**Long term alpine summit vegetation dynamics driven by climate warming and fire**

1 **Supplementary Material**

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# Summit-level environmental factors

## Cumulative growing degrees

Using data from 2004 and 2022, state and transition stages were quantified using the LIT structural survey data for the 10 summits. The 2004 state was then compared to the 2022 state. This was then related to the fire surveys completed post the 2007 fire. We described the probability of a vegetation lifeform or substrate undergoing a transition from 2004 to 2022 from a conditional distribution (Samuels, 2003):

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| --- | --- |
|  |  |

where is the lifeform or substrate observed in 2022 and is the lifeform or substrate observed in 2004 at a point along the LIT. *F* is the fire history of summits during the study period. Thus, the probability of change was calculated as the proportion of points at a given site, given the fire history, divided by the total number of points along a transect. A transition of a given lifeform or substrate indicated structural change where a threshold was crossed (Scheffer et al., 2001). Probabilities of state and transitions were displayed through a schematic structural change model.

## Climate change

Summit was defined as:

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where is the daily minimum air temperature and is the daily maximum air temperature for each day, , above the threshold of 0 °C, , in the growing season (October-March) of a particular year, , for each summit, . A threshold of 0 °C was chosen because of the strong link with the physiology and growth of alpine plant species (Löffler & Pape, 2020).

The CGD over 23 years (1999–2022) was used for analysis of summit vegetation cover change. The CGD was determined from 1999 to 2022 to generate a time series that is pertinent to the vegetation surveys to examine the climate history prior to each survey. We selected 1999 to 2004 as our baseline and subsequently summed the CGD between survey periods (i.e. 1999-2004, 2005-2012, 2013-2017 and 2018-2022).

# Data analysis

## 4.1. Factors influencing summit vegetation transitions

Prior to analysis, we first tested for collinearity between variables with a determinant of the correlation matrix. We assessed collinearity using the Pearson correlation value (threshold of r < 0.7) (Dormann et al., 2013). To compare the magnitude of effects between covariates with different units, we centred all covariates on their associated means and divided them by one standard deviation (Gelman & Hill, 2007). The advantage of centring and standardising is that it allows for simpler interpretation, with intercepts interpreted as responses to average conditions and slope terms as partial dependencies conditional on other continuous variables being at their mean (Camac et al., 2017).

We constructed both Bayesian Generalised Additive Mixed Models (GAMM) and Bayesian Generalised Linear Mixed Models (GLMM) to analyse the data. Mixed effect models are appropriate for hierarchical data structures (e.g. transects nested within sites), as they can partition variation at multiple levels and account for observation error (Gelman & Hill, 2007; Kéry et al., 2012). GAMMs extend GLMMs by incorporating non-parametric smooth functions to account for potential non-linear relationships in the data (Hastie & Tibshirani, 1990). We compared GAMMs and GLMMs to test if modelling non-linear trends improved model fit and explained more deviance compared to GLMMs. A 5-fold cross-validation method was used to select the model form with the highest predictive capacity based on the expected log pointwise predictive density (ELPD) (Vehtari et al. 2017). There was no significant difference between the Bayesian Generalised Additive Mixed Models (GAMM) and Bayesian Generalised Linear Mixed Models (GLMM) for all models (Table S3). Therefore, the more parsimonious and simpler GLMM models were selected for inference.

For each model, we used Bayesian inference and fitted models using the R package brms (Bürkner, 2021). Specifically, we ran the models using four chains, sampling between 2000 interations. The first 1000 iterations of each chain were discarded and treated as warm-up/burn-in, leaving a total of 4000 posterior samples across chains (Camac et al., 2017). We determined chain convergence using the Brooks-Gelman-Rubin convergence diagnostic (Brooks & Gelman, 1998). Posterior inferences were then made using these 4000 samples. We assessed the adequacy of the models by posterior predictive checks, comparing replicated data generated under the fitted models to the observed data (Figs. S7-8). Below, we describe the model structure, parameters and priors used in these models.

Lifeform cover, , and each summit, *j*, and each sample period, *t*, was modelled as random realisation from a binomial distribution:

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Here, is the estimated likelihood of a lifeform being intercepted on summit, *j*, at time, *t,* and is the total number of lifeforms or substrates along a line intercept transect. We modelled, on the logit scale as a linear function of summit elevation (, time-since-fire () and cumulative growing degrees (). We included interactions between and because the impact of on vegetation cover will depend on how long a summit has remained unburnt. We also included random intercept effects for site, , and survey year, . Random effects were included for several critical reasons, including accounting for the non-independent structure of observations within sites and over time, estimating group-level effects and providing a means to predict new group levels (Camac et al., 2017). Model intercepts, , and coefficients, β, were estimated using weakly informative student's t priors. These student's t priors are the brms package default priors (Bürkner, 2021). Partial dependency plots were then created for the average site and the average year. was modelled separately for forbs, graminoids and shrubs, but the three models are structurally similar. Figs. S6-8 show the conditional modes of the random effects (site and year) from the fitted models.

# Supplementary Figures

**Table S1** Summary of site details, including abiotic features, year permanent plot established, the plant community type, and the cessation of cattle grazing. Site environmental variables and disturbance regimes information obtained from Lawrence (1995), Department of Sustainability and Environment (2005) and Bureau of Meteorology (2022).

|  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Study site** | **Elevation (m)** | **Location** | **Year establi-shed** | **Plant community** | **Mean annual min temp in 2022 (°C)** | **Mean annual max temp in 2022 (°C)** | **Annual precip in 2022 (mm)** | **Size approx of plot (m2)** | **Cessation of cattle grazing** | **Geology** |
| Mt Specula-tion | 1668 | -37.1253, 146.6433 | 2004 | *Poa fawcettiae, Hovea montana* and *Podolobium alpestre* open grassy heathland | 4.6 | 11.9 | 1843.1 | 1197 | 1960 | Snowy Plains Formation |
| Little Spion Kopje | 1670 | -36.8263, 147.2815 | 2012 | *Grevillea australis* and *Poa hothamensis* dominatedopen grassy heathland | 2.8 | 9.3 | 2378.2 | 1444 | 1992 | Cobungra Granite |
| King Billy (No. 2) | 1690 | -37.2024, 146.600 | 2004 | *Poa fawcettiae, Hovea montana* and *Podolobium alpestre* open grassy heathland | 4.2 | 11.2 | 1923.9 | 2418 | 1989 | Bryce Plain Basalt |
| The Twins | 1705 | -37.027, 147.027 | 2012 | *Grevillea australis and Poa hothamensis dominated low open grassy heathland* | 4.7 | 12.4 | 1838.3 | 2254 | 1950s | Pinnak Sandstone |
| The Bluff | 1710 | -37.2346, 146.4899 | 2004 | *Hovea montana* dominated closed heathland | 5.0 | 12.4 | 1831 | 1742 | 1993 | Snowy Plains Formation |
| Mt Howitt West Peak | 1720 | -37.1756, 146.6410 | 2012 | *Poa fawcettiae* and *Hovea montana* dominated low open grassy heathland | 4.1 | 11.1 | 1780.9 | 954 | 1991 | Snowy Plains Formation |
| Mt Magdala | 1730 | -37.1897, 146.6212 | 2004 | *Poa fawcettiae and Hovea montana* open grassy heathland | 4.2 | 11.2 | 1923.9 | 1710 | 1992 | Snowy Plains Formation |
| Mt Howitt | 1740 | -37.1746, 146.6494 | 2012 | *Poa fawcettiae, Kunzea muelleri* and *Hovea montana* dominated low open-closed grassy heathland | 4.6 | 11.9 | 1843.1 | 1938 | 1991 | Snowy Plains Formation |
| Mt Stirling (Stanley Knob) | 1750 | -37.1279, 146.49893 | 2004 | *Poa fawcettiae* and *Podolobium alpestre* dominated open grassy heathland | 4.6 | 11.8 | 2044.4 | 1260 | 1960 | Mount Stirling Granodiorite |
| Mt Buller (West Knob) | 1805 | -37.1450, 146.42527 | 2004 | Open *Poa fawcettiae* and *Hovea montana* dominated open-closed grassy heathland | 4.5 | 11.6 | 2107.3 | 612 | 1958 | Mount Stirling Granodiorite/ Cobbannah Group |
| Feather-top North Peak | 1850 | -36.8911, 147.14060 | 2012 | *Poa* spp., *Acrothamnus montanus* & *Grevillea australis* dominated low open grassy heathland | 4.1 | 11.4 | 1948.4 | 561 | 1950s | Pinnak Sandstone |
| Mt. Fawcett (unoffic-al name) | 1870 | -36.8294, 147.31925 | 2012 | *Grevillea australis, Kunzea muelleri* and *Poa hiemata* dominatedopen grassy heathland | 2.8 | 9.3 | 2378.2 | 5000 | 1992 | Cobungra Granite |
| Mt Hotham | 1900 | -36.9745, 147.1322 | 2004 | *Kunzea muelleri* dominated low alpine open heathland | 3.6 | 10.5 | 1920.3 | 5000 | 1956 | Pinnak Sandstone |
| Mt Bogong (Hooker Plateau) | 1970 | -36.7328, 147.3057 | 2004 | *Celmisia costiniana* and *Poa fawcettiae* dominated tall grassy alpine herbfield | 3.1 | 9.9 | 1973.2 | 5000 | 1950s | Complex gneiss/ Omeo Metamorphic Complex |

**Table 2** Fire history of study summits

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| **Study site** | **Elevation (m)** | **Year of last known recent fire/s** | **Total percent burnt from 2003 (%)** | **Fire history reference** |
| Mt Speculation | 1660 | 2007 | 100 | DEECA 2022 |
| Little Spion Kopje | 1670 | 2003 | 100 | DEECA 2022 |
| King Billy (No. 2) | 1690 | 2007 | 63.54 | Observed |
| The Twins | 1705 | 2003, 2007, 2013 | 100 | DEECA 2022 |
| The Bluff (South Knob) | 1710 | 2007 | 100 | DEECA 2022 |
| Mt Howitt West Peak | 1720 | 2007 | 83.96 | Observed |
| Mt Magdala | 1730 | 2007 | 69.63 | Observed |
| Mt Howitt | 1740 | 2007 | 18.17 | Observed |
| Mt Stirling (Stanley’s Knob) | 1750 | 2007 | 100 | DEECA 2022 |
| Mt Buller (West Knob) | 1805 | 2007 | 100 | DEECA 2022 |
| Feathertop North Peak | 1850 | 2003, 2007, 2013 | 100 | Observed |
| Mt. Fawcett | 1870 | 2003 | 100 | DEECA 2022 |
| Mt Hotham | 1900 | 1939 | 0 | DEECA 2022 |
| Mt Bogong (Hooker Plateau) | 1950 | 1939 | 0 | DEECA 2022 |

**Table 3** K-fold cross-validation results comparing two models, generalised linear mixed models (GLMM) and generalised additive mixed (GAMM) models, showing the expected log pointwise predictive density (ELPD) difference and the standard error (SE) of the difference in ELPD.

|  |  |  |  |
| --- | --- | --- | --- |
| **Models** | **Equation** | **ELPD difference** | **SE difference** |
| a) Forbs | GAMM | 0 | 0 |
|  | GLMM | -117.8 | 201.1 |
| c) Shrubs | GAMM | -202.4 | 138.8 |
|  | GLMM | 0 | 0 |
| b) Graminoids | GAMM | 0 | 0 |
|  | GLMM | -296.1 | 138.2 |

**Fig. S1** The study area with the recent Australian Alpine Bioregion fire history that affected the study summitsA map of different countries/regions

Description automatically generated with medium confidence. Left: (a) Location of the study area in SE Australia and (b) study summits shown in relation to the total area affected by recent fires in the Australian alpine bioregion. Right: Study summits in relation to areas affected by the recent fires in (c) 2003, (d) 2007, and (e) 2013.

A mountain with a mountain range

Description automatically generated with medium confidence

**Fig. S2** The layout of the sampling methodology of the summits. The layout of the sampling methodology of the summits. Showing the position of line intercept transects and the five 1 m2 quadrats on each aspect from the highest summit point (HSP). Image of Mt Feathertop west peak, Australia.



**Fig. S3** Forb model posterior predictive checks.



**Fig. S4** Shrub model posterior predictive checks.



**Fig. S5** Graminoid model posterior predictive checks.

A graph of a number of numbers

Description automatically generated with medium confidence

**Fig. S6** The conditional modes of the random effects (site and year) from the fitted forb model.

A graph of the same type of graph

Description automatically generated with medium confidence

**Fig. S7** The conditional modes of the random effects (site and year) from the fitted shrub model.

A graph of a bar graph

Description automatically generated with medium confidence

**Fig. S8** The conditional modes of the random effects (site and year) from the fitted graminoid model.

A diagram of a fire

Description automatically generated

**Fig. S9** Diagrammatic summary of the major interactions and feedbacks involving disturbance (fire and climate warming) and regeneration of dominants in the alpine vegetation showing positive (blue) and negative (red) feedbacks, adapted from Camac et al. (2017) and Williams (1987). A warmer climate and an increased frequency of extreme events, such as fires, will result in positive outcomes for shrub species, particularly for obligate seeder shrubs. Increased fire frequencies will create more bare ground for shrubs to recruit and establish, resulting in increased landscape flammability. Fire negatively affects forbs and reduces fixed litter required for the regeneration of forb species. Too frequent fire may negatively affect shrub survival with warming.

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