Occupancy estimation of wild species in a palm oil plantation using unstructured data

Arco J. van Strien [1], Erik Meijaard [2 *], Nardiyono [3], Syafiie Suief [2], Syahmi Zaini [2]

Second draft 30 June 2025

[1] Arco van Strien Data Analysis, Leiden, the Netherlands

[2] Borneo Futures, Bandar Seri Begawan, Brunei Darussalam

[3] Austindo Nusantara Jaya, Jakarta, Indonesia

* Corresponding author

Keywords: o*ccupancy models, spOccupancy, citizen science, unstructured data, detection, Bayesian method, mammals, birds, reptiles*

Abstract

In 2020-2024, plantation workers at a large oil palm plantation in West Kalimantan recorded sightings of wild species of several species groups. They did not use a standardized field method and produced no comprehensive reports, but recorded only one or a few species per visit. Such unstructured data are generally viewed as challenging for statistical analysis. Here, we used occupancy models to estimate what proportion of spatial units (both non-natural and forest) a given species occupied annually in the plantation. Models with different covariates were tested for species for which most data were available: 13 birds, 7 mammals, among which the iconic Orangutan *Pongo pygmaeus,* and 3 reptiles. For each species, the model which best fitted the data was selected. Two shortcomings in our data complicated the analyses. First, occupancy models require detection and non-detection records, but because no fixed species lists were used, there is no unique way to generate non-detections. We generated non-detection records in several ways and ran the models again to evaluate the consequences for occupancy estimates. Second, imbalances in sampling may occur because of a lack of sampling design to select study sites. Most concerning are sites were surveyed only once in 2020-2024. We ran the models without those sites to examine whether results were different. Although the shortcomings mentioned turned out not to distort our results, the occupancy estimates were imprecise for many study species because of low detection rates, and extra efforts are needed to improve that.

Introduction

The expansion of oil palm (*Elaeis guineensis* Jacq.) plantations in tropical areas affects wildlife negatively (Fitzherbert *et al.* 2008; Meijaard *et al.* 2018; Marsh *et al.* 2025). Over time, the palm oil industry has been increasingly willing to mitigate the negative effects by taking protection and management measures. Examples are setting aside areas with High Conservation Values (HCV-areas) which are protected against illegal logging, burning and land-clearing (HCV Resource Network 2017) and the protection of "forest islands" within plantations (Paterno *et al.* 2024).

Effective biodiversity protection and management measures require detailed knowledge about local wildlife, but collecting sufficient local data is often hard in tropical areas (Maharani *et al*. 2025). Furthermore, protection and management measures are more likely to succeed if there is considerable support among plantation workers and other stakeholders. We believe that both obtaining more data and increasing support can go hand in hand by encouraging plantation workers and others to collect sighting records of wild species.

For these two reasons, in 2019, the Indonesian oil palm company Austindo Nusantara Jaya (ANJ) launched a special program, called PENDAKI which is the Indonesian acronym for Care for Biodiversity, to stimulate the recording of sightings of wild animals and plants by plantation workers in their concessions (Maharani *et al*. 2025). One of these areas is the KAL ("Kayung Agro Lestari") oil palm estate in West Kalimantan. This estate contains hundreds of production blocks planted with oil palms and several small forest islands (total area 9583 ha; Fig. 1). The estate also includes several large HCV-areas (together 3845 ha) with remnants of the original tropical moist forest. Since 2019, many observers have participated in the program to collect wildlife data, both in the planted areas and in the HCV-

areas. To enable everyone to participate, there are hardly any rules that observers must adhere to. For each sighting, location (identity of production block or forest site), date and species must be noted, as well as the number of individuals observed. Apart from this, there is no prescribed, standardized field method and most of the records are casual sightings.

To make these data usable for the management of plantations, the collected data need to be converted into relevant information, such as local differences in occurrence of species or in species diversity, which may then be related to environmental factors or management practices. Unfortunately, retrieving reliable information from casual sightings is challenging. Data as collected here are referred to in the scientific literature as unstructured or opportunistic data. (Van Strien *et al.* 2013; Kamp *et al.* 2016). Such data are collected by volunteer observers in many countries around the world and are also known as citizen science data (Silvertown 2009).

Because the field method is unstandardized, it is difficult to determine whether the difference in occurrence between two locations is real or is due to one location being more intensively studied than the other. For unstructured data, it is therefore mandatory to adjust for variation in field effort. This is not an easy task, especially if there is no information at all available about the field effort applied, as in the current study. It is extremely difficult to derive inferences on abundance of species from unstructured data (though see Johnston *et al*. 2025), but it is often feasible to estimate occupancy, *i.e.*, the proportion of spatial units occupied by the species. Analyses of unstructured data are particularly successful when occupancy models are used (Kéry *et al*. 2010; Van Strien *et al.* 2013; Isaac *et al.* 2014; MacKenzie *et al.* 2018). But not all applications have been fruitful (Kamp *et al.* 2016), and much will depend on the dataset available.

Our ultimate goal is to apply citizen science data with occupancy models on a routine basis to support nature management in large plantations in tropical regions (Maharani *et al.*

2025). This is an ambitious goal and as far as we know we are the first to scientifically explore this. Here we report on the first steps towards that goal. The aim of this paper is to develop custom occupancy models for species living in an oil palm plantation and to test whether several complications in the data might distort the results.

Material and methods

Area and data

Defining the production blocks and forest sites in the KAL as our sampling sites, we distinguish 463 sites in the KAL-area, 21 of which are completely covered with forest. The latter are not only the large HCV areas mentioned earlier, but also smaller forest islands within the estate which are not in use for palm oil production (Fig. 1). The other sites (from now on referred to as non-natural sites) are dominated by oil palms and infrastructure, but may also contain ponds, waterways and small patches of forest regrowth. The surface area of the non-natural sites is 30 ha on average but varies between sites (Fig. 1). Most forest sites are considerably larger, especially the HCV-sites, which unfortunately could not be split into smaller subsites because sightings in the HCV-sites were not precisely localized.

More than 400 observers provided data. Observers were allowed to record any species group they wanted. But because most records cover five species groups only - namely birds, mammals, reptiles, higher plants (*i.e.*, only *Magnoliopsida*) and insects (mainly butterflies and dragonflies), - we focused on these groups, abandoning data on other groups. This is our standard dataset, in which records are available from 387 sites for the 2020-2024 period. For about 200 sites, annual records are available (Table 1). On average, sites were visited 6-8 times per year (see Nvisits per site in Table 1), often by different observers who typically

118 reported only one or a few species (rarely > 10) per visit (see List length in Table 1). Some
119 sites which were never surveyed; these are mainly situated in recent plantings at the western
120 and eastern border of the estate. Records of the same species on the same date and site
121 collected by different observers were deduplicated because these may refer to the same
122 sighting as observers are frequently in the field together.
123
124 *Occupancy models*
125 Occupancy models aim to estimate occupancy of a species while considering the detection
126 probability (MacKenzie *et al*. 2018). This means that a different detection probability of a
127 species due to differences in *e.g.* field effort, observer experience or species abundance, does
128 not translate into a different occupancy estimate of the species (Kéry *et al*. 2010). This can be
129 particular useful for unstructured data because these models may still be able to properly
130 estimate occupancy even when no standardized field method has been used and no
131 information about field effort is available (Kéry *et al.* 2010; Van Strien *et al.* 2013; Isaac *et*
132 *al*. 2014). To be able to separate occupancy from detection, occupancy models consist of two
133 hierarchically coupled Generalized Linear Models (GLMs), one to describe the true state of
134 sites (presence or absence) and one to describe the detection in sites, given that the species
135 does occur (MacKenzie *et al*. 2018). Both submodels may be made a function of covariates,
136 which help to meet model assumptions that both occupancy and detection must be either
137 constant across sites and visits or otherwise differences should be modelled (MacKenzie *et al.*
138 2018). Covariates also offer opportunities to examine their effects on occupancy and
139 detection.
140 The occupancy submodel estimates the annual proportion of occupied sites in the
141 statistical population represented by the sampled sites. We estimated annual occupancy using

a multi-season model for single species (Doser *et al.* 2022b). Our most comprehensive submodel is specified as follows:

$z_{it} \sim \text{Bernoulli}(\psi_{it})$

[1]

$\text{logit}(\psi_{it})$ = intercept + year + habitat of site + distance to large forest + site size [2]

where z_{it} is the estimated occupancy (0 or 1) and ψ_{it} represents the occupancy probability of the species in site *i* and year *t.* Occupancy is modelled as a function of an intercept, year, habitat of the site, distance of the site to large forest and site size. Habitat of the site can be forest or non-forest; forest is taken when the site is a forest site or a non-natural site with a forest patch. Distance to large forest represents the distance of the center of a site to the nearest large forest areas; these are either forests around the estate or the HCV-areas within the estate. Site size is included to adjust for variation in surface area of the sites. Our main interest is in the annual occupancy estimates which we assessed for each species by summing the estimated z_i values over sites and year (finite sample occupancy; MacKenzie *et al.* 2018).

The detection submodel estimates detection per visit and the most comprehensive model is specified as:

$y_{ijt} \sim \text{Bernoulli}(p_{ijt} \times z_{it})$

[3]

logit(detection) = intercept + list length + habitat of observation + observer

[4]

in which the observations y_{ijt} indicate that the species was detected ($y_{ijt} = 1$) or not ($y_{ijt} = 0$) at location *i* during visit *j* in year *t.* The observations are considered as the product of occupancy z_{it} and the probability p_{ijt} of detecting the species in location *i* during visit *j* in year *t.* (MacKenzie *et al.* 2018). Detection is modelled as a function of an intercept, list length,

observer and habitat of observation. There are no year effects in this model because data were too sparse to estimate reliable detection estimates which vary between the years. Length of species lists per visit was used as covariate because we expected lower detections in shorter lists. We did not apply list length categories (as in Van Strien *et al*, 2013) but used list length as a linear detection predictor. Habitat of the observation can be forest or non-forest; forest is taken when the observation was in a forested part of a site; a species may be more difficult to spot there. Observer identity was modelled as a random effect to take into account the variation in detection between observers (Schmidt *et al.* 2023). Estimating detection *p* is only possible if repeated visits are available for at least some sites (MacKenzie *et al.* 2018). The replicated visits need to be done in a period of closure, meaning that the state of all locations (occupied or not occupied) has not changed during the period between the visits. In contrast to studies using European data (*e.g.,* Van Strien *et al.* 2013), we here consider an entire calendar year as the closure period, thereby assuming that the study species reside in the area all year round. This does not necessarily mean that a species is present in a site during the entire year, but rather that a species may use the site year-round (MacKenzie *et al.* 2018). Our preliminary analyses showed no effect of Julian date on detection, so we did not include Julian date as a covariate in the model.

Occupancy models require detection and non-detection records while our dataset only contains presence records (detections) of five species groups. We created a non-detection record for all species of these five groups not being observed during a field visit (Van Strien *et al.* (2013). We ran the models in a Bayesian framework using the R-package *spOccupancy* (Doser *et al*. 2022) in R v. 4.3.3 (R Core Team, 2024). All quantitative covariates (distance to large forest, site size and list length) were standardized to have mean 0 and standard deviation 1 (Doser *et al.* 2022). *spOccupancy* allows to account for spatial autocorrelation of occupancy sites, which may be useful for our study area where sites are adjacent to each

other. Unfortunately, the large inaccuracy in the locations of observations within the large HCV-sites made it impossible to apply a spatially explicit model. With the covariate distance-to-large-forest, however, we included a variable in the model describing spatial gradients in the study area.

More than 300 different species of the five species groups were reported in 2020-2024, but for the majority of them too few presence records have been collected to allow statistical analysis. Models were only run for species with at least five presence records each year and more than 150 records in total. These were 23 species: 13 birds, 7 mammals and 3 reptiles. To find the model which best fitted the data, we ran 18 different models per species. In these models, one or several covariates were omitted from the model described by [2] and [4] (see Table S1 for an overview of the 18 models). The model with the lowest value of the Widely Applicable Information Criterion (WAIC) was considered the best model (Doser *et al.* 2022). For these top models we performed posterior predictive checks to compute Bayesian *p*-values as a measure of model fit. More specific, following the recommendation of Doser & Kéry (2022), we used both the Freeman-Tukey statistic and the Chi-Square statistic, and grouped the data across sites as well as across replicates. Ideally, each Bayesian *p*-value is around 0.5.

We adopted the default priors of *spOccupancy* and ran the models with three parallel Markov chains of 60,000 iterations each, discarding the first 50,000 as burn-in and a thinning rate of 10. A parameter was considered significant when the 95% Bayesian credible interval (CRI) of the posterior sample of a parameter did not include 0. The standard deviation of the sample from the posterior distribution of parameter was interpreted as standard error of that parameter.

Alternative datasets

We created several alternative datasets to study the effect of two complications in the data and applied the same 18 models as for the standard dataset. Firstly, observers did not make complete checklists of species groups, nor did they use a fixed list of species to consider. Consequently, there is no unique way to generate non-detection records. If an observer only noticed, say, plant species, and ignored any sighting of the other four species groups, non-detections generated for other species groups are not justified. To examine if this affects occupancy estimates, we created three alternative datasets differing in the way non-detections were created: (1) we filtered data from the three most often reported groups (birds, mammals and reptiles) and discarded records from higher plants and insects. This implies that we generated non-detections for our 23 study species only from sightings of birds, mammals and reptiles and no longer from plants and insects, (2) in addition to using only data from these three species groups, we included only observers with records of the same species group as the study species. So, if the study species were a mammal, only sightings of observers reporting mammals were used to generate non-detections and the same goes for birds and reptiles; (3) in addition to using data from three species groups, we included only observers who had recorded all three species groups, thereby further reducing the number of observers (Table 2). The three extra datasets are called (1) Nondet3grp, (2) Nondet3grp+obs1grp and (3) Nondet3grp+obs3grp and occupancy results were compared with those of the standard dataset. All filtering actions reduced the number of non-detections, and to a lesser extent also the number of detections (Table 2).

Secondly, unstructured data as our dataset not only lack a standardized field method but also have no sampling design to properly select study sites. In our case, forest sites and non-natural sites surrounding forest sites have been oversampled, so the measurements might not be representatives for the entire estate (Boyd *et al.* 2023). On the other hand, data came from almost the entire area, which does not suggest obvious spatial bias. There is, however,

an imbalance in sampling which we are concerned about: 108 sites (28% of all 387 sites) have only been surveyed in one year, most frequent in 2024. If the differences in occupancy between 2020 and 2024 would depend on the sites that were surveyed only once, then we have no convincing evidence of a change. To check this, we created two more datasets: one in which all sites surveyed in one year only were deleted (Remove_sites1year) and one in which sites visited only in 2024 were deleted (Remove_sites2024), and compared annual occupancies. Obviously, these two datasets contain fewer sites than the standard dataset (Table 2).

Results

Standard dataset

Almost all models applied to the standard dataset converged according to the Gelman-Rubin Rhat statistic (Rhat < 1.1). Only nine out of 414 models (18 different models * 23 species) did not converge in all parameters, most frequently not in case of *Spilornis cheela,* a raptor bird species. The top model according to the WAIC-value varied between species (Table 3). For several species, the most comprehensive model (model 1 in table 3) fitted best, for example in case of *Hylobates albibarbis* (Gibbon) and *Pongo pygmaeus* (Orangutan). For other species simpler models performed better, *e.g.*, for *Liopeltis tricolor*, a snake species. The top model for the latter species contained only effects of site size, species list length and observer and no ecological variables at all. The Bayesian *p*-values produced by three out of the four tests for the top models were mostly between 0.2-0.75, suggesting a reasonable fit. But for half of the species *p*-values < 0.2 were obtained according to the Freeman-Tukey test when data were grouped across sites (Table 3).

265 Detection probability varied between species, with *Varanus salvator* (a large monitor
266 lizard) having the highest rate of 0.26 (Table 3). This means that *Varanus salvator* has been
267 reported during one-quarter of the visits to occupied sites. Here, a visit stands for a single
268 visit of an average observer collecting a species list of mean length outside forest habitat. For
269 most species detection is low, frequently even below 0.1 (Table 3). Detection increased with
270 longer species lists (Table 3; see example in Fig 2A). In line with our expectation, many
271 species appeared to be less visible in forest habitat, such as *Centropus sinensis*, a cuckoo
272 species (Table 3), although this may also be because these species spend less time in forest
273 habitat. In contrast some others were better detectable in forest habitat or spend more time in
274 forest habitat, *e.g.*, *Macaca nemestrina* (a monkey species). Furthermore, observer effects
275 were relevant for all species, as we already suspected. Models without observer effects
276 consistently finished low in the model selection.

277 Mean probability of occupancy of *Varanus salvator* is 0.97 (Table 4), suggesting that
278 this species makes use of the entire study area. *Pongo pygmaeus*, for example, has a much
279 lower mean occupancy of 0.26. Several species benefitted from the availability of forest
280 habitat in the site including *Macaca nemestrina*, *Macaca fascicularis* and *Pongo pygmaeus*
281 (Table 4). Furthermore, the distance to the nearest large forest affected the occupancy
282 probability for about half of the species. Not surprisingly, *Hylobates albibarbis* had a
283 significantly higher occupancy in sites with forest habitat and situated in the vicinity of large
284 forest areas (Table 4; Fig. 2B), and the same applies to *Pongo pygmaeus*. Some other species,
285 however, achieved their highest occupancy rate further away from the large forest, *e.g.*,
286 *Spilopelia chinensis*, a dove species). For almost all species, occupancy was higher in larger
287 sites (Table 4). Fig. 3 shows examples of annual occupancy, for *Pongo pygmaeus* and
288 *Amaurornis phoenicurus* (a waterbird species).
289

Alternative datasets

The models converged somewhat less often in the alternative datasets than in the standard dataset. To enable comparisons between datasets, we did not delete any of the species from the results. Often but not always the same model was selected as top model in the alternative dataset as in the standard set (Table S2). Mean detection in 2020-2024 derived from the three datasets with alternative procedures to generate non-detections was significantly higher than when based on the standard dataset (Fig. 4A; paired t-tests; $P<0.05$; $n=23$). This is not unexpected because the three alternative datasets all have fewer non-detection records than the standard data (Table 2). Mean occupancy estimates in 2020-2024, however, did not differ between those derived from the standard dataset and those based on the three alternative datasets (Fig. 4B; paired t-tests; $P>0.05$; $n=23$). Thus, the occupancy estimates do not appear to depend on the exact way non-detections were generated.

The two datasets created to study removal of poorly surveyed sites produced similar detection and occupancy estimates as found for the standard data (Fig. 4A & B; paired t-test; $P>0.05$; $n=23$). Also, differences between 2020 and 2024 derived from these datasets were strongly correlated with those based on the standard data (Pearson's $r > 0.99$; $P <0.01$; $n=23$).

Discussion

Many researchers who have to do with the collection and analysis of unstructured data have pointed out the downsides of these data: bias when field effort is not taken into account, spatial bias due to lack of sampling design, low detection when field efforts are limited and uncertainty about non-detections when it is not sure which species are being considered (*e.g.,* Altweg & Nichols 2019; Brown & Williams 2019). In some citizen science projects, these shortcomings are reduced by discouraging the collection of casual records and instead focusing on complete checklists, *i.e.*, lists of all species observed and identified by a

315 participant at a particular time and place (*e.g.,* eBird, see Kelling *et al.* 2019). This provides
316 more clarity about non-detections, and higher detection probabilities. If more information
317 about the observation process is provided, for example time spent or length of route during
318 the visit, there are more opportunities in statistical analyses to adjust for field effort (Johnston
319 *et al.* 2018; Van Strien *et al.* 2022). With a smartphone app such information may be
320 generated automatically (Altweg & Nichols 2019).

321 The collection of data in the KAL area is slowly moving in this direction. A subgroup
322 of observers has recently been selected to use a fixed list of species which should be recorded
323 when observed (Maharani *et al.* 2025). The hope is that this will lead to longer species lists.
324 This group will work with a smartphone app that can record the spatial coordinates of each
325 observation, which makes it possible to derive field efforts to some extent. The availability of
326 spatial coordinates makes it possible to localize observations on a small scale afterwards.
327 This will solve one of the obvious shortcomings of the current KAL data, namely the overly
328 large forest sites.

329 Still, it is not the intention to limit data collection to fixed lists only. On the contrary,
330 the idea remains to encourage as many workers as possible to participate in data collection, to
331 promote involvement in the protection of biodiversity. There may still be considerable
332 potential, because there are many observers who contributed only a few records so far. That
333 leaves us little choice but to deal with all shortcomings of the data. We have shown that the
334 occupancy estimates were unaffected by the way non-detection records were generated. The
335 fact that many records were collected by a relatively small group of dedicated observers can
336 partly explain this, as they collected records from all five groups. We also showed that
337 visiting sites only once did not influence the results. It is encouraging that the models yielded
338 meaningful relationships between occupancy and distance to large forest and forest habitat
339 preference. These relationships confirm existing knowledge, thereby enhancing confidence in

the usefulness of the data being collected in the KAL estate. With longer time series data, it may be interesting to study whether these relationships are changing over time. An increase in occurrence further away from large forest areas may indicate greater use of non-natural sites and/or higher permeability of the plantation.

But problems remain, the biggest one being the short species lists in our data (Table 1). This leads to the generation of many non-detections (one for each species not observed) which induces low detection rates per visit. Although there are quite a few replicated visits per site (Table 1), these do not fully compensate for the low detection and the result is that occupancy estimates for many species are far from precise (MacKenzie *et al.* 2018). Using simulation data, Kery & Royle (2016; p. 588) showed that the precision of the occupancy estimates becomes low when p is less than about 0.1-0.2. Most of our species have detection rates < 0.2 and indeed, annual occupancy estimates are imprecise, with standard errors of annual occupancy > 0.05 or even > 0.1 (Table 4). To improve this, more data are needed, preferably in the form of longer species lists. Another problem is that model fit was not yet sufficient for all species, which contributes to the uncertainty of inferences. The lack-of-fit test revealed that spatial variation in occupancy and detection is not yet adequately modeled for a number of species (Table 3; Doser & Kéry 2022). Model fit might be enhanced by including more adequate covariates as well as spatial autocorrelation in the model. With more annual data it also becomes more feasible to include year-dependent detection estimation. So far, we assumed detection probability was equal in all five years. But it is better to consider potential changes in detection, for example because of increasing average skill of observers (Kéry *et al*. 2010).

In conclusion, although we have made progress in model development and solved several data complications, more is needed to achieve our goal to use unstructured data for plantation management purposes. With more data, more precise occupancy estimates may be

obtained for the 23 study species, and the number of study species may be further expanded as well. Also, spatially finer applications will then become feasible.

Acknowledgement

Thanks are due to all the employees of Austindo Nusantara Jaya (ANJ) in the KAL estate who collected the wildlife data, and facilitated the implementation of the PENDAKI program. The KAL-database is managed by Priya Swayanuar and Claudia Retina Munthe. We received financial support from ANJ for data verification, analysis and write up. Fig 1. was created by Safwanah Ni'Matullah. We thank Willy van Strien for critically reading the manuscript, and XX peer reviewers for their constructive feedback.

References

Altwegg, R, Nichols, JD. Occupancy models for citizen-science data. Methods in Ecology & Evolution 2019; 1: 8-21.

Brown, ED, Williams, BK. The potential for citizen science to produce reliable and useful information in ecology. Conservation Biology 2019; 33: 561-569.

Boyd, RJ, Powney, GD, Pescott, OL. We need to talk about nonprobability samples. Trends in Ecology & Evolution 2023; 38: 521:531.

Doser, JW, Finley, AO, Kéry, M, Zipkin, EF. spOccupancy: an R package for single-species, multispecies and integrated spatial occupancy models. Methods in Ecology and Evolution 2022; 13:1670-1678.

Doser JW, Finley AO, Kéry M, Zipkin EF. Introduction to spOccupancy. https://doserlab.com/files/spoccupancy-web/articles/modelfitting. 2022b; accessed July 3, 2025.

390 Doser, JW, Kéry, M. Multi-Season Occupancy Models for Assessing Species Trends and
391 Spatio-Temporal Occurrence Patterns. https://doserlab.com/files/spoccupancy-
392 web/articles/spacetimemodelshtml. 2022; accessed July 3, 2025.
393 Fitzherbert EB, Struebig MJ, Morel, A, Danielsen F, Brulh CA, Donald PF, Phalan B. How
394 will oil palm expansion affect biodiversity? Trends in Ecology & Evolution 2008;
395 23:538-545.
396 HCV Resource Network. What are High Conservation Values? https://www.hcvnetwork.org/.
397 2017; accessed July 3, 2025.
398 Isaac, NJB, Van Strien, AJ, August, TA, De Zeeuw, MP, Roy, DB. Statistics for citizen
399 science: extracting signals of change from noisy ecological data. Methods in Ecology and
400 Evolution 2014; 5: 1052-1060.
401 Johnston, A, Fink, D, Hochachka, WM, Kelling, S. Estimates of observer expertise improve
402 species distributions from citizen science data. Methods in Ecology and Evolution 2018;
403 9: 88-97.
404 Johnston, A, Rodewald, AD, Strimas-Mackey, M, Auer, T, Hochachka, WM, Stillman, AN,
405 Davis, CL, Ruiz-Gutierrez, V, Dokter, AM, Miller, ET, Robinson, O, Ligocki, S, Oldham
406 Jaromczyk, L, Crowley, C, Wood, CL, Fink, D. North American bird declines are greatest
407 where species are most abundant. Science 2025; 388: 532-537.
408 Kamp, J, Oppel, S, Heldbjerg, H Nyegaard, T, Donald, PF. Unstructured citizen science data
409 fail to detect long-term population declines of common birds in Denmark. Diversity and
410 Distributions 2016; 22: 1024–1035.
411 Kelling, S, Johnston, A, Bonn, A, Fink, D, Ruiz-Gutierrez, V, Bonney, R, Fernandez, M,
412 Hochachka, WM, Julliard, R, Kraemer, R, Guralnick, R Using Semistructured Surveys to
413 Improve Citizen Science Data for Monitoring Biodiversity. BioScience, 2019; 69: 170–
414 179.

415 Kéry, M, Royle, JA, Schmid, H, Schaub, M, Volet, B, Häfliger G, Zbinden, N. Grid cell-
416 occupancy distribution modeling to correct population-trend estimates derived from
417 opportunistic observations. Conservation Biology, 2010; 24: 1388-1397.
418 Kéry, M, Royle, J. Applied Hierarchical Modeling in Ecology: Analysis of distribution.
419 abundance and species richness in R and BUGS. 2016; 1st. Edition Academic Press &
420 Elsevier, London, United Kingdom.
421 MacKenzie, DI, Nichols, JD, Royle, JA, Pollock, KH, Hines, JE, Bailey, LL. Occupancy
422 estimation and modeling: inferring patterns and dynamics of species occurrence. 2018;
423 2nd Edition. Elsevier, San Diego.
424 Maharani, N, Nardiyono, Munthe, CR, Ni'Matullah, SP, Sueif, S, Zaini, S, Supriatna, J,
425 Kusrini, M, Dennis, R, Van Balen, B, Van Strien, A, Meijaard, E. A novel citizen
426 science-based wildlife monitoring and management tool for oil palm plantations.
427 bioRxiv preprint 2025; doi: https://doi.org/10.1101/2025.01.12.632638
428 Marsh, CJ, Turner, EC, Blonder, BW, Bongalov, B, Both, S. et al. Tropical forest clearance
429 impacts biodiversity and function, whereas logging changes structure. Science 2025;
430 387: 171–175.
431 Meijaard, E, Garcia-Ulloa, J, Sheil, D, Wich, SA, Carlson, KM, Juffe-Bignoli, D, Brooks,
432 TM (2018) Oil Palm and Biodiversity. A Situation Analysis by the IUCN Oil Palm
433 Task Force. IUCN: Gland, Switzerland.
434 Paterno, GP, Brambach, F, Guerrero-Ramírez, N, Clara Zemp, D, Cantillo, AF, Camarretta,
435 N, Moura, CCM, Gailing, O, Ballauff, J, Polle, A, Schlund, M, Erasmi, S, Iddris, NA,
436 Khokthong, W, Sundawati, L, Irawan, B, Hölscher, D, Kreft, H. Diverse and larger tree
437 islands promote native tree diversity in oil palm landscapes. Science 2024; 386: 795-
438 802

R Core Team. R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. 2024; https://www.R-project.org/.

Schmidt, BR, Cruickshank, SS, Bühle, C, Bergamini, A. Observers are a key source of detection heterogeneity and biased occupancy estimates in species monitoring. Biological Conservation 2023; 283: 110102.

Silvertown, J. A new dawn for citizen science. Trends in Ecology & Evolution 2009; 24: 467-471.

Van Strien, AJ, Van Swaay, CAM, Termaat, T. Opportunistic citizen science data of animal species produce reliable estimates of distribution trends if analysed with occupancy models. Journal of Applied Ecology 2013; 50: 1450-1458.

Van Strien, AJ, Van Zweden, JS, Sparrius, LB, Odé, B. Improving citizen science data for long-term monitoring of plant species in The Netherlands. Biodiversity and Conservation 2022; 31:2781–2796.

Supporting information

Table S1 and S2

Table 1. Annual field effort in the KAL standard dataset. Nsites is the number of sites with observations, Nrecs is the total number of presence records, Nvisits per site is the mean number of visits per site, List length is the mean number of all observed species per visit.

Year	Nsites	Nrecs	Nvisits per site	List length
2020	191	3047	8.3	1.9
2021	232	4055	7.1	2.4
2022	139	4462	7.4	4.3
2023	185	3348	7.5	2.4
2024	269	2567	6.0	1.6

Table 2. Properties of datasets per species obtained under different procedures (see text for explanation). Nsites is the number of sites with observations of five or three species groups (depending on the dataset). Nvisits per site is the mean number of visits per site, List length is the mean number of all observed species per visit from 5 or 3 species groups. Nobservers is the number of observers. Ndetect. and Nnon-detect. are the mean number of detection and non-detection records of the 23 study species.

Dataset	Nsites	Nvisits /site/yr	List length	Nobservers	N detect.	Nnon-detect.
Standard data	387	7.2	2.4	372	534	6757
Nondet3grp	386	7.0	2.2	367	534	6499
Nondet3grp+obs1grp	382	7.1	2.3	255	534	6336
Nondet3grp+obs3grp	374	7.2	2.3	132	512	6135
Remove_sites1year	279	7.8	2.4	365	523	6570
Remove_sites2024	340	7.4	2.4	370	530	6681

Table 3. Detection parameter estimates under the top model per species. See Table S1 for the meaning of model ID's. Bayesian *p*-values are according to the Freeman-Tukey statistic with data grouped by sites (Doser & Kéry 2022). *p* is mean detection probability in 2020-2024 (±

se), *i.e.,* the backtransformed intercept as specified in formula [4]. Coefficients of list length, habitat of observation and observer are on the logit scale. No entry indicates that the covariate is not included in the model. Asterisks refer to significant differences from zero derived from 95% credible intervals.

Species	***Model ID***	***Bayesian p-value***	***p***	***List length***	***Habitat of observation***	***Observer***
Acridotheres javanicus	8	0.32	0.08 ± 0.01	0.69 *	-1.25 *	1.00 *
Alcedo meninting	1	0.07	0.02 ± 0.01	0.73 *	-0.4 *	3.33 *
Amaurornis phoenicurus	8	0.11	0.09 ± 0.01	0.67 *	-1.59 *	0.77 *
Anthracoceros malayanus	10	0.16	0.03 ± 0.01	0.48 *		1.23 *
Callosciurus notatus	7	0.61	0.04 ± 0.01	0.65 *		0.78 *
Callosciurus prevostii	3	0.23	0.02 ± 0.01	0.54 *	0.39 *	1.35 *
Centropus sinensis	8	0.34	0.17 ± 0.01	0.63 *	-0.63 *	0.37 *
Corvus enca	13	0.27	0.02 ± 0.01	0.46 *		2.14 *
Egretta garzetta	1	0.18	0.07 ± 0.01	0.49 *	-0.98 *	1.25 *
Elanus caeruleus	12	0.10	0.06 ± 0.01	0.6 *		1.24 *
Gracula religiosa	1	0.08	0.06 ± 0.01	0.46 *	-0.59 *	0.51 *
Halcyon smyrnensis	14	0.51	0.06 ± 0.01	0.69 *	-1.02 *	1.31 *
Hirundo tahitica	11	0.38	0.02 ± 0.01	0.41 *	-1.43 *	2.01 *
Hylobates albibarbis	1	0.06	0.04 ± 0.01	0.47 *	1.22 *	2.20 *
Liopeltis tricolor	15	0.31	0.01 ± 0.01	0.7 *		2.14 *
Macaca fascicularis	7	0.01	0.16 ± 0.02	0.59 *		1.56 *
Macaca nemestrina	1	0.02	0.07 ± 0.01	0.57 *	0.37 *	1.31 *
Malayopython reticulatus	2	0.37	0.05 ± 0.02	0.49 *	-1.37 *	3.10 *
Nannosciurus melanotis	1	0.03	0.05 ± 0.01	0.57 *	-0.39 *	1.72 *
Pongo pygmaeus	1	0.08	0.06 ± 0.02	0.55 *	0.99 *	2.93 *
Spilopelia chinensis	11	0.19	0.14 ± 0.01	0.59 *	-1.15 *	0.38 *
Spilornis cheela	13	0.28	0.01 ± 0.01	0.67 *		2.69 *
Varanus salvator	14	0.17	0.26 ± 0.02	0.86 *	-0.31 *	0.67 *

Table 4. Occupancy parameter estimates under the top model per species (see table 3 for model ID's). ψ is the mean finite sample annual occupancy, averaged over 2020-2024. SE is the standard error of annual occupancy, also averaged over 2020-2024. Coefficients of habitat of site, distance to forest and site size are on the logit scale. No entry indicates that the covariate is not included in the model. Asterisks refer to significant differences from zero derived from 95% credible intervals.

Species	***ψ***	***SE***	***Habitat of site***	***Distance to forest***	***Site size***
Acridotheres javanicus	0.65	0,09			1.83 *
Alcedo meninting	0.83	0,07	-1.21	0.45 *	1.34 *
Amaurornis phoenicurus	0.84	0,06			1.21
Anthracoceros malayanus	0.53	0,12	1.11	-0.61 *	
Callosciurus notatus	0.48	0,09	0.64	-0.66 *	1.55 *
Callosciurus prevostii	0.63	0,14	1.22		1.63 *
Centropus sinensis	0.84	0,05			1.71 *
Corvus enca	0.30	0,11	0.99		2.04 *
Egretta garzetta	0.69	0,08	-0.40	0.44 *	2.28 *
Elanus caeruleus	0.55	0,08		-0.64 *	1.42 *
Gracula religiosa	0.24	0,07	1.47 *	-0.38	2.14 *
Halcyon smyrnensis	0.57	0,09			
Hirundo tahitica	0.59	0,09		0.3	
Hylobates albibarbis	0.33	0,08	1.33 *	-1.22 *	1.53 *
Liopeltis tricolor	0.41	0,12			2.23 *
Macaca fascicularis	0.39	0,05	1.61 *	-0.58 *	1.69 *
Macaca nemestrina	0.47	0,09	1.10 *	-0.89 *	1.56 *
Malayopython reticulatus	0.38	0,10		-0.44 *	2.02 *
Nannosciurus melanotis	0.33	0,07	1.47 *	-0.31	2.05 *
Pongo pygmaeus	0.26	0,07	1.22 *	-0.59 *	2.08 *
Spilopelia chinensis	0.90	0,05		1.15 *	
Spilornis cheela	0.52	0,18	2.00 *		
Varanus salvator	0.97	0,02			1.83 *

Figure Legends

Fig. 1. Map of the KAL- estate in West Kalimantan, Indonesia.

Fig. 2. Relationship between (A) expected detection (± credible intervals) of *Varanus salvator* and the number of species observed during a visit and (B) between expected occupancy of *Hylobates albibarbis* and distance to large forest.

Fig. 3. Annual occupancy (± se) of (A) *Pongo pygmaeus* and (B) *Amaurornis phoenicurus.*

Fig. 4. (A) Mean detection ((± se; backtransformed intercept; see text) and (B) mean occupancy (± se) in 2020-2024 of 23 species. Each bar represents a different dataset. Asterisk indicates significant difference with standard dataset (paired t-test; $P < 0.05$; n= 23).

Table S1. Overview of models. Model 1 is the most comprehensive model described in the main text. The others are models in which one or more covariates have been omitted. No entry indicates that the covariate is not included in the model.

Model ID	Habitat of site	Distance to forest	Site size	List length	Observer	Habitat of observation
1	x	x	x	x	x	x
2		x	x	x	x	x
3	x		x	x	x	x
4	x	x		x	x	x
5	x	x	x		x	x
6	x	x	x	x		x
7	x	x	x	x	x	
8			x	x	x	x
9	x			x	x	x
10	x	x		x	x	
11		x		x	x	x
12		x	x	x	x	
13	x		x	x	x	
14				x	x	x
15			x	x	x	
16	x			x	x	
17		x		x	x	
18				x	x	

Table S2. Top model per species per dataset according to WAIC. See table S1 for the meaning of model IDs.

Species	Standard	Nondet3grp	Nondet3grp+obs1grp	Nondet3grp+obs3grp	Remove_sites1yr	Remove_sites2024
Acridotheres javanicus	8	8	8	8	8	8
Alcedo meninting	1	1	1	1	1	1
Amaurornis phoenicurus	8	8	3	8	8	8
Anthracoceros malayanus	10	10	10	10	10	10
Callosciurus notatus	7	12	12	7	7	12
Callosciurus prevostii	3	8	8	3	8	8
Centropus sinensis	8	3	8	3	8	8
Corvus enca	13	13	13	13	13	13
Egretta garzetta	1	1	1	2	2	2
Elanus caeruleus	12	12	12	7	12	7
Gracula religiosa	1	1	1	13	3	3
Halcyon smyrnensis	14	14	11	11	14	14
Hirundo tahitica	11	2	11	2	14	11
Hylobates albibarbis	1	1	1	1	1	1
Liopeltis tricolor	15	15	15	15	13	15
Macaca fascicularis	7	7	7	7	7	7
Macaca nemestrina	1	1	1	1	1	1
Malayopython reticulatus	2	2	2	2	2	2
Nannosciurus melanotis	1	1	1	3	1	3
Pongo pygmaeus	1	1	1	1	1	1
Spilopelia chinensis	11	11	11	11	11	11
Spilornis cheela	13	13	7	13	7	12
Varanus salvator	14	11	11	8	8	2

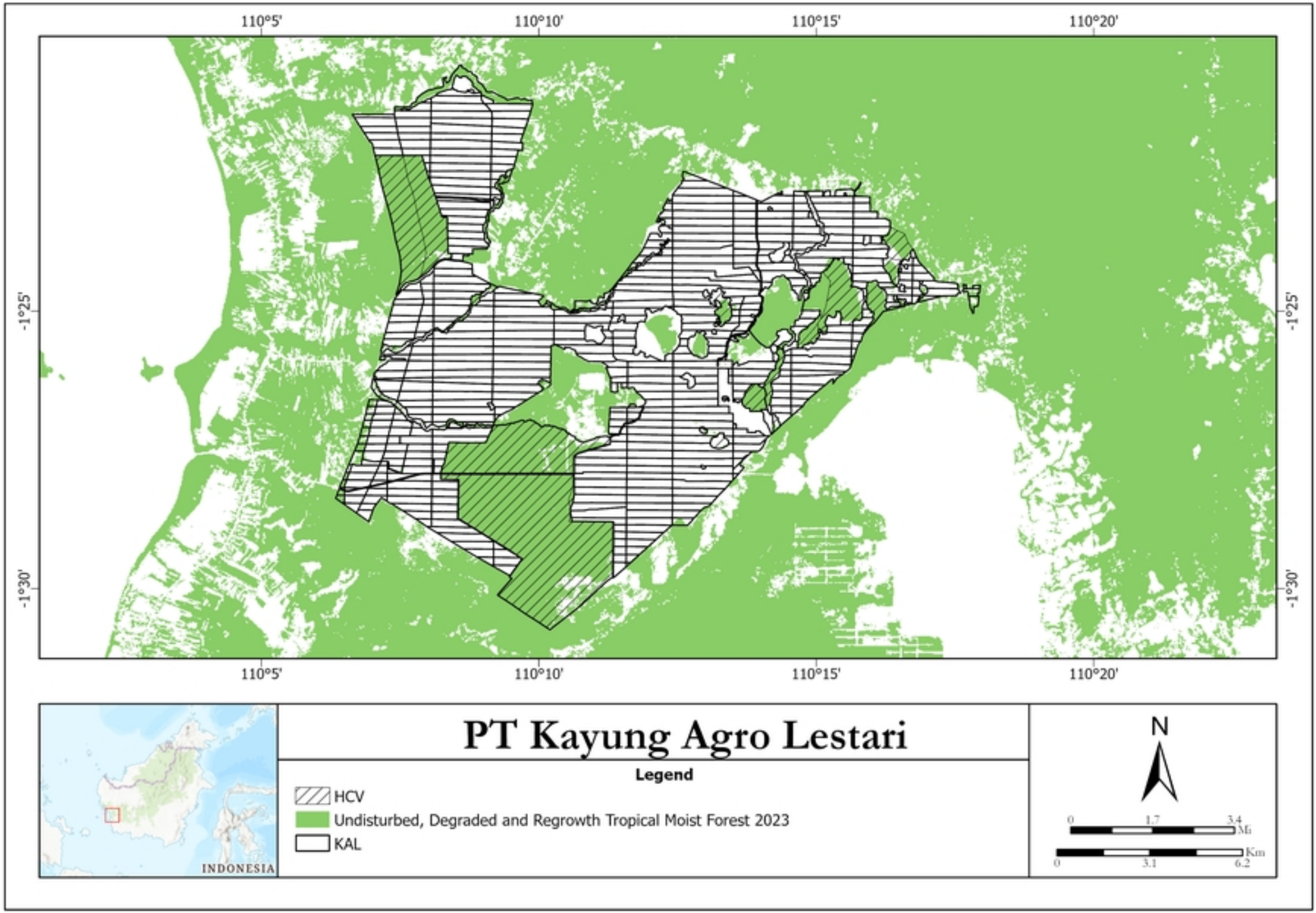
110°5'
110°10'
110°15'
110°20'
-1°25'
-1°30'
PT Kayung Agro Lestari
Legend
HCV
Undisturbed, Degraded and Regrowth Tropical Moist Forest 2023
KAL
INDONESIA
N
0
1.7
3.4
Mi
Km
0
3.1
6.2

Figure 1

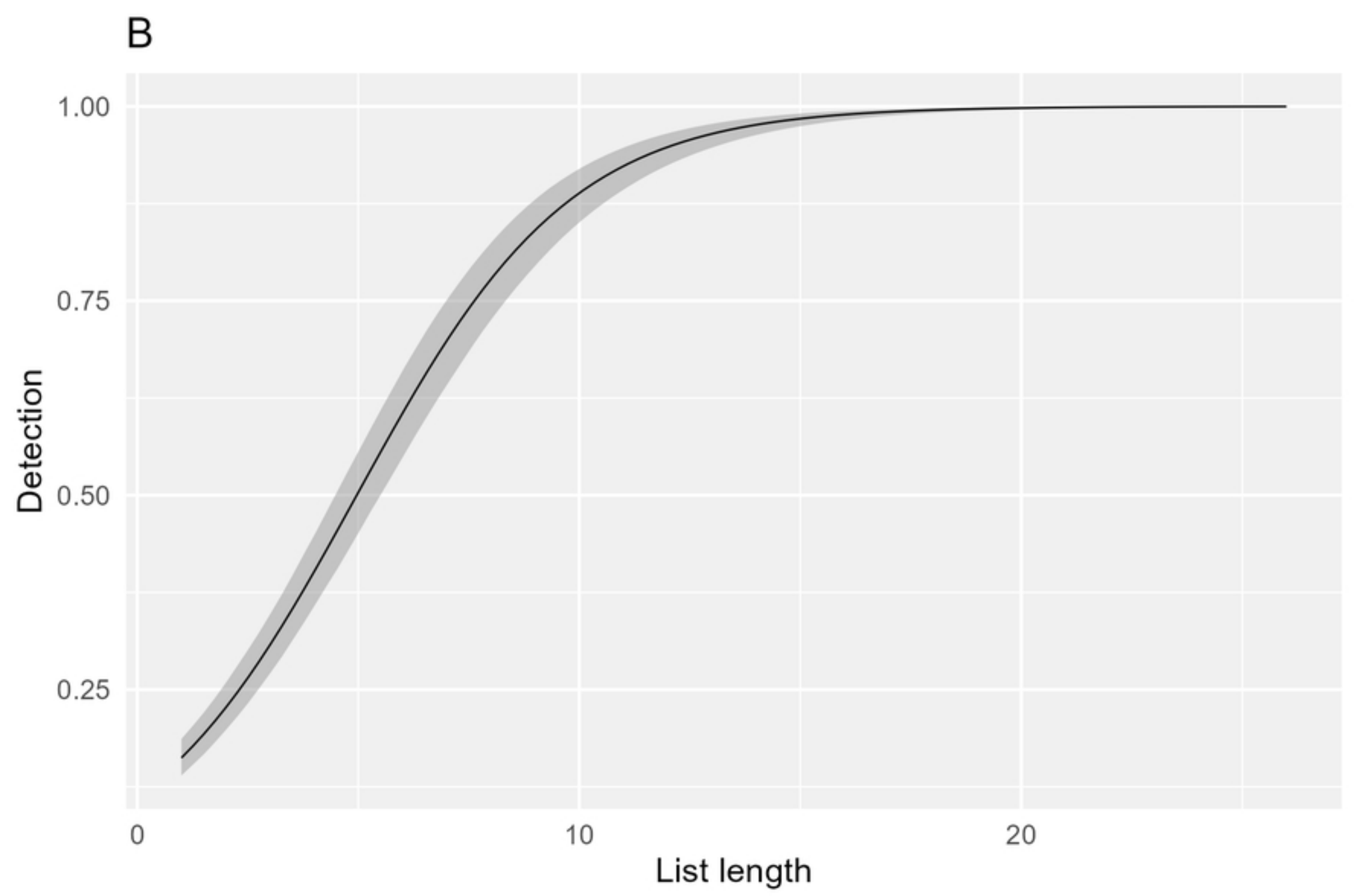

Figure 2A

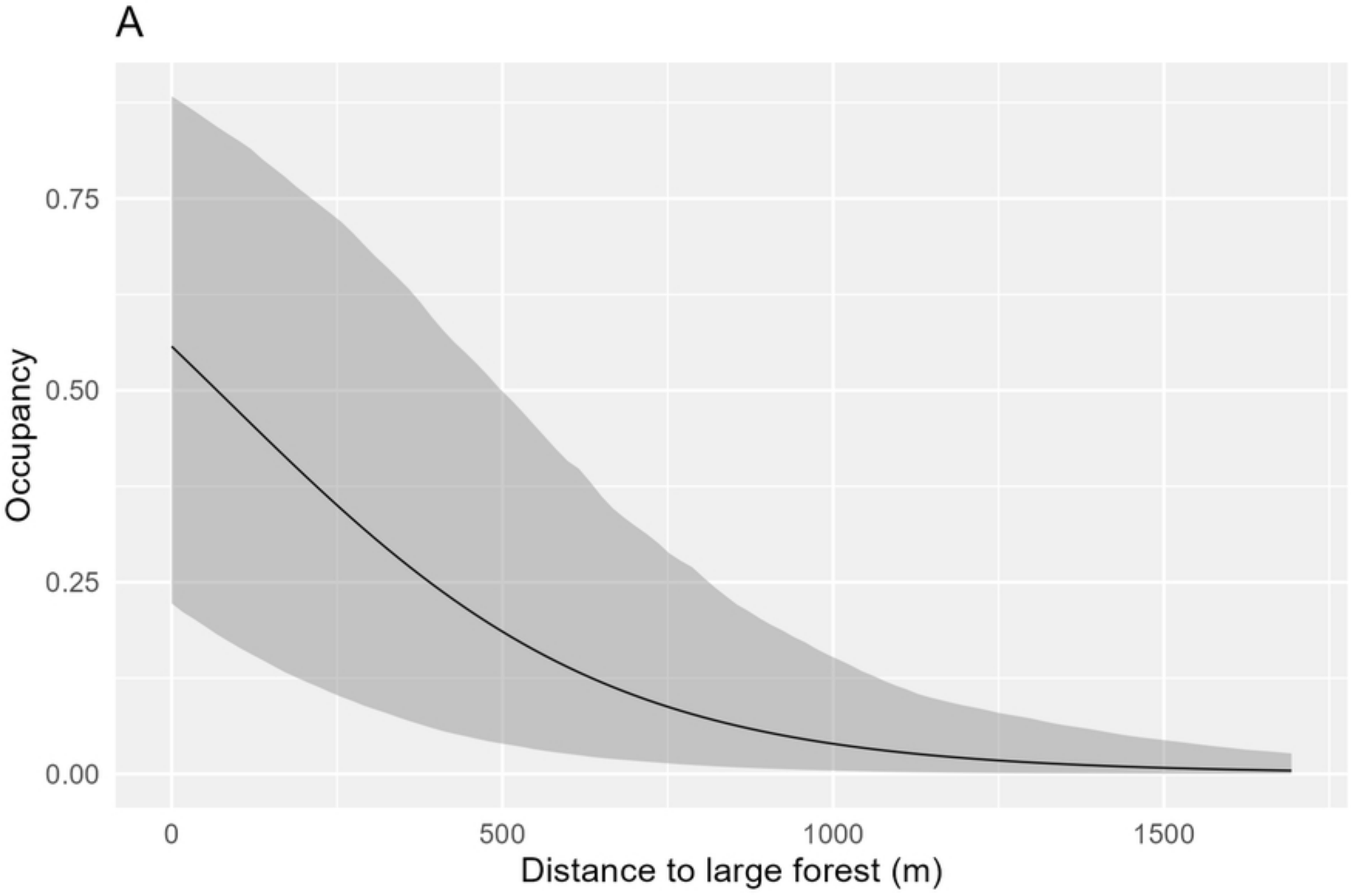
A
0.75
0.50
0.25
0.00
Occupancy
0
500
1000
1500
Distance to large forest (m)

Figure 2B

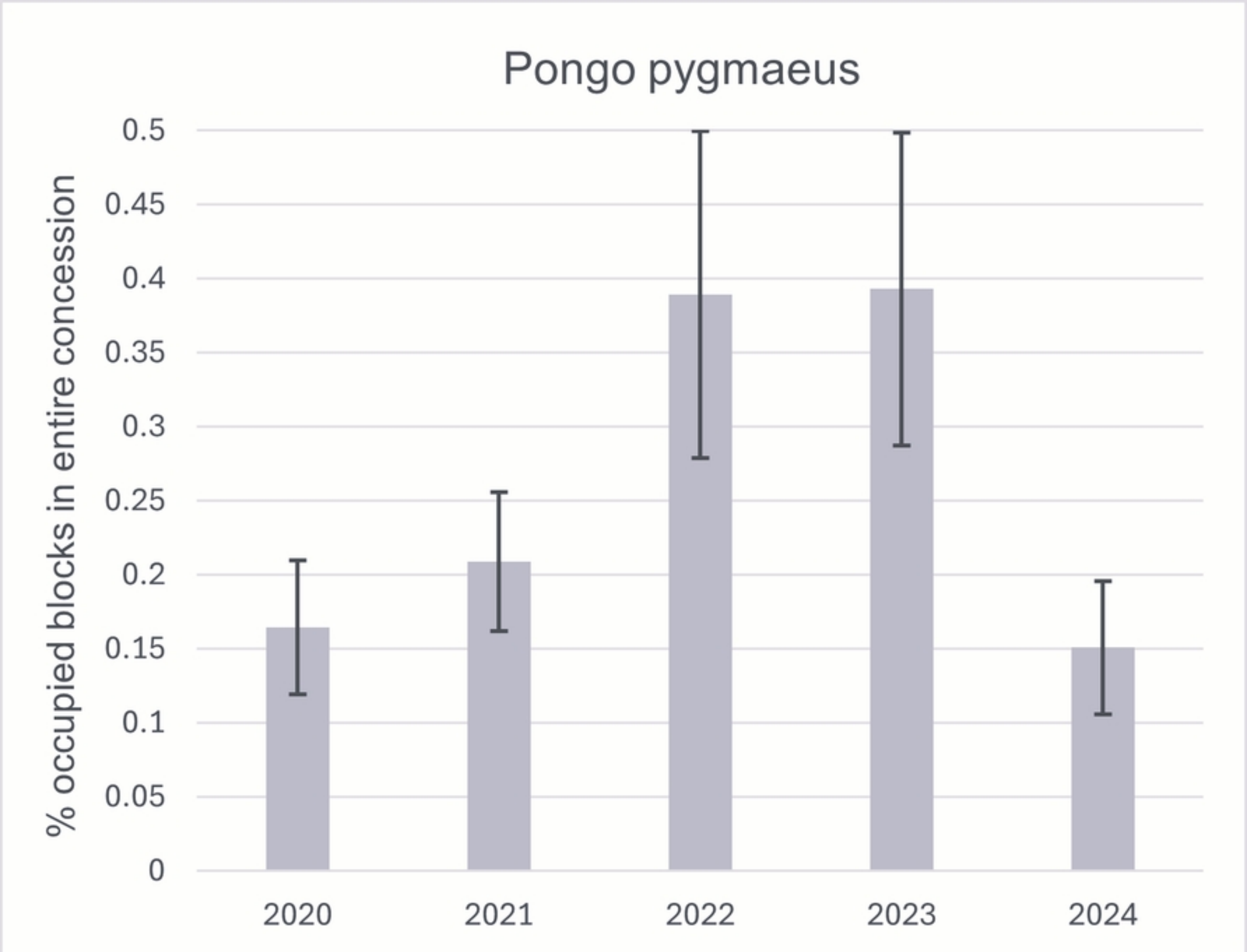
Pongo pygmaeus
% occupied blocks in entire concession
0.5
0.45
0.4
0.35
0.3
0.25
0.2
0.15
0.1
0.05
0
2020
2021
2022
2023
2024

Figure 3A

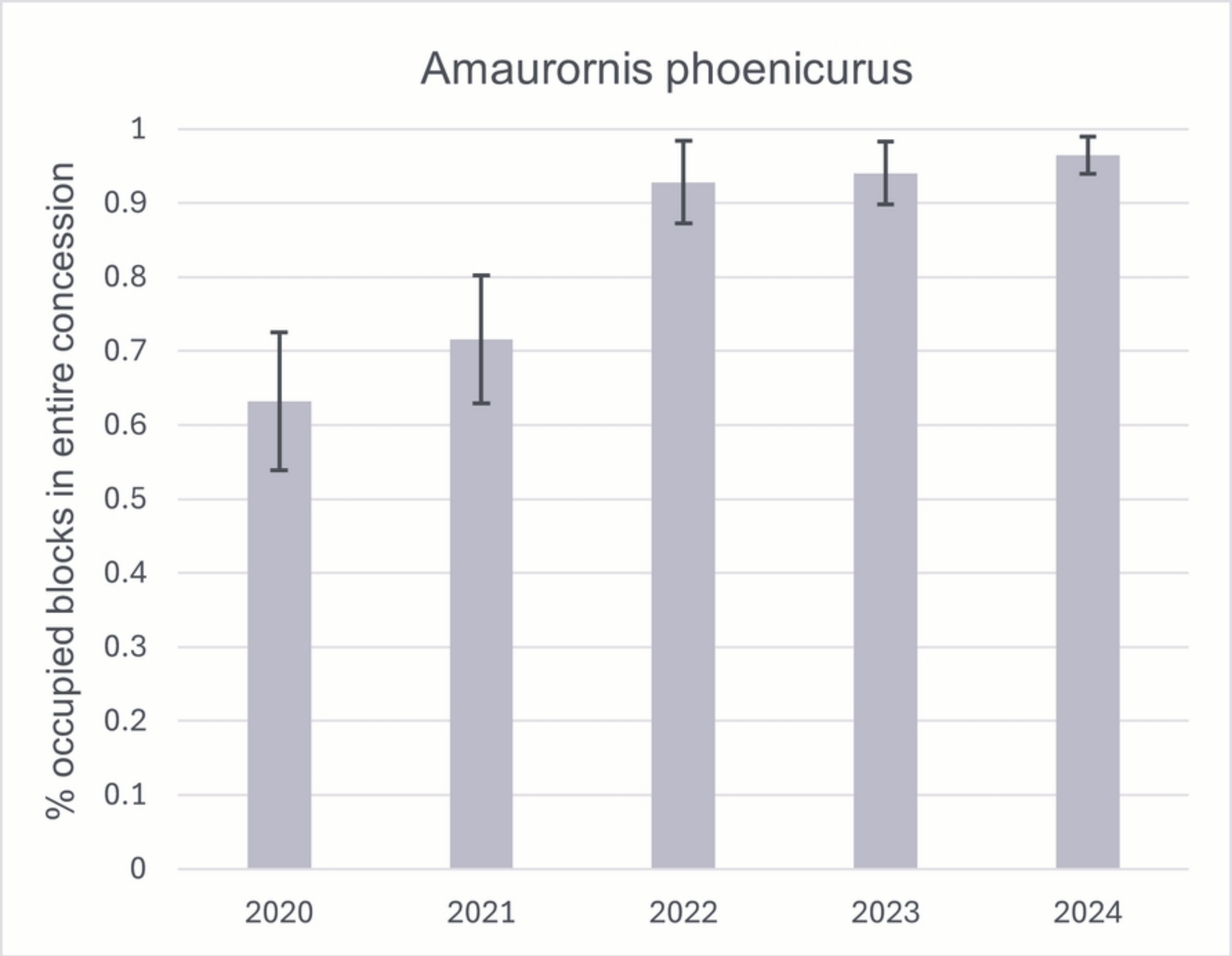
Amaurornis phoenicurus
% occupied blocks in entire concession
1
0.9
0.8
0.7
0.6
0.5
0.4
0.3
0.2
0.1
0
2020
2021
2022
2023
2024

Figure 3B

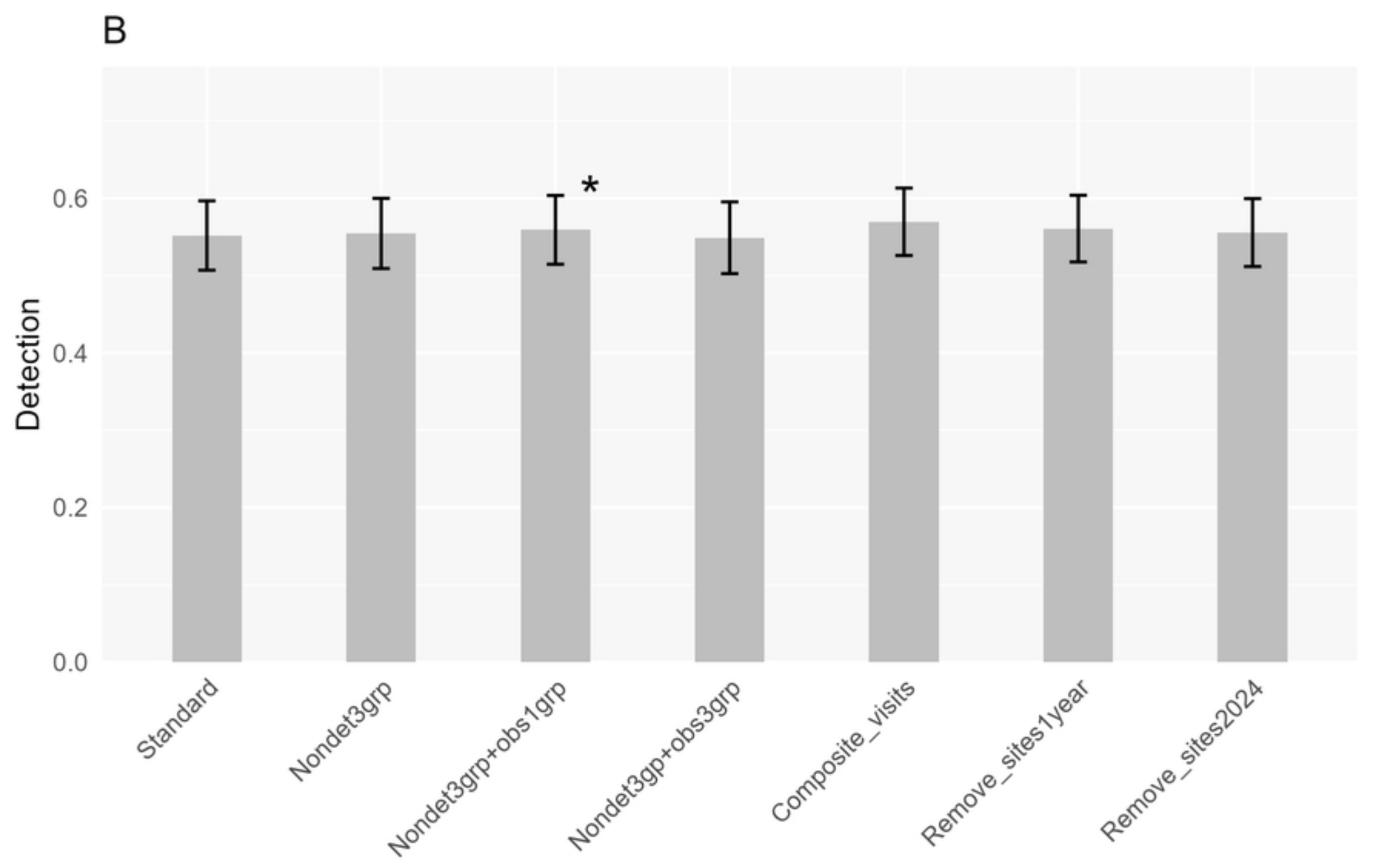
B
Detection
0.0
0.2
0.4
0.6
*
Standard
Nondet3grp
Nondet3grp+obs1grp
Nondet3gp+obs3grp
Composite_visits
Remove_sites1year
Remove_sites2024

Figure 4A

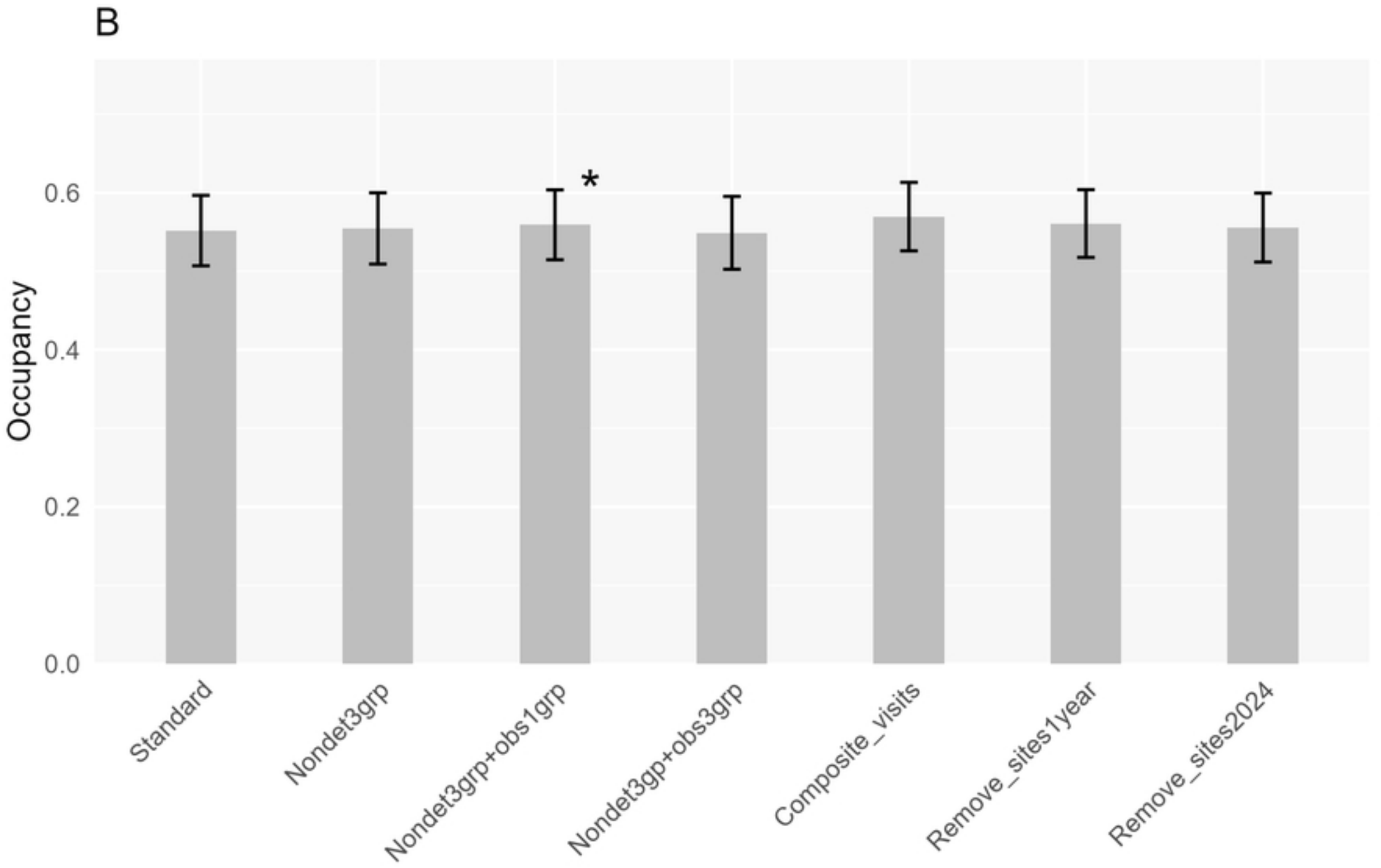
B
Occupancy
0.0
0.2
0.4
0.6
*
Standard
Nondet3grp
Nondet3grp+obs1grp
Nondet3gp+obs3grp
Composite_visits
Remove_sites1year
Remove_sites2024

Figure 4B