This is the peer reviewed version of the following article: Marshall, E., Valavi, R., O'Connor, L., Cadenhead, N., Southwell, D., Wintle, B.A. and Kujala, H. (2020) Quantifying the impact of vegetation-based metrics on species persistence when choosing offsets for habitat destruction. *Conservation Biology*, 13600; which has been published in final form at **https://doi.org/10.1111/cobi.13600**.

Quantifying the impact of vegetation-based metrics on species persistence when choosing offsets for habitat destruction

Abstract

Developers are often required by law to offset environmental impacts through targeted conservation actions. Most offset policies specify metrics that are used to calculate offset requirements, usually assessing vegetation condition or quality. Despite widespread use, there is little evidence to support the effectiveness of vegetation-based metrics for ensuring biodiversity persistence. Here, we compared performance of several commonly used metrics by simulating development and restoration within the Hunter Region of New South Wales, Australia. We measured development impacts and offset requirements using four metrics: 1) area only; 2) vegetation condition only; 3) area x habitat suitability, 4) condition x habitat suitability. We simulate development and subsequent offsetting through restoration within a virtual landscape, linking simulations to population viability models for three species; the squirrel glider (*Petaurus norfolcensis*), the powerful owl (*Ninox strenua*) and the northern brown bandicoot (*Isoodon macrourus*). Our results show that 1) gains in suitable habitat did not translate through to species persistence. No net loss could be achieved when performance of offsetting was assessed in terms of amount of suitable habitat, but not when outcomes were assessed in terms of persistence; 2) Maintenance of persistence was more likely when impacts were avoided, giving further support to better enforce the avoidance stage of the mitigation hierarchy; 3) When developments do impact areas of high suitability for species, it is essential that species are explicitly accounted for in the offset, rather than just vegetation or habitat alone. Declines due to a failure to account directly for species population dynamics and connectivity may overshadow the benefits delivered by producing large areas of suitable habitat; 4) Our modelling framework with just three species showed that the benefits delivered by offsets are species-specific, such that implementing offsets will be much more challenging in reality where multiple species need to be considered.

Introduction

Biodiversity offsetting is used around the globe to deliver conservation gains aimed at achieving a no net loss or a net gain of biodiversity to compensate for impacts caused by development (Bull et al. 2016a). However, lack of consistency in offset policies at different levels of governance (e.g. state versus federal), and different stages of offsetting make it difficult to consistently define the meaning of no net loss (Maron et al. 2018). Moreover, it is unclear whether offsets achieve their claimed conservation outcomes under current frameworks (zu Ermgassen et al. 2019). The ineffectiveness of biodiversity offsets has been attributed to inconsistent and unclear biodiversity metrics (Gibbons et al. 2018), and inadequate post-implementation monitoring and compliance at offset sites (Theis et al. 2019).

Accurately measuring biodiversity is challenging, and most offsetting metrics consist of simple habitat condition or area scores calculated based on vegetation surrogates (Marshall et al. 2019; zu Ermgassen et al. 2019). Popular offsetting metrics assign condition or quality scores to a site by assessing, scoring and weighting several vegetation attributes (Oliver et al. 2014). In the case of habitat condition scores varying across an area of impact, it is common to simply sum scores such that, for example, 25 hectares of perfect condition vegetation would receive the same overall offset score as 50 hectares of vegetation with half the condition (Marshall et al. 2019).

Reliance on habitat and vegetation-based offsetting metrics (Gibbons et al. 2018) can be problematic when such metrics do not strongly correlate with the ecological features that an offsetting program seeks to conserve (Kujala et al. 2015). Research has demonstrated that habitat attributes and vegetation-based surrogates fail to capture the extent of biodiversity that is often claimed (Cristescu et al. 2013; Hanford et al. 2016). Moreover, current offsetting metrics are likely to result in undervaluation of degraded or smaller patches, even when these are of high ecological importance (Wintle et al. 2019).

The premise of many offset policies is to ensure persistence of populations, species, ecosystems and communities (Maron et al. 2012). However, this goal is not currently supported by relevant metrics. No net loss policies require that offset sites deliver the same or higher vegetation condition scores compared to impact sites, but achieving this target alone may not ensure these sites will deliver long-term benefits or ensure persistence for populations or species (Gardner et al. 2013). Therefore, assessment of the ability of vegetation condition to act as a surrogate for species persistence would appear to be a necessary first step in offset policy evaluation. Research has suggested that combining vegetation condition measures with explicit species assessments in an adaptive management framework can be an effective approach to offset management (Drielsma et al. 2016). However, little quantitative research has tested how vegetation-based offset metrics truly function in relation to species persistence targets (Gelcich et al. 2017).

To address this research gap, we developed a simulation framework to compare performance of commonly used vegetation-based offset metrics with alternative metrics that include more detailed species data. Our framework combines a model simulating development and offsetting, with population viability analyses for three species in the Hunter Region, New South Wales (NSW), Australia. We aimed to understand how vegetation-based offset metrics capture development impacts on 1) habitat suitability and 2) persistence of target species.

Methods

Study region

The Hunter Region in New South Wales (NSW), Australia (Fig 1) extends approximately 120 to 310 km north of Sydney. The region has a long history of agriculture and coal mining, with future mines expected to occupy 21% of the Hunter Valley (90,500 hectares; Kujala, Whitehead, & Wintle, 2015). Future developments are intended to be targeted towards already cleared or degraded areas, however, there will likely be impacts on biodiversity which will need to be offset (NSW Government; Planning and Environment 2016).

Target species

This region is home to several susceptible species including the three considered here; the squirrel glider, powerful owl, and northern brown bandicoot. Squirrel gliders are hollow nesting, gliding marsupials widely distributed along the east coast of Australia (Sharpe & Goldingjay 2017). The powerful owl is a large owl with a wide home range found within south-eastern Australia (Soderquist & Gibbons 2007). Both species are considered vulnerable in New South Wales. Lastly, northern brown bandicoots are medium-sized ground dwelling marsupials, with short life-cycles, high population growth rates and moderate dispersal (Ramalho et al. 2018). This species is not currently considered threatened. These species were primarily selected because they are sufficiently well studied to build spatially explicit population models and because two are considered vulnerable in New South Wales, although none are federally listed. They would therefore be unlikely to be considered in offsets under the national legislation but may be assessed under state offset policies.

Habitat and species data

We used two types of raster maps to conduct our simulations; a vegetation condition map and species habitat suitability maps (Kujala et al. 2015). The vegetation condition map estimates the native vegetation condition for the Hunter Region at 100 m grid cell resolution, scored between zero and one depending on known land use categories. A zero value indicates areas containing no natural vegetation, whereas a value of 0.5 could indicate agricultural land with remnant vegetation. A value of one indicates extant and relatively undisturbed vegetation (Appendix A1). Species distribution models (SDMs; 100 m grid cell resolution) were built for each species using *MaxEnt* (Elith et al. 2011; Kujala et al. 2015), again with values ranging between zero and one (Appendix A2). Being based on presence-only data, the SDMs represent only relative habitat suitability for each species in the region (Guillera-Arroita et al. 2015). We interpreted MaxEnt's logistic output values as roughly indicative of relative carrying capacity (Merow et al. 2013), giving the fraction of maximum carrying capacity attainable for each species (Appendices A). As MaxEnt outputs are not comparable between species, we examined relative changes in total habitat suitability between scenarios only within species. Here we assumed that restoration efforts ensured maximum potential habitat suitability values from this layer could be achieved.

We multiplied our vegetation condition layer and SDMs to produce a proxy of current habitat suitability (Appendix A3) for each species, with values ranging between zero and one. The resulting current habitat suitability map for each species represented the baseline used to compute the impacts of each development and its required offset. This was also the baseline map used to define landscape structure and determine carrying capacity in our spatially explicit population viability analyses (PVAs).

Modelling framework

We used the above raster layers as inputs to simulate development impacts and calculate offset requirements within R v3.6 (The R Foundation for Statistical Computing 2017). All development and offset simulations used our current habitat suitability map as a baseline for each species. Each subsequent raster generated by the simulations was then used to represent habitat changes within the PVAs for each species.

Our modelling framework involved five steps: 1) simulate developments; 2) calculate offset requirements; 3) restore vegetation until offset requirements are met; 4) construct a landscape patch structure for the species in RAMAS; and 5) build population models in RAMAS for the species to predict population persistence (Fig 2). Restoration was assumed to return vegetation condition back to the highest level immediately. This assumption was consistent across all metrics. Because we were interested in comparing relative performance of offset metrics, rather than providing realistic predictions about restoration success, it was deemed unnecessary to perfectly characterise variation in restoration outcomes. Nonetheless, we acknowledge that this is a coarse simplification of likely success of restoration efforts (Maron et al. 2012). All R scripts have been deposited in a dedicated GitHub repository (Appendices B).

Development impacts

We simulated four development scenarios for each species; S1) large developments with strict avoidance; S2) large targeted developments; S3) small developments with strict avoidance; and S4) small targeted developments. All four scenarios had a total development footprint of 100,000 hectares (approximately 21% of the landscape). Large developments were each 10,000 hectares in size and occurred ten times in the landscape during one simulation (S1, S2). Small developments were 1,000 hectares and occurred 100 times (S3 and S4). S1 and S3 represented our strict avoidance scenarios where development was targeted towards the least suitable habitat for each species, based on species current habitat suitability. This aligns with offsetting best practices where strict adherence to the avoidance stage of the mitigation hierarchy is ideal (Phalan et al. 2017). In targeted development scenarios S2 and S4, development was equally directed to high suitability areas to represent a worst-case scenario. We also simulated two additional development scenarios where impacts were allocated randomly (Appendix B1; D7). Each scenario was repeated 50 times to account for spatial stochasticity. Development impacts reduced vegetation condition of impacted grid cells to zero.

Offset metrics and simulation

We calculated offset exchanges using four metrics: 1) area only; 2) vegetation condition only; 3) area x habitat suitability, and 4) condition x habitat suitability. The first metric (Area) was based solely on the area of habitat lost due to development, and the offset simply restored the same area of habitat elsewhere. The second metric (Condition) was calculated by summing the current habitat condition lost due to development, and restoration was required to enhance habitat condition by an equivalent amount elsewhere. The third metric (AreaXSDM), as with Area only, was based on the area lost due to development but differed in that offsets were restricted to an equivalent area in the landscape that was also suitable habitat for the species as modelled by the SDM (after applying a species-specific threshold to delineate habitat suitability; Appendix C1). The last metric (ConditionXSDM), as with Condition only, offset the summed current habitat condition lost due to development but restoration was again restricted to parts of the landscape which were suitable for the species as modelled by the SDM (Appendix B2).

These metrics are intended as coarse simplifications of offset metrics currently used in Australia. In New South Wales, offset legislation relies on the Biodiversity Assessment Method (BAM) which incorporates 30 measures of habitat and landscape to assess biodiversity (NSW Office of Environment and Heritage 2018). These are largely focused on habitat features. When species are accounted for in the BAM metric, they are usually a threatened or at-risk species, and measurements generally include species presence or absence as well as species habitat suitability. These are measures accounted for in the above metrics, albeit simplistically. We used a multiplier of two for all offset targets, meaning that offsets needed to deliver gains twice the amount lost. Large multipliers (e.g. ten or higher) are more likely to ensure no net loss , however, relatively low multipliers (e.g. two or three) are commonly used in practice (Laitila et al. 2014; Bull et al. 2016b). Multipliers in the BAM vary between one and three and depend species' sensitivity to loss and their sensitivity to offset gains. Therefore, the multiplier of two we have used here accounts for a moderate to high sensitivity to loss and a moderate to high potential gain (NSW Office of Environment and Heritage 2018).

For all repetitions of our development scenarios we restored impacts using all four metrics. A starting point for restoration was randomly selected within a buffer zone around the development (Appendix B). Each cell neighbouring the starting point was searched and restored until the total offset requirement was met. At the end of each simulation an updated raster layer was generated with the simulated developments, and offsets added to the species current habitat suitability layer.

Spatially explicit Population Viability Analysis (PVA)

Population Viability Analyses (PVAs) estimates the probability of a species persisting in a landscape given its habitat requirements, dispersal ability and demographic variables (Akçakaya & Root 2005). We built spatially explicit PVAs for each species using the software RAMAS GIS v5.1. First, we used the current habitat suitability maps of the species to develop the baseline patch structure and to simulate population dynamics over a 100-year time period prior to any developments or offsets. Patch structure is delineated by RAMAS using a habitat suitability threshold and species-specific information on dispersal (Akçakaya & Root, 2005; Fig 1). We used the species-specific maximum training sensitivity plus specificity (MTSS; Cardador et al., 2018) as our threshold, which was extracted from the *MaxEnt* model outputs (Appendix C1). We derived species-specific dispersal and demographic parameters from the literature and tested them through sensitivity analyses (Appendix C1; D1). We then re-ran the PVAs for each species, replacing the baseline patch structures with those generated from development and offset simulations.

Scenario Analysis

We ran 50 simulations per development scenario and 50 corresponding restorations for each metric, for all three species, for which PVAs were run for 1000 replicates over 100 years. We used two measures to evaluate metric effectiveness: 1) percentage change in total Habitat Suitability (HS) from baseline, calculated using the species' updated raster maps; and 2) percentage change in average Estimated Minimum Abundance (EMA) from baseline, calculated from the PVAs. EMA is the smallest population size that occurs across the duration of a simulation averaged across replicates (Wintle 2013). We examined confidence intervals around the 50 repeats to assess correlations between metric use and changes in HS and EMA from baseline. We also assessed changes in landscape structure by comparing mean number and size of suitable habitat patches in the landscape with minimum and maximum EMA values (Appendix E1).

Results

Change in habitat suitability

Development impacts

Impacts of development on the percentage change in HS were consistent across species but varied between scenarios. Development had the greatest impact on HS when it was targeted towards high suitability areas (S2 and S4). On average our simulations caused a 10.5% decline in HS for our species in scenarios S2 and S4 (±0.8%; Fig 3). Comparatively, when development impacts strictly avoided areas of importance in the landscape (S1 and S3), species lost on average 1.7% of their habitat (± 0.5%; Fig 3).

Offset metrics

The effectiveness of offset metrics in compensating for development impacts on HS varied between development scenarios and species. However, the Area only approach consistently failed to achieve no net loss of HS for all scenarios and species (Fig 3). Thus, simply compensating for the area lost did not produce enough habitat to match development impacts. Under the avoidance scenarios (S1 and S3), the three remaining metrics achieved net gains in HS for all species (Fig 3). However, when developments were targeted (S2 and S4) the benefits delivered by most metrics – except ConditionXSDM – were smaller. AreaXSDM failed to achieve a no net loss for the powerful owl and northern brown bandicoot in S2 and for all three species in S4. This is likely because in high impact development scenarios, even when offsets are targeted towards high suitability pixels (e.g. AreaXSDM), simply matching area alone will not compensate for enough of the lost condition to return the overall HS back to the species baseline level.

ConditionXSDM produced net gains in all four development scenarios across all three species. Notably, when using the ConditionXSDM metric, since offset requirements were extremely high, around 24% and 28% respectively of powerful owl and northern brown bandicoot offset requirements in S2 and S4 were not met. In these scenarios the simulation ran out of habitat to restore to match high offset requirements and still resulted in large net gains in HS compared to baseline.

The Condition only approach also achieved no net loss and sometimes net gains in HS for all species and scenarios; however, gains were smaller than the ConditionXSDM metric (Fig 3). Compensating for condition, particularly when coupled with information on SDMs, resulted in larger offset areas than area-based metrics (Appendix E2). For all species the ConditionXSDM metric resulted on average in patches 1.4 times larger than the other three metrics and 1.7 times larger than the species baselines patch structure (Fig 5).

Change in Estimated Minimum Abundance (EMA)

Development impacts

Development impacts on EMA were not proportional to impacts observed on HS and varied between species and scenarios (Fig 4). Declines in EMA were less dramatic when the size of the development was small (Fig 4; S3, S4), except for the powerful owl, for which highest declines were observed under the small targeted scenario (S4). Development impacts on squirrel glider EMA were higher than the other two species, particularly when the developments were targeted (Fig 4; S2, S4). Under all four development scenarios, changes in northern brown bandicoot EMA were minimal and even showed a small net gain in S4 (Fig 4). This could be due to the high reproduction rates of northern brown bandicoots as well as the influence of development on the landscape structure which may have been more favourable for this species.

Offset metrics

The four offset metrics varied notably, between species and scenarios, in the benefits they delivered to population persistence but generally most of the metrics failed to achieve net gains. In our worst-case scenarios, S2 and S4, no net loss in EMA was only rarely achieved, only for the northern brown bandicoot and powerful owl in some replicates, and only when using Area only and AreaXSDM (Fig 4). Generally, all three species suffered significant population declines across all metrics even when these metrics resulted in significant gains in HS (e.g. ConditionXSDM; Fig 3).

Development impacts on squirrel glider EMA were best offset when using metrics which included species-specific information on habitat suitability (SDM, Fig 4). When development impacts were small, and a strict avoidance approach was taken the two SDM inclusive metrics were able to achieve net gains for the squirrel glider. Comparatively, no net loss of EMA for powerful owls was only achieved in some simulations, generally when using the Area metric (Fig 4), even though this metric failed to achieve a no net loss in HS (Fig 3). Similarly, not net loss was achieved for northern brown bandicoots in some replicates when using the two area-based metrics (Fig 4). Condition-based approaches only resulted in no net loss for northern brown bandicoots in some simulations when the development impacts were untargeted (Fig 4; S1, S3). Across all three species, the ConditionXSDM metric, which produced the largest gains in HS, frequently failed to compensate for declines in EMA. In powerful owls and northern brown bandicoots, the use of this metric resulted in larger declines than development on its own (Fig 4).

Landscape configuration and population declines

Scenarios that resulted in more patches, generally resulted in higher EMA values for all species (Fig 5). The largest declines in EMA occurred when the development or offsets reduced the number of patches available in the landscape. Furthermore, across all species EMA was highest when patch size was smaller although this relationship was not as clear for the squirrel glider (Fig 5). It appears that in scenarios where patch size was large, such as for the ConditionXSDM metric (Appendix E3), there was a corresponding decline in the number of patches available and overall lower EMA values relative to the species' baselines. This is clear in northern brown bandicoots and powerful owls where ConditionXSDM produced extremely large patches with fewer patches available overall (Fig 5). This suggests that, at least for these species, producing large continuous offset patches may not ensure population persistence is maintained. Instead, scenarios which resulted in maintaining multiple patches had overall the highest EMA (Fig 5).

Discussion

Our study quantitatively demonstrates how habitat loss and mitigation of these losses translates to species persistence. Here we found that when performance of offsetting is measured in terms of total habitat gains, achieving no net loss, and even net gains is feasible using the metrics we tested. This was particularly apparent when information on a species' habitat suitability was included in offset calculations. In all four development scenarios, metrics which accounted for SDM values delivered the highest net gains in habitat suitability (HS; Fig 3). This may be important when developments are likely to impact core habitats and therefore require offsets to be strategically assigned to areas of high suitability (Gordon et al. 2011). Conversely, offset trades based solely on area lost versus area gained failed in all cases to deliver a no net loss in HS for all three species (Fig 3). Thus, simply accounting for area resulted in offsets which were too small to match development impacts in terms of lost HS. This is consistent with previous research showing that offset trades using only area-based metrics are unlikely to achieve no net loss, particularly without significant multipliers (Bull et al. 2016b; Sonter et al. 2019).

Despite significant gains in HS, none of the metrics were consistently effective at offsetting development impacts on species' populations (Fig 4). This case study is a simplified version of current offset procedures and we have only applied it to three species. Commonly, practitioners need to design offsets to provide benefits for multiple target species simultaneously. Here we only focused on single species outcomes, to keep comparisons between metrics as transparent as possible. However, these results are naturally further complicated when considering how metric choice could interplay with multiple species priorities (Whitehead et al. 2017). Our results highlight that, relying on vegetation condition, or even changes in HS for target species, as a measure of offset success, can be misleading. This was apparent in the vastly different outcomes we observed between HS and EMA (Fig 3; Fig 4). Depending solely on HS could result in the false interpretation that offset actions are having long-term benefits for the target species. This could lead to exacerbated species declines and nudge species of least conservation concern towards a declining trajectory, even when every offset requirement is being met (Maron et al. 2015). This is also consistent with previous research demonstrating that restoration actions based on vegetation metrics alone do not effectively account for target species or populations (Cristescu et al. 2013; Hanford et al. 2016).

We also demonstrate the difficulty in achieving no net loss at a landscape scale (Peterson et al. 2018). Even when each individual offset action delivers a no net loss this may not result in a landscape level benefit for the species. All four of the metrics we tested failed to account for structural and functional changes in the landscape for all three species (Fig 5). Understanding how landscape structure and connectivity drive population trajectories is essential to evaluate the impacts caused by developments and offsets (Moilanen et al. 2005; Rubio et al. 2015). Whilst basic landscape metrics, such as patch size and distance, are usually incorporated into offset metrics (Gibbons et al. 2016), these still largely fail to capture development impacts on species or populations (Crouzeilles et al. 2015). Recent research has demonstrated the benefits of accounting for connectivity in the planning stage of offsets, at least in terms of achieving no net loss targets (Bergès et al. 2020). Here, we have quantified the potential consequences of not accounting for species-specific connectivity. Our results show that the negative impacts of using only habitat-based metrics may be significant, vary greatly between metrics, and most alarmingly, are likely to go unnoticed unless changes in population dynamics are explicitly tested. These findings provide strong support for earlier calls, that both structural (e.g. patch size and distance) and functional connectivity metrics (e.g. metapopulation connectivity and capacity; Bojkovic et al., 2015; Moilanen et al., 2005) should be accounted for in early stages of impact assessment and offset planning to avoid unexpected declines in populations and species (Tarabon et al. 2019).

Exhaustive collection of data on ecology and demographic processes driving persistence is obviously not possible for all species (Birkeland & Knight-lenihan 2016). However, increased availability of abundance and demographic data may fill this information gap over time. Failing to capture complex processes which are involved in driving changes in population persistence at a landscape level is likely to exacerbate biodiversity declines, such as we observed here (Maron et al. 2016). Assessing species-specific metrics such as abundance or density, which are generally driven by ecosystem processes (Otto et al. 2014), alongside vegetation condition metrics, may better enable offsets to capture the key species and populations managers are aiming to protect (Mckenney & Kiesecker 2010; Schmeller et al. 2017). Inclusion of these data into offset approaches would likely improve offset outcomes for rarer, low density species with large home ranges, such as the powerful owl. Similarly, our use of HS information here, though largely ineffective at accounting for population persistence, did demonstrate benefits for delivering habitat gains in comparison to area or condition only metrics. This approach may be effective for species whose abundance is linearly correlated with habitat suitability. For example, the net gains in HS delivered using the ConditionXSDM metric resulted in some success for the squirrel glider populations so long as impacts were avoided where possible and ideally small (Fig 4).

Recent shifts in policy requirements have promoted using HS information where possible and additional information on populations and abundance when required (Queensland Government 2014). Our use of species-specific HS was an attempt to reflect rapidly changing offset policies and increased interest in incorporating more species-specific information into offset calculations (Moilanen & Kotiaho 2018). Although SDMs do not capture population level processes (Kujala et al. 2018), they do provide a more accurate description of HS than simple vegetation-based metrics (Guisan & Thuiller 2005). Data required to build SDMs is becoming more prevalent and are relatively easy to access and collate at large scales (Boykin et al. 2012). Use of SDMs within biodiversity offsetting may also provide developers with information necessary to avoid areas where biodiversity impacts are likely to be significant (Houdet & Chikozho 2014). Moreover, SDMs can explicitly target restoration efforts towards areas where habitat gains will be largest (Whitehead et al. 2017).

It is likely that there is no single way of overcoming the challenges associated with offsetting for every scenario and species. From this research we can make four key conclusions and recommend ways forward for offset policies. Firstly, and reinforcing earlier calls (Phalan et al. 2017), avoidance of impacts through careful placement of new development is the most effective way of ensuring that species persistence is maintained for important species. Given challenges associated with increasing complexity in current offsetting metrics, and the fact that some developments are not offsetable, avoiding and minimizing negative development impacts where possible is essential. Secondly, when developments do impact areas of high suitability for species, it is essential that species, not only their suitable habitat, are explicitly accounted for in offsets. We observed very different conservation outcomes when comparing habitat gains and species persistence. Ensuring the metrics used to assign offsets accurately reflect the values we aim to conserve is crucial (Cristescu et al. 2013; Hanford et al. 2016). This is further dependent on policy frameworks under which an offset is required, highlighting the importance of explicitly stating biodiversity targets in the planning stage (Maron et al. 2018).

Thirdly, whilst large offsets may have multiple benefits, this work demonstrates that more habitat does not necessarily translate into equal gains in persistence for all species. The implications of not accounting directly for species population dynamics and landscape structures may outweigh benefits delivered by producing large areas of suitable habitat (Figure 5). Where data is available, abundance and demographic variables should be included into offset calculations to ensure populations are tracked and development impacts on populations are accountable. Lastly, this work has demonstrated that benefits delivered by offsets are nuanced and species-specific. Therefore, impacts of metric choice should also be assessed for multiple species simultaneously to determine how these metrics align with achieving several persistence targets. These improvements may go some way towards mitigating development impacts on biodiversity and ensuring long-term conservation benefits.

References

Akçakaya HR, Root W. 2005. RAMAS GIS: Linking Spatial Data with Population Viability Analysis (version 5). Applied Biomathematics, Setauket, New York.

Bergès L, Avon C, Bezombes L, Clauzel C, Duflot R, Foltête JC, Gaucherand S, Girardet X, Spiegelberger T. 2020. Environmental mitigation hierarchy and biodiversity offsets revisited through habitat connectivity modelling. Journal of Environmental Management **256**.

Birkeland J, Knight-lenihan S. 2016. Biodiversity offsetting and net positive design. Journal of Urban Design **21**:50–66.

Bojkovic N, Petrovic M, Boz V, Anic I. 2015. Spatially continuous modeling approach for population persistence in road-fragmented landscapes. Applied Mathematical Modelling **39**:5174–5185.

Boykin KG, Kepner WG, Bradford DF, Guy RK, Kopp DA, Leimer AK, Samson EA, East NF, Neale AC, Gergely KJ. 2012. A national approach for mapping and quantifying habitat-based biodiversity metrics across multiple spatial scales. Ecological Indicators.

Bull JW, Gordon A, Watson JEM, Maron M, Carvalho S. 2016a. Seeking convergence on the key concepts in ‘no net loss’ policy. Journal of Applied Ecology **53**:1686–1693.

Bull JW, Lloyd SP, Strange N. 2016b. Implementation Gap between the Theory and Practice of Biodiversity Offset Multipliers. Conservation Letters **10**:656–669.

Cardador L, DÍaz-Luque JA, Hiraldo F, Gilardi JD, Tella JL. 2018. The effects of spatial survey bias and habitat suitability on predicting the distribution of threatened species living in remote areas. Bird Conservation International **28**:581–592.

Cristescu RH, Rhodes J, Frére C, Banks PB. 2013. Is restoring flora the same as restoring fauna? Lessons learned from koalas and mining rehabilitation. Journal of Applied Ecology **50**:423–431.

Crouzeilles R, Beyer HL, Mills M, Grelle CE V, Possingham HP. 2015. Incorporating habitat availability into systematic planning for restoration: A species-specific approach for Atlantic Forest mammals. Diversity and Distributions **21**:1027–1037.

DECCW. 2009. Lower Hunter Regional Conservation Plan.

Drielsma MJ, Foster E, Ellis M, Gill RA, Prior J, Kumar L, Saremi H, Ferrier S. 2016. Assessing collaborative, privately managed biodiversity conservation derived from an offsets program : Lessons from the Southern Mallee of New South Wales, Australia. Land Use Policy **59**:59–70. Elsevier Ltd.

Elith J, Phillips SJ, Hastie T, Dudík M, Chee YE, Yates CJ. 2011. A statistical explanation of MaxEnt for ecologists. Diversity and Distributions **17**:43–57.

Gardner TA et al. 2013. Biodiversity Offsets and the Challenge of Achieving No Net Loss. Conservation Biology:1–11.

Gelcich S, Vargas C, Carreras MJ, Castilla JC, Donlan CJ. 2017. Achieving biodiversity benefits with offsets : Research gaps , challenges , and needs. Ambio **46**:184–189. Springer Netherlands.

Gibbons P, Evans MC, Maron M, Gordon A, Le Roux DS, von Hase A, Lindenmayer DB, Possingham HP. 2016. A loss-gain calculator for biodiversity offsets and the circumstances in which No Net Loss is feasible. Conservation Letters **9**:252–259.

Gibbons P, Macintosh A, Louise A, Kiichiro C. 2018. Outcomes from 10 years of biodiversity offsetting. Gloabl Change Biology **24**:643–654.

Gordon A, Langford WT, Todd JA, White MD, Mullerworth DW, Bekessy SA. 2011. Assessing the impacts of biodiversity offset policies. Environmental Modelling and Software **26**:1481–1488. Elsevier Ltd. Available from http://dx.doi.org/10.1016/j.envsoft.2011.07.021.

Guillera-Arroita G, Lahoz-Monfort JJ, Elith J, Gordon A, Kujala H, Lentini PE, Mccarthy MA, Tingley R, Wintle BA. 2015. Is my species distribution model fit for purpose? Matching data and models to applications. Global Ecology and Biogeography **24**:276–292.

Guisan A, Thuiller W. 2005. Predicting species distribution : offering more than simple habitat models. Ecology Letters **8**:993–1009.

Hanford JK, Crowther MS, Hochuli DF. 2016. Effectiveness of vegetation-based biodiversity offset metrics as surrogates for ants. Conservation Biology **31**:161–171.

Houdet J, Chikozho C. 2014. The Valuation of Ecosystem Services in the Context of the new South African Mining and Biodiversity Guidelines : Implications for Theory and Practice. Page ALCRL 2014 International Conference - Sub - Theme 4.

Kujala H, Lahoz-monfort JJ, Elith J, Moilanen A. 2018. Not all data are equal : Influence of data type and amount in spatial conservation prioritisation. Methods in Ecology and Evolution.

Kujala H, Whitehead AL, Wintle BA. 2015. Identifying conservation priorities and assessing impacts and trade-offs of potential future development in the Lower Hunter Valley in New South Wales. Page The University of Melbourne, Melbourne, Victoria.

Laitila J, Moilanen A, Pouzols FM. 2014. A method for calculating minimum biodiversity offset multipliers accounting for time discounting, additionality and permanence. Methods in Ecology and Evolution **5**:1247–1254.

Maron M et al. 2016. Taming a Wicked Problem : Resolving Controversies in Biodiversity Offsetting. BioScience **66**:1–10.

Maron M, Brownlie S, Bull JW, Evans MC, von Hase A, Quétier F, Watson JEM, Gordon A. 2018. The many meanings of no net loss in environmental policy. Nature Sustainability **1**:19–27. Springer US. Available from http://www.nature.com/articles/s41893-017-0007-7.

Maron M, Bull JW, Evans MC, Gordon A. 2015. Locking in loss: Baselines of decline in Australian biodiversity offset policies. Biological Conservation **192**:504–512. Elsevier B.V. Available from http://dx.doi.org/10.1016/j.biocon.2015.05.017.

Maron M, Hobbs RJ, Moilanen A, Matthews JW, Christie K, Gardner TA, Keith DA, Lindenmayer DB, Mcalpine CA. 2012. Faustian bargains ? Restoration realities in the context of biodiversity offset policies. Biological Conservation **155**:141–148.

Marshall E, Wintle BA, Southwell D, Kujala H. 2019. What are we measuring ? A review of metrics used to describe biodiversity in offsets exchanges. Biological Conservation:108250. Elsevier. Available from https://doi.org/10.1016/j.biocon.2019.108250.

Mckenney BA, Kiesecker JM. 2010. Policy Development for Biodiversity Offsets : A Review of Offset Frameworks. Environmental Management:165–176.

Merow C, Smith MJ, Silander JA. 2013. A practical guide to MaxEnt for modeling species' distributions: What it does, and why inputs and settings matter. Ecography **36**:1058–1069.

Moilanen A, Franco AMA, Early RI, Fox R, Wintle BA, Thomas CD. 2005. Prioritizing multiple-use landscapes for conservation: methods for large multi-species planning problems. Proceedings of the Royal Society Biological Sciences **272**:1885–1891.

Moilanen A, Kotiaho JS. 2018. Planning biodiversity offsets: Twelve operationally important decisions.

NSW Government; Planning and Environment. 2016. Hunter Regional Plan 2036 Implementation Plan 2016-2018.

NSW Office of Environment and Heritage. 2018. Biodiversity Assessment Method Operational Manual – Stage 1. Available from www.environment.nsw.gov.au.

Oliver I, Eldridge DJ, Nadolny C, Martin WK. 2014. What do site condition multi-metrics tell us about species biodiversity? Ecological Indicators **38**:262–271.

Otto CR V, Roloff GJ, Thames RE. 2014. Comparing Population Patterns to Processes : Abundance and Survival of a Forest Salamander following Habitat Degradation. PLOS ONE **9**:1–8.

Peterson I, Maron M, Moilanen A, Bekessy S, Gordon A. 2018. A quantitative framework for evaluating the impact of biodiversity offset policies. Biological Conservation **224**:162–169.

Phalan B, Hayes G, Brookes S, Marsh D, Howard P, Costelloe B, Vira B, Kowalska A, Whitaker S. 2017. Avoiding impacts on biodiversity through strengthening the first stage of the mitigation hierarchy. Oryx.

Queensland Government. 2014. Queensland Environmental Offsets Policy, General Guide.

Ramalho CE, Ottewell KM, Chambers BK, Yates CJ, Wilson BA, Bencini R, Barrett G. 2018. Demographic and genetic viability of a medium-sized ground-dwelling mammal in a fire prone, rapidly urbanizing landscape. PLoS ONE **13**:1–21.

Rubio L, Bodin Ö, Brotons L, Saura S. 2015. Connectivity conservation priorities for individual patches evaluated in the present landscape: How durable and effective are they in the long term? Ecography **38**:782–791.

Schmeller DS et al. 2017. A suite of essential biodiversity variables for detecting critical biodiversity change. Biological Reviews. Available from http://doi.wiley.com/10.1111/brv.12332.

Sharpe DJ, Goldingjay RL. 2017. Home range of the Australian Squirrel Glider, Petaurus Norfolcensis (Diprotodontia). Journal of Mammalogy **88**:1515–1522.

Soderquist T, Gibbons D. 2007. Home-range of the Powerful Owl (Ninox strenua) in dry sclerophyll forest. Emu:177–184.

Sonter LJ, Barnes M, Matthews JW, Maron M. 2019. Quantifying habitat losses and gains made by U.S. Species Conservation Banks to improve compensation policies and avoid perverse outcomes. Conservation Letters:1–9.

Tarabon S, Bergès L, Dutoit T, Isselin-Nondedeu F. 2019. Maximizing habitat connectivity in the mitigation hierarchy. A case study on three terrestrial mammals in an urban environment. Journal of Environmental Management **243**:340–349. Elsevier. Available from https://doi.org/10.1016/j.jenvman.2019.04.121.

The R Foundation for Statistical Computing. 2017. RStudio.

Theis S, Ruppert JLW, Roberts KN, Minns CK, Koops M, Poesch MS. 2019. Compliance with and ecosystem function of biodiversity offsets in North American and European freshwaters. Conservation Biology **0**:1–12.

Whitehead AL, Kujala H, Wintle BA. 2017. Dealing with Cumulative Biodiversity Impacts in

Strategic Environmental Assessment: A New Frontier for Conservation Planning. Conservation Letters **10**:195–204.

Wintle BA. 2013. Principles of population viability analysis (PVA). Decision Point Online:1–6.

Wintle BA et al. 2019. Global synthesis of conservation studies reveals the importance of small habitat patches for biodiversity. Proceedings of the National Academy of Sciences **116**:909–914.

zu Ermgassen SOSE, Baker J, Griffiths RA, Strange N, Struebig MJ, Bull JW. 2019. The ecological outcomes of biodiversity offsets under “no net loss” policies: A global review. Conservation Letters:1–17. Available from https://onlinelibrary.wiley.com/doi/abs/10.1111/conl.12664.

Figures

Figure 1: Hunter Valley region, New South Wales, Australia.

Figure 2: Simulation modelling framework conducted within R (steps 1 to 3) and RAMAS GIS (steps 4 and 5). The maps represent habitat suitability on a scale of 0 to 1 with yellow indicating unsuitable habitat and the blue indicating most suitable habitat. The green squares (steps 2 and 3) represent grid cells in the landscape and their condition values. Development sites are chosen (the red points; step 1) and then cleared (red circles; step 1). The impacts of each development are calculated both in terms of area and condition lost (step 2). Vegetation condition is restored until the requirement is met either in terms of area or condition (step3). Each resulting map, including development without offsets and developments with offsets, is used in RAMAS GIS to build a patch map using the resulting landscape structure and species dispersal parameters (step 4). The patch map is then used in a spatially explicit population model which tracks abundance of the species through time (step 5).

Figure 3: Percentage change in Habitat Suitability (HS) from baseline (y-axis). Each column is a development scenario (S1: Large, Avoidance, S2: Large, targeted, S3: Small, Avoidance, and S4: Small, targeted) and each row is a species (squirrel glider, powerful owl and northern brown bandicoot). On the x-axis each metric is shown with confidence intervals (+/- SD) for each scenario, generated from 50 repetitions of each simulation. From left to right the first bar for each species (dark blue) represents the development impact, followed by Area only (blue), AreaXSDM (turquoise), Condition only (green), ConditionXSDM (yellow).

Figure 4: Percentage change in Estimated Minimum Abundance (EMA) from the species baseline. EMA (y-axis) was averaged across PVAS with the error bars demonstrating the variation in EMA produced by the simulation runs. Each column is a development scenario (S1: Large, Avoidance, S2: Large, targeted, S3: Small, Avoidance, and S4: Small, targeted) and each row is a species (squirrel glider, powerful owl and northern brown bandicoot). On the x-axis each metric is shown with confidence intervals (+/- SD) for each scenario, generated from 50 repetitions of each simulation. From left to right the first bar for each species (dark blue) represents the development impact, followed by Area only (blue), AreaXSDM (turquoise), Condition only (green), ConditionXSDM (yellow). Standard deviations are shown for each scenario, generated from 50 repetitions of each simulation.

Figure 5: Comparison of the Estimated Minimum Abundance values (y-axis) to average number of patches (x-axis; top panel) and the average size of patches (x-axis; bottom panel). The shapes indicate the metrics and the colours indicate the scenario (S1-S4). The black square with a cross through the middle represents the baseline value for number of patches relative to EMA. The trend line is the relationship between EMA and number or size of the patches as a linear regression.

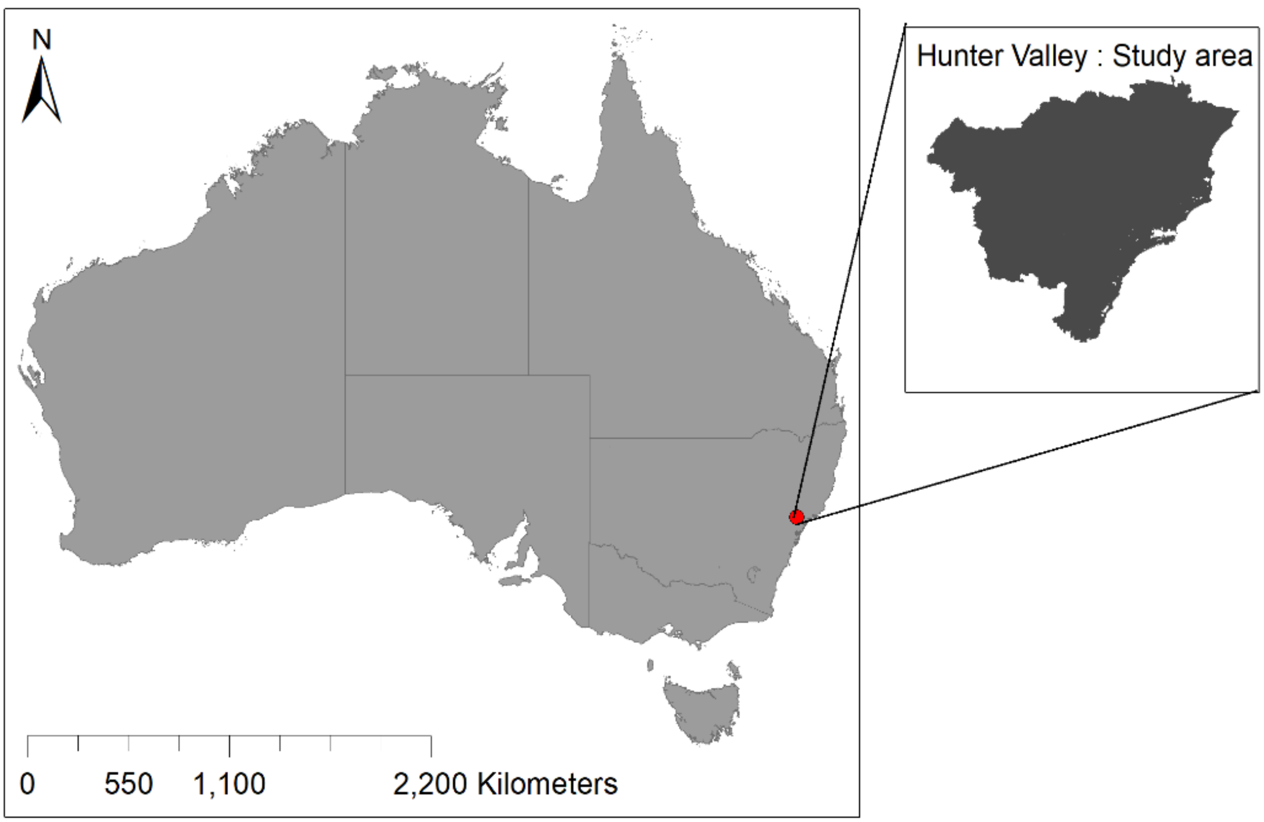

Figure 1: Hunter Valley region, New South Wales, Australia.

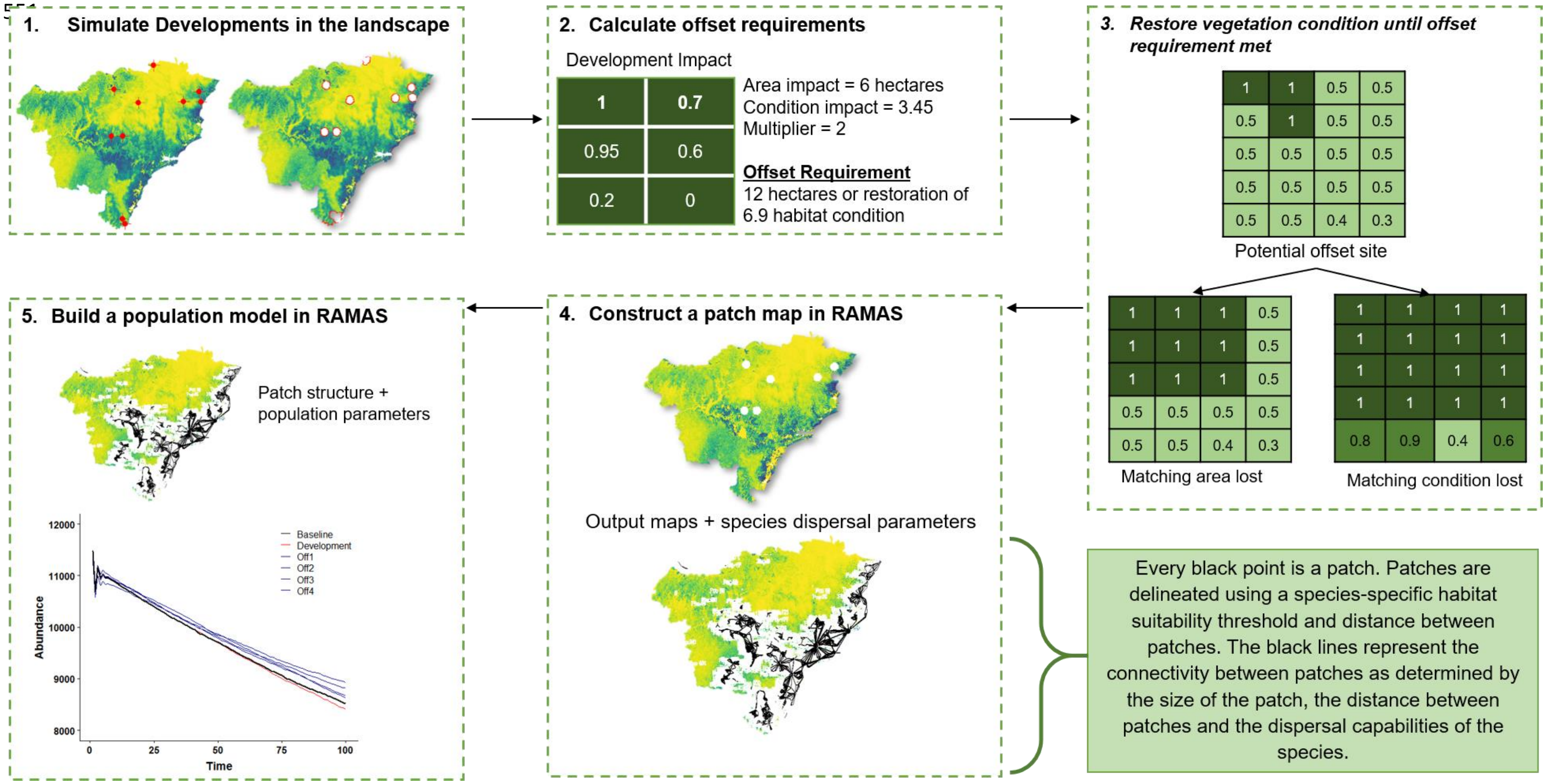

Figure 2: Simulation modelling framework conducted within R (steps 1 to 3) and RAMAS GIS (steps 4 and 5). The maps represent habitat suitability on a scale of 0 to 1 with yellow indicating unsuitable habitat and the blue indicating most suitable habitat. The green squares (steps 2 and 3) represent grid cells in the landscape and their condition values. Development sites are chosen (the red points; step 1) and then cleared (red circles; step 1). The impacts of each development are calculated both in terms of area and condition lost (step 2). Vegetation condition is restored using until the requirement is met either in terms of area or condition (step3). Each resulting map, including development without offsets and developments with offsets, is used in RAMAS GIS to build a patch map using the resulting landscape structure and species dispersal parameters (step 4). The patch map is then used in a spatially explicit population model which tracks abundance of the species through time (step 5).

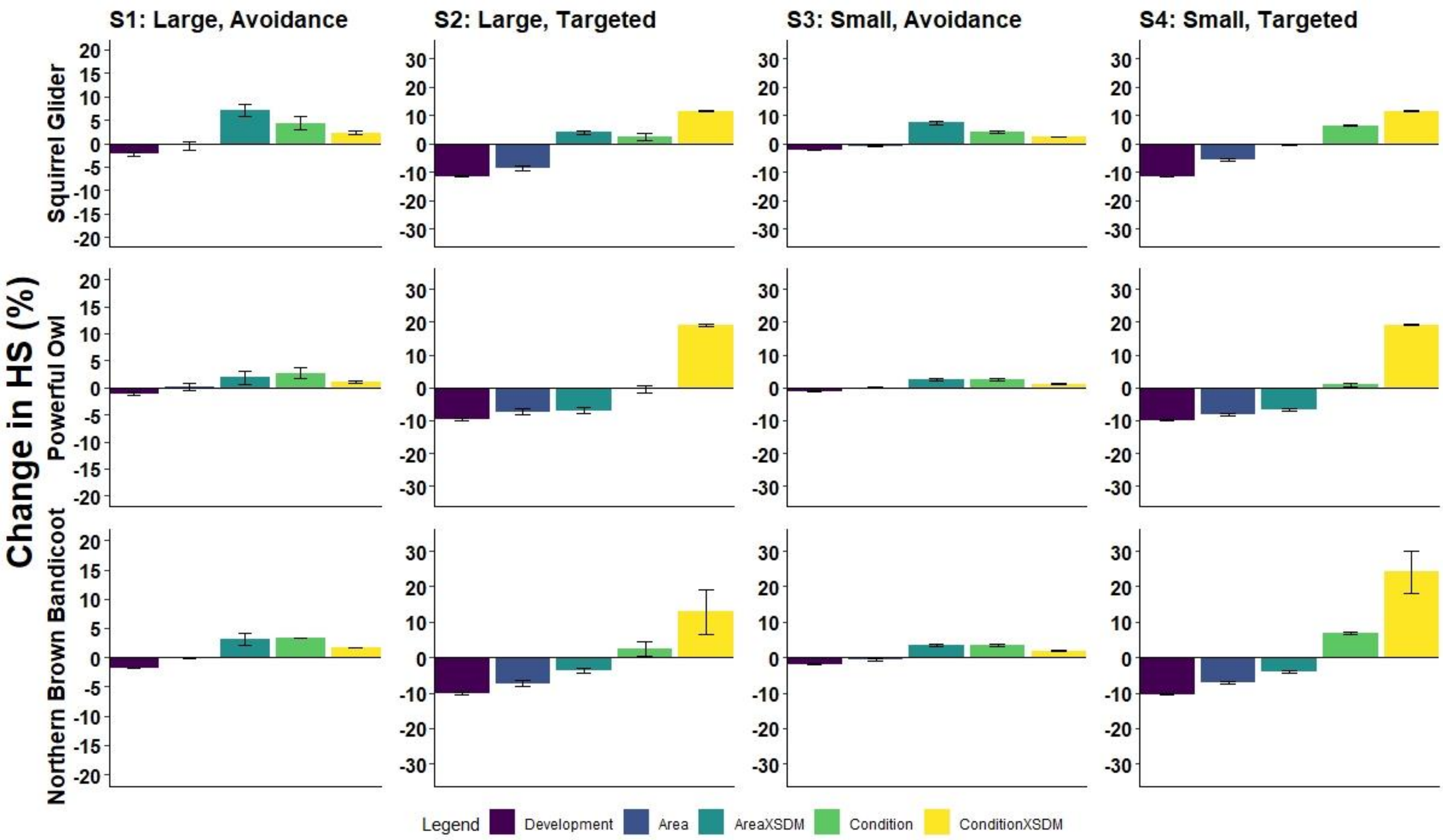

Figure 3: Percentage change in Habitat Suitability (HS) from baseline (y-axis). Each column is a development scenario (S1: Large, Avoidance, S2: Large, targeted, S3: Small, Avoidance, and S4: Small, targeted) and each row is a species (squirrel glider, powerful owl and northern brown bandicoot). On the x-axis each metric is shown with confidence intervals (+/- SD) for each scenario, generated from 50 repetitions of each simulation. From left to right the first bar for each species (dark blue) represents the development impact, followed by Area only (blue), AreaXSDM (turquoise), Condition only (green), ConditionXSDM (yellow).

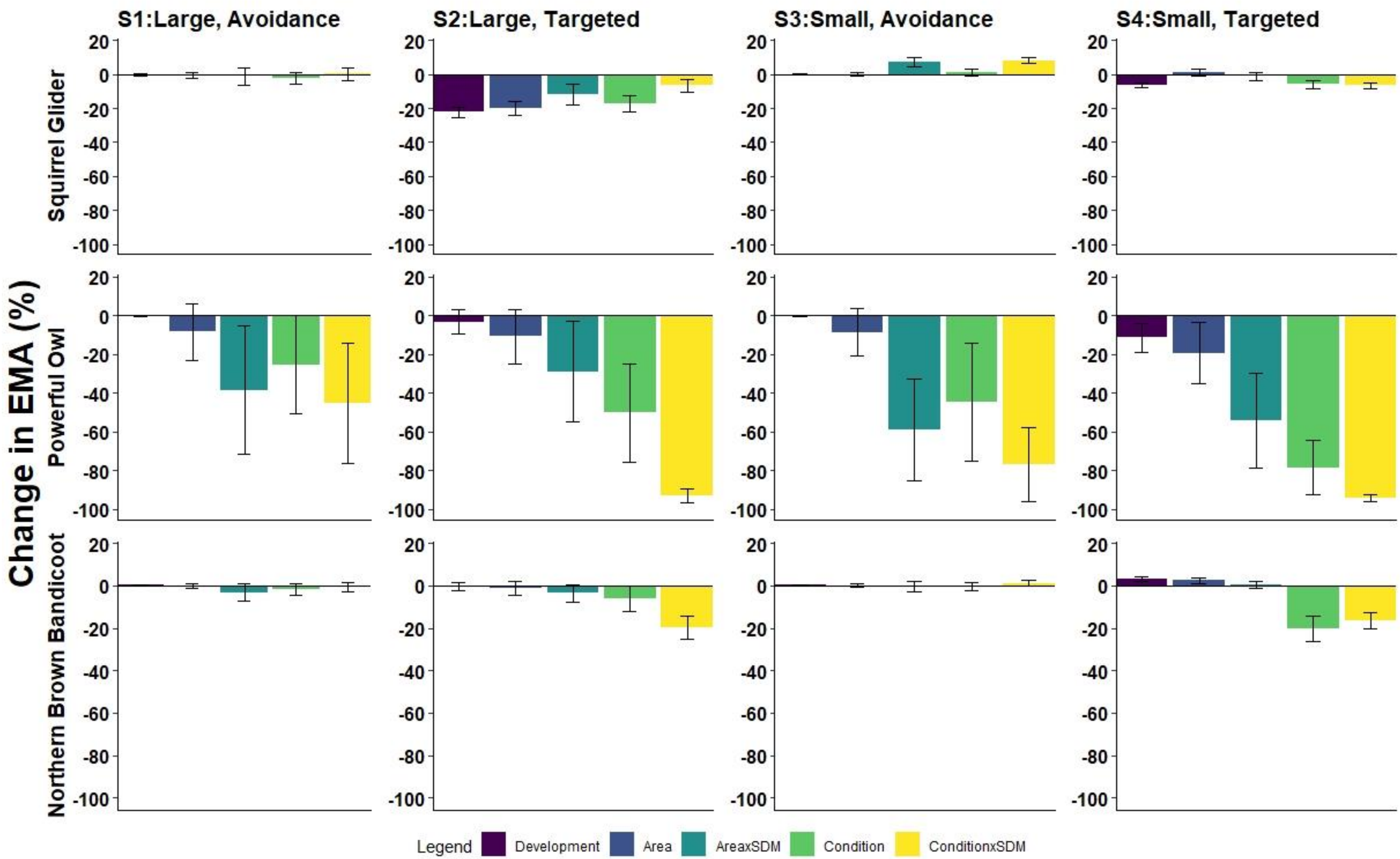

Figure 4: Percentage change in Estimated Minimum Abundance (EMA) from the species baseline. EMA (y-axis) was averaged across PVAS with the error bars demonstrating the variation in EMA produced by the simulation runs. Each column is a development scenario (S1: Large, Avoidance, S2: Large, targeted, S3: Small, Avoidance, and S4: Small, targeted) and each row is a species (squirrel glider, powerful owl and northern brown bandicoot). On the x-axis each metric is shown with confidence intervals (+/- SD) for each scenario, generated from 50 repetitions of each simulation. From left to right the first bar for each species (dark blue) represents the development impact, followed by Area only (blue), AreaXSDM (turquoise), Condition only (green), ConditionXSDM (yellow). Standard deviations are shown for each scenario, generated from 50 repetitions of each simulation.

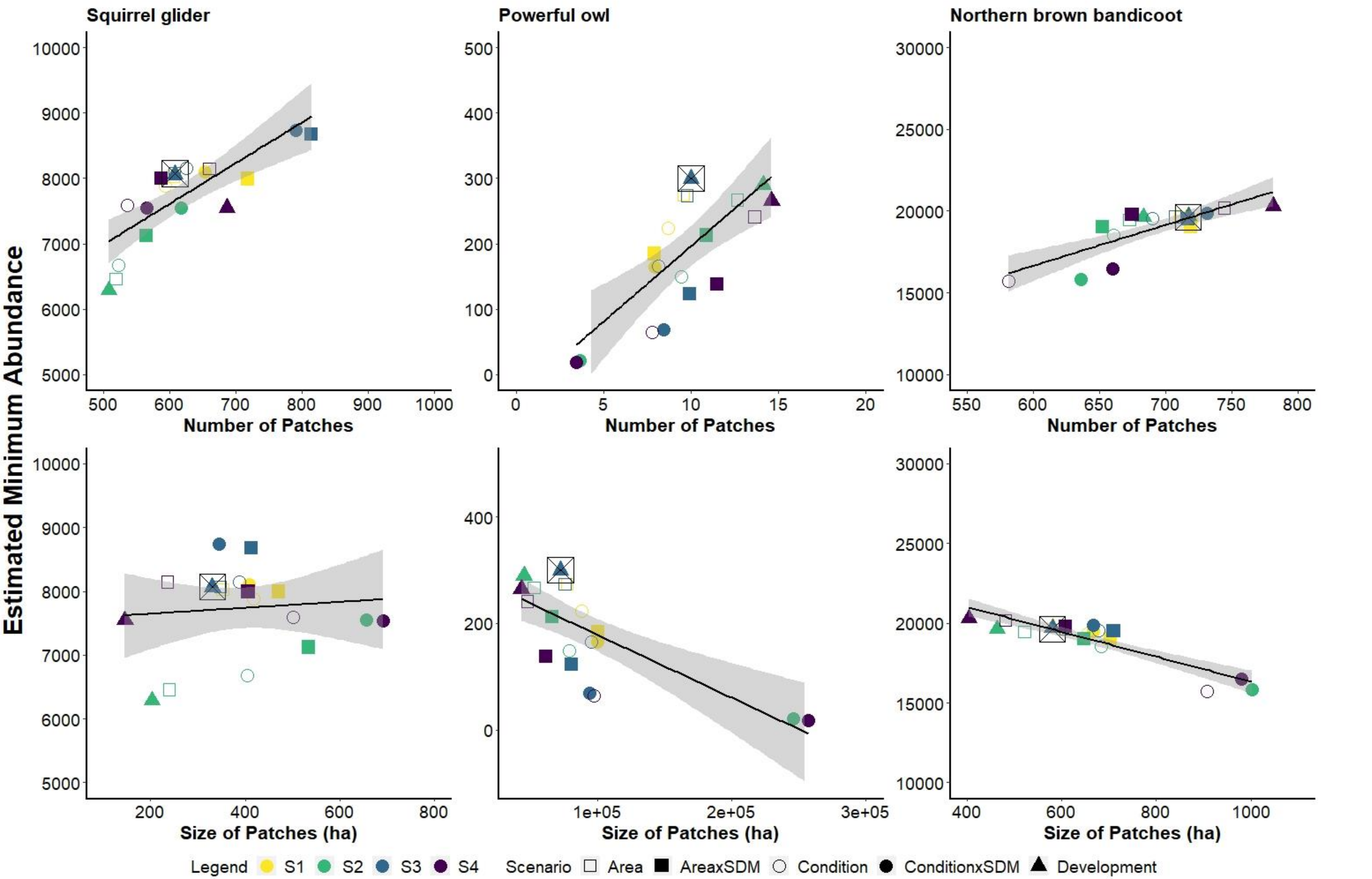

Figure 5: Comparison of the Estimated Minimum Abundance values (y-axis) to average number of patches (x-axis; top panel) and the average size of patches (x-axis; bottom panel). The shapes indicate the metrics and the colours indicate the scenario (S1-S4). The black square with a cross through the middle represents the baseline value for number of patches relative to EMA. The trend line is the relationship between EMA and number or size of the patches as a linear regression.

555