Accounting for fire impacts to improve the evidence base for tree-hollow modelling

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Executive summary

- Tree hollows provide essential habitat for a wide range of wildlife species. Hollow monitoring and conservation is critical for sustainable forestry. In New South Wales, FRAMES is a forest dynamics model and decision-support tool used to forecast forest dynamics, including hollow presence, under different management scenarios. A recent report by Gibbons (2024) identified a gap in FRAMES, noting that it does not explicitly account for the impact of fire on hollow-bearing tree collapse and recruitment.

- In this report, we develop models that predict the effects of fire on tree collapse and hollow recruitment in the range of diameter classes and species groups found within the Coastal Integrated Forestry Operations Approvals (CIFOA) region.

- *Mortality rate and fire*: Tree mortality increased with the severity of the 2019/20 wildfires, with mortality rates of 3.0%, 16.8%, and 28.3% in FESM classes 3 (*i.e.*, moderate fire severity), 4 (*i.e.*, high fire severity), and 5 (*i.e.*, extreme fire severity), respectively. Total mortality (including both standing dead trees and collapsed trees) followed a u-shaped curve related to tree size. Small trees ($<$ 20 cm diameter at breast height, DBH) experienced the highest mortality rates, medium-sized trees (20-100 cm DBH) experienced the lowest mortality rates, while large trees ($>$ 100 cm DBH) showed moderate vulnerability, particularly under severe and extreme fire conditions (FESM classes 4 and 5).

- *Hollow development and fire*: Tree size was the main factor influencing the presence of hollows in a tree. The number of past fires increased the probability of a tree having a hollow at a given size. Our analysis of the 2019/20 fires showed that fires in FESM class 3 (moderate fire severity) did not affect hollow recruitment, while fires that produced FESM classes 4 and 5 (*i.e.*, high and extreme fire severity) had effects similar to past fires.

- Fire can kill hollow-bearing trees; however, trees that survive are more likely to develop hollows due to fire damage. Integrating the fire-sensitive mortality and hollow recruitment models described here into FRAMES to forecast hollow abundance under different management scenarios would provide a clearer understanding of the consequences of different forest management scenarios on hollow-bearing tree abundance in NSW's State Forests. These models are intended to support FRAMES scenario testing rather than prescribe operational change.

1. Context

The Natural Resources Commission chairs the New South Wales Forest Monitoring Steering Committee, overseeing the implementation of the Coastal Integrated Forestry Operations Approvals (CIFOA) monitoring program. This program mandates the monitoring and evaluation of conditions to protect and recruit hollow-bearing trees, which provide essential habitat for a wide range of wildlife species. Hollow monitoring and conservation are critical for sustainable forestry. In NSW, the strategic planning for native forests is managed through the Forest Resource and Management Evaluation System (FRAMES). This decision-support tool includes a dynamic forest model that is continually updated to address evolving planning needs.

Recently, Gibbons (2024) identified a gap in FRAMES, noting that it does not explicitly account for the impact of fire on hollow collapse and recruitment. Given the increasing recognition of the importance of biodiversity and wildlife conservation in forestry, and the extent and severity of fires, this is an important issue to address. Gibbons (2024) recommended that mortality and hollow recruitment models be developed that explicitly account for the impact of fire on the collapse and recruitment of hollow-bearing trees.

Here, we address the need to incorporate the effects of fire on hollow recruitment and collapse to improve forest management in the Coastal IFOA region. In section 2 of the report, we used Native Forest Strategic Inventory (NFSI) data complemented with permanent sample plot (PSP) datasets and Western Sydney University (WSU) research plots to model tree mortality following the 2019/20 fires as a function of DBH, species, and fire severity class. In section 3, we used NFSI data to model hollow recruitment as a function of DBH, species, fire count and severity.

Table 1: Key terms and acronyms used in this report.

Acronym / Term	Definition
DBH	Diameter at breast height (1.3 m)
FESM	Fire Extent and Severity Mapping; fire severity class 1–5
FRAMES	Forest Resource and Management Evaluation System
Ghost trees	Collapsed trees not recorded in post-fire NFSI
HBT	Hollow-bearing tree
IFOA	Integrated Forestry Operations Approval. A set of environmental rules for how forestry operations can be carried out in State Forests and Crown Timber Lands in NSW
NFSI	Native Forest Strategy Inventory
PSP	Permanent Sample Plot
WSU	Western Sydney University

2. Analysis of tree mortality following the 2019/20 fires

Fire can kill trees and reduce the number of live hollow-bearing trees within a landscape. We used post-fire surveys to quantify tree mortality following the 2019/20 fires, combining data from the NSW Forest Monitoring Program (NFSI) and Western Sydney University

(WSU) to provide a comprehensive sample of species and conditions found in the Coastal IFOA region.

2.1. Data sources for tree mortality analysis

We used NFSI and WSU data to fit the mortality model, while PSP data were used to calibrate bias corrections for ghost trees (collapsed trees not recorded in NFSI).

NFSI data: The NSW NFSI is a comprehensive program designed to assess and monitor the state and dynamics of native forests in NSW's state forests. NFSI plots are selected using probabilistic sampling, which ensures data is representative of the broader population of trees found in NSW's native forests. Each plot consists of a 0.1-hectare fixed area circular plot (17.84-meter radius). In each plot, all trees with a diameter at breast height (DBH) above 10 cm are recorded and identified to species. Detailed measurements and attributes, including tree status (live, dead), the presence of likely or visible hollows, and recent fire damage, are also recorded.

In the coastal IFOA, 324 NFSI plots within the footprint of the 2019/20 fires were surveyed post-fire. Fire damage in NFSI data was assessed on a 7-level scale, where level 1 indicates live trees that were 'unaffected by fire' and level 7 indicates dead trees that were 'totally killed by fire'. In this report, we treated level 7 as observed fire-related mortality (binary response = 1) and levels 1 to 6 as live trees (binary response = 0). Additionally, note that level 7 in NFSI includes only standing dead trees. Trees that were completely consumed or that collapsed due to fire (*i.e.*, ghost trees) are covered in Section 2.4. A limitation of the NFSI dataset is that plots are primarily located in net harvest areas and underrepresent riparian exclusion zones, which may contain larger hollow-bearing trees and experience different fire severity patterns.

WSU data: To expand the range of tree sizes in our analysis and better capture the U-shaped mortality response (where both small and large trees are more sensitive to fire), we incorporated data collected by Western Sydney University (Bendall *et al.*, 2024a,b) between May 2022 and February 2023. Capturing this shape was important because previous work suggested such a pattern (Bendall *et al.*, 2024b), but our earlier exploratory analysis based on NFSI data lacked sufficient large trees to estimate it reliably. WSU plots are 0.1 ha and include smaller sub-plots (0.05 ha, 0.025 ha) to target smaller tree size classes (Bendall *et al.*, 2024b). Diameter at breast height over bark (DBH, measured at 1.3 m height) was measured for all trees >2.5 cm DBH. We filtered the WSU dataset to only contain plots measured within coastal IFOA regions and harmonised the species names to match the species codes in the NFSI database. Unlike the NFSI dataset, WSU data were observed as both full-kill (*i.e.*, dead stem with no evidence of resprouting) and top-kill (*i.e.*, dead stem with evidence of resprouting). To maintain consistency with the NFSI data, we only considered full-kill response in our analysis. Additionally, WSU data includes collapsed trees on the ground in their mortality estimates, so we consider that they have no 'ghost trees'.

PSP data: Permanent Sample Plots (PSP) are long-term monitoring plots established by NSW Forestry Corporation. Although the PSP dataset includes fewer plots than NFSI, it provides repeated measurements over time (longitudinal records). This allows us to compare pre- and post-fire surveys and identify trees that were present before the fire but are missing afterward, indicating they collapsed due to fire. We used PSP data to estimate and correct for the proportion of collapsed trees not recorded in the NFSI dataset (see Section 2.4 on ghost-tree correction).

2019/20 fire severity: Fire severity for the 2019/20 fires was assessed using the Fire Extent and Severity Mapping (FESM) system (DCCEEW, 2024), a remote-sensing assessment based on Sentinel-2 satellite imagery. The classification follows: FESM 1 = unburnt, FESM 2 = low severity (burnt understory, unburnt canopy), FESM 3 = moderate severity (partial canopy scorch), FESM 4 = high severity (complete canopy scorch, partial canopy consumption), FESM 5 = extreme (full canopy consumption).

We note that FESM class 2 was absent from the NFSI dataset provided by NSW Forestry Corporation. This class was also not represented in the WSU dataset, which specifically targeted higher severity classes (FESM 4 and 5). This absence is not critical to our analysis since fires that leave the canopy unburnt (as in FESM 2) would be expected to have minimal impact on hollow-bearing trees, which are predominantly larger trees with hollows in the trunk and canopy. The exception would be the potential formation of basal hollows, but these were not measured in the NFSI dataset. Consideration of basal hollow formation could be included in future modeling efforts, as noted in our perspectives section.

Species grouping: We analyzed the data both by individual species and by species groups. For the species group analysis, species were classified into 18 groups using a table provided by Forestry Corporation NSW. Forestry Corporation NSW noted that species can vary in growth and fire response depending on their region. For this reason, the study grouped species by region, distinguishing between the Southern (south of Sydney) and Central/Northeastern regions. For example, spotted gum (*Corymbia maculata*) is in Group 02 in the Northern and Central regions but in Group 11 in the Southern region (see Table A1 for the list of species studied and their assigned groups). These groupings are suitable for use as input in FRAMES.

Combined dataset summary: After merging the NFSI and WSU databases and removing species having fewer than 100 observations (a threshold chosen to ensure sufficient data to estimate reliable U-shaped mortality curves), our final dataset comprised 347 plots, 22 species, and 9,813 trees, distributed among three FESM classes: 3,819 trees in plots burned at FESM class 3, 3,523 trees in class 4, and 2,471 trees in class 5. The combined dataset expanded the DBH range from 2.5 to 210.0 cm (mean 27.3 cm), compared to the NFSI range of 10.0 to 146.2 cm (mean 26.0 cm). The average basal area was 26.1 m^2/ha (range: 0.2 to 84.6 m^2/ha), and live tree density averaged 405 stems per ha (range: 10 to 1,270 stems per ha). Observed fire-related tree mortality was 3.0% in FESM class 3, 16.8% in class 4, and 28.3% in class 5. The 347 plots were distributed across the four Coastal IFOA regions (see Fig. 1 for plot location).

2.2. Modelling fire-related mortality in NFSI and WSU data

Figure 2 shows observed mortality rates (stand dead and collapsed trees) stratified by DBH and FESM class. The analysis indicates a u-shaped relationship between tree size and mortality. Small trees exhibit high mortality rates, which decrease with increasing

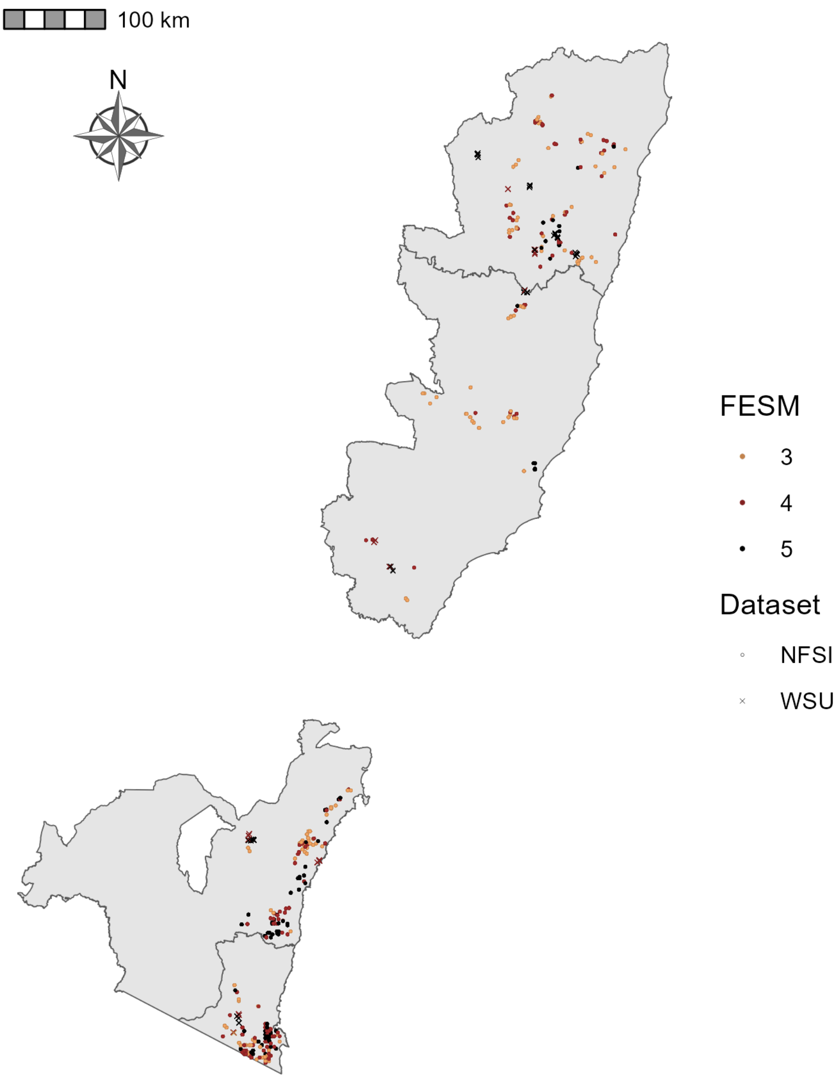

Figure 1: Location of the 380 NFSI and WSU plots within the coastal IFAO that burnt in 2019/20. The grey-shaded regions, listed from south to north, are Eden, southern, lower northeast, and upper northeast.

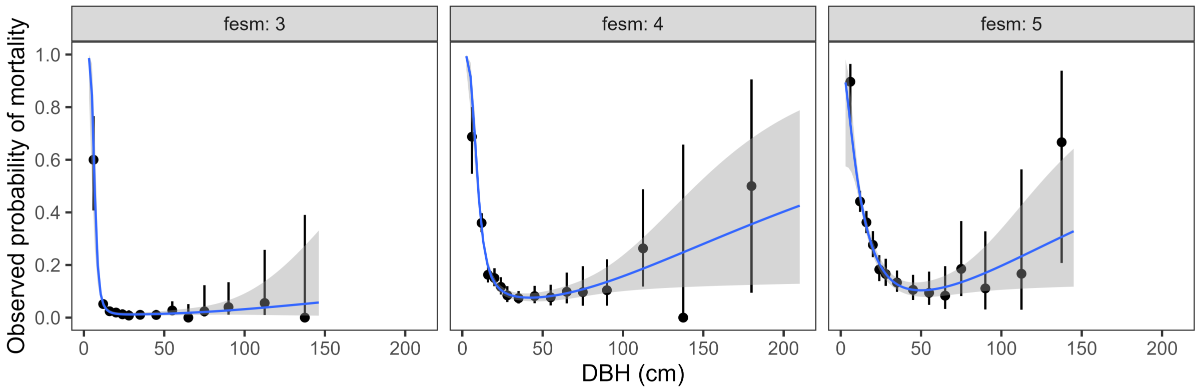

Figure 2: Observed probability of mortality per DBH and FESM classes in post-fire NFSI and WSU survey plots. Dots represent mean probabilities for each strata (*i.e.*, unique combination of DBH and FESM class), while error bars are 95% confidence interval for the strata. Solid blue lines represent Generalised Additive Models (GAM) fit to the data. Shaded areas are 95% CI for the GAM fit.

tree size until reaching a minimum for medium-sized trees, before increasing again for large trees. This pattern is most pronounced in high severity fire classes (FESM 4 and 5).

The observed U-shaped relationship between tree size and mortality suggests using a seven-parameter double logistic regression with three plateaux (left, middle, and right) that smoothly join. The seven-parameter double logistic mortality model is as follows:

$$\begin{aligned} p[i] &= P_{\text{small}}\, w_{\text{small}}[i]\,(1 - w_{\text{large}}[i]) \;+\; P_{\text{medium}}\,(1 - w_{\text{small}}[i])\,(1 - w_{\text{large}}[i]) \;+\; P_{\text{large}}\, w_{\text{large}}[i] \\ w_{\text{small}}[i] &= \frac{1}{1 + e^{S_{\text{small}}\,(D[i] - D_{50,\text{small}})}} \\ w_{\text{large}}[i] &= \frac{1}{1 + e^{-S_{\text{large}}\,(D[i] - D_{50,\text{large}})}} \end{aligned} \tag{1}$$

where $p[i]$ is the probability of mortality for tree i with DBH $D[i]$, and P_{small}, P_{medium}, and P_{large} represent the mortality probabilities at the small, medium, and large tree plateaux, respectively. The parameters S_{small} and S_{large} control the steepness of the transitions between size classes (*i.e.*, how abruptly mortality probability changes with tree size), while $D_{50,\text{small}}$ and $D_{50,\text{large}}$ represent the DBH values at which these transitions occur. The weights w_{small} and w_{large} are logistic functions that smoothly determine how the mortality probability transitions between the small, medium, and large tree plateaux based on DBH. The model ensures that the weighted contributions of the three plateaux sum to one for each DBH value.

We used the *brms* package (Bürkner, 2017) in R (R Core Team, 2024) to fit Eq. 1 to the combined NFSI and WSU post-fire survey data. We used a Bernoulli error term to model the distribution of observations (alive = 0, dead = 1) around the modelled mortality mean p_i.

Parameters were allowed to vary by FESM class and by species (as a species random effect) or by species group (as a species group random effect, following the classification used in FRAMES and shown in Table A1).

For bias correction, we incorporated an offset term in the model to account for ghost trees missing from the NFSI dataset (see Section 2.4 for details). Based on our analysis of PSP data (see section 2.4), we applied offsets (on the logit scale) of -0.64 for NFSI trees on P_{small} and -0.34 for NFSI trees for P_{medium} and P_{large}. No offset was applied to WSU

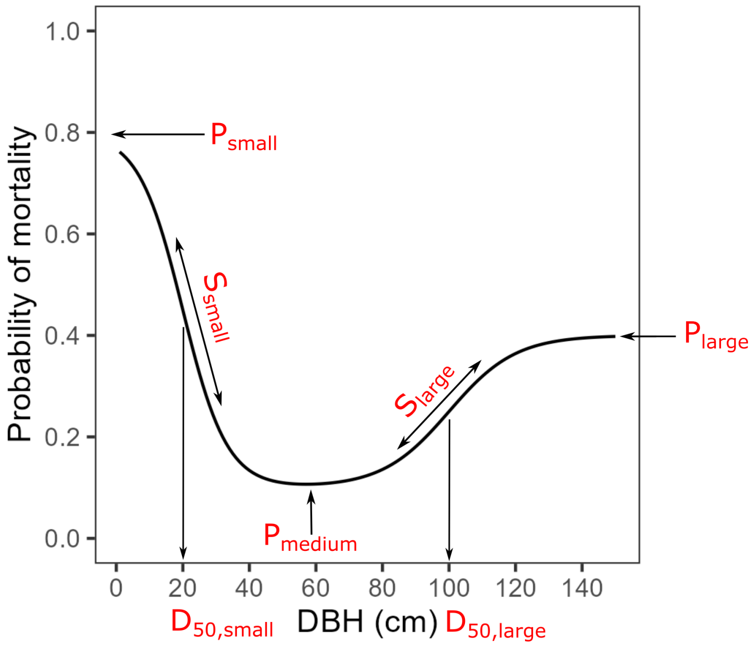

Figure 3: Illustration of a seven-parameters double logistic function and impact of the different parameters on the shape of the curve. The function is illustrated here with the following parameters: $P_{\text{small}} = 0.8$, $P_{\text{medium}} = 0.1$, and $P_{\text{large}} = 0.4$, $S_{\text{small}} = 0.2$, $D_{50,\text{small}} = 20$, $S_{\text{large}} = 0.1$, and $D_{50,\text{large}} = 100$.

data, which already includes collapsed trees. This adjustment effectively compensates for the artificially lower observed mortality rates in the NFSI dataset. The fitted model parameters (P_{small}, P_{medium}, and P_{large}) therefore already incorporate this correction, which means that no additional adjustments are needed when using the model for predictions.

2.3. Tree mortality results

Fig. 4 shows the modelled probability of mortality versus DBH by species and FESM class using the 7-parameter double logistic model (Eq. 1). This model captures mortality across three plateaux (P_{small}, P_{med}, P_{large}) connected by two sigmoid transitions, producing the observed U-shaped mortality pattern: higher mortality for small trees, lowest for medium-sized trees, and increasing again for larger trees. Species varied in fire sensitivity. Silvertop ash (STA) and the stringybark group (SBK) were particularly fire-sensitive, with large trees experiencing 25-50% mortality after full canopy consumption (FESM class 5). On the other hand, New England blackbutt (NEB) and spotted gum (SPG) showed high fire resistance, with less than 5% mortality in the 20-100 cm DBH range, even after full canopy consumption.

The transition from medium to large tree mortality (P_{med} to P_{large}) begins around 100 cm DBH and is most evident for messmate (MMT), which had the largest size range in our dataset. This uptick likely reflects accumulated fire scars (Bendall *et al.*, 2024b,a) that increase vulnerability in very large trees, a pattern that may also affect other species once they reach comparable sizes. The large-tree sigmoid transition reaches its mid-point ($\sim$ 50% mortality for FESM class 5) around 175 cm DBH, but our dataset contained few trees of this size. Consequently, the large-tree mortality plateau ($P_{large} \sim 95\%$ mortality for FESM class 5) remains uncertain as it represents extrapolation beyond our observed

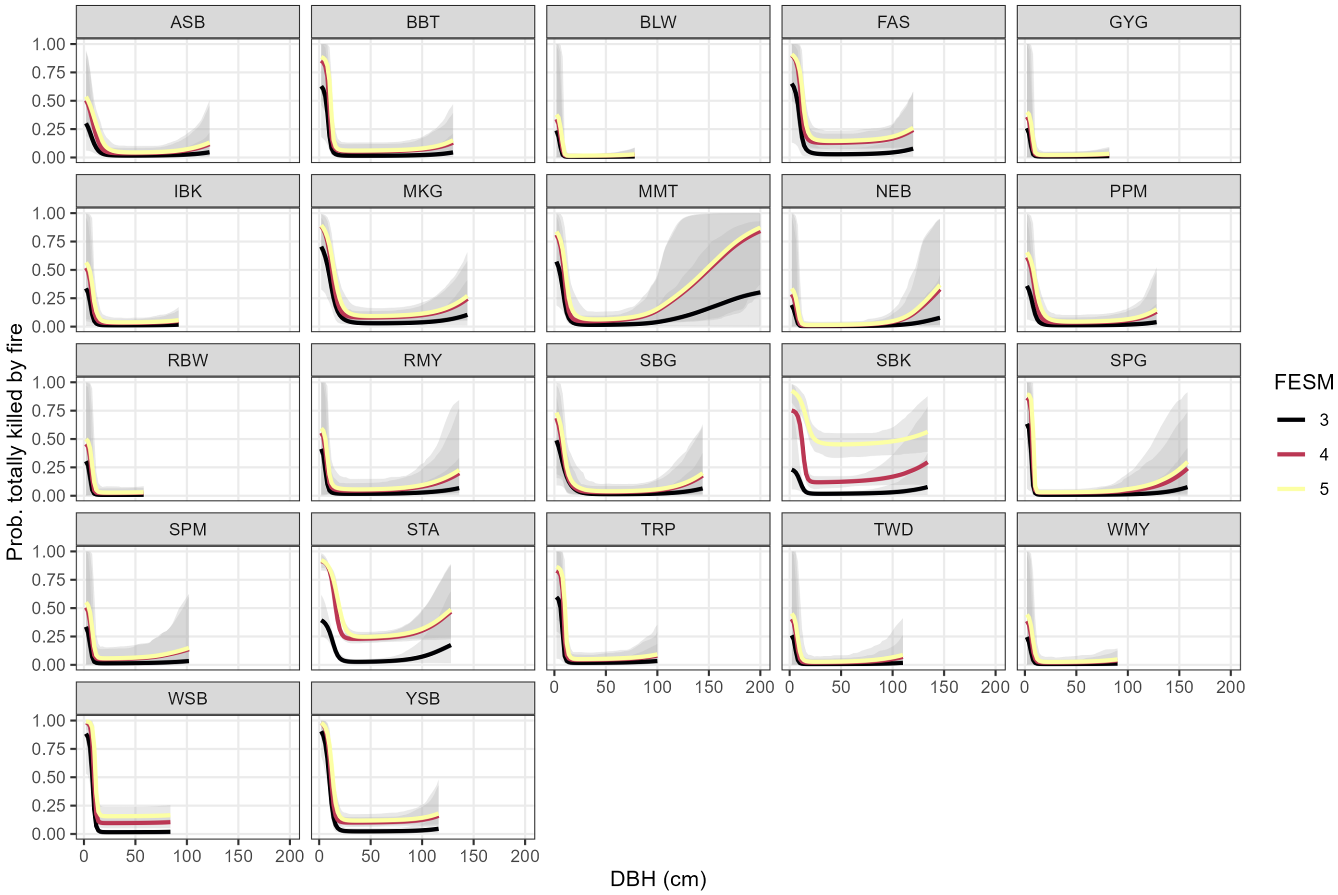

Figure 4: Modelled probability of mortality as a function of DBH and FESM per species (Eq. 1, with species code described in Table A1 and coefficients from Table A2) in post-fire NFSI and WSU data. Lines show mean modelled values with 95% credible intervals (shaded areas). Predictions are bias-corrected for ghost trees (see section 2.4) and limited to the DBH range observed for each species in the dataset.

data.

Parameter values for each species are shown in Table A2. The fit between observed and modelled mortality probabilities across species and DBH classes was excellent (Fig. 5), with no specific bias. Confidence intervals are wider for large trees because we have fewer observations in these size classes.

Results aggregated by species groups are shown in Fig. 6, with parameters in Table A3. Observed versus modelled mortality rates by species group and DBH classes are shown in Fig. 7. The central and northern blue gums, southern stringybarks, and southern silvertop ash groups were the most sensitive to fire.

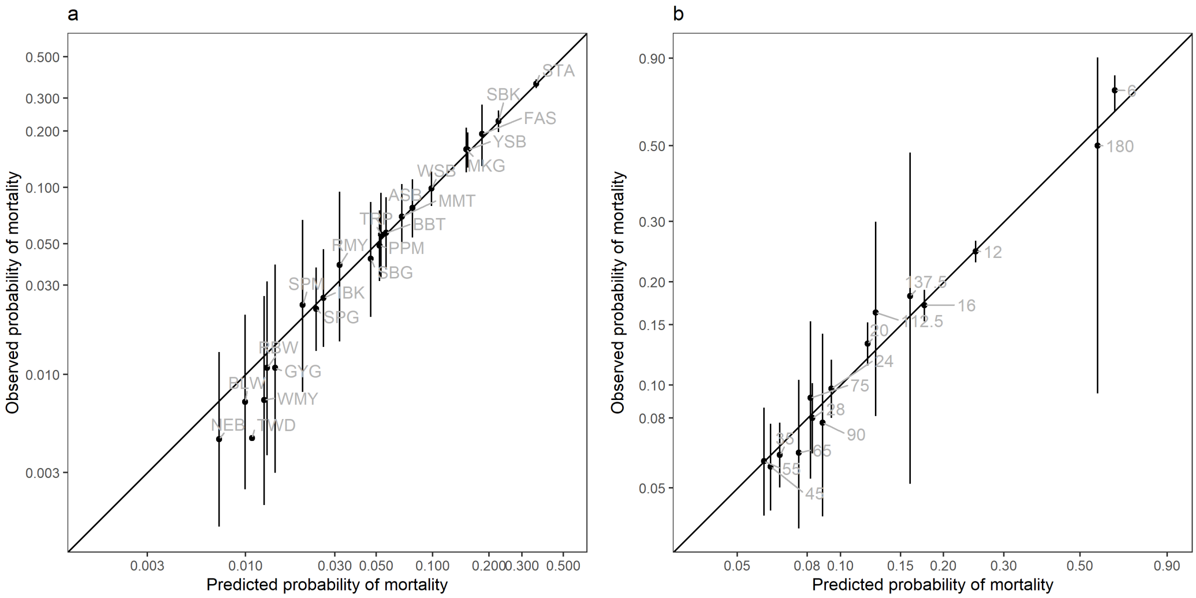

Figure 5: Comparison of observed and predicted mortality rates by (a) species code and (b) DBH class. Dots represent mean values, and error bars indicate 95% confidence intervals for observed mortality rates per strata. Light grey text denotes strata: species code in (a) and mid-range of DBH class in (b). The solid black diagonal line represents the 1:1 line, where observations equal predictions.

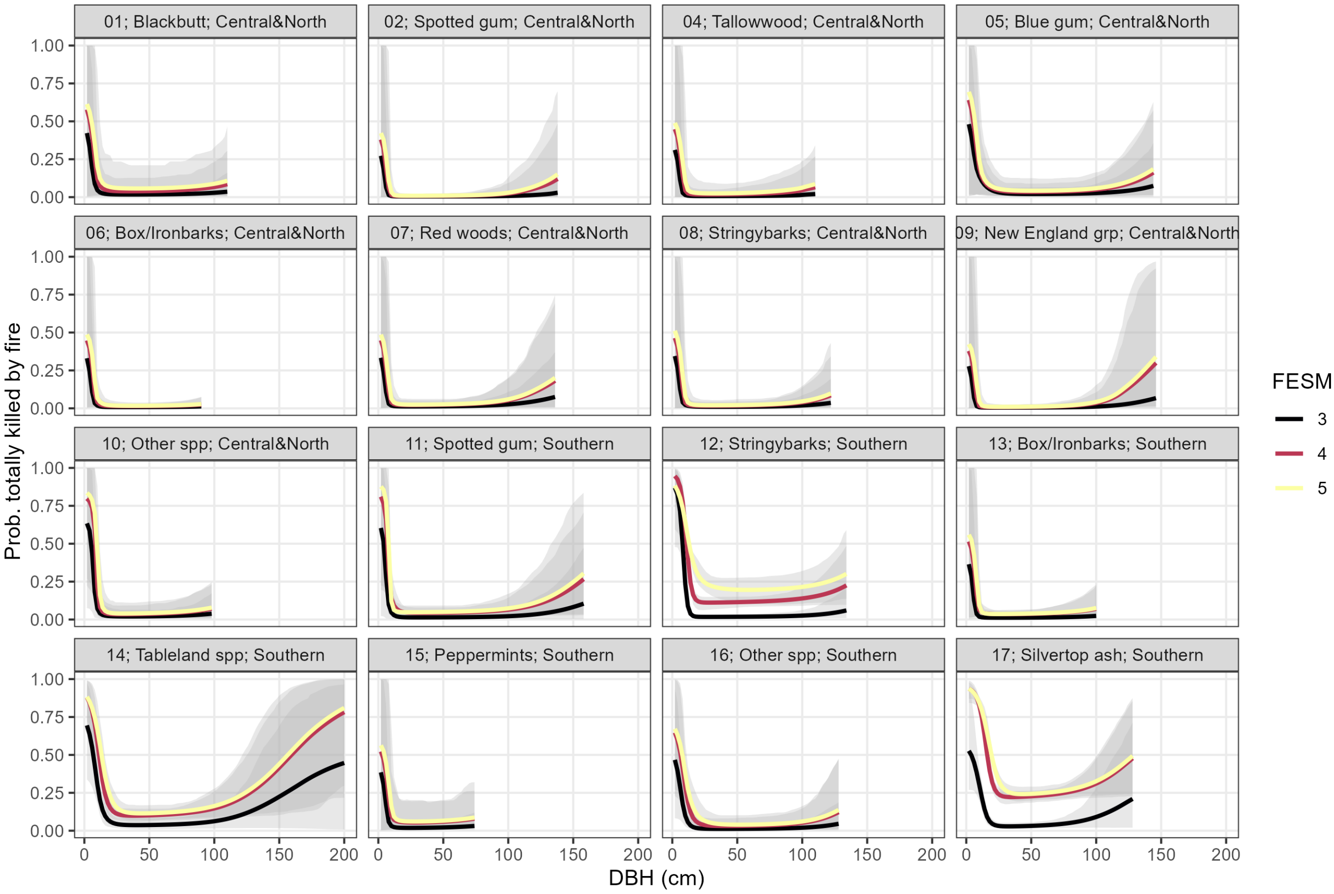

Figure 6: Modelled probability of mortality as a function of DBH and FESM class per species group (Eq. 1, with coefficients from Table A3) in post-fire NFSI and WSU data. Lines are mean modelled values and shaded areas are 95% credible intervals. Predictions were bias corrected to account for ghost trees (see section 2.4).

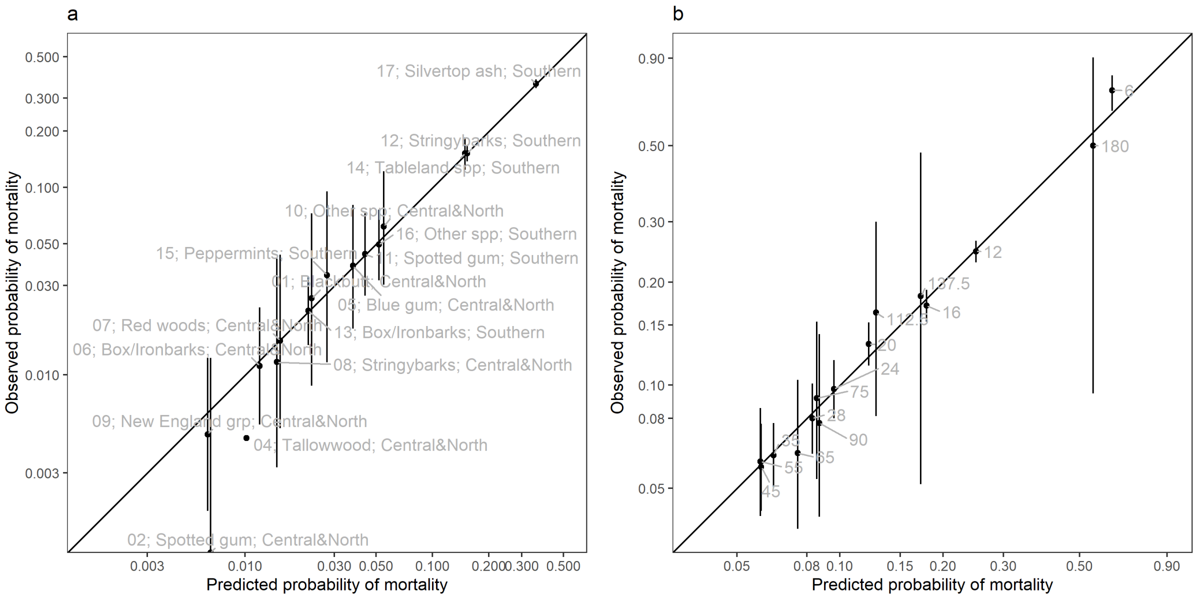

Figure 7: Comparison of observed and predicted mortality rates by (a) species group and (b) DBH class. Dots represent mean values, and error bars indicate 95% confidence intervals for observed mortality rates per strata. Light grey text denotes strata: species group in (a) and mid-range of DBH class in (b). The solid black diagonal line represents the 1:1 line, where observations equal predictions.

2.4. Correcting for mortality bias due to ghost trees in post-fire survey

Post-fire surveys can miss trees that collapsed due to fire, leading to a downward bias in estimated mortality rates. These missing trees, which we refer to as 'ghost trees', do not appear as fire damage class 7 in NFSI post-fire surveys. Note that while collapsed trees are excluded from NFSI surveys, they are included in WSU surveys, making this correction unnecessary for WSU data. In section 2.4, we develop a correction factor to address this bias in NFSI data. We derived this factor from a small set of permanent sample plots (PSPs) that have both pre- and post-fire survey data.

We assessed the prevalence of ghost trees using 29 PSPs in Eden, the South Coast, and North Coast regions of NSW. We used PSP data as they had both a pre- and post-fire survey that allowed us to quantify the prevalence of these missing trees. The results are summarised in Table 2. Ghost trees accounted for 4.5% of total trees in FESM class 3 (*i.e.*, 14 / (274 + 23 + 14)), 4.1% in FESM class 4, and 10.2% in FESM class 5. The same analysis stratified by DBH class is shown in Table 3.

Understanding odds, odds ratios, and logits in mortality bias correction.

What are 'odds'? Odds are a way to express the likelihood of an event happening compared to it not happening. For example, if we say the odds of something are 4 to 1, it means that the event is four times more likely to occur than not occur. Mathematically, the odds are calculated as:

$$odds = \frac{p}{1-p}$$

where p is the probability of the event occurring (*e.g.*, a tree dying), and $1-p$ is the probability of the event not occurring. To convert odds to probabilities, we use:

$$p = \frac{odds}{1 + odds}$$

For odds of 4 to 1, the calculation is $p = \frac{4}{1+4} = 0.8$. Therefore, an odds of 4 to 1 corresponds to a probability of 0.8.

What is an 'odds ratio'? An odds ratio compares the odds of an event happening under two different conditions. It quantifies how much more (or less) likely the event is in one situation compared to another. We can compare the odds of tree mortality with and without accounting for ghost trees (trees that have died but are not recorded in the NFSI data). For example, for FESM class 3 in Table 2, the odds of a tree being dead are 23 to 274 if we only consider observed dead trees. When we include ghost trees, the odds become 37 to 274. The odds ratio is thus: $\frac{37/274}{23/274} \sim 1.6$. This means that accounting for ghost trees increases the odds of observing a dead tree by a factor (multiplier) of 1.6.

What is a 'logit'? The logit is the natural logarithm (log) of the odds. It is often used in statistical analyses (*e.g.*, logistic regression) to keep probability values in the 0 to 1 range. The logit is calculated as:

$$logit = log(odds) = log(\frac{p}{1-p})$$

If we want to convert a logit value to a probability value, use the inverse-logit function:

$$p = \frac{1}{1 + exp(-logit)}$$

Why use odds ratios to adjust for ghost trees? In datasets such as the NFSI, where only standing dead trees are recorded, we can correct for missing ghost trees by using an odds ratio adjustment derived from data that includes both standing dead and ghost trees (*e.g.*, the PSP database). For example, a mortality probability of 0.8 for standing dead trees gives us odds of 4 to 1. We multiply the 4 to 1 odds by 1.6 to adjust for ghost trees and get a bias-corrected odds of 6.4. Applying the odds-to-probability conversion, this results in a bias-corrected probability of around 0.87.

If we tried to use a bias-correction factor directly on the probability scale, it could push probabilities over 1, which is not possible. For example, multiplying a baseline probability of 0.8 by 1.5 would give a probability of 1.2, which would be invalid.

Table 2: Analysis of live, dead, and ghost trees in the PSP database by FESM class

FESM	n_{obs_live}	n_{obs_dead}	n_{ghost}	Observed odds: $\frac{n_{obs\_dead}}{n_{obs\_live}}$	Actual odds: $\frac{(n_{obs\_dead}+n_{ghost})}{n_{obs\_live}}$	Odds ratio
3	274	23	14	0.084	0.135	1.609
4	318	35	15	0.110	0.157	1.429
5	305	64	42	0.210	0.348	1.656
Total	897	122	71	0.136	0.215	1.582

Table 3: Analysis of live, dead, and ghost trees in the PSP database by DBH class

DBH class (cm)	n_{obs_live}	n_{obs_dead}	n_{ghost}	Observed odds: $\frac{n_{obs\_dead}}{n_{obs\_live}}$	Actual odds: $\frac{(n_{obs\_dead}+n_{ghost})}{n_{obs\_live}}$	Odds ratio
0-15	204	56	49	0.275	0.515	1.875
15-30	420	46	14	0.110	0.143	1.304
30-100	273	20	8	0.073	0.103	1.400
Total	897	122	71	0.136	0.215	1.582

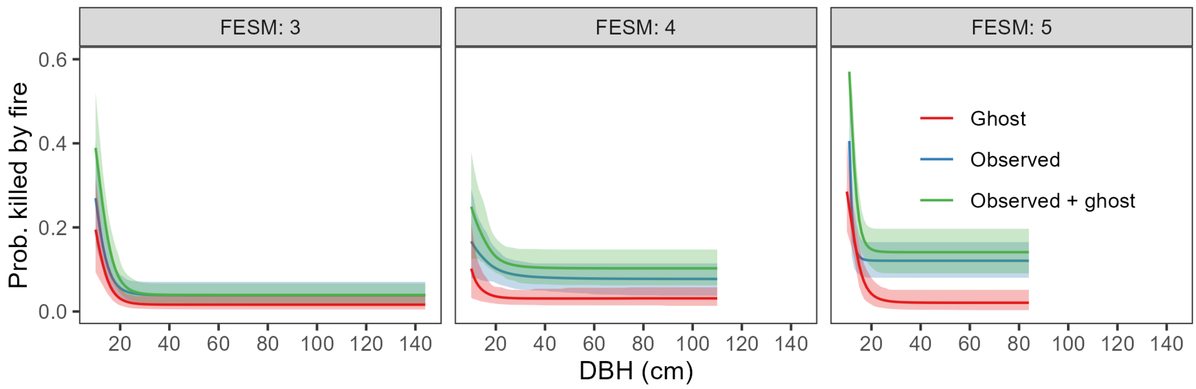

Figure 8: Probability of fire-related mortality versus tree size (DBH) for different FESM classes in the 29 PSPs with both pre- and post-fire surveys. The plot shows three categories: observed standing dead trees (blue), ghost trees that collapsed and were not recorded in post-fire surveys (red), and the combined total mortality (ghost + standing dead trees, green). Solid lines represent four-parameter logistic regressions fit to each category of data. Note that a four-parameter logistic model was used instead of a seven-parameter model due to the limited number of large trees in this subset of data, which prevents us from capturing the upward trend in mortality for the largest size classes (the right arm of the U-shaped pattern). Shaded areas show 95% credible intervals.

On average, accounting for collapsed ('ghost') trees increased mortality odds[1] by 1.6 relative to using standing-dead trees alone. The odds ratio is uniform across FESM classes (Table 2) but size-dependent: stems < 15 cm DBH show an odds ratio of 1.9, while stems ≥ 30 cm show 1.4 (Table 3, Fig. 8). These correspond to log-odds increments of $+0.64$ and $+0.34$, respectively, indicating that small trees are most under-counted.

We accounted for this bias in the seven-parameter model (Eq. 1) by offsetting the three plateau parameters for NFSI observations. In practice, we apply the correction by taking the logit transform of each plateau parameter, subtracting the appropriate offset (0.64 for P_{small} or 0.34 for P_{medium} and P_{large}), and then applying the inverse logit function to return to the probability scale:

$$\begin{aligned} P_{\text{small,obs}} &= \text{logit}^{-1}\big(\text{logit}(P_{\text{small}}) \;-\; 0.64\big), \\ P_{\text{medium,obs}} &= \text{logit}^{-1}\big(\text{logit}(P_{\text{medium}}) \;-\; 0.34\big), \\ P_{\text{large,obs}} &= \text{logit}^{-1}\big(\text{logit}(P_{\text{large}}) \;-\; 0.34\big). \end{aligned}$$

where logit represents the logit transform $\log\left(\frac{x}{1-x}\right)$ and logit^{-1} is the inverse logit function: $\frac{1}{1+\exp(-x)}$. No offset is applied to WSU data, which already include collapsed trees.

Because these offsets are applied during model fitting, the estimated plateaux (P_{small}, P_{medium}, and P_{large}) are already bias-corrected and directly comparable across datasets. Hence the mortality curves in Figs. 4 and 6 and the coefficients in Appendix Tables A2 and A3 are already bias-corrected.

We considered several alternative approaches to handling the ghost tree bias. One option would have been to allow P_{small}, P_{medium}, and P_{large} to vary across datasets, using the WSU parameter values when predicting. While this would have been more straightforward to implement, we retained the logit bias-correction approach developed in earlier iterations of this work (before the WSU dataset was available), given the statistical soundness of the method and the methodological investment already made. We also explored more complex methods such as data imputation, which involved adding virtual ghost trees to plots based on the observed profile of missing trees and using Monte Carlo methods to propagate uncertainty. However, this approach made it difficult to control the effects on modelled tree mortality and significantly increased computational demands. The odds ratio correction offers a more transparent solution that standardises mortality estimates across datasets.

[1]Using odds ratios rather than multiplicative or additive corrections prevents predictions above 100 %. For example, raising an 80 % baseline mortality by a factor of 1.5 would yield 120 %—impossible. Odds ratios keep predictions within 0–1.

3. Hollow-bearing tree recruitment

3.1. Material and methods

We used the NFSI database to assess hollow development and the impact of fire. This is a larger dataset than the one used to model tree mortality from the 2019/20 fires as it includes plots that did not burn in 2019/20 (*i.e.*, FESM class 1). After removing species that had less than 100 observations, we were left with 791 plots, 33 species, and 21243 trees. All plots were measured in 2021, 2022, or 2023. The plots are fixed plots of 0.1 hectares. All trees above 10 cm DBH were identified to species, measured for DBH, and their hollow status recorded.

Hollow status: Hollow status was recorded in the field in five classes ('unlikely', 'likely', 'visible', '3 or less visible', '4 or more visible') which we simplified to a binary variable (zero = 'unlikely', one = 'likely' or at least one or more visible hollow). All basal, stem, and branch hollows were included in the hollow status, though the specific hollow type was not recorded in the database. It should be noted that hollow data are based on hollows visible from the ground or inferred from tree characteristics, with no standardized hollow size criteria defined in the dataset.

On average, there were 23.8 hollow-bearing trees (HBT) per hectare in the NFSI data: 19.0 from live trees and 4.8 from standing dead trees. See Table 4 for a breakdown of HBT per hectare by FESM categories. In this report, we focused on live HBT, which represented the majority of HBT per hectare and were consistently recorded across datasets. Dead HBT were not analysed in detail because their inclusion would require separate modelling of hollow recruitment and collapse processes, which was beyond the scope of this study.

The probability of a live tree having a hollow increases with tree size. Results were similar with a stricter visible-only definition although hollow probabilities were slightly lower (see Fig. 9b). To be conservative, we included the 'likely' category as hollow presence (as in Fig. 9a).

Fire count: We used the NPWS Fire History map (`https://datasets.seed.nsw.gov.au/dataset/fire-history-wildfires-and-prescribed-burns-1e8b6`), to count the number of fires intersecting each plot. Although curated by NPWS, the fire-boundary polygons often extend beyond NPWS estate, and additional boundaries from the NSW Rural Fire Service and Forestry Corporation NSW are sometimes incorporated. Coverage outside NPWS estate is therefore broader than NPWS lands but not guaranteed to be complete. Fire counts were calculated by intersecting plot locations with annual fire polygon. We focused on fire counts per plot since 2000 as the fire history map becomes less reliable prior to this date. Since 2000, 265 plots (7980 trees) experienced no fires, 389 plots (9738 trees) experienced one fire, 107 plots (2644 trees) experienced two fires, 25 plots (721 trees) experienced three fires, and 5 plots (160 trees) experienced four or more fires.

2019/20 fire severity: Fire severity for the 2019/20 fires was assessed using the FESM system. We had 449 plots (56.8% of plots, 13,192 trees) with a FESM score of one (unburnt), 133 plots (16.8%, 3814 trees) with a FESM score of three (partial canopy scorch), 126 plots (15.9%, 2690 trees) with a FESM score of 4 (complete canopy scorch

Table 4: Number of hollow bearing trees (HBT) per hectare (including trees likely to have a hollow and trees that have visible hollows) for live trees and standing dead trees in different FESM classes. Inventory results for 2022 and 2023, when the NFSI inventory was updated to report hollow presence for dead trees.

FESM Class	Number of HBT per ha		
	Live trees	Standing dead trees	Total
1	20.8	3.6	24.4
3	21.1	8.1	29.2
4	15.0	3.8	18.8
5	14.1	5.5	19.6
Total	19.0	4.8	23.8

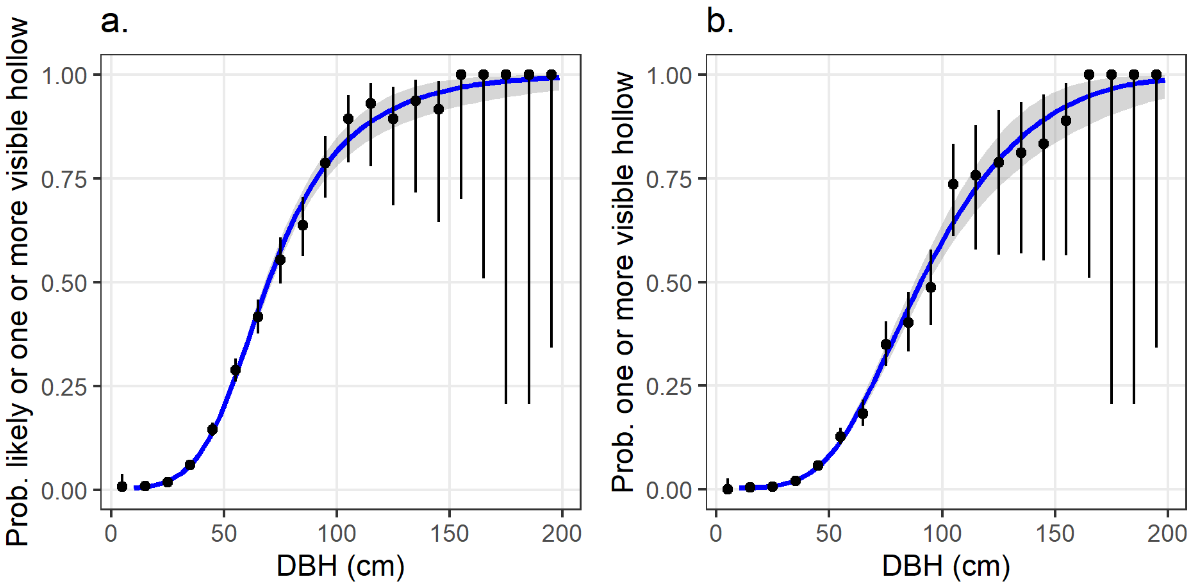

Figure 9: Probability of hollow versus DBH for two different hollow definitions. All trees and species were included. (a) Binary hollow response defined as being likely to have a hollow or as having at least one or more visible hollow. (b) Binary hollow response defined as having one or more visible hollow. Dots are mean hollow probability per DBH class. Error bars are 95% confidence intervals for the binned DBH class. The smoothed curved is a Generalised Additive Model (GAM) with a complementary log-log (cloglog) link, a log(DBH) smoothing spline term, and a Bernoulli distribution fitted to the data. The shaded area is the 95% confidence intervals of the GAM fit.

Table 5: Summary of observed tree hollow data from the NFSI, grouped by recent fire damage level

Recent fire damage level	n trees with hollows	n trees	Prop. hollows	
			Mean	95% CI range
1 - Not affected by fire	580	11320	0.051	0.047-0.055
2 - Fine branches killed (<5cm)	159	2502	0.064	0.055-0.074
3 - Large branches killed (>5cm)	598	4761	0.126	0.116-0.135
4 - Upper 25% of bole killed	94	1114	0.084	0.069-0.102
5 - Upper 50% of bole killed	82	805	0.102	0.083-0.125
6 - Upper 75% of bole killed	62	736	0.084	0.066-0.107

or partial canopy consumption), and 83 plots (10.5%, 1547 trees) with a FESM score of 5 (full canopy consumption).

Recent fire damage: Recent fire damage level per tree was assessed in the field on a 7-score scale: 1 - Not affected by fire, 2 - Fine branches killed (<5cm), 3 - Large branches killed (>5cm), 4 - Upper 25% of bole killed, 5 - Upper 50% of bole killed, 6 - Upper 75% of bole killed, and 7 - Totally killed by fire. Focusing on live trees, the proportion of hollows per recent fire damage level is shown in Table 5. Trees that were damaged by fire but that were still alive were more likely to have hollows, especially if they had a large branch or part of their stem killed. We did not include this detailed damage metric in the hollow-recruitment model because linking it directly to FESM would require an additional modelling step and could introduce error propagation. Instead, we incorporated fire severity through FESM class, which provides a consistent spatial predictor for landscape-level scaling. Future longitudinal studies could examine how cumulative fire damage from successive fires influences hollow recruitment and collapse.

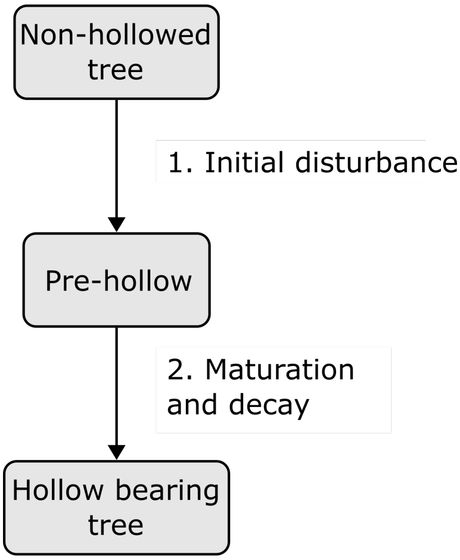

Figure 10: Conceptual model of hollow development

3.2. Conceptual model of hollow development

All hollow-development models are conditional on trees remaining standing. The estimated fire effects on hollow formation therefore apply only to surviving trees. The net effect of fire on hollow-bearing tree abundance comes from combining these conditional hollow-recruitment processes with the fire-sensitive mortality model described in Section 2. In this section, we focus only on hollow recruitment.

We conceptualise hollow development as a process that has two main phases: the initial disturbance phase and the hollow maturation phase. This conceptual model is illustrated in Fig. 10 and summarised below:

1. Initial disturbance: Trees without existing hollows are exposed to physical damage, such as partial crown collapse, branch breakage, or heartwood decay from termites. Such damage may create an opening that may lead to a pre-hollow or expose internal decay when a branch breaks.

2. Maturation and decay: With time and wood decay, the pre-hollow matures, developing into a size and condition suitable for wildlife habitat, providing shelter for various arboreal species. For tree species that decay quickly or whose branches are already decayed internally when they fall (*e.g.*, river red gums), this modelling phase might be unnecessary[2].

This framework is used as a working hypothesis to structure analysis, not as proof of mechanistic causation.

3.2.1. Modelling the initial disturbance phase

During the initial disturbance phase, trees without existing hollows may sustain physical damage (*e.g.*, partial crown collapse or branch breakage), leading to the formation of a

[2] In the NFSI, we found the maturation and decay phase complicates the modelling for little accuracy gain. This might be because most species form hollows when they are relatively small, with a 50% chance at 70 cm DBH (Figure 9). This contrasts with montane ash species such as *Eucalyptus regnans* and *E. delegatensis* in Victoria, which need to reach up to 150 cm DBH before having a 50% chance of having hollows (Fox *et al.*, 2008).

pre-hollow that can later develop into a mature hollow suitable for wildlife.

A potential starting point for this phase is to hypothesise that the risk of damage is proportional to the crown area. This is based on the assumption that trees with larger crowns have larger branches. If risk of damage is proportional to crown area it allows for a hazard-rate function that is proportional to the crown area of the tree. Assuming the crown radius is proportional to the diameter at breast height[3], the hazard rate would be proportional to DBH squared. This corresponds to a Weibull survival model (Collett, 2015) with an exponent parameter $k = 3$. In the Weibull model, the hazard rate follows:

$$hazard = bkD^{k-1} \tag{2}$$

where b is a multiplier controlling the rate of hollow formation and k controls the shape of the hazard-DBH relationship. For interpretation or simulation purposes, we may want to calculate the probability of a tree not developing a new pre-hollow in a given year given its current size D. This probability is obtained by taking the negative exponential transform of the hazard rate as follow:

$$\text{probability of no new pre-hollows} = exp(-bkD^{k-1})$$

The probability of developing a pre-hollow in a given year is then:

$$\text{prob. new pre-hollow} = 1 - exp(-bkD^{k-1})$$

The probability that a tree has no hollow (*i.e.*, the survival function) after n years is calculated as the product of the annual probabilities of not forming a new hollow over n successive years. The hazard function for each year depends on the tree's size in that year:

$$\begin{aligned}\text{No new hollow from years 1 to year n} = &(\text{prob. no new hollow in year 1}) \times \\ &(\text{prob. no new hollow in year 2}) \times \\ &(\text{prob. no new hollow in year 3}) \times \\ &\dots \\ &(\text{prob. no new hollow in year } n)\end{aligned}$$

A mathematically equivalent, but easier to calculate, method uses the cumulative hazard function up to DBH D[4]:

$$\text{cumulative hazard} = \int_0^D bkD^{k-1}dD = bD^k$$

We then calculate the survival function as the negative exponential of the cumulative hazard function:

[3] We might consider alternative allometries where crown radius is proportional to power functions of DBH. For example, if crown radius is proportional to $\text{DBH}^{0.8}$, then the hazard will be proportional to $\text{DBH}^{1.6}$. Alternatively, if pre-hollow formation is driven by the surface area of branches instead of crown area, which might follow a fractal filling space, then the hazard rate could be proportional to DBH raised to the power of 2 to 3. In this study, we start by considering a hazard proportional to DBH^2 (but this can be tested by making it a free parameter in the model, see Results section).

[4] One of the tricks to recovering a static hollow-DBH allometry from the dynamic hollow development process is to integrate the process with respect to size, not time.

$$\text{survival} = exp(-bD^k) \tag{3}$$

The hollow-DBH allometry (the probability that a tree of a given size has a hollow) is:

$$\text{probability of having a pre-hollow} = 1 - exp(-bD^k)$$

Since we have only one survey, we cannot directly observe hollow formation or fit the hazard function. However, we can use the hollow-DBH allometry (the quantitative relationship between tree size and hollow presence) to estimate parameters. Being able to scale from process to pattern (and *vice versa*) is one of the advantages of using a survival analysis framework instead of alternative methods (*e.g.*, logistic regression). Fitting the hollow-DBH allometry to 21,243 trees in the NFSI database gives a parameter b equal to 1.42×10^{-6} and an exponent k of 3.06 (95% CI: 2.95 to 3.17). This result supports our hypothesis that hollow development hazard is proportional to crown area. Because of this, we do not need to estimate the k parameter. Throughout the rest of the analyses, we fix it to three.

Although we do not use it further in the report, it is worth noting that we can use the time – or rather the size-to-event – distribution[5] to quantify at what size pre-hollows are typically created. The size-to-event distribution is obtained by multiplying the hazard function by the survival function:

$$\text{size-to-event distribution} = bkD^{k-1}exp(-bD^k) \tag{4}$$

3.2.2. Hollow maturation phase

Once a pre-hollow forms, fungi, insects, and other decomposers accelerate wood decomposition and hollow enlargement. The hollow matures into a size and condition suitable for various animal species to use for shelter and breeding. The time required for a pre-hollow to develop into a hollow may follow its own survival model. When decay is quick (as seems to be the case in the NFSI data), this phase can be ignored. But for species with slow hollow formation (*e.g.*, *Eucalyptus regnans* or *E. delegatensis* in Victoria, Fox *et al.*, 2008), this step might be essential to get accurate predictions[6].

For simplicity, assume a fixed delay δ (in cm) between pre-hollow initiation and a mature hollow[7]. Then the probability that a tree of diameter D has a hollow is:

$$\text{prob. hollow} = \begin{cases} 0, & \text{if } D - \delta < 0 \\ 1 - \exp\left(-b(D-\delta)^3\right), & \text{otherwise} \end{cases}$$

[5]The survival analysis framework links three complementary scales: hazard rate (Eq. 2), survival function (Eq. 3), and time-to-event distribution (Eq. 4); each scale providing a different insight into the modelled process.

[6]Increasing the k exponent to a higher power can create a shape similar to using a delay parameter; however, it complicates the interpretation of the parameters. For example, with $k = 5$, exposure to damage is proportional to DBH^4 or $crown\_area^2$. While possible, this is unlikely. We prefer to use the delay formulation rather than modifying the k exponent, as the former has a more straightforward biological interpretation.

[7]We could implement more complex delay functions than this step function. For example, the decay could have its own survival function; however, this would make the model more difficult to fit and it would be less transparent.

Note that if we use the hollow maturation phase equation, we need to use a threshold to avoid predicting negative probabilities when DBH is less than the delay period. This delay formulation is equivalent to a three-parameter (shifted) Weibull distribution with location δ. If we want to express the delay in years, we convert via the average DBH growth rate $\bar{g}_D$ (cm year^{-1}):

$$\text{delay}_{\text{years}} = \frac{\delta}{\bar{g}_D}.$$

3.2.3. Modelling the impact of fire on hollow recruitment

Fire can physically damage trees, killing branches or creating fire scars. This might increase the rate of hollow recruitment. To model this, we can choose between an additive hazard model, where the hazard rate increases regardless of tree size, or a proportional hazard model, where larger trees – which already have a greater chance of forming pre-hollows – are more affected. Additionally, we need to determine if the fire's impact is limited to the year of the fire (*i.e.*, a 'one-off') or if the increased hazard rate persists and compounds over time. These assumptions will have different impacts on the hazard rate function, with flow-on effects on the hollow-DBH allometries. In the next sections and in Figs. 11 and 12, we illustrate how this might work.

Hollow recruitment simulations with fire at specific years. In Figure 11, we explored how these four scenarios influence the hollow-DBH allometries through fire's impact on the hazard rate. We used a loop to simulate annual growth over 200 years. We used a baseline hazard function (in the absence of a fire): $hazard_i = 4.2610^{-6} D_i^2$ (*i.e.*, Eq. 2 with $b = 1.4210^{-6}$ and $k = 3$, which provided plausible trajectories for the NFSI data). At each step of the loop, we grew trees by 0.8 cm DBH[8] and calculated the annual probability of hollow recruitment for trees without hollows, using their current DBH at time i as $1 - e^{-hazard_i}$. We simulated deterministic fires at years 30 and 100, corresponding to DBH values of 24 cm and 100 cm, respectively. We assumed that trees survived these fires but that the fire impacted their probability of becoming a hollow bearing tree. Specifically, the fire impact adjusted the baseline hazard rate (indicated by the grey dashed line in Fig. 11) according to four scenarios (additive vs. proportional hazard models, and one-time vs. lasting fire effects and combination thereof). In our simulations, fire impacted the hazard rate (column 1 in Fig. 11), which in turn influenced the annual probability of hollow recruitment, the cumulative hazard, and the hollow-DBH allometry (columns 2 to 4 in Fig. 11).

In the one-off fire impact scenario (Figs. 11a. and b.), there are sharp peaks in the hazard rate the year of a fire, leading to jagged hollow-DBH allometries that mark the timing of specific fire events. By comparison, in the persistent fire impact scenario (Figs. 11c. and d.), the impact of fire lifts the hazard rate for all subsequent years, producing smoother hollow-DBH allometries. Note that in this simulation, we were able to track for the exact timing of each fire. However, in empirical data, it is usually impractical to record the exact time of each fire, which is why approximate functions using fire count were developed for practical use (see Eq. 5 to Eq. 8).

[8]The 0.8 cm year^{-1} growth rate was chosen as a representative average. It does not affect the hollow-DBH allometry because the model integrates the hazard with respect to diameter, not time.

Hollow recruitment simulations with stochastic fires. When we don't know the exact timing of fire events, stochastic simulations can offer valuable insights. They give us insights about the average response and the expected spread. Figure 12 use Monte Carlo simulations to incorporate fire stochasticity. Instead of fires occurring at fixed intervals, we assume a 2% chance of fire each year over a 200-year period. We ran 100 simulations per scenario to capture the variability in fire occurrence. For simplicity, we focus only on the hollow-DBH allometry (*i.e.*, equivalent to the fourth column in Fig. 11), as this is what is usually observed in empirical data.

The results show that additive hazard scenarios had the greatest impact on smaller trees (Fig. 12), because they typically haven't developed hollows yet, leaving more trees available for hollow recruitment. Proportional hazard scenarios had a greater impact on larger trees since the baseline hazard increases with tree size. Hollow-DBH allometries stemming from a one-off impact of fire tend to be jagged with a visible jump the year of the fire (however, as we noted earlier, we may not be able to detect these jumps if we only have static hollow-DBH allometry data). Persistent scenarios seemed to amplify the impact of DBH (*i.e.*, a fire-DBH interaction) compared to one-off scenarios since the impact of fire compounded over time.

Close form approximations for the hollow-DBH allometries under alternative fire impact scenarios. If we try to create closed-form survival functions approximating[9] these simulations, we integrate the hazard function and get:

- **One-off, additive hazard:**

$$1 - \exp(-b_0 \cdot \mathrm{D}^3)\exp(-b_1 \mathrm{fire\_count}) \tag{5}$$

  where b_0 is the same scale parameter (b) as in the baseline Weibull model (controlling the overall rate of hollow formation), and b_1 is a non-size-dependent coefficient representing the additive effect of fire count on hollow presence. The baseline Weibull survival curve is multiplied by $\exp(-b_1\ \mathrm{fire\_count})$, which lifts the curve for small trees.

- **Persistent impact, additive hazard:**

$$1 - \exp(-b_0 \mathrm{D}^3)\exp(-b_1\ \mathrm{fire\_count}\ \mathrm{D}) \tag{6}$$

  This also lifts the hollow-DBH allometry, but the lift is more uniform across all trees. The DBH term in $\exp(-b_1\ \mathrm{fire\_count}\ \mathrm{D})$ is an integration constant, meaning the fire impact persists in all subsequent years. It would be preferable to model this as a time-since-fire effect, but that would require keeping track of all the fires, which adds substantial complexity.

- **One-off, proportional hazard:**

$$1 - \exp\left(-e^{b_0 + b_1 \cdot \mathrm{fire\_count}} \mathrm{D}^3\right) \tag{7}$$

  This is the standard Weibull proportional hazard model often used in survival analysis when there are predictors (Collett, 2015). This is also similar to a cloglog regression with a Bernoulli distribution.

[9] These are approximations as it is impractical to know the exact date and time since each fire event. Instead, we used fire count and averaged the fire impact over the lifespan of the trees. However, this makes it more difficult identify the impact of specific fire events on hollow development.

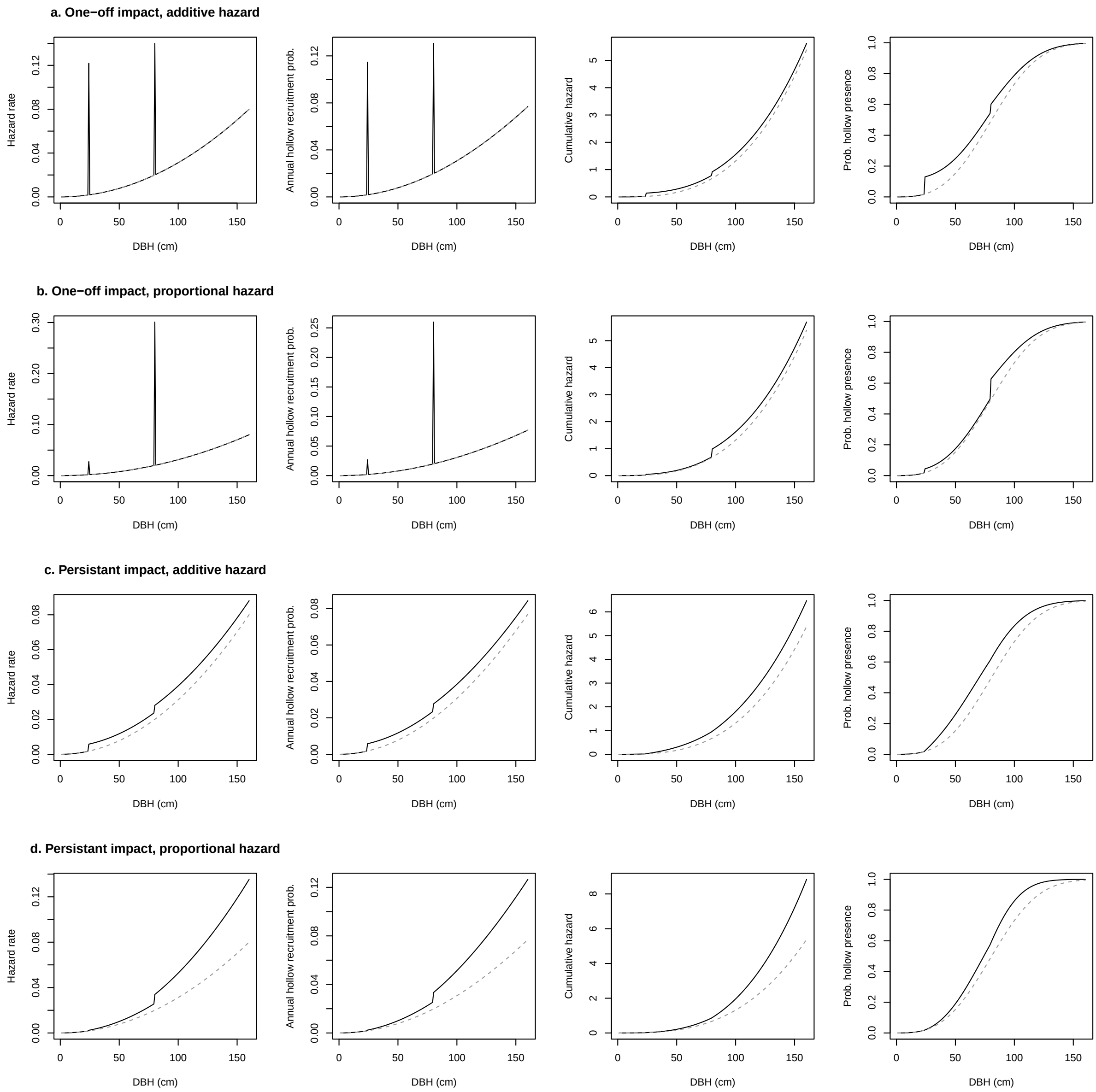

Figure 11: Deterministic simulations illustrating how different hypotheses about fire impacts might influence the hazard rate and, in turn, affect hollow-DBH allometries. The four alternative hypotheses for fire impact on the hazard rate were: (a) One-off, additive hazard: fire affects the hazard only in the year it occurs. The fire impact is additive (*i.e.*, it is independent of the DBH of the tree). (b) One-off, proportional hazard: Fire impact hazard only in the year it occurs. The fire impact is a multiplier of the baseline hazard rate for the year (hence it is called 'proportional hazard'). (c) Persistent impact, additive hazard: fire impacts the hazard in all subsequent years. (d) Persistent impact, proportional hazard. Dashed lines are simulations without fire (baseline). Solid lines are simulations with fires years 30 and 100. Simulation parameters were chosen to provide plausible trajectories that are similar to the NFSI data.

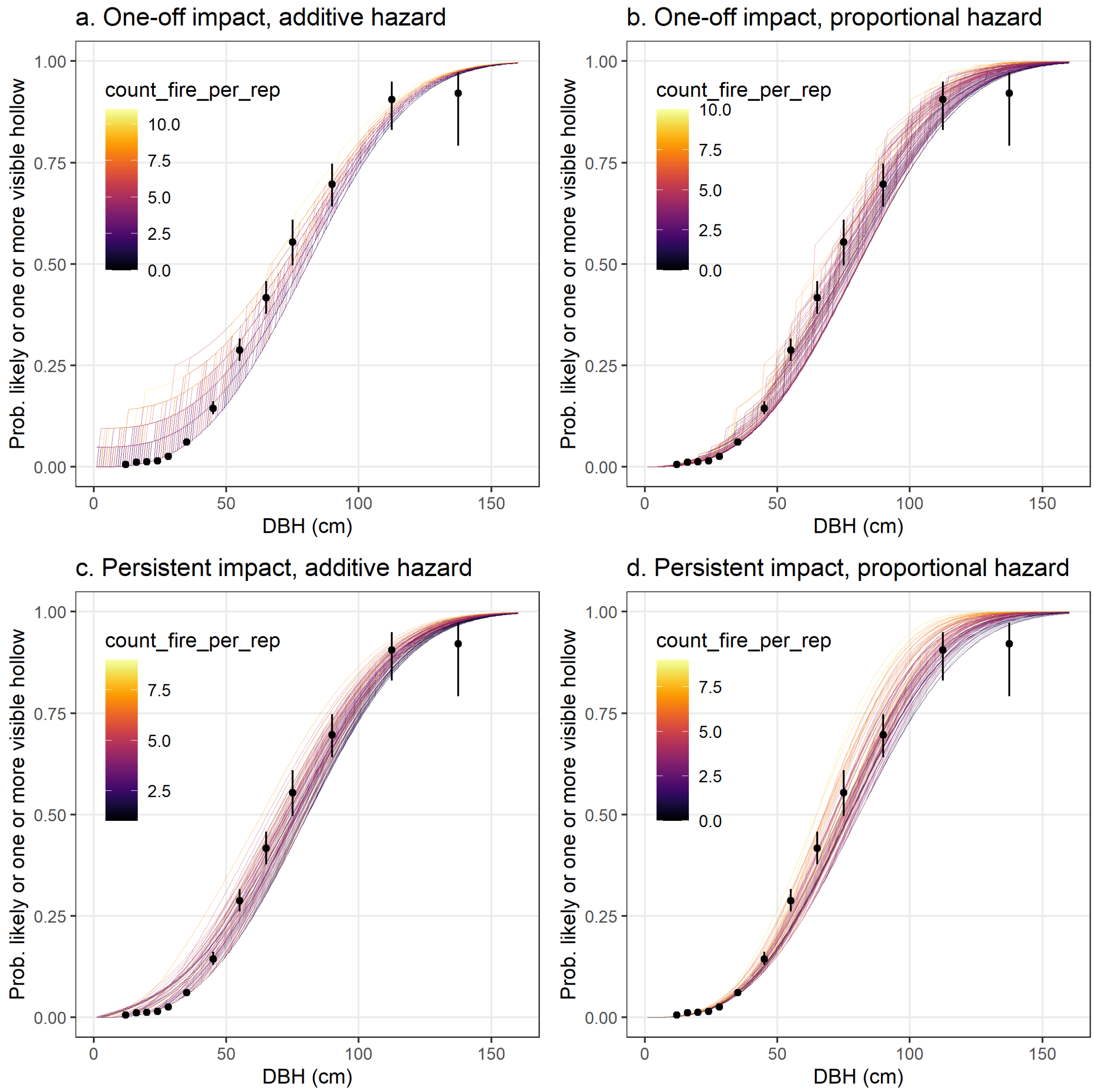

Figure 12: Stochastic simulations illustrating how different hypotheses about fire impacts influence the hollow-DBH allometry, depending on fire count. Different lines show different Monte Carlo replicates. We tested four hypotheses for how fire affects the hazard rate: (a) One-off, additive hazard: fire affects the hazard only in the year it occurs. The fire impact is additive (*i.e.*, it is independent of the DBH of the tree). (b) One-off, proportional hazard: Fire impact hazard only in the year it occurs. The fire impact is a multiplier of the baseline hazard rate for the year (hence it is called 'proportional hazard'). (c) Persistent impact, additive hazard: fire impacts the hazard in all subsequent years. (d) Persistent impact, proportional hazard. Dots and error bars represent observed hollow probabilities binned by DBH class from NFSI data for illustration purposes. Simulation parameters were chosen to provide plausible trajectories that are similar to the NFSI data.

- **Persistent impact, proportional hazard:**

$$1 - \exp\left(-e^{b_0 + b_1 \cdot \text{fire\_count} \cdot D} \mathrm{D}^3\right) \tag{8}$$

This is a proportional hazard model with an interaction between fire count and DBH.

We used the *brms* package in R to fit Eqs. 5, 6, 7, and 8 to the NSFI data. We allowed all parameters to vary among species (*i.e.*, a species random effect) or species group. We used a Bernoulli error term to model the distribution of observations (without hollow = 0, with hollow = 1) around the modelled hollow-DBH allometry.

Model performance was compared using leave-one-out cross-validation (LOO-CV) implemented in the 'loo' package (Vehtari *et al.*, 2017) in R. LOO-CV estimates out-of-sample predictive accuracy by sequentially omitting each observation and computing its predictive density under the fitted model. Models with lower LOO information criterion values have better predictive performance, and differences of 2-5 points are generally considered meaningful (Vehtari *et al.*, 2017).

With the exception of the one-off additive hazard model, the b_1 parameters from these approximate models should not be taken at face value. These models assume the impact of fire was there since the trees regenerated, and not in the specific year of the fire. The approximate models are not able to reproduce the jumps seen in the simulations (Fig. 12). There are several challenges: first, it would be cumbersome to reproduce the specific trajectory for each tree. Second, the fire history only goes back to 2000. And third, various trajectories might lead to the same probability of a tree having a hollow at a given DBH and we only have access to a single snapshot of this trajectory. Longitudinal data would help clarify these trajectories. Nontheless, despite their limitations, these approximate models can serve as a starting point to test hypotheses about fire and hollows and estimate an average impact of fire on the hollow-DBH allometry.

We can also expand the one-off proportional model to isolate the impact of the 2019/20 fire and compare it to past fires. Specifically, we considered the following model:

$$1 - \exp\left(-e^{b_0 + b_1 \cdot \text{fire\_count} + b_2 \cdot \text{FESM\_continuous}} \mathrm{D}^3\right) \tag{9}$$

In Eq. 9, the fire_count includes all fire counts since 2000, except the 2019/20 fire. The $b_2 \cdot$ FESM_continuous term isolates the effect of the 2019/20 fire. After initial testing, we found no significant impact of FESM class 3 on hollow recruitment, and that FESM 5 had a stronger effect than FESM 4. Therefore, we encoded a continuous FESM variable (FESM_continuous) where FESM 1 to 3 (no or moderate severity fire) were set to zero, FESM 4 to 0.5, and FESM 5 to one. We used the one-off proportional impact model for this analysis because it is easier to interpret than the persistent proportional impact model (and both models provide good fits to the data). This choice also allows a direct comparison of the b_1 and b_2 parameters – comparing the impact of a FESM 5 category in the 2019/20 fire with a single fire that occurred post-2000 – as both parameters are on the same scale.

3.3. Results on hollow development and fire

Impact of fire count since 2000. Of the four parametric models testing for fire count[10] (Eqs. 5, 6, 7, 8), the persistent proportional hazard model (Eq. 8) provided the best fit

[10] Note that the fire count tested here is the count of fires over a 24 year period. Trees older than 20 years are likely to have been exposed to an unknown number of additional fires prior to 2000.

to the NFSI data. This model shows that fire impact on hollow development is greatest for large trees. The one-off, proportional hazard model (Eq. 7) also had a good fit to the data, having a leave-one-out cross validation metric (Vehtari *et al.*, 2017) 20 points lower (*i.e.*, worse) than the persistent, proportional hazard model. In contrast, fire impact was not significant in the two additive hazard models, indicating that, provided they survived the fire, small trees do not immediately create hollows following fires.

The estimated hollow-DBH allometry for the persistent, proportional hazard model per species and species group is shown in Figs. 13 and 14. Parameters values are shown in Tables A4 and A5. The estimated hollow-DBH allometry for the one-off, proportional hazard model per species is shown in Fig. A1. For most species there was either a positive impact of fire on hollow probability (BBT, NEB, SBG, SPG) or no impact (BBX, BYW, GYG, RMY) (see Table A1 for species code). Fire had a strong negative impact on hollow probability for one species (PPM). The impact per species group is shown in Fig. 14 and the parameters are shown in Table A6.

Impact of the 2019/20 fire. Equation 9 allowed us to separate and compare the effects of fires since 2000 (except 2019/20) with the impact of the 2019/20 fire. The fire count plus FESM model (Eq. 9) performed as well as the persistent proportional hazard model (Eq. 8), with no significant difference in leave-one-out cross-validation metrics.

Despite the 2019/20 season being an exceptionally severe and widespread fire event, its effect on hollow recruitment was consistent with that of earlier fires (Figs. 15 and 16; see Table A6 for parameter values per species). This suggests that, in terms of hollow recruitment, the 2019/20 fires did not produce effects stronger than those observed from previous events. The 2019/20 fires are too recent to assess whether their impact on hollow recruitment is a one-off or if it is persistent. FESM class 3 (moderate-severity fire) had a non-significant effect on hollow recruitment, suggesting that only higher-severity fires cause sufficient damage to influence hollow formation. The impact per species group is shown in Fig. 17 and the parameters are shown in Table A7.

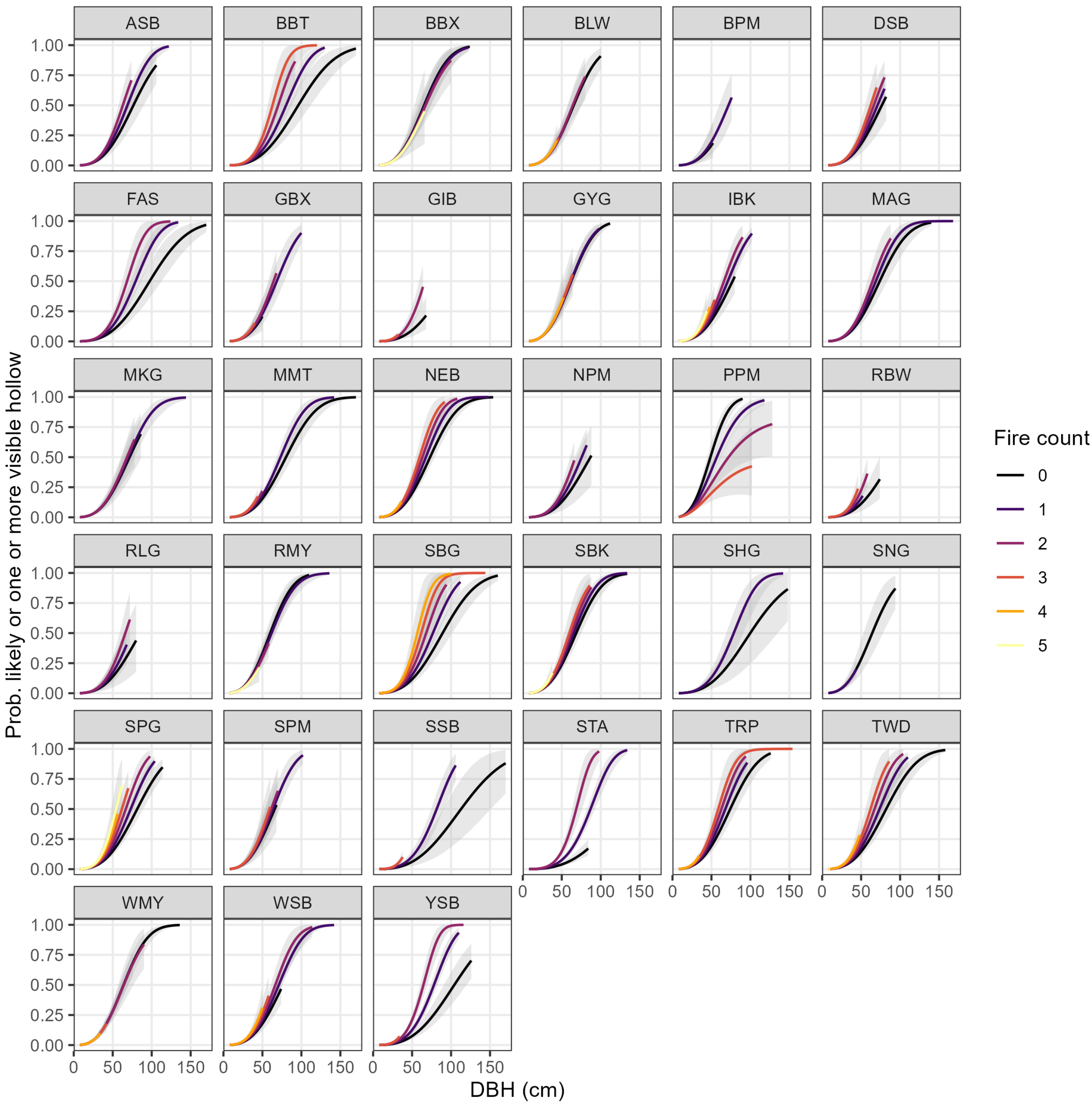

Figure 13: Fire sensitive hollow-DBH allometry per species (see Table A1 for species code). The model used is the 'persistent and proportional hazard' (Eq. 8), which had the best fit. Species-specific parameters are shown in Table A4.

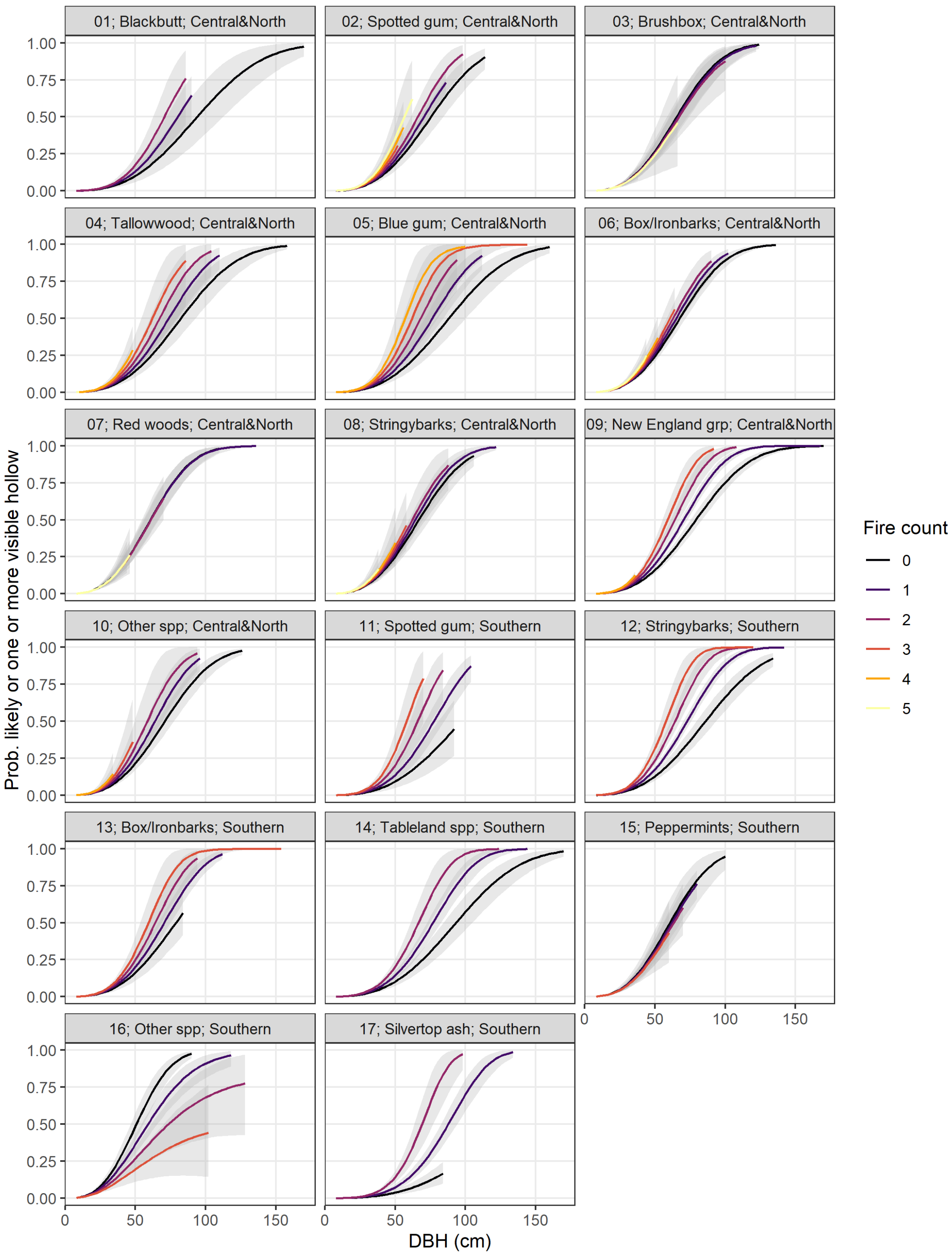

Figure 14: Fire sensitive hollow-DBH allometry per species group. The model used is the 'persistent and proportional hazard' (Eq. 8), which had the best fit. Species group-specific parameters are shown in Table A5.

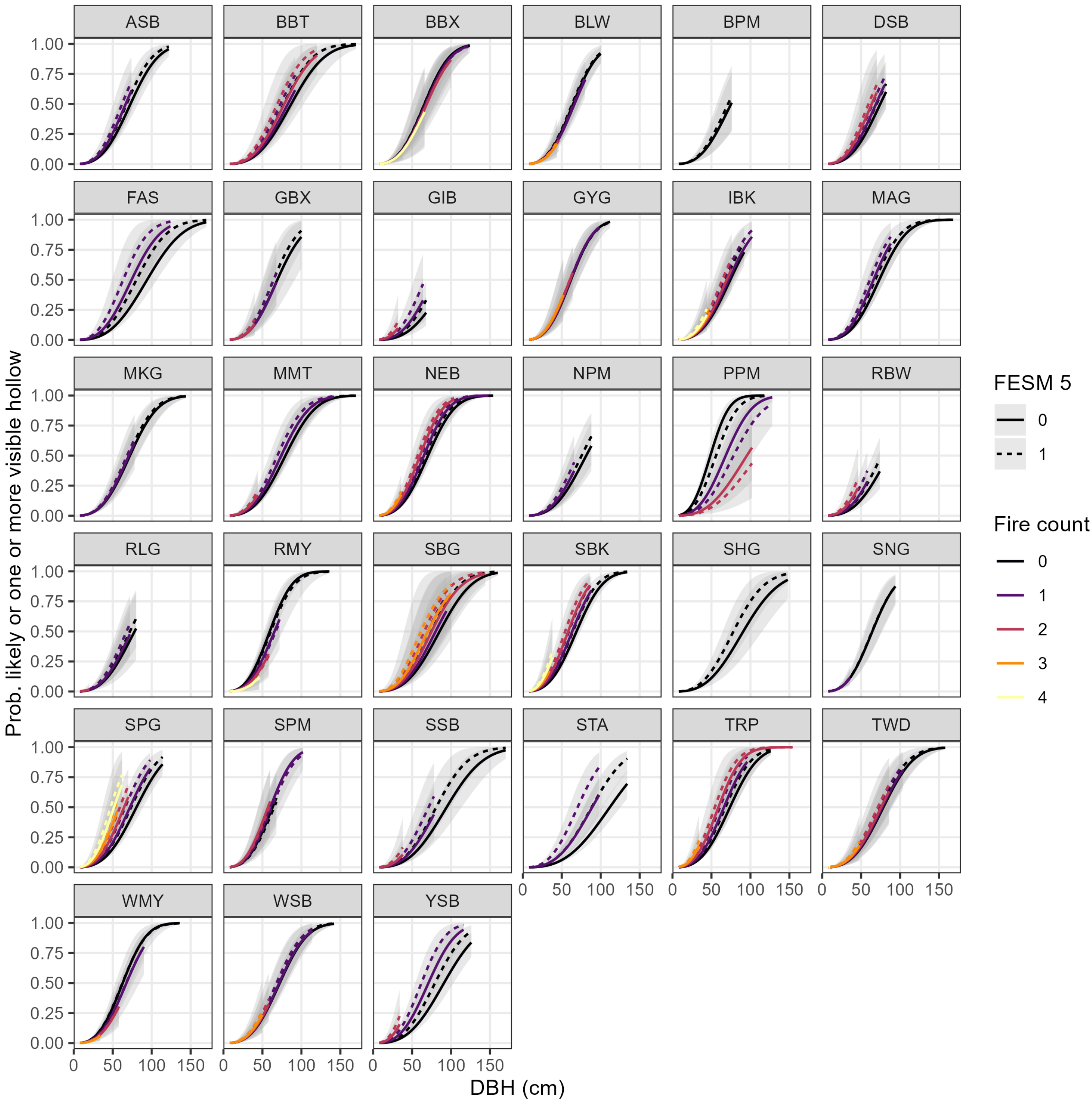

Figure 15: Hollow-DBH allometry per species per fire count since 2000 (excluding the 2019/20 fire) and FESM category in the 2019/20 fire. The model used is the 'one-off and proportional hazard' with both fire count and FESM class encoded as a continuous variable (FESM 1 to 3 = 0, FESM 4 = 0.5, FESM 5 = 1, see Eq. 9). Predictions for FESM 4, which are intermediate between unburnt and class 5, are not shown to avoid clutter. Species that respond positively to fire count also typically respond positively to having a partial or full canopy consumption in 2019/20. Species-specific parameters are shown in Table A6.

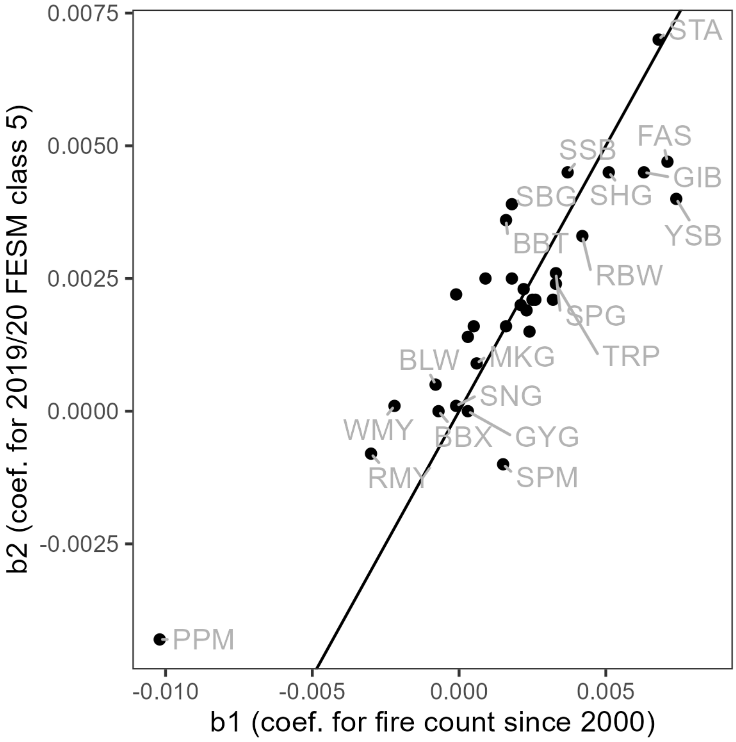

Figure 16: Relationship between species-specific parameters $b1$ and $b2$ in Eq. 9 (see Table A6 for the specific values). The solid 1:1 line shows $b1 = b2$. Species that respond positively to fire count since 2000 (minus the 2019/20 fire) also respond positively to the 2019/20 fire.

4. Discussion

Summary of the findings: We modelled tree mortality and hollow recruitment after fire in NSW's Coastal IFOA regions using NFSI, WSU, and PSP data. A seven-parameter double-logistic model captured the U-shaped mortality response based on DBH, species, and fire severity, while a Weibull model linked the observed hollow–DBH allometry to the process of hollow recruitment over time. Fire increased mortality while accelerating hollow formation in survivors. These results highlight the dual role of fire in hollow-bearing tree dynamics and suggest integrating these models into FRAMES to improve predictions of hollow availability under different fire and management scenarios.

Limitations and perspectives: Mortality estimates remain uncertain for very large trees ($>$ 200 cm DBH) due to limited data in this size range. Excess mortality in these trees may be more strongly influenced by factors such as pre-existing basal hollows (Bendall *et al.*, 2024b), fire scars, or the compounding effects of successive fires, rather than size alone. Additional data on very large trees and on fire damage and hollow characteristics would help clarify these relationships.

Another source of uncertainty arises from the timing of post-fire surveys, which were conducted between one and four years after fire events. Trees can continue to die for several years following fire. This means that earlier surveys may underestimate total mortality compared to later ones. This variability was not accounted for in the analysis which adds uncertainty to mortality estimates.

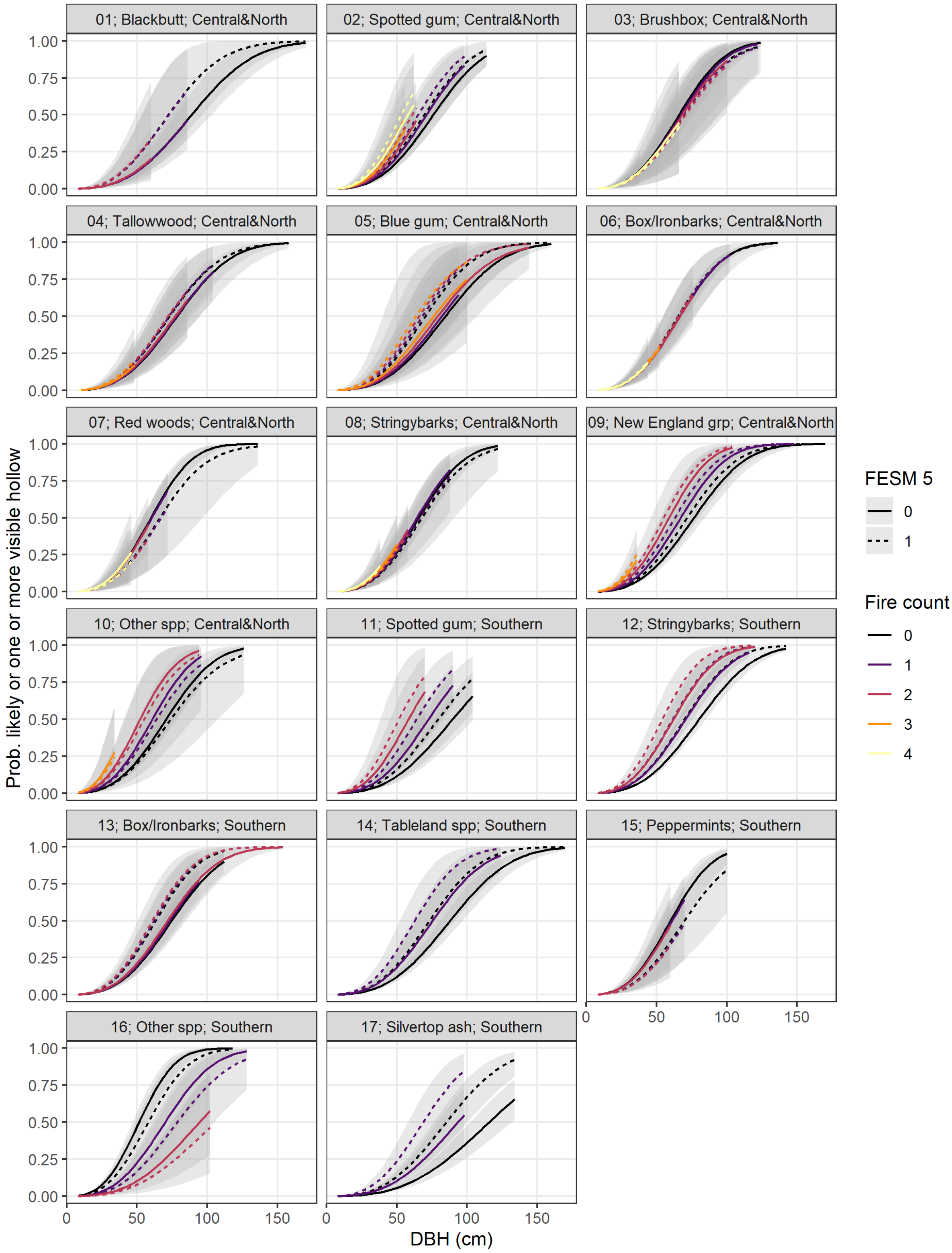

Figure 17: Hollow-DBH allometry per species group per fire count since 2000 (excluding the 2019/20 fire) and FESM category in the 2019/20 fire. The model used is the 'one-off and proportional hazard' with both fire count and FESM class encoded as a continuous variable (FESM 1 to 3 = 0, FESM 4 = 0.5, FESM 5 = 1, see Eq. 9). Predictions for FESM 4, which are intermediate between unburnt and class 5, are not shown to avoid clutter. Species-group specific parameters are shown in Table A7.

- Recommendations:
  - Collect additional data on very large trees (> 200 cm DBH) to better estimate the upper mortality plateau (P_{large}).
  - Use a more detailed classification of hollows (*e.g.*, distinguishing between basal, stem, and branch hollows), although perhaps accounting for pre-existing fire damage (instead of pre-existing basal hollows) might be sufficient for mortality modelling purposes (see discussion on modelling perspectives).
  - Recording collapsed trees in NFSI inventory plots would improve mortality estimates. Without these data, we only have partial mortality information and need to implement less reliable bias correction methods, such as the ghost tree correction described in section 2.4. WSU protocol already includes collapsed trees in their survey.
  - Collect longitudinal data with pre- and post-fire surveys to better detect compounding fire effects and facilitate identification of collapsed trees.
  - Consider delayed mortality in future work by explicitly modelling post-fire mortality as a function of time since fire.

Understanding and calibrating the impact of fire on hollow recruitment remains a challenge. The impact of the 2019/20 fire is still recent. We do not yet know whether fire impacts on hollow recruitment follow the one-off or persistent hypothesis (based on existing historical data, both models fitted the data relatively well). Unlike in simulations (Fig. 12), we do not know how many fires a tree experienced before 2000, or what the hollow-DBH relationship was at that time. This makes it difficult to identify the impact of post-2000 fires on the hollow-DBH allometry, especially since we only have a snapshot of the data in 2021-2023. The current model that we fit represents a smooth average fire impact on the hollow-DBH allometry. Yet, when forecasting, we might want to understand how each new fire might affect the hollow-DBH trajectory and how this trajectory might jump over time (as in Fig. 12).

While several uncertainties remain, the models developed here already provide a practical foundation for integration into decision-support systems. In terms of implementation in a decision-support tool such as FRAMES, this framework can be used to simulate hollow dynamics under alternative fire regimes and management strategies. If these smooth trajectories are acceptable, then we would recommend using the 'one-off proportional hazard' model (Eq. 7, parameters in Tables A8 and A9) for its simplicity and goodness-of-fit, which is nearly as good as the more complex models (Eqs. 8 and 9). This choice also avoids over-interpreting persistence from cross-sectional data. The main benefit of the model combining fire count and FESM classes (Eq. 9) is inference (not prediction), as it provides two independent estimates of fire impact on hollow development. The strong correlation between the effect size for fire count and FESM class (Fig. 16) indicates that different species have a specific and consistent response to fire. Species can respond positively, negatively, or not at all (*i.e.*, neutral). In terms of mechanism, we need to clarify if fire impact on hollow development is a one-off event (*i.e.*, the hypothesis underlying Eqs. 7 and 9) or if its effect is persistent (*i.e.*, the hypothesis underlying Eq. 8). To test these alternative hypotheses requires longitudinal data on hollow occurrence and dynamics.

- Recommendations:

- Collect longitudinal data. We need the dynamic trajectory of hollow recruitment, not just the static hollow-DBH allometry, if we want to better understand and forecast hollow recruitment.
- We suggest revisiting the NFSI plots every 5 to 10 years to compare the trajectories of hollow-bearing tree recruitment in unburnt areas and in burnt areas across a range of FESM classes.

Modelling perspectives: A more detailed fire damage model might improve our ability to jointly forecast tree mortality and hollow collapse. This is supported by evidence that trees with fire damage are more likely to contain hollows (Table 5) and that trees with existing fire scars are more likely to die in subsequent fires (Bluff, 2016). Incorporating fire damage could therefore provide a way to link these two processes. We suggest using the 7-level ordinal response scale to model fire damage response instead of the binary 0/1 tree mortality response in Eq. 1. This step would add complexity and may increase uncertainty in future predictions; however, it might also provide important insights on the impact of successive fires on tree mortality, hollow recruitment, and even carbon sequestration and timber yield. This might also provide guidance on the potential impact of repeated *fuel reduction* burns on hollow-bearing tree abundance.

Standing dead trees are an important but often overlooked source of hollows in forests. In this database, approximately 20% of hollow bearing trees per hectare are standing dead trees (Table 4). These trees originate from live trees that die and, over time, may develop hollows before eventually collapsing. The hollows they provide create important habitat for wildlife. A more complete understanding of hollow dynamics would also require modelling these standing dead trees, and, eventually, their transition to fallen logs, which we identify as an avenue for future work.

This report primarily focused on live hollow-bearing trees, but a more comprehensive approach would require modelling four distinct hollow compartments separately: (1) live hollow-bearing trees (this report), (2) standing dead hollow-bearing trees, (3) hollow-bearing logs, and (4) hollows in coarse woody debris. Each of these compartments would need its own models for hollow formation and loss and their response to fire. While our data includes standing dead trees, we did not model them separately, and the other two categories are not captured in our current dataset. Threlfall *et al.* (2019) provide relevant benchmarks and predictors of coarse woody debris in eastern Australian forests, which could inform future modelling efforts for these additional hollow resources. Understanding the processes driving all hollow types would offer valuable insights to improve environmental monitoring and habitat management.

- Recommendations:
  - Collect longitudinal data to characterise pre-fire conditions. Use a partial proportional odds model to differentiate impacts on mortality (class 7) versus damage levels (classes 1-6) (Peterson & Harrell, 1990) for flexibility.
  - Model the recruitment and collapse of standing dead trees as well as their likelihood of containing hollows. Future work could also extend this framework to fallen dead trees and coarse woody debris, which provide critical habitat for many ground-dwelling and burrowing species but are not represented in the current dataset

5. Conclusion

We used NFSI, WSU, and PSP data to model tree mortality and hollow recruitment after fires in Coastal IFOA regions. A seven-parameter double-logistic model captured the U-shaped mortality response based on DBH, species, and fire severity, while a Weibull model was used to link the observed hollow-DBH allometry to the process of hollow recruitment over time. Our results demonstrate that fire has two countervailing impacts on hollow-bearing tree dynamics in NSW forests. On the one hand, fire can kill hollow-bearing trees, reducing the density of hollow-bearing trees within the footprint of a fire. On the other hand, trees that survive a fire are more likely to develop hollows due to fire damage. This suggests that silvicultural approaches that increase the probability of tree survival may have long-term benefits for the number and persistence of hollow-bearing trees (Trouvé *et al.*, 2021). Integrating these modelling approaches into the FRAMES decision-support tool would strengthen its ability to forecast hollow abundance under different fire and management scenarios. Such integration would help managers better anticipate long-term habitat availability, evaluate trade-offs between fire regimes and biodiversity conservation, and design strategies that balance hazard reduction with the retention of wildlife habitat.

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A. Appendix

Table A1: Species code and species groups used in FRAMES. Blank cells indicate groups with no available data.

			Species group	
Species code	Common Name	Scientific name	Central & North regions	Southern region
ASB	Blueleaved Stringybark	*Eucalyptus agglomerata*	08; Stringybarks; Central&North	12; Stringybarks; Southern
BBT	Blackbutt	*Eucalyptus pilularis*	01; Blackbutt; Central&North	12; Stringybarks; Southern
BBX	Brush Box	*Lophostemon confertus*	03; Brushbox; Central&North	
BLW	Bloodwood group	*Eucalyptus* spp.	07; Red woods; Central&North	13; Box/Ironbarks; Southern
BPM	Broadleaved Peppermint	*Eucalyptus dives*		15; Peppermints; Southern
DSB	Diehard Stringybark	*Eucalyptus cameronii*	09; New England grp; Central&North	
FAS	Brown barrel/Cuttail	*Eucalyptus fastigata*	09; New England grp; Central&North	14; Tableland spp; Southern
GBX	Grey Box	*Eucalyptus moluccana / Eucalyptus dawsonii*	06; Box/Ironbarks; Central&North	13; Box/Ironbarks; Southern
GIB	Grey Ironbark	*Eucalyptus siderophloia / Eucalyptus paniculata*	06; Box/Ironbarks; Central&North	13; Box/Ironbarks; Southern
GYG	Grey Gum	*Eucalyptus propinqua / Eucalyptus punctata*	06; Box/Ironbarks; Central&North	13; Box/Ironbarks; Southern
IBK	Ironbark group	*Eucalyptus* spp.	06; Box/Ironbarks; Central&North	13; Box/Ironbarks; Southern
MAG	Manna Gum/Ribbon Gum	*Eucalyptus viminalis*	09; New England grp; Central&North	15; Peppermints; Southern
MKG	Monkey Gum/Mtn Grey Gum	*Eucalyptus cypellocarpa*	09; New England grp; Central&North	14; Tableland spp; Southern
MMT	Messmate	*Eucalyptus obliqua*	09; New England grp; Central&North	14; Tableland spp; Southern
NEB	New England Blackbutt	*Eucalyptus andrewsii ssp. campanulata*	09; New England grp; Central&North	
NPM	Narrowleaved Peppermint	*Eucalyptus radiata*	09; New England grp; Central&North	15; Peppermints; Southern
PPM	Peppermint group	*Eucalyptus* spp.	10; Other spp; Central&North	16; Other spp; Southern
RBW	Red Bloodwood	*Eucalyptus gummifera*	07; Red woods; Central&North	13; Box/Ironbarks; Southern
RLG	Roundleaved Gum	*Eucalyptus deanii*	09; New England grp; Central&North	
RMY	Red Mahogany	*Eucalyptus resinifera / Eucalyptus pellita*	07; Red woods; Central&North	13; Box/Ironbarks; Southern
SBG	Sydney blue Gum/Blue Gum	*Eucalyptus saligna*	05; Blue gum; Central&North	13; Box/Ironbarks; Southern
SBK	Stringybark group	*Eucalyptus* spp.	08; Stringybarks; Central&North	12; Stringybarks; Southern
SHG	Shining Gum	*Eucalyptus nitens*		14; Tableland spp; Southern
SNG	White Sallee/Snow Gum	*Eucalyptus pauciflora*	10; Other spp; Central&North	16; Other spp; Southern
SPG	Spotted Gum	*Corymbia maculata*	02; Spotted gum; Central&North	11; Spotted gum; Southern
SPM	Sydney Peppermint	*Eucalyptus piperita*	09; New England grp; Central&North	15; Peppermints; Southern
SSB	Silvertop Stringybark	*Eucalyptus laevopinea*	09; New England grp; Central&North	16; Other spp; Southern
STA	Silvertop Ash/Black Ash/Coast Ash	*Eucalyptus sieberi*	08; Stringybarks; Central&North	17; Silvertop ash; Southern
TRP	Turpentine	*Syncarpia glomulifera*	10; Other spp; Central&North	13; Box/Ironbarks; Southern
TWD	Tallowwood	*Eucalyptus microcorys*	04; Tallowwood; Central&North	
WMY	Mahogany, white (group)	*Eucalyptus acmenioides* or *E. umbra*	06; Box/Ironbarks; Central&North	
WSB	White Stringybark	*Eucalyptus globoidea*	08; Stringybarks; Central&North	12; Stringybarks; Southern
YSB	Yellow Stringybark	*Eucalyptus muelleriana*		12; Stringybarks; Southern

Table A2: Coefficient for the 7-P double logistic mortality model (Eq. 1) per species. Values show means with standard errors in brackets and include bias correction for ghost trees.

Species	FESM	P_{small}	P_{medium}	P_{large}	S_{small}	S_{large}	$D50_{small}$	$D50_{large}$
ASB	3	0.36 (0.29)	0.02 (0.01)	0.36 (0.34)	0.39 (0.28)	0.086 (0.060)	8.9 (3.4)	176 (44)
ASB	4	0.57 (0.26)	0.03 (0.02)	0.90 (0.24)	0.50 (0.50)	0.086 (0.060)	10.3 (3.7)	176 (44)
ASB	5	0.63 (0.24)	0.04 (0.02)	0.96 (0.16)	0.46 (1.18)	0.086 (0.060)	11.9 (4.4)	176 (44)
BBT	3	0.66 (0.26)	0.01 (0.01)	0.37 (0.34)	0.70 (0.41)	0.091 (0.074)	8.5 (1.2)	179 (37)
BBT	4	0.87 (0.15)	0.05 (0.03)	0.91 (0.22)	1.04 (0.71)	0.091 (0.074)	9.8 (1.2)	179 (37)
BBT	5	0.90 (0.14)	0.06 (0.03)	0.97 (0.12)	1.01 (0.66)	0.091 (0.074)	11.3 (1.4)	179 (37)
BLW	3	0.26 (0.35)	0.01 (0.00)	0.25 (0.30)	1.28 (2.58)	0.088 (0.060)	7.1 (3.9)	171 (41)
BLW	4	0.35 (0.40)	0.01 (0.01)	0.86 (0.28)	1.97 (5.47)	0.088 (0.060)	8.2 (4.2)	171 (41)
BLW	5	0.38 (0.41)	0.02 (0.01)	0.95 (0.17)	2.19 (3.90)	0.088 (0.060)	9.5 (5.2)	171 (41)
FAS	3	0.70 (0.28)	0.02 (0.02)	0.42 (0.34)	0.71 (1.09)	0.080 (0.053)	9.3 (1.6)	168 (36)
FAS	4	0.93 (0.11)	0.12 (0.04)	0.95 (0.16)	0.89 (0.98)	0.080 (0.053)	10.8 (1.6)	168 (36)
FAS	5	0.94 (0.10)	0.14 (0.05)	0.99 (0.07)	0.76 (0.97)	0.080 (0.053)	12.5 (1.9)	168 (36)
GYG	3	0.28 (0.36)	0.01 (0.01)	0.29 (0.31)	1.11 (1.27)	0.090 (0.079)	7.1 (2.8)	178 (41)
GYG	4	0.37 (0.40)	0.02 (0.01)	0.88 (0.26)	1.66 (2.42)	0.090 (0.079)	8.3 (3.2)	178 (41)
GYG	5	0.41 (0.41)	0.02 (0.01)	0.97 (0.14)	1.75 (2.56)	0.090 (0.079)	9.6 (3.9)	178 (41)
IBK	3	0.37 (0.35)	0.01 (0.01)	0.32 (0.32)	0.74 (0.90)	0.085 (0.060)	7.8 (2.8)	175 (41)
IBK	4	0.54 (0.36)	0.03 (0.01)	0.92 (0.20)	1.02 (1.07)	0.085 (0.060)	9.0 (3.1)	175 (41)
IBK	5	0.59 (0.35)	0.03 (0.02)	0.98 (0.10)	1.02 (1.83)	0.085 (0.060)	10.5 (3.7)	175 (41)
MKG	3	0.81 (0.18)	0.03 (0.02)	0.42 (0.34)	0.30 (0.17)	0.090 (0.106)	10.5 (1.8)	179 (40)
MKG	4	0.94 (0.08)	0.08 (0.03)	0.92 (0.20)	0.36 (0.21)	0.090 (0.106)	12.1 (1.6)	179 (40)
MKG	5	0.96 (0.07)	0.09 (0.03)	0.98 (0.11)	0.30 (0.19)	0.090 (0.106)	13.9 (1.9)	179 (40)
MMT	3	0.64 (0.24)	0.01 (0.01)	0.35 (0.33)	0.46 (0.38)	0.076 (0.051)	8.2 (1.9)	152 (30)
MMT	4	0.86 (0.14)	0.04 (0.02)	0.96 (0.11)	0.60 (0.48)	0.076 (0.051)	9.5 (1.9)	152 (30)
MMT	5	0.90 (0.12)	0.06 (0.04)	0.99 (0.03)	0.58 (0.63)	0.076 (0.051)	11.0 (2.3)	152 (30)
NEB	3	0.21 (0.31)	0.01 (0.00)	0.24 (0.28)	1.06 (1.09)	0.083 (0.060)	7.4 (4.0)	162 (30)
NEB	4	0.30 (0.36)	0.01 (0.01)	0.88 (0.23)	1.55 (1.86)	0.083 (0.060)	8.5 (4.3)	162 (30)
NEB	5	0.35 (0.38)	0.01 (0.01)	0.97 (0.13)	1.69 (2.34)	0.083 (0.060)	9.8 (5.1)	162 (30)
PPM	3	0.41 (0.29)	0.01 (0.01)	0.32 (0.32)	0.44 (0.21)	0.087 (0.063)	8.3 (2.3)	177 (47)
PPM	4	0.66 (0.24)	0.03 (0.02)	0.89 (0.25)	0.53 (0.34)	0.087 (0.063)	9.6 (2.4)	177 (47)
PPM	5	0.72 (0.22)	0.04 (0.02)	0.96 (0.15)	0.42 (0.36)	0.087 (0.063)	11.1 (3.0)	177 (47)
RBW	3	0.32 (0.36)	0.01 (0.00)	0.28 (0.31)	1.26 (2.07)	0.086 (0.063)	7.1 (2.5)	174 (38)
RBW	4	0.46 (0.40)	0.02 (0.01)	0.89 (0.25)	1.82 (3.41)	0.086 (0.063)	8.2 (2.9)	174 (38)
RBW	5	0.51 (0.40)	0.03 (0.02)	0.97 (0.13)	2.10 (5.23)	0.086 (0.063)	9.4 (3.4)	174 (38)
RMY	3	0.44 (0.40)	0.02 (0.01)	0.35 (0.33)	1.03 (1.43)	0.079 (0.048)	7.4 (2.4)	174 (36)
RMY	4	0.57 (0.38)	0.04 (0.03)	0.90 (0.23)	1.36 (2.21)	0.079 (0.048)	8.5 (2.8)	174 (36)
RMY	5	0.61 (0.37)	0.05 (0.03)	0.98 (0.11)	1.50 (2.89)	0.079 (0.048)	9.8 (3.3)	174 (36)
SBG	3	0.65 (0.28)	0.01 (0.01)	0.32 (0.33)	0.29 (0.26)	0.089 (0.062)	7.9 (3.7)	183 (46)
SBG	4	0.79 (0.25)	0.03 (0.02)	0.89 (0.24)	0.47 (0.47)	0.089 (0.062)	9.0 (4.0)	183 (46)
SBG	5	0.83 (0.23)	0.03 (0.03)	0.96 (0.16)	0.55 (0.75)	0.089 (0.062)	10.4 (4.8)	183 (46)
SBK	3	0.24 (0.18)	0.02 (0.01)	0.36 (0.33)	0.60 (0.34)	0.096 (0.141)	10.9 (1.8)	170 (39)
SBK	4	0.76 (0.14)	0.11 (0.03)	0.96 (0.14)	0.73 (0.36)	0.096 (0.141)	12.7 (1.4)	170 (39)
SBK	5	0.96 (0.04)	0.44 (0.06)	1.00 (0.04)	0.36 (0.32)	0.096 (0.141)	15.2 (2.3)	170 (39)
SPG	3	0.65 (0.30)	0.01 (0.00)	0.29 (0.31)	1.86 (2.58)	0.094 (0.116)	6.3 (0.9)	185 (47)
SPG	4	0.87 (0.17)	0.03 (0.01)	0.85 (0.29)	2.78 (4.07)	0.094 (0.116)	7.3 (0.8)	185 (47)
SPG	5	0.90 (0.15)	0.03 (0.01)	0.96 (0.15)	3.43 (3.57)	0.094 (0.116)	8.3 (0.9)	185 (47)
SPM	3	0.36 (0.38)	0.01 (0.01)	0.32 (0.31)	1.08 (1.15)	0.097 (0.192)	7.3 (2.9)	166 (41)
SPM	4	0.52 (0.40)	0.05 (0.04)	0.92 (0.20)	1.52 (1.76)	0.097 (0.192)	8.5 (3.3)	166 (41)

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Species	FESM	P_{small}	P_{medium}	P_{large}	S_{small}	S_{large}	$D50_{\mathrm{small}}$	$D50_{\mathrm{large}}$
SPM	5	0.56 (0.40)	0.05 (0.04)	0.98 (0.11)	1.63 (2.66)	0.097 (0.192)	9.8 (3.9)	166 (41)
STA	3	0.41 (0.12)	0.02 (0.01)	0.45 (0.34)	0.36 (0.14)	0.077 (0.070)	12.8 (1.6)	154 (38)
STA	4	0.92 (0.04)	0.22 (0.03)	0.97 (0.11)	0.41 (0.09)	0.077 (0.070)	15.1 (0.8)	154 (38)
STA	5	0.94 (0.04)	0.24 (0.03)	0.99 (0.05)	0.28 (0.09)	0.077 (0.070)	17.6 (1.2)	154 (38)
TRP	3	0.61 (0.31)	0.02 (0.01)	0.37 (0.34)	1.27 (1.19)	0.086 (0.066)	7.8 (1.0)	174 (45)
TRP	4	0.84 (0.19)	0.04 (0.02)	0.90 (0.24)	1.77 (1.88)	0.086 (0.066)	9.1 (0.9)	174 (45)
TRP	5	0.87 (0.17)	0.05 (0.02)	0.97 (0.14)	1.42 (1.22)	0.086 (0.066)	10.4 (1.2)	174 (45)
TWD	3	0.28 (0.34)	0.01 (0.00)	0.26 (0.30)	1.23 (2.36)	0.081 (0.051)	7.2 (2.9)	177 (45)
TWD	4	0.42 (0.39)	0.02 (0.02)	0.86 (0.27)	1.73 (2.56)	0.081 (0.051)	8.4 (3.3)	177 (45)
TWD	5	0.47 (0.39)	0.03 (0.02)	0.96 (0.15)	1.63 (2.39)	0.081 (0.051)	9.8 (4.0)	177 (45)
WMY	3	0.26 (0.34)	0.01 (0.00)	0.25 (0.29)	1.04 (1.02)	0.086 (0.065)	7.1 (2.6)	170 (34)
WMY	4	0.40 (0.38)	0.02 (0.01)	0.87 (0.26)	1.42 (1.34)	0.086 (0.065)	8.2 (2.9)	170 (34)
WMY	5	0.45 (0.38)	0.02 (0.02)	0.98 (0.10)	1.52 (2.28)	0.086 (0.065)	9.4 (3.5)	170 (34)
WSB	3	0.90 (0.12)	0.02 (0.01)	0.36 (0.34)	0.81 (0.27)	0.094 (0.098)	8.3 (0.8)	178 (43)
WSB	4	0.99 (0.02)	0.10 (0.03)	0.93 (0.18)	1.10 (0.43)	0.094 (0.098)	9.6 (0.5)	178 (43)
WSB	5	0.99 (0.01)	0.16 (0.04)	0.99 (0.08)	1.20 (0.53)	0.094 (0.098)	10.9 (0.5)	178 (43)
YSB	3	0.95 (0.06)	0.02 (0.01)	0.41 (0.35)	0.49 (0.18)	0.092 (0.084)	9.7 (1.0)	176 (45)
YSB	4	0.99 (0.02)	0.10 (0.02)	0.94 (0.19)	0.58 (0.18)	0.092 (0.084)	11.0 (0.7)	176 (45)
YSB	5	0.99 (0.01)	0.12 (0.03)	0.98 (0.11)	0.49 (0.18)	0.092 (0.084)	12.5 (0.8)	176 (45)

Table A3: Coefficient for the 7-P double logistic mortality model (Eq. 1) per species group. Values show means with standard errors in brackets and include bias correction for ghost trees.

Species	FESM	P_{small}	P_{medium}	P_{large}	S_{small}	S_{large}	$D50_{\mathrm{small}}$	$D50$
01; Blackbutt; Central&North	3	0.50 (0.38)	0.02 (0.01)	0.41 (0.35)	1.24 (1.86)	0.078 (0.060)	6.1 (3.1)	179
01; Blackbutt; Central&North	4	0.63 (0.38)	0.03 (0.03)	0.87 (0.26)	1.86 (3.34)	0.078 (0.060)	8.0 (3.9)	179
01; Blackbutt; Central&North	5	0.67 (0.37)	0.05 (0.09)	0.95 (0.19)	1.85 (3.50)	0.078 (0.060)	9.1 (4.6)	179
02; Spotted gum; Central&North	3	0.31 (0.39)	0.00 (0.00)	0.25 (0.30)	1.42 (2.13)	0.088 (0.089)	5.6 (3.3)	182
02; Spotted gum; Central&North	4	0.40 (0.42)	0.01 (0.01)	0.78 (0.34)	2.10 (3.67)	0.088 (0.089)	7.3 (4.0)	182
02; Spotted gum; Central&North	5	0.44 (0.43)	0.01 (0.01)	0.90 (0.26)	3.04 (7.30)	0.088 (0.089)	8.2 (4.4)	182
04; Tallowwood; Central&North	3	0.35 (0.39)	0.01 (0.01)	0.29 (0.33)	1.47 (3.07)	0.084 (0.090)	6.1 (4.3)	177
04; Tallowwood; Central&North	4	0.47 (0.42)	0.01 (0.01)	0.82 (0.32)	2.13 (4.52)	0.084 (0.090)	7.9 (5.3)	177
04; Tallowwood; Central&North	5	0.51 (0.42)	0.02 (0.02)	0.93 (0.22)	2.58 (6.00)	0.084 (0.090)	9.0 (6.0)	177
05; Blue gum; Central&North	3	0.63 (0.34)	0.02 (0.02)	0.43 (0.36)	0.96 (2.66)	0.084 (0.076)	6.2 (2.8)	188
05; Blue gum; Central&North	4	0.73 (0.32)	0.03 (0.02)	0.87 (0.27)	1.19 (2.59)	0.084 (0.076)	8.0 (3.5)	188
05; Blue gum; Central&North	5	0.77 (0.31)	0.04 (0.03)	0.94 (0.19)	1.37 (2.50)	0.084 (0.076)	9.1 (4.2)	188
06; Box/Ironbarks; Central&North	3	0.39 (0.40)	0.01 (0.00)	0.35 (0.33)	1.49 (2.78)	0.080 (0.061)	5.8 (2.3)	179
06; Box/Ironbarks; Central&North	4	0.48 (0.41)	0.01 (0.01)	0.83 (0.31)	1.91 (4.12)	0.080 (0.061)	7.6 (2.9)	179
06; Box/Ironbarks; Central&North	5	0.52 (0.41)	0.02 (0.01)	0.91 (0.25)	2.34 (6.51)	0.080 (0.061)	8.6 (3.3)	179
07; Red woods; Central&North	3	0.38 (0.41)	0.01 (0.01)	0.37 (0.34)	1.54 (3.30)	0.078 (0.057)	5.8 (2.9)	173
07; Red woods; Central&North	4	0.48 (0.43)	0.02 (0.01)	0.85 (0.28)	2.16 (4.04)	0.078 (0.057)	7.6 (3.6)	173
07; Red woods; Central&North	5	0.51 (0.43)	0.02 (0.02)	0.93 (0.21)	2.61 (5.16)	0.078 (0.057)	8.6 (4.1)	173
08; Stringybarks; Central&North	3	0.40 (0.39)	0.01 (0.01)	0.35 (0.34)	1.32 (1.89)	0.082 (0.069)	6.1 (3.4)	179
08; Stringybarks; Central&North	4	0.50 (0.42)	0.01 (0.01)	0.83 (0.31)	2.01 (4.08)	0.082 (0.069)	7.9 (4.3)	179
08; Stringybarks; Central&North	5	0.54 (0.42)	0.02 (0.01)	0.91 (0.24)	2.36 (6.45)	0.082 (0.069)	9.0 (5.0)	179
09; New England grp; Central&North	3	0.31 (0.39)	0.00 (0.00)	0.26 (0.30)	1.49 (2.53)	0.085 (0.081)	6.2 (6.3)	165
09; New England grp; Central&North	4	0.40 (0.42)	0.01 (0.00)	0.85 (0.28)	2.36 (4.02)	0.085 (0.081)	8.1 (8.6)	165
09; New England grp; Central&North	5	0.44 (0.43)	0.01 (0.01)	0.94 (0.20)	2.86 (6.87)	0.085 (0.081)	9.3 (10.0)	165
10; Other spp; Central&North	3	0.67 (0.31)	0.02 (0.01)	0.44 (0.36)	1.39 (2.17)	0.076 (0.060)	6.7 (1.4)	172
10; Other spp; Central&North	4	0.82 (0.23)	0.03 (0.02)	0.87 (0.27)	1.80 (2.70)	0.076 (0.060)	8.8 (1.5)	172
10; Other spp; Central&North	5	0.85 (0.21)	0.04 (0.03)	0.93 (0.21)	3.96 (26.92)	0.076 (0.060)	9.9 (1.7)	172
11; Spotted gum; Southern	3	0.67 (0.32)	0.01 (0.01)	0.39 (0.35)	1.86 (6.02)	0.078 (0.067)	5.5 (1.2)	189
11; Spotted gum; Southern	4	0.87 (0.20)	0.04 (0.02)	0.87 (0.25)	2.42 (7.07)	0.078 (0.067)	7.2 (1.4)	189
11; Spotted gum; Southern	5	0.89 (0.19)	0.05 (0.02)	0.94 (0.19)	2.99 (6.57)	0.078 (0.067)	8.1 (1.5)	189
12; Stringybarks; Southern	3	0.90 (0.14)	0.02 (0.01)	0.42 (0.36)	0.68 (0.14)	0.072 (0.052)	8.2 (0.9)	181
12; Stringybarks; Southern	4	0.97 (0.07)	0.11 (0.03)	0.93 (0.18)	0.55 (0.17)	0.072 (0.052)	10.6 (1.0)	181
12; Stringybarks; Southern	5	0.97 (0.06)	0.18 (0.07)	0.97 (0.12)	0.26 (0.12)	0.072 (0.052)	11.7 (1.5)	181
13; Box/Ironbarks; Southern	3	0.41 (0.41)	0.01 (0.01)	0.38 (0.34)	1.19 (1.40)	0.076 (0.061)	5.7 (2.1)	174
13; Box/Ironbarks; Southern	4	0.54 (0.41)	0.03 (0.01)	0.89 (0.24)	1.78 (2.89)	0.076 (0.061)	7.4 (2.5)	174
13; Box/Ironbarks; Southern	5	0.58 (0.40)	0.03 (0.01)	0.96 (0.16)	2.57 (7.00)	0.076 (0.061)	8.4 (3.0)	174
14; Tableland spp; Southern	3	0.80 (0.18)	0.03 (0.02)	0.54 (0.35)	0.36 (0.16)	0.068 (0.053)	8.3 (1.5)	164
14; Tableland spp; Southern	4	0.94 (0.08)	0.09 (0.03)	0.95 (0.14)	0.34 (0.13)	0.068 (0.053)	11.0 (1.3)	164
14; Tableland spp; Southern	5	0.96 (0.07)	0.10 (0.04)	0.98 (0.09)	0.28 (0.12)	0.068 (0.053)	12.5 (1.8)	164
15; Peppermints; Southern	3	0.43 (0.41)	0.02 (0.01)	0.43 (0.35)	1.28 (1.80)	0.070 (0.060)	6.1 (2.6)	169
15; Peppermints; Southern	4	0.55 (0.41)	0.04 (0.04)	0.91 (0.20)	1.83 (4.36)	0.070 (0.060)	7.9 (3.2)	169
15; Peppermints; Southern	5	0.59 (0.40)	0.05 (0.05)	0.96 (0.13)	2.07 (5.08)	0.070 (0.060)	9.0 (3.8)	169
16; Other spp; Southern	3	0.55 (0.32)	0.01 (0.01)	0.37 (0.35)	0.49 (0.25)	0.080 (0.070)	7.0 (2.4)	178
16; Other spp; Southern	4	0.73 (0.26)	0.03 (0.02)	0.86 (0.28)	0.50 (0.75)	0.080 (0.070)	9.2 (3.0)	178
16; Other spp; Southern	5	0.77 (0.24)	0.03 (0.03)	0.93 (0.22)	0.41 (0.51)	0.080 (0.070)	10.5 (3.5)	178
17; Silvertop ash; Southern	3	0.57 (0.23)	0.02 (0.01)	0.53 (0.35)	0.41 (0.15)	0.061 (0.049)	10.8 (2.2)	150
17; Silvertop ash; Southern	4	0.95 (0.05)	0.21 (0.05)	0.97 (0.10)	0.37 (0.09)	0.061 (0.049)	14.8 (0.9)	150
17; Silvertop ash; Southern	5	0.96 (0.04)	0.22 (0.05)	0.99 (0.07)	0.25 (0.06)	0.061 (0.049)	17.1 (1.2)	150

Table A4: Parameter values for the hollow-DBH allometry for the 'persistent, proportional hazard' model (Eq. 8) per species.

Species	b_0		b_1	
	Mean	SE	Mean	SE
ASB	-13.39	0.23	0.0047	0.0028
BBT	-14.07	0.24	0.0067	0.0022
BBX	-12.91	0.20	-0.0007	0.0019
BLW	-12.91	0.21	0.0004	0.0025
BPM	-13.52	0.48	0.0045	0.0037
DSB	-13.39	0.30	0.0033	0.0025
FAS	-14.11	0.22	0.0078	0.0025
GBX	-13.26	0.42	0.0031	0.0035
GIB	-14.15	0.44	0.0090	0.0037
GYG	-12.76	0.14	0.0004	0.0018
IBK	-13.41	0.21	0.0035	0.0021
MAG	-13.28	0.19	0.0031	0.0022
MKG	-13.19	0.28	0.0011	0.0031
MMT	-13.53	0.13	0.0038	0.0019
NEB	-13.24	0.12	0.0034	0.0015
NPM	-13.78	0.40	0.0057	0.0037
PPM	-12.03	0.15	-0.0082	0.0019
RBW	-13.92	0.39	0.0080	0.0036
RLG	-13.74	0.48	0.0059	0.0042
RMY	-12.66	0.16	-0.0014	0.0021
SBG	-13.84	0.17	0.0059	0.0020
SBK	-13.05	0.14	0.0023	0.0017
SHG	-14.20	0.43	0.0093	0.0038
SNG	-12.87	0.30	0.0000	0.0030
SPG	-13.57	0.14	0.0045	0.0016
SPM	-12.94	0.36	0.0018	0.0034
SSB	-14.57	0.39	0.0122	0.0040
STA	-14.98	0.22	0.0140	0.0027
TRP	-13.29	0.15	0.0039	0.0017
TWD	-13.59	0.17	0.0045	0.0020
WMY	-12.84	0.14	-0.0002	0.0020
WSB	-13.38	0.20	0.0032	0.0022
YSB	-14.31	0.21	0.0112	0.0023

Table A5: Parameter values for the hollow-DBH allometry for the 'persistent, proportional hazard' model (Eq. 8) per species group.

Species	b_0		b_1	
	Mean	SE	Mean	SE
01; Blackbutt; Central&North	-14.01	0.27	0.0060	0.0032
02; Spotted gum; Central&North	-13.34	0.16	0.0030	0.0018
03; Brushbox; Central&North	-12.91	0.18	-0.0006	0.0019
04; Tallowwood; Central&North	-13.61	0.17	0.0045	0.0022
05; Blue gum; Central&North	-13.81	0.18	0.0056	0.0022
06; Box/Ironbarks; Central&North	-13.01	0.09	0.0017	0.0014
07; Red woods; Central&North	-12.69	0.14	-0.0001	0.0018
08; Stringybarks; Central&North	-12.98	0.15	0.0017	0.0022
09; New England grp; Central&North	-13.48	0.08	0.0050	0.0011
10; Other spp; Central&North	-13.16	0.13	0.0049	0.0029
11; Spotted gum; Southern	-14.11	0.31	0.0088	0.0031
12; Stringybarks; Southern	-13.73	0.12	0.0068	0.0014
13; Box/Ironbarks; Southern	-13.48	0.2	0.0048	0.0021
14; Tableland spp; Southern	-13.98	0.17	0.0075	0.0022
15; Peppermints; Southern	-12.69	0.23	-0.0010	0.0027
16; Other spp; Southern	-12.15	0.14	-0.0076	0.0022
17; Silvertop ash; Southern	-15.03	0.25	0.0141	0.0030

Table A6: Parameter values for the hollow-DBH allometry with fire count since 2000 (excluding 2019/20) and a continuous encoding of FESM class for the 2019/20 fire (*i.e.*, FESM classes 1 and 3 = 0, FESM 4 = 0.5, and FESM 5 = 1) per species (Eq. 9).

Species	b_0		b_1		b_2	
	Mean	SE	Mean	SE	Mean	SE
ASB	-13.23	0.18	0.0026	0.0028	0.0021	0.0023
BBT	-13.77	0.22	0.0016	0.0021	0.0036	0.0026
BBX	-12.94	0.17	-0.0007	0.0017	0.0000	0.0024
BLW	-12.87	0.18	-0.0008	0.0019	0.0005	0.0021
BPM	-13.35	0.41	0.0016	0.0040	0.0016	0.0036
DSB	-13.31	0.21	0.0023	0.0026	0.0019	0.0028
FAS	-14.01	0.19	0.0071	0.0034	0.0047	0.0025
GBX	-13.09	0.36	-0.0001	0.0032	0.0022	0.0033
GIB	-14.05	0.31	0.0063	0.0033	0.0045	0.0032
GYG	-12.74	0.12	0.0003	0.0017	0.0000	0.0023
IBK	-13.29	0.15	0.0009	0.0014	0.0025	0.0021
MAG	-13.25	0.15	0.0032	0.0024	0.0021	0.0025
MKG	-13.21	0.19	0.0006	0.0027	0.0009	0.0025
MMT	-13.5	0.11	0.0021	0.0020	0.0020	0.0022
NEB	-13.13	0.1	0.0024	0.0012	0.0015	0.0020
NPM	-13.58	0.31	0.0022	0.0038	0.0023	0.0030
PPM	-12.02	0.16	-0.0102	0.0025	-0.0043	0.0030
RBW	-13.71	0.3	0.0042	0.0026	0.0033	0.0025
RLG	-13.46	0.45	0.0018	0.0039	0.0025	0.0028
RMY	-12.62	0.15	-0.003	0.0022	-0.0008	0.0028
SBG	-13.71	0.15	0.0018	0.0022	0.0039	0.0027
SBK	-13.07	0.12	0.0025	0.0013	0.0021	0.0018
SHG	-13.91	0.36	0.0051	0.0034	0.0045	0.0031
SNG	-12.87	0.23	-0.0001	0.0033	0.0001	0.0026
SPG	-13.53	0.14	0.0033	0.0011	0.0026	0.0018
SPM	-12.81	0.32	0.0015	0.0027	-0.0010	0.0031
SSB	-14.02	0.27	0.0037	0.0033	0.0045	0.0032
STA	-14.52	0.17	0.0068	0.0024	0.0070	0.0026
TRP	-13.27	0.12	0.0033	0.0016	0.0024	0.0023
TWD	-13.46	0.15	0.0005	0.0018	0.0016	0.0026
WMY	-12.79	0.13	-0.0022	0.0020	0.0001	0.0024
WSB	-13.21	0.15	0.0003	0.0017	0.0014	0.0023
YSB	-13.9	0.17	0.0074	0.0023	0.0040	0.0023

Table A7: Parameter values for the hollow-DBH allometry with fire count since 2000 (excluding 2019/20) and a continuous encoding of FESM class for the 2019/20 fire (*i.e.*, FESM classes 1 and 3 = 0, FESM 4 = 0.5, and FESM 5 = 1) per species group (Eq. 9).

Species group	b_0		b_1		b_2	
	Mean	SE	Mean	SE	Mean	SE
01; Blackbutt; Central&North	-13.84	0.24	-0.0002	0.0031	0.0060	0.0048
02; Spotted gum; Central&North	-13.36	0.14	0.0020	0.0012	0.0026	0.0029
03; Brushbox; Central&North	-12.94	0.17	-0.0006	0.0020	-0.0011	0.0044
04; Tallowwood; Central&North	-13.46	0.14	0.0002	0.0020	0.0020	0.0034
05; Blue gum; Central&North	-13.68	0.15	0.0009	0.0022	0.0054	0.0035
06; Box/Ironbarks; Central&North	-12.96	0.08	0.0000	0.0010	0.0005	0.0027
07; Red woods; Central&North	-12.65	0.12	-0.0003	0.0017	-0.0033	0.0044
08; Stringybarks; Central&North	-12.93	0.16	0.0006	0.0015	-0.0012	0.0037
09; New England grp; Central&North	-13.38	0.07	0.0039	0.0009	0.0018	0.0025
10; Other spp; Central&North	-13.15	0.12	0.0044	0.0021	-0.0017	0.0048
11; Spotted gum; Southern	-13.87	0.25	0.0064	0.0023	0.0036	0.0033
12; Stringybarks; Southern	-13.52	0.09	0.0038	0.0011	0.0041	0.0015
13; Box/Ironbarks; Southern	-13.31	0.16	0.0006	0.0016	0.0049	0.0025
14; Tableland spp; Southern	-13.80	0.14	0.0045	0.0027	0.0054	0.0029
15; Peppermints; Southern	-12.65	0.19	-0.0006	0.0026	-0.0048	0.0046
16; Other spp; Southern	-12.20	0.16	-0.0092	0.0024	-0.0036	0.0031
17; Silvertop ash; Southern	-14.63	0.19	0.0063	0.0028	0.0092	0.0028

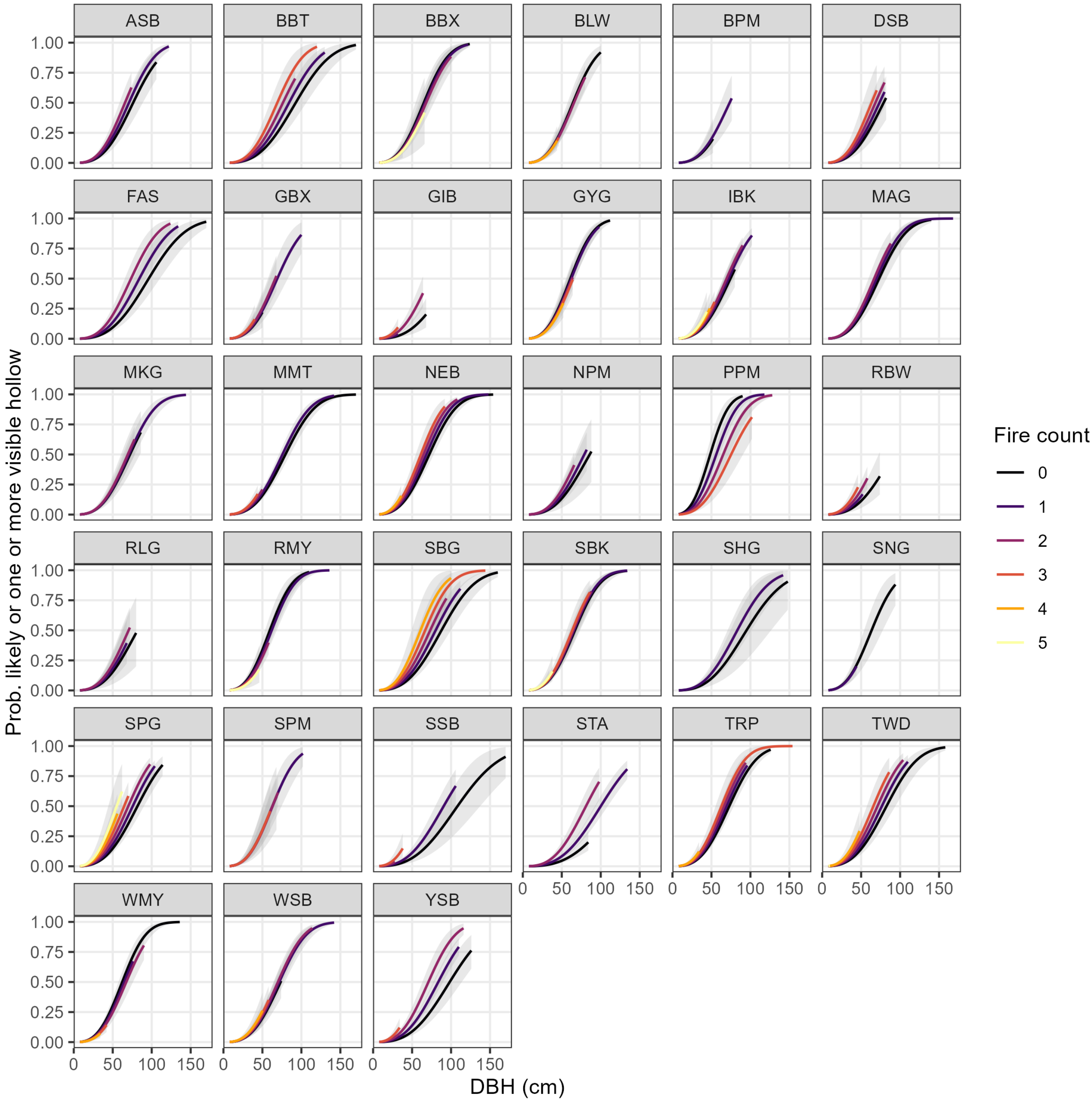

Figure A1: Fire sensitive hollow-DBH allometry per species. The model used is the 'one-off and proportional hazard' (Eq. 7). The impact of fire is typically less pronounced than for Eq. 8. Species-group specific parameters are shown in Table A8.

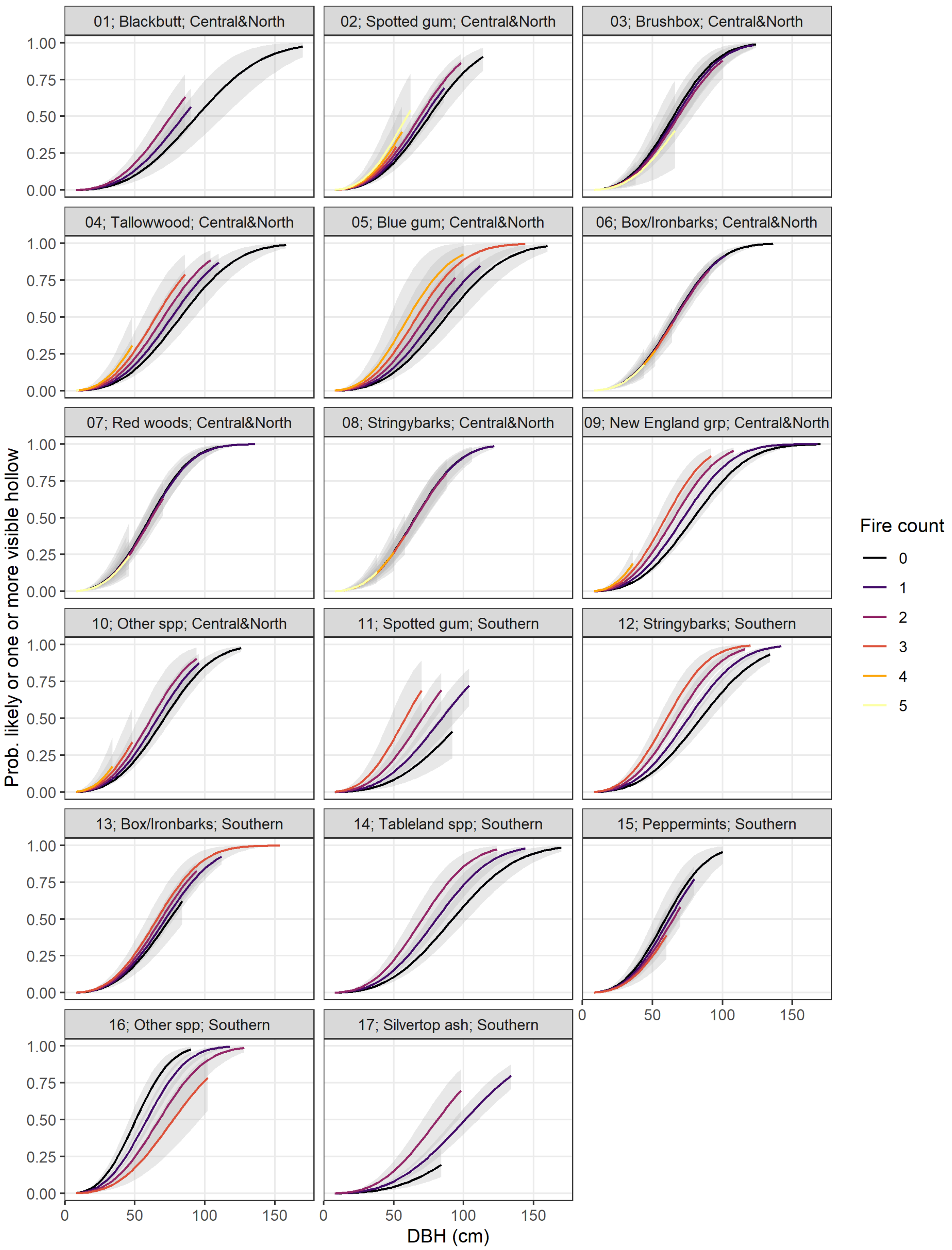

Figure A2: Fire sensitive hollow-DBH allometry per species group. The model used is the 'one-off and proportional hazard' (Eq. 7). Species-group specific parameters are shown in Table A9.

Table A8: Parameter values for the hollow-DBH allometry for the 'one-off, proportional hazard' model (Eq. 7) per species.

Species	b_0		b_1	
	Mean	SE	Mean	SE
ASB	-13.37	0.23	0.0022	0.0015
BBT	-13.96	0.22	0.0029	0.0012
BBX	-12.90	0.19	-0.0007	0.0012
BLW	-12.86	0.19	-0.0003	0.0011
BPM	-13.43	0.45	0.0017	0.0021
DSB	-13.48	0.29	0.0022	0.0016
FAS	-14.07	0.20	0.0040	0.0013
GBX	-13.20	0.46	0.0012	0.0022
GIB	-14.19	0.34	0.0048	0.0017
GYG	-12.70	0.14	-0.0006	0.0009
IBK	-13.30	0.21	0.0011	0.0011
MAG	-13.24	0.18	0.0014	0.0012
MKG	-13.21	0.28	0.0006	0.0017
MMT	-13.50	0.12	0.0015	0.0010
NEB	-13.20	0.12	0.0016	0.0009
NPM	-13.75	0.41	0.0027	0.0021
PPM	-12.01	0.17	-0.0044	0.0013
RBW	-13.91	0.38	0.0035	0.0017
RLG	-13.61	0.46	0.0024	0.0019
RMY	-12.63	0.17	-0.0012	0.0011
SBG	-13.79	0.18	0.0027	0.0011
SBK	-12.98	0.14	0.0005	0.0009
SHG	-14.05	0.37	0.0041	0.0018
SNG	-12.83	0.29	-0.0004	0.0016
SPG	-13.58	0.16	0.0023	0.0009
SPM	-12.81	0.39	0.0001	0.0018
SSB	-14.44	0.35	0.0055	0.0019
STA	-14.82	0.24	0.0063	0.0017
TRP	-13.23	0.12	0.0015	0.0008
TWD	-13.61	0.18	0.0023	0.0011
WMY	-12.76	0.13	-0.0012	0.0011
WSB	-13.26	0.22	0.0007	0.0012
YSB	-14.14	0.22	0.0049	0.0015

Table A9: Parameter values for the hollow-DBH allometry for the 'one-off, proportional hazard' model (Eq. 7) per species group.

Species	b_0		b_1	
	Mean	SE	Mean	SE
01; Blackbutt; Central&North	-14.01	0.28	0.0032	0.0019
02; Spotted gum; Central&North	-13.33	0.18	0.0014	0.0010
03; Brushbox; Central&North	-12.88	0.19	-0.0008	0.0013
04; Tallowwood; Central&North	-13.61	0.17	0.0024	0.0011
05; Blue gum; Central&North	-13.78	0.18	0.0027	0.0014
06; Box/Ironbarks; Central&North	-12.94	0.09	-0.0002	0.0008
07; Red woods; Central&North	-12.69	0.14	-0.0003	0.0010
08; Stringybarks; Central&North	-12.91	0.15	-0.0001	0.0010
09; New England grp; Central&North	-13.49	0.08	0.0029	0.0007
10; Other spp; Central&North	-13.16	0.12	0.0021	0.0013
11; Spotted gum; Southern	-14.23	0.33	0.0055	0.0019
12; Stringybarks; Southern	-13.68	0.13	0.0034	0.0009
13; Box/Ironbarks; Southern	-13.32	0.22	0.0013	0.0012
14; Tableland spp; Southern	-13.94	0.17	0.0040	0.0014
15; Peppermints; Southern	-12.62	0.24	-0.0013	0.0016
16; Other spp; Southern	-12.15	0.15	-0.0043	0.0013
17; Silvertop ash; Southern	-14.86	0.29	0.0065	0.0023