

1 Global birdwatching data reveal uneven consequences of the COVID-19 pandemic

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18 Abstract

19 Birdwatching is a global phenomenon involving many thousands of people. Citizen science
20 generates data providing insights into global patterns of bird distribution across space and
21 time, yet how the pandemic may cast a longer shadow remains unassessed. Here, we explore
22 whether pandemic restrictions influenced observations globally from 2020-May 2021,
23 considering also GDPc and tourism income. We analysed 10,338 bird species (93% of all bird
24 species) and found that whilst high-income regions recover to pre-pandemic assessment rates
25 quickly, middle and low-income regions remain at low levels. Furthermore, protected areas
26 see huge losses in recorded richness. Whilst observer count increased overall, the number of
27 bird species recorded dramatically decreased, especially in 2020. These trends are most
28 marked in developing countries and regions, especially where tourism is important. Due to
29 increased bushmeat consumption during the pandemic, some species may become more
30 threatened, but with no data we cannot yet discern such trends.

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38 **Keywords:** biodiversity, conservation, eBird, citizen science, SARS-CoV-2

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40 **Introduction**

41 Recording bird sightings has been popular for centuries, but citizen (community) science has
42 revolutionized the hobby (Sullivan et al. 2009; Sullivan et al. 2014). Platforms such as eBird
43 have transformed the way we understand bird distributions and behaviour, enabling us to
44 track migration, or shifts in ranges in a way previously unimagined (Supp et al. 2015; Walker
45 & Taylor 2017). Furthermore, with the fanaticism that surrounds some elements of “birding,”
46 new records and migrants are quickly noticed and shared, providing unique insights into how
47 species respond to climate and weather (La Sorte et al. 2019). Enabling the appreciation of
48 nature has a myriad of benefits, both in terms of making people more environmentally
49 conscious and bettering our data resources (Callaghan & Gawlik 2015; Sullivan et al. 2017).

50 While birdwatching and associated activities continue to peak yearly (Steven 2015),
51 the COVID-19 pandemic has transformed the way we live and observe nature. How it
52 impacted on bird observations, and the legacies for species’ long-term observations remains
53 largely unknown. The end of international travel for much of the world, as well as periodic
54 lockdowns and easing, might severely impact birdwatching, varying based on region
55 development state and reliance on tourist income, with potential downstream consequences to
56 species protections (Conradie & Van Zyl, 2016; Lindsey et al. 2020). Thus, whilst the
57 “anthropause” has been popularised as a “positive break” for biodiversity, including sighting
58 of species in urban environments which are typically associated with more natural areas
59 (Shrimpf et al. 2021), or by common species like sparrows calling more quietly due to less
60 background noise in some cities (Derryberry et al. 2020). However, the situation is actually
61 more complicated and understanding the negative implications or potential data loss,
62 particularly in more diverse regions, is difficult in the long-term. A recent paper explored
63 trends for North America in March-May 2020 for 82 selected species (Shrimpf et al. 2021),
64 but exploring these trends for a larger set of species in a more diverse range of regions and
65 across waves of the pandemic will be necessary to understand its broader consequences.
66 Heterogeneous responses are demonstrated by the inconsistency between studies, for example
67 in that a study in Spain no increase in probability of occurrence of birds in urban areas (Gordo
68 et al. 2021), although another found more observations there, as well as decreased records in
69 non-urban areas there and in Italy but not the UK (Basile et al. 2021). So far, all studies have
70 focused on developed countries, using different methods, making a global view imperative.
71 National income status impacts how birding and citizen science occurs in different regions, so
72 assessing these patterns in a broader range of situations and environments is essential to better
73 understanding the impacts of the pandemic. Here, we unpick how the various restrictions and
74 behaviours associated with the Covid-19 pandemic impacted on bird observations worldwide,
75 providing a unique window for viewing human behavioural changes in the face of a global
76 pandemic.

77 First, we explore overall trends in changing observations and how observed richness
78 correlates with access to different spaces and international travel to regions with different
79 economic statuses and reliance on tourism. We then examine how what was observed by
80 whom changed in terms of endangered and common species in rural, urban and agricultural
81 areas in concert with changing restrictions. As well as the rate of recovery to pre-pandemic
82 observations in different regions. Lastly, we discuss the implications of these changing
83 observations for different regions, particularly those reliant on tourist revenue, which is key
84 for conserving diversity in some of the most biodiverse areas on Earth.

85 **Methods**

86 *Modeling expected patterns and divergence from expected during pandemic*

87 We used an exponential smoothing state space model (ETS; Hyndman et al. (2002)) and the
88 number of species from 2015 to 2019 to build a model that predicts the number of species
89 from 2015 to 2021. ETS parameter: “AAA”. A three-character string identifying method
90 using the framework terminology of Hyndman et al. (2002) and Hyndman et al. (2008). The
91 first letter denotes the error type (“A”, “M” or “Z”) (“N”=none, “A”=additive,
92 “M”=multiplicative and “Z”=automatically selected); the second letter denotes the trend type
93 (“N”, “A”, “M” or “Z”); and the third letter denotes the season type (“N”, “A”, “M” or “Z”). We
94 then calculated the difference between the predicted and empirical number of species with the
95 formula (number of species-predicted species)/number of species. We then used the Mean and
96 Standard Deviation of absolute difference from 2015 to 2019 as a metric to evaluate the
97 model’s accuracy. Here, we focus on 62 regions that had sufficiently high-quality data for
98 analysis (mean and SD are higher than 10%, Supplemental text).

99 We then determined when areas were under pandemic restrictions, using the finest-
100 scale data available such that some countries might be split into multiple regions. Lockdown
101 type was based on daily restrictions (international tourist arrivals: UNWTO 2021, Lockdown
102 stringency, Mobility in different sectors, international travel restrictions: OurWorld in Data
103 2021, Tourist GDP: Knoema 2019; GDP: Hughes et al., 2021), but our analyses are monthly
104 so we calculated lockdown days per month (some restrictions=1 and hard lockdown=2; so
105 numbers close to 60 indicate harder lockdowns, multiplying days by lockdown classification).
106 Then we used the differences above to evaluate the change in number of species post-2019. If
107 the difference was higher than 10%, it means that the observed number of species is 10%
108 higher than predicted. Steps were repeated for the number of observations, events and
109 observers, then plotted to observe differences. The code is available at:
110 https://github.com/qiaohj/covidbirds/blob/master/lockdown/lockdown_stat.r

111 We then coded each successive period of lockdown, eased restrictions and no
112 restrictions and, using summary statistics in ArcMap 10.3, calculated the mean, maximum
113 and minimum difference between each of these periods and the prediction by the model for
114 each region. This enabled us to detect changes in observer responses to restrictions
115 throughout the pandemic and successive lockdowns.

116 *Changing birds by IUCN status and landuse type*

117 For each record in eBird (based on all data globally), we recorded the fields: scientific name,
118 longitude, latitude, and observation date. Via the information above, we categorised
119 urban/rural landuse types for each species before and during the pandemic.

120 For urban-rural classification, we used Europa (2019) and made a 500m buffer as an
121 indicator of urban areas, and all the other areas are labelled as rural areas. We extracted the
122 urban types for all the occurrences of a given species between 2015 to 2019, and calculated
123 the proportion of urban areas in the occurrences. If the proportion is larger than 66.7%, the
124 species was labelled as an urban-type species before the pandemic. Conversely, if the
125 proportion is lower than 33.3%, the label is rural-type, and between 33.3% and 66.7% are
126 mixed-type. We reclassified the species during the pandemic to compare before and during.

127 For landuse type, we used the Annual Plant Functional Types (PFT) classification in
128 MODIS Land Cover Type Product (MCD12Q1, Sulla-Menashe., in review, see Table S1 for
129 legend) as the standard to classify the landuse of the species before and after the pandemic.
130 We merged the 12 landuse types in PFT into three types, Cereal Croplands (7) and Broadleaf
131 Croplands (8) were regarded as ‘CROP’. Urban and Built-up Lands (9) were regarded as
132 ‘URBAN’ and all the other types were regarded as ‘PRISTINE’. If more than 33.3%
133 occurrences of a given species before/after pandemic were predominantly in the categories

134 listed above, the species was given a corresponding label. The landuse type of a species is
135 given in three characters ‘XXX’. The 1st number is 1 if the proportion of pristine is larger than
136 33.3%, and the 2nd number represents crop and the 3rd one is urban, calculated similarly. We
137 also analysed the occurrences before and after the pandemic of each species in eBird.
138 https://github.com/qiaohj/covidbirds/tree/master/species_modis

139 We mapped out whether species had been lost, gained or stayed stable relative to
140 former years, both for all species and for endangered species
141 https://github.com/qiaohj/covidbirds/blob/master/species_turnover/species_richness.r). These
142 were then imported into ArcMap 10.3, and the change in richness overall and for endangered
143 in protected areas during the pandemic relative to before the pandemic analysed. To do this,
144 we first dissolved protected areas (using the protected planet map:
145 <https://www.protectedplanet.net/en>, downloaded 21st March 2021) so that all overlapping
146 designations were removed and then used this to clip regions so we had National protected
147 area coverage. We then used the tabulate statistics tool to extract the average statistics for
148 each protected area, and analysed this for each month of 2020. Statistics gauged the
149 differences in richness in the pandemic relative to those prior, we also tabulated for how
150 many protected areas observations were recorded in 2019 relative to the same month in 2020
151 to assess how the representativeness of recording had changed.

152 *Changes in observer status (domestic vs international)*

153 To classify if an observer was largely domestic or international, we calculated the count of
154 regions that an observer uploaded from within a year.
155 (https://github.com/qiaohj/covidbirds/tree/master/observer_stat). Based on the results above,
156 we categorised the observers into two types, “international” who submitted the data from at
157 least two regions within a year, and “domestic” who submitted the data from one region in a
158 year. We grouped all the Schengen countries and the United Kingdom as a region because
159 people can travel throughout without visas, and they are adjacent to extensive transportation
160 networks.

161 After labelling the observers, we calculated the proportion of different observer types
162 from 2015 to 2021 in each region, and labelled the region type in a given year into two
163 categories; “international-based region” are regions where more than 50% of observers were
164 international observers in a year; for “domestic-based regions” at least 50% of observers are
165 domestic in a year. If the type of a region changed between 2015 and 2019, it was labelled as
166 “mixed before pandemic,” or “mixed after pandemic (the type changed in 2020 and 2021)”.

167 *Species loss and gain*

168 Whilst numbers of observers, events, and observations remained relatively similar, the
169 number of species in 2020 declined dramatically from previous years (Figure S1). For the
170 species lost and gained, we extracted the species list for each region before and after the
171 pandemic. To develop a comparable species list, in this analysis, we used 2019 as the year
172 before the pandemic, and 2020-2021 as the pandemic. Species gain means the species was
173 recorded for the first time in any given region during the pandemic, species loss indicates
174 species were recorded prior to the pandemic (in 2019) but not recorded during the pandemic
175 within a region. There will inevitably be some stochasticity, but equal weighting does show if
176 patterns in a region have changed if a region loses more species than it gains (or vice-versa)
177 due to changing observation patterns. In plots, each species status was reported for every
178 region it was recorded in. We also calculated the total events of each species in a given region
179 between 2019 to 2020 to represent species visibility.

180 **Results**

181 ***Global patterns of birding***

182 ***Changes in observation pattern during the pandemic***

183 From 2015-2021, the number of bird species observed showed demonstrable changes during
184 the pandemic, whereas the number of records, number of observers and numbers of
185 birdwatching events was largely unchanged (Figure S1). Prior to the pandemic, almost all
186 regions showed annual increases in the popularity of birdwatching, and the number of species
187 recorded. We analysed trends for 62 regions which had enough data to model. All 62 regions
188 had a minimum number of species below the prediction during 2020, with 25 of these having
189 a loss of over a 100% loss relative to the model and several regions having over 500 less than
190 the prediction (Peru and Ecuador), and nine regions had a mean of over 100 loss, with all but
191 three of these (India, Malaysia and Tanzania) falling in Latin America. Even for the
192 maximum value in the prediction, 19 regions are still below the expected values (Table S2).

193 For 2021, some regions did recover to pre-pandemic levels, yet only two regions did
194 not show a minimum below pre-pandemic levels (Belgium and Hong Kong), and 12 remained
195 at a loss of over 100 species (and eight of these have a mean loss of over 100). In total, only
196 17 regions had a mean of, or above pandemic levels, but 33 had maximums that exceeded
197 them for at least some time. In terms of the number of events across 2019-2020, the majority
198 of events globally recorded species both years (stable Figure S1), this was followed by events
199 where species were only sighted in 2019 but not 2020, and the fewest events not previously
200 recorded in a region. Mapping these impacts out, we see similar patterns in terms of areas
201 showing the greatest decreases in occurrences (Figure 1).

202 ***Recovery and rate of recovery***

203 Most regions implemented different levels of restrictions at different times, and understanding
204 these trends and their implications for observations is important (Figure 2; Figure S2, S3).
205 Regions that showed the greatest mean losses during the initial lockdown typically also
206 showed the greatest losses during subsequent periods, many of which were in developing
207 regions. Peru showed the greatest mean losses during the first lockdown (because regulations
208 were ongoing), but in Ecuador and Columbia whilst mean losses were similar to Peru during
209 the first lockdown they remained high as restrictions were eased, and increased again in
210 Colombia during the second lockdown. China has an interesting profile, though difficult to
211 adequately capture as no nationwide restrictions existed following the first lockdown, yet
212 mean losses remained through all subsequent periods. However, it should be noted that China
213 has its own system for bird recording (bird-tracker) and that like other countries with
214 languages which do not use Roman script, these countries may be particularly reliant on
215 international observers for sharing records via eBird. Similarly, many tropical regions showed
216 major losses, yet many developed regions showed relatively little mean difference between
217 observed and expected species richness, though maximum differences were often greater.
218 Furthermore, a subset of largely European countries showed mean losses during periods when
219 restrictions were being eased following lockdown (possibly due to a return to workplaces).
220 Interestingly, regions which had lower mean and maximum decreases also had fewer periods
221 of lockdown or eased regulations which showed a substantive difference from the model of
222 what would be expected in terms of seasonal change during previous years.

223 ***How these vary based on economic state, main correlates***

224 Whilst lockdowns were implemented widely, especially during initial phases of the pandemic,
225 how they impacted on behaviours varied. Changes in activity levels relative to the same
226 period in previous years in a range of places (grocery and pharmacy, parks, residential, retail
227 and recreation, transit stations, workplaces) were directly compared to differences between

228 the model and observations, and levels of international tourist arrivals. For 2020-21, we found
229 a significant relationship between the degree of loss and a number of the activity factors
230 ($p < .001$), including lockdown regulations, decreases in activity in grocery and pharmacy,
231 parks, workplaces and increases in activity in residential areas. When examined by reliance
232 on tourism as a percentage of GDP and region income status (based on IMF definitions),
233 different patterns emerge (Table S3a). Overall, the relationship between activity in any of
234 these sectors and the loss of recorded bird species is weaker and less significant in low-
235 income regions, stronger in middle-income regions and highest in high-income regions, with
236 negative relationships with activity in all sectors except residential, where positive
237 relationships existed (Figure S4a-b). When analysed by status for the 2020-21 period, high-
238 income regions showed the strongest relationship with lockdown status, international visitor
239 controls, and activity in retail and recreation, transit areas and workplaces; middle-income
240 regions showed significant relationships with activity in residential areas, retail and recreation
241 and workplaces (Figure S5); and low-income regions showed no significant relationships. In
242 terms of reliance on tourism for high proportions of GDP, those with a very low reliance on
243 tourism showed significant relationships between the difference between observed and
244 expected with lockdown status, grocery and pharmacy, retail and recreation and workplace
245 activity. Those with low tourist reliance showed relations with visitors in parks, and grocery
246 and pharmacy, whereas those with a medium reliance showed relationships between activity
247 in transit stations, retail and recreation and residential and those with high reliance only on
248 activity in parks where species may be directly observed.

249 When 2020 was evaluated independently (and more international travel data was
250 available- Table S3b), activity in transit stations was the strongest factor overall. For high-
251 income regions, activity in grocery and pharmacy, residential, retail and recreation and parks
252 were significantly related, whereas for middle-income regions only the relationship with retail
253 and recreation were significant and no predictors were significant for low-income regions. For
254 tourist reliance, those with very little reliance on tourism showed relationships between
255 international travel control, park visitors, residential, retail and recreation and workplace
256 activity. Those with a low reliance with international travel levels and residential levels, and
257 those with a higher reliance on tourism showed little significant relationship, though notably
258 most of these still remain at below pre-pandemic levels in terms of species recording.
259 Therefore, whereas developed regions could quickly “normalise” activities, diverse
260 developing regions remain at low levels of observation.

261 *IUCN status and changing patterns of where species are located and recorded*

262 Changing patterns of observation as well as relative disturbance impact on what species might
263 be observed in different parts of the landscape. We divided the landscape from two different
264 perspectives, one simply dividing urban and rural areas, and the other dividing the region into
265 “pristine”, agricultural, and “built-up” and looked at the relative change in the percentage of
266 records for each species recorded in each constituent part between threatened and non-
267 threatened species. We included a total of 10,338 bird species (93% of bird species) (and 348
268 subspecies) in analysis, though notably 9,505 of these were Least Concern (or Near
269 threatened), 29 data deficient, 666 vulnerable, 371 endangered and 115 critically endangered
270 (Table S4).

271 We used a total of 869.78 million records from 2016-2019, and 154.49 million
272 records from 2020 (representing about a 29% reduction in average records collected). For the
273 984 species recorded in previous years, there are no records in 2020. In total, there was an
274 82% reduction in the number of species records, with 76.4% in natural areas, 73.1% in
275 croplands and 71.1% in built-up areas. Many species were only recorded in natural areas

276 (Table S5, Figure S6). Only eight species of 10,686 showed no overall loss of records in 2020
277 compared to the average for former years; all other species were recorded less in 2020.
278 However, some species did show increases in specific types of landcover, though most of the
279 species with the greatest increases were actually subspecies, though certain species (i.e.
280 *Euptilotis neoxenus*) whilst showing decreases in the number of records overall showed
281 increases in the number of records in rural areas. Likewise, the data-deficient species
282 *Oceanites pincoyae* only had 33% of the average annual amount of data but a 300% increase
283 in pristine areas, these species have low sample sizes (Table S2) but the number of records for
284 these rare species showed the greatest losses. In total, 22 species showed increases in pristine
285 areas (and 13 in rural areas). Yet 9,407 species showed fewer records in natural areas. Some
286 cases are particularly interesting, for example *Pterocles decorates* shows an 88% reduction in
287 the number of records in total but a 1,100% increase in records in builtup areas, and 135
288 species in total show increases in the number of records in builtup areas, though all of these
289 show a decrease in the total number of records (though at least 6,072 species show a decrease
290 of records in urban areas). Similarly, 195 species showed increases in the number of records
291 in croplands, three of which had over 1000% increases, yet 4,616 species show decreases in
292 records of at least 10%. When explored based on threat the majority of species of all threat
293 classifications lost points, however threatened species showed few gains in any areas but
294 under 1-2% of all species showed gains in built-up areas (with 23-36% showing losses), and
295 under 4% of species showed gains in croplands (Table 1).

296 **Data from key areas and species**

297 Whilst changes in park activity correlate with the difference between observed and expected
298 values in some income classes, this does not differentiate urban parks from more extensive
299 protected areas which are key to biodiversity. However, results also show that low and
300 middle-income regions remain continuously low for records. When we examine protected
301 areas on a national basis and compare species observed to those observed in previous years
302 over the same period, we see broad-scale losses in the number of species observed in most
303 regions. In total, 203 regions had at least some data in protected areas, and 170 of these had at
304 least six months with data, yet all regions but two with 12 months of data showed on average
305 decreases in species observed in protected areas (Madagascar and Syria), and both these two
306 showed an average increase of under 3 species, whereas 92.4% of species show an average
307 loss of at least 10 species in protected areas, and 53 of these show a mean loss of over 50
308 species (Table S6). Notably, both these countries (Madagascar and Syria) are also outliers
309 when we examine the loss and gain of species (Figure 5). Furthermore, of the 118 of 203
310 regions which had all 12 months of data, 81 were negative for all 12 months, and 33 were
311 negative for at least 6 months. Similarly, 43 of the 114 regions with 12 months of data also
312 had a mean monthly diversity value below that of previous years for all months.

313 In terms of endangered species, some areas saw major losses in records of
314 endangered species in protected areas. For example, Tanzania saw a mean maximum loss of
315 endangered species in protected areas of eight species (though many lose more) and an
316 average loss of 3.2. South Africa saw similar losses of a mean maximum of 6.7 and a mean of
317 1.9. Kenya and Brazil showed similar losses of 6.5/2.3 and 6/1.6. Zimbabwe and Zambia also
318 showed significant losses of endangered species in protected areas with a loss of 11 species in
319 February 2020 and mean maximums in both cases of 5.42 and 5.25 species. These losses may
320 actually be more significant as data for all protected areas do not exist, and many protected
321 areas have no data for endangered species for much of 2020, for example, South Africa had
322 endangered species data for 113 protected areas in January 2020 to only 7 in April (Table S6).
323 Thus, many areas showed a huge loss of data, and many regions in Latin America and across

324 Africa had data on species from 200-500 protected areas in January 2020 to only 10-30
325 protected areas within a few months.

326 *Changing observer status*

327 Whilst the number of observers increased from 110,000 observers in 2016, this increased to
328 almost 180,000 by 2019, and up-to 225000 in January 2020. The count of one region
329 observers is the only one that increased after 2019 (Figure 3), but observers in more than one
330 region within the year all decreased dramatically, especially for observers who previously
331 visited high numbers of regions. Consequently, because of the pandemic, international
332 observers decreased and domestic observers increased. However, whilst species numbers did
333 change dramatically through lockdown, number of observers and observer events largely did
334 not (Figure S1). However, many developing regions may have seen losses in observed species
335 due to the loss of international observers, thus we analysed the changing status of bird
336 watchers in each region. Through the pandemic, international observers decreased and
337 domestic observers increased overall (Figure 4), and whilst between 2016-2019 the numbers
338 of domestic and international observers in different regions was approximately similar in
339 2020 the number of domestic observers increased whilst the number of international
340 observers decreased, and both decreased in 2021. These trends were persistent in most
341 regions, though very high GDP regions (Bermuda, UAE, Bahamas, Kuwait) maintained more
342 international observers than most other regions, and most lower-income regions saw a
343 transition from largely international observers to largely domestic observers, and middle-high
344 income regions maintained a large proportion of domestic observers.

345 **Discussion**

346 Recent years have seen a growing popularity of birdwatching and the sharing of data through
347 portals like eBird and iNaturalist in almost all regions. The popularity of these platforms has
348 grown exponentially in recent years, almost doubling the number of users between 2016 and
349 2020. However, patterns of activity through the pandemic differed massively as a
350 consequence of changes in international and domestic travel. Whilst some of these patterns
351 are likely to be temporary, they provide insights into the role and value of international travel
352 as a means of generating data, and may have long-term consequences given the importance of
353 ecotourism in some regions. These differences in observer activities must be carefully
354 accounted for in any future analyses of such data. Notably, whilst many regions showed a
355 similar number or slight increase in observers, most showed a loss in species and a decline in
356 the records of more threatened species during the pandemic. It is clear now that, contrary to
357 popular messaging of a net-benefit “anthropause,” there are real negative consequences of the
358 pandemic for biodiversity research, even when using data generated by the public.

359 *Patterns, trends, and implications*

360 Our analyses show that in regions with higher incomes, levels of activity in residential areas,
361 shopping areas and parks did have strong relationships with the difference in the number of
362 species expected and observed during the pandemic. Thus, unsurprisingly when residential
363 activity was high (during lockdown phases) and access to natural areas was lower, we see
364 decreases in the number of species recorded in developed regions, whereas as activity levels
365 resume more “normal” levels the difference in observed and expected decrease, with fastest
366 recoveries within higher income regions with a lower dependence on international tourism.
367 For middle-income regions, these patterns are slower, and there is a stronger relationship with
368 the amount of activity at transit stations, showing that regional movement contributes to
369 species recording. Additionally, whilst initial lockdowns showed major decreases in recorded
370 richness in almost all regions, these impacts dissipated in high-income regions through

371 successive stages of the pandemic and is less demonstrable in consecutive lockdowns, whilst
372 low-income regions do not show this recovery, and show much less relationship between
373 human activity and observations due at least in part to a common reliance on international
374 observers for record generation. Notably, even in regions that saw increases in the number of
375 observers, these observers did not increase the number of species recorded, as they may have
376 disproportionately focused on areas which were easy to access and thus unlikely to host less
377 common or novel species.

378 Furthermore, endangered species remain unlikely to be recorded in urban areas, and
379 thus decreased access to more remote and “pristine” habitat is associated with a loss of these
380 species. Common species (least concerned or near threatened) showed significant increases in
381 the proportion of records observed within urban areas, as suggested by Schrimpf et al. (2021),
382 but this is not true for most species with higher threat levels (via IUCN) and species classed
383 as data deficient often show the greatest levels of loss, so clearly the subset that they used
384 could not represent the full breadth of avian diversity. These patterns are also indicative of a
385 wider problem, this lack of data generation from natural habitats also indicates that protected
386 areas are visited less during the pandemic, and again the data shows this, with many low and
387 middle-income regions showing no data from around 80% of their protected areas within
388 months of the pandemic starting.

389 There are clearly strong patterns relating to GDPc, with many countries and regions
390 showing the largest losses and fewest gains being developing regions or islands (Figure 5),
391 with countries across Africa showing particularly interesting patterns (Figure 1, Figure 5).
392 This loss of data not only hampers long-term understanding of species activities, but with no
393 tourist income parks may struggle to protect rarer species, especially when security might be
394 lax due to a loss of tourist revenue needed to support rangers such that poachers have free
395 reign (World Ranger Challenge., 2021; Boyle 2020; Lindsay et al., 2020). This has led to
396 increased consumption of bushmeat across much of the African continent as well as parts of
397 Asia, exposing a wide suite of species to hunting for subsistence (InfoNile, 2021; Ghosal &
398 Casey., 2021; Borzee et al., 2020). These impacts should not be under-estimated; surveys
399 show that tourist revenues in regions like Kenya dropped by 96%, and that in a survey of 19
400 African countries, three quarters of regions surveyed said the pandemic hindered their ability
401 to monitor wildlife trade, whilst two thirds of rangers said hunting had increased (Baldwin.,
402 2021). Single reserves such as Hwange in Zimbabwe have seen increases in the numbers of
403 snares and traps of up to 8000%, and the loss of an estimated \$250 billion in tourist revenue
404 across Africa in 2020 alone may have long-term implications for conservation across the
405 region (Baldwin, 2021; Wildlife Ranger Challenge., 2021). Tourism has long been promoted
406 as a mechanism for regions to transition away from unsustainable hunting for subsistence, so
407 the loss of access to those incomes has major consequences for species in these regions
408 (Secretariat of the Convention on Biological Diversity, 2011).

409 Our results show hundreds of species recorded in previous years were not recorded
410 during the pandemic, particularly from protected areas. With increased hunting due to a loss
411 of revenue and a need for incomes, and the loss of data from these key areas, we do not yet
412 know the impact of this hunting on the status of these species. Furthermore, whilst the
413 “anthropause” has been heralded as positive for biodiversity (Derryberry et al. 2020), the
414 positive impacts have been largely temporary incursions of common, often generalist species
415 into urban areas (Rutz., 2020; Zulanga et al., 2021 Sumasgutner et al., 2021). Worryingly, the
416 ability of areas to recover post-covid may be hampered by the slow return of tourism needed
417 to fund local economies, the loss of rangers and other staff, and the suspension of
418 environmental regulations to stimulate economic recovery post-covid (Bobylev 2020). The
419 loss of staff during the pandemic means enforcing environmental regulations even after the

420 pandemic may be challenging, meaning more unsustainable development and hunting, and
421 less data to detect or understand the impacts, especially in regions which saw particularly high
422 economic losses during the pandemic (Kazaz & Walton, 2020; OHCHR 2020; Goodday,
423 2021).

424 *Synthesis*

425 Whilst the impact of the pandemic on wildlife globally has often been painted as positive,
426 from a reduction of use of natural areas and of pollution, former analysis has been both short-
427 term and has failed to account for parts of the world where rural incomes depend on tourism
428 (Schrimpf et al. 2021). The loss of this tourism not only means a dramatic reduction in the
429 number of protected areas with data, but also a loss of data from many high-diversity regions.
430 In concert, this means we cannot truly know the impact of subsistence hunting or poaching in
431 these key regions, due to a lack of monitoring data provided through international observers
432 within eBird, and a slow recovery in many of these regions. Birdwatching is still dominated
433 by observers from high-income regions, thus whilst activity in these regions linked explicitly
434 to pandemic-related regulations and were able to recover rapidly, this was not the case in the
435 most diverse parts of the planet. Gains in species records have also largely been limited to a
436 subset of species able to utilise highly-modified spaces, whereas endangered and data-
437 deficient species have shown major reductions in their levels of recording. We need measures
438 to support tourist-dependent economies, and to facilitate the return of tourists in a way that is
439 safe for local residents (as these regions are frequently also struggling to provide the medical
440 support needed to enable these regions to not be seen as “high-risk” by higher-income
441 economies). Ultimately, the long-shadow of covid, and covid regulations may continue to
442 hinder not only our ability to monitor biodiversity in key regions, but also to provide a means
443 of support for economies where tourism is crucial for both providing biodiversity data and
444 financially supporting conservation.

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556 QMY; Project administration: HJQ, QMY, XJZ; Supervision: QMY, XJZ; Writing – original
557 draft: ACH, HJQ, MCO; Writing – review & editing: ACH, HJQ, MCO, QMY, XJZ.

558 **Competing interests statement:** We declare no competing interests.

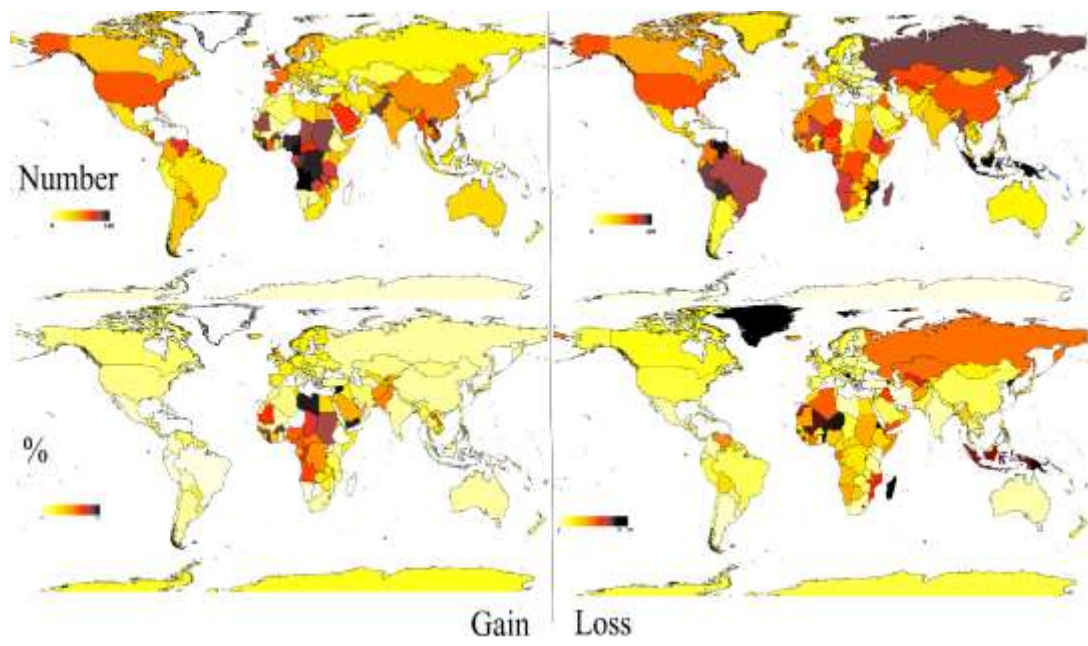


Figure 1. Loss and gain of species as a number and percentage of all species recorded in each region, for overall numbers see Figure S2.

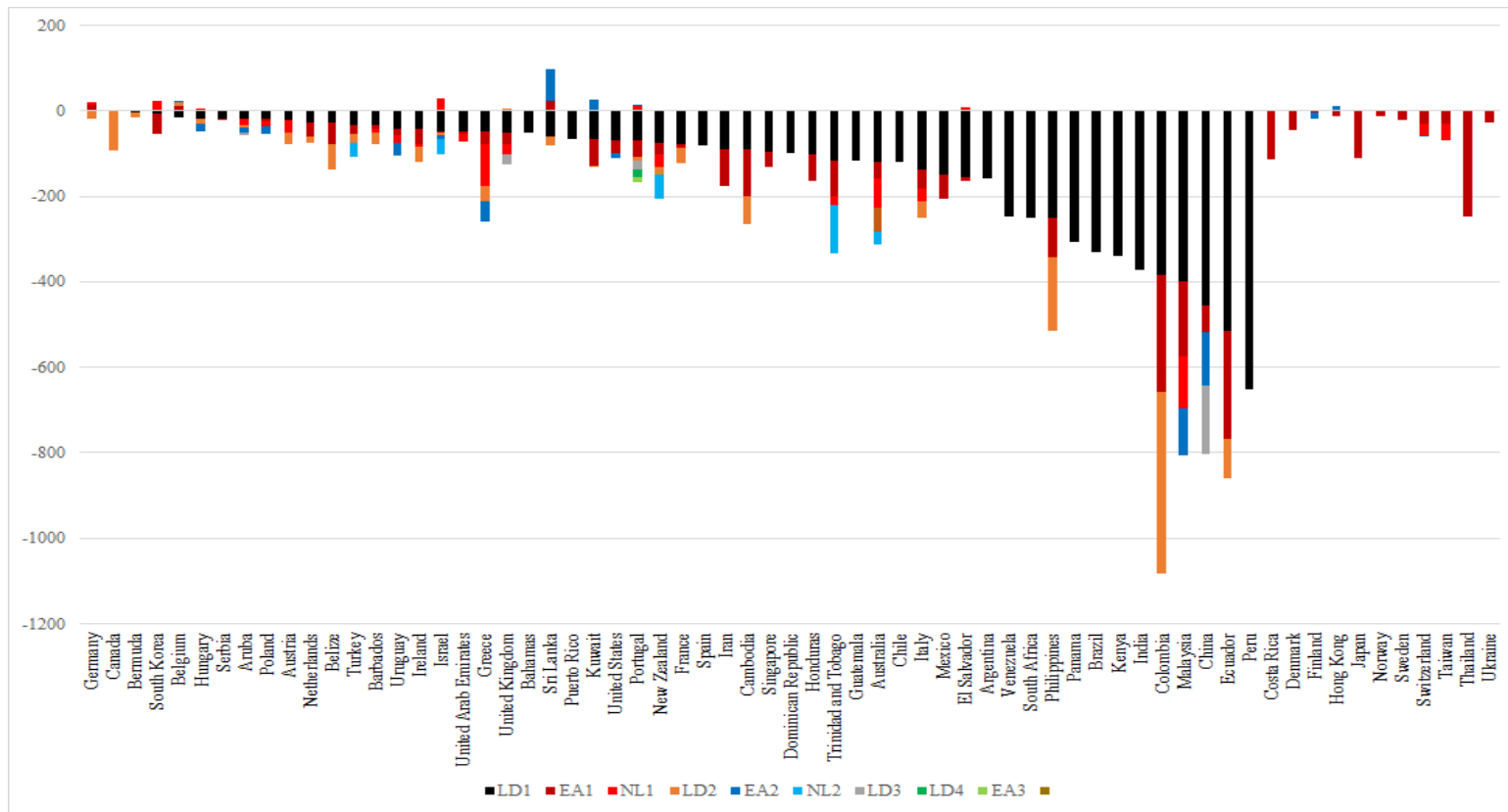


Figure 2. Minimum species difference from projection during each phase of lockdown (LD: Lockdown, EA: Eased restrictions, NL: No Lockdown, numbers are sequential in each region).

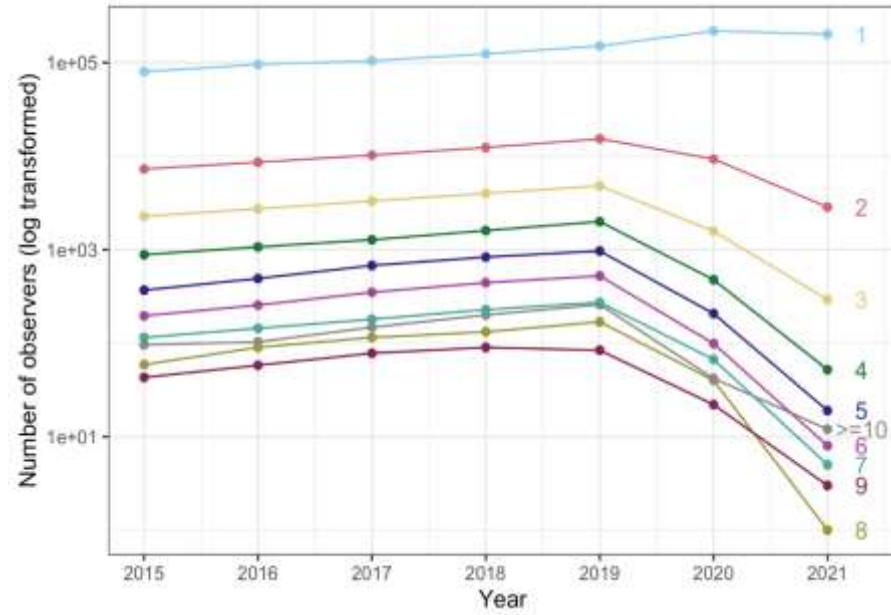


Figure 3. Number of observers visiting X number of regions to upload data per year.

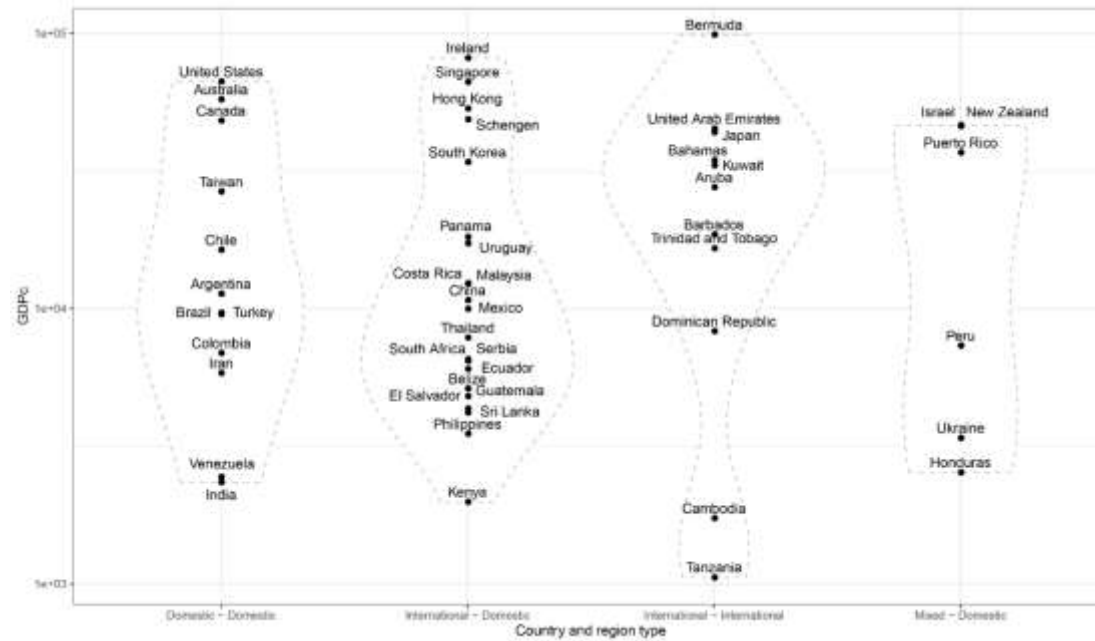


Figure 4. Observer status and origin before and during the pandemic (2020).

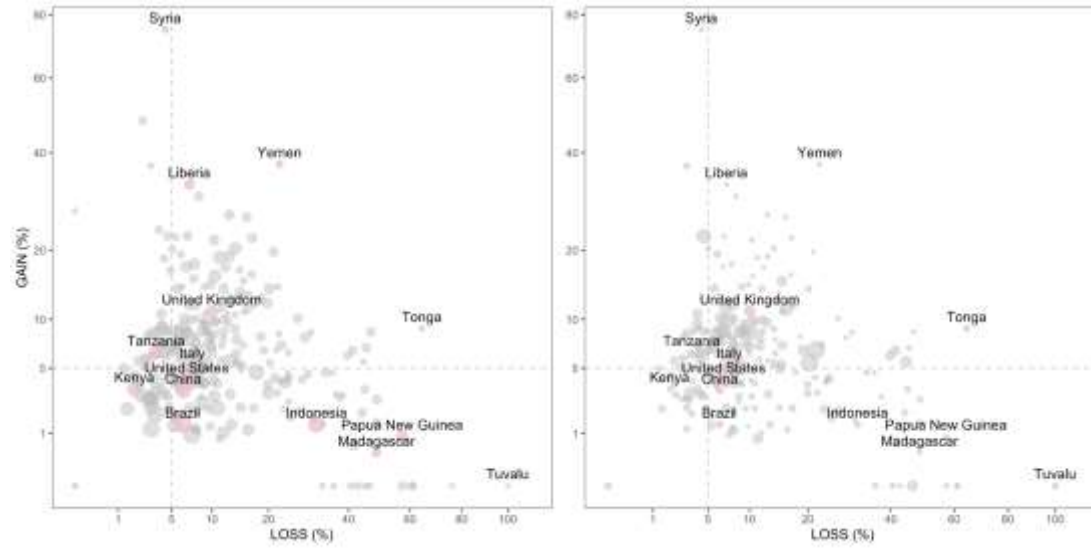


Figure 5. The loss or gain of species by region with richness (left) and GDPc (right)

Table 1. Number of species losing or gaining records in different landcover categories (nat: natural, crop: croplands).

	loss_all	nat_loss	nat_gain	buildup_loss	buildup_gain	crop_loss	crop_gain
common	8521	8468	14	5756	124	4438	178
CR	82	81	1	19	1	16	1
DD	9	8	1	1			
En	295	291	1	93	1	55	9
Vu	548	538	4	198	8	104	5

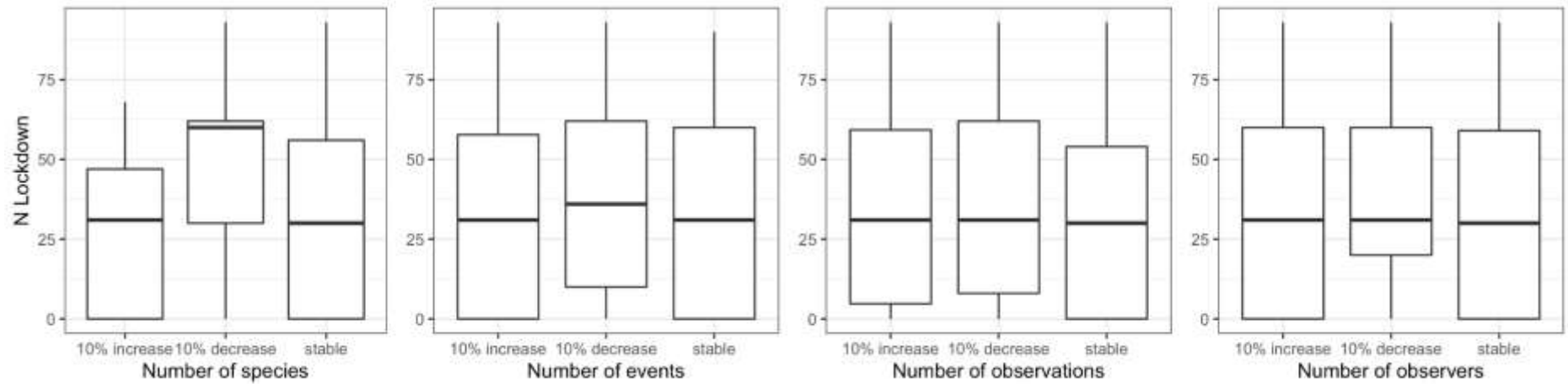


Figure S1. Changes in observers, events, number of observations and number of species during the pandemic.

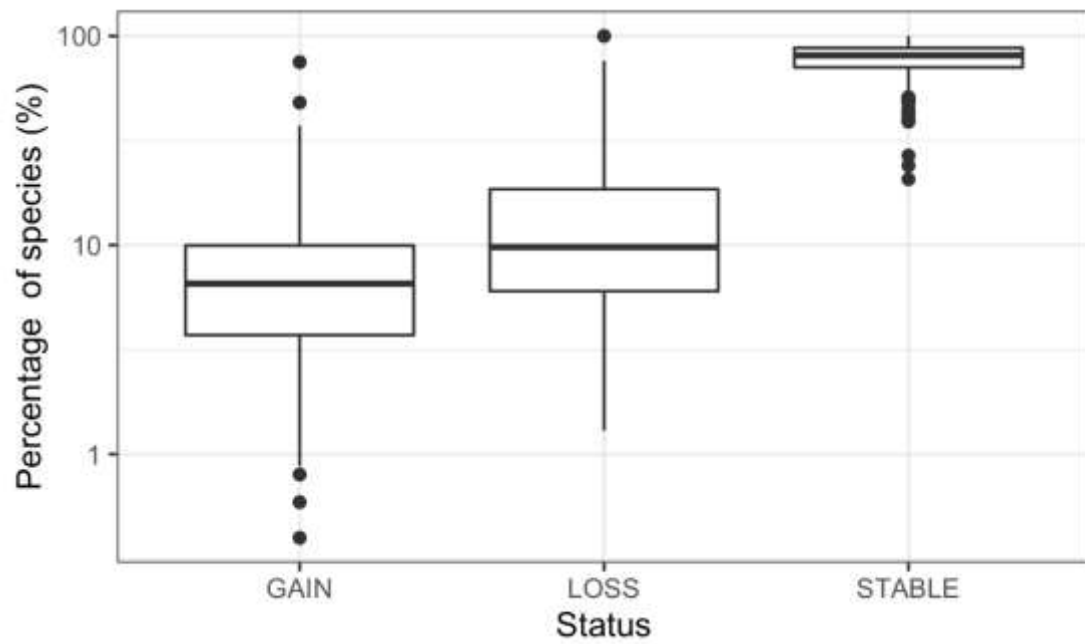


Figure S2. Changes in the number of species lost, gained or re-observed in any given region. The stable species (appeared in both 2019 and 2020) have the highest number of species. The loss species exceeds those gained

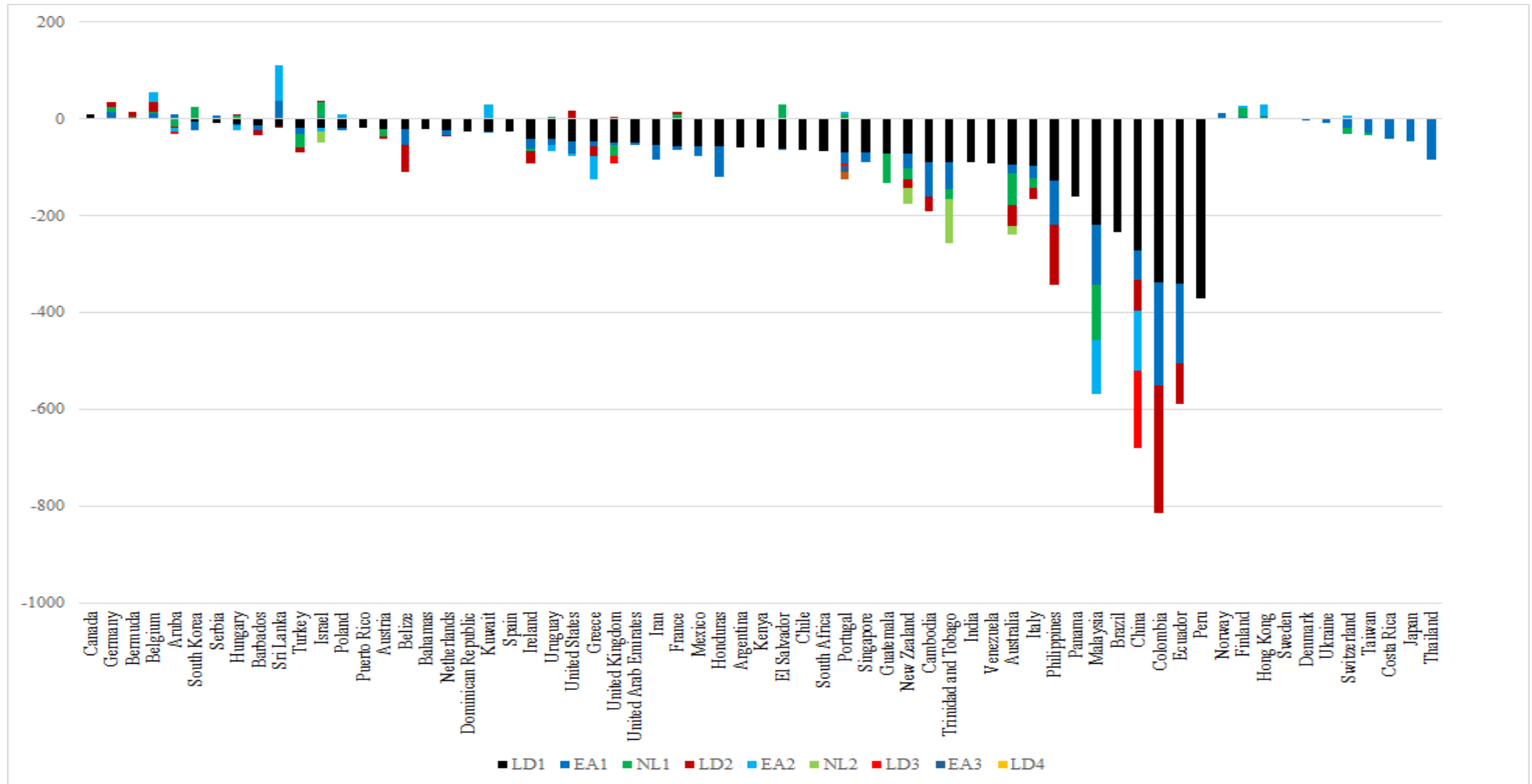


Figure S3. Mean differences between modelled expected and observed richness during each regulation period. LD=lockdown, EA=eased restrictions, NL=no lockdown.

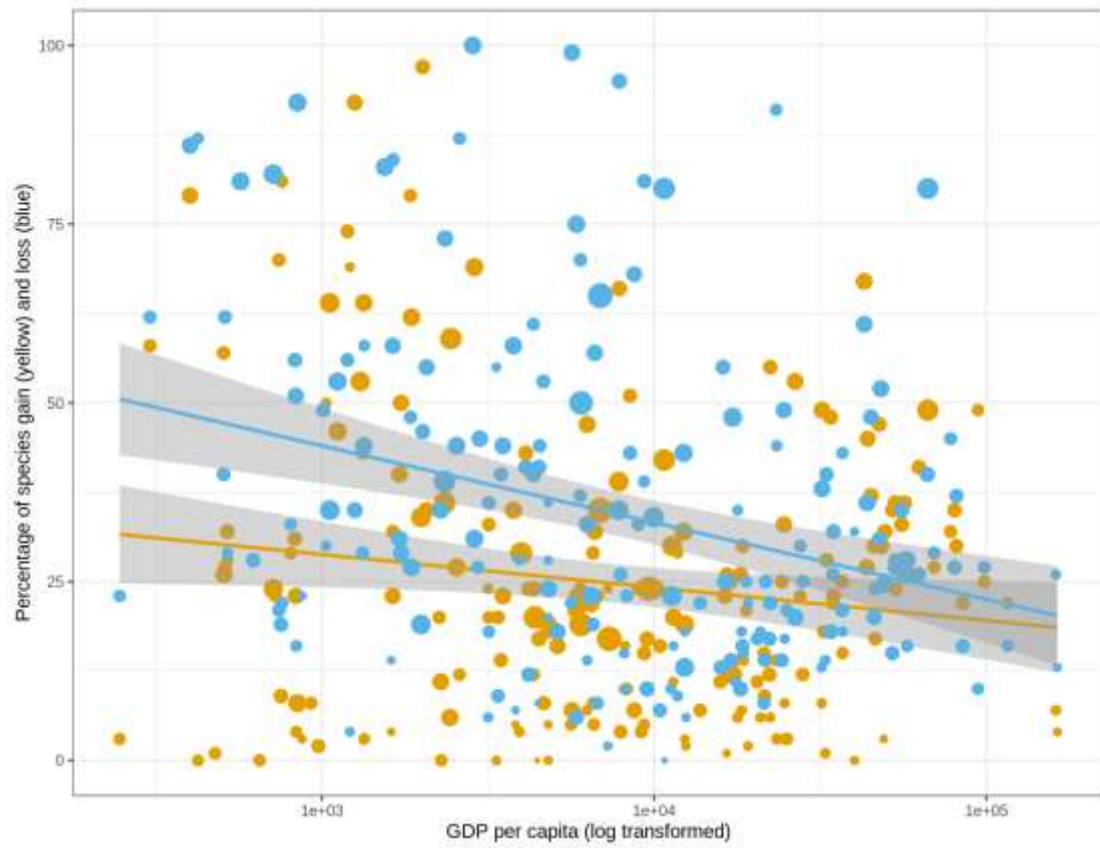
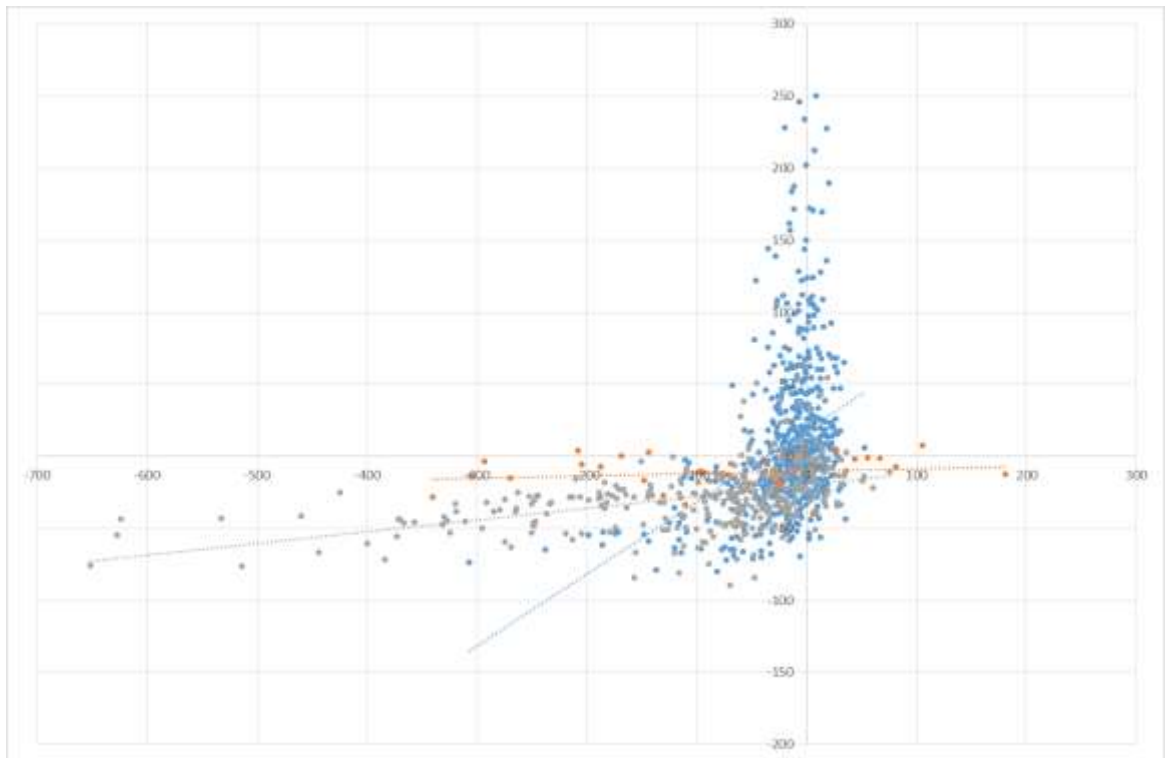


Figure S4a. The percentage of lost and gained by GDPc. The proportion of gained species decreased slightly along with GDPc, while the percentage of lost species greatly decreased, which means that lower-income regions have higher species loss. Point size indicates the number of species in a given region in 2015 to 2021



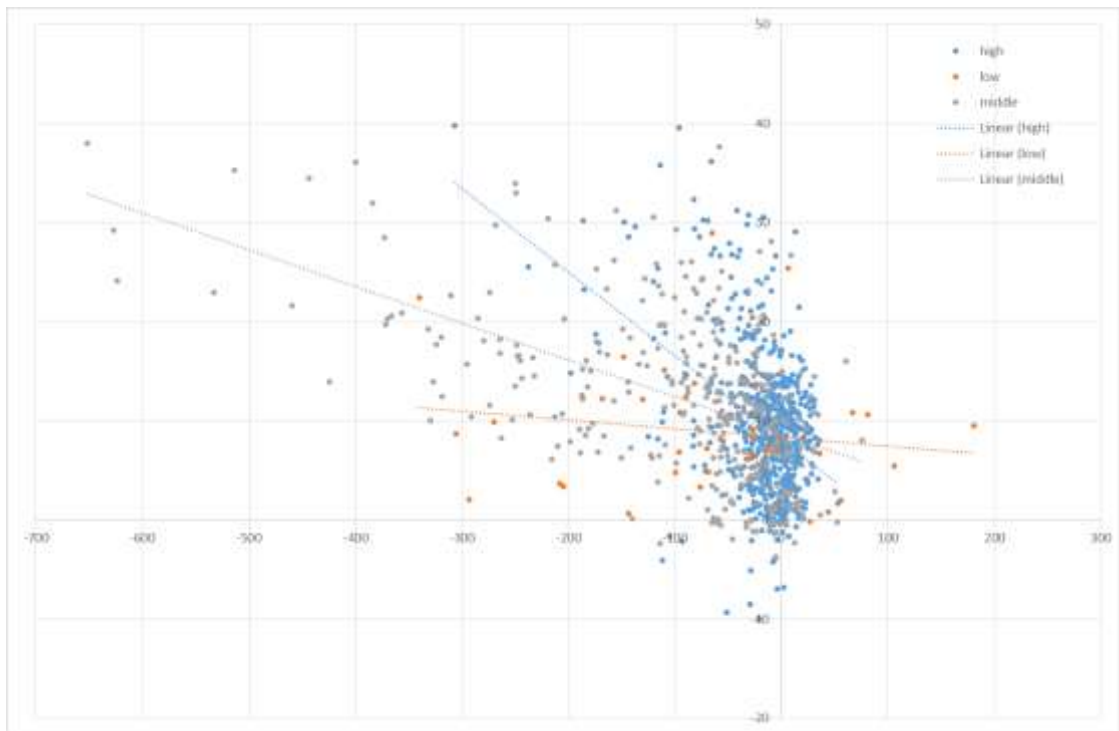
(Figure S5a) Workplace: Low income ($y = 0.0211x - 14.279$, $R^2 = 0.0435$); Middle income ($y = 0.1372x - 21.824$, $R^2 = 0.1189$); High income ($y = 0.0499x - 20.826$, $R^2 = 0.1485$)



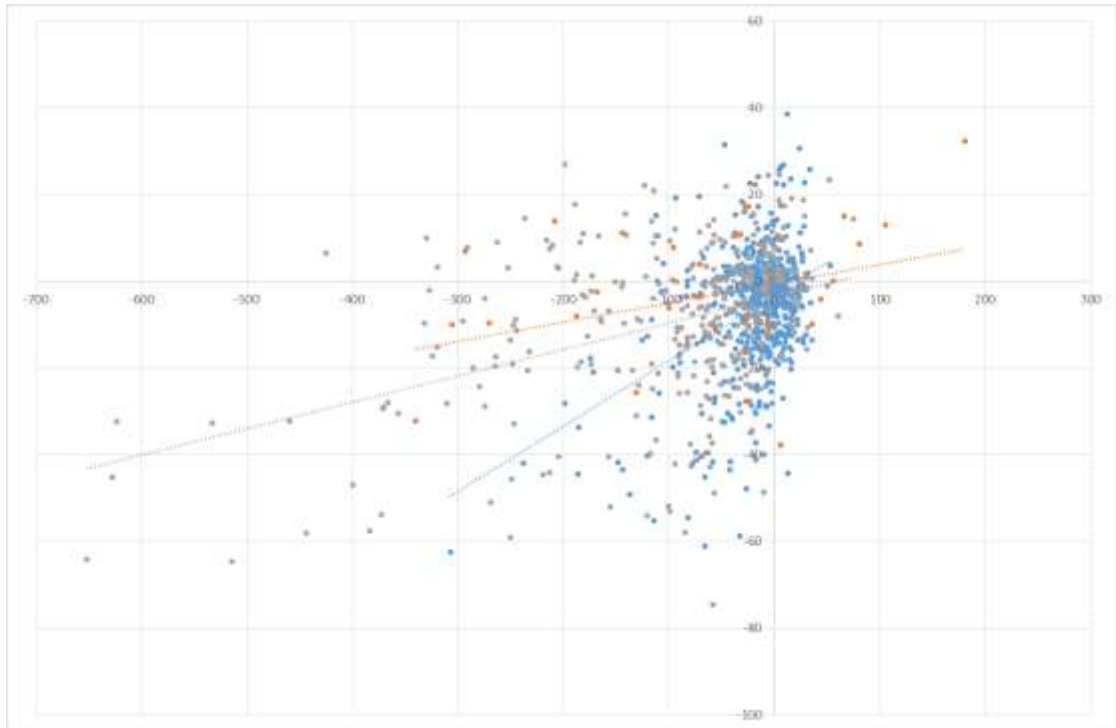
(Figure S5b) Parks: Low income ($y = 0.0162x - 10.26$, $R^2 = 0.0234$); Middle income ($y = 0.5005x + 18.506$, $R^2 = 0.1187$); High income ($y = 0.0812x - 19.981$, $R^2 = 0.1734$)



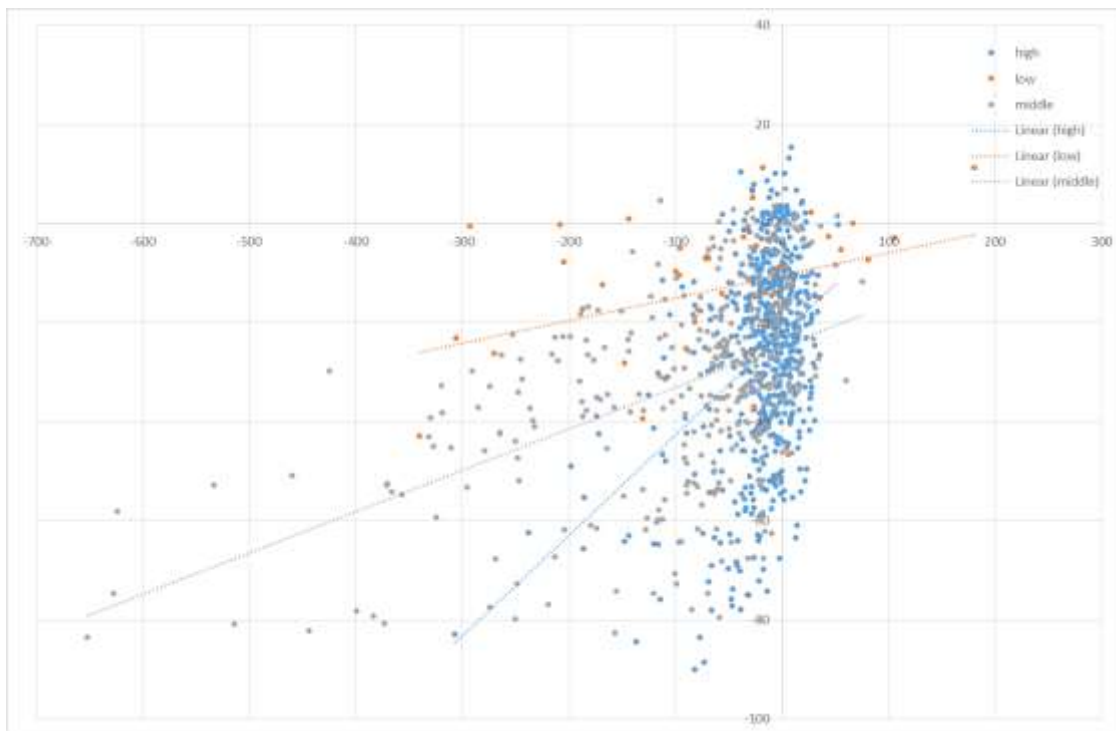
(Figure S5c) Transit: Low income ($y = 0.0486x - 12.366$, $R^2 = 0.043$); Middle income ($y = 0.1744x - 30.76$, $R^2 = 0.1208$); High income ($y = 0.0787x - 27.587$, $R^2 = 0.2053$)



(Figure S5d) Residential: Low income ($y = -0.0087x + 8.3458$, $R^2 = -0.0226$); Middle income ($y = -0.0843x + 8.0913$, $R^2 = -0.1711$); High income ($y = -0.0371x + 8.7417$, $R^2 = -0.2732$)



(Figure S5e) Grocery: Low income ($y = 0.044x - 0.5898$, $R^2 = 0.0941$); Middle income ($y = 0.0609x - 3.5044$, $R^2 = 0.1554$); High income ($y = 0.1509x - 3.2445$, $R^2 = 0.1633$)



(Figure S5f) Retail and recreational: ($y = 0.0456x - 10.418$, $R^2 = 0.1128$); Middle income ($y = 0.203x - 22.368$, $R^2 = 0.1341$); High income ($y = 0.0833x - 24.819$, $R^2 = 0.2388$)

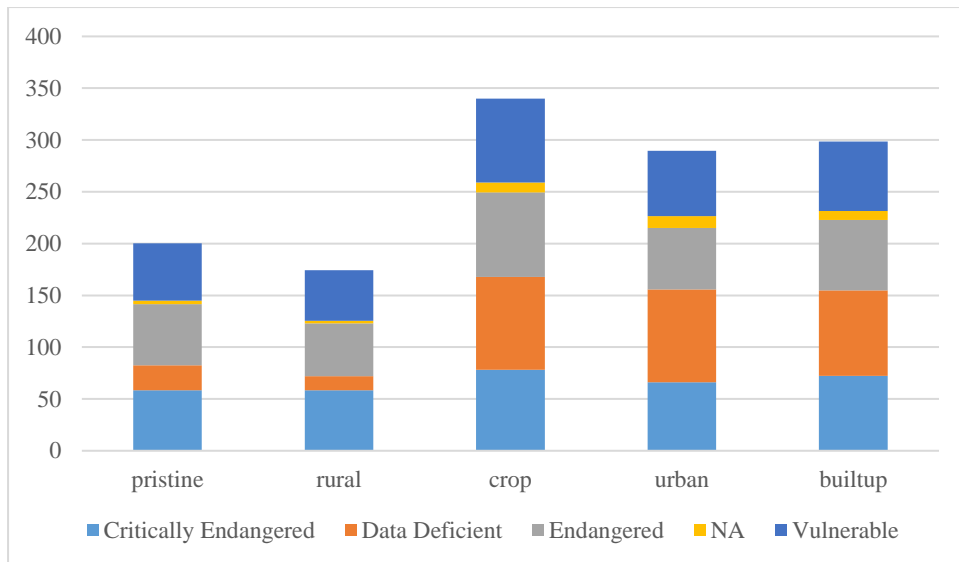


Figure S6a. The loss of species records based on threat status in different landuse types.

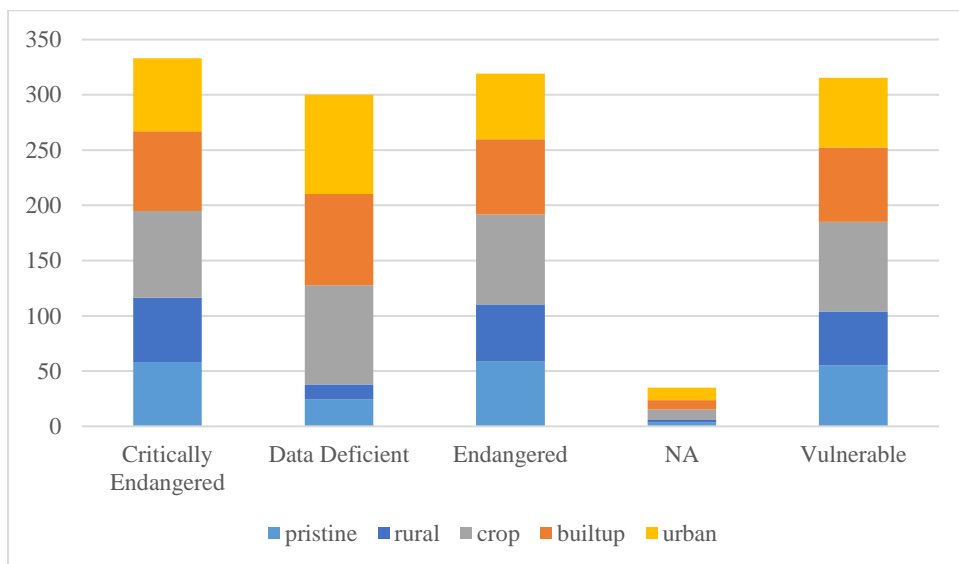


Figure S6b. The loss of species records based on threat status in different landuse types.

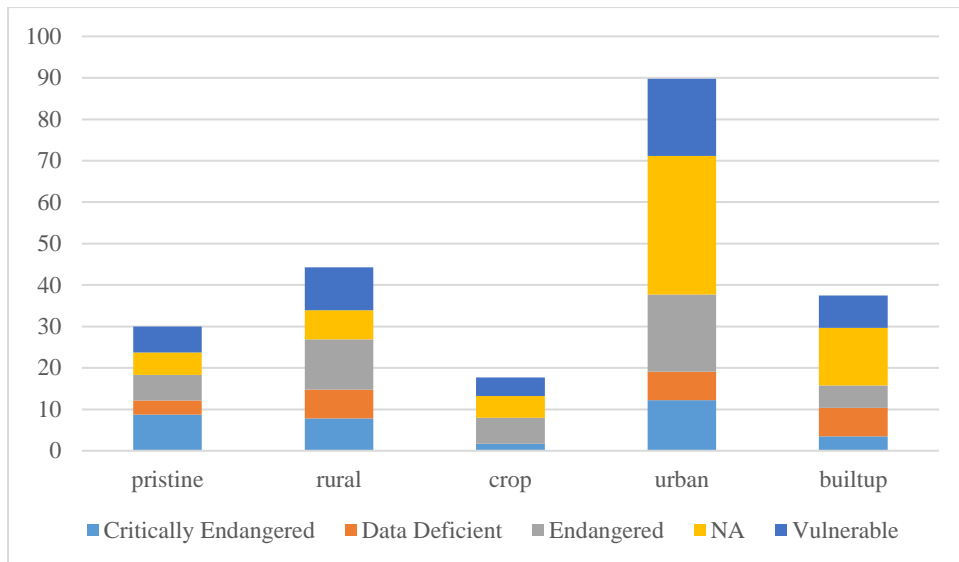


Figure S6c. Species showing at least a 5% gain of records based on threat status in different landuse types.

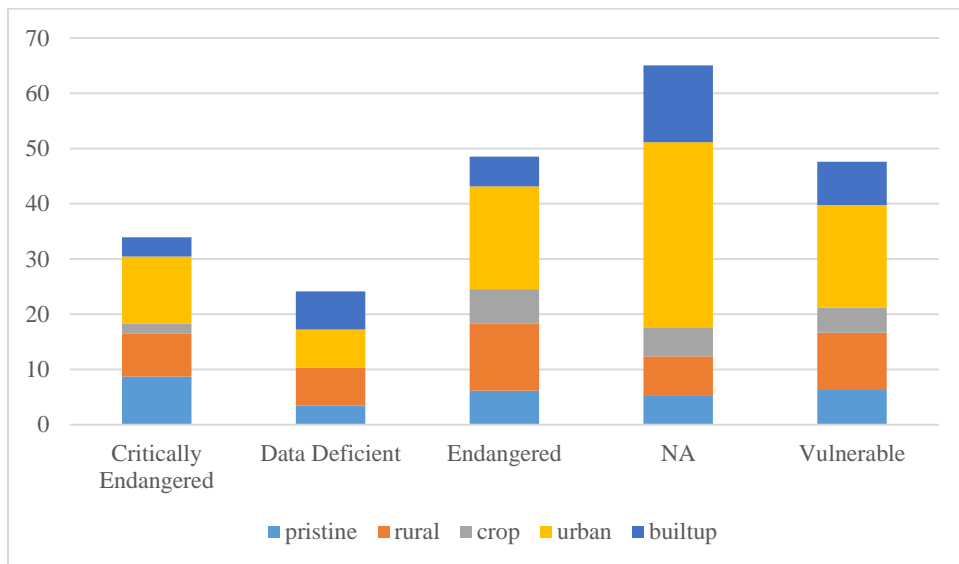


Figure S6d. Species showing at least a 5% gain of records based on threat status in different landuse types.

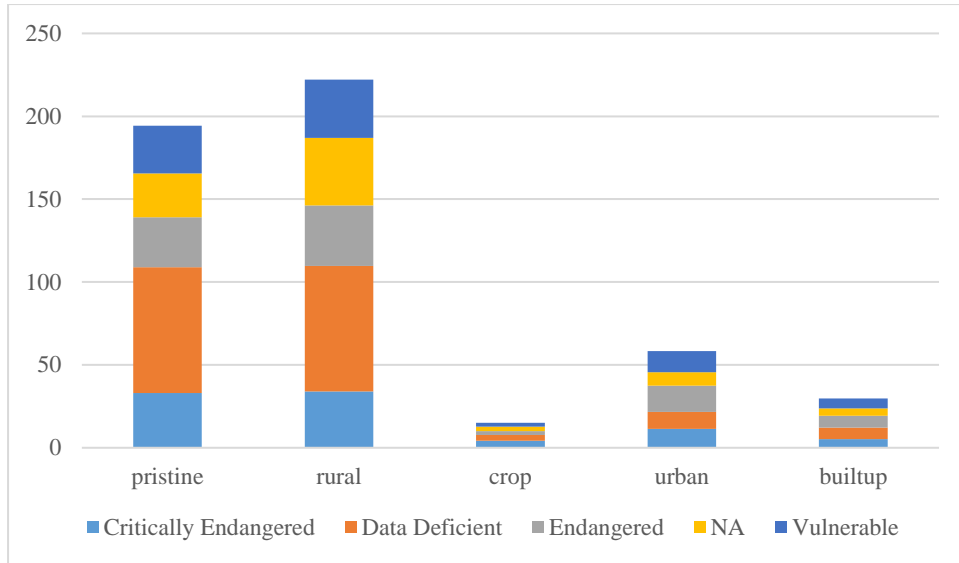


Figure S6e. Species showing at least a 5% loss of records based on threat status in different landuse types.

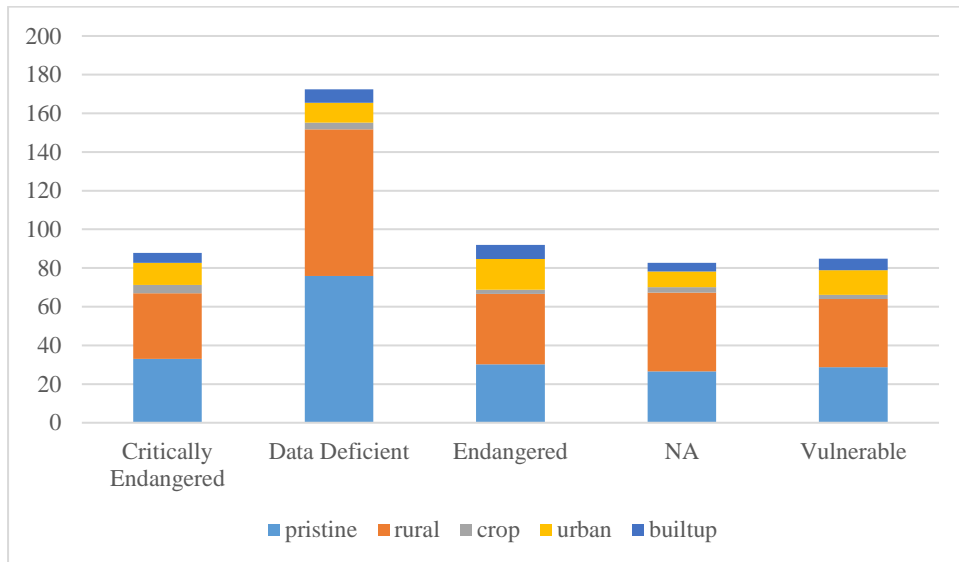


Figure S6f. Species showing at least a 5% loss of records based on threat status in different landuse types.

Name	Color	Hex	Value	Description
Water Bodies			0	At least 60% of area is covered by permanent water bodies.
Evergreen Needleleaf Trees			1	Dominated by evergreen conifer trees (>2m). Tree cover >10%.
Evergreen Broadleaf Trees			2	Dominated by evergreen broadleaf and palmate trees (>2m). Tree cover >10%.
Deciduous Needleleaf Trees			3	Dominated by deciduous needleleaf (larch) trees (>2m). Tree cover >10%.
Deciduous Broadleaf Trees			4	Dominated by deciduous broadleaf trees (>2m). Tree cover >10%.
Shrub			5	Shrub (1-2m) cover >10%.
Grass			6	Dominated by herbaceous annuals (<2m) that are not cultivated.
Cereal Croplands			7	Dominated by herbaceous annuals (<2m). At least 60% cultivated cereal crops.
Broadleaf Croplands			8	Dominated by herbaceous annuals (<2m). At least 60% cultivated broadleaf crops.
Urban and Built-up Lands			9	At least 30% impervious surface area including building materials, asphalt, and vehicles
Permanent Snow and Ice			10	At least 60% of area is covered by snow and ice for at least 10 months of the year.
Barren			11	At least 60% of area is non-vegetated barren (sand, rock, soil) with less than 10% vegetation.
Unclassified			255	Has not received a map label because of missing inputs

Table S1. Plant functional Types (PFTs) legend and class definitions from https://lpdaac.usgs.gov/documents/101/MCD12_User_Guide_V6.pdf

Table S2 (separate spreadsheet). Data for all countries and regions

Table S3a. Relations between recorded species and activity in different areas in regions with different income and tourism status for 2020 and 2021.

All	Overall	vlow_tour	low_tour	mid_tour	high_tour	high_incom	mid_incom	low_incom
p	< .001	< .001	< .001	< .001	0.323	< .001	< .001	0.204
R	0.476	0.564	0.451	0.79	0.361	0.488	0.551	0.48
R ²	0.227	0.318	0.203	0.624	0.131	0.238	0.304	0.23
Adjusted R ²	0.22	0.308	0.184	0.546	0.02	0.228	0.287	0.073
(Intercept)	< .001	< .001	< .001	< .001	< .001	< .001	< .001	< .001
(Intercept)	0.373	0.411	0.166	0.252	0.054	0.424	0.989	0.468
grocery_and_pharmacy_MEAN_Vistor	0.004	< .001	0.01	0.312	0.068	0.17	0.318	0.961
lockdown	0.011	0.04	0.597	0.525	0.078	0.002	0.934	0.839
MAX_international_travel_controls	0.484	0.806	0.976	0.716	0.102	0.001	0.822	0.312
parks_MEAN_Vistor	0.006	0.417	0.021	0.239	0.026	0.117	0.59	0.705
residential_MEAN_Vistor	< .001	< .001	0.125	0.047	0.611	0.368	< .001	0.468
retail_and_recreation_MEAN_Vistor	0.928	0.351	0.048	0.014	0.488	< .001	0.031	0.151
transit_stations_MEAN_Vistor	0.639	0.237	0.523	0.001	0.69	0.003	0.332	0.311
workplaces_MEAN_Vistor	0.044	0.015	0.265	0.191	0.123	0.037	0.003	0.751

Table S3b. Relationship between recorded species and activity in different functional areas in regions with different income and tourism status for 2020.

2020	Overall	vlow_tour	low_tour	mid_tour	high_tour	high_incom	mid_incom	low_incom
p	< .001	< .001	< .001	< .001	0.44	< .001	< .001	0.11
R	0.998	0.742	0.625	0.819	0.468	0.643	0.624	0.785
R ²	0.995	0.551	0.39	0.671	0.219	0.413	0.389	0.616
Adjusted R ²	0.995	0.535	0.359	0.542	0.006	0.395	0.358	0.328
(Intercept)	< .001	< .001	< .001	< .001	< .001	< .001	< .001	0.011
(Intercept)	0.136	0.98	0.841	0.714	0.65	0.78	0.755	0.556

grocery_and_pharmacy_MEAN_Vistor	0.065	0.479	0.587	0.048	0.23	0.06	0.916	0.244
lockdown	0.168	0.901	0.891	0.283	0.182	0.228	0.261	0.436
MAX_international_travel_controls	0.37	< .001	0.149	0.877	0.994	< .001	0.363	0.894
parks_MEAN_Vistor	0.63	< .001	0.834	0.192	0.465	< .001	0.963	0.335
residential_MEAN_Vistor	0.075	< .001	0.002	0.957	0.454	0.005	< .001	0.38
retail_and_recreation_MEAN_Vistor	0.99	0.133	0.24	0.778	0.821	0.296	0.518	0.676
transit_stations_MEAN_Vistor	< .001	0.118	0.38	0.221	0.608	0.129	0.114	0.817
unwto	0.086	0.657	0.022	0.942	0.228	0.827	0.904	0.706
workplaces_MEAN_Vistor	0.453	0.027	0.753	0.374	0.346	0.582	0.99	0.667

Table S4. Number of records for threatened species in 2019 vs 2020 and the percentage of records in 2020 relative to 2019.

	prepan	postpan	%prepan
Total	869781983	154488670	17.76
D Deficient	14100	757	5.37
C Endangered	175126	18976	10.84
Endangered	925751	113894	12.30
Vulnerable	6437227	931612	14.47
NA	862229823	153423437	17.79

Table S5 (separate spreadsheet). Species data on records in different landuse types before and during the pandemic.

Table S6 (separate spreadsheet). Protected area losses or gains in species changes between 2020 and former years.

Supplemental text

Countries and regions included in model assessment

Argentina, Aruba, Australia, Austria, Bahamas, Barbados, Belgium, Belize, Bermuda, Brazil, Cambodia, Canada, Chile, China, Colombia, Costa Rica, Denmark, Dominican Republic, Ecuador, El Salvador, Finland, France, Germany, Greece, Guatemala, Honduras, Hong Kong, Hungary, Iceland, India, Iran, Ireland, Israel, Italy, Japan, Kenya, Kuwait, Malaysia, Mexico, Netherlands, New Zealand, Norway, Panama, Peru, Philippines, Poland, Portugal, Puerto Rico, Serbia, Singapore, South Africa, South Korea, Spain, Sri Lanka, Sweden, Switzerland, Taiwan, Tanzania, Thailand, Trinidad and Tobago, Turkey, Ukraine, United Arab Emirates, United Kingdom, United States, Uruguay, Venezuela

Threatened species and relative changes in distributions

In terms of the average change in the percentage of records, very few areas showed significant increases in species richness, with the highest gain a 3.6% increase in the proportion of records in urban areas for LC/NT species and a 1.35% increase in the proportion of records in built-up areas, converse to a relative to a -10.95% change in rural areas, and a -9.2% change in rural areas, with a slight increase in crops (0.3%). Other threat levels show major losses on average when we look at the percentage of records in different parts of the landscape, with for example -66.65% losses of data deficient species in pristine environments (in part driven by the loss of 100% of records for multiple species, 689 species in total, 17/29 data deficient (DD) species), and rural areas saw a -68.7% loss of DD species. Furthermore, the relative reduction of the proportion of points in pristine areas was highest in data deficient species (-66.65%, followed by Critically endangered (-27.06%), Endangered (-19.17), Vulnerable (-18.56%) then LC/NT at -9.2. Conversely, built-up areas had little or no reductions for most threatened groups (in part because there are relatively few threatened species in these areas) and increases (1.35%) for LC/NT species. Croplands show similar but less pronounced trends to built-up areas.

When we look at the number of species in different groups showing these trends, 56.3% of species in pristine areas (64.9% in rural areas) have shown decreases in the percentage of records in pristine areas, and only 5.47% showed an increase of over 5% of records in pristine areas (7.43% in rural areas), whilst 27% of species showed an over 5% loss of points (40.3% in rural areas). Conversely, 63.3% of species showed increases in built-up areas (69.19% in urban), 13.11% of species showed an increase of over 5% and 4.64% show losses of over 5%. Agricultural areas show a 68.49% increase in sampling, with 5.2% of species showing increases of over 5% and 2.8% showing decreases of over 5%. Thus overall whilst agricultural areas showed the number of species showing losses, in terms of large losses agricultural areas only lost marginally more than pristine areas, with data-deficient species showing the greatest losses, but all threatened species also show losses

In terms of threatened species overall in terms of the absolute number showing losses, threatened species continue to show the greatest losses, with crops and natural areas showing the greatest losses. However, when it comes to significant losses (5% or more loss) both pristine and natural areas showed the greatest number of species showing these losses, whilst urban areas show the greatest gains of over 5%, particularly for common species.