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[**What shapes climate change perceptions in Africa: a random forest approach**]

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**Abstract**

[Climate change perceptions are fundamental for adaptation and environmental policy support. Although Africa is one of the most vulnerable regions to climate change, little research has focused on how climate change is perceived in the continent. Using random forest methodology, we analyse Afrobarometer data (N = 45,732), joint with climatic data, to explore what shapes climate change perceptions in Africa. We include 5 different dimensions of climate change perceptions: awareness, belief in its human cause, risk perception, need to stop it and self-efficacy. Results indicate that perceived agriculture conditions are crucial for perceiving climate change. Country-level factors and long-term changes in local weather conditions are among the most important predictors. Moreover, education level, access to information, poverty, authoritarian values and trust in institutions shape individual climate change perceptions. Demographic effects -including religion- seem negligible. These findings suggest policy makers and environmental communicators how to frame climate change in Africa to raise awareness, gather public support and induce adaptation.]

**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 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]. There are some factors that 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 beliefs [17,18]. But even when they are presented with the same information, it is processed differently depending on ideology. For instance, Hart and Nisbet [16] presented the same piece about possible CC impacts on health to US Democrats and Republicans. It increased CC risk perceptions and policy support among Democrats, but it resulted in a “boomerang effect” among Republicans, who left more convinced of their previous scepticism. This has been explained in terms of ideologically motivated reasoning [15]. To reduce cognitive dissonance and peer-pressure, novel information about CC is processed and assimilated so as to match previous beliefs, even when they conflict. Thus, ideology shapes how individuals perceive climate change [12,19].

Given the statistical nature of CC and the psychological distance to it, information about it does not usually elicit strong emotional responses, hindering its perception [9,20,21]. In contrast, personal experience of local weather is sensually and emotionally salient, so it can irrationally substitute rigorous but abstract scientific information [3,22–24]. Personal experience of extreme climate events such as hurricanes, floods or extreme temperatures increase CCP [25–27]. But the effect of personal experience also holds for short- and long-term temperature anomalies [24,28–31]. Therefore, personal experience of local weather is another factor that influences CCP.

Information about CC might be accessed, processed and assimilated through biased processes, but it can also be directly ignored. The psychological distance of CC contrasts with daily material concerns, relegating CC to irrelevance. In other words, people may have a “finite pool of worry" which may be full of more

immediate concerns than CC, limiting its perception [8]. In line with this hypothesis, GDP and GDP growth, unemployment and household income have been related to CCP [11,13,32–34].

Finally, religion has been found to have a significant influence on CCP. Like political ideology, religion can push people to group-thinking and motivated reasoning. For instance, an individual who believes in an almighty God is more likely to attribute CC to God's will rather than to human activity. Attending religious services and having religious beliefs have both been found to affect CCP [30,35–38]. Apart from religion, other demographics such as gender, race or age do not have consistent effects on CCP [10].

*CCP in Africa*

The projected impacts of climate change are unevenly distributed across regions, and Africa will be among the most affected [1]. Although adaptation is especially urgent in Africa, little research has focused on the cognitive barriers to adaptation in the continent. For instance, just 3% of studies meta analysed by Van Valkengoed and Steg [4] and 1.7% of those meta analysed by Hornsey et al. [10] were conducted in Africa. As predictors of CCP vary widely across regions [11,13], the applicability of non-African research is, at least, questionable.

Research on CCP in Africa is scarce. Beyond the local case-study level [32,39], there are few cross-African studies [11,13]. Moreover, these studies rely on the same surveys (Gallup Poll 2007-2010) and, due to data constraints, are able to include just a handful of CCP predictors. For instance, significant predictors such as ideology or local weather changes are not included in the analysis. Building upon that research, this study explicitly addresses what shapes climate change perceptions in Africa. The topic is approached holistically, as the importance of education, access to information, ideology, experience of local weather, religion, demographics and economic variables (among others) to predict individual CCP are assessed simultaneously. This analysis offers a clear picture of how CCP are constructed in Africa.

**Materials and Methods**

*Datasets*

For extracting CCP variables and most predictors, we use the 7th round of the Afrobarometer [7], conducted between 2016 and 2018. It comprises more than 45,000 observations from 34 African countries. Except for some small countries, it is georeferenced at the second administrative level (see SI 1). This allows a high resolution for relating CCP to climatic variables, a link unstudied beyond the first administrative level across Africa.

For constructing local weather variables, we use two different datasets. First, we obtain monthly precipitation, maximum and mean temperature for the period 1961-2019 from the CRU 4.0 dataset [40]. Second, we complement those variables with the standardized precipitation evapotranspiration index (SPEI), which robustly measures drought, from the SPEI 2.6 database [41]. Both datasets offer a spatial resolution of 0.5º x 0.5º.

*Measures*

CCP are the dependent variables in this study. Specifically, we include the following CCP variables. *CC awareness* accounts for the question “Have you heard about climate change or haven't you had the chance to hear about this yet?” (0-1). Those aware were asked the following questions. *Human cause*:“People have different ideas about what causes climate change. What about you, which of the following do you think is the main cause of climate change, or haven't you heard enough to say?” (1=human cause, 0=other). *CC risk perception*: “Do you think climate change is making life in [your country] better or worse, or haven't you heard enough to say?” (1=much better, 5=much worse). *Need to stop CC*: “Do you think that climate change needs to be stopped?” (0-1). Those who believed CC needs to be stopped were asked the last question. Self-efficacy: “How much do you think that ordinary [citizens] can do to stop climate change?” (0=nothing, 1=a little bit/a lot).

For climatic variables, first we superpose the CRU and SPEI data grids on the GADM second administrative level map of Africa. As some administrative areas intersect with more than one pixel, we aggregate their values using two alternative functions: mean and maximum. Further analysis is made with mean values, but it is also robust to the use of maximum values across grids. Second, we compute the long-term anomalies for temperature and precipitation data (SPEI is already standardised against a long-term baseline). We use annual values (the year before the individual was surveyed) standardised against the 1961-1990 baseline.

Additionally, 67 potential correlates to CCP are extracted from the Afrobarometer. They account for ideology, economic conditions, demographics, access to information, education, intention to migrate or agricultural perceptions, among others. As collinearity can bias variable importance measures in Random Forest [42], we conduct a Principal Component Analysis. This creates orthogonal linear combinations of highly correlated variables, reducing thus the problem of collinearity. Only combinations with a Cronbach’s alpha higher than 0.7 are kept, a conservative level often used in the field [14,38]. Adding Afrobarometer and climatic variables, we have 51 potential predictors of CCP. For all independent variables, missing values are handled using non-parametric imputation with the R package *missRanger* [43].

*Methods*

We analyse what shapes climate change perceptions in Africa using Random Forest methodology [44]. This machine-learning approach uses non-parametric recursive partitioning to produce models with high predictive accuracy [11]. It can handle high-dimensional (with a large number of predictors) multilevel datasets with high-level interactions and non-linear relations [42], so it is ideal for our dataset. For each dependent variable, we grow a random forest composed of 1,000 trees with a minimal node size of 5, using the *ranger* package in R [45]

Despite its advantages, Random Forests are not easily interpretable on their own. To interpret them, we use some additional measures. First, we compute the variable importance measure, that ranks predictors by their predictive power (including direct and indirect effects on the dependent variable). We use the corrected Gini method to do so, because it shows no bias towards predictors with more classes, in contrast to the permutation method [46]. This measure shows which are the most important predictors that shape CCP but does not assess whether they are significant or not. Second, we use the Altmann permutation method to compute p-values and test predictor significance, using 100 permutations for each forest, as recommended by the authors [47]. We use the *ranger* package in R [45] to compute those measures. Finally, we use partial dependence plots to illustrate the magnitude and direction

of the direct effects of significant predictors. Partial dependence plots work like marginal effects in logistic regression models: they predict responses for each level of the predictor while holding the rest of variables constant. We use the *randomForestSRC* package for generating these plots [48].

**Results**

*CC awareness*

Fig. 1A presents the most important predictors for being aware of climate change in Africa. Education level and the frequency of access to online news (via the internet and social media) are fundamental for CC awareness. Both have positive effects. Perceiving that climate conditions for agricultural production (*agric. cond.*) have changed in the last decade is positively related to CC awareness, but the effect is higher for perceived worsening (positive values), as Fig. 1B illustrates. Ideology and interest in politics are also important covariates. Authoritarians (being favourable to one-party rule) significantly decreases awareness, while talking about politics has the opposite effect. We find a gender gap for awareness, as women are about 5.4% less likely to know about climate change. Long-term changes in weather conditions at the second administrative level are important predictors of being aware of CC. Higher temperatures, lower precipitations and more severe droughts (SPEI) are associated with higher CC awareness, but their direct effects are of less magnitude than education, information or ideology. Regarding religion, we find mixed results: while being religious (any denomination) has a positive relation, supporting the rule of religious law reduces CC awareness. All predictors included in Fig. 1B are significant at 1%.

**Fig 1**



*Belief in human cause*

Fig 2A shows the most important predictors of believing in the human causation of CC. Local weather changes are the main predictors, above education, information or ideology. A 1 SD rise of mean temperatures is associated with almost a 6pp increase in belief in human cause. Changing precipitations have the opposite effect, with less magnitude.





**Discussion**

**Acknowledgements**

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**Figure legends**

**Figure x.** [listed one after another; do not add legend to figure files; do not embed figures in this file; present each figure with a short summary of 15 words followed by a more comprehensive description]

**Tables**

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