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Modelling Insurance Losses from Australian Bushfires

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Abstract: Each year, natural disasters continue to pose serious challenges to communities around the world. These events cause widespread destruction, disrupting lives, economies, and essential services. Their sudden and severe nature can strain resources, disrupt business operations, and have lasting economic consequences. Recent disasters, such as the January 2025 Southern California wildfires, provide a great deal of information on the major financial and human losses incurred by such catastrophes.

Australia is known for its vulnerability to certain natural disasters, particularly bushfires. Dry summers and overwhelming temperatures provide perfect conditions for fires to ignite and spread in the Australian environment. Across the country, bushfires cause irreparable damage to the environment, family homes, and irreplaceable assets, leading to major insurance losses yearly.

Individuals and families often protect themselves against the uncertainty of natural disasters through insurance policies. Insurance is critical to mitigating risks and protecting against unpredictable financial losses. In the context of natural disasters and their devastating consequences, the Australian insurance industry is dedicated to supporting both individuals and communities by promoting resilience and delivering effective results.

This study uses the Insurance Council of Australia's Historical Catastrophe Data (April 2025 release), which includes records dating back to 1967 and provides extensive financial and geographic information. By analysing this data, a model can be developed and applied to support future policies, risk assessment, and decision-making related to natural disaster impacts.

Analysing and modelling these data are difficult due to their complexity and the high proportion of missing values. To address these challenges, we first investigate the losses by type of catastrophic event, with a primary focus on bushfires. Recently, McAneney et al. 2019 analysed normalised insurance losses from 1966 to 2017 for the same data set using exposure and inflation normalisation to characterise long-term trends across Australian catastrophes. In our study, we extend this work by focusing exclusively on bushfire-related losses and employing generalised additive models within the GAMLSS framework to model the complex distributional features of the data (Stasinopoulos and Rigby 2008). GAMLSS offers broad distributional choices and covariate effects on multiple parameters, making it well suited to the highly skewed, heavy-tailed nature of insurance loss data.

Keywords: *Catastrophic events, bushfires, insurance losses, normalised loss data, GAMLSS*

1 INTRODUCTION

Australia experiences a wide range of natural hazards that can cause significant damage to property, infrastructure, and communities. Catastrophic events such as cyclones, earthquakes, floods, hailstorms, severe storms, tornadoes, damaging winds, and bushfires occur with varying frequency and severity across the country. These disasters not only disrupt daily life but also result in substantial economic losses, much of which is incurred by the insurance industry. Recent years have seen several high-impact natural disasters in Australia. The February–March 2022 east coast floods stands as the nation's costliest natural disaster on record, with insured losses of approximately AUD 6 billion (Insurance Council of Australia (2023, 2025)). The 2019–2020 "Black Summer" bushfires caused more than AUD 2.3 billion in insured losses and widespread environmental devastation (Australian Institute for Disaster Resilience 2020). Severe storms in 2023–2024 also resulted in substantial economic impacts, highlighting the recurrent and wide-ranging nature of catastrophic events across the country.

The primary data source for this study is the Insurance Council of Australia (ICA) Data Hub, which provides a detailed catalogue of all major catastrophe events in Australia from 1967 to 2025. For each event, the database records information such as location, duration (in days), year of occurrence, and insured loss value at the state level. All loss figures are normalised to 2022 Australian dollars, enabling meaningful comparisons over time. In addition to disaster loss data, the ICA Data Hub facilitates analysis of long-term trends, spatial patterns, and hazard-specific impacts across multiple event types. Over the study period, the database records 740 catastrophic events across all hazard types, dominated by cyclones, storms, and floods. Cumulative normalised insured losses totalled approximately \$166 billion (2022 AUD), of which bushfires contributed \$19.8 billion ($\approx 12\%$). While smaller in dollar terms than other hazards, bushfires remain a major source of insured losses in Australia.

Globally, bushfires represent one of the most destructive natural hazards, with tens of thousands of incidents occurring annually and burning millions of hectares of land. Beyond the tragic loss of life, they generate billions of dollars in economic damages each year. The United Nations has warned of an impending "global wildfire crisis," with the frequency and severity of such events projected to escalate in the coming decades (Sullivan et al. 2022). Insurance losses from wildfires have been growing faster than from many other natural catastrophes, with record-breaking events in the United States during 2017, 2018, and 2020 (Swiss Re 2021). Property damage accounts for the vast majority of wildfire losses. For example, in the United States, the 2018 Camp Fire in California destroyed nearly 26,000 structures and caused insured losses of approximately USD 10 billion, making it the most destructive wildfire in the state's history (Badger and Foley 2019; Hoover and Hanson 2021). Bushfires are the central focus of this study, as they are among the most destructive natural hazards in Australia, generating high-value insurance claims and producing far-reaching ecological, social, and economic consequences. Scientific evidence demonstrates that climatic and environmental conditions play a critical role in shaping bushfire dynamics. Hotter and drier conditions, earlier snowmelt, and prolonged droughts all increase fire risk, while large-scale climate drivers contribute to year-to-year variability (Huber and Gulledge (2011), Wuebbles et al. 2017). In particular, the frequency and intensity of bushfires in Australia are strongly influenced by temperature extremes, drought conditions, and large-scale climate systems such as the Southern Oscillation Index (SOI; an indicator of ENSO-related pressure anomalies between Tahiti and Darwin) and the Indian Ocean Dipole (IOD; an index of sea-surface temperature differences across the tropical Indian Ocean). Accordingly, this study incorporates these variables into the statistical analysis to better understand the drivers and patterns of bushfire-related losses.

To investigate factors influencing loss severity, we enhance the ICA database with complementary climate, environmental, and socioeconomic data sourced from the Bureau of Meteorology and the Australian Bureau of Statistics. These variables provide a basis for examining how hazard exposure, vulnerability, and socio-climatic conditions interact to shape insurance losses. Our modelling approach applies the Generalised Additive Models for Location, Scale and Shape (GAMLSS) framework, which offers flexibility in handling non-normal, highly skewed loss distributions and allows the incorporation of non-linear relationships between predictors and multiple distributional parameters. This methodology has previously been applied to wildfire loss modelling in the USA as a flexible semiparametric approach (Raveendran et al. 2025). Building on this methodology, the proposed analysis aims to generate new insights that can support more informed insurance risk assessment, pricing strategies, and policy development for managing bushfire-related losses in Australia.

2 DATA DESCRIPTION AND EXPLORATORY ANALYSIS

This study investigates and evaluates insurance losses caused by bushfires in Australia. The dataset used in this analysis includes information on the normalised loss value (2022), climate and environmental variables, socioeconomic variables, and spatial information. Table 1 presents the 12 explanatory variables; the normalised loss value is analysed as the response. The primary source of disaster loss data is the ICA Data Hub, which provides a detailed catalogue of all major catastrophe events in Australia, including cyclones, earthquakes, floods, hailstorm, storms, tornadoes, wind and bushfires. For each event, the database contains information such as the location, duration (in days), year of occurrence, and the amount of loss at the state level from 1967 to 2025.

Table 1. List of Variables for Modelling Bushfire Losses

Variable	Type	Source
Normalised Loss Value 2022	Continuous	ICA
State	Nominal	ICA
Year	Continuous	ICA
Duration	Continuous	ICA (derived)
State Population	Continuous	ABS
State Density	Continuous	ABS
State Area	Continuous	ABS
State Mean Temperature	Continuous	BOM
Yearly State Rainfall	Continuous	BOM
Gross State Product	Continuous	ABS
SOI	Continuous	BOM
IOD	Ordinal	BOM

Climate factors significantly influence the intensity and severity of bushfires, For climate data, we obtained state-level mean temperature, annual rainfall, SOI, and IOD values from the Bureau of Meteorology (BOM 2025). Environmental and socioeconomic conditions also play an important role in determining the extent of losses. Accordingly, we collected data on state population, population density, land area, and gross state product (GSP) from the Australian Bureau of Statistics (ABS 2025). Our study focuses on bushfire losses at the state level, analysing 49 recorded incidents between 1967 and 2022. Victoria and New South Wales recorded the highest number of incidents (13 of 49 each). In terms of total normalised losses, Victoria had the largest total (AUD 8.84 billion), followed by Tasmania (AUD 4.29 billion), while Western Australia recorded the lowest (AUD 0.50 billion). Figure 1 presents the total normalised losses from bushfires by the year.

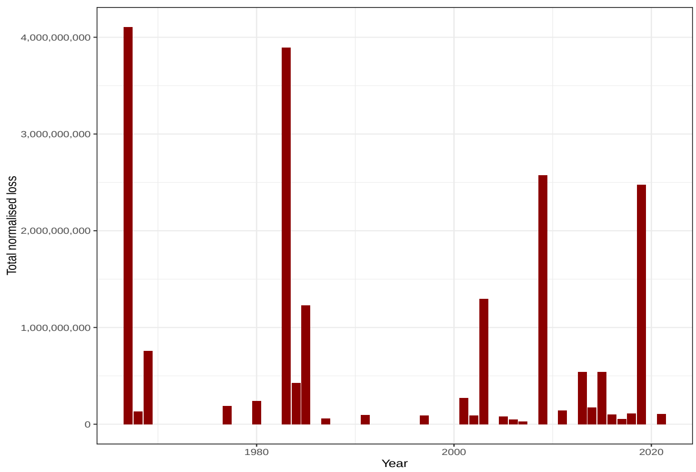

Figure 1. Total normalised losses from bushfires in 1967–2022

3 STATISTICAL MODELLING

Bushfire loss modelling is a critical task in the insurance industry, as it supports the assessment of potential financial impacts from these natural disasters. The distribution of bushfire losses is typically positively skewed, with many small claims and only a few extremely large losses, a pattern commonly observed in insurance data. In this study, we modelled the normalised insurance losses from bushfires using a log-normal distribution, which is well suited to capturing such skewed loss patterns.

This section describes the Lognormal (LOGNO) model based on the GAMLSS framework (Rigby and Stasinopoulos 2005), which offers a more flexible approach than the generalised linear model (Nelder and Wedderburn, 1972) and generalised additive model (Hastie and Tibshirani 1990) frameworks by allowing for a general distribution family instead of the exponential family distribution assumption for the response variable. This makes GAMLSS well-suited for modelling highly skewed and kurtotic continuous and discrete distributions. It also enables the distribution parameters of the response variable to be expressed as linear, nonlinear, parametric, or nonparametric additive functions of explanatory variables, with or without random effects. The use of nonparametric smoothing terms further allows for capturing complex nonlinear relationships between predictors and the response.

GAMLSS model framework can be described as follows: Let $\boldsymbol{y} = (y_1, y_2, \ldots, y_n)$ be a vector of n independent observations, and let $f(y_i|\boldsymbol{\theta}^i)$ be the conditional probability density function for y_i, given the vector of distribution parameters $\boldsymbol{\theta}_i = (\theta_{1i}, \theta_{2i}, \theta_{3i})^T = (\mu_i, \sigma_i, \pi_i)^T$. To relate the distribution parameters to explanatory variables, we use known monotonic link functions $g_k(\cdot)$, where $k = 1, 2, 3$. Following the notation from the existing papers (Rigby and Stasinopoulos, 2005; Stasinopoulos and Rigby, 2008), the GAMLSS model can be written as follows:

$$g_k(\boldsymbol{\theta}_k) = \boldsymbol{X}_k\boldsymbol{\beta}_k + \sum_{j=1}^{J_k} h_{jk}(\boldsymbol{x}_{jk}), \tag{1}$$

where $\boldsymbol{\theta}_k$ is a vector of length n; $\boldsymbol{X}_k$ is a known design matrix of fixed effects and h_{jk} is a smooth non-parametric function of $\boldsymbol{x}_{jk}$, which are vectors of length n.

Our framework includes two components in the LOGNO model: μ and σ, which represent the mean and dispersion of the distribution of loss amount. These components are modelled in terms of explanatory variables using the following link functions, respectively:

$$\begin{aligned}\mu &= \mathbf{X}_1\boldsymbol{\beta}_1 + \sum_{j=1}^{J_1} h_{j1}(x_{j1}) + \mathbf{Z}_1\boldsymbol{\gamma}_1,\\ \log(\sigma) &= \mathbf{X}_2\boldsymbol{\beta}_2 + \sum_{j=1}^{J_2} h_{j2}(x_{j2}) + \mathbf{Z}_2\boldsymbol{\gamma}_2,\end{aligned}$$

where $\mathbf{X}_k$ and $\boldsymbol{\beta}_k$, $k = 1, 2$, are the fixed-effect design matrices and corresponding coefficients, $h_{jk}(x_{jk})$, $k = 1, 2$, represent non-parametric smooth functions of predictors, $\mathbf{Z}_k$ and $\boldsymbol{\gamma}_k$, $k = 1, 2$, are the random-effect design matrices and random-effect coefficients.

4 RESULTS

In this section, we present the empirical study and the main results. We modelled normalised bushfire losses using a Lognormal (LOGNO) distribution within the Generalised Additive Models for Location, Scale and Shape (GAMLSS) framework, following a two-stage strategy: (i) variable selection and (ii) specification of each effect as parametric, smooth, or random. Candidate predictors (Table 1) were initially included in multivariate models for μ and $\log(\sigma)$. We use forward variable selection to find the model the lowest AIC. The LOGNO model for the parameters, μ and σ are given as:

$$\text{Loss} = \begin{cases}\mu = \alpha_1 + \beta_{11}\,\texttt{Year} + \beta_{12}\,\texttt{State} + \beta_{13}\,\texttt{SOI}_t + \beta_{14}\,\texttt{SOI}_{t-1} + \beta_{15}\,\texttt{IOD}_{t-1},\\ \log(\sigma) = \alpha_2 + \beta_{21}\,\texttt{Year} + \beta_{22}\,\texttt{IOD}_{t-1}.\end{cases}$$

The final model for μ retained `Year`, `State`, $\texttt{SOI}_t$ (current), $\texttt{SOI}_{t-1}$ (previous year), and $\texttt{IOD}_{t-1}$ (previous year), while $\log(\sigma)$ retained `Year` and $\texttt{IOD}_{t-1}$ (previous year). Table 2 reports parameter estimates and

Table 2. Model Fitting Results for the Normalised Loss

μ	Estimate	p-value
Intercept	151.874 (14.146)	$3.03 \cdot 10^{-11}$
`Year`	-0.066 (0.007)	$6.08 \cdot 10^{-10}$
`State`		0.00017
$\texttt{SOI}_t$	0.106 (0.015)	$2.19 \cdot 10^{-07}$
$\texttt{SOI}_{t-1}$	-0.118 (0.013)	$4.87 \cdot 10^{-10}$
$\texttt{IOD}_{t-1}$		0.00486
$\log(\sigma)$	Estimate	p-value
Intercept	-92.020 (5.208)	$2.30 \cdot 10^{-16}$
`Year`	$4.602 \cdot 10^{-2}(3.806 \cdot 10^{-4})$	$< 2 \cdot 10^{-16}$
$\texttt{IOD}_{t-1}$		0.00013

associated p-values, with all retained predictors statistically significant at $\alpha = 0.05$. We compared several LOGNO–GAMLSS specifications. An alternative model with additional climate–exposure terms in the scale equation achieved a slightly lower AIC, but its normalised quantile residuals (Q–Q and density) showed tail departures, indicating poorer calibration. We therefore retained the diagnostically superior current model. Figure 2 shows diagnostic plots for the best model. Residuals show no obvious patterns against fitted values or index, supporting the assumptions of homoscedasticity and independence. The residual density plot is close to normal with only minor deviations, and the Q–Q plot shows points closely aligned to the reference line within the confidence envelope, confirming that the model adequately captures the distributional structure of the data.

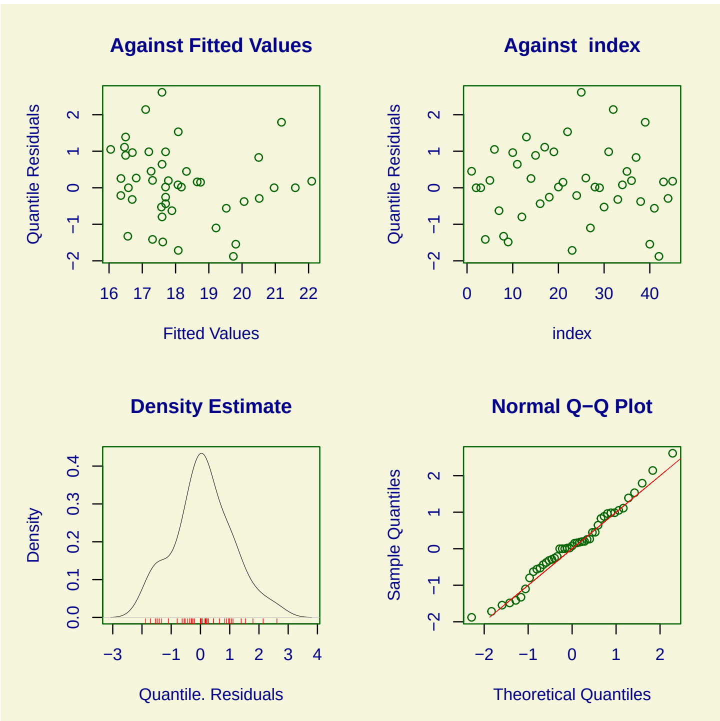

Figure 2. Diagnostic Plots for Bushfire Model

The negative coefficient on `Year` in μ indicates a downward trend in average loss magnitudes over time, as estimated by the model. $\texttt{SOI}_t$ is positive, whereas $\texttt{SOI}_{t-1}$ is negative, reflecting contrasting contemporaneous versus lagged ENSO effects. $\texttt{IOD}_{t-1}$ emerges as significant in both μ and σ, suggesting its importance in shaping not only the mean but also the variability of bushfire losses.

For the model of $\hat{\mu}$, we present the detailed effects of each variable graphically in Figure 3. The term plots for the μ (mean loss) show that the $\texttt{SOI}_t$ has an approximately linear *positive* effect— higher $\texttt{SOI}_t$ is associated with larger expected losses—whereas the previous year's index, $\texttt{SOI}_{t-1}$, has an approximately linear *negative* effect, consistent with contrasting contemporaneous and lagged ENSO influences. State effects are heterogeneous: the combined category (NSW; QLD; SA; VIC) and the ACT exhibit the largest positive shifts, NSW and WA are near zero or slightly negative, and SA, TAS, and VIC are modestly positive. For the IOD in the previous year, $\texttt{IOD}_{t-1}$, phase matters: the positive phase is associated with a pronounced negative shift in μ, whereas the neutral (and remaining) phases show small positive shifts. The grey bands denote 95% confidence intervals and widen for categories with fewer events.

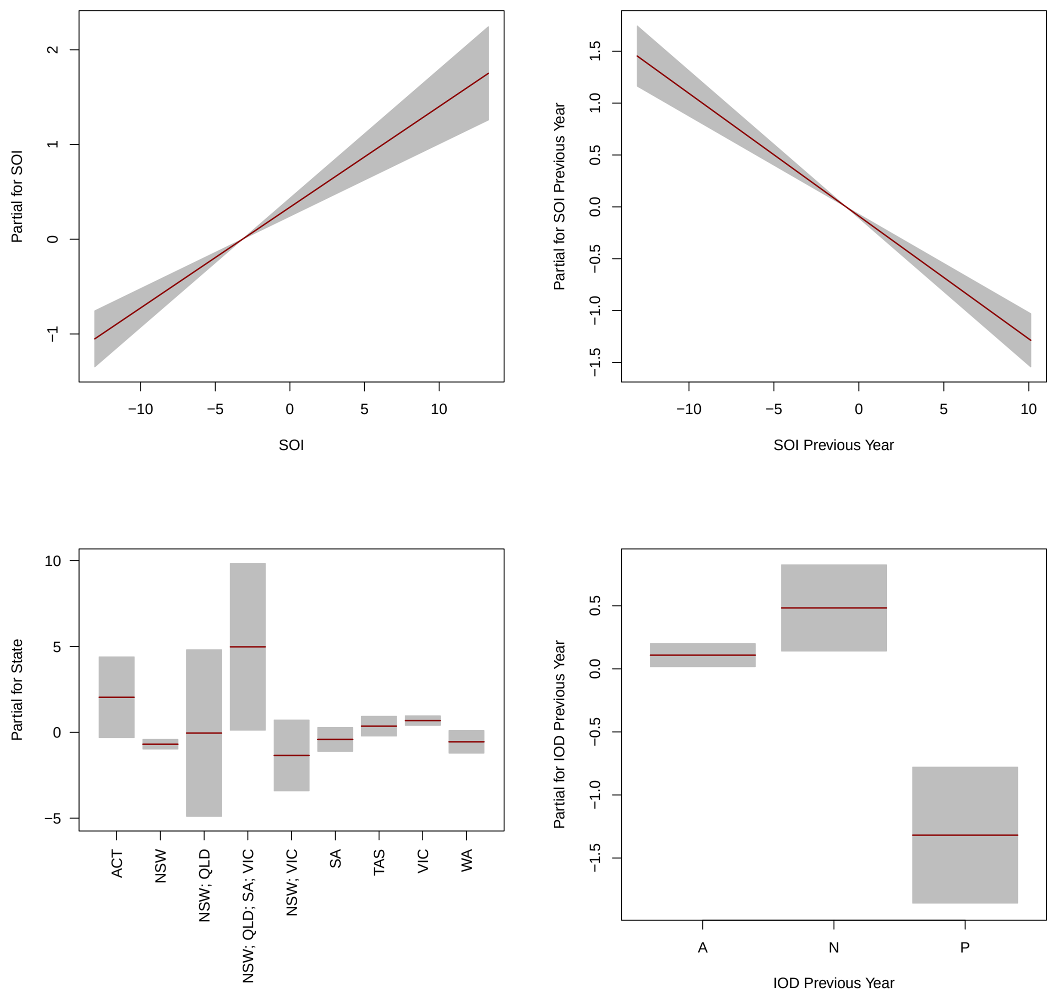

Figure 3. Term Plots for the Mean Parameter μ for Bushfire Model

5 CONCLUDING REMARKS AND DISCUSSION

In this paper, we applied a GAMLSS framework to analyse bushfire-related insurance losses in Australia using a lognormal (LOGNO) response. The framework allows both the location and scale parameters of the loss distribution to depend on covariates, while accommodating the strong right-skew typical of insurance data. A two-stage modelling strategy was implemented—forward variable selection followed by specification of effects as parametric or categorical. The final model retained Year, State, SOI (current and lagged), and IOD (lagged) for the mean component, with Year and lagged IOD for the scale component.

The proposed framework provides a valuable tool for quantifying uncertainty and variability in bushfire losses. By modelling not only mean effects but also scale dynamics, it offers a more robust basis for risk assessment and supports insurance pricing strategies, capital allocation, and policy development. The results highlight that bushfire-related insurance losses are strongly shaped by both climatic and temporal drivers, with ENSO- and IOD-related variables being as significant predictors. The observed downward trend in average losses over time may reflect improved mitigation strategies, building standards, and community preparedness, though further work is needed to separate these effects from potential data limitations.

There are several promising opportunities for future research. Incorporating accurate geographical locations of bushfires would allow for the application of advanced spatial models, enhancing the explanatory power of the statistical framework. Higher-resolution data on fire footprints and exposures could also enable the use of geostatistical or hierarchical approaches to better capture localised risk. Additionally, integrating richer socioeconomic and land-use variables may help explain state-level heterogeneity, while extending the analysis with climate scenario projections could provide valuable insights for long-term insurance planning and disaster resilience.

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