



University College London  
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# **Traits influence responses to land-use and climate change in terrestrial vertebrates**

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# **Declaration**

I, Adrienne Etard, confirm that the work presented in this thesis is my own. Some parts have been conducted in collaboration with other researchers, and the contributions of co-authors to specific Chapters are described in the *Thesis outline of contents, authorship and collaborations* on page 6. All else is appropriately referenced, and where information has been derived from other sources, I confirm that this has been indicated in the thesis.

# Acknowledgements

Firstly, I would like to thank my supervisors, Tim Newbold and Alex Pigot, whose guidance and continual support have been pivotal to the completion of this PhD thesis. A huge thanks to my primary supervisor, Tim Newbold, for making this PhD a fantastic experience. I am grateful for all the opportunities he has offered me, for his availability, his optimism, and for the kind, attentive, and constructive supervision. I am equally grateful to Alex Pigot for welcoming me into his lab, for his insights and feedback on my work, and for his advice. Thanks for the weekly lab meetings and chats that were once an essential part of the lockdown routine and made for stimulating conversations. I would also like to extend my thanks to Richard Pearson for sitting on my Upgrade committee.

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# Abstract

Human activities have profoundly impacted global biodiversity. Currently, anthropogenic land-use and climate change figure among the major threats to the world's fauna. However, not all species respond similarly to these pressures. Interspecific variability in responses to human threats is notably underpinned by the fact that different species possess different ecological characteristics, some of them allowing species to cope with environmental changes, while others confer a disadvantage to species in modified environments. Understanding what renders species sensitive to anthropogenic pressures is vital to inform and prioritise conservation efforts. Yet, in terrestrial vertebrates, a group for which ecological data is the most abundant, it remains unclear which traits are associated with higher sensitivity to human pressures. The aims of my thesis are to investigate whether and which traits are associated with land-use responses and climate-change sensitivity in terrestrial vertebrates, and to highlight some of the consequences for ecosystem functioning. I first assess the global availability of ecological trait data for terrestrial vertebrates, identifying understudied groups and regions (e.g., Central-African reptiles). I then show that, at global scales, disturbed land uses negatively impact the functional diversity of vertebrate assemblages. Further, I find that in all classes, higher sensitivity to land-use and climate change is associated with narrower ranges, smaller habitat breadth and inability to use human-modified habitats. Both land-use responses and climate-change sensitivity are unevenly distributed among dietary groups, highlighting potential food-web disruptions in assemblages under pressure. Finally, I show that land-use responses are influenced by species' energetic requirements, so that energetic fluxes within vertebrate assemblages are likely modified under human-driven land-use change. Although the large-scale consequences of biodiversity changes for ecosystem functioning remain to be fully understood, my thesis highlights a compositional reshaping of vertebrate assemblages under human pressure and furthers our understanding of anthropogenic impacts on biodiversity.

# Impact statement

As anthropogenic pressures on the world's biota keep increasing, it is vital to put into place conservation measures to prevent and reverse further species loss. Beyond ethical and moral considerations, there is an urgent need to protect biodiversity because it sustains a range of ecological processes essential to human well-being and planetary health. Effectively managing biodiversity and related ecosystem processes in a changing world requires an understanding of how different species respond to anthropogenic disturbances. My thesis integrates various data sources to investigate the influence of traits on species' land-use responses and on species' climate-change sensitivity – two of the most pressing threats to biodiversity – at global scales and comparatively across the four terrestrial vertebrate classes. By asking whether interspecific trait variation is associated with species' land-use responses and with climate-change sensitivity, my work consolidates our understanding of what renders species sensitive to environmental change, which can help prioritise conservation efforts.

Chapter 2 presents a trait data collection for terrestrial vertebrates, targeting seven commonly-used traits. I highlight the global taxonomic, geographical, and phylogenetic biases in the trait data, revealing knowledge gaps which could guide future data collection efforts. Chapter 2 was published in *Global Ecology and Biogeography* (Etard et al., 2020). The compiled data were made available and have since been used by other ecologists (e.g., Capdevila et al. (2022a)) and downloaded 272 times as of May 2022. Chapter 3 uses the collected trait data and reveals profound effects of land-use change on vertebrate functional diversity, which contributes to documenting global human impacts on vertebrates and also underlines the possible threats posed by land-use change to ecosystem processes sustained by vertebrates. Chapter 3 was published in *Ecology Letters* (Etard et al., 2022). In Chapter 4, I ask whether traits are associated with species' land-use responses and with species' climate-change sensitivity, comparatively across the four vertebrate classes. Chapter 4 thus puts into perspective the usefulness of trait data for understanding how species respond to these anthropogenic changes, which is valuable for conservation planning and prioritisation. In Chapter 5, I ask whether species' energetic requirements, estimated from metabolic rates, influence species persistence

in disturbed land uses. Chapter 5 thus integrates physiological data to further our fundamental understanding of how vertebrate species respond to land-use change and of the potential consequences for ecosystem functioning.

Beyond publishing two of my PhD Chapters, I have been able to disseminate my work at various international conferences (BES annual meetings in 2019, 2020 and 2021; BES Macroecology conference in 2019; IBS early-career conference in 2021). I will also present my PhD work at the IBS conference (June 2022, 10<sup>th</sup> Biennial meeting), and at the BES Macroecology conference (July 2022). I have contributed to the Living Planet Report 2020 (WWF, 2020) and to other published papers (Newbold et al., 2019, 2020b). Overall, my PhD work consolidates our knowledge of the role of vertebrate traits for understanding species responses to human pressures and highlights the value of trait data, and more widely, of ecological knowledge, for preserving vertebrate species in a changing world.

# **Thesis outline of contents, authorship and collaborations**

## **Chapter 1: General introduction**

Chapter 1 presents the background for this thesis, exposes the fundamental concepts, and highlights the research questions I investigated in the different Chapters.

## **Chapter 2: Global gaps and biases in trait data for terrestrial vertebrates**

In Chapter 2, I present an analysis of the global gaps and biases in terrestrial vertebrate trait data. To this end, I collate data on seven traits commonly measured in terrestrial vertebrates. I then evaluate the availability of these trait data across the vertebrate classes, assessing whether there are taxonomic, phylogenetic and spatial biases. This Chapter was published in *Global Ecology and Biogeography* in 2020 (DOI: 10.1111/geb.13184; Etard et al. (2020)). The paper was co-authored by Sophie Morrill who collated some of the data on reptile traits as part of an MRes project at UCL, and by Tim Newbold, who participated in the development of the research questions, provided detailed feedback on the analyses, and contributed to the writing of the paper.

## **Chapter 3: Intensive human land uses negatively affect vertebrate functional diversity**

In this Chapter, I investigate how land-use change affects the functional composition and functional diversity of local vertebrate assemblages. This Chapter was published in *Ecology Letters* in 2022 (DOI: 10.1111/ele.13926; Etard et al. (2022)) and co-authored by Alex Pigot and Tim Newbold, who helped construct the hypotheses, provided detailed feedback on the work, and took part in the writing of the paper.

## **Chapter 4: Narrow-ranging natural habitat specialists most sensitive to both land-use and climate change in terrestrial vertebrates**

In this Chapter, I assess whether ecological traits as well as geographical range area are associated with species' land-use responses and species' estimated climate-change sensitivity, comparatively among terrestrial vertebrate classes. Rhiannon Osborne-Tonner contributed to this Chapter by collecting data on amphibian and reptile diet during her MSci project at UCL, which I used to complement my datasets. This Chapter was conducted in collaboration with Tim Newbold who helped develop the research questions and provided detailed feedback on the work and on the writing.

## **Chapter 5: Energetic constraints and trophic group explain species persistence in disturbed land uses**

In Chapter 5, I evaluate the impacts of land-use change on community-level energetic requirements, and I assess whether species' energetic requirements influence species persistence in disturbed land uses. To this end, I use physiological data, compiling species resting metabolic rates (used as a proxy for energetic requirements) from the literature. Meghan Hayden and Laura Dee of the University of Colorado, Boulder, as well as Tim Newbold, contributed to the elaboration of the research questions for this Chapter. Meghan Hayden further contributed to this Chapter by retrieving information on net primary productivity for PREDICTS sites, using data from MODIS satellite imagery. All collaborators also provided feedback on the work and participated in writing the manuscript. This Chapter was submitted to a scientific journal and underwent a round of peer-review. I am preparing this Chapter for resubmission.

## **Chapter 6: General discussion**

This final Chapter summarises the main findings of my thesis and assesses their contributions to the field.

# Data and code access

## Code access

The main pieces of R code for Chapters 2, 3, 4 and 5 are available at: [https://github.com/AdrienneEtard/PhD\\_thesis\\_code](https://github.com/AdrienneEtard/PhD_thesis_code).

This document was compiled with L<sup>A</sup>T<sub>E</sub>X; the source code and files are available at: <https://github.com/AdrienneEtard/Thesis>

## Data

The data used in this thesis are freely accessible and sources are referenced throughout. In particular:

- the PREDICTS database (Hudson et al., 2014, 2017) can be downloaded from: <https://data.nhm.ac.uk/dataset/the-2016-release-of-the-predicts-database>;
- the trait datasets I compiled in Chapter 2 are available at: [https://figshare.com/articles/dataset/Global\\_gaps\\_in\\_terrestrial\\_vertebrate\\_trait\\_data/10075421](https://figshare.com/articles/dataset/Global_gaps_in_terrestrial_vertebrate_trait_data/10075421).

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# <sup>1</sup> 1 | General introduction

<sup>2</sup> Humans have been modifying Earth's ecosystems for thousands of years. Archaeological and palaeontological evidence suggest that human activities may have played a major role in the extinction of Australia's megafauna as early as fifty thousand years ago (Johnson et al., 2016; Miller et al., 2016; van der Kaars et al., 2017). The subsequent arrival of modern humans in other parts of the world has also been associated with extinctions, of the megafauna in particular (Broughton and Weitzel, 2018; Sandom et al., 2014). However, the global signature of human presence on Earth has never been as prominent as in recent decades. The past two hundred years have been characterised by a sharp increase in the rates of human-driven changes at the planetary scale, a phenomenon that has been termed 'the Great Acceleration' (Steffen et al., 2015).

<sup>10</sup> To emphasize the recent impacts of human activities on the Earth's systems, Crutzen and Stoermer (2000) proposed that we have entered a new geological epoch, which they called 'the Anthropocene'. Although the formal acceptance of this epoch and the timing of its start are still debated within the stratigraphic community (Lewis and Maslin, 2015; Monastersky, 2015), the coined term reflects the profound effects of humans on planetary processes and on the biosphere, such that its use has largely surpassed the geological field (Malhi, 2017).

<sup>16</sup> The Anthropocene can be characterised by Earth-system and socio-economic indicators (Biermann et al., 2016; Steffen et al., 2011). Two of the major signatures are the human-driven transformations of the land surface, and changes to atmospheric composition, which have led to the onset of anthropogenic climate change (Lewis and Maslin, 2015). Altogether, the development of human activities at unprecedented scales and magnitude has led to the alteration of many ecosystems. As a result of combined anthropogenic pressures, the world's biodiversity has been changing (Daru et al., 2021; Dirzo et al., 2014; Johnson et al., 2017; McGill et al., 2015). Decreases in a range of biodiversity indicators have been reported for many taxonomic groups (Butchart et al., 2010). Human-mediated invasions and translocations of species, coupled with local declines in native species, have promoted biotic homogenisation (Daru et al., 2021; Finderup Nielsen et al., 2019; Newbold et al., 2018). In addition, species have gone extinct at rates higher than expected from natural

26 background variability, with current extinction rates estimated to exceed those inferred from fossil records by  
27 a hundred to a thousand times (Barnosky et al., 2011; De Vos et al., 2015). Biodiversity loss and ecosystem  
28 change have become such major issues in the 21<sup>st</sup> century that the prevention of biodiversity erosion and  
29 the protection of ecosystems have become priority goals on international agendas (Convention on Biological  
30 Diversity, 2022; Hoban et al., 2020). Indeed, it is now well established that biodiversity is tightly linked  
31 with ecosystem functioning and ecosystem services delivery (Hooper et al., 2005; Millennium Ecosystem  
32 Assessment, 2005; Oliver et al., 2015), and thus ultimately with human well-being (Millennium Ecosystem  
33 Assessment, 2005). However, the difficulty in achieving global conservation goals – such as the failure to  
34 reach the Aichi targets (Buchanan et al., 2020) – highlights the need to strengthen global conservation efforts  
35 if we are to protect biodiversity and related ecosystem services from global threats (Butchart et al., 2016).

## 36 **1.1 Major drivers of global biodiversity change**

37 Currently, land-use change is the primary driver of global biodiversity loss, and is responsible for causing  
38 global declines in species richness and abundance through habitat modification (Chaudhary et al., 2018;  
39 Maxwell et al., 2016; Newbold et al., 2015; Nowakowski et al., 2018; Powers and Jetz, 2019). Although  
40 climate change is not currently the main driver of biodiversity change, the negative effects of climate change  
41 on biodiversity could equate those of land-use change in their magnitude by 2070 (Newbold, 2018). Other  
42 major drivers of biodiversity loss include overexploitation, pollution and the spread of non-native species. In  
43 this thesis, my focus is on land-use and climate change as global drivers of biodiversity change.

### 44 **1.1.1 Land-use change**

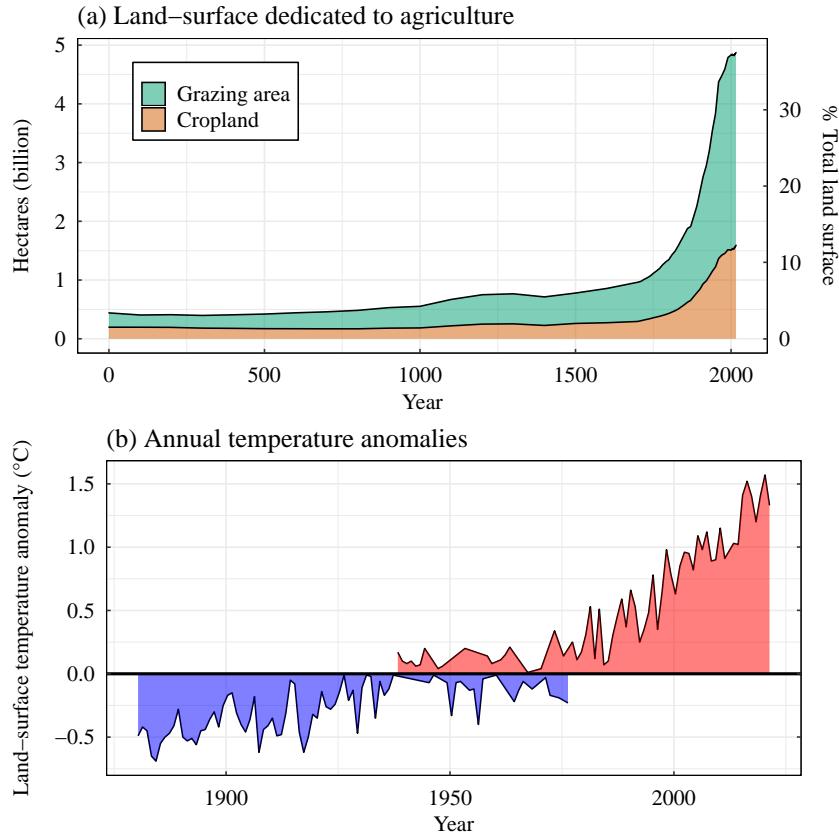
45 Land cover describes the physical aspect and composition of the land surface from dominant biotic and  
46 abiotic features, typically classifying the Earth's surface into determined sets of natural and artificial ensem-  
47 bles (e.g., grasslands, forests, man-made structures, waterbodies, etc; Grekousis et al. (2015)). Land cover  
48 can notably be characterised with satellite imagery (Wulder et al., 2018). Land use, however, describes the  
49 human intent behind a particular land cover (Lambin et al., 2001). Land-use change thus refers the pro-  
50 cess by which humans transform the landscape to achieve socio-economic needs. Land-use change includes  
51 transitions from natural to anthropogenic landscapes, as exemplified by agricultural-driven deforestation in  
52 tropical areas (Jayathilake et al., 2021). It also describes transitions between different forms of human-  
53 dominated land uses, such as the expansion of urban areas over agricultural lands (Ustaoglu and Williams,  
54 2017). Land-use change can also include transitions from anthropogenic land uses to natural habitats, for

example with the restoration of human-degraded landscapes (Banks-Leite et al., 2020). Land-use and land-cover classifications may overlap, and these two terms have often been used interchangeably (Comber et al., 2008). Although humans have been modifying terrestrial ecosystems for millennia – between 75% and 95% of the total land surface could have been altered by human activities at some point in history (Ellis et al., 2021, 2013) – it is only during the past three centuries that the terrestrial surface made the transition from mostly wild to mostly human-dominated (Ellis et al., 2010). The most important driver behind this transition has been agricultural expansion, with major increases in cropland and grazing areas from the mid-18<sup>th</sup> century onward (Figure 1.1a). In recent decades, the expansion of grazing areas and animal feed crops, fuelled by the rising demand for animal products, has been identified as the most important driver of land-use change (Alexander et al., 2015).

The effects of land-use change on biodiversity have been characterised at local, regional and global scales – although global-scale studies represent a small proportion of the published research (Davison et al., 2021). Overall, land-use change has a negative impact on species richness and abundance (Foley et al., 2005; Newbold et al., 2015). For example, urban areas, which have been expanding at faster rates than urban populations themselves (Seto et al., 2010), can have a considerable negative impact on biodiversity and ecosystem services, despite currently representing a small proportion of the terrestrial surface (about 1%; Goldewijk et al. (2017)). In particular, the expansion of impervious surfaces, which characterizes urban development, has been linked to a reduction in species richness (Souza et al., 2019; Yan et al., 2019) and to increases in environmental risks (e.g., due to flooding, Hou et al. (2022); or to heat-island effects). Another important aspect of land-use change for biodiversity outcomes and ecosystem service delivery is the level of intensity at which the land is used to fulfil its purpose. For instance, management practices in agricultural areas are a major determinant of local biodiversity and related ecosystem services such as pollination and pest control (Foley et al., 2005; Kehoe et al., 2015; Millard et al., 2021). In urban areas, introducing and managing green spaces can lead to positive biodiversity outcomes (Aronson et al., 2017; Ives et al., 2016), and can also help mitigate flooding risks and heat islands (Livesley et al., 2016). Yet, land-use intensity has not been explicitly considered by a majority of past studies investigating impacts of land-use change on biodiversity (Davison et al., 2021; Dullinger et al., 2021).

## 1.1.2 Climate change

According to the World Meteorological Organization, climate change is defined as long-term changes (i.e., over at least several decades) to the mean state or to the variability of the climate, attributable to human activity or to natural causes. There is a strong scientific consensus that current climate change (from ap-



**Figure 1.1: Characteristics of the ‘Great Acceleration’.** (a) Land surface (and % land-surface) used for agricultural purposes between year 0 and 2016. Data from the HYDE database (Goldewijk et al., 2017), downloaded from <https://ourworldindata.org/land-use> (24/01/2022). (b) Annual land-surface temperature anomaly between 1880 and 2021. Data retrieved from the National Oceanic and Atmospheric Administration – National Centers for Environmental Information, Climate at a Glance: Global Time Series, published April 2022, retrieved 06/05/2022 from <https://www.ncdc.noaa.gov/cag/>. The anomalies are calculated with reference to the global temperature average for the 20<sup>th</sup> century.

proximately 1850) is the result of human-driven changes to atmospheric composition (Crowley, 2000; Intergovernmental Panel on Climate Change, 2013; Maibach et al., 2014). Current manifestations of climate change include rising average temperatures (Valipour et al. (2021); Figure 1.1b), increases in the frequency of extreme events (Seneviratne et al., 2012), and changes in global rainfall patterns (Dore, 2005; Trenberth, 2011).

There is accumulating empirical evidence that climate change affects biodiversity globally, with documented changes in phenology (Inouye, 2022), in the geographical distributions of species (Chen et al., 2011; Lenoir and Svenning, 2015; Soroye et al., 2020), and in species physiology (Chown et al., 2010; Pörtner and Farrell, 2008). Climate-change impacts on individual species have consequences for whole communities, through disruptions of species interactions, which can in turn exacerbate impacts on individual species (Cahill et al., 2013; Kharouba et al., 2018).

97 **1.1.3 The future of biodiversity in the Anthropocene**

98 Projecting future land-use and climate-change impacts on biodiversity highlights the key role of human-  
99 development scenarios for global biodiversity outcomes (Newbold, 2018; Powell and Lenton, 2013), for the  
100 long-term viability of animal populations (Spooner et al., 2018), and for ecosystem processes and services  
101 (Lawler et al., 2014). As the world's population continues to grow and as the demand for food, energy and  
102 other commodities keeps rising, rates of global land-use and climate change are unlikely to slow without  
103 the implementation of strong international regulations and consumption changes (Intergovernmental Panel  
104 on Climate Change, 2022; Stehfest et al., 2019). Under current development scenarios ('business as usual'),  
105 future projections show that biodiversity will likely be negatively impacted overall, with decreases in species  
106 abundance, increases in extinction rates, and shifts in the distribution of species (Newbold, 2018; Pereira  
107 et al., 2010; Schipper et al., 2020). In this context, evaluating the effects of land-use and climate change  
108 on biodiversity and associated ecosystem services has become vital in order to put into place mitigation  
109 measures. Understanding how species have responded to past and current pressures can help assess how they  
110 are likely to respond to future pressures. In particular, understanding what makes species more sensitive to  
111 land-use and climate change can help conservation efforts and mitigate global human impacts on biodiversity.

112 **1.2 Ecological importance of terrestrial vertebrates and current threats**

113 In this thesis, I focus on terrestrial vertebrates, a group of more than 30,000 species that has been particu-  
114 larly well sampled and studied (Titley et al., 2017), and for which there is available ecological information  
115 for many species (such as geographical distributions, traits, occurrence, etc.), allowing for large-scale bio-  
116 diversity assessments (e.g., Jenkins et al. (2013)). Terrestrial vertebrates play significant roles in ecosystem  
117 functioning and support a wide range of processes, most notably as pollinators (Ratto et al., 2018), seed  
118 dispersers (Tiffney, 2004), regulators of lower trophic levels (Lin et al., 2018; Luck et al., 2012; Mooney  
119 et al., 2010; Salo et al., 2010; Zhang et al., 2018a), nutrient cyclers (Cunningham et al., 2018; Inger et al.,  
120 2016; Wilson and Wolkovich, 2011) and ecosystem engineers (Severtsov, 2012). Vertebrates are also impor-  
121 tant for human societies, both culturally and as sources of proteins (Albert et al., 2018; Alves et al., 2018;  
122 H irons et al., 2016), and feature among the most charismatic species in the public's eye (Albert et al., 2018;  
123 Courchamp et al., 2018).

124 Despite their cultural and ecological importance, terrestrial vertebrates are highly threatened by hu-  
125 man activities. The latest Living Planet Report revealed that vertebrate populations have decreased by  
126 70% on average since 1970 (WWF, 2020). According to the IUCN Red List of Threatened Species,

127 about 41% of assessed amphibian species, 26% of mammals, 21% of reptiles and 13% of birds are clas-  
128 sified as threatened with extinction (IUCN 2022, <https://www.iucnredlist.org/resources/>  
129 summary-statistics). A recent assessment of vertebrates listed in the IUCN Red List of Threatened  
130 Species highlights habitat destruction as the predominant human threat (Cox et al., 2022), but direct exploita-  
131 tion also features among the major factors of decline (Monastersky, 2014). Although climate change is not  
132 the principal driver of current population declines (Caro et al., 2022), the first extinction of a mammal (the  
133 Bramble Cay melomys, *Melomys rubicola*) attributed to anthropogenic climate was reported in 2016 (Wat-  
134 son, 2016). Future projections highlight that between 10% and 30% of vertebrate species could be locally  
135 lost by 2070 depending on climate-change scenarios (Newbold, 2018), and that up to one in six species could  
136 face extinction under current climate change (Urban, 2015). Further, despite having been well sampled and  
137 studied compared to other groups, there still remain important gaps and biases in our ecological knowledge  
138 of terrestrial vertebrates and of their responses to human threats (Hevia et al., 2017; Meiri and Chapple,  
139 2016; Meyer et al., 2015; Oliver et al., 2021).

## 140 1.3 Using trait-based approaches to understand global biodiversity change

### 141 1.3.1 Traits as common currencies across species

142 Despite the global average declines reported for vertebrate populations, not all species respond similarly to  
143 environmental changes (Dornelas et al., 2019; Leung et al., 2020): while some species are impacted nega-  
144 tively, others benefit from global environmental changes (Newbold et al., 2018; Thomas, 2013). One of the  
145 reasons why species differ in their ability to cope with disturbances is that species present different charac-  
146 teristics, or traits. In my thesis, I use the term ‘traits’ to refer to intrinsic characteristics, i.e. measurable  
147 at the level of an individual. Thus, although the formal definition of a trait can vary depending on studies,  
148 I adopt the definition of McGill et al. (2006), considering traits to be characteristics that are measurable at  
149 an organismal level, comparable across different species, and that likely influence organismal fitness and  
150 performance. I further make a distinction between ‘traits’ and ‘ecological characteristics’, notably in Chap-  
151 ter 4, where I refer to ‘ecological characteristics’ as encompassing traits and geographical range area (as  
152 geographical range area does not meet the strict definition of a trait).

153 The idea that species traits mediate species’ responses to environmental change was formalised in the  
154 ‘response-effect’ framework, developed in the field of plant ecology (Lavorel and Garnier, 2002), where  
155 traits that influence species’ responses to environmental change were termed ‘response traits’ (and those that  
156 underpin ecological processes were termed ‘effect traits’). One of the appeals of trait-based approaches is

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157 that individual species are no longer the fundamental unit of biodiversity investigations. Rather, traits become  
158 the focus and act as ‘common currencies’ across species, which is of particular interest for conservation when  
159 long-term population data are lacking. If species’ responses to human threats consistently relate to certain  
160 traits, it may be possible to generalise patterns, and estimate the responses of species for which population  
161 data are not available (Verberk et al., 2013).

### 162 **1.3.2 Using ecological traits to assess which species are at most risk from human-driven 163 changes**

(?) → Mission

164 Vertebrate ecological traits (which I distinguish from physiological traits, and which I define here as traits  
165 relating to the life-history, diet, morphology, and habitat use of species) have been used to explain species’  
166 responses to global changes. Past studies have notably investigated whether species extinction risk is associ-  
167 ated with species traits (Chichorro et al., 2019; Lebreton, 2011; Ripple et al., 2017), which is of high interest  
168 for conservation, but often lacks a consideration of specific threats (González-Suárez et al., 2013).

169 Other studies have focused on the influence of traits on species’ responses to particular human pressures.  
170 For example, a range of correlative trait-based approaches have been used to understand whether traits are as-  
171 sociated with species’ responses to climate change. On the one hand, past work has made use of spatial data  
172 to investigate species’ responses to climate change. For instance, some studies have focused on explaining  
173 interspecific variation in past or projected range shifts with traits (Di Marco et al., 2021; McCain and King,  
174 2014; Pacifici et al., 2017; Schloss et al., 2012). However, studying observed responses to climate change  
175 may be complicated by the fact that this requires disentangling the effects of climate change from effects of  
176 other drivers of change on observed responses (MacLean and Beissinger, 2017). Thus, other studies have  
177 used proxies instead of observed responses, which may provide complementary insights into the relation-  
178 ships between traits and species’ ability to track climate change. For instance, Estrada et al. (2018) used a  
179 ‘range-filling’ approach as a proxy for species’ ability to shift their distributions under climate change. The  
180 ‘range-filling’ approach consists of investigating interspecific differences between the realised and poten-  
181 tially suitable climatic niche of species, differences which are interpreted as being driven by intrinsic (i.e.,  
182 traits) and/or extrinsic factors (e.g., non-climatic environmental factors, biotic interactions, etc.) limiting the  
183 realised distribution of the species (Estrada et al., 2018; Svenning and Skov, 2004). Intrinsic factors found  
184 to constrain species’ realised distribution could also limit species’ ability to track climate change, and as  
185 such could confer higher climate-change sensitivity. On the other hand, demographic approaches relying on  
186 long-term population data have also been employed to explain population- and species’ responses to recent  
187 climate change (Spooner et al., 2018). These approaches may suffer from similar complications regarding

188 the disentangling of climatic and non-climatic effects on observed responses (Williams et al., 2022). Finally,  
189 ecological traits have been used in a predictive fashion, notably with frameworks aiming to assess species'  
190 vulnerability to climate change (Foden et al., 2013; Pacifici et al., 2015), assuming that given traits confer  
191 higher sensitivity to climate change.

192 Past studies have also investigated whether traits are associated with species' responses to habitat dis-  
193 turbance. Most of these studies have used spatial data, inferring effects of land-use change on biodiversity  
194 from 'space-for-time' substitutions (Davison et al., 2021; De Palma et al., 2018), such as in Newbold et al.  
195 (2013), Quesnelle et al. (2014) or Nowakowski et al. (2017).

196 Further, trait-based approaches have also been employed to understand the signature of human impacts  
197 on the diversity and variability of traits within ecological communities. To this end, a range of functional  
198 diversity indices have been developed (Legras et al., 2018; Schleuter et al., 2010). Functional diversity  
199 indices have been employed to evaluate the effects of land-use disturbance on the trait diversity of vertebrate  
200 assemblages (most often at local and regional scales; Flynn et al. (2009); La Sorte et al. (2018); Tinoco  
201 et al. (2018)), or to assess the projected effects of climate change on the trait diversity of vertebrate species  
202 (Stewart et al., 2022).

203 Although trait-based approaches using ecological traits have been widely employed to understand the  
204 effects of human-driven changes on vertebrate species, past studies have mostly been conducted at local to  
205 regional scales (Davison et al., 2021), and have tended to focus on given taxa among the vertebrate classes  
206 (Hevia et al., 2017). Thus, global comparative assessments of the relationships between ecological traits  
207 and species' responses to human pressures across terrestrial vertebrates are lacking. Because of the diver-  
208 sity of approaches used to investigate associations between species traits and human pressures in past work,  
209 and because of the different spatial scales and taxonomic focus of past studies, identifying a set of traits  
210 that emerge as important determinants of sensitivity to both land-use and climate change across terrestrial  
211 vertebrates remains challenging. For instance, Quesnelle et al. (2014) found that reproductive rates, as es-  
212 timated from litter or clutch sizes, were significantly associated with sensitivity to habitat loss in wetland  
213 vertebrates; however, Nowakowski et al. (2017) did not find any effect of clutch size on amphibian sensi-  
214 tivity to habitat modification. The meta-analysis by MacLean and Beissinger (2017) highlights the lack of  
215 consensus in published studies on the associations between traits and species' range shifts on under recent  
216 climate change. Thus, there remains a need to assess whether and which traits are associated with species'  
217 responses to human pressures in terrestrial vertebrates.

218 **1.3.3 Using physiological traits to understand land-use impacts on biodiversity and ecosys-  
219 tem functioning**

220 Physiological traits are typically measured to capture aspects of species' metabolism, performance or bio-  
221 chemistry. Recent decades have seen advances in large-scale studies linking physiological traits to macroe-  
222 cological patterns of species existence across levels of organisation (Burger et al., 2021; Chown et al., 2004),  
223 as exemplified by the development of the 'metabolic theory of ecology' (Brown et al., 2004; Gillooly et  
224 al., 2001). In particular, metabolic rates reflect the amount of energy used at the organismal level (I define  
225 metabolic rates here as the rates at which an organism processes available energy, which is often measured  
226 in the lab by estimating the amount of consumed O<sub>2</sub> by a whole organism over a period of time (Auer et al.,  
227 2017; Sadowska et al., 2015)). As energy is a fundamental currency across all living organisms, metabolic  
228 rates can be employed comparatively across species to investigate interspecific variation in energetic expen-  
229 diture. Thus, past studies have focused on understanding intraspecific variation in metabolic rates (Auer  
230 et al., 2017; Burton et al., 2011) as well as interspecific variation (such as variation in metabolic rates with  
231 temperature; Clarke and Fraser (2004); or variation in metabolic rates with longevity – e.g., testing the 'pace  
232 of life' theory; Stark et al. (2020)).

233 How species allocate their energy impacts almost all aspects of their persistence. Energetic expenditure  
234 relates to food intake, which itself is constrained by the amount of available energy in the environment. Thus,  
235 species' energetic requirements are ultimately constrained and influenced by trade-offs between energetic-  
236 expenditure allocation and resource intake (Auer et al., 2020). As land-use change profoundly modifies the  
237 amount and the types of resources available, it follows that land-use change should impact the total amount  
238 of energy processed by vertebrate assemblages. Further, the amount of energy required by species could  
239 also be an important predictor of species' ability to cope with a disturbed resource landscape. However,  
240 to my knowledge, no study has yet investigated how land-use change affects the energetic requirements of  
241 vertebrate assemblages, or whether species' energetic requirements influence how species respond to land-  
242 use change.

243 **1.3.4 Thesis aims**

244 As discussed above, studies investigating relationships between ecological traits and environmental change  
245 have mostly been conducted at local to regional scale (Davison et al., 2021; Hevia et al., 2017), and have  
246 mostly focused on single vertebrate classes or sub-taxa within particular classes. Thus, although response  
247 traits to land-use and climate change have been identified in various vertebrate taxa, whether the effects of

248 such traits can be generalised geographically and taxonomically remains largely uncertain, emphasising the  
249 need for global comparative assessments of the relationships between traits and species' responses to human  
250 threats.

251 In this thesis, I set out to fill in this gap by asking whether interspecific variation in ecological traits is as-  
252 sociated with species' land-use responses and with estimated climate-change sensitivity, at global scales, and  
253 comparatively across the four terrestrial vertebrate classes. Such an assessment helps to understand which  
254 species are at most risk from global changes, and may be useful for the prioritisation of conservation efforts.  
255 My thesis also aims to highlight some of the consequences of land-use change for ecosystem functioning,  
256 by investigating relationships between species energetic requirements (estimated from metabolic rates) and  
257 land-use differences.

258 Throughout my thesis, assemblage-level and species-level responses to land use and land-use intensity  
259 are assessed using a 'space-for-time' approach (De Palma et al., 2018). To this end, I use one of the most  
260 comprehensive databases recording species occurrence and abundance in different land uses (the PREDICTS  
261 database, Hudson et al. (2014, 2017)). I estimate sensitivity to climate change from properties of species'  
262 climatic niche space, and thus it is important to emphasize that this does not allow a consideration of species'  
263 *responses* to climate change. Indeed, it is difficult to capture the responses of many species to climate change,  
264 given that this requires disentangling the effects of climate change from that of other drivers of change over  
265 the considered time period (which can be complex; MacLean and Beissinger (2017)), and also requires  
266 gathering data on the occurrence or abundance of species over several decades (which may be particularly  
267 challenging when working at large taxonomic scales).

## 268 **1.4 Detailed aims, hypotheses and outline of the following Chapters**

269 The overarching aims of my thesis are to investigate whether species traits are associated with species' land-  
270 use responses and species' estimated climate-change sensitivity in terrestrial vertebrates, and to highlight  
271 some of the consequences of global changes for ecosystem processes sustained by terrestrial vertebrates.  
272 One of the obstacles that has hindered the application of trait-based approaches at large scales in animal  
273 taxa is the lack of a centralised repository for readily available trait data, as emphasized by the recent calls  
274 to compile and release trait data for animals (Junker et al., 2022; Kissling et al., 2018). Thus, collecting  
275 trait data and investigating the current availability of the data for terrestrial vertebrates is an important and  
276 necessary prerequisite to any analysis. In Chapter 2, I present a data collection of ecological traits for  
277 terrestrial vertebrates. Because using similar traits in the different vertebrate classes is necessary to be able

278 to make comparisons among vertebrate classes, I target seven classes of traits that are commonly used across  
279 taxonomic groups: body mass/size, lifespan, litter/clutch size, trophic level, diel activity, habitat breadth,  
280 and habitat specialisation (characterising whether a species is able to use artificial habitats). I am not able  
281 to consider intraspecific variation in the data compilation, since multiple measurements of trait values do  
282 not exist for many vertebrate species. Chapter 2 also assesses the availability of the trait data across the  
283 terrestrial vertebrate classes, and investigates whether the trait data present global taxonomic, phylogenetic  
284 and spatial biases. On the basis of past work (Titley et al., 2017), I predict that amphibians and reptiles are  
285 under-sampled compared to mammals and birds. Further, I hypothesize that trait data are less abundant for  
286 the narrower-ranging species and in species-richer regions.

287 At the assemblage level, the diversity of species traits can be summarised with functional diversity indices  
288 (Legras et al., 2018; Schleuter et al., 2010; Villéger et al., 2008). Past research has shown that land-use  
289 disturbances affect the functional composition of vertebrate assemblages (Flynn et al., 2009; Tinoco et al.,  
290 2018). However, to the best of my knowledge, a global assessment of how the functional diversity of local  
291 terrestrial vertebrate assemblages respond to land use and land-use intensity, within and across taxonomic  
292 classes, has not yet been undertaken. In Chapter 3, I aim to fill in this gap. To this end, I combine the trait  
293 data collected in Chapter 2 with the PREDICTS database, after imputing missing trait values (as described  
294 in Chapter 2). I hypothesize that the functional diversity of vertebrate assemblages in disturbed land uses is  
295 lower than in undisturbed areas. I further predict that decreases in functional diversity in disturbed land uses  
296 are driven by high levels of functional loss and that observed declines in functional diversity exceed those  
297 expected from random species loss.

298 Chapter 3 highlights the effects of land-use change on the functional composition of vertebrate assem-  
299 blages, but does not allow an assessment of the effects of particular traits on species' land-use responses,  
300 as multidimensional interspecific trait variation is summarised into single indices of functional diversity.  
301 Chapter 4 aims at assessing such effects, by investigating whether species traits are associated with species'  
302 land-use responses and species' climate-change sensitivity. In addition to the traits considered in Chapter 3,  
303 Chapter 4 includes dietary traits and species geographical range area. Although geographical range area is  
304 not a trait *per se*, it has been shown to influence species' responses to land-use and climate change (Newbold  
305 et al., 2018; Thuiller et al., 2005), and it is likely an important determinant of climate-change sensitivity.  
306 Thus, in Chapter 4, I define 'ecological characteristics' as encompassing both traits and geographical range  
307 areas. I investigate whether these ecological characteristics are associated with species' land-use responses  
308 on the one hand and with species' estimated climate-change sensitivity on the other hand, comparatively  
309 among the terrestrial vertebrate classes. To the best of my knowledge, Chapter 4 constitutes the first global

310 comparative assessment, across terrestrial vertebrate classes, of associations between species' ecological  
311 characteristics and both land-use responses and estimated climate-change sensitivity.

312 Chapter 5 develops our understanding of the impacts of land-use change on ecosystem functioning by  
313 focusing on species' energetic requirements, which is interesting for at least two reasons: first, because en-  
314 ergetic requirements relate to resource intake, and as such reflect the amount of energy that is processed by  
315 different trophic groups, which can inform about ecosystem functioning; second, because species persistence  
316 is constrained by trade-offs in energy allocation among diverse processes (e.g., maintenance, growth, repro-  
317 duction), such that energetic requirements are likely important determinants of species' ability to cope with  
318 disturbances. Yet, there has been no study so far investigating relationships between energetic requirements  
319 and land-use differences in terrestrial vertebrates. In Chapter 5, I collect resting metabolic rate estimates for  
320 vertebrates, that is, the estimated minimum amount of energy necessary for organismal maintenance (esti-  
321 mated at the species level), and I combine these estimates with the PREDICTS database. I then assess the  
322 effects of land use on the total energetic requirements of vertebrate assemblages (conceptually comparable  
323 to 'community metabolism'; Migné et al. (2015)). Second, I assess whether species' energetic requirements  
324 influence species persistence in disturbed land uses (after controlling energetic requirements for the effects of  
325 body mass and taxonomy, which explain most of the interspecific variation in metabolic rates; White (2011)).  
326 Assuming that there is less energy available in disturbed land uses, I hypothesize that the assemblage-level  
327 energetic requirements of vertebrates are lower in disturbed land uses compared to natural habitats, and that  
328 species with lower mass-independent energetic requirements are favoured over species with higher mass-  
329 independent energetic requirements in disturbed land uses. Chapter 5 highlights the impacts of land-use  
330 change on vertebrate community metabolism and develops our understanding of the factors that shape how  
331 species respond to changes in land use.

332 Finally, in Chapter 6, I summarise the findings of my thesis, I highlight some of the limitations, and I ex-  
333 amine the relevance of my findings for the field. By investigating whether traits are associated with species'  
334 land-use responses and climate-change sensitivity across the terrestrial vertebrates, my thesis furthers our  
335 understanding of what could render species more sensitive to human threats, underlines possible modifica-  
336 tions to ecosystem functioning, and stresses the role and usefulness of vertebrate trait data and ecological  
337 knowledge for understanding species- and community-level responses to human pressures.

<sup>338</sup> **2 | Global gaps and biases in trait data for**  
<sup>339</sup> **terrestrial vertebrates**

<sup>340</sup> **Keywords**

<sup>341</sup> Terrestrial vertebrates; traits; coverage; completeness; taxonomic biases; spatial biases; phylogenetic biases.

<sup>342</sup> **Abstract**

<sup>343</sup> Trait data are increasingly used in studies investigating the impacts of global changes on the structure and  
<sup>344</sup> functioning of ecological communities. Despite a growing number of trait data collations for terrestrial  
<sup>345</sup> vertebrates, there is to date no global assessment of the gaps and biases the data present. Here, I assess  
<sup>346</sup> whether terrestrial vertebrate trait data are taxonomically, spatially and phylogenetically biased. I compile  
<sup>347</sup> seven ecological traits and quantify coverage as the proportion of species for which an estimate is available.  
<sup>348</sup> For a species, I define completeness as the proportion of non-missing values across traits. I assess whether  
<sup>349</sup> coverage and completeness differ across classes and examine phylogenetic biases in trait data. To investi-  
<sup>350</sup> gate spatial biases, I test whether wider-ranging species have more complete trait data than narrow-ranging  
<sup>351</sup> species. Additionally, I test whether species-rich regions, which are of most concern for conservation, are  
<sup>352</sup> less well-sampled than species-poor regions. My results show that mammals and birds are well-sampled  
<sup>353</sup> even in species-rich regions. For reptiles and amphibians (herptiles), only body size presents a high cov-  
<sup>354</sup> erage (>80%), as well as habitat related variables (for amphibians). Herptiles are poorly sampled for other  
<sup>355</sup> traits. The shortfalls are particularly acute in some species-rich regions and for certain clades. Across all  
<sup>356</sup> classes, geographically rarer species have less complete trait information. Hence, trait information is less  
<sup>357</sup> available on average in some of the most diverse areas and in geographically rarer species, both critical for  
<sup>358</sup> biodiversity conservation. Gaps in trait data may impede our ability to conduct large scale analyses, while

359 biases can impact the validity of extrapolations. A short-term solution to the problem is to estimate missing  
360 trait data using imputation techniques, while a longer-term and more robust filling of existing gaps requires  
361 continued data collection efforts.

## 362 **2.1 Introduction**

363 Species traits are fundamental to ecological and evolutionary research. Comparative studies regularly use  
364 trait data across organisms to understand evolutionary processes and species coexistence (Escudero and  
365 Valladares, 2016; Zamudio et al., 2016), to investigate global patterns of life forms and functions (Díaz et  
366 al., 2016), or to assess species' vulnerability to environmental changes (Böhm et al., 2016; Pacifici et al.,  
367 2015; Pearson et al., 2014). Because traits influence species' ability to cope with environmental changes  
368 (Newbold et al., 2013) and underpin species' contributions to ecosystem processes (Lavorel and Garnier,  
369 2002; Violle et al., 2007; Wong et al., 2018), they play an increasingly important role in functional and  
370 conservation ecology.

371 Past and recent efforts to collate and release trait data in the public domain have facilitated the develop-  
372 ment of trait-based research. For instance, a global trait database has been published for plants (Kattge et al.,  
373 2011). As of May 2020, data from this database had been used in 297 publications since its release (Ac-  
374 tivity report, 18/06/2020, <https://www.try-db.org/TryWeb/Home.php>). Such databases hence  
375 constitute invaluable research tools and have the potential to greatly advance the field.

376 Vertebrates are one of the most studied taxa (Titley et al., 2017). There are now diverse sources of eco-  
377 logical traits for vertebrate groups (primates: Galán-Acedo et al., 2019; mammals: 'PanTHERIA', Jones et  
378 al., 2009; amniotes: Myhrvold et al., 2015; amphibians: 'AmphiBIO', Oliveira et al., 2017). These datasets  
379 stem from important efforts to collate published estimates of trait data and make them readily available. Trait  
380 data have also been made available on online platforms (for instance, the Global Assessment of Reptile Dis-  
381 tribution initiative: <http://www.gardinitiative.org/>; the IUCN Red List of Threatened Species:  
382 <https://www.iucnredlist.org/>; BirdLife data zone: <http://datazone.birdlife.org/>  
383 home).

384 Nevertheless, despite the importance of vertebrate species in global research outputs, there is no single  
385 source for vertebrate ecological traits. Consequently, researchers wishing to conduct comparative studies  
386 across vertebrate groups may have to collate trait data from a range of sources (such as in Cooke et al.  
387 (2019a,b) or in González-Suárez et al. (2018)), a time-consuming prerequisite which may be a limiting  
388 step of the research process. Indeed, collating data from heterogeneously-formatted sources presents many

389 challenges (Schneider et al., 2019), particularly when working across a large number of species. For instance,  
390 traits may be measured differently across datasets; units may be inconsistent; and taxonomic resolution and  
391 nomenclature may vary.

392 The lack of a curated, readily available global database for vertebrate ecological traits impedes our ability  
393 to conduct cross-taxon comparative studies at global scales. However, efforts to collate data into a single  
394 database are limited by the availability of underlying data. Because there exist important gaps in biodiversity  
395 knowledge (Hortal et al., 2015), trait datasets are often incomplete, with many species lacking estimates for  
396 many traits. The incompleteness of ecological trait data at the species level has been termed the ‘Raunkiær  
397 shortfall’ by Hortal et al. (2015). Furthermore, incomplete trait data are likely to be biased. Biases in trait data  
398 may be the consequence of uneven taxonomic and spatial collection effort, with a set of charismatic or easily  
399 detectable species being more completely sampled. For instance, González-Suárez et al. (2012) investigated  
400 biases in global trait information in mammals. They notably found that the availability of mammalian trait  
401 data was geographically and phylogenetically biased, with larger and more widely distributed species being  
402 better sampled. In addition, data availability also differed across IUCN Red List extinction risk categories,  
403 with threatened species (Critically Endangered, Endangered or Vulnerable) being less well sampled for traits  
404 than non-threatened species (Least Concern or Near Threatened).

405 A major issue with incomplete, biased data is the introduction of bias in subsequent analyses. Assessing  
406 the amount of missing data as well as the so-called ‘missingness mechanism’ – whether missing data are  
407 missing at random, as opposed to there being systematic biases in the way missing values are distributed, see  
408 Baraldi and Enders (2010) – is an important prerequisite. Indeed, there exist diverse techniques to deal with  
409 data missingness. The simplest one consists of retaining complete cases only by filtering out missing values  
410 (case deletion, see Nakagawa and Freckleton (2008)). Nevertheless, case deletion may lead to biased param-  
411 eter estimates and erroneous conclusions when values are not missing at random (González-Suárez et al.,  
412 2012). Therefore, it is critical to determine the most appropriate way to deal with data incompleteness. For  
413 instance, previous studies using terrestrial vertebrate trait data have employed multiple imputation techniques  
414 to fill in the gaps (Cooke et al., 2019a; González-Suárez et al., 2012). Yet, imputation techniques could be  
415 sensitive to non-randomness in trait data. Phylogenetic biases (where some clades are under-sampled com-  
416 pared to other clades) could notably impact the performance of several imputation approaches. It is thus  
417 vital to characterise the gaps in trait data prior to any analysis. However, there has been no study to date  
418 investigating global patterns in the availability of trait data across terrestrial vertebrates.

419 Here, I aim to assess the global state of trait data in terrestrial vertebrates. I focus on a set of traits that are  
420 available across the four classes and that are commonly used by ecologists: body size; litter or clutch size;

421 longevity; trophic level; activity time; habitat breath; and a measure of habitat specialisation. I quantify and  
422 compare the gaps in trait data across classes by calculating the coverage of each trait across species, and the  
423 completeness of trait estimates for each species (Box 1). I investigate taxonomic, spatial and phylogenetic  
424 biases in trait coverage and completeness.

425 Given that biodiversity research is globally biased towards birds and mammals (Titley et al., 2017),  
426 I hypothesise that herptiles are less well sampled for traits than mammals and birds, having both lower  
427 coverage and completeness.

428 Furthermore, building upon previous studies conducted on mammals (González-Suárez et al., 2012), I  
429 hypothesize that species rarity influences completeness, focusing on species geographical range size as one  
430 aspect of rarity. Widely distributed species could be better sampled than narrowly distributed species because  
431 their ranges overlap with more study sites, regardless of their abundance. As such, I test whether species  
432 geographical range size explains trait completeness.

433 It is well established that global research effort is distributed unequally (United Nations Educational  
434 Scientific and Cultural and Organization, 2015), with patterns underpinned by various geographical and so-  
435 cieconomic factors. For instance, countries with higher gross domestic product tend to host a larger number  
436 of research institutions (Martin et al., 2012). The proximity of research infrastructures and the accessibility  
437 of survey sites play an important part in explaining the global distribution of knowledge (Hortal et al., 2015).  
438 As a result of these factors, biodiversity data gaps tend to be greater in tropical areas (Collen et al., 2008).  
439 Tropical areas have the greatest species richness, and so these data biases are of great concern for biodiversity  
440 conservation. Whether species-rich regions are systematically under-sampled for traits compared to species-  
441 poor regions is thus important to assess, given the significance of species-rich areas for global conservation.  
442 Here, I investigate spatial biases in trait completeness, hypothesizing that species-rich areas are on average  
443 less well sampled than species-poor areas.

444 Finally, I investigate phylogenetic biases in the trait data. I assess whether particular clades have received  
445 more attention than others by looking for patterns in the distribution of trait completeness across the terminal  
446 branches of phylogenetic trees in each class.

### **Box 1. Definitions**

*functional*

*Trait:* Sensu stricto, a characteristic measurable at the level of an individual and that influences organismal fitness or performance (Violle et al., 2007). In this thesis, I broaden this definition to include ‘ecological’ traits (e.g., the number of habitats used by a species), where the relationship of a species to the surrounding environment needs to be considered. Ecological traits may be estimated by aggregating data across multiple individuals.

*Trait completeness:* For a given species, the proportion of traits for which an estimate is available.

*Trait coverage:* For a given trait, the proportion of species for which an estimate is available.

## **447 2.2 Methods**

448 I produced class-specific trait datasets that were made available on figshare ([https://figshare.com/articles/dataset/Global\\_gaps\\_in\\_terrestrial\\_vertebrate\\_trait\\_data/10075421/](https://figshare.com/articles/dataset/Global_gaps_in_terrestrial_vertebrate_trait_data/10075421/))  
449 2). Data compilation and all analyses were conducted with R version 3.5.1 (R Core Team, 2018). Distribution  
450 maps were processed using both R and the ‘ArcPy’ package available in ArcGIS v.10.6 (ESRI, 2011)  
451 (implemented in Python 2.7; van Rossum, G. (1995)).

### **453 2.2.1 Trait data collection**

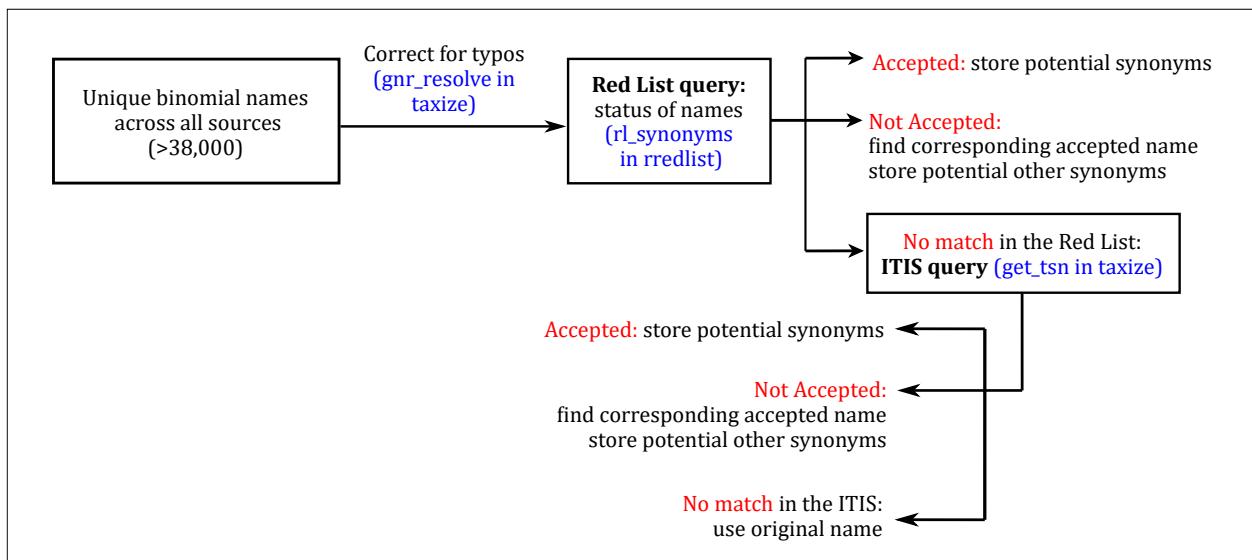
#### **454 Sources and taxonomic matching**

455 I used freely accessible secondary sources in my compilation (Table 2.1), selected for their broad taxonomic  
456 coverage and/or for their frequent use in macroecological studies. Across sources, similar species could  
457 appear under synonymous names. This was a potential problem for matching sources by binomial names.  
458 Indeed, synonymy can artefactually decrease trait coverage, when trait information is not available across  
459 all synonyms. Notably, difficulties arise when species have been divided into several subspecies or when  
460 different subspecies are clumped together. Systematic manual checks could not be applied considering the  
461 scale of the data collection (there were >39,000 unique binomial names across sources). I developed a  
462 procedure aiming at identifying one accepted name for each of the binomial names found across sources.  
463 When I could not find an accepted name, I used the original name. Figure 2.1 summarizes the main steps;  
464 similar solutions have been used in other large-scale studies (Cooke et al., 2019a).

465 Briefly, the procedure consisted of extracting synonyms from the IUCN (IUCN, 2020) or from the In-  
466 tegrated Taxonomic Information System (ITIS; <https://www.itis.gov/>), using the ‘rredlist’ (Cham-  
467 berlain, 2018) and ‘taxize’ (Chamberlain and Szöcs, 2013) R packages. One accepted name was assigned to

468 each synonym. I produced a "Synonym" dataset that I have also made available. I then normalized taxonomy  
469 across sources by replacing binomial names with their identified accepted name where applicable.

470 Given that different taxonomic backbones could be used to correct for taxonomy, I make two versions  
471 of the trait compilations available (corrected and not corrected for taxonomy), meaning that users are free to  
472 apply their own corrections; for example, taxonomy could be aligned to that of class-specific sources, such  
473 as The Reptile Database, the American Museum of Natural History's Amphibian Species of the World, the  
474 Mammal Diversity Database or the International Ornithological Congress World Bird List. Datasets cor-  
475 rected for taxonomy contain 11,634 species of birds, 5,381 mammals, 10,612 reptiles and 6,990 amphibians.  
476 Where no taxonomic correction was applied when matching sources, the compiled datasets contain 13,501  
477 birds, 5,791 mammals, 11,012 reptiles and 8,583 amphibians. For more information, see Appendix 1 (S2.1:  
478 'Taxonomic corrections'; Figure S2.1).



**Figure 2.1: Procedure used to identify the accepted names of species.** I extracted, where possible, the accepted names of species from either the IUCN Red List or the Integrated Taxonomic Information System (ITIS). Figure reproduced from Etard et al. (2020).

#### 479 **Compilation methods**

480 For continuous traits, I took the median value within species when multiple estimates were available from  
481 different sources, after removal of any repeated values, which were assumed to represent estimates duplicated  
482 across secondary compilations and derived from the same underlying primary sources. Although intraspe-  
483 cific variation is increasingly being recognized to have important effects on ecological systems (Bolnick  
484 et al., 2011; Des Roches et al., 2018; González-Suárez and Revilla, 2012; Siefert et al., 2015), it was not

**Table 2.1: Data sources for each trait.** Abbreviations: A = amphibians; B = birds; BL = body length; BM = body mass; DA = diel activity time; GL = generation length; H = habitat data; LCS = litter or clutch size; L/ML = longevity or maximum longevity; M = mammals; MA = age at sexual maturity; R = reptiles; RS = range size; TL = trophic level. Note. Data sources may contain more traits than shown here. Tick marks in parentheses indicate that the trait was present in the data source but that another closely related trait with a better coverage was used instead. The tilde character (~) before a tick mark indicates that I derived trophic levels from species diet. <sup>1</sup> <http://datazone.birdlife.org/home>; <sup>2</sup> <https://www.iucnredlist.org/resources/spatial-data-download>; <sup>3</sup> <http://apiv3.iucnredlist.org/api/v3/docs##general>. Table reproduced from Etard et al. (2020).

Sources	Taxa	Traits									
		BM	BL	L/ML	MA	GL	LCS	TL	DA	RS	H
Oliveira et al. (2017)	Amphibians	(✓)	✓	(✓)	✓		✓	~✓	✓		
Cooper et al. (2008)							✓				
Sodhi et al. (2008)			✓								
Wilman et al. (2014)	Birds	✓						~✓	✓		
BirdLife <sup>1</sup>		✓				✓					✓
Jones et al. (2009)	Mammals	✓	(✓)	(✓)	(✓)		✓		✓		
Kissling et al. (2014)								✓			
Gainsbury et al. (2018)								✓			
Wilman et al. (2014)		✓							✓		
Pacifici et al. (2015)		✓				✓					
Scharf et al. (2015)	Reptiles	✓		✓	(✓)		✓	✓	✓		
Vidan et al. (2017)										✓	
Stark et al. (2018)		✓		✓			✓		✓		
Schwarz and Meiri (2017)								✓			
Novosolov et al. (2017)		✓						✓			
Novosolov et al. (2013)							✓				
Slavenko et al. (2016)		✓									
Feldman et al. (2016)		✓									
Meiri (2018)					✓		✓	✓	✓		
Meiri et al. (2015)								✓	✓		
Roll et al. (2017)										✓	
Myhrvold et al. (2015)	B, M, R	✓	✓	✓	(✓)		✓				
IUCN (2020) <sup>2</sup>	A, B, M										✓
IUCN (2020) <sup>3</sup>	All										✓

485 feasible to obtain measures of intraspecific variability from all sources; therefore, estimates were provided  
 486 as a single measure for each species. For some species and some traits, measures were provided separately  
 487 for females and males. In such cases, I first obtained the mean of these two measures.

488 Across sources, there were multiple traits related to each of body size and lifespan. For instance, body  
 489 mass and/or body length information could be provided. Different proxies were also available for lifespan,

490 such as the age at sexual maturity or generation length. In such cases, I focused on the trait presenting the  
491 highest coverage.

492 • **Body size**

493 Adult body mass estimates were compiled for mammals, birds and reptiles. Body length information  
494 was compiled for amphibians, because the coverage for body length was higher than that for body  
495 mass. Body mass and body length are known to scale allometrically, although the allometric rela-  
496 tionship differs across amphibian clades (Santini et al., 2018). In the amphibian dataset, Pearson's  
497 correlation coefficient between log(Body mass) and log(Body length) was 0.71 (data points shown in  
498 Appendix 1, S2.2:‘Additional information for trait compilation’, Figure S2.2).

499 • **Longevity**

500 I defined longevity as the lifespan of an individual and maximum longevity as the longest lifespan  
501 reported. I used closely related traits when longevity/maximum longevity was not available or when  
502 longevity/maximum longevity had a poorer coverage than a related trait. I selected the age at sexual  
503 maturity for amphibians; Pearson's correlation coefficient between log(Age at sexual maturity) and  
504 log(Maximum longevity) was 0.55 (Appendix 1, Figure S2.2). I compiled the generation length for  
505 mammals and birds. The correlation between log(Generation length) and log(Longevity) was 0.74 for  
506 mammals and 0.70 for birds (data points shown in Appendix 1, S2.2, Figure S2.3). Finally, I used  
507 maximum longevity directly for reptiles.

508 • **Litter or clutch size**

509 The number of offspring (litter size) or eggs (clutch size) was compiled directly from the sources and  
510 treated as equivalent across classes. I reported measures of central tendencies provided by the sources  
511 where applicable; otherwise, I calculated range midpoints (mean of smallest and largest reported lit-  
512 ter/clutch sizes).

513 • **Trophic level**

514 In all classes, species were described as omnivores, carnivores or herbivores. For reptiles and mam-  
515 mals, this information was compiled directly from the sources. For amphibians and birds, trophic  
516 levels were not provided. For these two classes, I inferred trophic levels from dietary information  
517 (Table 2.1). For birds, I used the primary diet (based on food items recorded as composing  $\geq 50\%$   
518 of the diet of a species). Diet for amphibians was described without respect to the percentage use of  
519 food items; simply as a binary record of whether or not food items were used. In both cases, species

520 recorded to only consume plant-based resources (seeds, nectar, fruit or other plant material) were  
521 classified as herbivores. Species consuming only animal resources (invertebrates or vertebrates) were  
522 classified as carnivores. Species consuming a mixture of plant and animal resources were classified as  
523 omnivores.

524 • **Activity time**

525 Species were described as being either nocturnal or non-nocturnal. Despite a higher resolution of ac-  
526 tivity time information in some of the sources (e.g., species being described as cathemeral, crepuscular  
527 or diurnal), I adopted the classification of the source with the lowest resolution (EltonTraits: Wilman  
528 et al. (2014), for birds), in order to have consistent information across classes. As such, all species  
529 defined as diurnal, cathemeral or crepuscular were classified as non-nocturnal, as opposed to species  
530 classified as strictly nocturnal.

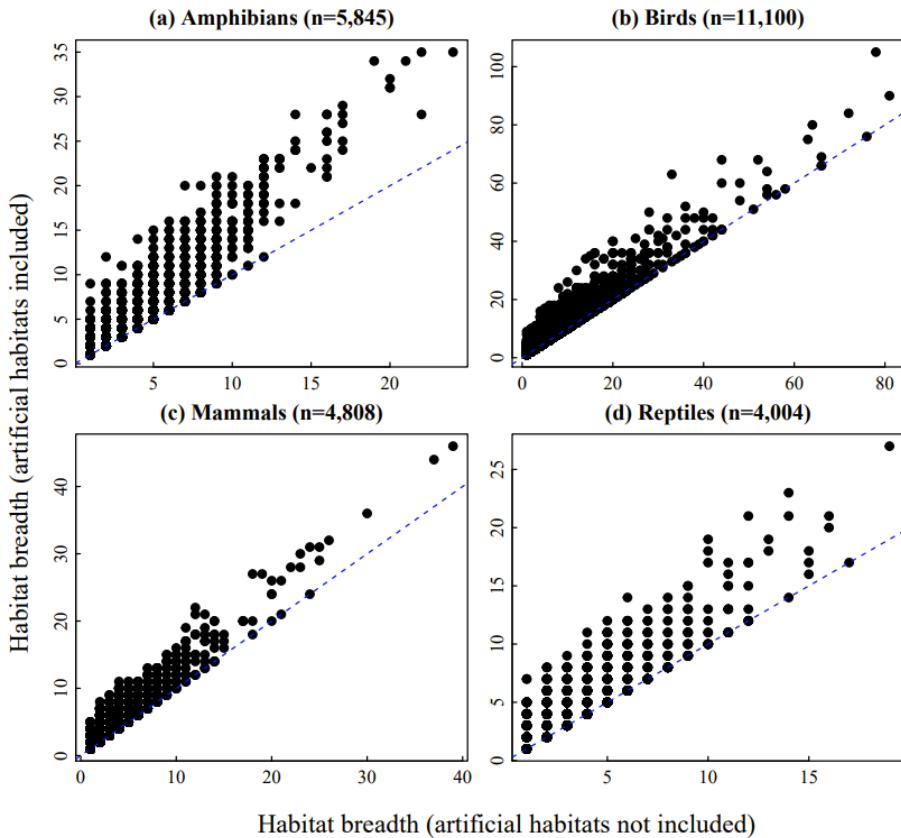
531 • **Habitat breadth**

532 I used IUCN habitat data (IUCN, 2020), which describe species habitat preferences and the suitabil-  
533 ity and importance of each habitat. I defined habitat breadth as the number of habitats a species was  
534 known to use, using level 2 of the IUCN Habitat Classification Scheme for description of habitat  
535 types (divided into: Forest, Savanna, Shrubland, Grassland, Wetland, Rocky areas, Caves and subter-  
536 ranean, Desert, Marine, Marine intertidal or coastal/supratidal, Artificial, Introduced vegetation, and  
537 Other/Unknown.) Note that the total number of habitats, determined by including those that qualify as  
538 artificial, correlates positively with the number of natural habitats used (Figure 2.2).

539 • **Use of artificial habitats**

540 For a species, I recorded whether any artificial habitat was reported to be suitable in the IUCN habitat  
541 data.

542 Finally, the compiled datasets contain an additional column, ‘Note’, where I reported species found to  
543 be extinct or extinct in the wild (EW). I used species Red List status and information from Meiri (2018) to  
544 flag such species. I reported 75 extinct/EW species for mammals, 160 for birds, 34 for amphibians and 53  
545 for reptiles. It is likely that the datasets contain extinct species that I could not flag, because they were not  
546 recorded as extinct in the sources I used.



**Figure 2.2: Number of natural and artificial habitats used by species against number of strictly natural habitats used by species.** Pearson's correlation coefficients show a high positive correlation between these two metrics of habitat breadth in all terrestrial vertebrate classes: 0.92 for amphibians (a), 0.95 for birds (b), 0.94 for mammals (c), and 0.90 for reptiles (d).

## 547 Phylogenies

548 I used class-specific phylogenetic trees downloaded on 13 April 2020. For mammals, I used ‘complete’  
 549 trees from Faurby et al. (2018, 2020), downloaded from <https://zenodo.org/record/3690867#.Xyc5wyhKhPZ>. For amphibians, birds and squamates, I obtained trees from <https://data.vertlife.org/>. The original sources were as follows: Jetz et al. (2012) for birds; Jetz and Pyron (2018) for amphibians; and Tonini et al. (2016) for squamates. For each class, a distribution of 1,000 trees was available.  
 550 For plotting purposes, I obtained consensus trees using the TreeAnnotator program of the BEAST software  
 551 (Bouckaert et al., 2019).

## 555 Species distributions

556 I obtained extent-of-occurrence distribution maps for reptiles from Roll et al. (2017), available at: <https://datadryad.org/stash/dataset/doi:10.5061/dryad.83s7k> (downloaded 13 April 2020).  
 557 For mammals and amphibians, species distribution maps were obtained from the IUCN Red List (IUCN  
 558

559 (2020), downloaded 13 April 2020); for birds, they were obtained from BirdLife International (<http://datazone.birdlife.org/species/requestdis>, downloaded 17 April 2020).

561 For amphibians, mammals and birds, I selected areas of extant or probably extant presence only. Addi-  
562 tionally, I selected areas where species were resident or present during the breeding season, and I excluded  
563 areas occupied during the non-breeding season or where species were considered vagrant.

564 In addition, for all classes, I excluded occupied areas that fell outside the known elevational limits of  
565 species, where such data were available. Lower and upper elevational limits were retrieved from the IUCN  
566 Red List (queried using the ‘rredlist’ package) and were available for approximately half of the species  
567 (Appendix 1, S2.3: ‘Cutting distribution maps by altitudinal limits’, Figure S2.4). Decreases in range sizes  
568 were observed after cutting distribution maps by the known elevational limits (Appendix 1, Figure S2.5).

569 **2.2.2 Investigating gaps and biases in trait data**

570 I used trait coverage and completeness to investigate taxonomic, phylogenetic and spatial biases in the trait  
571 data. Table 2.2 summarizes the sample sizes (number of species) in each of the following analyses. Note  
572 that species for which completeness was 0% were included in all analyses (for more details, see Figure 2.3).  
573 Also note that I did not filter out species identified as extinct or extinct in the wild, because they represented  
574 a small proportion of the datasets (0.48% for amphibians, 1.4% for both birds and mammals, and 0.50% for  
575 reptiles) and also because I could not exclude such species systematically, because it is likely that I did not  
576 flag them all.

**Table 2.2: Number of species for each analysis.** All species represented in the trait datasets were included in (1). All species from the class-specific phylogenetic trees or from the distribution maps that matched with species in the trait datasets were included in (2) and (3). *Table reproduced from Etard et al. (2020).*

	(1) Taxonomic biases	(2) Phylogenetic biases	(3) Spatial biases
Amphibians	6,990	6,170	5,650
Birds	11,634	8,315	10,802
Mammals	5,381	5,171	5,046
Reptiles	10,612	9,404	9,382

577 **Taxonomic biases**

578 I tested whether completeness varied across taxonomic class using pairwise Wilcoxon rank sum tests. I  
579 tested for the extent and performance of the taxonomic corrections by looking at trait coverage when taxo-  
580 nomic corrections are applied and when no correction is applied (Appendix 1, S2.4: ‘Impact of taxonomic  
581 corrections on trait coverage’, Figure S2.6).

582 **Phylogenetic biases**

583 Initially, to assess whether more closely related species were more likely to be similar in trait completeness,  
584 I estimated the phylogenetic signal in completeness with Pagel’s  $\lambda$  (Pagel, 1999) in each class. I used a boot-  
585 strapping approach, calculating  $\lambda$  for each of 50 trees randomly sampled in each class (using the ‘phylosig’  
586 function of the ‘phytools’ R package; Revell, 2012). I then estimated the mean and 95% confidence intervals  
587 (95% CIs) of  $\lambda$ . Sample sizes for computing  $\lambda$  (number of species represented in both the phylogenies and  
588 trait datasets) are shown in Table 2.2.

589 I then plotted within-family median completeness in phylogenetic trees built at the family level, using  
590 the consensus trees. Within-family median completeness was calculated using taxonomic information in the  
591 trait datasets (sample sizes shown in Table 2.2).

592 **Spatial biases**

593 I first investigated whether wider-ranging species were more likely to be better sampled than narrow-ranging  
594 species. I tested for a relationship between species range size and trait completeness. I fitted a generalized  
595 linear model with a Poisson error distribution (directly using the number of sampled traits, ‘N<sub>traits</sub>’, rather  
596 than the proportion (completeness)). Class was added as a predictor interacting with range size; thus the  
597 model was:

$$598 N_{traits} \sim \log(\text{Range size}) * \text{Class.}$$

599 Second, I mapped assemblage-level median completeness. Assemblages were characterized at the pixel level  
600 at 50 km<sup>2</sup> resolution. I determined pixel-level composition and richness by stacking species geographical  
601 distributions. I then calculated median completeness across species in each pixel. I show the resulting maps  
602 for herptiles in the main text, and for mammals and birds in Appendix 1 (Figure S2.7; median completeness  
603 was very high across most pixels for mammals and birds). In addition, I provide maps of assemblage-  
604 level mean completeness and standard deviation for all classes in Appendix 1 (Figures S2.8 and S2.9 show  
605 corresponding maps; Figure S2.10 shows standard deviation against species richness).

I then tested for a spatial correlation between species richness and median completeness. Given that median completeness was very high across most pixels for mammals and birds, I fitted such models for herptiles only. I fitted spatial autoregressive lag models to explain assemblage-level median completeness as a function of species richness (using the function ‘lagsarlm’ of the ‘spatialreg’ package (Bivand et al., 2013a; Bivand and Piras, 2015; Bivand et al., 2013b)). Given that responses could vary geographically, I included the biogeographical realm as an interacting factor (using the World Wide Fund for Nature (WWF) ecoregion shapefile to characterise realms, obtained from <https://www.worldwildlife.org/publications/terrestrial-ecoregions-of-the-world>); the considered realms were Afrotropics, Australasia, Indo-Malayan, Nearctic, Neotropics and Palaearctic. To improve normality, I arc-sin square-root transformed completeness values and log-transformed species richness. The ‘lagsarlm’ function allows for a consideration of spatial autocorrelation in the dependent variable by estimating the autoregressive lag coefficient,  $\rho$ , associated with an n-by-n matrix of spatial weights,  $W$ . The final model was:

$$\text{arcsin}(\sqrt{\text{Completeness}}) \sim \log(\text{Species richness}) * \text{realm} + \rho \cdot W \cdot \text{arcsin}(\sqrt{\text{Completeness}}).$$

The value of  $W$  was estimated using the functions ‘tri2nb’ and ‘nb2listw’ of the ‘spdep’ package (Bivand and Wong, 2018; Bivand et al., 2013b). Fitting the model using all grid cells was computationally intractable; therefore, I randomly sampled cells for this analysis (using 30% of the grid cells in each realm). I selected grid cells where species richness was higher than three to avoid sampling issues. I fitted separate models for amphibians and reptiles, because when adding class as an interacting predictor, the same cells (with the same coordinates) might be sampled for multiple classes, whereas the ‘tri2nb’ function does not tolerate duplicated coordinates.

## 2.3 Results

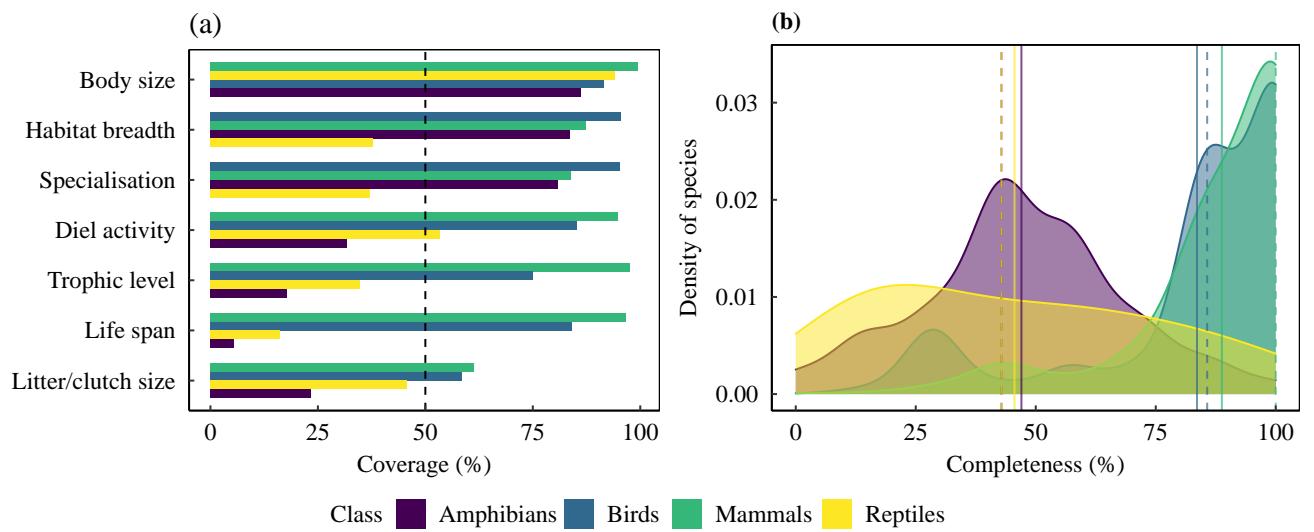
### 2.3.1 Taxonomic biases in trait information

Trait coverage for mammals and birds was overall high (Figure 2.3a; mean and median coverage across traits: 89% and 95% for mammals; 84% and 85% for birds). In both cases, litter/clutch size was the trait with the poorest coverage (61% for mammals and 59% for birds). Coverage exceeded 80% for all other traits (except trophic level for birds, at 75% coverage).

Conversely, trait coverage was more variable for herptiles, and poorer overall (Figure 2.3a; mean and median trait coverage: 47% and 32% for amphibians, 46% and 38% for reptiles). Coverage exceeded 80% only for body size in both reptiles and amphibians and for habitat related traits in amphibians only. In all

other cases coverage was <55%, with very little information available for longevity-related traits.

Trait completeness (proportion of non-missing trait values for a species) reflected similar biases (Figure 2.3b). The distribution of trait completeness varied significantly among classes (pairwise Wilcoxon rank sum test: p-value<0.0001 in all cases). Distributions were highly left skewed in mammals and birds (skewness: -2 and -1.6). 84% of all mammalian species and 80% of avian species fell in the 80–100% completeness range. Moreover, the completeness distribution was moderately right skewed for reptiles (skewness: 0.4), and slightly right skewed for amphibians (skewness: 0.02). 56% of all reptiles and 57% of amphibians fell in the 0-50% completeness range.



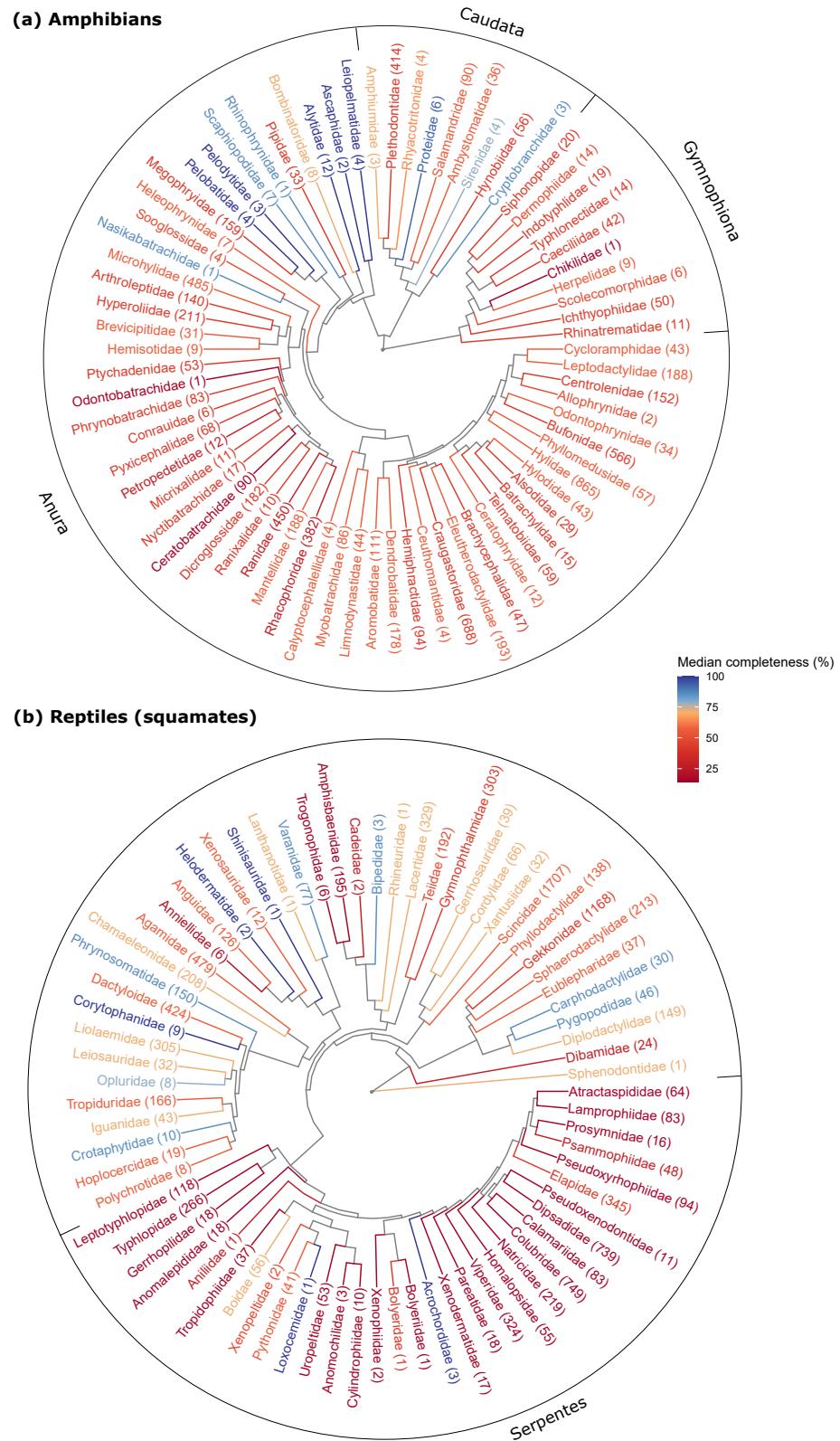
**Figure 2.3: Trait coverage and completeness across species.** (a) I defined coverage as the proportion of species for which an estimate is available for a given trait. The dashed line represents 50% coverage. (b) Trait completeness is the proportion of estimated traits for a species. Here, I show the distribution of completeness. Continuous lines represent the mean trait completeness for each class, whereas dashed lines represent the median trait completeness. Note that there were species with 0% completeness (230 species for amphibians – 3.3% of amphibian species in the trait dataset; 9 for birds – 0.077% of species; 7 for mammals – 0.13% of species; and 161 for reptiles – 1.5% of species). Species with 0% completeness were retained in the datasets when there was information for traits I did not select in the analyses, but no known value for the traits I did select. For instance, the body mass of the amphibian species *Rhinella centralis* was known, but other trait values (including body length) were missing, meaning that *Rhinella centralis* had 0% completeness for the set of traits I considered. *Figure reproduced from Etard et al. (2020)*.

### 2.3.2 Phylogenetic biases in trait completeness

As expected from the distribution of trait completeness in mammals and birds (Figure 2.3), within-family median trait completeness was high across most tips of the phylogenetic trees (Appendix 1, Figures S2.11 and S2.12; I present the avian and mammalian phylogenies in Appendix 1 because there was little variation in completeness across tips). For birds,  $\lambda$  was 0.71 ( $\pm 0.0053$ ). For mammals,  $\lambda$  was 0.78 ( $\pm 0.0035$ ). This indicated that, despite completeness generally being high across tips, the sampling was not evenly distributed across the phylogeny.

650 In herptiles, clusters of families with similar median trait completeness appeared (Figure 2.4). In am-  
651 phibians, groups of families belonging to the order *Anura* (frogs) showed both the best and worst median  
652 completeness (Figure 2.4a). The best-sampled families included the tailed frogs of the family *Ascaphidae*  
653 (two species) and species of the family *Leiopelmatidae* (four species endemic to New Zealand). The family  
654 *Ceratobatrachidae* (containing c. 90 species occurring in Southeast Asia and in some Pacific islands), the  
655 family *Ranidae* (true frogs, 450 species considered here) and the family *Rhacophoridae* (shrub frogs, 382  
656 species considered here) figured among the worst-sampled families. For amphibians,  $\lambda$  was  $0.63 (\pm 0.0039)$ .  
657 In reptiles, most snakes were poorly sampled, whereas families in other suborders appeared to be sampled  
658 better overall (Figure 2.4b). Within snakes, the pythons, boas, the three species of the family *Acrochordidae*  
659 and the python-like species of the family *Loxocemidae* were better sampled than other snake families. In  
660 reptiles,  $\lambda$  was  $0.69 (\pm 0.0032)$ . The sampling in herptiles was thus also uneven with regard to the phylogeny.

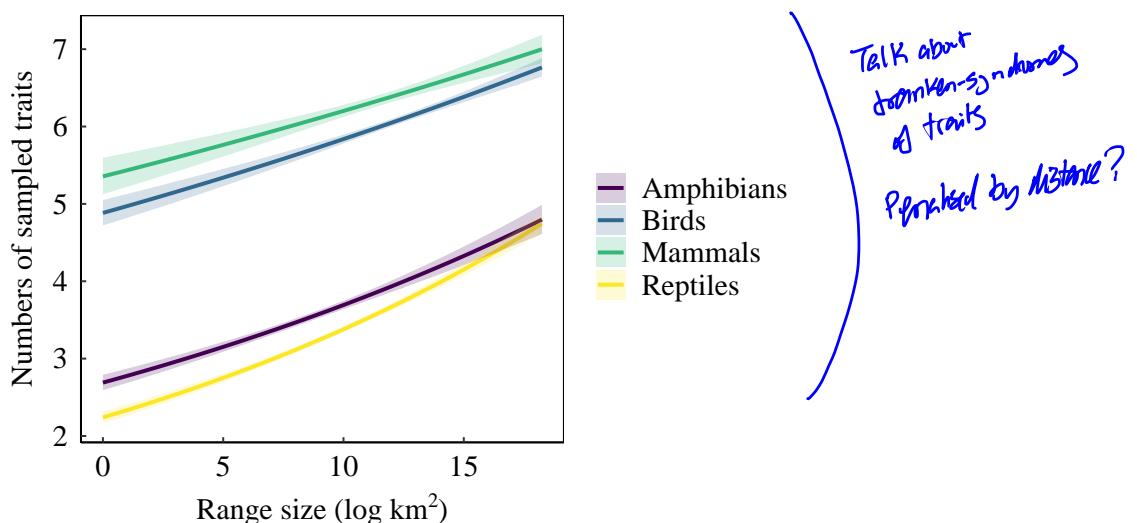
661 It is important to underline that Figure 2.4 shows within-family median completeness, masking the con-  
662 siderable variation in species richness across families, hence masking potential important variation in com-  
663 pleteness across species within families. For example, in the amphibian family *Allophrynididae* (three recog-  
664 nized species), the within-family median completeness was 50%; but the dataset comprised two species of  
665 completeness 14% and 86%, respectively. I present similar plots to those in Figure 2.4 showing the within-  
666 family standard deviation in completeness in Appendix 1 (Figure S2.13). Within-family standard deviation  
667 tended to increase with within-family species richness (Appendix 1, Figure S2.14).



**Figure 2.4: Within-family median trait completeness in herptiles.** The number next to each family name represents the number of species included in the calculation of the median. *Figure reproduced from Etard et al. (2020).*

### 668 2.3.3 Spatial biases in trait completeness

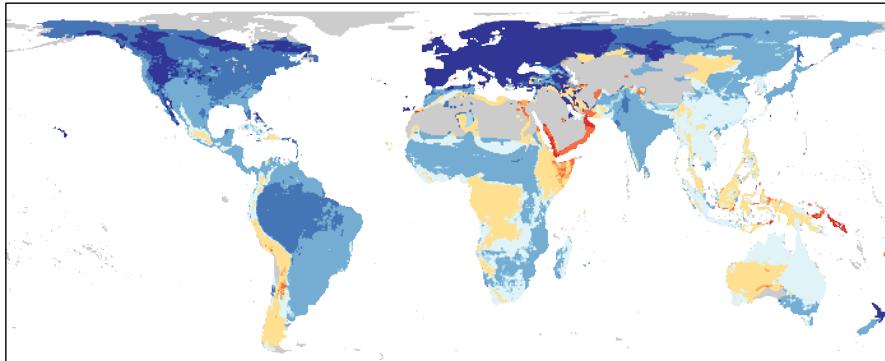
669 Range size was significantly correlated with the number of sampled traits. Larger range sizes were associated  
670 with a higher number of sampled traits (i.e., with higher completeness; Figure 2.5; Appendix 1, Table S2.1).  
671 Similar results were obtained when using distribution maps not cut by elevational limits (Appendix 1, Table  
672 S2.2; Figure S2.15). The rate of increase was steepest for reptiles, then for amphibians, then for birds and  
673 mammals (slope estimates for birds and mammals were not significantly different from each other; Appendix  
674 1, Table S2.1).



**Figure 2.5: Relationship between number of sampled traits and geographical range size.** The model was fitted using a Poisson error distribution. Class was added as a predictor interacting with range size. Rates of increase in number of sampled traits with range size were not significantly different for mammals and birds but differed for reptiles and amphibians, with the steepest rates of increase for reptiles. *Figure reproduced from Etard et al. (2020).*

675 There were marked spatial variations in median trait completeness in herptiles (Figure 2.6). North Amer-  
676 ica and Europe were well sampled for both amphibians and reptiles. However, Southeast Asia and the Congo  
677 basin were on average less well sampled. In other regions, contrasting patterns emerged between amphibians  
678 and reptiles. For instance, median completeness was poorer for amphibians than for reptiles in Australia,  
679 but opposite patterns were observed in South America. As in the phylogenetic analyses, assemblage-level  
680 median completeness could mask potential important variation in completeness within species of a given  
681 assemblage. Assemblage-level mean and standard deviation maps are shown in Appendix 1 (Figures S2.8  
682 and S2.9). There was a trend for increasing standard deviation with increasing species richness, with a larger  
683 spread in standard deviation at lower species richness (Appendix 1, Figure S2.10).

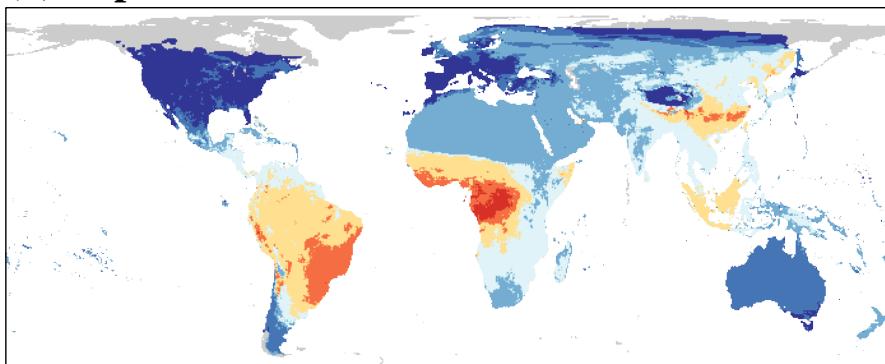
### (a) Amphibians



Median completeness:

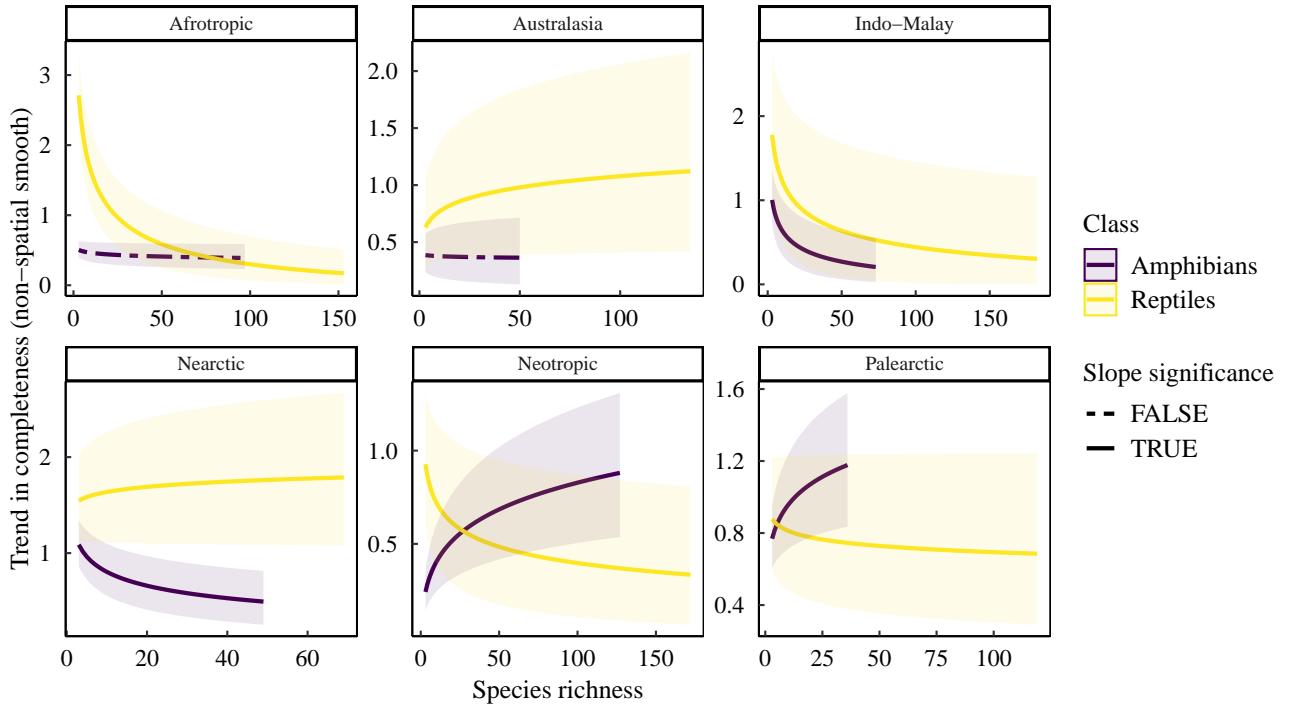
NA
0 – 10%
10 – 20%
20 – 30%
30 – 40%
40 – 50%
50 – 60%
60 – 70%
70 – 80%
80 – 90%
90 – 100%

### (b) Reptiles



**Figure 2.6: Spatial distribution of assemblage-level median trait completeness in herptiles.** Similar maps for birds and mammals are shown in Appendix 1 (Figure S2.7). *Figure reproduced from Etard et al. (2020).*

684 Spatial models showed that species richness explained median trait completeness in herptiles in most  
685 realms (Figure 2.7; Appendix 1, Tables S2.3 and S2.4); including spatial lags improved the models (am-  
686 phibians:  $\rho = 0.92$ , p-value < 0.0001; reptiles:  $\rho = 0.91$ , p-value < 0.0001). For reptiles, completeness was  
687 negatively correlated with species richness in the most species-rich realms (Afrotropics, Indo-Malayan and  
688 Neotropics) and in the Palaearctic; the relationship was steepest in the Afrotropics and shallowest in the  
689 Palaearctic. In the Australasian and Nearctic realms, completeness tended to increase with species richness.  
690 For amphibians, negative relationships were observed in the Indo-Malay and Nearctic realms, whereas pos-  
691 itive trends were observed in the Neotropics and the Palaearctic. The opposite trends between reptiles and  
692 amphibians observed in the Australasian and Neotropical realms reflected patterns observed on the maps.  
693 The Indo-Malayan was the only realm where median completeness tended to decrease with species richness  
694 for both reptiles and amphibians.



**Figure 2.7: Spatial model trends for herptiles.** The lines represent in-sample predictions ( $\pm$  standard error) for the trend components of the spatial models (trends after accounting for spatial autocorrelation). *Figure reproduced from Etard et al. (2020).*

## 695 2.4 Discussion

696 The results of this Chapter illustrate the taxonomic, spatial and phylogenetic dimensions of the knowledge  
 697 gaps in trait data, termed the Raunkiær shortfall by Hortal et al. (2015). To the best of my knowledge,  
 698 this work constitutes the first comparative assessment of global gaps for terrestrial vertebrate trait data,  
 699 despite their use in numerous studies. I showed that the trait data present important taxonomic, spatial and  
 700 phylogenetic biases, with contrasts in the availability of trait information between, on the one hand, herptiles  
 701 and, on the other hand, birds and mammals.

702 Birds and mammals are globally well sampled for the set of traits I considered, even in the most species-  
 703 rich assemblages. However, the availability of trait information for herptiles is lower overall and phyloge-  
 704 netically and geographically biased. Several factors could interplay to shape these patterns. For instance,  
 705 species that are more easily detectable (for example, wider ranging) and more charismatic are likely to be  
 706 better sampled. Diverse socio-economic predictors could also contribute to geographical biases in trait data  
 707 sampling; global biases in primary data collection are likely to be one of the most important contributors to  
 708 the patterns I highlighted. Nevertheless, biases in the data could have been introduced at later stages, notably  
 709 with the selection of sources and traits. The global compilation I obtained in this Chapter reflects, in part, the

710 interest and focus of the secondary data sources I used. It is possible that the addition of new sources from  
711 regional journals or other authorities could diminish spatial biases in the data by increasing coverage for  
712 certain areas. Nevertheless, I argue that by focusing on widely used traits, these results are likely to reflect  
713 the “true” availability of the data in primary sources and that the shortfalls for other, less used traits would  
714 be more pronounced.

715 I believe that the results presented here are robust to taxonomic uncertainty, although taxonomic match-  
716 ing might potentially be improved further using class-specific sources, such as the Reptile Database or Am-  
717 phibiaWeb, for identification of synonyms (but see Appendix 1, Figure S2.16). I have made two versions of  
718 the data compilations available, one in which my own corrections were applied and one using the original  
719 binomial names of the sources, meaning that users are free to use their own taxonomic backbones and iden-  
720 tify synonyms within the compilations. I believe that taxonomic matching is a recurring issue when working  
721 across thousands of species. Taxonomic synonymy artefactually inflates the numbers of identified species,  
722 potentially lowering trait coverage (whereas clumping subspecies together can have the opposite effect).  
723 Tackling this problem is difficult (Isaac et al., 2004; Jones et al., 2012), notably because there is no global  
724 curated database recording the status of species names, and also because of the nature of taxonomy and the  
725 debates around the species concept (May, 2011). Nevertheless, taxonomic uncertainty can have important  
726 consequences. For instance, Cardoso et al. (2017) showed that inaccuracies and errors in species checklists  
727 contributed to the overestimation of plant diversity in the Amazon (but see Freeman and Pennell (2021): the  
728 relative underdescription of species in tropical areas compared to temperate areas –‘taxonomic debt’, also  
729 referred to as ‘latitudinal taxonomic gradient’ by the authors– may lead to the underestimation of species  
730 richness at low latitudes).

731 Biases in trait data have important implications for conservation planning. Past studies have shown that  
732 narrow-ranging species, for which fewer trait data are available on average, have higher extinction risks  
733 (Collen et al., 2016; Purvis et al., 2000; Ripple et al., 2017) and are more negatively impacted by anthro-  
734 pogenic pressures than wider-ranging species (Newbold et al., 2018). Trait information is also less available  
735 for herptiles in tropical regions such as the Congo basin, Southeast Asia and South America, which are some  
736 of the most diverse areas of crucial importance for worldwide conservation (Barlow et al., 2018). Conse-  
737 quently, trait information is on average less available where potentially more crucial to conservation plan-  
738 ning. Indeed, trait information can be incorporated into vulnerability assessments and, as such, can help to  
739 prioritize conservation efforts. Species traits have been found to mediate species responses to environmental  
740 changes across diverse taxonomic groups, and thus can inform on the sensitivity of species to anthropogenic  
741 pressures (Flynn et al., 2009; Newbold et al., 2013; Nowakowski et al., 2017). Traits are now commonly

742 used to estimate species vulnerability or extinction risks (Pacifici et al., 2015; Ramírez-Bautista et al., 2020).  
743 As opposed to trend-based approaches, which rely on historical population trends (changes in abundance  
744 or shifts in distributions) to predict species' vulnerability and extinction risks, trait-based approaches rely  
745 on species' intrinsic sensitivity to particular threats. The appeal of trait-based approaches to extinction risk  
746 estimation is that, by providing mechanistic insights, they diminish the amount of population information  
747 needed. If the responses of species to a threat consistently relate to certain traits, it is possible to generalize  
748 patterns across species for which population data are less available (Verberk et al., 2013). Integrating traits  
749 into vulnerability assessments is hence of particular interest when field monitoring of species population  
750 sizes or distributions is difficult to achieve, but biases in the data could mean that such information is lacking  
751 for some of the most vulnerable species.

752 Traits that influence species responses to environmental changes have been termed 'response traits' (or  
753 'response-mediating traits'; Luck et al. (2012)), as opposed to 'effect traits' that underpin ecosystem func-  
754 tioning (Lavorel and Garnier, 2002). For instance, relative brain size and longevity have been characterized  
755 as response traits in birds (Newbold et al., 2013; Sayol et al., 2020), whereas dietary characteristics (e.g.,  
756 trophic levels or guilds) are both response and effect traits. Hortal et al. (2015) highlighted that, for plants,  
757 both response and effect traits have been investigated, whereas for vertebrates the research has been more  
758 focused on understanding species responses. This could be because the way vertebrate traits interact to shape  
759 some ecosystem processes has not yet been characterized well.

760 Ecosystem processes sustained by animals might be harder to quantify and might be influenced by a com-  
761 bination of traits. The traits compiled in this work are likely to have a role in diverse processes. Nevertheless,  
762 there was one important omission, in that I did not compile species diet in this Chapter, potentially the most  
763 straightforward trait to link with diverse processes, such as grazing, pollination, scavenging and seed dis-  
764 persal. From a practical perspective, I chose traits that had been estimated at least for some of the species  
765 in each class, and that were readily available. Diet was excluded because although estimates were available  
766 for amphibians, birds and mammals, there was no readily available database for reptilian diet. Movement or  
767 dispersal abilities were also excluded because information was not readily available for any class. Although  
768 I expect that species diet and dispersal abilities would present similar sampling biases to the ones presented  
769 in this work, the addition of such traits to the compilation would represent a valuable contribution and would  
770 notably facilitate studies looking at the functional roles of reptiles.

771 For practical reasons, I did not consider intraspecific trait variation. Intraspecific variation has been  
772 shown to have important effects on ecological systems, and a growing body of literature encourages trait-  
773 based research to include intraspecific variability (Guralnick et al., 2016). There have been several calls to

774 produce open-access, global trait datasets (Weiss and Ray, 2019), including a representation of intraspecific  
775 trait variation (Kissling et al., 2018). Notably, Schneider et al. (2019) designed a framework to store and  
776 share inter- and intraspecific trait data, accompanied by an R package to standardize the data in a proposed  
777 format. Such a proposition could constitute an important step towards the unification of individual datasets  
778 into a single, comprehensive database for ecological trait data.

779 The current spatial and taxonomic gaps in trait data might limit our ability to scale studies up, whereas  
780 biases in the data can affect the validity of extrapolations to groups or areas that are undersampled. More gen-  
781 erally, biases and gaps in biodiversity data can have important implications for ecological studies. Data gaps  
782 can hinder our ability to draw conclusions on observed macroecological patterns. For example, Chaudhary  
783 et al. (2016) proposed that marine species richness follows a bimodal distribution, peaking at mid-latitudinal  
784 locations, and argued that these patterns were not underpinned by knowledge gaps in species distributions.  
785 However, Menegotto and Rangel (2018) attributed the tropical dip in marine species richness to a lack of  
786 species distribution data, explained by lower sampling efforts in tropical areas ('Wallacean' shortfall; Hor-  
787 tal et al. (2015)). Biases and gaps in trait data could also affect studies in closely related fields, such as  
788 functional ecology – for instance, past studies have shown that functional diversity indices are sensitive to  
789 missing data (Májeková et al., 2016; Pakeman, 2014) – or community assembly (Perronne et al., 2017).

790 Ecologists should, therefore, take particular care when designing trait-based studies, because both data  
791 quality and data gaps are likely to influence the results and the generality of the conclusions. There exist  
792 diverse methods to deal with missing trait values, should data missingness be problematic. Complete removal  
793 of missing values ('case deletion') is commonly used but presents several issues, because it reduces sample  
794 size and statistical power and introduces potential bias in data subsamples (Nakagawa and Freckleton, 2008).  
795 For example, retaining complete cases only from the trait datasets would generate trait data disproportionately  
796 representative of mammals and birds, which would be problematic for conducting cross-taxon analyses in  
797 terrestrial vertebrates. As such, it is recommended that case deletion be applied only when data are missing  
798 completely at random, which is rarely the case (Peugh and Enders, 2004).

799 Alternatives to case deletion consist of filling in the gaps. In recent years, the development of imputation  
800 techniques has provided robust methods to handle missing data. Such imputation techniques have been used  
801 to complete trait datasets in recent studies (Cooke et al., 2019a). Penone et al. (2014) used a simulation ap-  
802 proach to evaluate the performance of four of these techniques, namely PhyloPars (Bruggeman et al., 2009),  
803 random forest algorithms as implemented in R with missForest (Stekhoven, 2016; Stekhoven and Bühlmann,  
804 2012), multivariate imputation by chained equations (MICE; van Buuren and Groothuis-Oudshoorn (2007))  
805 and k-nearest neighbour (kNN; Troyanskaya et al. (2001)). Penone et al. (2014) introduced missing values

806 (10%–80%) in a complete trait dataset of carnivorans and measured imputation performance in different  
807 scenarios. Given that phylogenetic non-randomness in missing trait values can impact imputation accuracy,  
808 Penone et al. (2014) removed values in three different ways (completely at random; with a phylogenetic  
809 bias; and with a body mass bias). Out of the four techniques, missForest and PhyloPars performed best when  
810 species phylogenetic position was included as a predictor of missing trait values. Such imputations appeared  
811 to be robust even when trait coverage was as low as 40%, which might be relevant for many reptilian and  
812 amphibian traits. The performance was not significantly affected by phylogenetic non-randomness of the  
813 data. Hence, missForest and PhyloPars appear to be well suited when traits are phylogenetically conserved,  
814 because they allow species phylogenetic position to be included as a predictor of missing trait values. The  
815 study by Penone et al. (2014) highlights that there are robust imputation techniques allowing to deal with  
816 incomplete trait data where biases might otherwise be problematic. Nevertheless, it is important to highlight  
817 that some imputation techniques, such as single or mean imputation, can be problematic because they do  
818 not allow an estimation of uncertainty and suffer from a lack of accuracy (Nakagawa and Freckleton, 2008);  
819 indeed, imputation techniques sometimes perform no better than case deletion. More work should be con-  
820 ducted to assess imputation performance in various contexts (e.g., Johnson et al. (2021)), and the datasets  
821 compiled in this Chapter might provide an opportunity for such studies.

822 Although robust imputation techniques can be useful for filling gaps in trait datasets, they are no substi-  
823 tute for continued data collection efforts. The results of this Chapter show that data are particularly lacking  
824 in herptiles, notably in the Afrotropics, the Neotropics and the Indo-Malayan realms. For these areas, incor-  
825 porating regional databases into existing datasets could contribute to the reduction of global gaps. I believe  
826 that both primary research and subsequent efforts to integrate new data and existing databases are required  
827 if we are to collectively strive towards the unification of trait databases.

828 To conclude, this work constitutes, to my knowledge, the first assessment of the global gaps and biases  
829 in terrestrial vertebrate trait information. I show that herptiles are undersampled compared with mammals  
830 and birds, with important spatial and phylogenetic variability in the availability of trait information. Impu-  
831 tation techniques are one possible solution to these problems. Nevertheless, I believe that primary research,  
832 combined with efforts to complete existing datasets, is the only way to fill the current data gaps genuinely  
833 and robustly. I hope that the compiled trait dataset and these findings can prove useful for guiding further  
834 data collection efforts and for conducting macroecological analyses.

835 **3 | Intensive human land uses negatively af-**

836 **fect vertebrate functional diversity**

837 **Keywords**

838 Land use; land-use intensity; terrestrial vertebrates; functional diversity; traits.

839 **Abstract**

840 Land-use change is the leading driver of global biodiversity loss, thus characterising its impacts on the func-  
841 tional structure of ecological communities is an urgent challenge. Using a database describing vertebrate  
842 assemblages in different land uses, I assess how the type and intensity of land use affect the functional di-  
843 versity of vertebrates globally. I find that human land uses alter local functional structure by driving declines  
844 in functional diversity, with the strongest effects in the most disturbed land uses (intensely used urban sites,  
845 cropland and pastures), and among amphibians and birds. Both tropical and temperate areas experience im-  
846 portant functional losses, which are only partially offset by functional gains. Tropical assemblages are more  
847 likely to show decreases in functional diversity that exceed those expected from species loss alone. These re-  
848 sults indicate that land-use change non-randomly reshapes the functional structure of vertebrate assemblages,  
849 raising concerns about the continuation of ecological processes sustained by vertebrates.

850 **3.1 Introduction**

851 Anthropogenic activities are profoundly transforming global biodiversity. Although multiple pressures act  
852 in combination, land-use change currently poses the greatest threat to biodiversity (Maxwell et al., 2016;  
853 Newbold et al., 2015). However, not all species respond similarly to land-use change. Traits have been found  
854 to explain species' sensitivity to land-use change in diverse groups (Newbold et al., 2013; Nowakowski et

al., 2017; Quesnelle et al., 2014; Todd et al., 2017). Previous work has also shown that land-use change leads to non-random modification of assemblage trait composition (or functional diversity) (Chapman et al., 2018; Colin et al., 2018; Flynn et al., 2009; La Sorte et al., 2018; Newbold et al., 2013; Tinoco et al., 2018). Since it is widely acknowledged that biodiversity, and in particular trait diversity, may promote ecosystem functioning and stability, modification to the trait composition of assemblages could have far-reaching and adverse impacts on ecological processes (Hooper et al., 2012; Magioli et al., 2021; Oliver et al., 2015; Tilman and Downing, 1994).

Terrestrial vertebrates support many processes, ranging from pollination (Ratto et al., 2018), to seed dispersal to the regulation of lower trophic levels (Letnic et al., 2012; Mooney et al., 2010; Salo et al., 2010; Zhang et al., 2018a). However, we lack a global understanding of how the functional diversity of entire vertebrate assemblages responds to changes in land use. Most previous studies have been conducted at regional or local scales (Davison et al., 2021), but these may not be representative of global patterns. Indeed, recent global syntheses have highlighted how biodiversity responses can differ substantially between regions and across latitudes, with higher sensitivity reported for the tropics (Matuoka et al., 2020; Millard et al., 2021; Newbold et al., 2020b). Another key issue is the taxonomic coverage of past work. Few studies investigating effects of land use on functional diversity have considered several vertebrate classes together, and comparative studies remain rare. Thus, how land-use change affects the functional diversity of local vertebrate assemblages at global scales, and the potential geographical and taxonomic variation in the effects, still largely remains to be explored.

Here, I aim to assess how human land use and land-use intensity affect the functional diversity of vertebrate assemblages, across and within taxonomic classes. Building on recent work (Matuoka et al., 2020; Millard et al., 2021; Newbold et al., 2020b), I investigate differences in response between tropical and temperate regions. I use multiple response metrics to quantify functional diversity. First, functional richness measures the breadth and variety of trait combinations represented in an assemblage (Legras et al., 2018). Second, functional dispersion quantifies how similar species in a given assemblage are in terms of their traits (Laliberté and Legendre, 2010). These metrics can mask important alterations of assemblage composition if functional losses are compensated for by functional gains. To address this, I consider pairwise measures between assemblages, to explore levels of functional loss and functional gain across land uses (Figure 3.1).

To this end, I combine (1) the trait data across terrestrial vertebrates collected in Chapter 2 with (2) global records of species occurrence in eight land-use types of differing intensity of use (the PREDICTS database: Hudson et al. (2014, 2017); Figure 3.1; Appendix 2, Table S3.1). The PREDICTS database is currently the most comprehensive database of sampled species occurrence, and for most records also

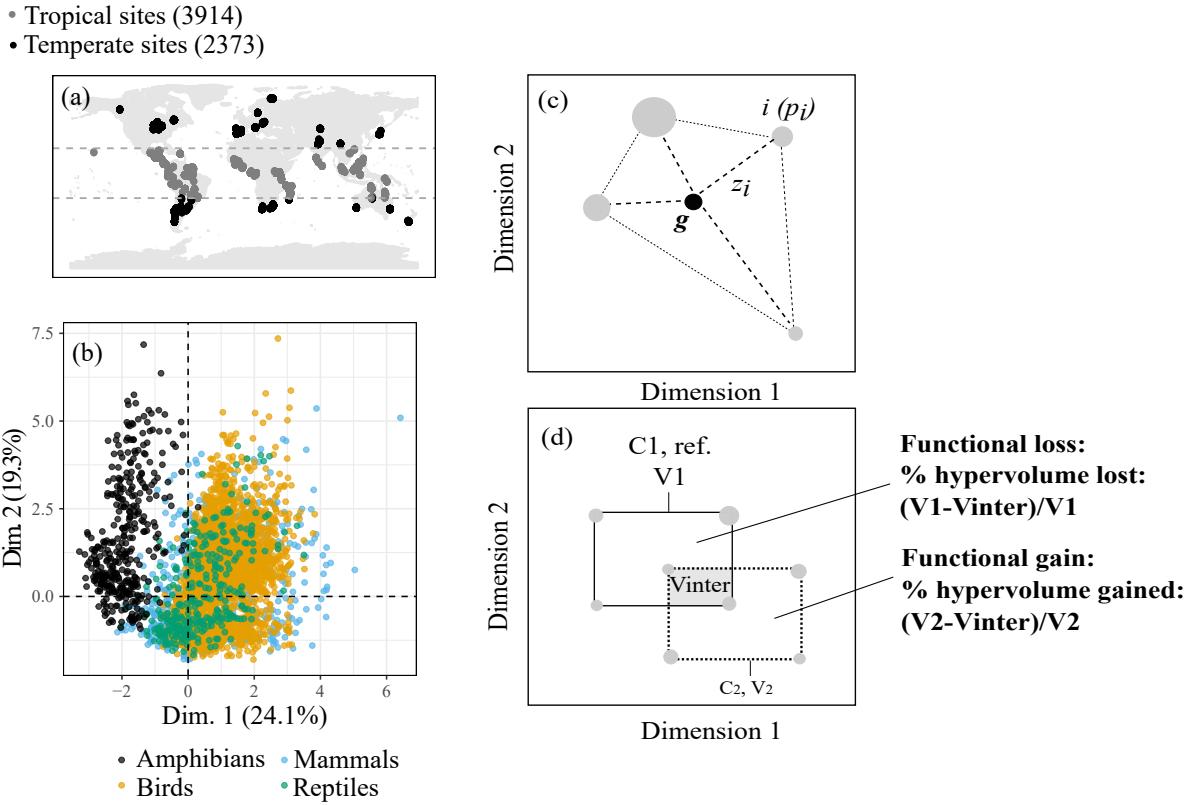
887 abundance, across multiple land uses of different land-use intensity. Using the PREDICTS database allows  
888 me to contrast biodiversity metrics among intact land uses (primary-vegetation sites, considered to be the  
889 undisturbed reference condition), and all other human land-use types. Specifically, I test the following  
890 hypotheses, both across and within taxonomic classes:

- 891 1. I expect decreases in functional diversity in human land uses compared to primary vegetation, caused  
892 by contractions of occupied trait space. I expect such effects to be more pronounced where land is  
893 used more intensively by humans. This hypothesis builds upon evidence that species with certain  
894 traits are more sensitive to land-use disturbance (Newbold et al., 2013), meaning that disturbed land  
895 uses will retain only disturbance-tolerant species, more functionally similar to one another. Given the  
896 reported higher sensitivity of tropical assemblages to land-use disturbance, I predict that such effects  
897 are stronger in the tropics.
- 898 2. I hypothesise that decreases in functional diversity in disturbed land uses exceed decreases expected  
899 by chance, given local species loss. Thus, I expect disturbed land uses to promote functional under-  
900 dispersion. Functional under-dispersion occurs when species within an assemblage are more similar,  
901 in term of their traits, than expected by chance (Cadotte and Tucker, 2017; Wong et al., 2018) – or,  
902 in other words, when functional dispersion is lower than expected given local species richness. I  
903 predict that under-dispersion is more likely to occur in the highly disturbed sites, in both temperate  
904 and tropical areas. This hypothesis is based on the idea that species are being removed non-randomly  
905 from sensitive areas of the trait space, and increasingly so with higher disturbance level.
- 906 3. Finally, I expect decreases in functional diversity in human land uses to be driven by high functional  
907 loss, whereby species are being removed from previously occupied areas of the trait space; I expect  
908 no functional gain. This hypothesis is based on the idea that the functional trait space in undisturbed  
909 land uses represents all of the possible regional trait combinations and that species with functional  
910 attributes rendering them unable to persist in altered conditions will be filtered out (Cornwell et al.,  
911 2006).

## 912 3.2 Methods

### 913 3.2.1 Vertebrate assemblages

914 I used vertebrate occurrence data from the PREDICTS database (Hudson et al., 2014, 2017), a collection of  
915 studies that recorded species occurrence across multiple land uses and land-use intensities. In PREDICTS,



**Figure 3.1: Overview of the study design and functional diversity metrics.** I used occurrence data for vertebrate species from the PREDICTS database ((Hudson et al., 2014, 2017); 180 studies; 431,170 records; 4,339 species; 6,758 sampled sites). (a) shows the spatial distribution of sites I consider. I combine occurrence data with trait data compiled in Chapter 2 to calculate functional diversity metrics. (b) is a representation of the trait data in two dimensions, plotted across PREDICTS vertebrates. Traits that contributed most to dimension 1 were lifespan (29%) and litter/clutch size (22%), while traits that contributed most to dimension 2 were habitat breadth (47%) and use of artificial habitats (35%). (c) and (d) present the conceptual framework for the calculation of the functional diversity metrics: local measures (c) and pairwise metrics (d). (c) Given a trait space, functional richness is calculated as the hypervolume occupied by the minimum convex hull encompassing all species (Villéger et al., 2008). Functional dispersion is calculated as the mean distance of the species to the centroid,  $g$  (Laliberté and Legendre, 2010). (d) I compute functional loss as the proportion of hypervolume lost from the reference assemblage, and I define functional gain as the proportion of hypervolume of the disturbed assemblage that was gained (proportion of novel trait space in the disturbed assemblage). *Figure reproduced from Etard et al. (2022).*

each study contains several sites, which may be clustered into spatial blocks. Assemblage and land-use data are available at the site level: one site is characterised by a unique land use of given land-use intensity and provides occurrence data for a set of sampled taxa (and the same set of taxa is sought at all other sites within a study). Sites located between  $23.5^{\circ}\text{N}$  and  $23.5^{\circ}\text{S}$  of latitude were considered tropical, and otherwise temperate (Figure 3.1).

Land uses in PREDICTS were assigned to the following categories, based on the descriptions of the habitat given by the original collectors of the data: primary vegetation (considered to be the undisturbed reference); secondary vegetation; plantation forest; pasture; cropland; urban (considered human, or disturbed; Appendix 2, Table S3.1; Hudson et al., 2014, 2017). Secondary vegetation is further divided into three cat-

925 egories: mature, intermediate and young, depending on the stage of recovery of the vegetation. Land-use  
926 intensity is reported as minimal, light or intense, according to criteria that depended on the land-use type in  
927 question (e.g., crop diversity, degree of mechanisation and chemical inputs in cropland, or bushmeat harvest-  
928 ing and selective logging in primary vegetation; Hudson et al., 2014). I excluded sites for which the land use  
929 could not be characterised or for which the stage of recovery of secondary vegetation was unclear. As the  
930 PREDICTS database is a collection of independent studies, the design of this study was not balanced: the  
931 sample size varied across land uses (Appendix 2, Figures S3.1 & S3.2), and across taxonomic groups (3,103  
932 species of birds; 531 mammals; 379 amphibians; 326 reptiles).

### 933 **3.2.2 Functional traits and diversity metrics**

934 Trait choice is a critical step when calculating functional diversity metrics, which are highly sensitive to  
935 trait selection (Mouillot et al., 2021). However, trait selection trades off with data availability. Here, a  
936 constraint was to use similar traits across the different classes. Thus, I used the seven traits compiled in  
937 Chapter 2 across terrestrial vertebrates. Most of these traits were available for at least 50% of the species  
938 in each class (except trophic level in amphibians and lifespan in herptiles; Appendix 2, Figure S3.4). In  
939 addition, I chose traits that were ecologically relevant, broadening the biological definition of traits (i.e.,  
940 a characteristic measurable at the level of an individual) to include measures of habitat breadth and habitat  
941 specialisation (still theoretically measurable at the level of an individual). The final set constituted seven traits  
942 that influence species' responses to environmental change: body mass, trophic level, lifespan, litter/clutch  
943 size, diel activity, habitat breadth and use of artificial habitats. These traits related to life-history, habitat  
944 specialisation and use of geographical space (e.g., habitat breadth significantly explains geographical range  
945 size in all classes; Appendix 2, Figure S3.3). Here, I did not consider estimations of dispersal abilities or  
946 home range size as these were available for a small fraction of the species (<3%, Paradis et al., 1998; Smith  
947 and Green, 2005; Sutherland et al., 2000; Whitmee and Orme, 2013), neither did I include geographical  
948 range size which is measured across many individuals, and hence cannot be considered a trait. As in Chapter  
949 2, I did not consider intraspecific trait variation, thus assuming no effect of the environment on trait values.

950 Trait coverage was variable among classes and traits, with important gaps for reptiles and amphibians  
951 (Appendix 2, Figures S3.4 & S3.5; Chapter 2). I imputed missing trait values using random forest algorithms  
952 ('missForest' package: Stekhoven and Bühlmann (2012), Stekhoven (2016)), including traits, taxonomic  
953 order and phylogenetic eigenvectors as predictors (Debastiani et al., 2021; Penone et al., 2014). To further  
954 assess the sensitivity of the results to imputation (see next section), I imputed missing trait values eight times,  
955 thereby obtaining eight sets of imputed traits. I randomly selected one imputed trait set for the calculation of

functional metrics. Imputations of missing trait values & imputation performance are detailed in Appendix 2, S3.2: ‘Trait data & imputation of missing trait values’ and S3.4: ‘Imputation performance’ (and Figures S3.6-S3.8). Post-imputation, continuous traits were  $\log_{10}$ -transformed (except habitat breadth which was square-rooted) and z-scored (standardised to unit variance and zero mean). In addition, I assessed whether the results were robust to imputation error using a subset of the PREDICTS data considering only species for which I had complete trait information (see next section).

Correlation among traits can be a safeguard against high sensitivity of functional metrics to trait omission, notably where omitted traits correlate strongly with traits that are already included in the calculation (Mouillot et al., 2021). Nevertheless, high multicollinearity among traits has been reported as potentially problematic for the calculation of functional diversity (Cadotte et al., 2011). Thus, I verified that the degree of multicollinearity among traits was not problematically high (with a threshold of 5 for variance inflation factors, Appendix 2, Table S3.3). Furthermore, I tested the sensitivity of the results to trait omission, by investigating whether adding geographical range size in the calculation of functional metrics was likely to affect the results.

### 3.2.3 Effects of land use and land-use intensity on FRic and FDis (Hypothesis 1)

For each assemblage, I measured functional richness using ‘FRic’ (Villéger et al., 2008), and functional dispersion using ‘FDis’ (Laliberté and Legendre (2010); Figure 3.1), from the ‘FD’ package (Laliberté and Legendre (2010); Laliberté et al. (2014)). I assessed the effects of land use, land-use intensity, and region (temperate versus tropical) on FRic and FDis across and within taxonomic classes using linear mixed-effects models ('lme4' package, Bates et al. (2015)). Land use and land-use intensity were not ranked in the models. A random intercept of study identity accounted for variation in experimental design across studies, while a random intercept representing spatial blocks of sampled sites, nested within study, accounted for spatial structuring within studies. To improve normality and bound predictions between 0 and 1, I transformed FRic and FDis using an arcsin-square-root transformation. The best-fitting model was sought using backwards stepwise model selection, starting with the most complex model that included all two-way interactions among the specified main effects. Model fits were compared using likelihood-ratio tests at each iteration of the selection procedure.

Across vertebrates, the starting models included the effects of land use, land-use intensity and region (temperate versus tropical). The best-fitting model for FRic was:

985  $\text{arcsin}(\sqrt{\text{FRic}}) \sim \text{Land use} + \text{Land-use intensity} + \text{Region} + \text{Land use : Land-use intensity} + \text{Land use : Region}$ .

987 (Model 1a)

988 For FDis, the best-fitting model did not include interactions between land use and region, but the main  
989 effect of region was retained:

990  $\text{arcsin}(\sqrt{\text{FDis}}) \sim \text{Land use} + \text{Land-use intensity} + \text{Region} + \text{Land use : Land-use intensity}$ .

991 (Model 1b)

992 To investigate differences in responses across classes, I pooled some of the land uses together, because  
993 otherwise, sample sizes would have been too low. Mature, intermediate and young secondary vegetation were  
994 grouped together as ‘Secondary vegetation’, and cropland and pasture were grouped together as ‘Agricultural  
995 land uses’. The starting models included the effects of land use, land-use intensity, region and taxonomic  
996 class. For FRic, the best model was:

997  $\text{arcsin}(\sqrt{\text{FRic}}) \sim \text{Land use} + \text{Land-use intensity} + \text{Region} + \text{Class} + \text{Land use : Land-use intensity} + \text{Land use : Class} + \text{Land-use intensity : Region} + \text{Class : Region}$ .

999 (Model 2a)

1000 For FDis, regional effects were dropped:

1001  $\text{arcsin}(\sqrt{\text{FDis}}) \sim \text{Land use} + \text{Land-use intensity} + \text{Class} + \text{Land use : Land-use intensity} + \text{Land use : Class} + \text{Land-use intensity : Class}$ .

1003 (Model 2b)

1004 To assess whether the results were robust to imputation error, I used a subset of the PREDICTS data  
1005 considering only species for which there were complete trait information (6,212 sites; 442 mammals; 1,975  
1006 birds; 78 reptiles; 9 amphibians), and I fitted models again to this data subset. I did not have enough complete  
1007 trait data among amphibians to be able to consider this class separately, so I first considered amphibians and  
1008 reptiles together (herptiles), and reptiles only. In addition, I complemented this validation with a sensitivity  
1009 analysis to variation in imputed values. I calculated FDis and FRic using each of the eight imputed trait  
1010 datasets and fitted the previous models to each set. I then qualitatively evaluated the congruence of the  
1011 estimates from the different models. Finally, because there tended to be more sites sampled in primary  
1012 vegetation than in other land uses (Appendix 2, Figures S3.1 & S3.1), I ran additional sensitivity tests to  
1013 assess whether the results were robust to resampling primary vegetation sites to a number equal to 50 (a  
1014 sample size close to the median number of sites sampled in land uses other than primary vegetation in both  
1015 regions (median = 37 for the temperate subset and 57 for the tropical subset, Appendix 2, Figure S3.1)).

1016 **3.2.4 Investigating functional under-dispersion (Hypothesis 2)**

1017 To assess whether effects of land use and land-use intensity on FDis differed from what would be expected  
1018 by chance given changes in local species richness, I generated null expectations of FDis at each site. I  
1019 randomised assemblage composition 500 times, drawing species from the corresponding study's species  
1020 pool while maintaining local species richness. For each site, I thus obtained a null distribution for FDis.  
1021 Then, I tested whether FDis differed from null expectations using Wilcoxon signed-rank tests. I created  
1022 a binary variable which was assigned 1 if FDis was significantly lower than null expectations at a given  
1023 site (significant under-dispersion), and 0 otherwise. I investigated how land use, land-use intensity, region  
1024 and taxonomic class affected the probability of occurrence of under-dispersion using a generalised linear  
1025 mixed-effects model with a binomial distribution of errors. The best-fitting model did not retain any effect  
1026 of taxonomic class:

1027  $P_{\text{under-dispersion}} \sim \text{Land use} + \text{Land-use intensity} + \text{Region} + \text{Land use : Land-use intensity} + \text{Land use : Region}$ .

1029 (Model 3)

1030 **3.2.5 Functional loss and functional gain (Hypothesis 3)**

1031 I calculated the proportion of trait space that was lost in disturbed land uses compared to reference land uses  
1032 (functional loss) and the proportion of trait space that was gained in disturbed land uses (functional gain)  
1033 (Figure 3.1c), across and within taxonomic classes. I selected studies where at least one site was sampled in  
1034 primary vegetation. I then made within study pairwise comparisons between reference assemblages, sampled  
1035 in primary vegetation, and disturbed assemblages. In addition, I considered all comparisons between pairs  
1036 of primary-vegetation sites, to create reference pairs. I then investigated how land use, land-use intensity  
1037 and region affected functional loss and gain across and within taxonomic classes using linear mixed-effects  
1038 models, controlling for study identity in the random effects. Across vertebrates, the best-fitting model for  
1039 functional loss was:

1040  $\text{arcsin}(\sqrt{\text{loss}}) \sim \text{Land use} + \text{Land-use intensity} + \text{Region} + \text{Land use : Land-use intensity} + \text{Land use : Region}$ .

1042 (Model 4a)

1043 For functional gain, one interaction term (land use with region) was dropped:

1044  $\arcsin(\sqrt{\text{gain}}) \sim \text{Land use} + \text{Land-use intensity} + \text{Region} + \text{Land use : Land-use intensity}.$

1045 (Model 4b)

1046 When considering the effects of taxonomic class, the best-fitting model for functional loss was:

1047  $\arcsin(\sqrt{\text{loss}}) \sim \text{Land use} + \text{Land-use intensity} + \text{Class} + \text{Region} + \text{Land use :}$

1048  $\text{Land-use intensity} + \text{Land use : Class} + \text{Land use : Region} + \text{Land-use intensity : Class}.$

1049 (Model 5a)

1050 For functional gain (Model 5b), the fitted effects were the same as those of Model 2b. More details about  
1051 the calculation of functional loss and gain can be found in Appendix S3.5.

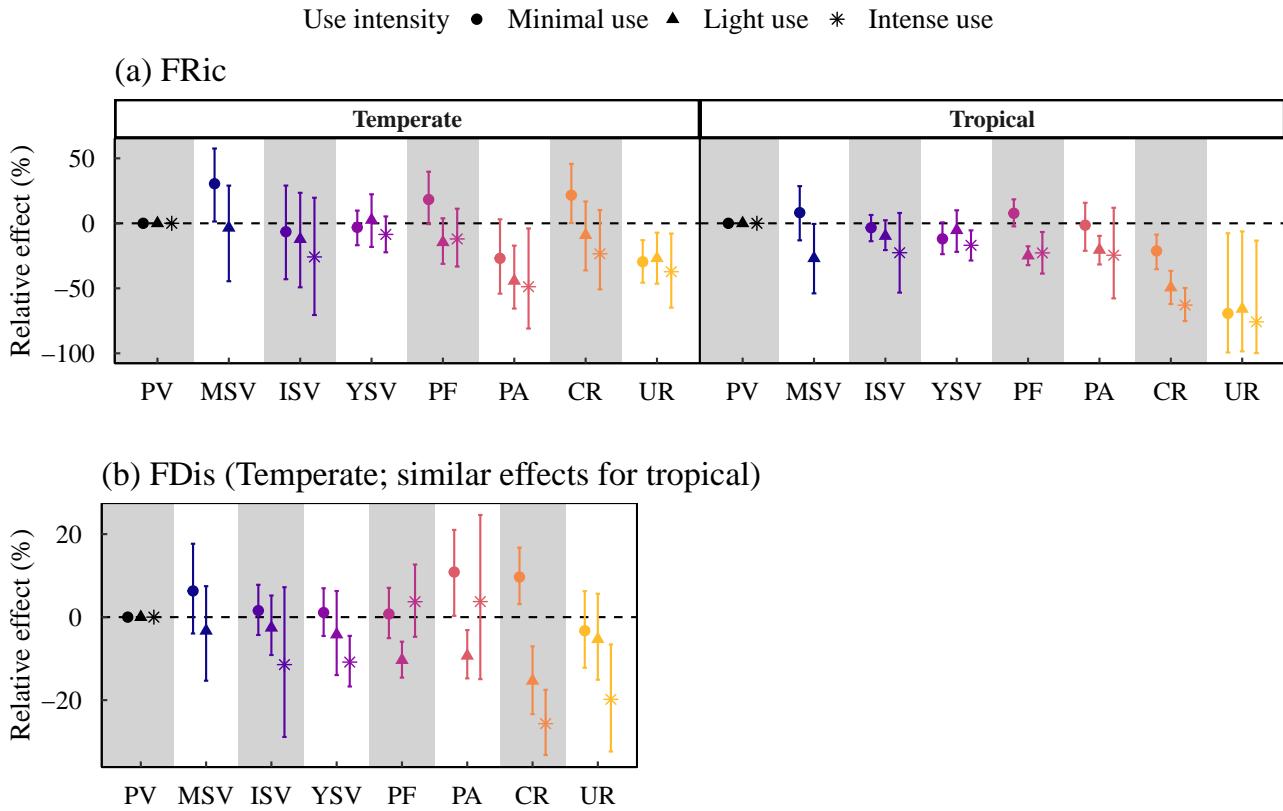
1052 All data analyses were conducted using R version 3.5.1 (R Core Team, 2018). I made the code available  
1053 on figshare (DOIs: <https://doi.org/10.6084/m9.figshare.14161883> and <https://doi.org/10.6084/m9.figshare.15163926>), as well as the main result datasets (<https://doi.org/10.6084/m9.figshare.15163971>).

### 1056 3.3 Results

#### 1057 3.3.1 Effects of land use on FRic and FDis

1058 Across all vertebrates, land use and land-use intensity significantly affected FRic and FDis (Figure 3.2).  
1059 FRic tended to decrease with increasing disturbance level and higher intensity of land use. For FRic, relative  
1060 effects differed between regions (Figure 3.2a). Although declines were overall more important for disturbed  
1061 tropical assemblages, significant declines were observed for the temperate assemblages (e.g., a 37% average  
1062 decline in intensely used urban areas; a 49% decline in pastoral areas of high land-use intensity). Never-  
1063 theless, tropical assemblages typically showed more important reductions in FRic. For instance, declines  
1064 averaged 63% for intensely used tropical cropland and 76% for urban areas. For FDis, relative effects were  
1065 similar in both regions (Figure 3.2b). The most important average declines were observed for urban assem-  
1066 blages of intense use (20% decline), and for lightly- and intensely used cropland (by 15% and 26%). Note  
1067 that confidence intervals around the estimated average declines were large in some cases, highlighting some  
1068 heterogeneity in the responses.

1069 Fitting the same models to the subset of species with complete trait data, I detected important declines in  
1070 functional diversity in a number of land uses, showing that the conclusions are robust to trait imputation un-  
1071 certainty (for example, FRic declined on average by 75% in intensely used temperate pastoral assemblages;  
1072 by 48% for intensely used tropical cropland; and FDis declined by an average 37% in intensely used tropical

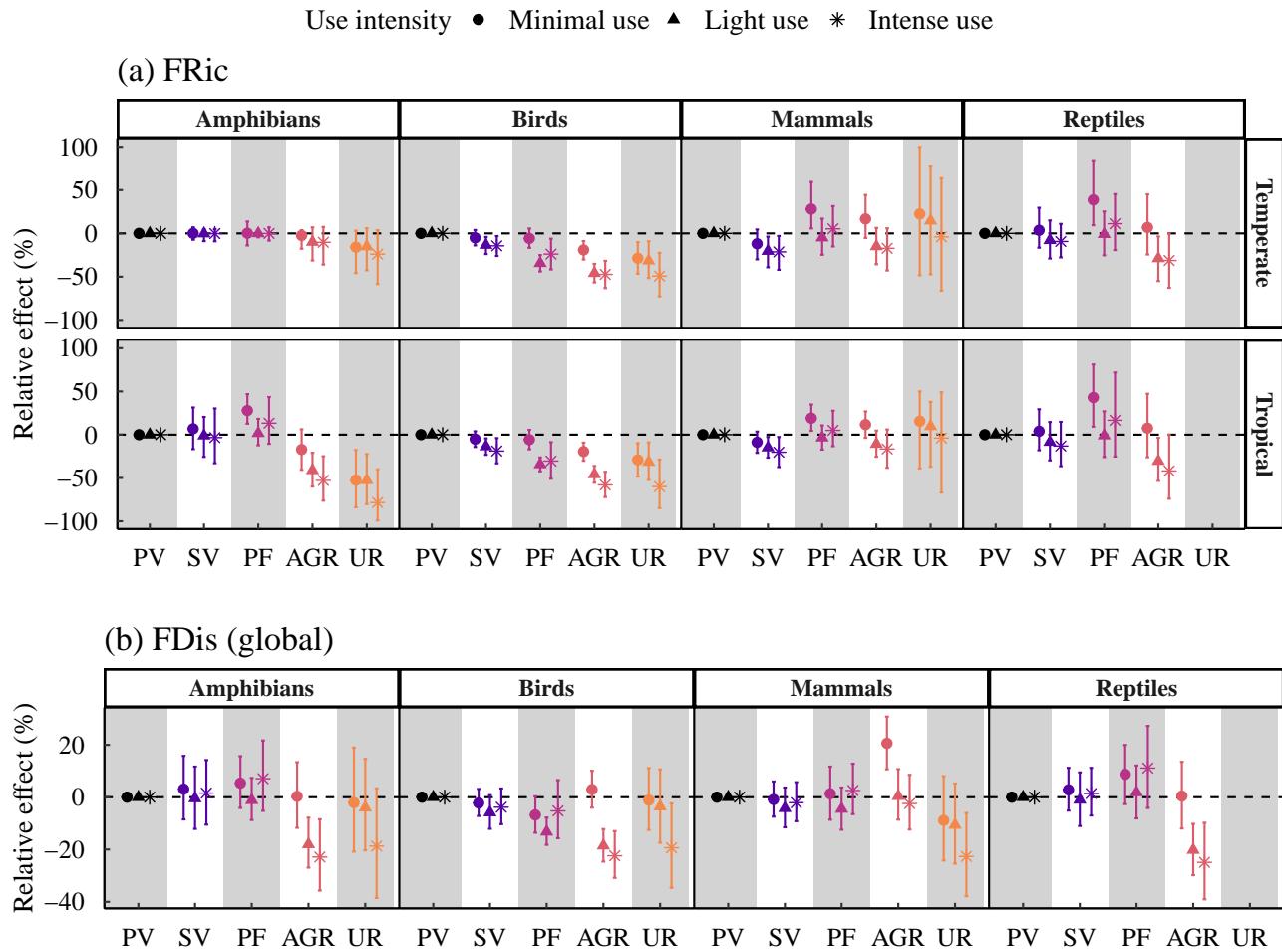


**Figure 3.2: Effects of land use, land-use intensity and region on FRic (a) and on FDis (b) across all PREDICTS vertebrates.** Effects were rescaled with reference to primary vegetation (PV) and are plotted as a % difference relative to PV within each land-use intensity. For FRic, the best-fitting model included interactions between land use and region, while these interactions were dropped for FDis, explaining the similar relative effects in both regions. Error bars represent 95% confidence intervals. MSV: mature secondary vegetation; ISV, intermediate secondary vegetation; YSV, young secondary vegetation; PF, plantation forest; PA, pasture; CR, cropland; UR, urban. Effects for intense use in MSV could not be estimated as there were not enough sampled sites. *Figure reproduced from Etard et al. (2022).*

1073 urban assemblages; Appendix 2, Figure S3.18). Furthermore, using the subset of species with complete trait  
 1074 data, I found that the results were not sensitive to the inclusion of geographical range size as an additional  
 1075 trait (Appendix 2, Figure S3.19). Finally, the results were not sensitive to variation across imputed trait val-  
 1076 ues (Appendix 2, Figure S3.20) and were also robust to resampling in primary-vegetation sites (Appendix 2,  
 1077 Figure S3.21).

1078 Responses of FRic and FDis to land use and land-use intensity differed among taxonomic classes (Figure  
 1079 3.3). Within-class effects for FDis were similar between regions. The most notable decreases were observed  
 1080 in lightly- and intensely used agricultural land uses in amphibians, birds and reptiles; and in intensely used  
 1081 urban land uses for birds and mammals. For FRic, the effects in tropical and temperate regions were qual-  
 1082 itatively similar in three out of four classes (birds, mammals and reptiles), although effect sizes tended to be  
 1083 bigger for tropical assemblages. Birds and reptiles showed reductions in disturbed land uses in both tropical

1084 and temperate regions, whereas I detected few significant effects for mammals. For birds, the most important  
 1085 average decline, of 50%, was observed in intensely used tropical urban land uses, while for reptiles I detected  
 1086 significant decreases in lightly- and intensely used agricultural sites (but I could not estimate effects for urban  
 1087 land uses due to the small sample size). Finally, the effects differed between tropical and temperate regions  
 1088 for amphibians, with no significant effects detected across temperate assemblages, but important reductions  
 1089 across tropical agricultural and urban assemblages.



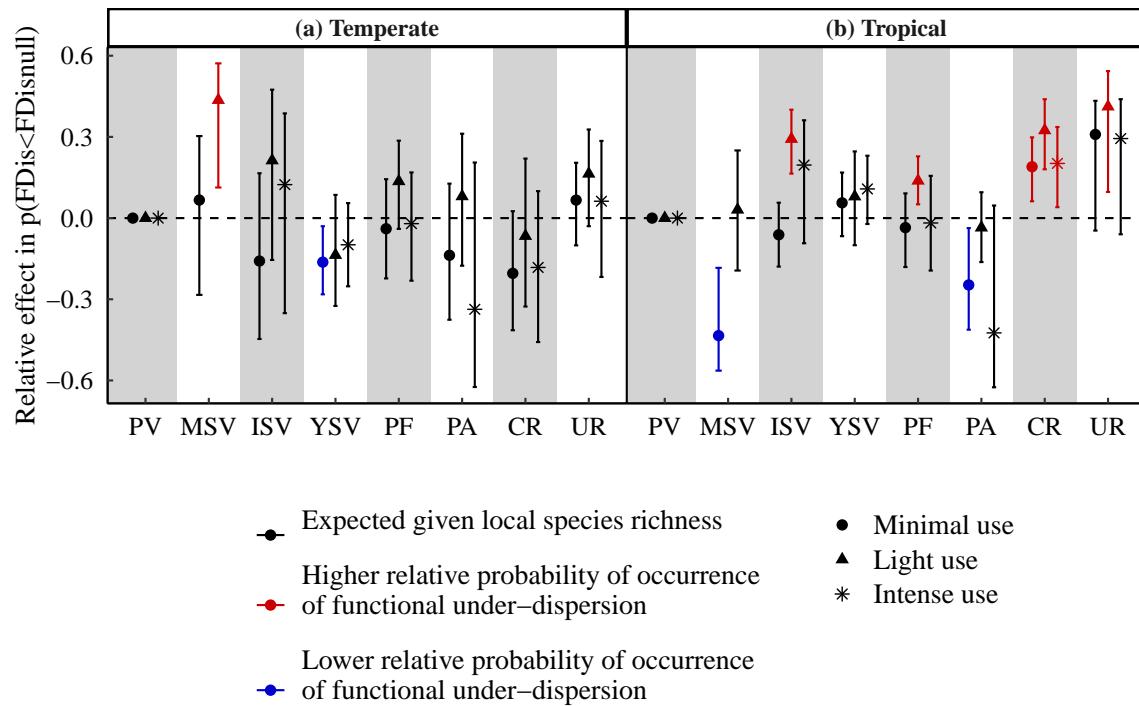
**Figure 3.3: Effects of land use, land-use intensity, region and taxonomic class on FRic (a) and FDis (b).** Effects were rescaled with reference to primary vegetation (PV) and are plotted as a % difference relative to PV within each land-use intensity. Error bars represent 95% confidence intervals. Effects for FRic were estimated from Model 2a, and from Model 2b for FDis. SV, secondary vegetation; PF, plantation forest; AGR, agricultural land uses (pasture and cropland); UR, urban. Effects for reptiles in urban land uses could not be estimated as there were not enough sampled sites. *Figure reproduced from Etard et al. (2022).*

1090 Fitting similar models only for species with complete trait data showed that these patterns are unlikely  
 1091 to be affected by imputation uncertainty for birds; for mammals and reptiles, the main results could even be  
 1092 conservative (Appendix 2, Figures S3.22, S3.23). Indeed, although confidence intervals around the estimates

1093 were large, I typically observed larger decreases in functional diversity when using the complete data subset,  
 1094 including an 86% decline in FRic for mammals in intensely used tropical agricultural areas. The results were  
 1095 also unaffected by variation across replicate sets of imputed trait values (Appendix 2, Figure S3.24).

### 1096 3.3.2 Changes in the probability of occurrence of functional under-dispersion

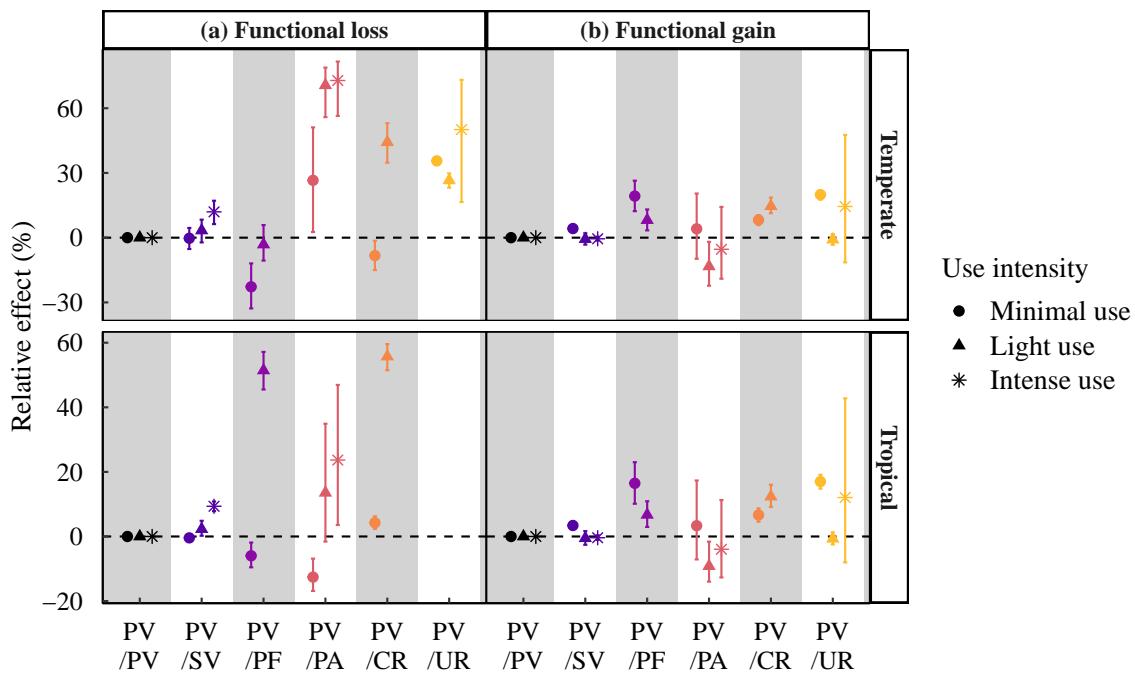
1097 Land use, land-use intensity and region significantly affected the probability of occurrence of functional  
 1098 under-dispersion across vertebrates. Functional under-dispersion was more likely to occur in tropical crop-  
 1099 land of all land-use intensities (Figure 3.4b), as well as in some of the lightly-used land uses (notably urban  
 1100 and plantation forest). Contrary to my expectations, and with the exception of tropical cropland, functional  
 1101 under-dispersion was not more likely to occur in intensely-used land uses. For minimally-used sites, changes  
 1102 in FDis were mostly consistent with changes expected given local species richness.



**Figure 3.4: Effects of land use, land-use intensity and region on the probability of occurrence of functional under-dispersion.** Error bars represent 95% confidence intervals. PV: primary vegetation; MSV, mature secondary vegetation; ISV, intermediate secondary vegetation; YSV, young secondary vegetation; PF, plantation forest; PA, pasture; CR, cropland; UR, urban. Effects are rescaled and represent the average difference in the probability of occurrence of functional under-dispersion between the reference (PV, probability of functional under-dispersion set at 0 within each land-use intensity) and the disturbed land uses. *Figure reproduced from Etard et al. (2022).*

### 1103 3.3.3 Functional loss and gain

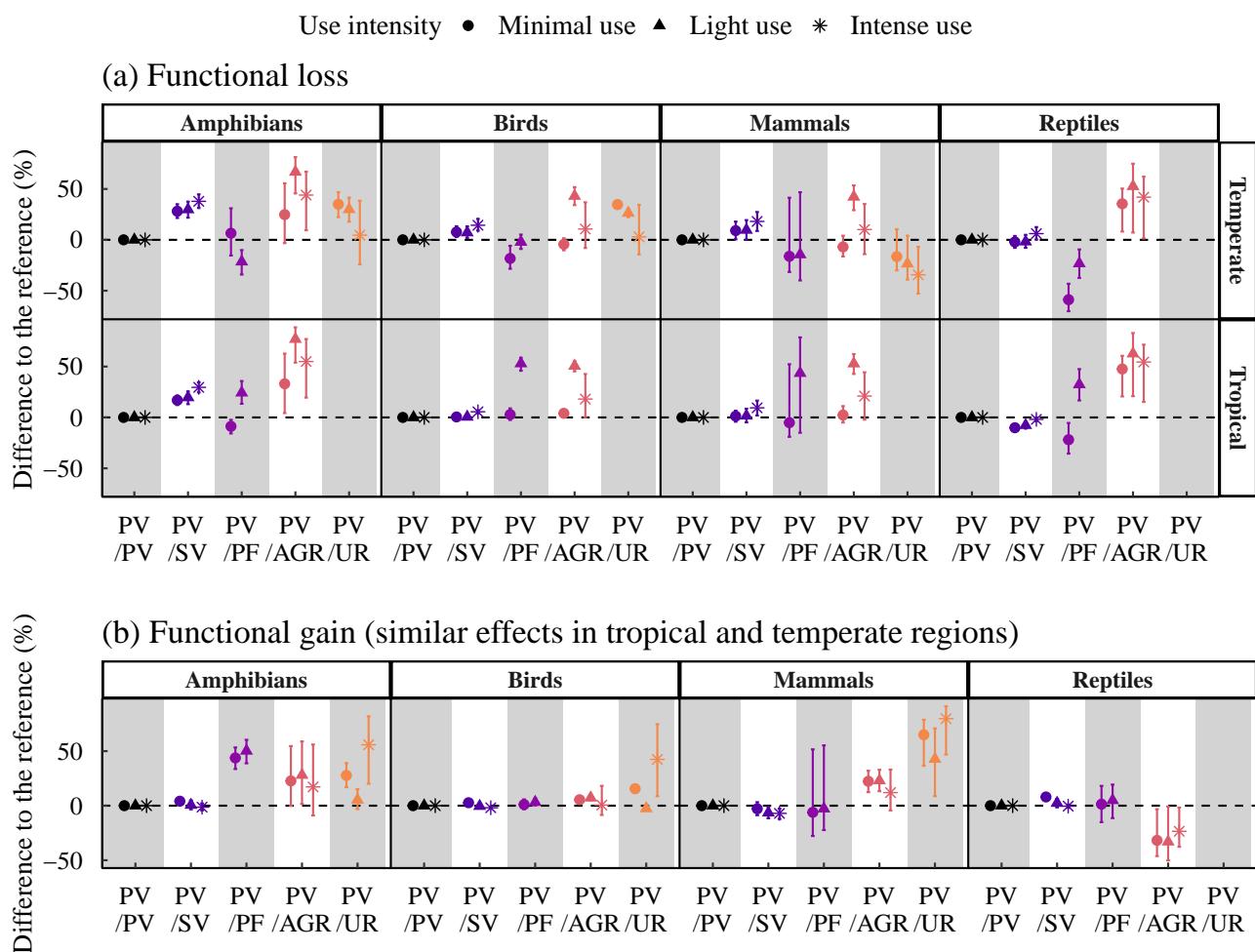
1104 Across and within vertebrate classes, I detected high levels of functional loss, exceeding the natural turnover  
 1105 between primary-vegetation sites, both in temperate and tropical regions. Across vertebrates (Figure 3.5a),  
 1106 functional loss was notably high in temperate pastures (+27% above reference for minimal use; +73% for  
 1107 intense use), temperate urban sites (+27% for light use; +50% for intense use; effects for tropical urban sites  
 1108 could not be estimated), temperate and tropical cropland (+44% and +56% respectively for light use; effects  
 1109 for intense use could not be estimated). Important levels of functional loss were also observed in tropical  
 1110 plantation forest of light use intensity (+51%; effects for the intense use could not be estimated). High  
 1111 levels of functional loss were also observed within each class (Figure 3.6a) (although not all effects could  
 1112 be estimated because of limited sample sizes, Appendix 2, Table S3.5). The highest losses were observed  
 1113 in agricultural areas for amphibians and reptiles, with important losses also observed in temperate urban  
 1114 areas for both birds and amphibians (+35% for minimal use; effects for tropical urban areas could not be  
 1115 estimated).



**Figure 3.5: Effects of land use and land-use intensity on (a) functional loss and (b) functional gain across pairs of sites in temperate areas and tropical areas.** PV: primary vegetation; SV, secondary vegetation; PF, plantation forest; PA, pasture; CR, cropland; UR, urban. Error bars represent 95% confidence intervals. Effects are rescaled and represent the average difference in functional loss and gain between the reference pairs (PV/PV, with loss and gain set at 0% within each land-use intensity), and pairs of primary vegetation with disturbed land uses. Negative effects mean that, on average, levels of functional loss (or gain) were lower than functional loss (or gain) observed between pairs of primary-vegetation sites, and not that there were absolute ‘negative losses’ or ‘negative gains’. *Figure reproduced from Etard et al. (2022).*

1116 Across vertebrates, average functional gain (average proportion of novel trait space in the disturbed  
 1117 assemblage) was moderate and on average did not exceed 20% in any disturbed land uses (Figure 3.5b).  
 1118 Patterns of functional gain were similar in both regions. The highest functional gains were observed for  
 1119 minimally-used urban sites and plantation forest (range: +16% to +20%). On the other hand, important  
 1120 levels of functional gain were observed in some classes (Figure 3.6b), with the highest functional gain for  
 1121 mammals (+80% in intensely used urban sites).

1122 Diagnostic plots (qq-plots and residual distributions) for the models are shown in Appendix 2, Figures  
 1123 S3.9–S3.17. Overall, the model residuals were appropriately distributed (but with some leptokurtic residual  
 1124 distributions, to which mixed-effect models are generally robust (Schielzeth et al., 2020)).



**Figure 3.6: Effects of land use, land-use intensity, region and taxonomic class on functional loss (a) and functional gain (b) across pairs of sites.** PV: primary vegetation; SV: secondary vegetation; PF: plantation forest; AGR: agricultural land uses (pasture and cropland); UR: urban. Error bars represent 95% confidence intervals. Effects are rescaled and represent the average difference in functional loss and gain between the reference pairs (PV/PV, with loss and gain set at 0% within each land-use intensity), and pairs of primary vegetation with disturbed land uses. Negative effects mean that, on average, levels of functional loss (or gain) were lower than functional loss (or gain) observed between pairs of primary-vegetation sites, and not that there were absolute ‘negative losses’ or ‘negative gains’. Figure reproduced from Etard et al. (2022).

1125 **3.4 Discussion**

1126 Here, I showed that the functional diversity of vertebrate assemblages is negatively impacted in human land  
1127 uses, particularly in the most intensely used land types. The results of this Chapter extend previous studies  
1128 that have been more taxonomically or geographically restricted (Flynn et al., 2009; Matuoka et al., 2020).  
1129 Matuoka et al. (2020) found that the functional diversity of tropical bird assemblages was negatively affected  
1130 by human disturbance, a pattern that did not appear in temperate assemblages. Yet, I found that functional  
1131 diversity was negatively affected in both tropical and temperate areas, with important functional losses in all  
1132 four vertebrate classes.

1133 Using multiple metrics allowed me to explore different facets of functional diversity. For instance, func-  
1134 tional gain could locally offset functional loss in some disturbed land uses. This could indicate that despite  
1135 no apparent negative effect on FRic, some disturbed land uses (e.g. lightly-used temperate cropland) could  
1136 experience important functional loss, and highlights the importance of using a variety of indicators. This  
1137 mechanism could be at play in mammalian assemblages, for which important levels of functional gain were  
1138 observed in agricultural and urban sites. Further, functional gain in disturbed land uses could indicate that  
1139 disturbances facilitate the introduction of functionally novel species, falling into previously unoccupied parts  
1140 of the trait space. This may be because non-native species are more likely to become established in disturbed  
1141 assemblages. Previous work has shown that land-use disturbance facilitates biological invasions in island  
1142 ecosystems (Jesse et al., 2018; Sánchez-Ortiz et al., 2019), but to my knowledge, this has not been tested  
1143 specifically across continental areas for invasive vertebrates (but see Pyšek et al. (2010)). It is also pos-  
1144 sible that disturbed areas harbour synanthropic species that do not occur in primary vegetation, leading to  
1145 substantial functional gain.

1146 Overall, the negative effects of land use on functional richness tended to be more pronounced in the  
1147 tropics. This is congruent with past studies that have found tropical biodiversity to be disproportionately  
1148 sensitive to human pressures (Martins and Pereira, 2017; Newbold et al., 2020b). There are a number of  
1149 potential explanations for this. First, it could be that a long history of intense land-use disturbance at large  
1150 scales in many temperate regions (e.g. Western Europe; Stephens et al. (2019)) means that biodiversity is  
1151 now less sensitive to new disturbances, because the most sensitive species have been filtered out (Balmford,  
1152 1996; “Habitat fragmentation causes immediate and time-delayed biodiversity loss at different trophic lev-  
1153 els” 2010; Le Provost et al., 2020; Munteanu et al., 2020). Species unable to cope with such disturbances  
1154 may have gone extinct in the past, while the remaining species would be more disturbance-tolerant (Betts  
1155 et al., 2019). Tropical regions, historically less disturbed at large scales, would then contain a higher pro-

portion of disturbance-sensitive species than temperate regions. Consequently, the functional richness in undisturbed tropical sites could be less resilient to new disturbances. This also highlights that time since land-use conversion could have important impacts on local functional diversity. Although I did not consider the effects of time since land-use conversion in this work (notably because PREDICTS contained data on time since land-use conversion only for about 22% of the sites), I expect that time since land-use conversion may affect assemblage composition, and thus, functional diversity, with potentially land-use-specific relationships between time since conversion and functional diversity (e.g., a positive relationship for recovering secondary vegetation or a negative relationship for urban areas; but I did not detect such effects when using the data subset for which there were information on time since land-use conversion [see Appendix 2, S3.8: ‘Model robustness – time since land-use conversion’]).

Second, it could be that tropical species are intrinsically more sensitive to disturbances than temperate species because of their evolutionary history. Natural climatic variability experienced by species as well as species history of exposure to disturbances have been proposed to influence sensitivity to disturbance. For instance, tropical species are, on average, nearer to their climatic limits than temperate species (Deutsch et al., 2008; Sunday et al., 2014). Tropical species could therefore experience more deleterious effects from interacting drivers of change, with land-use change bringing about novel climatic conditions pushing them beyond their tolerance limits (Frishkoff et al., 2016; Williams and Newbold, 2020).

In addition to filtering out sensitive species, land-use change is also expected to modify interactions among species, thereby influencing species persistence (Tylianakis et al., 2008; Valiente-Banuet et al., 2015). Although I detected a signal of functional under-dispersion (particularly in tropical cropland), which indicates that assemblages may be locally structured by environment filtering (Bregman et al., 2015), it is likely that several assembly rules underpin assemblage composition (Fournier et al., 2016). For instance, land-use changes could enhance competition among species, promoting over-dispersion by removing species that share similar resources. Such opposite signatures of environmental filtering and enhanced competition on functional dispersion could explain why I did not detect stronger effects of land use on functional under-dispersion occurrence.

Studies looking at impacts of global land use on functional diversity computed with species from all four terrestrial vertebrate classes remain rare. Lack of availability of standardised trait data across terrestrial vertebrates may have hindered such studies from being conducted in the past. To overcome this problem, I based the analyses on a large-scale collation of trait data (Chapter 2; Etard et al. (2020)), and I imputed missing trait values to obtain complete trait datasets in each class. I used random forest algorithms, currently thought to be one of the most robust technique for missing value imputations in trait datasets (Debastiani

et al., 2021; Johnson et al., 2021; Penone et al., 2014). Replicating the analyses on complete trait data subsets showed that imputation uncertainty did not affect the main conclusions of this work and that the negative effects of human land uses were in some cases even stronger when using the complete data subsets. Furthermore, the results were highly consistent across imputed datasets and so insensitive to variation across imputed values. Although missing value imputation can offer a robust filling of missing entries, this study highlights the existing taxonomic biases both in trait data availability and in PREDICTS studies, and thus stresses the need to pursue data compilation efforts, particularly for the least-sampled classes (reptiles and amphibians).

Another implication of trait data availability for vertebrates is that the choice of traits was constrained. Mouillot et al. (2021) showed that functional diversity metrics are sensitive to trait omission and that the sensitivity to trait omission decreases with increasing levels of correlation among traits. Here, I chose seven traits that were available across all classes at least for a subset of the species and that have been implicated in shaping species responses to environmental change. A notable omission was any metric of dispersal ability, which is likely to influence species' ability to respond to land-use change but is difficult to obtain for most species. In fact, past studies have shown that dispersal abilities can be predicted from ecological correlates, such as body mass, diet or geographical range size (Schloss et al., 2012; Sutherland et al., 2000). Since the results were robust to the omission of geographical range size, I am confident that the omission of dispersal abilities also does not affect the conclusions of this work.

Functional diversity metrics are often used as a proxy for ecosystem functioning because of the conceptual and mechanistic link between functional 'effect' traits and ecosystem processes (Lavorel and Garnier, 2002; Violle et al., 2007). In many studies focused on vertebrates, however, functional diversity metrics do not correlate with a given ecosystem function (Hatfield et al., 2018). Here, I did not explicitly target given ecosystem functions, but I argue that evidence of functional loss of vertebrate assemblages indicates that processes sustained by vertebrates are put at risk by land-use change. My results further show that some disturbed land uses are more likely to experience functional under-dispersion, particularly tropical cropland and tropical urban areas, which again indicates a potential imperilment of ecological processes. Indeed, in such cases, decreases in functional dispersion exceed changes expected from the chance removal of species; such non-random modifications indicate that certain areas of the functional trait space are more sensitive to land-use disturbance. Future work could investigate the impacts of land-use change on particular ecosystem functions. The integration of trophic information (beyond the trophic levels I used here) to the species-trait dataset could be an interesting step in that direction, as dietary traits relate to resource use and are, as such, probably the most straightforward traits to link with ecosystem functions. Furthermore, my results suggest

1220 that the functional loss experienced within a class is unlikely to be compensated for by the persistence of  
1221 functionally similar species in other classes. Indeed, I detected negative effects of human land use on func-  
1222 tional richness in at least three out of four vertebrate classes (amphibians, birds, and reptiles), in accordance  
1223 with past studies focusing on each of these groups (Gallmetzer and Schulze, 2015; Marcacci et al., 2021;  
1224 Riemann et al., 2017; Sol et al., 2020). Although overall mammalian functional richness was less affected,  
1225 high levels of functional gain suggest that the functional composition of mammalian assemblages is heavily  
1226 modified in disturbed land uses.

1227 To conclude, the results of this Chapter highlight the negative impacts of human land uses on multiple  
1228 dimensions of functional diversity, within and across terrestrial vertebrate classes, at a global scale. In  
1229 many disturbed sites, decreases in functional diversity exceed changes expected from species loss alone,  
1230 showing that human activities non-randomly reshape ecological assemblages. By intensifying functional  
1231 loss and promoting functional under-dispersion, land-use change could have deleterious effects on ecosystem  
1232 functioning, highlighting the necessity of putting into place effective conservation measures in the face of  
1233 anthropogenic change.

1234 **4 | Narrow-ranging natural habitat special-**

1235 **ists most sensitive to both land-use and**

1236 **climate change in terrestrial vertebrates**

1237 **Keywords**

1238 Land use; land-use intensity; climate change; sensitivity; CENFA; dietary traits ; life-history traits; speciali-  
1239 sation; geographical range area; terrestrial vertebrates.

alphabetical  
order

1240 **Abstract**

1241 Land-use and climate change are two of the most important pressures on terrestrial biodiversity. However,  
1242 the factors that explain interspecific variation in responses to these pressures remain unclear. Although it is  
1243 well established that extinction risk and some species' responses to human pressures relate to species traits,  
1244 we lack large-scale comparative assessments across multiple clades linking traits to multiple human pres-  
1245 sures. Here, I investigated whether a set of ecological characteristics that are commonly measured across  
1246 terrestrial vertebrates (that is, ecological traits and geographical range area) are associated with (1) species'  
1247 responses to different land-use types and (2) species' sensitivity to climate change. My aim was to test  
1248 whether generalisable patterns in species' responses to these pressures arise with regards to species' ecolog-  
1249 ical characteristics, which helps assess the global signature of human pressures on vertebrate biodiversity  
1250 and is also of interest for the prioritisation of conservation efforts. Among the set of characteristics I consid-  
1251 ered, I found that only three were consistently associated with both land-use responses and climate-change  
1252 sensitivity across terrestrial vertebrate classes: geographical range area, habitat breadth and specialisation  
1253 on natural habitats. The association of other traits with species' land-use responses and with climate-change

1254 sensitivity often depended on class and land-use type. My work highlights that narrow-ranged species with  
1255 narrow habitat breadth and natural habitat specialism are typically more sensitive to human pressures. Fur-  
1256 ther, I found that invertebrate eaters and fruit/nectar eaters tended to be negatively affected in disturbed land  
1257 uses in all classes, and that invertebrate- and plant/seed- eating birds had higher climate-change sensitiv-  
1258 ity, raising concerns about the continuation of ecological processes sustained by these species under global  
1259 changes. My work stresses the need for putting into place conservation and mitigation measures to protect  
1260 biodiversity and related services from human impacts.

## 1261 **4.1 Introduction**

1262 Land-use change is currently the most important driver of global biodiversity loss (Newbold et al., 2015)  
1263 and is likely to continue to cause species loss in the coming decades (Li et al., 2022; Powers and Jetz, 2019;  
1264 Stehfest et al., 2019). However, biodiversity faces multiple pressures acting in combination (Maxwell et al.,  
1265 2016). In particular, the impacts of climate change on biodiversity are projected to equate or even surpass  
1266 those of land-use change in their magnitude by 2070 (Newbold, 2018). Thus, it has become more vital than  
1267 ever to put into place mitigation and conservation measures to protect biodiversity from human pressures.

1268 It is now well established that species differ in their ability to cope with environmental changes (Ferreira  
1269 et al., 2022; Matich and Schalk, 2019; Newbold et al., 2013). As such, global average declines in biodiver-  
1270 sity indices mask substantial interspecific variation in responses to disturbances (Leung et al., 2020). Such  
1271 interspecific variation has important consequences for the prioritisation of conservation efforts and the defi-  
1272 nition of protected areas (Morelli et al., 2021). Mitigating the impacts of land-use and climate-change on the  
1273 world's biota requires to understand which species are put at most risk by these pressures, in other words to  
1274 understand the factors that are associated with species' sensitivity to land-use and climate change.

1275 By capturing key aspects of species' morphology, life-history, ecological strategies or demography, traits  
1276 can inform on species' use of resources and space, as well as on some community and population-level  
1277 processes (Capdevila et al., 2022b). As such, traits can help understand what drives species' responses  
1278 to environmental change. Thus, to explain interspecific differences in responses to human disturbance, a  
1279 number of studies have investigated whether species traits influence species' responses to human pressures,  
1280 in particular to land-use change (Newbold et al., 2013; Nowakowski et al., 2017; Quesnelle et al., 2014;  
1281 Tinoco et al., 2018) and climate change (Angert et al., 2011; Di Marco et al., 2021; Estrada et al., 2018;  
1282 McCain and King, 2014; Pacifici et al., 2017; Pearson et al., 2014; Schloss et al., 2012).

1283 From these past studies, several traits have been identified as important correlates of species' responses

1284 to land-use and climate change within vertebrate taxa (for example, body mass and generation length were  
1285 found to influence bird responses to land-use change in Newbold et al. (2013); and body mass and activity  
1286 time were found to be associated with mammal responses to climate change in McCain and King (2014)).  
1287 However, past work has mostly been conducted at local to regional scales (Davison et al., 2021; Hevia et  
1288 al., 2017), such that it remains unclear whether the effects of traits on species' responses to environmental  
1289 change can be generalised across vertebrate taxa and regions. Yet, at least two meta-analyses have inves-  
1290 tigated whether traits explained responses to human pressures across diverse taxa, one focused on climate-  
1291 change responses (MacLean and Beissinger, 2017), and one on species extinction risk (Chichorro et al.,  
1292 2019). MacLean and Beissinger (2017) found that habitat breadth and historic range limit were consistently  
1293 associated with interspecific variation in range shifts under contemporary climate change across a range of  
1294 taxa (including plants, birds and butterflies), but they did not detect any effect of life-history traits, such as  
1295 body size or fecundity. Similarly, Chichorro et al. (2019) highlighted the effects of geographical range area  
1296 and habitat breadth on species extinction risks in different taxa (including terrestrial vertebrates), with other  
1297 traits having inconsistent effects. However, as underlined by Chichorro et al. (2019), the studies included in  
1298 the meta-analysis often considered extinction risk without an explicit consideration of the pressures to which  
1299 the species were exposed. Yet, a given trait could be associated with opposite responses depending on the  
1300 pressure under consideration (González-Suárez et al., 2013).

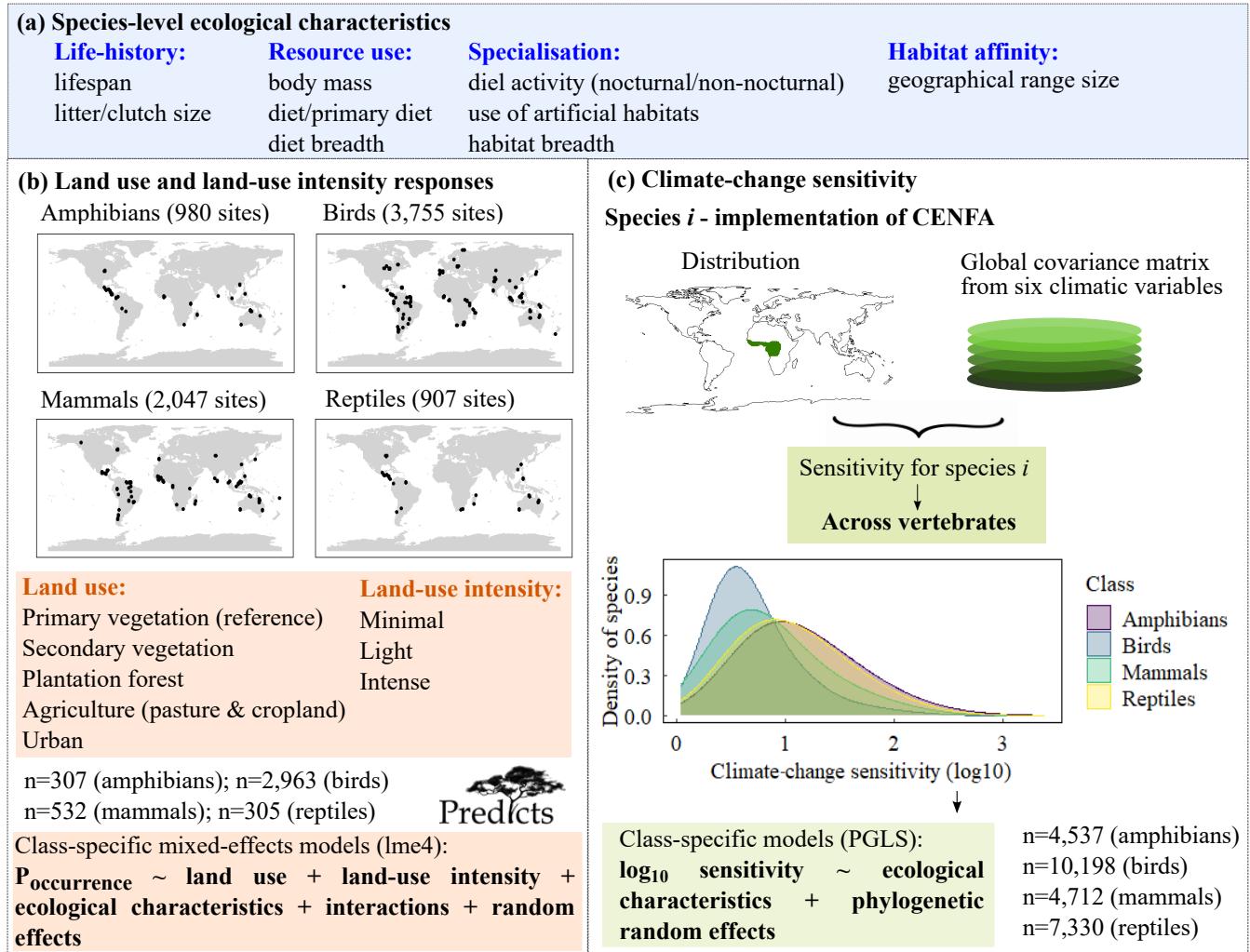
1301 Further, previous studies have often been restricted in their taxonomic coverage, with very few studies  
1302 considering several vertebrate classes together, so that comparative investigations among vertebrate classes  
1303 remain rare. In addition, there has not yet been a global assessment of the association between vertebrate  
1304 traits and both land-use responses and climate-change sensitivity. Here, I test whether general patterns in  
1305 species' land-use responses and climate-change sensitivity arise with regards to species traits. I include  
1306 species geographical range area in the analysis, as it is one aspect of rarity that has been shown to influence  
1307 species' responses to land use and to climate change (Newbold, 2018; Thuiller et al., 2005). Since geo-  
1308 graphical range area does not meet the strict definition of a trait, I henceforth refer to all traits and range  
1309 area as 'ecological characteristics'. Thus, I examine associations with a set of ecological characteristics that  
1310 are commonly measured across terrestrial vertebrates, at global scales (Figure 4.1a). Considering ecological  
1311 characteristics that are available at least for a subset of the species in each class allows for a cross-taxon  
1312 comparative assessment. Further, it also allows me to ask whether such commonly measured ecological  
1313 characteristics show consistent associations with species' land-use responses and climate-change sensitivity.  
1314 I ask two questions: (1) are any ecological characteristics associated with interspecific variation in responses  
1315 to land use and with climate-change sensitivity? (2) If so, are these ecological characteristics similar across

Performance  
in  
multiple  
models

1316 classes; are they similar between land-use responses and climate-change sensitivity; and are associations in  
1317 the same direction, such that I can identify a set of characteristics that are associated with a high sensitivity  
1318 of species to human pressures? Conversely, are such associations both taxon- and pressure- dependent?

1319 Given the different nature of the threats I consider, I use two independent approaches, one for land-use  
1320 change and one for climate-change sensitivity. Thus, I do not consider interactive effects between these  
1321 pressures. To infer species' responses to land-use change, I use a space-for-time substitution approach,  
1322 modelling occurrence probability across different land-use types (Figure 1b). I estimate species' expected  
1323 sensitivity to future climate change from properties of species' climatic niches (Figure 1c); species niche  
1324 properties have been shown to be strong indicators of species' climate-change sensitivity (Thuiller et al.  
1325 2005), and are also straightforward to use at large scales given the availability of species distribution data,  
1326 from which climatic niche spaces can be constructed. I then bring these two approaches together to look for  
1327 any emerging pattern in species' responses to land use or in their climate-change sensitivity, with regards to  
1328 species' ecological characteristics.

1329 Among the characteristics I consider (Figure 4.1a), some may directly influence species survival by me-  
1330 diating resource acquisition and use. These characteristics are body mass, diet, and diet breadth. Other  
1331 characteristics (e.g., lifespan and litter/clutch size) may indirectly affect species persistence over time by  
1332 influencing species reproductive output and demographic processes (Capdevila et al., 2022b). Finally, re-  
1333 sponds to human pressures are known to be dependent on species' degree of specialisation, which I capture  
1334 with characteristics reflecting specialisation in time (i.e., diel activity) and reflecting use of space (e.g., habi-  
1335 tation breadth and geographical range area).



**Figure 4.1: Framework of the study.** (a) I collected ecological trait data and geographical range areas across terrestrial vertebrates (termed ‘ecological characteristics’). I then used two independent approaches to assess the influence of these characteristics on species’ responses to land use and on species’ climate-change sensitivity. (b) To assess the influence of traits on responses to land use and land-use intensity in each vertebrate class, I combined the ecological characteristics with the PREDICTS database. (c) To estimate species’ sensitivity to climate change, I used the CENFA framework (Rinnan and Lawler, 2019), which relies on the combination of species’ distributions with climatic variables to estimate sensitivity from properties of the species’ climatic niche space. I then built class-specific models to assess whether the ecological characteristics were associated with species’ sensitivity to climate change.

1336 **4.2 Methods**

1337 **4.2.1 Ecological characteristics (Figure 4.1a)**

1338 **Traits**

1339 I obtained the six following traits from Chapter 2 (in which I presented a trait data compilation across  
1340 terrestrial vertebrates): body size (**body mass and/or length**, depending on the class); a proxy for species  
1341 lifespan (**generation length for mammals and birds; age at sexual maturity for amphibians; and maximum**  
1342 **longevity for reptiles**); litter or clutch size; diel activity; habitat breadth; and use of artificial habitats. I  
1343 chose these traits because 1) they were available across all vertebrate classes, at least for a subset of species,  
1344 allowing for a comparative assessment; and 2) they relate to species life-history, ecology, and resource use,  
1345 such that they might influence species' land-use responses and climatic niche properties (and thus expected  
1346 climate-change sensitivity). I could ~~not~~ capture intraspecific variation in trait values, and instead I used single  
1347 mean values for all traits.

Death traits?

Longevity

1348 I enhanced the trait data from Chapter 2 with species-level estimates of diet, lacking in the published  
1349 database but likely important for understanding species' sensitivity to human pressures. For birds and mam-  
1350 mals, I collected estimates of species primary diet (i.e., the diet inferred from the combination of food items  
1351 totalling more than 50% of species' consumption), from the EltonTraits database (Wilman et al., 2014). For  
1352 amphibians and reptiles, obtaining species *primary* diet was not possible, as there were no data available  
1353 on the relative consumption of different food items. For amphibians, the AmphiBIO database (Oliveira  
1354 et al., 2017) provided information on species consumption of different food items (just in terms of pres-  
1355 ence/absence in the diet, but without estimation of their percent use), so I inferred diet on the basis of these  
1356 reported food items (however the coverage was low, with more than 75% of the species missing diet infor-  
1357 mation; Appendix 3, Figure S4.1). For reptiles, there was no available data collection describing diet. For  
1358 both reptiles and amphibians, I supplemented the existing datasets with data on species consumption from  
1359 published sources (recording the presence/absence of different food items in species consumption; data com-  
1360 piled by Rhiannon Osborne-Tonner), for an additional 108 amphibians and for 239 reptiles (see Appendix 3,  
1361 S4.1: 'Compiling diet information').

How sure  
not  
involving?

1362 I standardised the diet data across the vertebrate classes, by grouping species in five different diet cate-  
1363 gories: vertebrate eaters; invertebrate eaters; plant/seed eaters; fruit/nectar eaters; and omnivores (for mam-  
1364 mals and birds, species were classified as omnivores when all food items had a percent use  $\leq 50\%$ ; and for  
1365 amphibians and reptiles, when species were known to consume both plant and animal matter, or both in-

1366 vertebrates and vertebrates). I also calculated species diet breadth – the total number of recorded food items  
1367 (in terms of presence/absence) known to be consumed by a species. More information on the compilation of  
1368 dietary information can be found in Appendix 3, S4.1: ‘Compiling diet information’.

### 1369 **Geographical range area**

1370 I used extent-of-occurrence maps from BirdLife International for birds (<http://datazone.birdlife.org/species/requestdis>), from the IUCN Red List for mammals and amphibians (IUCN, 2020), and  
1371 from Roll et al. (2017) for reptiles (all downloaded in April 2020). I excluded areas occupied during non-  
1372 breeding seasons and areas falling outside species known elevational limits (following Chapter 2). The range  
1373 maps were then converted to the raster format (‘raster’ package, version 3.5.15 Hijmans (2022)), and I esti-  
1374 mated species geographical range areas using a resolution of 1 km<sup>2</sup> with Behrmann’s equal-area projection.  
1375 Although range area cannot be considered a trait (which is a property measurable at the level of individual  
1376 organisms), I included range area in the analyses because past work has shown that range area is an important  
1377 correlate of species’ responses to land-use (Newbold et al., 2018) and climate change (Thuiller et al., 2005).  
1378 In addition, range area may correlate with other aspects of species’ ecology that I could not include directly  
1379 in the analysis because of limited data availability, such as dispersal ability (Capurucho et al., 2020).

Does not seem well justified what my analysis?

### 1381 **Phylogenies**

1382 I used information on species’ phylogenetic position in the imputations of missing trait values (see next  
1383 section), and also to control for phylogenetic relationships in the models investigating the association be-  
1384 tween species’ ecological characteristics and species’ estimated climate-change sensitivity. Class-specific  
1385 phylogenetic trees were downloaded April 2020 from <https://zenodo.org/record/3690867#.Xyc5wyhKhPZ> for mammals (Phylacine 1.2; Faurby et al. (2018, 2020)); and from <https://data.vertlife.org/> for amphibians (Jetz and Pyron, 2018), birds (Jetz et al., 2012) and squamates (Tonini  
1387 et al., 2016). For each class, I used a consensus tree obtained with the TreeAnnotator programme of the  
1388 BEAST software (Bouckaert et al. 2014), from an available distribution of 1000 trees.

#### 1390 **4.2.2 Imputations of missing trait values**

state here the any/mean/mode  
method

1391 For some of the traits and classes, there was a substantial proportion of missing trait values (Figure S4.1).  
1392 To fill these gaps, I imputed missing trait values using random forests, as implemented with the ‘missforest’  
1393 function of the ‘missForest’ package in R (version 1.4, Stekhoven (2016) and Stekhoven and Bühlmann  
1394 (2012)). ‘missforest’ is one of the best methods for missing-value imputations when working with continuous

1395 and categorical variables, and when including species phylogenetic position as a predictor (Debastiani et al.,  
1396 2021; Penone et al., 2014). After showing that several traits were strongly phylogenetically conserved  
1397 (Table S4.1), I included ten phylogenetic eigenvectors in the imputations (Penone et al., 2014), as well as  
1398 taxonomic orders as a categorical variable (included to account for the taxonomic positions of species that  
1399 were not represented in the phylogenies). Full details are given in Appendix 3 (S4.2: ‘Imputing missing  
1400 trait values’). After imputation, continuous traits were  $\log_{10}$ -transformed to improve normality (except for  
1401 habitat and diet breadth, which I square-root transformed; this transformation was more appropriate here  
1402 because the distributions of habitat breadth and diet breadth tended to be less right-skewed than that of the  
1403 other traits, and the range of values was smaller).

Did you validate imputation approaches?

#### 1404 4.2.3 Characterizing the influence of traits on species’ land-use responses (Figure 4.1b)

##### 1405 Vertebrate assemblage composition

1406 To compare vertebrate assemblages in different land-use types, I used the PREDICTS database (Hudson  
1407 et al., 2014, 2017). PREDICTS is a collection of independent studies that have sampled biodiversity in sites  
1408 of varying land use and land-use intensity. Samples are mostly of species abundance, sometimes species  
1409 occurrence, and rarely just overall species richness. It is one of the most comprehensive such databases  
1410 to date, with 4,107 vertebrate species sampled across 7,689 sites considered in this work (Figure 4.1b). In  
1411 PREDICTS, sites are assigned to one of the following land-use categories: primary vegetation (native vege-  
1412 tation); secondary vegetation, plantation forest, pasture, cropland, and urban (disturbed land uses; see Table  
1413 S4.2 and Hudson et al. (2014, 2017) for more details). Each site is also characterised in terms of land-use  
1414 intensity based on land-use-specific criteria (such as mechanisation degree, crop diversity and agricultural  
1415 inputs for cropland; Hudson et al. (2014)). Land-use intensity is divided into three categories to reflect the  
1416 degree of human transformation and impacts on the land: minimal, light or intense. Here, I considered  
1417 minimally-used primary vegetation to be the least-disturbed reference land use against which I compare all  
1418 other land-use types. I grouped pasture and cropland together into a category I termed ‘agricultural’. As the  
1419 design of the PREDICTS database is not balanced, sample sizes varied among classes and land-use types  
1420 (Figure S4.3).

##### 1421 Full models (all-predictor models)

1422 Within each vertebrate class, I investigated whether interactions among the ecological characteristics, land  
1423 use and land-use intensity explained species occurrence probability. I fitted four binomial mixed-effects

what hypotheses?  
Fishing  
expedition

1424 models (one for each class), using the ‘lme4’ package (version 1.1-23; Bates et al. (2015)), with random  
1425 effects accounting for study, site and species identity to account for the nested design of the database, taxo-  
1426 nomic non-independence, and repeated observations among species. I did not consider interactions among  
1427 the ecological characteristics, but I included interactions between land use and ecological characteristics, and  
1428 between land-use intensity and ecological characteristics. Before fitting the models, I checked the degree of  
1429 multicollinearity among explanatory variables using generalised variance inflation factors (GVIF; Fox and  
1430 Monette (1992)), with a threshold of 5 for the detection of multicollinearity (Tables S4.3-S4.8). For amphibi-  
1431 ans and reptiles, including both diet and diet breadth was problematic, so I excluded diet from the set of  
1432 predictors for these classes on the basis of the GVIF scores. Models investigating the effects of diet were  
1433 built separately (see next section, ‘Partial models’).

1434 I did not use phylogenetic random effects directly in the models because of the computational load re-  
1435 quired by such models when working with several hundred or thousands of species. However, I checked the  
1436 phylogenetic signal in the models’ residuals using Pagel’s  $\lambda$  (Pagel, 1999). Thus, in each class, the model  
1437 fitted was:

1438

1439  $P_{\text{occurrence}} \sim \text{land use} + \text{land-use intensity} + \text{species-level ecological characteristics} +$   
1440  $\text{land use : species-level ecological characteristics} +$   
1441  $\text{land-use intensity : species-level ecological characteristics} +$   
1442  $(1|\text{study identity}) + (1|\text{site identity}) + (1|\text{species identity}).$

1443

1444 To verify that the models’ estimates were robust to any violation of distributional assumptions, I fitted  
1445 the models again using a Bayesian framework (using the ‘MCMCglmm’ package version 2.32, Hadfield  
1446 (2010)).

#### 1447 **Partial models (single-predictor models)**

1448 In addition to the full models, I fitted partial models for each class. These were fitted to visualise occurrence  
1449 patterns for each trait independently of other traits. The structure of the models was similar to that of the full  
1450 models, except that I included a single species-level characteristic at a time in each model.

#### 1451 **Effects of categorical ecological characteristics on species’ occurrence probability (Figure 4.2a)**

1452 The influence of categorical traits on species’ responses to land use and land-use intensity can be visualised  
1453 in two ways: either by comparing occurrence probability in different land-use types relative to species with

Weak  
w/t's  
dissim

1454 similar traits (I term such effects ‘among land-use type effects’, Figure 4.2a); or by comparing occurrence  
1455 probability in a given land-use type relative to species with different traits (I term such effects ‘within land-  
1456 use type effects’, Figure 4.2a).

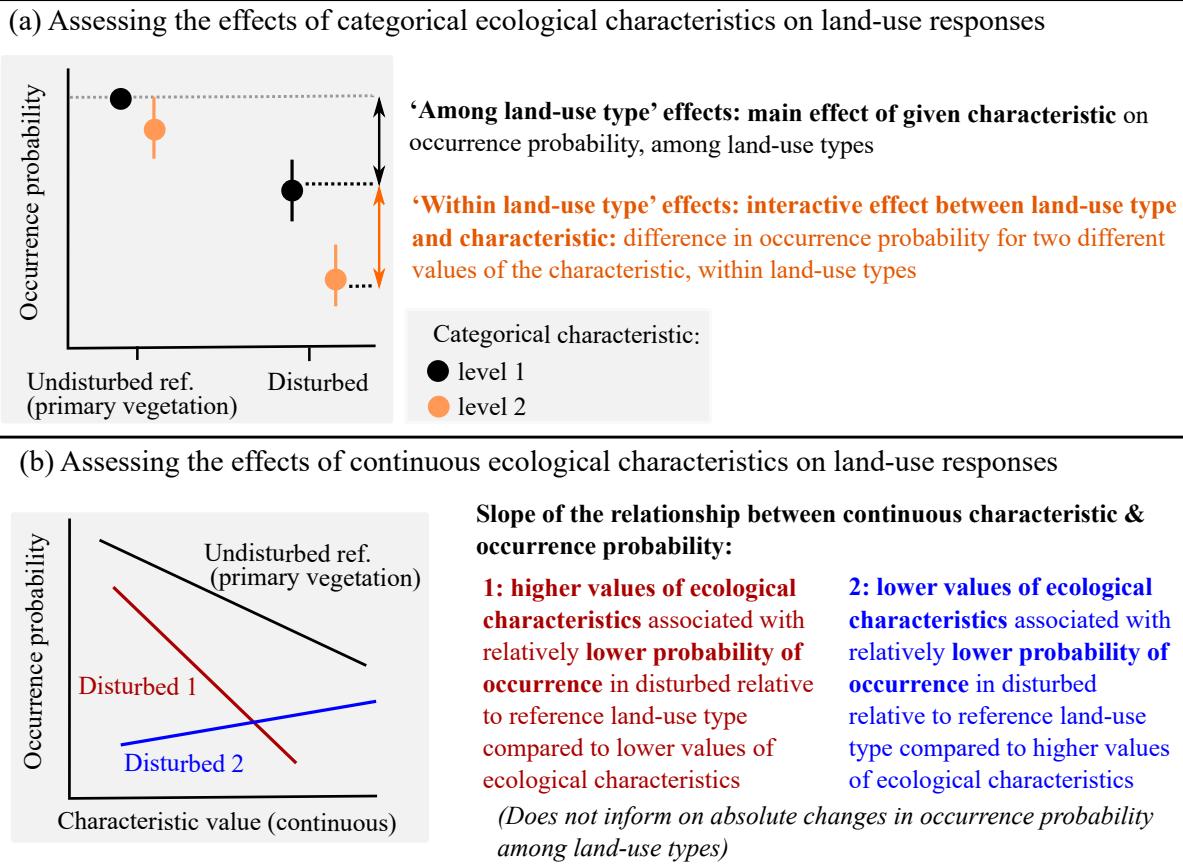
- 1457
- Within land-use type effects (Figure 4.2a): from the full, all-predictor models fitted for each class, I  
1458 focused on the interactive effects between land use and ecological characteristics (and between land-  
1459 use intensity and ecological characteristics). These interactions indicated whether, in a given land-use  
1460 type, there were any significant differences in occurrence probability between species with different  
1461 traits. In other words, I looked at whether any trait level lowered or increased occurrence probability  
1462 in each land-use type, compared to a reference trait level. I used this approach for all the categorical  
1463 predictors, except diet (interpreting within land-use type effects for primary diet being complicated by  
1464 the fact that there were more than two levels for this trait).

1465

  - Among land-use type effects (Figure 4.2a): from a partial model, I predicted occurrence probability  
1466 in the different land uses for all different levels of the trait. The partial models allowed to visualise  
1467 occurrence patterns across land-use types for single explanatory variables, without having to account  
1468 for the values of other variables. I used this approach to evaluate the influence of diet on species’  
1469 land-use responses.

1470 **Effects of continuous ecological characteristics on species’ occurrence probability (Figure 4.2b)**

1471 For a given continuous ecological characteristic, any effect of land use or land-use intensity can be as-  
1472 sessed through changes in the slope of the relationship between the ecological characteristic and occurrence  
1473 probability (Figure 4.2b). When an ecological characteristic negatively impacts occurrence probability in a  
1474 disturbed land use, I expect the slope of the relationship to be more negative than the slope for the reference  
1475 land use (minimally-used primary vegetation). Focussing on slopes does not allow to infer absolute changes  
1476 in occurrence probability across land-use types (e.g., a positive slope in a disturbed land use does not mean  
1477 that there are absolute increases in occurrence probability in that land use, but only that higher values of the  
1478 ecological characteristic are associated with relatively higher occurrence probability in that land-use type).  
1479 This is because I do not assess changes in the mean occurrence probability here (which would require to  
1480 consider the intercept of the relationship between the ecological characteristic and occurrence probability in  
1481 different land-use types). Thus, I only capture ‘within land-use type’ effects for continuous predictors.



**Figure 4.2: Assessing the effects of ecological characteristics on species’ land-use responses: methodology for (a) categorical characteristics and (b) continuous characteristics.** (a) For all categorical characteristics, except diet, I look at ‘within land-use type’ effects, asking whether there are significant differences in occurrence probability among species with different ecological characteristics in a given land-use type. For diet, I look at ‘among land-use type’ effects, comparing species occurrence probability in disturbed land uses versus that in primary vegetation (I chose this approach here because visualising ‘within land-use type’ effects for diet is complicated by the fact that there were more than two levels for this categorical trait). (b) For continuous characteristics, I focus on the relationship with occurrence probability, and I investigate how the slope of this relationship is affected by land-use type, i.e. a ‘within land-use type’ effect.

#### 1482 Validation on complete trait data subset (no imputed trait values)

1483 To assess whether the results were robust to trait imputation uncertainty, I fitted the models again for the  
 1484 subset of species for which I had complete, non-imputed data for all ecological characteristics. The models’  
 1485 structure was unchanged for birds and mammals. For amphibians, I excluded both diet and litter/clutch size  
 1486 because of multicollinearity issues, and I also excluded lifespan proxy and body mass (as there were too  
 1487 many missing values in the dataset, 85% and 59% respectively). For reptiles, I excluded both diet and body  
 1488 mass because of multicollinearity issues.

1489 **4.2.4 Characterizing the influence of traits on species' sensitivity to climate change (Figure**  
1490 **4.1c)**

1491 I estimated climate-change sensitivity across vertebrate species using the 'Climate-niche Factor Analysis'  
1492 (CENFA) approach developed by Rinnan and Lawler (2019), implemented with the 'CENFA' R package  
1493 version 1.1.1 (Rinnan, 2021). CENFA is a spatial approach for estimating species' climate-change sensitivity,  
1494 exposure, and vulnerability. CENFA combines distribution data with climatic variables to estimate sensitivity  
1495 and vulnerability from properties of species' climatic niches (see Rinnan and Lawler (2019) for details).  
1496 CENFA has been used in previous studies focused on a small number of species or on a few taxonomic  
1497 groups, but to my knowledge has not yet been applied across all terrestrial vertebrates.

*+ details  
missing*

1498 **Historical climate data** *Give context to the results → What for?*

1499 I used global climate data from WorldClim version 2.1 (Fick and Hijmans, 2017). I downloaded 19 climatic  
1500 variables at a resolution of 2.5 arcminutes ( $\sim 4.6 \text{ km}^2$  at the Equator). I removed variables that were strongly  
1501 collinear with any other climatic variables (using a threshold of 0.65 for Spearman correlation coefficients).  
1502 I obtained six groups of intercorrelated variables (using the 'removeCollinearity' function from the 'virtu-  
1503 alspecies' R package version 1.5.1 (Leroy et al., 2015); Figure S4.4), and randomly selected one climatic  
1504 variable in each group. The final set comprised six climatic variables: annual mean temperature (bio1), mean  
1505 diurnal temperature range (bio2), maximum temperature of the warmest month (bio5), annual precipitation  
1506 (bio12), precipitation seasonality (bio15), and precipitation of the coldest quarter (bio19).

1507 **Estimating climate-change sensitivity from CENFA**

1508 All climatic variables and distribution files were re-projected to a resolution of  $5 \text{ km}^2$  in the Behrmann  
1509 equal-area projection. I picked this resolution because the coarser the resolution, the more climate-change  
1510 sensitivity tended to be underestimated for narrowly distributed species (Figures S4.5 & S4.6). However,  
1511 finer resolutions demand a large amount of memory space when working at global scales across all terrestrial  
1512 vertebrates. I found the  $5\text{-km}^2$  resolution to be an acceptable trade-off between computational load and  
1513 accuracy of the sensitivity estimations. However, when working at  $5\text{-km}^2$  resolution, there were still some  
1514 narrowly distributed species for which sensitivity was likely underestimated (Figure S4.6). Thus, I chose to  
1515 exclude species with a range area  $\leq 100 \text{ km}^2$  from further analyses (i.e., excluding narrow-ranging species  
1516 whose distributions could intersect up to 4 grid cells). In doing so, the sample size was reduced by 660  
1517 species for amphibians, by 142 species for birds, by 129 species for mammals, and by 615 species for

1518 reptiles (the final sample sizes were: n=4,537 for amphibians; n=10,198 for birds; n=4,721 for mammals;  
1519 n=7,330 for reptiles). My results were overall robust to the exclusion of these species (see Results section).

1520 I then combined the climate data with the species' distributions to estimate sensitivity to climate change,  
1521 applying the CENFA framework across terrestrial vertebrates (Figure 4.1c). Further details of the imple-  
1522 mentation of the CENFA framework are given in Appendix 3 (S4.5: 'Implementing Climate-niche Factor  
1523 Analysis across terrestrial vertebrates').

#### 1524 **Climate-change sensitivity models**

1525 I used phylogenetic least-square (PGLS) regressions, implemented in the 'caper' R package version 1.0.1  
1526 (Orme et al., 2018), to assess the effects of ecological characteristics on species' estimated sensitivity to  
1527 climate change, while controlling for phylogenetic relationships among species. I combined the ecological  
1528 characteristics and the phylogenies using the 'comparative.data' function from the 'caper' package, and then  
1529 built class-specific models to explain climate-change sensitivity with the ecological characteristics (Figure  
1530 4.1c). Before fitting the models, I checked for multicollinearity among the predictors using GVIF scores.  
1531 Across all classes, the models included all the main effects of the ecological characteristics, except for am-  
1532 phibians, for which I dropped diet breadth (which was strongly collinear with diet; Tables S4.9-S4.13). For  
1533 the continuous predictors, I fitted third-order polynomials to allow for non-linearity of the responses (I in-  
1534 cluded third order polynomials for the climate-change sensitivity models but not for the land-use models  
1535 because the PGLS model had a simpler structure than the land-use models, were less computationally inten-  
1536 sive, and also because the number of estimated parameters was already high for the land-use models without  
1537 allowing for third-order polynomials). As such, the general form of the PGLS models was:

1538  $\log_{10}(\text{climate-change sensitivity}) \sim \text{poly}(\log_{10}(\text{continuous ecological characteristics}), 3) +$

1539 categorical ecological characteristics +

1540 phylogenetic random effects.

Demonstrate  
not overparametrised

#### 1541 **Models' robustness**

1542 To check whether the results were robust to the exclusion of species whose range area was  $\leq 100 \text{ km}^2$ , I  
1543 repeated the models on all species (including those with range area  $\leq 100 \text{ km}^2$ : n=5,208 for amphibians;  
1544 n=10,340 for birds; n=4,844 for mammals; n=7,951 for reptiles)... and?

1545 Finally, to assess the degree to which the results were robust to trait imputation uncertainty, I fitted the  
1546 models again for the subset of species for which I had empirical (i.e., non-imputed) trait estimates. Diet  
1547 was excluded for amphibians and reptiles on the basis of high collinearity (GVIF>5). I fitted first-order

Explains why

1548 polynomials here because of the substantially reduced sample size compared to the main models.

## 1549 4.3 Results

### 1550 4.3.1 Land-use responses

#### 1551 'Within land-use type' effects (Table 4.1a)

1552 Land-use, land-use intensity, species' ecological characteristics and their interactions had significant effects  
1553 on species occurrence probability. Significant interactive effects between land use and ecological charac-  
1554 teristics (and between land-use intensity and ecological characteristics) reflected differences in the ability  
1555 of species with different ecological characteristics to cope within the disturbed land-use types (Table 4.1a).  
1556 Across all classes, species with narrower geographical range areas, smaller habitat breadth and inability to  
1557 exploit artificial habitats showed greater decreases in occurrence probability within disturbed land uses, than  
1558 species with larger range areas, larger habitat breadth and ability to exploit artificial habitats (the only ex-  
1559 ceptions were opposite effects found for mammals and reptiles for habitat breadth in two of the land-use  
1560 types). The effects of the other ecological characteristics differed in direction depending on class and land  
1561 use, impeding any generalisation (Table 4.1a). For instance, I found that being smaller and longer-lived was  
1562 associated with decreases in occurrence probability for birds found in agricultural areas, but with increases  
1563 in occurrence probability for urban birds; and that longer-lived species tended to be more negatively affected  
1564 for mammals and reptiles, whereas I found evidence of opposite trends for amphibians.

Misratation?

1565 I would like to highlight that the 'within land-use type' effects summarised in Table 4.1a do not nec-  
1566 essarily reflect occurrence patterns among land-use types. For example, in all classes, 'among land-use  
1567 type' effects derived from partial models showed that occurrence probability in disturbed land uses was  
1568 strongly negatively affected for natural habitat specialists, compared with primary vegetation levels (Figure  
1569 S4.7). On the other hand, in most classes and disturbed land uses, artificial habitat users either increased or  
1570 showed no significant difference in occurrence probability. One exception was for reptiles, where the effect  
1571 of habitat specialisation was mostly non-significant within land-use types (Table 4.1a), with both natural  
1572 habitat specialists and artificial habitat users showing important declines in some disturbed land uses (e.g.,  
1573 intensely-used agricultural areas, Figure S4.7d). Similarly, the occurrence probability of both nocturnal and  
1574 non-nocturnal species was negatively impacted in disturbed land uses compared with primary vegetation  
1575 (Figure S4.8), such that land-use responses were not distinguishable between nocturnal and non-nocturnal  
1576 species for all classes and land-use types.

Complement w/ a diagram of expectations too

**Table 4.1: Summary of the effects of the ecological characteristics (except for primary diet) on (a) species' responses to disturbed land uses ('within land-use type' effects) and (b) species' climate-change sensitivity, for each class of terrestrial vertebrates.** The symbol - indicates where a characteristic has a significant negative effect on occurrence probability within a disturbed land-use type (within any of the land-use intensities), or where the characteristic renders species significantly more sensitive to climate change. A + indicates a significantly positive effect of a characteristic on occurrence probability in a land-use type (within any of the land-use intensities), or significantly lower sensitivity to climate change. For the land-use effects, I report 'within land-use type' effects here, that is, within a disturbed land use whether there were significant differences in occurrence probability among species with different trait values (see Figure 4.2). These effects were derived from the interactive terms of the full, all-predictor models.

Predictors															(b) Climate-change sensitivity: - <=> more sensitive + <=> less sensitive					
(a) "Within land-use type" effects of the species-level characteristics on occurrence probability - <=> more sensitive; + <=> less sensitive															(b) Climate-change sensitivity: - <=> more sensitive + <=> less sensitive					
Secondary vegetation			Plantation forest				Agricultural				Urban				Habitat affinity	Specialisation	Resource use	Life-history		
-	-	-	-	(-)	-	0	-	0	-	-	-	0	-	0	NA	More narrowly-distributed	-	-	-	-
0	-	0	+	-	-	-	0	-	-	0	-	0	-	+	NA	Smaller habitat breadth	-	-	-	-
-	-	(-)	-	-	-	0	0	-	-	-	0	0	-	-	NA	Natural habitat specialist	(-)	-	-	-
0	+	+	-	-	+	0	+	-	+	+	-	0	0	0	NA	Non-nocturnal	-	0	0	(+)
-	0	+	(-)	-	0	+	+	-	0	0	+	0	-	0	NA	Narrower diet breadth	NA	0	-	0
0	0	+	0	(+)	+	+	0	0	-	0	-	0	+	0	NA	Smaller body mass	-	+	-	-
+	0	0	0	0	-	0	0	+	-	0	0	0	0	-	NA	Smaller litter/clutch size	-	+	+	0
(-)	0	(+)	+	0	0	0	+	-	+	(+)	+	0	-	0	NA	Shorter-lived	(+)	-	0	-

1577 **Effects of diet on species' occurrence probability (Figure 4.3)**

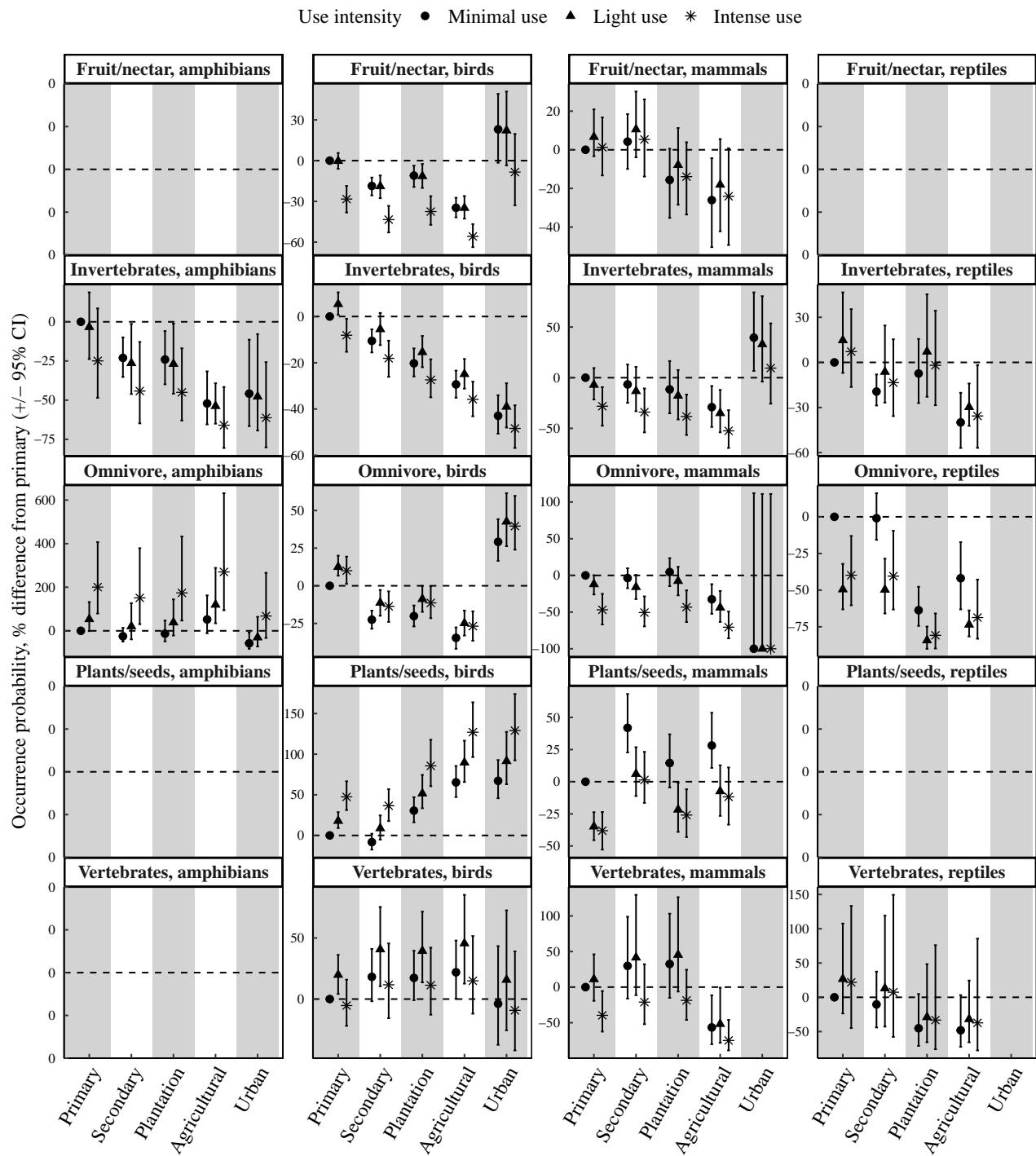
1578 In all classes, diet had significant effects on occurrence probability in disturbed land uses (Figure 4.3).  
1579 Changes in occurrence probability in disturbed land uses differed among classes and dietary groups. Overall,  
1580 invertebrate eaters tended to be negatively affected in disturbed land uses (e.g., -66% average declines in  
1581 occurrence probability for amphibians in intensely used agricultural areas, compared with minimally-used  
1582 primary vegetation). Omnivores were both negatively and positively impacted, showing both important  
1583 decreases (e.g., -81% for reptiles in intensely used plantation forest) as well as strong increases (e.g., +43%  
1584 for lightly used urban areas in birds). Overall, fruit/nectar eaters showed important declines in occurrence  
1585 probability for mammals and birds, as opposed to plants/seeds eaters, whose occurrence probability tended  
1586 to be strongly positively affected for birds, and dependent on land-use intensity for mammals (with increases  
1587 in minimally-used land-types, but not in more intensely-used land-types). Finally, I also detected significant  
1588 changes in occurrence probability for vertebrate eaters, with some declines for mammals in agricultural areas  
1589 (-75% on average in intense uses), but also some increases (e.g., +43% on average for birds in lightly used  
1590 agricultural areas).

1591 **Explanatory power for the full models & variance explained by each characteristic (Figure 4.4)**

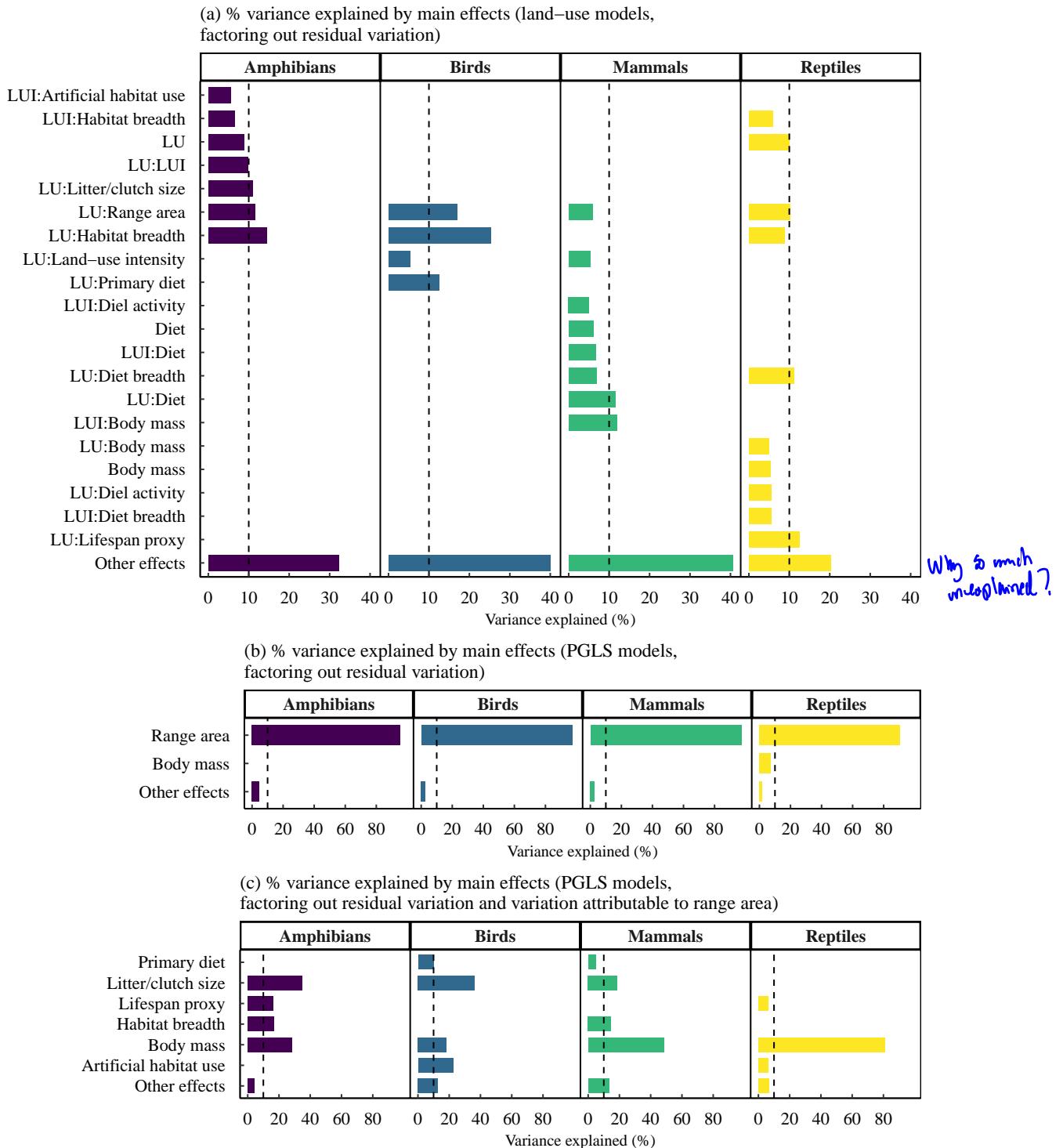
1592 Overall, land use, land-use intensity and the ecological characteristics explained a small amount of the total  
1593 variation in species' occurrence probability (marginal R<sup>2</sup>: 0.15 for amphibians; 0.054 for birds; 0.15 for  
1594 mammals; 0.13 for reptiles), in part because the random effects explained a substantial proportion (condi-  
1595 tional R<sup>2</sup>: 0.59 for amphibians; 0.61 for birds; 0.72 for mammals; 0.57 for reptiles). The relative importance  
1596 of traits explaining the most variation differed among classes, with interactions between land use and habitat  
1597 breadth explaining the most variation in amphibians and birds, but interactions between land use and body  
1598 mass explaining the most variation for mammals, and interactions between land use and lifespan explaining  
1599 the most variation for reptiles (Figure 4.4a).

1600 Finally, the models' diagnostics showed evidence of deviations from distributional assumptions (diag-  
1601 nistic plots for the full models are shown in Figures S4.9-S4.12). However, when estimated from a Bayesian  
1602 framework, the models' estimates were mostly congruent (results not shown), so the frequentist approach I  
1603 used with 'lme4' was robust despite the deviations from distributional assumptions. The phylogenetic sig-  
1604 nals in the models' residuals were low and not significant (Pagel's  $\lambda < 0.01$  for amphibians and reptiles,  $p \approx$   
1605 1;  $\lambda = 0.13$  for mammals,  $p = 0.09$ ;  $\lambda = 0.01$  for birds,  $p = 0.56$ ), despite not having included phylogenetic  
1606 random effects.

Vindear



**Figure 4.3: Predicted occurrence probability as a function of land use, land-use intensity, diet and their interactions, for each class of terrestrial vertebrates** (mean  $\pm$  95% confidence interval; the predictions are rescaled with reference to minimally-used primary vegetation). The predictions were obtained from the partial models fitted for each class, considering only diet among the ecological characteristics. Empty plots are drawn where there were no data for a diet category for a given class. Effects could not be estimated for urban reptiles, as well as for urban vertebrate, fruit/nectar and plant/seed eaters for mammals because there were no sampled species. Primary: primary vegetation; Secondary: secondary vegetation; Plantation: plantation forest; Agricultural: cropland and pasture.

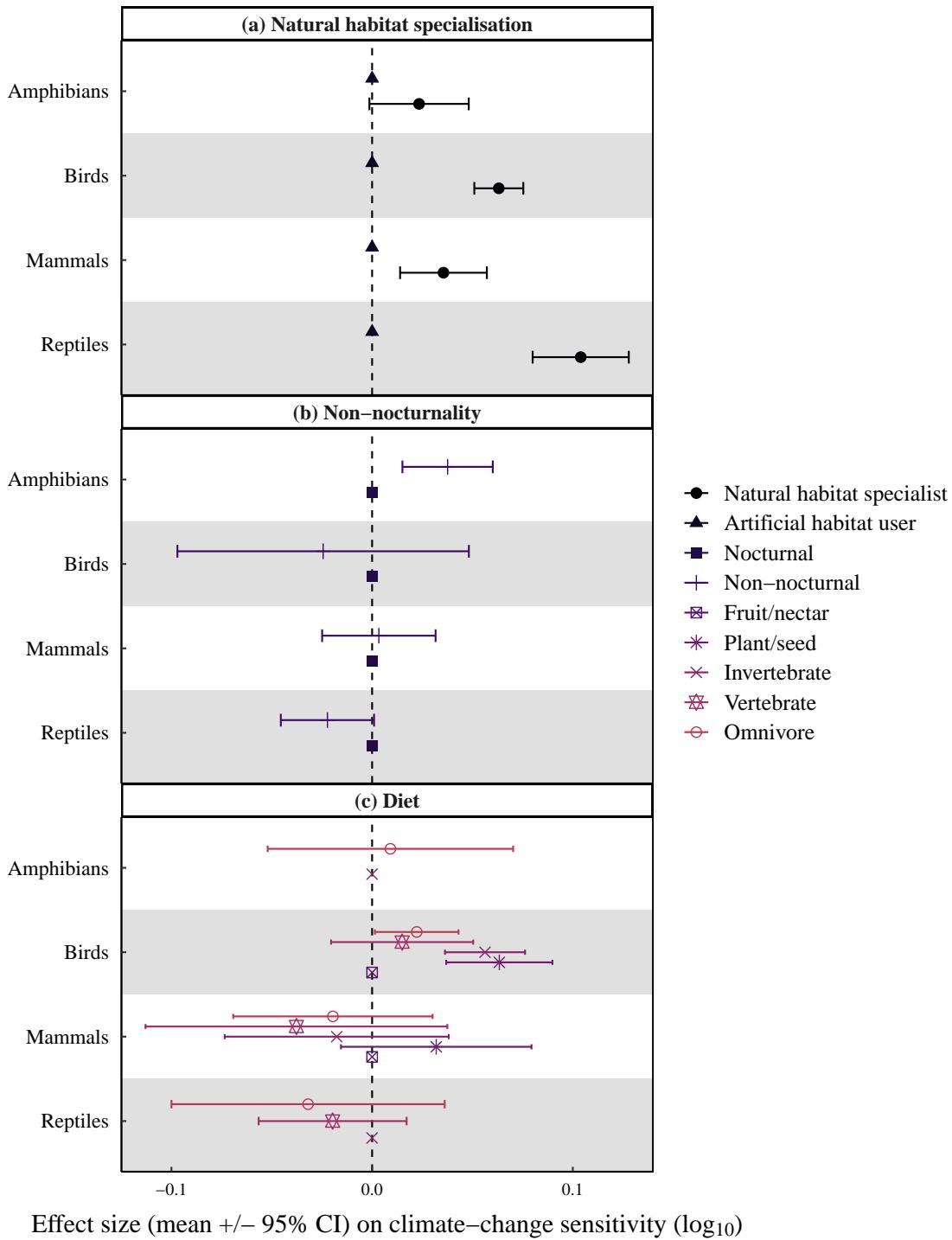


**Figure 4.4: Proportion of the explained variance attributable to each of the main effects for (a) the mixed-effects models fitting the effects of land use, land-use intensity, and ecological characteristics on species occurrence probability (after factoring out residual variation); (b) for the phylogenetic least-squares regressions investigating whether the ecological characteristics explained climate-change sensitivity (after factoring out residual variation); and (c) for the phylogenetic least-squares regressions investigating whether the ecological characteristics explained climate-change sensitivity (after factoring out the variance explained by geographical range area and the residual variation). The dashed vertical lines mark 10% explained variance (for visualisation purposes). I individually show all the effects that explain more than 5% of the overall variation. Effects that individually explain less than 5% of the overall variation are grouped together as 'Other effects'. LU: land use; LUI: land-use intensity.**

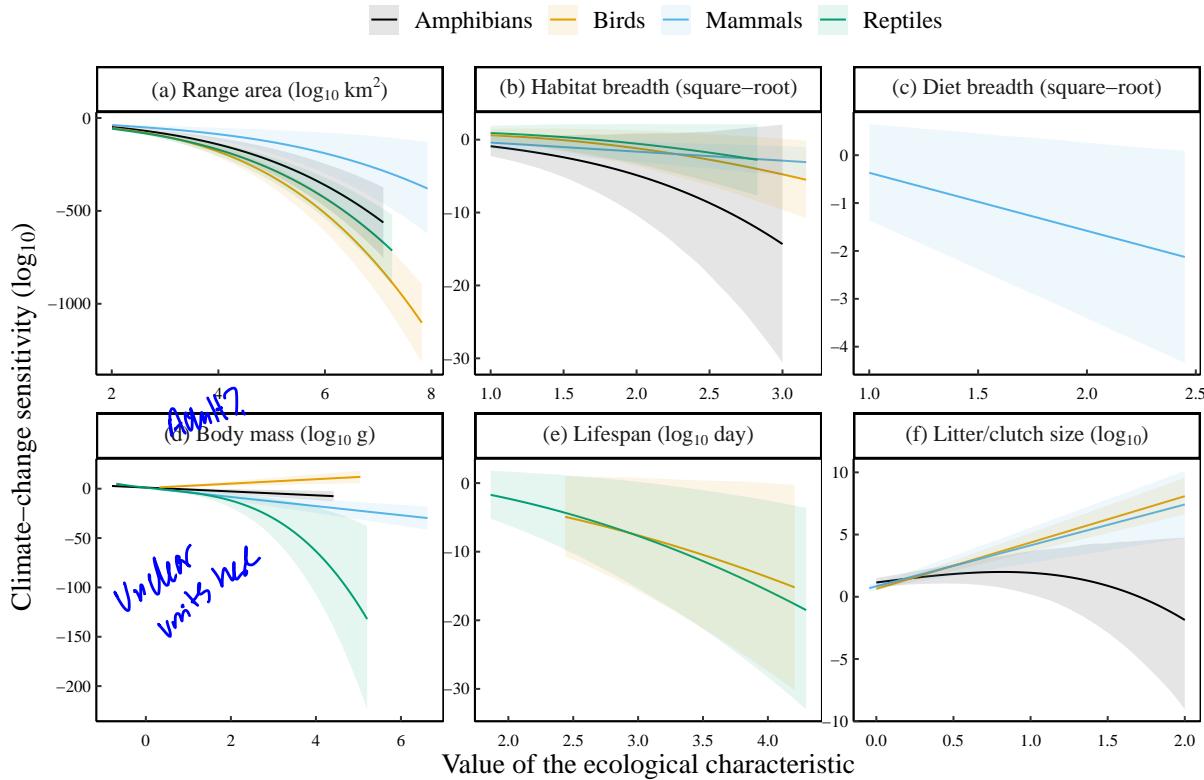
1607 **4.3.2 Climate-change sensitivity**

1608 The ecological characteristics were significantly associated with climate-change sensitivity in all classes  
1609 (Tables 4.1b & 4.2, Figures 4.5 & 4.6); models' coefficients shown in Tables S4.14-S4.17). Overall, climate-  
1610 change sensitivity was highest for amphibians (median  $\log_{10}$ -sensitivity: 1.1; 95% interpercentile range:  
1611 0.40-2.2), then reptiles (median  $\log_{10}$ -sensitivity: 1.0; 95% interpercentile range: 0.32-2.1), then mammals  
1612 (median  $\log_{10}$ -sensitivity: 0.76; 95% interpercentile range: 0.22-2.0) and birds (median  $\log_{10}$ -sensitivity:  
1613 0.62; 95% interpercentile range: 0.21-1.77). In all classes, narrower geographical range area, smaller habitat  
1614 breadth and being specialised on natural habitats were consistently associated with higher climate-change  
1615 sensitivity (Table 4.1b). However, other characteristics did not have consistent associations with climate-  
1616 change sensitivity across classes, in different cases varying in both significance and direction. For instance,  
1617 I found opposite associations between body mass and climate-change sensitivity for mammals, amphibians  
1618 and reptiles on the one hand, and birds on the other hand.

1619 The PGLS models explained an important proportion of the overall variation in estimated climate-change  
1620 sensitivity (adjusted  $R^2 = 0.64$  for amphibians; 0.62 for birds; 0.63 for mammals and reptiles). Geographical  
1621 range area explained the majority of this variation in climate-change sensitivity (about 60% in all classes;  
1622 Figure 4.4b), which largely reflects the design of the CENFA approach. When factoring out residual variation  
1623 and variation explained by geographical range area, the relative importance of the traits as correlates of  
1624 climate-change sensitivity varied among classes (Figure 4.4c), with body mass explaining the most variation  
1625 for mammals and reptiles, and litter/clutch size explaining the most variation for amphibians and birds.



**Figure 4.5: Estimated effects of the categorical traits on climate-change sensitivity, from the PGLS models fitted in each class (mean effect  $\pm$  95% confidence interval).** For each categorical trait, I show the effect size for all levels referring to the reference level (vertical dashed line). (a) For artificial habitat use, the reference level is ‘Artificial habitat user’; (b) for diel activity, the reference level is ‘Nocturnal’; (c) for diet, the reference level for mammals and birds is ‘Fruit/nectar’ eaters, but it is ‘Invertebrate’ eaters for amphibians and reptiles.



**Figure 4.6: Effects of the continuous ecological characteristics on climate-change sensitivity, estimated from the PGLS models in each class.** The lines represent the estimated relationships between climate-change sensitivity and ecological characteristics; the shaded areas are 95% confidence intervals. I plotted the estimated relationships only when they were found to be significant.

## 1626 Robustness of the PGLS models

1627 The PGLS models were robust to distributional assumptions (Figures S4.13-S4.16). When fitting the models  
 1628 on all species (including those with range area  $\leq 100\text{km}^2$ ), I found that the relationship between climate-  
 1629 change sensitivity and geographical range area was reversed in all classes (with smaller-ranging species  
 1630 estimated to be less sensitive). This result is likely an artefact caused by the underestimation of climate-  
 1631 change sensitivity for the most narrow-ranging species, which would support the exclusion of such species  
 1632 from the analysis. Other results were generally not sensitive to the exclusion of species whose range area  
 1633 was  $\leq 100\text{ km}^2$  (Figure S4.17).

**Table 4.2: ANOVA summaries for the PGLS models investigating the associations between the species-level ecological characteristics and species' estimated climate-change sensitivity.**

Class	Model terms	Df	Sum Square	Mean Square	F-value	Pr(>F)
Amphibians	poly(log <sub>10</sub> (Body mass, 3))	3	9.85E-02	3.28E-02	3.41E+01	9.03E-22 ***
	poly(log <sub>10</sub> (Lifespan proxy), 3)	3	5.62E-02	1.87E-02	1.94E+01	1.60E-12 ***
	poly(log <sub>10</sub> (Litter/clutch size), 3)	3	1.22E-01	4.07E-02	4.22E+01	6.68E-27 ***
	poly(log <sub>10</sub> (Range area), 3)	3	7.30E+00	2.43E+00	2.52E+03	0.00E+00 ***
	poly(sqrt(Habitat breadth), 3)	3	5.86E-02	1.95E-02	2.03E+01	4.69E-13 ***
	Specialisation	1	3.17E-03	3.17E-03	3.29E+00	6.96E-02 .
	Diel activity	1	1.03E-02	1.03E-02	1.07E+01	1.07E-03 **
Birds	Diet	3	8.61E-04	2.87E-04	2.98E-01	8.27E-01
	poly(log <sub>10</sub> (Body mass, 3))	3	5.78E-02	1.93E-02	2.87E+01	1.87E-18 ***
	poly(log <sub>10</sub> (Lifespan proxy), 3)	3	1.55E-02	5.18E-03	7.70E+00	3.87E-05 ***
	poly(log <sub>10</sub> (Litter/clutch size), 3)	3	1.15E-01	3.83E-02	5.70E+01	1.63E-36 ***
	poly(log <sub>10</sub> (Range area), 3)	3	1.10E+01	3.66E+00	5.45E+03	0.00E+00 ***
	poly(sqrt(Habitat breadth), 3)	3	1.29E-02	4.30E-03	6.39E+00	2.53E-04 ***
	poly(sqrt(Diet breadth), 3)	3	1.01E-02	3.38E-03	5.02E+00	1.77E-03 **
Mammals	Specialisation	1	7.10E-02	7.10E-02	1.06E+02	1.15E-24 ***
	Diel activity	1	1.58E-03	1.58E-03	2.34E+00	1.26E-01
	Primary diet	4	3.15E-02	7.88E-03	1.17E+01	1.70E-09 ***
	poly(log <sub>10</sub> (Body mass, 3))	3	9.00E-02	3.00E-02	3.44E+01	5.41E-22 ***
	poly(log <sub>10</sub> (Lifespan proxy), 3)	3	7.32E-03	2.44E-03	2.80E+00	3.85E-02 *
	poly(log <sub>10</sub> (Litter/clutch size), 3)	3	3.46E-02	1.15E-02	1.32E+01	1.33E-08 ***
	poly(log <sub>10</sub> (Range area), 3)	3	6.83E+00	2.28E+00	2.61E+03	0.00E+00 ***
Reptiles	poly(sqrt(Habitat breadth), 3)	3	2.73E-02	9.11E-03	1.05E+01	7.50E-07 ***
	poly(sqrt(Diet breadth), 3)	3	8.64E-03	2.88E-03	3.31E+00	1.94E-02 *
	Specialisation	1	8.99E-03	8.99E-03	1.03E+01	1.33E-03 **
	Diel activity	1	6.08E-06	6.08E-06	6.98E-03	9.33E-01
	Primary diet	4	9.32E-03	2.33E-03	2.67E+00	3.04E-02 *
	poly(log <sub>10</sub> (Body mass), 3)	3	8.53E-01	2.84E-01	3.18E+02	3.24E-194 ***
	poly(log <sub>10</sub> (Lifespan proxy), 3)	3	6.40E-02	2.13E-02	2.39E+01	2.25E-15 ***

1634 **4.3.3 Validations on complete trait data**

1635 Running the land-use and PGLS models again using data subsets for which I had empirical, non-imputed  
1636 values only for the ecological characteristics showed that the conclusions of this work are likely robust  
1637 to imputation uncertainty. Overall, across all classes, the associations of geographical range area, habitat  
1638 breadth and use of artificial habitats with sensitivity to climate change and land-use responses were consistent  
1639 with the main models (Table S4.10, Figure S4.18).

1640 **4.4 Discussion**

1641 Here, I investigated whether species' ecological characteristics were associated with species' sensitivity to  
1642 two human pressures (climate change and land-use change), across terrestrial vertebrate classes. Overall, I  
1643 found that geographical range area, habitat breadth and specialisation on natural habitats were consistently  
1644 associated with sensitivity to both pressures across terrestrial vertebrate classes: narrower ranges, narrower  
1645 habitat breadth and inability to exploit artificial habitats were associated with more negative land-use re-  
1646 sponds and with higher climate-change sensitivity. My results are in line with previous meta-analyses that  
1647 have found species' extinction risks to be associated with habitat breadth and range area (Chichorro et al.,  
1648 2019), range shifts under contemporary climate change to be associated with species' historical range limits  
1649 and habitat breadth (MacLean and Beissinger, 2017), and with many other studies on land-use responses or  
1650 extinction risks (Newbold et al., 2018; Nowakowski et al., 2017; Purvis et al., 2000; Ripple et al., 2017).  
1651 However, to the best of my knowledge, this work constitutes the first global study to compare patterns among *vulnerability*  
1652 vertebrate classes and between the two major human pressures of climate change and land use. The results  
1653 of this Chapter have important implications for conservation, as they mean that land-use and climate change  
1654 are non-randomly affecting all terrestrial vertebrates, with a consistently higher risk for geographically rarer  
1655 species and habitat specialists. Geographical rarity has been employed by the IUCN for many years in vul-  
1656 nerability assessments (Rodrigues et al., 2006), and this work provides further support for its integration in  
1657 large-scale assessments. My results also lend support to the idea that habitat specialisation is a likely indica-  
1658 tor of species' sensitivity to both land-use and climate change across all vertebrates, thus indices reflecting  
1659 habitat specialisation should be highly relevant to consider in large-scale vulnerability assessments, as done  
1660 by Foden et al. (2013).

1661 This work further highlights the class-specific associations between most traits and likely responses to  
1662 human-driven environmental changes, but again highlighting a non-random reshaping of vertebrate biodi-  
1663 versity under global changes. In the case of land use, I find that the directionality of the responses not only

1664 often depends on taxonomic class but also on land-use type, further complicating the patterns. In line with  
1665 past work highlighting the low explanatory power of traits when used to explain species' responses to human  
1666 pressures (Angert et al., 2011; Cannistra and Buckley, 2021; Verberk et al., 2013), I found that most traits  
1667 explained a small proportion of the interspecific variation in land-use responses and in climate-change sensi-  
1668 tivity. The only exception was range area, which explained a large proportion of the interspecific variation in  
1669 climate-change sensitivity. Given that the estimates of climate-change sensitivity were based on properties of  
1670 species' climatic niches (Rinnan and Lawler, 2019), it was not surprising that range area explained such an  
1671 important part of the interspecific variation in sensitivity, as it is likely that broader range areas are associated  
1672 with broader climatic tolerances, and thus with lower estimated climate-change sensitivity on average.

1673 Despite their generally low explanatory power, traits have been used to assess species vulnerability to  
1674 human threats, in particular to climate change (Böhm et al., 2016; Foden et al., 2013). One of the con-  
1675 ceptual appeals behind the use of traits is that if clear patterns in responses to environmental change can  
1676 be identified across taxa, then it could be possible to generalize their effects in space and time (Hamilton  
1677 et al., 2020; Verberk et al., 2013), which is of interest for conservation -- notably for data-deficient species  
1678 and/or those lacking estimates of abundance or population sizes. This work does not provide support for the  
1679 generalisation at large scales of the effects of life-history and dietary traits on sensitivity to either land-use or  
1680 climate change. The class-specific influence of traits on climate-change sensitivity, coupled with their low  
1681 explanatory power, could be one of the reasons why trait-based approaches have been shown to perform less  
1682 well and show less congruence than trend-based approaches (which rely on the use of long-term population  
1683 data) for climate-change vulnerability assessments (Wheatley et al., 2017). Indeed, low explanatory power  
1684 is likely to be particularly problematic for drawing inferences and predictions on species' responses to envi-  
1685 ronmental change from traits. I would like to emphasize that this does not mean that life-history and dietary  
1686 traits are unimportant for understanding species' responses; it means, however, that the effects of traits and  
1687 their relative importance and predictive power could depend on interactions between the considered taxa and  
1688 the pressures affecting them.

1689 Further, it is possible that general underlying patterns remain undetected or are being masked by inter-  
1690 actions and trade-offs among traits, which I did not consider here. For instance, larger species tend to have  
1691 larger dispersal distances and movement abilities (Jenkins et al., 2007), which could be beneficial to resource  
1692 acquisition in disturbed areas (Hillaert et al., 2018); however, such species also tend to have higher energetic  
1693 requirements (White, 2011) and lower reproductive output, which could be detrimental to their persistence in  
1694 the face of environmental change. Interactions and trade-offs among traits have been shown to be important  
1695 for understanding which species are likely to persist in disturbed environments (Sayol et al., 2020), but little

1696 is known about their potential effects at large scales and for different types of pressure. Thus, developments  
1697 of my work could focus on the effects of trait interactions on species' sensitivity to climate change and  
1698 land-use responses. I was also unable to consider intraspecific variation in this work. Intraspecific variation  
1699 and the potential for acclimation and evolutionary adaptation are likely important determinants of species'  
1700 ability to cope with human disturbance (Carlson et al., 2014; Rohr et al., 2018), but considering such effects  
1701 at large scales is challenging because of the lack of available data.

1702 Moreover, I investigated climate-change sensitivity and land-use responses separately, meaning that I  
1703 did not consider the combined effects of these pressures. However, human pressures act in combination  
1704 (Capdevila et al., 2022a; Harfoot et al., 2021; Segan et al., 2016), and a number of confounding factors and  
1705 threats that I could not account for could possibly influence species' sensitivity. For example, larger species  
1706 might be more sensitive to warming than smaller species (Hantak et al., 2021; Merckx et al., 2018), but larger  
1707 species could also be better able to persist in fragmented landscapes, such that habitat fragmentation and cli-  
1708 mate warming may have opposite effects on the responses of such species. Further, larger species might also  
1709 be disproportionately exposed to other threats such as overexploitation and human-wildlife conflicts (Rip-  
1710 ple et al., 2014, 2017). Interactions among traits, among types of pressure, and among traits and pressures  
1711 should ideally be considered together to understand species' responses to human disturbances (Hantak et al.,  
1712 2021). However, considering all these effects simultaneously may be challenging because of data-limitation  
1713 issues, model complexity, and difficulty in assessing and disentangling individual and interactive effects. In  
1714 addition, I would like to emphasize that my results, based on correlative assessments of the associations be-  
1715 tween ecological characteristics and species' sensitivity to climate change and species' land-use responses,  
1716 do not allow to infer any causal links between traits and species' responses to global changes. Reinforcing  
1717 our mechanistic understanding of how traits influence species' ability to cope with different disturbances  
1718 may help understand opposite signatures of human impacts on vertebrate trait diversity (e.g., on body mass  
1719 (Hantak et al., 2021; Merckx et al., 2018; Rapacciulo et al., 2017; Ripple et al., 2014, 2017)). Further work  
1720 could help elucidate the mechanistic links between species traits and responses to environmental change,  
1721 perhaps supported by long-term population data and demographic models (Hernández-Yáñez et al., 2022).

1722 To conclude, the results of this Chapter indicate that land-use and climate change are likely to impact  
1723 terrestrial vertebrates non-randomly with respect to their ecological characteristics, which could have impor-  
1724 tant consequences for ecosystem functioning (Duffy, 2003; Luck et al., 2012). I found that narrow-ranging  
1725 species, species with smaller habitat breadth and species with natural habitat specialisation are disproportio-  
1726 nately sensitive to both land-use and climate change. Further, I detected substantial declines in occur-  
1727 rence probability of certain dietary groups in disturbed land-use types, most notably invertebrate eaters

1728 and fruit/nectars eaters in all classes. I also found higher climate-change sensitivity for invertebrate- and  
1729 plant/seed-eating birds. My findings thus highlight the potential risks from global changes for ecosystem  
1730 processes and services sustained by those species, such as pest control, seed dispersal or pollination (Civan-  
1731 tos et al., 2012; Fricke et al., 2022; González-Varo et al., 2013), highlighting the need to put into place  
1732 mitigation and conservation measures in the face of global changes.

Disperser could be  
much tighter

# 1733 5 | Energetic constraints and trophic group 1734 explain species persistence in disturbed 1735 land uses

## 1736 Keywords

1737 Land use; land-use intensity; metabolic rates; energetic constraints; energetic requirements; terrestrial vertebrates; trophic group; occurrence.

## 1739 Abstract

1740 Land-use change is the primary driver of global biodiversity loss. In terrestrial vertebrates, previous work  
1741 has shown that sensitivity to land-use change depends on species traits, but the extent to which energetic  
1742 constraints explain species' responses to disturbed land uses remains largely unexplored. Here, I investigate  
1743 relationships between the energetic requirements of terrestrial vertebrates (estimated from resting metabolic  
1744 rates) and land-use change, at two levels of organisation. First, at the assemblage level, I hypothesize that  
1745 total energetic requirements in disturbed land uses are lower than in undisturbed land uses, assuming that  
1746 there is less energy available in these areas overall. Second, after controlling for the effects of body mass and  
1747 taxonomy on metabolic rates, I predict that species with relatively lower energetic expenditure are favoured  
1748 over species with relatively higher energetic expenditure in disturbed land uses, as resource efficiency will  
1749 be beneficial in these resource-poor environments. Because trophic group influences species' ability to  
1750 assimilate various types of food, I investigate whether my predictions are consistent among trophic groups  
1751 (here, omnivores, carnivores or herbivores). The results challenged both hypotheses. I found that total  
1752 assemblage-level energetic requirements did not systematically decrease in disturbed land uses. For instance,

Is this a  
good paper?  
*link not  
clear*

1753 I detected significant increases for urban areas in all trophic groups, highlighting that disturbed areas may not  
1754 be as energy-poor as I initially assumed. Second, I found a positive effect of metabolic rates (after controlling  
1755 for body mass and taxonomy) on species probability of occurrence across all trophic groups for at least one  
1756 of the most disturbed land uses I considered (pasture, cropland and urban). Species for which there are  
1757 exploitable resources in disturbed environments may benefit from having larger mass-independent energetic  
1758 expenditure: they may display a set of characteristics rendering them more able to cope with disturbances  
1759 and more able to acquire available resources, such as higher activity levels or bigger brain sizes. The findings  
1760 of this Chapter highlight that land-use change has substantial impacts on vertebrate community metabolism.

## 1761 **5.1 Introduction**

1762 Land-use change is currently the strongest driver of global biodiversity declines (Maxwell et al., 2016;  
1763 Newbold et al., 2015), with major and long-lasting impacts on the structure and functioning of ecological  
1764 communities (Bregman et al., 2016; Fukasawa and Akasaka, 2019; Magioli et al., 2021; Marcacci et al.,  
1765 2021). With land-use change likely to continue to intensify (Stehfest et al., 2019), it is vital to put into  
1766 place conservation and mitigation measures to minimise future losses of biodiversity and negative impacts  
1767 on ecosystem functioning. To this end, pressing questions remain as to what renders species able or unable  
1768 to cope with human disturbance, and how losses of sensitive species might influence ecosystem functioning  
1769 (Dirzo et al., 2014; Young et al., 2016).

1770 Land-use change acts as an environmental filter affecting species persistence (Edwards et al., 2021;  
1771 Evans et al., 2018). Past studies have shown that sensitivity to land-use change is distributed unevenly across  
1772 the tree of life (Nowakowski et al., 2018), and across behavioural (Lowry et al., 2013; Samia et al., 2015)  
*define* 1773 and **ecological strategies** (De Palma et al., 2015; Møller, 2009; Newbold et al., 2013). For instance, long-  
1774 lived and large forest specialist birds respond more negatively to land-use change than generalist species  
1775 (Newbold et al., 2013). In addition, human land uses impose energetic constraints on species, by modifying  
1776 the amount and type of available resources (Inger et al., 2016; Zuñiga-Palacios et al., 2021). Consequently,  
1777 land-use change brings about modifications in dietary and foraging strategies (Møller, 2009; Ramesh et al.,  
1778 2017; Sévèque et al., 2020), which can have cascading effects on local trophic structure (e.g., mesopredator  
1779 release; Crooks and Soulé (2010)). The impacts of land-use change on biodiversity also depend on land-  
1780 use intensity (Davison et al., 2021; Newbold et al., 2015), that is, the magnitude of human disturbance in  
1781 a given land-use type, which can vary importantly according to local practices and management (Dullinger  
1782 et al., 2021). In particular, land-use intensity affects the types and availability of resources (by homogenising

1783 resources for example), which in turn may affect biodiversity patterns (Weiner et al., 2011).

1784 Energetic requirements are likely to be important predictors of species' ability to cope with a disturbed  
1785 environment where resource availability and resource types are strongly impacted (Auer et al., 2020). Past  
1786 research has shown that metabolic rates (the amount of energy required for organismal maintenance and for  
1787 other processes such as growth and reproduction) are heritable and subject to selection, for instance with  
1788 species in energy-rich environments having evolved faster metabolic rates than species in less energy-rich  
1789 environments (Mueller and Diamond, 2001). However, metabolic rates have received less attention than  
1790 other life-history traits in studies aiming to understand different species' responses to land-use change. Body  
1791 mass, known to explain much of the variation in metabolic rates (Bushuev et al., 2018; Hudson et al., 2013;  
1792 White and Seymour, 2003), has been considered in past studies examining effects of land-use disturbance on  
1793 assemblage composition (Hevia et al., 2017). Since metabolic rates correlate positively with body mass, the  
1794 effects of land-use change on local energetic requirements have been indirectly assessed through investiga-  
1795 tions of changes in body-mass composition along land-use gradients (Newbold et al., 2020a; Tinoco et al.,  
1796 2018). However, to the best of my knowledge, no study has yet directly reported the effects of land-use  
1797 change on assemblage-level energetic requirements.

Is it a  
limit?

Body mass is important

Unrelated

1798 Thus, the first objective of this Chapter is to investigate how land-use change impacts assemblage-level  
1799 energetic requirements in terrestrial vertebrates. To this end, I use metabolic rates as a proxy for maintenance  
1800 energetic requirements at the species level. I predict that, at the assemblage level, total energetic requirements  
1801 in disturbed land uses are lower than in undisturbed land uses. This prediction relies on the assumption that  
1802 there is less energy available overall in disturbed land uses than in undisturbed land uses (Figure 5.1c), with  
1803 disturbed land uses being characterised by human appropriation of net primary productivity (Krausmann et  
1804 al., 2013). Because species' ability to exploit particular resources and meet energetic demands also depends  
1805 on food types and diet (McNab, 1986; Mendoza and Araújo, 2019), I test whether this prediction holds  
1806 true within trophic groups (i.e., within herbivores, omnivores, and carnivores). Here, I consider energetic  
1807 requirements at the assemblage level, not controlling for species' body mass, to obtain estimates of total  
1808 energy expenditure in different land-use types (Figure 5.2a). Thus, any changes in assemblage-level energetic  
1809 requirements could be ultimately driven by shifts in the size-spectrum of local assemblages.

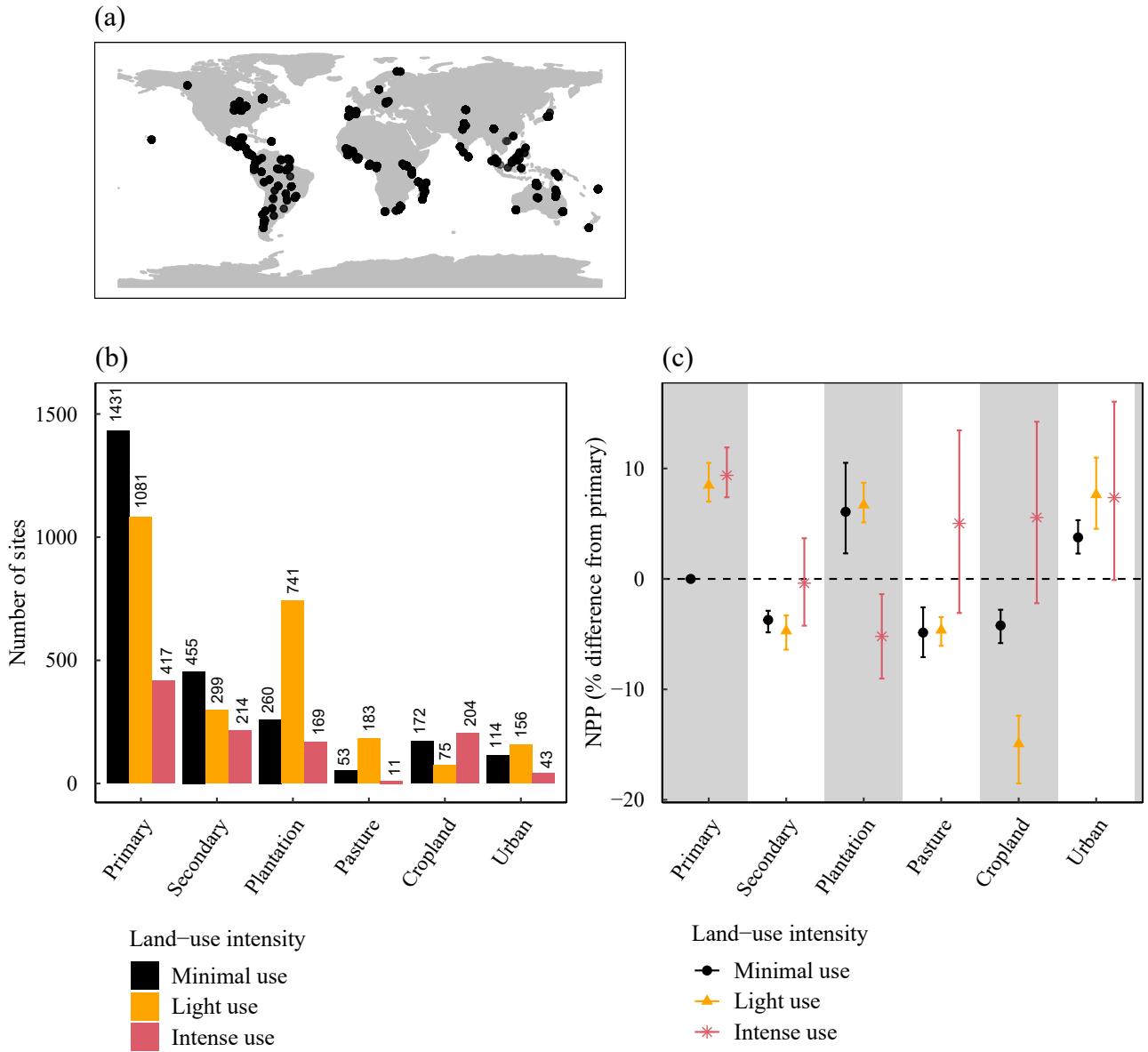
In what  
direction?

1810 Body mass explains much of the variation in metabolic rates, but species with similar body masses still  
1811 display important variation in metabolic rates (Mueller and Diamond, 2001). Some of this variation can  
1812 be explained by taxonomic position (which also accounts for differences in thermoregulatory strategy be-  
1813 tween endotherms and ectotherms). However, there remains substantial interspecific variation in metabolic  
1814 rates even after accounting for body mass and taxonomic affiliation (Mueller and Diamond, 2001; White

1815 and Kearney, 2013). Food availability and food type might explain this residual variation in metabolic rates  
1816 among species (Mueller and Diamond, 2001). Species that evolved in areas with abundant resources assim-  
1817 ilate and burn calories at high rates, regardless of their body mass – while species that evolved with limiting  
1818 resources could process resources at lower rates, irrespectively of their body mass (Mueller and Diamond,  
1819 2001). Building upon this idea and the ‘allocation’ principle (i.e., the trade-offs in resource allocation; Auer  
1820 et al. (2020)), species with lower energetic expenditure (than expected from body mass and taxonomy) may  
1821 be able to cope with food scarcity better than those with larger energy expenditure (than expected from  
1822 body mass and taxonomy). Indeed, regardless of their body mass, such species should need fewer resources  
1823 to meet energetic demands (Clarke and Fraser, 2004). Thus, as land-use disturbance modifies the types and  
1824 abundance of resources, I expect species energetic requirements –after removing the effects of body mass and  
1825 taxonomic position– to influence responses to land-use change. Yet, whether energetic constraints explain  
1826 species’ responses to land-use change in terrestrial vertebrates has not been investigated before (Hevia et al.,  
1827 2017). Thus, the second objective of this Chapter is to characterise the influence of energetic constraints  
1828 on species occurrence probability in disturbed land uses, compared to undisturbed land uses. I approximate  
1829 energetic constraints at the species level from residual variation in metabolic rates, that is, the variation not  
1830 explained by body mass or taxonomy. I predict that species with negative deviations (lower rates than ex-  
1831 pected from body mass and taxonomy) are more likely to persist in disturbed land uses than species with  
1832 positive deviations (higher rates than expected from body mass and taxonomy; Figure 5.2b). Given that  
1833 trophic group can influence resource acquisition and species’ ability to assimilate various types of food, I  
1834 investigate whether this prediction is consistent among trophic groups.

1835 To test both predictions, I use a space-for-time substitution approach, obtaining vertebrate assemblage  
1836 composition data from the PREDICTS database (Hudson et al., 2014, 2017). I combine this database with  
1837 trophic-group information (characterising species as either omnivores, herbivores, or carnivores), and with  
1838 species-level estimates of resting metabolic rates and body mass.

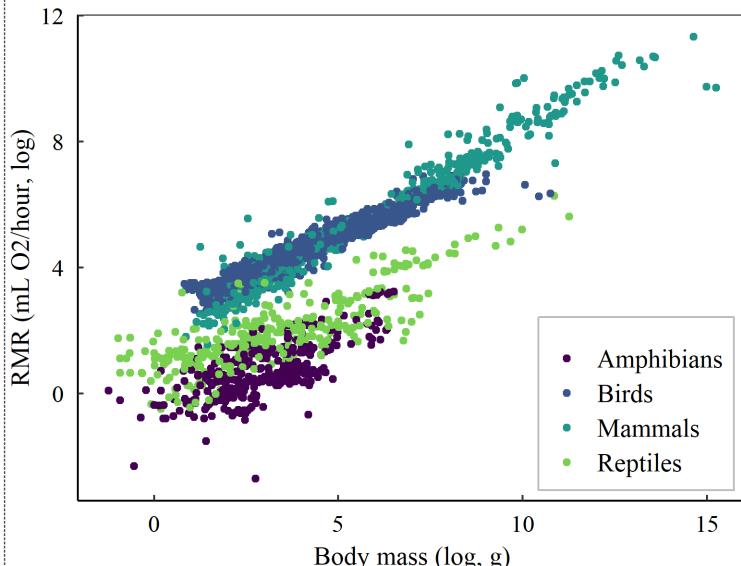
What about  
resource  
acquisition?  
In what  
way?  
good  
but explain  
why &  
explicitly  
limitations?



**Figure 5.1:** (a) Spatial distribution of the sampled sites from the PREDICTS database for terrestrial vertebrates (6,484 sites); (b) Number of sites in each land-use and land-use-intensity category; (c) Net primary productivity by land use and land-use intensity (derived from MODIS satellite imagery), with model predictions plotted relative to minimally used primary vegetation (and rescaled with reference to that land-use type). Primary: primary vegetation; secondary: secondary vegetation; plantation: plantation forest.

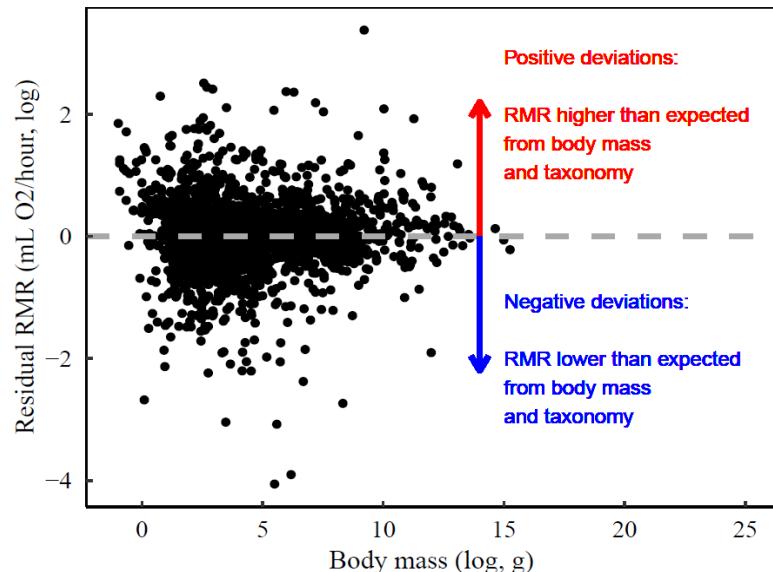
Too busy

**(a) Assemblage-level:** there is less energy available to utilize by vertebrate assemblages in disturbed land uses than in undisturbed land uses.



**(b) Species-level:** species with lower energetic expenditure than expected from body mass and taxonomy (negative deviations) do better in disturbed land uses than species with higher energetic expenditure than expected from body mass and taxonomy (positive deviations).

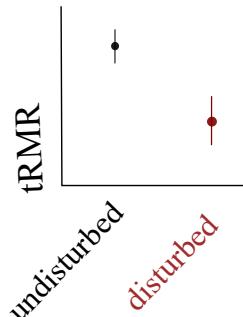
residuals of  
 $\log(\text{RMR}) \sim \log(\text{BM}) + (1|\text{Class/Order/Family})$



901

**Prediction 1:** within all trophic groups, total assemblage-level **mass-dependent** metabolic rates decrease in disturbed land uses compared to undisturbed land uses.

Assemblage level:  
 $t\text{RMR} = \sum_i (\text{RMR}_i * a_i)$

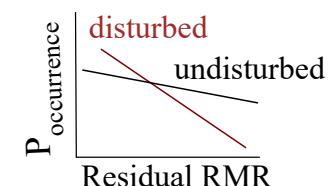


Across assemblages - model 1:  
 $\log(t\text{RMR}) \sim \text{LU} + \text{LUI} + \text{TG} + \text{LU:LUI} + \text{LU:TG} + \text{LUI:TG} + \text{LU:LUI:TG} + RE$

**Prediction 2:** within all trophic groups, species occurrence probability in disturbed land uses is negatively affected by **residual RMR**. The slope of the relationship between occurrence probability and residual RMR is significantly lower than the slope estimate for the undisturbed land uses.

Across species - model 2:

$$\begin{aligned} P_{\text{occurrence}} \sim & \text{LU} + \text{LUI} + \text{resRMR} + \text{TG} + \\ & \text{LU:LUI} + \text{LU:TG} + \text{LU:resRMR} + \\ & \text{LUI:TG} + \text{LUI:resRMR} + \text{TG:resRMR} + \\ & \text{LU:TG:resRMR} + \text{LUI:TG:resRMR} + RE \end{aligned}$$



**Figure 5.2: Framework for the predictions and models.** I use resting metabolic rates (RMR) as a proxy for the amount of energy processed by vertebrate species. **(a)** I hypothesize that there is less energy overall that can be utilized by vertebrate species in disturbed land uses compared to undisturbed land uses. As such, I expect decreases in assemblage-level total metabolic rates ( $t\text{RMR}$ ).  $t\text{RMR}$  is calculated as the sum, over all species occurring at a site, of species RMR ( $\text{RMR}_i$ ) weighted by species abundance ( $a_i$ ). **(b)** After removing the effects of body mass and taxonomy, I expect species with lower energy expenditure than expected to do better than species with higher energy expenditure than expected. I predict that the slope of the relationship between residual RMR and occurrence probability is more negative in disturbed land uses than in undisturbed land uses. For both (a) and (b), I test whether the predictions are consistent among trophic groups. LU: Land use; LUI: land-use intensity; TG: trophic group; RE: random effects. In *model 1*, random effects include the identity of the PREDICTS studies from which the assemblages are derived. In *model 2*, random effects include study, site, and species identity.

not correlated?

1839 **5.2 Methods**

1840 **5.2.1 Vertebrate assemblage composition**

1841 I obtained vertebrate assemblage composition in different land uses from the PREDICTS database (Hudson  
1842 et al., 2014, 2017). The PREDICTS database is a large collection of published studies that measure bio-  
1843 diversity across different land uses and is one of the most comprehensive global databases of its type. In  
1844 each PREDICTS study, species occurrence and often abundance were recorded across different sites. Each  
1845 site was assigned to one of the following land-use types: primary vegetation (natural, undisturbed vegeta-  
1846 tion), secondary vegetation (recovering after complete destruction of primary vegetation), plantation forest  
1847 (woody crops), pasture (areas grazed by livestock), cropland (herbaceous crops) and urban (built-up areas).  
1848 The land-use categories were assigned based on habitat descriptions from the original studies (Hudson et al.,  
1849 2014), sometimes in consultation with the original study authors. Each site was also classified in terms of  
1850 land-use intensity as either minimal, light or intense. The land-use-intensity assignment was also made on  
1851 the basis of the habitat description in the original studies, and depended on criteria specific to each land use  
1852 (such as degree of mechanisation, yield or chemical inputs for cropland; or the amount of green space in  
1853 urban areas; Hudson et al. (2014)).

1854 I subset the PREDICTS database for studies that sampled terrestrial vertebrates, and for which both land  
1855 use and land-use intensity had been characterised. I thus obtained 181 studies for 4,238 species sampled  
1856 across 6,484 sites (Figure 5.1a). Sample sizes varied across land uses and land-use intensities (Figure 5.1b).

1857 **5.2.2 Energy availability by land-use type and land-use intensity**

1858 The predictions of this Chapter rely on the assumption that resource types and abundance are modified in  
1859 disturbed environments, with less energy available in disturbed compared to undisturbed land uses overall.  
1860 To test this assumption, I used terrestrial net primary productivity (NPP) across land uses as a proxy for ) good  
1861 available energy. NPP quantifies the amount of atmospheric carbon fixed by plants and accumulated as  
1862 biomass. NPP estimates were derived by Meghan Hayden, using imagery from the Moderate Resolution  
1863 Imaging Spectroradiometer (MODIS) on board NASA's Terra satellite. NPP estimates were based on a  
1864 yearly composite of measures made at 8-day intervals, captured at 500-m spatial resolution (Running and  
1865 Zhao, 2015). Meghan Hayden obtained NPP for 4,062 of the PREDICTS sites used in the analysis (matching  
1866 the sites to the NPP data using the sampling year available in PREDICTS). I fit a linear mixed-effects model  
1867 ('lme4' package, version 1.1-23, Bates et al. (2015)) explaining site-level NPP by land use and land-use

1868 intensity, with a random intercept accounting for study identity, to control for differences in experimental  
1869 design across studies. Model predictions showed that NPP decreased significantly in several land uses (e.g.,  
1870 pasture and cropland) compared with the primary vegetation reference level, although the strength and in  
1871 some cases direction of the difference varied among land-use and land-use intensity combinations (e.g.,  
1872 increases in urban land uses; Figure 5.1c).

### 1873 **5.2.3 Resting Metabolic Rates (RMR) & imputations of missing RMR values**

1874 As a proxy for species-level energetic expenditure, I used estimates of the minimum amount of energy re-  
1875 quired for organismal maintenance, i.e., basal metabolic rates (BMR) for endotherms, and resting metabolic  
1876 rates (RMR) for ectotherms. From the literature, I obtained estimates of BMR for 719 species of birds and  
1877 685 mammals, and estimates of RMR for 126 amphibians and 173 reptiles (Appendix 4, Table S5.1). For  
1878 endotherms, BMR are measured when species are in their thermoneutral zone, that is, when there is little to  
1879 no energy expenditure allocated to thermoregulation. Thus, BMR estimates were derived from lab studies  
1880 that mostly measured oxygen consumption of the organisms at rest under controlled conditions and in the  
1881 thermoneutral zone of the species. For an ectotherm, there is no ‘basal’ metabolic rate, as body tempera-  
1882 ture mainly depends on environmental temperature. Their metabolic rates follow a hump-shaped relationship  
1883 with environmental temperature, highest at an optimal temperature which corresponds to a performance peak.  
1884 To be able to compare endotherms’ BMR with ectotherms’ RMR, Stark et al. (2020) used the metabolic rates  
1885 that correspond to a performance peak for both groups (i.e., BMR in the thermoneutral zone for endotherms,  
1886 and metabolic rates at optimal temperature for ectotherms). Thus, I used the data compiled in Stark et al.  
1887 (2020) for ectotherms, and from the sources specified in Table S5.1 for endotherms. The units for BMR  
1888 and RMR were standardized to mL of dioxygen consumed per hour (mLO<sub>2</sub>/h). As in Stark et al. (2020), I  
1889 henceforth refer to both basal and resting metabolic rates as RMR.

→ Unclear  
or  
obtained?

1890 For the species occurring in PREDICTS, initial data coverage for RMR was poor (Table S5.1), necessi-  
1891 tating imputation of missing values. To do so, I first measured the phylogenetic signal in BMR and RMR  
1892 ( $\log_e$ -transformed), using Pagel’s  $\lambda$  (Pagel, 1999), to assess whether metabolic rates were sufficiently phylo-  
1893 genetically conserved to be estimated from species’ phylogenetic position. I obtained class-specific phyloge-  
1894 netic trees from Jetz et al. (2012) for birds, from Faurby et al. (2018, 2020) for mammals, from (Tonini et al.,  
1895 2016) for reptiles (squamates), and from Jetz and Pyron (2018) for amphibians (all downloaded in April  
1896 2020). For each class, I randomly sampled 100 trees. To account for phylogenetic uncertainty, I calculated  
1897 Pagel’s  $\lambda$  for each sampled tree and reported the median value, as well as the 2.5<sup>th</sup> and 97.5<sup>th</sup> percentiles  
1898 (Table S5.1).

biased? Bring + to paper

1899 In addition to being highly phylogenetically conserved (Table S5.1), RMR correlate strongly with body  
1900 mass (Figure 5.2a). Thus, I imputed missing values using body-mass information (see next section), phy-  
1901 logenetic relationships and taxonomic orders as predictors (Penone et al., 2014). For each class, I used a  
1902 consensus phylogenetic tree from which I summarised phylogenetic relationships in the form of five phy-  
1903 logenetic eigenvectors. Including more eigenvectors had little impact on the imputed values (results not  
1904 shown). Consensus trees were obtained with the TreeAnnotator programme of the BEAST software (Bouck-  
1905 aert et al., 2014). Missing RMR values were imputed using random forests algorithms implemented in R  
1906 using the ‘missForest’ package (version 1.4; Stekhoven (2016) and Stekhoven and Bühlmann (2012)).

*Strength / adequacy of imputation?*

#### 1907 **5.2.4 Trophic group and body mass information**

1908 I used body mass and trophic group information for terrestrial vertebrates compiled in Chapter 2. Body  
1909 mass was compiled as a single measure at the species level, meaning I was unable to consider intraspecific ~~disassim~~  
1910 variation. Trophic group described species as either carnivores, omnivores, or herbivores. Because there  
1911 were gaps in the availability of the data, more so for trophic group than for body mass (Chapter 2), I imputed  
1912 the missing trait values (independently of RMR imputations), then used both imputed and empirical body  
1913 mass values for imputations of missing RMR values. To impute missing body mass and trophic groups, I  
1914 used random forests algorithms (again, using the ‘missForest’ R package), including as additional predictors  
1915 phylogenetic information, added in the form of 10 phylogenetic eigenvectors (Diniz-Filho et al., 2012) fol-  
1916 lowing Penone et al. (2014), and also taxonomic order. I considered a wider set of life-history traits in the  
1917 missing values imputations: lifespan, litter/clutch size, habitat breadth and use of artificial habitats (compiled  
1918 in Chapter 2). Phylogenetic eigenvectors were extracted from the class-specific phylogenies using the ‘PVR’  
1919 package (Santos, 2018).

#### 1920 **5.2.5 Effects of land use, land-use intensity and trophic group on assemblage-level total 1921 RMR (prediction 1; Figure 5.2a)**

1922 Assemblage-level total RMR (tRMR) was obtained by summing abundance-weighted RMR for the species  
1923 occurring in each site; abundance data were available for 125 of the 181 PREDICTS studies I considered  
1924 (sampling 3,487 species across 4,644 sites). I fitted a linear mixed-effects model to explain  $\log_e$ -tRMR as  
1925 a function of land use, land-use intensity and trophic group, with a random intercept accounting for study  
1926 identity to control for differences in experimental design across studies. I started with a model allowing all  
1927 two-way interactions among the predictors. I then tested whether adding the three-way interaction among  
1928 land use, land-use intensity and trophic group improved the fit of the model, using a likelihood-ratio test.

1929 The model that included the three-way interaction was retained ( $P \ll 0.01$ ; *model 1*, Figure 5.2). In addition,  
1930 because it is well established that resting metabolic rates are influenced by temperature (Clarke and  
1931 Fraser, 2004), I checked whether including annual mean temperature in the model affected the conclusions.  
1932 Annual mean temperature at each PREDICTS site was estimated from WorldClim version 2.1 (Fick and  
1933 Hijmans, 2017), using a 2.5 arc-minute resolution. Adding annual mean temperature did not improve model  
1934 fit (likelihood-ratio test:  $P=0.113$ ), thus I did not consider its effects any further.

1935 **Model validation.**

1936 To ensure that imputation uncertainty did not affect the conclusions, I refitted *model 1* using the subset of  
1937 species ( $n = 426$ ) from PREDICTS for which there were empirical RMR information (i.e., excluding imputed  
1938 RMR values).

1939 **Disentangling the effects of body mass and abundance on tRMR.**

*not defined?*

1940 Since RMR correlates strongly with body mass, changes in tRMR are likely to be driven in part by changes  
1941 in the size-spectrum of ecological assemblages. I fitted an additional model to explain changes in species'  
1942 abundance (given presence) by land use, land-use intensity, trophic group, body mass and their interactions,  
1943 to understand the role of shifts in the body mass of species on observed changes in tRMR (Appendix 4,  
1944 Figure S5.1).

1945 **5.2.6 Effects of land use, land-use intensity, trophic group and residual RMR on species  
1946 occurrence probability (prediction 2; Figure 5.2b)**

1947 To control for the effects of body mass and taxonomy on RMR, I used the residual variation in RMR after  
1948 accounting for these variables, from a linear mixed-effects model fitting  $\log_e$ -RMR as a function of  $\log_e$ -  
1949 body mass with nested random taxonomic effects (1|Class/Order/Family; Figure 5.2). Hence, I used a metric  
1950 that describes how much more energy (positive deviations) or less energy (negative deviations) than expected  
1951 from body mass and taxonomic position a species spends for organismal maintenance. Similar approaches  
1952 have been used in previous papers (Furness and Speakman, 2008; Naya et al., 2013). As detailed earlier, I  
1953 expect species with lower residual RMR to do better in disturbed land uses than species with higher residual  
1954 RMR (prediction 2; Figure 5.2b) because, given any body mass, investing less energy in maintenance could  
1955 contribute to persistence in a context of resource scarcity.

1956 To test the second prediction, I fitted a binomial mixed-effects model explaining species occurrence  
1957 with land use, land-use intensity, trophic group and residual RMR. I started with a complete model that

1958 included all two-way interactions among the main effects. Because I wanted to test whether the second  
1959 prediction was valid for each trophic group, I needed to account for potential differences in the slope of the  
1960 relationships between occurrence probability and residual RMR among trophic groups. Thus, I performed  
1961 a forward stepwise selection procedure to test whether adding three-way interactions among (1) land use,  
1962 trophic group and residual RMR and (2) among land-use intensity, trophic group and residual RMR improved  
1963 model fit, using likelihood-ratio tests. The final model included both three-way interactions (Figure 5.2b;  
1964 *model 2*). I fitted random effects that accounted for species identity, as well as for study and site identity  
1965 within PREDICTS.

1966 **Model validation.**

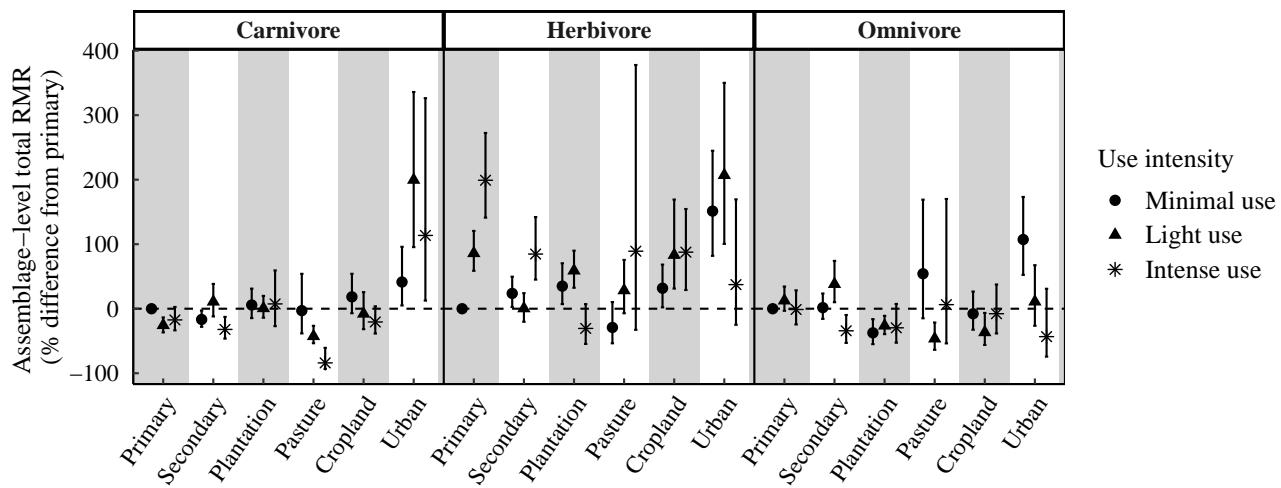
1967 I checked the phylogenetic signal in the model residuals using Pagel's  $\lambda$  (Pagel, 1999). Non-significant  
1968 phylogenetic signal in the residuals would indicate that fitting species identity in the model's random effects  
1969 was sufficient to account for residual phylogenetic variation in RMR. Further, to assess the potential effects  
1970 of imputation uncertainty on the results, I again fitted *model 2* on the data subset for the 489 species with  
1971 collected empirical RMR values, across 5,948 sites in 151 studies (i.e., excluding imputed values).

1972 **5.3 Results**

1973 **5.3.1 Effects of land use, land-use intensity and trophic group on assemblage-level total  
1974 RMR**

1975 Land use, land-use intensity, trophic group and their interactions had significant effects on assemblage-level  
1976 total RMR (Figure 5.3). Overall, and contrary to my expectations, assemblage-level total RMR did not  
1977 show systematic decreases in disturbed land uses. In fact, urban land uses were associated with strong  
1978 significant increases in tRMR in all trophic groups (e.g., a 200% average increase in tRMR in lightly-used  
1979 urban areas for carnivores, compared with primary vegetation levels; +207% on average in lightly-used urban  
1980 areas for herbivores; +107% for minimally-used urban areas for omnivores). In other land uses, responses  
1981 depended on trophic group and land-use intensity. Whilst for herbivores, disturbed land uses were typically  
1982 associated with increases in tRMR, I detected decreases in tRMR for omnivores and carnivores in several  
1983 land uses, most notably in intensely-used pasture for carnivores (-84%). Such effects could reflect changes  
1984 in the size-spectrum of local assemblages (Appendix 4, Figure S5.2). For instance, in minimally-used urban  
1985 areas, larger herbivores tended to occur at higher abundances compared to primary vegetation level; and in  
1986 intensely-used pastures, carnivores tended to occur at lower abundances overall (Figure S5.2).

1987 The model residuals were appropriately distributed (see diagnostic plots in Appendix 4, Figure S5.3).  
 1988 Investigating the sensitivity of the results to imputation uncertainty showed that the conclusions were robust  
 1989 to the removal of all imputed estimates of RMR (the correlation coefficient was 0.72 between the two sets of  
 1990 model coefficients; Figure S5.4). Comparing model predictions showed that effects were mostly congruent,  
 1991 although there were some differences (Figure S5.5). In particular, for herbivores, effect sizes tended to be  
 1992 bigger for the model fitted on empirical data compared with the model that included imputed data. Thus, the  
 1993 main results appear to be conservative if anything. The model fitted on empirical data had larger standard  
 1994 errors, likely due to the reduction in sample size.

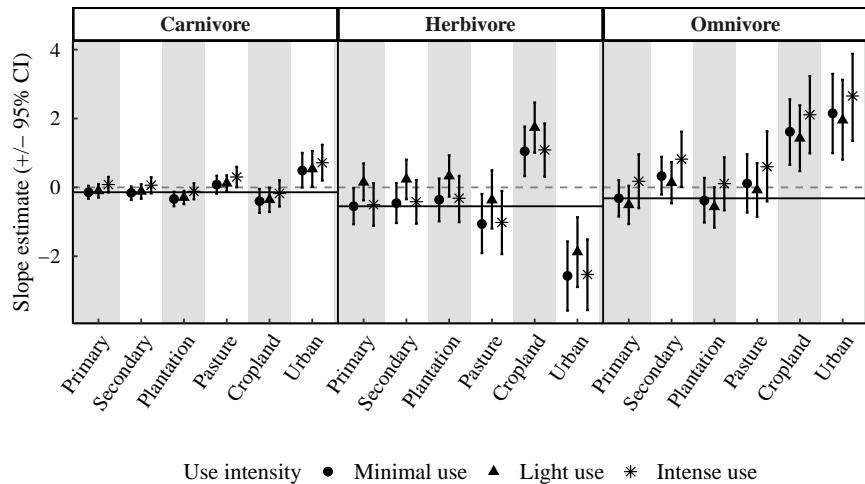


**Figure 5.3: Effects of land use, land-use intensity and trophic group on assemblage-level total RMR (mean estimate  $\pm 95\%$  confidence interval).** Model predictions are rescaled with reference to minimally-used primary vegetation, considered to be the undisturbed baseline. Primary: primary vegetation; secondary: secondary vegetation; plantation: plantation forest.

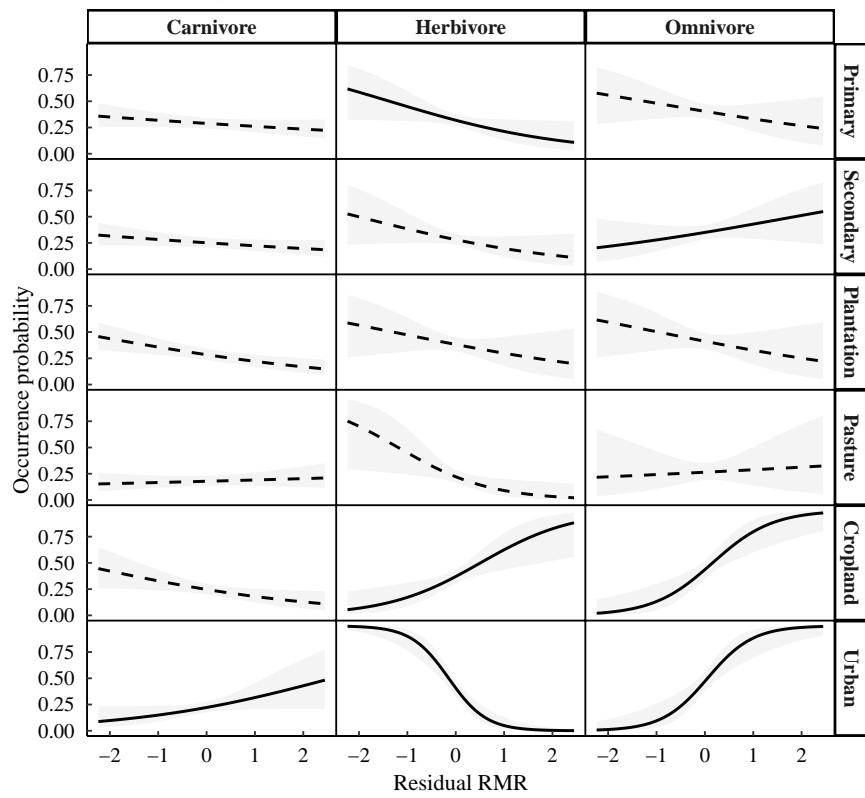
### 1995 5.3.2 Effects of land use, land-use intensity, trophic group and residual RMR on species' occurrence probability

1997 Species' occurrence probability was significantly affected by land use, land-use intensity, trophic group,  
 1998 residual RMR and their interactions (Figures 5.4, 5.5). Contrary to my expectations, species with higher  
 1999 residual RMR (relative to their body mass and taxonomic position) tended to do better than species with lower  
 2000 residual RMR in a number of disturbed land uses. Overall, land-use type was more important for determining  
 2001 the relationship between occurrence probability and residual RMR than land-use intensity (Figure 5.4a).

(a) Slope of the relationships between occurrence probability (log-odds) and residual RMR



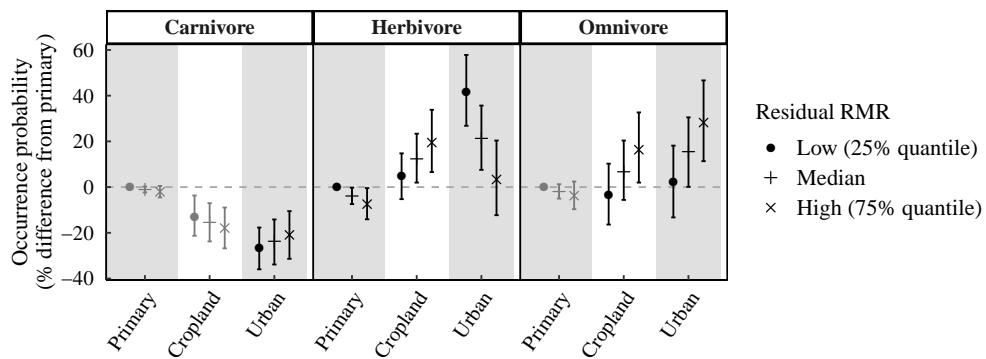
(b) Predicted effects of residual RMR on occurrence probability (minimal use intensity)



**Figure 5.4:** (a) Slope estimates for the relationship between residual RMR and occurrence probability in each land-use type and for the three levels of land-use intensity (mean estimate  $\pm 95\%$  confidence interval). The black horizontal line indicates the slope for the reference level (primary vegetation) for minimal land-use intensity. The grey dashed line marks 0. (b) Effect of residual RMR on species probability of occurrence within each trophic group and for each land-use type. I plotted the predictions for minimal land-use intensity only. Solid lines represent significant relationships (with slopes significantly different from 0), and dashed lines are plotted where the slope was not significantly different from 0. Shaded areas represent 95% confidence intervals. Primary: primary vegetation; secondary: secondary vegetation; plantation: plantation forest.

For minimally-used primary vegetation (reference), residual RMR tended to be negatively associated with species occurrence probability in all trophic groups (but with a significant slope for herbivores only; Figure 5.4a). However, the directionality of this relationship was reversed in some disturbed land uses in all trophic groups (secondary vegetation, cropland and urban for omnivores; cropland for herbivores; urban for carnivores), with significant positive slopes, also significantly higher than those observed for primary vegetation (Figure 5.4a); in these land uses, residual RMR was thus positively associated with occurrence probability. One notable exception was the opposite pattern for urban herbivores (Figure 5.4b), where residual RMR had a more negative effect on occurrence probability than in minimally-used primary vegetation.

~~I would like to emphasize that~~ positive effects of residual RMR on occurrence probability in some of the most disturbed land uses (e.g., urban for carnivores) do not mean that there were absolute increases in species occurrence probability in disturbed land uses compared to primary vegetation (and vice-versa). I illustrate this point in Figure 5.5. For carnivores with a median value for residual RMR, occurrence probability was reduced by an average 24% in urban land uses compared to primary vegetation (but there was a significant positive association between residual RMR and occurrence probability for carnivores in urban areas; Figure 5.4).



**Figure 5.5: Predicted occurrence probabilities (mean effect  $\pm$ 95% confidence interval) in primary vegetation (primary) and for the most disturbed land uses where residual RMR was found to have a significant effect on occurrence probability.** For visualisation purposes, I discretised residual RMR in three levels. The predicted probabilities of occurrence were rescaled with reference to primary vegetation for the lowest value of residual RMR (25% quantile). Here, the predictions are plotted for minimal land-use intensity (effects would be similar for light and intense land-use intensities). Black points and error bars are plotted where the relationship between occurrence probability and residual RMR was significant (and dark grey points and error bars represent non-significant trends).

Finally, the model showed some degree of deviation from distributional assumptions (diagnostic plots, Appendix 4, Figure S5.6). Nevertheless, the model's coefficients were similar when estimated with a Bayesian framework, suggesting that the estimates were robust (Figure S5.7). The phylogenetic signal in the model residuals was weak and non-significant ( $\lambda=0.004$ ,  $P=0.24$ ). Re-fitting the model using the com-

2021 plete data subset (i.e., excluding imputed RMR estimates) showed that the conclusions are likely robust to  
2022 imputation uncertainty (Figure S5.8), with congruent results overall, although there were a few differences  
2023 in the predictions between the two models – notably, for herbivores in urban land uses (Figure S5.8).

2024 **5.4 Discussion**

2025 The results of this Chapter provide insights into the relationship between land-use change and energetic  
2026 requirements at two levels of organisation (at the assemblage level and the species level), and contradict  
2027 both my initial predictions. I found that total energetic requirements did not show systematic decreases in  
2028 disturbed land uses. On the contrary, there were strong increases in all trophic groups, most notably in urban  
2029 land uses. Further, in all trophic groups, species with higher energetic expenditure (than expected from body  
2030 mass and taxonomy) tended to do better in some of the most disturbed land uses (that is, cropland and urban)  
2031 than species with lower energetic expenditure (than expected from body mass and taxonomy).

2032 At the assemblage level, the results first highlight the effects of land-use change on vertebrate com-  
2033 munity metabolism. Contrary to my expectations, I found differing effects of land use on total energetic  
2034 requirements among trophic groups, reflecting changes in the size-spectrum of ecological assemblages (i.e.,  
2035 changes in the distribution of abundance along the body-mass gradient). On the one hand, decreases in total  
2036 energetic requirements, such as observed for carnivores in intensely used pastures, are likely due to overall  
2037 reductions in local abundance (with carnivorous species in pastures perceived as a threat to livestock (Eeden  
2038 et al., 2018); or because of increased competition for fewer resources). On the other hand, increases in total  
2039 energetic requirements could reflect higher levels of resource intake in some disturbed land-use types. On the  
2040 basis of net primary productivity, I hypothesized that there would be fewer resources available in disturbed  
2041 areas. However, it could be that the carrying capacity of some disturbed land-use types actually increases  
2042 for some trophic groups compared to that of primary vegetation, because of the presence of novel or more  
2043 abundant food sources. For instance, in urban areas, both wildlife feeding and the presence of anthropogenic  
2044 food sources, such as human refuse or pet food, could lead to an increase in resource availability all year-  
2045 round for species with a non-specialised diet that are able to exploit such food sources (Fischer et al., 2012).  
2046 Past research on urban carnivores has shown that some species have adapted to urban environments by ex-  
2047 ploiting anthropogenic food sources, and also benefit from physical protection (with some human structures  
2048 providing shelter) and from reduced occurrence of natural enemies (Bateman and Fleming, 2012). Herbi-  
2049 vores and omnivores could also benefit from increased resources in urban areas, notably where the urban  
2050 matrix includes semi-natural habitats, which is congruent with observed increases in occurrence probability

*Does  
this  
make  
sense  
Time  
since  
disturbance*

2051 in minimally used urban areas for these trophic groups. Further, anthropogenic ‘bottom-up food forcing’ has  
2052 been shown to affect food-web dynamics, with decreases in predation rates, loss of anti-predator abilities  
2053 (Geffroy et al., 2020) and mesopredator release (Fischer et al., 2012). Thus, in urban areas, increases in  
2054 anthropogenic food sources could provide support for a higher abundance of medium-sized species released  
2055 from predation, increasing total energetic requirements.

2056 I hypothesized that resource availability would be the main driver behind changes in energetic require-  
2057 ments. However, resource availability likely interacts with other factors to explain the patterns. In particular,  
2058 past work has shown that brain size is an important determinant of species’ ability to cope with disturbance,  
2059 notably in urban settings (Sayol et al., 2020). Since brain size scales allometrically with body mass, it is  
2060 possible that I observe increases in total energetic requirements where having larger brains is advantageous  
2061 for resource acquisition, and in turn where resources are both exploitable and abundant enough to sustain  
2062 the larger energetic expenditures associated with bigger brain sizes. In addition, body size, which explains  
2063 an important proportion of the interspecific variation in mobility, likely interacts with characteristics of the  
2064 landscape (such as fragmentation) with consequences for species persistence in disturbed land uses (Merckx  
2065 et al., 2018). Hence, the patterns I observe in this Chapter could emerge from interactions and trade-offs  
2066 among resource availability, diet, body size and human management of the landscape. *Why not examined?*

2067 At the species level, the results underline the role of energetic constraints on species’ responses to land-  
2068 use change. After controlling for the effects of body mass and taxonomy, I found that residual energetic  
2069 expenditure was significantly associated with species occurrence probability in disturbed land uses. Con-  
2070 trary to my expectations, in several disturbed land uses and in all trophic groups, species with higher residual ener-  
2071 getic expenditure tended to have a higher occurrence probability than species with lower residual ener-  
2072 getic expenditure. It could be that species with lower residual energetic requirements are less well equipped  
2073 than species with higher residual energetic requirements at making use of the available food sources in dis-  
2074 turbed land uses. Species in disturbed land uses may need to display higher levels of feeding innovation  
2075 (Coogan et al., 2018), have larger brains (Sayol et al., 2020), or be bolder and more active to make use of  
2076 the available resources. In mammals, past research has shown that larger brains are associated with larger  
2077 residual energetic expenditure (Isler and Van Schaik, 2006). At the individual level, past research suggests  
2078 that metabolic rates are linked to differences in behaviour, with bolder and more active individuals exhibiting  
2079 higher metabolic rates than less active individuals, with consequences for food acquisition (Biro and Stamps,  
2080 2010). Although I am not aware of similar evidence at the species level, I propose that residual metabolic  
2081 rates interact with species’ ecological traits, behavioural traits and foraging strategy in influencing species’  
2082 responses to land use. Among species with an adaptable diet, able to make use of the resources available

2083 in a disturbed landscape, those with higher residual metabolic rates could present a set of behavioural char-  
2084 acteristics that render them better at acquiring the available resources, hence be more able to cope with  
2085 land-use disturbance. This could be the case for urban carnivores and omnivores, as well as herbivores in  
2086 cropland. Thus, it is possible that disturbed land uses favour species with higher residual resting metabolic  
2087 rates because such species are overall better competitors when faced with disturbance. In addition, release  
2088 from predation in some disturbed land uses – most notably in urban areas – could favour bolder species, as  
2089 they become less exposed to predation risks. Conversely, and in accordance with my initial hypothesis, the  
2090 results suggest that when there are no or few exploitable resources in disturbed areas, spending less energy  
2091 than expected from body mass and taxonomy might be beneficial for persistence (this could be the case for  
2092 urban herbivores, which include species specialised on fruit, nectar, and other plant materials; some of these  
2093 resources likely become less abundant in disturbed areas).

2094 To summarise, I propose that, for species with adaptable diets, increases in exploitable resources cou-  
2095 pled with decreases in predation rates could lead to increases in overall energetic expenditure, associated Explain  
2096 with shifts towards assemblages composed of a higher abundance of medium-sized, bolder, more active and  
2097 larger-brained species. On the other hand, species with specialised diets might be better able to persist and  
2098 cope with resource scarcity when their energetic expenditure is lower than expected from body mass. These  
2099 ideas could be further tested by considering more refined dietary groups (as those compiled in Chapter 4)  
2100 rather than trophic groups, as diet should be easier to link with resource availability in a given land-use type.  
2101 This could constitute a development for this work.

2102 Finally, I would like to emphasize that energetic budget allocation is a fundamental aspect of organismal  
2103 fitness (Burger et al., 2021). Past studies suggest that individuals exposed to food scarcity can lower their  
2104 energetic expenditure to increase their chances of survival. For instance, Zhang et al. (2018b) showed that,  
2105 subjected to food restrictions, the Chinese bulbul (*Pycnonotus sinensis*) was able to lower its basal metabolic  
2106 rate not only passively through body and organ mass reductions, but also by modifying enzymatic activity  
2107 and metabolism in the muscles and liver. Other studies have also found that bird nestlings downregulate  
2108 energetic costs allocated to maintenance when exposed to food shortage (Brzék and Konarzewski, 2001;  
2109 Moe et al., 2004), or to disturbances such as urban noise (Brischoux et al., 2017). Intraspecific variation  
2110 in energetic expenditure could affect individual responses to land-use change, which in turn could affect  
2111 species' ability to adapt to human pressures. However, the lack of spatially explicit estimates of metabolic  
2112 rates precluded its consideration in this Chapter.

2113 To conclude, the findings of this Chapter suggest important effects of land-use change on energetic  
2114 fluxes, and thus potentially on ecosystem functioning. Further research is warranted as to the effects of these

2115 energetic patterns for ecosystem processes. Indeed, assemblage-level energy fluxes may serve as important  
2116 indicators of change for ecosystem processes, such as decomposition (Barnes et al., 2014). Understanding  
2117 these impacts is particularly important given increasing land-use change and biodiversity loss across the  
2118 globe.

Final paragraph  
would be stronger

## 2119 6 | General discussion

2120 In recent centuries, large-scale anthropogenic modifications to the Earth's systems have accelerated and  
2121 reached unprecedented levels (Steffen et al., 2015). Two of the major signatures of human impacts on the  
2122 Earth's systems are the transformation of the land surface (Ellis et al., 2010), notably fuelled by the rising  
2123 demand for agricultural goods, and anthropogenic climate change onset by human-driven modifications to  
2124 atmospheric composition (Lewis and Maslin, 2015). Such transformations have had important impacts on  
2125 the world's biota. By modifying species' habitats at large scales and altering local climatic conditions at  
2126 rates exceeding natural variability, human changes have put biodiversity under pressure (Maxwell et al.,  
2127 2016). Empirical evidence showing the extent and magnitude of human impacts on biodiversity has been  
2128 accumulating (Daru et al., 2021; Newbold et al., 2015; Young et al., 2016). In particular, land-use and climate  
2129 change have already driven declines in species richness and abundance, and altered species distributions,  
2130 phenology and physiology (Butchart et al., 2010; Chen et al., 2011; Chown et al., 2010; Dirzo et al., 2014;  
2131 Inouye, 2022; Lenoir and Svenning, 2015; Newbold et al., 2015; Pörtner and Farrell, 2008; Soroye et al.,  
2132 2020), and increased extinctions rates to unprecedented levels (Barnosky et al., 2011; Ceballos et al., 2015;  
2133 De Vos et al., 2015) – in some cases putting hundreds of millions of years of evolution at risk (IUCN,  
2134 2020; Nowakowski et al., 2018). As anthropogenic pressures on biodiversity are unlikely to reduce given  
2135 current scenarios of human development (Stehfest et al., 2019), and as international targets aiming to protect  
2136 biodiversity and related ecosystem services have failed to be met (Buchanan et al., 2020), it is vital that we  
2137 keep pursuing conservation and mitigating efforts to minimise or even reverse human impacts on biodiversity.

2138 Human pressures impact species unevenly; for instance, past work has highlighted phylogenetic and  
2139 spatial biases in species vulnerability to human pressures (Ducatez and Shine, 2017; Fritz et al., 2009;  
2140 Weeks et al., 2022; Yessoufou et al., 2012). Some species (termed 'winners' in past work) may benefit  
2141 from global changes, while other species (termed 'losers') are likely to decline. Understanding the factors  
2142 that underpin interspecific variation in responses to human pressures is valuable to conservation planning,  
2143 as it can help target and prioritise species at most risk from different threats. One of the reasons why

species differ in their responses to environmental change is that species possess different characteristics, or traits. In my thesis, following McGill et al. (2006), I defined traits as characteristics measurable at the level of an individual (i.e., intrinsic), comparable across different species, with likely impacts on organismal fitness or performance. Asking whether species traits relate to species' responses to land-use and climate change can thus help understand interspecific differences in responses to human threats (Munstermann et al., 2022), and may help assess which species are more likely to be 'winners' or 'losers' under particular threatening processes. However, past studies that have tackled this question in terrestrial vertebrates have often been limited in both taxonomic and spatial coverage, so that it remains unclear whether there are general patterns in trait-sensitivity associations with human pressures across vertebrate species. Further, comparative studies of the sensitivity to both land-use and climate change among terrestrial vertebrate classes have been lacking. Understanding whether different human pressures are likely to favour similar species across diverse taxonomic groups could help conservation efforts. In my thesis, I aimed to fill in these gaps, investigating whether and which traits are associated with land-use responses and climate-change sensitivity comparatively across terrestrial vertebrates and at global scales. My thesis also aimed to highlight some of the possible consequences for ecosystem functioning.

To this end, I started by compiling trait data across terrestrial vertebrates, and by assessing the gaps and biases in the availability of trait data (Chapter 2). Bringing together these compiled data and a database containing species records in different land-use types (PREDICTS), I assessed the effects of land use and land-use intensity on the functional diversity of local terrestrial vertebrate assemblages (Chapter 3). I then asked whether species ecological characteristics (in which I included species ecological traits and species geographical range area) were associated with species' land-use responses and with species' estimated climate-change sensitivity, comparatively across the four vertebrate classes (Chapter 4). Finally, I investigated the effects of land use and land-use intensity on the total energetic requirements of vertebrate assemblages, and I further assessed whether species' energetic requirements influenced species' land-use responses (Chapter 5). In this final Chapter, I synthesise the key findings of my work, and I assess their contributions to the broader knowledge and their relevance for the field. I highlight some of the limitations of my work and further challenges, notably reflecting on the current challenges to the application of trait-based approaches at large scales in animal taxa.

## 2172 6.1 Gaps and biases in the knowledge of terrestrial vertebrates

2173 Although terrestrial vertebrates have been extensively studied in the past, there remain important gaps in our  
2174 knowledge. Some of these gaps are illustrated in Chapter 2, which demonstrates the biases in the availability  
2175 of ecological trait data (i.e., the ‘Raunkiær’ shortfall (Hortal et al., 2015)). After collating data for seven  
2176 commonly-used ecological traits, I showed that the sampling of these traits presented taxonomic, phyloge-  
2177 netic and spatial biases. Mammals and birds were overall well sampled for most traits (with a median trait  
2178 coverage of 85% for birds, and of 95% for mammals). However, amphibians and reptiles presented acute  
2179 gaps, with a 32% median coverage for amphibians, and 38% for reptiles. Chapter 2 further showed that such  
2180 gaps were non-randomly distributed with regards to species phylogenetic position, with certain clades being  
2181 under-sampled compared to others (for example, the family *Ranidae*, or true frogs ; or the blind snakes of  
2182 the family *Typhlopidae*, and the worm snakes of the family *Amphisbaenidae*). Hence, Chapter 2 showed that  
2183 amphibians and reptiles are understudied compared to mammals and birds. Knowledge gaps are thus acute  
2184 for the most diverse vertebrate class (reptiles) as well as for the most threatened vertebrate class (amphibians;  
2185 IUCN (2020)).

2186 Chapter 2 also highlights that knowledge gaps for amphibians and reptiles were non-randomly distributed  
2187 across geographical space. For instance, the availability of trait data was significantly positively associated  
2188 with species richness in several biogeographic realms (e.g., in the Australasian realm for reptiles, and in  
2189 the Neotropics for amphibians), and significantly negatively associated with species richness in other realms  
2190 (e.g., in the Indo-Malayan realm for both amphibians and reptiles). Chapter 2 thus highlighted some critically  
2191 under-sampled regions for traits in amphibians and reptiles (e.g., the Congo-Basin). As discussed in Chapter  
2192 2, such geographical biases may be driven by uneven primary data collection efforts, themselves possibly  
2193 explained by interacting socioeconomic factors (Collen et al., 2008; Hortal et al., 2015; Martin et al., 2012;  
2194 United Nations Educational Scientific and Cultural and Organization, 2015). Importantly, Chapter 2 shows  
2195 that trait information may be less available in some of the most species-rich regions, critically important  
2196 for global biodiversity conservation (Barlow et al., 2018). Chapter 2 further showed that, in all classes, the  
2197 availability of trait information depended on species’ rarity (captured by geographical range area), with more-  
2198 widely distributed species being on average better sampled for traits than less widely distributed species.  
2199 Such trends could be explained by a sampling bias towards more easily detectable species, and is concerning  
2200 as narrow-ranging species have been shown to be at higher risks of extinction (Chichorro et al., 2019).

2201 It is worth highlighting that I targeted traits that are commonly used by ecologists in Chapter 2; knowl-  
2202 edge gaps are likely to be even more important when looking at other traits, that are maybe less frequently

used (such as dispersal abilities, which are available for a small fraction of vertebrate species only, despite their likely importance for understanding species' responses to anthropogenic pressures; Schloss et al. (2012); Lenoir and Svenning (2015)). Chapter 4 and Chapter 5 provide with an illustration of this point: in Chapter 4, no information about reptile diet could be obtained from an existing published database; while in Chapter 5, the availability of physiological data on resting metabolic rates was limited to a small number of species, even in mammals and birds. Further, lack of available data prevented me from considering intraspecific variation in my thesis, despite its likely importance for understanding species- and assemblage-level responses to human-driven change (Carlson et al., 2014; Guralnick et al., 2016; Rohr et al., 2018).

*Explain*

The 'Raunkiær' shortfall, coupled with the lack of a centralised repository for animal trait data, may have been a major hindrance to the application of trait-based approaches at large scales in vertebrate species. In my thesis, I employed imputation techniques throughout to estimate missing trait values. However, complementing existing datasets with empirical data is the only way to fill the current data gaps robustly. It may be that integrating regional databases, potentially in different languages, could help fill some of the gaps.

Finally, many studies have called for the integration and standardisation of trait databases (Junker et al., 2022; Kissling et al., 2018; Schneider et al., 2019; Weiss and Ray, 2019), to produce open-access, interoperable, and unified products. Developing an appropriate framework for data standardisation and integration would require overcoming implementation and conceptual difficulties, notably pertaining to the definition of comparable traits across organisms and to the integration of taxonomic nomenclatures (Salguero-Gómez et al., 2021). However, integration and standardisation of trait databases would represent a major step for animal ecology, preventing the duplication of research efforts, promoting collaboration and opening new research avenues. By highlighting the current gaps in terrestrial vertebrate trait data, Chapter 2 could help guide future collection efforts.

## 6.2 Functional reshaping of local vertebrate assemblages under land-use change

In Chapter 3 and Chapter 5, my thesis highlights two different dimensions of the functional reshaping of vertebrate assemblages under land-use change. While Chapter 3 focuses on the functional diversity of local vertebrate assemblages by using various indices to summarise the diversity of ecological traits across vertebrate assemblages of the PREDICTS database, Chapter 5 makes use of physiological data to quantify energetic requirements at the assemblage level. To my knowledge, my work constitutes the first global assessment of the responses of functional diversity to land use and land-use intensity across vertebrate classes,

*unnecessary*

2233 and of the changes in total vertebrate energetic requirements with land use and land-use intensity.

### 2234 **6.2.1 Functional diversity and functional composition (Chapter 3)**

2235 In Chapter 3, after combining the trait data compiled in Chapter 2 with the PREDICTS database, I investi-  
2236 gated how land use and land-use intensity affects the functional diversity (i.e., functional richness and func-  
2237 tional dispersion) as well as the functional composition (i.e., functional loss and functional gain) of terrestrial  
2238 vertebrate assemblages, across and within vertebrate classes, at global scales. I investigated potential spatial  
2239 variation in responses by looking for differences between temperate and tropical areas. The findings of this  
2240 Chapter are threefold. First, across all vertebrate species, the functional diversity of vertebrate assemblages  
2241 is negatively impacted by human land uses. Both functional richness and functional dispersion showed im-  
2242 portant average decreases in some disturbed land uses (e.g., a 63% average decline in functional richness in  
2243 intensely-used tropical cropland; a 20% average decline in intensely-used urban areas). Further, decreases in  
2244 functional dispersion exceeded the decreases expected from species loss in a number of disturbed land uses  
2245 (most notably in tropical cropland), providing evidence of functional clustering of vertebrate assemblages  
2246 in these land uses. Second, Chapter 3 highlights the spatial and taxonomic variation in responses: overall,  
2247 functional richness tended to be more negatively affected in the tropics than in temperate areas (but responses  
2248 were similar between the two areas for functional dispersion). The functional diversity of amphibians and  
2249 birds was overall more negatively impacted than that of mammals and reptiles. Finally, Chapter 3 showed  
2250 that vertebrate assemblages in disturbed land uses were subject to high levels of functional loss, and in some  
2251 cases functional gain, highlighting important functional turnover in vertebrate assemblages.

2252 Chapter 3 thus highlights that the functional composition of vertebrate assemblages is reshaped in dis-  
2253 turbed land uses. My results are mostly line with previous studies that have been more taxonomically or  
2254 geographically restricted (Flynn et al., 2009; Marcacci et al., 2021; Matuoka et al., 2020). Although the  
2255 functional diversity of tropical areas emerges as being more sensitive than that of temperate areas, I also  
2256 found important decreases in functional diversity in temperate areas, a pattern that had not been detected in  
2257 past work (Matuoka et al., 2020). My results indicate that land-use change is a potential threat to ecosystem  
2258 processes, in particular those sustained by species falling in sensitive areas of the trait space. Further, losses  
2259 of functional diversity in tropical areas are particularly problematic given that those areas are more species-  
2260 rich than temperate areas, harbour many biodiversity hotspots and protected areas, and are currently sub-  
2261 jected to some of the highest rates of land-use change (Hansen et al., 2013; Laurance et al., 2012; Spracklen  
2262 et al., 2015).

2263 **6.2.2 Energetic requirements (Chapter 5)**

2264 In Chapter 5, I combined the PREDICTS database with species-level estimates of resting metabolic rates.  
2265 I investigated whether the total energetic requirements of vertebrate assemblages differed among different  
2266 land-use types and trophic groups (classified as omnivores, herbivores, and carnivores). Contrary to my  
2267 expectations, I found that the minimum amount of energy required by vertebrate assemblages did not show  
2268 systematic decreases in disturbed land-use types. Across all three trophic groups, total energetic require-  
2269 ments (estimated from total abundance-weighted resting metabolic rates) even showed strong increases in  
2270 some disturbed land uses (e.g., an average increase of 200% in lightly-used urban areas for carnivores).  
2271 These findings highlight that disturbed land uses have significant impacts on ecosystem functioning and em-  
2272 phasize that land-use change may promote significant changes to the local energetic balance of vertebrate  
2273 assemblages. To my knowledge, this work constitutes the first direct global quantification of the impacts of  
2274 land-use and land-use intensity on vertebrate energetic requirements. My findings are tightly linked to stud-  
2275 ies that have investigated changes in the body mass composition of vertebrate assemblages under land-use  
2276 change (e.g., Newbold et al. (2020b)), and also to studies drawing from food-web theory (e.g, impacts of  
2277 habitat loss and fragmentation on the body size distribution in a trophic chain; Hillaert et al. (2020)).

2278 Altogether, the findings of Chapter 3 and 5 show that land-use change reshapes the functional compo-  
2279 sition of vertebrate assemblages. Land-use change may reduce native ecological trait diversity, constricting  
2280 used areas of the trait space, thus potentially disrupting ecosystem processes sustained by the native species  
2281 that are located in sensitive areas of the trait space. Further work could investigate the contributions of non-  
2282 native species to the functional reshaping of local vertebrate assemblages. Changes in species composition  
2283 in disturbed land uses have consequences for ecosystem functioning, notably significantly impacting the  
2284 amount of energy locally processed by vertebrate species.

2285 **6.3 Uneven sensitivity of vertebrate species to land-use and climate change**

2286 In Chapter 4 and Chapter 5, I investigated associations between species-level characteristics and species'  
2287 sensitivity to land-use and climate change. Chapter 4 focuses on ecological characteristics (ecological traits  
2288 and geographical range area), and to my knowledge constitutes the first work to investigate associations  
2289 between species' ecological characteristics and two human pressures, at global scales and comparatively  
2290 across vertebrate classes. Chapter 5 uses physiological data and focuses on species' energetic requirements.  
2291 To my knowledge, there has yet not been a study investigating whether species' energetic requirements

2292 influence species' responses to land use and land-use intensity in vertebrate species.

### 2293 6.3.1 Ecological characteristics (Chapter 4)

2294 In Chapter 4, I complemented the trait data from Chapter 2 with species-level dietary information and geo-  
2295 graphical range area. On the one hand, I combined these species-level data with the PREDICTS database,  
2296 and I investigated how species' ecological characteristics influenced their responses to land use and land-use  
2297 intensity. On the other hand, after estimating climate-change sensitivity from properties of species' climatic  
2298 niche space, I investigated the associations between species' ecological characteristics and climate-change  
2299 sensitivity. First, I found that narrower ranges, smaller habitat breadth, and inability to exploit artificial habi-  
2300 tats were consistently associated with more negative land-use responses and higher climate-change sensitiv-  
2301 ity across vertebrate classes. Second, the associations of other traits were both class- and pressure-dependent.  
2302 Overall, invertebrate eaters and fruit/nectar eaters tended to be negatively affected in disturbed land uses in  
2303 all classes; in addition, invertebrate- and plant/seed-eating birds had higher climate-change sensitivity.

2304 Chapter 4 thus highlights that both land-use and climate change are likely to favour similar species,  
2305 that is, wider-ranging species, those with larger habitat breadth and those able to use artificial habitats. My  
2306 work aligns with previous analyses on extinction risks (Chichorro et al., 2019) and climate-change responses  
2307 (MacLean and Beissinger, 2017), and shows that similar species might be favoured by both these human  
2308 pressures. Further, the narrow-ranging species, which are on average less well known for trait data (as  
2309 shown in Chapter 2) and potentially for many other aspects of their biology, are those that are more likely  
2310 to be more sensitive to human pressures. Such species may however make distinct and unique contributions  
2311 to ecosystem functioning (Dee et al., 2019; Mouillot et al., 2013). Further investigations of the ecosystem  
2312 processes sustained by these geographically rarer species and their contributions to ecosystem functioning  
2313 may be helpful to the mitigation of human impacts.

2314 I would like to underline some of the limitations of this work: first, as discussed in Chapter 4, I consid-  
2315 ered land-use change and climate change separately, thus not accounting for potentially interactive effects  
2316 between these pressures. However, human pressures are likely to interact, and combined effects of land-  
2317 use and climate change could have more deleterious (synergetic) effects than individual pressures acting  
2318 independently (Williams et al., 2022; Williams and Newbold, 2020). Second, my findings rely on the use  
2319 of the PREDICTS database (in this Chapter and in Chapters 3 and 5) and on the use of geographical dis-  
2320 tributions, and as such I used a 'space-for-time' approach to infer land-use responses and climate-change  
2321 sensitivity from spatial data (Blois et al., 2013). Thus, I assumed that vertebrate assemblages and current  
2322 species distributions were at equilibrium (De Palma et al., 2018), and I did not consider potential recovery

2323 effects, long-term population declines or any other temporal dynamics. However, it is likely that populations  
2324 are not at equilibrium (Damgaard, 2019; De Palma et al., 2018). For instance, Sales et al. (2022) showed  
2325 that range contractions of megafaunal mammals over the Late Pleistocene could lead to an underestimation  
2326 of the realised climate niches of these species when using current distribution data, so that the estimated  
2327 climate-change sensitivity of these species may be overestimated (Sales et al., 2022). Further, biotic lags and  
2328 delays in biodiversity responses emphasise the need to account for land-use history (De Palma et al., 2018;  
2329 Le Provost et al., 2020). Using long-term species records and population data may provide insights into the  
2330 long-term effects of land-use and climate change on vertebrate species.

2331 Finally, in Chapter 4, I conducted a correlative assessment of the associations between species ecological  
2332 characteristics and species' responses to land use and species' climate-change sensitivity. I found a number  
2333 of significant associations, but traits had overall low explanatory power in the models, thus putting into  
2334 question the degree to which traits can be used to infer species' responses to environmental change. Further,  
2335 my results do not allow for mechanistic interpretations of how traits influence species' responses to land-use  
2336 and climate change. Using long-term population data, mechanistic models and *in silico* and field experiments  
2337 may help uncover some of these mechanisms (Boult and Evans, 2021; Ries et al., 2004).

### 2338 **6.3.2 Mass-independent energetic requirements (Chapter 5)**

2339 Chapter 5 highlights the effects of the interactions between species' energetic requirements and trophic  
2340 group on responses to land use and land-use intensity (after controlling metabolic rates for the effects of  
2341 body mass and taxonomy, which explain a large proportion of the interspecific variation in metabolic rates).  
2342 The key finding from this analysis contradicted my initial prediction: in all trophic groups, species with  
2343 larger energetic expenditure (relative to body mass and taxonomy) tended to do better in some of the most  
2344 disturbed land-use types, compared to species with lower energetic expenditure. Thus, my work highlights  
2345 that land-use change may favour species that have higher rates of mass-independent energy consumption,  
2346 which could be linked with interspecific differences in behaviour, as discussed in Chapter 5 in more details.  
2347 Species with larger energetic expenditure may display a set of characteristics that render them better able to  
2348 cope with anthropogenic disturbances, such as higher activity levels (Biro and Stamps, 2010; Coogan et al.,  
2349 2018). Such species may also have a larger brain (a metabolically more consuming organ per unit mass; Isler  
2350 and Van Schaik (2006)), which could play a significant role on species' ability to persist in disturbed areas  
2351 (Sayol et al., 2020).

2352 Finally, I would like to emphasise that my work gives important indications of how human pressures  
2353 may affect ecosystem functioning. For example, the higher sensitivity of invertebrate eaters to both land-use

2354 and climate change may indicate that the processes that such species underpin, such as pest control, might be  
2355 put at risk (Civantos et al., 2012). However, we lack large-scale quantifications and empirical measurements  
2356 of ecosystem processes sustained by vertebrates (Luck et al., 2012; Wenny et al., 2011). Linking verte-  
2357 brate traits to particular ecosystem functions at large scales remains challenging, maybe because of a lack  
2358 of empirical data, but also maybe because ecosystem processes sustained by vertebrate species are difficult  
2359 to quantify (potentially because of the mobility of these species). Vertebrates nevertheless contribute signif-  
2360 icantly to ecosystem functioning (Breviglieri and Romero, 2017; Ratto et al., 2018; Wandrag et al., 2015;  
2361 Zhang et al., 2018a), emphasising the need to mitigate human impacts on them.

## 2362 **6.4 Relevance of the findings to conservation** *Too short*

2363 Overall, my findings show that land-use and climate change may favour similar vertebrate species: ‘winners’  
2364 are likely to be wider-ranging species that are able to occupy diverse habitats, including human-disturbed  
2365 habitats; ‘winners’ might also be able to allocate more energy to sustain higher activity levels. On the other  
2366 hand, ‘losers’ are likely narrow-ranging species, with natural habitat specialism and unlikely to be able to  
2367 persist in human-disturbed areas. Thus, considerations of geographical rarity and specialisation indices ap-  
2368 pear to be highly relevant for characterising species at risk from both land-use and climate change when  
2369 working at large scales and across all terrestrial vertebrates. In fact, such criteria have been employed by  
2370 the IUCN Red List for assessing species’ extinction risk (Rodrigues et al., 2006), as well as in predictive  
2371 vulnerability assessments (e.g., Foden et al. (2013)). Further, considerations of species’ geographical rar-  
2372 ity and specialisation can be useful to species-based as well as area-based conservation prioritization, for  
2373 instance for identifying key areas for biodiversity conservation and for targeting species of interest (Asaad  
2374 et al., 2017; Mace et al., 2006). My results thus lend support to the idea that vulnerability assessments and  
2375 hierarchisation frameworks should take geographical rarity and specialisation into account (Le Berre et al.,  
2376 2019).

## 2377 **6.5 Conclusion**

*Avoid!*

2378 My thesis constitutes, to my knowledge, the first attempt to use trait-based approaches at global scales to  
2379 investigate associations between sensitivity to human pressures and species traits, comparatively across the  
2380 terrestrial vertebrate classes and human pressures (land-use and climate change). I demonstrated that there  
2381 exist major gaps and biases in our global ecological knowledge of terrestrial vertebrate species, particularly  
2382 affecting amphibians and reptiles and some of the most species-rich regions, which is problematic given the

*not true*

2383 higher sensitivity of these areas to human pressures. My work indicates that land-use and climate change  
2384 are reshaping vertebrate biodiversity. I highlighted two dimensions of such functional reshaping, using  
2385 ecological characteristics on the one hand, and physiological data on the other hand. Land-use and climate  
2386 change may tend to favour species that are wider-ranging, have larger habitat breadth and are able to use  
2387 artificial habitats; and land-use change alone tends to favour species that are able to allocate more energy to  
2388 organismal maintenance than expected from body mass and taxonomy. Thus, my work lends further support  
2389 to the idea that human activities promote the homogenisation of the biota, with a set of ‘winning’ species  
2390 likely to benefit from global changes at the expense of sensitive ‘losers’, putting at risk ecosystem processes  
2391 sustained by those sensitive species. Overall, my work highlights the necessity of strengthening conservation  
2392 and mitigation efforts in the face of global human-driven changes.

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# **Appendix 1: Supporting information for Chapter 2**

## **S2.6 Taxonomic corrections**

Across the different sources of trait data, similar species could appear under different binomial names. This was a problem when matching datasets by species. Moreover, it is possible that within a source, a given species was appearing under two or more different, synonymous names. As such, taxonomic synonymy created duplicated rows for the same species, overall falsely increasing the total number of species and potentially inflating the number of missing trait values. Taxonomic synonymy was hence a major issue. Due to the large number of species across datasets, extensive manual checks could not be applied. The presence of typos in species names had the same effect as synonymy, erroneously duplicating species. I attempted to correct for taxonomy first by correcting for typos, and second by identifying species which were entered under non-accepted names and replacing these with the accepted name. To this end, I developed an automated procedure, complemented with a few manual entries where errors were opportunistically spotted. Such errors in taxonomy were notably spotted when attempting to retrieve trait data for subsets of species, for analyses not directly related to the work conducted here. Taxonomic synonymy was as such checked manually for 91 species (56 birds, 7 mammals and 28 reptiles); in that case, information was extracted from other diverse sources (such as the Reptile Database (<http://www.reptile-database.org/>); Avibase (<https://avibase.bsc-eoc.org/avibase.jsp?lang=EN&pg=home>); AmphibiaWeb (<https://amphibiaweb.org/>); and additional manual checks using the IUCN Red List for mammals). A column in the Synonym dataset mentions where manual checks were applied (in which case the Synonym dataset was manually corrected).

### **Automated procedure and outputs**

#### **Extracting names from the IUCN Red List and the Integrated Taxonomic Information System (ITIS)**

The objectives of the automated procedure were to (1) extract species synonymous binomial names from the

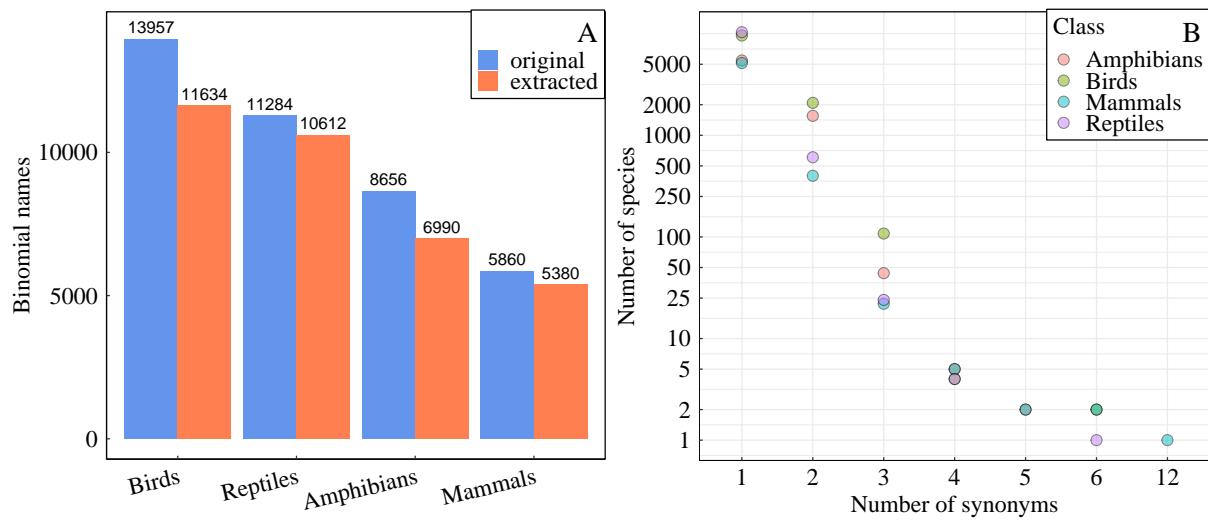
IUCN Red List or from the ITIS, using the ‘rredlist’ (Chamberlain, 2018) and ‘taxize’ (Chamberlain and Szöcs, 2013) R packages; and (2) identify the status of each name (accepted or not accepted). I started by generating a list of all names featuring in any of the sources. These ‘original’ names were corrected for typos (using the ‘gnr\_resolve’ function in the ‘taxize’ package). Then, the IUCN Red List was queried and any listed synonyms were stored, as well as the status of each synonym (accepted or not accepted). When species were not found in the IUCN Red List, synonyms were extracted from the ITIS. When species were not found in the ITIS either, corrected names (original names corrected for typos) were used. Family and order designations were extracted using the same procedure and some entries were retrieved from the Global Biodiversity Information Facility taxonomic backbone when not available in the IUCN Red List or in the ITIS (GBIF, <https://www.gbif.org/tools/species-lookup>).

**NB:** for species entered with the forms *Genus cf.*, *Genus aff.* or *Genus spp.*, the accepted binomial name was left empty.

**Output.** I generated a ‘Synonym’ dataset containing records of binomial names (14,124 recorded names for birds; 8,743 for amphibians; 6,090 for mammals; and 11,678 for reptiles), and for each I recorded their status and their potential synonyms.

**Harmonising taxonomy in trait datasets.** Taxonomy across datasets was finally homogenised by replacing synonyms with a uniquely identified accepted name. As a consequence, the total number of identified unique species decreased (Figure S2.1a). The species presenting the highest number of synonyms was the East African mole rat (*Tachyoryctes splendens*), for which I found 12 synonymous names (Figure S2.1b).

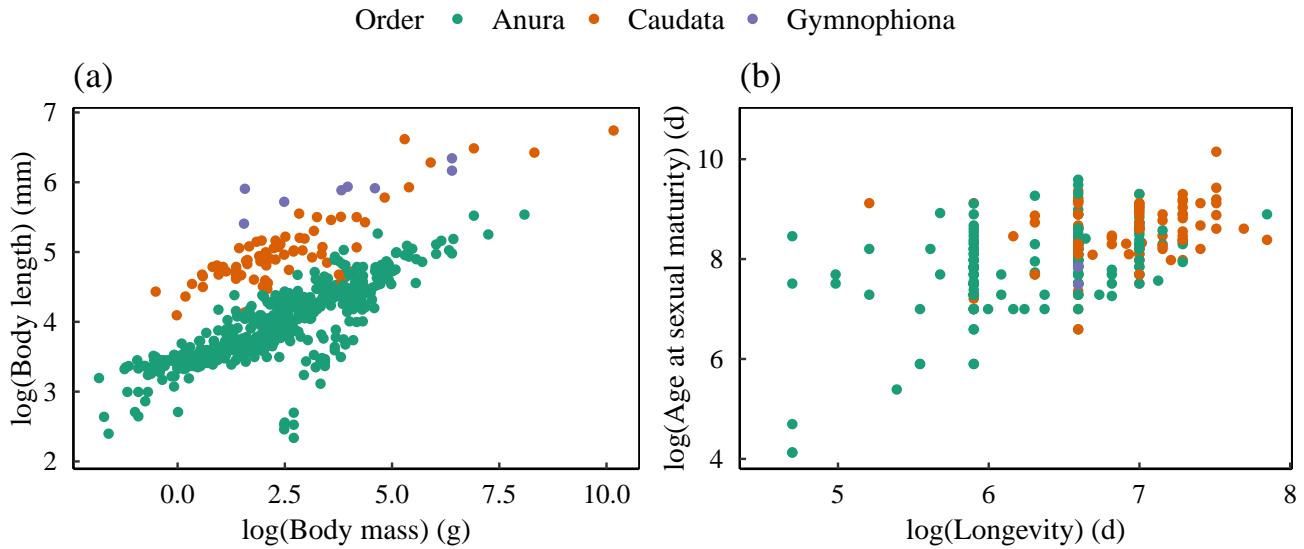
The automated procedure was not perfect, and taxonomic errors are likely to have persisted in the trait datasets. The IUCN Red List and the ITIS were not comprehensive taxonomic sources, and for clades with high degrees of synonymy in names, such as reptiles or amphibians, neither the IUCN Red List or the ITIS contained enough information. Taxonomy may be further improved by using class-specific sources in an automated procedure.



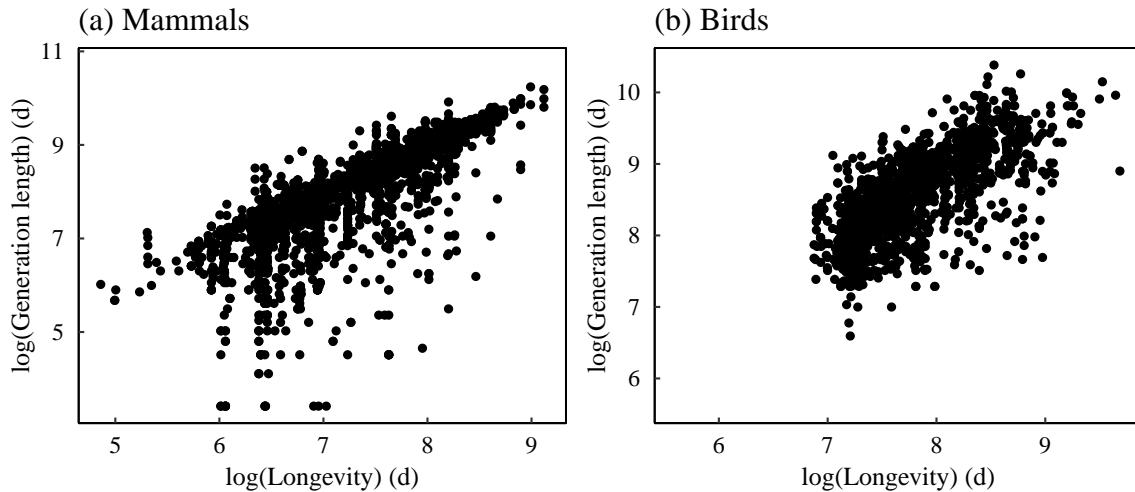
**Figure S2.1: Difference in species number before and after taxonomic correction (A) and distribution of number of synonyms across datasets (B).** (A) shows the number of species (binomial names) extracted from all sources (blue bars), and the number of uniquely identified accepted names (in red). Replacing non-accepted synonyms by one identified accepted name reduced the number of species in all classes, with the largest reduction for birds. (B) shows the distribution of the number of synonymous names. In all four classes, more than 5,000 species were known under one name only. Nevertheless, a large number of species had two identified synonyms (range: 400 species for mammals - 2086 for birds). The most potentially replicated species was the East African mole rat *Tachyoryctes splendens*, for which 12 synonyms were identified.

## S2.7 Additional information for trait compilation

### Correlations among closely related traits

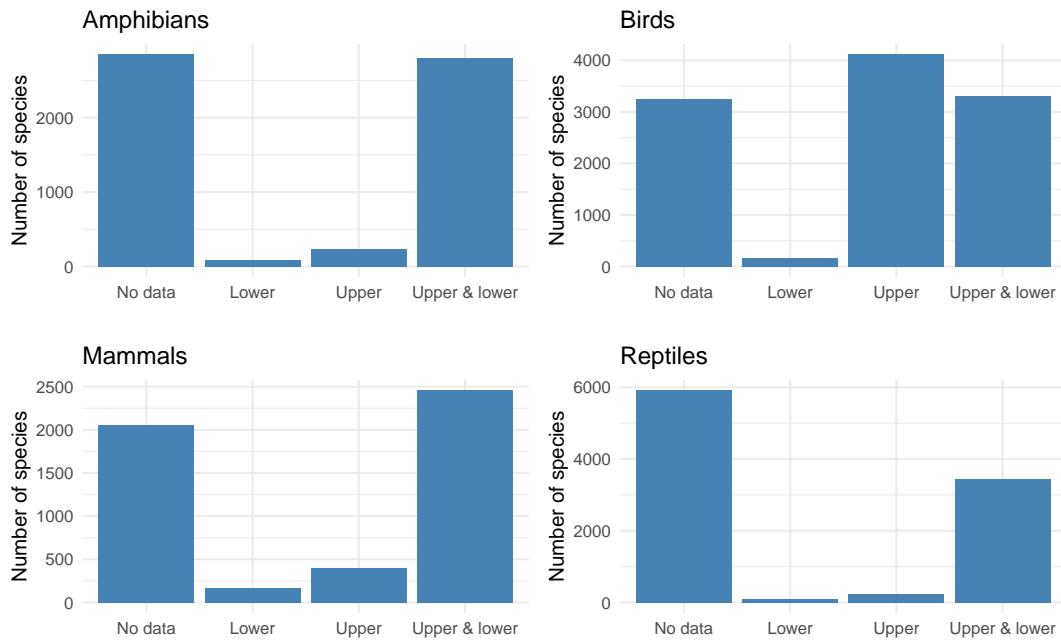


**Figure S2.2:** (a) Body mass versus body length and (b) longevity versus age at sexual maturity in amphibians. Pearson's correlation coefficient was 0.71 in (a) and 0.55 in (b) (taxonomic order was considered in these coefficients).

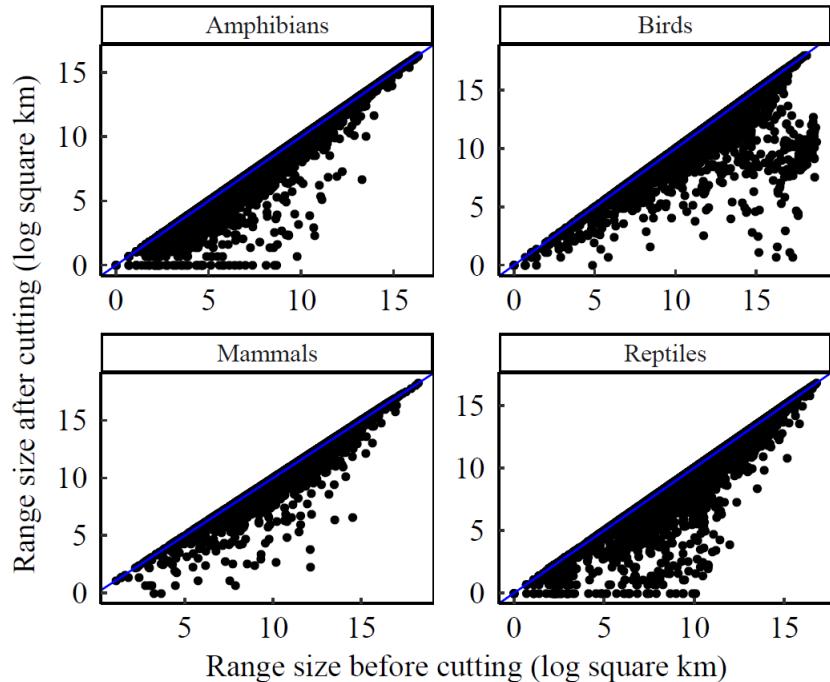


**Figure S2.3:** Generation length versus longevity data in (a) mammals and (b) birds. Pearson's correlation coefficient was 0.74 in (a) and 0.70 in (b).

## S2.8 Cutting distribution maps by altitudinal limits

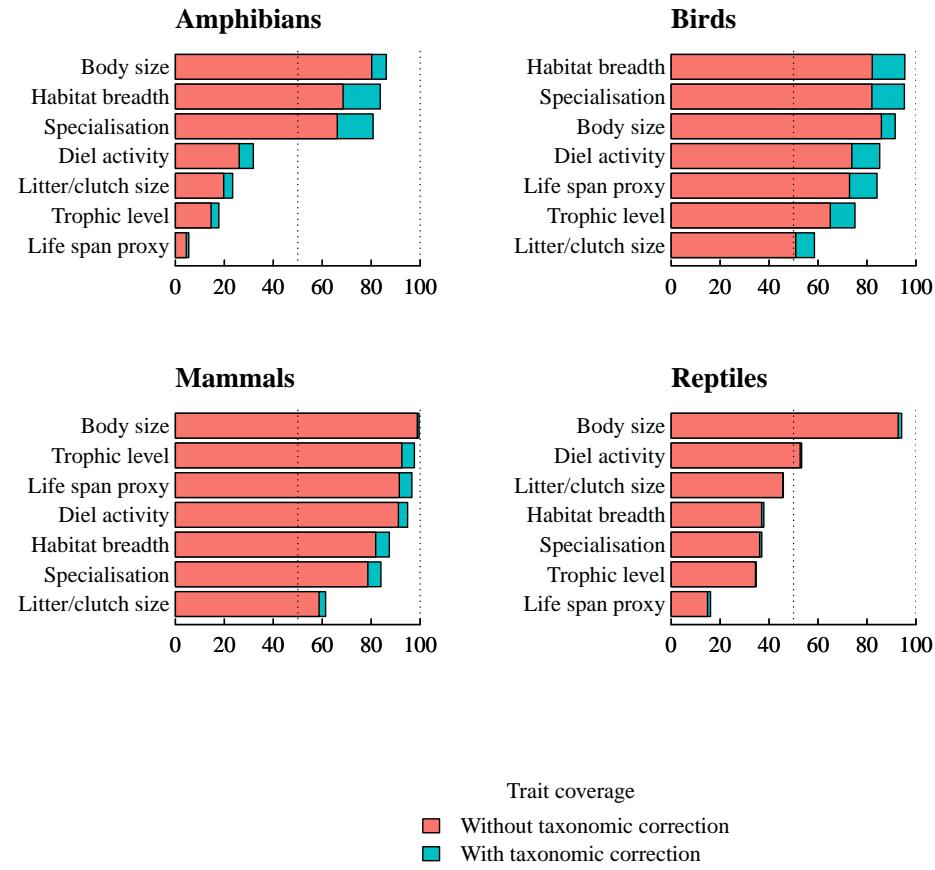


**Figure S2.4: Availability of altitudinal limits across species.** Upper and lower altitudinal limits were extracted from the IUCN Red List (IUCN, 2020).



**Figure S2.5: Range sizes before versus after cutting the range maps by altitudinal limits.**

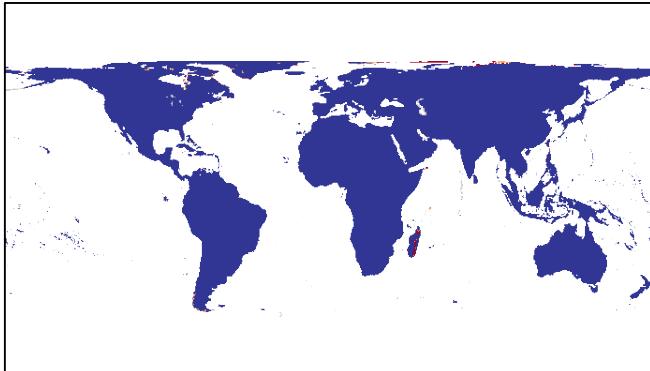
## S2.9 Impact of taxonomic corrections on trait coverage



**Figure S2.6: Trait coverage when no taxonomic correction is applied before matching sources by binomial names, versus when I applied the described procedure.** The identification of synonymous names resulted in an increase in trait coverage in most cases.

**S2.10 Assemblage-level median, mean and standard deviation of trait completeness (maps)**

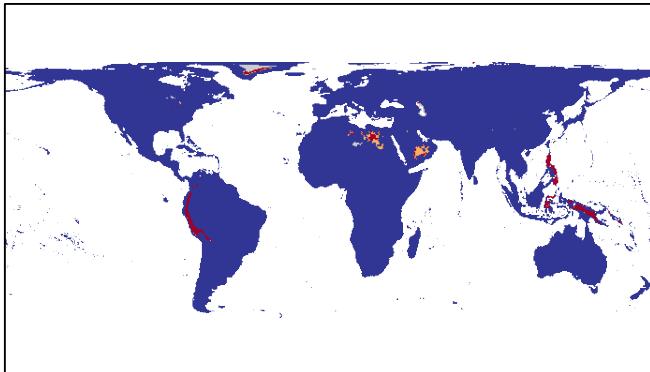
**(a) Mammals**



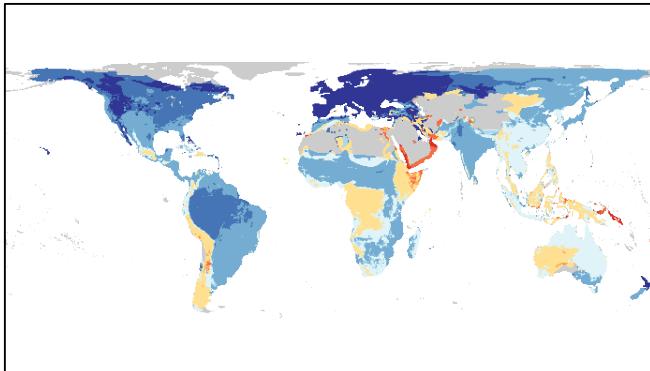
Median completeness  
(birds and mammals):

- NA
- 80 – 90%
- 90 – 91%
- 91 – 92%
- 92 – 93%
- 93 – 94%
- 94 – 95%
- 95 – 96%
- 96 – 97%
- 97 – 98%
- 98 – 99%
- 99 – 100%

**(b) Birds**



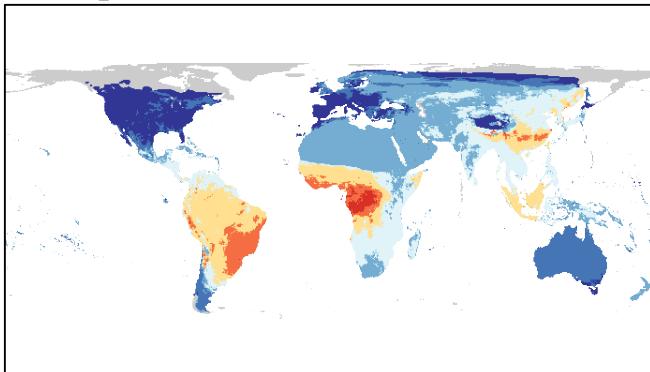
**(c) Amphibians**



Median completeness  
(herptiles):

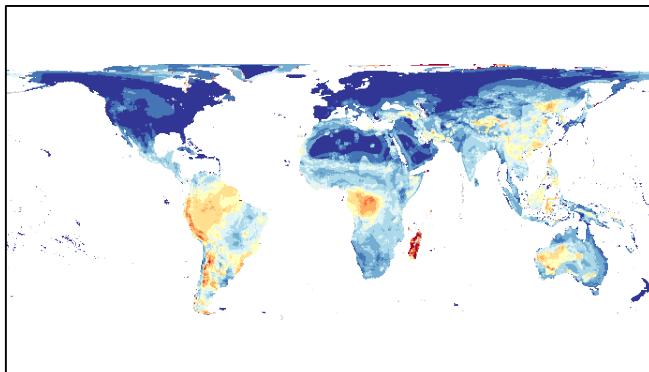
- NA
- 0 – 10%
- 10 – 20%
- 20 – 30%
- 30 – 40%
- 40 – 50%
- 50 – 60%
- 60 – 70%
- 70 – 80%
- 80 – 90%
- 90 – 100%

**(d) Reptiles**



**Figure S2.7: Spatial distribution of assemblage-level median trait completeness in each class.** Note that the color breaks differ for mammals and birds and for herptiles.

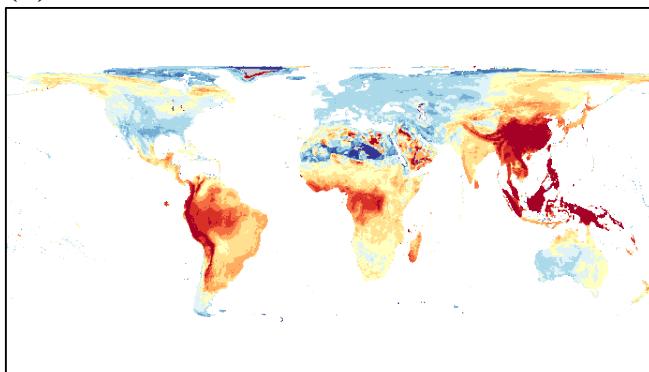
**(a) Mammals**



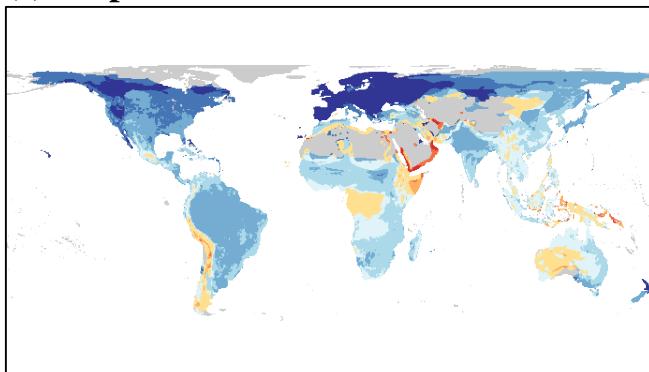
Mean completeness  
(birds and mammals):

- NA
- 80 – 90%
- 90 – 91%
- 91 – 92%
- 92 – 93%
- 93 – 94%
- 94 – 95%
- 95 – 96%
- 96 – 97%
- 97 – 98%
- 98 – 99%
- 99 – 100%

**(b) Birds**



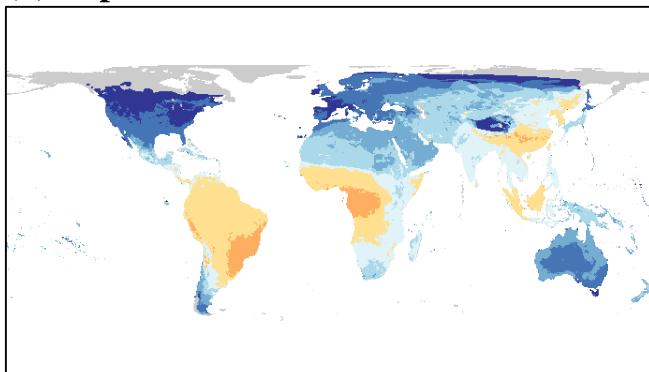
**(c) Amphibians**



Mean completeness  
(herptiles):

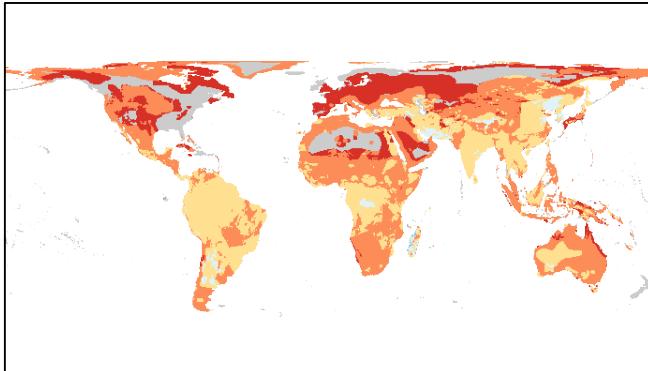
- NA
- 0 – 10%
- 10 – 20%
- 20 – 30%
- 30 – 40%
- 40 – 50%
- 50 – 60%
- 60 – 70%
- 70 – 80%
- 80 – 90%
- 90 – 100%

**(d) Reptiles**



**Figure S2.8:** Spatial distribution of assemblage-level mean trait completeness in each class. Note that the color breaks differ for mammals and birds and for herptiles.

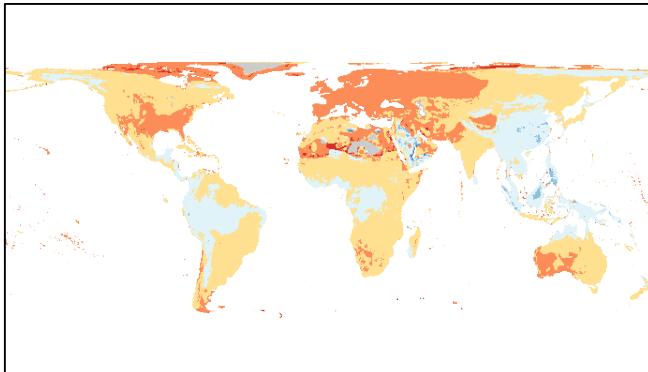
**(a) Mammals**



Standard deviation  
of completeness  
(birds and mammals):

- NA
- 0 – 5%
- 5 – 10%
- 10 – 15%
- 15 – 20%
- 20 – 25%
- 25 – 30%

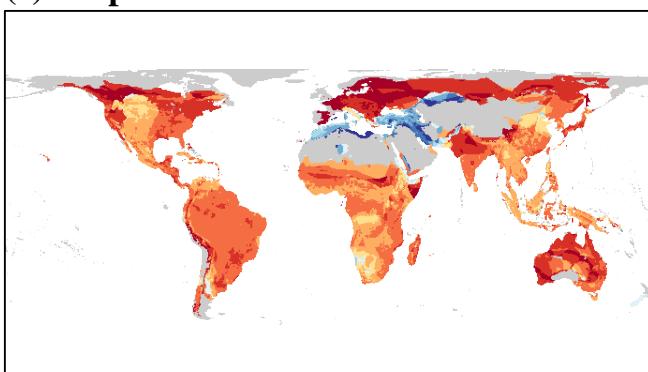
**(b) Birds**



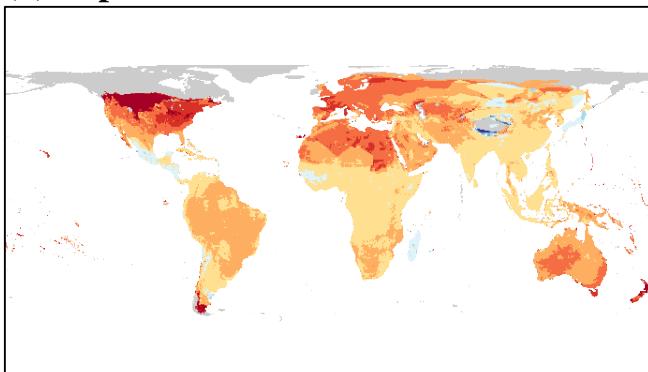
Standard deviation  
of completeness  
(herptiles):

- NA
- 0– 10%
- 10 – 15%
- 15 – 20%
- 20 – 25%
- 25 – 30%
- 30 – 35%
- 35 – 40%
- 40 – 50%
- 50 – 60%
- 60 – 75%

**(c) Amphibians**



**(d) Reptiles**



**Figure S2.9: Spatial distribution of assemblage-level standard deviation of trait completeness in each class.** Note that the color breaks differ for mammals and birds and for herptiles.

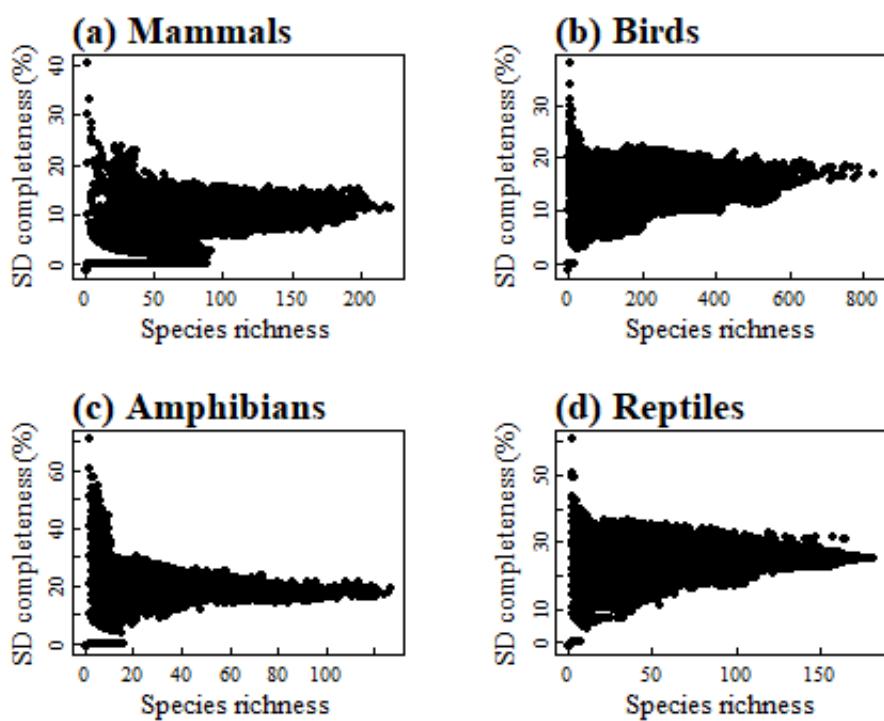
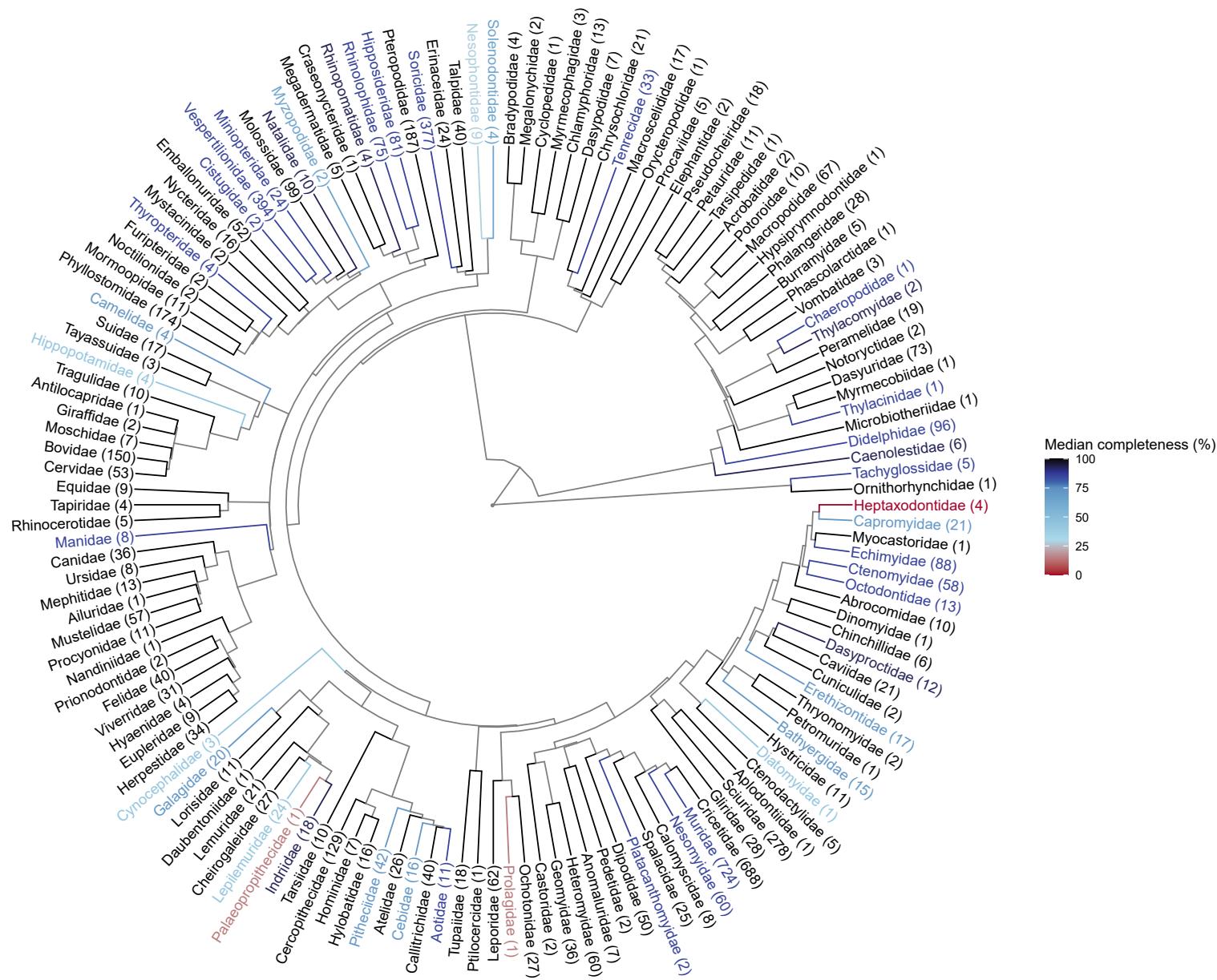
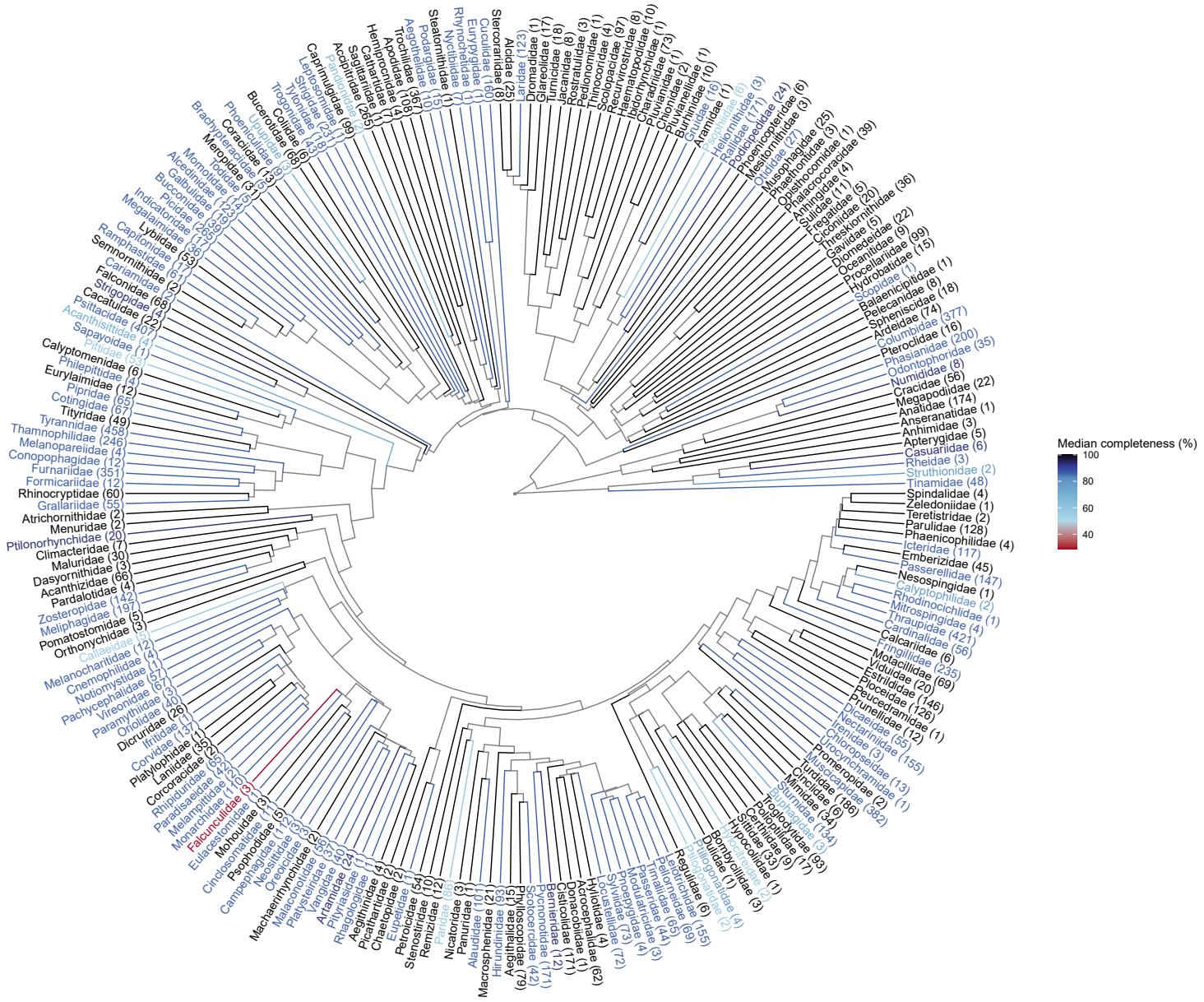


Figure S2.10: Assemblage-level species richness against standard deviation in trait completeness in each class.

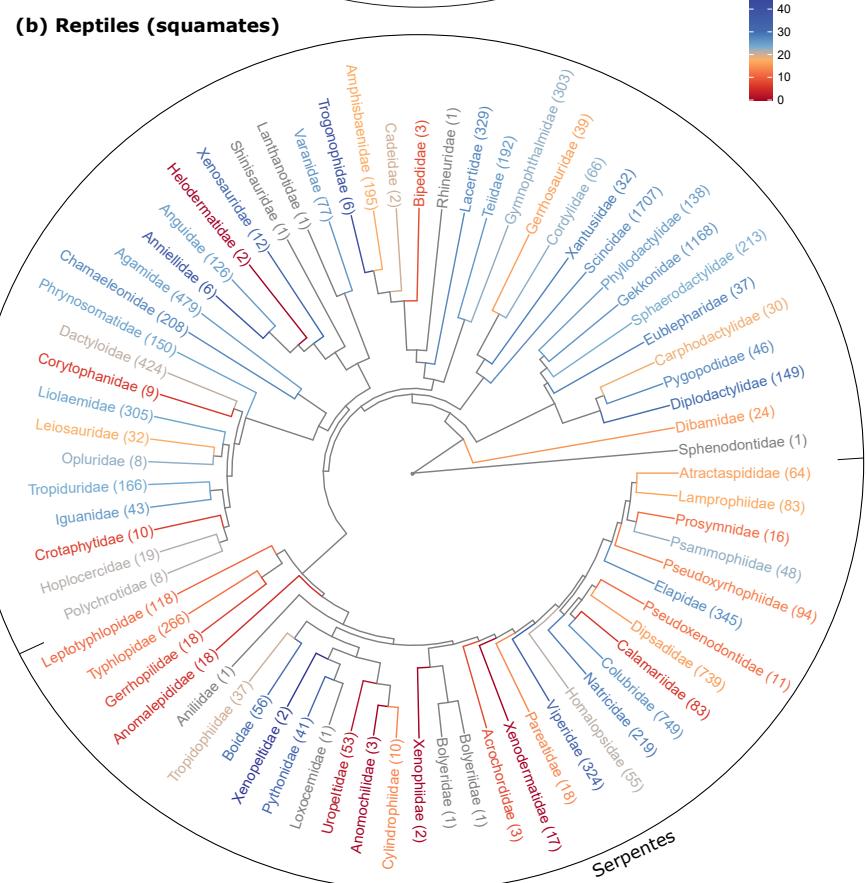
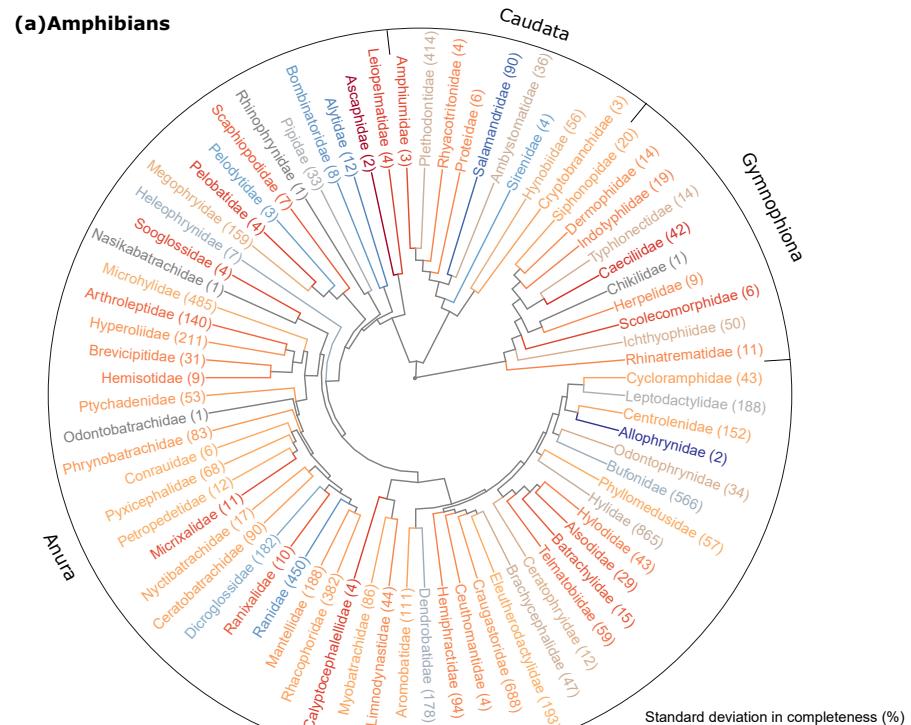
## **S2.11 Phylogenetic patterns in trait completeness**



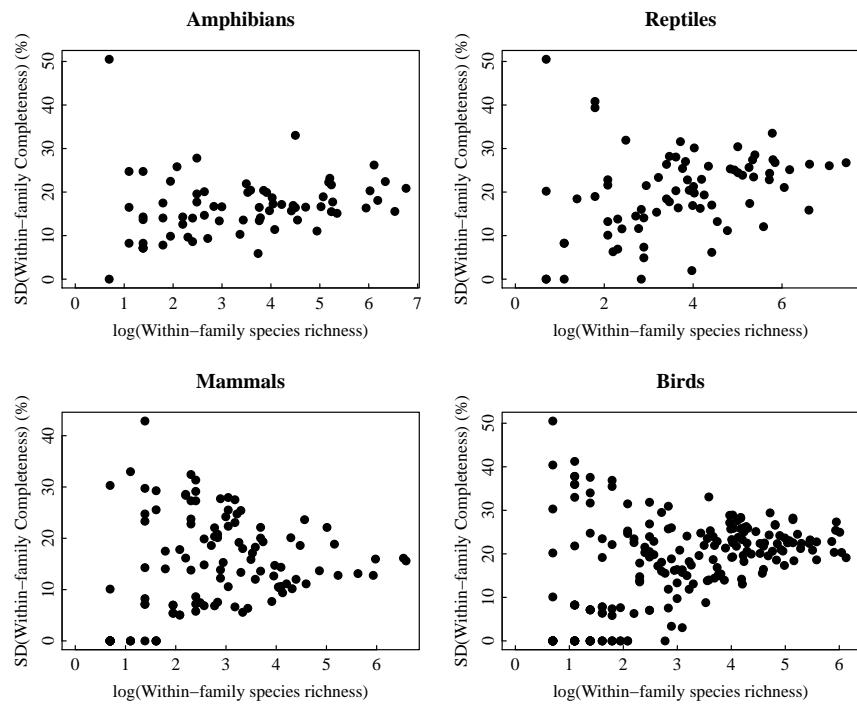
**Figure S2.11:** Within-family median trait completeness in mammals.



**Figure S2.12:** Within-family median trait completeness in birds.



**Figure S2.13:** Within-family standard deviation in trait completeness (herptiles).



**Figure S2.14: Within-family species richness against the within-family standard deviation of trait completeness.**

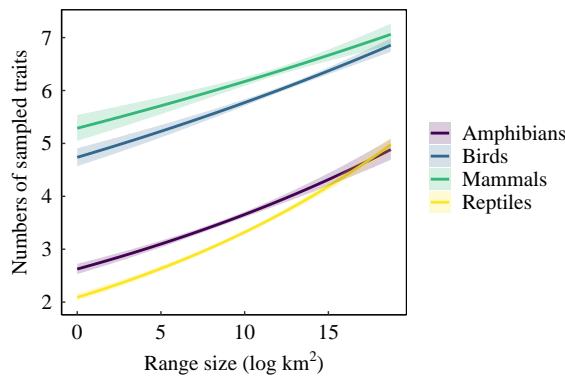
## S2.12 Poisson model summaries

**Table S2.1: Coefficients of the model investigating whether species range size explained the number of sampled traits.** Class was added as an interacting predictor. The reference level for class is mammals. The model was fitted using a Poisson error distribution.

	Estimate	Std. Error	z value	Pr(> z )
Intercept	1.678	0.022	76.809	< 2e - 16
log Range Size	0.015	0.002	8.086	6.16e - 16
Class Birds	-0.092	0.028	-3.350	0.000809
Class Amphibians	-0.689	0.029	-24.099	< 2e - 16
Class Reptiles	-0.872	0.027	-31.856	< 2e - 16
log Range Size:Class Birds	0.003	0.002	1.415	0.157
log Range Size:Class Amphibians	0.017	0.003	6.427	1.30e - 10
log Range Size:Class Reptiles	0.026	0.002	11.159	< 2e - 16

**Table S2.2: Coefficients of the model investigating whether species range size explained the number of sampled traits, using range maps not cut by altitudinal limits.** Class was added as an interacting predictor. The reference level for class is mammals. The model was fitted using a Poisson error distribution.

	Estimate	Std. Error	z value	Pr(> z )
Intercept	1.665	0.023	72.070	< 2e - 16
log Range Size	0.015	0.002	8.167	3.16e - 16
Class Birds	-0.110	0.029	-3.763	0.0002
Class Amphibians	-0.700	0.030	-23.721	< 2e - 16
Class Reptiles	-0.928	0.029	-32.403	< 2e - 16
log Range Size:Class Birds	0.004	0.002	1.840	0.066
log Range Size:Class Amphibians	0.018	0.003	6.564	5.24e - 11
log Range Size:Class Reptiles	0.031	0.002	12.630	< 2e - 16



**Figure S2.15: Relationship between number of sampled traits and geographical range size using distribution maps not cut by altitudinal limits.** The model was fitted using a Poisson error distribution. Class was added as a predictor interacting with range size. Rates of increase were not significantly different for mammals and birds, but differed for reptiles and amphibians, with steeper rates of increase for reptiles overall.

## S2.13 Spatial model summaries

**Table S2.3: Spatial model summary for amphibians.** The spatial model was fitted to explain assemblage-level median completeness with species richness. Biogeographic realm was added as an interacting explanatory variable.

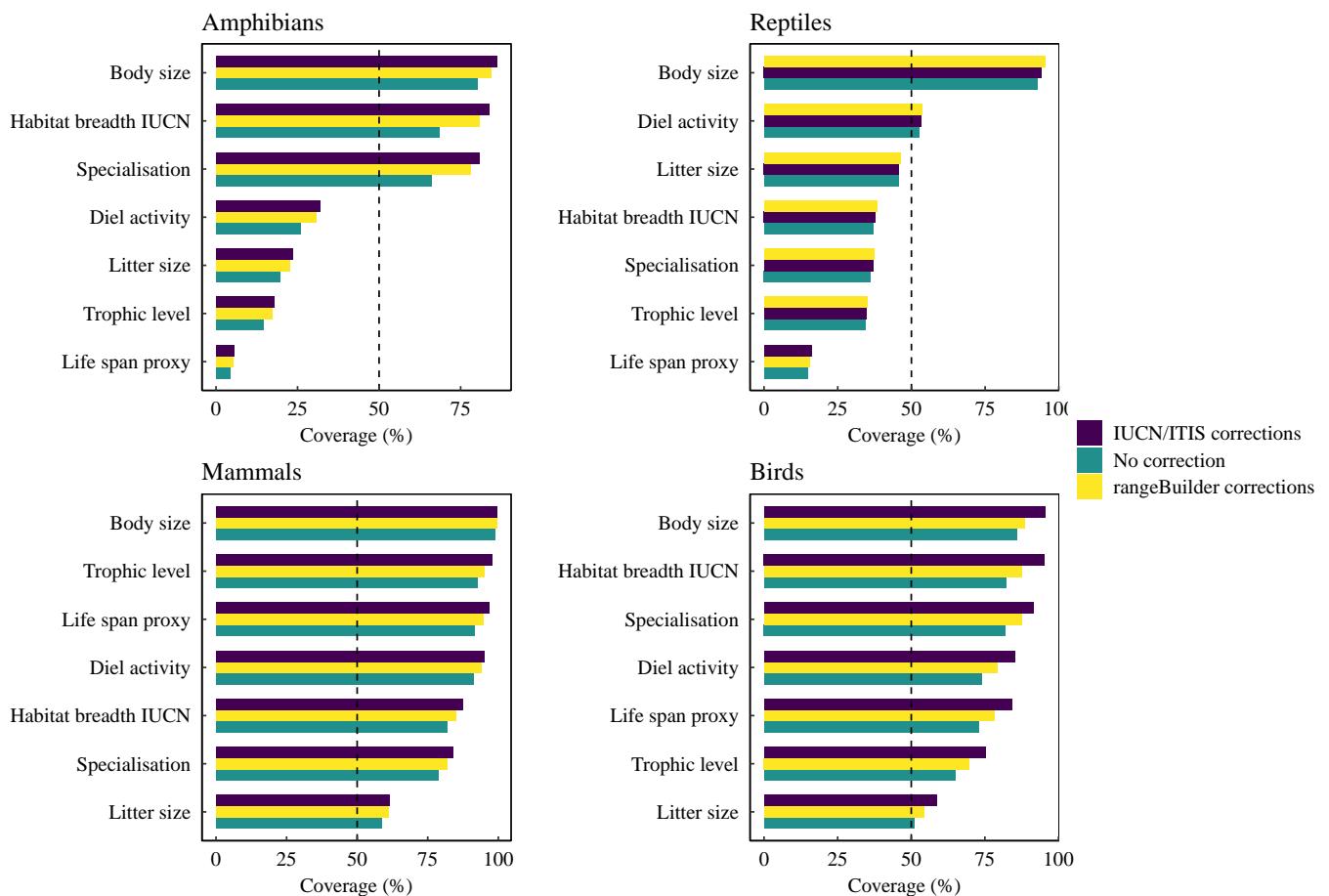
	Estimate	Std. Error	z value	Pr(> z )
Intercept - Realm: Afrotropic	0.0738	0.0064	11.4908	0
log(Species richness)	-0.0025	0.0017	-1.4261	0.1538
Realm: Australasia	-0.0109	0.0095	-1.1453	0.2521
Realm: Indo-Malay	0.0455	0.0119	3.8294	0.0001
Realm: Nearctic	0.0441	0.0082	5.3905	0.000000
Realm: Neotropic	-0.0377	0.0083	-4.5538	0.00001
Realm: Palearctic	0.0047	0.0067	0.6992	0.4844
log(Species richness):Australasia	0.0018	0.0038	0.4789	0.6320
log(Species richness):Indo-Malay	-0.0147	0.0039	-3.7294	0.0002
log(Species richness):Nearctic	-0.0097	0.0030	-3.2003	0.0014
log(Species richness):Neotropic	0.0144	0.0026	5.6454	0.000000
log(Species richness):Palearctic	0.0109	0.0029	3.7358	0.0002

**Table S2.4: Spatial model summary for reptiles.** The spatial model was fitted to explain assemblage-level median completeness with species richness. Biogeographic realm was added as an interacting explanatory variable.

	Estimate	Std. Error	z value	Pr(> z )
Intercept - Realm: Afrotropic	0.2001	0.0144	13.9349	0
log(Species richness)	-0.0316	0.0031	-10.0547	0
Realm: Australasia	-0.1284	0.0189	-6.7851	0
Realm: Indo-Malay	-0.0453	0.0263	-1.7215	0.0852
Realm: Nearctic	-0.0788	0.0140	-5.6366	0.000000
Realm: Neotropic	-0.0932	0.0145	-6.4425	0
Realm: Palearctic	-0.1030	0.0131	-7.8787	0
log(Species richness):Australasia	0.0386	0.0046	8.4019	0
log(Species richness):Indo-Malay	0.0124	0.0061	2.0397	0.0414
log(Species richness):Nearctic	0.0346	0.0038	9.1601	0
log(Species richness):Neotropic	0.0220	0.0034	6.4231	0
log(Species richness):Palearctic	0.0286	0.0033	8.6153	0

## S2.14 Trait coverage and taxonomic matching

Here, I briefly explore the robustness of my work to taxonomic uncertainty by comparing trait coverage obtained with the procedure I developed for taxonomic matching against trait coverage obtained when extracting synonyms from class-specific sources, which could potentially contain more taxonomic information than the ITIS or the IUCN Red List, notably for herptiles. I corrected the datasets for taxonomy again using the ‘rangeBuilder’ R package (Rabosky et al., 2016), which allows to extract accepted names from class-specific sources. Overall, my results are robust to the use of a different taxonomic backbone (Figure S2.16); the main conclusions of this work are likely unaffected by taxonomic uncertainty.



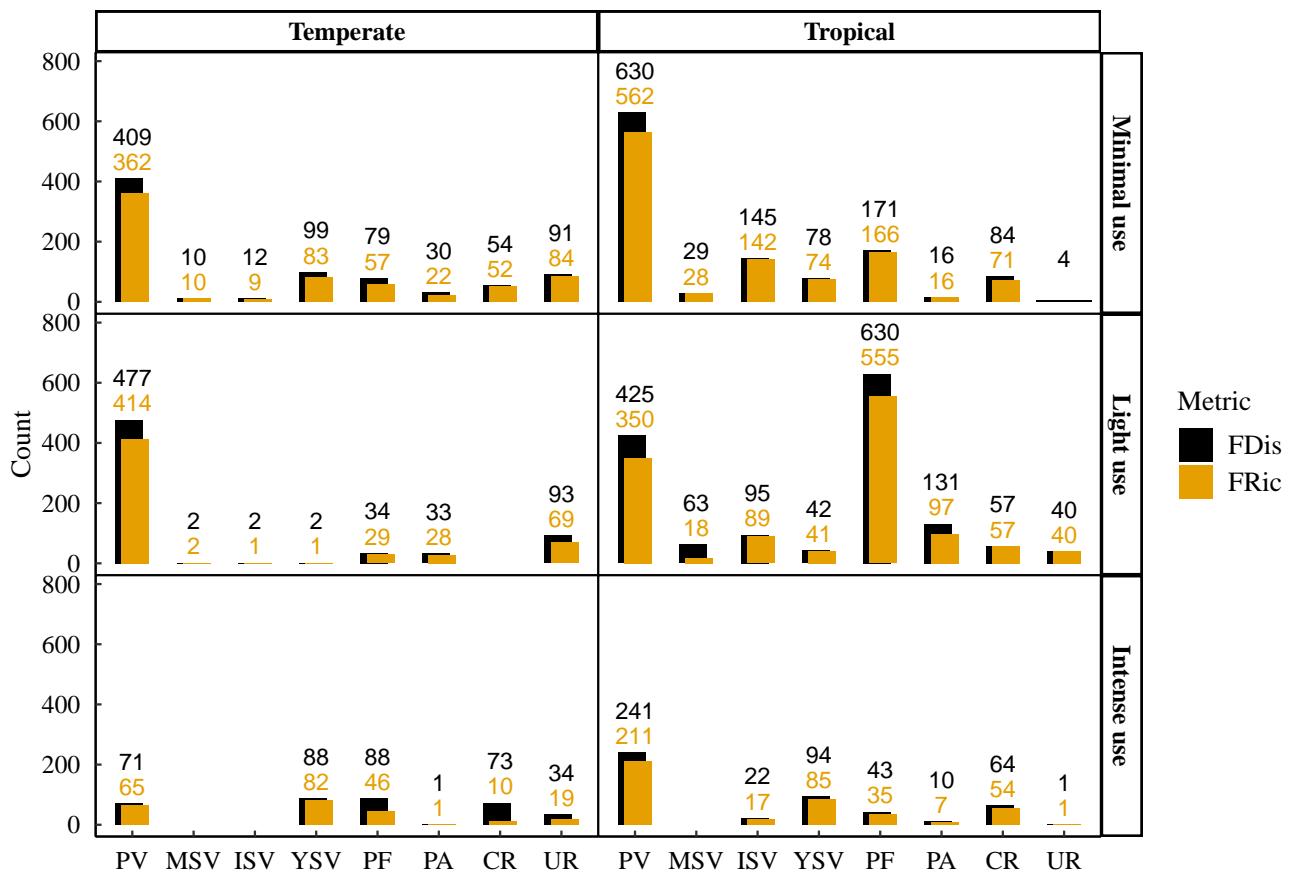
**Figure S2.16: Comparison of trait coverage among datasets corrected for taxonomy in different ways:** using the described procedure (purple bars); using datasets corrected for taxonomy with the ‘rangeBuilder’ package (yellow bars; Rabosky et al. (2016)); and using datasets uncorrected for taxonomy (green bars).

# Appendix 2: Supporting information for Chapter 3

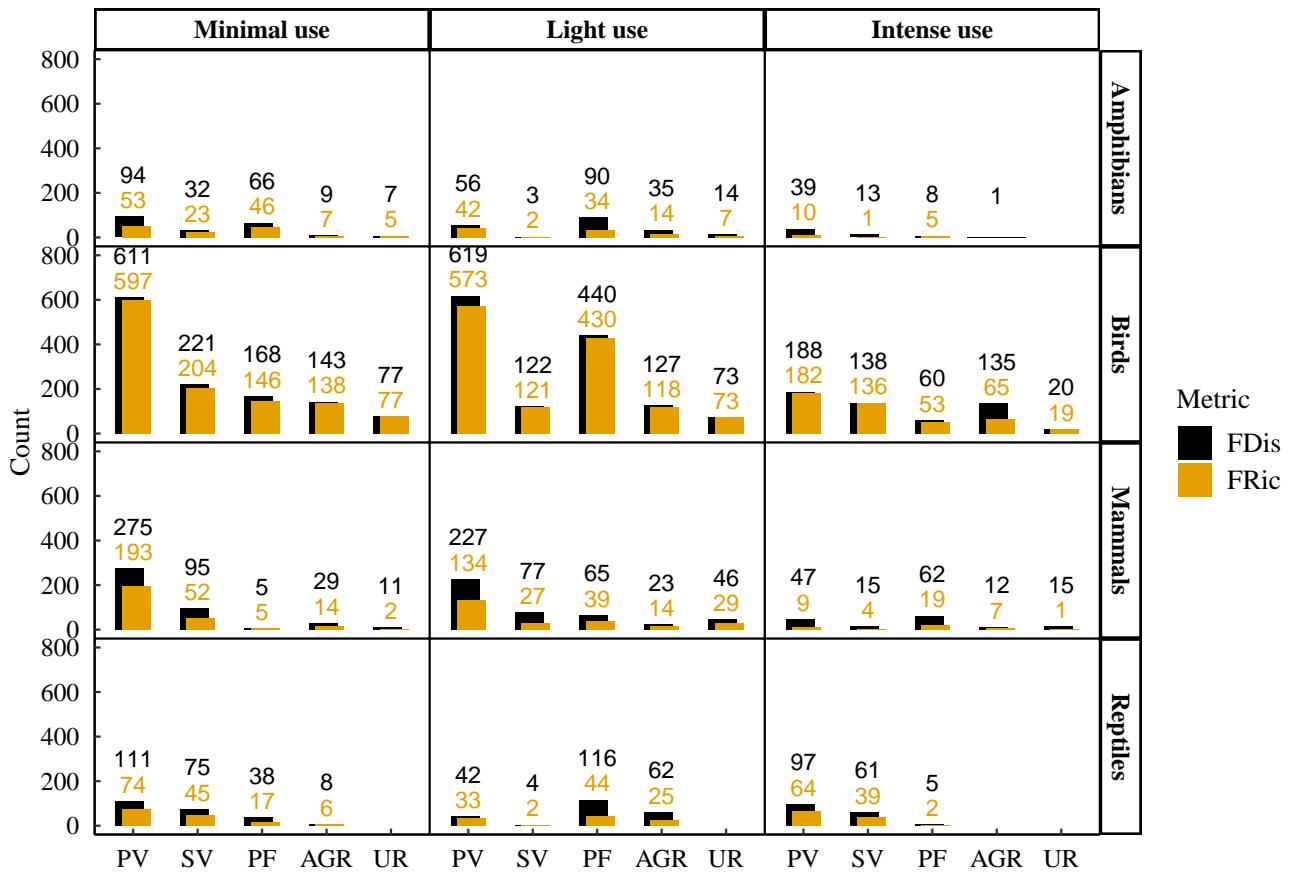
## S3.1 Land-use categories in PREDICTS and sample sizes

**Table S3.1: Land-use categories in the PREDICTS database.** See Hudson et al. (2014, 2017) for more details.

Land-use category	Definition
Primary vegetation	Native vegetation, undisturbed since its establishment under current climatic conditions. No known alterations due to human activities or to extreme natural events.
Mature secondary vegetation	Vegetation recovering after complete destruction of primary vegetation & where succession is near complete – the structure approaches that of primary vegetation.
Intermediate secondary vegetation	Vegetation recovering after complete destruction of primary vegetation at a mid-successional stage.
Young secondary vegetation	Vegetation recovering after complete destruction of primary vegetation at an early successional stage.
Plantation forest	Previously cleared areas planted with crop trees or shrubs grown and harvested for human consumption or for commercial purposes (includes wood, fruit, oil, biofuel, rubber, etc).
Pasture	Areas grazed by livestock, permanently or regularly. Can be improved through cultivation techniques.
Cropland	Previously cleared areas planted with herbaceous crops and harvested for human or animal consumption (including animal feed and crops used in the food industry), or for commercial purposes (e.g., crops grown for the textile industry).
Urban	Previously cleared areas built up by humans. Vegetation is managed for civic or personal purposes.



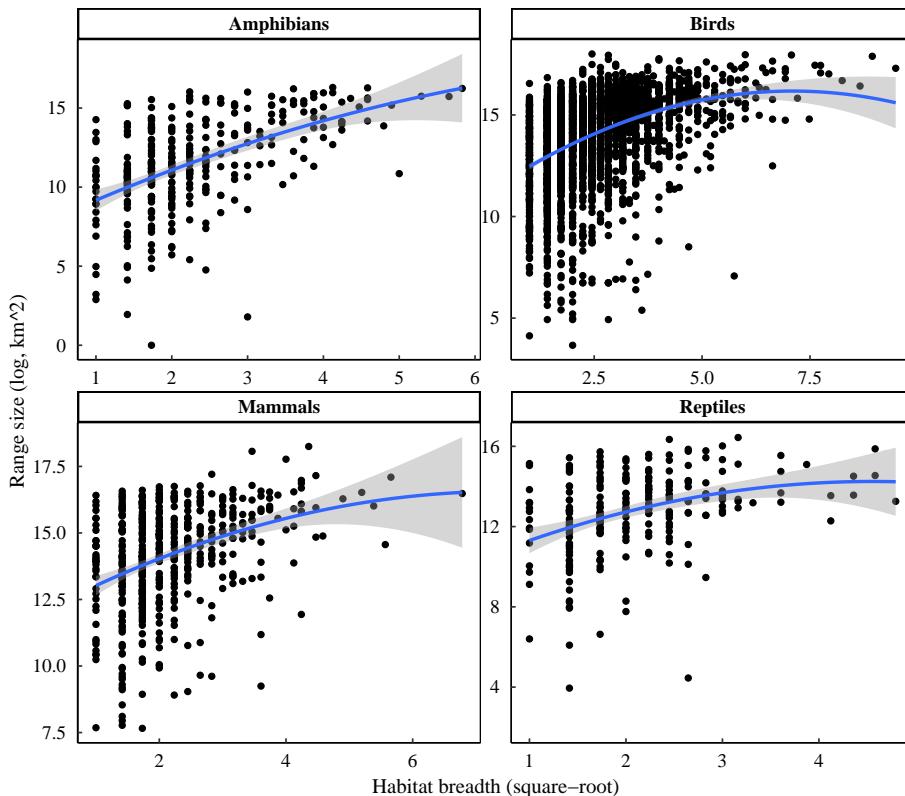
**Figure S3.1: Number of sites in each land use and land-use intensity for which FRic and FDis were calculated, across all species.** The number of sites for FRic can be smaller than the number of sites for FDis because FRic could not necessarily be computed for all assemblages in which FDis was estimated (in assemblages where species richness was 2 or 3, FRic could not be computed).



**Figure S3.2: Number of sites in each land use, land-use intensity and for which FRic and FDis were calculated, within each class.** The number of sites for FRic can be smaller than the number of sites for FDis because FRic could not necessarily be computed for all assemblages in which FDis was estimated (in assemblages where species richness was 2 or 3, FRic could not be computed).

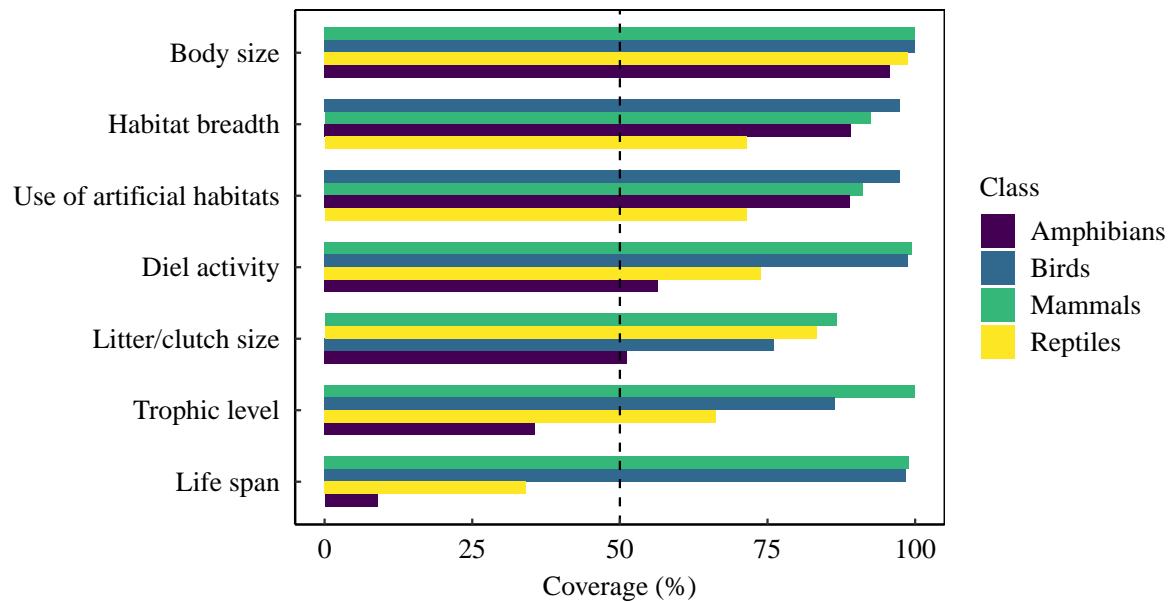
## S3.2 Trait data & imputation of missing trait values

I used the compilation of trait data across terrestrial vertebrates from Chapter 2. I selected seven traits that were available at least for a subset of the species in each class: body mass, trophic level, lifespan, litter/clutch size, diel activity, habitat breadth and use of artificial habitats. These traits related to life-history, habitat specialisation and use of geographical space (for instance, habitat breadth is a significant predictor of geographical range size in all classes, Figure S3.3).

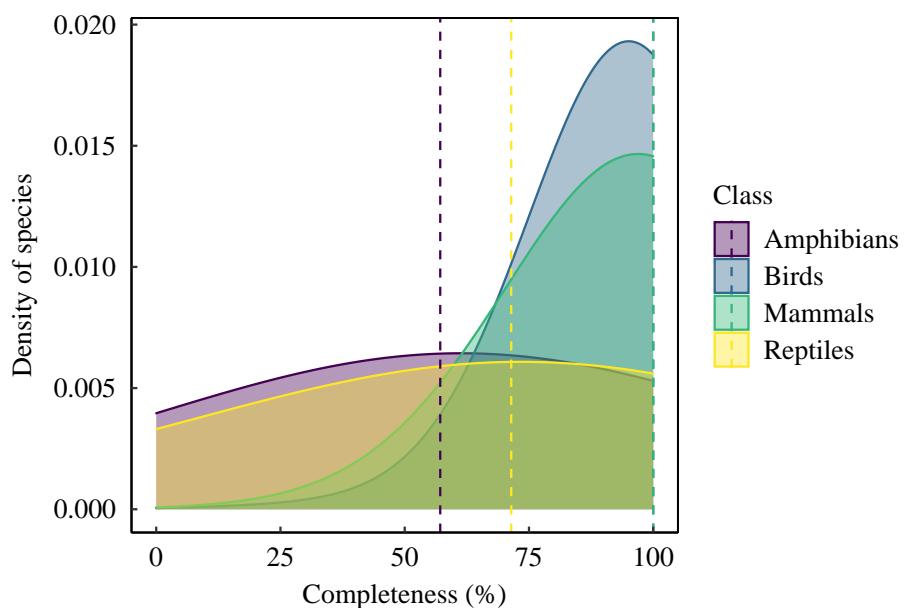


**Figure S3.3: Relationship between habitat breadth and geographical range size across species in each class.** The derivation of geographical range sizes is described in Chapter 2. The blue lines are the lines of best fit for the regression of geographical range size against habitat breadth in each class, allowing for a quadratic term in the models ( $\text{range size} \sim \text{habitat breadth} + \text{habitat breadth}^2$ ); the shaded areas are the 95% confidence interval of the lines of best fit.

Trait-data coverage was highly variable among classes and traits, with important geographical and phylogenetic biases in trait data for reptiles and amphibians (Chapter 2; Figure S3.4, Figure S3.5). To obtain complete species-trait datasets, I imputed missing trait values. Further, in order to assess the sensitivity of the models to variation in imputed values, I imputed the missing trait values eight independent times. This allowed me to assess the congruence of the model predictions when using the different imputed trait datasets in the analyses.



**Figure S3.4: Trait coverage for the vertebrate species sampled in the PREDICTS database.** For a given trait, coverage is calculated as the percentage of species for which an estimate was available.



**Figure S3.5: Distribution of trait completeness across the vertebrate species sampled in the PREDICTS database.** For a given species, trait completeness is calculated as the proportion of traits for which an estimate was available. Dashed lines represent the median trait completeness.

### S3.2.1 Choice of imputation technique

There exist several imputation techniques (Debastiani et al., 2021; Johnson et al., 2021; Penone et al., 2014), such as K-nearest neighbour (Troyanskaya et al., 2001), multivariate imputation by chained equations (van Buuren and Groothuis-Oudshoorn, 2007), random forest algorithms (implementable in R with the ‘missForest’ function from the ‘missForest’ package; Stekhoven, 2016; Stekhoven and Bühlmann, 2012), and phylogenetic imputations (implementable in R with PhyloPars, Bruggeman et al., 2009). Penone et al. (2014) assessed the performance of these four techniques and showed that ‘missforest’ and ‘PhyloPars’ performed better when traits were phylogenetically conserved, and when the species phylogenetic position was included as a predictor of missing trait values. ‘PhyloPars’ can only handle continuous data, while ‘missForest’ is compatible with mixed-type (including categorical) data. When no phylogenetic information was included, ‘mice’ was found to be the best method, with fast imputations of mixed-type data (Penone et al., 2014). Therefore, to assess whether ‘missForest’ or ‘mice’ was more appropriate here, I measured the phylogenetic signal in the traits. For continuous traits, I used Pagel’s  $\lambda$  (Pagel, 1999), and for categorical traits I used Borges’  $\delta$  (Borges et al., 2018). Strong phylogenetic signals would indicate that traits are phylogenetically conserved, and hence ‘missForest’ would be the most suited approach for imputing missing trait values, with the inclusion of species’ phylogenetic positions as a predictor.

### S3.2.2 Phylogenetic signal in traits

Across all classes, similar traits were used for calculating functional diversity metrics: body mass, litter/clutch size, lifespan (using different proxies in different vertebrate classes: generation length for birds and mammals, longevity for reptiles, and age at sexual maturity for amphibians), trophic level, diel activity, habitat breadth and use of artificial habitats. In addition, I included some class-specific traits for the imputations, as certain class-specific traits could be useful predictors of other traits (such as body length for instance in amphibians (Santini et al., 2018)). Table S3.2 details the traits that were included for the imputations in each class and the phylogenetic signal for each of these traits. Continuous traits were log-10 transformed before assessing Pagel’s  $\lambda$  to improve normality. Pagel’s  $\lambda$  was estimated using the ‘phylosig’ function of the ‘phytools’ package (Revell, 2012), and Borges’  $\delta$  was assessed using code provided by Borges et al. (2018), available at : [https://github.com/mrborges23/delta\\_statistic](https://github.com/mrborges23/delta_statistic). To test for the significance of  $\delta$ , I generated null distributions of  $\delta$  for each categorical trait by randomising trait vectors 50 times, and calculating  $\delta$  for each randomised vector – following the guidelines proposed by Borges et al. (2018). I then tested whether the observed medians were greater than the null distributions using one-sided Wilcoxon rank sum tests.

I used class-specific phylogenies to estimate phylogenetic signal, all downloaded on 13th April 2020. Trees from Faurby et al. (2018, 2020) were used for mammals (downloaded from <https://zenodo.org/record/3690867#.Xyc5wyhKhPZ>). For amphibians, birds and reptiles (squamates only), I downloaded trees from <https://data.vertlife.org/>. Trees were from Jetz et al. (2012) for birds, from Jetz and Pyron (2018) for amphibians and from Tonini et al. (2016) for squamates. For each class, I downloaded a distribution of 1,000 trees, from which I obtained consensus trees to estimate phylogenetic signal (to that end, I used the TreeAnnotator programme of the BEAST software (Bouckaert et al., 2014)).

**Table S3.2: Phylogenetic signal in continuous and categorical traits.** BM: body mass; BL: body length; GL: generation length; MA: age at sexual maturity; ML: maximum longevity; L: longevity; LCS: litter/clutch size; HB: habitat breadth; TL: trophic level; DA: diel activity; UA: use of artificial habitats. Continuous traits were log-10 transformed to improve normality before estimating Pagel's  $\lambda$  – except for habitat breadth which was square-rooted. A star indicates a significant signal (p-value<0.05 for the log-likelihood ratio test in the case of  $\lambda$ ; and a significant difference from the simulated null distribution of  $\delta$  for categorical traits). 'NA' indicates traits that were not considered for a given class. All traits showed significant phylogenetic signal, with signals for BM, BL, L, GL, MA and LCS being particularly strong (above 0.8) across the four classes.

Class	Pagel's $\lambda$								Borges' $\delta$		
	BM	BL	GL	MA	ML	L	LCS	HB	TL	DA	UA
<b>Amphibians</b>	0.98*	0.94*	NA	0.85*	0.82*	NA	0.93*	0.99*	18*	3.4*	4.5*
<b>Birds</b>	0.99*	NA	0.97*	NA	NA	NA	0.95*	0.60*	13*	32e3*	1.8*
<b>Mammals</b>	0.99*	NA	0.97	NA	NA	NA	0.99	0.71	26*	17*	1.3*
<b>Reptiles</b>	1.0*	NA	NA	NA	0.94*	0.98*	1.0*	0.52*	6.3*	6.4*	1.4*

### S3.2.3 Implementation of ‘missforest’ imputations

As phylogenetic signals were strong in many categorical and continuous traits (Table S3.2), I imputed missing trait values using random forest algorithms, as implemented in R with ‘missforest’ from the ‘missForest’ package (Stekhoven, 2016; Stekhoven and Bühlmann, 2012). Another advantage of ‘missforest’ was that, being a non-parametric approach, no prior assumption about data distribution was required. The data were therefore not transformed prior to imputations. In addition, Penone et al. (2014) showed that including phylogenetic information did not decrease the accuracy of imputations for traits that were less phylogenetically conserved, such as habitat breadth in this work.

Phylogenetic relationships were included as additional predictors in the form of phylogenetic eigenvectors (Diniz-Filho et al., 2012), extracted from the phylogenies using the ‘PVR’ package (Santos, 2018). Following Penone et al. (2014), I included the first ten phylogenetic eigenvectors as additional predictors of missing trait values in each class, enough to minimise imputation error. As not all species were represented in the phylogenies, I also added taxonomic order as a predictor for all species. All traits in Table S3.2 were included in the imputations. Tuning parameters of ‘missforest’ were set to ten maximum iterations and to

one hundred trees grown in each forest.

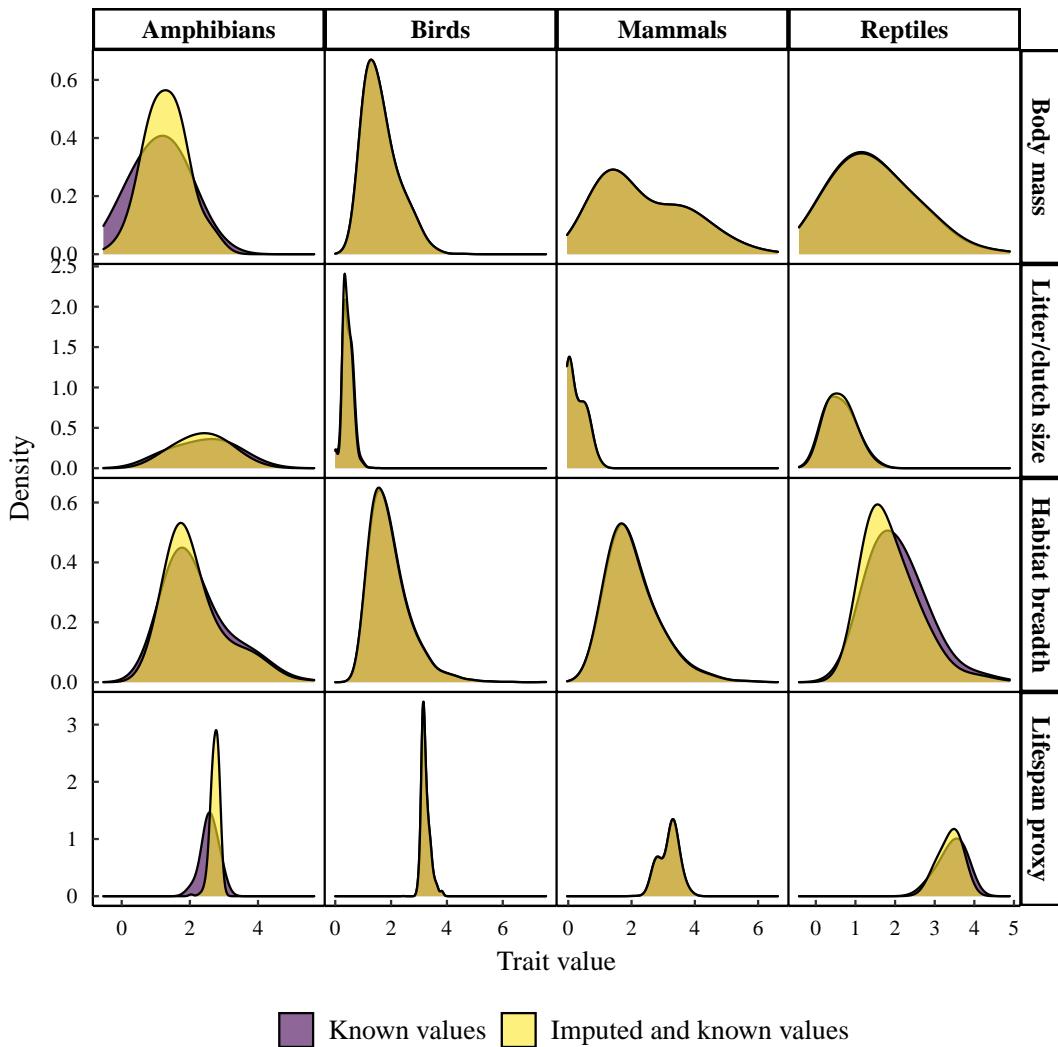
### S3.3 Degree of multicollinearity among traits

Multicollinearity among traits can be problematic when calculating functional diversity indices (Cadotte et al., 2011). After imputing missing trait values and before estimating functional metrics, I assessed whether the degree of multicollinearity among categorical and continuous traits was problematically high. To this end, I used generalised variance inflation factors (Fox and Monette, 1992). Given a regression model, variance inflation factors quantify the overestimation in the variance of estimated regression coefficients due to multicollinearity among the predictors. A GVIF value of 5 or 10 is commonly used as a threshold to select out collinear predictors (Dormann et al., 2013). I used the ‘stepwise.vif’ function of the ‘Rnalytica’ package (<https://github.com/awsm-research/Rnalytica>), with a threshold of 5, to determine the GVIF of each trait. I used the imputed traits from the 8<sup>th</sup> imputation iteration to assess whether multicollinearity was problematically high. Continuous traits were log-10 transformed (except for habitat breadth which was square-rooted). The degree of multicollinearity among traits was not detected to be problematically high, as all traits had a GVIF value below 2 (Table S3.3). As such, all seven traits were included in the calculation of the functional diversity indices.

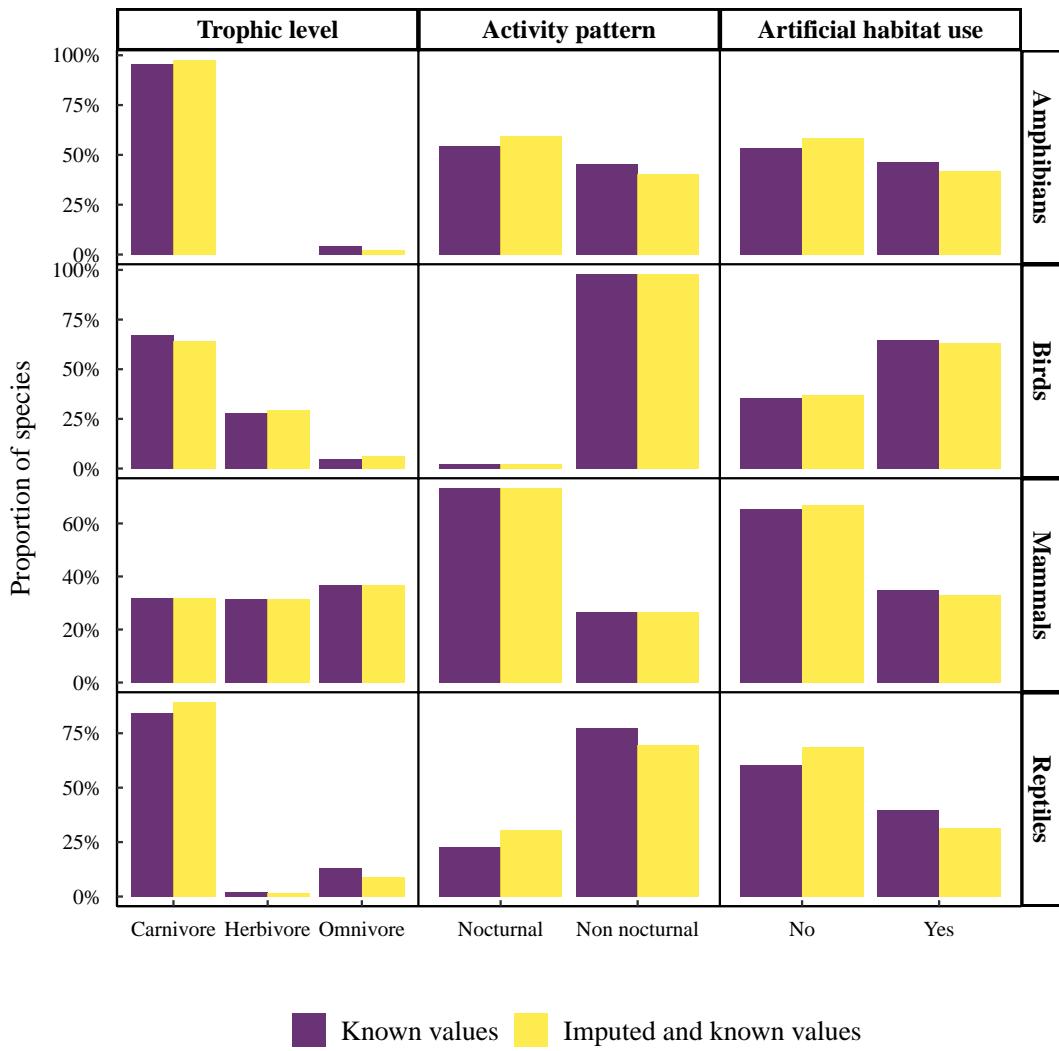
**Table S3.3: Variance inflation factors across considered (imputed) traits.**

Trait	GVIF
Diel activity	1.1
Trophic level	1.3
Use of artificial habitats	1.4
Body mass (log10)	1.5
Habitat breadth (square-root)	1.5
Litter/clutch size (log10)	1.6
Lifespan proxy (log10)	1.7

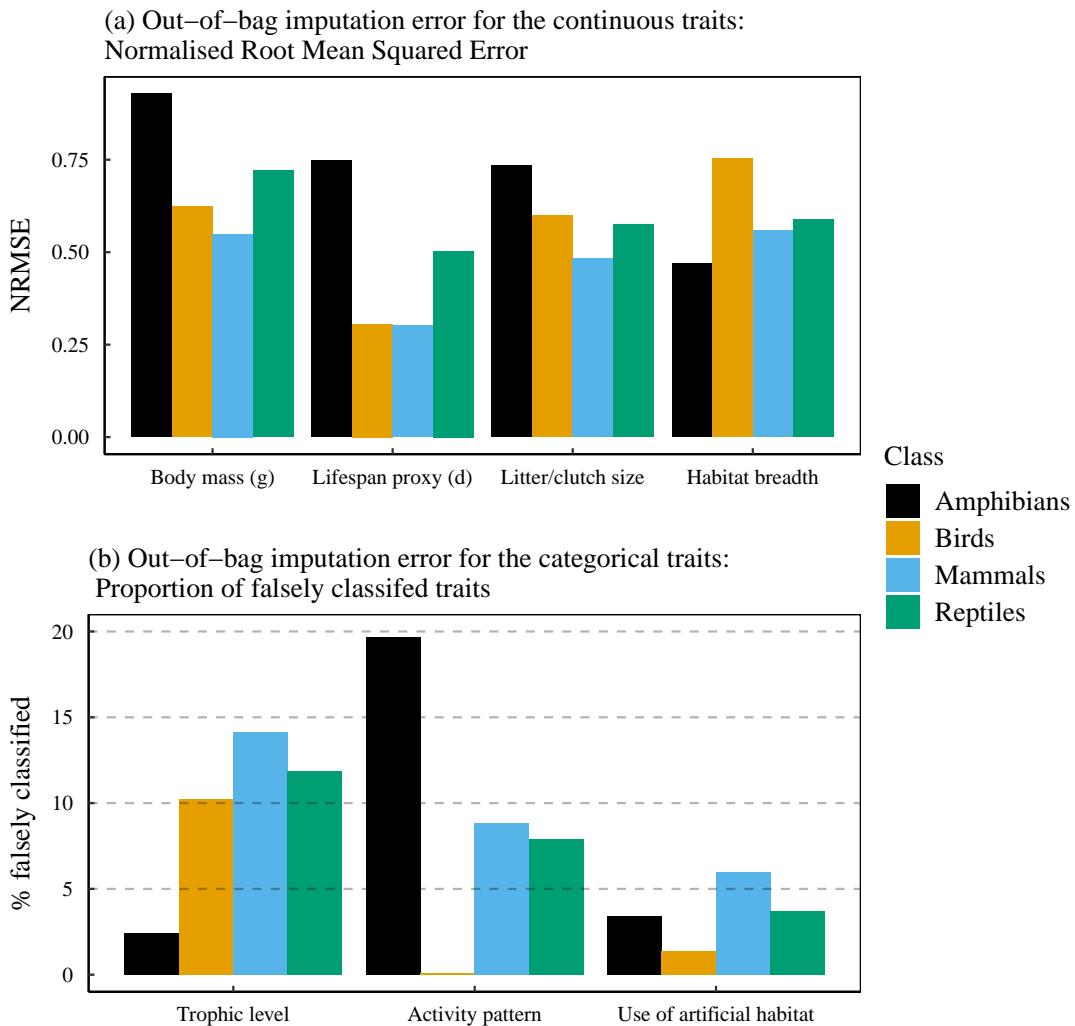
## S3.4 Imputation performance



**Figure S3.6:** Distribution of continuous traits considered in the calculation of the functional diversity metrics (shown as density plots), before and after missing value imputations, in each class and for the species occurring in the PREDICTS database. All traits were log<sub>10</sub>-transformed, except habitat breadth, which was square-rooted.



**Figure S3.7:** Frequency distribution for categorical traits considered in the calculation of the functional diversity metrics (shown as % of total species in each category) before and after missing value imputations, in each class, for the species occurring in the PREDICTS database.



**Figure S3.8: Out-of-bag imputation errors for the continuous traits (a) and categorical traits (b).** For continuous traits, the Normalised Root Mean Squared Error (NRMSE) was obtained by dividing the Mean Squared Error (MSE) by the variance of the known trait distribution, then square-rooting the result. The MSE was returned for each trait by the ‘missForest’ function (‘missForest’ package, Stekhoven, 2016; Stekhoven and Bühlmann, 2012) and corresponds to an out-of-bag error. For categorical traits, the error was estimated as the out-of-bag proportion of falsely classified traits.

### S3.5 Functional loss and functional gain

Across all vertebrates, I estimated functional loss and functional gain using 84 studies for the tropical subset and 39 studies for the temperate subset (51,514 and 30,470 pairwise comparisons between sites respectively, Table S3.4). Because of this large number of pairwise comparisons, I did not develop a null modelling approach (if I used 100 randomisations per pair of sites, I would need to compute functional loss and functional gain for more than 8 million pairs, which would be very computationally demanding). I grouped mature, intermediate and young secondary vegetation together in this analysis. I could not estimate the effects in all land uses (for instance, sample sizes for tropical urban sites were too small; Figure S3.1).

Within classes, I used 18 tropical studies and 1 temperate study for amphibians; 38 tropical studies and 21 temperate studies for birds; 28 tropical studies and 9 temperate studies for mammals; and 11 tropical studies and 7 temperate studies for reptiles. As sample sizes differed among pairs of land uses and land-use intensities (Table S3.5), I was not able to estimate all effects, notably for the intensely-used land uses.

To calculate functional loss and functional gain, the Gower distance matrix (obtained from the global species by trait dataset for the species occurring in PREDICTS) was first subsetted to the species occurring in a given pair of sites. Cailliez corrections were applied when the distance matrix was not Euclidian (Cailliez corrections consist of applying the smallest positive constant to the distances so as to make them Euclidian (Cailliez, 1983); ‘ade4’ R package (Dray et al., 2007)). I then performed a principal coordinates analysis on the (corrected) Gower distance matrix, retaining the first two axes to reduce the computational load in the calculation of convex hulls. Sites that contained fewer than three functionally different species were excluded (the computation of a convex hull requiring more species in the assemblage than PCoA axes). Then I estimated the hypervolume of trait space occupied by each assemblage of a given pair, as well as the volume of the shared trait space (intersection), from which I derived functional loss and functional gain.

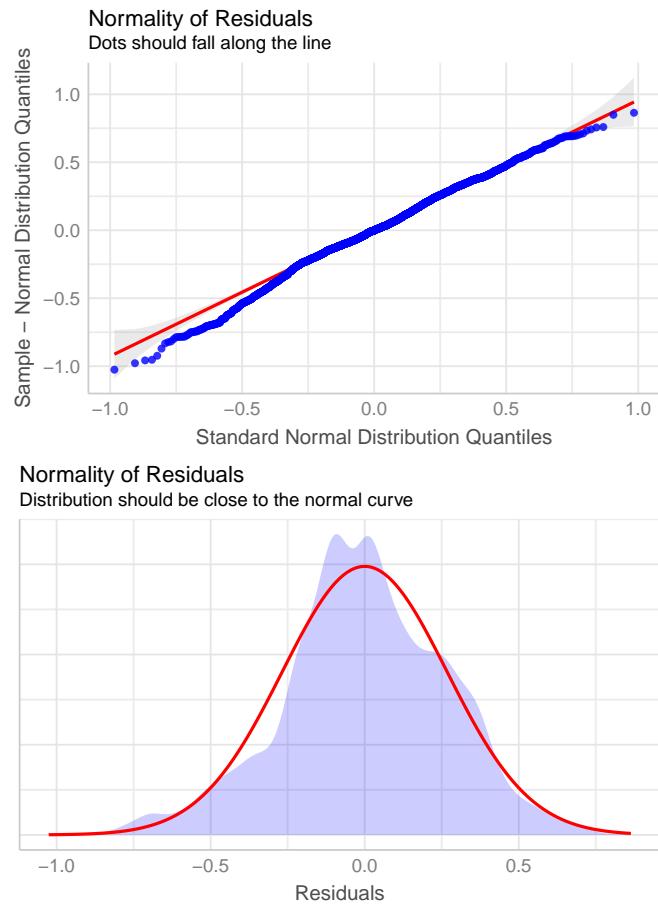
**Table S3.4: Sample sizes (number of pairs of sites) for the calculation of functional loss and functional gain across all species.**

Region	Pairs	Minimal use	Light use	Intense use
Temperate	PV-PV	7626	22546	492
	PV-SV	511	72	–
	PV-PF	9	166	–
	PV-PA	8	40	–
	PV-CR	150	–	–
	PV-UR	6306	1197	7
Tropical	PV-PV	8547	4016	16722
	PV-SV	6584	1124	9713
	PV-PF	580	1378	–
	PV-PA	36	20	22
	PV-CR	1700	1088	–
	PV-UR	–	–	–

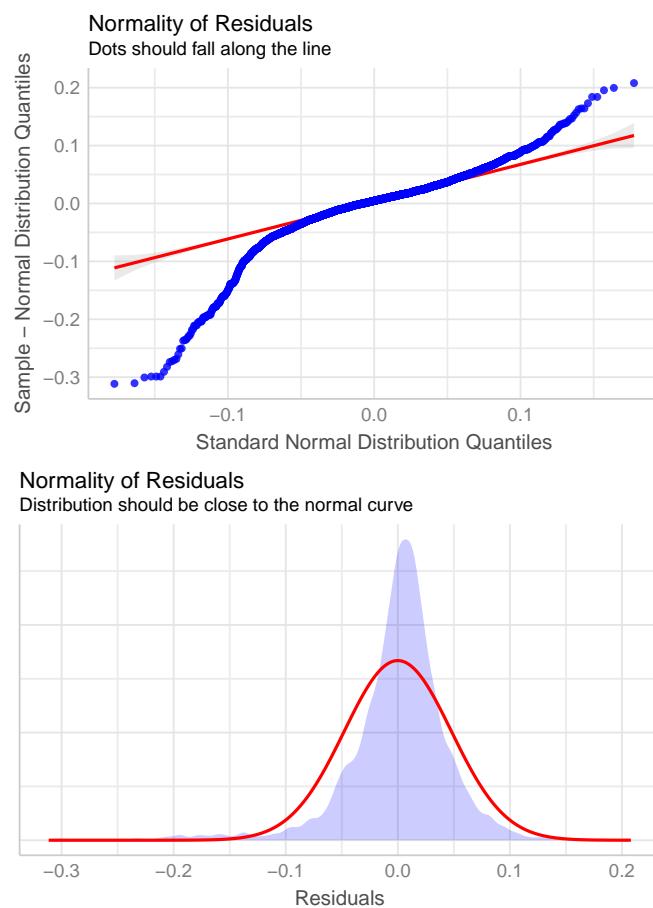
**Table S3.5: Sample sizes (number of pairs of sites) for the calculation of functional loss and functional gain within each class.**

Class	Region	Pair of land uses	Minimal use	Light use	Intense use
Amphibians	Temperate	PV/PV	–	45	–
Amphibians	Temperate	PV/SV	8	70	–
Amphibians	Temperate	PV/AGR	3	–	–
Amphibians	Temperate	PV/UR	6	100	–
Amphibians	Tropical	PV/PV	501	241	307
Amphibians	Tropical	PV/SV	838	–	90
Amphibians	Tropical	PV/PF	422	91	–
Amphibians	Tropical	PV/AGR	1	3	1
Birds	Temperate	PV/PV	7,382	19,300	491
Birds	Temperate	PV/SV	150	1	–
Birds	Temperate	PV/PF	9	166	–
Birds	Temperate	PV/AGR	145	40	–
Birds	Temperate	PV/UR	6,300	992	–
Birds	Tropical	PV/PV	5,059	3,117	9,014
Birds	Tropical	PV/SV	3,491	1,058	5,225
Birds	Tropical	PV/PF	156	994	–
Birds	Tropical	PV/AGR	1,626	1,085	–
Mammals	Temperate	PV/PV	110	3,030	–
Mammals	Temperate	PV/SV	25	–	–
Mammals	Temperate	PV/AGR	5	–	–
Mammals	Temperate	PV/UR	–	105	7
Mammals	Tropical	PV/PV	1,989	637	64
Mammals	Tropical	PV/SV	230	65	8
Mammals	Tropical	PV/PF	2	–	–
Mammals	Tropical	PV/AGR	109	20	21
Reptiles	Temperate	PV/PV	132	2	1
Reptiles	Temperate	PV/SV	250	1	–
Reptiles	Temperate	PV/AGR	5	–	–
Reptiles	Tropical	PV/PV	989	137	5,140
Reptiles	Tropical	PV/SV	1,760	1	3,456
Reptiles	Tropical	PV/PF	–	190	–

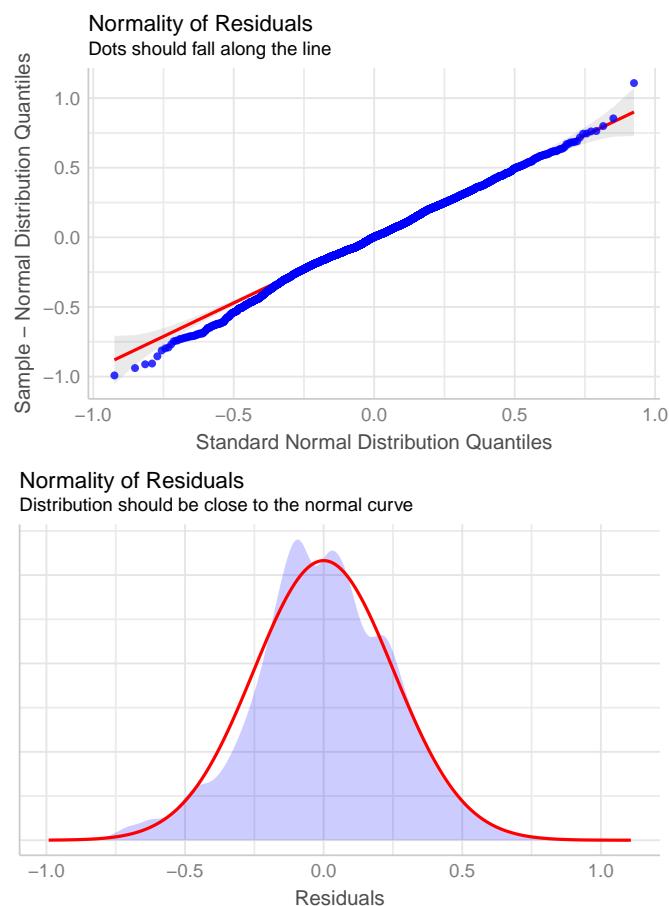
## S3.6 Diagnostic plots



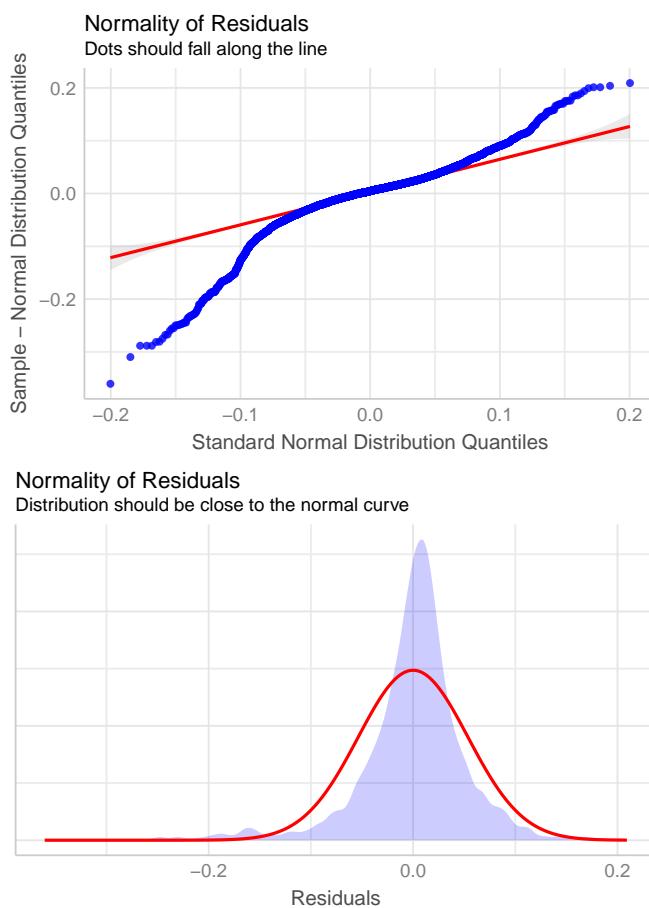
**Figure S3.9:** Diagnostic plots for Model 1a, obtained using the 'performance' R package (Lüdecke et al., 2021).



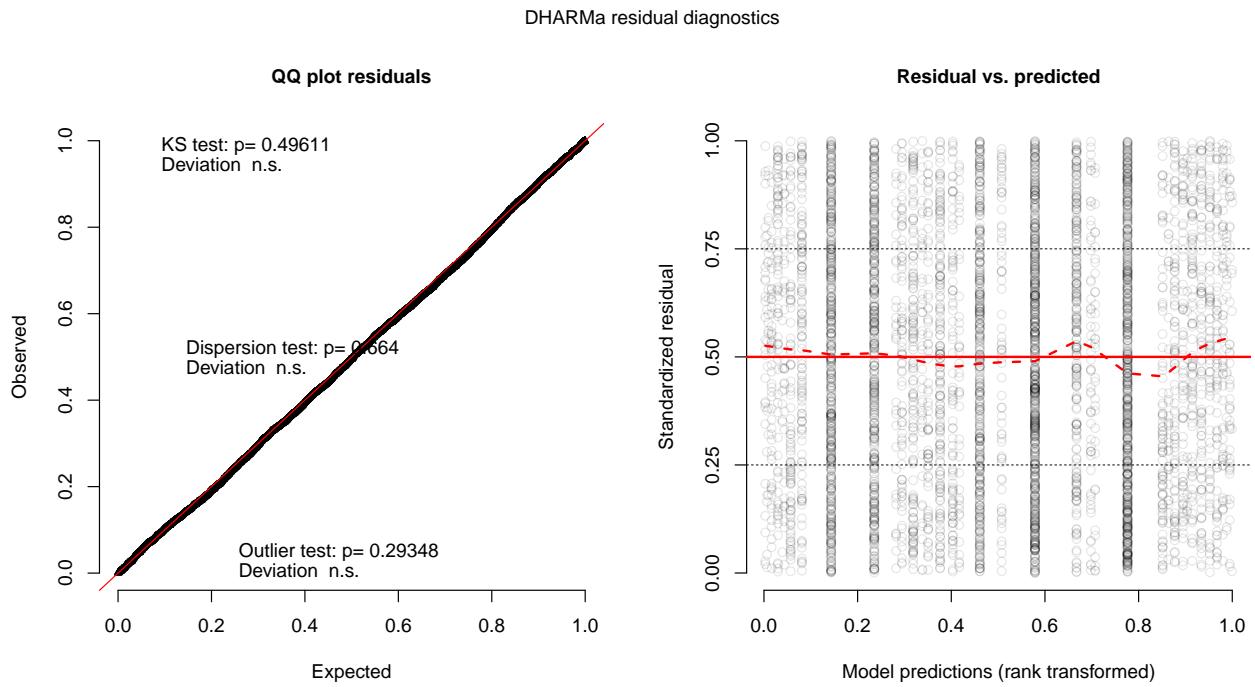
**Figure S3.10:** Diagnostic plots for Model 1b, obtained using the ‘performance’ R package (Lüdecke et al., 2021).



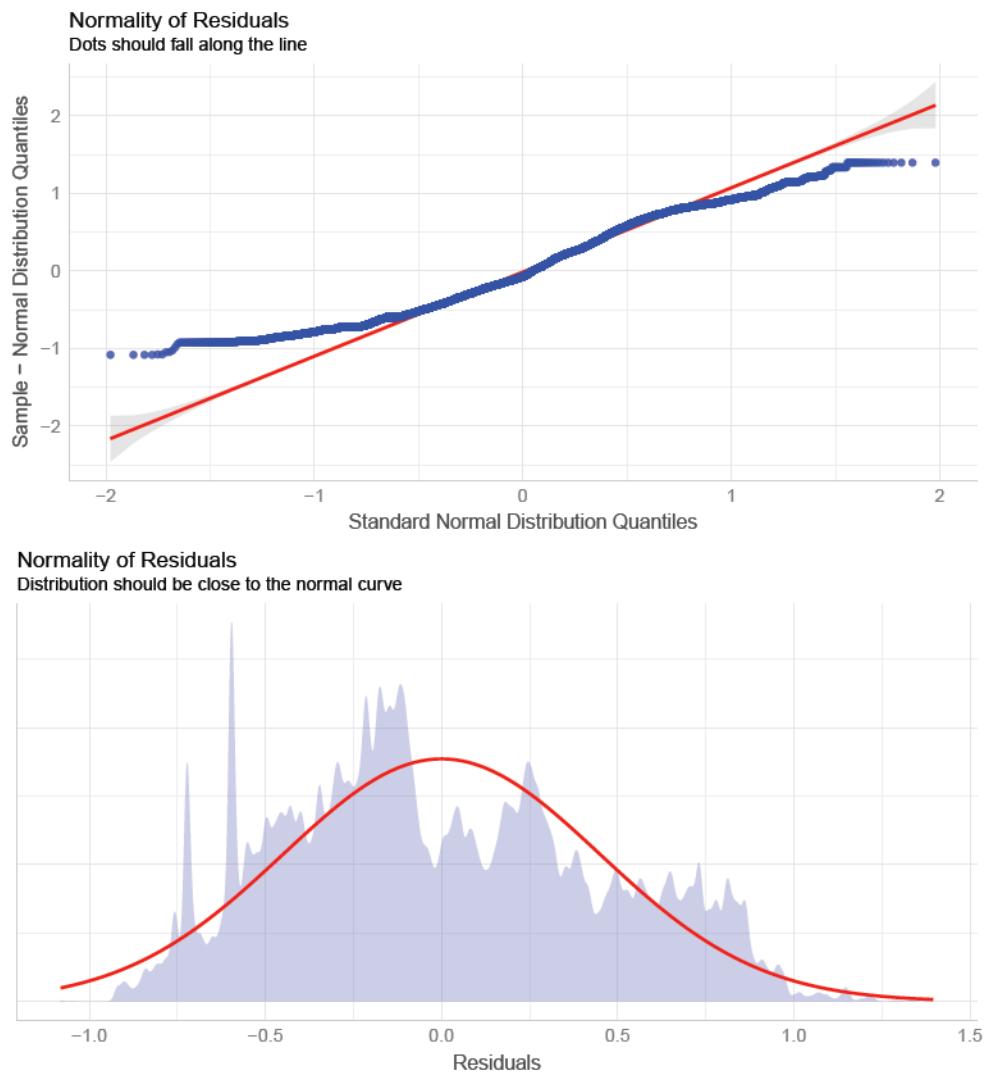
**Figure S3.11:** Diagnostic plots for Model 2a, obtained using the ‘performance’ R package (Lüdecke et al., 2021).



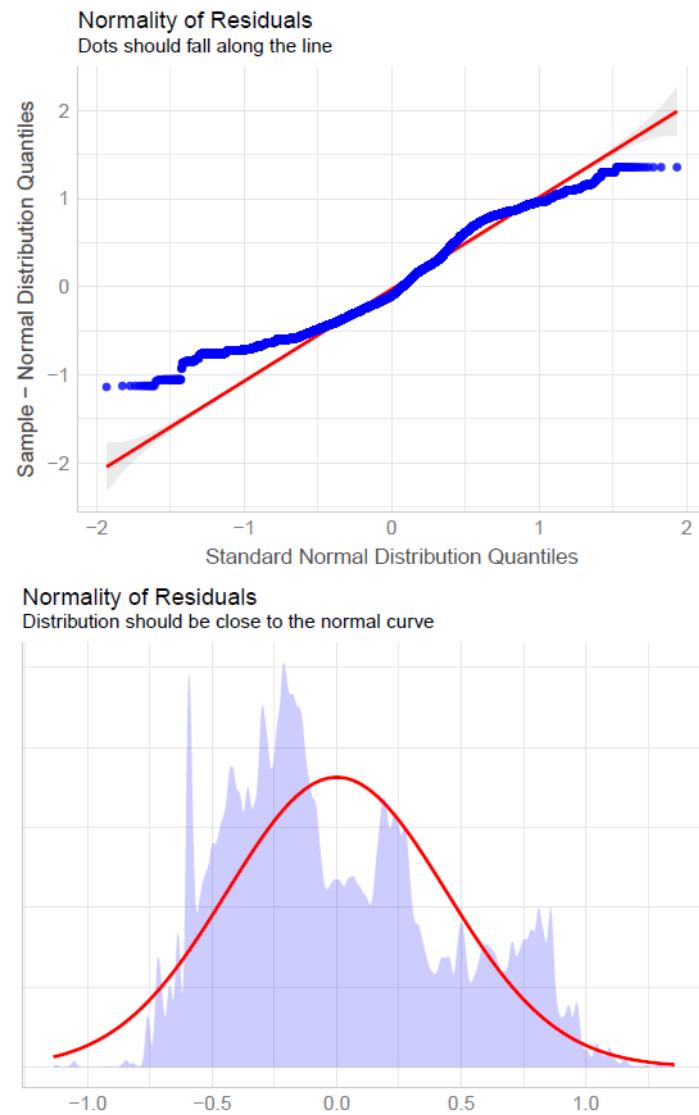
**Figure S3.12:** Diagnostic plots for Model 2b, obtained using the ‘performance’ R package (Lüdecke et al., 2021).



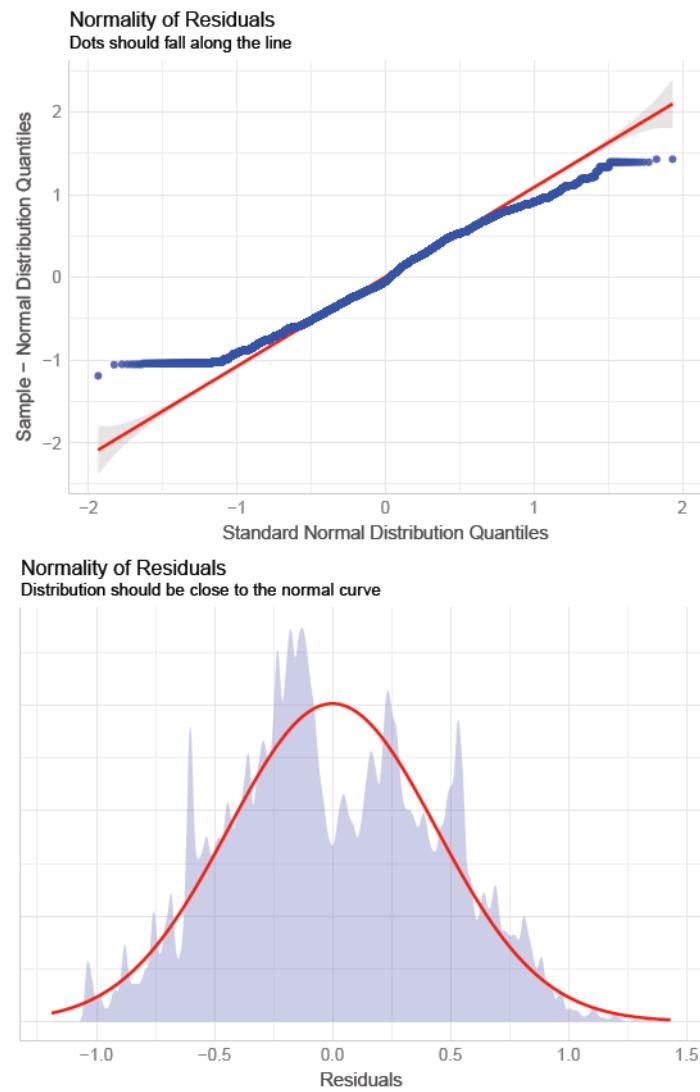
**Figure S3.13: Diagnostic plots for Model 3**, obtained using the ‘DHARMA’ R package (Hartig, 2021).



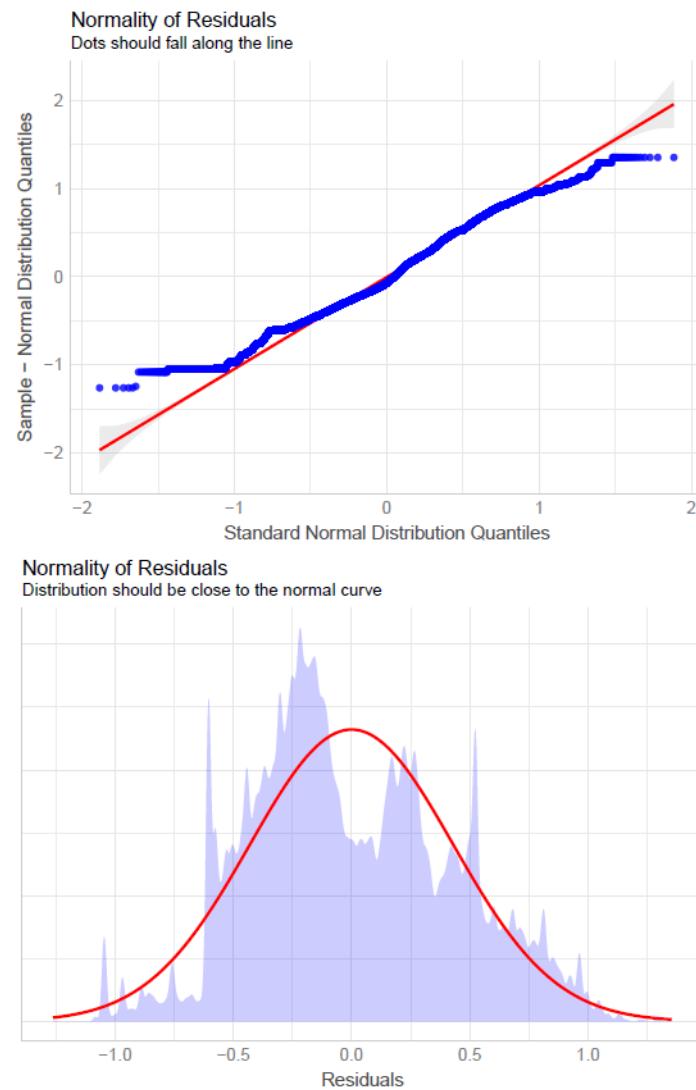
**Figure S3.14:** Diagnostic plots for Model 4a, obtained using the ‘performance’ R package (Lüdecke et al., 2021).



**Figure S3.15:** Diagnostic plots for Model 4b, obtained using the ‘performance’ R package (Lüdecke et al., 2021).

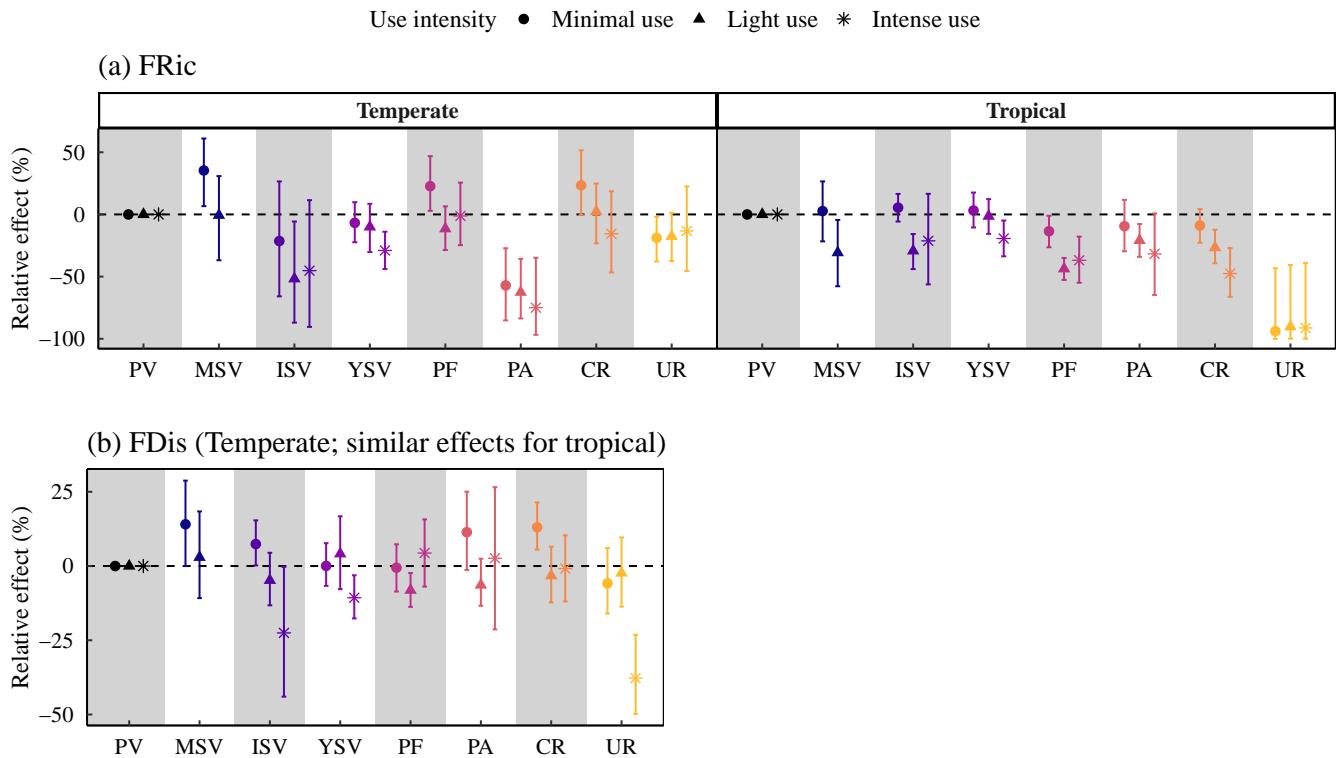


**Figure S3.16:** Diagnostic plots for Model 5a, obtained using the ‘performance’ R package (Lüdecke et al., 2021).

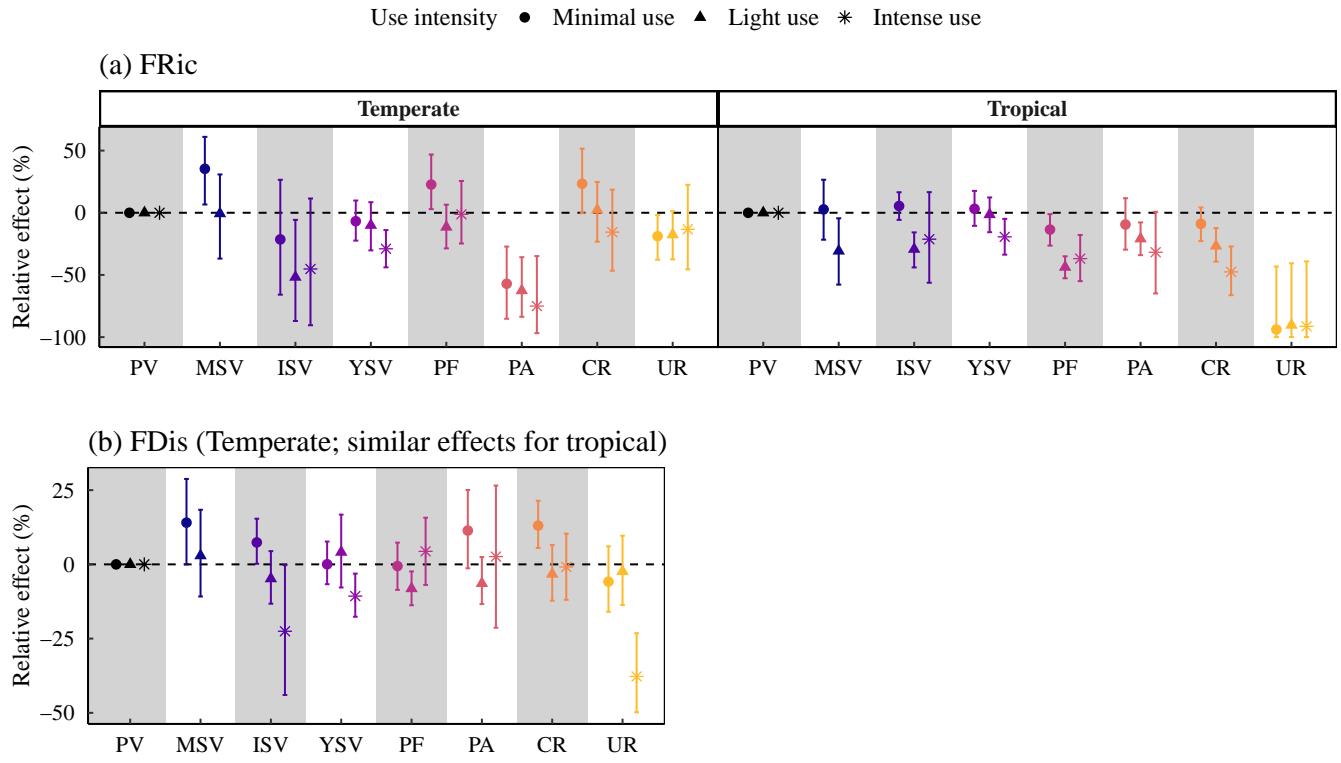


**Figure S3.17: Diagnostic plots for Model 5b**, obtained using the ‘performance’ R package (Lüdecke et al., 2021).

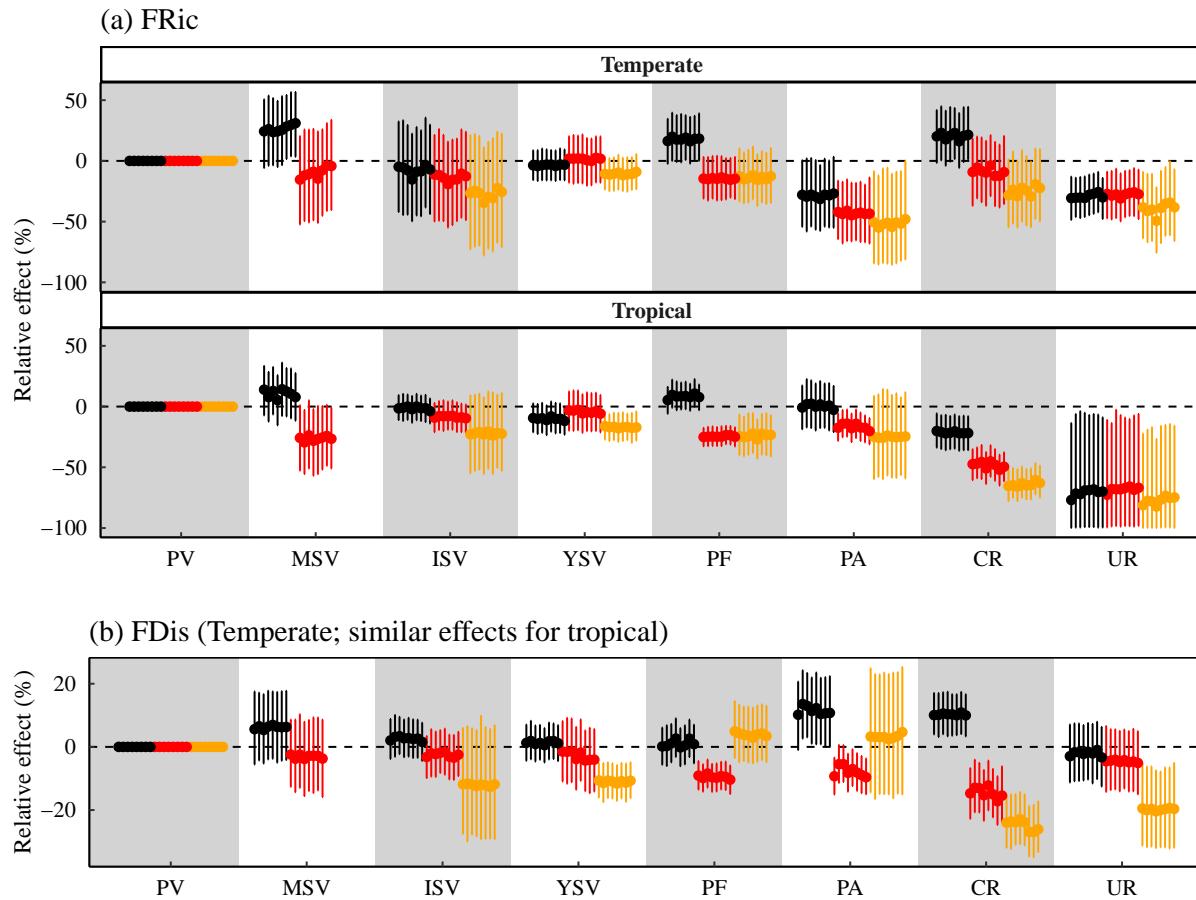
### S3.7 Model robustness



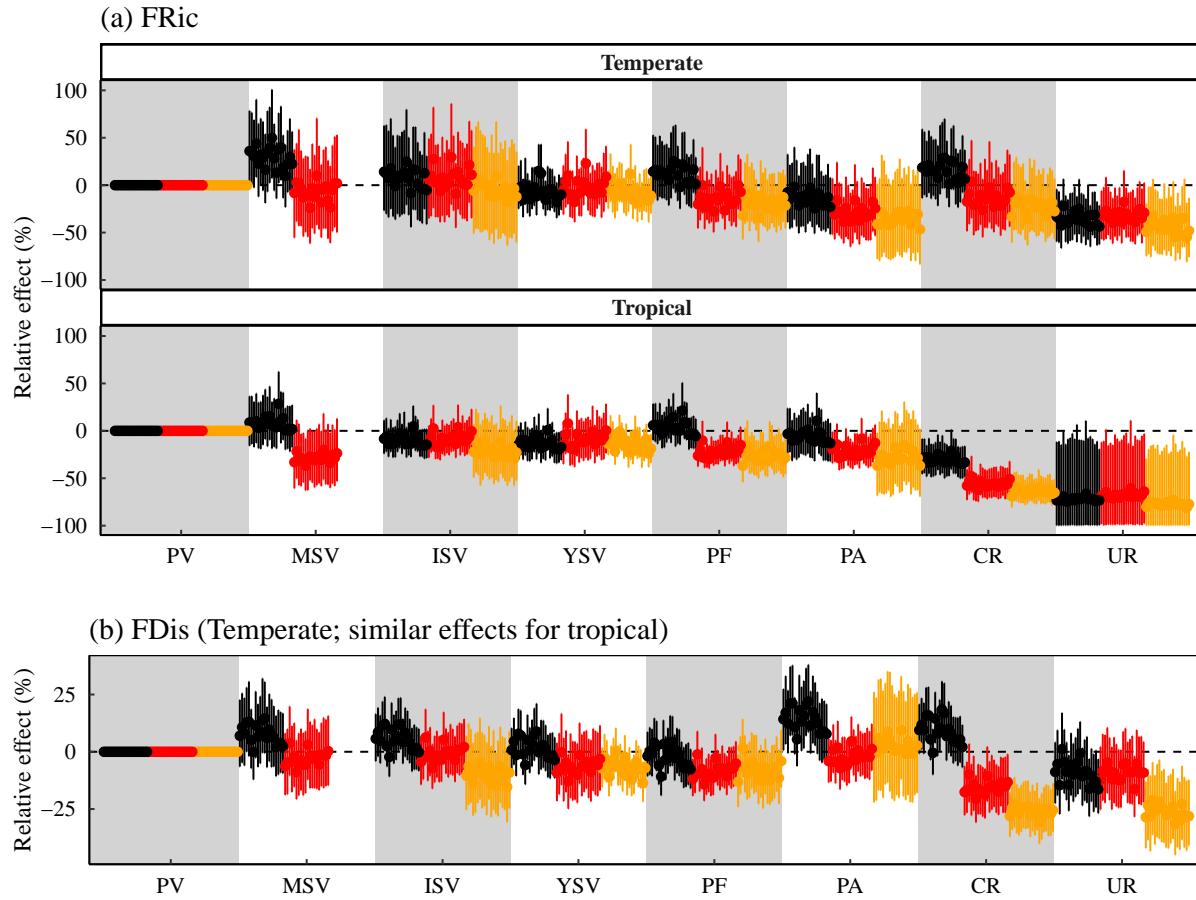
**Figure S3.18: Effects of land use, land-use intensity and region on FRic (a) and FDis (b) across vertebrates, for the subset of species with complete trait data (i.e., excluding species with less than 100% trait completeness).** Effects are plotted as a % difference relative to the reference land use (primary vegetation, PV). For FRic, I fitted **Model 1a**, which included the effects of land use, land-use intensity and region, as well as interactions between land use and land-use intensity and between land use and region. For FDis, I fitted **Model 1b**, which included effects of land use, land-use intensity and region, and interactions between land use and land-use intensity. Error bars represent 95% confidence intervals. MSV: mature secondary vegetation; ISV: intermediate secondary vegetation; YSV: young secondary vegetation; PF: plantation forest; PA: pasture; CR: cropland; UR: urban. Effects for Intense use in MSV could not be estimated as there weren't enough sampled sites.



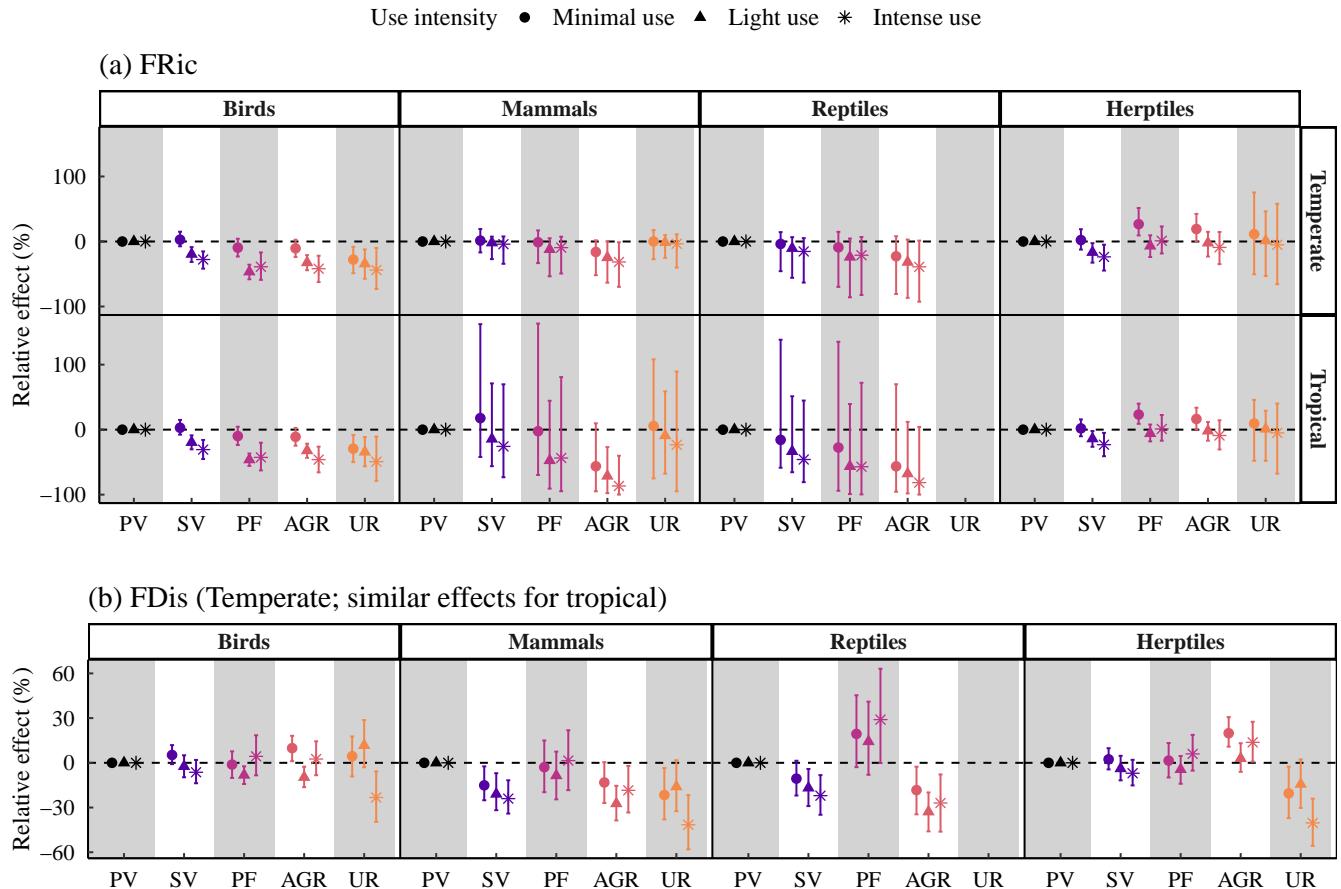
**Figure S3.19: Effects of land use, land-use intensity and region on FRic (a) and FDis (b), for the subset of species with complete trait data (i.e., excluding species with less than 100% trait completeness), with geographical range size as an additional trait considered in the calculation of functional diversity metrics.** Effects are plotted as a % difference relative to the reference land use (primary vegetation, PV). For FRic, I fitted **Model 1a**, which included the effects of land use, land-use intensity and region, as well as interactions between land use and land-use intensity and between land use and region. For FDis, I fitted **Model 1b**, which included effects of land use, land-use intensity and region, and interactions between land use and land-use intensity. Error bars represent 95% confidence intervals. MSV: mature secondary vegetation; ISV: intermediate secondary vegetation; YSV: young secondary vegetation; PF: plantation forest; PA: pasture; CR: cropland; UR: urban. Effects for Intense use in MSV could not be estimated as there weren't enough sampled sites.



**Figure S3.20: Effects of land use and land-use intensity on FRic (a) and FDis (b), obtained when calculating FRic and FDis with each set of imputed traits (eight in total). Effects are plotted as a % difference relative to the reference land use (primary vegetation, PV). For FRic, I fitted **Model 1a**, which included the effects of land use, land-use intensity and region, as well as interactions between land use and land-use intensity and between land use and region. For FDis, I fitted **Model 1b**, which included effects of land use, land-use intensity and region, and interactions between land use and land-use intensity. Error bars represent 95% confidence intervals. MSV: mature secondary vegetation; ISV: intermediate secondary vegetation; YSV: young secondary vegetation; PF: plantation forest; PA: pasture; CR: cropland; UR: urban. Effects for Intense use in MSV could not be estimated as there weren't enough sampled sites.**



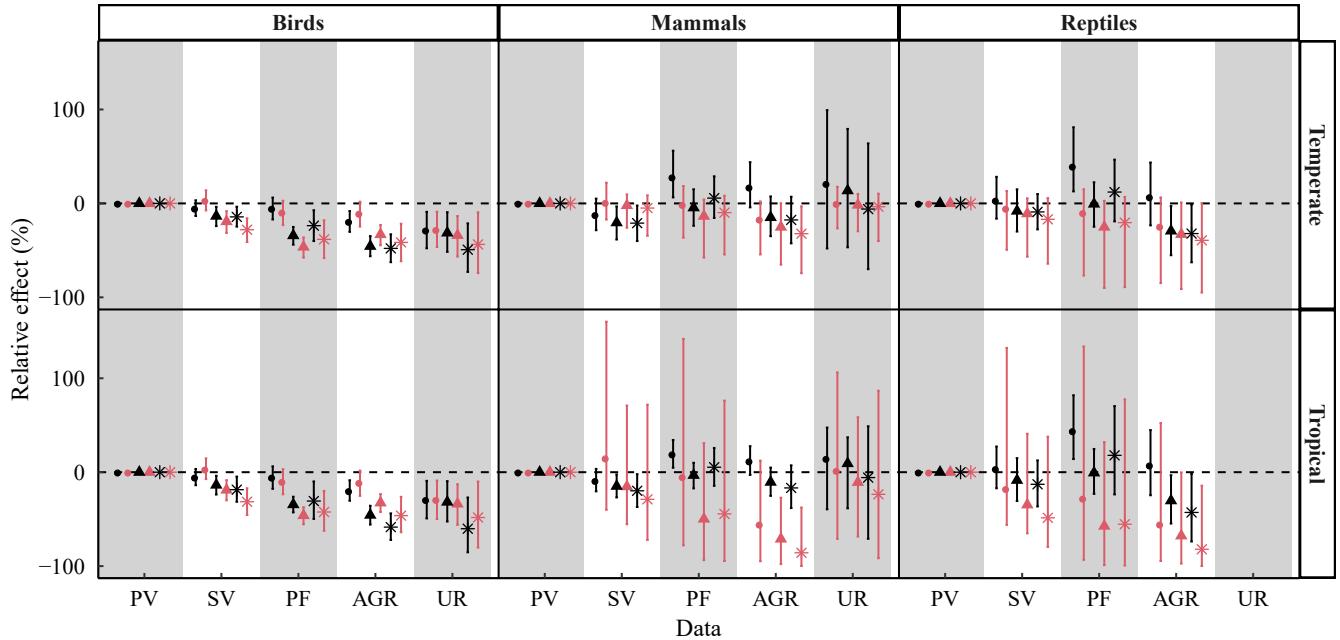
**Figure S3.21: Effects of land use and land-use intensity on FRic (a) and FDis (b), obtained when re-sampling primary vegetation sites twenty independent times.** I fixed the sample size for primary vegetation sites at 50. For FRic, we fitted **Model 1a**, which included the effects of land use, land-use intensity and region, as well as interactions between land use and land-use intensity and between land use and region. For FDis, I fitted **Model 1b**, which included effects of land use, land-use intensity and region, and interactions between land use and land-use intensity. Error bars represent 95% confidence intervals. MSV: mature secondary vegetation; ISV: intermediate secondary vegetation; YSV: young secondary vegetation; PF: plantation forest; PA: pasture; CR: cropland; UR: urban. Effects for Intense use in MSV could not be estimated as there weren't enough sampled sites.



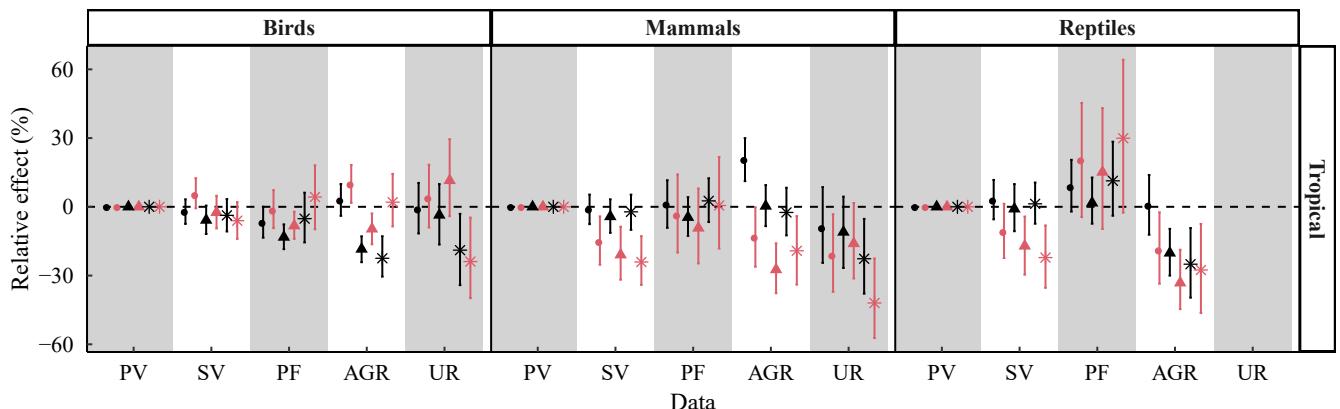
**Figure S3.22: Effects of land use, land-use intensity and taxonomic class on FRic (a) and FDis (c), for the subset of species with complete trait data (i.e., excluding species with less than 100% trait completeness).** Effects are plotted as a % difference relative to the reference land use (primary vegetation, PV). I did not include the effects of region here as sample sizes were not large enough for some classes. For FRic, the model included the effects of land use, land-use intensity and class, and interactions between land use and land-use intensity as well as land use and class. For FDis, the model included an additional interaction between land-use intensity and class. Error bars represent 95% confidence intervals. SV: secondary vegetation; PF: plantation forest; PA: pasture; CR: cropland; UR: urban. Effects for reptiles in urban land uses could not be estimated as there weren't enough sampled sites.

— complete and imputed trait data — complete trait data subset Use intensity • Minimal use ▲ Light use \* Intense use

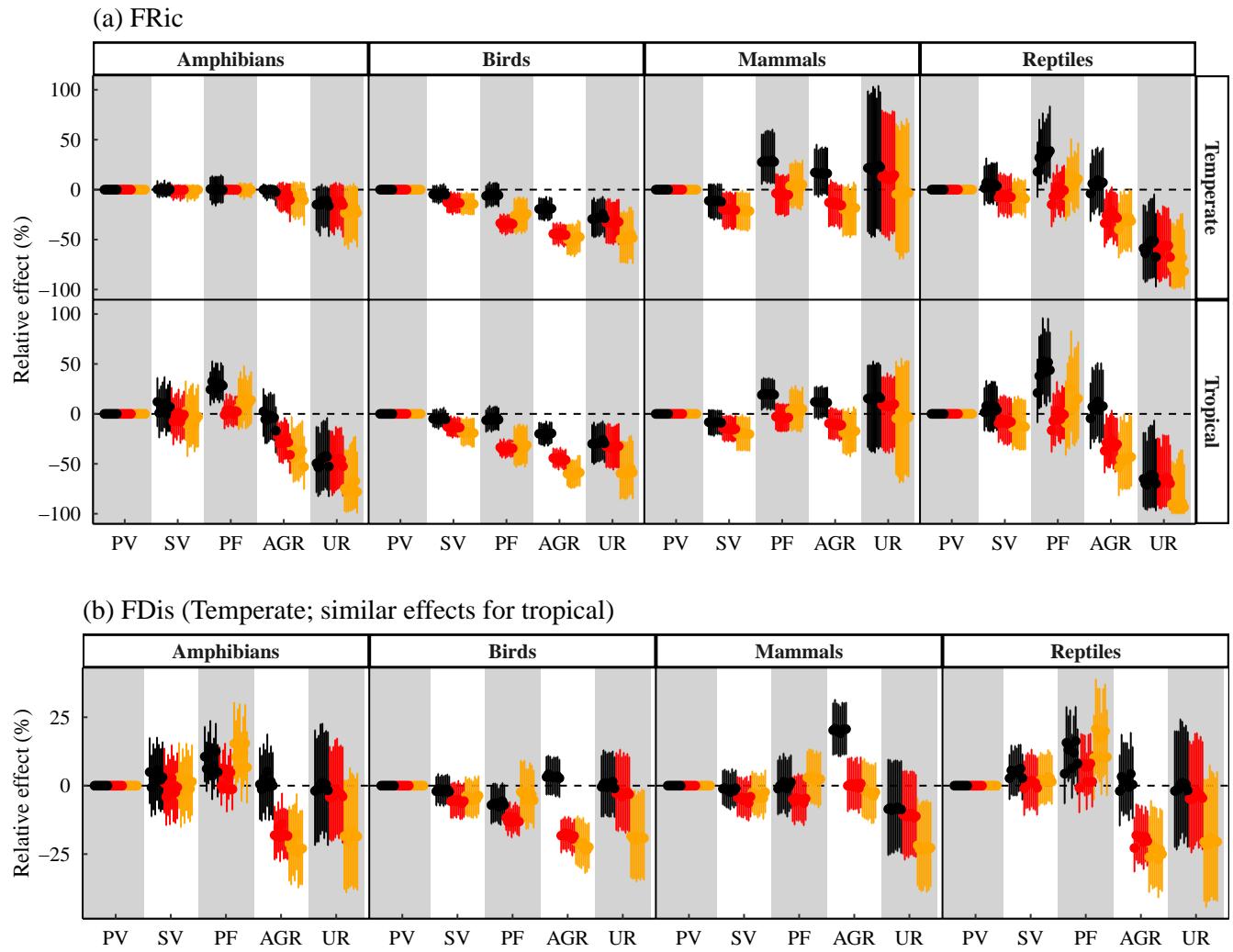
(a) FRic



(b) FDis



**Figure S3.23: Effects of land use, region, land-use intensity and taxonomic class on FRic and FDis obtained with the imputed trait data (black points) or with the complete data subsets (red points).** Effects are plotted as a % difference relative to the reference land use (primary vegetation, PV). For FRic, I fitted Model 2a, and I fitted Model 2b for FDis. Error bars represent 95% confidence intervals. SV: secondary vegetation; PF: plantation forest; AGR: agricultural (cropland and pasture); UR: urban. Effects for reptiles in urban land uses could not be estimated as there weren't enough sampled sites.



**Figure S3.24: Effects of land use, region, land-use intensity and taxonomic class on FRic and FDis, obtained when calculating FRic and FDis with each set of imputed traits (eight in total). Effects are plotted as a % difference relative to the reference land use (primary vegetation, PV). For FRic, I fitted Model 2a, and Model 2b for FDis. Error bars represent 95% confidence intervals. SV: secondary vegetation; PF: plantation forest; AGR: agricultural (cropland and pasture); UR: urban. Effects for reptiles in urban land uses could not be estimated as there weren't enough sampled sites.**

## S3.8 Model robustness – time since land-use conversion

Time since land-use conversion could have important impacts on assemblage composition and thus, on local functional diversity. I did not investigate these effects because PREDICTS contained data on time since land-use conversion only for about 22% of the sites, considerably reducing samples sizes. Here, I investigated whether the results are likely robust to the inclusion of time since land-use conversion using the subset of sites for which time since land-use conversion was provided. To this end, I found the best-fitting models explaining FRic and FDis, using backwards stepwise selection, starting with complete models that included the effects of land use, time since land-use conversion, region, land-use intensity (for FRic only) and all two-way interactions among these predictors.

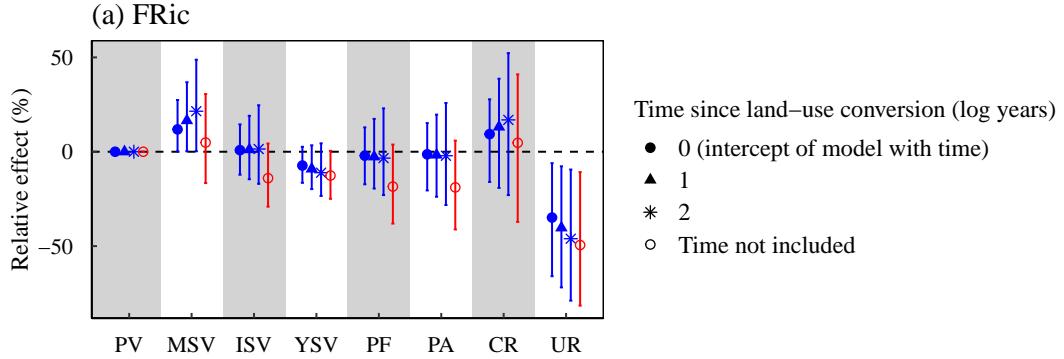
- For FRic, the best-fitting model included the main effects of land use and time since land-use conversion, but no interaction between these predictors. The model's summary (Table S3.6) showed that time since conversion had a significant negative effect on FRic, but the relationship between FRic and time since land-use conversion was similar in different land uses (as there were no interactions between land use and time since conversion retained in the best-fitting model, such that the slopes were similar in different land uses, and so the rate at which FRic decreased with time was similar in different land uses). The intercept was only different for urban land uses (significantly lower). Thus, based on this data subset, I expect time since land-use conversion to have a similar effect in different land-use types.

**Table S3.6:** Summary of the model explaining FRic by land use and time since land-use conversion, fitted on the subset of data for which there are information on time since land-use conversion.

	Estimate	Std. Error	t value
Intercept: Primary vegetation	1.156	0.073	15.921
Mature secondary vegetation	0.178	0.093	1.907
Intermediate secondary vegetation	0.018	0.072	0.249
Young secondary vegetation	-0.078	0.051	-1.532
Plantation forest	-0.018	0.082	-0.224
Pasture	-0.005	0.093	-0.054
Cropland	0.133	0.152	0.875
Urban	-0.316	0.133	-2.368
Time since conversion (log years)	-0.094	0.021	-4.566

I then compared this model's predictions with a simpler model that did not account for time since land-use conversion ( $\text{FRic} \sim \text{Land use}$ ). The predictions (Figure S3.25) showed that including time since land-use

conversion did not bias the results, as I found a similar significant effect with both models in urban land uses, and elsewhere the effects were congruent. Thus, given this data subset, I argue that the results are robust to the inclusion of time since land-use conversion.



**Figure S3.25:** Effects of land use on FRic for the model that includes time since land-use conversion (blue points) versus the model that does not take time since land-use conversion into account (red points).

- For FDis, the best-fitting model included the main effects of land use, time since land-use conversion as well as interactions between land use and time since land-use conversion (I did not consider land-use intensity in the starting model because of sample size issues). Nevertheless, the main effect of time since land-use conversion was not significant (Table S3.7), and the relationship between time since land-use conversion and FDis was also not significant in most disturbed land uses (except for plantation forest). Thus, I argue the available data do not allow us to properly investigate the relationship between time since land-use conversion and FDis.

**Table S3.7:** Summary of the model explaining FDis by land use and time since land-use conversion, fitted on the subset of data for which I have information on time since land-use conversion.

	Estimate	Std. Error	t value
Intercept: Primary vegetation	0.366	0.011	32.219
Mature secondary vegetation	0.032	0.055	0.577
Intermediate secondary vegetation	-0.015	0.050	-0.298
Young secondary vegetation	0.020	0.015	1.386
Plantation forest	0.074	0.023	3.213
Pasture	-0.017	0.048	-0.346
Cropland	-0.013	0.042	-0.317
Urban	0.031	0.054	0.573
Time since conversion (log years)	-0.004	0.004	-1.186
Mature secondary vegetation:Time since conversion (log years)	-0.005	0.015	-0.335
Intermediate secondary vegetation:Time since conversion (log years)	0.011	0.016	0.650
Young secondary vegetation:Time since conversion (log years)	-0.008	0.007	-1.170
Plantation forest:Time since conversion (log years)	-0.023	0.007	-3.077
Pasture:Time since conversion (log years)	0.010	0.015	0.688
Cropland:Time since conversion (log years)	0.007	0.012	0.620
Urban:Time since conversion (log years)	-0.016	0.022	-0.714

# **Appendix 3: Supporting information for Chapter 4**

## **S4.1 Compiling diet information**

For mammals and birds, diet information was obtained from the EltonTraits database (Wilman et al., 2014). Before processing the data, the taxonomy was aligned to that of the trait datasets compiled in Chapter 2. Primary diet – that is, the diet inferred from the combination of food items that represent more than 50% of species consumption – was directly available for birds, but not for mammals. For both classes, diet was described as the percent use of different food items (namely: invertebrates, vertebrates – either ectotherms, endotherms, fish or unknown –, carrion, fruit, nectar, seed or other plant material). In order to have a consistent classification scheme across mammals and birds, I chose not to use the provided primary diet for birds, and instead I applied my own procedure to infer primary diet from recorded food items across birds and mammals. I first grouped the different vertebrate food items together with carrion to create a single ‘vertebrate’ food item category. I then used the percent uses of the food items to infer primary diet, classifying species’ primary diet into the following categories: vertebrate eaters; invertebrate eaters; plant/seed eaters; fruit/nectar eaters; and omnivores [these categories are similar to those employed for birds’ primary diet in EltonTraits]. When all food items had a percent use below (or equal to) 50% percent, species were classified as omnivores. For each species, I calculated diet breadth as the number of consumed food items (regardless of the percent use of those items; I kept vertebrate food items grouped together in the calculation of diet breadth, such that I did not count carrion as a separate food item).

For amphibians, diet information was partly extracted from the AmphiBIO database (Oliveira et al., 2017), and partly compiled from the literature (see next paragraph). In AmphiBIO, diet information was recorded as the consumption of six food items (leaves, flowers, seeds, fruit, arthropods and vertebrates), but the percent use of these items was not recorded (only whether they were consumed or not). From AmphiBIO, I classified amphibians into the different diet categories, depending on the combinations of consumed food

items (with species consuming both plant and animal matter classified as omnivores; species consuming both vertebrates and invertebrates also classified as omnivores; and species consuming plant or seed only, fruit or nectar only, vertebrates only or invertebrates only classified into the corresponding groups).

To increase diet data coverage for amphibians, I used data compiled by Rhiannon Osborne-Tonner, collected during her MSci project at UCL. Rhiannon Osborne-Tonner collected data from published papers and from the grey literature, targeting species occurring in the PREDICTS database (which I used for inferring land-use responses). Using these data, I was able to supplement my datasets with diet information for an additional 108 amphibians from 26 published sources (all found to be invertebrate eaters; see below for the list of sources). For reptiles, there was no readily available diet information (except for trophic level information, see Chapter 2). Thus, I used diet data compiled by Rhiannon Osborne-Tonner, collected from the literature, again specifically targeting reptiles occurring in the PREDICTS database. I was thus able to add diet information for 239 reptiles. Finally, I calculated diet breadth across amphibians and reptiles from the recorded food items. The diet data compiled by Rhiannon Osborne-Tonner are available at: [https://figshare.com/articles/Reptile\\_Diet\\_csv/12024309](https://figshare.com/articles/Reptile_Diet_csv/12024309) (DOI: 10.6084/m9.figshare.12024309.v1) and [https://figshare.com/articles/Untitled\\_Item/12024312](https://figshare.com/articles/Untitled_Item/12024312) (DOI: 10.6084/m9.figshare.12024312.v4).

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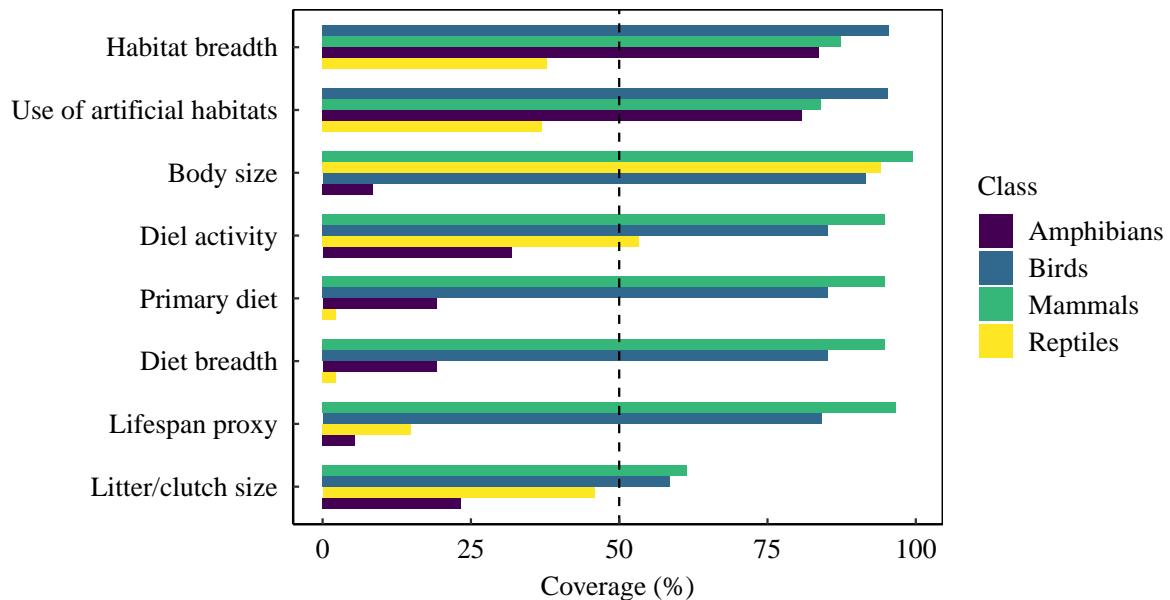
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### **Complementary data sources for reptiles**

The 148 sources are listed in the dataset available from [https://figshare.com/articles/Reptile\\_Diet\\_csv/12024309](https://figshare.com/articles/Reptile_Diet_csv/12024309) (DOI: 10.6084/m9.figshare.12024309.v1).

## S4.2 Imputing missing trait values

### S4.2.1 Trait data coverage



**Figure S4.1:** Trait coverage, including coverage for diet information, calculated as the proportion of species for which trait values are not missing. The dashed line represents 50% coverage.

### S4.2.2 Phylogenetic signal in traits

I measured the phylogenetic signal in traits using Pagel's  $\lambda$  (for continuous traits) and Borges'  $\delta$  (for categorical traits). I found evidence of phylogenetic conservatism in all traits.

**Table S4.1: Phylogenetic signal in continuous and categorical traits.** BM: body mass; BL: body length; GL: generation length; MA: age at sexual maturity; ML: maximum longevity; L: longevity; LCS: litter/clutch size; HB: habitat breadth; DA: diel activity; UA: use of artificial habitats. Continuous traits were log-10 transformed to improve normality before estimating Pagel's  $\lambda$  – except for habitat breadth and diet breadth which were square-rooted. A star indicates a significant signal ( $P<0.05$  for the log-likelihood ratio test in the case of  $\lambda$ ; and a significant difference from the simulated null distribution of  $\delta$  for categorical traits). 'NA' indicates traits that were not considered for a given class.

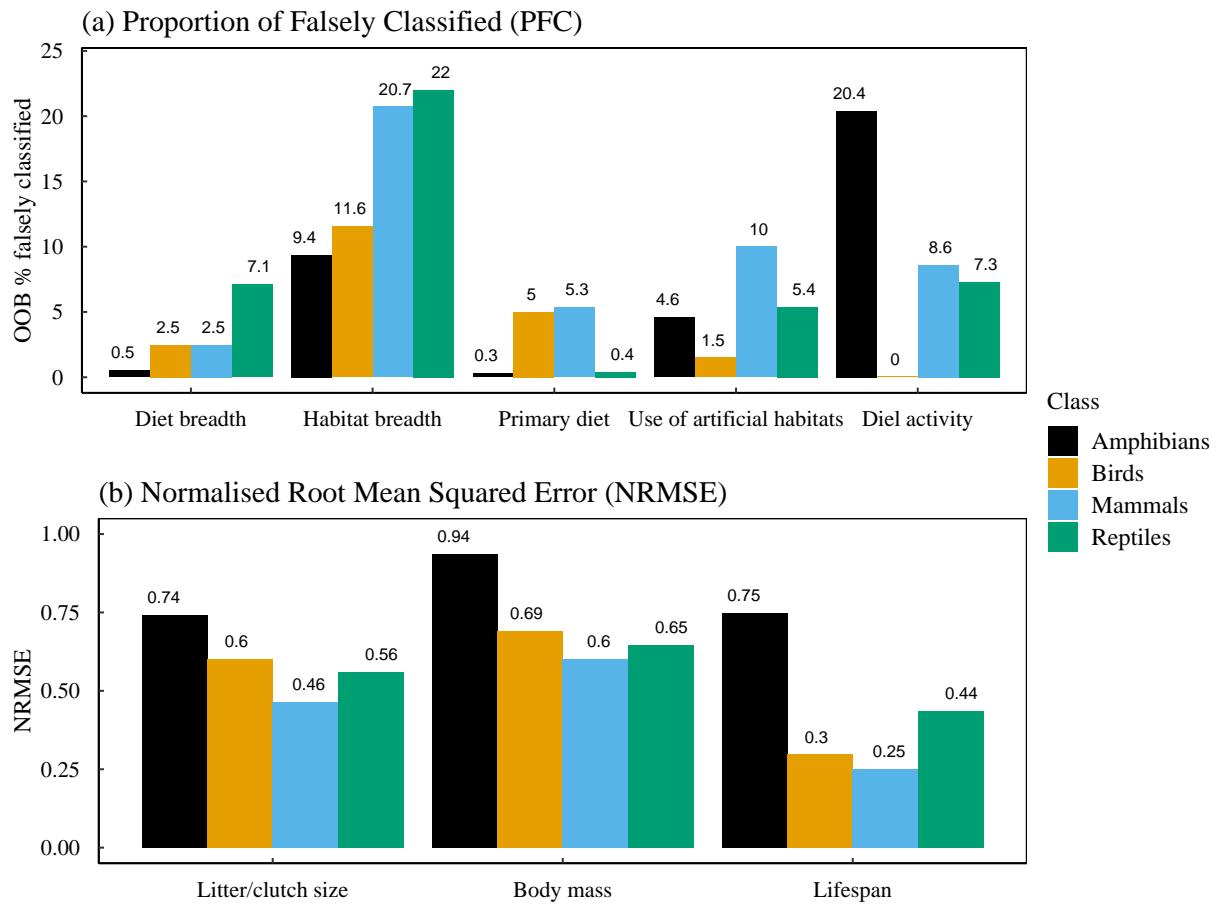
Class	Pagel's $\lambda$										Borges' $\delta$		
	BM	BL	GL	MA	ML	L	LCS	HB	Diet breadth	Diet	DA	UA	
<b>Amphibians</b>	0.98*	0.94*	NA	0.85*	0.82*	NA	0.93*	0.99*	0.61*	3.4*	3.4*	4.5*	
<b>Birds</b>	0.99*	NA	0.97*	NA	NA	NA	0.95*	0.60*	0.72*	6.4*	32e3*	1.8*	
<b>Mammals</b>	0.99*	NA	0.97	NA	NA	NA	0.99	0.71	0.99*	26*	52*	1.3*	
<b>Reptiles</b>	1.0*	NA	NA	NA	0.94*	0.98*	1.0*	0.52*	0.84*	2.2*	6.4*	1.4*	

### **S4.2.3 Implementation of missing value imputations**

I imputed missing trait values using random forest algorithms, as implemented in R with ‘missForest’ (Stekhoven, 2016; Stekhoven and Bühlmann, 2012). Phylogenetic relationships were included as additional predictors in the form of phylogenetic eigenvectors (Diniz-Filho et al., 2012), extracted from the phylogenies using the PVR package (Santos, 2018). I used class-specific phylogenetic trees from <https://zenodo.org/record/3690867#.Xyc5wyhKhPZ> for mammals (Phylacine 1.2; Faurby et al. (2018, 2020)); and from <https://data.vertlife.org/> for amphibians (Jetz & Pyron 2018), birds (Jetz et al. 2012) and squamates (Tonini et al. 2016). For each class, I used a consensus tree obtained with the TreeAnnotator programme of the BEAST software (Bouckaert et al. 2014), from an available distribution of 1000 trees.

Following Penone et al. (2014), I included the first ten phylogenetic eigenvectors as additional predictors of missing trait values in each class. As not all species were represented in the phylogenies, I also added taxonomic order as a predictor for all species. All traits in Table S4.1 were included in the imputations. Habitat & diet breadth were considered as categorical variables for the imputations (and so, discretised), in order to ensure that only integer estimates were obtained from the imputations for these traits. Tuning parameters of ‘missforest’ were set to ten maximum iterations and to one hundred trees grown in each forest.

### **S4.2.4 Imputation error**

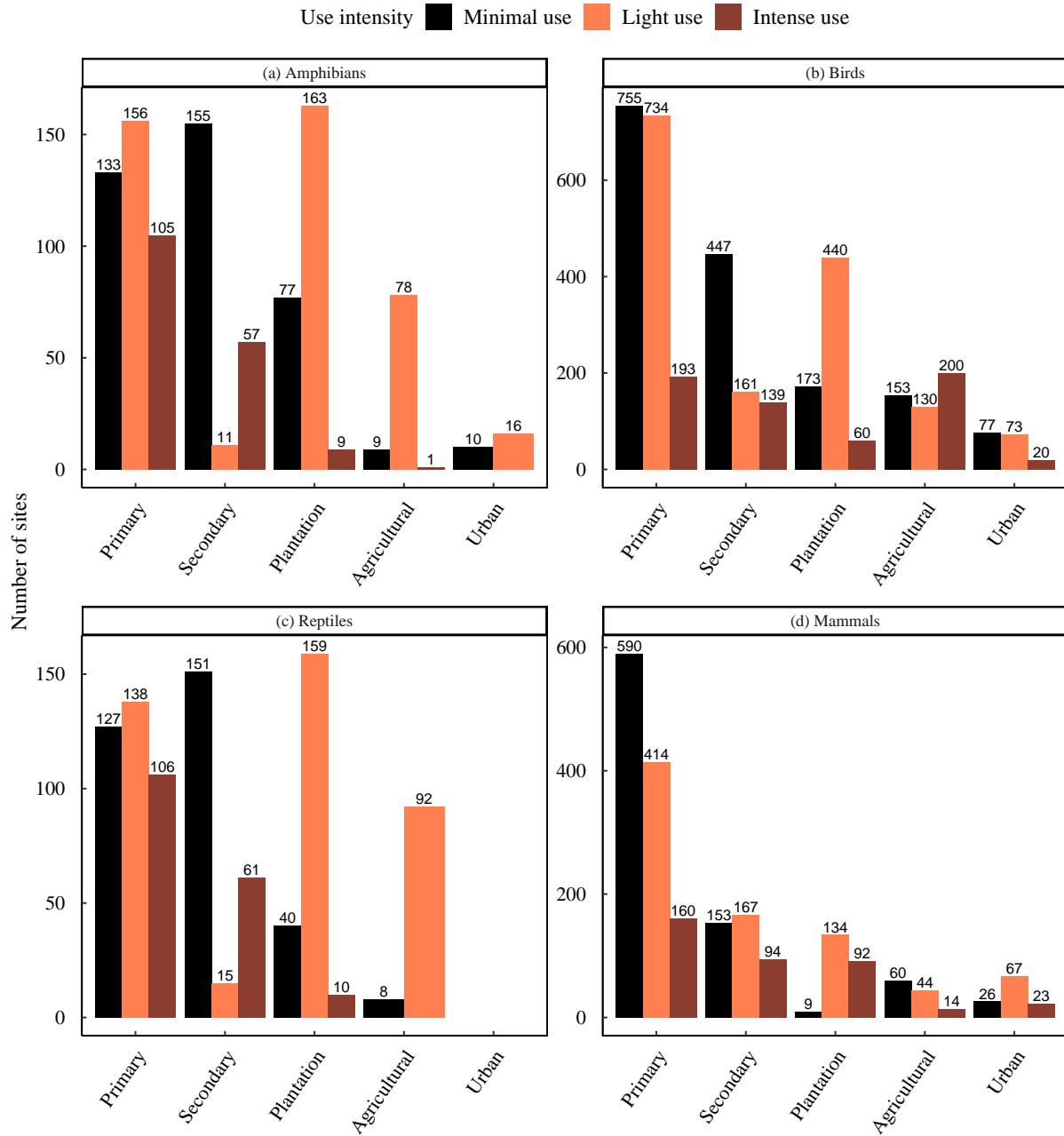


**Figure S4.2: Out-of-bag estimation of imputation errors for the traits included in the analyses.** (a) For the categorical traits, I show the proportion of falsely classified traits ('PFC', out-of-bag estimates); (b) For the continuous traits, I calculate the normalised root-mean-squared error (NRMSE), from the out-of-bag mean square error that I divide by the standard deviation of the known trait distribution. The lower the NRMSE, the lower the imputation error, with values close to 0 indicating lower imputation error and values close to 1 tending to indicate higher imputation error.

### S4.3 Land-use types in PREDICTS and sample sizes (number of sampled sites across classes)

**Table S4.2: Land-use categories in the PREDICTS database.** See Hudson et al. (2014, 2017) for more details.

Land-use category	Definition
Primary vegetation	Native vegetation, undisturbed since its establishment under current climatic conditions. No known alterations due to human activities or to extreme natural events.
Mature secondary vegetation	Vegetation recovering after complete destruction of primary vegetation & where succession is near complete – the structure approaches that of primary vegetation.
Intermediate secondary vegetation	Vegetation recovering after complete destruction of primary vegetation at a mid-successional stage.
Young secondary vegetation	Vegetation recovering after complete destruction of primary vegetation at an early successional stage.
Plantation forest	Previously cleared areas planted with crop trees or shrubs grown and harvested for human consumption or for commercial purposes (includes wood, fruit, oil, biofuel, rubber, etc).
Pasture	Areas grazed by livestock, permanently or regularly. Can be improved through cultivation techniques.
Cropland	Previously cleared areas planted with herbaceous crops and harvested for human or animal consumption (including animal feed and crops used in the food industry), or for commercial purposes (e.g., crops grown for the textile industry).
Urban	Previously cleared areas built up by humans. Vegetation is managed for civic or personal purposes.



**Figure S4.3: Sample sizes (number of PREDICTS sites) for the different land-use types, in each class.**

## S4.4 Land-use responses: multicollinearity checks among the models' explanatory variables

**Table S4.3: Generalised Variance Inflation Factors among the candidate explanatory variables for the mixed-effects model fitted across amphibians, prior to the exclusion of diet.** The model aimed at investigating the effects of land use, land-use intensity and the species-level ecological characteristics on species occurrence probability.

Predictor	GVIF
Diel activity	1.7
Lifespan proxy ( $\log_{10}$ )	1.8
Specialisation	1.8
Range area ( $\log_{10}$ )	2.0
Body mass ( $\log_{10}$ )	2.0
Land use	2.0
Litter/clutch size ( $\log_{10}$ )	2.5
Land-use intensity	2.6
Habitat breadth (square-root)	3.2
Diet breadth (square-root)	22.8
Primary diet	23.6

**Table S4.4: Generalised Variance Inflation Factors among the explanatory variables for the mixed-effects model fitted across amphibians (after the exclusion of diet),** looking at the effects of land use, land-use intensity and the species-level ecological characteristics on species occurrence probability.

Predictor	GVIF
Diel activity	1.6
Diet breadth (square-root)	1.7
Lifespan proxy ( $\log_{10}$ )	1.8
Specialisation	1.8
Range area ( $\log_{10}$ )	1.9
Land use	2.0
Body mass ( $\log_{10}$ )	2.0
Litter/clutch size ( $\log_{10}$ )	2.4
Land-use intensity	2.6
Habitat breadth (square-root)	3.1

**Table S4.5: Generalised Variance Inflation Factors among the explanatory variables for the mixed-effects model fitted across birds**, looking at the effects of land use, land-use intensity and the species-level ecological characteristics on species occurrence probability.

Predictor	GVIF
Diel activity	1.1
Land use	1.2
Land-use intensity	1.2
Litter/clutch size ( $\log_{10}$ )	1.3
Range area ( $\log_{10}$ )	1.4
Diet breadth (square-root)	1.5
Specialisation	1.6
Lifespan proxy ( $\log_{10}$ )	1.7
Habitat breadth (square-root)	1.8
Body mass ( $\log_{10}$ )	1.9
Primary diet	2.3

**Table S4.6: Generalised Variance Inflation Factors among the explanatory variables for the mixed-effects model fitted across mammals**, looking at the effects of land use, land-use intensity and the species-level ecological characteristics on species occurrence probability.

Predictor	GVIF
Diel activity	1.2
Range area ( $\log_{10}$ )	1.2
Specialisation	1.4
Land-use intensity	1.4
Diet breadth (square-root)	1.7
Land use	1.8
Habitat breadth (square-root)	1.8
Litter/clutch size ( $\log_{10}$ )	2.7
Body mass ( $\log_{10}$ )	3.0
Lifespan proxy ( $\log_{10}$ )	3.4
Primary diet	4.4

**Table S4.7: Generalised Variance Inflation Factors among the candidate explanatory variables for the mixed-effects model fitted across reptiles, prior to the exclusion of diet.** The model aimed at investigating the effects of land use, land-use intensity and the species-level ecological characteristics on species occurrence probability.

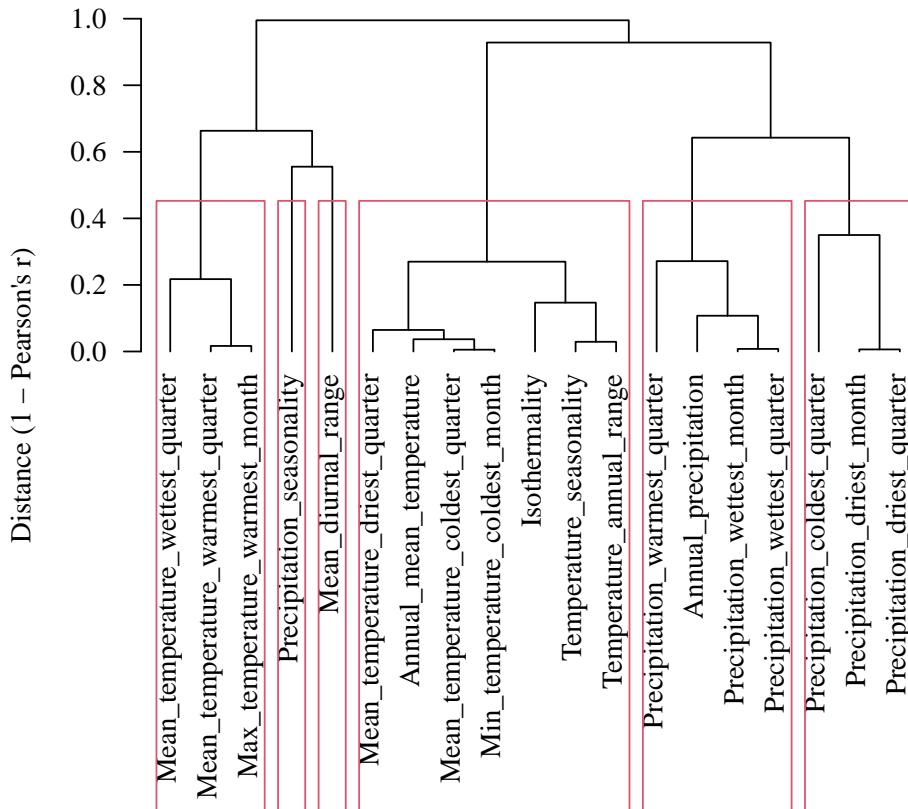
Predictor	GVIF
Diel activity	1.1
Specialisation	1.3
Range area ( $\log_{10}$ )	1.3
Habitat breadth (square-root)	1.6
Lifespan proxy ( $\log_{10}$ )	1.9
Litter/clutch size ( $\log_{10}$ )	2.8
Land use	3.2
Land-use intensity	3.5
Body mass ( $\log_{10}$ )	3.9
Diet breadth (square-root)	5.8
Primary diet	9.9

**Table S4.8: Generalised Variance Inflation Factors among the explanatory variables for the mixed-effects model fitted across reptiles (*after the exclusion of diet*),** looking at the effects of land use, land-use intensity and the species-level ecological characteristics on species occurrence probability.

Predictor	GVIF
Diel activity	1.1
Diet breadth (square-root)	1.2
Specialisation	1.2
Range area ( $\log_{10}$ )	1.3
Habitat breadth (square-root)	1.6
Lifespan proxy ( $\log_{10}$ )	1.9
Litter/clutch size ( $\log_{10}$ )	2.7
Land use	3.2
Body mass ( $\log_{10}$ )	3.2
Land-use intensity	3.4

## S4.5 Implementing Climate-niche Factor Analysis across terrestrial vertebrates

### S4.5.1 Historical climate data: groups of intercorrelated variables



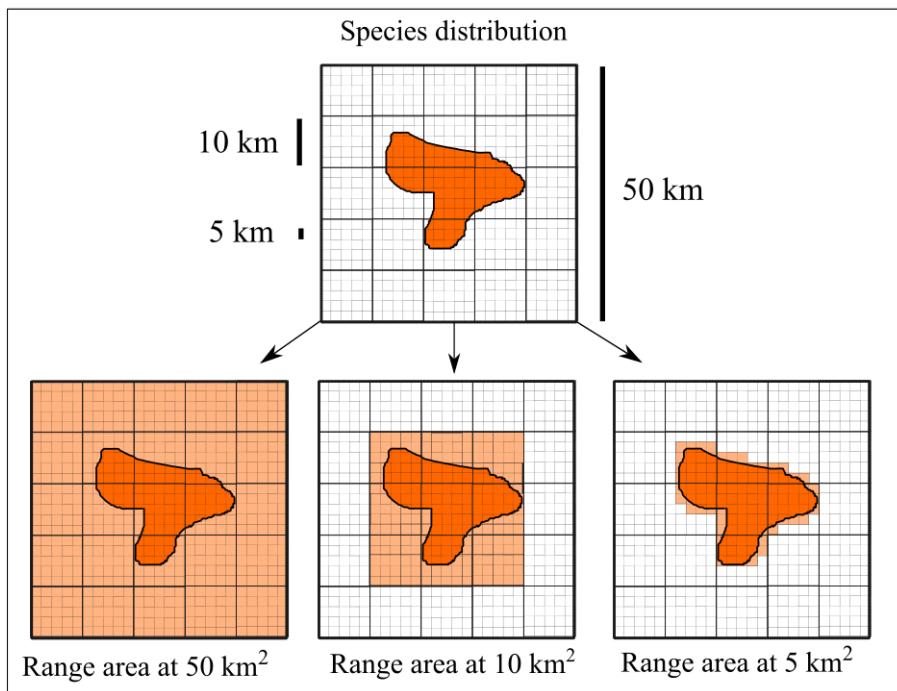
**Figure S4.4:** Groups of intercorrelated climatic variables using a cutoff of 0.65 for Pearson's correlation coefficient, obtained using the ‘removeCollinearity’ R function (‘virtualspecies’ package, Leroy et al. (2015)). Variables figuring in the same red boxes were correlated with Pearson's correlation coefficient > 0.65.

### S4.5.2 CENFA estimation and resolution

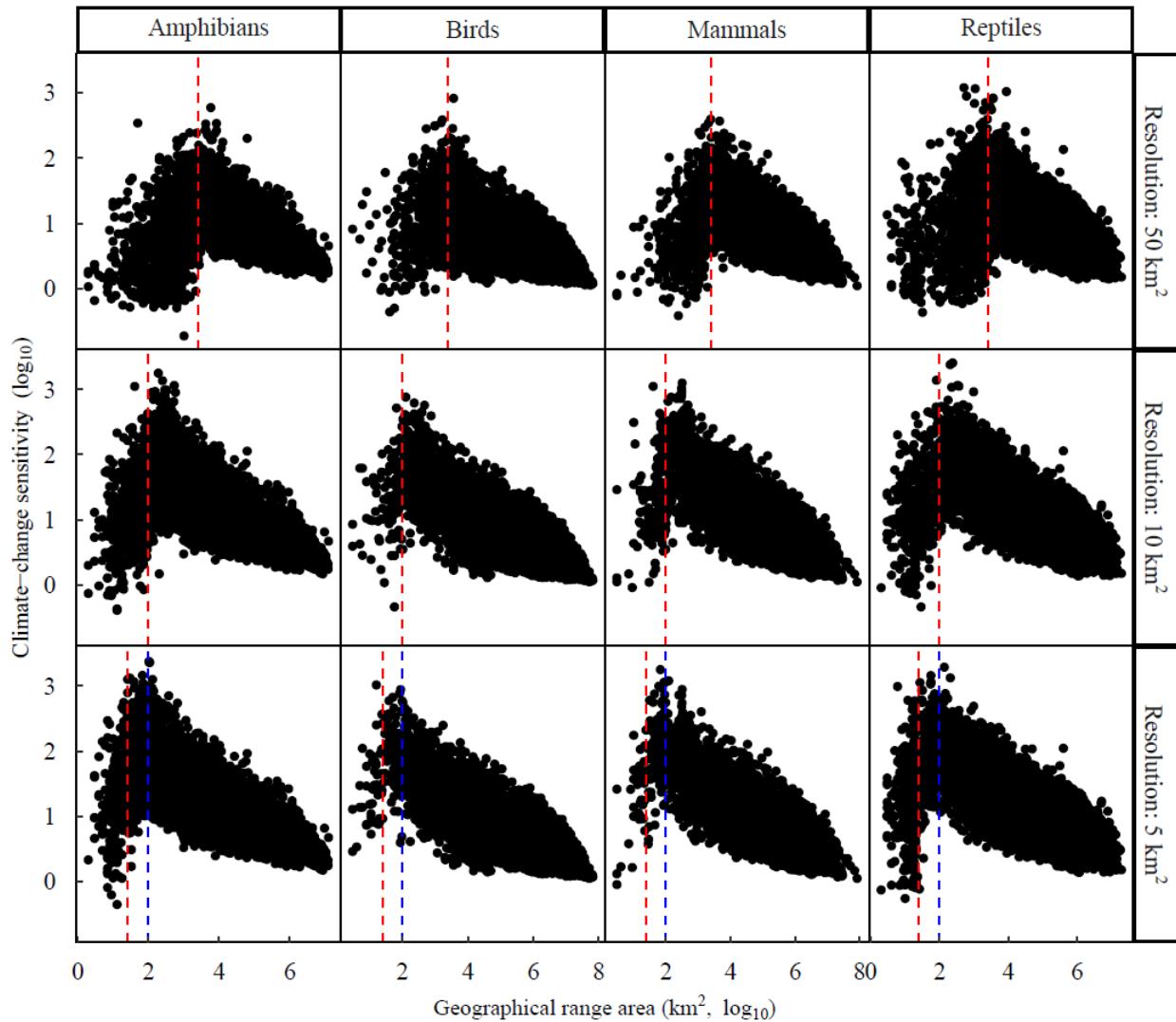
I estimated climate-change sensitivity across terrestrial vertebrates with the CENFA framework using three different resolutions for the species distribution files and the climatic variables: 50 km<sup>2</sup>, 10 km<sup>2</sup> and 5 km<sup>2</sup>. The finer the resolution, the better the species' distribution is likely to be captured, particularly for narrow-ranging species (Figure S4.5). When working with coarser resolutions, the actual geographical distribution of a narrow-ranging species might be overestimated (Figure S4.5), such that the climatic niche breadth of the species might also be overestimated; consequently, its climate-change sensitivity may be underestimated. However, finer resolutions are more computationally demanding, which can be limiting when working across

several thousand species.

Thus, I looked for a resolution that provided the best compromise between accuracy of sensitivity estimation and computational load (Figure S4.6). Hence, I chose to work with a resolution of  $5 \text{ km}^2$ . At this resolution, there were still some narrow-ranging species for which sensitivity was likely overestimated (Figure S4.6). To prevent any impact of these species on the analyses, I removed species with the smallest geographical range areas, using a conservative threshold of  $100 \text{ km}^2$  for geographical range area (Figure S4.6).



**Figure S4.5: Possible impact of resolution on estimated geographical range area.** I represent a virtual distribution for a species (orange shape). The species distribution is more accurately captured at finer resolutions (e.g.,  $5 \text{ km}^2$ ) than at coarser resolutions (e.g.,  $10 \text{ km}^2$  or  $50 \text{ km}^2$ ). A possible consequence is that coarser resolutions can tend to disproportionately overestimate the geographical range area of narrow-ranging species, because the aggregation of grid cells where the species is found to be present can artificially augment the amount of occupied area at coarser resolutions, and relatively more so if the species is narrow-ranging.



**Figure S4.6:** Estimated climate-change sensitivity estimations at three different resolutions ( $50 \text{ km}^2$ ,  $10 \text{ km}^2$  and  $5 \text{ km}^2$ ) against geographical range area (estimated at  $1 \text{ km}^2$ ). With the red dashed lines, I highlight the range areas that correspond to the surface area of one grid cell (i.e.,  $2,500 \text{ km}^2$ ,  $100 \text{ km}^2$  and  $25 \text{ km}^2$  respectively). Climate-change sensitivity was estimated using the CENFA framework (Rinnan and Lawler, 2019). I chose to work at a resolution of  $5 \text{ km}^2$  and I excluded species whose range area was  $\leq 100 \text{ km}^2$  (blue dashed line), that is, species whose distribution could intersect up to four grid cells at a resolution of  $5 \text{ km}^2$ .

## S4.6 Climate-change sensitivity models: multicollinearity checks among models' explanatory variables

**Table S4.9: Generalised Variance Inflation Factors among the candidate explanatory variables for the phylogenetic least-square regression fitted across amphibians, prior to the exclusion of diet breadth.** The model aimed at investigating the association between the species-level ecological characteristics and species climate-change sensitivity.

Predictor	GVIF
Diel activity	1.1
Lifespan proxy ( $\log_{10}$ )	1.2
Range area ( $\log_{10}$ )	1.3
Body mass ( $\log_{10}$ )	1.4
Litter/clutch size ( $\log_{10}$ )	1.5
Specialisation	1.6
Habitat breadth (square-root)	1.9
Primary diet	17.1
Diet breadth (square-root)	17.1

**Table S4.10: Generalised Variance Inflation Factors among the explanatory variables for the phylogenetic least-square regression fitted across amphibians, after excluding diet breadth.** The model aimed at investigating the association between the species-level ecological characteristics and species climate-change sensitivity.

Predictor	GVIF
Diel activity	1.1
Primary diet	1.1
Lifespan proxy ( $\log_{10}$ )	1.2
Range area ( $\log_{10}$ )	1.3
Body mass ( $\log_{10}$ )	1.4
Litter/clutch size ( $\log_{10}$ )	1.5
Specialisation	1.6
Habitat breadth (square-root)	1.9

**Table S4.11: Generalised Variance Inflation Factors among the explanatory variables for the phylogenetic least-square regression fitted across birds.** The model aimed at investigating the association between the species-level ecological characteristics and species climate-change sensitivity.

Predictor	GVIF
Diel activity	1.1
Range area ( $\log_{10}$ )	1.2
Litter/clutch size ( $\log_{10}$ )	1.3
Diet breadth (square-root)	1.5
Specialisation	1.6
Habitat breadth (square-root)	1.8
Lifespan proxy ( $\log_{10}$ )	1.9
Body mass ( $\log_{10}$ )	2.0
Primary diet	2.1

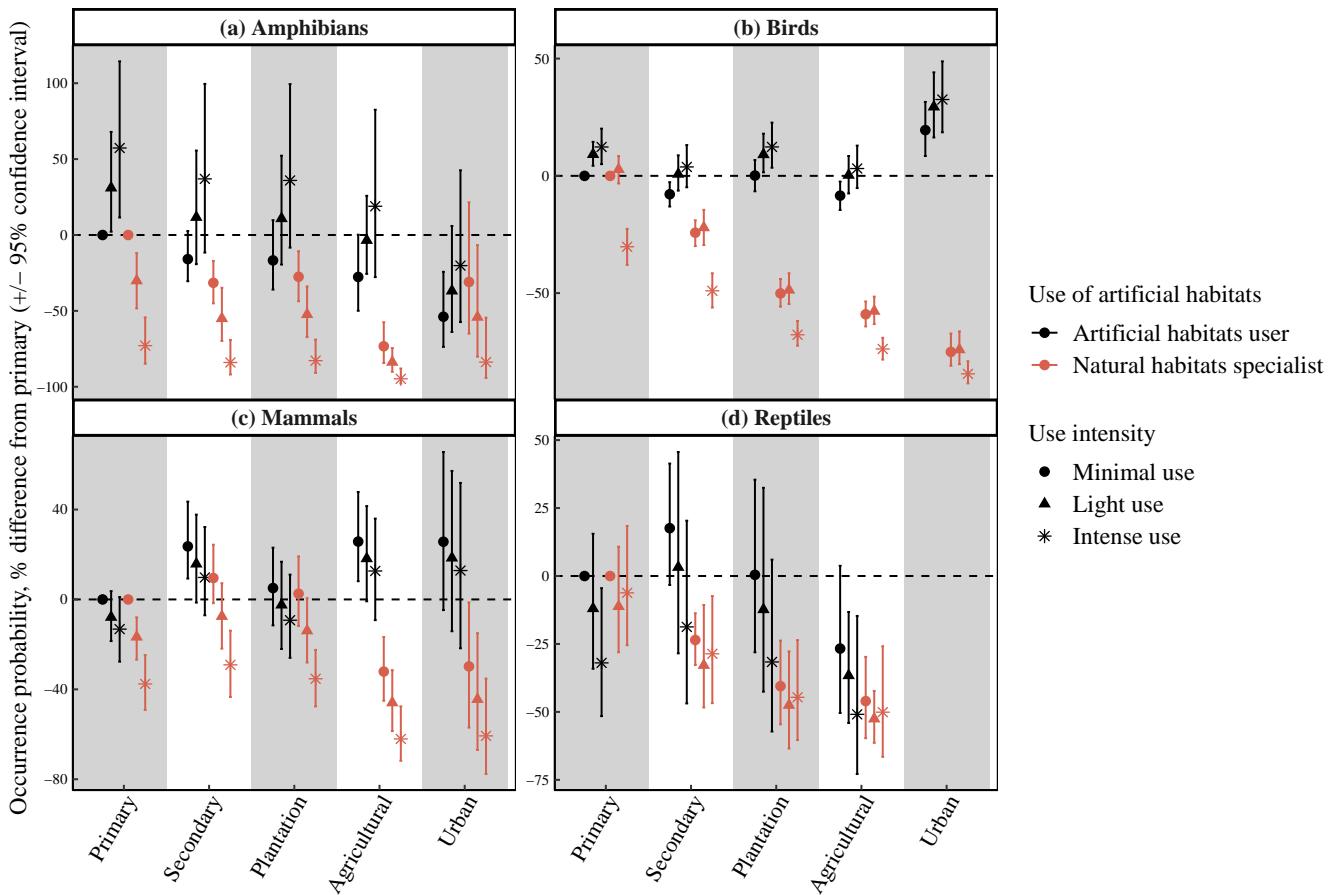
**Table S4.12: Generalised Variance Inflation Factors among the explanatory variables for the phylogenetic least-square regression fitted across mammals.** The model aimed at investigating the association between the species-level ecological characteristics and species climate-change sensitivity.

Predictor	GVIF
Range area ( $\log_{10}$ )	1.2
Diel activity	1.3
Specialisation	1.3
Habitat breadth (square-root)	1.5
Diet breadth (square-root)	1.6
Body mass( $\log_{10}$ )	2.3
Litter/clutch size ( $\log_{10}$ )	2.4
Primary diet	2.7
Lifespan proxy ( $\log_{10}$ )	3.0

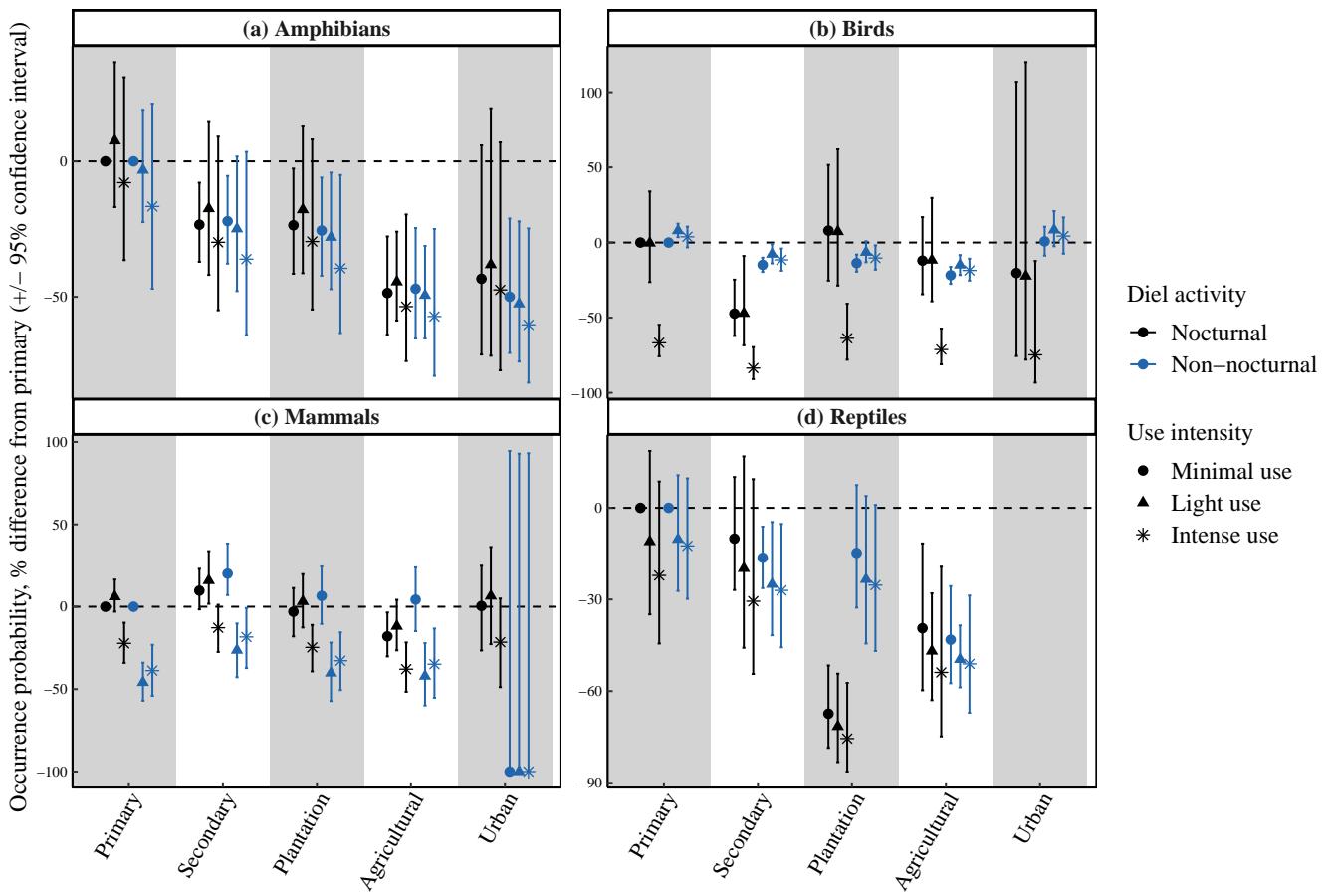
**Table S4.13: Generalised Variance Inflation Factors among the explanatory variables for the phylogenetic least-square regression fitted across reptiles.** The model aimed at investigating the association between the species-level ecological characteristics and species climate-change sensitivity.

Predictor	GVIF
Diel activity	1.1
Range area( $\log_{10}$ )	1.2
Specialisation	1.4
Habitat breadth (square-root)	1.5
Lifespan proxy ( $\log_{10}$ )	1.6
Litter/clutch size ( $\log_{10}$ )	2.0
Body mass ( $\log_{10}$ )	2.9
Diet breadth (square-root)	2.9
Primary diet	3.6

## S4.7 Land-use responses: occurrence probability predictions from the partial models for artificial habitat use and diel activity

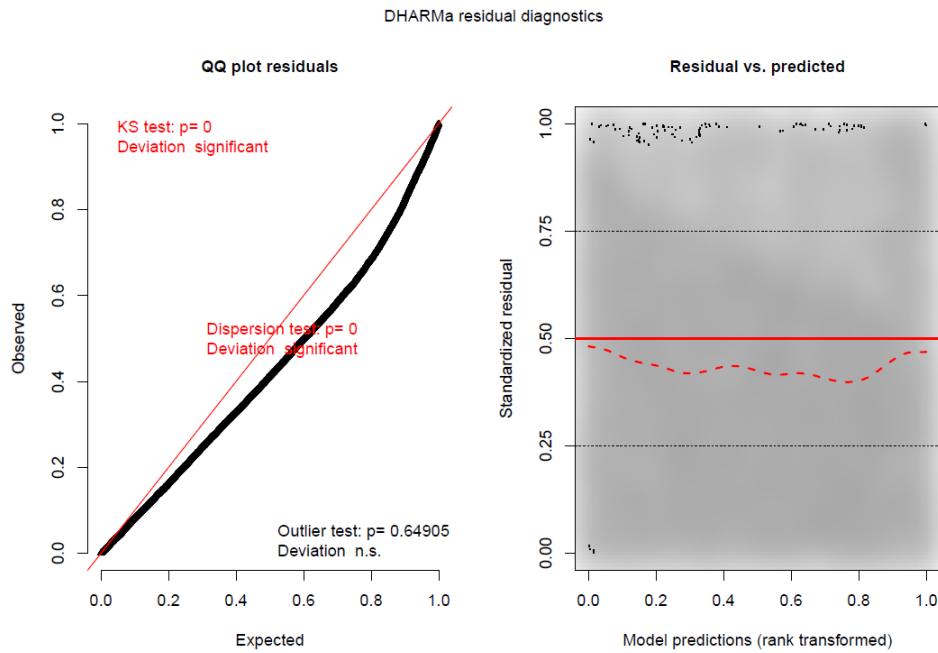


**Figure S4.7: Predicted occurrence probability as a function of land use, land-use intensity, artificial habitat use and their interactions, for each class of terrestrial vertebrates** (mean  $\pm$  95% confidence interval; the predictions are rescaled with reference to minimally-used primary vegetation). The predictions were obtained from the partial models fitted in each class for artificial habitat use. Effects could not be estimated for urban reptiles, as there weren't any sampled sites. Primary: primary vegetation; Secondary: secondary vegetation; plantation: plantation forest; agricultural: cropland and pasture.

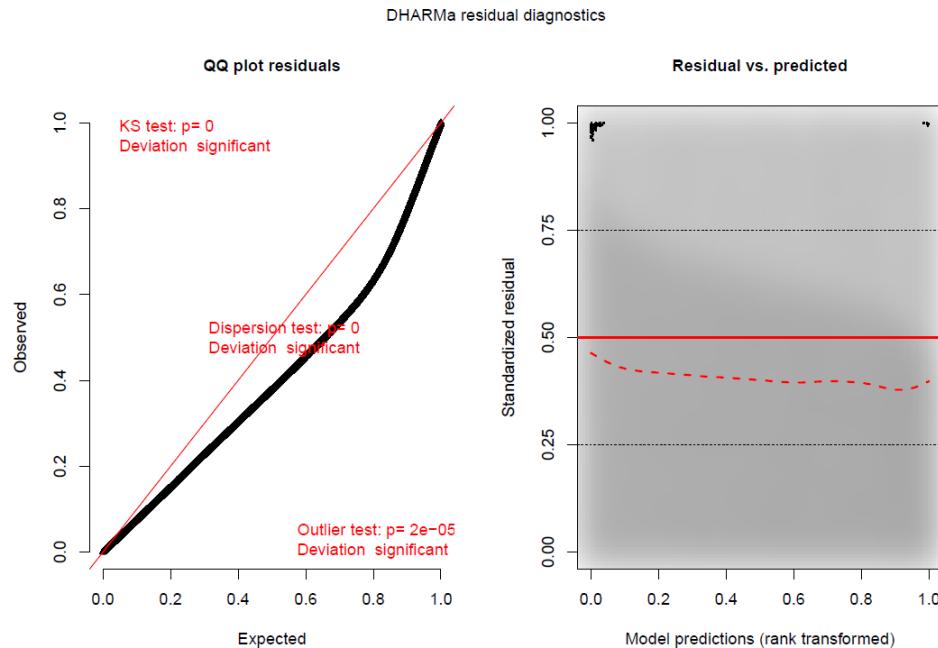


**Figure S4.8: Predicted occurrence probability as a function of land use, land-use intensity, diel activity and their interactions, for each class of terrestrial vertebrates** (mean  $\pm 95\%$  confidence interval; the predictions are rescaled with reference to minimally-used primary vegetation). The predictions were obtained from the partial models fitted in each class for diel activity. Effects could not be estimated for urban reptiles, as there weren't any sampled sites. Error bars are large for non-nocturnal urban mammals because there were very few sampled species (only five). Primary: primary vegetation; Secondary: secondary vegetation; plantation: plantation forest; agricultural: cropland and pasture.

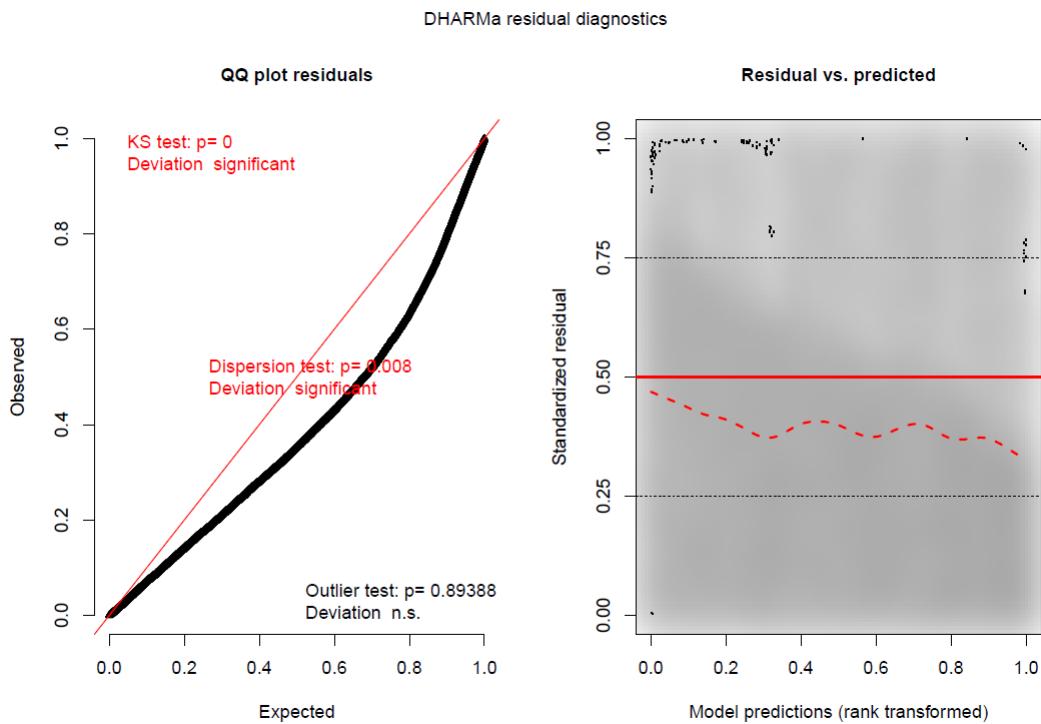
## S4.8 Land-use responses: diagnostic plots for the full models



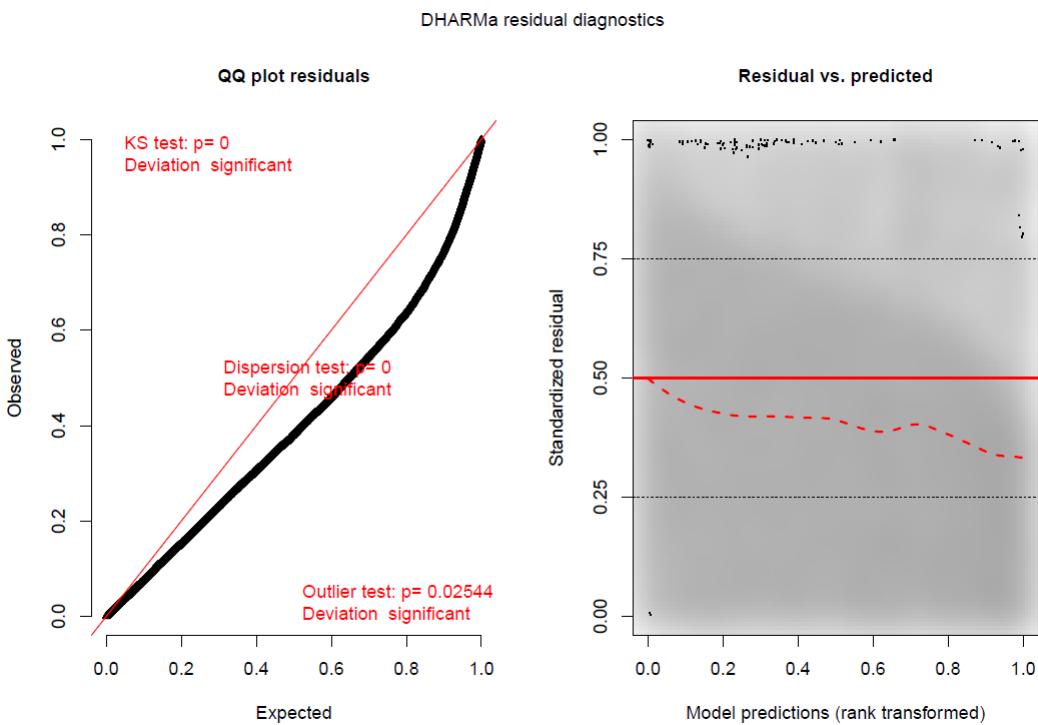
**Figure S4.9:** Diagnostic plots for the mixed-effects model fitted on amphibians, looking at the effects of land use, land-use intensity and the species-level ecological characteristics on species occurrence probability (full model). The diagnostic plots were obtained from the ‘DHARMA’ R package (Hartig, 2021).



**Figure S4.10:** Diagnostic plots for the mixed-effects model fitted on birds, looking at the effects of land use, land-use intensity and the species-level ecological characteristics on species occurrence probability (full model). The diagnostic plots were obtained from the ‘DHARMA’ R package (Hartig, 2021).



**Figure S4.11: Diagnostic plots for the mixed-effects model fitted on mammals**, looking at the effects of land use, land-use intensity and the species-level ecological characteristics on species occurrence probability (full model). The diagnostic plots were obtained from the ‘DHARMA’ R package (Hartig, 2021).



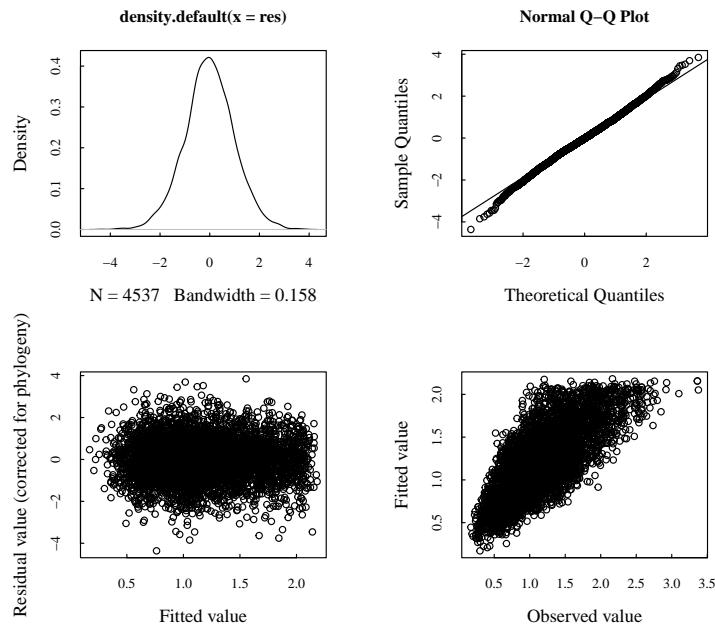
**Figure S4.12: Diagnostic plots for the mixed-effects model fitted on reptiles**, looking at the effects of land use, land-use intensity and the species-level ecological characteristics on species occurrence probability (full model). The diagnostic plots were obtained from the 'DHARMA' R package (Hartig, 2021).

## S4.9 Climate-change sensitivity: model summaries and diagnostic plots

### S4.9.1 Summaries & diagnostic plots for models fitted on species with range area $>100 \text{ km}^2$

**Table S4.14: Summary for the PGLS model fitted on amphibians, investigating associations between species-level ecological characteristics and climate-change sensitivity, excluding species whose range area was  $\leq 100 \text{ km}^2$  (sample size: n=4,537).**

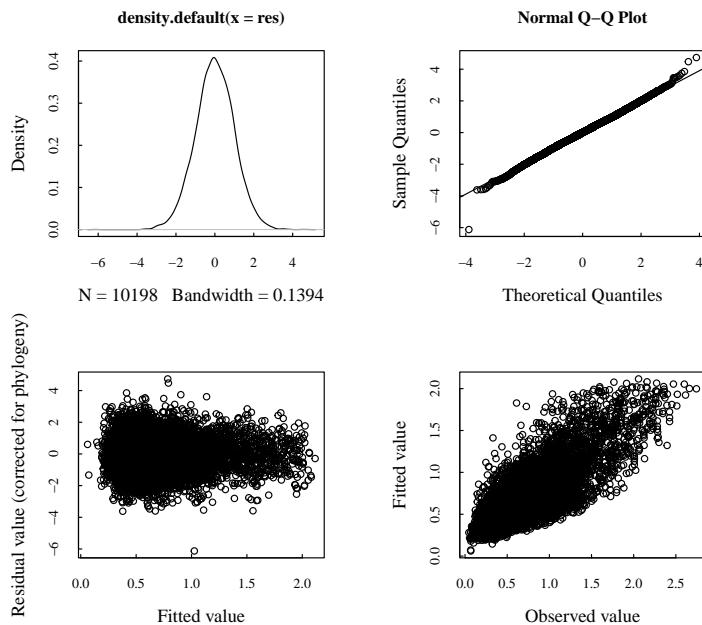
	Estimate	Std. Error	t value	Pr(> t )
Intercept	1.15	0.21	5.49	< 0.001
$\log_{10}(\text{Body mass})$	-1.97	0.61	-3.22	0.001
$\log_{10}(\text{Body mass})^2$	-0.26	0.42	-0.60	0.55
$\log_{10}(\text{Body mass})^3$	0.46	0.37	1.24	0.22
$\log_{10}(\text{Lifespan proxy})$	-0.21	0.59	-0.36	0.72
$\log_{10}(\text{Lifespan proxy})^2$	-0.14	0.43	-0.32	0.75
$\log_{10}(\text{Lifespan proxy})^3$	0.58	0.35	1.66	0.10
$\log_{10}(\text{Litter/clutch size})$	1.59	0.54	2.96	0.003
$\log_{10}(\text{Litter/clutch size})^2$	-0.06	0.38	-0.16	0.87
$\log_{10}(\text{Litter/clutch size})^3$	-0.74	0.31	-2.37	0.02
$\log_{10}(\text{Range area})$	-26.60	0.34	-77.15	< 0.001
$\log_{10}(\text{Range area})^2$	4.27	0.29	14.57	< 0.001
$\log_{10}(\text{Range area})^3$	-1.65	0.28	-5.96	< 0.001
square-root(Habitat breadth)	-2.26	0.43	-5.32	< 0.001
square-root(Habitat breadth) <sup>2</sup>	0.81	0.30	2.67	0.01
square-root(Habitat breadth) <sup>3</sup>	-0.59	0.28	-2.10	0.04
Specialisation: Natural habitat specialist	0.02	0.01	1.85	0.06
Diel activity: Non-nocturnal	0.04	0.01	3.28	0.001
Primary diet: Omnivore	0.01	0.03	0.29	0.77
Primary diet: Plants/seeds	0.04	0.13	0.31	0.76
Primary diet: Vertebrates	0.13	0.15	0.87	0.39



**Figure S4.13: Diagnostic plots for the PGLS model fitted on amphibians, investigating associations between species-level ecological characteristics and climate-change sensitivity, excluding species whose range area was  $\leq 100 \text{ km}^2$  (sample size: n=4,537).**

**Table S4.15: Summary for the PGLS model fitted on birds, investigating associations between species-level ecological characteristics and climate-change sensitivity, excluding species whose range area was  $\leq 100 \text{ km}^2$  (sample size: n=10,198).**

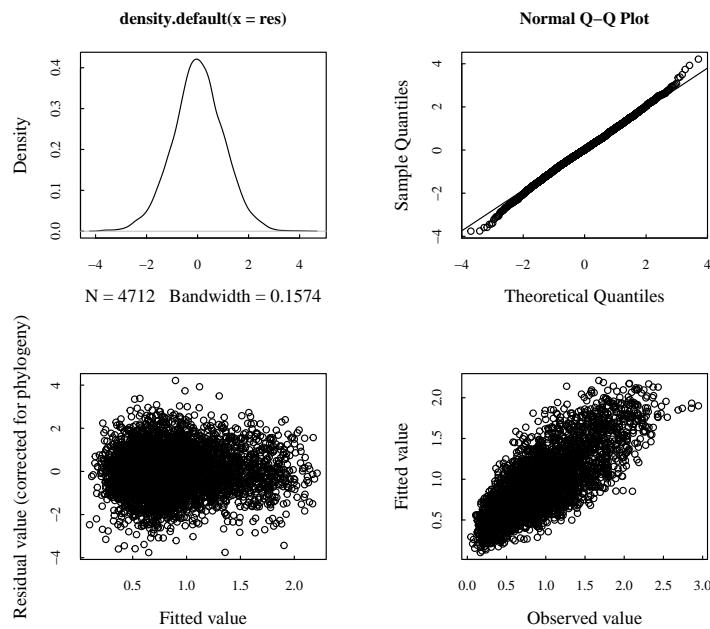
	Estimate	Std. Error	t value	Pr(> t )
Intercept	0.64	0.08	7.91	< 0.001
$\log_{10}(\text{Body mass})$	2.24	0.67	3.36	0.001
$\log_{10}(\text{Body mass})^2$	0.16	0.42	0.37	0.71
$\log_{10}(\text{Body mass})^3$	-0.22	0.37	-0.60	0.55
$\log_{10}(\text{Lifespan proxy})$	-0.23	0.59	-0.38	0.70
$\log_{10}(\text{Lifespan proxy})^2$	-0.84	0.39	-2.16	0.03
$\log_{10}(\text{Lifespan proxy})^3$	-0.10	0.28	-0.36	0.72
$\log_{10}(\text{Litter/clutch size})$	3.72	0.39	9.46	< 0.001
$\log_{10}(\text{Litter/clutch size})^2$	-0.42	0.33	-1.26	0.21
$\log_{10}(\text{Litter/clutch size})^3$	-0.40	0.27	-1.47	0.14
$\log_{10}(\text{Range area})$	-30.69	0.27	-113.09	< 0.001
$\log_{10}(\text{Range area})^2$	7.22	0.24	29.92	< 0.001
$\log_{10}(\text{Range area})^3$	-2.73	0.23	-11.74	< 0.001
square-root(Habitat breadth)	0.86	0.33	2.59	0.01
square-root(Habitat breadth) <sup>2</sup>	-0.89	0.24	-3.63	< 0.001
square-root(Habitat breadth) <sup>3</sup>	-0.22	0.23	-0.95	0.34
square-root(Diet breadth)	-0.50	0.31	-1.64	0.10
square-root(Diet breadth) <sup>2</sup>	-0.11	0.25	-0.44	0.66
square-root(Diet breadth) <sup>3</sup>	0.32	0.24	1.36	0.18
Specialisation: Natural habitat specialist	0.06	0.01	10.13	< 0.001
Diel activity: Non-nocturnal	-0.02	0.04	-0.66	0.51
Primary diet: Invertebrates	0.06	0.01	5.53	< 0.001
Primary diet: Omnivores	0.02	0.01	2.09	0.04
Primary diet: Plants/seeds	0.06	0.01	4.69	< 0.001
Primary diet: Vertebrates	0.01	0.02	0.83	0.41



**Figure S4.14: Diagnostic plots for the PGLS model fitted on birds, investigating associations between species-level ecological characteristics and climate-change sensitivity, excluding species whose range area was  $\leq 100 \text{ km}^2$  (sample size: n=10,198).**

**Table S4.16: Summary for the PGLS model fitted on mammals, investigating associations between species-level ecological characteristics and climate-change sensitivity, excluding species whose range area was  $\leq 100 \text{ km}^2$  (sample size: n=4,712).**

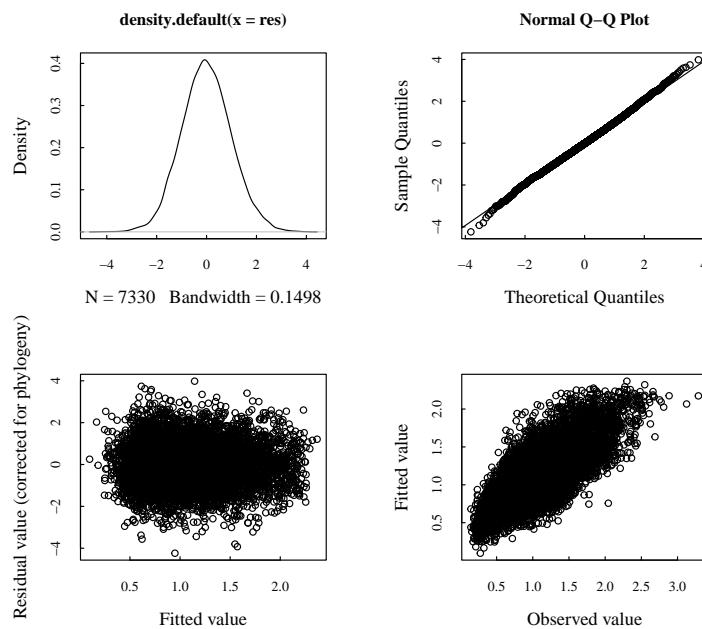
	Estimate	Std. Error	t value	Pr(> t )
Intercept	0.84	0.16	5.37	< 0.001
$\log_{10}(\text{Body mass})$	-4.62	0.94	-4.93	< 0.001
$\log_{10}(\text{Body mass})^2$	0.40	0.56	0.72	0.47
$\log_{10}(\text{Body mass})^3$	0.59	0.44	1.33	0.18
$\log_{10}(\text{Lifespan proxy})$	1.60	1.03	1.55	0.12
$\log_{10}(\text{Lifespan proxy})^2$	-0.79	0.49	-1.60	0.11
$\log_{10}(\text{Lifespan proxy})^3$	-0.15	0.43	-0.35	0.73
$\log_{10}(\text{Litter/clutch size})$	3.29	0.71	4.63	< 0.001
$\log_{10}(\text{Litter/clutch size})^2$	0.06	0.42	0.14	0.89
$\log_{10}(\text{Litter/clutch size})^3$	-0.16	0.33	-0.47	0.64
$\log_{10}(\text{Range area})$	-24.17	0.31	-78.21	< 0.001
$\log_{10}(\text{Range area})^2$	4.15	0.28	15.09	< 0.001
$\log_{10}(\text{Range area})^3$	-0.90	0.26	-3.45	0.001
square-root(Habitat breadth)	-1.24	0.34	-3.60	< 0.001
square-root(Habitat breadth) <sup>2</sup>	0.22	0.27	0.82	0.41
square-root(Habitat breadth) <sup>3</sup>	-0.03	0.26	-0.10	0.92
square-root(Diet breadth)	-1.21	0.47	-2.55	0.01
square-root(Diet breadth) <sup>2</sup>	0.33	0.36	0.91	0.36
square-root(Diet breadth) <sup>3</sup>	0.11	0.34	0.33	0.74
Specialisation: Natural habitat specialist	0.04	0.01	3.22	0.001
Diel activity: Non-nocturnal	0.003	0.01	0.23	0.82
Primary diet: Invertebrates	-0.02	0.03	-0.62	0.54
Primary diet: Omnivores	-0.02	0.03	-0.77	0.44
Primary diet: Plants/seeds	0.03	0.02	1.32	0.19
Primary diet: Vertebrates	-0.04	0.04	-0.98	0.33



**Figure S4.15: Diagnostic plots for the PGLS model fitted on mammals, investigating associations between species-level ecological characteristics and climate-change sensitivity, excluding species whose range area was  $\leq 100 \text{ km}^2$  (sample size: n=4,712).**

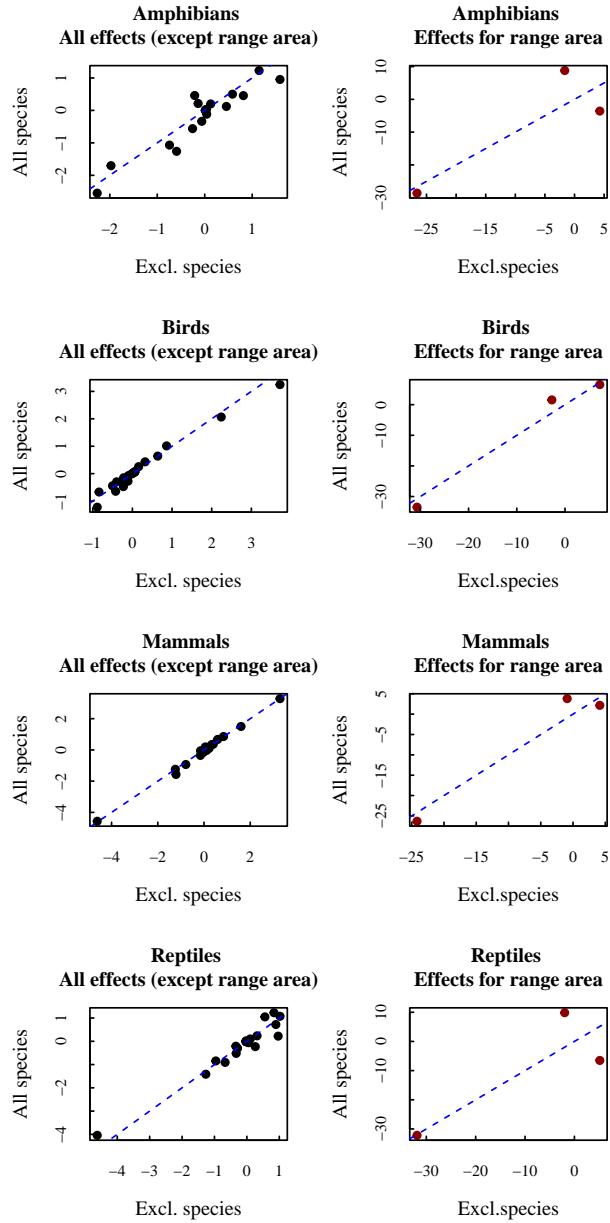
**Table S4.17: Summary for the PGLS model fitted on reptiles, looking at the effects of species-level ecological characteristics on climate-change sensitivity, excluding species whose range area was  $\leq 100 \text{ km}^2$  (sample size: n=7,330).**

	Estimate	Std. Error	t value	Pr(> t )
Intercept	1.02	0.13	7.70	< 0.001
$\log_{10}(\text{Body mass})$	-4.62	0.62	-7.47	< 0.001
$\log_{10}(\text{Body mass})^2$	0.97	0.41	2.35	0.02
$\log_{10}(\text{Body mass})^3$	-0.96	0.33	-2.90	0.004
$\log_{10}(\text{Lifespan proxy})$	0.89	0.51	1.74	0.08
$\log_{10}(\text{Lifespan proxy})^2$	-1.27	0.39	-3.27	0.001
$\log_{10}(\text{Lifespan proxy})^3$	-0.29	0.33	-0.88	0.38
$\log_{10}(\text{Litter/clutch size})$	0.84	0.68	1.24	0.22
$\log_{10}(\text{Litter/clutch size})^2$	-0.34	0.45	-0.76	0.45
$\log_{10}(\text{Litter/clutch size})^3$	0.26	0.35	0.74	0.46
$\log_{10}(\text{Range area})$	-31.88	0.31	-101.48	< 0.001
$\log_{10}(\text{Range area})^2$	5.15	0.27	19.03	< 0.001
$\log_{10}(\text{Range area})^3$	-1.97	0.26	-7.53	< 0.001
square-root(Habitat breadth)	0.56	0.35	1.59	0.11
square-root(Habitat breadth) <sup>2</sup>	-0.67	0.27	-2.49	0.01
square-root(Habitat breadth) <sup>3</sup>	0.05	0.26	0.21	0.83
square-root(Diet breadth)	-0.33	0.37	-0.90	0.37
square-root(Diet breadth) <sup>2</sup>	-0.02	0.27	-0.08	0.94
square-root(Diet breadth) <sup>3</sup>	0.31	0.26	1.22	0.22
Specialisation: Natural habitat specialist	0.10	0.01	8.50	< 0.001
Diel activity: Non-nocturnal	-0.02	0.01	-1.88	0.06
Primary diet: Omnivore	-0.03	0.03	-0.92	0.36
Primary diet: Vertebrates	-0.02	0.02	-1.05	0.30



**Figure S4.16: Diagnostic plots for the PGLS model fitted on reptiles, investigating associations between species-level ecological characteristics and climate-change sensitivity, excluding species whose range area was  $\leq 100 \text{ km}^2$  (sample size: n=7,330).**

## S4.9.2 Effects for the PGLS models fitted on all species, against effects for the PGLS models fitted on species whose range area was $>100 \text{ km}^2$

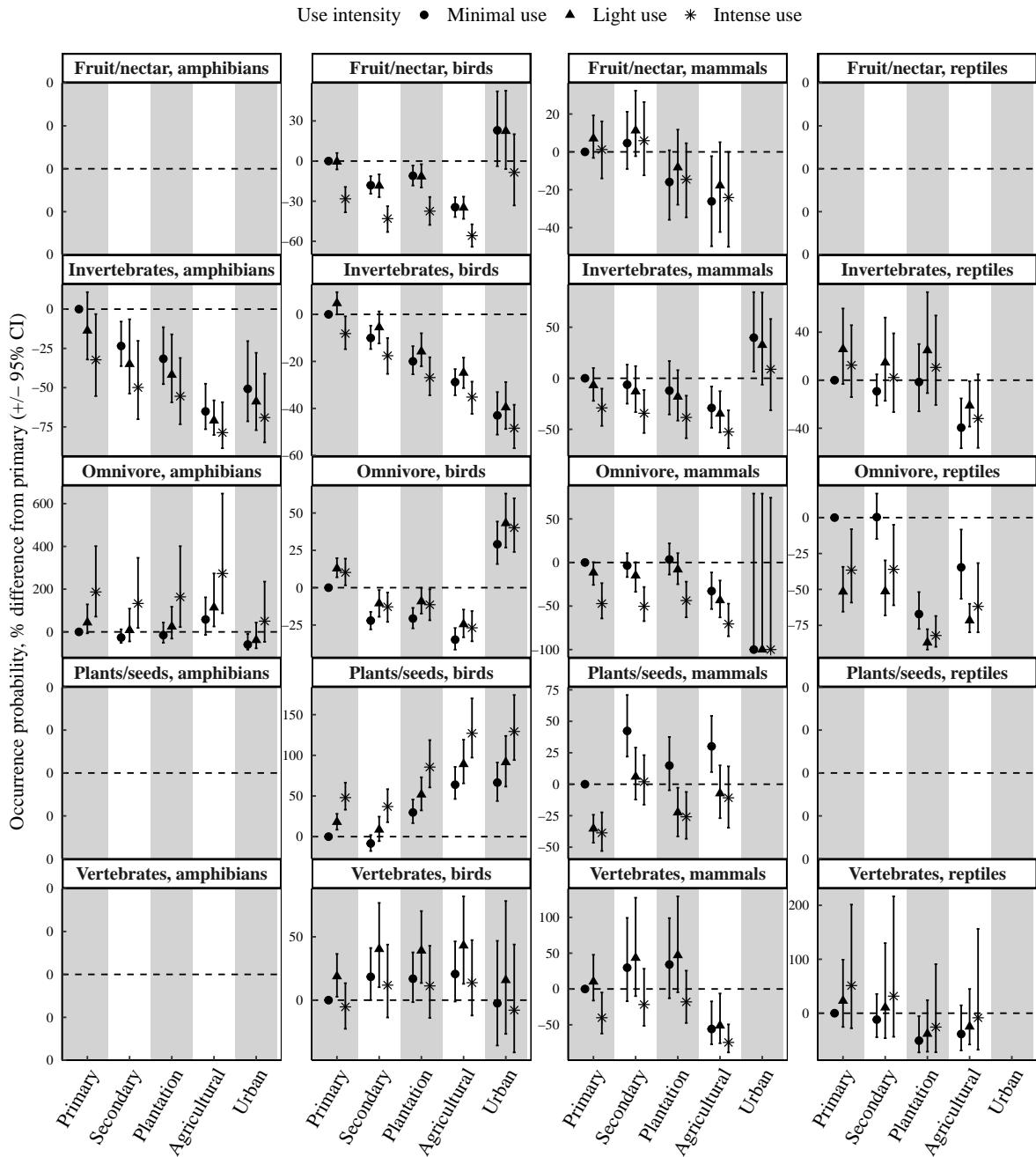


**Figure S4.17: Effects for the PGLS models investigating associations between species-level ecological characteristics and climate-change sensitivity**, either fitted on all species (y-axis), or fitted on the species whose range area was  $>100 \text{ km}^2$  (x-axis). Overall, the estimates from both sets of models were congruent, except for those estimated for geographical range area (I show the effects for range area separately from the effects of other characteristics). Across all classes, the relationship between sensitivity and geographical range area was reversed between the two sets of models. I found that sensitivity was positively associated with geographical range area when including all species, likely because of the underestimation of climate-change sensitivity for the most narrow-ranging species when working with a resolution of  $5 \text{ km}^2$  (see Figure S4.6). The dashed line is the identity line ( $y=x$ ).

## **S4.10 Validations on complete trait data subsets**

**Table S4.18: Summary of the effects of the ecological characteristics (except for diet) on (a) species' responses to disturbed land uses ('within land-use type' effects) and (b) species climate-change sensitivity, for each class of terrestrial vertebrates, from the models fitted on empirical trait values (excluding all imputed values).** The symbol  indicates where a characteristic has a significant negative effect on occurrence probability within a disturbed land-use type (within any of the land-use intensities), or where the characteristic renders species significantly more sensitive to climate change. A  indicates a significantly positive effect of a characteristic on occurrence probability in a land-use type (within any of the land-use intensities), or significantly lower sensitivity to climate change. For the land-use effects, I report 'within land-use type effects' here, that is, within a disturbed land use whether there were significant differences in occurrence probability among species with different trait values. These effects were derived from the interactive terms of the full models.

(a) "Within land-use type" effects of the species-level characteristics on occurrence probability - <=> more sensitive; + <=> less sensitive																Predictors				(b) Climate-change sensitivity: - <=> more sensitive + <=> less sensitive				
Secondary vegetation				Plantation forest				Agricultural				Urban												
																								
0	-	0	0	0	-	0	0	0	-	-	+	+	-	0	NA	More narrowly-distributed					-	-	-	(-)
0	-	0	0	-	-	0	0	-	-	0	-	-	-	0	NA	Smaller habitat breadth					0	-	-	-
-	-	0	0	0	-	0	0	-	-	-	+	0	-	0	NA	Natural habitat specialist					0	-	0	-
0	+	+	0	+	+	(+)	+	0	+	+	0	0	0	0	NA	Non-nocturnal					0	0	0	0
-	0	(+)	0	(-)	0	+	0	-	0	(+)	+	-	-	0	NA	Narrower diet breadth					0	0	0	0
NA	(+)	+	NA	NA	+	+	NA	NA	-	0	NA	NA	+	0	NA	Smaller body mass					0	(+)	-	0
NA	0	0	-	NA	-	(-)	0	NA	-	(-)	0	NA	0	-	NA	Smaller litter/clutch size					0	+	+	0
NA	0	0	-	NA	(-)	0	0	NA	+	0	+	NA	-	0	NA	Shorter-lived					(+)	0	0	0



**Figure S4.18: Predicted occurrence probability as a function of land use, land-use intensity, diet and their interactions in each class. The predictions were obtained from the partial models fitted in each class for diet, estimated using empirical trait data subsets (i.e., excluding imputed trait values).** Empty plots are drawn where there were no data for a diet category in a given class (e.g., amphibian fruit/nectar eaters). Effects could not be estimated for urban reptiles, as well as for urban vertebrate, fruit/nectar and plant/seed eaters for mammals because there were no sampled species. The predictions are rescaled with reference to minimally-used primary vegetation. Primary: primary vegetation; Secondary: secondary vegetation; plantation: plantation forest; agricultural: cropland and pasture.

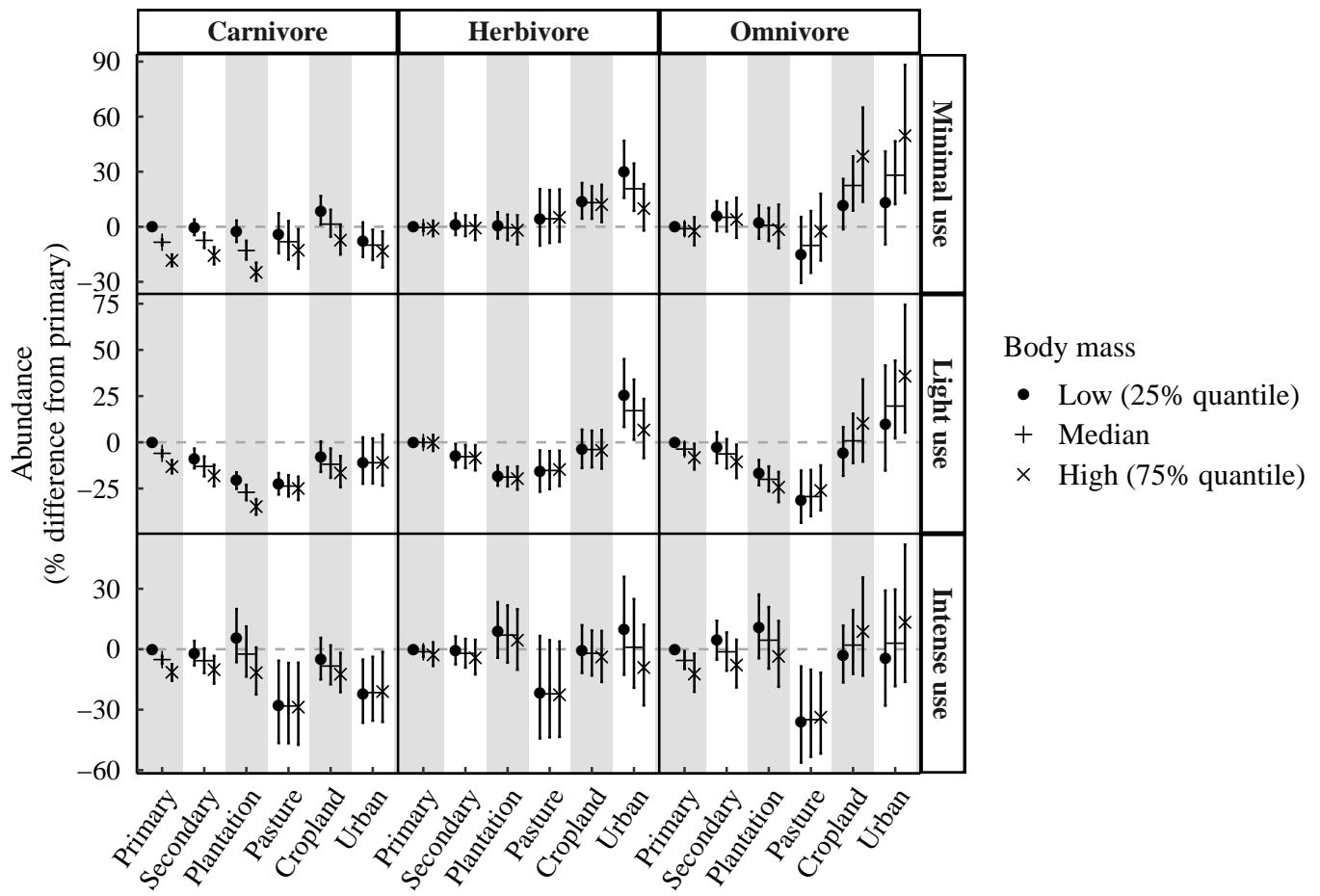
# Appendix 4: Supporting information for Chapter 5

**Table S5.1:** Number of species for which RMR data was collected in each class & data sources, initial RMR coverage for PREDICTS species and phylogenetic signal in RMR.

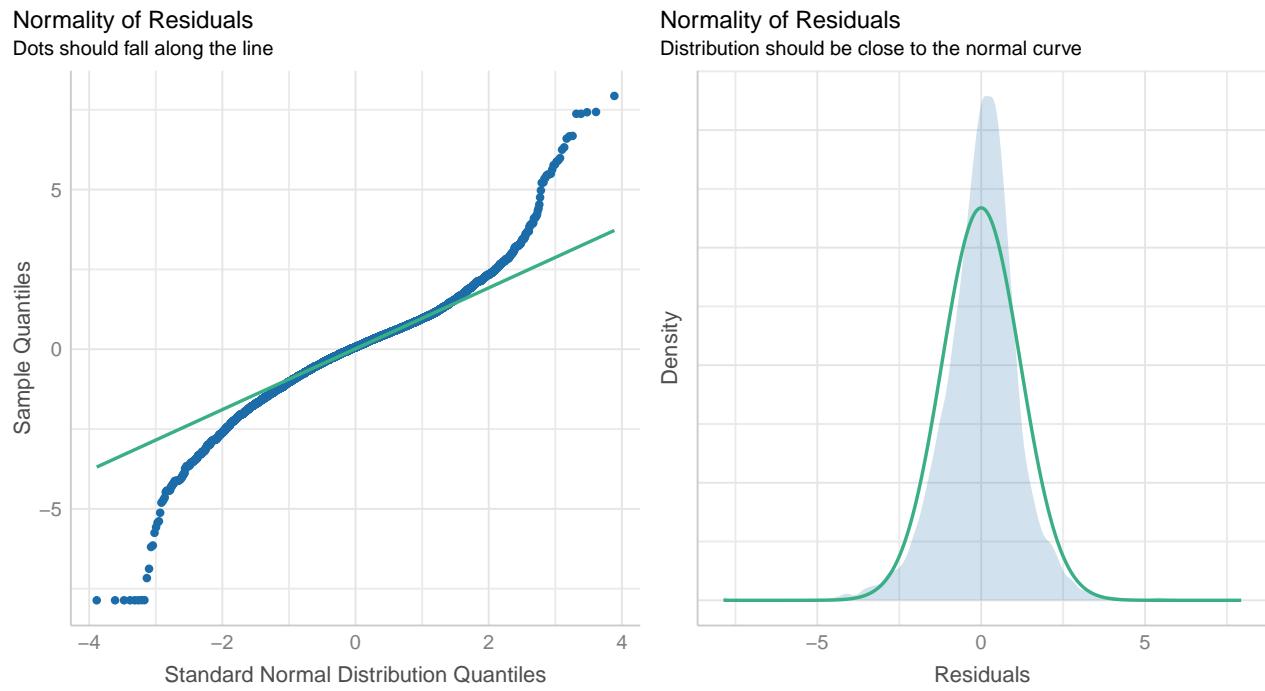
Class	RMR data	Coverage for PREDICTS species	Phylogenetic signal (Pagel's $\lambda$ , $\pm 95\%$ CI)
<b>Amphibians</b>	126 species from Stark et al. (2020)	16/379 species (4%)	0.89 (0.86-0.91)
<b>Birds</b>	719 species from McNab (2009) Fristoe et al. (2015) Londoño et al. (2015) Stark et al. (2020)	317/3129 species (10%)	0.97 (0.95-0.98)
<b>Mammals</b>	685 species from PanTHERIA (Jones et al., 2009) Fristoe et al. (2015) Stark et al. (2020)	148/556 species (27%)	0.99 (0.98-0.99)
<b>Reptiles</b>	173 species from Stark et al. (2020)	24/329 species (7.3%)	0.90 (0.86-0.92)

$$\begin{aligned} \log(\text{Abundance}) = & \text{LU} + \text{LUI} + \text{TG} + \log(\text{BM}) + \\ & \text{LU:LUI} + \text{LU:TG} + \text{LU:}\log(\text{BM}) + \text{LUI:TG} + \text{LUI:}\log(\text{BM}) + \text{TG:}\log(\text{BM}) + \\ & \text{LU:TG:}\log(\text{BM}) + \text{LUI:TG:}\log(\text{BM}) \end{aligned}$$

**Figure S5.1: Formula for the abundance model, used to understand the role of shifts in the body mass of species on observed changes in tRMR** (see Chapter 5, section 5.2.5, ‘Disentangling the effects of body mass and abundance on tRMR’). I fitted a model to explain changes in species abundance (given presence) by land use, land-use intensity, trophic group, body mass and their interactions. The model included all two-way interactions among these predictors. To account for potential differences in the slope of the relationship between abundance and body mass among the different trophic groups, I also included two three-way interactions in the model (among land use, trophic group and body mass; and among land-use intensity, trophic group and body mass). Random effects included study, site and species identity. LU: land use; LUI: land-use intensity; TG: trophic group; BM: body mass.

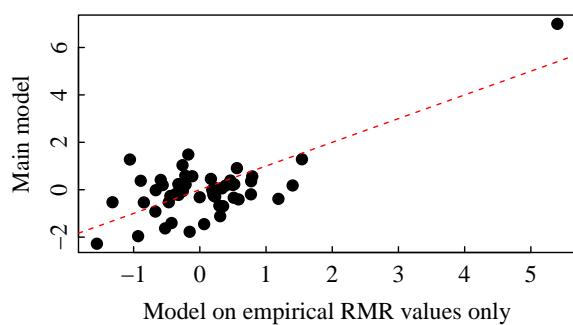


**Figure S5.2: Effects of land use, land-use intensity, trophic group, body mass and their interactions on assemblage-level total abundance**, estimated from the model specified in Figure S5.1. The predictions are rescaled with reference to minimally used primary vegetation, considered to be the undisturbed baseline. Primary: primary vegetation; secondary: secondary vegetation; plantation: plantation forest. For visualisation purposes, I plotted the predictions for three body mass levels (but body mass was considered as a continuous variable in the model).

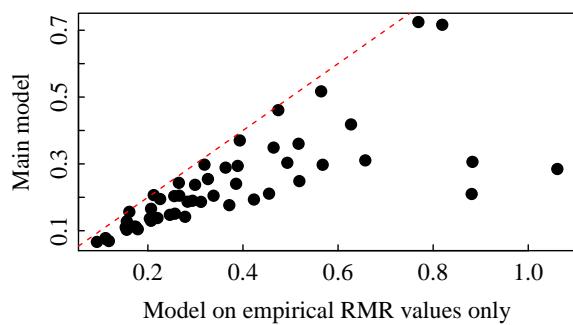


**Figure S5.3:** Diagnostic plots (qq-plot and residual distribution) for the linear mixed-effects model looking at the effects of land use, land-use intensity, trophic group and their interactions on assemblage-level total RMR (*model I*). The diagnostic plots were obtained with the ‘performance’ R package (Lüdecke et al., 2021).

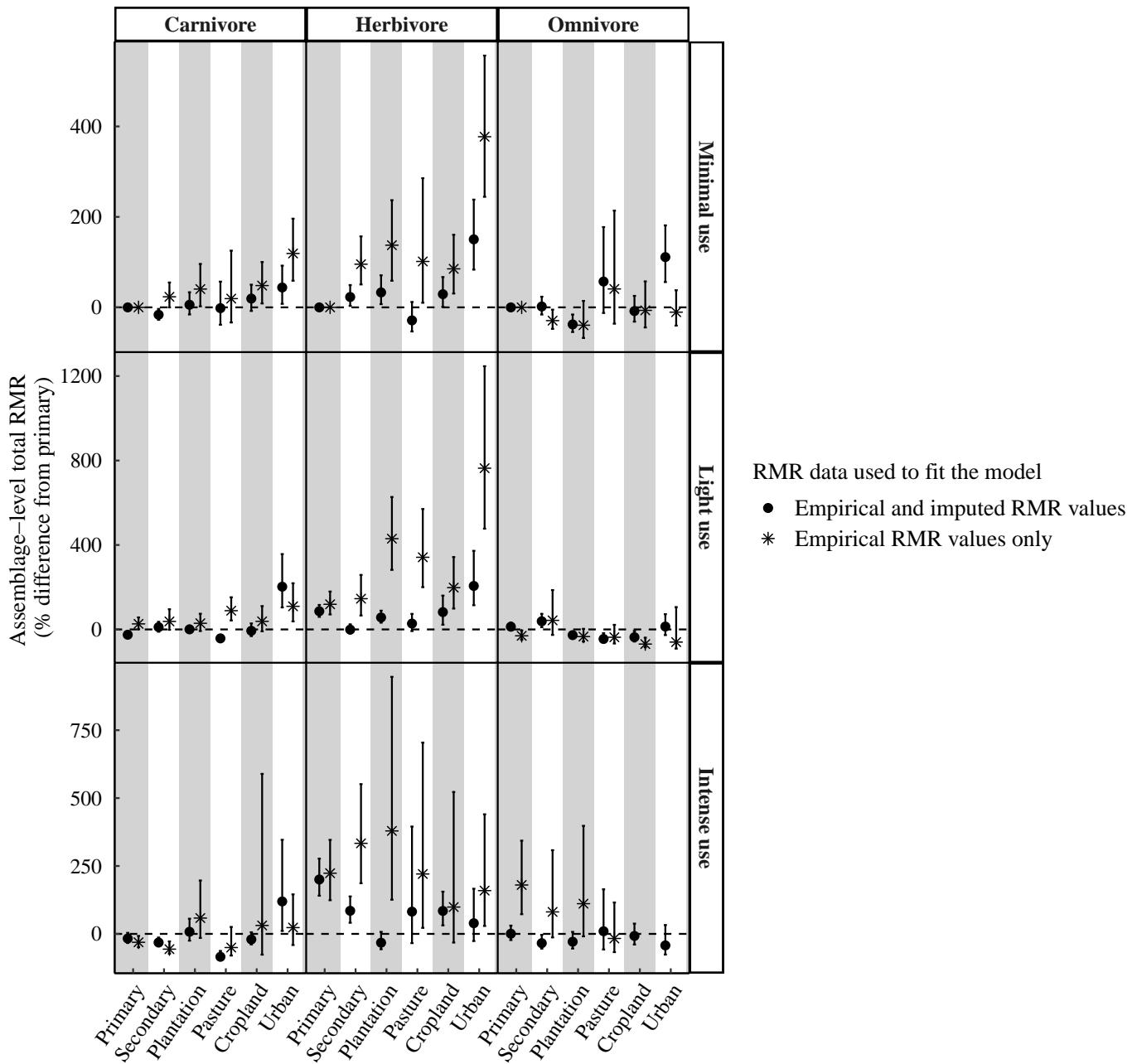
**(a) Coefficient estimates**



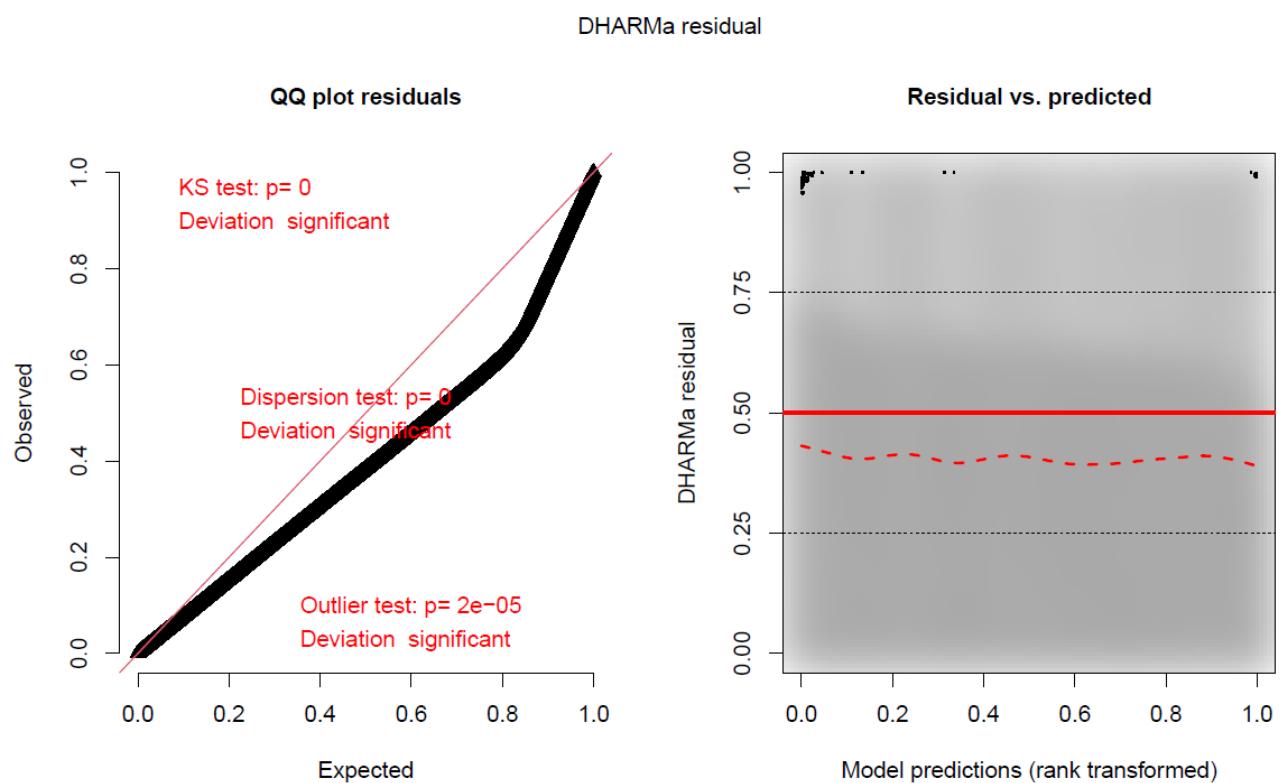
**(b) Standard error estimates**



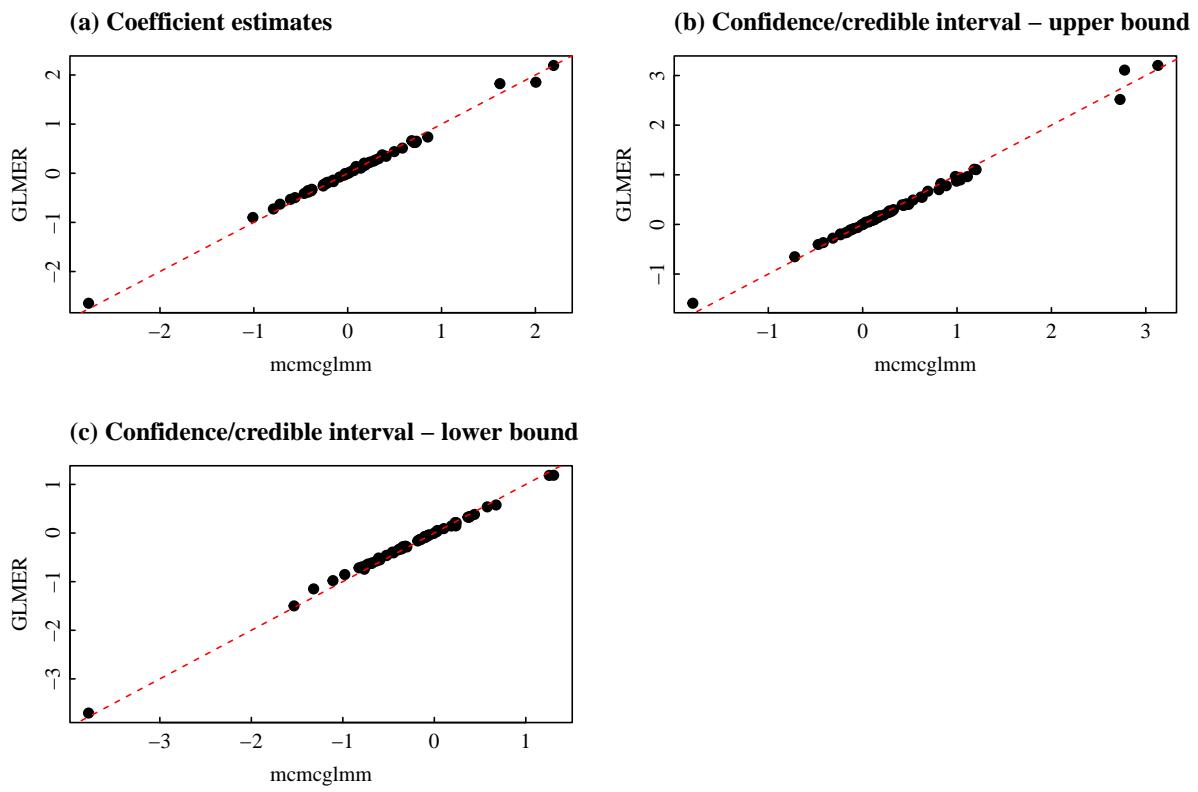
**Figure S5.4: Estimates for the models looking at the effects of land use, land-use intensity, trophic group and their interactions on assemblage-level total RMR.** I plotted the estimates from the model fitted on the empirical and imputed RMR values (*model 1*) on the y-axis, and the estimates from the model fitted on the empirical RMR values only on the x-axis.



**Figure S5.5: Effects of land use, land-use intensity, trophic level and their interactions on assemblage-level total RMR, estimated from the model fitted on the empirical and imputed RMR values (*model 1*) and from the model fitted on the empirical values only. The predictions are rescaled with reference to minimally used primary vegetation, considered to be the undisturbed baseline. Primary: primary vegetation; secondary: secondary vegetation; plantation: plantation forest.**

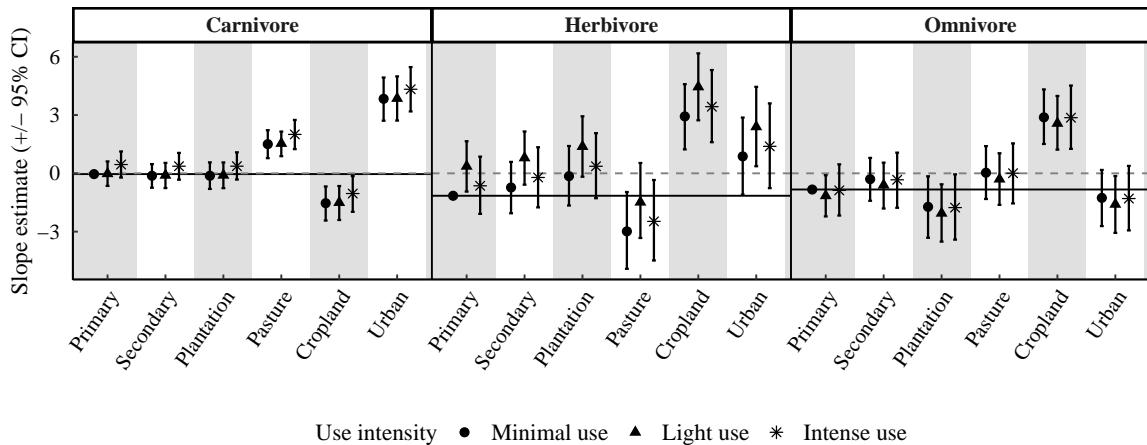


**Figure S5.6:** Diagnostic plots for the generalised mixed-effects model looking at the effects of land use, land-use intensity, trophic group, residual RMR and their interactions on species' probability of occurrence (*model 2*). The diagnostic plots were obtained with the 'DHARMA' R package (Hartig, 2021).

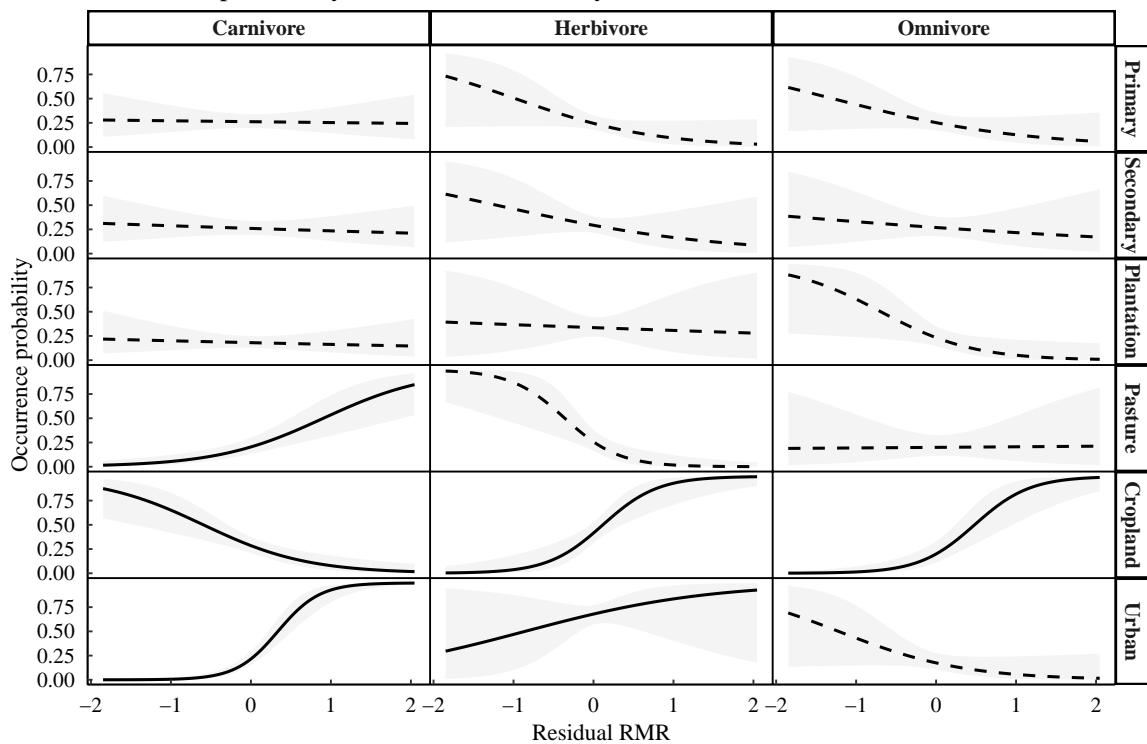


**Figure S5.7:** Model's coefficients from the occurrence model fitted using the 'lme4' package (Bates et al., 2015) against coefficients from the model fitted using a Bayesian framework with the 'MCMCglmm' package (Hadfield, 2010). The models were fitted to investigate the effects of land use, land-use intensity, trophic group and residual RMR on species occurrence probability (*model 2*).

(a) Slope of the relationships between occurrence probability (log-odds) and residual RMR



(b) Predicted effects of residual RMR on occurrence probability (minimal use intensity)



**Figure S5.8: (a) Slope estimates for the relationship between residual RMR and occurrence probability in each land-use type and for the three levels of land-use intensity, from the model fitted using the empirical RMR values (i.e., *model 2*, excluding imputed RMR values). The black horizontal line indicates the slope for the reference level (primary vegetation) for minimal land-use intensity. The grey dashed line marks 0. Error bars are 95% confidence intervals. (b) Effect of residual RMR on species probability of occurrence within each trophic level and for each land use-type from the model fitted using the empirical RMR values (i.e., *model 2*, excluding imputed RMR values). I plotted the predictions for minimal land-use intensity only. Solid lines represent significant relationships. Primary: primary vegetation; secondary: secondary vegetation; plantation: plantation forest.**

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