

# Validation of a globally-applicable method to measure urban tolerance of birds using citizen science data

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1 ABSTRACT

2 Understanding species-specific responses to urbanization is essential to mitigate and preserve  
3 biodiversity in the face of increasing urbanization, but a major challenge is how to estimate  
4 urban tolerances for a wide array of species applicable over disparate regions. A promising  
5 approach is to assess urban tolerance by integrating geo-referenced information on species  
6 detections from citizen science data with estimations of urbanization intensity based on  
7 remotely-sensed night-time lights. While such citizen science urbanness scores (CSUS) are  
8 cost-effective, intuitive, and easily-repeatable anywhere in the world, whether the scores  
9 accurately describe urban tolerance still awaits empirical verification. By analyzing >900 bird  
10 species worldwide, we find that CSUS correlates well with a standard measure of urban  
11 tolerance based on changes in abundance between urbanized and non-urbanized nearby  
12 habitats. Our analyses show that there is substantial variability in the relationship between  
13 these two metrics, but nevertheless highlights the potential for the CSUS approach in the  
14 future. Future improvements to the index, including incorporating rare species, and  
15 understanding the influence of intra-specific variability in response to urbanization, will be  
16 necessary to maximize the broad utility of the approach.

17

18 *Keywords:* big data; biodiversity; birds; citizen science; urban tolerance; urban ecology

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20

## 21 INTRODUCTION

22 Cities are novel environments relative to the evolutionary history of nearly all terrestrial  
23 organisms. In such artificial environments, natural vegetation is replaced by artificial  
24 structures (Kenneth et al. 2005), perturbations associated with human activities become  
25 pervasive, the levels of chemical, noise, and light pollution dramatically increase (Swaileh  
26 and Sansur 2006, Francis et al. 2011, La Sorte et al. 2017), and primary productivity  
27 substantially decreases (Milesi et al. 2003). These novel challenges may generate  
28 maladaptations, causing many species to avoid cities or lead to their failure to persist there  
29 (Sol et al. 2014). However, not all species are negatively affected by urbanization. In fact, in  
30 urban environments some species are even doing better than ever, to the point they become  
31 pests. With a projected increase in urban land cover of around 2-3 billion km<sup>2</sup> by 2050  
32 (Huang et al. 2019), identifying which species will be ‘losers’ or ‘winners’ when facing  
33 urbanization has become essential to assess the impact of urbanization on biodiversity and to  
34 help prioritize conservation plans within cities.

35

36 There has historically been a suite of vastly different approaches to quantify urban tolerance  
37 — defined as the ability of a species to persist in urban environments (reviewed in Sol et al.  
38 2013). Ranked from simple to complex, these include: (1) assigning species as being either  
39 ‘urban’ or ‘non-urban’ based on their presence in the respective habitats at any given time  
40 (Møller et al. 2009); (2) classifying species based on the mention of human-built structures in  
41 published habitat descriptions (Cardoso 2014); (3) classifying species based on breeding  
42 evidence in a city (e.g., Croci et al. 2008); (4) circulating surveys to birdwatchers and  
43 ornithologists to compile lists of common native breeding birds in their respective cities  
44 (Bonier et al. 2007); and (5) estimating species sensitivity to urbanization by quantifying  
45 changes in their relative abundances or densities along urbanization gradients (Evans et al.

46 2011, Sol et al. 2014, Sol et al. 2017, Sayol et al. 2020). Although the application of these  
47 metrics has largely improved our understanding of organismal responses to urbanization, they  
48 have limitations when it comes to uncovering patterns at large spatial scales. For example,  
49 categorizing species based on their presence/absence in cities fails to account for the  
50 continuous nature of species-specific responses to urbanization (Evans et al. 2011, Sol et al.  
51 2013, Callaghan et al. 2020), and is likely to inadequately identify species which do not  
52 tolerate cities well, but are present there through source-sink dynamics. It also ignores that a  
53 species can be absent in the city not because it cannot tolerate it, but because it is too scarce  
54 in the surrounding habitats to generate propagules (Sol et al. 2013, 2014). Moreover, a  
55 species categorized as an urban adapter in one city may be an urban avoider in another city.  
56 Measuring tolerance to urbanization using indices derived from surveys along urbanization  
57 gradients provides higher resolution, yet sampling assemblages over large regions is costly  
58 and time-consuming. This means that information is only available for some regions, mostly  
59 from highly-developed countries (Sol et al. 2020). Moreover, combining information from  
60 different regions is challenging because different studies often use different survey protocols  
61 and different definitions of urbanization gradients (but see Sol et al. 2014, 2020). A more  
62 general measure of urban tolerance — applicable from local to global scales — is clearly  
63 needed to enhance our understanding of organismal responses to urbanization.

64

65 Recently, Callaghan et al. (2019a, 2020a) proposed an alternative measure of urban tolerance  
66 that capitalizes on citizen science data, providing species-specific urbanness scores (CSUS,  
67 hereafter). The CSUS approach intersects broad-scale citizen science observations of species  
68 with estimates of human settlements based on globally available, remotely-sensed, VIIRS  
69 (Visible Infrared Imaging Radiometer Suite) night-time lights. Species' urban tolerances are  
70 defined as the median VIIRS night-time lights across their range of observations (urbanness

71 scores, hereafter). Assuming that species' observations are equally sampled in urban and non-  
72 urban areas, species with high urbanness scores are interpreted to be more urban-tolerant than  
73 species with low urbanness scores (Callaghan et al. 2020a).

74

75 Although the CSUS metric is based on occurrences rather than abundances, it has the  
76 advantage of being cost-effective, intuitive, and easily-repeatable anywhere in the world. The  
77 CSUS approach assumes that species' observations across an urbanization gradient represent  
78 a species' likelihood of using habitats along this urbanization gradient, and severe violations  
79 of this assumption could make the CSUS metric imprecise and thus unreliable in  
80 macroecological analyses. Therefore, a limitation of the approach is the need of relatively  
81 large numbers of observations to accurately capture the species-specific variation in response  
82 to urbanization. However, this limitation is currently less important in the "big data" era,  
83 particularly for taxonomic groups like plants and birds which are easy to observe and for  
84 which observations are rapidly accumulating worldwide. In birds, for example, the eBird  
85 project (Sullivan et al. 2009) currently has more than 800 million observations all over the  
86 worlds. In birds, the CSUS approach has been used to assess ecological and life-history traits  
87 associated with urban tolerance (Callaghan et al. 2019a) and assign community-measures of  
88 urbanness (Callaghan et al. 2019b), albeit this approach is currently restricted to the common  
89 species.

90

91 While the CSUS approach provides promise for advancing our understanding of species'  
92 tolerance to urbanization (see Callaghan et al. 2020a), its robustness remains to be  
93 demonstrated. Testing the general validity of the approach is the goal of the present study.  
94 Specifically, we estimate the urbanness scores for >900 species from 26 cities worldwide,  
95 and compare the scores with previously published information on species tolerance to

96 urbanization from the same regions estimated as changes in abundance between urban and  
97 non-urban surrounding environments. Our analyses show that there is substantial variability  
98 in the relationship between these two metrics, but nevertheless highlights the potential for the  
99 CSUS approach in the future.

100

## 101 METHODS

### 102 *Urbanness scores*

103 We followed Callaghan et al. (2019a, 2020a) to assign species-specific urbanness scores. We  
104 first gathered all available observations in the eBird citizen science dataset (version  
105 ebd\_relMay-2019; Sullivan et al. 2009) for the species from the 26 cities studied, excluding  
106 species that primarily rely on coast-lines and/or large water bodies (habitats that are little  
107 represented in the studied cities). After filtering the eBird data by removing potential outliers  
108 (see Callaghan et al. 2019b), we assigned a measure of VIIRS night-time lights to each  
109 observation. Monthly scenes of average radiance ( $\text{nW cm}^{-2} \text{sr}^{-1}$ ) between January 1<sup>st</sup>, 2014  
110 and January 1<sup>st</sup>, 2019 were used, and the temporal median radiance was calculated per pixel  
111 at the native 500 m resolution, which was reprojected into a pixel size of 5 km using a  
112 composite stack of the 2014-2019 VIIRS night-time light layers. Finally, we estimated the  
113 urbanness score for each species at two spatial scales: as the median value across all  
114 observations within a 250 km buffer around the city (regional scale) or the entire continent  
115 where a city was located (Table S1). A 250 km buffer was chosen to incorporate landscape-  
116 scale observations, and assumes that the common species sampled within this buffer have an  
117 equal opportunity to occupy the area throughout the buffer (i.e., their range encompasses the  
118 entire buffer), depending on habitat preferences (i.e., level of urban tolerance). A test with  
119 100 km buffer showed qualitatively similar results to that of a 250 km buffer. We used a  
120 random sampling analysis to test the influence of sample size in the estimation of urbanness

121 scores and found that at ~100 observations the variation in the urbanness score was  
122 significantly lower for most species (see Figure S1). Thus, we only estimated urbanness  
123 scores for species with a minimum of 100 eBird observations (Callaghan et al. 2019a).  
124 However, we note that a cutoff of 250 observations yielded qualitatively similar results. We  
125 also restricted the analyses to cities with a minimum of 10 species. After filtering, we were  
126 left with a total of 771 species from 25 cities for the regional-scale comparison (Figure S2),  
127 incorporating 22,839,841 species' observations. For the continental-scale comparison, after  
128 filtering, we were left with a total of 934 species from 26 cities (Figure 1; Figure S3),  
129 incorporating 226,388,416 species' observations.

130

#### 131 *Urban tolerance based on abundance data*

132 We used a dataset of bird assemblages across 26 cities worldwide (Sol et al. 2014, 2017,  
133 Sayol et al. 2020) to derive an abundance-based measure of urban tolerance (Figure 1). These  
134 data are a comprehensive compilation of published datasets incorporating characterized  
135 assemblages with local survey data available in both urban and nearby rural/natural habitats.  
136 The 26 cities were spread among 7 regions: Africa (N=1); Asia (N=4); Australia (N=3);  
137 Europe (N=5); New Zealand (N=1); North America (N=8); and South America (N=4). To the  
138 best of our knowledge, this is the most robust dataset available for comparison with the  
139 CSUS approach. Importantly, although we use these data to show the correlation with the  
140 CSUS approach, the data for the CSUS approach (i.e., eBird data) are generally globally-  
141 available (although heterogeneous across the world) as are the VIIRS night-time lights data.  
142 For each city in the dataset, bird abundances were available within built-up urban  
143 environments and in the surrounding non-urbanized habitats. The dataset comprises  
144 assemblages sampled in four types of habitats, ranging from natural vegetation, little  
145 urbanized environments, moderately urbanized environments, and highly urbanized

146 environments (Sol et al. 2020). The urban tolerance index of a species was estimated as the  
147 log-log difference between its abundance within (i.e., from the highest possible urbanization  
148 category a species was observed) and outside (i.e., natural vegetation) the city (see Sol et al.  
149 2014, Sayol et al. 2020). A positive value indicates that the species was more common in the  
150 city than in the surrounding natural habitats whereas a negative value indicates that the  
151 species was less common in the city than in the surrounding natural habitats. Because values  
152 close to zero are difficult to interpret (Sol et al. 2013), we further categorized the urban  
153 tolerance abundance index into four categories (*sensu* Sol et al. 2014; 2017): (1) Urban  
154 Absent (i.e., a species was observed only in wild areas); (2) Urban Increase (i.e., a species'  
155 abundance was greater in urban than in wild habitats); (3) Wild Increase (i.e., a species'  
156 abundance was greater in wild than in urban habitats); and (4) Wild Absent (i.e., a species  
157 was observed only in urban areas).

158

### 159 *Statistical analysis*

160 All analyses were conducted in R statistical software (R Core Team 2020). We tested the  
161 extent to which our CSUS approach is predicted by the local-scale abundance-based urban  
162 tolerance by means of a phylogenetic mixed-effects model. The response variable was log-  
163 transformed urbanness scores and the predictor variable was the local-scale abundance-based  
164 urban tolerance index. We used the MCMCglmm R-package (Hadfield 2010) to fit a mixed  
165 model that included both city and phylogeny as random effects. Cities were included as a  
166 random effect to account for possible significant differences among cities (e.g., level of  
167 urbanization, size, differing population density dynamics). For these models, we used an  
168 inverse-wishart priors for the random effects ( $V = 1$ ,  $\nu = 0.002$ ), and ran the models for  
169 1010000 iterations, with a burn-in of 10000 and a thinning interval of 1000, resulting in a  
170 posterior distribution of 1000 samples. We ensured that the autocorrelation of samples was

171 below 0.1 and that the model converged properly. We also fit these models with only the  
172 intercept to assess the variability in the response determined by phylogeny and city. The  
173 phylogenetic tree included in the models was a MCC tree from the posterior distribution of  
174 all trees with Ericsson backbone, extracted from the BirdTree.org project (Jetz et al. 2012).  
175 All models were run at the regional and continental scales separately. Lastly, we used a linear  
176 model to test how our urbanness measures categorically separated species, based on  
177 categorical classifications of the local-scale abundance-based urban tolerance index. Effect  
178 sizes of pairwise differences among categories were extracted using the emmeans R-package  
179 (Lenth 2020).

180

## 181 RESULTS

182 Our analyses revealed a good correspondence between the urbanness scores and the local-  
183 scale abundance-based urban tolerance indices. At the regional-scale, the urbanness scores  
184 showed a clear positive relationship, albeit with a small effect size, with the continuous  
185 version of the local-scale abundance-based urban tolerance index after controlling for city  
186 and phylogenetic effects (posterior mean and 95% C.I.  $\beta=0.035$  [0.028-0.043],  
187  $pMCMC<0.001$ ; Figure 2a; Figure S4a). We also found evidence for phylogenetic signal in  
188 the urbanness scores (Intra-class coefficient = 0.529, 95% C.I. = 0.525 to 0.533), and some  
189 heterogeneity among cities (Intra-class coefficient = 0.234, 95% C.I. = 0.230 to 0.238). The  
190 urbanness scores were also well-predicted by the categorical representation of the local-scale  
191 abundance-based urban tolerance (Figure 2a), with the lowest mean being derived from the  
192 urban absence category ( $1.49 \pm 2.28$ ), substantially lower than that in the wild absence  
193 category ( $4.31 \pm 6.34$ ) and the urban increase category ( $5.48 \pm 8.03$ ) and the pairwise effect  
194 sizes supported these comparisons (Table S2). When looking at city-specific correlations

195 (Figure S5; Table S3), all cities were positively correlated with the exception of Tornio, Santa  
196 Fe, La Paz, and Cayenne (average correlation = 0.16, range 0.005-0.44).

197

198 As with the regional-level analyses, the continental-scale analysis of urbanness scores also  
199 revealed a positive relationship with the local-scale abundance-based urban tolerance once  
200 city and phylogenetic effects were accounted for (posterior mean and 95% C.I.  $\beta=0.012$   
201 [0.005-0.018],  $pMCMC<0.001$ ); Figure 2b; Figure S4b). However, this relationship was  
202 much weaker than that for the regional-scale analysis (Figure S4). We also found evidence  
203 for phylogenetic signal in the urbanness scores calculated at the continental-scale (Intra-class  
204 coefficient = 0.910, 95% C.I. = 0.908 to 0.911), and less heterogeneity among cities (Intra-  
205 class coefficient = 0.041 95% C.I. = 0.040 to 0.042). The urbanness scores were also well-  
206 predicted by the categorical representation of the local-scale abundance-based urban  
207 tolerance (Figure 2b) with the lowest mean urbanness score being derived from the wild  
208 increase category ( $1.52 \pm 1.6$ ) followed by the urban absence category ( $1.57 \pm 3.43$ ) and the  
209 highest mean being derived from the wild absence category ( $3.58 \pm 7.30$ ) followed by urban  
210 increase ( $3.21 \pm 4.88$ ) and the effect sizes confirmed these patterns (Table S2). When looking  
211 at city-specific correlations (Figure S5; Table S3), nearly all cities had a positive correlation  
212 between both metrics (average correlation = 0.15, range 0.0002-0.48).

213

## 214 DISCUSSION

215 We leveraged increasingly available and accessible citizen science data and provided  
216 evidence that a simple and intuitive method of deriving species-specific urbanness scores  
217 correlates with local-level abundance data from 26 cities across the world (Figure 2), and that  
218 the accuracy improves with the number of observations used to assess the species-specific  
219 urbanness scores (Figure S1). This study is the broadest validation of the CSUS approach,

220 demonstrating its potential future utility in urban ecology. Importantly, while the CSUS  
221 approach showed correlation with local-scale survey data from a subset of worldwide cities  
222 (Figure 1), the data used to derive the CSUS approach are globally-applicable (i.e., eBird data  
223 are nearly global, albeit heterogeneously distributed; and VIIRS night-time lights are globally  
224 available).

225

226 The urbanness scores calculated at the regional-scale were more strongly related to the local-  
227 scale abundance-based urban tolerance than those derived from continental-scales, and the  
228 relationship at the continental scale was overall quite weak. However, both relationships were  
229 statistically significant and positive (Figure 2; Figure S4), confirming that continental-scale  
230 data correlates, albeit weakly, with regional-scale responses to urbanization (Callaghan et al.  
231 2020a). The main advantage of a continental-scale approach is to broaden species coverage  
232 by increasing the number of observations. In our case, this meant an increase from 771 to 934  
233 species by the addition of species which met the threshold for the minimum number of  
234 observations. However, the use of a continental-scale approach likely comes at a cost of more  
235 variability in species-specific responses, and as the sample sizes continue to increase in  
236 global citizen science data, regional-scale urbanness scores will likely be easier to calculate  
237 for a broader suite of species (i.e., more species will meet the necessary sample thresholds).

238

239 Although we found a consistent correspondence between the urbanness scores and local-scale  
240 abundance-based urban tolerance (Figure 2), there still remained variability among cities,  
241 especially at the regional scale (i.e., 23% of the variability in the model was explained by  
242 city). The cities that showed the weakest correlation (e.g., Valencia) tended to be coastal  
243 cities, where the VIIRS night-time lights measures are more likely to be affected by large  
244 bodies of water. The differences among cities could also be a result of the differing

245 likelihoods of detection for species in different regions or the differing patterns of use in  
246 eBird among the different regions in our analysis. For example, cities in the US were all  
247 relatively well-correlated, with Gainesville having the highest correlation among cities  
248 ( $R^2=0.44$ ), and Iowa ( $R^2=0.26$ ), and Minneapolis/St. Paul ( $R^2=0.24$ ) were also strongly-  
249 correlated, likely reflecting the fact that the United States is where eBird data are currently  
250 most numerous. There are many other city-specific differences that likely influences the  
251 variability among cities, including the connectivity of green areas, the compactness of a city  
252 (i.e., land sharing vs land sparing), the biophysical characteristics of a city, and the human  
253 population density throughout a city. Each of these factors should be further explored in the  
254 context of how the CSUS performs on a city-by-city basis. Although more research is needed  
255 to fully understand the differences among cities, our results suggest that as eBird, and other  
256 large-scale citizen science projects, grow in popularity in other parts of the world, the utility  
257 of our approach may also increase.

258

259 Importantly, we found evidence of phylogenetic effects in the urbanness scores at both the  
260 regional and continental scales, confirming previous results (Sol et al. 2014) with a  
261 conceptually distinct metric. The existence of phylogenetic effect suggests that closely-  
262 related species tend to respond to urbanization in a similar way. This is to be expected  
263 considering that some of the adaptations found to affect tolerance to urbanization, like an  
264 encephalized brain or a slow life history strategy, are highly conserved phylogenetically.  
265 Interestingly, we found a much stronger effect of phylogeny when considering urbanness  
266 scores calculated at the continental-scale than the regional-scale, likely a result of  
267 macroecological differences in habitat use reflected by phylogeny over the larger  
268 macroecological scales. Our CSUS approach provides the necessary data to further

269 disentangle the degree to which urban tolerance is phylogenetically conserved for many  
270 species.  
271

272 Our CSUS approach clearly shows promise, but future work should build upon this  
273 foundation and improve this approach to further maximize its utility and validity. First, we  
274 currently focus on macro-ecological patterns (i.e., regional to continental scales), but it is  
275 possible this approach could be used to further inform more localized patterns. For example,  
276 some species change their adaptability to urbanization through time (e.g., Evans et al. 2009),  
277 and future research should test the ability of this approach to appropriately track species'  
278 changes to urban tolerance through time; both intra-annually and inter-annually. For example,  
279 the utility of VIIRS night-time lights for understanding intra-annual patterns of individual  
280 gulls at a local-scale using GPS-tracking data has recently highlighted the potential for future  
281 work on local-scale urban tolerance (Ramírez et al. 2020). Second, we currently only look at  
282 the presence or absence of a species across an urbanization gradient. Yet, eBird data can  
283 provide relative abundance estimates across this gradient. Future work should thus test  
284 whether there are significant differences between presence/absence and abundance-weighted  
285 measures of the CSUS approach because abundance-weighted measures could provide  
286 valuable insights and more power to differentiate among species-specific responses to  
287 urbanization (e.g., Sol et al. 2020). Third, our approach does not account for the differing  
288 levels of available urban habitat among species' geographic ranges, potentially influencing  
289 our urbanness scores (Callaghan et al. 2020b). For example, a species may be often observed  
290 in urban areas, yet have a low urbanness score because its geographic range is relatively non-  
291 urban. Indeed, this is probably why we found a stronger relationship for regional-scale  
292 urbanness scores than continental-scale urbanness scores when compared with the local-scale  
293 abundance-based urban tolerance index. At a regional-scale (i.e., a 250km buffer) it would be

294 unlikely that species' have significantly differing range sizes and most species found within  
295 the city likely have ranges that encompassed the entire regional-buffer, whereas at a  
296 continental-scale species' geographic ranges would more likely differ and thus the available  
297 urban habitat for that species could also differ; and this probably differentially affects  
298 generalists and specialists. However, methods which account for the available urban habitat  
299 in a species' range (e.g., by standardizing urbanness scores by a range-wide urbanness  
300 measure) may further enhance our CSUS approach and this should be formally tested  
301 (Callaghan et al. 2020b). Fourth, the CSUS approach relies on the median of the distribution,  
302 potentially missing multimodal responses of a given species. A multimodal distributional  
303 response to urbanization is likely a result of sampling biases from citizen science data, where  
304 birdwatchers preferentially go to known sites for specific species. However, it is also possible  
305 that a given species could show intra-specific variability in their response to urbanization, for  
306 example where one population of a species is an urban adapter in one part of its range but an  
307 urban avoider in another part of its range. We suggest that at the regional-scale (i.e., 250 km  
308 buffer) this is unlikely to be the case because for the common species, they are most likely  
309 able to use any part of the habitat within that buffer. But at continental-scales, it is possible  
310 for species to have differing levels of urban tolerance. Currently, our approach cannot  
311 disentangle multimodal responses to urbanization, but future development should investigate  
312 possible statistical approaches to assess multimodal responses and when this represents  
313 biological variability versus underlying sampling biases. And lastly, while we demonstrate  
314 this approach with data using birds, many other taxa are increasingly studied in urban areas  
315 using citizen science projects, such as bees (Mason and Arathi 2019), butterflies (Matteson et  
316 al. 2012), and mammals (Williams et al. 2015). Therefore, our approach should be formally  
317 implemented using other taxa, potentially relying on broad-scale citizen science projects such  
318 as iNaturalist.

319

320 Current methods of assigning urban tolerance to species have been fundamental in enhancing  
321 our understanding of biodiversity responses to urbanization, but they also have limitations  
322 concerning their interpretation and sampling biases (Sol et al. 2013, 2020). Our approach also  
323 has limitations, as described above, yet it extends previous methods by providing a  
324 continuous measure of tolerance for most species and regions of the planet. Moreover,  
325 integrating our approach with previous metrics will likely provide much promise in our  
326 ability to better predict the responses of biodiversity to urbanization (e.g., Fithian et al. 2014).  
327 The CSUS approach should be used to further our understanding of the effects of  
328 urbanization on biodiversity in under-studied regions where professionally-collected data are  
329 often lacking (e.g., tropical regions), across broad taxonomic coverage (e.g., including many  
330 more species than previously possible), through time (e.g., intra- and inter-annual changes in  
331 responses to urbanization), and across spatial scales (e.g., understanding how species respond  
332 to urbanization at different scales). In conclusion, we showed that there is strong potential in  
333 our CSUS approach, especially at regional scales, and future work should further unlock this  
334 potential and utilize this approach to make broad-scale comparisons advancing urban  
335 ecological and conservation research.

336

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345

346 REFERENCES

- 347 Aceves-Bueno, E., Adeleye, A.S., Bradley, D., Brandt, W.T., Callery, P., Feraud, M., Garner,  
348 K.L., Gentry, R., Huang, Y., Mccullough, I., Pearlman, I., Sutherland, S.A.,  
349 Wilkinson, W., Yang, Y., Zink, T., Anderson, S.E. & Tague, C. (2015) Citizen  
350 Science as an Approach for Overcoming Insufficient Monitoring and Inadequate  
351 Stakeholder Buy-in in Adaptive Management: Criteria and Evidence. *Ecosystems*, **18**,  
352 493–506.
- 353 Bonier, F., Martin, P.R. & Wingfield, J.C. (2007) Urban birds have broader environmental  
354 tolerance. *Biology Letters*, **3**, 670–673.
- 355 Callaghan, C.T., Major, R.E., Wilshire, J.H., Martin, J.M., Kingsford, R.T. & Cornwell, W.K.  
356 (2019a) Generalists are the most urban-tolerant of birds: a phylogenetically controlled  
357 analysis of ecological and life history traits using a novel continuous measure of bird  
358 responses to urbanization. *Oikos*, **128**, 845–858.
- 359 Callaghan, C.T., Major, R.E., Lyons, M.B., Martin, J.M., Wilshire, J.H., Kingsford, R.T. &  
360 Cornwell, W.K. (2019b) Using citizen science data to define and track restoration  
361 targets in urban areas. *Journal of Applied Ecology*, **56**, 1998–2006.
- 362 Callaghan, C.T., Major, R.E., Cornwell, W.K., Poore, A.G.B., Wilshire, J.H. & Lyons, M.B.  
363 (2020a) A continental measure of urbanness predicts avian response to local  
364 urbanization. *Ecography*, **43**, 528–538.
- 365 Callaghan, C.T., Benedetti, Y., Wilshire, J.H., and Morelli, F. 2020b. Avian trait  
366 specialization is negatively associated with urban tolerance. *Oikos* early view:  
367 <https://doi.org/10.1111/oik.07356>
- 368 Cardoso, G.C. (2014) Nesting and acoustic ecology, but not phylogeny, influence passerine  
369 urban tolerance. *Global Change Biology*, **20**, 803–810.

370 Croci, S., Butet, A. & Clergeau, P. (2008) Does Urbanization Filter Birds On The Basis Of  
371 Their Biological Traits? *The Condor*, **110**, 223–240.

372 Er, K.B., Innes, J.L., Martin, K. & Klinkenberg, B. (2005) Forest loss with urbanization  
373 predicts bird extirpations in Vancouver. *Biological Conservation*, **126**, 410–419.

374 Evans, K.L., Gaston, K.J., Frantz, A.C., Simeoni, M., Sharp, S.P., McGowan, A., Dawson,  
375 D.A., Walasz, K., Partecke, J., Burke, T. & Hatchwell, B.J. (2009) Independent  
376 colonization of multiple urban centres by a formerly forest specialist bird species.  
377 *Proceedings of the Royal Society B: Biological Sciences*, **276**, 2403–2410.

378 Evans, K.L., Chamberlain, D.E., Hatchwell, B.J., Gregory, R.D. & Gaston, K.J. (2011) What  
379 makes an urban bird? *Global Change Biology*, **17**, 32–44.

380 Fithian, W., Elith, J., Hastie, T. & Keith, D.A. (2014) Bias correction in species distribution  
381 models: pooling survey and collection data for multiple species. *Methods in Ecology  
382 and Evolution*, **6**, 424–438.

383 Francis, C.D., Ortega, C.P. & Cruz, A. (2011) Noise Pollution Filters Bird Communities  
384 Based on Vocal Frequency. *PLoS One*, **6**.

385 Hadfield, J.D. (2010) MCMC methods for multi-response generalized linear mixed models:  
386 the MCMCglmm R package. *Journal of Statistical Software*, **33**, 1–22.

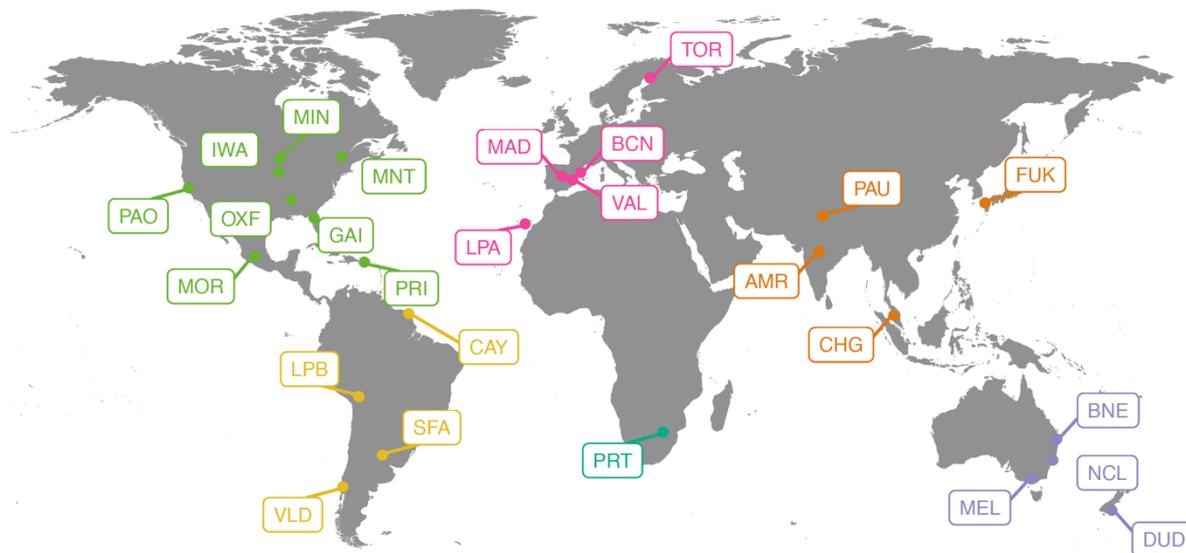
387 Huang, K., Li, X., Liu, X. & Seto, K.C. (2019) Projecting global urban land expansion and  
388 heat island intensification through 2050. *Environmental Research Letters*, **14**, 114037.

389 Jetz, W., Thomas, G.H., Joy, J.B., Hartmann, K., & Mooers, A.O. (2012) The global diversity  
390 of birds in space and time. *Nature*, **491**, 444–448.

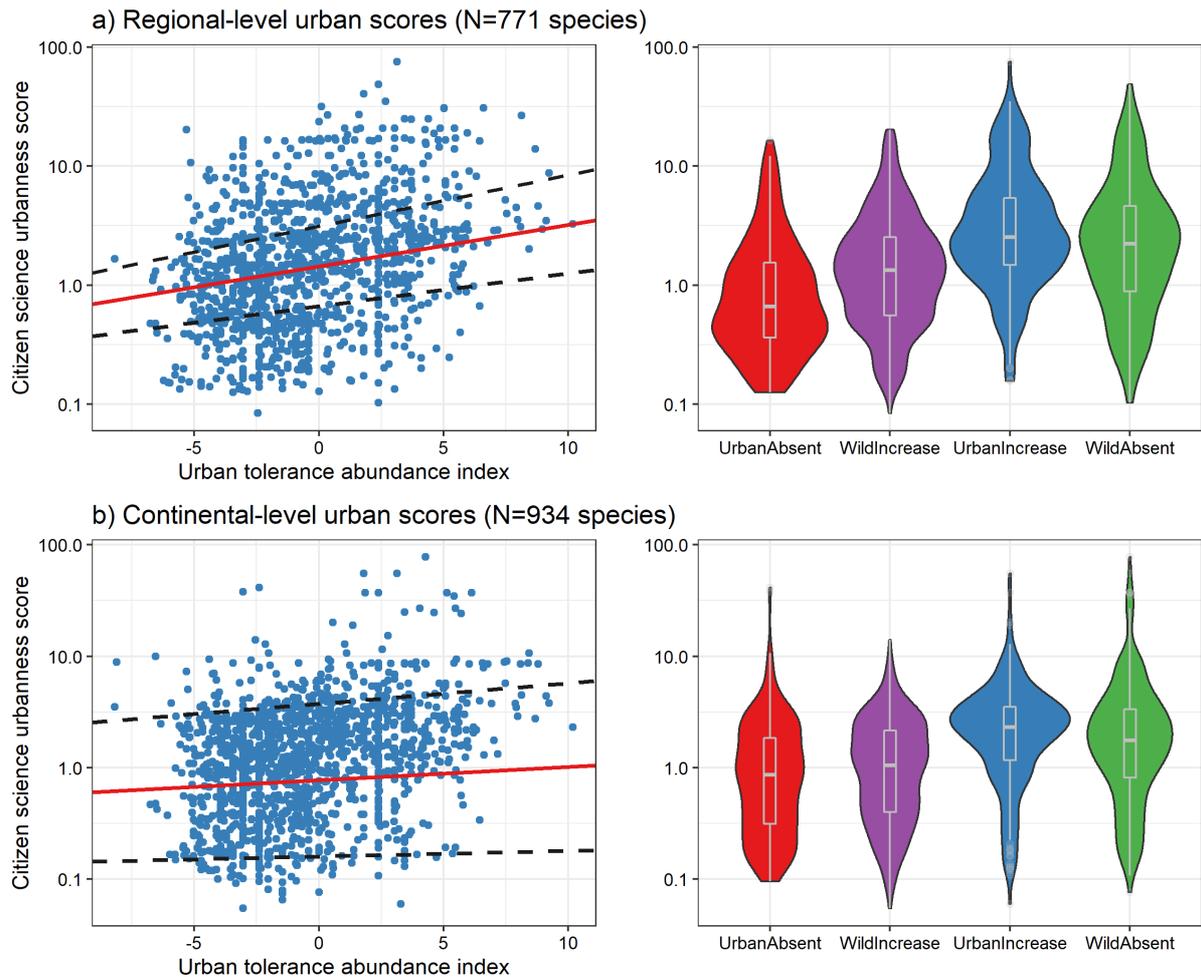
391 Kenneth, B.H., Innes, J.L., Martin, K., & Klinkenberg, B. (2005) Forest loss with  
392 urbanization predicts bird extirpations in Vancouver. *Biological Conservation*, **126**,  
393 410–419.

- 394 Mason, L., & Arathi, H. S. (2019). Assessing the efficacy of citizen scientists monitoring  
395 native bees in urban areas. *Global Ecology and Conservation*, **17**, e00561.
- 396 Matteson, K. C., Taron, D. J., & Minor, E. S. (2012). Assessing citizen contributions to  
397 butterfly monitoring in two large cities. *Conservation Biology*, **26**, 557–564.
- 398 McKinley, D.C., Miller-Rushing, A.J., Ballard, H.L., Bonney, R., Brown, H., Cook-Patton,  
399 S.C., Evans, D.M., French, R.A., Parrish, J.K., Phillips, T.B., Ryan, S.F., Shanley,  
400 L.A., Shirk, J.L., Stepenuck, K.F., Weltzin, J.F., Wiggins, A., Boyle, O.D., Briggs,  
401 R.D., Chapin, S.F., Hewitt, D.A., Preuss, P.W., \* Soukup, M.A. (2017) Citizen  
402 science can improve conservation science, natural resource management, and  
403 environmental protection. *Biological Conservation*, **208**, 15–28.
- 404 McKinney, M.L. (2006) Urbanization as a major cause of biotic homogenization. *Biological*  
405 *Conservation*, **127**, 247–260.
- 406 Milesi, C., Elvidge, C.D., Nemani, R.R. & Running, S.W. (2003) Assessing the impact of  
407 urban land development on net primary productivity in the southeastern United States.  
408 *Remote Sensing of Environment*, **86**, 401–410.
- 409 Møller, A.P. (2009) Successful city dwellers: a comparative study of the ecological  
410 characteristics of urban birds in the Western Palearctic. *Oecologia*, **159**, 849–858.
- 411 Pocock, M.J.O., Tweddle, J.C., Savage, J., Robinson, L.D. & Roy, H.E. (2017) The diversity  
412 and evolution of ecological and environmental citizen science. *PloS One*, **12**.
- 413 Ramírez, F., Afán, I., Bouten, W., Carrasco, J.L., Forero, M.G. & Navarro, J. (2020) Humans  
414 shape the year-round distribution and habitat use of an opportunistic scavenger.  
415 *Ecology and Evolution*.
- 416 Sayol, F., Sol, D. & Pigot, A.L. (2020) Brain Size and Life History Interact to Predict Urban  
417 Tolerance in Birds. *Frontiers in Ecology and Evolution*, **8**.

- 418 Sol, D., Lapiedra, O. & González-Lagos, C. (2013) Behavioural adjustments for a life in the  
419 city. *Animal Behaviour*, **85**, 1101–1112.
- 420 Sol, D., Bartomeus, I., González-Lagos, C. & Pavoine, S. (2017) Urbanisation and the loss of  
421 phylogenetic diversity in birds. *Ecology Letters*, **20**, 721–729.
- 422 Sol, D., González-Lagos, C., Moreira, D., Maspons, J. & Lapiedra, O. (2014) Urbanisation  
423 tolerance and the loss of avian diversity. *Ecology Letters*, **17**, 942–950.
- 424 Sol, D., Trisos, C., Múrria, C., Jeliaskov, A., González-Lagos, C., Pigot, A.L., Ricotta, C.,  
425 Swan, C.M., Tobias, J.A. & Pavoine, S. (2020) The worldwide impact of urbanisation  
426 on avian functional diversity. *Ecology Letters*.
- 427 Sorte, F.A.L., Fink, D., Buler, J.J., Farnsworth, A. & Cabrera-Cruz, S.A. (2017) Seasonal  
428 associations with urban light pollution for nocturnally migrating bird populations.  
429 *Global Change Biology*, **23**, 4609–4619.
- 430 Sullivan, B.L., Wood, C.L., Iliff, M.J., Bonney, R.E., Fink, D. & Kelling, S. (2009) eBird: A  
431 citizen-based bird observation network in the biological sciences. *Biological  
432 Conservation*, **142**, 2282–2292.
- 433 Swaileh, K.M. & Sansur, R. (2006) Monitoring urban heavy metal pollution using the House  
434 Sparrow (*Passer domesticus*). *Journal of Environmental Monitoring*, **8**, 209–213.
- 435 Williams, R.L., Stafford, R., & Goodenough, A.E. (2015) Biodiversity in urban gardens:  
436 Assessing the accuracy of citizen science data on garden hedgehogs. *Urban  
437 Ecosystems*, **18**, 819–833.
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441 **Figure 1.** A map showing the 26 cities used in our analysis, colored by general region.  
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**Figure 2.** a) The relationship between our citizen science urbanness measure calculated at the regional-scale (i.e., within a 250 km buffer) and the urban tolerance abundance index for each city shown on a continuous scale and on a categorical scale. b) The same relationship, but shown with urban scores calculated using the continental-level spatial scale (see Table S1). The red line represents the slope and intercept extracted from our MCMCglmm and accounts for the random effect of city and phylogenetic effects, and the black dashed lines represent the 95% CI surrounding the slope. A species may be included more than once, if it is detected in different cities.