1 **Threatened species impact assessments: survey effort requirements based**
2 **on criteria for cumulative impacts**

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18 ABSTRACT

19 **Aim:** Environmental Impact Assessments (EIAs) often involve establishing whether a species
20 of concern is present at the site considered for development. When surveys falsely conclude
21 that sites are unoccupied, species prevalence in the region is cumulatively reduced. We argue
22 that setting an acceptable level of induced decline in species occurrence provides a defensible
23 strategy to determine minimum survey effort requirements. We investigate methods for
24 setting such requirements.

25 **Location:** Eastern Australian, although we demonstrate methods applicable wherever species
26 detection data are available to inform survey design.

27 **Methods:** We use probability theory to investigate required survey effort when aiming to
28 limit decline in species occurrence. We use optimization tools to provide a method that, in
29 addition, minimizes overall survey costs. We demonstrate the methods using data for an
30 Australian gliding marsupial.

31 **Results:** A method based on ensuring a constant probability of occupied site
32 misclassification directly links with a prescribed acceptable decline in occurrence.
33 Optimization results indicate that, under particular conditions, a cost-efficient survey effort
34 allocation can be achieved by setting a constant posterior probability of occupancy at sites
35 where the species is not detected, provided the target level is set in accordance with the
36 acceptable decline in occurrence. Our results provide a critical examination of the approach
37 recently proposed by Wintle *et al.* (2012) for determining minimum survey effort
38 requirements.

39 **Main conclusions:** EIA survey effort requirements should explicitly link uncertainty in
40 establishing species absence with the broader consequences of failing to detect species

41 presence in places subject to proposed impacts. A direct method, which involves keeping a
42 constant probability of occupied site misclassification, only requires information about
43 species detectability. Alternatively, a method that minimizes overall survey costs can be used.
44 This approach also requires occupancy probability estimates so its performance relies on
45 availability of an informative species distribution model.

46 **Keywords** (6-10): environmental impact assessment, false absence, imperfect detection,
47 monitoring, occupancy survey, *Petauroides volans*, survey effort

48 INTRODUCTION

49 Surveys that seek to establish whether a species can be considered absent or not from a site
50 play a role in a range of scenarios: from the ecological study of diversity, species
51 composition and turnover (McArdle 1990; Olea and Mateo-Tomás 2011) to more applied
52 settings such as the surveillance for invasive species (Hauser and McCarthy 2009),
53 conservation planning (Olea and Mateo-Tomás 2011) or the declaration of species extinction
54 (Reed 1996). Such surveys of species occupancy are particularly relevant for environmental
55 impact assessments (EIAs), which, among other things, aim to determine whether
56 development can be allowed to proceed at a site despite the risk of adversely affecting a
57 threatened species that might occupy the site. The accuracy of occupancy surveys has
58 implications for conservation. If the presence of a species of concern is overlooked, the site
59 might not receive proper protection or management. However, full certainty regarding
60 species absence from a site can never be achieved practically when the detection of species is
61 imperfect. Some uncertainty must be accepted; an important part of survey design is,
62 therefore, identifying the amount of effort needed to satisfy conservation goals.

63 The design of EIA occupancy surveys is fundamentally affected by the fact that the costs of
64 detecting and missing the species are borne by two distinct agents that have different
65 objectives: ‘society’ and developers (Fig. 1a). There are other applications in which a single
66 agent bears all these costs (Fig. 1b). For instance, in invasive species surveillance, the costs
67 of surveying, early management of sites (triggered by detection) and late management of sites
68 (as a consequence of the species going undetected in the survey despite being present) are
69 typically borne by the same agent, and can all be directly expressed in monetary terms. This
70 situation gives rise to an immediate economic trade-off with respect to survey effort, and
71 lends this type of problem to be naturally framed in terms of total cost optimization in a

72 decision-analytic framework (Hauser and McCarthy 2009; Guillera-Arroita et al. 2014). The
73 situation is different in the context of EIA surveys. There is no naturally emerging trade-off
74 to balance the economic and social costs of development and therefore regulation is needed:
75 regulators have to set the minimum survey effort with which developers need to comply. This
76 requirement should ultimately consider the consequences that false negatives (failed
77 detections when the species is present) can have on the *species*.

78 A common approach to design occupancy surveys determines the amount of effort needed to
79 ensure that the probability of misclassifying an occupied site as empty is at a level considered
80 acceptable (McArdle 1990). This method has been applied to inform surveys for a range of
81 taxa including amphibians (Parris et al. 1999; Pellet and Schmidt 2005), reptiles (Kéry 2002)
82 including birds (Olea and Mateo-Tomás 2011), mammals (Wintle et al. 2005; Guillera-
83 Arroita et al. 2010) and plants (Garrard et al. 2008). Hereafter, we refer to this strategy as
84 ‘method 1’. The rationale behind ‘method 1’ has an analogy in statistical terms (Reed 1996):
85 we have a ‘null hypothesis’ that the species is present at the site, and we want to evaluate
86 whether this hypothesis can be rejected based on the observed survey data; the probability of
87 wrongly establishing species absence (hereafter $\text{Pr}(\text{undet}|\text{occ})$) is analogous to the probability
88 of Type I error or significance level.

89 Wintle *et al.* (2012) pointed out that it is not rare to find misinterpretations of the above
90 probability as the probability that the species is present at a site where it has not been
91 detected (hereafter $\text{Pr}(\text{occ}|\text{undet})$). Indeed, confusing a conditional probability with its inverse
92 is a common logical fallacy (Bar-Hillel 1980); importantly these two quantities represent
93 different things (Fig. 2). Investing enough survey effort at a site to ensure that the probability
94 of misclassifying the site as empty is 0.05 does not imply that, if not detected, the species is
95 present with probability 0.05. Wintle *et al.* (2005; 2012) explained how survey design would

be approached if the aim were to keep $\Pr(\text{occ}|\text{undet})$ at a given level. However they did not explore the interpretation and implications for the species of using such strategy (hereafter ‘method 2’).

In this paper we investigate methods to determine survey effort requirements for EIA occupancy surveys while explicitly considering the survey objectives. We argue that the determination of minimum survey effort requirements should be underpinned by explicit assessment of the broader consequences of failing to detect species present in places subject to proposed impacts. In other words, survey design should reflect our tolerance of the *cumulative* impact that development can potentially have on the species. With this in mind, we reinterpret the method traditionally used for setting minimum survey effort requirements (‘method 1’) and evaluate the implications of using instead the method proposed by Wintle *et al.* (2012) (‘method 2’). We show that ‘method 1’ satisfactorily provides a direct link to the cumulative impacts of development on the species. We then demonstrate how, although not providing such a direct link, ‘method 2’ can be a suitable and cost-efficient strategy under particular conditions and provided a meaningful probability target is chosen. We discuss how the performance of ‘method 2’ depends on the availability of quality data about the species distribution. We illustrate the application of these methods by designing surveys for the greater glider *Petauroides volans*.

SURVEY EFFORT REQUIREMENTS FOR EIAs

Model and probabilities

In this section, we review some basic concepts relevant for the rest of the paper. We consider a sampling protocol in which a number of surveys is carried out at a site to determine whether a species is present. We assume independence among surveys, no changes in the occupancy status of the site during the survey period and no false detections. We denote ψ_i the

probability that site i is occupied by the species, p_i the probability of detecting the species during a survey if site i is occupied, and K_i the number of surveys carried out at that site.

Three probabilities are particularly relevant for our discussion (Fig. 2). First, the probability that the species remains undetected after K_i surveys conditional to the site being occupied

$$\Pr(\text{undet}|\text{occ}) = (1 - p_i)^{K_i}. \quad (1)$$

Second, the probability that the site is occupied conditional on the species not being detected in K_i surveys, which is calculated using Bayes' theorem as (Wintle et al. 2005)

$$\Pr(\text{occ}|\text{undet}) = \frac{\Pr(\text{occ}) \Pr(\text{undet}|\text{occ})}{\Pr(\text{undet})} = \frac{\psi_i(1 - p_i)^{K_i}}{\psi_i(1 - p_i)^{K_i} + (1 - \psi_i)}. \quad (2)$$

Third, the joint probability that the species is present and remains undetected at the site after K_i surveys

$$\Pr(\text{occ}\&\text{undet}) = \psi_i(1 - p_i)^{K_i}. \quad (3)$$

Let us now consider that we have some knowledge about p_i and ψ_i (*e.g.*, the predictions obtained from a model) that we can use to inform the design of our current survey. One strategy ('method 1') is to keep the probability of occupied site misclassification, $\Pr(\text{undet}|\text{occ})$, at a level considered acceptable; we denote that level $\alpha^{[1]}$. From equation 1 we deduce that the number of visits required at site i for $\Pr(\text{undet}|\text{occ})$ to be at a given level $\alpha^{[1]}$ is

$$K_{M_i}^{[1]} = \frac{\ln(\alpha^{[1]})}{\ln(1 - p_i)}. \quad (4)$$

An alternative strategy ('method 2') is to keep the probability of occupancy at sites where the species is not detected during the survey, $\Pr(\text{occ}|\text{undet})$, at a level rendered acceptable; we

140 denote that level $\alpha^{[2]}$. From equation 2, we have that the number of visits required at site i for
 141 $\Pr(\text{occ}|\text{undet})$ to be at a given level $\alpha^{[2]}$ (or below) is

$$142 \quad K_{M_i}^{[2]} = \begin{cases} \frac{\ln\left(\frac{1 - \psi_i}{\psi_i} \cdot \frac{\alpha^{[2]}}{1 - \alpha^{[2]}}\right)}{\ln(1 - p_i)}, & \text{if } \alpha^{[2]} \leq \psi_i \\ 0, & \text{otherwise.} \end{cases} \quad (5)$$

143 Assuming that surveys continue only until the species is detected, up to a maximum of K_{M_i}
 144 surveys, the expected number of surveys that would actually be carried out at a site i is (see
 145 Appendix S1.a in Supporting Information for derivation)

$$146 \quad \mathbb{E}[K_i] = (1 - \psi_i)K_{M_i} + \psi_i \frac{p_i^*}{p_i}, \quad (6)$$

147 where $p_i^* = 1 - (1 - p_i)^{K_{M_i}}$ is the probability of detecting the species at the site if occupied,
 148 *i.e.* $1 - \Pr(\text{undet}|\text{occ})$.

149 **Linking survey effort to the acceptable cumulative impacts of development**

150 Broadly, the objective of the regulator is to ensure that the potential impacts of developments
 151 on a species are acceptable. The regulator's role involves setting requirements: how much
 152 survey effort (here number of surveys, K_{M_i}) developers have to expend at a site proposed for
 153 development to “prove” that the species is absent and so to be allowed to proceed (or proceed
 154 without extra costs of mitigating or offsetting the impact). Here we argue that survey effort
 155 requirements consider the broad consequences that false negatives can have on the species. A
 156 defensible approach is to focus on the proportional decline in species occurrence that would
 157 potentially be induced by developments over the whole area of interest (*i.e.*, the area that is
 158 considered subject to development). The idea is to take into account the *cumulative impacts*
 159 of developments, ensuring that site-specific survey effort determinations consider the

consequences that multiple individual development actions would eventually have for the species. Occupancy declines are often used as a measure of extinction risk. For instance, the proportional decline in area of occupancy over an interval of time is an element considered by the IUCN in the criteria for assessing the conservation status of species (IUCN 2001).

Interpretation of proposed methods for setting EIA survey requirements

We can now evaluate the two methods proposed in the literature for establishing occupancy survey effort requirements in the context of EIAs, from the point of view of the cumulative impacts of development for the species. We assume that sites are developed if the species is not detected and that development causes local extinction. The method traditionally proposed ('method 1'), which relies on keeping $\Pr(\text{undet}|\text{occ})$ at a given target level for all sites (i.e., follow eqn. 4, e.g. Kéry 2002), has the benefit of a clear interpretation in terms of the cumulative impact of future development for the species. The target level chosen for $\Pr(\text{undet}|\text{occ})$ directly represents the eventual proportional decline d in species occupancy if all the sites are candidates for development using this rule. In other words, $\Pr(\text{undet}|\text{occ})$ represents the proportion of occupied sites lost to development (Fig 2a). For instance, if species occupancy probability across the area of interest is initially ψ and the allowed error level is 5% (i.e., we set a target $\Pr(\text{undet}|\text{occ}) = \alpha^{[1]} = 0.05$), the expected species occupancy after all sites are considered for development would be $\psi_f = \Pr(\text{occ}\&\text{det}) = \Pr(\text{det}|\text{occ})\Pr(\text{occ}) = (1 - \alpha^{[1]})\psi = 0.95\psi$. That is, species occupancy is expected to decline by 5% within that geographic domain (i.e., $d = 0.05$). These simple calculations obviously disregard other factors that might drive further occupancy changes during this period. The key is that, by design, the relative impact that false absences in EIA surveys can have on the status of the species is known and this is independent of its actual prevalence.

In contrast, ‘method 2’, which addresses survey design by setting instead a target level for $\Pr(\text{occ}|\text{undet})$ (i.e., follow eqn. 5; Wintle et al. 2012), does *not* have a straightforward interpretation in terms of the eventual consequences of future development for the species. The chosen target level, $\alpha^{[2]}$, represents the prevalence of the species in the sample of sites that are allowed to proceed to development (Fig. 2b). However, this is not directly a quantity of interest in our context. We instead are concerned about the chances that occupied sites will be lost to development (Fig. 2a). A given target $\alpha^{[2]}$ can be translated into the corresponding target levels for the probability of occupied site misclassification that are implicitly set at each site i . These probabilities are

$$\alpha_i^{[1]} = \begin{cases} \frac{\alpha^{[2]}}{1 - \alpha^{[2]}} / \frac{\psi_i}{1 - \psi_i}, & \text{if } \alpha^{[2]} \leq \psi_i \\ 1, & \text{otherwise.} \end{cases} \quad (7)$$

Following ‘method 2’ hence implies that, the lower ψ_i , the higher the accepted probability of falsely establishing absence ($\alpha_i^{[1]}$) and consequently fewer non-detections are needed to declare species absence. At sites where occupancy probability is lower than the target level (i.e., $\psi_i < \alpha^{[2]}$) a 100% error is allowed. Therefore, no surveys are required, leading to an automatic loss if the site were occupied by the species. To understand the impact that setting a particular target level $\alpha^{[2]}$ can have on the *overall* population, one needs to consider the average occupancy probability over the area of interest ($\bar{\psi}$), as the same target $\alpha^{[2]}$ leads to different declines depending on $\bar{\psi}$ (Fig. 3). Disregarding for simplicity the saturation to one in eqn. 7, we obtain that the species occupancy decline resulting from setting a target level $\alpha^{[2]}$ for $\Pr(\text{occ}|\text{undet})$ is

$$d = \frac{\sum_{i=1}^n (\psi_i \alpha_i^{[1]}) / n}{\bar{\psi}} = \frac{\alpha^{[2]}}{1 - \alpha^{[2]}} / \frac{\bar{\psi}}{1 - \bar{\psi}},$$

204 where $\bar{\psi} = \frac{1}{n} \sum_{i=1}^n \psi_i$, and n is the total number of sites; correspondingly, the target $\alpha^{[2]}$ that
 205 leads to an overall occupancy decline d is

$$206 \quad \alpha^{[2]} = \frac{\bar{\psi}d}{\bar{\psi}d + (1 - \bar{\psi})} \cdot \quad (8)$$

207 In summary, a given target $\alpha^{[2]}$ results in very different declines depending on the species: a
 208 small decline if a species is common (high $\bar{\psi}$), with greater declines the rarer a species is
 209 (Fig. 3 and Fig. S1). This strongly warns against determining survey effort requirements
 210 using ‘method 2’ by simply setting an arbitrary target level for $\Pr(\text{occ}|\text{undet})$.

211 **Setting cost-efficient survey requirements (assuming surveys stop after detection)**

212 We can reconsider the determination of survey effort requirements with the aim of setting a
 213 rule that, while meeting our constraint in terms of maximum allowed overall occupancy
 214 decline d , minimizes the *overall* survey effort for the developers (i.e. the combined expected
 215 survey effort required over all the potential sites). We will refer to this approach as ‘method
 216 3’. We solve this constrained optimization using the Kuhn-Tucker conditions (Winston 2004,
 217 pp. 670-675) treating for simplicity the number of visits as a continuous variable. We do not
 218 discuss any further the details of this optimization because our focus is on interpreting the
 219 meaning of the different survey design methods rather than on the mathematical derivation (a
 220 detailed step-by-step explanation of the derivation is available in Appendix S1.b). Here we
 221 simply present a summary of the results (box in Figure 4), a series of equations and the
 222 algorithm for calculating site-specific survey effort requirements. We also note that ‘method
 223 3’ allocates survey effort with priority to sites with high occupancy and detectability (the
 224 expression in eqn. 9 decreases as the odds of site occupancy increase and as detectability
 225 increases).

Exploration of the optimization results leads to a noteworthy finding for the situation in which detection probability is equal across sites (*i.e.*, $p_i = p$), and some survey effort is requested at all sites (*i.e.*, $s = n$), which happens when all sites fulfil the condition

$$\frac{\psi_i}{1 - \psi_i} > \frac{\bar{\psi}d}{1 - \bar{\psi}}, \quad (13)$$

that is, when the occupancy probability of any site is not too low compared to the average (more precisely, when the odds ratio between ψ_i and $\bar{\psi}$ is larger than d). In this case, the optimal survey effort requirement is given by a simpler expression (Appendix S1.b)

$$K_{M_i} = \frac{1}{\ln(1 - p)} \ln \left(\frac{1 - \psi_i}{\psi_i} \cdot \frac{\bar{\psi}d}{1 - \bar{\psi}} \right), \quad i = 1, 2, \dots, n.$$

This expression corresponds to keeping a constant $\Pr(\text{occ}|\text{undet})$ across sites (eqn. 5), as in ‘method 2’, with the target level $\alpha^{[2]}$ for $\Pr(\text{occ}|\text{undet})$ chosen to ensure that the occupancy decline meets target d (eqn. 8). This link between ‘method 3’ and ‘method 2’ provides a formal interpretation of the design strategy proposed by Wintle *et al.* (2012) and helps us understand its applicability. The result implies that, under certain limited conditions, a suitable and cost-efficient survey effort allocation can be achieved with ‘method 2’, provided the target level is set in accordance with the acceptable decline in occurrence.

Setting cost-efficient survey requirements (assuming maximum survey costs at all sites)

In general, we expect occupancy surveys to terminate after the first detection of the species. Hence, our cost minimization above is made with respect to the *expected* survey effort required at each site. We can obtain an equivalent solution for scenarios where survey costs are directly proportional to the level of effort requested to provide evidence of species absence, *i.e.* K_{M_i} . For instance, this could happen if surveys involve post-processing of

samples (e.g. camera-trap data or DNA analysis), which is carried out after all K_{M_i} survey visits are completed. Since we believe this scenario is less likely, we only present these results in detail in Appendix S1.c. Here we highlight a finding obtained when considering scenarios where detectability is constant (*i.e.*, $p_i = p$) and some survey effort is requested at all sites (which here happens if $\psi_i > \bar{\psi}d$). It can be shown that, in such scenarios, setting cost-efficient survey effort requirements corresponds to keeping a constant $\text{Pr}(\text{occ}\&\text{undet})$ across sites, with the target level for $\text{Pr}(\text{occ}\&\text{undet})$ chosen to ensure that the occupancy decline is our target d (*i.e.*, $\alpha^{[3]} = \bar{\psi}d$).

CASE STUDY: MINIMUM SURVEY EFFORT REQUIREMENTS FOR THE GREATER GLIDER

The greater glider *Petauroides volans* is a nocturnal folivorous gliding marsupial endemic to eastern Australia. It inhabits eucalyptus-dominated forests and has a distribution ranging from northern Queensland to central Victoria. It depends on old-growth forest elements including trees with large hollows for nesting and is therefore of management concern in areas subject to timber harvesting or other activities such as fire management that can remove large, old trees. Greater gliders are primarily detected using nocturnal visual spotlight search (DSE 2011). In a study in southeastern Australia, Wintle *et al.* (2005) estimated that the probability of detecting the species at sites where present was 0.5 (95% CI: 0.37-0.65) for a single survey based on 40 minutes of spotlighting within a circular area of 80 m radius. We used this estimate to derive survey effort requirements using the methods discussed in the previous section.

To obtain estimates of greater glider occupancy probabilities, we built a species distribution model (SDM) using a nation-wide database of greater glider detection records derived from state-owned datasets (see Appendix S3 for details about data compilation and modeling). We

fitted a set of generalized linear models (GLM) in R (R Development Core Team 2011) to variables derived from nationally mapped datasets reflecting mean temperatures, precipitation, solar radiation and forest height (Simard et al. 2011; Williams et al. 2012) which are thought to influence the distribution of the greater glider (Wintle 2003). We carried out model selection using AIC to identify the best model in the candidate set. The data available did not allow us to account for detectability explicitly in our SDM (but we explore the potential implications of this and other aspects of SDM quality in Appendix S4; see *Discussion*). We undertook a 10-fold cross-validation (Hastie et al. 2009) to estimate the predictive performance of the chosen model in terms of its calibration, measured using Miller's calibration statistic (Pearce and Ferrier 2000), and predictive discrimination, measured using the area under the receiver operating characteristics curve (ROC: Pearce and Ferrier 2000). The 10-fold cross-validation indicated that the model had excellent calibration and good predictive discrimination. The GLM fitted to the data was used to predict the probability of greater glider occupancy at all 1km grid cells across forested areas in mainland eastern Australia (Fig. 4).

Assuming a maximum acceptable occupancy decline of 10%, using the direct method ('method 1') we obtain that $K_M = 3.3$ unsuccessful visits are required before establishing species absence at any site. Using the method that minimizes overall expected survey costs ('method 3'), survey effort requirements vary from 0 to 11.9 visits depending on the characteristics of the sites (Fig 5), with a greater number of non-detections required at those sites predicted to be more likely to contain the species. The expected number of visits ($\mathbb{E}[K_i]$) that would need to be carried out ranges from 0 to 2.6 (mean 1.87), while with the direct method ranges from 1.8 to 3.3 (mean 2.55). Hence, 'method 3' implies 26.6% less survey effort than 'method 1' overall. Savings depend on the assumed detectability and the decline

level accepted. For instance, considering in our glider scenario $p = 0.25$ and $d = 0.30$, in survey effort savings are about 35%.

DISCUSSION

EIA survey design: problem framing and key findings

We have dealt with the design of occupancy surveys that are aimed at establishing the presence/absence of a species from a site at a particular instance as part of EIAs. We found that being explicit about the risk context allows proposed survey methods to be meaningfully interpreted and correctly applied. Our work highlights the need to address study design with full consideration of the goals pursued by the survey and the specific characteristics of the problem at hand. Not all ‘occupancy surveys’ are the same. There are other types of ‘occupancy surveys’, associated with problems involving different assumptions and goals; consequently their design is best approached from a different angle. For instance, we briefly discussed how the design of similar surveys can be addressed in the context of invasive species surveillance by minimizing total costs (Hauser and McCarthy 2009; Guillera-Aroita et al. 2014). Another important type of ‘occupancy surveys’ are those aimed at estimating the *proportion* of occupied sites across an area while accounting for imperfect detection (MacKenzie et al. 2002); a sensible target for their design is to maximize estimator precision in some form (MacKenzie and Royle 2005; Bailey et al. 2007; Guillera-Aroita et al. 2010; Guillera-Aroita and Lahoz-Monfort 2012).

We have argued that meaningful minimum survey effort requirements for EIA surveys should be predicated on the tolerable (to a regulator on behalf of society) *overall* decline in species occurrence caused by development of areas that were incorrectly classified as not containing the species of interest. Deriving survey effort requirements by setting a constant $\text{Pr}(\text{undet}|\text{occ})$ at all sites (‘method 1’), as traditionally proposed, has the benefit of a direct

link with the eventual occupancy decline. Wintle *et al.* (2012) suggested that $\text{Pr}(\text{occ}|\text{undet})$ might be a more useful criterion for EIA survey design because it assigns less survey effort at sites deemed *a priori* less likely to contain the species. However, a strategy based on keeping a constant $\text{Pr}(\text{occ}|\text{undet})$ at all sites ('method 2') does *not* have a direct interpretation in terms of the consequences of eventual development for the species. A given probability target leads to very different occupancy declines depending on the prevalence of the species, with declines increasing for less common species. This warns against determining survey effort requirements using 'method 2' by simply setting an arbitrary target level for $\text{Pr}(\text{occ}|\text{undet})$.

The probability $\text{Pr}(\text{occ}|\text{undet})$ that is the focus in 'method 2' directly relates to the proportion of sites that are occupied among those proceeding to development. In some applications, the equivalent proportion might be the most meaningful quantity to focus on as a target. For instance, in surveys aimed at establishing whether a site is clean of a toxic pollutant prior to allowing habitation, a logical aim is to ensure that the proportion of approved sites that are polluted is small enough. As a contrast, in our EIA context, rather than worrying about the proportion of developed sites that contained the species, we worry about the proportion of occupied sites that would eventually be lost (Figure 1). This difference in aims has its roots in a key difference between these two applications regarding the implications of occupancy and detection. In the pollutant case, "occupied" sites are detrimental (*i.e.*, polluted) and non-detection means that a site is kept (*i.e.*, allowed for inhabitation); the worry is in controlling the chances that the sites kept are "bad". In the EIA case, occupied sites are beneficial (*i.e.*, the species is present) and non-detection means that a site is lost (*i.e.*, developed and the species removed); the worry is in controlling the chances that "good" sites are lost.

Despite not being suitable as a target by itself, we found that a strategy based on keeping $\text{Pr}(\text{occ}|\text{undet})$ at a constant level can be a cost-efficient optimal design strategy, provided the chosen target level for $\text{Pr}(\text{occ}|\text{undet})$ is appropriately coupled to the acceptable occupancy

decline. This observation follows because, under particular conditions, ‘method 2’ is equivalent to the cost optimization method we analyse (‘method 3’). This property only holds where the detection probability in the EIA surveys is the same for all sites, survey costs are proportional to the number of survey visits carried out (*i.e.*, surveys stop after first detection), and there are no sites with very low occupancy probabilities compared to the mean (eqn. 13). Yet, these are conditions that might frequently apply when designing EIA surveys and, although we also provide the optimization results for the more general case, our finding is noteworthy as it conveniently implies a relatively simple solution to the problem of identifying the design that minimizes overall survey costs. We also found that, when survey costs are proportional to the number of survey visits required, a strategy based on choosing a target value for $\Pr(\text{occ} \& \text{undet})$ is the most cost-efficient under equal detectability.

Both under ‘method 1’ and under the cost-optimization ‘method 3’, surveys are designed to meet a target acceptable decline in overall species occupancy. The difference between the methods is in the specification of the site-specific survey efforts that are required to meet that decline target. Cost optimization for survey design ultimately leads to reduced survey effort for sites with lower occupancy probability, that is, a larger proportion of occupied sites will potentially be removed from lower occupancy probability categories. This can be desirable if lower occupancy corresponds to poorer habitat quality. However, it can be problematic if it corresponds to a naturally lower occupancy in a different habitat type that is also of interest. In such situations stratifying the design of surveys based on habitat type might be valuable if a species is to be protected across all habitat types. Note also that cost savings can get diluted if surveys involve multiple species of different characteristics.

In our derivations we have considered a sampling protocol with discrete separate visits, yet equivalent results and discussion apply to continuous sampling protocols (Garrard et al. 2008;

Guillera-Arroita et al. 2011) where survey design amounts to determining the length of a single survey visit (Appendix S1.d).

EIA survey design: implementation issues

Our findings provide the theoretical framework for EIA occupancy survey design. However, implementation must consider practicalities that largely revolve around the three main pieces of information required: the acceptable decline level, species detectability and species occupancy. The choice of acceptable decline level is not a statistical issue; it involves considering the rarity of the species as well as value judgments. The existence value of a species, and therefore the ‘cost’ of a given increase in extinction risk, are inevitably subjective. Nevertheless, it is important that such valuation is explicit and that survey design faithfully reflects those social or policy preferences.

Regarding detectability, it is crucial to ensure that the estimates used refer, or are at least comparable, to the survey methods that are to be used. The regulator needs to specify the sampling protocol, so that, to the extent possible, the assumed detectability per visit is as expected. The survey effort calculations assume independence between surveys. A correlation in outcomes results in a smaller effective survey effort and, therefore, a larger Type I error (McArdle 1990). Ideally, direct estimates of species detectability would be obtained. However, this might not always be feasible, especially when dealing with many species. Alternatives include the use of estimates from similar species or extrapolation through models that link detectability to species traits (Garrard et al. 2013).

‘Method 3’ also requires knowledge about species occupancy probabilities, i.e. the predicted distribution of the species, giving an estimate of the probability that a species will occupy various parts of the landscape (usually obtained using a distribution model). Therefore, its performance depends not only on the quality of the estimates of detectability, but also on the

quality of the SDM predictions, both of which are used to prioritize survey effort allocation across sites. As the SDM becomes less informative, we can less categorically establish where the species is present or where it is absent. Hence, the efficiency gain introduced by ‘method 3’ is reduced as relevant covariates are left out of the model (Table S4.1a in Appendix S4), which may also imply that the target decline is not met. In the extreme case where the SDM involves no covariates (predictions are constant across space), ‘method 3’ is equivalent to ‘method 1’. Furthermore, when disregarded, imperfect detection can bias the estimation of species distributions (MacKenzie et al. 2002; Tyre et al. 2003; Lahoz-Monfort et al. 2014). The impact of ignoring detectability in the SDM is only a reduction in the efficiency of ‘method 3’ provided that detectability is constant across all sites (this refers to the detectability in the surveys that collected the data used to fit the SDM). However, disregarding detectability when heterogeneous may have more serious consequences, leading to unknown potential declines (Table S4.1b).

Another limitation is that “presence-background” methods often used to model habitat relationships at best only predict an index of *relative* habitat suitability, which is not a true occupancy probability (Hastie and Fithian 2013; Phillips and Elith 2013; Guillera-Arroita et al. in press), while the optimization calculations in ‘method 3’ require knowledge about *probability* of occupancy (ψ). Hence, predictions from such SDMs are in principle unsuitable for use with ‘method 3’ unless they can be re-calibrated to provide probability of occupancy estimates. However, note again that the impact of scaling occupancy probabilities by a constant is only on the efficiency of ‘method 3’ (as in the case of disregarding constant detectability); the percentage decline target is still met (Table S4.2). The quality of presence-background SDMs can also be compromised by sampling bias (Phillips et al. 2009; Guillera-Arroita et al. in press).

Given the risks when design rules involving poor estimates of ψ are applied, ‘method 1’ provides a *more robust* approach as it only requires information about species detectability and hence it is particularly advisable where the quality of available SDMs is questionable. Whether or not it is worth using ‘method 3’ in preference to ‘method 1’ will depend on the degree of uncertainty in the SDM, the magnitude of the financial saving that can be obtained using ‘method 3’, the risk of failing to meet the expected decline, and the degree to which that risk can be tolerated by regulators (the trade-off between providing financial savings for developers and risk).

Considerations about uncertainty are also relevant for implementation of the methods. The estimates of occupancy and detection probabilities that are used for survey design will have some associated uncertainty and a decision needs to be made regarding how to account for parameter uncertainty when setting survey effort requirements. Possible approaches include choosing to be conservative or taking most likely values, while formal methods to account for this type of uncertainty in the optimization could be considered as a future development (McCarthy et al. 2010). Also, detectability may differ among survey visits due to external factors. Strategies to deal with this include choosing a representative (or conservative) detectability value and accounting for potential major sources of heterogeneity when standardizing the sampling protocol. Other aspects related to species occupancy and detection include that probability values depend on the scale at which occupancy and detectability are measured (site size), and a meaningful scale might vary among species and applications. On the other hand, development applications can cover areas of arbitrary size, so survey effort requirements must be scaled according to the application at hand.

Finally, we note that survey design methods underlying impact assessments usually treat occupied sites as effectively replaceable. This is indeed the general assumption behind the

methods we have investigated. In the context of the cost optimization method, we have discussed the value of stratifying the design when different habitats are of distinct value for the species. Similarly, sites in different areas may be important at different stages of the life history of the species (e.g. overwintering vs. breeding grounds) and may require separate attention. In these situations, the acceptable impacts of development may differ among strata. Spatial considerations can also be important. For instance, the impacts of development at a site can be greater if it disrupts critical metapopulation processes such as dispersal. Here we have provided general guidance about how to weigh up key considerations in impact assessment survey design: the probability of site occupancy, the probability of detection if present, the cost of surveys and some expression for the cost of failing to detect a species where present (in terms of contribution to an overall decline). While each of these parameters may vary in particular assessment situations, responsible assessment should involve explicit consideration of each using the sort of logic we have presented.

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BIOSKETCH

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Author contributions: G.G-A. and J.L-M. conceived the ideas; G.G-A. derived the optimization results; B.W. built the glider distribution model; G.G-A. led the writing, and all authors contributed substantially to revisions.

SUPPORTING INFORMATION

Additional supporting information may be found in the online version of this article:

Appendix S1 Mathematical derivations

Appendix S2 Computer code

Appendix S3 Greater glider distribution model

Appendix S4 Exploration of the effect of SDM quality on method 3

Figure S1 Graphical illustration of the outcome of surveys based on methods 1 and 2

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Figures

Figure 1 Expected costs influencing the design of surveys aimed to detect a species in: (a) a system with two agents (impact assessment) and (b) a system with one agent (management of an invasive species). Arrows indicate who bears the cost and how expected costs are affected by increasing survey effort (dashed = increase, solid = decrease). Increasing survey effort increases the expected cost of surveys and the expected cost associated with detection, while it decreases the expected cost associated with the species going undetected. In (a) there is no naturally emerging trade-off so regulation about survey effort is needed to balance economic and social costs. In (b) the same agent bears all costs, some of which increase with survey effort while others decrease, resulting in a natural trade-off that directly leads to an optimal amount of survey effort.

Figure 2: Interpretation of (a) $\Pr(\text{undet}|\text{occ})$, (b) $\Pr(\text{occ}|\text{undet})$ and (c) $\Pr(\text{undet}\&\text{occ})$. Each circle represents a site (grey = occupied, white = empty). The top arrow ('1') indicates sites where the species is detected, and the bottom arrow ('0') sites without detection. The ratio between the number of sites with a thick outline and the number of sites encompassed by the dashed line represent the proportions associated with each of these three probabilities. In threatened species impact assessments we focus in controlling (a), *i.e.*, the proportion of occupied sites lost. In some other applications, such as the determination of whether sites are pollutant-free to be acceptable for inhabitation, the natural focus is in controlling (b), *i.e.*, the proportion of polluted ("occupied") sites among those approved.

Figure 3: Proportional decline in species occupancy eventually induced by development when survey effort requirements are set following ‘method 2’, that is, by keeping a fixed probability of occupancy at sites where the species is not detected, $\Pr(\text{occ}|\text{det})$. Lines correspond to different target probability levels (0.05: solid, 0.10: dashed, 0.15: dotted). The decline is plotted as a function of initial average species occupancy (*i.e.*, prevalence). The same target leads to very different occupancy declines depending on how common a species is, with higher declines for rare species.

Key quantities - The expected survey effort at site i , $\mathbb{E}[K_i]$, is given in eqn. 6, and $\sum_{i=1}^n \psi_i (1 - p_i)^{K_{M_i}} / n\bar{\psi}$ is the expected proportional decline in species occupancy due to the cumulative effects of development.

Problem formulation - Choose the set of site-specific minimum survey effort requirements K_{M_i} that is the solution to the following constrained optimization: $\min \{\sum_{i=1}^n \mathbb{E}[K_i]\}$ subject to $\sum_{i=1}^n \psi_i (1 - p_i)^{K_{M_i}} / n\bar{\psi}$ (with all $K_{M_i} \geq 0$).

Optimization solution - It is optimal to arrange sites in ascending order of the following magnitude

$$\frac{1}{p_i} - \frac{1 - \psi_i}{\psi_i \ln(1 - p_i)}, \quad (9)$$

requiring survey effort to be allocated only to the bottom s sites, where s is a number to be determined (hereafter we denote S the set of sites where survey effort is requested and S' the set of remaining sites). The optimal survey effort is

$$K_{M_i} = \begin{cases} \frac{1}{\ln(1 - p_i)} \ln \left(\frac{1 - \psi_i}{\psi_i \ln(1 - p_i)} \left(\frac{1}{p_i} - \frac{\lambda_{n+1}}{n\bar{\psi}} \right)^{-1} \right), & i \in S \\ 0, & i \in S', \end{cases} \quad (10)$$

where λ_{n+1} fulfills

$$\frac{1}{n\bar{\psi}} \left[\sum_{i \in S} \frac{1 - \psi_i}{\ln(1 - p_i)} \left(\frac{1}{p_i} - \frac{\lambda_{n+1}}{n\bar{\psi}} \right)^{-1} + (n - s) \bar{\psi}_{S'} \right] = d, \quad (11)$$

with $\bar{\psi}_{S'}$ denoting the average occupancy of sites in set S' . Once sites are prioritized according to eqn. 9, the number of sites s is determined as that fulfilling the following condition

$$n\bar{\psi} \left[\frac{1}{p_s} - \frac{1 - \psi_s}{\psi_s \ln(1 - p_s)} \right] < \lambda_{n+1} \leq n\bar{\psi} \left[\frac{1}{p_{s+1}} - \frac{1 - \psi_{s+1}}{\psi_{s+1} \ln(1 - p_{s+1})} \right], \quad (12)$$

where p_s and ψ_s are the detection and occupancy probabilities at the s^{th} ranked site.

Summary algorithm: The procedure to find the optimal survey effort requirements involves the following steps (we provide code for implementation in Appendix S2):

- 1) order sites according to the priority given by eqn. 9;
 - 2) use eqn. 11 to obtain (numerically) λ_{n+1} for all potential set sizes $s = 1, \dots, n$;
 - 3) retain the set size s that fulfills eqn. 12, which minimizes expected survey cost;
 - 4) keep the corresponding set of K_{M_i} as the solution to the problem (eqn. 10);
-

Figure 4 Resulting expressions for the optimization in ‘method 3’. Details about the derivation are provided in Appendix S1 and code for implementation in Appendix S2.

Figure 5 The predicted distribution of suitable habitat for greater gliders in eastern Australian forests (left) and the locations of glider detections since 1990 (right). See details in Appendix S3.

Figure 6 Greater glider minimum survey effort requirements (left) and expected number of survey visits needed (right) based on the cost optimization method ('method 3'), assuming an acceptable occupancy decline of 10% (i.e. $d = 0.1$) and detectability at occupied sites $p = 0.5$.