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Human pressure drives biodiversity–multifunctionality relationships in large Neotropical wetlands

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Many studies have shown that biodiversity regulates multiple ecological 61 functions that are needed to maintain the productivity of a variety of ecosystem types. 62 What is unknown is how human activities may alter the 'multifunctionality' of 63 64 ecosystems through both direct impacts on ecosystems and indirect effects mediated by the loss of multifaceted biodiversity. Using an extensive database of 72 lakes spanning 65 four large Neotropical wetlands in Brazil, we demonstrate that species richness and 66 67 functional diversity across multiple larger (fish and macrophytes) and smaller (microcrustaceans, rotifers, protists, and phytoplankton) groups of aquatic organisms 68 are positively associated with ecosystem multifunctionality. Whereas the positive 69 70 association between smaller organisms and multifunctionality broke down with increasing human pressure, this positive relationship was maintained for larger 71 organisms despite the increase in human pressure. Human pressure impacted 72 73 multifunctionality both directly and indirectly through reducing species richness and functional diversity of multiple organismal groups. These findings provide further 74 empirical evidence about the importance of aquatic biodiversity for maintaining wetland 75 multifunctionality. Despite the key role of biodiversity, human pressure reduces the 76 diversity of multiple groups of aquatic organisms, eroding their positive impacts on a 77 78 suite of ecological functions that sustain wetlands.

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Human activities are causing biodiversity to decline worldwide^{1,2}, which has led 84 to an interest in how biodiversity loss might alter the functioning of ecosystems³. Most 85 studies have revealed positive and saturating effects of biodiversity on single ecosystem 86 functions⁴. Empirical evidence suggests that species are ecologically unique and can 87 play complementary roles in natural systems, thus varying in their contributions to 88 different functions³⁻⁵. As a consequence, the effect of biodiversity on ecosystem 89 90 functioning is stronger – and the relationship is non-saturating – when multiple functions are considered (hereafter 'multifunctionality')⁵⁻⁸. Therefore, it has been 91 increasingly recognized that biodiversity and multifunctionality are strongly associated. 92 93 This recognition has led to the prediction that as biodiversity declines in humandominated ecosystems, their ability to sustain multiple ecosystem functions is impaired, 94 ultimately altering the biodiversity-multifunctionality relationship^{3,9-13}. Current 95 96 evidence supporting the anthropogenic impacts on biodiversity-multifunctionality relationships are scarce and comes mostly from experimental manipulations of single 97 trophic levels¹⁰⁻¹³. It is possible that these studies under-estimate human impacts on 98 biodiversity and ecosystem multifunctionality since natural systems are comprised of 99 multiple organismal groups of varying trophic levels, and different trophic levels may 100 combine to have stronger impacts on multifunctionality⁵⁻⁷. Further research applying a 101 multitrophic perspective is needed to develop a more mechanistic understanding of the 102 103 consequences of human pressures for biodiversity-ecosystem functioning relationships 104 in natural systems worldwide.

Here, we used a unique dataset from 72 lakes distributed across four large
Neotropical wetlands of Brazil (Amazon, Araguaia, Pantanal and Paraná) to test how
the cumulative effect of multiple human pressures impacts the relationship between
biodiversity and multifunctionality. These four wetlands provide a unique opportunity

109 to test the influence of human pressures across broad spatial scales as the lakes span a 3,700,000 km² gradient of distinct human activities (Fig. 1). We quantified human 110 pressure on the wetland using the Human Footprint (HFP) index¹⁴, which was extracted 111 for each lake individually (see Methods). The HFP is a recently developed index that 112 incorporates eight different human pressures: (i) built environments, (ii) crop land, (iii) 113 pasture land, (iv) human density, (v) night-time lights, (vi) railways, (vii) roads, and 114 (viii) navigable waterways into a standardized cumulative index of human pressure¹⁴. 115 This index provides an interesting opportunity to understand how human pressures are 116 affecting biodiversity-multifunctionality relationships in natural to human-dominated 117 systems. 118

119 We compiled data on the species richness and functional diversity of seven taxonomic groups, including fish, aquatic macrophytes, microcrustaceans, rotifers, 120 phytoplankton, ciliates, and testate amoebae. These data comprised 1,465 plant, animal, 121 and microbial species. Because biodiversity-multifunctionality relationships can be 122 multi-dimensional⁶⁻⁷, we also used measures of multidiversity (joint diversity of all 123 organismal groups, both for species richness and functional diversity)¹⁵. Studies 124 considering multidiversity have found strong biodiversity-multifunctionality 125 relationships⁶⁻⁸. To estimate functional diversity, we focused on a core set of 126 independent organismal traits that mediate the species response to human pressures 127 (Supplementary Table 1): body size, resource-use (e.g., feeding groups, growth forms, 128 and mixotrophy), and mobility (e.g., migration ability, propagation method, and cell 129 motility) traits. These traits are often linked to multiple ecosystem functions in 130 wetlands. For instance, body size, feeding groups, and migration ability are related to 131 metabolism, multitrophic biomass production, and nutrient cycling¹⁶⁻¹⁷. We further 132 quantified ecosystem multifunctionality by using a set of 11 variables that included 133

nutrient concentrations (in situ measurements of N and P water concentrations), 134 metabolism (daily changes in water O₂ concentration), biomass at multiple trophic 135 levels (algae, herbivores, carnivores, detritivores, and omnivores), microorganism 136 abundance (bacterial cell densities), availability of photosynthetically active radiation 137 (light availability underwater), and variation in habitat complexity under water 138 (variation in plant above-bottom cover). Together, these variables measure 139 140 environmental characteristics that are directly linked to ecosystem functions. A detailed rationale for each variable is provided in Supplementary Table 2. We quantified 141 multifunctionality using three common approaches: (i) the averaging multifunctionality 142 index, (ii) the multi-threshold multifunctionality index, and (iii) multiple single 143 functions. The averaging approach takes the average of the standardized values of each 144 single function. In contrast, the multi-threshold considers the number of functions that 145 146 simultaneously surpass a range of thresholds, which are expressed as a percentage of the highest observed level of functioning (here, 1-99%). These three approaches are 147 148 complementary, and when taken together, they provide a robust estimation of how multiple functions (averaging and multi-pillar approach), as well as single functions, 149 respond to biodiversity enhancement^{5-8,18}. 150

Because no studies have examined the broad-scale relationships between 151 biodiversity and ecosystem multifunctionality across wetlands, we first established 152 whether species richness and the functional diversity of the seven organismal groups 153 were, in fact, related to multifunctionality as previous narrow-scale evidence 154 suggests^{17,19}. For this, we employed multiple linear mixed models considering species 155 richness and functional diversity as predictors and multifunctionality as the response. 156 After confirming a consistent relationship, we also used linear mixed model to 157 determined how human pressures alter these biodiversity-multifunctionality 158

relationships. Lastly, we used structural equation models (SEMs) to investigate the direct
and indirect biodiversity-mediated pathways by which human pressure can influence
multifunctionality in wetlands.

162 **Results and discussion**

163 Across four hyperdiverse Neotropical wetlands, we found significant positive relationships between the diversity of single groups of aquatic organisms and the 164 multidiversity of all groups with ecosystem multifunctionality (Figs. 2 and 3, and 165 Supplementary Table 3). This finding was consistent for both species richness and 166 167 functional diversity (Figs. 2 and 3). Our model averaging procedure revealed that the biodiversity of organismal groups was best predictors of multifunctionality, even after 168 accounting for influence of other well-known drivers of multifunctionality such as 169 170 space, climate (precipitation and temperature), and aquatic properties (conductivity, pH 171 and water level (Supplementary Table 4). The positive association between aquatic 172 biodiversity and multifunctionality persisted regardless of how the measures of multifunctionality were weighted (Supplementary Figs. 1 and 2). The multi-threshold 173 approach provided additional evidence showing that the mean minimum threshold at 174 175 which the species richness of organismal groups had its strongest effects on 176 multifunctionality averaged 57% (range 5-92%, Supplementary Fig. 3). Similarly, the mean minimum threshold at which functional diversity had its strongest effects on 177 multifunctionality was 91% (range 70-99%, Supplementary Fig. 4). The diversity of 178 179 aquatic organism groups was also positively associated with most of the individual 180 ecosystem functions, although each organismal group was more closely associated with specific functions (Supplementary Tables 5 and 6). Here, fish diversity was strongly 181 182 related to multitrophic biomass, macrophyte diversity was most strongly related to light 183 availability and habitat complexity, whereas microorganism diversity was most related

to nutrient concentrations and ecosystem metabolism (Extended Data Figs. 1 and 2). 184 Finally, aquatic biodiversity had stronger effects on multifunctionality than other 185 multifunctionality drivers (Extended Data Figs. 3 and 4; SEM: total effect of composite 186 species richness on multifunctionality 0.79, total effect of composite functional 187 diversity on multifunctionality 0.72). Collectively, our broad-scale dataset revealed 188 strong and consistent associations between the diversity of multiple groups of aquatic 189 190 organisms and ecosystem multifunctionality. These results underline the important role of multiple elements of biodiversity in driving the ecosystem functioning in Neotropical 191 wetlands^{15-16,18}, as in other ecosystem types such as drylands⁸ and forest⁷. 192

The close association between biodiversity and multifunctionality, suggests that 193 biodiversity loss might impact the ability of wetlands to maintain their functioning⁴⁻⁸. 194 Analysis of the relationship between HFP and biodiversity revealed a decline in species 195 richness and functional diversity with increasing HFP (Supplementary Figs. 5 and 6). 196 To test how this affected the relationship between biodiversity and multifunctionality, 197 we examined how interaction HFP x biodiversity influenced the slope of biodiversity-198 multifunctionality relationships. While the isolated effect of species richness on 199 multifunctionality was positive for most organismal groups, the interactive HFP x 200 201 species effect was negative (Fig. 4a). Similarly, the isolated effect of functional diversity on multifunctionality was positive, but the interactive HFP x functional 202 diversity effect was strongly negative (Fig. 5a). This suggests that human pressure can 203 204 alter the relationship of both species' richness and functional diversity with multifunctionality. By decomposing the effect of biodiversity on multifunctionality 205 through low, medium, and high HFP intensity, we found that the positive effect of 206 species richness and functional diversity on multifunctionality declined from low to 207 high HFP intensity (Fig. 4b and Fig. 5b). In particular, the effect of the diversity of 208

209 smaller organisms (such as microcrustaceans, testate amoebae, ciliates, and rotifera) on 210 multifunctionality shifted from positive at low HFP intensity to neutral or negative at high HFP intensity (Figs 4 and 5). By contrast, the positive effect of the diversity of 211 larger organisms (such as fish and macrophytes) on multifunctionality was maintained 212 despite increased HFP. These results illustrate how the ability of smaller organisms to 213 promote multifunctionality is sensitive to human pressure and simultaneously highlight 214 215 the importance of larger organisms for maintaining ecosystem functioning in a humandominated world²⁰. 216

The changes in the magnitude and direction of the relations between and 217 biodiversity and multifunctionality suggest that such relationships can be context-218 dependent in wetlands²¹. This is more evident for smaller groups of aquatic organisms 219 as their effects on multifunctionality changed from positive at low HFP intensity to 220 negative at high HFP intensity. Using a structural equation model, we disentangled the 221 direct and biodiversity-mediated, indirect pathways by which human pressures affect 222 multifunctionality. We demonstrate that the direct effect of HFP on multifunctionality 223 was consistently negative across all wetlands (Fig. 6a, Supplementary Tables 8-10). 224 This is consistent with the fact that the studied wetlands cover regions with intensive 225 226 human activities (Fig. 1). Most of the studied wetlands cover areas of simultaneous crops of soy and sugarcane, and pasturelands grazed by cattle²²⁻²⁵ and Paraná wetland is 227 located downstream of one of the most populated areas on the planet²². Consequently, 228 multiple human pressures can jointly affect the integrity of these wetlands by decreasing 229 biodiversity and ecosystem multifunctionality (Supplementary Fig. 7). 230

Beyond their direct negative effect on multifunctionality, HFP had large indirect negative effects on the multifunctionality mediated by declining species richness and functional diversity (Fig. 6). Although indirect negative effects of human pressure were

driven by the decline in the diversity of most organismal groups, these effects were 234 strongly mediated by fish diversity (Fig. 6b,d). This is consistent with the fact that fish 235 diversity has greatest influence on functioning of wetlands^{16,17}, and loss in fish diversity 236 is known to impact multiple ecosystem functions²⁶. The negative indirect biodiversity-237 mediated effects of human pressure on multifunctionality were also consistent across 238 wetlands (Supplementary Table 11). Combined with the fact that the positive effects of 239 240 biodiversity on multifunctionality decreased with increasing HFP (Fig. 4), our results highlight that, if the human pressures continue to increase²⁷, preservation of biodiversity 241 for maintaining multifunctionality will not be sufficient unless they are accompanied by 242 243 a reduction of human pressures. Seen in the light of the increasing human influence on 244 natural landscapes, our results illustrate the importance of considering multiple pathways through which human pressures can influence ecosystem multifunctionality. 245

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247 Conclusion

248 We have provided the first empirical evidence of a positive broad-scale relationship between the diversity of multiple groups of aquatic organisms and the 249 250 multifunctionality of wetland ecosystems. We demonstrate that a positive association between aquatic biodiversity and multifunctionality occurs for both single metrics of 251 diversity as for those combined into a multidiversity. These positive relationships are 252 253 also apparent for the seven groups of aquatic organisms, although larger organisms are more strongly linked to multifunctionality than smaller organisms. Collectively, our 254 255 findings highlight the importance of aquatic biodiversity for maintaining ecosystem multifunctionality and their associated services²⁸. It is imperative that biodiversity 256 conservation be a key management priority in wetlands²⁹ and that ecosystem 257 258 management targets the joint conservation of multiple components of aquatic

biodiversity, from vertebrates to plants and microorganisms. We have also shown that 259 human pressures degrade the positive relationship between biodiversity and 260 261 multifunctionality, which occur both directly and indirectly as human pressures reduce 262 the biodiversity needed to maintain numerous ecosystem functions. These findings demonstrate that human pressures are degrading multifunctionality through multiple 263 pathways. Consequently, conserving the functioning of wetlands will be a major 264 challenge as human pressures continue to increase in these ecosystems worldwide²⁹⁻³⁰. 265 More broadly, reducing human pressures must be addressed urgently in wetlands as 266 267 these systems rank among the most diverse and productive ecosystems globally, providing a suite of functions and services essential for human well-being. 268

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270 Methods

271 Study sites and data collection. The study comprised the four largest South American wetlands -272 Amazon, Araguaia, Pantanal, and Paraná – encompassing a subcontinental spatial area of approximately 273 3,700,000 km² and 72 lake ecosystems (Fig. 1). These wetlands are subject to distinct intensities of 274 human pressure. Amazon is a global biodiversity hotspot and is more preserved than Araguaia and 275 Pantanal that are both subject to moderate human pressure (Fig. 1). Paraná includes 150 constructed 276 dams³¹ and faces the strongest human pressure among the four wetlands. The climate ranges from 277 subtropical to tropical, with a mean annual temperature of 16 - 29°C and a mean precipitation of 1,300 -2,000 mm year-1³². The field data were collected between August and May 2011 and 2012. The wetland 278 279 lakes were surveyed under the Brazilian program "National System for Research in Biodiversity" 280 (Sisbiota Brazil). The field surveys were designed to include lakes representing a wide range of climate, human pressure, and environmental conditions. They followed a standardized sampling protocol and the 281 282 sampling effort was the same in all lakes³². In order to provide a comprehensive assessment of aquatic 283 communities, we performed one sampling during the dry season and another during the wet season in 284 each lake. The sampling included fish, aquatic macrophytes, microcrustaceans (cladocerans and 285 copepods), rotifers, phytoplankton, testate amoebae, and ciliates. A detailed sampling protocol for each 286 taxon is available in the Supplementary Methods.

287 Diversity measure. We quantified the species richness of the seven taxonomic groups of aquatic 288 organisms in all 72 lakes. After identifying each individual to species level, we determined 325 fish 289 species, 87 macrophyte species, 99 microcrustacean species, 124 rotifer species, 598 phytoplankton 290 species, 124 testate amoebae species, and 108 ciliate species. Sample coverage was equal for all wetlands, 291 but the locations differed in total number of individuals present. Therefore, we calculated estimated 292 species richness as the Chao index with abundance-based data using the R package iNEXT³³, which is 293 based on rarefaction and extrapolation of Hill numbers and provides an unbiased estimate of asymptotic 294 species richness and enables comparisons among wetlands with different numbers of individuals. We 295 used the Chao species richness because richness is the most commonly used and simplest metric of 296 biodiversity⁵⁻⁸. We also measured the key functional traits for all organismal groups. We focused on the 297 traits that are known to govern the patterns of spatial distribution and individual fitness, and which also 298 influence ecosystem processes^{16,34}. These traits fall into the three broad categories: (i) body size 299 (maximum body length for animal taxa or cell volume for phytoplankton), (ii) resource and habitat use 300 traits (feeding groups for animal taxa, growth form for macrophytes, nitrogen fixation or mixotrophy for 301 microorganisms), and (iii) mobility traits (dispersal ability for animal taxa, propagation means for 302 macrophytes, and cell motility for microorganisms). The literature sources used for functional 303 classification and the predicted impact of each trait on ecosystem functions can be found in 304 Supplementary Table 1. In order to determine the functional diversity (FD) of each organismal group, we 305 calculated functional dispersion - i.e., the mean distance in multidimensional trait space of the individual 306 species to the centroid of all species³⁵. This measure provides a robust estimate of functional diversity. 307 Because the relationship between biodiversity and ecosystem functioning can be multi-dimensional on both the predictor (biodiversity) and response side (multifunctionality)⁶⁻⁷, we also estimated a 308 multidiversity index including the diversity of the seven organismal groups¹⁵. We first standardized the 309 310 diversity values of each organismal group between 0 and 1 (species richness or functional diversity) by 311 scaling them to the maximum observed value, and then we average these standardized diversity values¹⁵. 312 This procedure ensures that the diversity of each organism group contributes equally to the multidiversity 313 of the wetlands. We calculated separately the multidiversity index for species richness and functional 314 diversity. The multidiversity index has been widely used because it reflects very well the biodiversity-315 multifunctionality relationships in multitrophic ecosystems^{8,11,15,17}.

316 Assessing ecosystem functions and properties. In each lake, 11 ecosystem variables regulated by 317 aquatic organisms and belonging to a wide range of ecosystem functions and properties were measured 318 (see Supplementary Table 2). These functions and properties included: (i) nutrient concentrations 319 represented by in situ measurements of total phosphorous (mg L⁻¹) and total nitrogen (mg L⁻¹) available in 320 the water. Total phosphorus and nitrogen cover all fractions of these nutrients, including nitrate, nitrite, 321 ammonia, particulate phosphate, dissolved organic phosphate, and orthophosphate. We took water 322 samples in each lake and in the laboratory, nitrogen was quantified according to Mackereth et al.³⁶, while 323 phosphorus was quantified following³⁷. (ii) Ecosystem metabolism represented by the daily variation of 324 dissolved oxygen in the water (mg L⁻¹ day⁻¹), which was measured from dawn to dusk in each lake using a 325 digital oximeter portable YSI aid (Digimed). We use the mean of daily oxygen variation as it represents 326 the change in the metabolic underwater regime³⁸. (iii) Multitrophic standing biomass was represented by 327 the biomass of algae, carnivorous fish, omnivorous fish, herbivorous fish, and detritivorous fish. Algae 328 standing biomass was quantified using biovolume (individuals per mm L^{-1}) of identified algae species. Biovolume was estimated by multiplying the abundance of each species by their mean volume³⁹. Fish 329 330 were classified into trophic groups using information from feeding trials and gut content analysis^{16,32}. 331 Afterwards, the fish counts within each trophic group were converted to biomass (g m⁻²) using published 332 species-specific length-weight relationships⁴⁰. (iv) Availability of photosynthetically active radiation 333 represented by light availability under water (m). We quantified light availability under water by the 334 depth of the euphotic zone, which represents the depth (m) of the lake where there is sufficient light 335 incidence for autotrophs. The euphotic zone was calculated as Secchi depth multiplied by 1.7, where 1.7 336 is a correction factor for estimating the light available under water³². (v) Microorganism abundance (cells 337 mL^{-1}) was quantified using bacterial abundance. To record the accumulative abundance of bacteria, we 338 took water samples at the subsurface (approximately 30 cm below the air-water interface) at the central, 339 deepest region of each lake using polyethylene flasks. Bacteria were analyzed from water samples treated 340 with a fixative solution composed of alkaline Lugol's solution, borate buffered formalin, and sodium 341 thiosulfate that was filtered through black Nuclepore filters (0.2 and 0.8 µm, respectively) and stained 342 with fluorochrome DAPI (4,6- diamidino-2-phenylindole⁴¹. Bacterial quantification was done with an 343 epifluorescence microscope at a magnification of ×1000 (Olympus BX51). (vi) Variation of underwater 344 habitat complexity was quantified based on variations in the above-ground cover of aquatic plants (m⁻²). 345 We estimated the area of all leaves and culm of each plant species. We then summed the area of all leaves 346 and culm to obtain the above-ground area cover by each individual. We calculated the standard deviation

of the above-ground area cover between all plant species and used this standard deviation as a proxy ofvariation in the above-ground vegetal cover.

349 Pairwise correlation between ecosystem functions. To assess the potential for a trade-off between 350 individual ecosystem characteristics, we calculated Pearson correlation coefficients between each pair of 351 individual standardized functions. Of the possible 45 combinations of pairwise functions, we found only 352 seven strong correlations (r = 0.5; Supplementary Fig. 8). To remove any bias in our multifunctionality 353 index, the highly correlated functions were down-weighted in its calculation (Supplementary Fig. 9), as described in Manning et al.⁴². Ecosystem functions were grouped into clusters according to their 354 correlations. This weighted approach indicated three different clear clusters: (1) aboveground plant cover, 355 356 (2) available N and P, light availability underwater, daily oxygen variation, and algal biomass, and (3) 357 carnivore biomass, omnivore biomass, detritivore biomass, omnivore biomass, and bacterial abundance. 358 Weighted multifunctionality was then calculated as the average of all variables within each cluster. For 359 instance, each function within cluster 2 was weighted with a weight of 0.2. These functions were then 360 averaged into a standardised variable. We repeated the analyses of the relationship between biodiversity 361 and multifunctionality for the weighted multifunctionality to determine whether the results differed 362 between weighted and non-weighted multifunctionality (see ref.⁴²).

363 Assessing ecosystem multifunctionality. To obtain robust and quantitative multifunctionality indexes 364 for each lake, we used three multifunctionality approaches: (1) the averaging multifunctionality index, (2) the multi-threshold multifunctionality index, and (3) the multiple single functions index¹⁸. To obtain the 365 366 averaging ecosystem multifunctionality index, we standardized all 11 ecosystem functions between 0 and 367 1 (rawFunction – min(rawFunction) / (max(rawFunction) – min(rawFunction)) and then calculated their 368 means. The averaging ecosystem multifunctionality index is the most commonly used index in the multifunctionality literature^{5,18}, but has the limitations that the number of functions with high performance 369 370 are impossible to obtain and it does not allow for potential trade-offs between functions. To take these 371 limitations into account, we used the multi-threshold index. This index calculates how many functions 372 simultaneously exceed a predefined percentage of the maximum observed value of each individual 373 function. Because the selection of any threshold is arbitrary, analysing multiple thresholds of maximum 374 functioning is recommended¹⁸. We analysed the effect of the diversity of each organismal group on 375 multifunctionality across the full range of thresholds from 1% to 99%. We used the mean of the three

376 largest values of each ecosystem variable across all lakes as the observed maximum to reduce the impact377 of potential outliers.

378 Assessing the Human Footprint on wetlands. We used the global Human Footprint (HFP) map as a 379 surrogate of the cumulative human-induced pressure on the wetlands¹⁴. This map is constructed from an 380 ensemble of eight human pressure: (i) the extent of built environments, (ii) crop land, (iii) pasture land, 381 (iv) human population density, (v) night-time lights, (vi) railways, (vii) roads, and (vii) navigable 382 waterways. To facilitate comparison among pressures, each pressure was weighted (details on the 383 weightings are provided below). The pressures were weighted according to their relative intensity¹⁴. For 384 example, (i) constructed environments are areas related to urban settlements such as buildings and urban 385 areas. The pressure of built environments was assigned a score of 10 (i.e., a score of 10 is assigned if 386 there are built environments, otherwise a score of 0 is assigned). (ii) Crop land is characterized by 387 monocultures with high inputs of pesticides and fertilizers. In terms of HFP, the crop land pressures 388 received a score between 0 and 7, where 7 indicates intensive agriculture and 0 indicates the absence of 389 crop lands. (iii) Pasture land includes some of the major land uses worldwide and is characterized by 390 cattle and sheep farming. The pressure of pastures on wetlands was assigned a score of 4, which was 391 scaled from 0 to 4 using the %pasture for each 1 km² pixel. (iv) Human population is an important 392 underlying driver of the global change of natural ecosystems. Human density was mapped using gridded 393 population downscaled to match the 1 km^2 resolution. All areas with a population above 1,000 394 people/km² were assigned a pressure score of 10. For less populated areas, the pressure score is 395 logarithmically scaled using the following estimation: Pressure score = $3.333 \times \log$ (population density + 396 1). (v) Night-time lights include electric infrastructure related to more rural areas that are not part of built 397 environments. To calculate the pressure of night-time lights, the areas were divided into 10 quantiles of 398 increased night-time light intensity associated with scores between 1 and 10, while areas with no lights 399 were assigned a zero score. (vi) Railways are essential human infrastructures that influence natural 400 ecosystems. The direct pressure of railways was assigned a score of 8 for a distance of 0.5 km on either 401 side of the railway. (vii) Likewise, roads modify the landscape where they are built. The direct and 402 indirect pressure of roads on wetlands was assigned a score of 8 for 0.5 km (direct impact), while nearby 403 areas up to 15 km received a score value that decayed exponentially on either side of the road (indirect 404 impact). (viii) Navigable waterways act as conduits for people to access nature, resulting in impacts on

405 wetlands. The pressure of navigable waterways was assigned a score of 4, which decayed exponentially

406 out to 15 km away from the water banks. For full details of HFP estimation see $refs^{2,14}$.

407 The average HFP of the 1 km² pixels (cell-size resolution) overlapping each lake was extracted 408 to derive the cumulative pressure, and this average HFP ranged between 0 and 50 (cumulative sum of all 409 individual human pressures). The average HFP was extracted using the 'raster' R package43 through a 410 global HFP map that was available for the year 2009. The eight human pressures are not mutually 411 exclusive, and may co-occur in the same wetland or vary among and within wetlands. The HFP was 412 initially developed to represent human pressures in terrestrial systems¹⁴, but most of these human 413 pressures extensively affect wetland ecosystems. For instance, Brazil has experienced rapid expansion of 414 urban areas⁴⁴. Along with the increase in human populations in the vicinity of wetlands, there has been an 415 increased pressure on these ecosystems from sewage, cattle and sheep pastures, railways, roads, and 416 navigable waterways⁴⁵. We found negative correlations between the individual human pressures with 417 biodiversity and multifunctionality, which suggest that the use of the HFP in our study is robust 418 (Supplementary Fig. 7).

419 Statistical analyses. Linking aquatic biodiversity to multifunctionality. First, to determine the direct link 420 between aquatic biodiversity and average multifunctionality across four wetland ecosystems, we fitted a 421 series of linear mixed effects models (LMMs) to the surveyed data. Specifically, we tested the 422 relationship of (i) species richness and (ii) functional diversity of single organismal groups, and (iii) 423 multidiversity with the ecosystem multifunctionality. The models were run using the function lme in the 424 'nlme' package⁴⁶. We included wetlands and two sampling periods as our random structure, and allowed 425 the intercept and slopes to vary by wetland. The assumptions of normality, linearity, and 426 homoscedasticity were verified using graphical diagnostics (QQ plots and residual plots). To determine 427 the importance of other biotic and abiotic variables besides biodiversity for multifunctionality, we 428 included other well-known drivers of multifunctionality such as space (distance from equator), climate 429 (temperature and mean annual precipitation), and aquatic properties (pH, conductivity, and water level; 430 see Supplementary Methods). We performed a model averaging procedure that calculated all possible 431 subset models and chose from this set those subset models with the lowest values ($\Delta AICc \leq 2$) of the 432 Akaike Information Criterion corrected for small sample size (AICc). This analysis was conducted using 433 the R-package MuMIn⁴⁷.

434 Using LMMs we also assessed the relationship of species richness and functional diversity of 435 single organismal groups and multidiversity with each of the 11 individual ecosystem functions. This 436 allowed us to compare the multifunctionality results to the performance of individual functions. Priori to 437 these analyses, we standardized all individual ecosystem functions (z-scored: mean-centred and divided 438 by the SD) to better meet model assumptions. Even so, for some functions, the residuals were highly 439 heteroscedastic. We then modelled the variance using the function varIdent, with diversity nested by 440 wetlands as the stratum. We considered quadratic terms for some ecosystem functions to evaluate 441 potential nonlinear relationships.

442 We also modelled aquatic diversity against the number of functions above a threshold using 443 generalized linear mixed effects model (GLMMs), assuming a Gaussian error distribution in the MASS 444 package⁴⁸. Because we wanted to know whether the relationships between species richness and functional 445 diversity with ecosystem multifunctionality varied as a function of organismal group and among the four 446 wetlands, we fitted the GLMM individually to each organismal group. We then extracted and plotted the 447 linear coefficient (fitted values) of the relationship between biodiversity and each threshold level (1 to 448 99%; 99 thresholds) to each wetland system. This led us to examine changes in the shape of the fitted 449 curve for each wetland at multiple thresholds.

450 Effect of human pressure on biodiversity-multifunctionality relationships. We conducted linear mixed-451 effect models between human footprint (HFP) and biodiversity (species richness and functional diversity 452 of single organismal groups and multidiversity). We found strong negative effects of HFP on biodiversity 453 (Supplementary Figs. 5 and 6), allowing us to determine whether HFP altered the relationship between 454 biodiversity and ecosystem multifunctionality. We then added interaction terms for HFP × species 455 richness and HFP × functional diversity of each single organismal group and multidiversity to the mixed-456 effects models and measured the estimated coefficients of these interactions on ecosystem 457 multifunctionality. Since biodiversity and HFP are both continuous variables, analyse their interactions 458 could result in an interaction predictor that is collinear with the main effect⁴⁹. Thus, we centered these 459 variables by subtracting the sample mean from all input variable values. The mean of the centered 460 variables is zero and the collinearity is reduced. We also scaled all the variables, dividing them by their 461 standard deviations to interpret parameter estimates from models at a comparable scale. Since HFP is a 462 continuous covariate, there are an infinite number of values we can use to analysis the effect of 463 biodiversity on multifunctionality. For a better interpretation of the interactive effect, we selected three

values (thresholds) of the scaled HFP: (i) a mean value (0), a value of standard deviation above the mean
(1), and a value of standard deviation below the mean (-1). This is a common approach to analyse
interaction between continuous predictors⁵⁰. These three HFP values can be interpreted as three levels of
HFP intensity, low intensity (below average), moderate intensity (on average) a high intensity (above
average). The slopes of each relationship between HFP and species richness, functional diversity, and
ecosystem multifunctionality are similar among wetlands, suggesting absence of any bias in our results
(Supplementary Fig. 10).

471 Pathways by which human pressure affects multifunctionality. To disentangle the direct and biodiversity-472 mediated pathways by which HFP affects multifunctionality, we ran structural equation modelling (SEM) 473 using the R package lavaan⁵¹. Considering that all seven organismal groups worked in combination to 474 determine multifunctionality (Fig. 2 and 3), we used their diversity to construct composite variables in our 475 SEM. We combined the species richness and functional diversity of the seven organismal groups to 476 construct a composite index for species richness and functional diversity, respectively. A composite index 477 collapses the effects of multiple related variables into a single composite effect, thus representing a good 478 way to analyse complex multivariate relationships in SEM⁵². We accounted for six ecosystem drivers: 479 distance from equator, climate (mean annual temperature and precipitation), and aquatic characteristics 480 (pH, conductivity, and water level) in the SEM. The SEM was fitted based on a meta-model 481 (Supplementary Fig. 11). We calculated the standardized direct coefficients for each pathway within the 482 model. We also estimated the indirect effect of HFP on multifunctionality mediated by diversity (species 483 richness and functional diversity) of single organismal groups. To do so, we multiplied the coefficient of 484 HFP on diversity (species richness and functional diversity) of a given organism group by the 485 standardized loading of this organism group on composite. Finally, we multiplied the above result by the 486 coefficient of composite on multifunctionality (Supplementary Table 11). We applied multigroup 487 analysis in the SEM to evaluate whether (i) the effects of selected predictors (HFP, biodiversity, climate, 488 space, and aquatic properties) on multifunctionality, as well as (ii) the effect of HFP on biodiversity 489 varied across wetlands. We considered the four wetlands as the grouping variable (Amazon, Araguaia, 490 Pantanal, and Paraná). We constructed a SEM model in which all parameters were free to differ between 491 wetlands and a model in which all parameters were fixed (i.e., constrained to a single value determined by 492 all wetlands). We compared the free model with the constrained model, where non-significant differences 493 indicated no variation in pathway coefficients by wetlands, whereas significant difference indicated that

- 494 pathway coefficients varied by wetlands. Because we found significant differences between the free and
- 495 restricted/constrained model for both species richness and functional diversity, our next step was to
- 496 understand which pathways differed. We only analysed the differences (multigroup) of the pathways
- 497 including multifunctionality and biodiversity (species richness and functional diversity; Supplementary
- 498 Table 10). Differences between other pathways within the model were not analysed. We evaluated the
- 499 SEM fit using the comparative fit index (CFI; the model has a good fit when $CFI \ge 0.95$) and the root
- 500 MSE of approximation test (RMSEA; the model has a good fit when RMSEA \leq 0.05). For our species
- richness model, the CFI was 0.997 and the RMSEA was 0.041, and for our functional diversity model the
- 502 CFI was 0.998 and the RMSEA was 0.026, indicating a good model fit. All analyses were conducted in R
- **503** version 3.4.4⁵³.

504 Data availability

- 505 The data that support the findings of this study are publicly available on Zenodo Digital
- 506 Repository at https://doi.org/10.5281/zenodo.6406782

507 Code availability

- 508 The code that supports the findings and figures of this study is available on Zenodo Digital
- 509 Repository at https://doi.org/10.5281/zenodo.6406786

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525 Author contributions

- 526 D.A.M., F.M.L-T., G.Q.R., and R.P.M developed the original ideas presented in the manuscript; FA.L-T.
- 527 and L.F.M.V coordinated all the field operations; Human Footprint calculation was performed by T.S.S.
- 528 Functional analysis was performed by D.A.M. Statistical modelling was performed by D.A.M. The first
- 529 draft of the paper was written by D.A.M., and further drafts were written by D.A.M., G.Q.R., R.P.M.,
- 530 P.K., and B.J.C., and all of the authors contributed to the subsequent drafts.

- 531 Competing interests
- 532 The authors declare no competing interests.
- 533

534 Captions of main Figures 1-6.

535 Fig. 1| Intensity of the Human Footprint (HFP) across Brazil and the four Neotropical 536 wetlands (Amazon, Araguaia, Pantanal, and Paraná). Activity data maps of the wetlands (built environments, crop land, pasture land, human population density, night-time lights, 537 railways, roads, and navigable waterways) used in the HFP analysis in this study were extracted 538 from ref¹⁴. The HFP data ranged from 0 to 50 according to the pressure of a suite of human 539 540 activities. The HFP data on the four focal wetlands included low intensity (HFP < 1) and 541 moderate/high intensity of human pressures (HFP ≤ 18). Overall, Amazon and Araguaia had a relatively low/mean HFP intensity, while Pantanal and Paraná had mean/high HFP intensity. 542 Colored rectangles represent each of the focused wetlands. The points within the rectangles 543 544 highlight the sampling lakes in each wetland (n=72 lakes).

545 Fig. 2| Relationship between the species richness of aquatic organisms and

multifunctionality in Neotropical wetlands. The linear association between multifunctionality 546 547 and the species richness of the seven selected taxonomic groups, and the composite metric of 548 their joint richness (multidiversity; standardized between 0 and 1)¹⁵ in four Neotropical 549 wetlands; n = 72 lakes. Statistical analysis was performed using linear mixed-effect models. 550 Dashed black and solid lines are predicted (fitted) values from LMMs for overall and local trends (for each wetland ecosystem), respectively. Shaded areas show 95% confidence interval 551 for the overall trend. $R^2 = marginal$ (i.e., variance of the fixed effects). *P < 0.05, **P < 0.01, 552 553 ***P < 0.01. The richness of microcrustaceans, testate amoebae, and phytoplankton was log-554 transformed prior to the analysis. Full model results are provided in Supplementary Table 3. Multifunctionality is represented by the averaging index, which reflects changes in the average 555 556 level of the 11 ecosystem functions. Very high averaging index levels (close to 1) mean that all 557 functions reach their maximum level of performance simultaneously. By contrast, the lowest values (close to 0) mean all functions are at their minimum level of performance. Organisms' 558 illustrations are from João Vitor Fonseca da Silva, Graduate Program in Compared Biology 559 560 (PGB), State University of Maringá (http://www.pgb.uem.br/corpodiscente/doutorado).

561 Fig. 3| Relationship between the functional diversity of aquatic organisms and

562 **multifunctionality in Neotropical wetlands.** The linear association between multifunctionality 563 and the functional diversity of the seven selected taxonomic groups, and the composite metric of

- their joint functional diversity (multidiversity; standardized between 0 and 1)¹⁵ in four
- 565 Neotropical wetlands; n = 72 lakes. Statistical analysis was performed using linear mixed-effect
- 566 models. Dashed black and solid lines are predicted (fitted) values from LMMs for overall and
- 567 local trends (for each wetland ecosystem), respectively. Shaded areas show 95% confidence
- interval for the overall trend. R^2 = marginal (i.e., variance of the fixed effects). *P < 0.05, **P < 0.01, ***P < 0.01. The richness of microcrustaceans, testate amoebae, and phytoplankton was
- 570 log-transformed prior to the analysis. Full model results are provided in Supplementary Table 3.
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- 572 level of the 11 ecosystem functions. Very high averaging index levels (close to 1) mean that all
- 573 functions reach their maximum level of performance simultaneously. By contrast, the lowest
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- 576 (PGB), State University of Maringá (http://www.pgb.uem.br/corpodiscente/doutorado).

577 Fig. 4| Effect of Human Footprint (HFP) on the relationship between functional diversity

- **and multifunctionality in Neotropical wetlands. a**, Standardized coefficients (mean±s.e.m.)
- 579 from LMMs for the isolated effect of species richness and the interactive HFP x species richness
- 580 effect on multifunctionality. Model summary statistics is provided in Supplementary Table 7. **b**,

- 581 ecosystem multifunctionality as a function of the species richness of single organismal groups
- 582 and multidiversity on wetlands subject to low (solid blue line), medium (dashed black line), and
- high (solid red line) HFP intensity. The lines are predicted (fitted) values from LMMs models, 583
- in which the effect of species richness on multifunctionality is mediated at three levels of HFP, 584 585 (i) medium: mean = 0; (ii) high: the standard deviation above the mean = +1; and (iii) low: the
- 586 standard deviation below the mean = -1. Species richness and human footprint were mean-
- centered to remove the high collinearity⁴⁸. All variables were scaled to interpret parameter 587
- estimates at a comparable scale. Multifunctionality is represented by the averaging index. 588
- 589 Organisms' illustrations are from João Vitor Fonseca da Silva, Graduate Program in Compared
- 590 Biology (PGB), State University of Maringá (http://www.pgb.uem.br/corpodiscente/doutorado).
- 591 Fig. 5| Effect of Human Footprint (HFP) on the relationship between functional diversity
- 592 and multifunctionality in Neotropical wetlands. a, Standardized coefficients (mean±s.e.m.)
- from LMMs for the isolated effect of functional diversity and the interactive HFP x functional 593 594 diversity effect on multifunctionality. Model summary statistics is provided in Supplementary
- 595 Table 7. **b**, ecosystem multifunctionality as a function of the functional diversity of single
- 596 organismal groups and multidiversity on wetlands subject to low (solid blue line), medium
- (dashed black line), and high (solid red line) HFP intensity. The lines are predicted (fitted) 597
- 598 values from LMMs models, in which the effect of species richness on multifunctionality is
- 599 mediated at three levels of HFP, (i) medium: mean = 0; (ii) high: the standard deviation above
- 600 the mean = +1; and (iii) low: the standard deviation below the mean = -1. Functional diversity
- and human footprint were mean-centered to remove the high collinearity⁴⁸. All variables were 601 602 scaled to interpret parameter estimates at a comparable scale. Multifunctionality is represented
- 603 by the averaging index. Organisms' illustrations are from João Vitor Fonseca da Silva, Graduate
- 604 Program in Compared Biology (PGB), State University of Maringá
- 605 (http://www.pgb.uem.br/corpodiscente/doutorado).
- 606 Fig. 6| The relationship between Human Footprint, climate, and water properties, and
- 607 biodiversity, and ecosystem multifunctionality. a,c Structural equation modelling (SEM) 608 allowed to disentangle the direct and indirect-biodiversity mediated effects of HFP on 609 multifunctionality. Aquatic species richness, **a-b**, and functional diversity **c-d**, represented by a 610 hexagon, were obtained through composite variables⁴⁸, including information about the diversity of seven taxonomic groups of aquatic organisms (see methods section). We accounted 611 612 for multiple ecosystem drivers, including distance from the equator, climate (temperature and 613 precipitation), and aquatic properties (pH, conductivity, and water level). We grouped the 614 different categories of drivers (climate, space, and water properties) into the same box for 615 graphic simplicity; nevertheless, it does not represent latent variables. Solid black and dashed 616 gray arrows represent significant pathways ($P \le 0.05$) and non-significant pathways ($P \ge 0.05$), respectively. The thickness of the significant pathways (arrows) represents the magnitude of the 617 618 standardized regression coefficient. Numbers adjacent to arrows are the standardized effect size. R^2 s for component models are given in the Supplementary Table 12. Significance levels are *P 619 < 0.05, **P < 0.01, ***P < 0.001. For simplicity, we grouped the effects of ecosystem drivers 620 621 (distance, HFP, climate and water properties) on the diversity of each of the seven taxonomic 622 group in BOXES. Specifically, BOX A represents the effect of distance from the equator, BOX B the effect of HFP, BOX C the effect of climate, and BOX D the effect of water properties. 623 624 Full model outputs and information about boxes A–D is provided in Supplementary Tables 8
- 625 and 9. **b.d.** represent the standardized indirect effects of the human footprint on
- 626 multifunctionality mediated by species richness and the functional diversity of each organismal
- 627 group used to compute the composite diversity (see Supplementary Table 11). Organisms'
- illustrations are from João Vitor Fonseca da Silva, Graduate Program in Compared Biology 628 629
 - (PGB), State University of Maringá (http://www.pgb.uem.br/corpodiscente/doutorado).
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731 732 733 734 735 736 737	 49. 50. 51. 52. 	 Venables, W. N. & Ripley, B. D. Modern Applied Statistics with S (Springer, 2002). Schielzeth, H. Simple means to improve the interpretability of regression coefficients. Meth. <i>Ecol. Evol.</i> 1, 103–113 (2010). Aiken, L. S. West, S. G. Multiple Regression: Testing and Interpreting Interactions. Sage Publications, Inc. (1991). Rosseel, Y. lavaan: an R package for structural equation modeling. <i>J. Stat. Softw.</i> 48, 1–36 (2015). Grace, J. B. & Bollen, K. A. Representing general theoretical concepts in structural equation models: the role of composite variables. <i>Environ. Ecol. Stat.</i> 15, 191–213 (2008).
731 732 733 734 735 736 737 738	 49. 50. 51. 52. 53. 	 Venables, W. N. & Ripley, B. D. Modern Applied Statistics with S (Springer, 2002). Schielzeth, H. Simple means to improve the interpretability of regression coefficients. Meth. <i>Ecol. Evol.</i> 1, 103–113 (2010). Aiken, L. S. West, S. G. Multiple Regression: Testing and Interpreting Interactions. Sage Publications, Inc. (1991). Rosseel, Y. Iavaan: an R package for structural equation modeling. <i>J. Stat. Softw.</i> 48, 1–36 (2015). Grace, J. B. & Bollen, K. A. Representing general theoretical concepts in structural equation models: the role of composite variables. <i>Environ. Ecol. Stat.</i> 15, 191–213 (2008). R Development Core Team. R: A Language and Environment for Statistical Computing. (2020).
731 732 733 734 735 736 737 738	 49. 50. 51. 52. 53. 	 Venables, W. N. & Ripley, B. D. Modern Applied Statistics with S (Springer, 2002). Schielzeth, H. Simple means to improve the interpretability of regression coefficients. Meth. <i>Ecol. Evol.</i> 1, 103–113 (2010). Aiken, L. S. West, S. G. Multiple Regression: Testing and Interpreting Interactions. Sage Publications, Inc. (1991). Rosseel, Y. Iavaan: an R package for structural equation modeling. <i>J. Stat. Softw.</i> 48, 1–36 (2015). Grace, J. B. & Bollen, K. A. Representing general theoretical concepts in structural equation models: the role of composite variables. <i>Environ. Ecol. Stat.</i> 15, 191–213 (2008). R Development Core Team. R: A Language and Environment for Statistical Computing. (2020).
731 732 733 734 735 736 737 738 739	 49. 50. 51. 52. 53. 	 Venables, W. N. & Ripley, B. D. Modern Applied Statistics with S (Springer, 2002). Schielzeth, H. Simple means to improve the interpretability of regression coefficients. Meth. <i>Ecol. Evol.</i> 1, 103–113 (2010). Aiken, L. S. West, S. G. Multiple Regression: Testing and Interpreting Interactions. Sage Publications, Inc. (1991). Rosseel, Y. Iavaan: an R package for structural equation modeling. <i>J. Stat. Softw.</i> 48, 1–36 (2015). Grace, J. B. & Bollen, K. A. Representing general theoretical concepts in structural equation models: the role of composite variables. <i>Environ. Ecol. Stat.</i> 15, 191–213 (2008). R Development Core Team. R: A Language and Environment for Statistical Computing. (2020).
731 732 733 734 735 736 737 738 739	 49. 50. 51. 52. 53. 	 Venables, W. N. & Ripley, B. D. Modern Applied Statistics with S (Springer, 2002). Schielzeth, H. Simple means to improve the interpretability of regression coefficients. Meth. <i>Ecol. Evol.</i> 1, 103–113 (2010). Aiken, L. S. West, S. G. Multiple Regression: Testing and Interpreting Interactions. Sage Publications, Inc. (1991). Rosseel, Y. Iavaan: an R package for structural equation modeling. <i>J. Stat. Softw.</i> 48, 1–36 (2015). Grace, J. B. & Bollen, K. A. Representing general theoretical concepts in structural equation models: the role of composite variables. <i>Environ. Ecol. Stat.</i> 15, 191–213 (2008). R Development Core Team. R: A Language and Environment for Statistical Computing. (2020).
731 732 733 734 735 736 737 738 739 740	 49. 50. 51. 52. 53. 	 Venables, W. N. & Ripley, B. D. Modern Applied Statistics with S (Springer, 2002). Schielzeth, H. Simple means to improve the interpretability of regression coefficients. Meth. <i>Ecol. Evol.</i> 1, 103–113 (2010). Aiken, L. S. West, S. G. Multiple Regression: Testing and Interpreting Interactions. Sage Publications, Inc. (1991). Rosseel, Y. Iavaan: an R package for structural equation modeling. <i>J. Stat. Softw.</i> 48, 1–36 (2015). Grace, J. B. & Bollen, K. A. Representing general theoretical concepts in structural equation models: the role of composite variables. <i>Environ. Ecol. Stat.</i> 15, 191–213 (2008). R Development Core Team. R: A Language and Environment for Statistical Computing. (2020).
731 732 733 734 735 736 737 738 739 740	 49. 50. 51. 52. 53. 	 Venables, W. N. & Ripley, B. D. Modern Applied Statistics with S (Springer, 2002). Schielzeth, H. Simple means to improve the interpretability of regression coefficients. Meth. <i>Ecol. Evol.</i> 1, 103–113 (2010). Aiken, L. S. West, S. G. Multiple Regression: Testing and Interpreting Interactions. Sage Publications, Inc. (1991). Rosseel, Y. Iavaan: an R package for structural equation modeling. <i>J. Stat. Softw.</i> 48, 1–36 (2015). Grace, J. B. & Bollen, K. A. Representing general theoretical concepts in structural equation models: the role of composite variables. <i>Environ. Ecol. Stat.</i> 15, 191–213 (2008). R Development Core Team. R: A Language and Environment for Statistical Computing. (2020).
731 732 733 734 735 736 737 738 739 740 741	49.50.51.52.53.	 Venables, W. N. & Ripley, B. D. Modern Applied Statistics with S (Springer, 2002). Schielzeth, H. Simple means to improve the interpretability of regression coefficients. Meth. <i>Ecol. Evol.</i> 1, 103–113 (2010). Aiken, L. S. West, S. G. Multiple Regression: Testing and Interpreting Interactions. Sage Publications, Inc. (1991). Rosseel, Y. lavaan: an R package for structural equation modeling. <i>J. Stat. Softw.</i> 48, 1–36 (2015). Grace, J. B. & Bollen, K. A. Representing general theoretical concepts in structural equation models: the role of composite variables. <i>Environ. Ecol. Stat.</i> 15, 191–213 (2008). R Development Core Team. R: A Language and Environment for Statistical Computing. (2020).
731 732 733 734 735 736 737 738 739 740 741	49.50.51.52.53.	 Venables, W. N. & Ripley, B. D. Modern Applied Statistics with S (Springer, 2002). Schielzeth, H. Simple means to improve the interpretability of regression coefficients. Meth. <i>Ecol. Evol.</i> 1, 103–113 (2010). Aiken, L. S. West, S. G. Multiple Regression: Testing and Interpreting Interactions. Sage Publications, Inc. (1991). Rosseel, Y. Iavaan: an R package for structural equation modeling. <i>J. Stat. Softw.</i> 48, 1–36 (2015). Grace, J. B. & Bollen, K. A. Representing general theoretical concepts in structural equation models: the role of composite variables. <i>Environ. Ecol. Stat.</i> 15, 191–213 (2008). R Development Core Team. R: A Language and Environment for Statistical Computing. (2020).
731 732 733 734 735 736 737 738 739 740 741 742	49.50.51.52.53.	 Venables, W. N. & Ripley, B. D. Modern Applied Statistics with S (Springer, 2002). Schielzeth, H. Simple means to improve the interpretability of regression coefficients. Meth. <i>Ecol. Evol.</i> 1, 103–113 (2010). Aiken, L. S. West, S. G. Multiple Regression: Testing and Interpreting Interactions. Sage Publications, Inc. (1991). Rosseel, Y. Iavaan: an R package for structural equation modeling. <i>J. Stat. Softw.</i> 48, 1–36 (2015). Grace, J. B. & Bollen, K. A. Representing general theoretical concepts in structural equation models: the role of composite variables. <i>Environ. Ecol. Stat.</i> 15, 191–213 (2008). R Development Core Team. R: A Language and Environment for Statistical Computing. (2020).
731 732 733 734 735 736 737 738 739 740 741 742	49.50.51.52.53.	 Venables, W. N. & Ripley, B. D. Modern Applied Statistics with S (Springer, 2002). Schielzeth, H. Simple means to improve the interpretability of regression coefficients. Meth. <i>Ecol. Evol.</i> 1, 103–113 (2010). Aiken, L. S. West, S. G. Multiple Regression: Testing and Interpreting Interactions. Sage Publications, Inc. (1991). Rosseel, Y. lavaan: an R package for structural equation modeling. <i>J. Stat. Softw.</i> 48, 1–36 (2015). Grace, J. B. & Bollen, K. A. Representing general theoretical concepts in structural equation models: the role of composite variables. <i>Environ. Ecol. Stat.</i> 15, 191–213 (2008). R Development Core Team. R: A Language and Environment for Statistical Computing. (2020).
731 732 733 734 735 736 737 738 739 740 741 742 743	49.50.51.52.53.	 Venables, W. N. & Ripley, B. D. Modern Applied Statistics with S (Springer, 2002). Schielzeth, H. Simple means to improve the interpretability of regression coefficients. Meth. <i>Ecol. Evol.</i> 1, 103–113 (2010). Aiken, L. S. West, S. G. Multiple Regression: Testing and Interpreting Interactions. Sage Publications, Inc. (1991). Rosseel, Y. lavaan: an R package for structural equation modeling. <i>J. Stat. Softw.</i> 48, 1–36 (2015). Grace, J. B. & Bollen, K. A. Representing general theoretical concepts in structural equation models: the role of composite variables. <i>Environ. Ecol. Stat.</i> 15, 191–213 (2008). R Development Core Team. R: A Language and Environment for Statistical Computing. (2020).
731 732 733 734 735 736 737 738 739 740 741 742 743	49. 50. 51. 52. 53.	 Venables, W. N. & Ripley, B. D. Modern Applied Statistics with S (Springer, 2002). Schielzeth, H. Simple means to improve the interpretability of regression coefficients. Meth. <i>Ecol. Evol.</i> 1, 103–113 (2010). Aiken, L. S. West, S. G. Multiple Regression: Testing and Interpreting Interactions. Sage Publications, Inc. (1991). Rosseel, Y. Iavaan: an R package for structural equation modeling. <i>J. Stat. Softw.</i> 48, 1–36 (2015). Grace, J. B. & Bollen, K. A. Representing general theoretical concepts in structural equation models: the role of composite variables. <i>Environ. Ecol. Stat.</i> 15, 191–213 (2008). R Development Core Team. R: A Language and Environment for Statistical Computing. (2020).
731 732 733 734 735 736 737 738 739 740 741 742 743 744	49. 50. 51. 52. 53.	 Venables, W. N. & Ripley, B. D. Modern Applied Statistics with S (Springer, 2002). Schielzeth, H. Simple means to improve the interpretability of regression coefficients. Meth. <i>Ecol. Evol.</i> 1, 103–113 (2010). Aiken, L. S. West, S. G. Multiple Regression: Testing and Interpreting Interactions. Sage Publications, Inc. (1991). Rosseel, Y. Iavaan: an R package for structural equation modeling. <i>J. Stat. Softw.</i> 48, 1–36 (2015). Grace, J. B. & Bollen, K. A. Representing general theoretical concepts in structural equation models: the role of composite variables. <i>Environ. Ecol. Stat.</i> 15, 191–213 (2008). R Development Core Team. R: A Language and Environment for Statistical Computing. (2020).
731 732 733 734 735 736 737 738 739 740 741 742 743 744	49. 50. 51. 52. 53.	 Venables, W. N. & Ripley, B. D. Modern Applied Statistics with S (Springer, 2002). Schielzeth, H. Simple means to improve the interpretability of regression coefficients. Meth. <i>Ecol. Evol.</i> 1, 103–113 (2010). Aiken, L. S. West, S. G. Multiple Regression: Testing and Interpreting Interactions. Sage Publications, Inc. (1991). Rosseel, Y. Iavaan: an R package for structural equation modeling. <i>J. Stat. Softw.</i> 48, 1–36 (2015). Grace, J. B. & Bollen, K. A. Representing general theoretical concepts in structural equation models: the role of composite variables. <i>Environ. Ecol. Stat.</i> 15, 191–213 (2008). R Development Core Team. R: A Language and Environment for Statistical Computing. (2020).

746 Captions of Extended Data Figures 1-4.

747 Extended Data Fig. 1| The relationship between the species richness of aquatic organisms 748 and single ecosystem functions in neotropical wetlands. Significant links between the species 749 richness of single taxonomic groups and multidiversity (joint richness of seven taxonomic 750 groups of aquatic organisms) with 11 individual ecosystem functions. Statistical analysis was 751 performed using linear mixed-effect models. The solid colored lines are predicted values of the LMMs and show the significant relationships between each taxonomic group and each 752 753 individual ecosystem function. Non-significant relationships are not shown. Full model results 754 are provided in Supplementary Table 5. All single ecosystem functions are scaled (z-score 755 standard) for better graphical interpretation. Organisms' illustrations are from João Vitor 756 Fonseca da Silva, Graduate Program in Compared Biology (PGB), State University of Maringá

757 (http://www.pgb.uem.br/corpodiscente/doutorado).

758 Extended Data Fig. 2| The relationship between the functional diversity of aquatic

759 organisms and single ecosystem functions in neotropical wetlands. Significant links between

the functional diversity of single taxonomic groups and multidiversity (joint functional diversity

of seven taxonomic groups of aquatic organisms) with 11 individual ecosystem functions.
 Statistical analysis was performed using linear mixed-effect models. The solid colored lines are

762 Statistical analysis was performed using linear mixed-effect models. The solid colored lines are 763 predicted values of the LMMs and show the significant relationships between each taxonomic

764 group and each individual ecosystem function. Non-significant relationships are not shown. Full

- 765 model results are provided in Supplementary Table 6. All single ecosystem functions are scaled
- 765 (z-score standard) for better graphical interpretation. Organisms' illustrations are from João
- 767 Vitor Fonseca da Silva, Graduate Program in Compared Biology (PGB), State University of
- 768 Maringá (http://www.pgb.uem.br/corpodiscente/doutorado).

769 Extended Data Fig. 3| Importance of species richness and ecosystem drivers for

multifunctionality in neotropical wetlands. Standardized total effects (direct plus indirect
 effects) of seven ecosystem drivers and species richness to multifunctionality. The results were

derived from the structural equation models (Fig. 5a). Species richness represents a composite

variable that includes information about the species richness of seven groups of aquatic

organisms. For the complete estimated model, see Supplementary Table 8.

775 Extended Data Fig. 4| Importance of functional diversity and ecosystem drivers for

776 multifunctionality in neotropical wetlands. Standardized total effects (direct plus indirect

effects) of seven ecosystem drivers and functional diversity to multifunctionality. The results
were derived from the structural equation models (Fig. 5c). Functional diversity is a composite

- variable that includes information about the functional diversity of seven groups of aquatic
- 780 organisms. For the complete estimated model, see Supplementary Table 9.
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- 782