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1 Beyond Wealth and Governance in Terrestrial
2 Protected Area Coverage :
3 The Role of Population Behavioural Traits *

4 Cathleen Petit-Cailleux ® Valentin Journé ® Etienne Dagorn

5 **Abstract**

6 Biodiversity loss demands urgent action, and protected area are one of the corner-
7 stone of biodiversity conservation measure. While conservation efforts are known to be
8 driven by economic and political factors, there is an absence of literature addressing the
9 potential role played by behavioural traits at the population level. We investigated how
10 population-level behavioural traits influence the proportion of terrestrial protected area
11 by using large-scale cross-cultural surveys and geospatial data from 75 countries. We
12 show that behavioural traits explain more variation in protected area coverage than eco-
13 nomic indicators alone. Furthermore, trust is negatively associated with protected area
14 coverage at the country level, suggesting that high-trust societies rely more on informal
15 conservation practices. These findings challenge conventional models focused on eco-
16 nomic and governance drivers and highlight the need for policies that align with pop-
17 ulation behaviours. Integrating behavioural insights into conservation planning could
18 unlock more effective biodiversity conservation strategies in the era of environmental
19 changes.

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20 **keyword**

21 Protected area; behavioural traits; biodiversity conservation policy; trust ;

22

23 **Data and code availability statement**

24 Data and code supporting our results will be accessible on GitHub: [https://github.com/](https://github.com/ValentinJourne/EconomyEcologyPA)
25 [ValentinJourne/EconomyEcologyPA](https://github.com/ValentinJourne/EconomyEcologyPA). All analyses used R software (1) (v4.3.0) and pub-
26 lished R packages.

27

28 **Author contributions**

29 All authors designed and wrote the study. ED and CPC gathered the data and VJ led the
30 analysis.

31

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41 sociales).

Introduction

We are entering the era of the sixth mass extinction of biodiversity. The last estimates from the Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services (IPBES) indicate that approximately one million species worldwide are at risk of extinction in the coming decades due to global environmental changes (2; 3; 4; 5). In response to this growing threat, the implementation of protected areas has emerged as a strategy to conserve local and global biodiversity. Protected areas are specifically designated geographic regions that are recognized, dedicated, and managed—through legal or other effective means—to achieve the long-term conservation of biodiversity (6). For this reason, in 2022, 194 countries have adopted the 30x30 target aiming to conserve 30% of the Earth's land and sea through the implementation of protected areas and other area-based conservation measures(7; 8). Global political awareness of biodiversity protection has grown, as evidenced by the expansion of protected areas from 14.1% to 15.3% of global terrestrial and freshwater environments (excluding Antarctica) and from 2.9% to 7.5% of marine environments between 2010 and 2019 (9; 10). However, despite these advances, the relatively modest increase in global terrestrial protected areas and the ambitious 2030 targets underscore that current efforts remain insufficient to address the biodiversity crisis.

To explain this discrepancy between engagement and final implementation in real conditions, several studies have examined the factors driving countries to establish these areas. A common assumption is that wealthier countries may implement more ecological conservation measures (11; 12; 13). However, the gross domestic product (GDP) of a country, a common indicator of national wealth, does not fully explain the proportion of protected area within a country (14). Instead, the human development index (HDI), which considers factors such as educational attainment, life expectancy, and per capita income, or more globally socio-economics data coupled with environmental data emerged as more robust predictors of protected area coverage (15; 16; 17). Lower GDP per capita, along with political and educational limitations, could limit protected areas coverage. In contrast, a country with strong political institutions is a proxy of a government's ability to implement policies, and a country with high level of education is associated with greater public concern for environmental protection (18). Moreover, the location of protected areas since 2010 cannot be solely explained by differences in countries' wealth or economic and social development (10; 17). While traditional socio-economic predictors such as GDP and HDI provide valuable insights, they fail to account for the behavioural and cultural factors that shape conservation policies.

Human behaviour is increasingly recognized as a critical factor in implementing policies to mitigate climate change (19; 20; 21) and biodiversity loss (12; 22). For instance, trust is often the foundation of successful community-managed forests, fisheries, and grazing lands, where collective action prevents over-exploitation and supports sustainable re-

80 sources use (23; 24). Individual behavioural traits also play a role in environmental out-
 81 comes, where more altruist individual have been shown to reduce consumption of harmful
 82 environmental products (25). However, biodiversity conservation challenges does not arise
 83 necessarily from individual actions alone but from the interactions of multiple actors across
 84 various levels (22). For example, during the COVID-19 pandemic, populations with higher
 85 levels of trust delayed the implementation of restrictive measures and adopted less strin-
 86 gent policies (26). Consequently, the aggregation of behavioural traits at the population
 87 level offers a framework to explore collective responses to environmental crises, shaping
 88 both policy-making and conservation strategies.

Table 1: Summary of population behavioural traits, meaning, and hypothesized relationship to protected areas surface.

Behavioural traits	Meaning	Hypothesis	Supported
Altruism	A concern for the well-being of others, often lead to actions that benefit others at a personal cost.	More altruistic populations are expected to support policies that benefit to the environment, leading to higher proportion of protected areas.	No
Patience	Preference for long-term rewards over immediate gains, reflect inter-temporal decision-making.	More patient populations may favour long-term environmental policies, leading to greater protected area proportion.	No
Risk-taking	The willingness to engage in behaviours or decisions that involve uncertainty and potential loss.	Populations with high risk-taking tendencies may be less inclined to implement protected areas due to the ambiguity of climate change impacts, resulting in lower proportion of protected areas.	No
Trust	The belief in the reliability and goodwill of others, foster cooperative behaviour.	Higher trust levels might reduce the need for formal conservation measures resulting in lower proportion of protected areas.	Yes

89 Our study examine how population-level behavioural traits influence the proportion of
 90 terrestrial protected area across 75 countries. The study includes countries from diverse
 91 regions across the world, with different level of protected area coverage, and with be-
 92 havioural traits representing diverse cultural settings (Figure 1). Our analysis focuses on
 93 four behavioural traits—trust, altruism, patience, and risk-taking— and takes into account
 94 economic, social, and political factors. These behavioural traits operate within governance

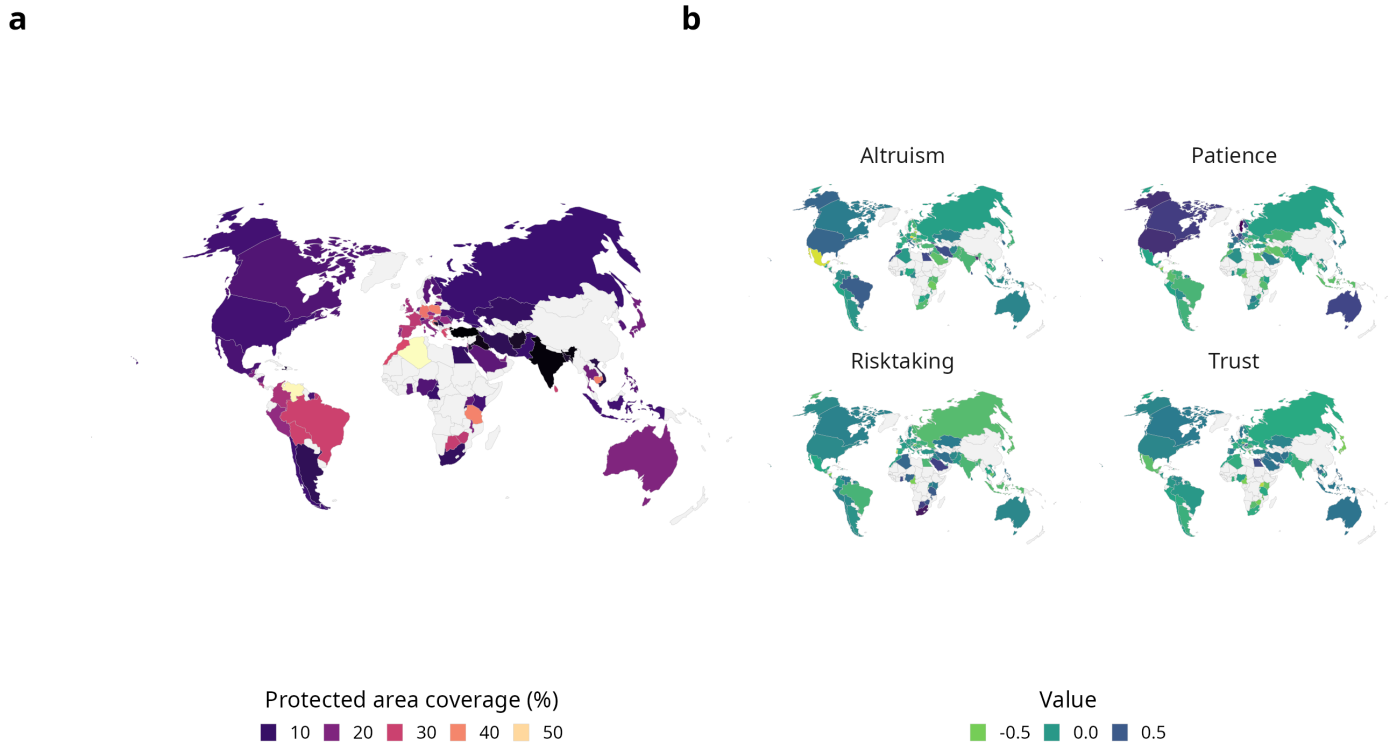


Figure 1: The 75 countries used in the analysis showing protected area coverage and behavioural traits values (data displayed in Van der Grinten IV projection). a) Percentage of terrestrial protected areas coverage for the 75 countries studied. The percentage of protected area coverage per country corresponds to the sum of the non-overlapping surface of regional, national, and international terrestrial protected areas over the total terrestrial surface of a main country. b) Maps of population behavioural traits value (altruism, patience, risk-taking and trust) for the 75 countries studied. Behavioural traits are standardised (29). Countries not included in our study are colored in pale grey.

95 frameworks, influencing whether conservation outcomes stem from top-down policies (e.g.
 96 U.S. National Parks implemented in 1872 (27)), or bottom-up initiatives (e.g. Nepal's com-
 97 munity forestry programs in the 90's (28)). We hypothesize that behavioural traits contribute
 98 to higher variation in protected area proportion than economic or governance indicators
 99 alone. Furthermore, higher levels of trust may reduce reliance on formal conservation poli-
 100 cies, while altruistic and patient populations are likely to advocate for stronger protections.
 101 Conversely, risk-taking populations may resist stringent measures due to their tolerance
 102 for environmental uncertainty (Table 1). By integrating behavioural traits into conservation
 103 research, this study contributes to a growing interdisciplinary dialogue on how human be-
 104 haviour drives collective responses to global challenges.

105 Results

106 The coverage of terrestrial protected areas, as a percentage of each country's total land
 107 area, range from $\sim 0.02\%$ in Lybia to 58% in Cyprus (CI95% = 0.6 - 44%). The percentage
 108 of protected areas was higher in Latin America and Caribbean ($20.7 \pm 12.4\%$), followed

109 by Europe and Central Asia ($20.5 \pm 11.8\%$), Sub-Saharan Africa ($18.3 \pm 9.5\%$), East Asia
110 and Pacific ($16.7 \pm 10.2\%$), Middle East and North Africa ($13.0 \pm 14.6\%$), North America
111 ($12.8 \pm 1.2\%$) and South Asia ($9.8 \pm 11.9\%$) (Fig.1). On average most protected areas are
112 regional with $18.9 \pm 16.4\%$, followed then by national protected areas with $3.49 \pm 6.58\%$ and
113 international protected areas with $1.59 \pm 2.80\%$. Larger surface of protected areas came
114 from Not Reported category (*The IUCN management category has not been reported*) or
115 Not Assigned category (*A protected area whereby the data provider has chosen not to use*
116 *the IUCN management categories*), with respectively $6.01 \pm 10.8\%$ and $6.51 \pm 12.0\%$ (Fig
117 A-2). The average proportion of other IUCN categories (I, II, III, IV, V, VI) remained below
118 5%.

119 In order to take into account the combined effects of economic, political and urban char-
120 acteristics on protected area coverage, while also addressing the strong correlation among
121 them, we undertook a principal component analysis (PCA) to summarise these charac-
122 teristics at the country level. We retained the first two axis representing 81.6 % in total
123 dataset inertia (dimension 1 = 64.7%, dimension 2 = 16.9%). The first axis synthesized
124 most predictors related to politics and economy (referred as Governance & Economic axis),
125 whereas the second axis summarized population density and urban areas percentage re-
126 ferred as Population & Urbanisation axis (Figure A-1). A lower value of PCA1 indicates
127 countries with stronger governance indicators and greater wealth or Human Development
128 Index (HDI), while a higher value of PCA2 suggests a denser population and a larger share
129 of urban areas (see Figure A-1). These two PCA axis were then included as predictors in
130 the subsequent analysis (see Beta-regression analysis).

131 Models incorporating behavioural traits provided stronger explanatory power for cross-
132 country differences in protected area coverage (pseudo- $R^2 = 0.05$) compared to models
133 based solely on economic indicators such as the Human Development Index (pseudo- R^2
134 = 0.03) or Gross Domestic Product (pseudo- $R^2 = 0.03$). When behavioural traits were
135 analysed alongside a broader set of economic and political controls derived from principal
136 component analysis (PCA), they demonstrated comparable explanatory performance to the
137 PCA-based models focused on Governance & Economic axis and Population & Urbani-
138 sation axis alone (pseudo- $R^2 = 0.05$ and 0.06, respectively). Notably, models combining
139 behavioural traits with Governance & Economic axis and Population & Urbanisation axis
140 outperformed (pseudo- $R^2 = 0.12$) those relying solely on socio-economic and political vari-
141 ables.

142 In the best-fitting model, we found that trust is significantly and negatively associated
143 with protected area coverage (slope estimate = -0.69, $p = 0.038$; Fig. 2 and Table A-2, Fig.
144 A-6). In contrast, other behavioural traits—altruism, patience, and risk-taking—showed
145 weaker and non-significant relationships with protected area coverage ($p > 0.1$). Addition-
146 ally, Governance & Economics axis (PCA axis 1) was negatively related to protected area
147 implementation ($p = 0.034$), suggesting that countries with stronger economic and political

Table 2: Model selection based on pseudo- R^2 using Global Preferences Survey. In all models, protected area coverage is defined as response. Values in bold represent the best model selected here according to pseudo- R^2 . Additional models based only on the Human Development Index (HDI) or Gross Domestic Product (GDP) have been tested. Governance & Economic axis and Population & Urbanisation axis corresponds, respectively to the first and second axis of the PCA. behavioural traits correspond here to Altruism, Trust, Patience and Risk taking. Model table selection based on log-likelihood is reported in Table A-1. Coefficients are provided in Tables A-2 and B for additional models.

<i>Predictors included</i>	<i>Pseudo-R^2</i>
Behavioural traits + Governance & Economic axis + Population & Urbanisation axis	0.12
Governance & Economic axis + Population & Urbanisation axis	0.06
Behavioural traits	0.05
Human Development Index (HDI)	0.03
Gross Domestic Product (GDP)	0.03

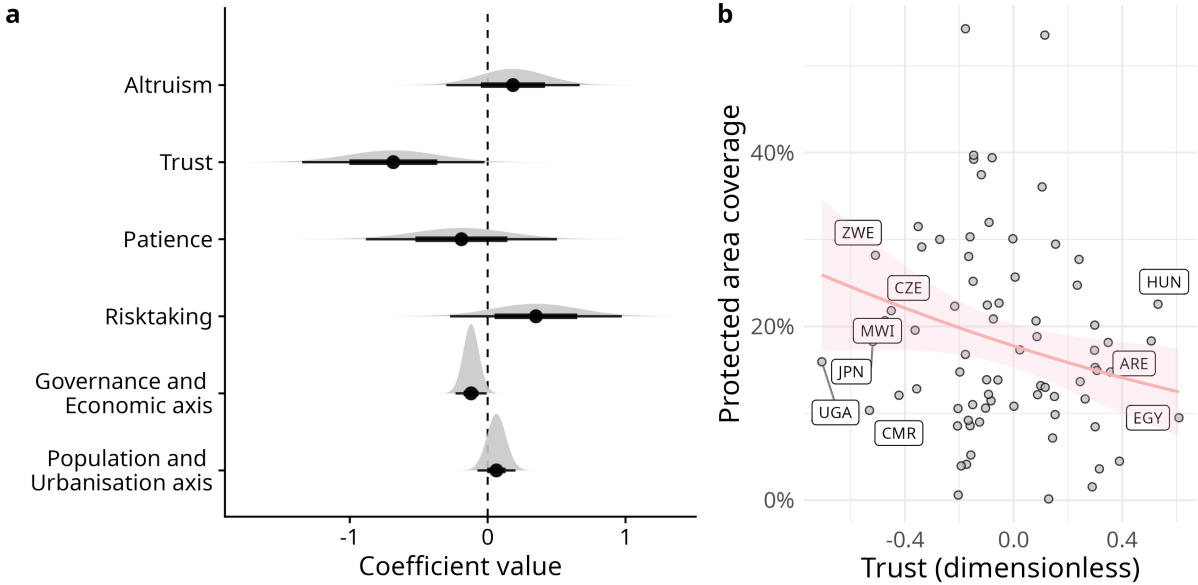


Figure 2: Summary of behavioural traits effects on protected area coverage (N = 75 countries). a) Coefficient plot from the best fitting beta-regression model, including behavioural traits (i.e. altruism, trust, patience, risk-taking) and Governance & Economic axis and Population & Urbanisation axis (pseudo- $R^2 = 0.13$). Each dot represents the slope effect (average estimate) with quantile intervals. The density estimator of sample data is reported with the black thick line containing 66% of the density and the thinner line contains 95% of the density data. Coefficient values are reported in Table A-2. b) Relationship between the percentage of protected area coverage and trust, derived from the panel Figure 2a. Each dots represent country observations. The beta-regression is reported in pink with the 95% confidence interval. Isocode: ARE, United Arab Emirates; EGY, Egypt; HUN, Hungary; CMR, Cameroon; CZE, Czechia; UGA, Uganda; JPN, Japan; MWI, Malawi; ZWE, Zimbabwe.

148 institutions have more formal protected areas. Importantly, the magnitude of the effect of
 149 the trait trust was 5.75 times greater than the Governance and Economic axis and 11.12

150 times greater than the Population and urbanisation axis. These patterns remained consis-
151 tent across robustness checks, including bootstrap procedures (Table A-3) and analyses
152 using the 7th Wave of the European Values Survey (see Supplementary Section B). The
153 magnitude of the effect is slightly weaker in the complementary analysis due to differences
154 in the measurement of behavioural traits, but the direction and statistical significance of the
155 main results remain consistent.

156 Discussion

157 Reversing biodiversity loss requires innovative policies that effectively regulate human ac-
158 tivity, with protected areas serving as a cornerstone strategy for safeguarding ecosystems
159 within designated regions. While extensive evidence underscores the importance of these
160 measures, there remains a persistent gap in international action to establish and main-
161 tain protected areas for biodiversity conservation. A critical challenge lies in understand-
162 ing what drive both the creation and effectiveness of such areas. Previous research has
163 yielded mixed findings on the effect on economic and governance drivers on conservation
164 efforts (17; 30; 15). Our findings contribute to this gap of knowledge by highlighting the
165 role of behavioural traits at the population level—such as trust, altruism, patience, and risk
166 preferences—in shaping conservation outcomes. These results challenge the prevailing
167 assumption that only economic and political factors drive conservation policy.

168 Our major findings aligns with research highlighting the heterogeneity in terrestrial pro-
169 tected area coverage across countries, often attributed to disparities in socio-economic de-
170 velopment (15; 14; 31) and governance quality (12). While wealthier countries with stronger
171 governance systems tend to have larger surface of protected area, our results suggest that
172 governance and economy have lower influence than population-level behavioural traits. No-
173 tably, a one standard deviation increase in the behavioural trait trust is associated with a
174 0.6% decrease in protected area coverage—an effect nearly six times stronger than eco-
175 nomic and governance factors alone.

176 Trust may also act as a substitute for formal governance, fostering informal conservation
177 practices and strengthening community-driven stewardship. In high-trust societies, individ-
178 uals are more likely to engage in collective action for the common good (32). This result
179 suggest that collective action can sustain common goods (33; 34). In contrast, the other
180 behavioural traits—altruism, patience, and risk-taking—do not show significant association
181 with protected area coverage. The non-significant relationship with altruism aligns with find-
182 ings that protected areas often emerge from institutional frameworks and tenure systems
183 rather than altruistic motives (35). Cai et al (36) found that patience correlates with climate
184 policy implementation. Yet our study does not identify a similar link between patience and
185 protected area coverage. One possible explanation is that climate policies are typically for-
186 mulated at the national level, requiring long-term commitments and intertemporal trade-off,

187 which align with patient societies. In comparison, protected areas can be established at
188 different scale, from local to national levels initiatives. With regard to the final trait, desig-
189 nated risk-taking, the absence of statistical significance does not preclude the possibility of
190 its impact on conservation decisions. Risk-taking trait may assume a more significant role
191 during the implementation stage or when modifying conservation measures, rather than in
192 determining the coverage of protected areas (37).

193 Integrating population-level behavioural traits enhances our understanding of protected
194 area coverage; yet a significant proportion remained unexplained. While our model ac-
195 counts for approximately 12% of the observed variance, the remaining 88% underscores
196 the complexity of conservation dynamics. Investigating mechanisms at different spatial and
197 temporal scales—from national measures to local socio-ecological dynamics, as well as
198 historical, cultural, and environmental contexts—is crucial. For example, the effectiveness
199 of community-managed conservation areas in Nepal (28) and indigenous-led stewardship
200 in the Amazon (38) illustrates how governance structures, cultural traditions, and environ-
201 mental conditions shape conservation outcomes. Additionally, protected area coverage
202 does not always reflect conservation effectiveness (39). Hence the integration of local pop-
203 ulation characteristics could provide insights often overlooked in national-level analyses.
204 Furthermore, the cross-sectional approach of our study limits the ability to capture tem-
205 poral changes in both behavioural traits and protected area coverage. While conservation
206 policies evolve in response to environmental threats, political shifts, and economic condi-
207 tions (40; 41; 42), behavioural norms also adapt to crises and policy interventions (43). A
208 natural extension of this work would be to integrate historical archives to examine the imple-
209 mentation of protected areas and local governance structures using text analysis of regional
210 and local newspapers. Such an approach would complement our study by offering a tem-
211 poral perspective on the relationship between population characteristics and protected area
212 development over time.

213 Understanding population-level behavioural traits is crucial for explaining global hetero-
214 geneity in biodiversity conservation and advancing more effective conservation strategies
215 (22). Our study offers the first large-scale perspective on the relationship between be-
216 havioural science and the environment, which has primarily relied on individual-level ap-
217 proaches. Specifically, in high-trust societies, policymakers can harness trust to foster col-
218 laboration among stakeholders, facilitating the implementation of effective bottom-up biodi-
219 versity conservation policies. Conversely, governments overseeing populations with lower
220 trust levels may need to rely on formal regulations and enforcement mechanisms to en-
221 courage pro-environmental behaviours. Integrating behavioural insights into conservation
222 planning could unlock more effective and context-specific strategies to safeguard biodiver-
223 sity in an era of unprecedented environmental change.

224 **Material & Methods**

225 **Terrestrial protected area coverage**

226 National-level commitment to biodiversity preservation is assessed through the establish-
227 ment of protected areas (44). We used the World Database on Protected Areas ((45),
228 version November 2023) to extract data on the location, boundaries, and year of establish-
229 ment of protected areas from a total of the 75 countries available in open-source. Terrestrial
230 protected areas were extracted for each country and are categorised with IUCN criteria be-
231 tween I, highly restrictive or no-take, and VI least restrictive IUCN category. To avoid the
232 under-representation of international protected areas at the country level, we also extracted
233 national and regional protected areas within each country, including not assigned and not
234 reported categories.

235 The coverage of protected areas may overlap according to their regulation (e.g. regional
236 protected areas overlap international protected areas). We first combined all spatial geome-
237 tries of all three features, regional, international and national protected areas all together
238 in one large spatial feature (46). We then extracted terrestrial country boundaries to de-
239 termine the coverage of terrestrial protected areas for each country by using the Database
240 of Global Administrative Areas (GDAM, <https://gadm.org/data.html>, (47)). We deter-
241 mined the percentage of the protected area by dividing the total surface of the terrestrial
242 protected area by the total area of the country. All extraction and cleaning of the protected
243 area was done by using the R package `wdpar` (48).

244 Our approach is based on the methodology from (10). The proportion of protected
245 areas might be higher than those reported from Protected Planet reference (45) because
246 this methodology would include eventually more protected areas, either regional or national
247 (see Figure A-2a).

248 **Population's behavioural traits**

249 Population's behavioural traits represent behaviours that are usually observed in laboratory
250 experiments where individuals are faced with monetary trade-offs to elicit their behaviours.
251 Such behavioural traits possess substantial explanatory power as they are associated with
252 observable outcomes at the individual (e.g. (49)), and country level (e.g. (50)). We derived
253 the experimental behavioural traits measures of risk-taking, patience, altruism and interper-
254 sonal trust from the Global Preferences Survey (GPS, (29; 51)) for a total of 75 countries.
255 Those countries represent approximately 90% of the world's population and more than
256 90% of the global Gross Domestic Product in 2012. The Global Preferences Survey initially
257 contained risk-taking, patience, altruism, interpersonal trust, and also positive and negative
258 reciprocity. To ensure the internal validity of these measures, the Global Preferences Survey
259 employed a novel validation process that assesses behavioural traits through survey ques-

260 tions linked to incentivised experimental economic games. Falk et al. (51) implemented
261 in the Global Preferences Survey survey the set of questions that maximize the variance
262 of each preference under scrutiny. By relating these preferences to behaviours observed
263 in controlled lab environments, the approach confirmed that the results are reliable and
264 consistent (internal validity). Furthermore, the survey included a diversity of participants
265 making the population behaviour response more representative of the population (external
266 validity) (see Supplementary Material A). We did not use the positive and negative reci-
267 procity traits because of the strong correlation between reciprocity (negative-positive) to
268 other traits (26). For the measures of behavioural traits, we aggregated observations at the
269 national level and standardized the result at the international level. More details about the
270 behavioural traits database are reported in the Supplementary Section A and in the refer-
271 ences (51; 26). We reported relation among traits in Figure A-5. We ran similar analysis
272 by using a second survey of population behavioural traits, the 7th Wave - European Values
273 Survey (EVWS, (52)). The second survey included three behavioural traits that are similar
274 to Global Preferences Survey; altruism, trust and patience (69% countries overlapping be-
275 tween the Global Preferences Survey and Wave - European Values Survey). Results of the
276 analysis with EVWS survey are reported in the Supplementary Section B B and provided
277 quantitatively the same outcomes.

278 **Economic, Political and Urban areas**

279 We included a sets of controlling variables, with population's behavioural traits and the
280 implementation of protected areas.

281 **Economic & Political variables:** We used the Gros Domestic Product (GDP) per capita,
282 population density, Human Development Index (HDI) and Worldwide Governance Indicators
283 as these variable have been documented as main drivers of protected area (12; 17). Pop-
284 ulation density has been extracted from World Bank data (53). The Human Development
285 Index (HDI), extracted from the United Nations Development Programme, is a composite
286 measure that assesses a country's overall development based on three key dimensions:
287 health (life expectancy at birth), education (mean years of schooling and expected years
288 of schooling), and standard of living (gross national income per capita) (54). Finally, we
289 considered the effectiveness of a government to implement policy using the Worldwide
290 Governance Indicators (55) that considered five dimensions of governance: Voice and Ac-
291 countability, Political Stability, Regulatory Quality, Rule of Law, and Control of Corruption.

292 **Urban areas variable:** We chose the total urban areas percentage as a descriptive fac-
293 tor of land availability that can not be converted as a protected area surface. We ex-
294 tracted this variable from the Organisation for Economic Co-operation and Development

295 (<http://stats.oecd.org>, version October 2023).

296 **Analysis**

297 **Multivariate analysis to summarise economic-political-urban areas data**

298 To address the strong correlations between predictors related to economics, political gov-
299 ernance, urban areas (Figure A-4) and to reduce bias model estimates caused by a large
300 number of predictors for a relatively low sample size (<80 observations), we used principal
301 components analysis (PCA) to summarise the information from these variables by using the
302 R package `ade4` ((56), version 1.7-22) (57).

303 **Relation between protected areas and behavioural traits**

304 We aimed to determine whether population behavioural traits were significantly associated
305 with the percentage of protected areas while accounting for the political, land-use, and eco-
306 nomic context of each country. We used a beta regression, with the total proportion of
307 terrestrial protected areas as the response variable and population behavioural traits (altru-
308 ism, trust, patience, and risk-taking) as fixed predictors. We also included the two PCA axes
309 as additional fixed effects. The two PCA axis are control variables to capture governance,
310 economic, and land-use effects. The beta distribution is a family of continuous probability
311 distributions defined on the interval (0, 1) in terms of two positive parameters, that is why
312 the beta regression was chosen because the response variable is a proportion scaled be-
313 tween 0 and 1. We tested additional models that would include the combination of either
314 behavioural traits only or PCA axis only, or both as predictors. We also tested two more ad-
315 ditional models that would include only GDP or only HDI as fixed predictors. We compared
316 the different models by using the pseudo- R^2 and log-likelihood (58). In the main text, we
317 reported the results coming from the model with higher pseudo- R^2 and log-likelihood. Anal-
318 ysis was done with `glmmTMB` ((59), version 1.1.9). We extracted and visualized the model
319 coefficients with `ggdist` ((60), version 3.3.2) which reports the average estimate and den-
320 sity of the estimator. We assessed the model's diagnostic with the `DHARMa` package (61)
321 (version 0.4.6). All the models did not present any modeling issues based on model's diag-
322 nostics. We used a bootstrap procedure to check the consistency of the results because of
323 the relatively low sample by using the R package `performance` ((62), version 0.11.0) and
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Online Appendix

469

Beyond Wealth and Governance in Terrestrial Protected Area Coverage : The Role of Population Behavioural Traits

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473	A Measuring behavioural Traits	A-1
474	B Additional analysis with the Wave - European Values Survey	A-3
475	B Supplementary Tables	A-5
476	C Supplementary Figures	A-11

477 **A Measuring behavioural Traits**

478 **The Global Preferences Survey**

479 The Global Preferences Survey (GPS) dataset (51) provides insights into fundamental be-
 480 havioural traits across social and non-social domains, including attitudes toward financial
 481 risk, patience, altruism, and trust. In standard economic theory, risk preferences are charac-
 482 terized by the curvature of the utility function (convex for risk-taking, linear for risk-neutral,
 483 and concave for risk-averse); time preferences reflect the valuation of inter-temporal re-
 484 wards (with patience indicating a preference for delayed gratification); and pro-social pref-
 485 erences incorporate considerations for others' well-being and intentions (e.g., altruism and
 486 trust) (63).

487 The table A-1 provides a comprehensive definition of the variables created in the survey
 488 Global Preferences Survey.

Table A-1: Preference measures in the Global Preferences Survey

Preference	Quantitative item	Qualitative item
The Willingness to take risks	Sequence of five interdependent questions, following a staircase procedure [†] : "Please imagine the following situation. You can choose between a sure payment of a particular amount of money, or a draw, where you would have an equal chance of getting amount x or getting nothing. We will present to you five different situations. What would you prefer: a draw with a 50 percent chance of receiving amount x, and the same 50 percent chance of receiving nothing, or the amount of y as a sure payment?"	"Please tell me, in general, how willing or unwilling you are to take risks. Please use a scale from 0 to 10, where 0 means "completely unwilling to take risks" and a 10 means you are "very willing to take risks". You can also use any numbers between 0 and 10 to indicate where you fall on the scale, like 0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10."
Patience	Sequence of five interdependent questions, following a staircase procedure [†] : "Suppose you were given the choice between receiving a payment today or a payment in 12 months. We will now present to you five situations. The payment today is the same in each of these situations. The payment in 12 months is different in every situation. For each of these situations, we would like to know which you would choose. Please assume there is no inflation, i.e., future prices are the same as today's prices. Please consider the following: Would you rather receive 100 Euro today or x Euro in 12 months?"	"How willing are you to give up something that is beneficial for you today in order to benefit more from that in the future?"
Trust	-	"I assume that people have only the best intentions."
Altruism	"Imagine the following situation: Today you unexpectedly received 1,000 Euro. How much of this amount would you donate to a good cause? (Values between 0 and 1000 are allowed.)"	"How willing are you to give to good causes without expecting anything in return?"

† The staircase procedure has a tree structure that works as follows: *i*) all subjects are exposed to the same initial choice between A) a lottery payment (for risk preferences) or a payment at a later date (for time preferences) and B) a safe payment (for risk preferences) or a payment today (for time preferences); *ii*) depending on their choice, they are next exposed to a second price list with a different B) option; and *iii*) they repeat step *ii*) several times.

489 The selection of the survey items relies on an ex-ante validation procedure, which con-
 490 sists in selecting from a large set of survey questions the items that best predict incentivized

491 choices in the laboratory (see (51) for details on the procedure).

492 **The World Values Survey**

493 The World Values Survey is an international survey documenting the evolution of individual
494 beliefs, values, and motivations over time and across many different societies. Of the seven
495 waves conducted since 1981, this study relies on the 7th waves carried out between 2016
496 and 2021. As a bonus, the 7th wave data is complemented by additional data from the
497 European Values Survey which asks similar questions but is specific to Europe, to create
498 the joint WVS/EVS database (52). We use this survey to serve as alternative measures
499 of behavioural traits and to perform a sensitivity to change analysis across the pool of
500 countries.

- 501 • **Times preferences.** We construct our measure of patience from the question that
502 presents respondents with a list of qualities that children can be encouraged to learn
503 at home, asking them to indicate whether or not they consider each quality to be
504 especially important (up to a maximum of five qualities). We consider a respondent
505 to be patient if they select “Thrift, saving money and things.”
- 506 • **Trust.** The interpersonal trust measures are based on a question asking respondents
507 to rank how much they trust people from several groups, using a 4-point Likert-scale
508 ranging from “not at all” to “a great deal.” The groups are “Your family,” “Your neighbor-
509 hood,” “People you know personally,” “People you meet for the first time,” “People of
510 another religion,” and “People of another nationality.” Interpersonal trust is determined
511 to be narrow if it is restricted to the item “People you meet for the first time”. This
512 item indeed appears to most closely match the behavioural measure of interpersonal
513 trust in the standard trust game. The global version of interpersonal trust is computed
514 as the sum of responses from all items. The results remain consistent regardless of
515 whether the narrow or global version of interpersonal trust is used. Therefore, we
516 report only the results based on narrow interpersonal trust to maintain consistency
517 across datasets and avoid redundancy..
- 518 • **Altruism.** We construct our measure of patience using, once again, the question
519 that presents respondents with a list of qualities where children can be encouraged
520 to learn at home, asking them to indicate whether or not they consider each quality to
521 be especially important (up to a maximum of five qualities). In this case, we consider
522 a respondent to be altruistic if they select “Unselfishness.”

Table A-2: Model selection based on pseudo-R² using the for Wave - European Values Survey. Values in bold represent the best model selected here according to log-likelihood and pseudo-R². Additional models based only on the Human Development Index (HDI) or Gross Domestic Product (GDP) have been tested. Governance & Economic axis and Population & Urbanisation axis corresponds, respectively to the first and second axis of the PCA. behavioural traits correspond here to Altruism, Trust, Patience and Risk taking. Model table selection based on log-likelihood is reported in Table A-6. Coefficients are provided in Table A-5

<i>Predictors included</i>	<i>Pseudo-R²</i>
behavioural traits + Governance & Economic axis + Population & Urbanisation axis	0.23
Governance & Economic axis + Population & Urbanisation axis	0.14
Human Development Index (HDI)	0.07
behavioural traits	0.03
Gross Domestic Product (GDP)	0.03

523 **B Additional analysis with the Wave - European Values**
 524 **Survey**

525 **Wave - European Values Survey (EVWS):** The second measure of population behavioural
 526 traits is taken from EVS (European)/WVS (Wave 7th Values Survey) (52), abbreviated
 527 EVWS hereafter. This database initially includes 79 countries (2017–2021) and also in-
 528 cludes several questions on trust ranging from institutional to interpersonal trusts (e.g.
 529 neighbors, strangers, community groups). The *narrow* trust is the score related to strangers
 530 and is likely closest to the Global Preferences Survey measure. The *global* trust adds up the
 531 scores from all the survey questions on trust in others. We used here the narrow trust, as
 532 the relationship between population behavioural traits and policy making is similar whether
 533 considering interpersonal or global trust (26). This database does not contain data related
 534 to risk-taking.

535 After extraction, we obtained a list of 75 countries with both protected area coverage and
 536 behavioral traits. We then ran a PCA to summarise variance explained from economic-
 537 political and urban areas, because the list of countries is different from Global Preference
 538 Survey database. We retained the first two axis representing 84.6% of the total dataset
 539 inertia (dimension 1 = 67.3%, dimension 2 = 17.3%). We then used beta-regression as in
 540 the main text.

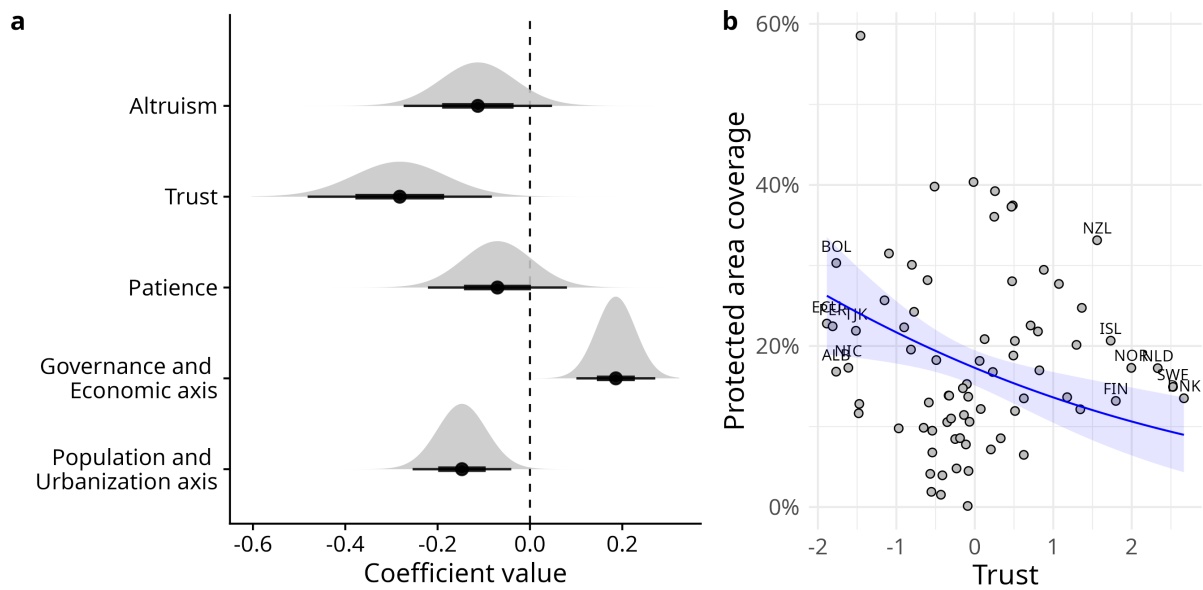


Figure A-1: Summary of behavioural traits effects on protected area coverage (N = 75 countries). a) Coefficient plot from the Wave - European Values Survey beta-regression model, including behavioural traits (i.e. altruism, trust, patience, risk-taking) and Governance & Economic axis and Population & Urbanisation axis (pseudo- $R^2 = 0.13$). Each dot represents the slope effect (average estimate) with quantile intervals. The density estimator of sample data is reported with the black thick line containing 66% of the density and the thinner line contains 95% of the density data. Coefficient values are reported in Table A-5. b) Relationship between the percentage of protected area coverage and trust, derived from panel a. Each dots represent country observations. The beta-regression is reported in pink with the 95% confidence interval.

B Supplementary Tables

Table A-1: Model selection based on log-likelihood using Global Preferences Survey. In all models, protected area coverage is defined as response. Values in bold represent the best model selected here according to log-likelihood and pseudo-R². Additional models based only on the Human Development Index (HDI) or Gross Domestic Product (GDP) have been tested. Governance & Economic axis and Population & Urbanisation axis corresponds, respectively to the first and second axis of the PCA. behavioural traits correspond here to Altruism, Trust, Patience and Risk taking. Coefficients are provided in Table B.

<i>Predictors included</i>	<i>Log-Likelihood</i>
Behavioural traits + Governance & Economic axis + Population & Urbanisation axis	67.901
Governance & Economic axis + Population & Urbanisation axis	65.109
Behavioural traits	64.904
Human Development Index (HDI)	64.068
Gross Domestic Product (GDP)	63.576

Table A-2: Coefficient estimates from beta regression models fitted either with GPS survey (top) or EVWS survey (bottom) from the best fitting model (higher pseudo R² and loglikelihood). Model coefficients are reported with average estimate, standard deviation (SD), low and high CI 95%, and p-value. Section A presents the definition of variables in both datasets.

<i>Dataset</i>	<i>Predictor</i>	<i>Estimate</i>	<i>SD</i>	<i>CI025</i>	<i>CI975</i>	<i>pvalue</i>
GPS	(Intercept)	-1.500	0.089	-1.700	-1.400	0.000
	Altruism	0.180	0.240	-0.290	0.660	0.452
	Trust	-0.690	0.330	-1.300	-0.035	0.038
	Patience	-0.180	0.350	-0.860	0.500	0.604
	Risk taking	0.350	0.310	-0.260	0.960	0.265
	Governance & Economic axis	-0.120	0.056	-0.230	-0.009	0.034
	Population & Urbanisation axis	0.062	0.069	-0.073	0.200	0.366
EVWS	(Intercept)	-1.600	0.083	-1.800	-1.500	0.000
	Altruism	-0.130	0.079	-0.280	0.028	0.107
	Trust (global)	-0.230	0.093	-0.420	-0.052	0.011
	Patience	-0.064	0.078	-0.220	0.089	0.412
	Governance & Economic axis	-0.170	0.041	-0.250	-0.091	0.000
	Population & Urbanisation axis	-0.140	0.054	-0.240	-0.029	0.012

Table A-3: Coefficient estimates from beta regression after bootstrap procedure. Model fitted either with GPS survey (top) or EVWS survey (bottom) from the best model (higher pseudo R² and loglikelihood). Model coefficients are reported with average, low and high CI95% and p-value. Section A presents the definition of variables in both datasets. We limited the number of bootstrap iterations to 100.

<i>Dataset</i>	<i>Predictor</i>	<i>Estimate</i>	<i>CI025</i>	<i>CI975</i>	<i>pvalue</i>
GPS	(Intercept)	-1.587	-1.767	-1.368	< .001
	Altruism	0.218	-0.324	0.713	0.50
	Trust	-0.737	-1.410	-0.111	0.04
	Patience	-0.286	-0.921	0.453	0.40
	Risk taking	0.409	-0.203	0.958	0.14
	Governance & Economic axis	-0.137	-0.233	-0.027	0.04
	Population & Urbanisation axis	0.048	-0.06	0.223	0.52
EVWS	(Intercept)	-1.632	-1.782	-1.485	< .001
	Altruism	-0.137	-0.285	0.034	0.14
	Trust (global)	-0.230	-0.383	-0.051	< .001
	Patience	-0.069	-0.222	0.101	0.34
	Governance & Economic axis	-0.172	-0.233	-0.1	< .001
	Population & Urbanisation axis	-0.124	-0.242	-0.028	0.02

	All traits	Altruism	Trust	Patience	Risk taking	All traits and PCA1	All traits and PCA2	Full
(Intercept)	-1.514*** (0.091)	-1.493*** (0.092)	-1.509*** (0.092)	-1.494*** (0.091)	-1.497*** (0.091)	-1.542*** (0.090)	-1.516*** (0.090)	-1.541*** (0.089)
Altruism	0.105 (0.254)	-0.006 (0.252)				0.178 (0.249)	0.121 (0.253)	0.183 (0.249)
Trust	-0.548+ (0.329)		-0.414 (0.313)			-0.620+ (0.324)	-0.642+ (0.335)	-0.684* (0.329)
Patience	0.369 (0.236)			0.315 (0.225)		-0.241 (0.350)	0.375 (0.235)	-0.190 (0.350)
Risk taking	0.153 (0.283)				0.231 (0.279)	0.428 (0.309)	0.081 (0.286)	0.350 (0.315)
Governance & Economic axis (PCA1)						-0.129* (0.056)		-0.120* (0.056)
Population & Urbanisation axis (PCA2)							0.087 (0.071)	0.064 (0.069)
Num.Obs.	75	75	75	75	75	75	75	75
R2	0.052	0.000	0.020	0.021	0.007	0.110	0.069	0.122

Table A-4: Sample results table with GPS survey. PCA1 referred to the axis related to governance and economy, and PCA2 referred to the axis related to population and urbanization.

	All traits	Trust	Altruism	Patience	All traits and PCA1	All traits and PCA2	Full
(Intercept)	-1.520*** (0.086)	-1.515*** (0.088)	-1.518*** (0.087)	-1.517*** (0.088)	-1.606*** (0.085)	-1.528*** (0.085)	-1.643*** (0.083)
Trust	0.046 (0.081)	0.023 (0.080)			-0.197* (0.095)	0.021 (0.079)	-0.282** (0.093)
Altruism	-0.150+ (0.084)		-0.139+ (0.082)		-0.109 (0.079)	-0.160+ (0.083)	-0.113 (0.076)
Patience	-0.034 (0.082)			-0.032 (0.081)	-0.085 (0.077)	-0.024 (0.081)	-0.070 (0.074)
Governance & Economic axis (PCA1)					0.152*** (0.041)		0.186*** (0.041)
Population & Urbanisation axis (PCA2)						-0.127+ (0.072)	-0.147* (0.061)
Num.Obs.	75	75	75	75	75	75	75
R2	0.032	0.001	0.027	0.002	0.174	0.076	0.232

Table A-5: Sample results table with EVWS survey. PCA1 referred to the axis related to governance and economy, and PCA2 referred to the axis related to population and urbanization.

Table A-6: Model selection based on log-likelihood using the Wave - European Values Survey. Values in bold represent the best model selected here according to log-likelihood and pseudo-R². Additional models based only on the Human Development Index (HDI) or Gross Domestic Product (GDP) have been tested. Governance & Economic axis and Population & Urbanisation axis corresponds, respectively to the first and second axis of the PCA. behavioural traits correspond here to Altruism, Trust, Patience and Risk taking. Coefficients are provided in Table A-5

<i>Predictors included</i>	<i>Log-Likelihood</i>
behavioural traits + Governance & Economic axis + Population & Urbanisation axis	77.356
Governance & Economic axis + Population & Urbanisation axis	72.268
Human Development Index (HDI)	69.143
behavioural traits	67.359
Gross Domestic Product (GDP)	66.989

542 **C Supplementary Figures**

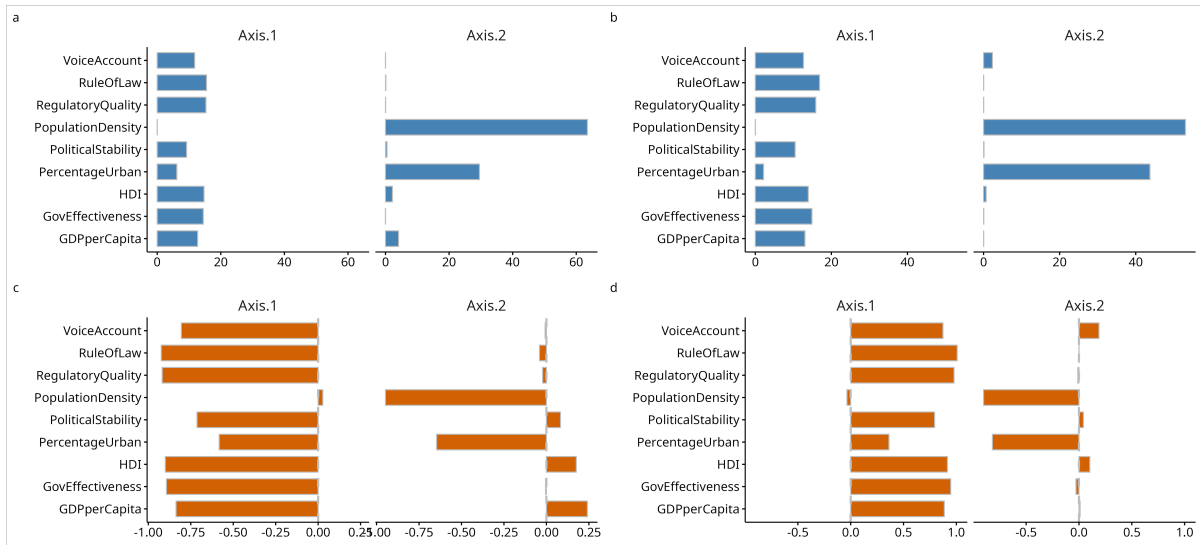


Figure A-1: Contribution and loadings from principal component analysis (PCA) based on GPS survey (left) and EVWS survey (right) list of countries. a) Contribution to the first two PCA axis based on GPS survey. b) Contribution to the first two PCA axis based on EVWS survey. c) Summary of PCA loadings based on GPS survey. d) Summary of PCA loadings based on EVWS survey.

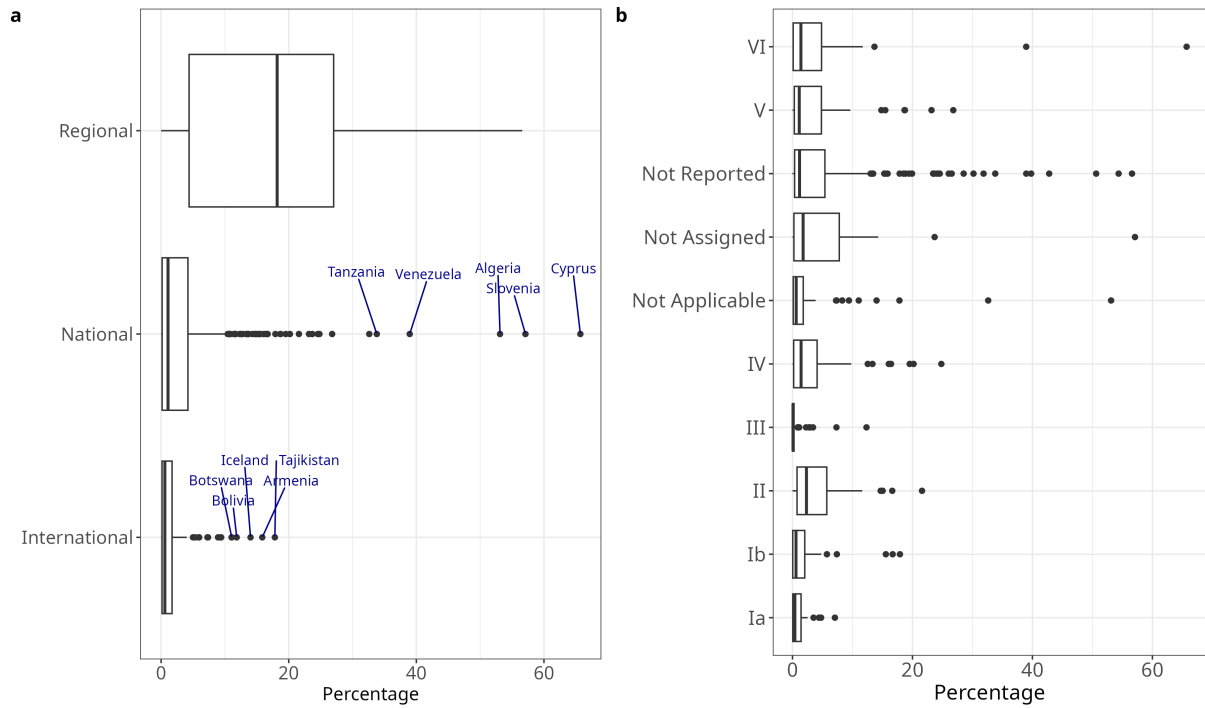


Figure A-2: a) Distribution of percentages according to the implementation scale of the protected area (regional, national, and international terrestrial protected areas). A more detailed map of the total surface according to protected area design (i.e. international, national or regional only) is reported in Fig A-3. b) Percentage of protected area according to IUCN categories. [more details on not reported, assigned, applicable.]

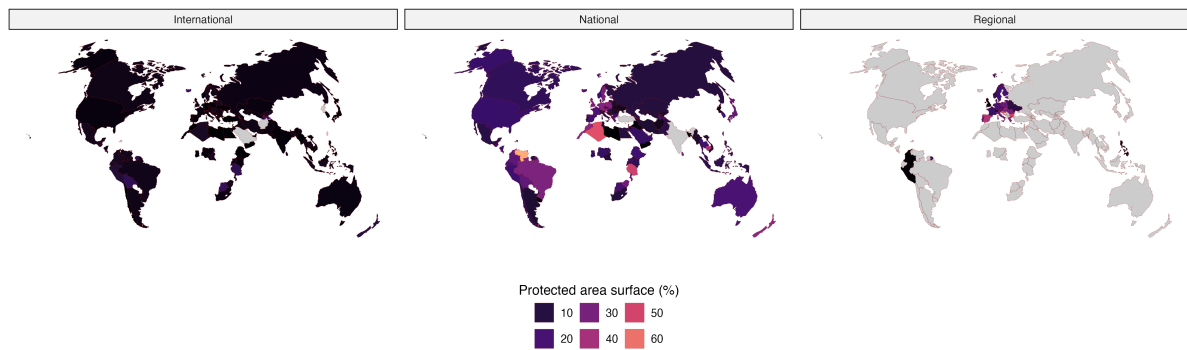


Figure A-3: Total percentage of protected areas (from the 75 unique countries in total) according to the type of protected areas - international, national, or regional. Maps are restricted to the 75 distinct countries used in our analysis. The grey colour represents no data source. (Map is displayed in Vander Grinten IV projection).

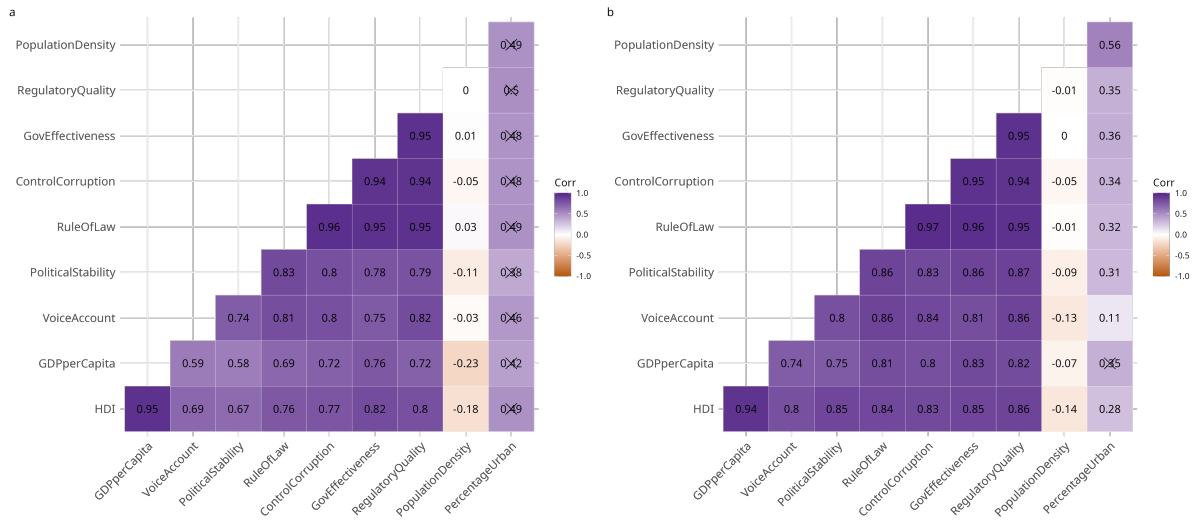


Figure A-4: Pearson correlation matrix of economic and governance variables. (a) Correlation matrix for countries included in the GPS dataset. (b) Replication of (a) for countries included in the WVS dataset. Crossed cells indicate correlation coefficients which are not statistically different from zero ($p > 0.1$).

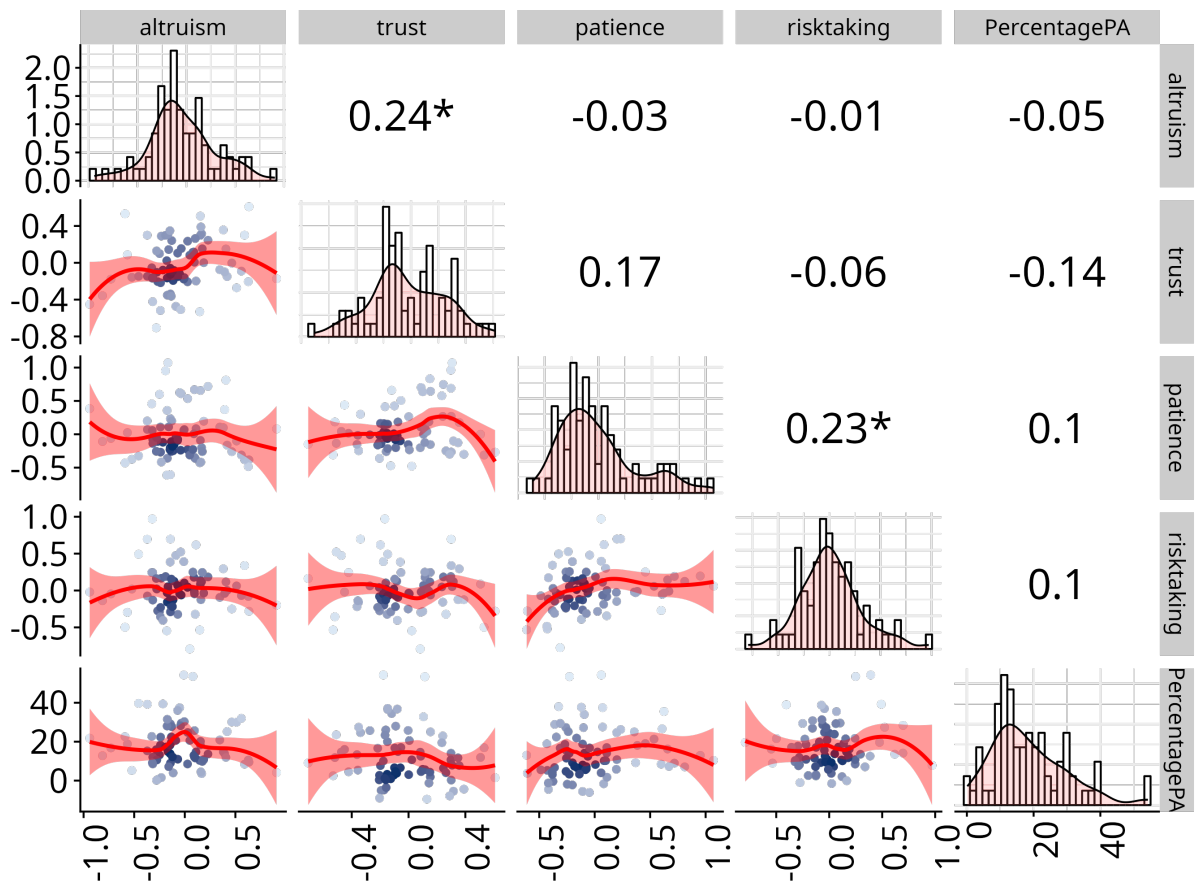


Figure A-5: Comparisons among behavioral traits and protected area coverage: scatter plots of all combination of traits and protected area coverage, data distributions, and their correlation. For correlations, we used Pearson correlation with *** for P-values <0.001, ** for 0.001, * for 0.01. The lower panel presents kernel density estimation of data, from pale to dark blue for higher density data observation, and each dots represent values of each countries. The red line is loess regression with CI95.

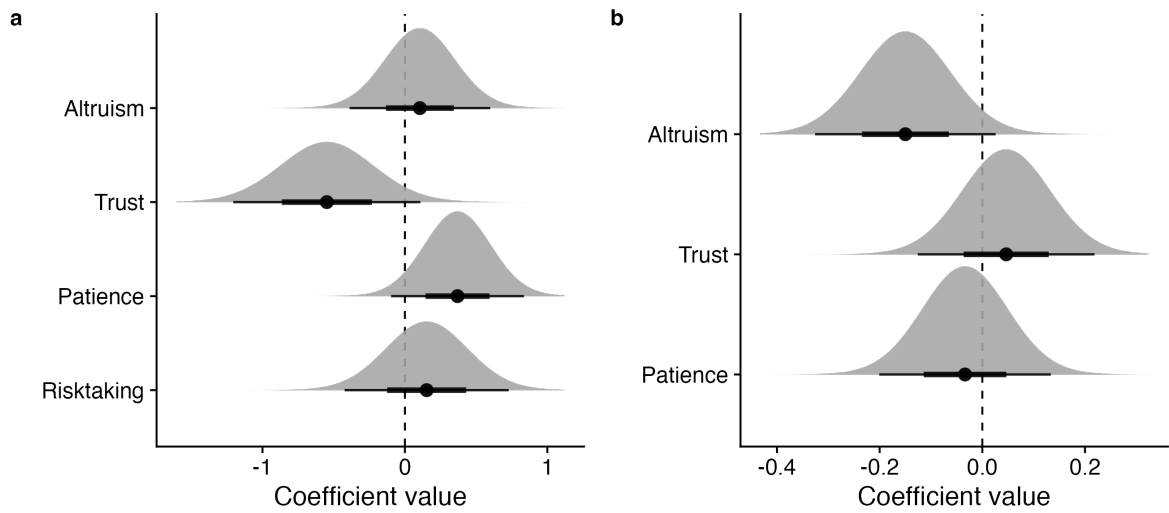


Figure A-6: Summary of behavioural traits effects on protected area coverage without controls (N = 75 countries). a) Coefficients estimates based on GPS dataset and b) Coefficients estimates based on EVWS survey. In a) Summary of behavioural traits effects on the percentage of protected areas as a response (N = 75 countries). Each dot represents the slope effect (average estimate) and its quantile intervals. For both plots, we reported the density estimator for sample data. The black thick line contains 66% of the density and the thinner line contains 95% of the density.