Integrating public land fire data and satellite imagery improves fire frequency estimates across the landscape

Felicity E. Charles[1*] 0000-0002-7241-2720
April E. Reside[1] 0000-0002-0760-9527
Patrick T. Moss[2] 0000-0003-1546-9242
Annabel L. Smith[1] 0000-0002-1201-8713

[1]School of the Environment, The University of Queensland, Gatton, 4343, QLD, Australia
[2]School of Earth and Atmospheric Sciences, Queensland University of Technology, Brisbane City, 4000, QLD, Australia
[*]Correspondence: f.charles@uq.edu.au

Running headline: Improving landscape fire frequency estimates

Keywords: burnt area mapping, fire management, Landsat, predictive modelling, satellite fire data, Sentinel, species distribution model, remote sensing

Abstract

Background

Effective fire management requires accurate knowledge of fire history, often derived from satellite imagery. However, satellites are not well suited to detecting low intensity fires.

Aims

We aimed to improve satellite-derived fire frequency estimates by incorporating mapped fire history data from public land and environmental co-variation.

Methods

Using a generalisable workflow, we applied boosted regression trees, generalised linear, and generalised additive models to predict fire frequency in an eastern Australia case study. Performance of raw and modelled satellite-derived fire frequencies were tested by correlating them with higher-quality public land fire mapping.

Key results

Satellite-derived data underestimated fire frequency, especially in infrequently burnt areas (i.e., 1-6 fires in the past 36 years). Generalised linear and generalised additive models improved the correlations, relative to the baseline (Pearson's $r = 0.331$), to 0.577 and 0.526 respectively.

Conclusions

Generalised linear and generalised additive models improved fire frequency estimates and were most useful at low fire frequencies. Generalised linear models also had some utility for mapping higher fire frequencies.

Implications

Satellite-derived fire mapping is widely used in fire science but is likely to underestimate fire activity. Our approach can improve the accuracy of estimates derived from satellite data for fire management and research.

Summary

Satellite-derived fire history data are widely used in fire management and research, but these data often underestimate fire frequency. We present a generalisable predictive modelling framework and show that it can improve accuracy of fire frequency estimates derived from satellite data, ultimately assisting fire management for conservation and human safety.

Introduction

Fire has shaped the structure and composition of ecosystems for millennia, with variation in fire regimes driven by global climatic patterns such as El Niño-Southern Oscillation, and by anthropogenic influences such as cultural and prescribed burning (Bird *et al.* 2016; Williamson *et al.* 2016; Moura *et al.* 2019; Fang *et al.* 2021; Kelly *et al.* 2023). However, contemporary fire regimes are changing rapidly due to climate change (Moritz *et al.* 2012; Le Page *et al.* 2017; Harvey *et al.* 2022), land clearing, fire suppression, and inappropriate fire management policies (Rogers *et al.* 2020; Jones *et al.* 2022; Kelly *et al.* 2023; Kreider *et al.* 2024; Sayedi *et al.* 2024). In the 21st century, fire regime changes have been marked by multiple large intense wildfires affecting vast areas of Australia, Europe, and North and South America (Castellnou *et al.* 2018; Coen *et al.* 2018; Gustafsson *et al.* 2019; Collins *et al.* 2021; D'Angelo *et al.* 2022; González *et al.* 2022). These 'megafires' (i.e., those which burn over 10,000 ha, Linley *et al.* 2022) are likely to increase into the future (Khorshidi *et al.* 2020), along with increasing extreme fire weather and longer fire seasons, especially in mid- to high-latitudes (Moritz *et al.* 2012; Flannigan *et al.* 2013; Le Page *et al.* 2017; Dowdy *et al.* 2019). In regions where fire suppression is the dominant management strategy, vegetation encroachment can increase wildfire risk (Moura *et al.* 2019; Kelly *et al.* 2023; Sayedi *et al.* 2024) and threaten species which rely on fire for reproduction (Corlett 2016; Kelly *et al.* 2020; Lavery *et al.* 2021; Bachman *et al.* 2024). Thus, there is a global need to address fire regime changes and manage fire at large scales.

Understanding ecosystem function relies on knowledge of historical fire regimes which occur on evolutionary timescales (i.e., centuries to millions of years, Moss *et al.* 2013; Mariani *et al.* 2017; Mackenzie *et al.* 2020), or ecological timescales (i.e., decadal scales, Smith *et al.* 2016; Le Breton *et al.* 2023; Plumanns-Pouton *et al.* 2024). Fire history on ecological timescales is related to the generation times of plant and animal species and is especially important for understanding the impacts of rapid global change (Charles *et al.* 2025). Prior to the availability of satellite imagery in the 1970s, multi-decadal fire history data were mainly derived from aerial imagery; on-ground surveys; tree-ring fire scar analyses; dendroecological techniques with radiocarbon analyses; and age reconstruction of fire sensitive species establishing after major fires (Mouillot *et al.* 2005; Conedera *et al.* 2009; Wood *et al.* 2010; Greene *et al.* 2017; Fedrigo *et al.* 2019; Queensland Parks and Wildlife Service 2023). These multi-decadal datasets can be limited in spatiotemporal coverages (Conedera *et al.* 2009; Duane *et al.* 2015) and disrupted by jurisdictional boundaries, producing discontinuous datasets (Liu *et al.* 2019b; Phelps *et al.* 2021; Welch 2021; Ryu *et al.* 2023). Such data also suffer from inaccuracies related to the heterogenous, patchily burnt areas being labelled as a single homogenous fire (Loschiavo *et al.* 2017; Duff *et al.* 2019). Gathering and processing burnt area data manually is also time intensive which limits its geographic breadth and hence, applicability. Furthermore, aerial or ground-based fire data are often incomplete due to changes in mapping system, government policies (e.g., reporting guidelines), or spatial scales (e.g., omission of small scale fires less than 1 ha or mapping only completed for public land) (Pausas *et al.* 2012; San-Miguel-Ayanz *et al.* 2012; Welch 2021; Queensland Parks and Wildlife Service 2023; Ryu *et al.* 2023; Duane *et al.* 2025). Improved workflows are needed to ensure that future fire history data collection is standardised and that existing data can be used to reconstruct fire histories, while accounting for inaccuracy or incompleteness.

Satellite-derived imagery circumvents some of the issues with aerial or ground-based data and is frequently used to reconstruct fire histories (D'Este *et al.* 2020; Elia *et al.* 2020; Gincheva *et al.* 2024; Orero *et al.* 2024; Ramsey *et al.* 2024) and map fire severity (Redmond *et al.* 2002; Collins *et al.* 2018; Collins *et al.* 2020; Gibson *et al.* 2020; Saulino *et al.* 2020). Several satellite-derived fire maps are available at different resolutions and spatial coverages, such as the 500 m Global Fire Atlas; global 250 m Moderate Resolution Imaging Spectroradiometer (MODIS) burned area product; and Landsat or Sentinel-2 products at finer resolutions (e.g., 30 and 10 m, respectively) (Maier *et al.* 2012; Fisher *et al.* 2015; Andela *et al.* 2019; Ruscalleda-Alvarez *et al.* 2021; Gincheva *et al.* 2024). However, satellite derived fire products also have drawbacks. They can misclassify burned areas (van den Berg 2021; Gincheva *et al.* 2024), and satellite imagery used to derive burnt areas often have resolutions too coarse to capture small fires at scales relevant to management (Fisher *et al.* ; Ruscalleda-Alvarez *et al.* 2021). Another source of inaccuracy in satellite-derived fire products is their inability to capture low intensity understorey fires (Randerson *et al.* 2012; Gincheva *et al.* 2024; Khairoun *et al.* 2024), particularly in forested ecosystems with dense canopies (Loschiavo *et al.* 2017). The resolution at which satellite products record the landscape also limits the documentation of low intensity fires (due to their patchy nature) meaning that fire frequency is often underestimated (Fisher *et al.* 2015; Collett 2021; van den Berg 2021). Low intensity and understorey fires can be detected by combining satellite data with high resolution airborne digital sensor imagery (e.g., McCarthy *et al.* 2017; Woodgate *et al.* 2025). However, this is resource intensive, in terms of time and expert personnel, and is likely prohibitive for mapping over large spatiotemporal scales. As a result, fire histories on decadal timeframes are often unknown or inaccurate (Galizia *et al.* 2021; Ruscalleda-Alvarez *et al.* 2021; Gincheva *et al.* 2024; Khairoun *et al.* 2024). In Australia, the North Australia Fire Information system (NAFI) maps 80% of the continent using MODIS, focusing on the dominant arid and savanna ecosystems (Fisher *et al.* 2015; Gincheva *et al.* 2024; Fisher 2026). However, NAFI does not map much of the forested ecosystems of the south-eastern part of the continent, where highly biodiverse regions intersect densely populated urban areas, making fire history knowledge in these regions particularly important for fire management. Thus, there is a strong need for approaches which can improve estimates of multi-decadal fire history at landscape scales, both in Australia and globally.

We aimed to develop a workflow to predict fire frequency (i.e., a cumulative count of the number of fires in a period of time) by improving the accuracy of estimates of landscape-scale fire frequency derived from satellite data. We integrated satellite-derived fire frequency estimates (response variable) with more accurate, manually verified public land fire frequency estimates and environmental co-variation (predictor variables) to develop an environmentally informed model of fire frequency. In other words, we used data from inside the public estate to improve the accuracy of fire frequency estimates for areas outside the public estate where data are solely derived from satellite imagery. Environmental factors including climate, terrain, and vegetation productivity were included in our analysis as they drive spatiotemporal dynamics of fire regimes by affecting fuel availability and flammability (Cary *et al.* 2006; Bradstock 2010; Duane *et al.* 2015). Thus, our approach treated fire history data in the same way as species distribution modelling workflows treat species whose presence depends on a specific niche (Wisz *et al.* 2013; He *et al.* 2019).Three different model types were evaluated by examining correlations between public land fire data and modelled fire history estimates. We expected modelled estimates to have stronger correlations with public land fire data compared to unmodelled values from satellite-derived imagery. We begin by outlining a general workflow which can be applied to any landscape where manually-verified fire history data is available. We then present a case study of our approach in southeast Queensland, Australia. Our data, code, and modelling workflow are publicly available and can be customised for applications in other regions, enabling downstream analysis of fire histories across landscapes.

Methods

Overview of workflow to improve fire frequency estimate accuracy

The first stage of the workflow involves obtaining historical fire data and gridded continuous environmental data (Fig. 1a). Environmental data can include variables most likely to influence fire occurrences in a given landscape, such as climate (e.g., temperature and precipitation), terrain (e.g., elevation and slope), and site productivity (e.g., percent soil clay, foliage projective cover, vegetation aggregation) (Cary *et al.* 2006; Bradstock 2010; Duane *et al.* 2015). Data are then cropped to the study region and reformatted to align spatial resolution and coordinate reference systems among layers (Fig. 1a). In the second stage, available historical fire data is reformatted such that the fire metric of interest (e.g., fire frequency, fire return interval, time since last fire, or fire seasonality) can be calculated using standard GIS functions for the relevant time period (Fig. 1b). Here we focus on fire frequency (i.e., a cumulative count of the number of fires in a period of time). Modelling the relationship between fire history data derived from satellite imagery and fire data mapped on public land allows projections of fire history to areas that are unmapped (i.e., outside the recorded region) or inaccurately mapped (i.e., incorrectly mapped as unburnt due to burnt areas obscured by cloud cover, or dense and/or overstorey vegetation).

Presence points are created from burned grid cells and depending on the completeness of the fire data, absences can be created in a number of ways. For fire history records where unburnt areas are accurately mapped, the true absences should be used directly. For incomplete fire history records, two methods can be used to create 'absence' points. Pseudoabsence points can be created outside of a pre-defined buffer around each presence point (see Barbet-Massin *et al.* 2012; Broussin *et al.* 2024). Alternatively, a large number of background points can be randomly created across the study region. We recommend the second option (i.e., background points) as pseudoabsences may exclude areas unlikely to burn due to their close proximity to presence points (Broussin *et al.* 2024), potentially leading to some over-estimation of low fire frequencies. A presence-absence/background dataset can then be produced by extracting fire and environmental data for the presence and absence/background points.

Prior to modelling (the third stage of the workflow), backwards stepwise elimination and variable correlation tests can be used to exclude non-informative and/or highly correlated variables (see Valavi *et al.* 2022). The extent of spatial autocorrelation should be calculated to produce spatially explicit presence-background datasets to be used for model training (e.g., 80% of the data) and model evaluation (e.g., 20% of the data for evaluating Area Under the

Receiver Operating Characteristic Curve, AUC_{ROC}; and Precision-Recall Gain curves, AUC_{PRG}). We recommend investigating multiple modelling methods to account for differing strengths and weaknesses among models (Li *et al.* 2013; Elith *et al.* 2020; Valavi *et al.* 2022; Harris *et al.* 2024). If using boosted regression trees (BRT), hyperparameter tuning should be performed to determine optimal settings for tree complexity and learning rate (see Elith *et al.* 2008). Spatially explicit training data can then be used to run BRT, generalised linear (GLM), and generalised additive (GAM) models (Fig. 1c). Generalised additive model tuning can be performed after modelling, and models should be re-run if model fit requires improvement.

In the fourth stage, spatial fire frequency predictions can be produced from each model using predictor variables (more accurate fire frequency data and environmental co-variates) (Fig. 1d). In the fifth and final stage, models and predictions are evaluated by examining predictive performance, correlations of modelled estimates to unmodelled estimates, comparative histograms of estimates, and comparison of modelled estimates to ecologically informed fire regime guidelines for particular vegetation types. Predictive performance can be evaluated by comparing spatial prediction maps and by using the spatially explicit model evaluation dataset in standard evaluation procedures for species distribution modelling workflows (e.g., AUC_{ROC} and AUC_{PRC}, variable relative contributions; Valavi *et al.* 2022) (Fig. 1e). Examining correlations between unmodelled and modelled fire frequency estimates to more accurate fire frequency data (i.e., public land data) allows estimation of accuracy improvements. We also recommend evaluating how unmodelled and modelled fire frequency estimates are distributed across fire frequencies (e.g., comparative histograms of the estimates). If ecologically informed fire regime management guidelines are available (e.g., similar to Queensland Herbarium 2024), we recommend evaluating whether estimates are ecologically valid given the vegetation type.

Case study region

Our case study focused on the southeast Queensland Interim Biogeographic Regionalisation of Australia (IBRA) bioregion, Australia, limited to the border with New South Wales (Fig. 2). The region has a subtropical climate with mean annual rainfall ranging from 600 mm to 2000 mm (Australian Bureau of Meteorology 2024a). Throughout the region, mean maximum temperatures range from 21 °C to 33 °C in summer and 18 °C to 24 °C in winter (Australian Bureau of Meteorology 2024b). Coastal areas generally experience more moderate temperatures and higher rainfall than inland areas. The IBRA is dominated by dry sclerophyll forest (Department of Climate Change 2024), which accumulates fuel load quickly (Cochrane 1968; Gilroy *et al.* 2009; Gould *et al.* 2011). Public land in the region is dominated by remnant native vegetation cover; however, it also includes production native forests and plantations, managed resource protection areas, and areas of other intensive land uses including mining and waste (Department of Agriculture 2024).

Ecologically informed fire regime recommendations suggest variable high to low fire frequency regimes (i.e., mosaics of fire return intervals from 4 to 20 years to create spatiotemporal mosaics of fire, Neldner *et al.* 2019; Queensland Herbarium 2024). In the subtropics, many dry sclerophyll systems have a grassy understorey and the recommended fire regimes are for low intensity, cool season burns that scorch the ground layer while avoiding burning the trees (Neldner *et al.* 2019). This type of burning can maintain ground layer plant diversity (Dooley *et al.* 2023; Gaskell *et al.* 2026) while also minimising weed invasion (Debuse *et al.* 2014). Bushfires in the region generally occur in late winter and spring (Sullivan *et al.* 2012). Prescribed burning on public land is conducted across large areas (e.g., ~ 600,000 to 1 million ha, Department of Environment 2020a; Department of Environment and Science 2021, 2023) during winter (Eliott *et al.* 2020; Department of Environment and Science 2022b) (Fig. 2). On private land, properties are burned for wildfire hazard reduction, woody vegetation control, ecosystem restoration, and weed control (Toledo *et al.* 2012; Edwards *et al.* 2016; McCormack *et al.* 2024). However, private land can be more prone to frequent fire due to management attitudes and objectives which do not necessarily align with ecosystem conservation, reduced management abilities, and increased ignitions resulting from the wildland-urban interface (Aslan *et al.* 2024). Cultural burning also takes place on public and private land (Williamson 2021; Greenwood *et al.* 2022; Williamson 2022).

Between September 2019 and February 2020, wildfires affected 3.1 million hectares of public land managed by Queensland Parks and Wildlife Service and nearby private land, in an event that was unprecedented in spatial scale and intensity (Legge *et al.* 2022). These wildfires occurred following a multi-year drought during extreme fire weather conditions (Nolan *et al.* 2020; Udy *et al.* 2024), resulting in extensive areas burnt at high severity with canopy scorch or consumption (Dickman 2021; Nolan *et al.* 2021). These fires occurred in drastically different conditions to prescribed burns (Morgan *et al.* 2020) and resulted in a suite of negative ecological impacts (Marsh *et al.* 2022). In 2021-2022, prescribed burning was conducted across a smaller area (358,563 ha) as a result of the wildfire (Department of Environment and Science 2022a).

Modelling methods

We conducted all analyses in R version 4.5.1 (R Core Team 2018). Modelling methods included machine-learning and traditional regression models commonly used in species distribution and fire predictive modelling (Bistinas *et al.* 2014; Li *et al.* 2022; Valavi *et al.* 2022). Spatial data were manipulated (e.g., cropped, reprojected, aggregated, disaggregated) using the `terra` R package version 1.8-60 (Hijmans 2025), unless otherwise specified. All spatial data layers (Table 1) were projected to a standard coordinate reference system (EPSG 3577: GDA94/Australian Albers); spatial extent (i.e., southeast Queensland IBRA, Fig. 2); and resolution of 30 m. We masked spatial data to exclude water bodies, limiting predictions to land.

Historical fire data pre-processing

Satellite fire history data were obtained for 1987 – 2016 from Landsat at 30 m resolution, and for 2017 – 2023 from Sentinel-2 at 10 m resolution (Collett 2021; van den Berg 2021) (Table 1). Each of these datasets are produced as yearly composites with values denoting month of burn. As such, the data do not indicate cells burnt more than once in a month (which is unlikely, although possible), nor do they indicate if the fire was a wildfire or a prescribed burn. Thus, despite differences in conditions which drive wildfires and prescribed burns (Clarke *et al.* 2019; Hunter *et al.* 2020), we were unable to distinguish between these fire types with available data. For Landsat, burnt areas are automatically detected from significant changes in reflectance, relative to the previous reflectance value, which arise from the presence of charcoal or ash, removal of foliage, or scorch (Collett 2021). For Sentinel, burnt areas are automatically detected from imagery using differenced bare soil fraction relative to the previous fractional cover values (van den Berg 2021). Satellite burnt areas were reclassified such that month values of 1-12 were assigned a value of 1 and areas with no data (i.e., unburnt and no data areas – water or masked agricultural crops) were assigned a value of 0. Fire frequency was then calculated as the cumulative count of cells assigned 1 for Landsat and Sentinel data separately. To avoid issues with downscaling fire history data to finer resolutions (e.g., changes in minimum values) (Atkinson *et al.* 2000; Ekström *et al.* 2015; Park *et al.* 2019), Sentinel-2 data was scaled up through cell value averaging during aggregation to 30 m resolution after pre-processing. Landsat derived fire frequencies from 1987 – 2016 and Sentinel-2 derived fire frequencies from 2017 – 2023 were then combined into one dataset to provide fire frequencies over 1987 to 2023.

Public land fire data were obtained from Queensland Parks and Wildlife Service (Table 1) (Queensland Parks and Wildlife Service 2023). These data consisted of spatial maps of wildfire and prescribed burn area perimeters in public estates (e.g., national parks and state forests) between 1930 and 2024 (Queensland Parks and Wildlife Service 2023). Public land fire data were mapped through field observations and Global Position System (GPS) capture; digitations from paper-based records and aerial imagery; and burnt area analyses of satellite imagery. This post hoc mapping of fire history records prior to the 2000s meant the data were incomplete (Eliott *et al.* 2020; Queensland Parks and Wildlife Service 2023). To address this incompleteness while reducing major temporal coverage losses, we subset the public land fire data to match the temporal coverage of the satellite data (i.e., 1987 – 2023). These data were then converted to raster format with 5 m resolution, assigning cell values as the count of overlapping polygons using `terra` (Hijmans 2025). The final public land fire frequency dataset was then aggregated to a 30 m resolution using the `gdalUtilities` R package version 1.2.5 (O'Brien 2023).

Gridded environmental and climate data pre-processing

To represent environmental variation which influences fire probability, we used continuous gridded spatial data on the following environmental variables (Table 1): terrain (elevation, slope, aspect, and topographic position index); site productivity (topographic wetness index, foliage projective cover, soil percent clay, and broad vegetation group); and climate (temperature seasonality and precipitation seasonality). Terrain attributes were expected to influence fire probability and fire behaviour patterns through their effect on vegetation structure, productivity, and solar radiation exposure (e.g., with variation in aspect) (Del-Toro-Guerrero *et al.* 2019; Cheng *et al.* 2023). Site productivity attributes were expected to influence fire probability through their effects on fuel accumulation and fuel moisture (Cary *et al.* 2006; Bradstock 2010; Duane *et al.* 2015). Climatic variables were expected to influence fire weather conditions which drive fire probability (Cary *et al.* 2006). Precipitation seasonality was also expected to influence vegetation productivity as it drives the regularity of fuel moisture and flammability (Bradstock 2010) while capturing variation in wet and dry seasons (Wang *et al.* 2024), highly relevant to our subtropical study region. These environmental predictors were processed to standardise resolution, projection, and spatial extent using `gdalUtilities` in the same way as the fire data (see Table 1). The SRTM-derived 1 Second Digital Elevation Model Version 1.0 was used to derive aspect and degrees of slope using `terra` (Geoscience Australia 2011) (Table 1). Topographic position index was derived from the Digital Elevation Model using the `landform` R package version 0.2 (Alberti 2023).

Consistent with other predictive modelling studies which used long-term average climate data (e.g., Syphard *et al.* 2008; D'Este *et al.* 2020), we formatted climate and vegetation datasets such that they represented averages across their relevant time periods. Climate seasonality measures were derived from daily datasets for precipitation, minimum temperature and maximum temperature (Jeffrey *et al.* 2001; SILO 2025c, 2025b, 2025a). For precipitation, we calculated average monthly precipitation per year, which was used for subsequent seasonality calculations (SILO 2025c). For temperature, we calculated average daily temperature from daily minimum and maximum measurements, which were then averaged for each month per year and used for subsequent seasonality calculations (SILO 2025b, 2025a). Seasonality indices (i.e., precipitation seasonality and temperature seasonality) were then calculated as the standard deviation of the average monthly measurement × 100, per year (Fick *et al.* 2017). Final precipitation and temperature seasonality values were then produced as the long-term average of these seasonality measures across all years for the study region. Foliage projective cover (FPC) measures the amount of woody mid- and over-story vegetation (Department of Environment 2024b) and is provided as 0-100% foliage cover. The 2014 data required reclassification as values of 1-100% were denoted as 100-200, and 0% was denoted by values above 200 or below 100. We then calculated average FPC from the reclassified 2012 – 2014 and 2018 – 2023 datasets. Broad Vegetation Groups (BVG) in Queensland are classified categorically and assigned numerical codes which we used to model vegetation type (Neldner *et al.* 2023; Department of Environment 2024a), and the data were converted to raster using `terra` (Hijmans 2025). Soil percent clay data were available for each stratum in our study region (e.g., 0 to 0.05 m, 0.05 to 0.1 m, etc) and these were processed to produce the average soil percent clay from 0 to 2 m.

For each environmental predictor, we replaced cells with no data (i.e., NA) with single imputation (Łopucki *et al.* 2022), such that NAs were replaced by an average from the surrounding cells using `terra`. Foliage projective cover had large areas mapped as NA due to mapping only mid- and over-story vegetation of >0.5 ha (Department of Environment 2024b). However, single imputation was still considered appropriate for FPC as underestimation was already present due to a lack of understorey data (Department of Environment 2024b). For BVG data, no interpolation was performed as the data were complete.

Presence-background points dataset

Our datasets suffered from a lack of definitively identifiable unburnt areas from 1987 to 2023 (Eliott *et al.* 2020; Queensland Parks and Wildlife Service 2023). As our aim was to improve satellite-derived estimates of fire frequency for areas outside of public land, we used public land fire data to produce background points in place of absences (see Liu *et al.* 2019a; Grimmett *et al.* 2020; Valavi *et al.* 2022). As such, we restricted model training and testing to areas where more accurate fire history data were available (i.e., public estate land). Prior to producing presence and absence/background points, we set a random seed for reproducibility. Presence points were created as a random sample of 10,000 points in areas of public land fire frequency ≥1 (i.e., presence points must have burnt at least once) using `terra` (Hijmans 2025). For presence points, values were assigned as the fire frequency value from the cell (i.e., presences represent the fire frequency of the cell). Background points were then created as a random sample of 80,000 points across public land in the study region, irrespective of the location of presence points. Therefore, an 'absence' could occur in the same location as a presence, consistent with recent statistical approaches (Liu *et al.* 2019a; Valavi *et al.* 2022;

Whitford *et al.* 2024). For satellite fire frequency and environmental predictors, we used a custom function (see Golding *et al.* 2016) which resampled NA values primarily occurring at the edges of landmasses, by replacing the NA with the nearest non-NA value. For the public land fire frequency data, NAs were assigned 0s as the data were restricted to public estates and some of these areas had no fire records for the time period. Data for each environmental predictor were extracted for all presence and background points, and these datasets were then combined into a single dataset (hereafter 'presence-background data').

Model selection

Variable selection

Prior to modelling, we used two methods to examine correlations among predictor variables to eliminate the risk of including highly correlated or non-informative variables. First, we used Spearman's rank correlation coefficient (ρ) to test for highly correlated variables (e.g., Spearman's rank correlation coefficient, $\rho \geq |0.8|$, Duane *et al.* 2015; Valavi *et al.* 2022) using the `ggstatsplot` R package version 0.13.3 (Patil 2021). Second, to eliminate non-informative variables we fit a global linear model and used Akaike Information Criterion (AIC) backward stepwise elimination (e.g., Syphard *et al.* 2008; Elia *et al.* 2020) in the `MASS` R package version 7.3-65 (Venables *et al.* 2002). No variables were above the correlation threshold or uninformative, so all were retained.

Spatial blocking and spatial autocorrelation

Predictive modelling requires independent training and evaluation data (Hastie *et al.* 2009) which, for predicting to new areas can be spatially blocked (see Roberts *et al.* 2017). Spatial blocking reduces the propensity for overfitting due to spatial dependencies between biological processes and biasing of estimates due to spatial autocorrelation (Roberts *et al.* 2017; Hao *et al.* 2020). To determine the distance over which spatial autocorrelation occurred, we fit an initial variogram using the `blockCV` R package version 3.2-0 (Valavi *et al.* 2019) to inform parameter settings (e.g., psill, model, range, and nugget). Subsequent variograms were fit using the `gstat` R package version 2.1-4 (Pebesma 2004; Gräler *et al.* 2016). Variograms were fit iteratively with parameters adjusted until the final outputs were the same as those used for fitting the current variogram. The size of blocks for spatially explicit data was determined by the final range value returned by the variogram. Presence-background data were then split into spatially explicit blocks of 29,109 m, randomly allocating points to five data partitions in a checkerboard pattern with an 80% to 20% training to evaluation split. The allocation of data to these five partitions was performed such that the number of points for a particular fire frequency was balanced across partitions (e.g., for a fire frequency of 2, each of the five training partitions had *ca.* 8000 points while each of the five evaluation partitions had *ca.* 2000 points).

Predictive modelling

We used three different modelling approaches to estimate landscape-scale fire frequency: Boosted Regression Trees (BRT), Generalised Linear Models (GLM), and Generalised Additive Models (GAM). Each of these models differ in their technical and conceptual approach with BRT being less easily interrogated but used commonly in species distribution modelling (Soykan *et al.* 2014; Elith *et al.* 2020) and fire applications (Sachdeva *et al.* 2018; Kalantar *et al.* 2020). Generalised linear models and GAMs are a traditional statistical modelling approach and often perform well in modelling species distributions (e.g., Meynard *et al.* 2007; Murase *et al.* 2009; Valavi *et al.* 2022). Our goal was to compare the three model types to determine which improved accuracy of satellite-derived fire frequency estimates when compared to the more accurately mapped public fire data. In all models, the response variable was satellite-derived fire frequency from Landsat and Sentinel-2. All models were fit with a Poisson distribution; log link function, appropriate for count data; and a random seed set prior to modelling, for reproducibility.

The ratio of presence to background points in our data was small (1:8), resulting in zero-inflation. Thus, following Valavi *et al.* (2022), we compared three weighting approaches for BRT modelling to balance the contribution of background points to model fitting: (1) no weighting; (2) down-weighting backgrounds points (the total summed weight of background points equalled the total weight of presences); and (3) infinitely weighted logistic regression (background points with a very large weight, hereafter 'Infinite BRT'). Based on BRT model performance, we then selected either (2) down-weighting or (3) infinite weighting for GLM and GAM model fitting.

<u>Boosted regression tree modelling</u>

Boosted regression tree hyperparameters were optimised prior to modelling by creating a data frame with all combinations of: number of trees (500, 600, …, 10,000); tree complexity (1, 2, …, 8); number of minimum observations in node (50, 100, or 200); and learning rate (0.1, 0.05, …, 0.0001) (see Elith *et al.* 2008). Using the training subset of presence-background data a BRT model was then trained in the `caret` R package version 7.0-1 (Kuhn 2008) with a 10-partition cross-validation method and grid search pattern. The optimised tree complexity of 8 and learning rate of 0.1 were used in subsequent modelling. Each BRT model was run using the `dismo` R package version 1.3-16 with these parameter settings (Hijmans *et al.* 2024). The relative contribution of each environmental predictor to model fit was calculated internally by BRT and was extracted from the model for comparison between models.

Generalised linear and generalised additive modelling

Generalised linear models and GAMs were used with background point down-weighting applied in the same manner as for BRT. Generalised linear models were run in base R (R Core Team 2023) and GAMs in the `mgcv` R package version 1.9-3 (Wood 2004, 2011, 2017). Generalised additive models fit non-linear relationships by summing smooth functions of each variable, applying marginal basis functions, and controlling the basis dimensions of each variable (Wood 2004, 2011). We used tensor product smooth functions ('te') which apply separate penalties to each variable making them useful for variables in different units (Wood 2006, 2017). We also specified cyclic cubic regression spline ('cc') marginal basis functions for climatic variables to stop the smoother shrinking to zero and random effect ('re') marginal basis functions for BVG to account for the categorical nature of the data (Wood 2017). Generalised additive model smoothness was further controlled by specifying the basis dimension ('*k*') to determine knot spacing (i.e., the amount of 'wiggliness' in the response) (Wood 2017). We adjusted *k* for each variable separately until *k*-index values and expected degrees of freedom were not close together and diagnostic plots showed reasonable fit. The relative influence of each environmental predictor on GLM and GAM models was calculated using `glmm.hp` version 0.1-8 and `gam.hp` version 0.0-3 R packages (Lai *et al.* 2022; Lai *et al.* 2024). These functions calculate individual contributions of each predictor towards marginal R^2 (Lai *et al.* 2022; Lai *et al.* 2024), and we extracted the normalised relative contribution for each variable to model fitting which was comparable to BRT relative influence calculations.

Predicting fire frequency and evaluating model performance

Spatial predictions of fire frequency were produced from each model using the environmental predictors in `terra` (Hijmans 2025). Predictions were extracted for presence and background points to evaluate model performance using commonly used species distribution modelling metrics in the `precrec` R package version 0.14.5 (Saito *et al.* 2016): AUC_{ROC} and AUC_{PRG}. Additional statistics were calculated including mean squared error; average deviance of observed and predicted values using a Poisson distribution through `dismo` (Hijmans *et al.* 2024); and Pearson's coefficient of determination through the `stats` R package (R Core Team 2023).

Model performance was further validated by examining the correlation between public fire frequency data and modelled fire frequency at presence points. We compared these to the correlation between public land fire frequency and unmodelled satellite-derived fire frequency ('observed'). Where the correlation coefficient of the modelled data was greater than that of the observed value (r = 0.331), we considered that model to have improved estimates of fire frequency. We provided AUC values for their familiarity and comparison to other species distribution modelling studies, evaluating AUC following Araújo *et al.* (2005). However, these statistics may not be reliable, especially for presence-background/pseudoabsence models (see, Lobo *et al.* 2008; Jiménez *et al.* 2020). Thus, we also used histograms and maps displaying the density distribution of fire frequencies to visually compare observed and modelled fire frequencies.

Finally, we compared fire frequencies from public data, unmodelled satellite data, and modelled predictions for each BVG. Broad vegetation groups followed those recognised in southeast Queensland's fire regime group classification system (Department of the Environment 2012; Queensland Herbarium 2024), based on Queensland's BVG (Neldner *et al.* 2019). These can be grouped broadly as fire-prone vegetation: open forests and woodlands; *Melaleuca* communities; heath communities; grasslands; and coastal fringing forests and headlands, and fire-sensitive vegetation: rainforests, dry vine forests and brigalow communities; wet tall open forests; mangroves and saltmarsh; and riparian, foredune, coral cay island and beach ridge communities. For each aggregation, 1,000 random points were produced and public land fire frequency, modelled and unmodelled satellite-derived fire frequency data were extracted. Using the ecologically informed fire regime management guidelines (Department of the Environment 2012; Queensland Herbarium 2024), we calculated the minimum and maximum fire frequency recommendation over a 36-year period. This was then used to determine the ecological validity of our fire frequency estimates, classifying whether fire frequencies were within, higher, or lower than recommended ranges and how these compared across observed and modelled fire frequencies.

Results

Our results showed that the accuracy of satellite-derived fire frequency estimates can be improved by modelling its relationship with public land fire and environmental data.

Correlation between modelled satellite-derived fire frequencies and unmodelled public land fire frequency ranged from -0.084 to 0.576 (Table 2). From 1987-2023, fire frequency for unmodelled satellite data ranged from 0 to 29 fires, while on public land it ranged from 0 to 12 fires. Across model types, the maximum predicted fire frequency varied: GLM = 29; GAM = 40; down-weighted BRT = 130; unweighted BRT = 115; and Infinite BRT = 9. Over-estimation of fire frequencies (i.e., >30 fires in the past 36 years) was limited to less than 1% of the landscape. All models showed similar performance in terms of AUC_{ROC} and AUC_{PRG} (AUC_{ROC} = 0.707 to 0.776; AUC_{PRG} = 0.705 to 0.796), but GLM and GAM estimates resulted in the largest increases in correlation relative to the observed values (r = 0.577 and 0.523, respectively, Table 2). The down-weighted and unweighted BRT only weakly increased correlations compared to the observed value (r = 0.437 and 0. 375, respectively, Table 2). The Infinite BRT had the lowest correlation (r = -0.084; Table 2).

The relative contribution of environmental variables to estimates of fire frequency varied among model types, with foliage projective cover having the highest relative contribution to fitting of all models (Fig. 3). Public land fire frequency was the second-highest contributor for down-weighted and third-highest contributor for unweighted BRT, but did not contribute to Infinite BRT model fitting (Fig. 3). For the generalised linear model, and to a lesser extent the generalised additive model, foliage projective cover and public land fire frequency were the main contributors, capturing almost all variability.

Compared with public land fire data, observed satellite-derived fire data underestimated areas that burned infrequently (i.e., 1-6 fires) but estimated more areas to have burned frequently (≥7 fires) than public land fire data (Fig. 4a). Predictions from the GLM resulted in a large decrease in areas classified as unburnt which substantially improved classification of areas burnt 1-2 times (Fig. 4b). Predictions from the GAM also significantly reduced areas classified as unburnt, but not to the same extent as the GLM (Fig. 4b, c). The GLM and GAM both underestimated fire frequencies >2 but the GLM was more likely to capture higher fire frequencies (Fig 4b, c). Predictions from down-weighted and unweighted BRT were similar to the GLM and GAM, generally underestimating most common fire frequencies (i.e., 1-5 fires) but did not reduce areas classified as unburnt to the same extent (Fig. 4d-f). The Infinite BRT resulted in the most severe underprediction (Fig. 4f). Predictions from all models generally improved estimates of landscape-scale fire frequency with more areas mapped as having burnt at least once (Fig. 5). However, the GLM was slightly better at representing the spatial extent of higher fire frequencies than other models (Fig. 5c-g). Predictions from BRT resulted in larger areas remaining as unburnt, including areas mapped burnt for public land fire data (e.g., southeast Queensland's offshore islands) (Fig. 5 b, e-g).

The distribution of fire frequencies in vegetation aggregations was highly variable (Fig. 6). For fire-prone sclerophyllous vegetation (Fig. 6a-e), most cells were predicted to have a fire frequency that was within or lower than ecological recommendations. Open forests and woodlands were within or lower than recommendations, with GLM and GAM predicting most cells to have burnt once or twice (Fig. 6a). Less than 1% of cells for open forests and woodlands were burnt at frequencies higher than recommended, and this was not well captured by GLM or GAM predictions (Fig. 6a). For *Melaleuca* and heath communities, the GLM better captured the range of fire frequencies than the GAM, and most cells were predicted to have burnt at frequencies lower than recommended (Fig. 6b, c). For *Melaleuca* and heath communities that were burnt more frequently than recommended, the GLM better captured these fire frequencies than the GAM (Fig. 6b, c). For grasslands, the GLM predicted most cells to have fire frequencies higher than ecologically recommended, but these were limited to less than 1% of cells (Fig. 6d). The GLM best captured the prevalence of cells burnt below recommendations for grasslands and the range of fire frequencies for cells burnt within recommendations (Fig. 6d). For coastal forests and headlands, most cells were predicted to have burnt less frequently than recommended, and this was similar to the observed data (Fig. 6e). For these communities, the GLM best captured cells burnt within and lower than recommendations and the maximum fire frequency for cells burnt higher than recommended (Fig. 6e).

For fire-sensitive vegetation (Fig. 6f-i), GLM and GAM predictions resulted in a large reduction of cells classified as unburnt by observed fire frequencies, but underestimated cells burnt at higher fire frequencies. For mangroves and saltmarsh vegetation and riparian, foredune and beach ridges vegetation aggregations, most cells were classified to have burnt once or twice, with the GLM better capturing the range of fire frequencies than the GAM (Fig. 6f, h). For rainforests, vine forests and brigalow and wet tall open forest vegetation aggregations, most cells were predicted to have burnt once (Fig. 6 g, i). However, the range of fire frequencies was better captured by the GAM for rainforest and the GLM for wet tall open forests (Fig. 6g, i). Thus, the GLM predictions generally produced more useful estimates of fire frequency in both fire-prone and fire-sensitive vegetation aggregations (Fig. 6).

Discussion

Accurate fire history data are generally unavailable for areas outside of public land, and some regions rely solely on less accurate satellite data to capture fire histories (Galizia *et al.* 2021; Ruscalleda-Alvarez *et al.* 2021; Khairoun *et al.* 2024). Our study showed that unmodelled estimates from satellite data underestimated fire frequency compared to public land data, especially in infrequently burnt areas (i.e., 1-6 fires). This is important because satellite-derived fire mapping is widely used in fire science (e.g., Ruscalleda-Alvarez *et al.* 2021; De Luca *et al.* 2022; Miranda *et al.* 2022) and researchers often assume it is accurate. Here, we improved the accuracy of fire frequency estimates derived from satellite imagery by modelling its relationship with public land fire and environmental data. The famous aphorism attributed to George Box – '*all models are wrong, but some are useful*' – is a useful mindset for interpreting the relevance of these models. The GLM and GAM tended to underestimate fire frequency in areas burnt more than twice (i.e., they were 'wrong'), but they were 'useful' in identifying areas likely to have burned once or twice, which had been undetected by satellite imagery. Therefore, the models enabled us to more accurately understand landscape scale fire frequency in the past 36 years (i.e., 1987 – 2023). The GLM and GAM improved estimates of landscape scale fire frequency, with correlation increases of 0.25 and 0.20, respectively. While all models performed similarly, models with a greater contribution from public land fire frequency to model fitting also showed greater correlation improvements (GAM and GLM), likely due to improved modelling of relationships between environmental attributes and known fire occurrences. Conversely, BRTs had variable predictive capacity across fire frequencies possibly due to lower contribution of public land fire frequency to model fitting and did not significantly reduce areas mapped as unburnt. Thus, the GLM and GAM were more accurate than BRTs and were especially useful at mapping fire in areas otherwise mapped as unburnt by satellite-derived fire data.

Modelled fire frequencies from the GLM and GAM were generally similar to observed public land data and unmodelled satellite-derived fire frequencies for fire-prone sclerophyllous vegetation aggregations (Neldner *et al.* 2019). In sclerophyllous vegetation, we expect high fire frequencies (i.e., ≥5 fires over 36 years) as this vegetation accumulates fuel load quickly (Cochrane 1968; Gilroy *et al.* 2009; Gould *et al.* 2011; Benwell 2024). Re-classification of unburnt areas as burnt once or twice in these aggregations might be accurate as cells burnt at these fire frequencies were within or lower than ecologically informed fire regime recommendations (Department of Environment and Science 2022b). Thus, the GLM would be an effective model type for predicting fire frequency in sclerophyll vegetation aggregations as it better captures the wider gradient of fire frequencies than the GAM. In grasslands, the GLM predicted high fire frequencies (12 – 20 fires) for some cells which exceeded ecological recommendations, but grasslands typically have high fire frequencies (Archibald *et al.* 2013; Cruz *et al.* 2022; Simpson *et al.* 2022; Yates *et al.* 2023). Furthermore, invasion by high biomass grasses result in increased fire frequencies (Miller *et al.* 2010; Setterfield *et al.* 2013; van Klinken *et al.* 2018; Simpson *et al.* 2022). Although this might have contributed to higher than recommended fire frequencies, more research is needed to confirm this.

The ecological fire regime recommendations for fire-sensitive vegetation aggregations is ‘do not intentionally burn’, ‘no fire’ or ‘as required’ (Department of Environment and Science 2022b). However, the unmodelled satellite-derived and public land fire data suggest several areas of these vegetation types have burnt at least once over the past 36 years. The GLM and GAM predictions captured this prevalence of fire-sensitive vegetation to have burnt at least once but also resulted in large reductions of unburnt cells. This reduction was not substantial for mangrove or riparian vegetation when compared to unmodelled satellite-derived estimates, likely due to low overstorey vegetation which would otherwise limit capture of understorey vegetation by satellite imagery. For rainforest and wet tall open forest vegetation, the GLM and GAM predicted few cells classified to have burnt more than twice in 36 years, which did not accurately reflect observed public land or unmodelled satellite-derived estimates. However, these vegetation aggregations are not highly flammable and typically burn infrequently (as little as once in 100 years) (Campbell *et al.* 2006; Cawson *et al.* 2018; Thorley *et al.* 2023; Benwell 2024). Thus, the GLM would be an appropriate model type for predicting fire frequency in fire-sensitive vegetation as it generally did not result in predictions of extremely high fire frequencies like the GAM for non-flammable vegetation.

In Australia, rainforest is typically found within gullies surrounded by more flammable sclerophyllous vegetation with wet tall open forests forming a boundary between rainforest and open forests and woodlands (Neldner *et al.* 2019; Fensham *et al.* 2024; Thomsen *et al.* 2025). In southeast Queensland, public land fire history data showed that more than 60% of rainforest patches had been affected by wildfire in the past 36 years, potentially linked to suboptimal open forest and woodland vegetation fire regimes (Queensland Parks and Wildlife Service 2023; Thorley *et al.* 2023). Our results showed 55% of open forest and woodlands had burnt at fire frequencies lower than ecologically recommended from modelled and unmodelled estimates (Queensland Herbarium 2024). A large number of cells for wet tall open forests and rainforests were classified as having burnt at least once from 1987 to 2023 for both modelled and unmodelled fire frequency estimates. Low fire frequencies, coupled with highly flammable fuel (Cawson *et al.* 2018; Benwell 2024) and drought, can result in high intensity fires in sclerophyll vegetation which can penetrate rainforest margins (Collins *et al.* 2021; Laidlaw *et al.* 2022; Thorley *et al.* 2023; Bird *et al.* 2025). Increased fire in rainforest margins reduces the cover of fire-retardant rainforest species and facilitates encroachment of flammable species, potentially resulting in fire regime and vegetation community changes (Cochrane *et al.* 2008; Fletcher *et al.* 2020; Thorley *et al.* 2023; Fensham *et al.* 2024). Another reason for higher-than-expected fire frequencies may be driven by training of our model within public estate land and projecting predictions outside of public estates where vegetation, by its nature, is necessarily different. For tens of thousands of years, Indigenous people managed vegetation across Australia using fire, but European colonisation supressed this practice, leading to fuel build up and vegetation changes (e.g., vegetation thickening) (Moss *et al.* 2015; Mackenzie *et al.* 2020; Stewart *et al.* 2020; Hoffman *et al.* 2021; Greenwood *et al.* 2022; Mariani *et al.* 2022; Hanson *et al.* 2023). Further climate-change driven fire regime shifts are expected to intensify during the 21st century (Moritz *et al.* 2012; Di Virgilio *et al.* 2019; Dowdy *et al.* 2019; Canadell *et al.* 2021), which may contribute to further vegetation shifts and threats to fire sensitive species (Walsh *et al.* 2013; Dudley *et al.* 2019; Lavery *et al.* 2021; Thomsen *et al.* 2025). Thus, improving landscape-scale historical fire information could assist conservation and mitigation actions, and our workflow contributes towards that goal.

Our analysis necessarily focussed on biophysical drivers which represent proximate mechanisms driving fire trends (Cary *et al.* 2006; Bradstock 2010; Duane *et al.* 2015). Social drivers might be ultimate causes, and are likely correlated with biophysical drivers (Gibbons *et al.* 2012; Penman *et al.* 2014; Parisien *et al.* 2016; Chuvieco *et al.* 2021; Jones *et al.* 2022). Including correlated social drivers might have reduced the accuracy of model estimates, so we did not attempt that here. It would also add intangible complexity arising from different fire management strategies across land tenures, temporally variable fire management attitudes, and arson which, in some instances, may not be easily associated with human settlements (Chuvieco *et al.* 2010; Parisien *et al.* 2016; Chuvieco *et al.* 2021; Jones *et al.* 2022). In other fire-prone regions such as Spain, ignitions in the past 50 years have been strongly associated with human activity, compared with non-human sources, although human ignitions have declined more recently due to fire prevention and suppression policies

(Rodrigues *et al.* 2016). In our analysis, urbanisation is likely to have been at least partially captured by FPC as urban areas typically have lower woody vegetation cover (Rayner *et al.* 2025). Future studies could incorporate social variables in a similar modelling workflow to the one presented here.

Our workflow can be used to improve predictions of landscape-scale fire frequency from those derived from satellite data and assess whether fire regimes fall within the range of ecological recommendations (Department of Environment and Science 2022b). Researchers can tailor the modelling workflow to the spatial extent and temporal period of interest and select the model type providing the most accurate estimation for the context and vegetation type. Where researchers have access to more accurate fire history data than satellite-derived estimates, this should be used as a priority. Our workflow can be used for instances where fire history data from on ground surveying or satellite-derived imagery is incomplete or shows discrepancies in fire history for parts of the land. Where researchers are interested in understanding simply whether the land has burnt recently or not, a GLM or GAM could be used as results from these models were similar. Where researchers want to better characterise high fire frequencies (e.g., more than 4 fires), the GLM would be appropriate for all vegetation types. While the GLM might underestimate higher fire frequencies in fire-sensitive vegetation, occurrences of higher fire frequencies were rare and generally not captured by the GAM. In future, the accuracy of our models could be improved by incorporating data more directly related to fire occurrences such as lightning strikes (Song *et al.* 2024) and/or spatial occurrence records of fire ephemeral plant species (Baker *et al.* 2005). Such data could more clearly indicate fire occurrences and their relationship with environmental attributes. Our predictive modelling workflow could aid fire management and conservation practices by improving the accuracy of estimates of fire frequency from those derived from satellite data.

Data availability

A preprint version of this article is available on EcoEvoRxiv at https://doi.org/10.32942/X24331. Data and code are available as an archived Zenodo repository (Charles *et al.* 2026): https://doi.org/10.5281/zenodo.18226822.

Acknowledgements

Valuable feedback from Mark Ooi, Sabine Kasel, four anonymous reviews and the editor improved the manuscript. Infrastructure from the University of Queensland's Research Computing Centre High Performance Computing facilities supported this research. Andrew Meiklejohn contributed advice in the early development of this project. Christina Buelow assisted with initial fire frequency mapping and spatial data processing in R.

Conflict of interest statement

The authors declare no conflicts of interest.

Declaration of Funding

This research was supported by a University of Queensland Research Training Program (RTP) Scholarship.

References

Alberti G (2023) landform: topographic position index-based landform classification. R package version 0.2. (The Comprehensive R Archive Network: Vienna, Austria) Available at https://CRAN.R-project.org/package=landform [Verified 1 August 2023]

Andela N, Morton DC, Giglio L, Paugam R, Chen Y, Hantson S, van der Werf GR, Randerson JT (2019) The Global Fire Atlas of individual fire size, duration, speed and direction. *Earth System Science Data* **11**(2), 529-552. doi:https://doi.org/10.5194/essd-11-529-2019

Araújo MB, Pearson RG, Thuiller W, Erhard M (2005) Validation of species–climate impact models under climate change. *Global Change Biology* **11**(9), 1504-1513. doi:https://doi.org/10.1111/j.1365-2486.2005.01000.x

Archibald S, Lehmann CER, Gomez-Dans JL, Bradstock RA (2013) Defining pyromes and global syndromes of fire regimes. *Proceedings of the National Acadamey of Science* **110**(16), 6442-6447. doi:10.1073/pnas.1211466110

Aslan C, Tarver R, Brunson M, Veloz S, Sikes B, Epanchin-Niell R (2024) Experiences with wildfire are associated with private landowners' management decisions, relationships, and perceptions of risk. *Landscape and Urban Planning* **247**, 105067. doi:https://doi.org/10.1016/j.landurbplan.2024.105067

Atkinson PM, Tate NJ (2000) Spatial scale problems and geostatistical solutions: a review. *The Professional Geographer* **52**(4), 607-623. doi:https://doi.org/10.1111/0033-0124.00250

Australian Bureau of Meteorology (2024a) Average annual, seasonal and monthly rainfall maps - Queensland (Dataset). (Australian Bureau of Meterology Australian Bureau of Meterology: Australia). Available at http://www.bom.gov.au/climate/maps/averages/rainfall/?period=an&region=qd [Verified 6 January 2025]

Australian Bureau of Meteorology (2024b) Average monthly and annual temperature maps - Queensland (Dataset). (Australian Bureau of Meterology Australian Bureau of Meterology: Australia). Available at http://www.bom.gov.au/climate/maps/averages/temperature/?maptype=mxt&period=win&region=qd [Verified 6 January 2025]

Bachman SP, Brown MJM, Leão TCC, Nic Lughadha E, Walker BE (2024) Extinction risk predictions for the world's flowering plants to support their conservation. *New Phytologist* **242**(2), 797-808. doi:https://doi.org/10.1111/nph.19592

Baker KS, Steadman KJ, Plummer JA, Merritt DJ, Dixon KW (2005) Dormancy release in Australian fire ephemeral seeds during burial increases germination response to smoke water or heat. *Seed Science Research* **15**(4), 339-348. doi:https://doi.org/10.1079/SSR2005222

Barbet-Massin M, Jiguet F, Albert CH, Thuiller W (2012) Selecting pseudo-absences for species distribution models: how, where and how many? *Methods in Ecology and Evolution* **3**(2), 327-338. doi:https://doi.org/10.1111/j.2041-210X.2011.00172.x

Benwell A (2024) Fire responses of flora in a sclerophyll–rainforest vegetation complex in the Nightcap Range, north coast, New South Wales. *Australian Journal of Botany* **72**(1), BT23049. doi:https://doi.org/10.1071/BT23049

Bird RB, Bird DW, Codding BF (2016) People, El Niño southern oscillation and fire in Australia: fire regimes and climate controls in hummock grasslands. *Philosophical Transactions of the Royal Society B: Biological Sciences* **371**(1696), 20150343. doi:https://doi.org/10.1098/rstb.2015.0343

Bird RR, Zsoldos RR, Jimenez Sandoval MV, Watson SJ, Smith AL (2025) Wildfire in rainforest margins is associated with variation in mammal diversity and habitat use. *Wildlife Research* **52**(2), WR24103. doi:https://doi.org/10.1071/WR24103

Bistinas I, Harrison SP, Prentice IC, Pereira JMC (2014) Causal relationships versus emergent patterns in the global controls of fire frequency. *Biogeosciences* **11**(18), 5087-5101. doi:https://doi.org/10.5194/bg-11-5087-2014

Bradstock RA (2010) A biogeographic model of fire regimes in Australia: current and future implications. *Global Ecology and Biogeography* **19**(2), 145-158. doi:https://doi.org/10.1111/j.1466-8238.2009.00512.x

Broussin J, Mouchet M, Goberville E (2024) Generating pseudo-absences in the ecological space improves the biological relevance of response curves in species distribution models. *Ecological Modelling* **498**, 110865. doi:https://doi.org/10.1016/j.ecolmodel.2024.110865

Campbell ML, Clarke PJ (2006) Response of montane wet sclerophyll forest understorey species to fire: evidence from high and low intensity fires. *Proceedings of the Linnean Society of New South Wales* **127**(1), 63-73. [In English]

Canadell JG, Meyer CP, Cook GD, Dowdy A, Briggs PR, Knauer J, Pepler A, Haverd V (2021) Multi-decadal increase of forest burned area in Australia is linked to climate change. *Nat Commun* **12**(1), 6921. doi:https://doi.org/10.1038/s41467-021-27225-4

Cary GJ, Keane RE, Gardner RH, Lavorel S, Flannigan MD, Davies ID, Li C, Lenihan JM, Rupp TS, Mouillot F (2006) Comparison of the sensitivity of landscape-fire-succession models to variation in terrain, fuel pattern, climate and weather. *Landscape Ecology* **21**(1), 121-137. doi:https://doi.org/10.1007/s10980-005-7302-9

Castellnou M, Guiomar N, Rego F, Fernandes P (2018) Fire growth patterns in the 2017 mega fire episode of october 15, central Portugal. In 'Advances in Forest Fire Research'. (Ed. DX Viegas) pp. 447-453. (University of Coimbra: Coimbra, Portugal) https://doi.org/10.14195/978-989-26-16-506_48

Cawson JG, Duff TJ, Swan MH, Penman TD (2018) Wildfire in wet sclerophyll forests: the interplay between disturbances and fuel dynamics. *Ecosphere* **9**(5), e02211. doi:https://doi.org/10.1002/ecs2.2211

Charles FE, Reside AR, Smith AL (2025) The influence of changing fire regimes on specialised plant-animal interactions. *Philosophical Transactions of the Royal Society B-Biological Sciences*. doi:https://doi.org/10.1098.rstb.2023.0448

Charles FE, Smith AL (2026) Data and code: Integrating public land and satellite imagery improves fire frequency estimates across the landscape (version 0.3 peer review pre-release) (Dataset). (FE Charles Zenodo: Brisbane, Queensland, Australia). Available at https://doi.org/10.5281/zenodo.15133643 [Verified 4 April 2025]

Cheng Z, Aakala T, Larjavaara M (2023) Elevation, aspect, and slope influence woody vegetation structure and composition but not species richness in a human-influenced landscape in northwestern Yunnan, China. *Frontiers in Forests and Global Change* **6**. [In English] doi:https://doi.org/10.3389/ffgc.2023.1187724

Chuvieco E, Justice C (2010) Relations between human factors and global fire activity. In 'Advances in Earth Observation of Global Change'. (Eds E Chuvieco, J Li, X Yang) pp. 187-199. (Springer: Dordrecht, Netherlands) https://doi.org/10.1007/978-90-481-9085-0_14

Chuvieco E, Pettinari ML, Koutsias N, Forkel M, Hantson S, Turco M (2021) Human and climate drivers of global biomass burning variability. *Science of The Total Environment* **779**, 146361. doi:https://doi.org/10.1016/j.scitotenv.2021.146361

Clarke H, Gibson R, Cirulis B, Bradstock RA, Penman TD (2019) Developing and testing models of the drivers of anthropogenic and lightning-caused wildfire ignitions in south-eastern Australia. *Journal of Environmental Management* **235**, 34-41. doi:https://doi.org/10.1016/j.jenvman.2019.01.055

Cochrane GR Fire ecology in southeastern Australian sclerophyll forests. Proceedings of Proceedings of Annual (8th) Tall Timbers Fire Ecology Conference, 1968, Tallahassee, Florida, United States of America. (Ed. EV Komarek) pp. 15-40. (Tall Timbers Research, Inc.) Available at https://talltimbers.org/wp-content/uploads/2014/03/Cochrane1968_op.pdf

Cochrane MA, Laurance WF (2008) Synergisms among fire, land use, and climate change in the Amazon. *Ambio* **37**(7-8), 522-527. [In eng] doi:https://doi.org/10.1579/0044-7447-37.7.522

Coen JL, Stavros EN, Fites-Kaufman JA (2018) Deconstructing the King megafire. *Ecological Applications* **28**(6), 1565-1580. doi:https://doi.org/10.1002/eap.1752

Collett L (2021) Annual Fire Scars - Landsat, QLD DES algorithm, QLD coverage (Dataset). (Terrestrial Ecosystem Research Network (TERN) TERN: Brisbane, Queensland, Australia). Available at http://geonetwork.tern.org.au/geonetwork/srv/eng/catalog.search#/metadata/461074b3-5272-4e4e-886f-df26bd2426ad, https://portal.tern.org.au/annual-scars-landsat-qld-coverage [Verified 2021-12-01]

Collins L, Bradstock RA, Clarke H, Clarke MF, Nolan RH, Penman TD (2021) The 2019/2020 mega-fires exposed Australian ecosystems to an unprecedented extent of high-severity fire. *Environmental Research Letters* **16**(4), 044029. doi:https://doi.org/10.1088/1748-9326/abeb9e

Collins L, Griffioen P, Newell G, Mellor A (2018) The utility of random forests for wildfire severity mapping. *Remote Sensing of Environment* **216**, 374-384. doi:https://doi.org/10.1016/j.rse.2018.07.005

Collins L, McCarthy G, Mellor A, Newell G, Smith L (2020) Training data requirements for fire severity mapping using landsat imagery and random forest. *Remote Sensing of Environment* **245**, 111839. doi:https://doi.org/10.1016/j.rse.2020.111839

Conedera M, Tinner W, Neff C, Meurer M, Dickens AF, Krebs P (2009) Reconstructing past fire regimes: methods, applications, and relevance to fire management and conservation. *Quaternary Science Reviews* **28**(5), 555-576. doi:https://doi.org/10.1016/j.quascirev.2008.11.005

Corlett RT (2016) Plant diversity in a changing world: status, trends, and conservation needs. *Plant Diversity* **38**(1), 10-16. doi:https://doi.org/10.1016/j.pld.2016.01.001

Cruz MG, Alexander ME, Kilinc M (2022) Wildfire rates of spread in grasslands under critical burning conditions. *Fire* **5**(2), 55. doi:https://doi.org/10.3390/fire5020055

CSIRO (2024) Soils and Landscape Grid of Australia – the modelled-value for clay (%) (Dataset). (CSIRO TERN Landscapes: Australia). Available at https://esoil.io/TERNLandscapes/Public/Pages/SLGA/GetData-COGSDataStore_SLGA.html [Verified 12 April 2024]

D'Angelo G, Guimond S, Reisner J, Peterson DA, Dubey M (2022) Contrasting stratospheric smoke mass and lifetime from 2017 Canadian and 2019/2020 Australian megafires: global simulations and satellite observations. *Journal of Geophysical Research: Atmospheres* **127**(10), e2021JD036249. doi:https://doi.org/10.1029/2021JD036249

D'Este M, Ganga A, Elia M, Lovreglio R, Giannico V, Spano G, Colangelo G, Lafortezza R, Sanesi G (2020) Modeling fire ignition probability and frequency using Hurdle models: a cross-regional study in southern Europe. *Ecological Processes* **9**(1), 54. doi:https://doi.org/10.1186/s13717-020-00263-4

De Luca G, Silva JMN, Modica G (2022) Regional-scale burned area mapping in Mediterranean regions based on the multitemporal composite integration of Sentinel-1 and Sentinel-2 data. *GIScience & Remote Sensing* **59**(1), 1678-1705. doi:https://doi.org/10.1080/15481603.2022.2128251

Debuse VJ, Lewis T (2014) Long-term repeated burning reduces Lantana camara regeneration in a dry eucalypt forest. *Biological Invasions* **16**(12), 2697-2711. doi:https://doi.org/10.1007/s10530-014-0697-y

Del-Toro-Guerrero FJ, Kretzschmar T, Bullock SH (2019) Precipitation and topography modulate vegetation greenness in the mountains of Baja California, México. *International*

Journal of Biometeorology **63**(10), 1425-1435. [In eng] doi:https://doi.org/10.1007/s00484-019-01763-5

Department of Agriculture, Fisheries and Forestry (2024) Land use of Australia 2020-2021 (Dataset). (A Government Department of Agriculture, Fisheries and Forestry: Australia). Available at https://www.agriculture.gov.au/abares/aclump/land-use/land-use-of-australia-2010-11-to-2020-21#downloads [Verified 23 October 2025]

Department of Climate Change, Energy, the Environment, and Water (2024) Australia - present major vegeation groups and subgroups - NVIS version 7.0 (Dataset). (Department of Climate Change, Energy, the Environment, and Water Australian Government: Canberra, ACT, Australia). Available at https://fed.dcceew.gov.au/datasets/5e70b5afc36a4c458a2cceb313eb3889/about [Verified

Department of Environment, Science and Innovation (2024a) Remnant 2021 broad vegetation groups - Queensland (Dataset). (Q Government Queensland Spatial Catalogue: Brisbane, Queensland, Australia). Available at https://qldspatial.information.qld.gov.au [Verified 8 January 2025]

Department of Environment, Science, and Innovation (2020a) Annual report 2019-2020, pp. 26. (Department of Environment and Science: Brisbane, Queensland, Australia) Available at https://www.parliament.qld.gov.au/Work-of-the-Assembly/Tabled-Papers/docs/5620T1773/5620t1773.pdf

Department of Environment, Tourism, Science and Innovation (2020b) Landsat foliage projective cover - Queensland 2014 (Dataset). (Queensland Department of Environment, Tourism, Science and Innovation Queensland Spatial Catalogue: Brisbane, Queensland, Australia). Available at https://www.data.qld.gov.au/dataset/landsat-foliage-projective-cover-queensland-2014 [Verified 6 April 2023]

Department of Environment, Tourism, Science and Innovation (2020c) Wooded extent and foliage projective cover - Queensland 2012 (Dataset). (Queensland Department of Environment, Tourism, Science and Innovation Queensland Spatial Catalogue: Brisbane, Queensland, Australia). Available at https://www.data.qld.gov.au/dataset/wooded-extent-and-foliage-projective-cover-queensland-2012/resource/3b28cb6d-85a3-4c83-a7bd-82bfa9b36c93 [Verified 20 August 2025]

Department of Environment, Tourism, Science and Innovation (2020d) Wooded extent and foliage projective cover - Queensland 2013 (Dataset). (Queensland Department of Environment, Tourism, Science and Innovation Queensland Spatial Catalogue: Brisbane, Queensland, Australia). Available at https://www.data.qld.gov.au/dataset/wooded-extent-and-foliage-projective-cover-queensland-2013 [Verified 20 August 2025]

Department of Environment, Tourism, Science and Innovation (2022) Statewide Landcover and Trees Study (SLATS) Sentinel - 2 - 2018 Foliage Projective Cover (FPC) Queensland (Dataset). (Queensland Department of Environment, Tourism, Science and Innovation Queensland Spatial Catalogue: Brisbane, Queensland, Australia). Available at https://www.data.qld.gov.au/dataset/statewide-landcover-and-trees-study-slats-sentinel-2-2018-foliage-projective-cover-fpc-queensland [Verified 17 April 2024]

Department of Environment, Tourism, Science and Innovation (2024b) Statewide Landcover and Trees Study (SLATS) Sentinel - 2 Foliage Projective Cover (FPC) Queensland (Dataset). (Queensland Department of Environment, Tourism, Science and Innovation Queensland Spatial Catalogue: Brisbane, Queensland, Australia). Available at https://www.data.qld.gov.au/dataset/statewide-landcover-and-trees-study-queensland-sentinel-2-series [Verified 16 April 2024]

Department of Environment, Tourism, Science and Innovation (2025a) Statewide Landcover and Trees Study (SLATS) Sentinel - 2 - 2022 Foliage Projective Cover (FPC) Queensland - Whole of state (Dataset). (Queensland Department of Environment, Tourism, Science and Innovation Queensland Spatial Catalogue: Brisbane, Queensland, Australia). Available at https://www.data.qld.gov.au/dataset/statewide-landcover-and-trees-study-queensland-sentinel-2-series/resource/e1d7f5b4-4a39-4931-be91-a8fa3e52c1e7 [Verified 16 April 2024]

Department of Environment, Tourism, Science and Innovation (2025b) Statewide Landcover and Trees Study (SLATS) Sentinel - 2 - 2023 Foliage Projective Cover (FPC) Queensland - Whole of state (Dataset). (Queensland Department of Environment, Tourism, Science and Innovation Queensland Spatial Catalogue: Brisbane, Queensland, Australia). Available at http://qldspatial.information.qld.gov.au/catalogue/custom/search.page?q=%22Statewide Landcover And Trees Study (SLATS) Sentinel-2 - 2023 woody vegetation extent - Queensland - Whole of state%22 [Verified 16 April 2024]

Department of Environment and Science (2021) Annual report 2020-2021, pp. 23. (Department of Environment and Science: Brisbane, Queensland, Australia) Available at https://www.parliament.qld.gov.au/Work-of-the-Assembly/Tabled-Papers/docs/5721T1534/5721t1534.pdf

Department of Environment and Science (2022a) Annual report 2021-2022, pp. 13. (Department of Environment and Science: Brisbane, Queensland, Australia) Available at https://www.des.qld.gov.au/__data/assets/pdf_file/0027/287163/annual-report-2021-22.pdf

Department of Environment and Science (2022b) Queensland Parks and Wildlife Service planned burn guidelines: southeast Queensland bioregion of Queensland. (Department of Environment and Science, Queensland Government: Queensland, Australia) Available at https://parks.des.qld.gov.au/__data/assets/pdf_file/0030/305688/Bp2005-SEQ-planned-burn-guidelines.pdf

Department of Environment and Science (2023) Annual report 2022-2023, pp. 17. (Department of Environment and Science: Brisbane, Queensland, Australia) Available at https://www.detsi.qld.gov.au/__data/assets/pdf_file/0013/324040/annual-report-2022-2023.pdf

Department of the Environment, Tourism, Science and Innovation (2012) Fire regime groups - southeast Queensland (Dataset). (Queensland Department of Environment, Science, and Innovation Queensland Spatial Catalogue: Brisbane, Queensland, Australia). Available at https://qldspatial.information.qld.gov.au/ [Verified 20th November 2025]

Di Virgilio G, Evans JP, Blake SAP, Armstrong M, Dowdy AJ, Sharples J, McRae R (2019) Climate change increases the potential for extreme wildfires. *Geophysical Research Letters* **46**(14), 8517-8526. doi:https://doi.org/10.1029/2019GL083699

Dickman CR (2021) Ecological consequences of Australia's "Black Summer" bushfires: managing for recovery. *Integrated Environmental Assessment and Management* **17**(6), 1162-1167. doi:https://doi.org/10.1002/ieam.4496

Dooley M, Lewis T, Schmidt S (2023) Fire frequency has a contrasting effect on vegetation and topsoil in subcoastal heathland, woodland and forest ecosystems, south-east Queensland, Australia. *Austral Ecology* **48**(8), 1865-1887. doi:https://doi.org/10.1111/aec.13427

Dowdy AJ, Ye H, Pepler A, Thatcher M, Osbrough SL, Evans JP, Di Virgilio G, McCarthy N (2019) Future changes in extreme weather and pyroconvection risk factors for Australian wildfires. *Scientific Reports* **9**(1), 10073-10011. doi:https://doi.org/10.1038/s41598-019-46362-x

Duane A, Moghli A, Coll L, Vega C (2025) On the evidence of contextually large fires in Europe based on return period functions. *Applied Geography* **176**, 103539. doi:https://doi.org/10.1016/j.apgeog.2025.103539

Duane A, Piqué M, Castellnou M, Brotons L (2015) Predictive modelling of fire occurrences from different fire spread patterns in Mediterranean landscapes. *International Journal of Wildland Fire* **24**(3), 407-418. doi:https://doi.org/10.1071/WF14040

Dudley A, Butt N, Auld TD, Gallagher RV (2019) Using traits to assess threatened plant species response to climate change. *Biodiversity and Conservation* **28**(7), 1905-1919. doi:https://doi.org/10.1007/s10531-019-01769-w

Duff TJ, Cawson JG, Penman TD (2019) Determining burnability: predicting completion rates and coverage of prescribed burns for fuel management. *Forest Ecology and Management* **433**, 431-440. doi:https://doi.org/10.1016/j.foreco.2018.11.009

Edwards A, Gill N (2016) Living with landscape fire: landholder understandings of agency, scale and control within fiery entanglements. *Environment and Planning D: Society and Space* **34**(6), 1080-1097. doi:https://doi.org/10.1177/0263775816645588

Ekström M, Grose MR, Whetton PH (2015) An appraisal of downscaling methods used in climate change research. *WIREs Climate Change* **6**(3), 301-319. doi:https://doi.org/10.1002/wcc.339

Elia M, Giannico V, Spano G, Lafortezza R, Sanesi G (2020) Likelihood and frequency of recurrent fire ignitions in highly urbanised Mediterranean landscapes. *International Journal of Wildland Fire* **29**(2), 120-131. doi:https://doi.org/10.1071/WF19070

Eliott M, Lewis T, Venn T, Srivastava SK (2020) Planned and unplanned fire regimes on public land in south-east Queensland. *International Journal of Wildland Fire* **29**(5), 326-338. doi:https://doi.org/10.1071/WF18213

Elith J, Graham C, Valavi R, Abegg M, Bruce C, Ferrier S, Ford A, Guisan A, Hijmans RJ, Huettmann F*, et al.* (2020) Presence-only and presence-absence data for comparing species distribution modeling methods. *Biodiversity Informatics* **15**(2), 69-80. [In English] doi:https://doi.org/10.17161/bi.v15i2.13384

Elith J, Leathwick JR, Hastie T (2008) A working guide to boosted regression trees. *Journal of Animal Ecology* **77**(4), 802-813. doi:https://doi.org/10.1111/j.1365-2656.2008.01390.x

Fang K, Yao Q, Guo Z, Zheng B, Du J, Qi F, Yan P, Li J, Ou T, Liu J*, et al.* (2021) ENSO modulates wildfire activity in China. *Nature Communications* **12**(1), 1764. doi:https://doi.org/10.1038/s41467-021-21988-6

Fedrigo M, Stewart SB, Kasel S, Levchenko V, Trouvé R, Nitschke CR (2019) Radiocarbon dating informs tree fern population dynamics and disturbance history of temperate forests in southeast Australia. *Radiocarbon* **61**(2), 445-460. doi:https://doi.org/10.1017/RDC.2018.119

Fensham RJ, Laffineur B, Browning O (2024) Fuel dynamics and rarity of fire weather reinforce coexistence of rainforest and wet sclerophyll forest. *Forest Ecology and Management* **553**, 121598. doi:https://doi.org/10.1016/j.foreco.2023.121598

Fick SE, Hijmans RJ (2017) WorldClim 2: new 1-km spatial resolution climate surfaces for global land areas. *International Journal of Climatology* **37**(12), 4302-4315. doi:https://doi.org/10.1002/joc.5086

Fisher R (2026) NAFI fire year summary report 2025. (Charles Darwin University and NAFI: Northern Territory, Australia) Available at https://nafi-fire-report-2025.lkvl.net/ [Verified 13th April 2026]

Fisher R, Edwards AC (2015) Fire extent mapping: procedures, validation and website application. In 'Carbon accounting and savanna fire management', pp. 57-72. (CSIRO Publishing: Victoria, Australia) Available at https://doi.org/10.1071/9780643108523.ch03 [Verified 5/11/2026]

Flannigan M, Cantin AS, de Groot WJ, Wotton M, Newbery A, Gowman LM (2013) Global wildland fire season severity in the 21st century. *Forest Ecology and Management* **294**, 54-61. doi:https://doi.org/10.1016/j.foreco.2012.10.022

Fletcher M-S, Cadd HR, Mariani M, Hall TL, Wood SW (2020) The role of species composition in the emergence of alternate vegetation states in a temperate rainforest system. *Landscape Ecology* **35**(10), 2275-2285. doi:https://doi.org/10.1007/s10980-020-01110-9

Galizia LF, Curt T, Barbero R, Rodrigues M (2021) Assessing the accuracy of remotely sensed fire datasets across the southwestern Mediterranean Basin. *Natural Hazards and Earth System Sciences* **21**(1), 73-86. doi:https://doi.org/10.5194/nhess-21-73-2021

Gallant J, Austin J (2012) Topographic Wetness Index derived from 1" SRTM DEM-H. v2 (Dataset). (CSIRO CSIRO: Australia). Available at https://doi.org/10.4225/08/57590B59A4A08 [Verified 18 August 2023]

Gaskell C, Campbell SD, Wolff D, Lebbink G, Smith AL (2026) Diverse soil seedbanks are resilient to reintroducing low-intensity fire in a subtropical grassy woodland. *Journal of Applied Ecology* **63**(5), e70409. doi:https://doi.org/10.1111/1365-2664.70409

Geoscience Australia (2011) SRTM-derived 1 second digital elevation models version 1.0 (Dataset). (Australian Government Geoscience Australia: Australia). Available at https://elevation-direct-downloads.s3-ap-southeast-2.amazonaws.com/1sec-dem/69816.zip [Verified 18 October 2023]

Gibbons P, van Bommel L, Gill AM, Cary GJ, Driscoll DA, Bradstock RA, Knight E, Moritz MA, Stephens SL, Lindenmayer DB (2012) Land management practices associated with house loss in wildfires. *PLoS One* **7**(1), e29212. doi:https://doi.org/10.1371/journal.pone.0029212

Gibson R, Danaher T, Hehir W, Collins L (2020) A remote sensing approach to mapping fire severity in south-eastern Australia using sentinel 2 and random forest. *Remote sensing of environment* **240**, 111702. doi:https://doi.org/10.1016/j.rse.2020.111702

Gilroy J, Tran C (2009) A new fuel load model for eucalypt forests in southeast Queensland. *The Proceedings of the Royal Society of Queensland* **115**, 137-143. [In English]

Gincheva A, Pausas JG, Edwards A, Provenzale A, Cerdà A, Hanes C, Royé D, Chuvieco E, Mouillot F, Vissio G*, et al.* (2024) A monthly gridded burned area database of national wildland fire data. *Scientific Data* **11**(1), 352. doi:https://doi.org/10.1038/s41597-024-03141-2

Golding N, Hudson L, Patching H (2016) Streamline functions for species distribution modelling in the SEEG research group: R - seegSDM. (GitHub: Oxford, United Kingdom) Available at https://github.com/SEEG-Oxford/seegSDM/blob/master/R/seegSDM.R [Verified 1 May 2024]

González ME, Galleguillos M, Lopatin J, Leal C, Becerra-Rodas C, Lara A, San Martín J (2022) Surviving in a hostile landscape: *Nothofagus alessandrii* remnant forests threatened by mega-fires and exotic pine invasion in the coastal range of central Chile. *Oryx* **57**, 228-238. doi:https://doi.org/10.1017/S0030605322000102

Gould JS, Lachlan McCaw W, Phillip Cheney N (2011) Quantifying fine fuel dynamics and structure in dry eucalypt forest (*Eucalyptus marginata*) in Western Australia for fire management. *Forest Ecology and Management* **262**(3), 531-546. doi:https://doi.org/10.1016/j.foreco.2011.04.022

Gräler B, Pebesma E, Heuvelink G (2016) Spatio-temporal interpolation using gstat. *The R journal* **8**(1), 204-218. doi:https://doi.org/10.32614/rj-2016-014

Greene GA, Daniels LD (2017) Spatial interpolation and mean fire interval analyses quantify historical mixed-severity fire regimes. *International Journal of Wildland Fire* **26**(2), 136-147. doi:https://doi.org/10.1071/WF16084

Greenwood L, Bliege Bird R, Nimmo D (2022) Indigenous burning shapes the structure of visible and invisible fire mosaics. *Landscape Ecology* **37**(3), 811-827. doi:https://doi.org/10.1007/s10980-021-01373-w

Grimmett L, Whitsed R, Horta A (2020) Presence-only species distribution models are sensitive to sample prevalence: evaluating models using spatial prediction stability and accuracy metrics. *Ecological Modelling* **431**, 109194. doi:https://doi.org/10.1016/j.ecolmodel.2020.109194

Gustafsson L, Berglind M, Granström A, Grelle A, Isacsson G, Kjellander P, Larsson S, Lindh M, Pettersson LB, Strengbom J*, et al.* (2019) Rapid ecological response and intensified knowledge accumulation following a north European mega-fire. *Scandinavian Journal of Forest Research* **34**(4), 234-253. doi:https://doi.org/10.1080/02827581.2019.1603323

Hanson JM, Welsh KJ, Moss PT, Gadd P (2023) Implications of sea level variability on the formation and evolution of subtropical Rainbow Beach patterned fen complexes, Queensland, Australia. *The Holocene* **33**(1), 49-60. doi:https://doi.org/10.1177/09596836221126120

Hao T, Elith J, Lahoz-Monfort JJ, Guillera-Arroita G (2020) Testing whether ensemble modelling is advantageous for maximising predictive performance of species distribution models. *Ecography* **43**(4), 549-558. doi:https://doi.org/10.1111/ecog.04890

Harris J, Pirtle JL, Laman EA, Siple MC, Thorson JT (2024) An ensemble approach to species distribution modelling reconciles systematic differences in estimates of habitat utilization and range area. *Journal of Applied Ecology* **61**(2), 351-364. doi:https://doi.org/10.1111/1365-2664.14559

Harvey BJ, Enright NJ (2022) Climate change and altered fire regimes: impacts on plant populations, species, and ecosystems in both hemispheres. *Plant Ecology* **223**(7), 699-709. [In English] doi:https://doi.org/10.1007/s11258-022-01248-3

Hastie T, Tibshirani R, Friedman J (2009) 'Elements of statistical learning: data mining, inference, and prediction.' 2nd edn. (Springer: New York, New York, United States of America) https://doi.org/10.1007/978-0-387-84858-7

He T, Lamont BB, Pausas JG (2019) Fire as a key driver of Earth's biodiversity. *Biological Reviews* **94**(6), 1983-2010. doi:https://doi.org/10.1111/brv.12544

Hijmans RJ (2025) terra: spatial data analysis. R package version 1.8.60. (The Comprehensive R Archive Network: Vienna, Austria) Available at https://CRAN.R-project.org/package=terra [Verified 20 August 2025]

Hijmans RJ, Phillips S, Leathwick JR, Elith J (2024) dismo: species distribution modelling. R package version 1.3-16. (The Comprehensive R Archive Network: Vienna, Austria) Available at https://CRAN.R-project.org/package=dismo [Verified 20 August 2025]

Hoffman KM, Davis EL, Wickham SB, Schang K, Johnson A, Larking T, Lauriault PN, Quynh Le N, Swerdfager E, Trant AJ (2021) Conservation of Earth’s biodiversity is embedded in Indigenous fire stewardship. *Proceedings of the National Academy of Sciences* **118**(32), e2105073118. doi:https://doi.org/10.1073/pnas.2105073118

Hunter ME, Robles MD (2020) Tamm review: the effects of prescribed fire on wildfire regimes and impacts: a framework for comparison. *Forest Ecology and Management* **475**, 118435. doi:https://doi.org/10.1016/j.foreco.2020.118435

Jeffrey SJ, Carter JO, Moodie KB, Beswick AR (2001) Using spatial interpolation to construct a comprehensive archive of Australian climate data. *Environmental Modelling & Software* **16**(4), 309-330. doi:https://doi.org/10.1016/S1364-8152(01)00008-1

Jiménez L, Soberón J (2020) Leaving the area under the receiving operating characteristic curve behind: an evaluation method for species distribution modelling applications based on presence-only data. *Methods in Ecology and Evolution* **11**(12), 1571-1586. doi:https://doi.org/10.1111/2041-210X.13479

Jones MW, Abatzoglou JT, Veraverbeke S, Andela N, Lasslop G, Forkel M, Smith AJP, Burton C, Betts RA, van der Werf GR*, et al.* (2022) Global and regional trends and drivers of fire under climate change. *Reviews of Geophysics* **60**(3), e2020RG000726. doi:https://doi.org/10.1029/2020RG000726

Kalantar B, Ueda N, Idrees MO, Janizadeh S, Ahmadi K, Shabani F (2020) Forest fire susceptibility prediction based on machine learning models with resampling algorithms on remote sensing data. *Remote Sensing* **12**(22), 3682. doi:https://doi.org/10.3390/rs12223682

Kelly LT, Fletcher M-S, Oliveras Menor I, Pellegrini AFA, Plumanns-Pouton ES, Pons P, Williamson GJ, Bowman DMJS (2023) Understanding fire regimes for a better Anthropocene. *Annual Review of Environment and Resources* **48**, 207-235. doi:https://doi.org/10.1146/annurev-environ-120220-055357

Kelly LT, Giljohann KM, Duane A, Aquilue N, Archibald S, Batllori E, Bennett AF, Buckland ST, Canelles Q, Clarke MF*, et al.* (2020) Fire and biodiversity in the Anthropocene. *Science* **370**(6519), 929. doi:https://doi.org/10.1126/science.abb0355

Khairoun A, Mouillot F, Chen W, Ciais P, Chuvieco E (2024) Coarse-resolution burned area datasets severely underestimate fire-related forest loss. *Science of the Total Environment* **920**, 170599. doi:https://doi.org/10.1016/j.scitotenv.2024.170599

Khorshidi MS, Dennison PE, Nikoo MR, AghaKouchak A, Luce CH, Sadegh M (2020) Increasing concurrence of wildfire drivers tripled megafire critical danger days in southern California between 1982 and 2018. *Environmental Research Letters* **15**(10), 104002. doi:https://doi.org/10.1088/1748-9326/abae9e

Kreider MR, Higuera PE, Parks SA, Rice WL, White N, Larson AJ (2024) Fire suppression makes wildfires more severe and accentuates impacts of climate change and fuel accumulation. *Nature Communications* **15**(1), 2412. doi:https://doi.org/10.1038/s41467-024-46702-0

Kuhn M (2008) Building predictive models in R using the caret package. *Journal of Statistical Software* **28**(5), 1-26. doi:https://doi.org/10.18637/jss.v028.i05

Lai J, Tang J, Li T, Zhang A, Mao L (2024) Evaluating the relative importance of predictors in Generalized Additive Models using the gam.hp R package. *Plant Diversity* **46**(4), 542-546. doi:https://doi.org/10.1016/j.pld.2024.06.002

Lai J, Zou Y, Zhang S, Zhang X, Mao L (2022) glmm.hp: an R package for computing individual effect of predictors in generalized linear mixed models. *Journal of Plant Ecology* **15**(6), 1302-1307. doi:https://doi.org/10.1093/jpe/rtac096

Laidlaw MJ, Hines HB, Melzer RI, Churchill TB (2022) Beyond bushfire severity: mapping the ecological impact of bushfires on the Gondwana rainforests of Australia world heritage area. *Australian Zoologist* **42**(2), 502-513. doi:https://doi.org/10.7882/az.2022.027

Lavery T, Lindenmayer D, Blanchard W, Carey A, Cook E, Copley P, Macgregor NA, Melzer R, Nano C, Prentice L*, et al.* (2021) Counting plants: the extent and adequacy of monitoring for a continental-scale list of threatened plant species. *Biological Conservation* **260**, 109193. doi:https://doi.org/10.1016/j.biocon.2021.109193

Le Breton T, Schweickle L, Dunne C, Lyons M, Ooi M (2023) Fire frequency and severity mediate recruitment response of a threatened shrub following severe megafire. *Fire Ecology* **19**(1), 67. doi:https://doi.org/10.1186/s42408-023-00217-z

Le Page Y, Morton D, Hartin C, Bond-Lamberty B, Pereira JMC, Hurtt G, Asrar G (2017) Synergy between land use and climate change increases future fire risk in Amazon forests. *Earth System Dynamics* **8**(4), 1237-1246. doi:https://doi.org/10.5194/esd-8-1237-2017

Legge S, Woinarski JCZ, Scheele BC, Garnett ST, Lintermans M, Nimmo DG, Whiterod NS, Southwell DM, Ehmke G, Buchan A*, et al.* (2022) Rapid assessment of the biodiversity impacts of the 2019–2020 Australian megafires to guide urgent management intervention and recovery and lessons for other regions. *Diversity and Distributions* **28**(3), 571-591. doi:https://doi.org/10.1111/ddi.13428

Li W, Xu Q, Yi J, Liu J (2022) Predictive model of spatial scale of forest fire driving factors: a case study of Yunnan Province, China. *Scientific Reports* **12**(1), 19029. doi:https://doi.org/10.1038/s41598-022-23697-6

Li X, Wang Y (2013) Applying various algorithms for species distribution modelling. *Integrative Zoology* **8**(2), 124-135. doi:https://doi.org/10.1111/1749-4877.12000

Linley GD, Jolly CJ, Doherty TS, Geary WL, Armenteras D, Belcher CM, Bliege Bird R, Duane A, Fletcher M-S, Giorgis MA*, et al.* (2022) What do you mean, 'megafire'? *Global Ecology and Biogeography* **31**(10), 1906-1922. doi:https://doi.org/10.1111/geb.13499

Liu C, Newell G, White M (2019a) The effect of sample size on the accuracy of species distribution models: considering both presences and pseudo-absences or background sites. *Ecography* **42**(3), 535-548. doi:https://doi.org/10.1111/ecog.03188

Liu D, Xu Z, Fan C (2019b) Predictive analysis of fire frequency based on daily temperatures. *Natural Hazards* **97**(3), 1175-1189. doi:https://doi.org/10.1007/s11069-019-03694-1

Lobo JM, Jiménez-Valverde A, Real R (2008) AUC: a misleading measure of the performance of predictive distribution models. *Global Ecology and Biogeography* **17**(2), 145-151. doi:https://doi.org/10.1111/j.1466-8238.2007.00358.x

Łopucki R, Kiersztyn A, Pitucha G, Kitowski I (2022) Handling missing data in ecological studies: ignoring gaps in the dataset can distort the inference. *Ecological Modelling* **468**, 109964. doi:https://doi.org/10.1016/j.ecolmodel.2022.109964

Loschiavo J, Cirulis B, Zuo Y, Hradsky BA, Di Stefano J (2017) Mapping prescribed fire severity in south-east Australian eucalypt forests using modelling and satellite imagery: a case study. *International Journal of Wildland Fire* **26**(6), 491-497. doi:https://doi.org/10.1071/WF16167

Mackenzie L, Moss P, Ulm S (2020) A late-Holocene record of coastal wetland development and fire regimes in tropical northern Australia. *The Holocene* **30**(10), 1379-1390. doi:https://doi.org/10.1177/0959683620932970

Maier SW, Russell-Smith J (2012) Measuring and monitoring of contemporary fire regimes in Australia using satellite remote sensing. In 'Flammable Australia: fire regimes, biodiversity and ecosystems in a changing world'. (Ed. AMG Ross A Bradstock, Richard J Williams) pp. 79-95. (CSIRO Publishing: Collingwood, Victoria, Australia)

Mariani M, Connor SE, Theuerkauf M, Herbert A, Kuneš P, Bowman D, Fletcher M-S, Head L, Kershaw AP, Haberle SG*, et al.* (2022) Disruption of cultural burning promotes shrub encroachment and unprecedented wildfires. *Frontiers in Ecology and the Environment* **20**(5), 292-300. doi:https://doi.org/10.1002/fee.2395

Mariani M, Fletcher M-S (2017) Long-term climate dynamics in the extra-tropics of the south pacific revealed from sedimentary charcoal analysis. *Quaternary Science Reviews* **173**, 181-192. doi:https://doi.org/10.1016/j.quascirev.2017.08.007

Marsh JR, Bal P, Fraser H, Umbers K, Latty T, Greenville A, Rumpff L, Woinarski JCZ (2022) Accounting for the neglected: invertebrate species and the 2019–2020 Australian megafires. *Global Ecology and Biogeography* **31**(10), 2120-2130. doi:https://doi.org/10.1111/geb.13550

McCarthy G, Moon K, Smith L (2017) Mapping fire severity and fire extent in forest in Victoria for ecological and fuel outcomes. *Ecological Management & Restoration* **18**(1), 54-65. doi:https://doi.org/10.1111/emr.12242

McCormack PC, Miller RK, McDonald J (2024) Prescribed burning on private land: reflections on recent law reform in Australia and California. *International Journal of Wildland Fire* **33**(1), WF22213. doi:https://doi.org/10.1071/WF22213

Meynard CN, Quinn JF (2007) Predicting species distributions: a critical comparison of the most common statistical models using artificial species. *Journal of Biogeography* **34**(8), 1455-1469. doi:https://doi.org/10.1111/j.1365-2699.2007.01720.x

Miller G, Friedel M, Adam P, Chewings V (2010) Ecological impacts of buffel grass (*Cenchrus ciliaris* L.) invasion in central Australia – does field evidence support a fire-invasion feedback? *The Rangeland Journal* **32**(4), 353-365. doi:https://doi.org/10.1071/RJ09076

Miranda A, Mentler R, Moletto-Lobos Í, Alfaro G, Aliaga L, Balbontín D, Barraza M, Baumbach S, Calderón P, Cárdenas F*, et al.* (2022) The Landscape Fire Scars database: mapping historical burned area and fire severity in Chile. *Earth System Science Data* **14**(8), 3599-3613. doi:https://doi.org/10.5194/essd-14-3599-2022

Morgan GW, Tolhurst KG, Poynter MW, Cooper N, McGuffog T, Ryan R, Wouters MA, Stephens N, Black P, Sheehan D*, et al.* (2020) Prescribed burning in south-eastern Australia: history and future directions. *Australian forestry* **83**(1), 4-28. doi:https://doi.org/10.1080/00049158.2020.1739883

Moritz MA, Parisien M-A, Batllori E, Krawchuk MA, Van Dorn J, Ganz DJ, Hayhoe K (2012) Climate change and disruptions to global fire activity. *Ecosphere* **3**(6), 49. doi:https://doi.org/10.1890/ES11-00345.1

Moss P, Mackenzie L, Ulm S, Sloss C, Rosendahl D, Petherick L, Steinberger L, Wallis L, Heijnis H, Petchey F*, et al.* (2015) Environmental context for late Holocene human occupation of the South Wellesley Archipelago, Gulf of Carpentaria, northern Australia. *Quaternary International* **385**, 136-144. doi:https://doi.org/10.1016/j.quaint.2015.02.051

Moss PT, Tibby J, Petherick L, McGowan H, Barr C (2013) Late Quaternary vegetation history of North Stradbroke Island, Queensland, eastern Australia. *Quaternary Science Reviews* **74**, 257-272. doi:https://doi.org/10.1016/j.quascirev.2013.02.019

Mouillot F, Field CB (2005) Fire history and the global carbon budget: a 1°× 1° fire history reconstruction for the 20th century. *Global Change Biology* **11**(3), 398-420. doi:https://doi.org/10.1111/j.1365-2486.2005.00920.x

Moura LC, Scariot AO, Schmidt IB, Beatty R, Russell-Smith J (2019) The legacy of colonial fire management policies on traditional livelihoods and ecological sustainability in savannas: impacts, consequences, new directions. *Journal of Environmental Management* **232**, 600-606. doi:https://doi.org/10.1016/j.jenvman.2018.11.057

Murase H, Nagashima H, Yonezaki S, Matsukura R, Kitakado T (2009) Application of a generalized additive model (GAM) to reveal relationships between environmental factors and distributions of pelagic fish and krill: a case study in Sendai Bay, Japan. *ICES Journal of Marine Science* **66**(6), 1417-1424. doi:https://doi.org/10.1093/icesjms/fsp105

Neldner V, Butler D, Guymer G (2019) 'Queensland's regional ecosystems: building and maintaining a biodiversity inventory, planning framework and information system for Queensland version 2.' (Queensland Herbarium, Department of Science, Informatoin Technology and Innovation: Brisbane, QLD, Australia)

Neldner V, Niehus RE, Wilson BA, McDonald WJF, Ford AJ, Accad A (2023) The vegetation of Queensland. Descriptions of the Broad Vegetation Groups Version 6.0. (Queensland Government Department of Environment and Science: Brisbane, Queensland, Australia) Available at https://www.des.qld.gov.au/__data/assets/pdf_file/0029/81929/descriptions-of-broad-vegetation-groups.pdf

Nolan RH, Boer MM, Collins L, Resco de Dios V, Clarke H, Jenkins M, Kenny B, Bradstock RA (2020) Causes and consequences of eastern Australia's 2019–20 season of mega-fires. *Global Change Biology* **26**(3), 1039-1041. doi:https://doi.org/10.1111/gcb.14987

Nolan RH, Bowman DMJS, Clarke H, Haynes K, Ooi MKJ, Price OF, Williamson GJ, Whittaker J, Bedward M, Boer MM*, et al.* (2021) What do the Australian Black Summer fires signify for the global fire crisis? *Fire* **4**(4), 97. doi:https://doi.org/10.3390/fire4040097

O'Brien J (2023) gdalUtilities: wrappers for 'GDAL' utilities executables. (The Comprehensive R Archive Network: Vienna, Austria) Available at https://github.com/JoshOBrien/gdalUtilities/, https://joshobrien.github.io/gdalUtilities/ [Verified 5 October 2023]

Orero L, Omondi EO, Omolo BO (2024) A Bayesian model for predicting monthly fire frequency in Kenya. *PLoS One* **19**(1), e0291800. doi:https://doi.org/10.1371/journal.pone.0291800

Parisien M-A, Miller C, Parks SA, DeLancey ER, Robinne F-N, Flannigan MD (2016) The spatially varying influence of humans on fire probability in North America. *Environmental Research Letters* **11**(7), 075005. doi:https://doi.org/10.1088/1748-9326/11/7/075005

Park N-W, Kim Y, Kwak G-H (2019) An overview of theoretical and practical issues in spatial downscaling of coarse resolution satellite-derived products. *Korean Journal of Remote Sensing* **35**(4), 589-607. [In Ko] doi:https://doi.org/10.7780/KJRS.2019.35.4.8

Patil I (2021) Visualizations with statistical details: the 'ggstatsplot' approach. *Journal of Open Source Software* **6**(61), 3167. doi:https://doi.org/10.21105/joss.03167

Pausas JG, Fernández-Muñoz S (2012) Fire regime changes in the western Mediterranean Basin: from fuel-limited to drought-driven fire regime. *Climatic Change* **110**(1), 215-226. doi:https://doi.org/10.1007/s10584-011-0060-6

Pebesma EJ (2004) Multivariable geostatistics in S
the gstat package. *Computers & Geosciences* **30**(7), 683-691. doi:https://doi.org/10.1016/j.cageo.2004.03.012

Penman TD, Bradstock RA, Price OF (2014) Reducing wildfire risk to urban developments: Simulation of cost-effective fuel treatment solutions in south eastern Australia. *Environmental Modelling & Software* **52**, 166-175. doi:https://doi.org/10.1016/j.envsoft.2013.09.030

Phelps N, Woolford DG (2021) Guidelines for effective evaluation and comparison of wildland fire occurrence prediction models. *International Journal of Wildland Fire* **30**(4), 225-240. doi:https://doi.org/10.1071/WF20134

Plumanns-Pouton E, Swan M, Penman T, Kelly LT (2024) How do intervals between fires influence canopy seed production and viability? *Functional Ecology* **38**(9), 1915-1930. doi:https://doi.org/10.1111/1365-2435.14619

Queensland Herbarium (2024) Regional ecosystem fire management guidelines (Dataset). (Queensland Department of Environment, Science, and Innovation Queensland Government: Brisbane, Queensland, Australia). Available at https://www.qld.gov.au/__data/assets/file/0025/384046/fire-management-guidelines-v13.1.csv [Verified 8 January 2025]

Queensland Parks and Wildlife Service (2023) Fire history - Queensland Parks and Wildlife Service (Dataset). (Queensland Parks and Wildlife Service Queensland Spatial: Brisbane, Queensland, Australia). Available at https://www.data.qld.gov.au/dataset/fire-history-queensland-parks-and-wildlife-service [Verified 18 August 2023]

R Core Team (2018) The R Project for statistical computing. (R Foundation for Statistical Computing: Vienna, Austria) Available at https://www.r-project.org [Verified 12th September 2020]

R Core Team (2023) R: a language and environment for statistical computing. (R Foundation for Statistical Computing: Vienna, Austria) Available at https://www.R-project.org/ [Verified 1 August 2023]

Ramsey S, Jones S, Reinke K (2024) Review of approaches and challenges for the validation of satellite-based active fire products in savannah ecosystems. *International Journal of Wildland Fire* **33**(10), WF23202. doi:https://doi.org/10.1071/WF23202

Randerson JT, Chen Y, van der Werf GR, Rogers BM, Morton DC (2012) Global burned area and biomass burning emissions from small fires. *Journal of Geophysical Research: Biogeosciences* **117**, G04012. doi:https://doi.org/10.1029/2012JG002128

Rayner CJ, Brunt T, Smith AL (2025) The impact of a decade of urbanisation on a semi-aquatic mammal in a subtropical freshwater ecosystem. *Landscape Ecology* **40**(8), 175. doi:https://doi.org/10.1007/s10980-025-02197-8

Redmond R, Winne C, Opitz D, Mangrich M (2002) Classifying and mapping wildfire severity: a comparison of methods. *Photogrammetric Engineering & Remote Sensing* **71**. doi:https://doi.org/10.14358/PERS.71.11.1311

Roberts DR, Bahn V, Ciuti S, Boyce MS, Elith J, Guillera-Arroita G, Hauenstein S, Lahoz-Monfort JJ, Schröder B, Thuiller W*, et al.* (2017) Cross-validation strategies for data with temporal, spatial, hierarchical, or phylogenetic structure. *Ecography* **40**(8), 913-929. doi:https://doi.org/10.1111/ecog.02881

Rodrigues M, Jiménez A, de la Riva J (2016) Analysis of recent spatial–temporal evolution of human driving factors of wildfires in Spain. *Natural Hazards* **84**(3), 2049-2070. doi:https://doi.org/10.1007/s11069-016-2533-4

Rogers BM, Balch JK, Goetz SJ, Lehmann CER, Turetsky M (2020) Focus on changing fire regimes: interactions with climate, ecosystems, and society. *Environmental Research Letters* **15**(3), 030201. doi:https://doi.org/10.1088/1748-9326/ab6d3a

Ruscalleda-Alvarez J, Moro D, van Dongen R (2021) A multi-scale assessment of fire scar mapping in the Great Victoria Desert of Western Australia. *International Journal of Wildland Fire* **30**(11), 886-898. doi:https://doi.org/10.1071/WF21019

Ryu G, Charalambou C (2023) Historical bushfire boundaries - version 1.0. (Geoscience Australia: Canberra, Australia) Available at https://ecat.ga.gov.au/geonetwork/srv/eng/catalog.search#/metadata/147763 [Verified 7th November 2024]

Sachdeva S, Bhatia T, Verma AK (2018) GIS-based evolutionary optimized gradient boosted decision trees for forest fire susceptibility mapping. *Natural Hazards* **92**(3), 1399-1418. doi:https://doi.org/10.1007/s11069-018-3256-5

Saito T, Rehmsmeier M (2016) Precrec: fast and accurate precision–recall and ROC curve calculations in R. *Bioinformatics* **33**(1), 145-147. doi:https://doi.org/10.1093/bioinformatics/btw570

San-Miguel-Ayanz J, Schulte E, Schmuck G, Camia A, Strobl P, Liberta G, Giovando C, Boca R, Sedano F, Kempeners P*, et al.* (2012) Comprehensive monitoring of wildfires in Europe: the European Forest Fire Information System (EFFIS). In 'Approaches to Managing Disaster - Assessing Hazards, Emergencies and Disaster Impacts'. (Ed. JP Tiefenbacher) pp. 87-108. (IntechOpen: Rijeka, Croatia) https://doi.org/10.5772/28441

Saulino L, Rita A, Migliozzi A, Maffei C, Allevato E, Garonna AP, Saracino A (2020) Detecting burn severity across mediterranean forest types by coupling medium-spatial resolution satellite imagery and field data. *Remote Sensing* **12**(4), 741. doi:https://doi.org/10.3390/rs12040741

Sayedi SS, Abbott BW, Vannière B, Leys B, Colombaroli D, Romera GG, Słowiński M, Aleman JC, Blarquez O, Feurdean A*, et al.* (2024) Assessing changes in global fire regimes. *Fire Ecology* **20**(1), 18. doi:https://doi.org/10.1186/s42408-023-00237-9

Setterfield SA, Rossiter-Rachor NA, Douglas MM, Wainger L, Petty AM, Barrow P, Shepherd IJ, Ferdinands KB (2013) Adding fuel to the fire: the impacts of non-native grass invasion on fire management at a regional scale. *PLoS One* **8**(5), e59144. doi:https://doi.org/10.1371/journal.pone.0059144

SILO QGLP (2025a) SILO - Australian climate data from 1889 to yesterday - daily maximum temperature (Dataset). (QGLP SILO Queensland Government: Brisbane, Queensland, Australia). Available at https://s3-ap-southeast-2.amazonaws.com/silo-open-data/Official/annual/index.html [Verified 30th July 2025]

SILO QGLP (2025b) SILO - Australian climate data from 1889 to yesterday - daily minimum temperature (Dataset). (QGLP SILO Queensland Government: Brisbane, Queensland, Australia). Available at https://s3-ap-southeast-2.amazonaws.com/silo-open-data/Official/annual/index.html [Verified 30th July 2025]

SILO QGLP (2025c) SILO - Australian climate data from 1889 to yesterday - daily rainfall (Dataset). (QGLP SILO Queensland Government: Brisbane, Queensland, Australia).

Available at https://s3-ap-southeast-2.amazonaws.com/silo-open-data/Official/annual/index.html [Verified 30th July 2025]

Simpson KJ, Archibald S, Osborne CP (2022) Savanna fire regimes depend on grass trait diversity. *Trends in Ecology & Evolution* **37**(9), 749-758. doi:https://doi.org/10.1016/j.tree.2022.04.010

Smith AL, Landguth EL, Bull CM, Banks SC, Gardner MG, Driscoll DA (2016) Dispersal responses override density effects on genetic diversity during post-disturbance succession. *Proceedings of the Royal Society B-Biological Sciences* **283**(1827), 20152934-20152934. doi:https://doi.org/10.1098/rspb.2015.2934

Song Y, Xu C, Li X, Oppong F (2024) Lightning-induced wildfires: an overview. *Fire* **7**(3), 79. doi:https://doi.org/10.3390/fire7030079

Soykan CU, Eguchi T, Kohin S, Dewar H (2014) Prediction of fishing effort distributions using boosted regression trees. *Ecological Applications* **24**(1), 71-83. doi:https://doi.org/10.1890/12-0826.1

Stewart PLCF, Moss PT, Farrell R (2020) Land change analysis of Moon Point vegetation on Fraser Island, east coast, Queensland, Australia. *International Journal of Ecology and Environmental Science* **46**(1), 25-39.

Sullivan AL, McCaw WL, Cruz MG, Matthews S, Ellis PF, Williams RJ, Bradstock RA, Gill AM (2012) Fuel, fire weather and fire behaviour in Australian ecosystems. In 'Flammable Australia: fire regimes, biodiversity and ecosystems in a changing world'. (Eds RA Bradstock, AM Gill, RJ Williams) pp. 51-77. (CSIRO Publishing: Collingwood, Vic) https://doi.org/10.1071/9780643104839 06.51.78.2012.6

Syphard AD, Radeloff VC, Keuler NS, Taylor RS, Hawbaker TJ, Stewart SI, Clayton MK (2008) Predicting spatial patterns of fire on a southern California landscape. *International Journal of Wildland Fire* **17**(5), 602-613. doi:https://doi.org/10.1071/WF07087

Thomsen AM, Lemmon J, Allen V, Mills CH, Keith DA, Ooi MKJ (2025) Evidence for state shift and generation of fire feedback loops in mesic forest driven by extreme fire severity and high fire frequency. *Environmental Research Letters* **20**(4), 044021. doi:https://doi.org/10.1088/1748-9326/adbf30

Thorley J, Srivastava SK, Shapcott A (2023) What type of rainforest burnt in the south east Queensland's 2019/20 bushfires and how might this impact biodiversity. *Austral Ecology* **48**(3), 616-642. doi:https://doi.org/10.1111/aec.13293

Toledo D, Kreuter UP, Sorice MG, Taylor CA (2012) To burn or not to burn: ecological reoration, lability cocerns, and the rle of pescribed brning asociations. *Rangelands* **34**(2), 18-23. doi:https://doi.org/10.2111/RANGELANDS-D-11-00037.1

Udy DG, Vance TR, Kiem AS, Holbrook NJ, Abram N (2024) Australia’s 2019/20 Black Summer fire weather exceptionally rare over the last 2000 years. *Communications Earth & Environment* **5**(1), 317. doi:https://doi.org/10.1038/s43247-024-01470-z

Valavi R, Elith J, Lahoz-Monfort JJ, Guillera-Arroita G (2019) blockCV: an r package for generating spatially or environmentally separated folds for k-fold cross-validation of species distribution models. *Methods in Ecology and Evolution* **10**(2), 225-232. doi:https://doi.org/10.1111/2041-210X.13107

Valavi R, Guillera-Arroita G, Lahoz-Monfort JJ, Elith J (2022) Predictive performance of presence-only species distribution models: a benchmark study with reproducible code. *Ecological Monographs* **92**(1), e01486. doi:https://doi.org/10.1002/ecm.1486

van den Berg D (2021) Sentinel-2 fire scars - QLD DES algorithm, QLD coverage. (Terrestrial Ecosystem Research Network: Australia) Available at https://portal.tern.org.au/metadata/TERN/7b6d2b84-cbf3-46e8-aa8c-c49352f9ffd5 [Verified 7th November 2024]

van Klinken RD, Friedel MH (2018) Unassisted invasions: understanding and responding to Australia's high-impact environmental grass weeds. *Australian Journal of Botany* **65**(8), 678-690. doi:https://doi.org/10.1071/BT17152

Venables WN, Ripley BD (2002) 'Modern applied statistics with S.' 4th edn. (Springer: New York, New York, United States of America) https://doi.org/10.1007/978-0-387-21706-2

Walsh JC, Watson JEM, Bottrill MC, Joseph LN, Possingham HP (2013) Trends and biases in the listing and recovery planning for threatened species: an Australian case study. *Oryx* **47**(1), 134-143. doi:https://doi.org/10.1017/S003060531100161X

Wang X, Luo M, Song F, Wu S, Chen YD, Zhang W (2024) Precipitation seasonality amplifies as Earth warms. *Geophysical Research Letters* **51**(10), e2024GL109132. doi:https://doi.org/10.1029/2024GL109132

Welch K (2021) Creating a comprehensive western American/Canadian fire dataset, 1880-2018. Master of Arts Masters, Western Washington University, Bellingham, Washington, United States of America.

Whitford AM, Shipley BR, McGuire JL (2024) The influence of the number and distribution of background points in presence-background species distribution models. *Ecological Modelling* **488**, 110604. doi:https://doi.org/10.1016/j.ecolmodel.2023.110604

Williamson B (2021) Cultural burning in New South Wales: challenges and opportunities for policy makers and Aboriginal peoples. Report number 9781925286571
1925286576, Centre for Aboriginal Economic Policy Research (ANU), Canberra, ACT, Australia. https://doi.org/10.25911/Q1PY-8E04

Williamson B (2022) Cultural burning and public forests: convergences and divergences between Aboriginal groups and forest management in south-eastern Australia. *Australian Forestry* **85**(1), 1-5. doi:https://doi.org/10.1080/00049158.2022.2054134

Williamson GJ, Prior LD, Jolly WM, Cochrane MA, Murphy BP, Bowman DMJS (2016) Measurement of inter- and intra-annual variability of landscape fire activity at a continental scale: the Australian case. *Environmental Research Letters* **11**(3), 035003. doi:https://doi.org/10.1088/1748-9326/11/3/035003

Wisz MS, Pottier J, Kissling WD, Pellissier L, Lenoir J, Damgaard CF, Dormann CF, Forchhammer MC, Grytnes J-A, Guisan A*, et al.* (2013) The role of biotic interactions in shaping distributions and realised assemblages of species: implications for species distribution modelling. *Biological Reviews* **88**(1), 15-30. doi:https://doi.org/10.1111/j.1469-185X.2012.00235.x

Wood SN (2004) Stable and efficient multiple smoothing parameter estimation for generalized additive models. *Journal of the American Statistical Association* **99**(467), 673-686. doi:https://doi.org/10.1198/016214504000000980

Wood SN (2006) Low-rank scale-invariant tensor product smooths for generalized additive mixed models. *Biometrics* **62**(4), 1025-1036. doi:https://doi.org/10.1111/j.1541-0420.2006.00574.x

Wood SN (2011) Fast stable restricted maximum likelihood and marginal likelihood estimation of semiparametric generalized linear models. *The Journal of the Royal Statistical Society, Series B (Statistical Methodology)* **73**(1), 3-36. doi:https://doi.org/10.1111/j.1467-9868.2010.00749.x

Wood SN (2017) 'Generalized additive models: an introduction with R.' 2nd edn. (Taylor & Francis Group: New York, New York, United States of America) https://doi.org/10.1201/9781315370279

Wood SW, Hua Q, Allen KJ, Bowman DMJS (2010) Age and growth of a fire prone Tasmanian temperate old-growth forest stand dominated by *Eucalyptus regnans*, the world's tallest angiosperm. *Forest Ecology and Management* **260**(4), 438-447. doi:https://doi.org/10.1016/j.foreco.2010.04.037

Woodgate W, Phinn S, Devereux T, Aryal RR (2025) Bushfire recovery at a long-term tall eucalypt flux site through the lens of a satellite: combining multi-scale data for structural-functional insight. *Remote Sensing of Environment* **317**, 114530. doi:https://doi.org/10.1016/j.rse.2024.114530

Yates C, Evans J, Vernooij R, Eames T, Muir E, Holmes J, Edwards A, Russell-Smith J (2023) Incentivizing sustainable fire management in Australia's northern arid spinifex grasslands. *Journal of Environmental Management* **344**, 118384. doi:https://doi.org/10.1016/j.jenvman.2023.118384

Table 1 Spatial fire, environmental, climate, and terrain variables used to predict fire frequency in the study region of southeast Queensland, Australia.

Data were resampled using the nearest neighbour method (i.e., the default resampling tool in the `gdalUtilities` R package).

Environmental variable	Raw resolution	Resampled resolution	Temporal resolution	Data source
Annual fire scars: Landsat, QLD DES algorithm, QLD coverage	30 m	Unchanged	1987-2016	Collett 2021
Sentinel-2 fire scars: QLD DES algorithm, QLD coverage	10 m	30 m	2017-2023	van den Berg 2021
Public land fire history	5 m	30 m	1930-2024	Queensland Parks and Wildlife Service 2023
Daily rainfall	5 km	30 m	1987-2023	Jeffrey *et al.* 2001, SILO 2025c
Daily minimum temperature	5 km	30 m	1987-2023	Jeffrey *et al.* 2001, SILO 2025b
Daily maximum temperature	5 km	30 m	1987-2023	Jeffrey *et al.* 2001, SILO 2025a
Topographic wetness index	30 m	Unchanged	2000	Gallant *et al*. 2012
Foliage projective cover				
- Woody extent and foliage projective cover 2012	25 m	30 m	1988-2012	Department of Environment 2020c
- Woody extent and foliage projective cover 2013	30 m	Unchanged	1988-2013	Department of Environment 2020d

- Landsat 2014	30 m	Unchanged	1998-2014	Department of Environment 2020b
- Statewide Landcover and Trees Study (SLATS) Sentinel-2 2018	30 m	Unchanged	2018	Department of Environment 2022
- Statewide Landcover and Trees Study (SLATS) Sentinel-2	10 m	30 m	2019, 2020, 2021, 2022, 2023	Department of Environment 2024b
Remnant 2021 Broad Vegetation groups - Queensland	100 m	30 m	2017-2024	Department of Environment 2024a
Soil % clay, from 0 to 2 m	90 m	30 m	2021	CSIRO 2024
SRTM-derived 1 Second Digital Elevation Model Version 1.0, used to derive elevation, aspect, slope, and topographic position index	30 m	Unchanged	2001-2015	Geoscience Australia 2011

Table 2 Evaluation statistics comparing predictive performance among generalised linear, generalised additive, and boosted regression tree (BRT) models of fire frequency.

Pearson's correlation coefficient (*r*) indicates the correlation between predictive fire frequency and fire frequency derived from public land fire history data within the public estate of southeast Queensland, Australia.

Evaluation statistic	Generalised linear model	Generalised additive model	Down-weighted BRT	Unweighted BRT	Infinite BRT
Correlation (*r*) with public land fire	0.577	0.526	0.437	0.375	-0.08
AUC_{ROC}	0.771	0.767	0.776	0.773	0.707
AUC_{PRG}	0.796	0.786	0.788	0.792	0.705

AUC_{ROC} = Area Under the Receiver Operating Characteristic Curve; AUC_{PRG} = Area Under the Precision-Recall Gain Curve; Infinite BRT = Infinitely weighted logistic regression BRT

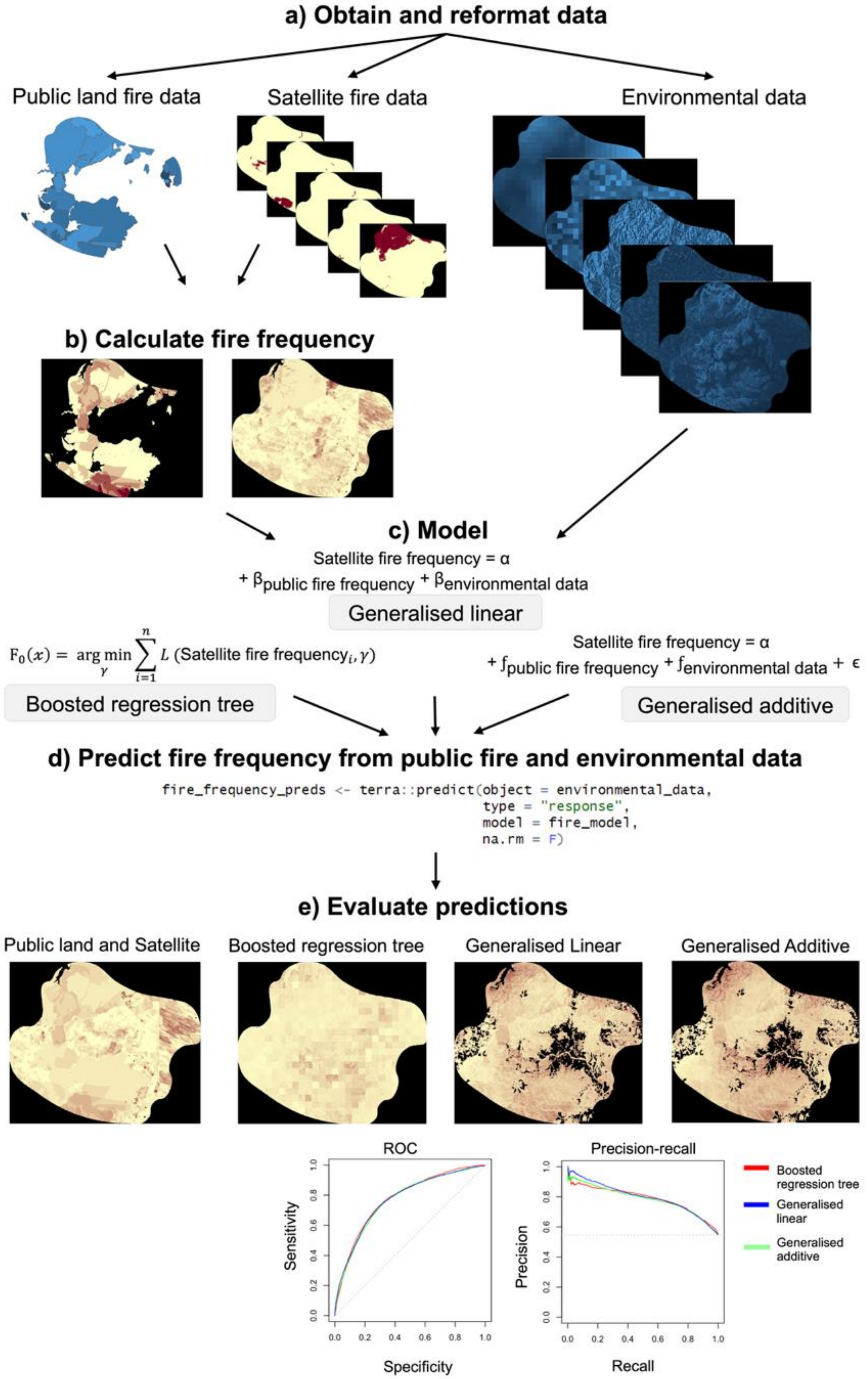

Fig. 1 Generalisable workflow for improving fire frequency estimates using predictive modelling: (a) obtain and reformat fire (e.g., public land and satellite, where available) and environmental (e.g., climate, site productivity,

terrain) data; (b) calculate fire frequency from fire history data; (c) run models; (d) produce spatial predictions; and (e) evaluate predictions by comparison of spatial predictions and model performance statistics. The workflow could be used with any fir regime parameter of interest, e.g. substituting fire frequency for fire return interval, time since last fire, or fire seasonality.

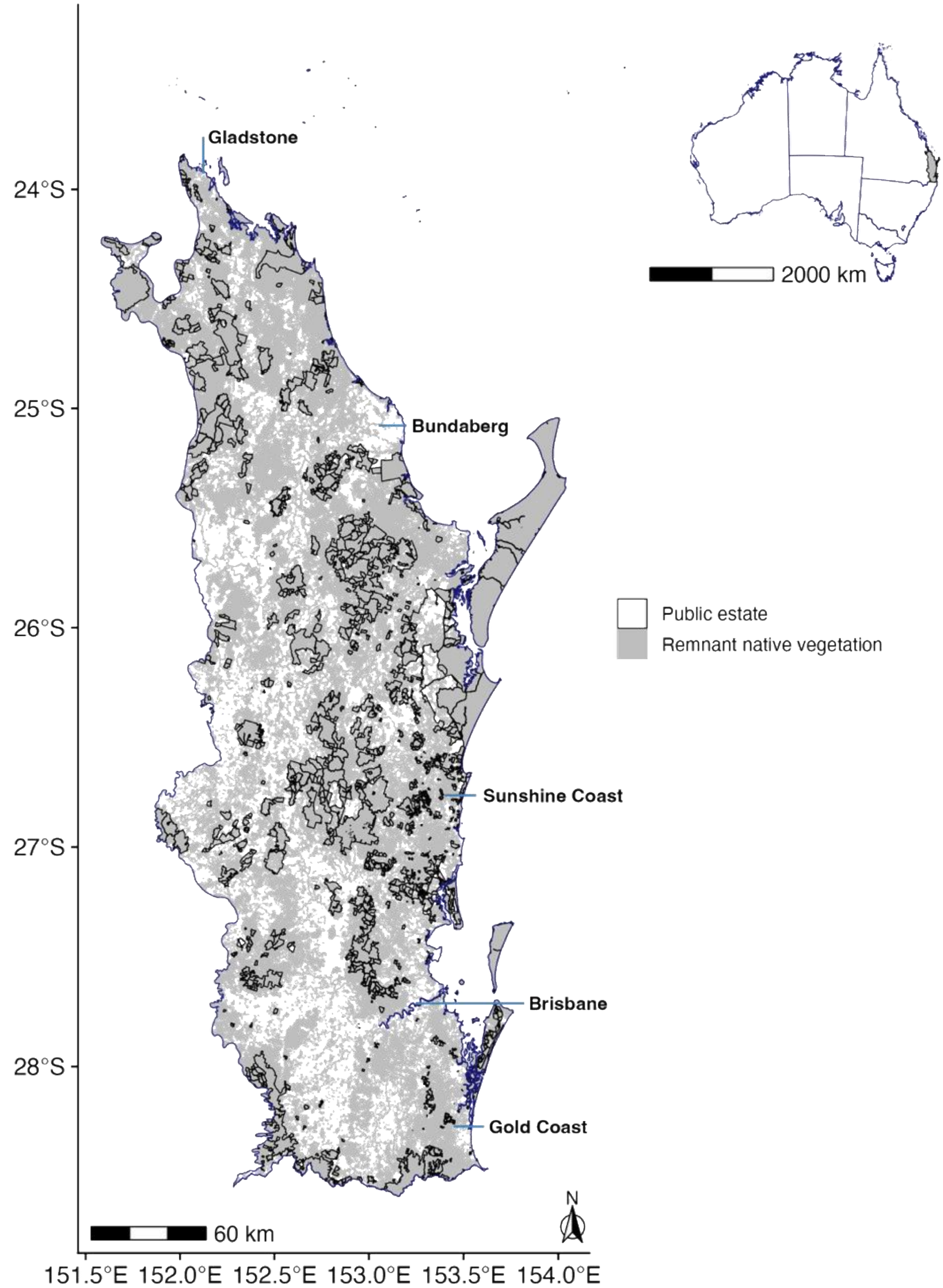

Fig. 2 Remnant native vegetation cover and public estate land managed by Queensland Parks and Wildlife Service in the case study region of southeast Queensland, Australia.

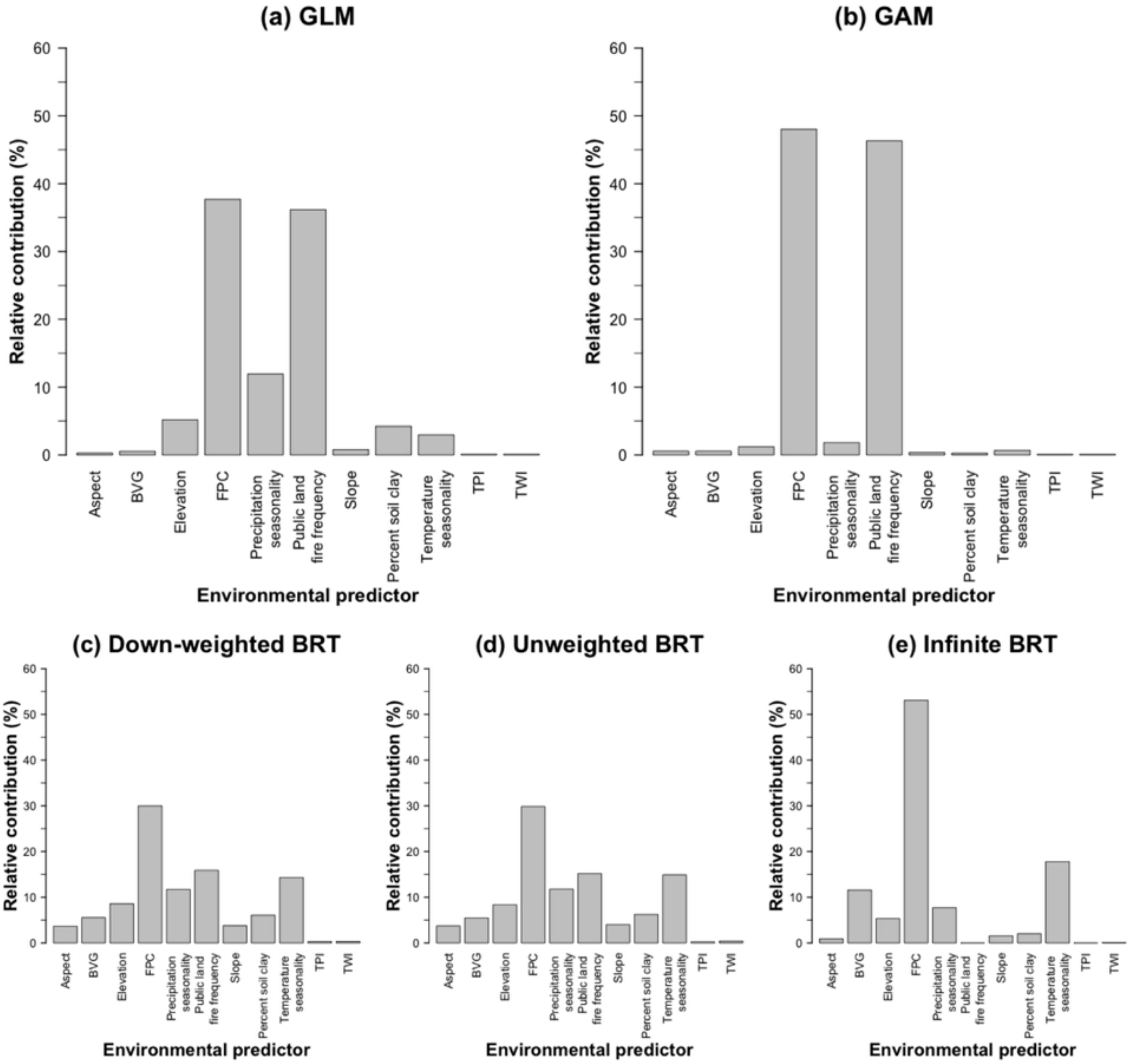

Fig. 3 Relative contributions of environmental predictors to modelling satellite fire frequency for (a) generalised additive (GAM); (b) generalised linear (GLM); (c) Down-weighted BRT; (d) unweighted BRT; (e) infinitely weighted logistic regression BRT (Infinite BRT). FPC = Foliage Projective Cover; TPI = Topographic Position Index; TWI = Topographic Wetness Index. The relative contribution axis was truncated at 60% as no variables' contribution to modelling exceeded 55%.

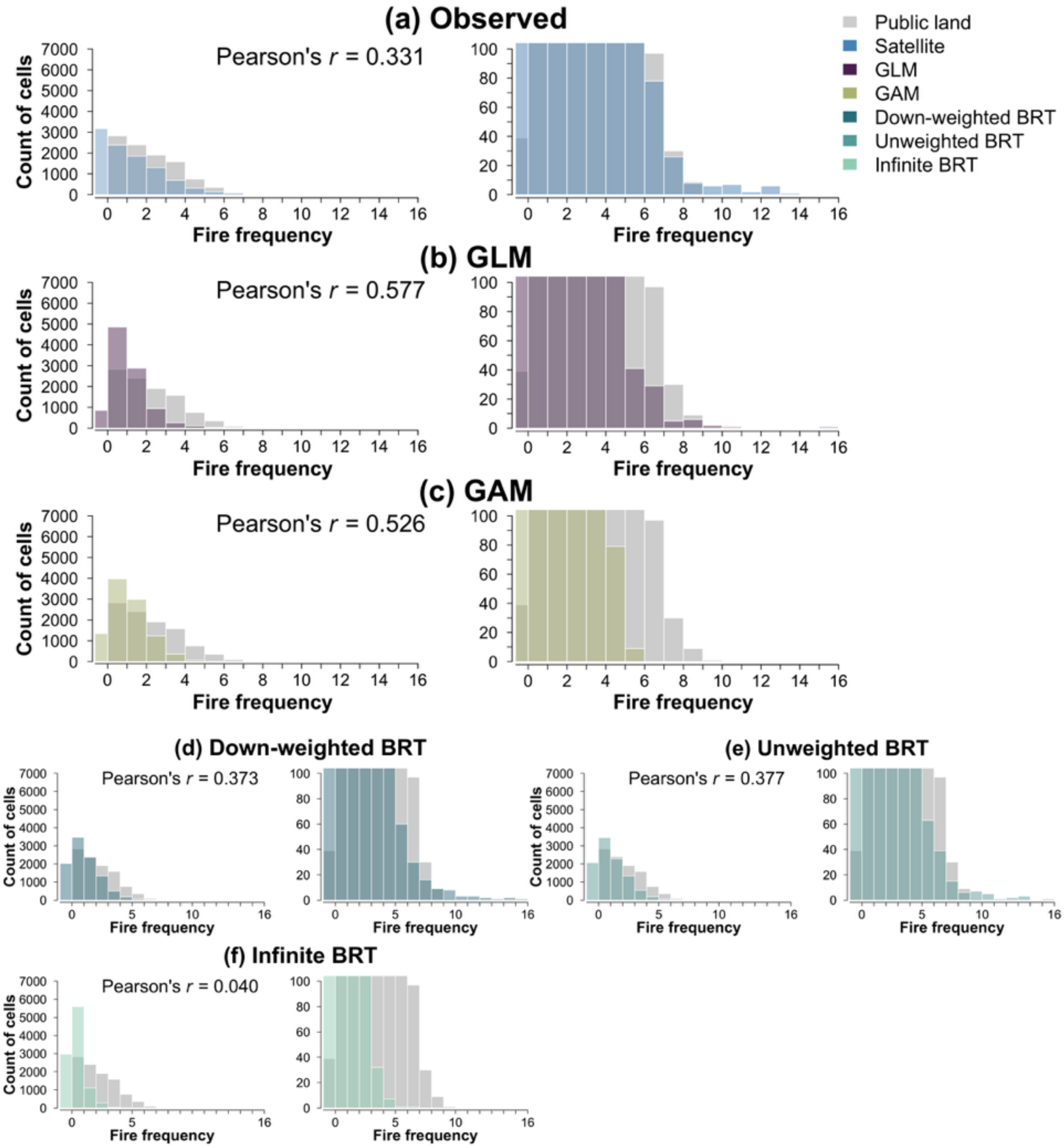

Fig. 4 Comparisons of fire frequency estimates between public land fire history data ('public'), raw, unmodelled satellite data ('satellite') and predictions from a range of model types. The right-hand panel for each model type shows cell counts below 100 to enable comparisons at high fire frequencies (fire frequencies ≥4 had very low cell counts and were difficult to visualise). All fire frequency estimates were compared against the public land fire data as a baseline, with fire frequency at presence points ranging from 0 to a maximum of 16 fires depending on the model. (a) Observed = satellite and public land, (b) generalised linear (GLM), (c) generalised additive (GAM), (d) down-weighted Boosted Regression Tree (BRT), (e) unweighted BRT, and (f) Infinitely Weighted Logistic Regression BRT (Infinite BRT) model predictions.

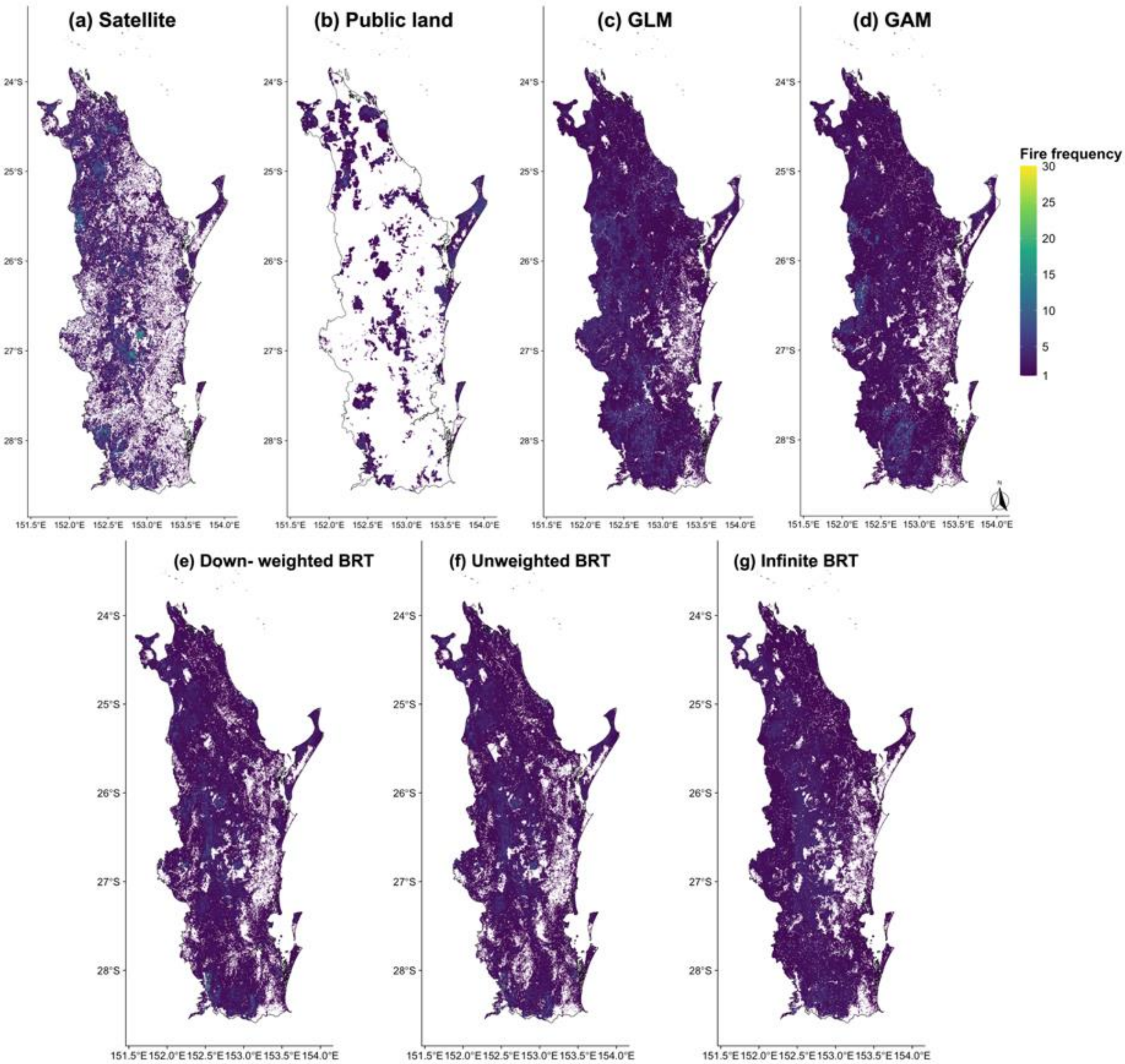

Fig. 5 Fire frequency from 1987 to 2023 in southeast Queensland, Australia derived from (a) observed satellite and (b) public land fire history data. The observed fire frequencies were compared to predictions from: (c) generalised linear model (GLM), (d) generalised additive model (GAM), (e) down-weighted BRT, (f) unweighted BRT, and (g) Infinitely Weighted Logistic Regression (Infinite BRT). White areas are those mapped as unburned. The maximum estimated fire frequency varied across model types: (a) satellite data = 29; (b) public data = 12; (c) GLM = 29; (d) GAM = 40; (e) down-weighted BRT = 130; (f) unweighted BRT = 115; (g) Infinite BRT = 9. Fewer than 1% of cells had fire frequencies >30 from 1987 to 2023 for GAM, unweighted BRT, and down-weighted BRT. Thus, to aid visualisation, fire frequencies >30 are not shown but can be extracted from the database provided online (Charles *et al.* 2026).

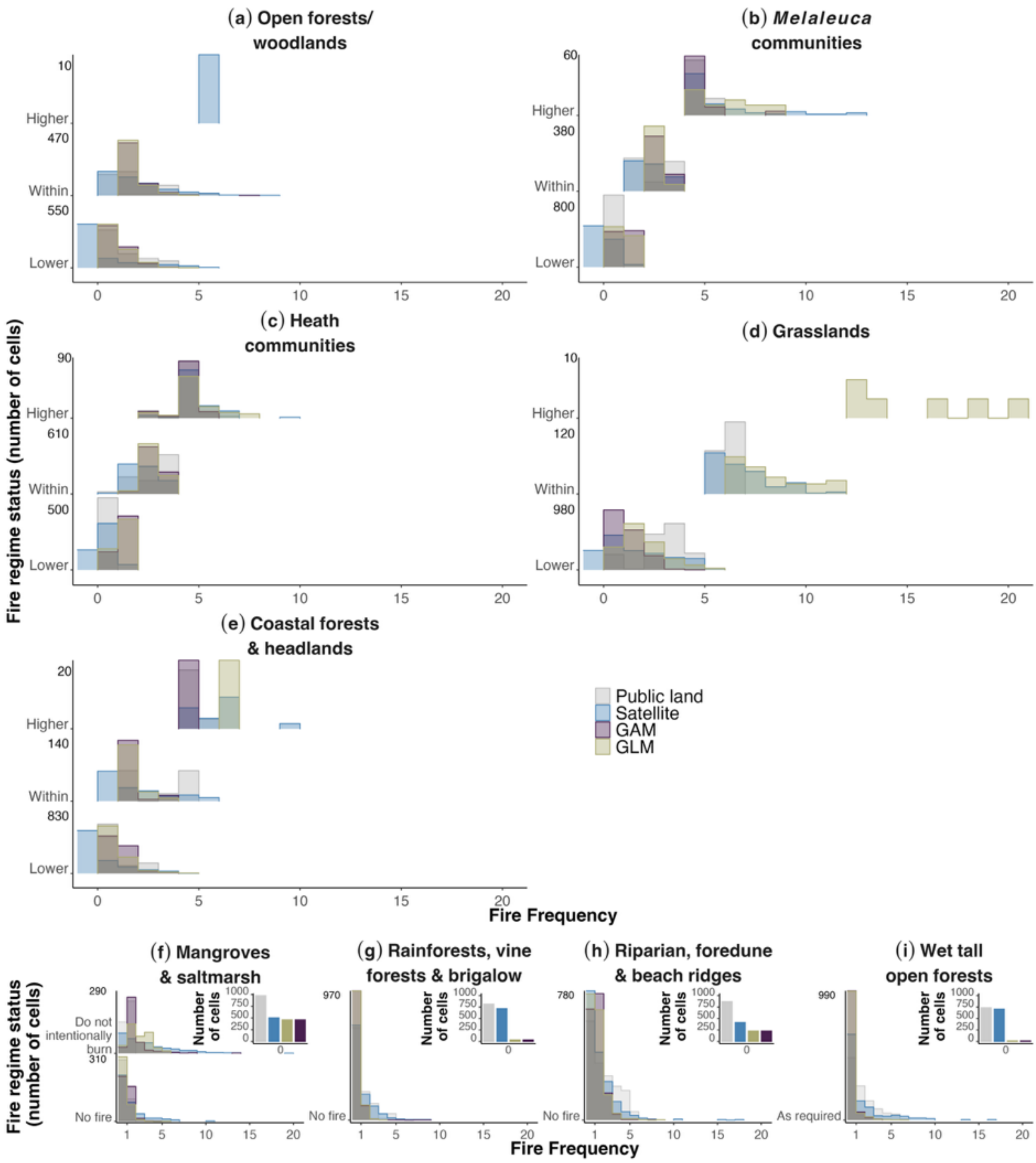

Fig. 6 Distributions of fire frequencies from 1987 to 2023 across broad vegetation aggregations in southeast Queensland, Australia relative to ecologically informed fire regime recommendations. For 1000 random points within each broad vegetation aggregation, the number of cells (y-axis) for each fire frequency (x-axis) are shown, categorising whether the fire regimes were within, higher, or lower than ecological recommendations. The maximum number of cells for each fire regime status category is presented on the y-axis. Broad vegetation aggregations were classified as fire-prone vegetation: (a) open forests and woodlands; (b) *Melaleuca* communities; (c) heath communities; (d) grasslands; and (e) coastal forests and headlands, or fire sensitive vegetation: (f) mangroves and saltmarshes; (g) rainforests, vine forests, and brigalow; (h) riparian, foredune, and

beach ridges; and (i) wet tall open forests. Recommendations for fire sensitive vegetation (f – i) are: 'do not intentionally burn', 'no fire' or 'as required'. Estimated fire for these vegetation types were dominated by zeros, and the zero values were, thus, plotted as an inset to aid visualisation. Fire frequency estimates are presented from public land fire history data ('public'); raw, unmodelled satellite data ('satellite'); and predictions from a Generalised Linear Model (GLM) and a Generalised Additive Model (GAM). The range of fire frequency differed between datasets from zero fires to satellite data and GLM predictions = 20; GAM predictions = 14; and public land fire data = 7.