Improving landscape fire frequency estimates by integrating public land fire data and satellite imagery

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Abstract

Background

Contemporary fire regimes are changing rapidly, and effective fire management requires knowledge of fire history, often derived from satellite imagery. Satellites, however, are not well suited to detecting low intensity fires, meaning fire history data are often inaccurate.

Aims

We aimed to improve satellite fire frequency estimates by incorporating data from fire history on 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.

Key results

Relative to unprocessed satellite data, generalised linear and generalised additive models improved correlations with public land fire data by 0.39 and 0.25, respectively. Generalised linear models estimated low fire frequencies well (≤2 fires), whereas generalised additive models predicted higher fire frequencies (≥3 fires) more accurately.

Conclusions

For mapping land as burnt or unburnt, generalised linear models are most appropriate. For understanding the total number of fires over time, and for most vegetation types, predictions from generalised additive model are most appropriate.

Implications

Our approach can improve the accuracy of fire frequency estimates from satellite data, to assist fire management and conservation. However, model selection will depend on the application and vegetation type.

Summary

Historical fire data are widely used in fire management and research, but these data are often incomplete, which limits our ability to manage fire for conservation and human safety. We present a generalisable application of predictive modelling which can improve landscape-scale fire frequency estimates from satellite data.

Introduction

Fire has shaped the structure and composition of ecosystems for millennia, with variation in fire regimes driven by global climatic patterns such El Niño-Southern Oscillation, and by anthropogenic influences such as cultural 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 and Enright 2022), land clearing, fire suppression, and inappropriate fire management policies (Rogers *et al.* 2020; 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 an urgent 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 and Fletcher 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 related to 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, and tree-ring fire scar analyses (Mouillot and Field 2005; Greene and Daniels 2017; Queensland Parks and Wildlife Service 2023). These multi-decadal fire datasets can be limited in spatiotemporal coverages (Duane *et al.* 2015) and disrupted by jurisdictional boundaries, producing discontinuous datasets (Liu *et al.* 2019b; Phelps and Woolford 2021; Ryu and Charalambou 2023). Gathering and processing such fire scar 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 systems and government policies (Queensland Parks and Wildlife Service 2023; Ryu and Charalambou 2023). Another major issue is that these data are usually restricted to public land, leaving little knowledge of contemporary fire histories outside public estates. Some studies have attempted to account for incompleteness in public land fire history (e.g., restricting analyses to recent years with stricter reporting guidelines and more accurate mapping methods, Eliott *et al.* 2020), but generalisable workflows for reconstructing fire histories are lacking.

Satellite derived imagery has circumvented 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; Orero *et al.* 2024; Ramsey *et al.* 2024). Several fire-related satellite products are available at different resolutions and spatial coverages, such as the 500 m Global Fire Atlas, global 250m Moderate Resolution Imaging Spectroradiometer MODIS burned area product, and Landsat or Sentinel-2 products at smaller scales (e.g., 30 and 10 m, respectively) scales (Maier and Russell-Smith 2012; Andela *et al.* 2019; Ruscalleda-Alvarez *et al.* 2021). However, satellite derived fire products also suffer from drawbacks. They can misclassify burned areas (van den Berg 2021), and their resolution is often too coarse to capture small fires at scales relevant to management (Ruscalleda-Alvarez *et al.* 2021). Another source of inaccuracy in satellite fire products is their inability to capture low intensity understorey fires (Randerson *et al.* 2012; Khairoun *et al.* 2024) meaning that fire frequency is often underestimated (Collett 2021; van den Berg 2021). Low intensity understorey fires can be detected by combining satellite data with high resolution airborne digital sensor imagery (e.g., McCarthy *et al.* 2017) but this method is resource intensive, in terms of time and expert personnel, and is likely prohibitive for mapping over large spatiotemporal scales. As a result, despite the importance of knowing how often and at what intervals burning has taken place over decadal timescales is often unknown (Galizia *et al.* 2021; Ruscalleda-Alvarez *et al.* 2021; Khairoun *et al.* 2024). Thus, there is a strong need for approaches which can improve estimates of multi-decadal fire history at landscape scales.

Here, we aimed to develop a method to predict fire frequency outside of public estates and improve the accuracy of landscape-scale fire frequency estimates from satellite data. We used a novel application of species distribution modelling to improve estimates of satellite fire frequency by integrating data of fire history on public land and environmental co-variation. Environmental factors including climate, terrain, and vegetation productivity drive fire cycles and govern 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 treats 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 frequency estimates. We expected correlations would be higher between public land fire data and the modelled values than the unmodelled values from the satellite imagery. We begin by outlining a general workflow which can be applied to any landscape where fire history data is available. Following this, we 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 history across landscapes.

Methods

General workflow to improve fire frequency estimates

Patchy satellite historical fire data can be improved by modelling the spatial relationship with environmental factors, and where available, more accurately mapped public land historical fire data. Modelling these relationships allows projections of fire history to areas that are unmapped (i.e., unburnt areas) or inaccurately mapped (i.e., outside region where fire history information has been recorded). We recommend investigating multiple modelling methods to account for differing strengths and weaknesses among models (Li and Wang 2013; Elith *et al.* 2020; Valavi *et al.* 2022; Harris *et al.* 2024). 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 and foliage projective cover) (Cary *et al.* 2006; Bradstock 2010; Duane *et al.* 2015). Data are then cropped to the study region and reformatted to align the spatial resolution and coordinate reference systems across layers (Fig. 1a). In the second stage, available historical fire data is reformatted such that the fire metric of interest can be calculated using standard GIS functions (Fig. 1b). Here we focus on fire frequency (i.e., the cumulative count of cells which burned over the time period), but other metrics could include fire return interval, time since last fire, or fire seasonality for the relevant time period.

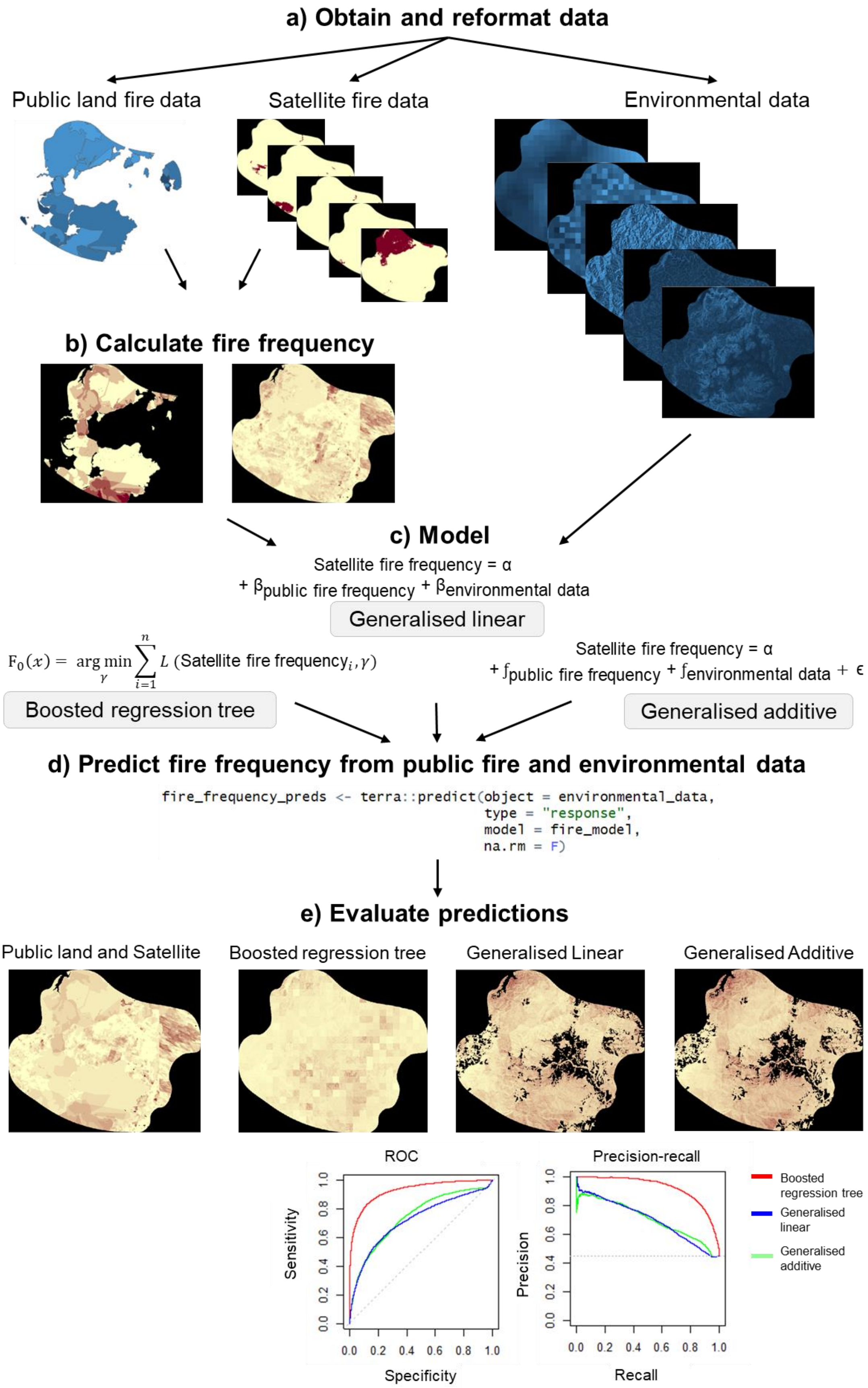

Fig. 1 Generalisable workflow for improving fire frequency estimates using predictive modelling: (a) obtaining and reformatting fire (e.g., public land and satellite, where available) and environmental (e.g., climate, site

productivity, terrain) data; (b) calculate fire frequency from fire history data; (c) run models; (d) produce spatial predictions; and (e) evaluate predictions by comparing of spatial predictions and model performance statistics.

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 (i.e., true absences), these can be absence points. 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 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 redundant 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 (i.e., 80% of the data) and model evaluation (i.e., 20% of the data for evaluating Area Under the Receiver Operating Characteristic Curve (AUC_{ROC}) and Precision-Recall Gain curves (AUC_{PRG}). 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 the environmental predictors (Fig. 1d). In the fifth and final stage, models are evaluated using the spatially explicit model evaluation dataset. Predictive performance can be evaluated by comparing spatial prediction maps and by using standard evaluation procedures for species distribution modelling workflows (e.g., AUC_{ROC} and AUC_{PRC}; Valavi *et al.* 2022) (Fig. 1e). Further model evaluation can be performed by comparing observed and predicted fire frequency correlations and fire frequency histograms.

Case study region

Our case study focused on southeast Queensland, Australia, extending from Bauple in Queensland, south to northern New South Wales, and from the east coast, west to Toowoomba, Queensland (Fig. 2). The region has a subtropical climate with mean annual rainfall ranging from 600 mm to 2000 mm (Australia Bureau of Meteorology 2024a). Mean maximum temperatures range throughout the region from 21 °C to 33 °C in summer and 18 °C to 24 °C in winter (Australia Bureau of Meteorology 2024b). Coastal areas within the region generally experience more moderate temperatures and higher rainfall. Fires in the region generally occur in late winter and spring with prescribed burning in public estates typically conducted in winter (Eliott *et al.* 2020; Department of Environment and Science 2022) (Fig. 2). In 2021-2022, prescribed burning was conducted across 358 563 ha of Queensland by Queensland Parks and Wildlife Service (Department of Environment 2024a). Between September 2019 and February 2020, wildfires affected 3.1 million hectares of public and nearby land managed by Queensland Parks and Wildlife Service, in an event that was unprecedented in spatial scale and intensity (Legge *et al.* 2022). On private land, properties are burned for fire hazard reduction, woody vegetation control, ecosystem restoration, and weed control, and as a cultural practices (Toledo *et al.* 2012; Edwards and Gill 2016; Greenwood *et al.* 2022; McCormack *et al.* 2024).

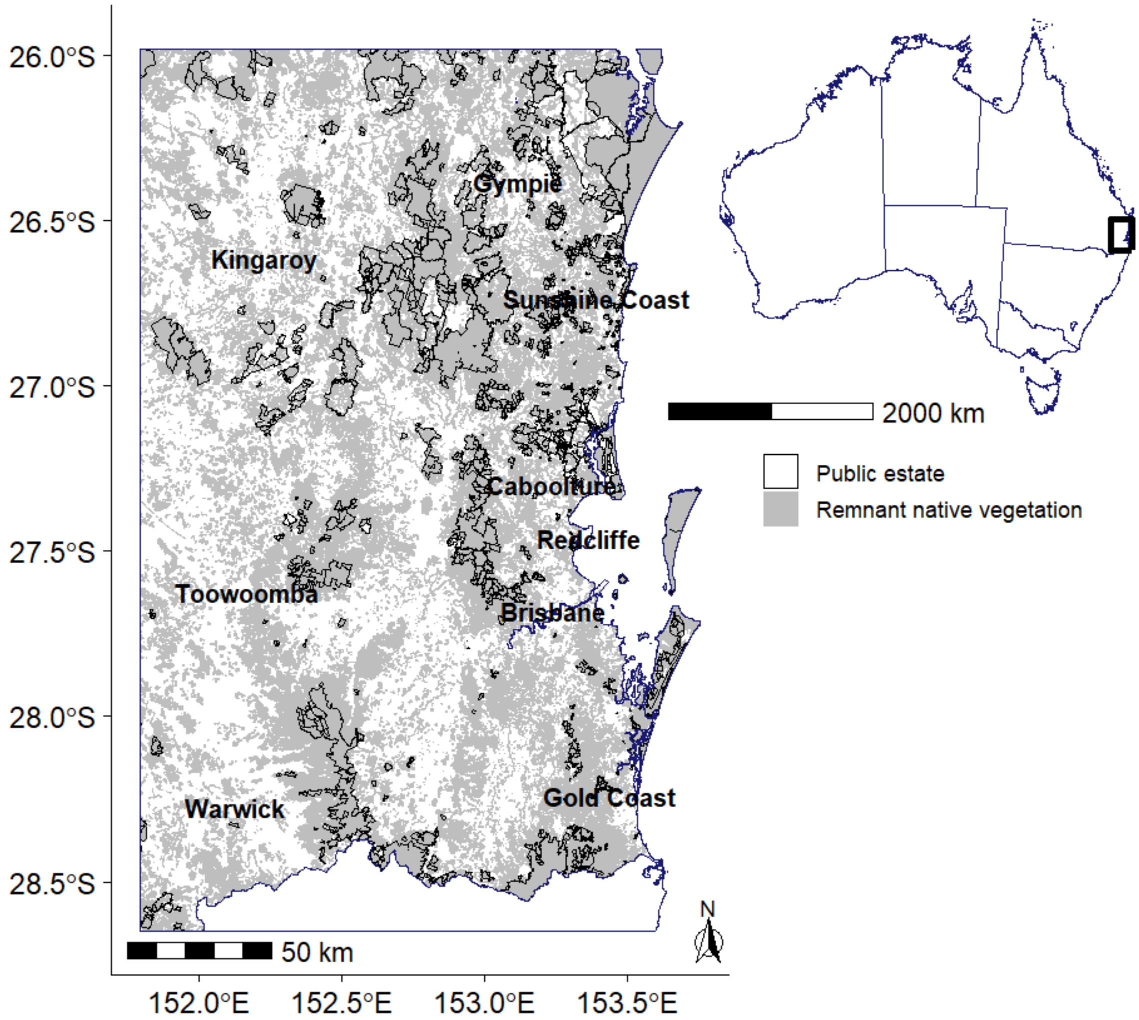

Fig. 2 Remnant native vegetation cover and the public estate, managed by Queensland Parks and Wildlife Service, in the case study region of southeast Queensland, Australia.

Modelling methods

We conducted all analyses in R version 4.3.1 (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 terra version 1.7-78 (Hijmans 2024), unless otherwise specified. All spatial data layers (Table 1) were projected to a standard coordinate reference system (EPSG 3577: GDA94/Australian Albers); extent (Fig. 2); and to a resolution of 30 m. We masked spatial data to exclude water bodies, limiting predictions to land.

Historical fire data pre-processing

Satellite fire scar data were obtained from Landsat (1987-2016, 30 m) and Sentinel (2017 – 2023, 10 m) fire scar data (Collett 2021; van den Berg 2021). Each of these datasets are produced as yearly composites with values denoting month of burn. Due to high computational demand, the study region was subdivided into eight blocks for processing. For each subdivision block, satellite fire scar values were reclassified such that values of 1-12 were assigned 1s and no data values (i.e., unburnt and no data areas – water or agricultural crop masked) were assigned 0s. Fire frequency (i.e., a count of the number of fires in the past 36 years) was then calculated as the cumulative count of cells assigned 1 for each subdivision block, for Landsat and Sentinel data separately. Upon completion of this pre-processing, Sentinel fire data was then aggregated to 30 m resolution by averaging cell values. For each subdivision block, the cumulative sum of fire frequencies for 1987-2023 was calculated, combining Sentinel and Landsat data. Finally, each subdivision block was merged into one dataset representing satellite fire frequency data for the study region from 1987-2023.

Public land fire data were obtained from Queensland Parks and Wildlife Service. These data consisted of spatial maps of burn scar extents 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 subset 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 fasterize version 1.0.5 (Ross 2023). The final public land fire frequency dataset was then aggregated to a 30m resolution using gdalUtilities 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 predictors (Table 1): terrain (elevation, slope, aspect, and topographic position index); site productivity (topographic wetness index, foliage projective cover, and soil percent clay); and climate (temperature seasonality, precipitation seasonality, and average diurnal temperature range). 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 levels (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 captures 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 study extent using gdalUtilities (see Table 1), in the same way as the fire data. A Digital Elevation Model was used to derive aspect and degrees of slope using terra. Topographic position index was derived from the Digital Elevation Model using landform version 0.2 (Alberti 2023).

Table 1 Spatial 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 gdalUtilities).

Environmental variable	**Raw resolution**	**Resampled resolution**	**Temporal resolution**	**Data source**
Mean diurnal temperature range	1 km	30 m	1970-2000	(Fick and Hijmans 2017)
Temperature seasonality	1 km	30 m	1970-2000	(Fick and Hijmans 2017)
Precipitation seasonality	1 km	30 m	1970-2000	(Fick and Hijmans 2017)
Topographic wetness index	30 m	Unchanged	2000	(Gallant and Austin 2012)
Foliage projective cover				
- Landsat 2014	30 m	Unchanged	1998-2014	(Department of Environment 2020)
- 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	(Department of Environment 2024b)
Soil % clay from 0 to 2m	90 m	30 m	2021	(CSIRO 2024)
Elevation, aspect, slope, topographic position index	30 m	Unchanged	2001-2015	(Geoscience Australia 2011)

Foliage projective cover (FPC) data is provided as 0-100% foliage cover, but the 2014 data required reclassification as values of 0-100% were denoted as 100-200, and 0% was denoted by values above 200 or below 100. We then calculated average FPC from the reclassified 2014 and 2018-2021 datasets. 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 (NA) with single imputation (Łopucki *et al.* 2022), such that NAs were replaced by an average from the surrounding cells using terra as nearby cells are likely to be similar. 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).

Presence-background points dataset

Our datasets suffered from a lack of definitively identifiable unburnt areas from 1987-2023 (Eliott *et al.* 2020; Queensland Parks and Wildlife Service 2023). As our aim was to improve 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). Prior to producing presence/absence 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 using terra (Hijmans 2024). Background points were then created as a random sample of 80,000 points across southeast Queensland irrespective of the location of presence points, such that 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 irrelevant variables. Firstly, 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 ggstatsplot version 2.1-1 (Patil 2021). No variables were above this correlation threshold, so all were retained. Secondly, to eliminate irrelevant variables we fit a global linear model and ran Akaike Information Criterion (AIC) backward stepwise elimination (e.g., Syphard *et al.* 2008; Elia *et al.* 2020) using MASS version 7.3-60 (Venables and Ripley 2002). Soil percent clay was excluded during stepwise elimination and was removed from presence-background and environmental predictors data.

Spatial blocking

Predictive modelling requires independent training and evaluation data (i.e., AUC_{ROC} and AUC_{PRG} evaluation) (Hastie *et al.* 2009) which, for predicting to new areas, should also be spatially blocked (see Roberts *et al.* 2017). This 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). We used variograms to determine the extent of spatial autocorrelation for the satellite fire frequency data. An initial variogram was computed using blockCV version 3.1-4 (Valavi *et al.* 2019) to inform parameter settings (e.g., psill, model, range, and nugget) for subsequent fitting of variograms using gstat version 2.1-1 (Pebesma 2004; Gräler *et al.* 2016). We fitted variograms iteratively with parameters adjusted until the final outputs were the same as those used for fitting, with the final range value used to inform spatially explicit block size. Satellite fire frequency was used to randomly but equally allocate points restricted to areas of public land fire data to five training and evaluation dataset partitions in a checkboard pattern. This resulted in each partition for a given satellite fire frequency having a 4:1 ratio of training to evaluation 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 use a traditional statistical modelling approach and often perform well in modelling species distributions (e.g., Meynard and Quinn 2007; Murase *et al.* 2009; Valavi *et al.* 2022). Our goal was to compare the three model types to determine which method improved estimates of satellite fire frequency when compared to the more accurately mapped public fire data. In all models, the response variable was satellite fire frequency derived 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.

Boosted regression tree modelling

Boosted regression trees hyperparameters were optimised prior to modelling by creating a data frame with all combinations of: number of trees (500, 600, …, 10000); 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 caret version 6.0-94 (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.

The ratio of presence to background points in our data was small (2:8) thus, following Valavi *et al.* (2022), we used three weighting approaches to balance their contribution: (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’). Each BRT model was then run using dismo version 1.3-14 (Hijmans *et al.* 2023).

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 mgcv version 1.9-1 (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 (Wood 2017). Generalised additive model smoothness was further controlled by specifying the basis dimension ('*k*') to determine knots 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.

Predicting fire frequency and evaluating model performance

Spatial predictions of fire frequency were produced from each model using the environmental predictors through terra (Hijmans 2024). Predictions were extracted for presence and background points to evaluate model performance using commonly used species distribution modelling metrics in precrec version 0.14.4 (Saito and Rehmsmeier 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.* 2023); and Pearson's coefficient of determination through stats (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 correlations to the correlation between public land fire frequency and unmodelled satellite fire frequency ('observed'). Where the correlation coefficient of the modelled data was greater than that of the observed value (r = 0.252), 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 and Soberón 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 broad vegetation aggregations. Broad vegetation aggregations followed those recognised in Queensland's Broad Vegetation Group (BVG) classification system: rainforests = 1-7; sclerophyll = 8-27; grassland and shrubland = 28-33; and wetland, mangrove and saltmarsh = 34-35 (Neldner *et al.* 2019). For each aggregation, fire frequency at 1,000 random points was extracted from public land, modelled and unmodelled satellite fire frequency data.

Results

Our results showed that the accuracy of satellite fire frequency estimates can be improved by modelling its relationship with public land fire and environmental data; with correlations ranging from 0.004 to 0.638 (Table 2). From 1987-2023, fire frequency for unmodelled satellite data ranged from 0 to 26 fires, while on public land it ranged from 0 to 12 fires. Across model types, the maximum predicted fire frequency varied: GLM = 14; GAM = 18; down-weighted BRT = 50; unweighted BRT = 38; and Infinitely BRT = 9. This tendency for models to under- or over-estimate maximum fire frequency was considered to be a minor problem as fire frequencies >18 were less than 1% of the landscape. The largest increases in correlation relative to the observed values were for the GLM and GAM (r = 0.638 and 0.503, respectively, Table 2), but these models had poorer performance than the down-weighted BRT (AUC_{ROC} = 0.722 and 0.742, respectively, Table 2). Down-weighted and unweighted BRT predictions had the highest performance (AUC_{ROC} = 0.930 and 0.754, respectively), but only weakly increased correlations (Table 2). Furthermore, the Infinite BRT had the poorest performance and lowest correlation (r = 0.004; Table 2). The relative contribution of environmental variables to estimates of fire frequency varied among model types, with the best predictor being public land fire frequency for GLM and GAM and temperature seasonality for the BRT models (Fig. 3). Public land fire frequency was the third best predictor for down-weighted and unweighted BRT, but did not contribute to Infinite BRT modelling (Fig. 3).

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	0.638	0.503	0.329	0.332	0.004
AUC_{ROC}	0.722	0.742	0.930	0.754	0.660
AUC_{PRG}	0.703	0.707	0.927	0.707	0.574

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

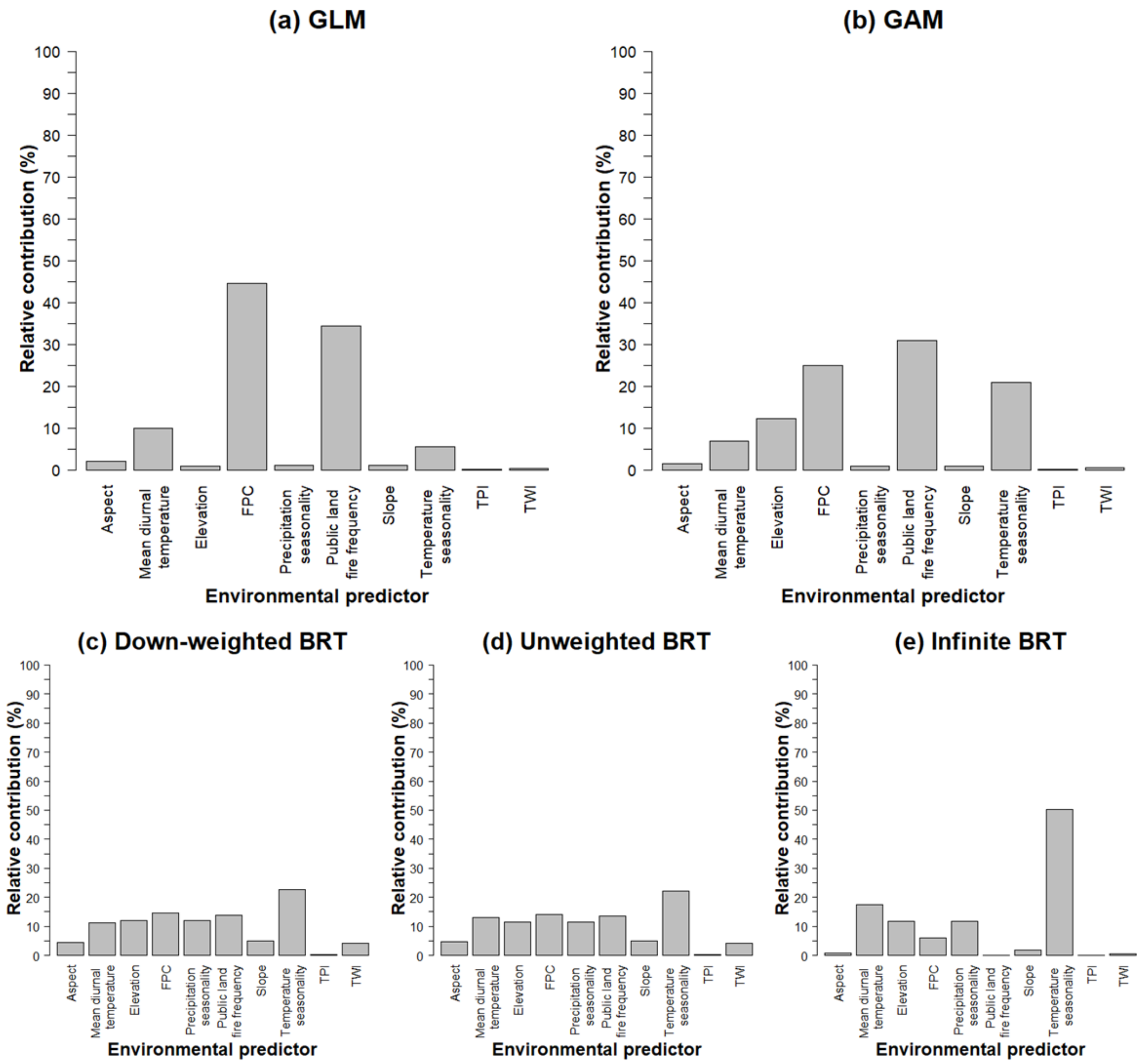

Fig. 3 Relative contributions of environmental predictors to modelling satellite fire frequency for (a) generalised additive (GAM); (b) generalised linear (GLM); (c) Down-weighted BRT; (d) unweighted BRT; (e) infinitely weighted logistic regression BRT (Infinite BRT). FPC = Foliage Projective Cover; TPI = Topographic Position Index; TWI = Topographic Wetness Index.

As expected, unmodelled estimates from satellite data underestimated fire frequency, especially in infrequently burnt areas (i.e., 1-6 fires). However, in frequently burnt areas (i.e., ≥7 fires), satellite data identified more 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 GAM was more likely to capture higher fire frequencies (Fig 4b, c). Thus, the GLM was slightly better at classifying areas as burnt or unburnt, while the GAM was slightly better at classifying areas burnt multiple times. 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). Furthermore, the Infinite BRT resulted in the most severe underprediction (Fig. 4f). Therefore, while our predictive models typically underpredicted fire frequencies >2, our predictions significantly reduced unburnt area classification (Fig. 4a-e). Predictions from the GLM and GAM generally improved estimates of landscape-scale fire frequency with more areas mapped as having burnt at least once (Fig. 5c, d). However, the GAM was slightly better at representing the spatial extent of higher fire frequencies than the GLM (Fig. 5a-d). While BRT predictions also improved representation of higher fire frequencies, these models predicted larger areas as unburnt (Fig. 5e-g).

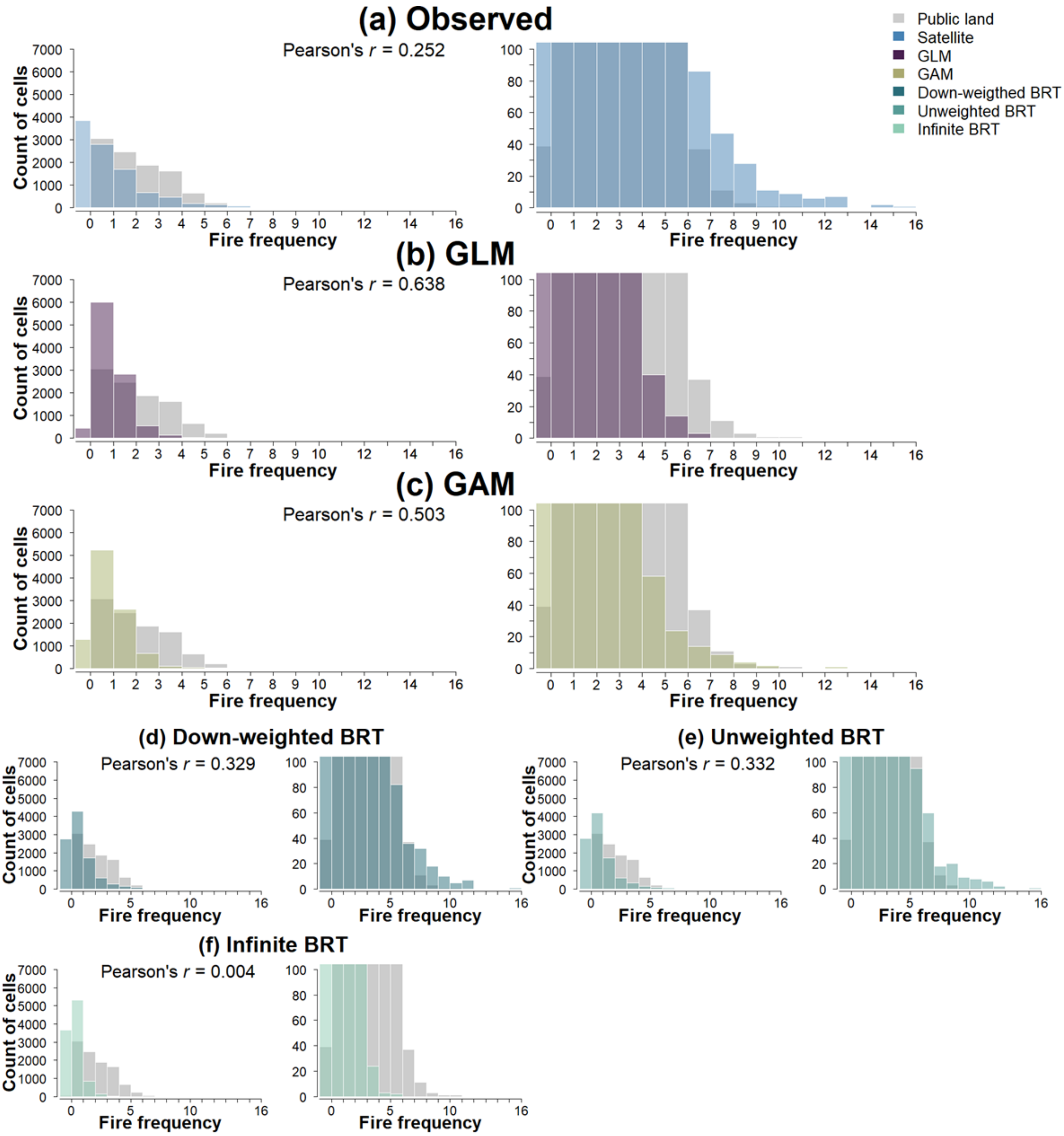

Fig. 4 Comparisons of fire frequency estimates between public land fire history data ('public'), raw, unmodelled satellite data ('satellite') and prediction from a range of model types. The right-hand panel for each model type shows cell counts below 100 to enable comparisons at high fire frequencies (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) unweighted Boosted Regression Tree (BRT), (e) down-weighted BRT, and (f) Infinitely Weighted Logistic Regression BRT (Infinite BRT) model predictions.

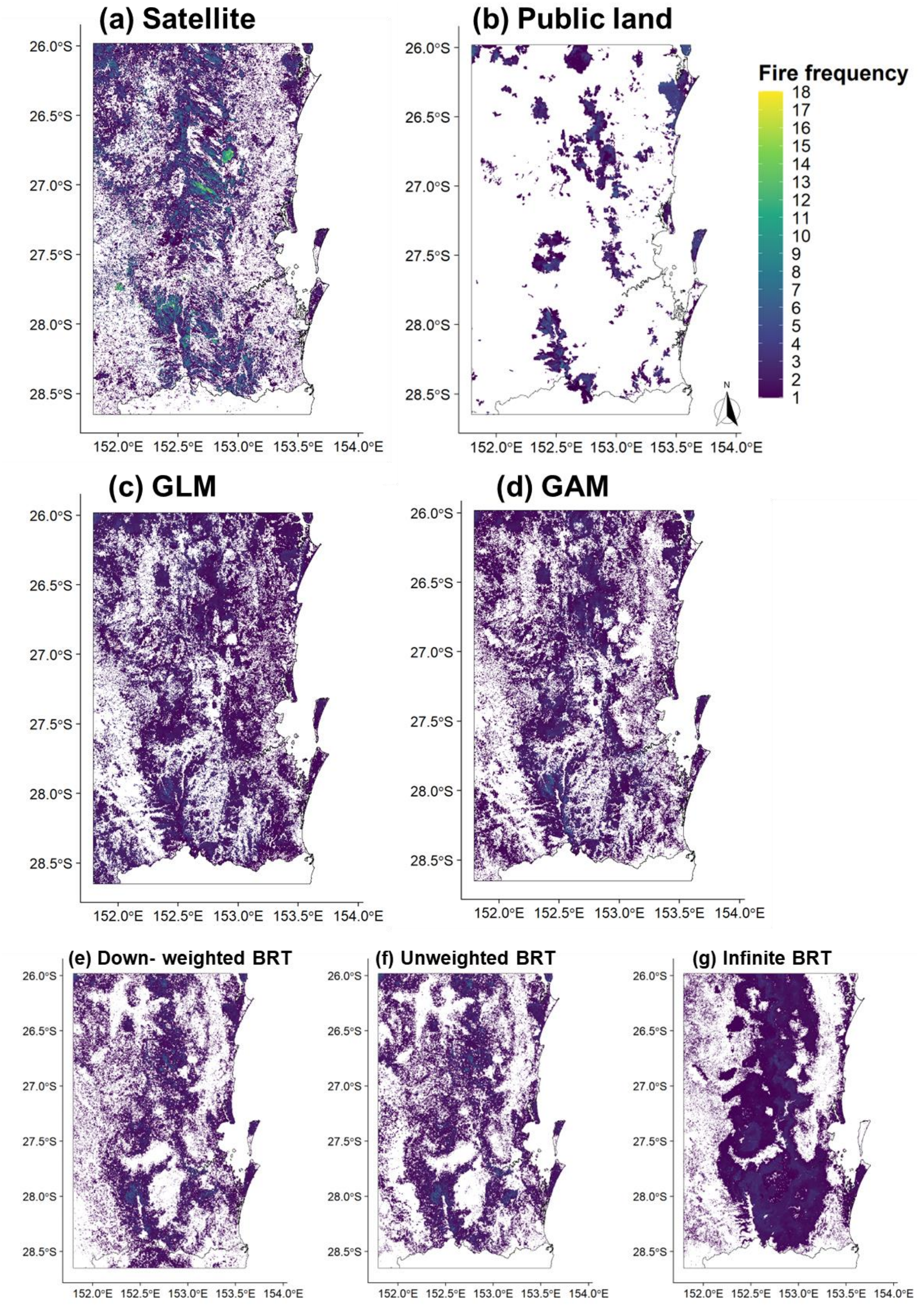

Fig. 5 Fire frequency from 1987 to 2023 in southeast Queensland, Australia derived from (a) observed satellited and (b) public land fire history data. White areas are those mapped as unburned. The observed fire frequencies were compared to predictions from: (c) generalised linear model (GLM), (d) generalised additive model (GAM),

(e) down-weighted BRT, (f) unweighted BRT, and (g) Infinite BRT. The maximum estimated fire frequency varied across model types: (a) satellite data = 26; (b) public data = 12; (c) GLM = 14; (d) GAM = 18; (e) down-weighted BRT = 50; (f) unweighted BRT = 38; (g) Infinite BRT = 9. Fewer than 1% of cells had fire frequencies >18 fires in the past 36 years for satellite, unweighted BRT, and down-weighted BRT. Thus, to aid visualisation, fire frequencies >18 are not shown but can be extracted from the database provided online (Charles and Smith 2025).

The distribution of fire frequencies in vegetation aggregations was highly variable (Fig. 6). In rainforest, the GLM and GAM tended to classify unburned areas as burned, and thus, overpredicted fire activity (Fig. 6a). However, the GAM did this to a lesser extent than the GLM (Fig. 6a). In sclerophyll vegetation, areas classified as unburnt for public land and unmodelled satellite data were commonly modelled as having burnt once rather than spreading along the gradient of fire frequencies, this was especially evident for the GLM (Fig. 4b-c, Fig 6b). In grassland and shrubland, GLM and GAM predictions for unburnt areas were similar to that of unmodelled satellite fire frequency (Fig. 6c). The GLM and GAM resulted in some overprediction of grassland and shrublands areas burnt once but the GAM tended to spread previously unburnt areas along the fire frequency gradient more than the GLM (Fig. 6c). In wetland, mangrove and saltmarsh, overprediction was evident for low fire frequencies (i.e., 1 fire) but for higher fire frequencies, underprediction was more evident in the GLM than the GAM (Fig. 6d). Thus, GAM predictions, while resulting in some overprediction at low fire frequencies (i.e., 1 fire), produced more useful estimates through its capture of higher fire frequencies than the GLM across different broad vegetation aggregations (Fig. 6).

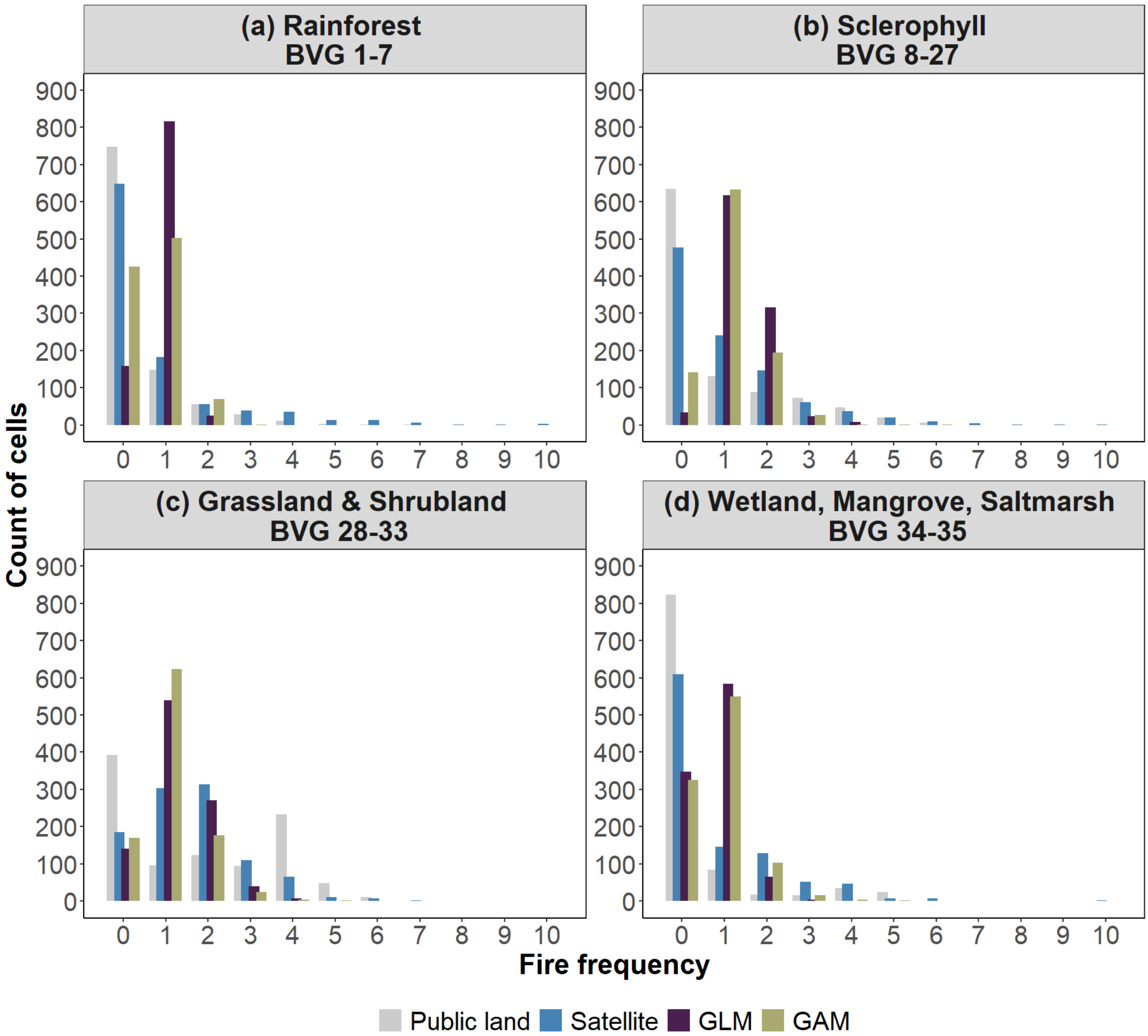

Fig. 6 Distributions of estimated fire frequencies from 1987 to 2023 across broad vegetation aggregations: (a) rainforest; (b) sclerophyll vegetation; (c) grassland and shrubland, and (d) wetland, mangrove and saltmarsh, derived from Broad Vegetation Groups (BVG) in Queensland, Australia. Fire frequency 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 = 10; public land fire data and GAM predictions = 7; and GLM predictions = 5.

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). Here, we improved the accuracy of fire frequency estimates from satellite data by modelling its relationship with public land fire and environmental data. Our resulting models conform to the famous aphorism, attributed to George Box: “all models are wrong, but some are useful”. 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 satellites. Therefore, our models enables us to more accurately classify the landscape as burnt or unburnt in the past 36 years (i.e., 1987-2023). The GLM and GAM improved estimates of landscape scale fire frequency, with correlation increases of 0.39 and 0.25, respectively, likely due to the high relative contribution of public land fire frequency to these models. Correlation improvements were likely due to a higher relative contribution of higher accuracy public land fire frequency to the GLM and GAM predictive modelling, improving modelling of relationships between environmental attributes and satellite fire frequency. Conversely, the BRTs did not significantly reduce areas mapped as unburnt and had variable predictive capacity across fire frequencies, possibly due to a lower relative contribution of public land fire frequency to BRT predictive modelling. 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 data.

Modelled fire frequencies from the GLM and GAM tightly matched observed fire frequencies in shrubland and grassland, and to wetland, mangrove and saltmarsh vegetation. This is likely due to low overstorey vegetation which would otherwise limit satellite imagery capture of understorey vegetation. However, for shrubland and grassland and wetland, mangrove and saltmarsh vegetation, we recommend using a GAM as it was better able to capture higher fire frequencies. In sclerophyll and rainforest vegetation, selection of model type is less clear, as unburnt areas were mapped as having burnt once or twice. For sclerophyll vegetation, we expect high fire frequencies (i.e., ≥5 fires over 36 years) as this vegetation type accumulates fuel load quickly (Gilroy and Tran 2009; Cawson *et al.* 2018; Benwell 2024). It seems likely that the re-classification of unburnt areas as burnt once or twice in this aggregation is accurate. Thus, the GAM would be an effective model type for predicting fire frequency in sclerophyll vegetation as it captures a wider gradient of fire frequencies. Conversely, rainforests typically burn infrequently, as little as once in 100 years (Thorley *et al.* 2023; Benwell 2024). It seems unlikely that the re-classification of unburnt areas to areas burnt once (or more) over 36 years is an accurate reflection of rainforest fire history. Considering that rainforests comprise less than 15% of remnant vegetation in southeast Queensland, our predictive models may not be useful for this vegetation type (Neldner *et al.* 2019). For rainforest vegetation, predictive models would be more useful when specifically fitted to this vegetation type.

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). In Australia, rainforest is typically found within gullies surrounded by more flammable sclerophyllous vegetation (Neldner *et al.* 2019; Fensham *et al.* 2024). Public fire history data shows that more than 60% of these rainforest patches have been affected by wildfire in the past 36 years, potentially linked to suboptimal sclerophyll vegetation fire regimes (Queensland Parks and Wildlife Service 2023; Thorley *et al.* 2023). Our results showed fire frequency in sclerophyllous vegetation was substantially lower than the recommended fire return interval for this vegetation type (i.e., less than 5-6 fires over 36 years, Queensland Herbarium 2024). 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 abundance of fire-retardant rainforest species and facilitates encroachment of flammable species, potentially perpetuating fire regime and vegetation community changes (Cochrane and Laurance 2008; Fletcher *et al.* 2020; Thorley *et al.* 2023; Fensham *et al.* 2024). Further climate-change driven fire regime shifts are expected to intensify during the 21st century driven by climate change (Moritz *et al.* 2012; Di Virgilio *et al.* 2019; Dowdy *et al.* 2019; Canadell *et al.* 2021), which may contribute to vegetation shifts and threats to fire sensitive species (Walsh *et al.* 2013; Dudley *et al.* 2019; Lavery *et al.* 2021). Thus, accurate landscape-scale historical fire information is needed for conservation and mitigation actions, and our workflow can contribute to that goal.

Our workflow can be used to improve predictions of the landscape-scale fire frequency and assess fire regimes suitability for some vegetation types. The choice of predictive model will depend on context and vegetation type. Where researchers are interested in understanding simply whether the land has burnt recently or not, the GLM would be most appropriate. Where researchers want to better characterise high fire frequencies (e.g., more than 4 fires in the past 40 years), the GAM would be appropriate for most vegetation types. However, we recommend trialling new modelling approaches for estimating fire history in rainforest vegetation, due to its unique context. In future, the accuracy of our models could be improved by incorporating data more directly related to fire occurrences such as lightning strikes. These data were unavailable for our study, but might more clearly indicate relationships between environmental attributes and wildfire occurrences. Our predictive modelling workflow may aid fire management and conservation practices by improving the accuracy of fire frequency estimates.

Data availability

Data and code are available as an archived Zenodo repository (Charles and Smith 2025): https://doi.org/10.5281/zenodo.15133643.

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Conflict of interest statement

The authors declare that we have no conflicts of interest.

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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

Australia 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]

Australia 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

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

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 (2025) Fire frequency predicitive modelling (Version 0.1 Peer review pre-release) (Dataset). (FE Charles, Zenodo: Brisbane, QLD, 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

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). 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

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

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

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 Environment, Science, and Innovation (2024a) Annual report 2023-2024, pp. 15. (Department of Environment, Science, and Innovation: Brisbane, Queensland, Australia) Available at https://www.desi.qld.gov.au/__data/assets/pdf_file/0024/356550/annual-report-2023-24.pdf.pdf

Department of Environment, Tourism, Science and Innovation (2020) Landsat foliage projective cover - Queensland 2014 (Dataset). (Queensland Department of Environment, Tourism, Science and Innovation Queensland Spatial Catalogue: Brisbane, QLD, 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 (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, QLD, 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, QLD, 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 and Science (2022) 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

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

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, 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

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

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, Lohmann L, Loiselle B, Moritz C, Overton J, Peterson AT, Phillips S, Richardson K, Williams S, Wiser SK, Wohlgemuth T, Zimmermann NE (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, He M, Trouet V (2021) ENSO modulates wildfire activity in China. *Nature Communications* **12**(1), 1764. doi:https://doi.org/10.1038/s41467-021-21988-6

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

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]

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]

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]

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

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, Stridh B, Sävström T, Thor G, Wikars L-O, Mikusiński G (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 (2024) terra: Spatial Data Analysis. R package version 1.7-78. (The Comprehensive R Archive Network: Vienna, Austria) Available at https://CRAN.R-project.org/package=terra [Verified 28 April 2023]

Hijmans RJ, Phillips S, Leathwick JR, Elith J (2023) dismo: species distribution modelling. R package version 1.3-14. (The Comprehensive R Archive Network: Vienna, Austria) Available at https://CRAN.R-project.org/package=dismo [Verified 1 August 2023]

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

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

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, Fortin M-J, Hermoso V, Herrando S, Keane RE, Lake FK, McCarthy MA, Moran-Ordonez A, Parr CL, Pausas JG, Penman TD, Regos A, Rumpff L, Santos JL, Smith AL, Syphard AD, Tingley MW, Brotons L (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

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, Scheele BC, Sinclair S, Southwell D, Stuart S, Wilson M, Woinarski J (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, Gray J, Metcalfe DJ, Page M, Rumpff L, van Leeuwen S, Williams D, Ahyong ST, Chapple DG, Cowan M, Hossain MA, Kennard M, Macdonald S, Moore H, Marsh J, McCormack RB, Michael D, Mitchell N, Newell D, Raadik TA, Tingley R (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, Haslem A, Jones GM, Kelly LT, Lee CKF, Nolan RH, Parr CL, Pausas JG, Price JN, Regos A, Ritchie EG, Ruffault J, Williamson GJ, Wu Q, Nimmo DG (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

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, Stevenson J, Adeleye M, Cadd H, Hopf F, Briles C (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

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

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, Jacobsen G (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 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, Queensland, Australia)

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

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

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

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, QLD, 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) 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

Roberts DR, Bahn V, Ciuti S, Boyce MS, Elith J, Guillera-Arroita G, Hauenstein S, Lahoz-Monfort JJ, Schröder B, Thuiller W, Warton DI, Wintle BA, Hartig F, Dormann CF (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

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

Ross N (2023) fasterize: fast polygon to raster conversion. R package version 1.0.5. (The Comprehensive R Archive Network: Vienna, Austria) Available at https://CRAN.R-project.org/package=fasterize [Verified 28 April 2023]

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

Sayedi SS, Abbott BW, Vannière B, Leys B, Colombaroli D, Romera GG, Słowiński M, Aleman JC, Blarquez O, Feurdean A, Brown K, Aakala T, Alenius T, Allen K, Andric M, Bergeron Y, Biagioni S, Bradshaw R, Bremond L, Brisset E, Brooks J, Brugger SO, Brussel T, Cadd H, Cagliero E, Carcaillet C, Carter V, Catry FX, Champreux A, Chaste E, Chavardès RD, Chipman M, Conedera M, Connor S, Constantine M, Courtney Mustaphi C, Dabengwa AN, Daniels W, De Boer E, Dietze E, Estrany J, Fernandes P, Finsinger W, Flantua SGA, Fox-Hughes P, Gaboriau DM, M.Gayo E, Girardin MP, Glenn J, Glückler R, González-Arango C, Groves M, Hamilton DS, Hamilton RJ, Hantson S, Hapsari KA, Hardiman M, Hawthorne D, Hoffman K, Inoue J, Karp AT, Krebs P, Kulkarni C, Kuosmanen N, Lacourse T, Ledru M-P, Lestienne M, Long C, López-Sáez JA, Loughlin N, Niklasson M, Madrigal J, Maezumi SY, Marcisz K, Mariani M, McWethy D, Meyer G, Molinari C, Montoya E, Mooney S, Morales-Molino C, Morris J, Moss P, Oliveras I, Pereira JM, Pezzatti GB, Pickarski N, Pini R, Rehn E, Remy CC, Revelles J, Rius D, Robin V, Ruan Y, Rudaya N, Russell-Smith J, Seppä H, Shumilovskikh L, T.Sommers W, Tavşanoğlu Ç, Umbanhowar C, Urquiaga E, Urrego D, Vachula RS, Wallenius T, You C, Daniau A-L (2024) Assessing changes in global fire regimes. *Fire Ecology* **20**(1), 18. doi:https://doi.org/10.1186/s42408-023-00237-9

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

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.

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

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

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]

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

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 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, Heikkinen RK, Høye TT, Kühn I, Luoto M, Maiorano L, Nilsson M-C, Normand S, Öckinger E, Schmidt NM, Termansen M, Timmermann A, Wardle DA, Aastrup P, Svenning J-C (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