Occupancy trend analysis for Southern Brown Bandicoot in Eden, New South Wales

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Summary

An occupancy trend analysis for Southern Brown Bandicoots was undertaken for annual camera trapping data collected between 2009 and 2023. After accounting for variable detection probability, occupancy was found to decline from the start of the study to a low in 2019 and 2020 at the peak of a major drought and immediately after the black summer fire. Drought-breaking rains from 2020-2023 led to a sharp rise in occupancy so that in 2023 virtually 100 % of sites were occupied. Changes in the probability of detection mirrored this pattern for occupancy and likely reflects increased abundance (and detectability) after the fires. This long-term dataset has proved extremely valuable in highlight the effects of drought and rain on occupancy trends together with little impact of the black summer fires. However, fire 15-30 years ago was negatively associated with initial occupancy. The reasons for this remain unclear but may relate to changes in habitat suitability where sites had previously burnt compared to those that were not burnt in that time period (e.g. shrub/regrowth eucalypt dominance post-fire). Small sample sizes (n=40 sites) may have limited the discriminating power required to identify additional covariates associated with initial occupancy. The analyses also revealed no detectable impact of timber harvesting or cat activity. Changes in cat and/or fox activity with the increased abundance of small mammals needs to be closely monitored in the future.

Background

We present an updated multi-season occupancy analysis of Southern Brown Bandicoot trends to include surveys undertaken after the Black Summer fires and during a period of high rainfall. A previous analysis of annual camera trapping data for this species between 2009/10 and 2019 found a declining trend associated with reduced rainfall and complex fire patterns, but not timber harvesting (Gonsalves and Law, 2021). That report presents detailed interpretations of the data, discusses limitations of the monitoring and presents recommendations for program.

An additional four years of monitoring are included in this report, all of which were undertaken after the Black Summer fires. Details on camera trapping methods, covariates used in the analysis and modelling approach can be found in Gonsalves and Law (2021). A summary for covariate data is supplied in Appendices 1 & 2.

Environmental conditions during the study

Conditions across study sites were variable at the start of the study (Appendix 1). A 200 m buffer around sites contained on average 16 %, 38 %, 14 %, 1 %, 24 %, 5 % and <1 % of Messmate/Yellow Stringybark communities, Silvertop/Ash Communities, Stringybark Coastal, Woollybutt/Mixed Coastal Eucalypt, Yertchuk, Heath/Scrub/She-oak and rainforest communities, respectively. Sites were on average 176 m ASL and sampled a range of topographic positions from gullies through to ridges. Almost 30 % of the landscape within 200 m of each site was mapped as habitat exclusions that were unavailable for harvesting. On average, 40 % of the landscape within 200 m of each site was unharvested. In all, 12 %, 4 % of the landscape was harvested <5 years and 5-10 years, respectively, prior to surveys in 2009-10. Approximately 22 % of the landscape had been harvested 10-30 years or >30 years prior to 2009-10 surveys, respectively. At the time of initial surveys, ~11 % of the landscape within 200 m of each site was unburnt. Recent fire (<5 years old) affected 15 % of the landscape, whereas 36 %, 21 % and 16 % of the landscape had burnt 5-15 years, >15-30 years and >30 years prior to surveys in 2009-10, respectively. Lidar metrics revealed greatest cover at the 2-4 m and 8-12 m vegetation strata. The activity of cats was low during the initial survey. No fox activity was detected at the start of the survey.

Some of these conditions changed over time as monitoring progressed (Appendix 2). For example, the extent of forest around each site that was affected by recent (<5 years old) fire reduced from 15 % in 2009-10 to 7 % of the landscape by 2019 but increased to 100 % in 2020 following the Black Summer fires. The extent of areas that was unharvested within 200 m of each site reduced over the course of monitoring from 40 % to 35 % of the landscape, on average. Annual rainfall fluctuated among years, including below average rainfall in the years immediately preceding the Black Summer fires and then above average rainfall post-fire. Cat activity was generally low throughout the monitoring period until 2022 (2 years post-fire) when activity increased by 4-8 times. Fox activity was ~89 % lower than cat activity and as such was not included in modelling.

Detection probability

A single covariate model was initially supported (Table 1). This model allowed detection to vary by year of sampling, indicating that yearly variation in detection probability was a better predictor of detection probability than all other covariates assessed. Adding a covariate (season) to this top model improved the AIC by >2 points but there was no further improvement to AIC by the addition of a third covariate, so a 2-covariate model was retained when modelling initial occupancy, colonisation and extinction.

A single 2-covariate model for detection probability had support (Table 1). Detection probability varied with year of sampling and season. Detection probability was lowest in 2017, 2019 and 2020 and was highest in 2022 and 2023 (Fig. 1a). In a year with the highest detection probability when spring and autumn were both sampled, detection probability was 18 % higher in autumn (0.26) compared to spring (0.22) (Fig. 1b). Detection probability pre- 2019-20 fires was 0.10±0.01 and more than doubled post-fire (0.26±0.01). This result is likely to be a reflection of higher abundance after the drought-breaking rains (post-fire) leading to higher detection probability. With 14 days of sampling with two cameras, there was 77 % confidence of an absence at a site pre-fire, whereas this increased to 99 % post-fire (Fig. 2). It is important to note that this assumes nightly detection probability is constant among days. Beyond 14 days, this is unlikely to be the case and sampling effort required to be 95 % confident of SBB absence is likely to be greater than reported in Fig. 2. Nevertheless, this highlights the importance of accounting for detection probability in analyses.

Table 1. Model summary for detection probability models. Grey shading indicates models with support.

Number of covariates	Model	DAIC	weight	npar	neg2ll
Single covariate	psi(.),gam(.),eps(.),p(Year)	0	1	17	4357.72
	psi(.),gam(.),eps(.),p(cam_model)	148.92	0	5	4530.64
	psi(.),gam(.),eps(.),p(post-fire)	157.03	0	5	4538.75
	psi(.),gam(.),eps(.),p(season)	296.83	0	5	4678.55
	psi(.),gam(.),eps(.),p(effort)	344.49	0	5	4726.21
	psi(.),gam(.),eps(.),p(.)	354.46	0	4	4738.19
Two-covariate	psi(.),gam(.),eps(.),p(Year+season)	0	0.82	18	4350.82
	psi(.),gam(.),eps(.),p(Year+cam_model)	4.76	0.076	18	4355.58
	psi(.),gam(.),eps(.),p(Year)	4.91	0.07	17	4357.72
	psi(.),gam(.),eps(.),p(Year+effort)	6.36	0.034	18	4357.17

DAIC = delta AIC (difference in AIC score between the top model and other models) .

weight = model weight (explanatory power).

npar = number of parameters in the model.

neg2ll = negative 2 x log-likelihood.

psi = initial occupancy.

gam = colonisation

eps = extinction probability.

Year = year of surveys.

cam_model = model of camera used for surveys.

post-fire = period of sampling (pre- or post-fire categories).

season = season of sampling (autumn or spring).

effort = number of cameras (to deal with occasions when one camera trap failed).

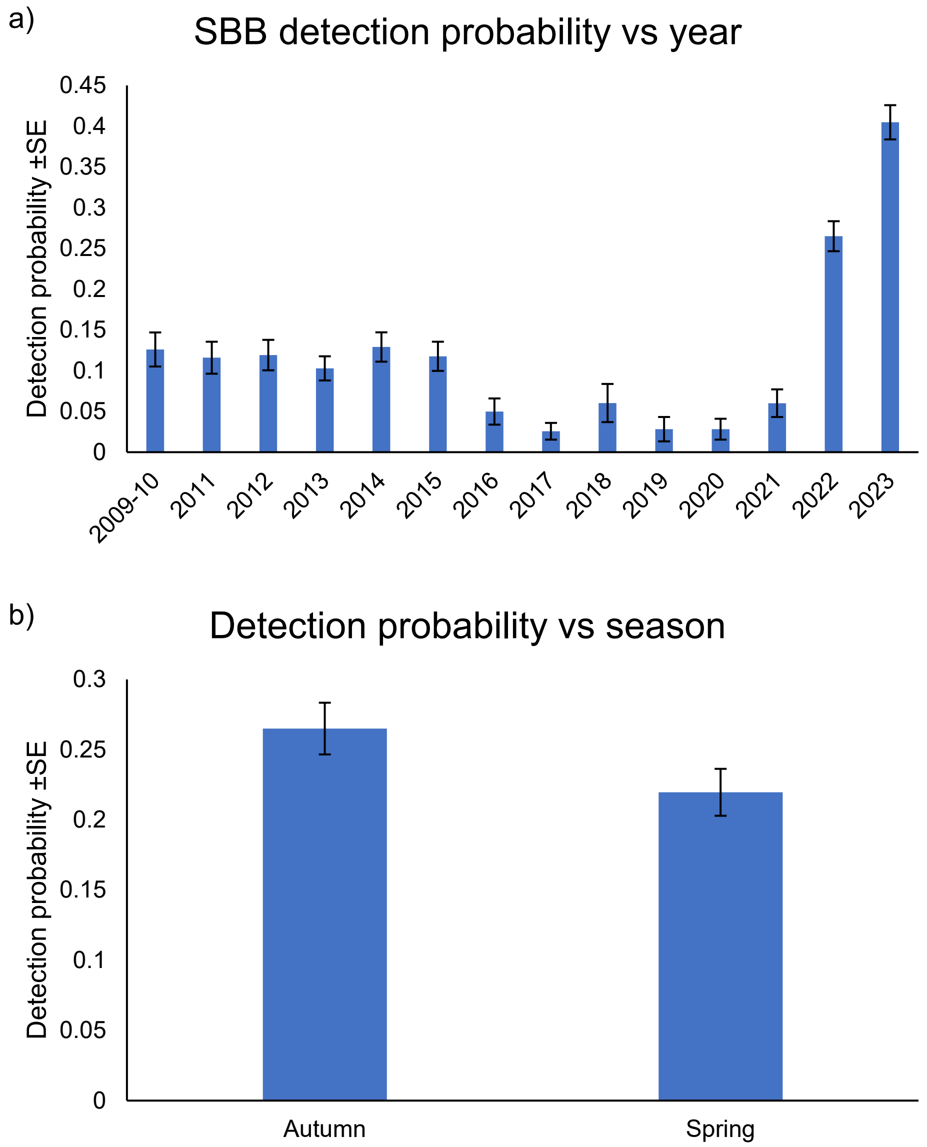

Fig. 1. Column graphs illustrating nightly detection probability among (a) years and in (b) autumn and spring.

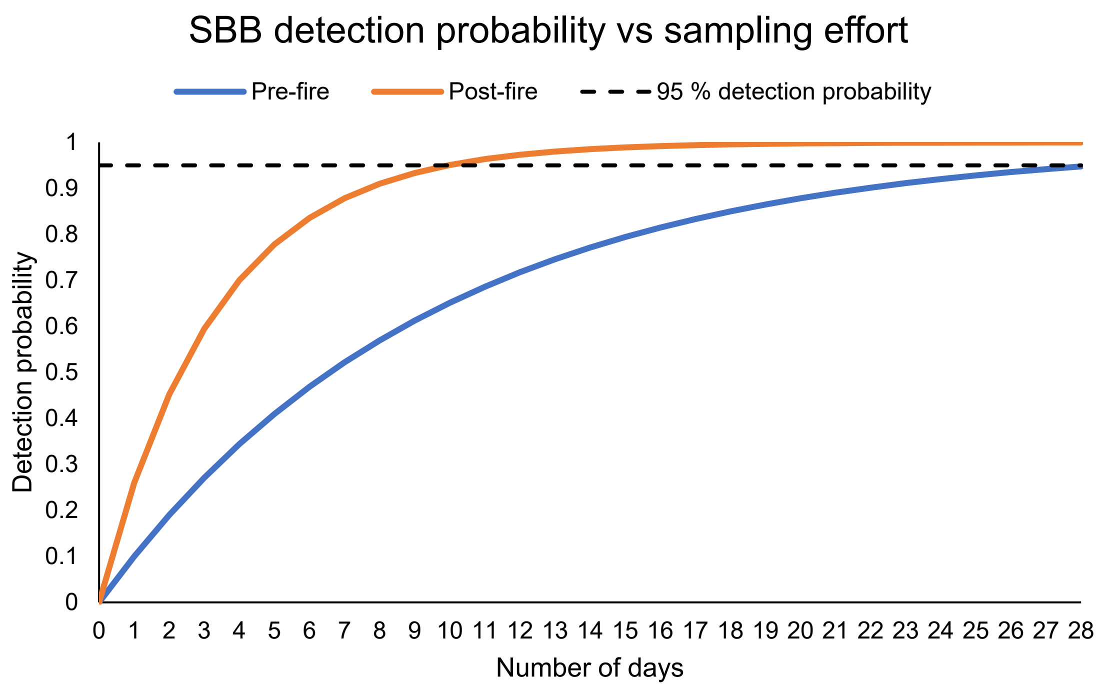

Fig. 2. Cumulative detection probability curves pre- and post-fire. Curves assume nightly detection probability is constant among days. Beyond 14 days, this is unlikely to be the case and curves likely underestimate the sampling effort required to be 95 % confident of SBB absence.

Initial occupancy

In all, a single covariate model for initial occupancy had support (Table 2). The addition of covariates to this model did not improve AIC of the top model by >2 points and so this model was retained. This model allowed occupancy to vary with the presence of fire of the 15-30 year age-class within the site buffer which was associated with higher vegetation density in the 2-6 m height class (likely to be shrubs) relative to other sites (Fig. 3). Occupancy was 0.41 ± 0.09 at sites that were unburnt by fire of this age-class, whereas sites with any fire of this age class (n=9 sites; extent 64 - 100 %) were unoccupied.

Under median conditions (unburnt by fire in the 15-30 year age class), initial occupancy was 0.41±0.09.

Table 2. Model summary for initial occupancy models. Grey shading indicates models with support. See Appendix 1 for description of the covariates denoted in brackets after 'psi', 'gam' and 'eps'.

Model	DAIC	weight	npar	neg2ll
psi(Int_Fire_15-30yrs),gam(.),eps(.),p(year+season)	0	0.3696	19	4343.06
psi(TPI_stretched),gam(.),eps(.),p(year+season)	2.77	0.0927	19	4345.83
psi(TPI),gam(.),eps(.),p(year+season)	2.78	0.0919	19	4345.85
psi(NonForest),gam(.),eps(.),p(year+season)	3.31	0.0706	19	4346.37
psi(lidar_8-10m),gam(.),eps(.),p(year+season)	4.81	0.0334	19	4347.87
psi(Int_Logging_5-10yrs),gam(.),eps(.),p(year+season)	4.97	0.0309	19	4348.03
psi(lidar_6-8m),gam(.),eps(.),p(year+season)	5.11	0.0287	19	4348.17
psi(Woollybutt_MixedCoastalEucalypt),gam(.),eps(.),p(year+season)	5.36	0.0254	19	4348.42
psi(Old_Logging_>30yrs),gam(.),eps(.),p(year+season)	5.45	0.0242	19	4348.52
psi(lidar_10-12m),gam(.),eps(.),p(year+season)	6.03	0.0181	19	4349.09
psi(Recent_Fire_<5yrs),gam(.),eps(.),p(year+season)	6.18	0.0168	19	4349.24
psi(Rainforest),gam(.),eps(.),p(year+season)	6.2	0.0167	19	4349.26
psi(Heath_Scrub_She_oak),gam(.),eps(.),p(year+season)	6.36	0.0154	19	4349.42
psi(lidar_4-6m),gam(.),eps(.),p(year+season)	6.77	0.0125	19	4349.83
psi(lidar_12-14m),gam(.),eps(.),p(year+season)	6.79	0.0124	19	4349.85
psi(Int_Fire_5-15yrs),gam(.),eps(.),p(year+season)	6.93	0.0116	19	4349.99
psi(lidar_0-2m),gam(.),eps(.),p(year+season)	7.16	0.0103	19	4350.22
psi(Stringybark_Coastal),gam(.),eps(.),p(year+season)	7.22	0.01	19	4350.29
psi(Elevation),gam(.),eps(.),p(year+season)	7.3	0.0096	19	4350.37
psi(unburnt),gam(.),eps(.),p(year+season)	7.31	0.0096	19	4350.37
psi(Unlogged),gam(.),eps(.),p(year+season)	7.44	0.0089	19	4350.51
psi(Recent_Logging_<5yrs),gam(.),eps(.),p(year+season)	7.57	0.0084	19	4350.63
psi(Non-exclusion),gam(.),eps(.),p(year+season)	7.65	0.0081	19	4350.71
psi(modelled_habitat_exclusion),gam(.),eps(.),p(year+season)	7.65	0.0081	19	4350.72
psi(lidar_14-15m),gam(.),eps(.),p(year+season)	7.65	0.008	19	4350.72

psi(Old_Fire_>30yrs),gam(.),eps(.),p(year+season)	7.69	0.0079	19	4350.75
psi(Messmate_YellowStringybarkcommunities),gam(.),eps(.),p(year+season)	7.7	0.0079	19	4350.76
psi(SilvertopAshCommunities),gam(.),eps(.),p(year+season)	7.73	0.0077	19	4350.79
psi(Yertchuk_communities),gam(.),eps(.),p(year+season)	7.73	0.0077	19	4350.8
psi(lidar_2-4m),gam(.),eps(.),p(year+season)	7.74	0.0077	19	4350.8
psi(Int_Logging_10-30yrs),gam(.),eps(.),p(year+season)	7.74	0.0077	19	4350.8
psi(FT),gam(.),eps(.),p(year+season)	11.08	0.0015	24	4344.14

DAIC = delta AIC (difference in AIC score between the top model and other models) .

weight = model weight (explanatory power).

npar = number of parameters in the model.

neg2ll = negative 2 times log-likelihood.

psi = initial occupancy.

gam = colonisation

eps = extinction probability.

Year = year of surveys.

cam_model = model of camera used for surveys.

post-fire = period of sampling (pre- or post-fire categories).

season = season of sampling (autumn or spring).

effort = number of cameras (to deal with occasions when one camera trap failed).

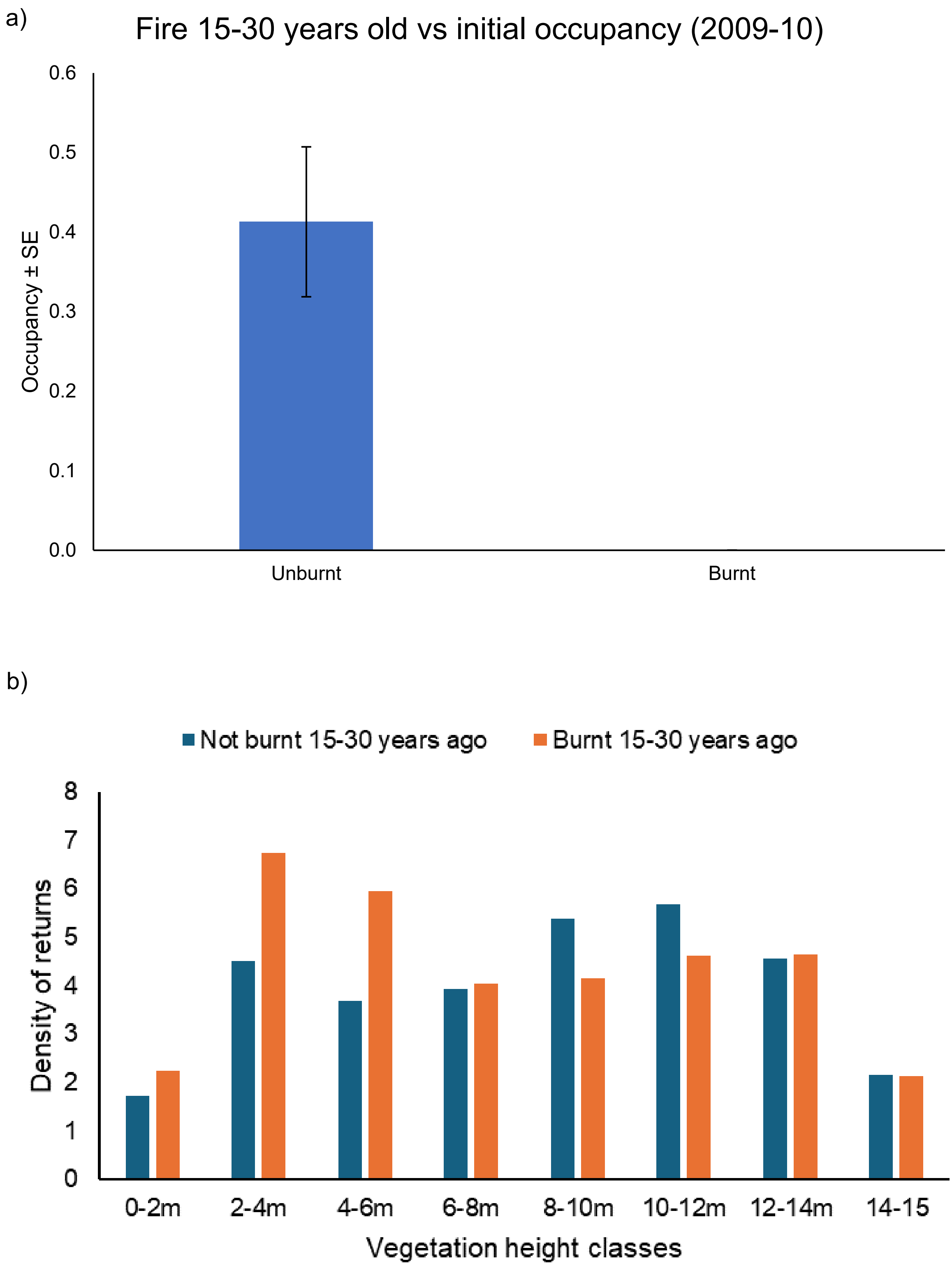

Fig. 3. Column graphs illustrating a) initial occupancy at sites that were unburnt or burnt by fires in the 15-30 year age class and b) lidar metrics (density of returns) for different vegetation height classes in sites that were unburnt or burnt by fires in the 15-30 year age class.

Extinction probability

There was a single covariate model that had support for extinction probability (Table 3). This model allowed extinction probability to vary with year of sampling (Fig. 4a). The next best model allowed extinction probability to vary by the interaction of 1-year lagged annual rainfall (i.e., rainfall in the calendar year preceding sampling) and extent of unburnt forest (Fig. 4b). A reduction in extinction probability with the amount of annual rainfall in the year preceding sampling was greater at sites that had been burnt than those that hadn't been burnt at any time prior to sampling, but noting that evidence for this relationship was weak.

Table 3. Model summary for extinction probability models. Grey shading indicates models with support. See Appendix 1 for description of the covariates denoted in brackets after 'psi', 'gam' and 'eps'.

Model	DAIC	weight	npar	neg2ll
psi(fire_1530),gam(.),eps(year),p(year+season)	0	0.9806	31	4289.69
psi(fire_1530),gam(.),eps(lagrainfall*unburnt),p(year+season)	8.62	0.0132	22	4316.31
psi(fire_1530),gam(.),eps(lagrainfall),p(year+season)	10.12	0.0062	20	4321.8
psi(fire_1530),gam(.),eps(Recent fire (<5yrs)),p(year+season)	23.89	0	20	4335.57
psi(fire_1530),gam(.),eps(fire),p(year+season)	24.94	0	20	4336.63
psi(fire_1530),gam(.),eps(Old fire (>30 yrs)),p(year+season)	25.84	0	20	4337.53
psi(fire_1530),gam(.),eps(cat activity),p(year+season)	25.96	0	20	4337.65
psi(fire_1530),gam(.),eps(Intermediate fire (5-15 yrs)),p(year+season)	28.4	0	20	4340.09
psi(fire_1530),gam(.),eps(Intermediate fire (15-30 yrs)),p(year+season)	28.95	0	20	4340.63
psi(fire_1530),gam(.),eps(Intermediate logging (10-30 yrs)),p(year+season)	29.2	0	20	4340.89
psi(fire_1530),gam(.),eps(.),p(year+season)	29.38	0	19	4343.06
psi(fire_1530),gam(.),eps(CUSUM_lag),p(year+season)	29.49	0	20	4341.18
psi(fire_1530),gam(.),eps(Intermediate logging (5-10 yrs)),p(year+season)	30.7	0	20	4342.38
psi(fire_1530),gam(.),eps(Old logging (>30 yrs)),p(year+season)	31.19	0	20	4342.88
psi(fire_1530),gam(.),eps(log),p(year+season)	31.34	0	20	4343.03
psi(fire_1530),gam(.),eps(Recent logging (<5yrs)),p(year+season)	31.37	0	20	4343.06

DAIC = delta AIC (difference in AIC score between the top model and other models) .

weight = model weight (explanatory power).

npar = number of parameters in the model.

neg2ll = negative 2 x log-likelihood.

psi = initial occupancy.

gam = colonisation

eps = extinction probability.

Year = year of surveys.

cam_model = model of camera used for surveys.

post-fire = period of sampling (pre- or post-fire categories).

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effort = number of cameras (to deal with occasions when one camera trap failed).

a)

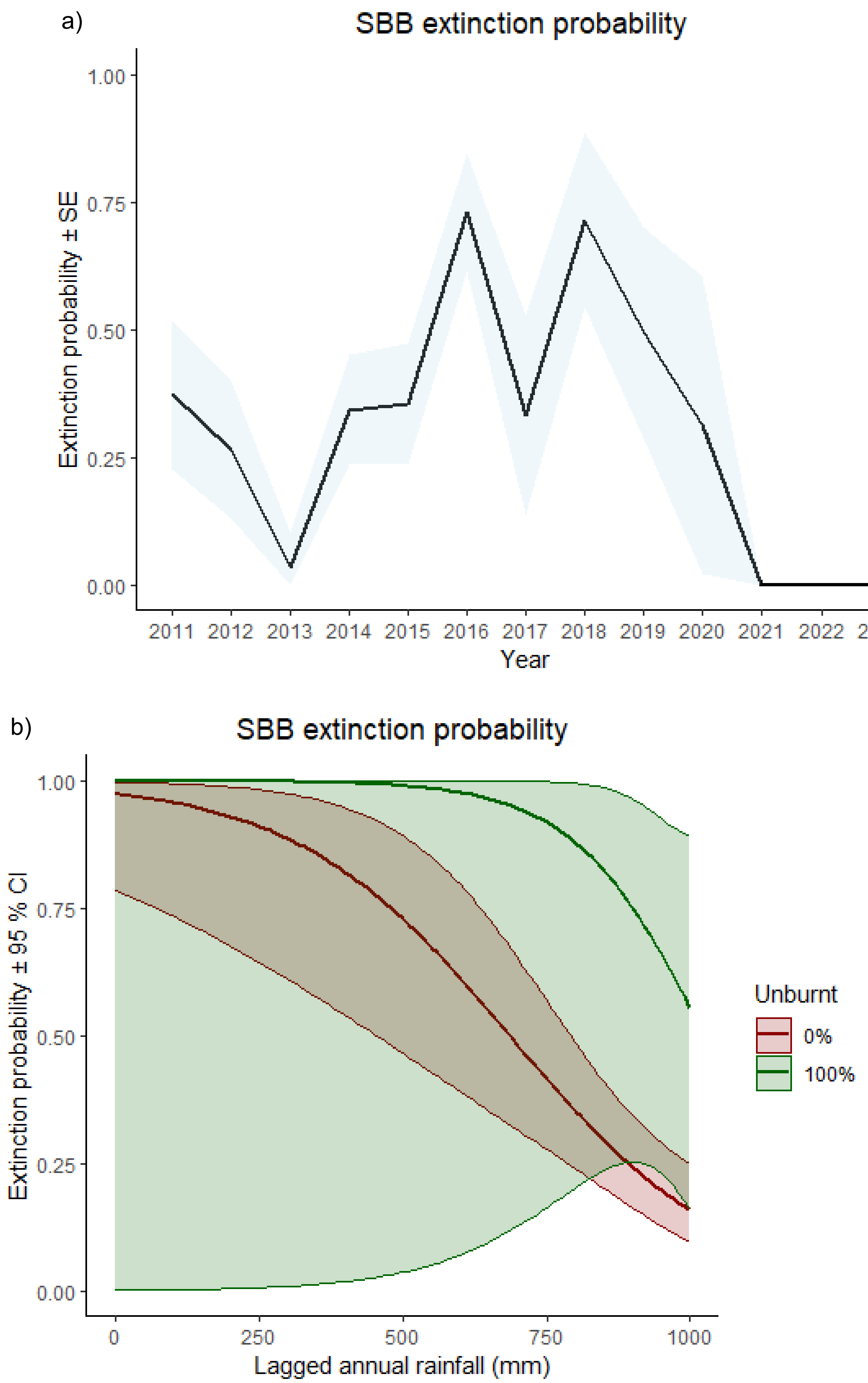

Fig. 4. Response plots illustrating the relationship between extinction probability and a) year of sampling, and b) the interaction of lagged annual rainfall by extent of unburnt forest (0 % or 100 %) in each year of sampling.

Colonisation probability

There were two single covariate models that had support for colonisation probability (Table 4). The top model allowed colonisation probability to vary with year of sampling (Fig. 5a). The other supported model allowed colonisation probability to vary positively with 1-year lagged annual rainfall (i.e., rainfall in the calendar year preceding sampling) (Fig. 5b).

Table 4. Model summary for colonisation probability models. Grey shading indicates models with support. See Appendix 1 for description of the covariates denoted in brackets after 'psi', 'gam' and 'eps'.

Model	DAIC	weight	npar	neg2ll
psi(fire_1530),eps(.),gam(year),p(year+season)	0	0.536	31	4268.88
psi(fire_1530),eps(.),gam(lagrainfall),p(year+season)	0.65	0.388	20	4291.53
psi(fire_1530),eps(.),gam(lagrainfall*unburnt),p(year+season)	3.91	0.076	22	4290.79
psi(fire_1530),eps(.),gam(cat activity),p(year+season)	37.97	0	20	4328.85
psi(fire_1530),eps(.),gam(rainfall),p(year+season)	41.7	0	20	4332.58
psi(fire_1530),eps(.),gam(Old fire (>30 yrs)),p(year+season)	44.34	0	20	4335.22
psi(fire_1530),eps(.),gam(CUSUM_lag),p(year+season)	44.4	0	20	4335.28
psi(fire_1530),gam(.),eps(Recent fire (<5yrs)),p(year+season)	44.69	0	20	4335.57
psi(fire_1530),eps(.),gam(Recent logging (<5yrs)),p(year+season)	49.48	0	20	4340.36
psi(fire_1530),eps(.),gam(Intermediate fire (15-30 yrs)),p(year+season)	49.81	0	20	4340.69
psi(fire_1530),eps(.),gam(.),p(year+season)	50.18	0	19	4343.06
psi(fire_1530),eps(.),gam(Intermediate logging (5-10 yrs)),p(year+season)	50.38	0	20	4341.26
psi(fire_1530),eps(.),gam(Intermediate logging (10-30 yrs)),p(year+season)	50.7	0	20	4341.57
psi(fire_1530),eps(.),gam(fire),p(year+season)	51.13	0	20	4342
psi(fire_1530),eps(.),gam(Old logging (>30 yrs)),p(year+season)	51.89	0	20	4342.77
psi(fire_1530),eps(.),gam(log),p(year+season)	52.17	0	20	4343.05
psi(fire_1530),eps(.),gam(Intermediate fire (5-15 yrs)),p(year+season)	52.18	0	20	4343.06

DAIC = delta AIC (difference in AIC score between the top model and other models) .

weight = model weight (explanatory power).

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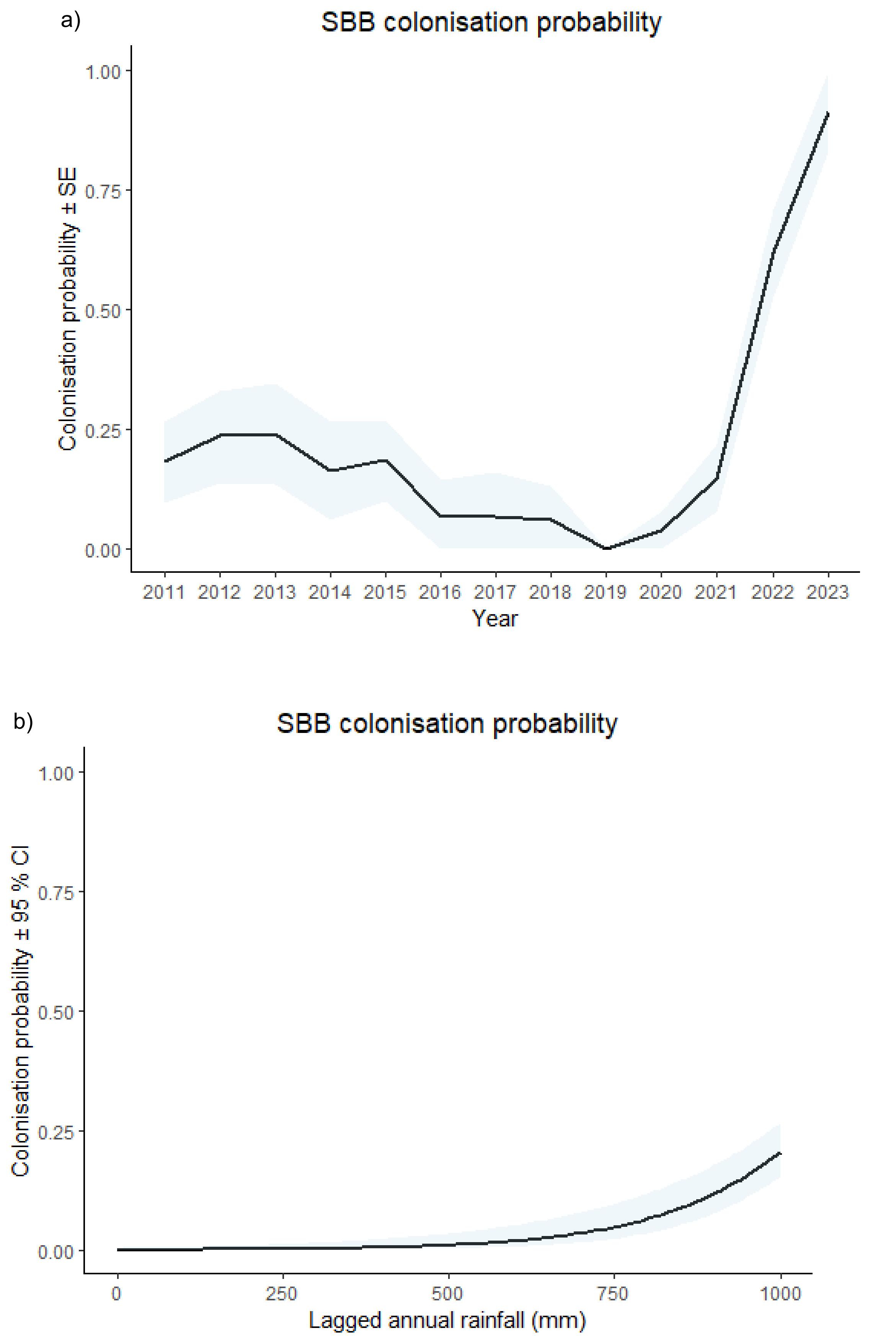

Fig. 5. Response plots illustrating the relationship between colonisation probability and a) year of sampling and b) lagged annual rainfall.

Trend

Naïve occupancy fluctuated among years (Fig. 6), but was lowest in the period between 2016 and 2019, after which the trend increased to occupancy of almost 1 by autumn 2023.

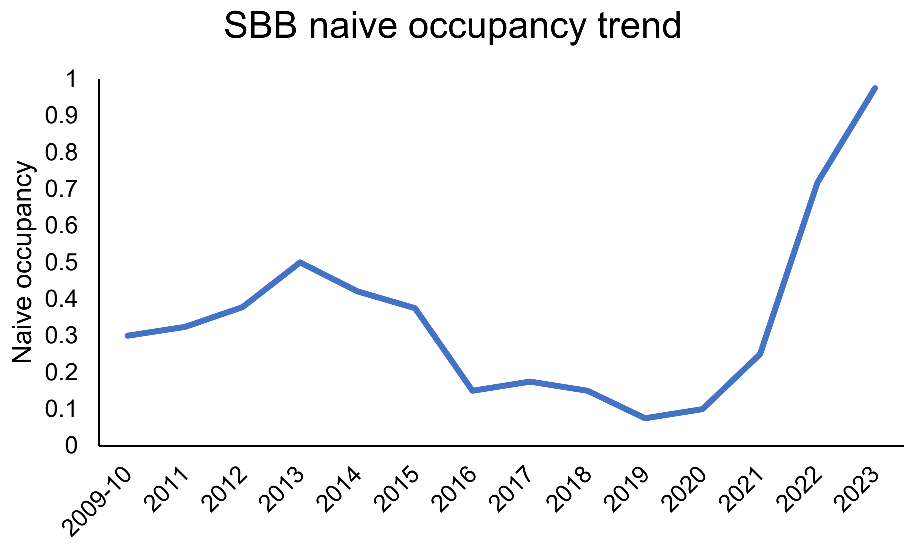

Fig. 6. Line graph illustrating trend for naïve occupancy between 2009-10 and 2023.

Modelled occupancy under median conditions for variables associated with initial occupancy was moderate (~0.4-0.5), but fluctuated within the bounds of error from 2009-10 to 2015 before a sharp reduction (53 % reduction to ~0.18) in 2016 (Fig. 7). A slight upward trend was observed in 2017, though with great uncertainty due to low detection probability in this year. From 2018-2020, occupancy was low (~0.14) before occupancy increased rapidly after drought-breaking rains and one year after the black summer fires such that occupancy by southern brown bandicoots was approaching 1 in 2023 (Fig. 7).

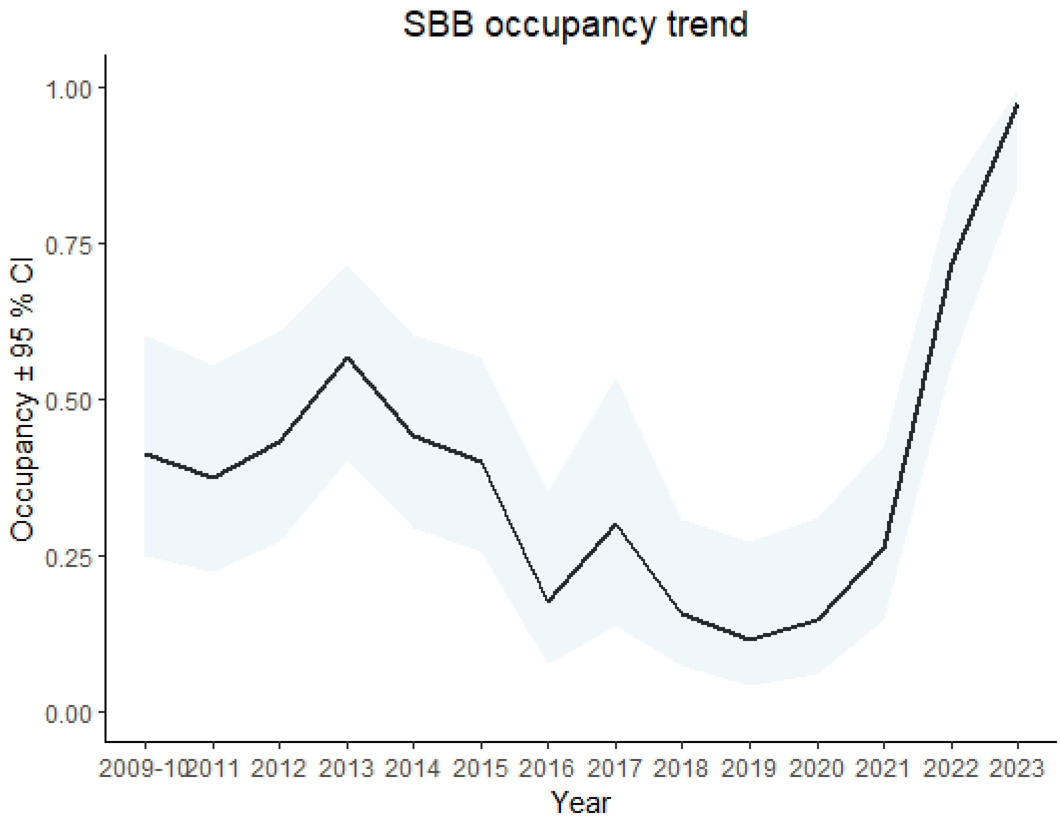

Fig. 7. Line graph illustrating trend for modelled occupancy between 2009-10 and 2023.

Recommendations

Several recommendations were made in an earlier analysis (16/5/2021). It is important to regularly review recommendations when conditions in the study area change and changes are evident in the population size of SBB. As such, revised recommendations are provided below.

Management

- Habitat exclusion zones (16 out of 40 sites had no exclusion) and unlogged forest appeared to have little benefit for this species at the sites monitored given neither influenced occupancy nor dynamic parameters (i.e., colonisation and extinction). However, we acknowledge the limitation of relatively low number of sites and suggest future monitoring expands the number of sites, potentially without exclusions to provide a more rigorous test of their effectiveness. An alternative is to re-analyse the data to consider SBB activity using n-mixture models that account for detectability rather than occupancy models.
- Disperse harvesting treatments in space and time to ensure it continues to have a minor influence on SBB occupancy or dynamic parameters that influence occupancy.

- Review/reconsider how habitat is defined for the SBB. Greater weight should be given to upper slopes where understorey (shrub) cover is open. Particular forest types (e.g., Yertchuk) do not appear to have a strong association with SBB occupancy, rather preferred habitat occurs under a range of different forest types.
- Aim for mosaic burning patterns that maintain some unburnt forest in the 15-30 years age class.
- No association between SBB occupancy and cat activity was detected in this study, most likely owing to low levels of cat activity for the majority of the monitoring period. Given widespread occupancy of SBB and an apparent boom in abundance (as reflected by increased detection probability) in recent monitoring years, feral cat impacts may become more detectable. Feral cat and fox populations should continue to be closely monitored and an assessment of methods for controlling cats should be undertaken if there is evidence of an increase in activity of this introduced predator. It is possible that fox baiting helped to ameliorate the effects of drought prior to 2018, but it could also have allowed increased feral cat activity and cat predation. Any new baiting program should be accompanied with monitoring to assess effectiveness and consider keeping some sites unbaited for comparison (e.g. Claridge et al. 2019).

Monitoring

- Continue to monitor SBB given recent high rainfall and widespread occupancy of the species and look for early warning signs of growing cat and fox populations. This can be done by tracking trends in activity of these species using camera trap data from the SBB monitoring sites.
- Consider including a measure of habitat complexity each year to specifically record ground cover and taller understorey cover (e.g. Claridge et al. 2019 or Hradsky et al. 2017). Similarly, given the interactive relationship between rainfall and the extent of fire on extinction probability, future analyses may consider the influence of prescribed fire and wildfire separately to tease out whether this relationship is uniform for both forms of fire.
- Continue with two cameras per site to avoid drop in detection probability. Use of peanut butter and oats bait can be maintained to be consistent with previous monitoring. However, given modelling can account for variation in detection probability, other baits could be trialled, e.g., truffle oil for the genus *Isoodon* (Paull et al. 2011) or tuna oil that is effective for small mammals and introduced predators (Pers. comm. - P. Gibbons).
- Review sampling design.

- The existing design may be amended to increase duration of deployments beyond 14 days (30 days - Claridge et al. 2019) in autumn when detection probability is greater. i.e., focus sampling effort in autumn instead of sampling in spring. Declining detection rates with time since deployment (14-day period) has been reported for the genus *Isoodon* (Paull et al. 2011), so an assessment should be made early on to establish whether the trade-off of ceasing spring sampling is offset by longer duration sampling in autumn.

- Add additional sites to target higher suitability habitat (upper slope areas with less understorey cover), but without exclusion areas.

- Regularly tag photos and maintain careful record keeping of dates that cameras were deployed. Online tools such as Wildlife Insights may assist with this process.
- Undertake analysis of data more frequently (e.g., every three years) to assess whether management is affecting (positively or negatively) trends in SBB occupancy.
- Analyse other species from dataset, giving priority to long-nosed potoroos, which were more commonly recorded by cameras than SBB.

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Appendix 1. Environmental and disturbance site covariates used to model initial occupancy (2009-2010).

Variable	Description	Units	Min	Max	Mean
Messmate/Yellow Stringybark communities	Extent of messmate and yellow stringybark communities	Proportion within 200 m	0	0.759165	0.160972
Silvertop/Ash Communities	Extent of silvertop and ash communities	Proportion within 200 m	0	0.983656	0.381346
Stringybark Coastal	Extent of stringybark coastal communities	Proportion within 200 m	0	0.867684	0.136021
Woollybutt/Mixed Coastal Eucalypt	Extent of woollybutt and mixed coastal eucalypt communities	Proportion within 200 m	0	0.240996	0.010062
Yertchuk communities	Extent of yertchuk communities	Proportion within 200 m	0	1	0.241279
Heath/Scrub/She_oak	Extent of heath, scrub and she-oak	Proportion within 200 m	0	0.591594	0.053309
Rainforest	Extent of rainforest	Proportion within 200 m	0	0.075316	0.003291
Elevation	Elevation at point equidistant from both camera points	m ASL	25	420	175.875
TPI	Topographic position index. Lower scores associated with gullies	Mean TPI score within 200 m	-9.98026	24.73685	0.957728
TPI_stretched	Stretched topographic position index	Mean stretched TPI score within 200 m	85	231	131.075
Modelled_habitat_exclusion	Southern Brown Bandicoot modelled habitat excluded from harvest	Extent (m^2) within 200 m	0	125640	37680.03
Non_exclusion	Areas available for harvest	Extent (m^2) within 200 m	0	125640	88286.89
unlogged	Extent of forest that was unharvested	Proportion within 200 m	0	1	0.396059
log_l5	Extent of forest that was harvested <5 years ago	Proportion within 200 m	0	0.92991	0.122899
log_510	Extent of forest that was harvested 5-10 years ago	Proportion within 200 m	0	0.532725	0.041291
log_1030	Extent of forest that was harvested 10-30 years ago	Proportion within 200 m	0	0.956297	0.224269
log_g30	Extent of forest that was harvested >30 years ago	Proportion within 200 m	0	1	0.215482
fire_l5	Extent of forest that was burnt <5 years ago	Proportion within 200 m	0	1	0.1488
fire_515	Extent of forest that was burnt 5-10 years ago	Proportion within 200 m	0	1	0.356339
fire_1530	Extent of forest that was burnt 15-30 years ago	Proportion within 200 m	0	1	0.213356
fire_g30	Extent of forest that was burnt >30 years ago	Proportion within 200 m	0	1	0.1628
unburnt	Extent of forest that was unburnt	Proportion within 200 m	0	1	0.112196
r_50_dens_0_2m	Density of lidar returns from 0-2 m	Number of returns	0	5.7	1.8425

r_50_dens_2_4m	Density of lidar returns from 2-4 m	Number of returns	0.1	20.1	5.0175
r_50_dens_4_6m	Density of lidar returns from 4-6 m	Number of returns	0.2	21.2	4.2075
r_50_dens_6_8m	Density of lidar returns from 6-8 m	Number of returns	0.6	11.4	3.9675
r_50_dens_8_10m	Density of lidar returns from 8-10 m	Number of returns	0.8	18.4	5.11
r_50_dens_10_12m	Density of lidar returns from 10-12 m	Number of returns	0.8	17.1	5.445
r_50_dens_12_14m	Density of lidar returns from 12-14 m	Number of returns	0.8	12.4	4.5825
r_50_dens_14_15	Density of lidar returns from 14-15 m	Number of returns	0.4	4.1	2.15
Annual_rainfall_total_2009	Annual rainfall in year of sampling	mm	953.5	953.5	953.5
Cats	Cat activity	No. of images per camera per deployment	0	3	0.4

Appendix 2. Environmental and disturbance site covariates used to model colonisation and extinction probability (2011-2023).

Year	Metric	fire_l5	fire_515	fire_1530	fire_g30	unburnt	unlogged	log_l5	log_510	log_1030	log_g30	AnnualRainfall	Cats	LagAnnualRainfall	CUSUM_lag
2011	Min	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	868.40	0.00	953.50	-813.26
2011	Max	1.00	1.00	1.00	1.00	1.00	1.00	0.93	0.53	0.95	1.00	868.40	6.00	953.50	-813.26
2011	Mean	0.15	0.34	0.19	0.20	0.11	0.40	0.12	0.04	0.19	0.25	868.40	0.43	953.50	-813.26
2012	Min	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1140.80	0.00	868.40	-799.94
2012	Max	1.00	1.00	1.00	1.00	1.00	1.00	0.93	0.99	0.95	1.00	1140.80	6.00	868.40	-799.94
2012	Mean	0.12	0.27	0.28	0.20	0.11	0.40	0.09	0.06	0.19	0.26	1140.80	0.55	868.40	-799.94
2013	Min	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	910.20	0.00	1140.80	-511.21
2013	Max	1.00	1.00	1.00	1.00	1.00	1.00	0.88	0.93	0.95	1.00	910.20	11.00	1140.80	-511.21
2013	Mean	0.15	0.27	0.23	0.23	0.11	0.40	0.05	0.10	0.20	0.26	910.20	1.15	1140.80	-511.21
2014	Min	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1064.80	0.00	910.20	-453.28
2014	Max	1.00	1.00	1.00	1.00	1.00	1.00	0.64	0.93	0.83	1.00	1064.80	43.00	910.20	-453.28
2014	Mean	0.12	0.30	0.24	0.23	0.11	0.39	0.05	0.09	0.18	0.28	1064.80	2.28	910.20	-453.28
2015	Min	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1011.90	0.00	1064.80	-240.55
2015	Max	1.00	1.00	1.00	1.00	1.00	1.00	0.37	0.93	0.83	1.00	1011.90	11.00	1064.80	-240.55
2015	Mean	0.08	0.19	0.36	0.25	0.11	0.40	0.03	0.11	0.17	0.29	1011.90	1.15	1064.80	-240.55
2016	Min	0.00	0.00	0.00	0.00	0.00	-0.02	0.00	0.00	0.00	0.00	911.90	0.00	1011.90	-83.72
2016	Max	1.00	1.00	1.00	1.00	1.00	1.00	0.37	0.93	0.99	1.00	911.90	9.00	1011.90	-83.72
2016	Mean	0.09	0.20	0.36	0.25	0.08	0.39	0.03	0.08	0.20	0.29	911.90	1.23	1011.90	-83.72
2017	Min	0.00	0.00	0.00	0.00	0.00	-0.02	0.00	0.00	0.00	0.00	623.20	0.00	911.90	-23.30
2017	Max	1.00	1.00	1.00	1.00	1.00	1.00	0.37	0.93	0.99	1.00	623.20	7.00	911.90	-23.30
2017	Mean	0.10	0.20	0.36	0.25	0.08	0.38	0.04	0.09	0.19	0.30	623.20	1.55	911.90	-23.30
2018	Min	0.00	0.00	0.00	0.00	0.00	-0.02	0.00	0.00	0.00	0.00	549.50	0.00	623.20	-253.87
2018	Max	1.00	1.00	1.00	1.00	1.00	1.00	0.42	0.88	0.99	1.00	549.50	8.00	623.20	-253.87
2018	Mean	0.09	0.13	0.44	0.25	0.08	0.38	0.05	0.05	0.23	0.29	549.50	1.00	623.20	-253.87
2019	Min	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	542.90	0.00	549.50	-546.24
2019	Max	1.00	1.00	1.00	1.00	1.00	1.00	0.53	0.64	0.93	1.00	542.90	3.00	549.50	-546.24
2019	Mean	0.07	0.17	0.42	0.25	0.08	0.37	0.06	0.05	0.23	0.30	542.90	0.33	549.50	-546.24

2020	Min	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1003.80	0.00	542.90	-858.41
2020	Max	1.00	0.00	0.00	0.00	0.00	1.00	0.51	0.37	0.93	1.00	1003.80	38.00	542.90	-858.41
2020	Mean	1.00	0.00	0.00	0.00	0.00	0.37	0.05	0.03	0.23	0.32	1003.80	1.58	542.90	-858.41
2021	Min	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1288.80	0.00	1003.80	-709.68
2021	Max	1.00	0.00	0.00	0.00	0.00	1.00	0.51	0.37	0.93	1.00	1288.80	10.00	1003.80	-709.68
2021	Mean	1.00	0.00	0.00	0.00	0.00	0.37	0.05	0.03	0.22	0.34	1288.80	1.18	1003.80	-709.68
2022	Min	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1154.30	0.00	1288.80	-262.86
2022	Max	1.00	0.00	0.00	0.00	0.00	1.00	0.63	0.37	0.93	1.00	1154.30	57.00	1288.80	-262.86
2022	Mean	1.00	0.00	0.00	0.00	0.00	0.35	0.08	0.04	0.21	0.32	1154.30	4.20	1288.80	-262.86
2023	Min	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	816.20	0.00	1154.30	36.37
2023	Max	1.00	0.00	0.00	0.00	0.00	1.00	0.63	0.42	0.93	1.00	816.20	150.00	1154.30	36.37
2023	Mean	1.00	0.00	0.00	0.00	0.00	0.35	0.06	0.05	0.22	0.32	816.20	8.75	1154.30	36.37