.9 #seed survival

#S<-c(0.90,0.90,0.90,0.90,0.90,0.90,0.90,0.90,0.90,0.90,0.99,0.95,0.97) #vector with survival rates for the four classes

c(0.90)^c(1/11) #Calculate survival rate for juveniles

S<-c(rep(0.99,11),0.90,0.95,0.97) #vector with survival rates

c(0.20)^c(1/11) #Calculate growth rates for juveniles (0.09 is the growth value for vegetative)

G12.seeder<-0.86 #vegetative to small adult -

G23.seeder<-G12.seeder

G34.seeder<-G12.seeder

G45.seeder<-G12.seeder

G56.seeder<-G12.seeder

G67.seeder<-G12.seeder

G78.seeder<-G12.seeder

G89.seeder<-G12.seeder

G910.seeder<-G12.seeder

G1011.seeder<-G12.seeder

G1112.seeder<-G12.seeder

G1213.seeder<-0.08 #small to medium adult

G1314.seeder<-0.06#medium to large adult

Fec<-c(0,0,0,0,0,0,0,0,0,0,0,70,250,2300) #vector with fecundities of the four classes

Gr.fire<-0.08 #germination rate in a fire year

Gr<-0.06 #germination rate without fire

# fi.mort<-c(0.99,0.93,0.4,0.4) #additional mortality in fire years for the four classes

rst<-c(0,0,0,0,0,0,0,0,0,0,0,0,0,0) #proportion in class 2 to 4 that are reset by fire to class 1

c(0.93)^c(1/11) #Calculate mortality rates for juveniles

fi.mort.seeder<-c(rep(0.99,11), 0.93, 0.93, 0.4)

#fi.mort.seeder<-c(rep(0.9934244,11), 0.5, 0.5, 0.18) #additional mortality in fire years

Fec.seeder<-Fec*1 #vector with fecundities of the four classes

mat.nofire.seeder<-matrix(c(Ssbk*(1-Gr), Fec.seeder[1]*Ssbk*(1-Gr), Fec.seeder[2]*Ssbk*(1-Gr), Fec.seeder[3]*Ssbk*(1-Gr),
Fec.seeder[4]*Ssbk*(1-Gr), Fec.seeder[5]*Ssbk*(1-Gr), Fec.seeder[6]*Ssbk*(1-Gr),Fec.seeder[7]*Ssbk*(1-Gr),Fec.seeder[8]*Ssbk*(1-Gr),
Fec.seeder[9]*Ssbk*(1-Gr), Fec.seeder[10]*Ssbk*(1-Gr), Fec.seeder[11]*Ssbk*(1-Gr), Fec.seeder[12]*Ssbk*(1-Gr),
Fec.seeder[13]*Ssbk*(1-Gr), Fec.seeder[14]*Ssbk*(1-Gr),

              Sseed*Gr,Fec.seeder[1]*Sseed*Gr+S[1]*(1-G12.seeder), Fec.seeder[2]*Sseed*Gr, Fec.seeder[3]*Sseed*Gr,
Fec.seeder[4]*Sseed*Gr, Fec.seeder[5]*Sseed*Gr, Fec.seeder[6]*Sseed*Gr, Fec.seeder[7]*Sseed*Gr, Fec.seeder[8]*Sseed*Gr,
Fec.seeder[9]*Sseed*Gr, Fec.seeder[10]*Sseed*Gr, Fec.seeder[11]*Sseed*Gr, Fec.seeder[12]*Sseed*Gr,
Fec.seeder[13]*Sseed*Gr,Fec.seeder[14]*Sseed*Gr,
```

```
               0,S[1]*G12.seeder,S[2]*(1-G23.seeder),0,0,0,0,0,0,0,0,0,0,0,0,

               0,0,S[2]*G23.seeder,S[3]*(1-G34.seeder),0,0,0,0,0,0,0,0,0,0,0,

               0,0,0,S[3]*G34.seeder,S[4]*(1-G45.seeder),0,0,0,0,0,0,0,0,0,0,

               0,0,0,0,S[4]*G45.seeder,S[5]*(1-G56.seeder),0,0,0,0,0,0,0,0,0,

               0,0,0,0,0,S[5]*G56.seeder,S[6]*(1-G67.seeder),0,0,0,0,0,0,0,0,

               0,0,0,0,0,0,S[6]*G67.seeder,S[7]*(1-G78.seeder),0,0,0,0,0,0,0,

               0,0,0,0,0,0,0,S[7]*G78.seeder,S[8]*(1-G89.seeder),0,0,0,0,0,0,

               0,0,0,0,0,0,0,0,S[8]*G89.seeder,S[9]*(1-G910.seeder),0,0,0,0,0,

               0,0,0,0,0,0,0,0,0,S[9]*G910.seeder,S[10]*(1-G1011.seeder),0,0,0,0,

               0,0,0,0,0,0,0,0,0,0,S[10]*G1011.seeder,S[11]*(1-G1112.seeder),0,0,0,

               0,0,0,0,0,0,0,0,0,0,0,S[11]*G1112.seeder,S[12]*(1-G1213.seeder),0,0,

               0,0,0,0,0,0,0,0,0,0,0,0,S[12]*G1213.seeder,S[13]*(1-G1314.seeder),0,

               0,0,0,0,0,0,0,0,0,0,0,0,0,S[13]*G1314.seeder,S[14]),nrow =15,byrow=TRUE)

mat.nofire.seeder


mat.fire.seeder<-matrix(c(Ssbk*(1-Gr.fire), Fec.seeder[1]*Ssbk*(1-Gr.fire), Fec.seeder[2]*Ssbk*(1-Gr.fire), Fec.seeder[3]*Ssbk*(1-Gr.fire),
Fec.seeder[4]*Ssbk*(1-Gr.fire), Fec.seeder[5]*Ssbk*(1-Gr.fire), Fec.seeder[6]*Ssbk*(1-Gr.fire), Fec.seeder[7]*Ssbk*(1-Gr.fire),
Fec.seeder[8]*Ssbk*(1-Gr.fire), Fec.seeder[9]*Ssbk*(1-Gr.fire), Fec.seeder[10]*Ssbk*(1-Gr.fire), Fec.seeder[11]*Ssbk*(1-Gr.fire),
Fec.seeder[12]*Ssbk*(1-Gr.fire), Fec.seeder[13]*Ssbk*(1-Gr.fire),Fec.seeder[14]*Ssbk*(1-Gr.fire),

               Sseed*Gr.fire, Fec.seeder[1]*Sseed*Gr.fire+S[1]*(1-fi.mort.seeder[1])*(1-G12.seeder),
Fec.seeder[2]*Sseed*Gr.fire+S[2]*(1-fi.mort.seeder[2])*rst[2],

              Fec.seeder[3]*Sseed*Gr.fire+S[3]*(1-fi.mort.seeder[3])*rst[3], Fec.seeder[4]*Sseed*Gr.fire+S[4]*(1-
fi.mort.seeder[4])*rst[4], Fec.seeder[5]*Sseed*Gr.fire+S[5]*(1-fi.mort.seeder[5])*rst[5], Fec.seeder[6]*Sseed*Gr.fire+S[6]*(1-
fi.mort.seeder[6])*rst[6], Fec.seeder[7]*Sseed*Gr.fire+S[7]*(1-fi.mort.seeder[7])*rst[7], Fec.seeder[8]*Sseed*Gr.fire+S[8]*(1-
fi.mort.seeder[8])*rst[8], Fec.seeder[9]*Sseed*Gr.fire+S[9]*(1-fi.mort.seeder[9])*rst[9], Fec.seeder[10]*Sseed*Gr.fire+S[10]*(1-
fi.mort.seeder[10])*rst[10], Fec.seeder[11]*Sseed*Gr.fire+S[11]*(1-fi.mort.seeder[11])*rst[11], Fec.seeder[12]*Sseed*Gr.fire+S[12]*(1-
fi.mort.seeder[12])*rst[12], Fec.seeder[13]*Sseed*Gr.fire+S[13]*(1-fi.mort.seeder[13])*rst[13], Fec.seeder[14]*Sseed*Gr.fire+S[14]*(1-
fi.mort.seeder[14])*rst[14],

              0,S[1]*(1-fi.mort.seeder[1])*G12.seeder,S[2]*(1-fi.mort.seeder[2])*(1-rst[2])*(1-G23.seeder),0,0,0,0,0,0,0,0,0,0,0,0,

              0,0,S[2]*(1-fi.mort.seeder[2])*G23.seeder,S[3]*(1-fi.mort.seeder[3])*(1-rst[3])*(1-G34.seeder),0,0,0,0,0,0,0,0,0,0,0,

              0,0,0,S[3]*(1-fi.mort.seeder[3])*G34.seeder,S[4]*(1-fi.mort.seeder[4])*(1-rst[4])*(1-G45.seeder),0,0,0,0,0,0,0,0,0,0,

              0,0,0,0,S[4]*(1-fi.mort.seeder[4])*G45.seeder,S[5]*(1-fi.mort.seeder[5])*(1-rst[5])*(1-G56.seeder),0,0,0,0,0,0,0,0,0,

              0,0,0,0,0,S[5]*(1-fi.mort.seeder[5])*G56.seeder,S[6]*(1-fi.mort.seeder[6])*(1-rst[6])*(1-G67.seeder),0,0,0,0,0,0,0,0,

              0,0,0,0,0,0,S[6]*(1-fi.mort.seeder[6])*G67.seeder,S[7]*(1-fi.mort.seeder[7])*(1-rst[7])*(1-G78.seeder),0,0,0,0,0,0,0,

              0,0,0,0,0,0,0,S[7]*(1-fi.mort.seeder[7])*G78.seeder,S[8]*(1-fi.mort.seeder[8])*(1-rst[8])*(1-G89.seeder),0,0,0,0,0,0,

              0,0,0,0,0,0,0,0,S[8]*(1-fi.mort.seeder[8])*G89.seeder,S[9]*(1-fi.mort.seeder[9])*(1-rst[9])*(1-G910.seeder),0,0,0,0,0,

              0,0,0,0,0,0,0,0,0,S[9]*(1-fi.mort.seeder[9])*G910.seeder,S[10]*(1-fi.mort.seeder[10])*(1-rst[10])*(1-G1011.seeder),0,0,0,0,

              0,0,0,0,0,0,0,0,0,0,S[10]*(1-fi.mort.seeder[10])*G1011.seeder,S[11]*(1-fi.mort.seeder[11])*(1-rst[11])*(1-
G1112.seeder),0,0,0,

              0,0,0,0,0,0,0,0,0,0,0,S[11]*(1-fi.mort.seeder[11])*G1112.seeder,S[12]*(1-fi.mort.seeder[12])*(1-rst[12])*(1-
G1213.seeder),0,0,

              0,0,0,0,0,0,0,0,0,0,0,0,S[12]*(1-fi.mort.seeder[12])*G1213.seeder,S[13]*(1-fi.mort.seeder[13])*(1-rst[13])*(1-
G1314.seeder),0,

              0,0,0,0,0,0,0,0,0,0,0,0,0,S[13]*(1-fi.mort.seeder[13])*G1314.seeder,S[14]),nrow=15,byrow=TRUE)


mat.fire.seeder
```

```
#***********************************************
#optimal fire cycle: reseeder
#***********************************************
#
ts.length<-20000 #set desired length of time series
r<-rep(NA,ts.length-1)
fi.fr.seeder<-seq(0,0.3,0.01) #set fire frequency (probability per year)
temp.nf <-rep(NA, 15)
lambdaS.seeder<-fi.fr.seeder
for (j in 1:length(fi.fr.seeder)) {
  environment<-c(0,rep(NA,ts.length-2))
  for (i in 2:(ts.length-1)) environment[i]<-ifelse(environment[i-1]==1,0,ifelse(runif(1,0,1)<fi.fr.seeder[j],1,0))
  temp.nf<-c(0.2,0.2,0.2,0.2,0.2,0.2,0.2,0.2,0.2,0.2,0.2,0.2,0.2,0.2,0.2) #adds starting values for population vector
  N<-sum(temp.nf)
  for (i in 1:(ts.length-1)) {ifelse(environment[i]==1,temp.nf<-mat.fire.seeder%*%temp.nf,temp.nf<-mat.nofire.seeder%*%temp.nf)
    N<-sum(temp.nf[1:14])
    r[i]<-log(N)
    temp.nf<-temp.nf/N}
  lambdaS.seeder[j]<-mean(r[1001:length(r)])}

#Plot
oldpar<-par(mfcol=c(1,1),mar=c(5,6,1,0),oma=c(1,5,0,1))
plot(fi.fr.seeder,lambdaS.seeder,pch=19,xlab="Fire frequency [p]",ylab="",cex.lab=2, xlim =c(0,50)) #ylim=c(-0.04,0.07), axes=F,
lines(lowess(fi.fr.seeder,lambdaS.seeder,f=1/3))
# axis(side=1,at=c(0,0.2,0.4,0.6),cex.lab=2,cex.axis=2,las=1)
# axis(side=2,at=c(-0.04,-0.02,0,0.02,0.04,0.06),cex.lab=2,cex.axis=2,las=1)
abline(h=0)
mtext("Log stochastic growth rate", side=2, line=1.5,outer=TRUE,cex=2)
par<-oldpar

#graph using fire return intervals
#---------------------------------
oldpar<-par(mfcol=c(1,1),mar=c(5,6,1,0),oma=c(1,5,0,1))
plot((1/fi.fr.seeder[-1])+1,lambdaS.seeder[-1],pch=19,xlab="Fire return interval (years)",ylab="",cex.lab=2, bty="n", ylim = c(-0.6,0.1), xlim = c(0,50)) #ylim=c(-0.04,0.07),axes=F,
lines(lowess((1/fi.fr.seeder[-1])+1,lambdaS.seeder[-1],f=1/1))
#axis(side=1,at=c(2,20,40,60,80,100),cex.lab=2,cex.axis=2,las=1)
# axis(side=2,at=c(-0.04,-0.02,0,0.02,0.04,0.06),cex.lab=2,cex.axis=2,las=1)
abline(h=0)
mtext(expression(paste("Log stochastic growth rate (log ", lambda, "s)")), side=2, line=1.5,outer=TRUE,cex=2)
```

```
par<-oldpar


##########################

## SUMMER VS WINTER PLOT ##

##########################

# # To do this you need to run the code above for the winter model. Then run the code below:

# fi.fr.seeder.winter = fi.fr.seeder

# lambdaS.seeder.winter = lambdaS.seeder

#Next run the same code as above that you ran for the winter model (up to line 91), but for the summer model.

#Now run the code below (DON'T RUN THE TWO LINES ABOVE AGAIN)

fi.fr.seeder.summer = fi.fr.seeder

lambdaS.seeder.summer = lambdaS.seeder

#Now make a plot with both winter and summer

# winDat = data.frame(fi.fr.seeder=fi.fr.seeder.winter[-1], lambdaS.seeder=lambdaS.seeder.winter[-1])

# sumDat = data.frame(fi.fr.seeder=fi.fr.seeder.summer[-1], lambdaS.seeder=lambdaS.seeder.summer[-1])

# plotDat = rbind(winDat, sumDat)

# plotDat$season = c(rep('Winter',nrow(winDat)), rep('Summer',nrow(sumDat)))

# library(ggplot2)

# sw=ggplot(plotDat, aes(x=1/fi.fr.seeder, y=lambdaS.seeder)) +

#   geom_hline(yintercept = 0) +

#   geom_line(aes(linetype=season), size =1)  +

#   theme_bw(base_size=18) +

#    labs(

#     x = 'Fire-return interval (years)',

#     y = expression(paste("Log stochastic growth rate (log ", lambda, "s)")),

#     size = 14 ) +   theme(legend.key = element_rect(colour = "transparent", fill = "transparent"),legend.position = c(0.2, 0.8), axis.line = element_line(size=1, colour = "black"),

#

#             panel.grid.major = element_blank(),

#            panel.grid.minor = element_blank(), panel.border = element_blank(),

#      panel.background = element_rect("white"),axis.text.y = element_text(size=14, color = "black"), axis.text.x = element_text(size=14, color ="black"),

#                       axis.ticks = element_line(colour = "black") )+theme(axis.title.x = element_text(color="black", size=14), axis.title.y = element_text(color="black", size=14)) #face="bold" ))

# sw +xlim(0, 50)+ylim(-0.05, 0.1)

#

#

#

#


##########################
```

```
#looking for the optimum fire frequencies
#----------------------------------------
lowess((1/fi.fr.seeder[-1])+1,lambdaS.seeder[-1],f=1/3)
max(lowess((1/fi.fr.seeder[-1])+1,lambdaS.seeder[-1],f=1/3)$y)
which.max(lowess((1/fi.fr.seeder[-1])+1,lambdaS.seeder[-1],f=1/3)$y)


#************************************************
#stochastic sensitivity: reseeder
#************************************************
#
vr<-c("Sseed","S1","S2","S3","S4","S5", "S6", "S7", "S8","S9", "S10","S11","S12", "S13","S14", "G12","G23","G34","G45","G56",
"G67","G78","G89", "G910","G1011", "G1112", "G1213", "G1314", "Fec2","Fec3","Fec4","Fec5","Fec6","Fec7","Fec8", "Fec9","Fec10",
"Fec11", "Fec12", "Fec13", "Fec14", "Gr.fire","Gr","fi.mort1", "fi.mort2","fi.mort3","fi.mort4","fi.mort5", "fi.mort6", "fi.mort7", "fi.mort8",
"fi.mort9", "fi.mort10", "fi.mort11","fi.mort12","fi.mort13","fi.mort14","rst2","rst3","rst4","rst5", "rst6", "rst7", "rst8", "rst9","rst10",
"rst11","rst12", "rst13", "rst14","Ssbk")
vr2<-c("Seed survival","Survival vegetatives","Survival small adults","Survival medium adults",
       "Survival large adults","Growth from vegetative to small adult","Growth from small to medium adult",
       "Growth from medium to large adult","Fecundity small adults","Fecundity medium adults","Fecundity large adults",
       "Germination rate after fire","Germination rate no fire","Fire mortality vegetatives","Fire mortality small adults",
       "Fire mortality medium adults","Fire mortality large adults","Probability being reset during fire: small adults",
       "Probability being reset during fire: medium adults","Probability being reset during fire: large adults","Seed survival in seed bank")
sendiff<-0.01 #set desired difference for sensitivity analysis
ts.length<-10000 #set desired length of time series
temp.nf<-rep(NA,15)
r<-rep(NA,ts.length-1)
lambdaSens<-rep(NA,length(vr))
initial<-c(0.2,0.2,0.2,0.2,0.2,0.2,0.2,0.2,0.2,0.2,0.2,0.2,0.2,0.2,0.2) #adds starting values for population vector
initial = rep(0.06666667,15)
temp.nf<-initial
N<-sum(temp.nf)
sv<-rep(0,length(vr))
fi.fr<-0.00 #set fire frequency (probability per year) 1/0.15 ~ 6.7 year fire-return interval
environment<-c(0,rep(NA,ts.length-2))
for (i in 2:(ts.length-1)) environment[i]<-ifelse(environment[i-1]==1,0,ifelse(runif(1,0,1)<fi.fr,1,0))
for (i in 1:(ts.length-1)) {ifelse(environment[i]==1,temp.nf<-mat.fire.seeder%*%temp.nf,temp.nf<-mat.nofire.seeder%*%temp.nf)
  N<-sum(temp.nf[1:15])
  r[i]<-log(N)
  temp.nf<-temp.nf/N}
lambdaS<-mean(r[1001:length(r)])
lambdaS
for (j in 1:length(vr)) {
  temp.nf<-initial
```

```
N<-sum(temp.nf)

sv[j]<-sendiff

mat.nofire.seeder.s<-matrix(c((Ssbk+sv[71])*(1-(Gr+sv[43])),

                Fec.seeder[1]*(Ssbk+sv[71])*(1-(Gr+sv[43])),

                (Fec.seeder[2]+sv[29])*(Ssbk+sv[71])*(1-(Gr+sv[43])),

                (Fec.seeder[3]+sv[30])*(Ssbk+sv[71])*(1-(Gr+sv[43])),

                (Fec.seeder[4]+sv[31])*(Ssbk+sv[71])*(1-(Gr+sv[43])),

                (Fec.seeder[5]+sv[32])*(Ssbk+sv[71])*(1-(Gr+sv[43])),

                (Fec.seeder[6]+sv[33])*(Ssbk+sv[71])*(1-(Gr+sv[43])),

                (Fec.seeder[7]+sv[34])*(Ssbk+sv[71])*(1-(Gr+sv[43])),

                (Fec.seeder[8]+sv[35])*(Ssbk+sv[71])*(1-(Gr+sv[43])),

                (Fec.seeder[9]+sv[36])*(Ssbk+sv[71])*(1-(Gr+sv[43])),

                (Fec.seeder[10]+sv[37])*(Ssbk+sv[71])*(1-(Gr+sv[43])),

                (Fec.seeder[11]+sv[38])*(Ssbk+sv[71])*(1-(Gr+sv[43])),

                (Fec.seeder[12]+sv[39])*(Ssbk+sv[71])*(1-(Gr+sv[43])),

                (Fec.seeder[13]+sv[40])*(Ssbk+sv[71])*(1-(Gr+sv[43])),

                (Fec.seeder[14]+sv[41])*(Ssbk+sv[71])*(1-(Gr+sv[43])),

                (Sseed+sv[1])*(Gr+sv[43]),

                Fec.seeder[1]*(Sseed+sv[1])*(Gr+sv[43])+(S[1]+sv[2])*(1-(G12.seeder+sv[16])),

                (Fec.seeder[2]+sv[29])*(Sseed+sv[1]) *(Gr+sv[43]),

                (Fec.seeder[3]+sv[30])*(Sseed+sv[1]) *(Gr+sv[43]),

                (Fec.seeder[4]+sv[31])*(Sseed+sv[1]) *(Gr+sv[43]),

                (Fec.seeder[5]+sv[32])*(Sseed+sv[1]) *(Gr+sv[43]),

                (Fec.seeder[6]+sv[33])*(Sseed+sv[1]) *(Gr+sv[43]),

                (Fec.seeder[7]+sv[34])*(Sseed+sv[1]) *(Gr+sv[43]),

                (Fec.seeder[8]+sv[35])*(Sseed+sv[1]) *(Gr+sv[43]),

                (Fec.seeder[9]+sv[36])*(Sseed+sv[1]) *(Gr+sv[43]),

                (Fec.seeder[10]+sv[37])*(Sseed+sv[1]) *(Gr+sv[43]),

                (Fec.seeder[11]+sv[38])*(Sseed+sv[1]) *(Gr+sv[43]),

                (Fec.seeder[12]+sv[39])*(Sseed+sv[1]) *(Gr+sv[43]),

                (Fec.seeder[13]+sv[40])*(Sseed+sv[1]) *(Gr+sv[43]),

                (Fec.seeder[14]+sv[41])*(Sseed+sv[1])*(Gr+sv[43]),

                0,(S[1]+sv[2])*(G12.seeder+sv[16]),(S[2]+sv[3])*(1-(G23.seeder+sv[17])),0,0,0,0,0,0,0,0,0,0,0,0,

                0,0,(S[2]+sv[3])*(G23.seeder+sv[17]),(S[3]+sv[4])*(1-(G34.seeder+sv[18])),0,0,0,0,0,0,0,0,0,0,0,

                0,0,0,(S[3]+sv[4])*(G34.seeder+sv[18]),(S[4]+sv[5])*(1-(G45.seeder+sv[19])),0,0,0,0,0,0,0,0,0,0,

                0,0,0,0,(S[4]+sv[5])*(G45.seeder+sv[19]),(S[5]+sv[6])*(1-(G56.seeder+sv[20])),0,0,0,0,0,0,0,0,0,

                0,0,0,0,0,(S[5]+sv[6])*(G56.seeder+sv[20]),(S[6]+sv[7])*(1-(G67.seeder+sv[21])),0,0,0,0,0,0,0,0,

                0,0,0,0,0,0,(S[6]+sv[7])*(G67.seeder+sv[21]),(S[7]+sv[8])*(1-(G78.seeder+sv[22])),0,0,0,0,0,0,0,

                0,0,0,0,0,0,0,(S[7]+sv[8])*(G78.seeder+sv[22]),(S[8]+sv[9])*(1-(G89.seeder+sv[23])),0,0,0,0,0,0,

                0,0,0,0,0,0,0,0,(S[8]+sv[9])*(G89.seeder+sv[23]),(S[9]+sv[10])*(1-(G910.seeder+sv[24])),0,0,0,0,0,
```

```
                0,0,0,0,0,0,0,0,0,(S[9]+sv[10])*(G910.seeder+sv[24]),(S[10]+sv[11])*(1-(G1011.seeder+sv[25])),0,0,0,0,

                0,0,0,0,0,0,0,0,0,0,(S[10]+sv[11])*(G1011.seeder+sv[25]),(S[11]+sv[12])*(1-(G1112.seeder+sv[26])),0,0,0,

                0,0,0,0,0,0,0,0,0,0,0,(S[11]+sv[12])*(G1112.seeder+sv[26]),(S[12]+sv[13])*(1-(G1213.seeder+sv[27])),0,0,

                0,0,0,0,0,0,0,0,0,0,0,0,(S[12]+sv[13])*(G1213.seeder+sv[27]),(S[13]+sv[14])*(1-(G1314.seeder+sv[28])),0,

                0,0,0,0,0,0,0,0,0,0,0,0,0,(S[13]+sv[14])*(G1314.seeder+sv[28]),(S[14]+sv[15])),nrow=15,byrow=TRUE)


mat.fire.seeder.s<-matrix(c((Ssbk+sv[71])*(1-(Gr.fire+sv[42])),

              Fec.seeder[1]*(Ssbk+sv[71])*(1-(Gr.fire+sv[42])),

              (Fec.seeder[2]+sv[29])*(Ssbk+sv[71]) *(1-(Gr.fire+sv[42])),

              (Fec.seeder[3]+sv[30])*(Ssbk+sv[71])*(1-(Gr.fire+sv[42])),

              (Fec.seeder[4]+sv[31])*(Ssbk+sv[71])*(1-(Gr.fire+sv[42])),

              (Fec.seeder[5]+sv[32])*(Ssbk+sv[71])*(1-(Gr.fire+sv[42])),

              (Fec.seeder[6]+sv[33])*(Ssbk+sv[71])*(1-(Gr.fire+sv[42])),

              (Fec.seeder[7]+sv[34])*(Ssbk+sv[71])*(1-(Gr.fire+sv[42])),

              (Fec.seeder[8]+sv[35])*(Ssbk+sv[71])*(1-(Gr.fire+sv[42])),

              (Fec.seeder[9]+sv[36])*(Ssbk+sv[71])*(1-(Gr.fire+sv[42])),

              (Fec.seeder[10]+sv[37])*(Ssbk+sv[71])*(1-(Gr.fire+sv[42])),

              (Fec.seeder[11]+sv[38])*(Ssbk+sv[71])*(1-(Gr.fire+sv[42])),

              (Fec.seeder[12]+sv[39])*(Ssbk+sv[71])*(1-(Gr.fire+sv[42])),

              (Fec.seeder[13]+sv[40])*(Ssbk+sv[71])*(1-(Gr.fire+sv[42])),

              (Fec.seeder[14]+sv[41])*(Ssbk+sv[71])*(1-(Gr.fire+sv[42])),

              (Sseed+sv[1])*(Gr.fire+sv[42]),

              Fec.seeder[1]*(Sseed+sv[1])*(Gr.fire+sv[42])+(S[1]+sv[2])*(1-(fi.mort.seeder[1]+sv[44]))*(1-(G12.seeder+sv[16])),

              (Fec.seeder[2]+sv[29])*(Sseed+sv[1]) *(Gr.fire+sv[42]),

              (Fec.seeder[3]+sv[30])*(Sseed+sv[1])*(Gr.fire+sv[42]),

              (Fec.seeder[4]+sv[31])*(Sseed+sv[1])*(Gr.fire+sv[42]),

              (Fec.seeder[5]+sv[32])*(Sseed+sv[1])*(Gr.fire+sv[42]),

              (Fec.seeder[6]+sv[33])*(Sseed+sv[1])*(Gr.fire+sv[42]),

              (Fec.seeder[7]+sv[34])*(Sseed+sv[1])*(Gr.fire+sv[42]),

              (Fec.seeder[8]+sv[35])*(Sseed+sv[1])*(Gr.fire+sv[42]),

              (Fec.seeder[9]+sv[36])*(Sseed+sv[1])*(Gr.fire+sv[42]),

              (Fec.seeder[10]+sv[37])*(Sseed+sv[1])*(Gr.fire+sv[42]),

              (Fec.seeder[11]+sv[38])*(Sseed+sv[1])*(Gr.fire+sv[42]),

              (Fec.seeder[12]+sv[39])*(Sseed+sv[1])*(Gr.fire+sv[42]),

              (Fec.seeder[13]+sv[40])*(Sseed+sv[1])*(Gr.fire+sv[42]),

              (Fec.seeder[14]+sv[41])*(Sseed+sv[1])*(Gr.fire+sv[42]),

              0,(S[1]+sv[2])*(1-(fi.mort.seeder[1]+sv[44]))*(G12.seeder+sv[16]),

              (S[2]+sv[3])*(1-(fi.mort.seeder[2]+sv[45]))*(1-(rst[2]+sv[58]))*(1-(G23.seeder+sv[17])),

              (S[3]+sv[4])*(1-(fi.mort.seeder[3]+sv[46]))*(rst[3]+sv[59]),

              (S[4]+sv[5])*(1-(fi.mort.seeder[4]+sv[47]))*(rst[4]+sv[60]),
```

```
                    (S[5]+sv[6])*(1-(fi.mort.seeder[5]+sv[48]))*(rst[5]+sv[61]),

                    (S[6]+sv[7])*(1-(fi.mort.seeder[6]+sv[49]))*(rst[6]+sv[62]),

                    (S[7]+sv[8])*(1-(fi.mort.seeder[7]+sv[50]))*(rst[7]+sv[63]),

                    (S[8]+sv[9])*(1-(fi.mort.seeder[8]+sv[51]))*(rst[8]+sv[64]),

                    (S[9]+sv[10])*(1-(fi.mort.seeder[9]+sv[52]))*(rst[9]+sv[65]),

                    (S[10]+sv[11])*(1-(fi.mort.seeder[10]+sv[53]))*(rst[10]+sv[66]),

                    (S[11]+sv[12])*(1-(fi.mort.seeder[11]+sv[54]))*(rst[11]+sv[67]),

                    (S[12]+sv[13])*(1-(fi.mort.seeder[12]+sv[55]))*(rst[12]+sv[68]),

                    (S[13]+sv[14])*(1-(fi.mort.seeder[13]+sv[56]))*(rst[13]+sv[69]),

                    (S[14]+sv[15])*(1-(fi.mort.seeder[14]+sv[57]))*(rst[14]+sv[70]),

                    0,0,(S[2]+sv[3])*(1-(fi.mort.seeder[2]+sv[45]))*(G23.seeder+sv[17]),(S[3]+sv[4])*(1-(fi.mort.seeder[3]+sv[46]))*(1-(rst[3]+sv[59]))*(1-(G34.seeder+sv[18])),0,0,0,0,0,0,0,0,0,0,0,

                    0,0,0,(S[3]+sv[4])*(1-(fi.mort.seeder[3]+sv[46]))*(G34.seeder+sv[18]),(S[4]+sv[5])*(1-(fi.mort.seeder[4]+sv[47]))*(1-(rst[4]+sv[60]))*(1-(G45.seeder+sv[19])),0,0,0,0,0,0,0,0,0,0,

                    0,0,0,0,(S[4]+sv[5])*(1-(fi.mort.seeder[4]+sv[47]))*(G45.seeder+sv[19]),(S[5]+sv[6])*(1-(fi.mort.seeder[5]+sv[48]))*(1-(rst[5]+sv[61]))*(1-(G56.seeder+sv[20])),0,0,0,0,0,0,0,0,0,

                    0,0,0,0,0,(S[5]+sv[6])*(1-(fi.mort.seeder[5]+sv[48]))*(G56.seeder+sv[20]),(S[6]+sv[7])*(1-(fi.mort.seeder[6]+sv[49]))*(1-(rst[6]+sv[62]))*(1-(G67.seeder+sv[21])),0,0,0,0,0,0,0,0,

                    0,0,0,0,0,0,(S[6]+sv[7])*(1-(fi.mort.seeder[6]+sv[49]))*(G67.seeder+sv[21]),(S[7]+sv[8])*(1-(fi.mort.seeder[7]+sv[50]))*(1-(rst[7]+sv[63]))*(1-(G78.seeder+sv[22])),0,0,0,0,0,0,0,

                    0,0,0,0,0,0,0,(S[7]+sv[8])*(1-(fi.mort.seeder[7]+sv[50]))*(G78.seeder+sv[22]),(S[8]+sv[9])*(1-(fi.mort.seeder[8]+sv[51]))*(1-(rst[8]+sv[64]))*(1-(G89.seeder+sv[23])),0,0,0,0,0,0,

                    0,0,0,0,0,0,0,0,(S[8]+sv[9])*(1-(fi.mort.seeder[8]+sv[51]))*(G89.seeder+sv[23]),(S[9]+sv[10])*(1-(fi.mort.seeder[9]+sv[52]))*(1-(rst[9]+sv[65]))*(1-(G910.seeder+sv[24])),0,0,0,0,0,

                    0,0,0,0,0,0,0,0,0,(S[9]+sv[10])*(1-(fi.mort.seeder[9]+sv[52]))*(G910.seeder+sv[24]),(S[10]+sv[11])*(1-(fi.mort.seeder[10]+sv[53]))*(1-(rst[10]+sv[66]))*(1-(G1011.seeder+sv[25])),0,0,0,0,

                    0,0,0,0,0,0,0,0,0,0,(S[10]+sv[11])*(1-(fi.mort.seeder[10]+sv[53]))*(G1011.seeder+sv[25]),(S[11]+sv[12])*(1-(fi.mort.seeder[11]+sv[54]))*(1-(rst[11]+sv[67]))*(1-(G1112.seeder+sv[26])),0,0,0,

                    0,0,0,0,0,0,0,0,0,0,0,(S[11]+sv[12])*(1-(fi.mort.seeder[11]+sv[54]))*(G1112.seeder+sv[26]),(S[12]+sv[13])*(1-(fi.mort.seeder[12]+sv[55]))*(1-(rst[12]+sv[68]))*(1-(G1213.seeder+sv[27])),0,0,

                    0,0,0,0,0,0,0,0,0,0,0,0,(S[12]+sv[13])*(1-(fi.mort.seeder[12]+sv[55]))*(G1213.seeder+sv[27]),(S[13]+sv[14])*(1-(fi.mort.seeder[13]+sv[56]))*(1-(rst[13]+sv[69]))*(1-(G1314.seeder+sv[28])),0,

                    0,0,0,0,0,0,0,0,0,0,0,0,0,(S[13]+sv[14])*(1-(fi.mort.seeder[13]+sv[56]))*(G1314.seeder+sv[28]),(S[14]+sv[15])*(1-(fi.mort.seeder[14]+sv[57]))*(1-(rst[14]+sv[70]))),nrow=15,byrow=TRUE)



  for (i in 1:(ts.length-1)) {ifelse(environment[i]==1,temp.nf<-mat.fire.seeder.s%*%temp.nf,temp.nf<-mat.nofire.seeder.s%*%temp.nf)

    N<-sum(temp.nf[1:15])

    r[i]<-log(N)

    temp.nf<-temp.nf/N}

  lambdaSens[j]<-mean(r[1001:length(r)])

  sv[j]<-0}

parm<-c(Sseed,S[1:14],G12.seeder,G23.seeder,G34.seeder,G45.seeder,G56.seeder,G67.seeder,G78.seeder,G89.seeder,G910.seeder,G1011.seeder,G1112.seeder,G1213.seeder,G1314.seeder,Fec.seeder[2:14],Gr.fire,Gr,fi.mort.seeder[1:14],rst[2:14],Ssbk)

sens<-(exp(lambdaSens)-exp(lambdaS))/sendiff

elas<-sens*parm/exp(lambdaS)

paste(vr,parm,round(sens,2),round(elas,2),sep=": ")
```

```
paste(vr,round(sens,2),sep=": ")

sensDat = data.frame(var=vr,sens=round(sens,2))

sensDat

sensDat[order(abs(sensDat$sens),decreasing = T),]


write.csv(sensDat, file = "FRIsummer.csv")
```