1   **Original Manuscript**

2   [**What shapes climate change perceptions in Africa? A random forest approach**]

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8   **Abstract**

9   Climate change perceptions are fundamental for adaptation and environmental policy

10   support. Although Africa is one of the most vulnerable regions to climate change,

11   little research has focused on how climate change is perceived in the continent. Using

12   random forest methodology, we analyse Afrobarometer data (N = 45,732), joint with

13   climatic data, to explore what shapes climate change perceptions in Africa. We

14   include 5 different dimensions of climate change perceptions: awareness, belief in its

15   human cause, risk perception, need to stop it and self-efficacy. Results indicate that

16   perceived agriculture conditions are crucial for perceiving climate change. Country-

17   level factors and long-term changes in local weather conditions are among the most

18   important predictors. Moreover, education level, access to information, poverty,

19   authoritarian values, and trust in institutions shape individual climate change

20   perceptions. Demographic effects -including religion- seem negligible. These findings

21   suggest policymakers and environmental communicators how to frame climate

22   change in Africa to raise awareness, gather public support and induce adaptation.

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Introduction

The importance of climate change perceptions

Current projections assess that climate change (CC) will likely have "severe, irreversible and pervasive impacts for people and ecosystems" [1]. Urgent mitigation and adaptation strategies are needed at both the social and individual level. However, these measures are not being implemented rapidly enough. Apart from material and institutional constraints, some cognitive barriers hinder adaptation [2,3]. Among those cognitive barriers, climate change perceptions (CCP) stand out [4]. Therefore, it is fundamental to understand how individuals perceive climate change in order to induce behavioural changes and gather policy support [5,6].

Despite the strong scientific consensus on the existence and projected impacts of CC, a relevant fraction of the public deny its existence, underestimate its risks or believe it is a natural process that cannot be stopped [7]. In contrast with the scientific consensus, there is a huge variance among individual and public CCP. Previous research has established a wide array of factors that explain this divergence [8–10].

What shapes CCP in the Global North

Reasonably, having access to information is fundamental for being aware of CC and its causes [11]. Likewise, higher levels of education have been associated with greater awareness and concern [12,13]. However, other studies find that information, scientific literacy or education level are not correlated to CCP [14–16]. Some factors mediate how people access, process and assimilate information. One of those factors is ideology, which influences CCP in various ways. Ideology affects the choice of information sources, as individuals seek those that match and reinforce their previous

51   beliefs [17,18]. But even when they are presented with the same information, it is

52   processed differently depending on ideology. For instance, Hart and Nisbet [16]

53   presented the same piece about possible CC impacts on health to US Democrats and

54   Republicans. It increased CC risk perceptions and policy support among Democrats,

55   but it resulted in a "boomerang effect" among Republicans, who left more convinced

56   of their previous scepticism. This has been explained in terms of ideologically

57   motivated reasoning [15]. To reduce cognitive dissonance and peer pressure, novel

58   information about CC is processed and assimilated to match previous beliefs, even

59   when they conflict. Thus, ideology shapes how individuals perceive climate change

60   [12,19].

61

62   Given the statistical nature of CC and the psychological distance to it, information

63   about it does not usually elicit strong emotional responses, hindering its perception

64   [9,20,21]. In contrast, personal experience of local weather is sensually and

65   emotionally salient, so it can irrationally substitute rigorous but abstract scientific

66   information [3,22–24]. Personal experience of extreme climate events such as

67   hurricanes, floods or extreme temperatures increases CCP [25–27]. But the effect of

68   personal experience also holds for short- and long-term temperature anomalies

69   [24,28–31]. Therefore, personal experience of local weather is another factor that

70   influences CCP.

71

72   Information about CC might be accessed, processed, and assimilated through biased

73   processes, but it can also be directly ignored. The psychological distance of CC

74   contrasts with daily material concerns, relegating CC to irrelevance. In other words,

75   people may have a "finite pool of worry" which may be full of more

76 immediate concerns than CC, limiting its perception [8]. In line with this hypothesis,

77 GDP and GDP growth, unemployment and household income have been related to

78 CCP [11,13,32–34].

79

80 Finally, religion has been found to have a significant influence on CCP. Like political

81 ideology, religion can push people to group-thinking and motivated reasoning. For

82 instance, an individual who believes in an almighty God is more likely to attribute CC

83 to God's will rather than to human activity. Attending religious services and having

84 religious beliefs have both been found to affect CCP [30,35–38]. Apart from religion,

85 other demographics such as gender, race or age do not have consistent effects on CCP

86 [10].

87

88 *CCP in Africa*

89 The projected impacts of climate change are unevenly distributed across regions, and

90 Africa will be among the most affected [1]. Although adaptation is especially urgent

91 in Africa, little research has focused on the cognitive barriers to adaptation in the

92 continent. For instance, just 3% of studies meta-analysed by Van Valkengoed and

93 Steg [4] and 1.7% of those meta-analysed by Hornsey et al. [10] were conducted in

94 Africa. As predictors of CCP vary widely across regions [11,13], the applicability of

95 non-African research is, at least, questionable.

96

97 Research on CCP in Africa is scarce. Beyond the local case-study level [32,39], there

98 are few cross-African studies [11,13]. Moreover, these studies rely on the same

99 surveys (Gallup Poll 2007-2010) and, due to data constraints, just include a handful of

100 CCP predictors. For instance, significant predictors such as ideology or local weather

5

101 changes are not included in the analysis. Building upon that research, this study

102 explicitly addresses what shapes climate change perceptions in Africa. The topic is

103 approached holistically, as the importance of education, access to information,

104 ideology, experience of local weather, religion, demographics, and economic

105 variables (among others) to predict individual CCP are assessed simultaneously. This

106 analysis offers a clear picture of how CCP are constructed in Africa.

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108

109 **Materials and Methods**

110 *Datasets*

111 For extracting CCP variables and most predictors, we use the 7th round of the

112 Afrobarometer [7], conducted between 2016 and 2018. It comprises more than 45,000

113 observations from 34 African countries. Except for some small countries, it is

114 georeferenced at the second administrative level (see SI 1). This allows a high

115 resolution for relating CCP to climatic variables, a link unstudied beyond the first

116 administrative level across Africa.

117

118 For constructing local weather variables, we use two different datasets. First, we

119 obtain monthly precipitation, maximum and mean temperature for the period 1961-

120 2019 from the CRU 4.0 dataset [40]. Second, we complement those variables with the

121 standardized precipitation evapotranspiration index (SPEI), which robustly measures

122 drought, from the SPEI 2.6 database [41]. Both datasets offer a spatial resolution of

123 0.5º x 0.5º.

124

125

126 *Measures*

127 CCP are the dependent variables in this study. Specifically, we include the following

128 CCP variables. *CC awareness* accounts for the question "Have you heard about

129 climate change or haven't you had the chance to hear about this yet?" (1=yes, 0=no).

130 Those aware were asked the following questions. *Human cause*: "People have

131 different ideas about what causes climate change. What about you, which of the

132 following do you think is the main cause of climate change, or haven't you heard

133 enough to say?" (1=human cause, 0=other). *CC risk perception*: "Do you think

134 climate change is making life in [your country] better or worse, or haven't you heard

135 enough to say?" (0=better/the same, 1=worse). *Need to stop CC*: "Do you think that

136 climate change needs to be stopped?" (0-1). Those who believed CC needs to be

137 stopped were asked a last question. *Self-efficacy*: "How much do you think that

138 ordinary [citizens] can do to stop climate change?" (1=a little bit/a lot, 0=nothing).

139

140 For climatic variables, we first superpose the CRU and SPEI data grids on the GADM

141 second administrative level map of Africa. As some administrative areas intersect

142 with more than one pixel, we aggregate their values using two alternative functions:

143 mean and maximum. Further analysis is made with mean values, but it is also robust

144 to the use of maximum values across grids. Second, we compute the long-term

145 anomalies for temperature and precipitation data (SPEI is already standardised against

146 a long-term baseline). We use annual values (the year before the individual was

147 surveyed) standardised against the 1961-1990 baseline.

148

149 Additionally, 67 potential correlates to CCP are extracted from the Afrobarometer.

150 They account for ideology, economic conditions, demographics, access to

151 information, education, intention to migrate or agricultural perceptions, among others.

152 As collinearity can bias variable importance measures in Random Forest [42], we

153 conduct a Principal Component Analysis. This creates orthogonal linear combinations

154 of highly correlated variables, reducing thus the problem of collinearity. Only

155 combinations with a Cronbach's alpha higher than 0.7 are kept, a conservative level

156 often used in the field [14,38]. Adding Afrobarometer and climatic variables, we have

157 51 potential predictors of CCP. For all independent variables, missing values are

158 handled using non-parametric imputation with the R package *missRanger* [43].

159

160 *Methods*

161 We analyse what shapes climate change perceptions in Africa using Random Forest

162 methodology [44]. This machine-learning approach uses non-parametric recursive

163 partitioning to produce models with high predictive accuracy [11]. It can handle high-

164 dimensional (with a large number of predictors) multilevel datasets with high-level

165 interactions and non-linear relations [42], so it is ideal for our dataset. For each

166 dependent variable, we grow a random forest composed of 1,000 trees with a

167 minimum node size of 5, using the *ranger* package in R [45]

168

169 Despite its advantages, Random Forests are not easily interpretable on their own. To

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

171 importance measure, that ranks predictors by their predictive power (including direct

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

173 do so, because it shows no bias towards predictors with more classes, in contrast to

174 the permutation method [46]. This measure shows which are the most important

175 predictors that shape CCP but does not assess whether they are significant or not.

176   Second, we use the Altmann permutation method to compute p-values and test

177   predictor significance, using 100 permutations for each forest, as recommended by the

178   authors [47]. We use the *ranger* package in R [45] to compute those measures.

179   Finally, we use partial dependence plots to illustrate the magnitude and direction

180   of the direct effects of significant predictors. Partial dependence plots work like

181   marginal effects in logistic regression models: they predict responses for each level of

182   the predictor while holding the rest of the variables constant. We use the

183   *randomForestSRC* package for generating these plots [48].

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185

186   **Results**

187   *CC awareness*

188   Fig 1 presents the most important predictors for being aware of climate change in

189   Africa. Education level and the frequency of access to online news (via the internet

190   and social media) are fundamental for CC awareness. Both have positive effects.

191   Perceiving that climate conditions for agricultural production (*agric. cond.*) have

192   changed in the last decade is positively related to CC awareness, but the effect is

193   higher for perceived worsening (positive values), as Fig 1B illustrates. Ideology and

194   interest in politics are also important covariates. Authoritarians (being favourable to

195   one-party rule) significantly decreases awareness, while talking about politics has the

196   opposite effect. We find a gender gap for awareness, as women are about 5.4% less

197   likely to know about climate change. Long-term changes in weather conditions at the

198   second administrative level are important predictors of being aware of CC. Higher

199   temperatures, less rainfall, and more severe droughts (SPEI) are associated with

200   higher CC awareness, but their direct effects are of less magnitude than education,

9

201 information, or ideology. Speaking a western language has a significant impact of

202 almost +4% on CC awareness. Regarding religion, we find mixed results: while being

203 religious (any denomination) has a positive relation, supporting the rule of religious

204 law reduces CC awareness.

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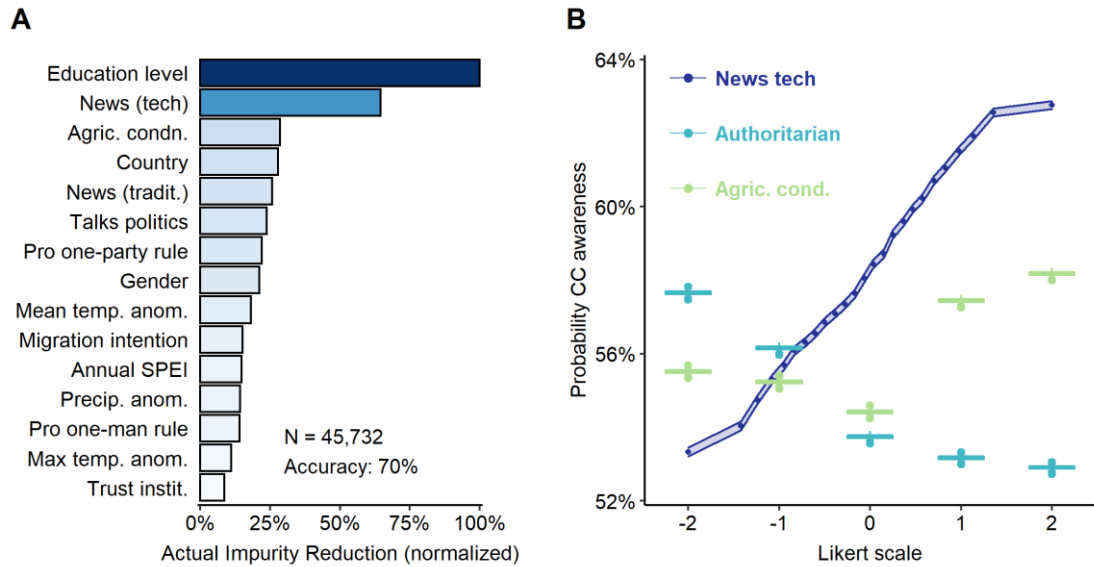
Fig 1. Key predictors of climate change awareness.

(A) Top 15 predictors of CC awareness. (B) Partial dependence plot of direct effects of access to online news (*news tech*), being favourable to one-party rule (*authoritarian*) and perceived agricultural conditions (*agric. cond.*)

211

Belief in human cause

Fig 2 shows the most important predictors of believing in the human causation of CC.

Local weather changes are the main predictors, above education, access to

information or ideology. A 1 SD rise of mean temperatures is associated with almost a

6% increase in the belief that CC is caused by human action, as illustrated in Fig 2B.

Changing precipitations have the opposite effect but with less magnitude. Education

level and access to online information also have important positive effects over the

belief in the human causation of CC. Trust in institutions and authoritarian and

220   intolerant —towards other religions, ethnic groups, and nationalities— ideologies are

221   associated with reduced belief. Agricultural and drought perceptions remain important

222   for predicting this dimension of CCP. Finally, being religious is insignificant for

223   predicting the belief in the anthropogenic nature of CC.
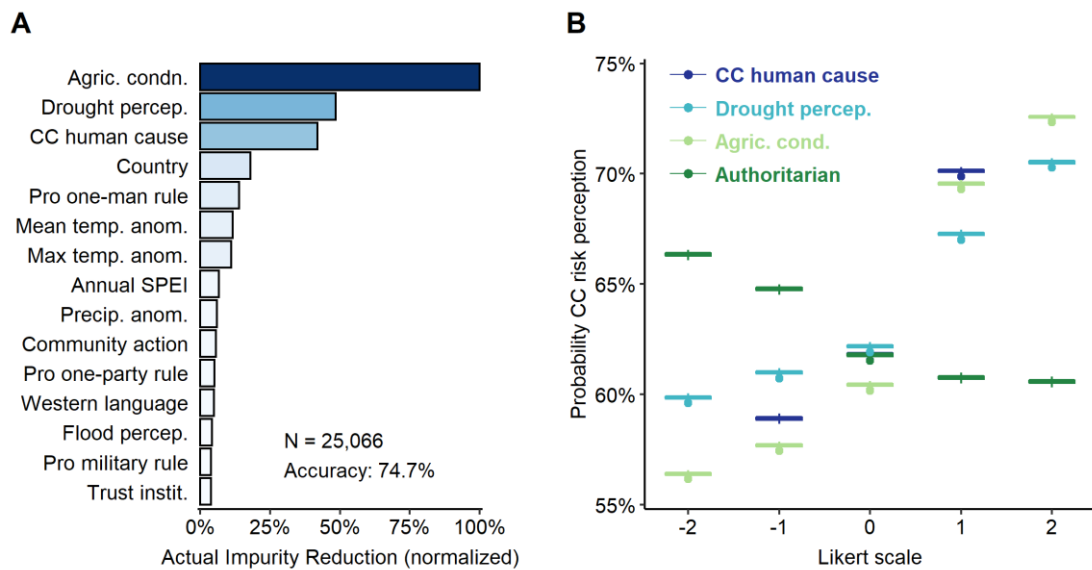
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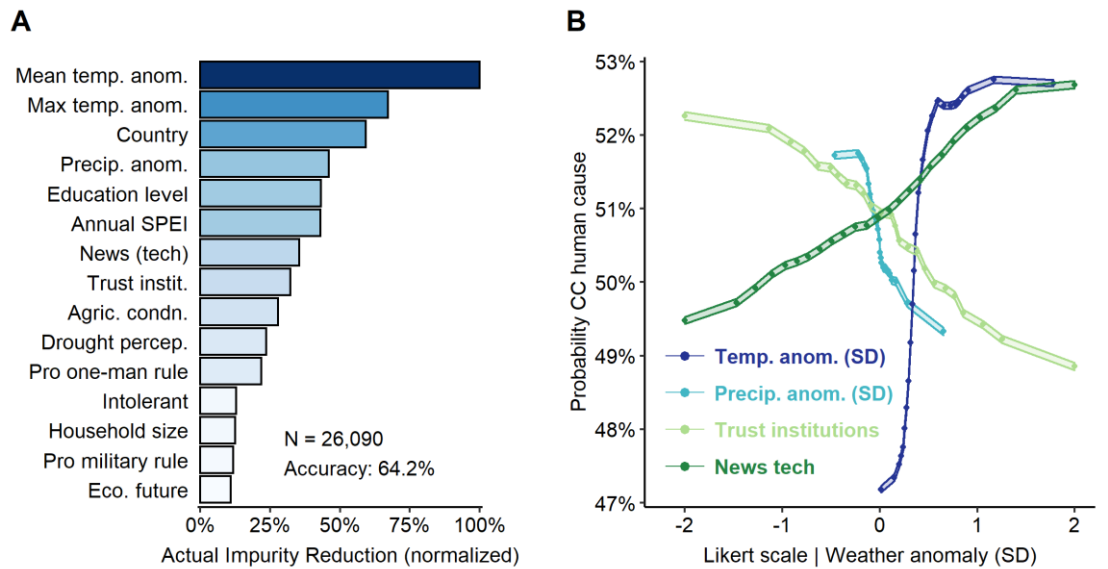
226 **Fig 2. Key predictors of belief in human causation of climate change.**

227 (A) Top 15 predictors of belief in human causation of CC. (B) Partial dependence plot of direct effects

228 of mean temperature anomalies (*temp. anom.*), precipitation anomalies (*precip. anom.*), trust in

229 institutions (*trust* institutions) and access to online news (*news tech*).

230

231 *CC risk perception*

232 The key predictors of CC risk perceptions are presented in Fig 3. Perceived

233 agricultural conditions, followed by drought perception, are crucial for assessing the

234 risks CC poses to citizens in Africa. Those who perceive better agricultural conditions

235 are less likely to consider CC as a risk than those who perceive no changes, whereas

236 those who perceive worse conditions are significantly more likely. Believing in the

237 human cause of CC is positively related to risk perceptions. Local weather changes

238 maintain their importance. Temperature anomalies have a positive effect, while the

239   effect is the opposite for precipitation. Authoritarianism —supporting one-man, one-

240   party or military rule, is negatively related to perceived risks. Again, trust in

241   institutions is associated with reduced risk perception. Poverty, on the other hand,

242   shows the opposite direction: households with fewer resources perceive greater risks

243   from CC than wealthier ones, both in urban and rural areas. Finally, speaking a

244   western language reduces risk perception by almost 6%.

245

246

247   **Fig 3. Key predictors of climate change risk perception.**

248   (A) Top 15 predictors of CC risk perception. (B) Partial dependence plot of direct effects of belief in

249   human causation of CC (*CC human cause*), perceived severity of droughts (*drought percep.*), perceived

250   agricultural conditions (*agric. cond.*) and being favourable to one-man rule (*authoritarian*).

251

252   *Need to stop CC*

253   As Fig 4 shows, CC risk perceptions and the belief in human causation of CC are the

254   top predictors of the need to stop it. Both have important positive impacts on the

255   belief that action is needed, with a maximum effect of more than 15% for risk

256   perception and 12% for human cause. Like other dimensions of CCP, support for

257   action against CC is positively related to worse agricultural conditions and higher

258   temperature anomalies, and negatively to rainfall anomalies. Individuals with fewer

259   resources and with democratic values are more convinced of the need to stop CC,

260   whereas authoritarians and western languages speakers are less convinced. Perceived

261   corruption has a non-monotonous effect. Both higher and lower perceived corruption

262   levels lead to decreased action support, while moderate perceptions lead to higher

263   probabilities.

264
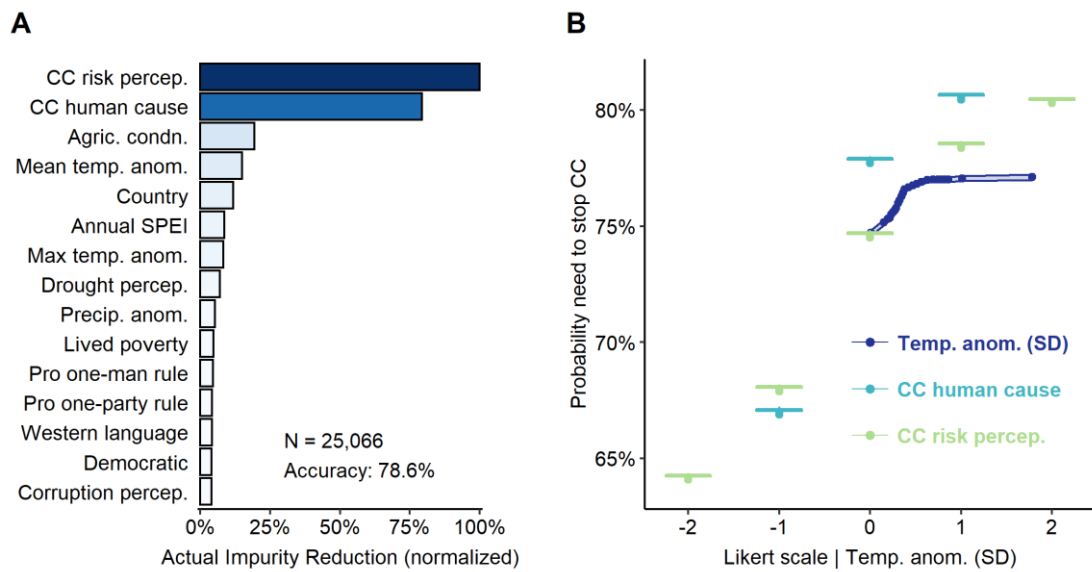
266   **Fig 4. Key predictors of believing climate change must be stopped.**

267   (A) Top 15 predictors of need to stop CC. (B) Partial dependence plot of direct effects of mean

268   temperature anomalies (*temp. anom.*), belief in human causation of CC (*CC human cause*), and

269   perceived risk from CC (*CC risk percep.*) on the need to stop CC.

270

271   *Self-efficacy*

272   Fig 5 present the key predictors of self-efficacy — the perceived effectiveness of

273   ordinary African citizens' environmental action. Logically, believing that CC is

274   caused by human action is the most important covariate of thinking that human action

275   can mitigate its impacts. Far behind it, we find temperature anomalies, education

276   level, CC risk perceptions and access to information, which also increase self-

13

277 efficacy. Again, intolerant and authoritarian values are associated with reduced CCP.

278 Households with fewer resources feel less empowered to fight against CC. Trust in

279 institutions and speaking a western language increase self-efficacy. Finally,

280 religiousness has a positive effect of about 1.5%.

281

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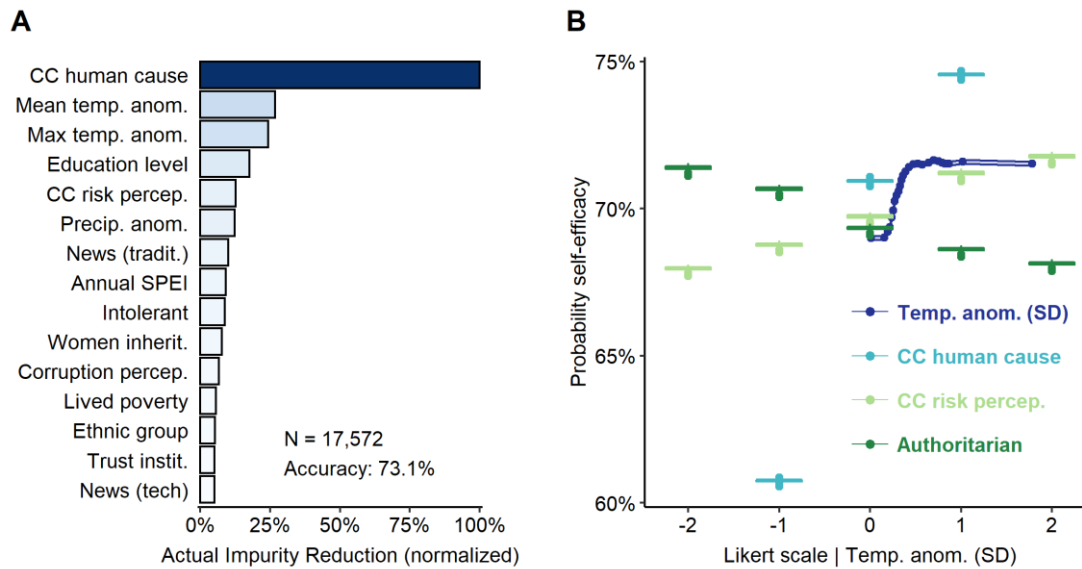
283 **Fig 5. Key predictors of environmental self-efficacy.**

284 (A) Top 15 predictors of self-efficacy. (B) Partial dependence plot of direct effects of mean

285 temperature anomalies (*temp. anom.*), belief in human causation of CC (*CC human cause*), perceived

286 risk from CC (*CC risk percep.*) and being favourable to one-man rule (*authoritarian*) on self-efficacy.

287

288

289 **Discussion**

290 These results show what shapes climate change perceptions (CCP) in Africa.

291 Although each dimension of CCP has its unique set of predictors, some common

292 patterns emerge from the analysis. First, the importance of perceived agriculture

293 conditions stands out. Those individuals who perceive worsening agriculture

294 conditions show higher awareness and perceived risk, more support for stopping CC

295 and are more likely to believe it is caused by human action. The huge importance of

14

296 the primary sector in terms of employment and export revenues makes agriculture a

297 close and great concern to African citizens [49]. Thus, perceiving how CC is already

298 affecting agriculture may reduce the psychological distance to CC. It is not a

299 problem for "others" in space and time, it is happening here and now [50]. However,

300 this relation also poses a challenge. CC has uneven impacts, and agriculture in some

301 regions may benefit from changes in local climate [49]. Those who perceive those

302 improvements are less likely to perceive CC and support or take environmental

303 action. More efforts should be made to highlight the global nature of climate change

304 and its overall negative impacts. These findings suggest environmental discourse in

305 Africa could focus on the negative impacts of CC on agriculture to raise CCP,

306 impulse individual adaptation and mobilise public support.

307

308 Second, attributing climate change to human activity increases risk perceptions,

309 support for mitigation, and self-efficacy. If CC is *unnatural*, it is *extraordinary* and

310 thus riskier, but also stoppable. Besides, attributing the cause of CC to human action

311 might increase personal responsibility and, therefore, induce corrective responses

312 [51,52]. This points to the convenience of spreading and highlighting the human

313 origin of CC to impulse behavioural changes and mitigation strategies in Africa.

314

315 Risk perceptions are positively associated with self-efficacy and the need to stop CC.

316 While some previous studies in the US and UK pointed to fatalism or climate despair

317 [2,53,54]—where higher risks discourage self-efficacy and action support, the

318 opposite seems to be true for Africa. This could be the result of motivated control

319 —feeling more empowered to feel secure from a greater risk [55], or increased

320 personal concern with CC [56]. Either way, framing CC as a critical risk will not

15

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

322   action [4].

323

324   Local weather conditions are among the most important predictors in all models, and

325   on average they are more important than education, access to information or ideology.

326   Previous research had found that *perceived* changes in local temperature were the

327   most important predictor of CC risk perception in some African countries [11].

328   Building upon it, this study shows that *actual* long-term anomalies in temperature and

329   rainfall at the second administrative level predict individual CCP across various

330   dimensions. Attribute substitution and emotional salience may explain the importance

331   of personal experience with local weather conditions for CCP [9,24]. Besides,

332   qualitative evidence suggests that some communities in Africa understand climate

333   change not as a global but a local phenomenon [35]. Therefore, local weather changes

334   may be used to prime CC and encourage mitigation and adaptation, but the link

335   between those local changes and the global nature of CC should be highlighted.

336

337   Information and education have great predictive power for being aware of CC and

338   believing it has a human origin, the most analytical dimensions of CCP. On the other

339   hand, they have less predictive power for more affective dimensions, such as risk

340   perception or the need to stop CC. The limited emotional salience of CC information

341   compared with personal experience or motivated reasoning might account for this

342   divergence [9,20,21]. Nevertheless, the importance of information is contingent on

343   language. Not speaking French, English or Portuguese hinders understanding climate

344   terminology, which frequently lacks accurate translations to African languages [35].

16

345   Greater efforts should be made to translate to African languages the nature, causes

346   and effects of CC.

347

348   Material conditions had previously been found to influence CCP, mainly by the

349   mechanism known as the "finite pool of worry" [8]. According to it, worse material

350   conditions limit CCP, as they create more urgent and pressing concerns to worry

351   about. However, poverty has significant positive effects on risk perceptions and the

352   need to stop CC across African countries. In contrast with the finite pool of worry

353   hypothesis, poorer households are the most worried about the present and future

354   effects of climate change. Their income and assets are the most vulnerable to climatic

355   risks, so CC is an urgent concern for them [50,57].

356

357   Ideology has a significant impact on CCP in Africa. Authoritarian and intolerant

358   ideologies are related to reduced CC awareness, belief in its human origin, risk

359   perceptions, the need to stop CC and self-efficacy. These values have been consistent

360   and negatively linked to CCP in other regions of the world [10]. Ideology influences

361   what information people access, and how they process and assimilate it [15–19].

362   Authoritarians, through these mechanisms, disregard CC to justify their support for

363   maintaining the status quo. These findings suggest it could be convenient to shape CC

364   discourse to engage the authoritarian public. To do so, environmental discourse can

365   frame policy and individual action as patriotism, innovation, or prosocial behaviour

366   [58], and focus risk communication on the possible effects of CC on migration,

367   security and public order

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17

369   Political institutions play a crucial role in informing the public about CC and

370   developing and implementing large-scale adaptation strategies. Therefore, trusting

371   institutions has been found to reduce CC risk perceptions and increase policy support

372   [6,59]. In Africa, trusting institutions shows a distinct pattern. It is associated with

373   reduced CC awareness, belief in its human cause and risk perceptions. While the

374   relation to risk perception is logical, the negative effect of trust on awareness and

375   belief in human causation is surprising. Further research should address the possible

376   mechanisms behind these findings.

377

378   Demographic variables such as gender, age or race have trivial overall importance.

379   We only find an important gender gap for CC awareness. Women are less likely to be

380   aware of climate change, as previous case studies in Africa had suggested [35,60].

381   Except for that, demographics are not among the most important predictors, in

382   line with anterior research [10,11,13]. Moreover, although religion has been found to

383   shape CCP in other settings [37,38], we find religion and religiousness to be mostly

384   insignificant to predict CCP in Africa.

385

386   Urgent action is needed to limit the impacts of CC on ecosystems, economies, and

387   political institutions in Africa. Knowing what shapes individual climate change

388   perceptions across the continent contributes to the endeavour of raising awareness and

389   policy support and encouraging self-efficacy and adaptive behaviour.

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395
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