1 **What shapes climate change beliefs in Africa?**

2 **A random forest approach**

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Abstract

Although Africa is the most vulnerable region to climate change, little research has focused on how climate change is perceived by Africans. Using random forest methodology, we analyse survey and climate data from second-order political boundaries to explore what shapes climate change beliefs in Africa. We include five different dimensions of climate change beliefs: climate change awareness, belief in anthropogenic climate change, risk perception, the need to stop climate change, and self-efficacy. Based on our criteria our results identify five key determinants of what shapes climate change beliefs: (1) climate change in Africa is largely perceived through its negative impacts on agriculture. (2) Actual changes in local climate conditions increase climate change beliefs. (3) Authoritarian and intolerant ideologies lessen climate change awareness, reduce the belief in its human origins, and diminish risk perception and the belief that it must be stopped. (4) Women are less likely to be aware of climate change, and (5) not speaking French, English or Portuguese hinders the understanding of climate beliefs. Our results could help policy makers better understand the need to jointly consider the complexities of individual beliefs and hydroclimatic data for the development of more accurate adaptation and mitigation strategies to combat the impacts of climate change in Africa.

Introduction

Current projections suggest that climate change will likely have "severe, irreversible and pervasive impacts for people and ecosystems" [1]. Urgent mitigation and adaptation strategies are needed at all levels of analysis to lessen the impact from climate change. However, such mitigation strategies are not being implemented quickly enough [2]. Aside from material, institutional, and political constraints, there are some relevant cognitive barriers at the individual level that delay their implementation (e.g., the belief that climate change is *not* caused by human activities) [3,4]. Among these barriers, beliefs regarding climate change stand out [5]. Understanding what shapes *climate change beliefs* (CCBs) is crucial for policy makers to implement effective adaptation and mitigation strategies [5,6], especially in Africa—given current projections as the continent that will be most affected by climate change [1]. For instance, despite strong scientific consensus about the existence of anthropogenic climate change only 51% of Africans believe that human activity is the main cause behind climate change [7]. These gaps in climate change beliefs erode public support towards environmental policies and limit individual behavioural changes that could reduce greenhouse gas emissions [8–10].

Despite this, little research has focused on what shapes climate change beliefs in Africa. Recent metanalyses suggest that fewer than 5% of published articles included African countries in their sample [5,10]. As CCBs and its predictors vary widely across regions [11,12], the applicability of non-African research is, at least, questionable. This study aims to narrow this gap. We make three major contributions to the existing literature. First, we offer a specific representation of what shapes African citizens' climate change beliefs by using disaggregated data across second-order political boundaries within 33

3

59   countries. Second, we employ a novel machine learning methodology within the social

60   sciences (random forest) to precisely classify the impact of a diverse number of

61   variables on climate change beliefs. Finally, we take a holistic approach that

62   incorporates most of the previous predictors identified largely in Western countries to

63   examine whether they hold true in Africa.

64

65   The remainder of this article is structured as follows. First, we briefly review the current

66   literature on the factors that shape climate change beliefs. We then explain our data

67   collection and operationalization process, as well as the specification of our random

68   forest models. Finally, we discuss the main findings aggregated across different

69   dimensions to offer clear patterns of what shapes climate change beliefs in Africa.

70

71   What shapes climate change beliefs

72   There is widespread recognition that climate change is real and that its observable

73   consequences can already be appreciated — such as more frequent floods and droughts

74   in Eastern Africa, extreme precipitation trends in Central Europe and dryer conditions

75   that increase wildfires in North America [13,14]. Nonetheless, anthropologic climate

76   science denial persists among the public—either because individuals lack sufficient

77   information, have a poor understanding of the matter, or because they associate climate

78   science with conspiracy theories (e.g., willful ignorance). Recent survey data from

79   Africa suggests that only 56 % of the continent's population have heard about climate

80   change and about 20% believe that ordinary citizens can do nothing to stop climate

81   change [7]. What shapes these individual climate change beliefs? A growing number

82   of interdisciplinary studies suggest four possible answers. First, despite the growing

83   availability of climate change information, much of it remains inaccessible for many

84   and those who do have access to it are unable to understand the complex science behind

85   such phenomenon. Second, despite having access to climate change information,

86   people's religious beliefs or political ideology can lead to a clash of ideas that can often

87   result in a biased interpretation of facts. Third, scientific information about climate

88   change is too abstract, leaving people to interpret climate change trough their own

89   personal experience with local climate conditions. Finally, people have a "finite pool

90   of worry"—more urgent concerns than climate change—pushing climate change

91   concerns to the backburner.

92

93   **Barriers to climate change information**

94   This argument suggests that individuals do not form correct beliefs about climate

95   change because they face barriers to accessing climate information. For instance, not

96   having a cellphone or not having access to the internet are important barriers to

97   discovering current debates, facts and stories about climate change, reducing the

98   amount of information that can improve CCBs [11,12]. Similar studies indicate the

99   importance of social media platforms as forums for climate debates among the public

100   [15]; however, these platforms can also serve as echo chambers where previous beliefs

101   are not contrasted, but continuously reinforced [16]. Another important barrier to

102   information access is education, given that it provides a more detailed understanding of

103   the climate cycle and how humans negatively impact it. Moreover, in-depth case study

104   evidence suggests that even when climate change information is available, a less

105   educated public may lack the tools to understand it, inducing incorrect beliefs [17]. This

106   is further corroborated by large-N studies that find a statistical relationship between

107   higher levels of education and more accurate climate change beliefs [10–12,18,19].

108

Biased interpretation

By contrast, others suggest that even when information is attainable, people's political and religious beliefs often clash with climate science facts, leading to a bias in the interpretation of climate facts in order to reconcile them with conflicting beliefs and thus reduce cognitive dissonance [20]. This phenomenon, known as motivated reasoning, has been shown to influence individual CCBs, mainly for political and religious motivations [4,10,21]. For instance, Hart and Nisbet [22] conducted an experiment where they presented Republican and Democratic voters in the United States with the same news story about possible climate change-related impacts on human health. Their study found that the impact of this information was different along party lines: Democrats risk perception and support for green policies increased, while among Republican the information produced a "boomerang effect" by reinforcing their sceptical views. Therefore, even when presented with the same information, this can be interpreted biasedly to avoid compromising political beliefs. Likewise, what people consider to be credible information vary depending on ideological proximity to the source, and other political variables, such as participation, trust in institutions and political perceptions also shape climate change beliefs [8,23–25].

Similarly, religious beliefs induce individuals to interpret climate change facts in a way that avoids conflict with their beliefs. For instance, there is evidence of Africans who attribute climate events to Allah ("Allah brings the rain. The one who causes the drought is Allah."), Yahweh ("We gather in church and pray for rain. There is nothing we can do."), or local deities ("whose anger can unleash flooding and destruction") [17]. Therefore, individuals who believe in a deity are more likely to attribute climate change and its repercussions to that deity's whim rather than to human activity [26].

134 Similarly, attending religious services has been linked to more incorrect CCBs [27].

135 However, these effects may vary across religions [28,29]. Thus, even when people have

136 access to rigorous information and the ability to understand it, politically or religiously

137 motivated reasoning can lead to incorrect beliefs.

138

139 Understanding climate change trough personal experiences

140 A second psychological approach suggests that individuals perceive climate change as

141 a distant phenomenon which is more likely to affect people living in other regions and

142 in the distant future [30]. This psychological distance from climate change often results

143 in a lack of emotional responses to it [31,32]. As a consequence, individuals try to make

144 sense of the changing natural world around them using more available and emotionally

145 salient cues, such as local climate or extreme weather events and their consequences

146 [30]. This so-called attribute substitution suggests that personal experiences, which are

147 easily accessible and emotionally close to the individual, often replace science-based

148 evidence and climate change facts [4,33]. Previous literature has found that individuals

149 who experience extreme climate-related events such as hurricanes, floods, or

150 temperature anomalies tend to perceive climate change as a greater risk [27,34–39].

151 Even less extreme events, such as a hotter-than-usual day, can make people more aware

152 of and concerned about climate change [40], and to donate more money to

153 environmental charities [41]. To sum, personally experiencing climate anomalies can

154 enhance climate change beliefs.

155

156 Climate change facts take a backseat

157 A final argument postulates that individuals have more urgent daily concerns (e.g.,

158 "bread and butter" issues), which relegate climate science information and its possible

159 consequences to the backburner [11,12,42–44]. In other words, CCBs are deemed less

160 important than immediate day-to-day concerns. This does not suggest that people do

161 not care about climate change and its consequences, but rather, they are seen as distant

162 occurrences that can be dealt with when they disrupt or exacerbate more pressing

163 matters [45].

164

165 **Demographics**

166 Besides the four previously discussed pathways that account for the climate change

167 information and beliefs linkages, previous research also finds that gender, age, and

168 ethnicity can play a role in shaping CCBs — yet a lack of consensus remains within the

169 literature. When it comes to gender, some studies find that women are less aware of

170 climate change than men but have higher risk perception [17,19,31,46], while others

171 find no statistical relationship between gender and climate change beliefs [10,12,47,48].

172 Some studies have suggested that differences in the access to climate information could

173 explain this difference [49]. Regarding age, many studies find that young people have

174 more accurate climate change beliefs, however, this relationship is opposite in rural

175 areas, where young rural dwellers are less aware of climate change [10]. Arguably, in

176 rural areas agricultural experience gained with time provides knowledge about changes

177 in the climate cycle [42,50]. Finally, race only appears to have a consistent influence

178 on climate change beliefs in North America, where non-white individuals show more

179 concern and a higher risk perception than whites, a phenomenon known as white-male

180 effect [9,46,51]. Nevertheless, this effect is not generally supported by cross-country

181 evidence [10]. In conclusion, evidence about demographic effects on CCBs remains

182 elusive, and these effects seem largely eclipsed by the aforementioned information

183 approaches [10,19].

184

185   The discussion above identifies multiple factors that shape individual climate change

186   beliefs. However, little research has included African countries in their analysis

187   [11,12,50]. Those that do often include a limited number of predictors, which in turn,

188   limit the understanding of what shapes CCBs in the African continent. This study aims

189   to fill these gaps within the literature.

190

191   Research design

192   Methods

193   We analyse what shapes climate change beliefs in Africa using a random forest

194   approach [52]. Random forest is a machine-learning approach that uses non-parametric

195   recursive partitioning to produce models with high predictive accuracy [11,53]. It can

196   handle high-dimensional (large number of predictors) multilevel datasets with high-

197   level interactions and non-linear relations [54], so it is ideal for our dataset. For each

198   dependent variable, we grow a classification random forest composed of 1,000 trees

199   with a minimum node size of five. We use the *ranger* package in R, which is particular

200   suit for high-dimensional data and offers a fast implementation that minimizes

201   computational burden[55]. Its optimized computation and parallelized processing are

202   most suitable for our high-dimensional and extensive dataset. To the best of our

203   knowledge, this is the first study to jointly combine survey and climate data at the

204   second administrative level to explore what shapes climate change beliefs across 33

205   African countries.

206

207 Despite its advantages, random forest models are not easily interpretable on their own.

208 To interpret them, we use some additional measures. First, we compute the variable

209 importance measure, which ranks predictors by their predictive power (including direct

210 and indirect effects on the dependent variable). We use the corrected Gini method to do

211 so, because it shows no bias towards predictors with more classes, in contrast to the

212 impurity importance, at a similar computational cost [56]. This measure shows which

213 are the most important factors that shape CCBs. Second, we use partial dependence

214 plots to illustrate the magnitude and direction of the direct effects of significant

215 predictors. Partial dependence plots work like marginal effects in logistic regression

216 models: they predict responses for each level of the predictor while holding constant

217 the rest of the variables. The code and data used for this analysis is available online.

218

219 **Data**

220 **Dependent variables**

221 Data for our dependent variables are largely drawn from the Afrobarometer, which uses

222 a clustered, stratified (by administrative units and by urban or rural location), multi-

223 stage and area probability sampling design[7]. We particularly use data from the

224 seventh round of surveys (R7), conducted between 2016 and 2018 —the first time the

225 Afrobarometer included climate change-related questions. The dataset is comprised of

226 more than 45,000 observations from 33 African countries. This data is georeferenced

227 at second-order political boundaries (see S1 for a detailed variable speciation). This

228 allows us to overlay our climate variables to the same areas where the Afrobarometer

229 surveys were conducted.

230

231 We include five different dichotomous specifications for climate change beliefs Our

232 first specification, climate change *awareness,* measures whether survey respondents

233 have heard about the existence or climate change or not. Second, we account for the

234 respondents' belief that *human activity* is the main cause behind the current changes

235 befalling the world's climate. Third, we are interested on whether respondents

236 developed a *risk perception* from a changing climate that is making life worse in their

237 country. Our final two specification examine respondent's beliefs on whether climate

238 change *needs to be stopped* and whether ordinary citizens can help mitigate against it—

239 a variable known in the literature as *self-efficacy*.

240

241 Independent variables

242 We include 67 independent variables from the Afrobarometer. We include 7 variables

243 to account for access to information, 33 for political ideology and participation, 4 for

244 religion, 10 for economic conditions, 9 for demographics, and 4 for agricultural

245 experience and perceptions. All variables are grounded on previous findings within the

246 literature on climate change beliefs. Descriptive statistics, their corresponding

247 Afrobarometer questions and coding scheme are included in the S1 online appendix.

248

249 Additionally, we include four climate variables to assess the impact of local climate

250 change on CCBs. Our first three variables are precipitation maximum and mean

251 temperature. Data is from the Climate Research Unit (CRU TS) 4.0 dataset [57]. The

252 time-series data is drawn from 0.5° x 0.5° gridded data. We generate our precipitation

253 and temperature anomalies for each second-level political boundaries by calculating the

254 monthly deviation from the long-term (1961-1990) mean for that month and dividing it

255 by the panel's standard deviation [58]. We then annualize these anomalies by averaging

256 the monthly anomalies of the 12 months before each respondent was surveyed.

257 Therefore, we end having long-term anomalies for precipitation and maximum and

258 mean temperatures, for the year before the survey was conducted. We then intersect our

259 climate anomalies over with the second-level political boundaries where each

260 georeferenced Afrobarometer survey was conducted. Once we overlay our data, we

261 assign both the maximum and mean values of temperature and precipitation for each

262 region. We assign both the maximum value as well as the mean to examine if people's

263 beliefs are shaped by climate extremes or gradual changes.

264

265 To improve the robustness of our analysis, we also include a measurement of drought

266 for each administrative unit. We employ the 3-months standardized precipitation

267 evapotranspiration index (SPEI-3) from the SPEI 2.6 database [59]. Since the SPEI is

268 also presented as 0.5º x 0.5º gridded data, the data extraction procedure is identical to

269 the other climate variables. Given that the SPEI data is already presented as deviations

270 from a long-term baseline, to annualize our variables we take the average of the 12

271 previous months from the date the survey was conducted.

272

273

Results and discussion

275 In this section we present and discuss the empirical results from our random forest

276 analysis on what shapes climate change beliefs in Africa. Some common patterns

277 emerge from the analysis among the results from our five different models. We discuss

278 these patterns by order of statistical relevance to each outcome variable. Fig 1 shows

279   the main results for climate change awareness, belief anthropogenic climate change,

280   and climate change-related risk perception.

281   [FIG 1]

282   **Fig 1. Key predictors for climate change awareness, anthropogenic climate change, and climate**

283   **change-related risk perception.**

284   Top 15 predictors of climate change awareness (A) (69.4% prediction accuracy), human causation of

285   climate change (C) (63.4% prediction accuracy), and risk perception (E) (73.9% prediction accuracy).

286   (B) Partial dependence plot (PDP) of gender (*female*), access to online news (*news tech*), being

287   favourable to one-party rule (*authoritarian*), and perceived agricultural conditions (*agric. cond.*) about

288   climate change awareness. (D) PDP of mean temperature anomalies (*temp. anom.*), precipitation

289   anomalies (*precip. anom.*), trust in institutions (*trust* institutions), and access to online news (*news tech*)

290   over belief in human causation of climate change. (F) PDP of belief in human causation of CC (*CC*

291   *human cause*), perceived severity of drought (*drought percep.*), perceived agricultural conditions (*agric.*

292   *cond.*) and being favourable to one-man rule (*authoritarian*) over climate change risk perception.

293

294   First, the importance of perceived agricultural conditions stands out. Respondents'

295   who perceive worsening agricultural conditions show greater awareness and perceived

296   risk, more support for stopping climate change, and are more likely to believe in

297   anthropogenic climate change. Indeed, Fig 1E shows that perceived agricultural

298   conditions are the main predictor for climate change risk perception. Arguably, the

299   importance of the agriculture sector in terms of employment —more than 50% of

300   employees across Sub-Saharan Africa work in agriculture— makes agriculture a strong

301   concern to African citizens [2]. Thus, perceiving how climate change is already

302   affecting agriculture may reduce its psychological distance. Our results suggest that for

303   Africans climate change is not a problem for *others* across space and time, but rather a

304   phenomenon that is happening *here* and *now* and it is affecting personally [60]. This

305   implies that policy makers should further highlight the global nature of climate change

306   and its overall negative impacts on agriculture to raise CCBs, impulse individual

307   adaptation, and mobilise public support.

308

309   Second, attributing climate change to human activity increases risk perception, support

310   for mitigation, and self-efficacy (Figs 1 and 2). If climate change is unnatural, it is

311   extraordinary and thus riskier. Also, if climate change is human induced, its impacts

312   can also be mitigated by human action. Besides, believing it is human caused can

313   increase personal responsibility and, therefore, induce corrective responses [5,61,62].

314   This points to the convenience of spreading and highlighting the human origin of

315   climate change to impulse behavioural changes and mitigation strategies in Africa.

316

317   [FIG 2]

318   **Fig 2. Key predictors of need to stop climate change and self-efficacy.**

319   Top 15 predictors of need to stop climate change (A) (79.5% prediction accuracy) and self-efficacy (C)

320   (74.1% prediction accuracy). (B) Partial dependence plot (PDP) of mean temperature anomalies (*temp.*

321   *anom.*), belief in human causation (*CC human cause*), perceived worsening of agricultural conditions

322   (*agric. cond.*), and perceived risk from climate change (*CC risk percep.*) over need to stop climate

323   change. (D) Partial dependence plot of mean temperature anomalies (*temp. anom.*), belief in human

324   causation (*CC human cause*), perceived risk from climate change (*CC risk percep.*) and being favourable

325   to one-man rule (*authoritarian*) over self-efficacy

326

327

328   Fig 2 shows that risk perception is positively associated with self-efficacy and the need

329   to stop climate change. While some previous studies in the United States and United

330   Kingdom point to fatalism or climate despair [3,63,64] —where higher perceived risks

331   discourage self-efficacy and action support, the opposite seems to be true for Africa.

332   This could be the result of motivated control —feeling more empowered in order to feel

333   safe from a greater risk [65], or increased personal concern with climate change [66].

334   Either way, explaining why climate change is a critical risk for Africa will not

335   discourage the African public, but it might encourage policy support and personal

336   action [5].

337

338   As suggested by previous research, access to information and education are good

339   indicators for believing in anthropogenic climate change and being aware of it.

340   However, both indicators show a slight negative effect when it comes to more affective

341   dimensions such as risk perception or believing climate change must be stopped. The

342   limited emotional salience of climatic information compared with personal experience

343   or motivated reasoning may account for this divergence [30–32]. Nevertheless, it must

344   be noted that the importance of information is contingent on language (Fig 1D). Not

345   speaking French, English or Portuguese hinders the understanding of climate

346   terminology, which frequently lacks accurate translations to African languages [17].

347   Greater efforts should be made to translate the nature, causes, and impacts of climate

348   change to African languages.

349

350   Local changes in climate conditions are among the most important predictors across all

351   models. Overall, they are more important than access to news, political ideology, or

352   demographics (see Table 1). Previous research finds that *perceived* changes in local

353   temperatures were the most important predictor of climate risk perception in some

354   African countries [11]. Building upon these findings, this study shows that *actual* long-

355   term anomalies in temperature, rainfall, and drought at second-order boundaries do

356   more to shape individual climate change beliefs than the above mentioned. Attribute

357   substitution and emotional salience may explain the importance of personal experience

with local weather conditions for CCBs [30,40]. In fact, qualitative evidence suggests that some communities in Africa understand climate change not as a global phenomenon but a local one [17]. Therefore, local weather changes may be used to prime climate change and encourage mitigation and adaptation measures, but the link between those local changes and the global patterns of climate change should be highlighted.

Table 1. Direction of relation of key predictors to CCBs

	Awareness	Human causation	Risk perc.	Need to stop	Self-efficacy
Agric. conditions	+	+	+	+	
Human causation			+	+	+
Risk perception				+	+
Education level	+	+		+	+
Temp. anomaly	+	+	+	+	+
Online information	+	+			
Authoritarian	-		-		-
Lived poverty			+	+	
Gender (female)	-				

Predictors ordered by overall importance across models for the top 15 predictors.

Material conditions had previously been found to influence climate change beliefs [45]. According to the "finite pool of worry" hypothesis, worse material conditions limit CCBs, as they create more urgent and pressing concerns for individuals to worry about. However, across African countries poverty has significant positive effects on climate risk perception and the belief climate change must be stopped. In contrast to the finite

373   pool of worry hypothesis, households with fewer resources are the most concerned

374   about the present and future effects of climate change. Climate change is a close and

375   urgent concern for them, as their income and assets are the most vulnerable to climatic

376   risks [60,67].

377

378   Political ideology also has a significant impact on CCBs in Africa. Authoritarian and

379   intolerant ideologies lessen climate change awareness, risk perception, belief that it

380   must be stopped and self-efficacy. Authoritarian and hierarchical values have been

381   consistent and negatively linked to climate change beliefs in other regions of the world

382   [10]. Ideology influences what information people access, and how they process and

383   assimilate it [19–22]. Our findings imply that authoritarian individuals are more likely

384   to disregard climate change to justify their support for maintaining the status quo. These

385   findings also suggest that it would be convenient for policy makers to reshape

386   environmental discourses to better engage the authoritarian public. To do so,

387   environmental policy and individual action can be framed as patriotism, innovation, or

388   prosocial behaviour [68], and the focus of risk communication can be on the possible

389   effects of climate change on human security and public order [69] .

390

391   Like ideology, previous research has suggested that religion prompts motivated

392   reasoning, shaping thus CCBs. Overall, declaring oneself religious is mostly

393   insignificant to predict CCBs. However, we do observe some significant differences

394   across religions in Africa: Catholic and Orthodox Christians are more likely to believe

395   in the anthropogenic nature of climate change and that it must be stopped, while Sunni

396   Muslims shows the opposite trend. These findings illustrate the importance of actively

397 engaging religious leaders to communicate environmental messages, giving them the

398 tools for doing so effectively [17,28].

399

400 Finally, we find that demographic variables such as gender or race have some

401 importance for CCBs. We find an important gender gap for awareness, as well as

402 slightly negative effects for other dimensions of climate change beliefs. Women are

403 less likely to be aware of climate change, as previous case studies in Africa had

404 suggested [17,49,70]. In this case, differences in access to climate information do not

405 explain this gender gap, so further research should address this issue. Besides, we find

406 ethnicity to be related to risk perception and self-efficacy. Overall, Black Africans show

407 more concern and self-efficacy than other ethnic groups, among whom Arab Africans

408 are the less concerned. Therefore, we cannot talk about a "white male" effect [51]

409 because White Africans do not especially neglect risks (in contrast to Arab Africans)

410 nor women show more concern, rather the opposite. Finally, age and agricultural

411 experience are insignificant across all models, contradicting previous findings within

412 the literature [42,50].

413

414 **Conclusion**

415 There is a lack of consensus within the literature for what shapes climate change beliefs

416 and most studies conducted on this topic are usually limited to Western developed

417 nations. Our results show several relevant findings for what shapes climate change

418 beliefs across 33 African countries, using a large-*N* and high-dimensional dataset. First,

419 actual changes in local climate conditions are stronger predictors of climate change

420 beliefs in Africa than access to information, political ideology, or demographics across

421 different model specifications. Similarly, worsening perceptions of climate conditions

422   for agriculture is a strong predictor for all five dimensions for climate change beliefs.

423   Second, our analysis also reveals that authoritarian and intolerant ideologies overall

424   decrease climate change beliefs. Third, not speaking French, English or Portuguese

425   hinders the understanding of climate beliefs. Finally, there is a small but important

426   gender gap across different dimensions. Combined, our results suggest that more

427   different causal mechanisms underly climate change beliefs than previously assumed

428   [11]. We strongly believe that in-depth case-studies should further examine the

429   complex causal mechanisms that shape climate change beliefs across different African

430   countries to improve our understanding in order to implement the best mitigation and

431   adaptation strategies for the region.

432

Acknowledgements

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Supporting information

S1 File. Operationalization. Descriptive statistics, coding, and corresponding questions from the Afrobarometer of all variables.