

Protected areas have a mixed impact on waterbirds, but management helps

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1 **Protected areas have a mixed impact on waterbirds, but** 2 **management helps**

3
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26 **Summary Paragraph**

27 International policy is focused on increasing the proportion of the Earth's surface that is
28 protected for nature^{1,2}. While studies show that protected areas prevent habitat loss³⁻⁶, there is
29 a surprising lack of evidence for their impact on species' populations: existing studies are
30 local scale or use simple designs that lack appropriate controls⁷⁻¹³. We explore how 1506
31 protected areas have impacted the trajectories of 27,055 waterbird populations across the
32 globe using a robust Before-After-Control-Intervention study design, which compares
33 protected and unprotected populations in the years before and after protection. We show that
34 the simpler study designs typically used to assess protected area effectiveness (before-after
35 and control-intervention) incorrectly estimate impact for 37-50% of populations, such as
36 misclassifying positively impacted populations as negatively impacted, and vice versa. Using
37 our robust study design, we find that protected areas have a decidedly mixed impact on
38 waterbirds, with a strong signal that areas managed for waterbirds or their habitat are more
39 likely to benefit populations, and a weak signal that larger areas are more beneficial than
40 smaller ones. Calls to conserve 30% of the Earth's surface by 2030 are gathering pace¹⁴, but
41 we show that protection alone does not guarantee good biodiversity outcomes. As countries
42 gather to agree the new Global Biodiversity Framework, targets must focus on creating and
43 supporting well-managed protected and conserved areas that measurably benefit populations.

44 **Introduction**

45 Protected areas have been the cornerstone of conservation practice for over a century. Nearly
46 16% of land and 7% of the ocean are now designated as protected areas¹⁵, and there are
47 prominent calls for the Convention on Biological Diversity to set an area-based target of 30%

48 coverage from protected areas and other effective area-based conservation measures by
49 2030². Given the importance to humanity of addressing biodiversity loss¹⁶, it is crucial that
50 the next decade's biodiversity conservation targets are informed by evidence of the most
51 effective conservation strategies and actions^{3,17}.

52
53 Optimizing where protected areas are placed to most efficiently conserve species and their
54 habitat has been a major research theme in conservation science for decades¹⁸. However, until
55 recently, robust attempts (those making an explicit effort to account for confounding factors)
56 to evaluate the performance of protected areas have been lacking^{19,20}. A number of studies
57 have shown that protected areas slow habitat loss, particularly in forests³⁻⁶, however intact
58 habitat does not guarantee the health of populations²¹. Studies attempting to address this
59 problem by quantifying the impact of protected areas on population health and persistence
60 have suffered from a lack of suitable controls¹⁹. To accurately estimate the impact of a
61 protected area, it is necessary to understand what would have happened in the absence of
62 protection²² and most do this by using either Before-After or Control-Intervention study
63 designs. Before-After studies compare populations pre- and post-protected area
64 designation^{7,13}, but cannot ascertain whether the observed difference was caused by the
65 protected area or other factors that changed in the same time period. Control-Intervention
66 studies compare populations between protected and unprotected sites⁸⁻¹², but cannot ascertain
67 whether the observed difference was due to the effectiveness of the protected area, or because
68 it was placed where populations were already performing well.

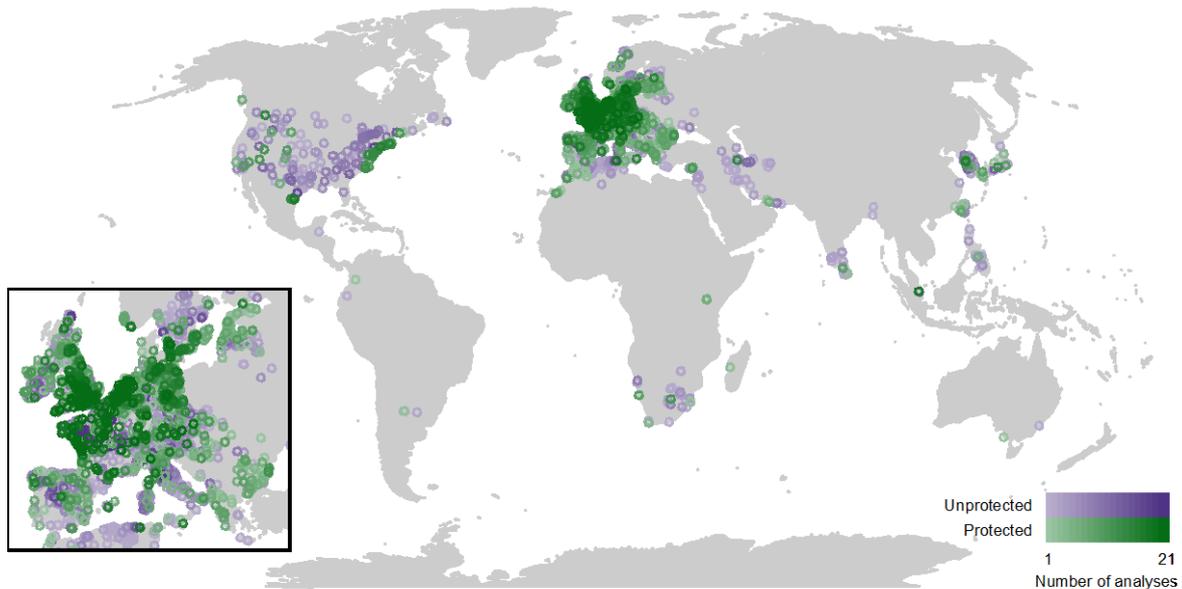
69
70 Combining these designs into a Before-After-Control-Impact (BACI) framework – where
71 populations in protected and unprotected sites are compared before and after the date of
72 protected area designation – can overcome these limitations²³, and even approximate
73 causality²⁴. The recent emergence of large biodiversity databases in ecology provides an
74 opportunity to test protected-area impact on populations under a BACI framework, but this
75 has not been done.

76
77 Using one of the largest global data sets of bird population counts, compiled from citizen
78 science initiatives and NGO- and government-led monitoring programmes in 68 countries,
79 we present the first robust, global-scale assessment of protected area impact on populations.
80 We examined how 1,506 protected areas have impacted the population trajectories of 27,055
81 waterbird populations, where 'population' is defined as a particular species at a particular site
82 (Fig 1). Waterbirds are an appropriate taxonomic group with which to explore impact, given
83 their broad distribution and ability to respond rapidly to changes in site quality²⁵. We asked
84 three questions: 1) How much do the study designs typically used to assess protected area
85 effectiveness cause misleading conclusions, compared to a BACI study design?; 2) What is
86 the impact of protected areas on waterbird populations?; and 3) What factors contribute to
87 protected area impact?

88
89 We estimated impact using Before-After, Control-Intervention and BACI study designs. For
90 BACI and Control-Intervention analyses, we matched protected populations to similar
91 unprotected populations using a combination of exact matching and Mahalanobis distance
92 matching (see Methods). We considered the wide range of ways in which populations may
93 respond to protection by counting cases where local immigrations or extinctions had
94 occurred; and using generalized linear models to assess both immediate changes in
95 population numbers and longer-term changes in population trend (an extension of the
96 traditional BACI study design that considers only average change in population size²⁴). We
97 used these measures to classify populations into three broad groups: positive, negative, or no

98 impact from protection (see legends of Fig. 3 and Extended Data Figs. 3 & 4 for the full
99 range of population responses and what they were classified as).

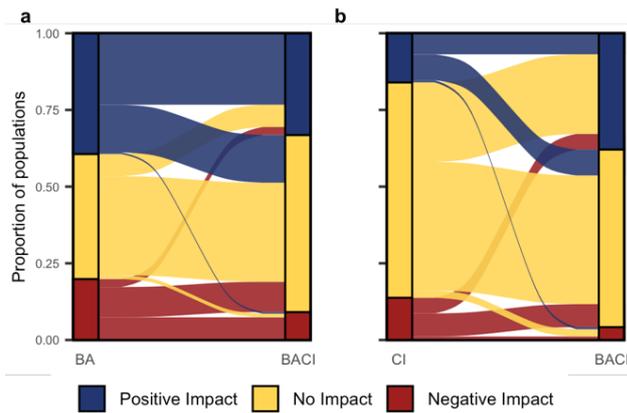
100
101 To explore the sensitivity of our results to different parameter decisions (such as years of
102 sampling required, the maximum geographical distance between sites, or the strictness of
103 Mahalanobis matching), we ran our entire analysis 21 times: one ‘focal analysis’ using our
104 best guess parameter estimates, plus 20 analyses using estimates sampled from a plausible
105 range for each parameter (‘full parameter analyses’; see methods and Extended Data Table
106 1).



108
109 **Figure 1. Map of study sites.** Locations of protected (green; n=1506) and unprotected (purple; n=3343) sites
110 used across analyses. Darker colours mean a given site was used in a greater number of analyses, to a maximum
111 of 21 (our focal analysis and 20 full parameter analyses; there are 864 protected sites in the focal analysis). See
112 Fig S1 for a map of just the sites used in the focal analysis.

113 **Before-After and Control-Impact estimates**

114 We found that estimates of protected area effectiveness varied markedly based on study
115 design, and that studies using Before-After or Control-Intervention designs can lead to highly
116 misleading conclusions. In our focal analysis, 37% of populations using Before-After, and
117 50% of populations using Control-Intervention, had different outcomes to those in the BACI
118 analysis (Fig 2). These changes were not simply a result of BACI detecting positive or
119 negative signals where other designs could not: 41% (Before-After) and 57% (Control-
120 Intervention) of populations that were apparently positively impacted were shown to be not
121 impacted, or even negatively impacted under a BACI analysis (Fig 2). Changes to negative
122 impacts were even more striking, with 63% (Before-After) and 92% (Control-Intervention) of
123 apparently negatively impacted populations shown to be not impacted or positively impacted
124 by protection under a BACI analysis (Fig 2). The findings from our full parameter analyses
125 were similar (Extended Data Fig 1). Before-After models were also heavily impacted by
126 regression to the mean (see Supplementary Information 5), an additional reason to consider
127 them unreliable. These results show that relying on Before-After or Control-Intervention
128 studies can distort the picture of a protected area’s impact.

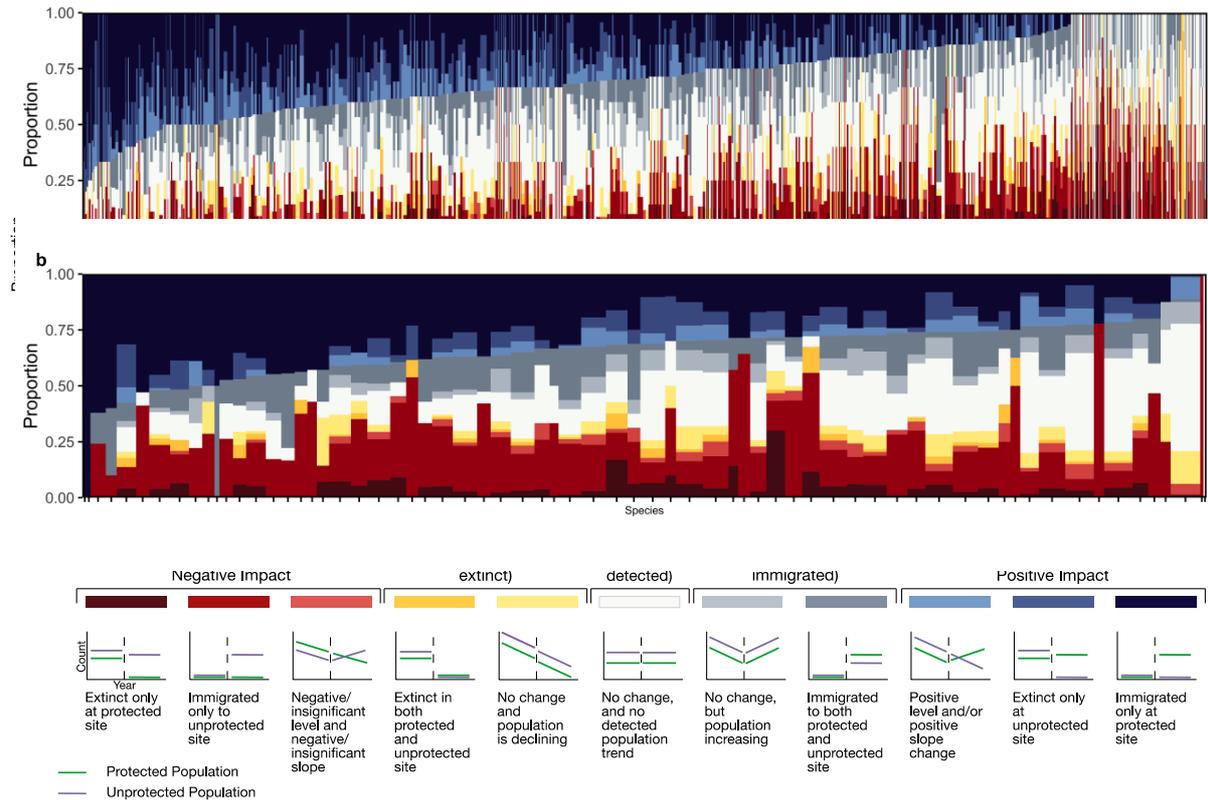


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Figure 2. Changes in estimates of protected area impact under different study designs. The change in protected area effectiveness outcome when estimated under a Before-After vs BACI framework (a) or a Control-Intervention vs BACI framework (b). Y axes show proportion of populations in each category under Before-After/Control-Intervention on the left, and BACI on the right. Colour movement shows how our estimate of the impact of protected areas on populations change between study designs. Note that these figures only contain populations where we could obtain both Before-After and BACI (n=6006) or Control-Intervention and BACI (n=3609) estimates of protected area effectiveness. This figure is based on our focal analysis, see Extended Data Fig 1 for changes in outcome across all full parameter analyses.

139 **BACI estimates of protected area impact**

140 We found a mixed impact of protected areas on populations when using a BACI approach.
141 Within nearly all sites, populations showed a range of responses from positive to negative (in
142 the focal analysis the proportion of positively impacted populations within a site ranged from
143 0 to 1, mean = 0.25 ± 0.21 sd, Fig. 3a). Impacts on populations were similarly variable when
144 grouped by species (in the focal analysis the proportion of positively impacted populations
145 within a species ranged from 0 to 1, mean = 0.36 ± 0.17 sd, Fig. 3b). In our focal analysis,
146 27% of all populations were positively impacted by protected areas (blues), 21% were
147 negatively impacted (reds), and for 48% we could detect no impact of protection (greys,
148 white, yellows) (our full parameter analyses produced similar results, see Extended Data Fig.
149 2). Four percent of populations were excluded because of model failure. Of the 48% of cases
150 where we could not detect any difference between protected and unprotected populations,
151 85% of these (41% of all populations; whites and greys, Fig. 3) were increasing, or had no
152 trend. These cases are difficult to define as a success or failure as, while the protected area
153 did not have a demonstrably positive impact compared to an unprotected area, the protected
154 population appeared to be healthy.
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Figure 3. Estimates of protected area impact under a BACI study design. Proportion of populations (n=7313) showing various responses to protection, per site (panel a; n=864) and per species (panel b; n=67), when calculated in a BACI framework. Each species/site is one vertical bar, with the proportion of their populations in each category shown on the y axis. Bar width is scaled to the number of populations of that species/site in the dataset, log scaled in the case of species, with a wider bar meaning the species/site has more populations. Each colour represents a different way a population can respond to protection, and an example of each response is shown at the bottom. This figure is based on our focal analysis, see Extended Data Fig 3 for the proportion of populations within each broad outcome category across all full parameter analyses.

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Regardless, over a quarter of populations showed a negative response (Fig. 3). These are formed from two groups: (i) negatively impacted populations i.e. those that perform worse in protected areas relative to matched controls (21%, reds) and (ii) populations for which there was no positive or negative signal of protection and which were either declining in protected areas at a similar rate to unprotected populations, or where both protected and unprotected populations went locally extinct (7%, yellows). Importantly, half of these negative responses (14% of populations overall), do not occur in sites designated for waterbirds or their habitat (i.e. Ramsar Sites²⁶ or Special Protected Area – Birds Directive²⁷ sites) and so we might not necessarily expect a positive impact in these cases and thus should not consider these to be cases where protected areas have not worked.

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We consider protected area impact exclusively in the context of how protected areas support the persistence of populations, which ignores the potential benefit of protection on the maintenance of the habitats in which these populations occur. Our dataset was restricted to sites where monitoring occurred: if habitat change meant that waterbirds were no longer found at a site, monitoring would likely cease²⁸. Thus, we could not consider such sites as counterfactuals, and so could not account for protected areas having prevented complete habitat conversion. We also do not consider the potential for protected areas to defend against future threats, for instance, protecting a future climate refuge. In sum, it is important to

185 remember that the results presented here about the impact of protected areas on populations
186 are above and beyond these already-known benefits^{3-5,29,30}.

187
188 Our results are also likely to underestimate the positive impact of protection as we were
189 restricted to species for which we were able to obtain adequate matches between protected
190 and unprotected populations, resulting in a bias towards common species (Supplementary
191 Information 10). Common species tend to have more generalist habitat requirements³¹ and so
192 may fare better in degraded sites than rarer species. They are also less likely to be the target
193 of specific interventions, which in some cases could actively impede them; for instance,
194 water could be kept at levels appropriate for rare waders, but not for common ducks. To
195 explore whether this affected our results, we assessed whether outcomes varied between
196 regionally threatened and non-threatened species in Europe (Supplementary Information 11;
197 a global analysis was not possible due to data restrictions). We did not find any differences in
198 the impact of protected areas between these groups, possibly because there was only a small
199 set of threatened species in our data, though a recent study³² similarly found no difference
200 between rare and common species when studying population trends.

201 **Predictors of protected-area impact**

202 We show that the mere designation of a protected area does not necessarily bring benefits to
203 populations. Given this, we used cumulative link mixed models, where the response variable
204 was the impact (positive, no or negative), to investigate which species and protected-area
205 characteristics predict outcomes for populations, based on our BACI framework (see Fig 4).
206 The models had random intercepts for country, site, species, and spatial grid cell. Our
207 explanatory variables included a management variable, which broadly categorized sites as
208 either ‘waterbird-managed’ (Ramsar or Special Protected Area – Birds Directive sites), or
209 ‘mixed-management’ (sites either not designated for waterbirds or their habitat, or of
210 unknown management status).

211
212 Management for waterbirds was consistently positively correlated with protected area success
213 (Fig. 4). Larger protected areas were also almost always positively correlated with success,
214 though significantly so in only a few analyses (Fig. 4). No other site or species-based
215 characteristic was consistently positively or negatively associated with success (Fig. 4;
216 Extended Data Fig. 5). Depending on the analysis, a large, waterbird-managed area could
217 increase the likelihood of a positive impact on a population anywhere from 1 to 25
218 percentage points (mean weighted by model confidence = 9 percentage points; see
219 Supplementary Information 13) compared to a small, mixed-management area.

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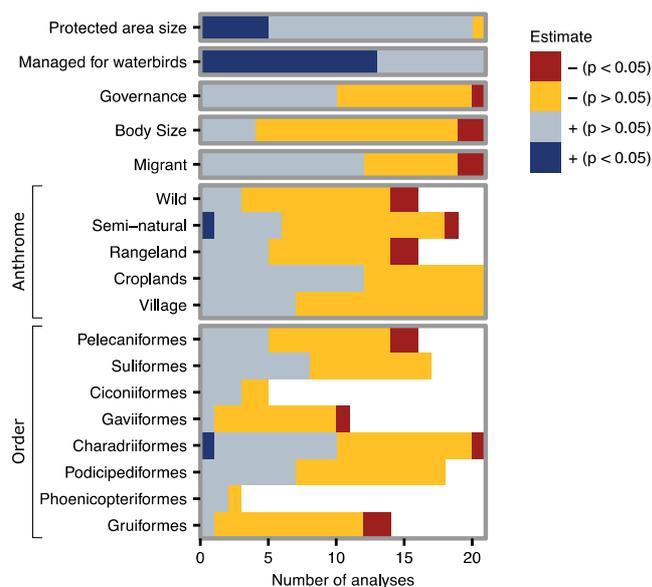


Figure 4. Predictors of protected area impact. Number of analyses (20 full parameter analyses plus one analysis with focal parameter estimates), that found significantly positive or negative (blue, red) or insignificantly positive or negative (grey, yellow) relationships between various predictors and protected area impact. Orders are measured relative to Anseriformes, and Anthromes relative to Urban. For odds ratios of each estimate, plus confidence intervals, see Extended Data Fig. 5.

These values are likely to underestimate the positive impact of management. Our classification of sites into waterbird-managed sites and mixed-management sites is a simple metric of diverse on-the-ground practices (a more nuanced classification is not possible at the global scale) and inevitably, some mixed-management sites are likely to be managed for waterbirds, and management quality will vary within waterbird-managed sites^{33,34}. Both these factors would reduce the observed difference between the two management classifications, meaning the true difference is likely higher. That waterbird-managed sites perform better emphasizes the need for effective management to avoid negative outcomes, and suggests that policy needs to focus on setting and adhering to ambitious management targets.

The weak positive association between protected area size and impact adds a new element to the ‘Single Large or Several Small’ protected area debate that considers which is better for conserving biodiversity. Studies have agreed that several smaller protected areas typically provide higher species richness than a few large areas³⁵, but that larger areas are critical for persistence of larger species³⁶. Our results demonstrate the importance of larger protected areas for supporting populations of waterbirds through time. This is concerning given many protected areas across the world are small and many are currently being downsized³⁷.

While our analysis includes data from 68 countries across 6 continents, the data are biased towards Europe, North America and East Asia; a common problem in large-scale ecological studies³⁸. There are a number of initiatives in less-studied areas of the world to increase the supply and quality of ecological data³⁹⁻⁴³; supporting and incorporating efforts such as these will be vital to informing truly global evaluations of conservation effectiveness.

Our results show a mixed impact of protected areas, supporting concerns raised over protected area efficacy in recent years^{44,45}. We had expected that, given their ability to move between sites²⁵, waterbirds would show a more immediate and positive signal of protection

257 than other non-mobile taxa, such as reptiles, where positive signals might not be apparent
258 until multiple generation cycles of improved breeding rate had occurred. The lack of signal
259 could be due to poor or limited management of many protected areas, or it could be due to
260 forces that cannot be controlled within the borders of a protected area. Waterbirds rely on
261 water, and threats such as pollution, upstream dam installation and sea level rise cannot be
262 managed by a protected area, and can have devastating consequences⁴⁶⁻⁴⁸. Terrestrial taxa
263 will be less impacted by such threats and therefore may experience more positive responses
264 to protection⁴⁹, although beyond border threats are not limited to those affecting water:
265 climate change, air pollution and disease have the potential to impact all species⁴⁹. Finding
266 solutions to conserving species in the face of these more ubiquitous threats is a key
267 conservation challenge.

268 **Conclusions**

269 The parties to the UN Convention on Biological Diversity will soon decide on the post-2020
270 Global Biodiversity Framework, which will set nature conservation policy for the decade
271 ahead. It is likely to include a commitment to protect and conserve 30% of Earth protected by
272 2030 (and there are growing calls for this to reach 50% by 2050¹⁴). Researchers have warned
273 that such calls must consider the social and political context in which conservation operates,
274 or risk undermining conservation support⁵⁰. Our results raise additional concerns about the
275 ‘30 by 30’ approach by showing protection alone does not guarantee optimal biodiversity
276 outcomes. Halting biodiversity loss requires improvements to the performance of existing
277 protected areas, and action to address ubiquitous threats beyond area borders. Ever-increasing
278 area-based targets must be accompanied by equally ambitious targets that ensure protected
279 area effectiveness.

280

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302 **Author Contributions**

303 H.S.W., J.P.G.J., J.G., B.I.S., T.A., R.A.F., A.J. and W.J.S. conceived the study. D.B., T.L.,
304 T.M. and S.N. provided waterbird count data which H.S.W. and T.A. collated. H.S.W.
305 performed analysis, produced figures and wrote the text with advice from all authors,
306 especially J.P.G.J., J.G., B.I.S., T.A., A.J. and W.J.S. All authors contributed to the review of
307 the manuscript before submission for publication and approved the final version.

308 **Competing Interests**

309 The authors declare no competing interests.

310 **Code availability**

311 The code used to produce all analysis and figures are archived on Zenodo,
312 doi:10.5281/zenodo.5794483. Code are also available on GitHub
313 <https://github.com/hannahwauchope/PAImpact> , this is the recommended mode of access as
314 it will contain any updates or clarifications.

315 **Data Availability**

316 The waterbird count data used in this study are collated and managed by Wetlands
317 International and the National Audubon Society, and are available on request
318 (<http://iwc.wetlands.org/index.php/> ; <http://netapp.audubon.org/cbcobservation/> respectively).
319 All the data that pertain to explanatory variables are freely available, as specified in Extended
320 Data Tables 1 and 2.

321 **Methods**

322 We published a pre-analysis plan for this paper laying out our planned analysis before we
323 looked in detail at the data⁵¹. Pre-analysis plans are useful to reduce the risk of cherry picking
324 or HARKing (hypothesizing after results are know) which has led to a replication crisis in
325 science⁵². As much as possible, we have followed the methods we set out, however we
326 discovered a number of factors we had not considered (for instance, the potential for
327 immigrations and extinctions and the fact that both trend and immediate change must be
328 considered, see²⁴). The conceptual basis of our revised methodology is described in detail in
329 Wauchope et al²⁴, and Supplementary Information 7 describes the choices we've made that
330 deviate from the pre-analysis plan and why.

331 *Overview*

332 A brief summary of our workflow is as follows: we took yearly counts of 749 waterbird
333 species at 45,745 sites across the world from the International Water Census and Christmas
334 Bird Count. Of these, we wanted to find populations, here defined as a certain species at a
335 certain site, that occurred in a protected area *and* where yearly counts had begun before the
336 protected area was designated. For our Before-After (hereafter BA) analysis, we then
337 assessed how each population at each of those sites changed from before to after the
338 protected area was designated. For Control-Intervention (hereafter CI) and BACI analysis, we
339 matched each of these protected populations to unprotected populations surveyed over the
340 same period, that were similar based on a number of site and species characteristics. For CI,
341 we compared populations in the years after the protected area was designated between
342 unprotected and protected population pairs. For BACI, we compared change in protected

343 populations from before to after protected area designation, and then compared this to the
344 before-after change in matched unprotected populations over the same period.

345
346 Whether BA, CI or BACI, we then classified the impact to the population as positive,
347 negative or no impact from protection. Next, we looked to see whether our conclusions about
348 impact varied when we analysed a population in a BA, CI or BACI framework. We found
349 BA and CI analyses to be unreliable, so discarded them at this point. Finally, we looked to
350 see whether there were correlates that predicted protected area impact have, by running
351 cumulative link models on BACI data. These correlated outcome (Positive, Negative or No
352 impact) to a range of site and species level predictors such as protected area size, species
353 body size, land use type and whether the site was managed for waterbirds. Finally, we ran
354 sensitivity tests varying a range of parameters that were used to make analytical decisions to
355 test the robustness of conclusions.

356
357 All analysis was completed using R v4.0.3⁵³ and QGIS v3.10⁵⁴, data figures and base maps
358 were produced using the R package ggplot2⁵⁵, impact legends were produced using
359 Inkscape⁵⁶.

360 *Time Series Preparation*

361 We took site-specific annual counts from two long term surveys: the International Waterbird
362 Census (IWC), coordinated by Wetlands International, and the Christmas Bird Count (CBC),
363 run by the National Audubon Society. We used Wetland International’s definition of
364 “waterbird”, and took any species from the corresponding families (list of families in
365 Supplementary Information 2). Our initial dataset consisted of 749 species at 45,475 sites,
366 spanning 1940 to 2018. We then restricted our data to only sites surveyed in December to
367 February. We imputed zeroes, by taking any site where a species has been observed, and
368 recording any years where the species was not mentioned as ‘0’ years.

369
370 As CBC data is not standardized for effort, we required that these species showed a log-linear
371 relationship with effort (i.e. the rate of new individuals detected in a search slows with
372 increased effort). For each species, we ran a simple negative binomial generalized linear
373 model in R, using the glm.nb function from package MASS⁵⁷, using all available CBC data
374 for that species:

$$\log(E(\text{Count}_i)) = \beta \log(h_i) \quad (1)$$

376 Where *Count* is all counts of a species and h_i is the number of survey hours for each count.
377 We retained CBC data for all species where there was a significant positive relationship
378 between count and effort.

379 *Protected (and Unprotected) Area Data*

380 We first created a dataset of counts at protected sites. We took our protected area data from
381 the World Database on Protected Areas (‘Protected Planet’)⁵⁸, downloading the full dataset of
382 all protected areas globally, and overlaying our sites to determine which fell in protected
383 areas. Some coastal site coordinates fell just outside the land cover layer that protected areas
384 are aligned to, so we snapped all sites to the base terrestrial layer used by Protected Planet⁵⁹,
385 but by no more than 10km. We removed any sites where the designation status was proposed,
386 and any UNESCO biosphere reserves as these are often not afforded formal protection⁶⁰. We
387 next removed any sites where there was no information about designation date. In some
388 cases, there were multiple protected area data entries for a site, in these cases we took the

389 earliest designation year given. Finally, we reduced the count dataset to only the 10 years
390 before and after the designation date of whichever protected area the survey site fell within,
391 requiring that at least 7 years before and after were surveyed (we tested the number of years
392 restricted from 5-15 years, and number of years measured from 4-13; Extended Data Table 1a
393 and b, respectively).

394

395 We next created a dataset of counts at unprotected sites for CI and BACI analysis. For
396 Christmas Bird Count data, surveying is conducted in a circle with a radius of 12.07km. If
397 there is a protected site in this circle, we cannot be sure that the counts are not being biased
398 by protection. Therefore, we only counted sites as unprotected if no protected area occurred
399 in the entire circle. For IWC data, we included sites that were at least 1km from a protected
400 area, to avoid any confounding of results from spill-over effects⁶¹ (we sensitivity tested this
401 threshold from 500m to 5km; Extended Data Table 1c). We consider sites to be unprotected
402 until the point in time when a protected area was designated at that site. For instance, a site,
403 A, could be designated as a protected area in the year 2000, but this would mean that counts
404 before this point, say, from the 1980s, would be of waterbirds at a site not experiencing any
405 benefit of protection. We could therefore match a protected site from the 1980s to Site A's
406 counts in the 1980s, and treat A's counts as unprotected at this time.

407

408 *BA, CI and BACI Datasets*

409 In all cases, we defined the “after” period as being the years after, but not including, the
410 designation date of the PA. We also defined cases of ‘all zeros’ to account for local
411 immigrations and extinctions. Waterbirds are highly mobile and can quickly immigrate to, or
412 emigrate from a site. In these cases we cannot assess a change in trend between, for instance,
413 a before period where there are individuals absent and an after period when they have
414 immigrated to the site (for a detailed explanation of why immigrations and extinctions pose a
415 problem for trend analysis, see²⁴). Theoretically, we should only consider cases with only
416 zero counts in a before or after period as ‘all zero’ local immigrations or extinctions, but
417 because waterbirds are able to appear as vagrants at a site, we chose to classify cases where at
418 least 70% of years were zero counts as all zeroes. We tested this threshold from 60 – 80%
419 (Extended Data Table 1d). It's important to note that any sites where the species had never
420 occurred would not be included in the dataset, so even in cases of all zeroes the species is
421 known to be able to occur at the site.

422

423 To create the BA dataset, we took all protected populations where there were cases of counts
424 (as opposed to all zeroes) in either the before period, after period or both. We subset the BA
425 dataset to only protected populations that also occur in the BACI dataset.

426

427 To create the CI dataset, we took all protected populations with counts (as opposed to all
428 zeroes) in the after period, and matched these to unprotected populations also with counts
429 over the same time period (see matching below). We subset the CI dataset to only protected
430 populations that also occur in the BACI dataset.

431

432 To create the BACI dataset, we matched protected and unprotected populations, requiring
433 that at least one period (either protected before, protected after, unprotected before, or
434 unprotected after) had counts (as opposed to all zeroes).

435 *Matching*

436 Data preparation

437 We developed a statistical matching method to achieve matching of BACI and CI analyses.
438 The covariates we used for matching, how we prepared them and justification for their use
439 are given in Extended Data Table 2, broadly they encompass variables related to climate,
440 land use and human impact. We removed highly correlated variables by first calculating the
441 variance inflation factor (using the VIF function from the usdm package in R⁶²) of all
442 covariates, and iteratively removing variables with a VIF greater than four until none were
443 over four⁶³. We next removed variables with a Pearson's Correlation Coefficient of over 0.7.
444

445 For BACI, we matched only on covariates in the years prior to designation (as protected and
446 unprotected sites might be expected to differ in the years after protected area designation,
447 especially on covariates related to human impact). For CI, we matched on covariates only in
448 the years after designation, as we choose to be blind to the 'before' period in this analysis.
449

450 We then proceeded with matching, separately for each species. The following describes the
451 procedure for one species.
452

453 Mahalanobis Distances

454 We used Mahalanobis distance matching to evaluate how similar protected and unprotected
455 sites were. Though Mahalanobis distance has been criticized in the past for performing
456 poorly when matching on many covariates^{64,65}, recent criticisms of the most commonly used
457 matching method, Propensity Score Matching⁶⁶, meant we were interested to test other
458 options and found Mahalanobis distance matching to perform markedly better in comparisons
459 (Supplementary Information 9).
460

461 Mahalanobis Distance (md) computes the distance between points in multivariate space. The
462 Mahalanobis distance between two sets of points is calculated as follows:
463

$$464 \quad md_{(x,y)} = \sqrt{(x - y)^T S^{-1} (x - y)} \quad (2)$$

465 Where x and y are vectors containing values for each covariate (in our case, therefore, the list
466 of covariate values for sites x & y) and S is the covariance matrix of the covariates.
467

468 This formula requires each site to have one value for each covariate, so we took means of the
469 values for the years pre- (BACI) or post- (CI) designation.
470

471 For each species, we created a large matrix with protected sites in columns and unprotected
472 sites in rows, with Mahalanobis distance values populating the rows. Because we wanted to
473 match exactly on the years only prior to protected area designation, we first created separate
474 matrices (using function mahal from R package DOS⁶⁷), each containing only protected areas
475 designated in a certain year (See Extended Data Fig. 6a, b for an example). Mahalanobis
476 distance requires at least two protected sites to work (to be able to calculate the covariance
477 matrix), and so we could not build Mahalanobis distance matrices for years where only one
478 protected area in our dataset was designated. This resulted in a minimal loss of sites.
479

480 These Mahalanobis distance matrices were then combined into the larger distance matrix
481 containing all the sites across all designation years that the species occurred in (Extended
482 Data Fig. 6c).
483

484 Exact Matching

485 We required that sites were exactly matched on a number of criteria, where sites failed they
 486 were excluded from the Mahalanobis distance matrix (Extended Data Fig. 6d). For each
 487 protected site, we removed unprotected sites not of the same anthrome category, continent,
 488 and migratory status. We also removed any sites greater than 500km from the protected area
 489 (we tested this value from 100km to 2500km; Extended Data Table 1e).

491 For BACI analysis, we needed to satisfy the parallel trends assumption^{24,68}, which specifies
 492 that the trends of control and intervention populations in the ‘before’ period must be parallel.
 493 To test this, we modelled the difference in trends between each protected and potential
 494 unprotected matched site. We used a negative binomial glm (glm.nb, R package MASS⁵⁷):

$$\log(E(Count_{i,j})) = \alpha + \beta_1 Y_i + \beta_2 CI_j + \beta_3 Y_i CI_j + \text{offset}(\log(h_i)) + \epsilon \quad (3)$$

496 Where the count of the population in year i at site j is predicted by the Year (Y), a binary term
 497 that is 1 for the protected site and zero for the unprotected site (CI) and the interaction
 498 between the two. Log of effort is included as an offset for CBC data (effort is held at 1 for
 499 IWC data). We also checked for temporal autocorrelation and adjusted the model if it was
 501 present (see “Temporal Autocorrelation” below). If the interaction coefficient (β_3) was
 502 significant ($p < 0.05$), then there was a significant difference between the trend of the two
 503 populations, and the unprotected population was discarded.

505 If no unprotected sites met the exact match criteria, the protected site did not have a match
 506 and was excluded (e.g. Extended Data Fig. 6d, Site E).

508 Picking Matches

509 Next, we ran an optimized greedy nearest-neighbour algorithm to select, from the
 510 Mahalanobis distance matrix (with any sites not satisfying exact match criteria excluded), the
 511 unprotected site with the smallest Mahalanobis distance. We ran this without replacement,
 512 meaning each protected site could be matched to only one unprotected site, to ensure no
 513 pseudoreplication. A greedy algorithm works through the dataset, picking the best match for
 514 each successive protected site and removing the matched unprotected site from the potential
 515 matching pool as it goes. However, greedy algorithms have a tendency to get stuck in local
 516 optima⁶⁹, so to account for this, we ran the greedy algorithm 1000 times, each time
 517 randomizing the order of protected sites that the greedy algorithm would work through. We
 518 found the global distance for each iteration and used the set with the smallest global distance
 519 (Extended Data Fig. 6e, e.g. with randomisations in the figure a smaller global distance
 520 would be detected).

522 Evaluating Match Quality

523 Once we had our matched sets for each species, we needed to ensure that the matches were of
 524 a high enough quality to be used. This was done by assessing the covariate balance between
 525 matched and unmatched sites for each species using the ‘standardised difference in means’
 526 (SDiM), which is calculated using the following formula⁷⁰:

$$d_{cov} = \frac{\bar{T}_{cov} - \bar{C}_{cov}}{\sqrt{\frac{\text{var}(\mathbf{T}_{cov}) - \text{var}(\mathbf{C}_{cov})}{2}}} \quad (4)$$

528 Where T_{cov} is the values of covariate cov for protected sites (mean from the years before and
 529 equal to designation), C_{cov} is the same for unprotected sites, var is the variance of each of
 530 these and d_{cov} is the standardized mean difference between protected and unprotected sites.
 531 We assessed the SDiMs to see whether they were below 0.25 for all covariates^{65,71} (we
 532 sensitivity tested this threshold from 0.1 to 0.25; Extended Data Table 1f). If they were not,
 533 the matched pair with the greatest distance was removed and the SDiM checked again. Once
 534 all covariates had a SDiM of <0.25 (or the relevant sensitivity value), the remaining matched
 535 pairs were considered the ‘final’ matched dataset for that species (Extended Data Fig. 6f). If
 536 less than 80% of the sites that a species occurred in were remaining, we discarded the
 537 species, to ensure that the matched set was not biased to a certain subset of all sites for that
 538 species (we sensitivity tested this value from 50-90%; Extended Data Table 1g).

539 *Assessing Protected Area Impact*

540 Following the framework set out by²⁴, we defined a number of ways that a population could
 541 respond to protection. Broadly, populations can respond to a protected area by immigrating to
 542 the area, going locally extinct from the area, showing a change in trend, or by showing an
 543 immediate change, i.e. an immediate increase or decrease in the number of individuals (See
 544 legends of Fig 3, Extended Data Figs 3 and 4).

545
 546 For comparing BA, a population could show an immediate change or change in trend, or the
 547 population could immigrate to the site or go locally extinct at the site (Extended Data Fig. 3).
 548 For comparing BACI, the BA changes were compared between protected and unprotected
 549 sites. For example, a population could be stable in the period before protection, and declining
 550 in the period after – this would be a negative BA trend change (Extended Data Fig. 3). But if
 551 a matched unprotected population was also stable in the before period, but declining at a
 552 *faster* rate in the after period, then the BACI trend change would be positive (Fig. 3), as the
 553 protected area had slowed the decline of the protected species, even if it hadn’t halted it. If
 554 the unprotected population was declining at a similar rate to the protected population in the
 555 after period, this would be a case of no impact under a BACI framework (Fig. 3). For
 556 comparing CI, only the difference in trend between protected and unprotected populations
 557 was considered (Extended Data Fig. 4).

558
 559 All BA, CI or BACI time periods with all zeroes were categorised as immigrations or
 560 extinctions, for instance, in BACI analysis if protected population had no counts in the before
 561 period, but did in the after period, while the matched unprotected site had no counts in the
 562 before and after period, this would be classified as a local immigration (and a positive impact
 563 of the protected area).

564
 565 For time periods with all counts we ran the following models. In all cases Y represents the
 566 year, centred around the year of protected area designation so that year of designation equals
 567 zero. BA is a binary term that is 0 in the years before protected area designation, and 1 in the
 568 years after; note that this isn’t included in the CI model as only ‘after’ years are used. CI is a
 569 binary term that is 0 for the unprotected population and 1 for the protected population; note
 570 that the CI term isn’t included in the BA model as this model does not include unprotected
 571 populations. Finally, each model includes an offset term for effort (h), to account for variable
 572 effort in CBC data. For IWC data, effort is always set to 1 and so does not contribute to the
 573 model. All models were negative binomial glms, run using R package MASS⁵⁷.

574 BA

$$575 \log(E(Count_i)) \sim \beta_0 + \beta_1 BA_i + \beta_2 Y_i + \beta_3 BA_i Y_i + \text{offset}(\log(h_i)) + \epsilon \quad (5)$$

576 β_1 gives the immediate change and β_3 gives the trend change²⁴.

577

578 CI

$$\log(E(\text{Count}_i)) \sim \beta_0 + \beta_1 \text{CI}_i + \beta_2 Y_i + \beta_3 \text{CI}_i Y_i + \text{offset}(\log(h_i)) + \epsilon \quad (6)$$

579

580 β_3 gives the difference in trend between protected and unprotected sites.

581

582 BACI

583

$$\log(E(\text{Count}_{i,j})) \sim \beta_0 + \beta_1 \text{BA}_i + \beta_2 \text{CI}_j + \beta_3 T_i + \beta_4 \text{BA}_i \text{CI}_j + \beta_5 \text{BA}_i Y_i + \beta_6 \text{CI}_j Y_i + \beta_7 \text{BA}_i \text{CI}_j Y_i + \text{offset}(\log(h_i)) + \epsilon \quad (7)$$

584 B_4 gives the immediate change and β_7 gives the trend change²⁴. We excluded any cases where
585 β_6 was significant as this indicates a significant difference between protected and unprotected
586 trends in the before period, meaning the parallel trends assumption is not satisfied. Though
587 we checked for this in matching, running a full model containing ‘after’ data as well (cf only
588 before data, as in matching) meant that very occasionally this term became significant,
589 presumably because of an increase in power.

590

591 In a small proportion of populations, models failed to converge. In these cases, we removed
592 the population from analysis.

593

594 Temporal Autocorrelation

595 Time series data are vulnerable to the effects of temporal autocorrelation, where counts in
596 one year are impacted by counts in the years before, and as a result are not independent, as
597 models assume. Being mobile, we expect less temporal autocorrelation in waterbird data than
598 for sessile species (waterbird population numbers can change markedly at a site year to year),
599 but nevertheless we checked for, and accounted for, temporal autocorrelation in our data. For
600 each population model (whether BA, CI or BACI; and also for the models used to check for
601 parallel trends in the matching stage), we checked for temporal autocorrelation using three
602 implementations of the Durbin-Watson test in R: `durbinWatsonTest` from package `car`⁷²,
603 `testTemporalAutocorrelation` from package `DHARMA`⁷³, and `dwtest` from package `lmtest`⁷⁴.
604 Though each of these implementations performs the same test, variations in methodology
605 meant we found some population models had significant temporal autocorrelation under one,
606 but not another. To be conservative, we decided that if a population had significant
607 autocorrelation under any of the three tests, we considered there to be temporal
608 autocorrelation. If this was the case, we re-ran the population model as a negative binomial
609 generalised linear mixed model (using `glmer.nb` from package `lme4`⁷⁵) including a random
610 intercept for Year for BA analyses, and Site:Year for CI and BACI analyses, to account for
611 the autocorrelation.

612

613 Classifying Outcomes

614 We then classified outcomes. We aimed to be generous for assigned positive outcomes, and
615 so for BA and BACI, a significantly ($p < 0.05$) positive immediate or trend change (even if the
616 other was significantly negative) meant that the protected area was classed as having had a
617 positive impact on the population. If both immediate and trend were insignificant, then the
618 protected area had had no impact. And if either was negative and the other insignificant, or if

619 both were significantly negative, the protected area was classed as having had a negative
620 impact. We conducted a supplementary analysis to see whether relaxing this p-value would
621 result in detecting more positive impacts, see Supplementary Information 12.

622

623 For CI, a significantly positive difference between protected and unprotected trends was
624 classed as a positive impact, significantly negative was a negative impact, and an
625 insignificant difference no impact.

626 *Drivers of change*

627 To explore the predictors of protected area effectiveness, we considered body mass, species
628 migratory status, taxonomic order, the broad anthrome category (i.e. land use type) of the
629 protected area, protected area size, and country governance¹¹. See Extended Data Table 3 for
630 details of how each covariate was obtained.

631

632 To test how these covariates might correlate to protected area effectiveness, we ran
633 cumulative link mixed effects models that allow for ordinal predictors and random factors,
634 with the response term being a three-level factor: negative impact, no impact, or positive
635 impact. To account for spatial autocorrelation, we included a random intercept for “grid cell”,
636 with sites each assigned to a gridcell of size 2* Max distance between protected and
637 unprotected sites (Table 1e). In this way errors are grouped by sites that are closer together.
638 In some of the 21 analyses, typically those with smaller sample sizes, including both country
639 and grid cell as random factors meant the model could not converge; in these cases we
640 retained only country as a random factor. We used the clmm function from R package
641 ‘Ordinal’⁷⁶. The model specification was as follows:

642

$$\begin{aligned} 643 \quad Impact_{i,j,k} \sim & \beta_1 MigatoryStatus_i + \beta_2 \log(BodyMass)_i + \beta_3 Order_i + \beta_4 Anthrome_j \\ 644 & + \beta_5 RamsarSPA_j + \beta_6 \log(PA\ Area)_j + \beta_7 MeanGovernance_k + (1|i) \\ 645 & + (1|k) + (1|k:j) + (1|m) + (1|m:j) \epsilon \end{aligned}$$

646

647 Where i , j , k and m are species, site, country and gridcell, respectively. In some sensitivity
648 tests some covariates did not have sufficient populations to be able to test them, in these cases
649 certain levels of the covariate were removed (e.g. if there were not enough populations of a
650 particular taxonomic order) or in some cases the entire covariate was removed. Not all
651 protected areas have area data reported, and so we had to run models only on the subset of
652 data where area data was available. To ensure this reduced set was not misrepresenting the
653 full dataset, we also ran models without the protected area Area covariate and on the full
654 dataset; results were broadly similar (Supplementary Information 8), and in the case of BACI,
655 waterbird-managed sites were more strongly positively associated with outcomes.

656

657 We estimated the effect size of management and protected area size using the function
658 `ggpredict` from R package `ggeffects`⁷⁷, which returns odds ratios from the cumulative link
659 mixed models. We estimated effect size for water-bird managed vs mixed-managed sites, and
660 for 5 quintiles of $\log(\text{protected area size})$: 0.05, 0.25, 0.5, 0.75 and 0.95. For the effect size
661 reported in the manuscript, we compared the chance of a positive impact on a population in a
662 mixed-management site in the 0.05th size quintile to the chance of a positive impact on a
663 population in a waterbird-managed site in the 0.95th quintile.

664

665 Finally, some covariates violated the proportional odds ratio assumption upon which
666 cumulative link models rest. To check for the impact of this we ran individual binomial
667 generalized linear mixed-effects models (using function `glmer` from R package `lme4`⁷⁵) to

668 conduct pairwise comparisons of outcome levels. These models supported the general
669 conclusions made in this paper (see Supplementary Information 13 for further details).

670 *Full Parameter Analyses*

671 The focal analysis inevitably is based on somewhat arbitrary modelling choices. We therefore
672 ran our models an additional 20 times with a range of parameter values for decisions such as:
673 the number years of counts required before and after protection, the threshold at which we
674 classify All Zeroes, the maximum distance between protected and unprotected sites for an
675 acceptable match and how similar we required matched sites to be (Extended Data Table 1).
676 Testing all parameter combinations was computationally impractical so we used a latin
677 hypercube sampling method⁷⁸. This is a way to adequately sample a high dimensional
678 parameter space when random sampling is prohibitively inefficient; it creates multiple
679 combinations of covariates that together evenly sample the entire n dimensional sample
680 space. We randomly created 20 parameter combinations (using function randomLHS from
681 the R package ‘lhs’⁷⁹), which are displayed in Extended Data Table 1. We call these analyses
682 our ‘full parameter’ analyses.

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885 **Extended Data Table 1. Parameter estimates and sample sizes across analyses.** Shows focal parameter
886 estimates, plus 20 estimates from full parameter samples. Parameters are a) the maximum number of years of
887 data the sample can have, to either side of protected area (PA) designation; b) the minimum number of years
888 that must be sampled, to either side of protected area designation; c) the closest distance an unprotected site can
889 be to a protected area before it is excluded from analysis; d) the proportion of counts that must be zeroes for the
890 time period to be classified as “All Zeroes”; e) the maximum distance between paired protected and unprotected
891 sites; f) the standardised difference in means threshold for BACI and CI matching; g) the proportion of
892 populations that must be matched successfully to retain a species, for BACI and CI matching. h), i), j) show the
893 number of protected sites/species/populations in that analysis run (note that BA and CI will generally be a
894 subset of these). See Supplementary Information 4 for a further taxonomic break down of species in the focal
895 analysis.

Analysis	a) Total years to either side of PA designation	b) Min number of measured years to either side of PA designation	c) Min distance to PA for unprotected sites	d) Proportion of counts that are zero for period to be classified as “All Zeroes”	e) Max distance between protected and unprotected sites (matching, BACI/CI)	f) Standardised difference in means threshold (matching, BACI/CI)	g) Proportion of species’ populations that must be matched to retain species (matching, BACI/CI)	h) <i>N</i> Protected Sites	i) <i>N</i> Species	j) <i>N</i> Popula
Focal	10	7	1.00	0.70	500	0.25	0.70	864	67	7313
1	10	10	0.50	0.68	272	0.12	0.53	209	23	951
2	6	5	1.78	0.71	2091	0.19	0.72	933	77	12475
3	14	13	0.95	0.72	2500	0.25	0.50	282	63	4325
4	7	4	2.95	0.69	587	0.23	0.71	1328	68	6050
5	9	6	2.61	0.70	1986	0.15	0.87	953	17	2709
6	11	10	4.30	0.60	1542	0.21	0.68	395	34	1937
7	12	10	4.73	0.78	785	0.19	0.55	469	55	3784
8	5	4	1.36	0.76	100	0.24	0.63	492	51	1402
9	8	6	2.22	0.79	1390	0.20	0.84	952	66	11198
10	13	11	3.49	0.61	1121	0.14	0.53	309	11	677
11	15	10	3.37	0.62	454	0.17	0.90	493	32	1781
12	12	7	3.83	0.77	2199	0.11	0.81	543	4	686
13	9	8	1.95	0.64	1874	0.22	0.66	592	74	7465
14	5	4	1.56	0.74	1154	0.18	0.85	1115	74	13901
15	11	11	4.08	0.68	648	0.14	0.77	122	7	235
16	6	5	0.88	0.65	1676	0.16	0.64	930	74	11922
17	8	5	4.43	0.62	2402	0.23	0.60	1242	77	8738
18	10	9	3.13	0.80	1401	0.15	0.75	404	16	1184
19	15	10	5.00	0.66	192	0.10	0.57	392	33	1894
20	13	10	2.40	0.75	1010	0.13	0.80	334	5	519

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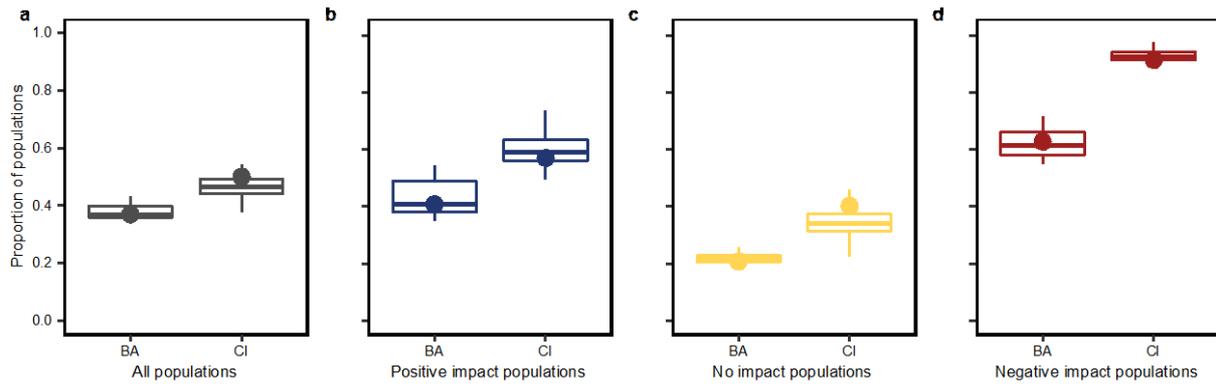
Extended Data Table 2. Covariates used to perform site matching. First, the three categorical variables (anthrome, region and migratory status) were used for exact matching. Next, all continuous variables were assessed for collinearity and highly collinear variables were removed. The remaining continuous variables were used to calculate mahalanobis distance.

Category and reason for inclusion	Variable	Data source	Resolution	Data transformation
Climate. This is a key variable that can determine suitability of a site for a species (meaning it is good to balance on) and also likelihood of being designated a PA.	Total annual precipitation (mm)	CRU TS4.01 80	0.5°, monthly (1961-2016)	Yearly sum of Jan-Dec
	Total precipitation December – February (mm)			Sum of Dec previous year and Jan & Feb current year
	Mean annual temperature (°C)			Mean, min, max of months Jan-Dec
	Minimum annual temperature (°C)			
	Maximum annual temperature (°C)			Mean, min, max of Dec previous year and Jan & Feb current year
	Mean temperature December – February (°C)			
	Minimum temperature December – February (°C)			
Maximum temperature December – February (°C)				
Fertiliser input. Eutrophication can affect waterbird populations ⁴⁸ , can be a metric of distance to farming land and therefore human impact as well as a measure of the potential value of land for uses other than protection.	Nitrogen (g N/m ² cropland/yr)	Lu & Tian ⁸¹	0.5°, yearly (1961–2013)	NA
	Phosphorous (g P/m ² cropland/yr)			
Land use. This is a direct measure of nearness to human impact, important for impacts to bird populations but also for likelihood of protected area designation – protected areas are less likely to be designated in areas suitable for agriculture and farming ⁸² .	Anthrome (categorical)	HYDE 3.2.001 83	5', centennial (10,000BC-1600AD) decadal (1700-2000), yearly (2001-2016)	Pre-2000 data taken from nearest decade
	Grazing land (km ² /gridcell)			Temporal linear interpolation to obtain yearly data between decades of 1960-2000
	Irrigated land (not rice; km ² /gridcell)			
	Irrigated land (rice; km ² /gridcell)			
	Pasture land (km ² /gridcell)			
	Rangeland (km ² /gridcell)			
	Rainfed crop land (no rice; km ² /gridcell)			
Rainfed crop land (rice; km ² /gridcell)				
Human presence.	Human population density (inhabitants/km ² pergridcell)			
	Total built up area (km ² per gridcell)			

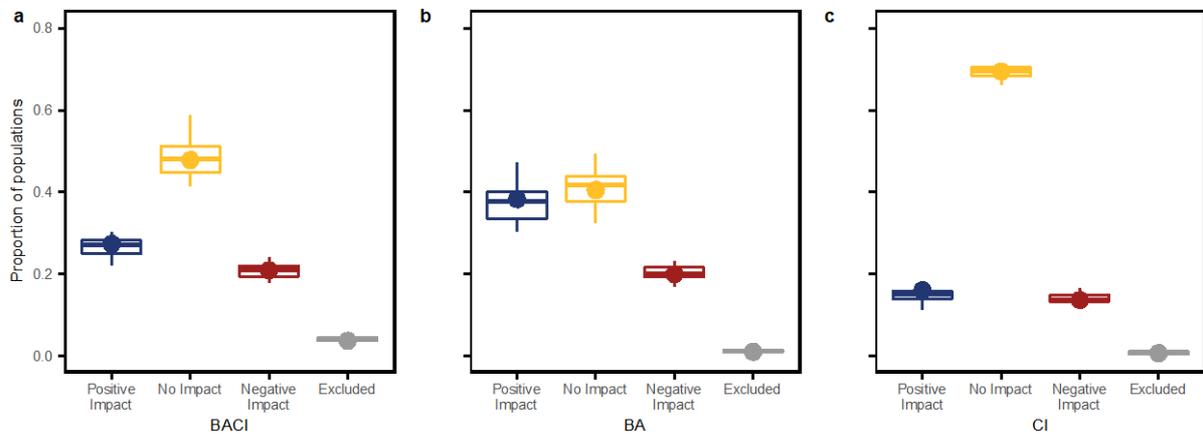
Protected areas are more likely to be designated in areas far from humans ⁸² , and human presence can also affect waterbird numbers either directly through hunting or through habitat degradation.	Rural human population count (inhabitants/gridcell)	WorldPop ⁸⁴	1km, yearly	Spatial bilinear interpolation to 5' grid cells
	Urban human population count (inhabitants/gridcell)			
	Travel time to nearest city			
Governance. Governance in a country is a significant predictor of protected area effectiveness ¹¹ , meaning it is important we compare protected areas with similar governance.	Mean of the six World Governance Index metrics (Control of Corruption, Government Effectiveness, Political Stability and Absence of Violence/Terrorism, Rule of Law, Regulatory Quality, Voice and Accountability)	World Bank ⁸⁵	By country, 1996, 1998, 2000, and yearly 2002-2016	Mean taken across all years because data is only available from 1996. Therefore, just one value per site for all years.
Water. Water presence is an important covariate for waterbirds, which rely on it for survival.	Surface water (presence/absence)	Pekel et al ⁸⁶	30m, 1985-2005	Converted to 5' gridcells by taking sum of 'presence' 30m ² cells in each
Elevation. Protected areas are biased towards where they can least prevent land conversion ⁸² which often results in them being in high elevation regions. Higher elevation sites are also likely to have less pressure and thus have lower biodiversity losses regardless of whether they are protected areas or not.	Elevation	WorldPop ⁸⁴	1km, NA	Spatial bilinear interpolation to 5' grid cells
Global Region. Because we are aiming to compare trends inside and outside protected areas, we wanted populations to at least be in similar regions to reduce unknown variance in comparisons.	Continent (categorical)	TM World Borders ⁸⁷	NA	NA
Migratory Status In some cases species have some migratory and some resident populations. To ensure we were not comparing between populations of different migratory types we exact matched on migratory status.	Migratory Status	Birdlife.org ⁸⁸	Species range polygons delineated by different migratory types	We classified each population (site species combination) based on the polygon the site fell within

Extended Data Table 3. Covariates used to assess what factors affect protected area impact.

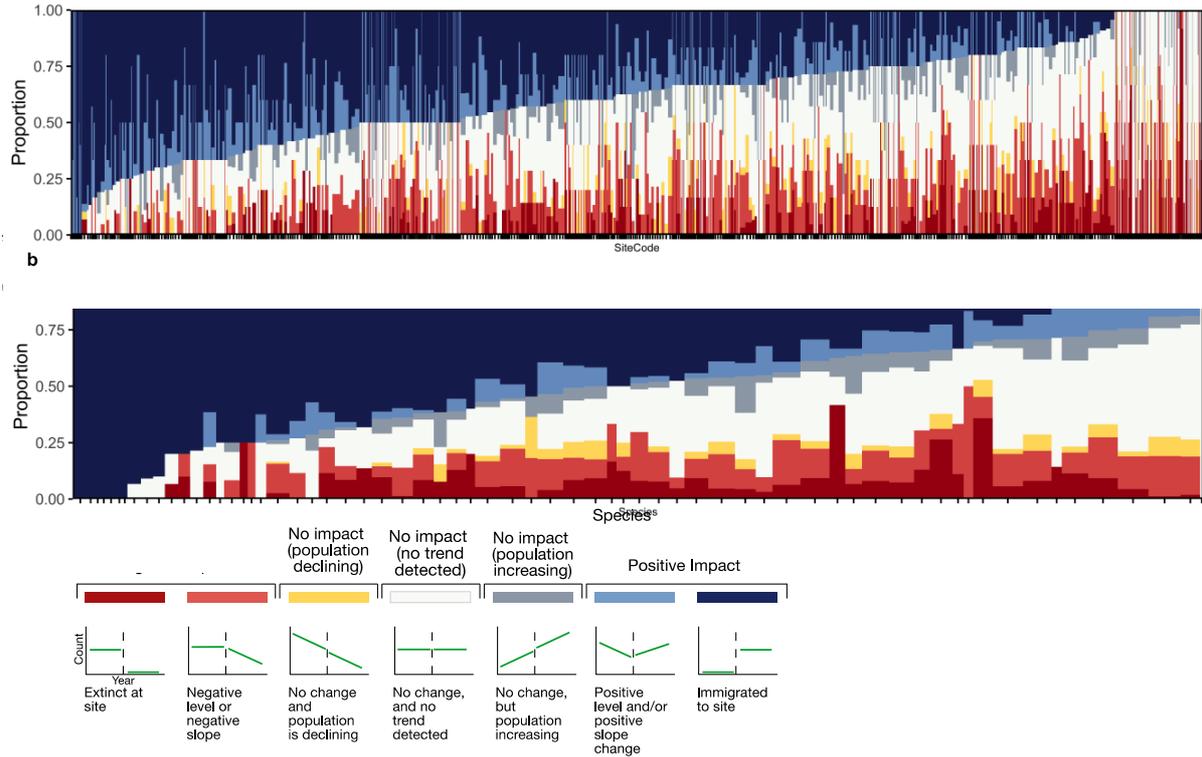
Category	Variable and Reason for Inclusion	Category/Levels	Source
Species	<p>Body Mass</p> <p>We expected larger species to respond better to protected areas¹⁰, due to the fact that larger bodied species are more vulnerable to hunting.</p>	Continuous	Wilman et al ⁸⁹
	<p>Taxonomic group</p> <p>Different taxonomic groups may respond differently to protection, so we looked for differences between orders.</p>	Categorical: Order	Birdlife.org ⁸⁸
Species (nested within Site)	<p>Migration Status.</p> <p>Because migrants are affected by other stressors than just those in their wintering site, we expect migrants will show less responsiveness to protected areas (and it is beyond the scope of this study to consider migratory networks). Some species are migrants in parts of their range and non-migrant in others, so categorised each population at each site separately.</p>	Categorical: Non-migrant, Migrant	Birdlife.org ⁸⁸
Site (nested in Country)	<p>Anthrome.</p> <p>We expected that sites in more remote regions (i.e. semi-natural, wild) will show less responsiveness to protection, as these sites are less likely to have been being exploited in the absence of protection.</p>	Categorical: Urban, Village, Croplands, Rangeland, Semi-natural, Wild	HYDE ⁸³ (see Extended Data Table 2)
	<p>Protected area size.</p> <p>We expected larger protected areas to perform better, because of reduced edge effects.</p> <p>In some cases, sites occurred in multiple protected areas that were of different sizes and had been designated at different times. In these cases, we used the size of the largest size protected area, if that area was designated earliest. If not, we took the mean of all areas.</p>	Continuous	World Database on Protected Areas ⁵⁸
	<p>Protected area Management.</p> <p>The best way to assess management would be with the Management Effectiveness Tracking Tool (METT⁹⁰) but unfortunately this is biased away from Europe and the USA, unlike our dataset, and only a few of the protected areas in our dataset are included in the METT.</p> <p>Instead, we chose to compare sites we know to be managed for birds to other sites, acknowledging that some of the ‘other’ sites may also be managed for waterbirds, but not having the power to ascertain management status of all cases. We created a category comprised of Ramsar and Special Protected Area (Birds Directive) sites, which encompasses 55-57% of populations. A full list of waterbird-managed and other sites is given in Supplementary Information 6.</p>	Categorical	World Database on Protected Area ⁵⁸
Country	<p>Governance.</p> <p>We expected sites in better governed areas to respond better to protection¹¹.</p>	Continuous	World Bank ⁸⁵ (see Extended Data Table 2)



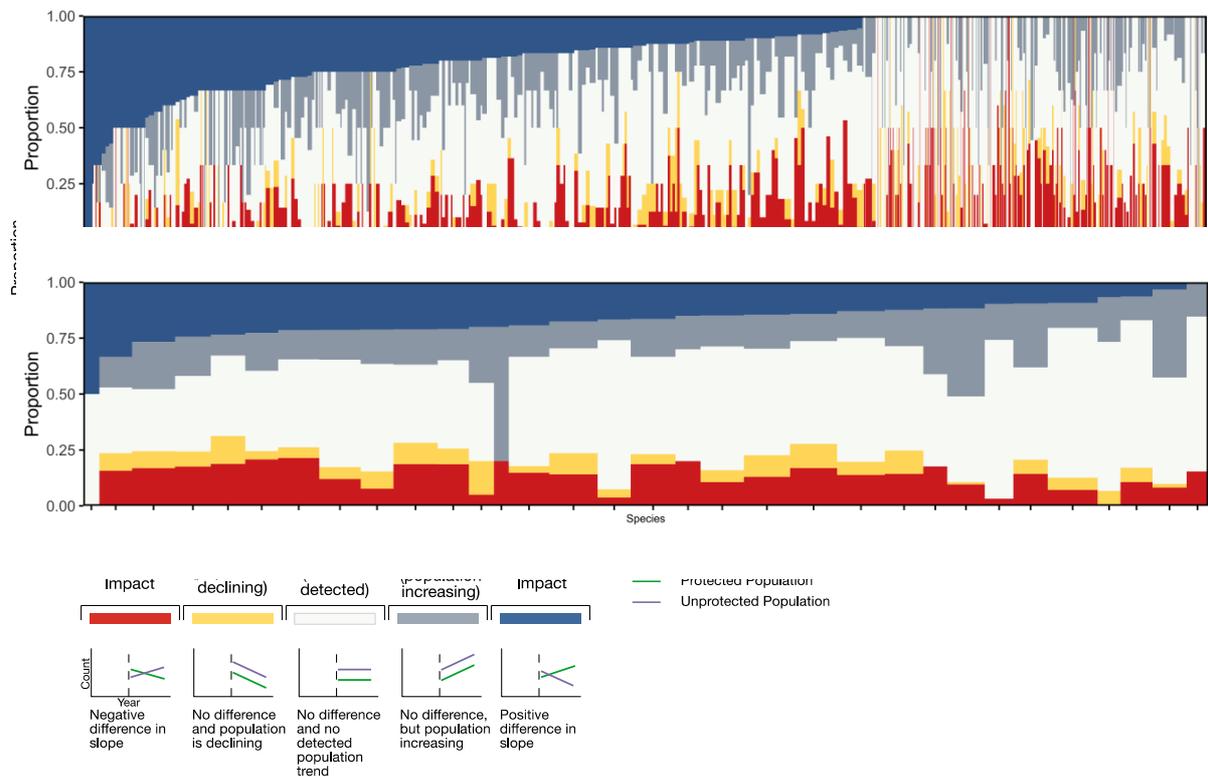
Extended Data Figure 1. Changes in estimates of protected area impact under different study designs, for all analyses. Proportion of Before-After (BA) or Control-Intervention (CI) populations that changed outcome when analysed under a BACI framework, by each analysis ($n=21$; 20 full parameter, plus one focal analysis). Shown for all populations (a), then the proportion of positive (b), no (c) or negative impact populations (d) that changed in outcome. Each point is an analysis, with boxplots showing distribution (box bounded by 25th and 75th percentiles, centre shows 50th percentile, whiskers extend to $1.5 \times \text{IQR}$ above 75th percentile, for maxima, or below 25th percentile, for minima). Large points show focal analysis estimates.



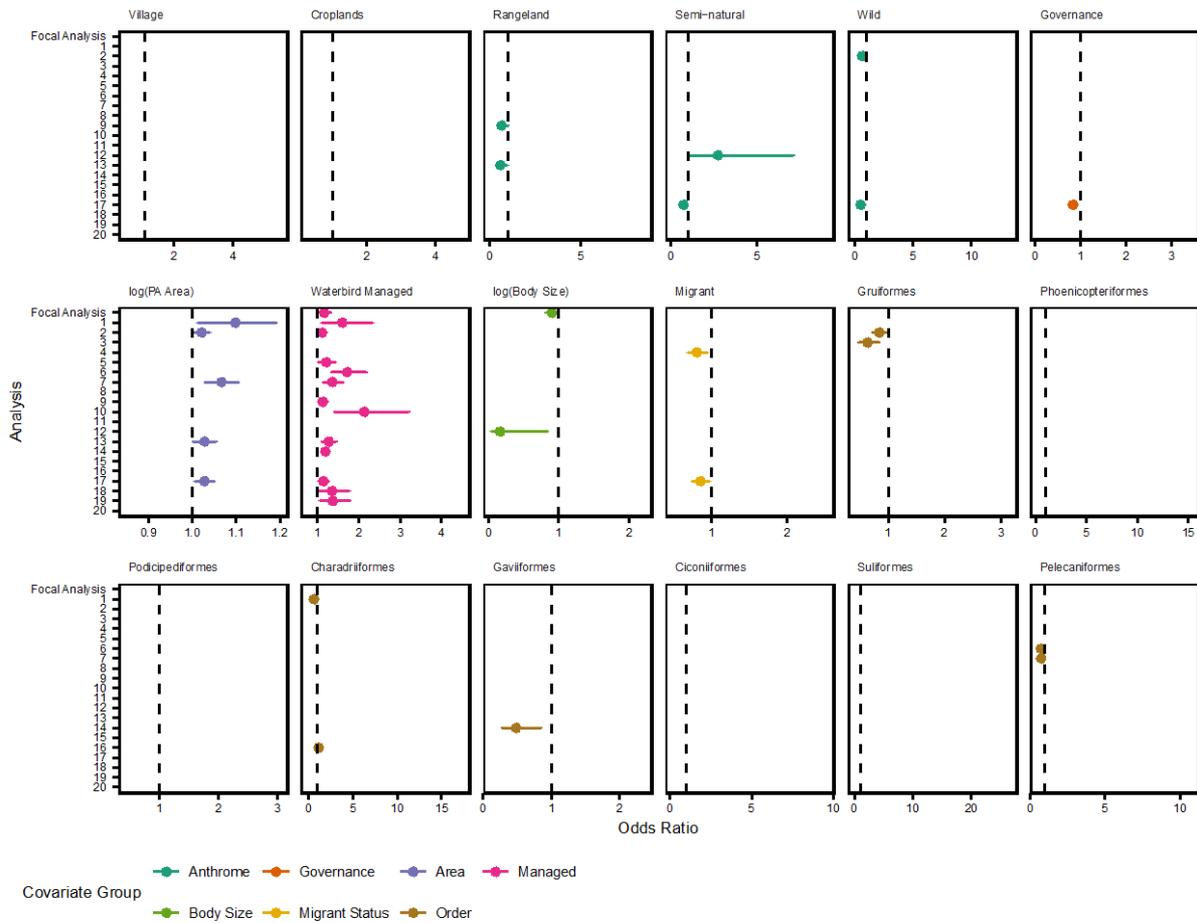
Extended Data Figure 2. Estimates of protected area impact under a BACI study design, for all analyses. Percentage of populations that have been positively, negatively or not impacted by protected areas, by each analysis ($n=21$; 20 full parameter analyses, plus one focal analysis). Each point is an analysis, with boxplots showing distribution (box bounded by 25th and 75th percentiles, centre shows 50th percentile, whiskers extend to $1.5 \times \text{IQR}$ above 75th percentile, for maxima, or below 25th percentile, for minima). Large points show estimates from focal analysis. Panels show estimates under BACI (a), Before-After (b) or Control-Intervention (c) frameworks.



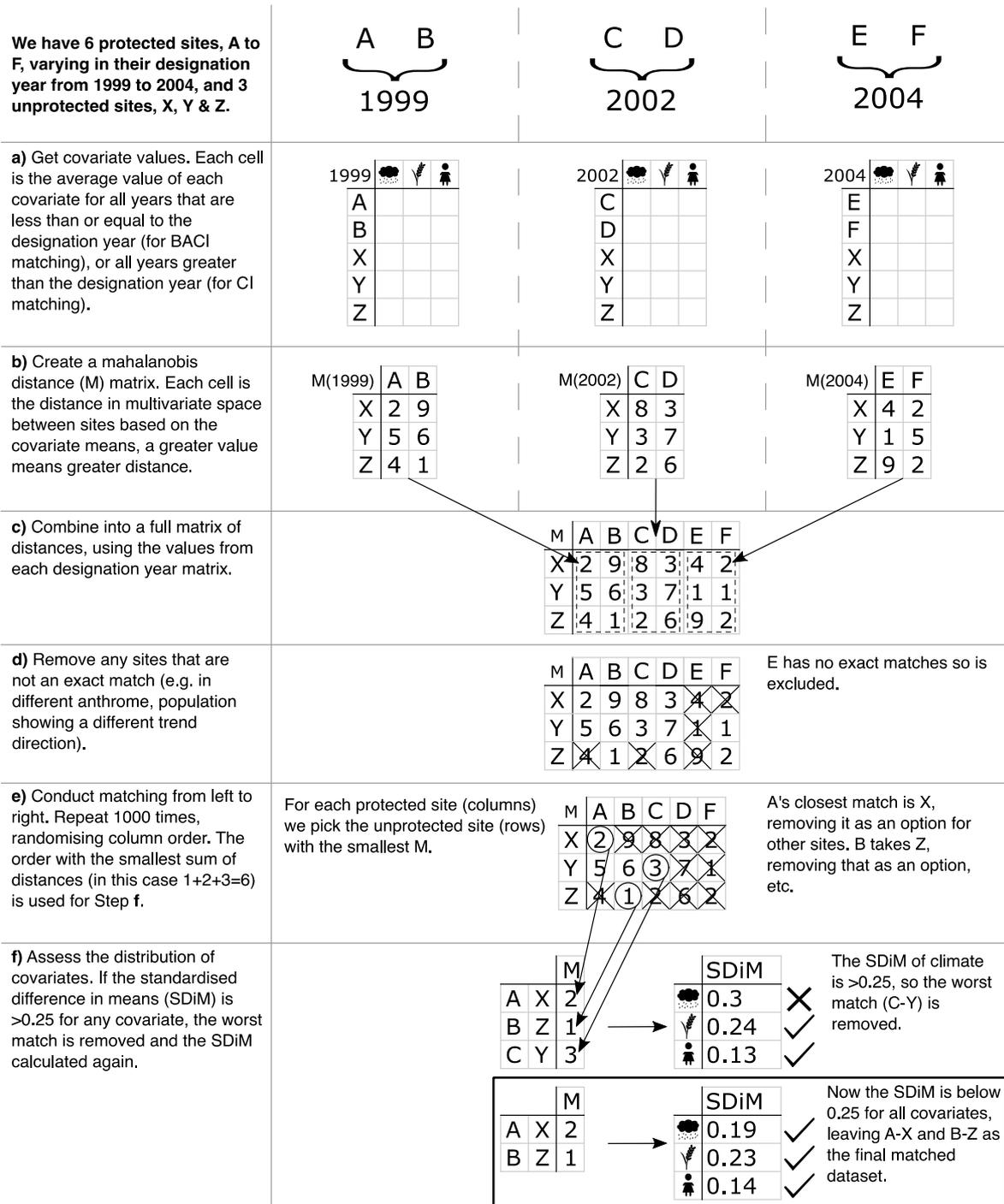
Extended Data Figure 3. Estimates of protected area impact under a BA study design. Proportion of populations ($n=6263$) showing various responses to protection, per site ($n=860$) and species ($n=66$), when response to protection is calculated in a BA framework. Each species/site is one bar, with the proportion of their populations in each category shown on the y axis. Bar width is scaled to the number of populations of that species/site in the dataset, log scaled in the case of species, with a wider bar meaning the species/site has more populations. Each colour represents a different way a population can respond to protection, and an example of each is shown at the bottom.



Extended Data Figure 4. Estimates of protected area impact under a CI study design. Proportion of populations (n=3783) showing various responses to protection, per site (a; n=698) and per species (b; n=32), when response to protection is calculated in a CI framework. Each species/site is one bar, with the proportion of their populations in each category shown on the y axis. Bar width is scaled to the number of populations of that species/site in the dataset, log scaled in the case of species, with a wider bar meaning the species/site has more populations. Each colour represents a different way a population can respond to protection, and an example of each is shown at the bottom.



Extended Data Figure 5. Predictors of protected area impact, with odds ratios and confidence intervals. Odds ratios for covariates predicting protected area (PA) effectiveness under a BACI framework. Estimated using cumulative link mixed models, points show model estimates, tails show 95% confidence intervals, and significance is indicated by bold colours ($p < 0.05$). Dashed line given at an odds ratio of one (ratios above one indicate a positive relationship, and below one a negative relationship). Y axis shows all analyses (20 full parameter analyses, plus one focal analysis, with the focal analysis given in the first row). Colours show covariate grouping. Orders are measured relative to Anseriformes, and Anthromes relative to Urban. Note that we expect continuous variables (PA Area, Body Size, Governance) to have smaller coefficients as they express odds ratios per unit increment.



Extended Data Figure 6. Schematic demonstrating matching procedure. Example of the matching procedure for one species, using a toy dataset of 6 protected sites (A to F) and 3 unprotected sites (X, Y and Z), with three dummy example covariates, climate (cloud), land use (wheat) and human population (person). See methods section “matching” for more detailed step by step walk through of this process.