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Scale mismatches between predictor and response variables in species distribution modelling: A review of practices for appropriate grain selection

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1 **Title:** Scale mismatches between predictor and response variables in species distribution modelling:  
2 a review of practices for appropriate grain selection

3

#### 4 **Abstract**

5 There is a lack of guidance on the choice of the spatial grain of predictor and response variables in species  
6 distribution models (SDM). This review summarises the current state of the art with regard to the following  
7 points: (i) the effects of changing the resolution of predictor and response variables on model performance;  
8 (ii) the effect of conducting multi-grain vs single-grain analysis on model performance; and (iii) the role of  
9 land cover type and spatial autocorrelation in selecting the appropriate grain size. In the reviewed literature,  
10 we found that coarsening the resolution of the response variable typically leads to declining model  
11 performance. Therefore, we recommend aiming for finer resolutions unless there is a reason to do otherwise  
12 (e.g., expert knowledge of the ecological scale). We also found that so far, the improvements in model  
13 performance reported for multi-grain models have been relatively low and that useful predictions can be  
14 generated even from single-scale models. In addition, the use of high-resolution predictors improves model  
15 performance; however, there is only limited evidence on whether this applies to models with coarser-  
16 resolution response variables (e.g. 100 km<sup>2</sup> and coarser). Low-resolution predictors are usually sufficient for  
17 species associated with fairly common environmental conditions but not for species associated with less  
18 common ones (e.g., common vs rare land cover category). This is because coarsening the resolution reduces  
19 variability within heterogeneous predictors and leads to underrepresentation of rare environments, which can  
20 lead to a decrease in model performance. Thus, assessing the spatial autocorrelation of the predictors at  
21 multiple grains can provide insights into the impacts of coarsening their resolution on model performance.  
22 Overall, we observed a lack of studies examining the simultaneous manipulation of the resolution of predictor  
23 and response variables. We stress the need to explicitly report the resolution of all predictor and response  
24 variables.

25

26

27 **Keywords:** Environmental niche modelling, Grain, Land cover, Predictor, Resolution, Scale, SDM, Variable

## 29 **1. Introduction**

30 Species distribution models (SDMs) are widely used to assess species–environment relationships and to make  
31 predictions of species distributions in both space and time (Elith and Leathwick, 2009; Ferrier et al., 2017;  
32 Wiersma et al., 2011). To this end, SDMs relate a biodiversity-related response variable (e.g., the geographic  
33 distribution of one or more species) to explanatory variables (i.e., predictors, covariates, or features). The  
34 strength of these relationships infere species’ niches, and can be used to predict a species’ occurrence in  
35 unsurveyed locations. Although SDMs are a fundamental tool for answering many ecological, evolutionary,  
36 and conservation-related questions, some methodological issues remain unresolved (Araújo et al., 2019;  
37 Moudrý et al., 2017; Rocchini et al., 2011; Santini et al., 2021).

38 One such issue is the choice of *spatial resolution*, or *grain*, of the input data (Dungan et al., 2002). It has been  
39 hypothesized that organisms respond to their environment more strongly at some grains than at others; these  
40 grains have been referred to as ‘ecological scales’ (Lecours et al., 2015), ‘characteristic scales’ (Holland et al.,  
41 2004), ‘intrinsic scales’ (Wu and Li, 2006) and ‘response grains’ (Mertes and Jetz, 2018). This concept  
42 implies that for every species, there are one or more grains that best capture the scales at which organisms  
43 most strongly respond to specific environmental variables. For example, it is assumed that climate constrains  
44 species distributions at broader spatial scales (e.g., at the extent of a whole continent, with phenomena that  
45 can be measured at a coarse resolution like  $> 100 \text{ km}^2$ ). At successively finer resolutions and over smaller  
46 geographic extents, topography or biotic interactions may be the dominant variables in controlling species  
47 distribution, whereas at even finer resolutions, microclimate, vegetation structure, or the presence of  
48 individual land cover categories such as water bodies might drive local species distribution (Austin and Van  
49 Niel, 2011; Field et al., 2009; Pearson and Dawson, 2003; Wiens, 1989). However, previous studies have  
50 suggested that some of the abovementioned variables may shape species distribution across multiple grains  
51 (e.g., Alexander et al., 2015; Bütikofer et al., 2020; Wisz et al., 2013). Consequently, the choice of grain  
52 adopted in models can strongly influence our ability to detect and measure species’ response to the  
53 environment (de Knegt et al., 2010; Huston, 2002; Levin, 1992; Soberón, 2007; Cord et al. 2014).

54 Ideally, both species occurrence data and predictor variables are available at relatively fine resolutions,  
55 allowing the researchers to coarsen the resolutions iteratively to find the best match between the predictor and  
56 response variables. While the response data should preferably be available at resolutions at which the species  
57 are expected to respond to the environment, predictor variables should be detailed enough to allow  
58 distinguishing important features of the environment that are hypothesized to affect species distribution (e.g.,  
59 a certain habitat type or specific microclimatic conditions). However, this is not always the case due to  
60 limitations in data availability. Usually, the original spatial resolution of different datasets that need to be  
61 integrated for modelling purposes varies significantly, and thus finding an optimal match remains a significant  
62 challenge.

63 It is a common practice to modify the resolution of the input data so that it matches the resolution at which the  
64 study is intended, for example, by averaging environmental variables within field plots. Both continuous (e.g.,  
65 bioclimatic variables, terrain characteristics such as slope) and categorical (e.g., land cover) predictors are  
66 often aggregated or resampled to match the resolution of the response variable ([Grohmann, 2015](#); [Moudrý et al., 2019](#)). While not commonly implemented, an alternative approach consists of retaining the discrepancy  
67 between the grain sizes of the response and predictor variables through hierarchical modelling. This allows  
68 modelling species distribution using fine-grain species data and coarse-grain environmental data ([McInerney  
69 and Purves, 2011](#)), coarse-grain species data using fine-grain environmental data ([Keil et al., 2013, 2014](#)), or  
70 modelling the grain-dependency of the species-environment relationships. The latter can be done using an  
71 extra parameter in the model to quantify the relationship across a continuum of spatial scales ([Keil & Chase,  
72 2019](#)).

74 Any end user should know how changing the spatial resolution of predictor and response variables can affect  
75 SDM performance and which data characteristics play a role in how profound the effect of changing the  
76 resolution will be. Therefore, here we review methodological issues related to the choice of the spatial  
77 resolution of predictor and response variables in SDM. In particular, we focus on the following issues: (i) the  
78 effects of changing the resolution of predictor and response variables on model performance, (ii) the effect of  
79 conducting multi-grain vs single-grain analysis on model performance, and (iii) the role of land cover type  
80 and spatial autocorrelation in the selection of appropriate grain sizes. Accordingly, we aim at providing  
81 recommendations for the critical assessment of the input data.

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## **2. Effects of changing the resolution of predictor and response variables on model performance**

Numerous studies examined the grain dependence of species-environment relationships (see the review by [Moudrý and Šímová, 2012](#)). Some authors coarsened the resolution of the response variable (section 2.1), others coarsened the resolution of predictor variables so that the resulting predictor was coarser than the response variable (section 2.2). Finally, in some studies the resolution of predictor variables was coarsened so that the resulting predictor was finer than the response variable (section 2.3). These three scenarios are shown in Figure 1. The distinction between these three approaches is often not made in the respective studies, and the effect of changing any resolution can be mistakenly understood as a single problem. We found no studies manipulating the resolution of predictors from finer to coarser resolution compared to the response variable, nor did we find studies manipulating the resolution of both the predictors and the response simultaneously (but see [Tobalske, 2002](#)).

### **2.1 How the resolution of the response variable affects model performance**

The availability of species data at a much coarser resolution than commonly used environmental variables (e.g., species occurrence locations only available aggregated at a municipal or county level; [Cheng et al., 2021](#); [Jetz et al., 2012](#)) can significantly limit our ability to model species-environment relationships. Studies using species data at such coarse resolutions are not uncommon, especially for less studied taxa. As examples of such data, we can name gridded atlases ([Jalas and Suominen, 1988](#); [Št'astný et al., 2021](#)), the resolutions of which can range from hundreds of meters to tens of kilometres. However, monitoring programs collecting atlas data are organizationally and financially demanding. The choice of grid resolution then becomes a trade-off between the level of detail and the feasibility of fieldwork. It is increasingly common to supplement

109 atlases with maps generated with SDMs (e.g., [Flousek et al., 2015](#); [Šťastný et al., 2021](#)). As field data may  
110 nowadays be gathered with the knowledge that they will also be used for modelling, it is important to know  
111 how the resolution of the response affects model performance.  
112 In studies specifically examining the effect of grain size of the response variable on SDM performance,  
113 response grain ranges from a few metres to hundreds of kilometres, depending on the predictors tested (Figure  
114 1a; Table 1; see review by [Miguet et al., 2015](#)). These studies typically ask: at what scale(s) is the species  
115 distribution most driven or constrained by specific environmental conditions? At finer resolutions, studies  
116 typically concentrate on the role of landscape structure (composition and configuration) in driving species  
117 distribution ([Heikkinen et al., 2007](#); [Holland et al., 2004](#); [Tobalske, 2002](#)). With coarser response grains,  
118 studies often include (bio)climatic variables ([Chauvier et al., 2022](#); [Kaliontzopoulou et al., 2008](#); [Seo et al.,](#)  
119 [2009](#)). Typically, such studies report declining model performance with the coarsening of the resolution of the  
120 response variable ([Chauvier et al., 2022](#); [Gábor et al., 2022a](#); [Heikkinen et al., 2007](#); [Kaliontzopoulou et al.,](#)  
121 [2008](#); [Seo et al., 2009](#); [Zarzo-Arias et al., 2022](#)), suggesting that modelling species at coarser resolutions is not  
122 optimal. However, these studies typically focus on the general performance of the models and do not report  
123 the effect of changing the response grain on the variables' importance, which may provide valuable insights  
124 into which variables shape species distributions at individual grain sizes (but see [Chauvier et al., 2022](#);  
125 [Hanberry, 2013](#)).

## 126 **2.2 How the resolution of the predictor variable (coarser than the** 127 **response variable) affects model performance?**

128 Instead of coarsening the resolution of the response variable, some studies have coarsened the resolution of  
129 predictor variables, so that the resulting predictor is coarser than the response variable (Figure 1b; Table 2).  
130 They came to different conclusions. [Ferrier and Watson \(1997\)](#) concluded that coarse environmental data lead  
131 to poorer model performance. [Graf et al. \(2005\)](#) found that the predictive power was highest at resolutions of  
132 about 1 and 2 km<sup>2</sup>. In contrast, [Guisan et al. \(2007\)](#) and [Pradervand et al. \(2014\)](#) concluded that coarsening the  
133 predictor variables' resolution did not substantially change model performance, meaning that refining the  
134 resolution may not be sufficient to improve the models.

135

136 **2.3 How the resolution of the predictor variable (finer than the**  
137 **response variable) affects model performance?**

138 Studies that manipulate the resolution of predictor variables, so that the resulting predictor was finer than the  
139 response variable (Figure 1c; Table 3), are mostly concerned with the importance of fine-scale habitat features  
140 for analyzing species-environment relationships (e.g., [Gottschalk et al., 2011](#); [Šímová et al., 2019](#)). They  
141 combine response variables at a coarse resolution with predictor variables at a fine resolution. These studies  
142 typically ask: do we need fine-resolution predictors to explain species distribution at a relatively coarse  
143 resolution?

144 High-resolution predictor variables suitable for modelling at multiple levels of detail may not be readily  
145 available for the particular study area, their acquisition may be prohibitively expensive (especially for studies  
146 conducted over large extents), and their use may require excessive data processing and significantly increase  
147 computational time ([Kissling et al. 2022](#); [Moudrý et al. 2022](#)). Hence, researchers face trade-offs between data  
148 detail and availability, data processing, and analytical optimization. Several studies have examined the  
149 importance of fine-grain habitat features for the analysis of species-environment relationships using a  
150 relatively coarse-grained response variable (Figure 1c; Table 3). In this type of study, authors typically use  
151 predictor variables of various origins, collected, for example, by remote sensing ([Leitão & Santos 2019](#)),  
152 fieldwork, or crowd-sourcing ([Šímová et al., 2019](#); [Thomas et al., 2002](#); [Venier et al., 2004](#)). Others have  
153 coarsened the grain of the original predictors to examine the grain dependency of species-environment  
154 relationships (e.g. [Gottschalk et al., 2011](#)).

155 [Thomas et al. \(2002\)](#) found that field-collected fine-grain predictors and predictor variables derived from a 30  
156 m digital elevation model lead to the same model performance at a 1 km resolution. [Seoane et al. \(2004\)](#)  
157 found that models derived from land cover at a 250 m resolution are comparable to those based on the same  
158 variables derived from satellite images at a 30 m resolution, in agreement with [Venier et al. \(2004\)](#).  
159 Consequently, it is commonly assumed that coarse-resolution habitat predictors at continental (e.g., CORINE  
160 Land cover; [Büttner et al., 2004](#)) or global (e.g., Global Consensus Land cover; [Tuanmu and Jetz, 2014](#))  
161 geographic extents are sufficient for use in combination with coarse-resolution responses.



162 However, it is essential to know if a given spatial resolution of a predictor variable captures the details that are  
163 important for explaining the distribution of the species of interest. [Gottschalk et al. \(2011\)](#) concluded that a  
164 higher spatial resolution of predictors could be essential for accurate predictions. In addition, they attributed  
165 the improvement in models using detailed land cover maps to the high level of detail in the species response  
166 variable (2 km diameter around survey points). This contrasts with results by [Šímová et al. \(2019\)](#) that  
167 demonstrated improvement in model performance when using high-resolution land cover data despite the  
168 coarse resolution of species data (12 x 11.2 km). They showed that the area and perimeter of water bodies  
169 derived from high-resolution land cover datasets (raster data at 30 m resolution) explain distributions of  
170 waterbirds better than predictors derived from coarser 1 km data. In line with these findings, it has been  
171 recently recommended to first coarsen the resolution of the predictors to match the resolution of the assumed  
172 ecological scale before calculating prediction metrics (e.g., standard deviation, Shannon-Wiener diversity  
173 index, or Rao's Q) at the resolution of a response variable ([Graham et al., 2019](#)). In this context, the recent  
174 finding by [Gábor et al. \(2022b\)](#), who showed that in the case of species inhabiting rare habitats, using simple  
175 binary predictors (i.e. presence/absence of the habitat) might be sufficient, is of particular interest.  
176 In conclusion, coarse-resolution land cover or terrain predictors may lack details to capture potentially  
177 suitable habitats such as wetlands or cliffs. Thus, using high-resolution data could benefit models utilizing  
178 coarser-resolution species data (e.g. from gridded atlases). The question of whether the need for fine-scale  
179 predictors is somehow related to the resolution of the response variable or whether it can be generalized  
180 should be further explored for different taxa and sets of predictors.

181

### 182 **3. Single-grain versus multi-grain analysis**

183 Up to this point, we have neglected discussing the possibility of considering species-environment  
184 relationships at multiple grains in a single model. Typically, experimental studies use a single grain for the  
185 response variable. Therefore, they implicitly assume the existence of a common ecological scale for all  
186 predictor variables. However, it has been shown that the ecological scale is variable-specific since species  
187 often respond to different environmental variables at different spatial scales, and sometimes even respond  
188 differently to a single environmental variable at multiple grains ([Leitão et al. 2010](#); [Lecours et al., 2020](#);

189 [Miguet et al., 2016](#); [Roilo et al. 2022](#)). However, despite theoretical concepts and extensive empirical  
190 evidence that species respond to their environment at different spatial grains (e.g. [Bergman et al., 2012](#); [Graf](#)  
191 [et al., 2005](#); [Holland et al., 2004](#); [Stuber and Fontaine, 2019](#); [Zweifel-Schielly et al., 2009](#)), the appropriate  
192 approach to select the grain of response variable remains unclear ([Jackson and Fahrig, 2015](#); [Martin and](#)  
193 [Fahrig, 2012](#); [Stuber and Gruber, 2020](#)). For example, [Mertes et al. \(2020\)](#) recognized two primary spatial  
194 grains at which species typically respond to their environment: they denoted the term “occupancy grain” for  
195 the grain equivalent to a species’ typical home range and the term “response grain” for the grain at which an  
196 individual uses an environmental resource. They also developed an optimization procedure for their  
197 identification. However, studies usually use grains of response variables coarser than the assumed occupancy  
198 and response grain, and it is unclear how to incorporate occupancy and response grains in such studies (but  
199 see [Graham et al., 2019](#)).

200

201 In theory, species distributions are driven by environmental variables at a range of scales ([Levin, 1992](#)), and  
202 there is no single “correct” spatial grain at which to characterize species-environment associations ([Mitchell et](#)  
203 [al., 2001](#); [Wiens, 1989](#)). Therefore, models using multiple grains should, in theory, outperform models that  
204 assume a common ecological scale for all variables. However, scale-sensitive applications that aim to align  
205 the grain of the response variable (or predictor variables; see [Graham et al., 2019](#)) with the ecological scale  
206 are rare ([McGarigal et al., 2016](#)). In addition, studies have come up with different conclusions. Some have  
207 suggested that the performance of models using multiple response variable grains is better than that of single-  
208 grain models ([Mertes et al., 2020](#)), while others have not drawn similar conclusions ([Martin and Fahrig,](#)  
209 [2012](#)). Of note is that the improvements reported for multi-grain models were often relatively low, in the order  
210 of hundredths of the area under the receiver operating characteristic curve (AUC) values ([Boscolo and](#)  
211 [Metzger, 2009](#); [Graf et al., 2005](#); [Kuhn et al., 2011](#); [Mateo Sánchez et al., 2014](#)). In other words, valuable  
212 predictions can still be generated from models using a single arbitrarily selected scale. Hence, it remains  
213 unclear whether the increased complexity caused by the use of multiple grains is beneficial, particularly in the  
214 case of SDMs used for the projection of species distributions under future climate conditions, which are  
215 generally uncertain (e.g. [Sinclair et al., 2010](#)).

216

#### 217 **4. Land cover types and spatial autocorrelation**

218 In an early study on the effect of spatial resolution on the performance of species-habitat relationships, [Karl et](#)  
219 [al. \(2000\)](#) suggested that the effects of coarsening the resolution depend on the heterogeneity of the  
220 environment. The difference in land cover types used in different analyses might, therefore, explain some  
221 contrasting findings. For example, [Seoane et al. \(2004\)](#) and [Venier et al. \(2004\)](#) observed no improvement in  
222 models when using finer-grain land cover data, while [Gottschalk et al. \(2011\)](#) and [Šímová et al. \(2019\)](#)  
223 observed a significant improvement. Both [Seoane et al. \(2004\)](#) and [Venier et al. \(2004\)](#) used data on common  
224 land cover types, such as the proportion of forests within mapping units. For homogeneous landscapes  
225 displaying strong spatial autocorrelation (e.g., large blocks of forests), land cover information does not change  
226 much when spatially aggregated to coarser resolutions. In contrast, [Šímová et al. \(2019\)](#) focused on water  
227 bodies, a land cover category that can become virtually invisible at coarser resolutions; coarsening the  
228 resolution often leads to a bias and underrepresentation of rare environments such as (especially linear) water  
229 bodies in certain landscapes. Similarly, [Seoane et al. \(2004\)](#) observed considerable improvement in models for  
230 riparian species when finer-resolutions predictors were used. This may be one of the reasons why [Tuanmu and](#)  
231 [Jetz \(2014\)](#) found that the Global Consensus Land Cover that has a spatial resolution of 1 km<sup>2</sup>  
232 (<https://www.earthenv.org/landcover>; see Table 2) performed worse for predicting aquatic species than  
233 species inhabiting other environments. Similarly, [Cord et al. \(2014\)](#) showed for 30 tree species that SDM  
234 performance was significantly positively correlated with the species-specific degree of association between  
235 the focal species and different land cover types.

236  
237 Environmental variables are typically spatially autocorrelated (i.e., values between two locations are more  
238 similar the closer the locations are in space; [Legendre, 1993](#)). This spatial autocorrelation can be quantified  
239 using an empirical variogram that can be used to calculate the characteristic distance within which spatial  
240 autocorrelation operates (i.e., the ‘range’ of an empirical variogram). Recently, [Mertes and Jetz \(2018\)](#)  
241 highlighted the importance of considering environmental autocorrelation for the ability of SDMs to estimate  
242 species-environment associations. Similar results were obtained by [Kühn \(2006\)](#) for species richness. More  
243 recently, [Smith and Santos \(2020\)](#) explored the effect of the resolution of predictor variables and their

244 autocorrelation on estimates of their importance. This body of literature shows that using coarser  
245 environmental data in SDMs without consideration of the autocorrelation can mischaracterize species-  
246 environment relationships (see [Miller, 2012](#), for review). This is particularly true for variables that vary  
247 rapidly over space; i.e. heterogeneous landscapes characterized by spatial autocorrelation with relatively small  
248 range values ([Mertes and Jetz, 2018](#)). Aggregating heterogeneous landscapes to a coarser resolution results in  
249 the loss of a portion of that heterogeneity ([Graham et al., 2019](#); [Karl et al., 2000](#); [Mertes and Jetz, 2018](#)).  
250 Lower autocorrelation means higher randomness; hence, very distinct values are aggregated together. In  
251 contrast, if there is strong autocorrelation, aggregating over a larger area does not change the value much  
252 because the values were similar even in the finer resolutions.

253 Importantly, the inherent spatial autocorrelation of both species occurrences and predictor variables can result  
254 in models that may inadvertently capture the spatial structure rather than true functional relationships ([Bahn  
255 and McGill, 2007](#)). Indeed, it has been shown that spatial autocorrelation can lead to SDMs with high  
256 discrimination ability even when there is no relationship between species occurrence and environmental  
257 variables ([Chapman, 2010](#); [Fourcade et al., 2018](#)) and that many SDMs, despite a good fit, are not  
258 significantly better than null models ([Osborne et al., 2022](#)). Therefore, it is a question of whether the loss of  
259 explanatory power accompanying the coarsening of the resolution is due to the use of an inappropriate scale  
260 (e.g. due to the lack of detail of potentially suitable environmental conditions) or due to changes in the spatial  
261 structure; hence, this loss of power should be further explored for different resolutions and predictors. In any  
262 case, selecting a relevant set of environmental predictors based on the known ecology of the species of interest  
263 is essential to ensure fitting SDMs with an appropriate ecological interpretation ([Fourcade et al., 2018](#)). In  
264 addition, it is necessary to carefully inspect whether SDMs estimated from the observed data perform better  
265 than those generated from the null occurrence distributions, for example by using the recently-developed  
266 “fauxcurrence” R package ([Osborne et al., 2022](#)).

267

## 268 **5. The ratio between the resolution of response and predictor variables**

269 A recently proposed standard protocol ([Zurell et al., 2020](#)) recommends reporting information on data,  
270 modelling techniques, validation, and underlying questions ([Araújo et al., 2019](#); [Michener and Jones, 2012](#);

271 [Rocchini and Neteler, 2012](#)). However, many studies still lack it (see [Feng et al., 2019](#) for a review). When  
272 evaluating the effect of changing the resolution of predictor variables, it is also important to consider the  
273 resolution of the response variable (i.e., species occurrences). The opposite is also true: when evaluating the  
274 role of the resolution of the response variable, one should be aware of the resolution of predictor variables.  
275 Although this may seem like a trivial recommendation, it remains infrequent that studies evaluating the effects  
276 of changing resolutions discuss their results with respect to the ratio between the resolutions of the response  
277 variable and predictor variables (but see [Moudrý and Šímová, 2012](#)). The ratio between the resolution of the  
278 response and the resolution(s) of the predictor variables differs among studies and might be the reason for  
279 reported contradicting results (Figure 1). For example, in studies evaluating the importance of finer-resolution  
280 predictors to explain species distributions, response grains can differ considerably (Table 4). It can be  
281 expected that for small ratios, coarsening of the resolution of predictor variables will have a minimal effect on  
282 model performance (e.g. [Seoane et al. 2004](#); [Venier et al. 2004](#)), while for high ratios (indicating a high  
283 difference between the resolutions of the response and predictor variables), considerable effects can be  
284 expected due to the aggregation of highly different values (e.g. [Gottschalk et al. 2011](#); [Šímová et al. 2019](#)).  
285 Practices could be improved by reporting the resolution of predictor variables as well as that of the response  
286 variable.

287

## 288 **6. Conclusions**

289 Spatial scale is one of the most critical issues in ecology and associated disciplines ([Levin, 1992](#)). Species  
290 respond to their environment at different scales, and processes controlling species distribution operate at  
291 various spatial scales. Unsurprisingly, the studies we reviewed found various optimal resolutions, depending  
292 on the species and ecosystems analyzed. Besides, most studies analyzing multiple species usually report only  
293 a general trend in models' behaviour with respect to changing resolution, and there are always some models  
294 that do not conform to the general pattern (e.g., [Guisan et al., 2007](#); [Pradervand et al., 2014](#)). Our review  
295 highlights that within the typically used resolutions (0.01 – 100 km<sup>2</sup>) finer-resolution models generally  
296 perform better. Besides, the use of coarse-resolution response variables has implications for the predicted  
297 distribution range ([Kunin, 1998](#)). When the resolution of the response variable is too coarse, there is a risk of

298 overestimating the occupied area (Connor et al., 2018; Hu and Jiang, 2010; Lauzeral et al., 2013; Seo et al.,  
299 2009). Moreover, Gábor et al. (2022a) recently showed that coarsening the resolution does not compensate for  
300 positional error in species occurrence data. Therefore, we recommend basing the choice of the resolution of  
301 the response variable on practical aspects, such as aiming for finer resolutions unless there is a reason to do  
302 otherwise (e.g., expert knowledge of the ecological scale of the species under study).

303

304 Coarsening the resolution of predictor variables has been shown to negatively affect model performance as it  
305 obscures fine-scale heterogeneity in environmental variables. Therefore, we recommend (1) using finer-  
306 resolution environmental variables when modelling species associated with rare environmental entities (e.g., a  
307 rare habitat type), even when using species occurrence data at a coarse resolution (Šimová et al., 2019). When  
308 species are associated with widespread environmental conditions, using low-resolution predictors is likely  
309 sufficient. However, we recommend (2) assessing spatial autocorrelation or thematic resolution of predictors  
310 at multiple grains to estimate the potential impacts of coarsening their resolution on model performance (i.e.  
311 to ensure that they preserve enough detail to distinguish environmental features that affect species distribution  
312 at a given resolution). Thirdly, (3) studies may benefit from considering multiple grains of the response  
313 variable within a single model, even though the improvements reported for multi-grain models have so far  
314 been *relatively* low, and we recognize that useful predictions can still be generated from single-scale models.  
315 Finally, (4) studies should explicitly report the resolutions of the predictor and response variables, following  
316 the standard ODMAP protocol recently proposed by Zurell et al. (2020).

317

## 318 **7. References**

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