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

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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. This approach means we could predict recent fire frequency with greater accuracy even if the target area is not inside the public estate. However, this requires manually-verified fire history data in the region with similar climate and vegetation; this approach may have reduced predictive accuracy if relying on environmental covariates alone. 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). The model can be used to predict what fire frequency would be outside of the public estate, by projecting the modelled relationship between public land fire frequency data and satellite-derived fire frequency, while drawing on spatial environmental covariation. Environmental variables can be taken from the whole study region where data are available. 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.

<u>Generalised linear and generalised additive modelling</u>

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.

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Conflict of interest statement

The authors declare no conflicts of interest.

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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

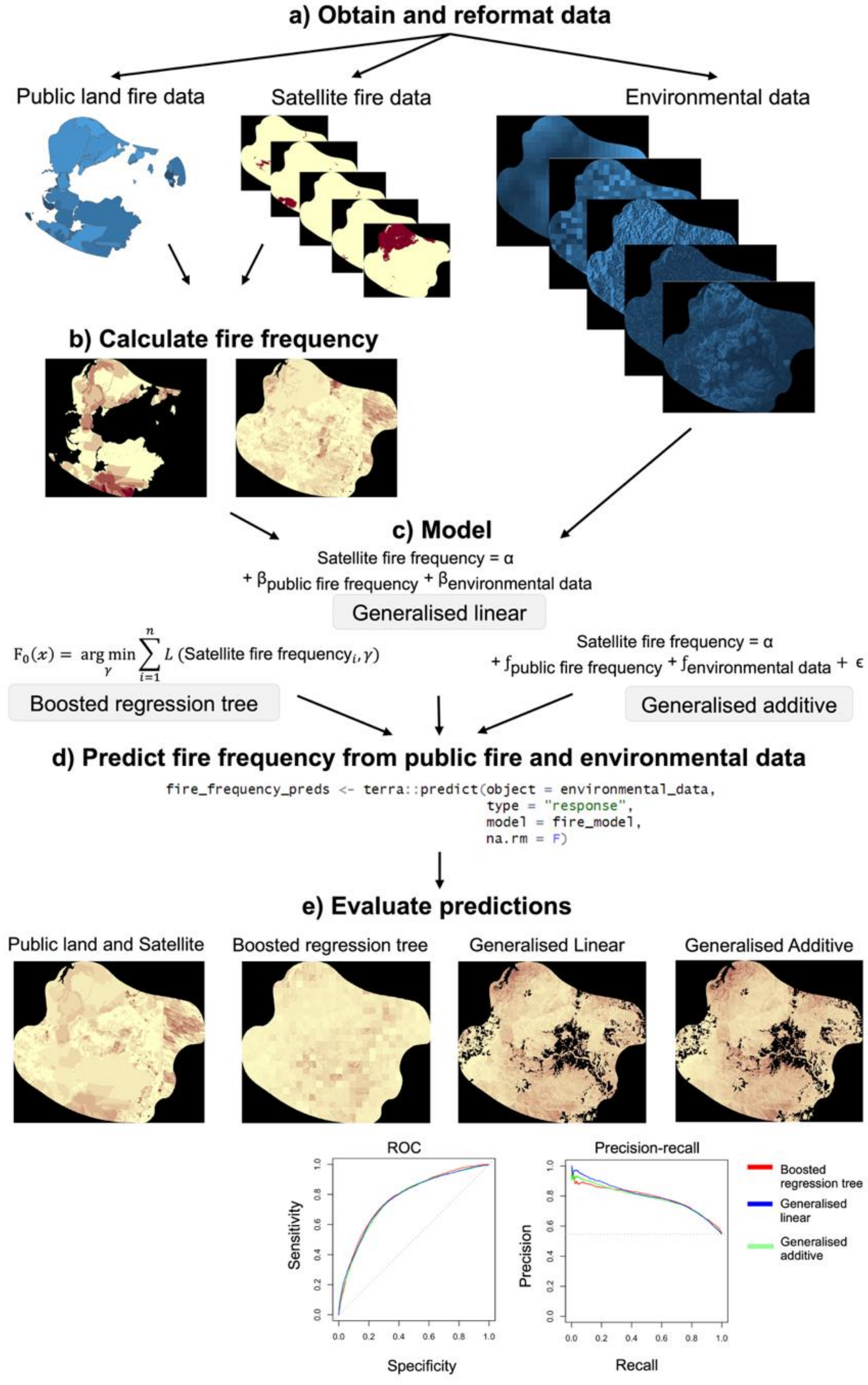

Fig. 1 Generalisable workflow for improving fire frequency estimates using predictive modelling: (a) obtain and reformat fire (e.g., public land and satellite, where available) and environmental (e.g., climate, site productivity,

terrain) data; (b) calculate fire frequency from fire history data; (c) run models; (d) produce spatial predictions using the modelled relationship between satellite-derived fire frequency, public land fire frequency and environmental co-variates, which can be projected outside the public estate; and (e) evaluate predictions by comparison of spatial predictions and model performance statistics. The workflow could be used with any fire regime parameter of interest, e.g. substituting fire frequency for fire return interval, time since last fire, or fire seasonality.

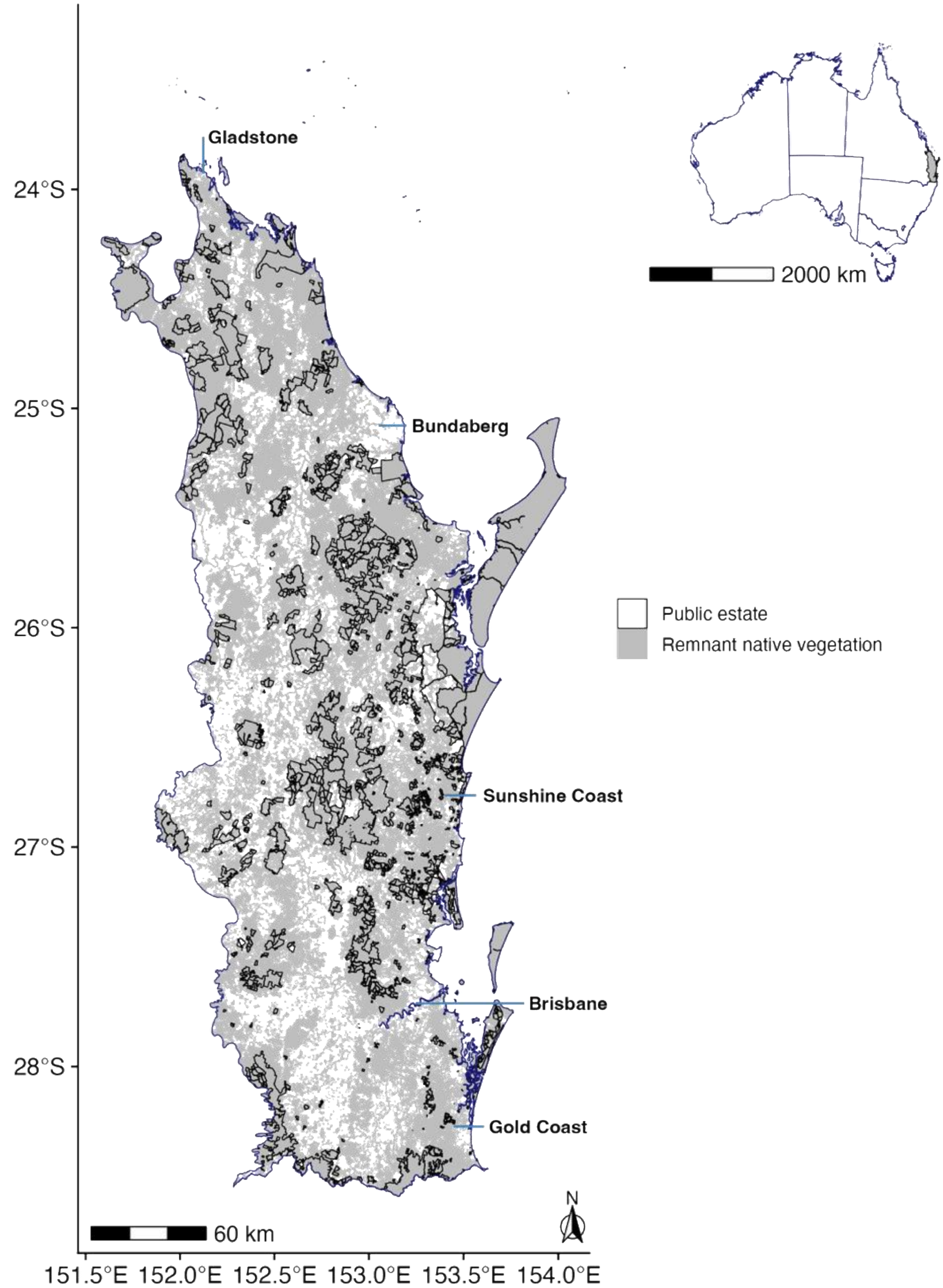

Fig. 2 Remnant native vegetation cover and public estate land managed by Queensland Parks and Wildlife Service in the case study region of southeast Queensland, Australia.

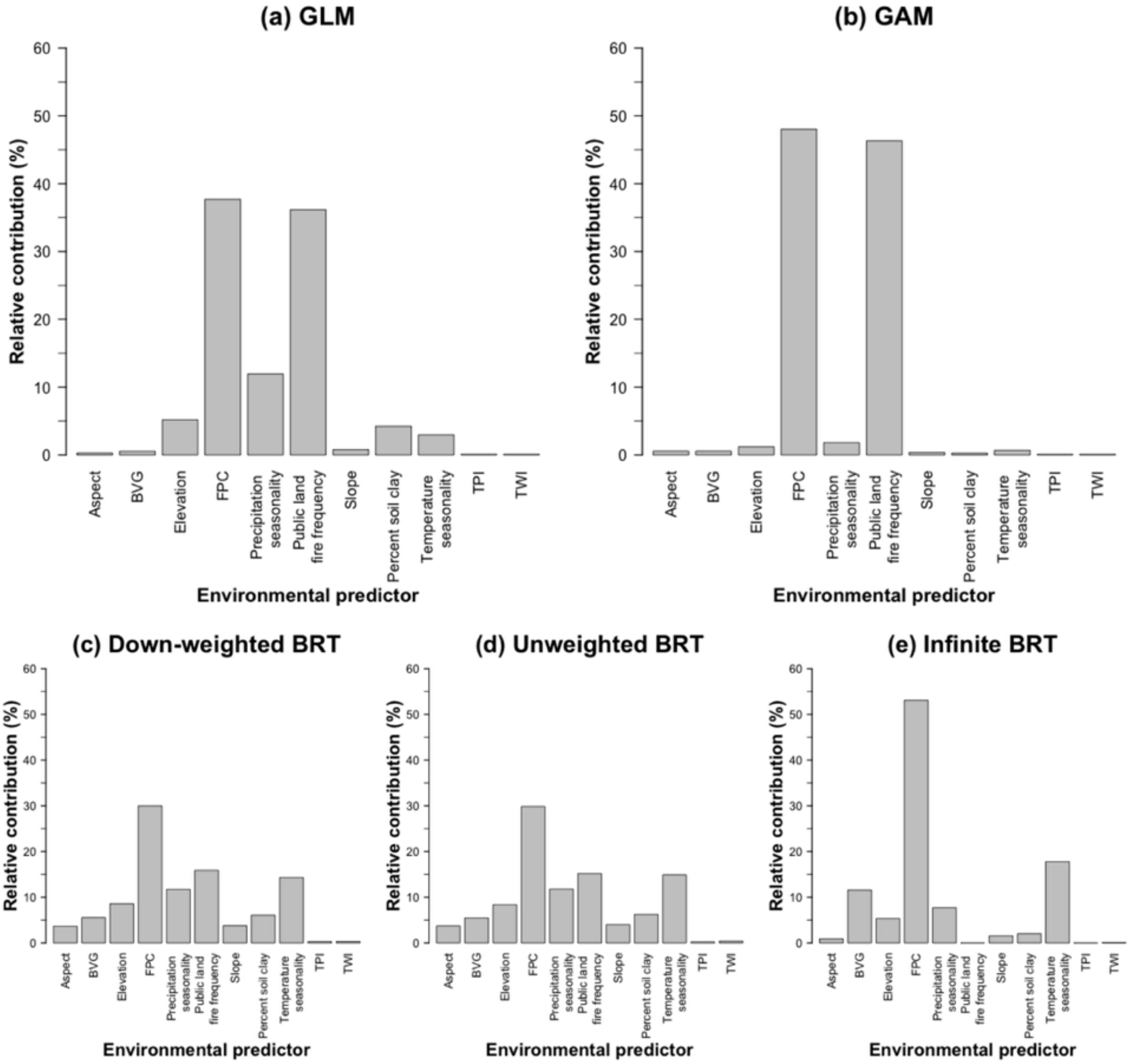

Fig. 3 Relative contributions of environmental predictors to modelling satellite fire frequency for (a) generalised additive (GAM); (b) generalised linear (GLM); (c) Down-weighted BRT; (d) unweighted BRT; (e) infinitely weighted logistic regression BRT (Infinite BRT). FPC = Foliage Projective Cover;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

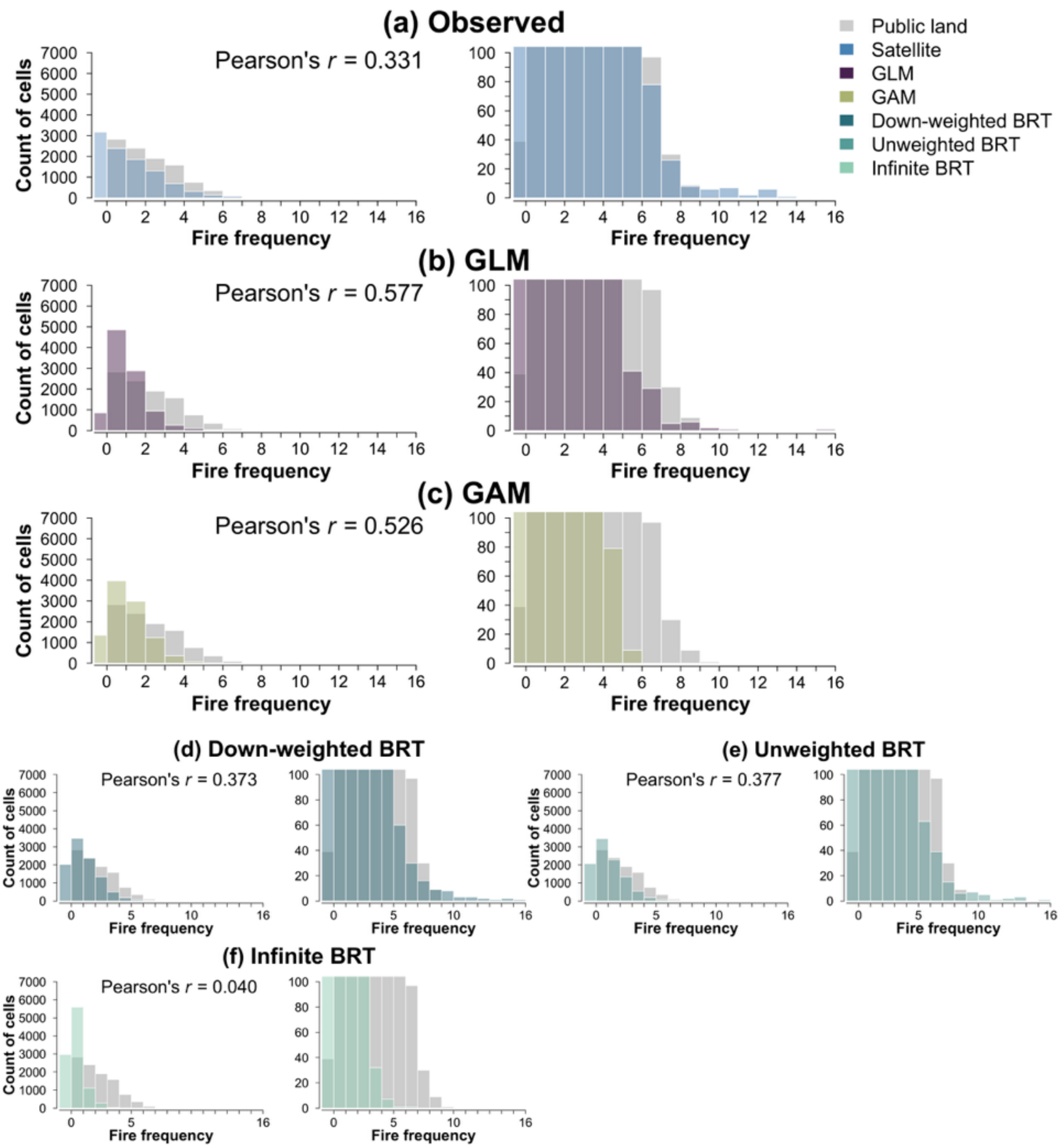

Fig. 4 Comparisons of fire frequency estimates between public land fire history data ('public'), raw, unmodelled satellite data ('satellite') and predictions from a range of model types. The right-hand panel for each model type shows cell counts below 100 to enable comparisons at high fire frequencies (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.

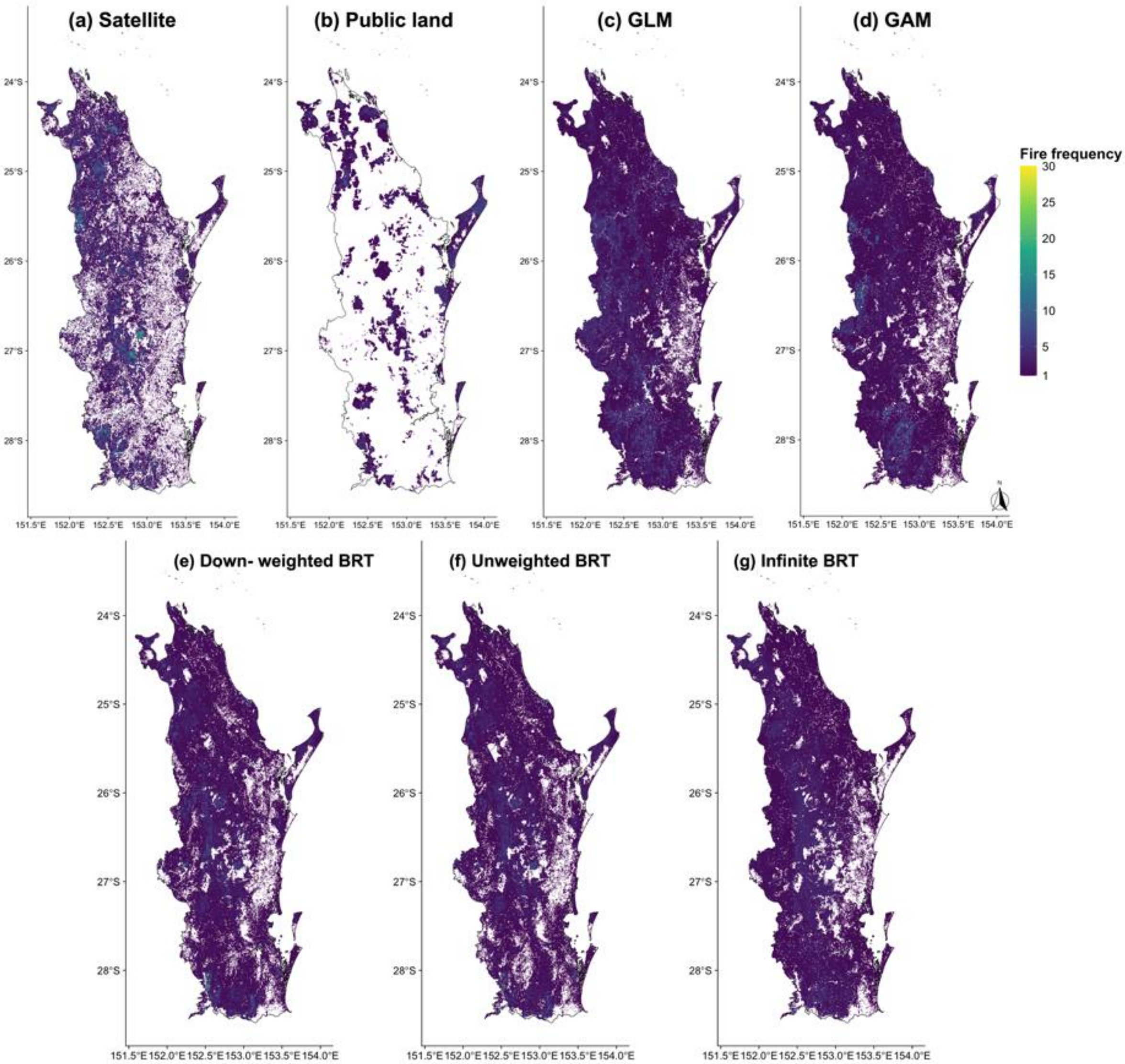

Fig. 5 Fire frequency from 1987 to 2023 in southeast Queensland, Australia derived from (a) observed satellite and (b) public land fire history data. The observed fire frequencies were compared to predictions from: (c) generalised linear model (GLM), (d) generalised additive model (GAM), (e) down-weighted 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).

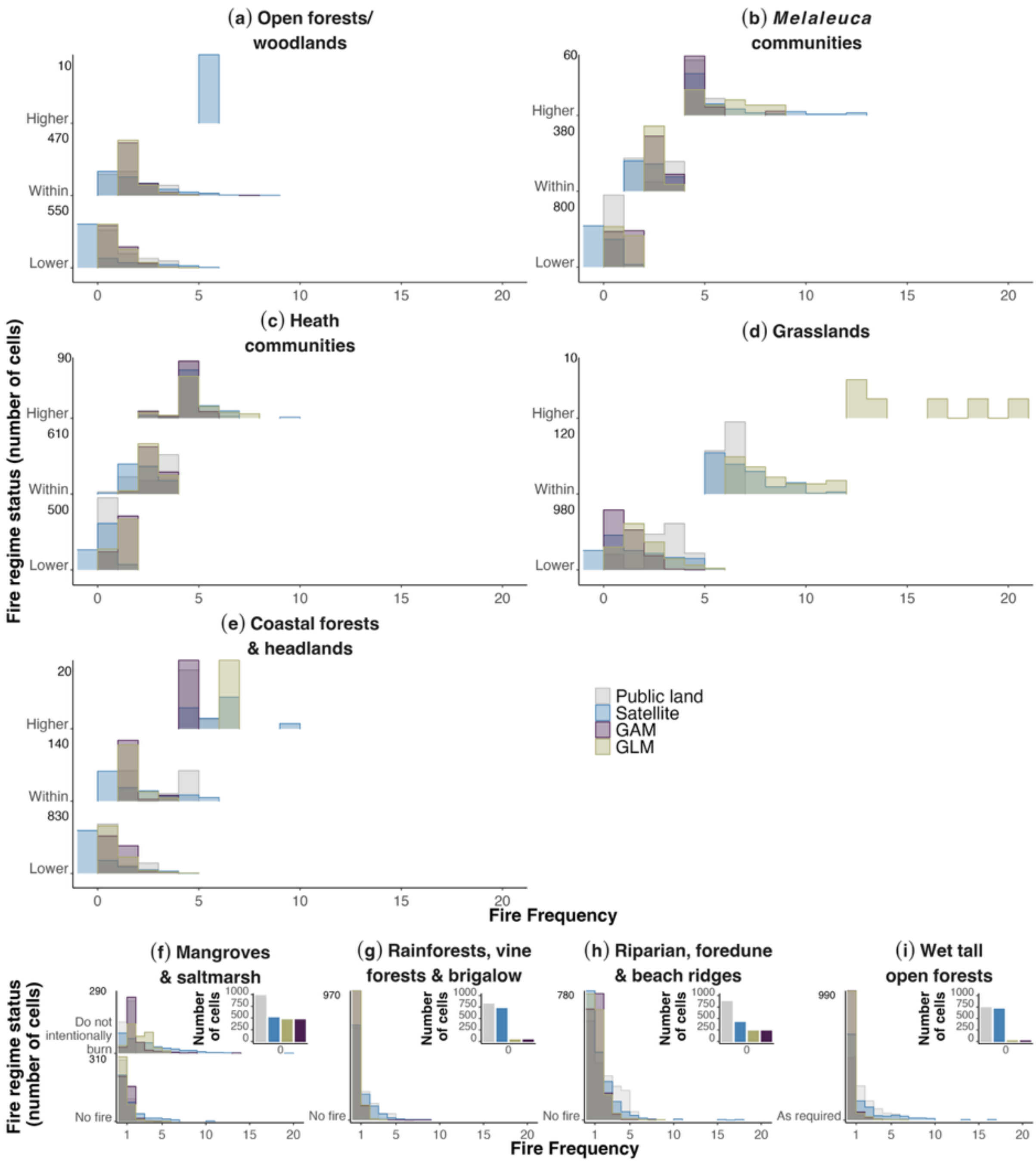

Fig. 6 Distributions of fire frequencies from 1987 to 2023 across broad vegetation aggregations in southeast Queensland, Australia relative to ecologically informed fire regime recommendations. For 1000 random points within each broad vegetation aggregation, the number of cells (y-axis) for each fire 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.